Imperial College London
Business School

Trading Strategies in Futures Markets

James Grant

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Abstract

The purpose of this thesis is to investigate trading strategies based on futures contracts. The first chapter demonstrates and analyzes the exceptional performance of both carry and momentum strategies in future markets across asset classes (commodities, bonds, equities, and currencies). Individual carry and momentum returns have low correlation, generating a significant diversification benefit in the combined portfolio and a Sharpe ratio of 1.4. Individually and combined, carry and momentum strategies have significant returns not explained by the CAPM or risk factor models. However, carry returns disappear after adjusting for lagged macroeconomic variables, suggesting performance is related to business cycle risk. Expected momentum returns are only weakly related to macroeconomic variables, but co-vary significantly with hedge fund capital flow - indicating returns are related to limits to arbitrage constraints of hedge funds.

The second chapter establishes the economic significance of carry and momentum trading signals. We use a model incorporating a time varying investment opportunity set into a parametric portfolio framework and derive optimal portfolio parameters. Without any ex-ante imposed relation, in-sample portfolio parameters are found to be consistent with the results of the first chapter. Furthermore, out-of-sample returns are found to be highly significant, robust to transaction costs and not compensation for traditional risk exposure, time-varying risk due to macroeconomic cycles, or funding liquidity. Out-of-sample returns are significantly related to pro-cyclical hedge fund capital flows, suggesting expected returns decrease with speculative capital.

The third chapter applies our parametric portfolio framework to assess the economic significance of predictors important in commodity markets since 2001. The studied predictors are widened to include hedging pressure and three market wide predictors found in the literature to forecast returns. In contrast to our results for the whole futures market, we find little evidence for economically significant commodity strategy returns for either individual or combined predictors.

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Declaration of Originality

'I herewith certify that this thesis constitutes my own work and that all material, which is not my own work, has been properly acknowledged'

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To my father

Introduction

Trading strategies are systematic rules to determine asset allocation. Behind their construction is the notion that contemporary information, whether asset specific or market wide, can predict expected returns. The performance of trading strategies is an intriguing feature for both financial economists - who read the implied predictability as a challenge for models of market efficiency - and financial practitioners - who exploit strategy performance for tactical portfolio allocation. Trading strategies have spurned a wealth of research from the academic community, examining the performance of strategies and the predictive power of the trading signals they are based on. Historically, these studies have generally focused on a single trading strategy in a single asset class. However, studying strategies in isolation can obscure common drivers across markets and types of strategy. To address this research gap, this thesis investigates various trading strategies in futures markets across different asset classes to compare the economic value of strategies, reveal common drivers of return, and understand the effect of trading strategies on the wider market.

In the first two chapters of this thesis we focus on the popular **carry** and **momentum** strategies, before broadening our choice of signals to include other predictors in the final chapter. Both carry and momentum trading strategies have large streams of literature. However, these streams have followed starkly different paths. Carry has traditionally been studied within currency markets, whereas, momentum finds its root in equity markets. We now discuss each of these veins of literature.

We define carry in the modern sense (Koijen, Moskowitz, Pedersen, and Vrugt (2013)) as a property embedded in the term structure of futures prices. Following Koijen, Moskowitz, Pedersen, and Vrugt (2013), we decompose the expected return on a futures contract into the expected return of the spot price and carry. This is a convenient definition since for any asset with a term structure, carry can be measured. Another way of thinking about carry is as the expected return from holding a futures contract until expiry when all market conditions remain the same. Carry is positive when the far-dated futures price is less than the near-dated, labeled backwardation, or negative when the near dated contract trades below the far-dated, labeled contango. Although the notion of carry was not unified across asset classes until the work of Koijen, Moskowitz, Pedersen, and Vrugt (2013), equal or similar concepts are found across asset classes. We now consider the relevant streams of literature that define carry for different asset classes that come under the futures market umbrella.

The earliest observations pertaining to carry in futures markets date back to analysis of the spread between spot and forward price of commodity futures. In Treatise on Money, economist John Maynard Keynes argued commodity futures markets exhibit **"normal backwardation"**, where the futures contract price is below that of the expected spot(Keynes (1930)), due to price pressure from producers. More recently, studies label the same phenomena a risk premium, examples for commodities include Bodie and Rosansky (1980), Dusak (1973) and Fama and French (1987). In a similar vein, Breeden (1980) relates commodity risk premia to consumption. An alternative but related explanation of the term structure of commodities is given by the **Theory of Storage**. The theory explains carry as the interest forgone in storing the commodity, warehousing costs, and a convenience yield from holding the inventory. Fama and French (1987) compare the Theory of Storage to the normal backwardation model. Due to the variation in the expected premium, Fama and French (1987) fail to find evidence for the risk premium model for individual commodities and only report weak evidence for combined portfolios of commodities. The evidence for the Theory of Storage is stronger, with variation in the futures basis significantly related to interest rate, warehousing costs, and inventories[1]. Recently a stream of literature has emerged looking at the connection between the commodity and financial markets. These studies argue who trades matters, both from perspective of the risk-bearing capacities of speculators and the hedging demand of commodity producers. From the speculators view, Etula (2013), emphasizes the balance sheet strength of securities brokers-dealers as an important determinant of risk premia and return volatility in commodity markets, Cheng, Kirilenko, and Xiong (2014) reach similar conclusions studying the activity of financial traders before and after the 2008 crisis. From the hedgers perspective, Acharya, Lochstoer, and Ramadorai (2013) relates the hedging pressure of producers to commodity risk premia and finds that decreases in hedging costs fluctuate with the strength of the financial sector.

We next turn to the currency carry literature, where the positive return on carry trades is a well recognised violation of uncovered interest-rate parity(UIP). The concept of UIP assumes that all currencies should have the same expected return. In a market where spot and currency futures are traded, futures contracts for currency pairs should be directly determined by the differential in interest rates between currencies. However, this has been shown to be violated with carry generating a positive return. One of the earliest examples of carry in currency markets is Meese and Rogoff (1983), who find significant returns are generated from borrowing in low interest currencies to invest in high interest currencies (see also the surveys of Froot and Thaler (1990), Lewis (1995) and Engel (1996)).

The persistent performance of currency carry has recently generated a spate of theories to explain the anomaly. Brunnermeier and Pedersen (2009) argue carry is generated by crash risk, predicated by reduced liquidity. Mancini, Ranaldo, and Wrampelmeyer (2013) also relate carry returns to liquidity and demonstrate similarities with bond markets. Farhi and Gabaix (2008) and Lustig and Verdelhan (2008) relate carry to consumption risk. Lustig, Roussanov, and Verdelhan

[1]The role of inventories represents a vein of literature itself. After Working (1933)'s initial study of annual wheat fluctuations, Brennan and Schwartz (1985) increase the frequency of observations to a monthly frequency and study more commodities (eggs, cheese, butter, wheat, and oats); Pindyck (1994) studies inventories for heating oil, copper, and lumber; and Geman and Nguyen (2005) for soybeans. Gorton, Hayashi, and Rouwenhorst (2012) relate inventories to convenience yield price measures including risk premia. Casassus and Collin-Dufresne (2005) introduce a stochastic convenience yield reduced form model. Frankel (2014) studies inventories and the carry trade.

(2011) argue currency carry is explained by a global risk factor. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) find carry returns are due to a peso problem. We also see similar themes in the commodities literature. For instance, Bailey and Chan (1993) find that basis reflects systematic macroeconomic risks common to all asset markets (proxied by divided yield and default spread). Consequently, commodity carry returns are related to macroeconomic factors. Liquidity is also a factor (Acharya, Lochstoer, and Ramadorai (2013)).

Most recently, Koijen, Moskowitz, Pedersen, and Vrugt (2013) study carry across a range of asset classes including global equities, global bonds, commodities, US Treasuries, credit, and options. Calculating carry across asset class reduces noise and provides a powerful lens with which to understand the fundamental drivers of carry. Other recent work links currency and commodity markets, such as Hong and Yogo (2012)'s study of predictability of open interest, and Bessembinder (1992) and De Roon, Nijman, and Veld (2000), who find futures markets to be segmented and that hedging pressure determines risk premiums.

The second trading strategy we consider is **momentum**. Momentum describes the empirical finding amongst stocks that past 'winners' outperform past 'losers'. For a given set of assets, this feature is traditionally examined by sorting assets based on past returns and forming a portfolio with a long position in the top performing assets and a short position in the worst performing assets. Using this methodology, Jegadeesh and Titman (1993) and Jegadeesh and Titman (2001) provide early examples of momentum for equity markets. They find that the relative stock outperformance uncovered by momentum strategies cannot be captured by linear factor models such as the CAPM models of Sharpe (1964) and Lintner (1965), or Fama and French (1993)'s 3 factor model. Indeed, although many pricing anomalies are explained by a combination of equity and bond factors (Fama and French (1996)), these common factors fail to explain momentum. The failure of time-varying expected returns embedded in these models appears to counter Fama (1970)'s efficient market hypothesis. Under this hypothesis, prices should incorporate all publicly available information. Therefore, past information, defined as past returns in the case of momentum, should not predict future returns.

The puzzle of momentum is not limited to US equity markets. Momentum is observed across a range of asset classes and subclasses. Moskowitz and Grinblatt (1999) argue the equity momentum observed by Jegadeesh and Titman (1993) is rooted in industry momentum. Momentum is observed internationally in stocks (Rouwenhorst (1998), Griffin, Ji, and Martin (2003), Griffin, Ji, and Martin (2005) and Leippold and Lohre (2012)) and between sorted portfolios of international equity indices (Chan, Hameed, and Tong (2000) and Bhojraj and Swaminathan (2006)). Nor is momentum limited to equities: Pirrong (2005), Baltas and Kosowski (2015) and Asness, Moskowitz, and Pedersen (2013) find momentum in futures markets; Miffre and Rallis (2007) and Shen, Szakmary, and Sharma (2007) specifically in commodity futures markets. In currencies markets, Okunev and White (2003) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) find the momentum anomaly. Moskowitz, Ooi, and Pedersen (2012) provide an overview of momentum across asset classes.

The ubiquitous presence of momentum across asset classes coupled with its persistence over time has led to a quest to reconcile its abnormal returns with the theories of asset pricing of the day. These explanations separate into two camps: rational and behavioural.

Rational expectations models require that market participants expectations of asset prices are equal to the true statistically expected values, though rational agents can still require compensation for bearing risk and the associated risk premium can be time-varying. Rational expectations theories of momentum relate the stock price autocorrelation of momentum to cross-sectional differences in the pricing kernel. For instance, Liu and Zhang (2008) find that recent winners load more on macroeconomic risk than past losers for short periods of time. Therefore, winners will have higher expected returns in the following period, with the converse true for losers. This relation supports positive expected returns from momentum portfolios; other examples are given by Berk, Green, and Naik (1999), Johnson (2002), Ahn, Conrad, and Dittmar (2003), and Sagi and Seasholes (2007).

An alternative rational argument to explain momentum is given by time-varying expected returns (Fama (1970)). For passive investments, variation in expected returns can be rationally predicted due to time-series variation in the pricing kernel related to business cycles, predicted by macroeconomic variables (Fama (1991) provides a review of this relation for equities, Weiser (2003) finds it for commodities). Chordia and Shivakumar (2002) and Griffin, Ji, and Martin (2003) apply this reasoning to explain equity momentum.

Behavioural models of momentum use arguments based on experimental psychology. From this perspective momentum is the result of agents' initial under-reaction or delayed over-reaction. Initial under-reaction can result from the slow diffusion of news (Hong and Stein (1999) and Hong, Lim, and Stein (2000)), conservatism (Barberis, Shleifer, and Vishny (1998)), and the disposition effect, where investors tend to ride losses and realize gains (Frazzini (2006)). Overreaction can be caused by representativeness (Barberis, Shleifer, and Vishny (1998)), the herd effect (Bikhchandani, Hirshleifer, and Welch (1992)), overconfidence and biased self-attribution (Daniel, Hirshleifer, and Subrahmanyam (1998)), positive feedback (Long, Shleifer, Summers, and Waldmann (1990)) or investor sentiment (Baker and Wurgler (2006)).

Momentum has traditionally been studied using long-short portfolios based on an asset's *relative* performance versus its peers. However, recently a new stream of literature has emerged that studies **time-series momentum** (Moskowitz, Ooi, and Pedersen (2012) and Baltas and Kosowski (2015)). Time-series momentum is a new portfolio formation methodology where the decision to go long or short the asset is based on each asset's *own* past performance. To differentiate the portfolio construction methodologies, traditional momentum is labeled **cross-sectional momentum**. Moskowitz, Ooi, and Pedersen (2012) note that the construction of time-series momentum is a closer match to the single risk asset theories, which pertain to explain cross-sectional momentum. This is the case for both rational (Berk, Green, and Naik (1999), Ahn, Conrad, and Dittmar (2003) and Liu and Zhang (2008)) and behavioural explanations (Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999)).

Another recent trend in the trading strategy literature studies the performance of trading strategies across asset classes and strategy types. By combining strategies, idiosyncratic noise is reduced, providing a powerful lens to uncover common factors influencing trading strategies in general. Koijen, Moskowitz, Pedersen, and Vrugt (2013) study carry across global equities, global bonds, commodities, US Treasuries, credit, and options. For momentum, Pirrong (2005) and Baltas and Kosowski (2015) study futures markets; encompassing commodities, precious metals, interest rate futures, and equity indices. Moskowitz, Ooi, and Pedersen (2012) study momentum across a range of asset classes: equities, bonds and various classes of futures contract. For a similar dataset, Asness, Moskowitz, and Pedersen (2013) study value and momentum strategies together. Carry and momentum have also been studied jointly for commodities (Fuertes, Miffre, and Rallis (2010)) and for currency markets (Burnside, Eichenbaum, and Rebelo (2011)).

Chapter 1 builds on the literature by jointly studying carry and momentum across the futures asset classes: commodities, currencies, bonds, equities and metals. The study is novel in two ways: (1) It is the first to analyze both carry and momentum across asset classes and (2) it introduces the concept of predictability of an asset's own signal, seen in Moskowitz, Ooi, and Pedersen (2012) for momentum, into carry strategies, generating the new concept of **time-series carry**. The second novel feature is in contrast to traditional studies of carry, which sort currency pairs by their spread, then form a long-short portfolio of the top and bottom quintile spreads.

We find low, but time varying, correlation between carry and momentum, leading to a significant diversification benefit to holding the combined portfolio. For the all asset class (global) portfolio, combining carry and momentum improves Sharpe ratio above that of the strategy portfolios, and reduces the frequency and magnitude of draw-downs. Individually, neither carry nor momentum is explained by the CAPM (Sharpe (1964)) or Fama and French (1993) factors. Furthermore, even when the strategies are considered in isolation by asset class, effectively reducing diversification benefit, returns are not explained by the CAPM model, with the exception of bond momentum.

To investigate the source of the phenomenal performance, particularly of the global portfolio, we focus on the relative importance of common systematic sources of risk premia and limits to arbitrage. We find that the returns across asset class are distinct from the "Value and Momentum Everywhere" factors of Asness, Moskowitz, and Pedersen (2013) and are not explained by Pastor and Stambaugh (2001)'s liquidity factors. However, carry returns do appear to be explained by business cycles and their relation to lagged macroeconomic factors, suggesting that carry returns are compensation for time-varying risk premia. This finding confirms those of Koijen, Moskowitz, Pedersen, and Vrugt (2013), who relate carry return dynamics to recession and expansion periods. Momentum returns are not explained by time-varying risk premia but co-vary significantly with hedge fund capital, suggesting momentum returns are greater when limits to arbitrage are imposed on hedge funds, similar to Acharya, Lochstoer, and Ramadorai (2013)'s findings for the commodity market.

Given the exceptional performance of carry and momentum strategies demonstrated in Chapter 1, Chapter 2 attempts to assess the economic value of carry and momentum predictors to an investor facing realtime capital allocation choices. Choosing portfolio weights based on realtime data provides an intuitive metric for the economic value of trading signals, removing the pernicious effects of look ahead bias and data snooping - a legitimate concern with the traditional ex-post evaluation of trading rules.

To test the out of sample strategy performance we construct parametric portfolio policies following the methodology of Brandt, Santa-Clara, and Valkanov (2009). For each asset, portfolio weights are parameterized as a linear function of the asset's carry and momentum trading signals in a given month. The parameters of the function are labeled the portfolio policy and are constant across assets and in time. The optimal portfolio policy is calculated ex-post to maximise the realised utility of past returns for an investor with constant relative risk aversion (CRRA). Out of sample returns are calculated iteratively, where each month portfolios weights are allocated based on the preceding months optimal policy.

We first estimate parametric portfolios in-sample from 1981 to 1991. Without any pre-imposed trading rules, the in-sample results confirm the carry and momentum predictive relations found in Chapter 1, seen as large and significant estimates for carry and momentum policy coefficients. Out-of-sample returns are estimated in the period from 1992 to 2012. The out-of-sample results confirm those of our in-sample analysis: parametric futures portfolios have significant policy parameter estimates, and are found to generate large and significant risk premia. The Sharpe ratio of the portfolio is 1.2, and the certainty equivalent gain for a CRRA investor in the dynamic portfolio policy portfolio versus the risk free rate is equal to 15%. To test whether the returns are due to the predictive properties of carry and momentum, and not to the commodity market or the dynamic portfolio allocation, we compare parametric portfolio returns with a dynamic allocation to a long only portfolio of futures based on past returns. Although the long only portfolio has significant returns over the risk free rate, the parametric portfolio retains a performance increase in certainty equivalent of 8% when compared to the long only portfolio.

We find no evidence that performance of parametric futures portfolios is explained by traditional risk factors or liquidity risk. However, we find performance is related to business cycles, consistent with the mechanism suggested by Chordia and Shivakumar (2002) and our findings in Chapter 1. We also find evidence that parametric portfolio returns are significantly related to hedge fund capital, supporting the hypothesis that futures markets are segmented (Duffie and Strulovici (2012)) from the wider economy and limits to arbitrage of capital constrained hedge funds lead to greater market inefficiencies, reflected by carry and momentum returns.

The relationships between carry and momentum strategies and hedge fund capital demonstrated in Chapters 1 and 2 have important implications for both market practitioners and policy makers. Practitioners should be aware that momentum returns, which may have looked attractive in times of reduced hedge fund liquidity, are likely to decrease when liquidity constraints are eased. For policy makers, who face a complex task of balancing the needs of many interests, our findings highlight that increasing capital requirements and regulation, such as the policy shift seen in reaction to the 2008 financial crisis, could have the unintended consequence of increasing inefficiency in futures markets.

Chapter 3 uses the parametric portfolio methodology to ask the question: Are predictors for commodity returns economically significant? We present a surprising finding that, despite the successes of the previous chapters for the futures market as a whole, there is little evidence of out-of-sample predictability in commodities since 2000. This result holds even when we add extra predictors known to have power in-sample for commodities markets; these are hedging pressure, defined as the net position of market participants classified as hedgers (De Roon, Nijman, and Veld (2000)), and three market wide predictors: the Baltic Dry Index (Bakshi, Panayotov, and Skoulakis (2011)), aggregate open interest of futures contracts (Hong and Yogo (2012)), and output gap growth, the difference between actual and expected GDP (Cooper and Priestley (2009)).

We start by estimating portfolio characteristics and returns based on a consistent set dataset of 19 commodities from 1990 to 2000. During this in-sample period we find highly significant returns for the portfolio based on all the characteristics, with a Sharpe of 2.1. For portfolios based on a single characteristic we find a mixed picture, momentum and market wide factors generate strong in-sample returns, but carry and hedging pressure fail to produce significant returns or parameter estimates.

To assess whether returns are economically significant, we follow DeMiguel, Garlappi, and Uppal (2009) and introduce the idea of an opportunity cost, the amount a representative investor would pay to switch from an equally weighted portfolio of commodity futures to the parametric portfolio. Out of sample, for the period from 2000 to 2013 we find no case, either for individual or combined characteristics, where an investor would pay a significant fee to switch from a naive long only portfolio. In fact, in many circumstances we find the investor would pay a fee to hold the equally weighted portfolio, rather than the commodity parametric portfolio. The poor performance of parametric commodity portfolios are robust to varying levels of investor risk aversion, different sub-classes of commodity, and different market regimes. In light of the previous chapters results, we therefore conclude that carry and momentum strategies perform well across asset classes individually and combined in-sample; that carry and momentum strategies perform well out-of-sample across asset classes; but neither carry, momentum, nor other popular predictors produce economically significant returns out-of-sample for commodities in the period since 2000.

Chapter 4 presents some concluding remarks.

Chapter 1

The returns to carry and momentum strategies[1]

I. Introduction

In this chapter we provide an in-depth empirical analysis of carry and momentum strategies across 55 global futures contracts spanning the asset classes bonds, currencies, commodities, equities and metals. We provide new evidence on the economic drivers of the individual and joint dynamics of the strategy returns within and across asset classes. Our study complements recent work on the individual strategy types across asset classes by Moskowitz, Ooi, and Pedersen (2012) for momentum, and Koijen, Moskowitz, Pedersen, and Vrugt (2013) for carry. Compared to the individual strategies, we find that combining carry and momentum improves Sharpe ratio, and reduces the frequency and magnitude of draw-downs. We show that neither the carry, momentum, nor combined strategy returns can be explained by traditional risk factors. From an economic perspective, however, we show that returns to carry strategies across asset classes can be explained by a set of lagged macroeconomic variables, consistent with the existence of time-varying risk premia. In contrast, momentum strategy returns cannot be accounted for by macroeconomic fluctuations, but are significantly related to measures of hedge fund capital flow. Studying these two findings together and over time our results show: While momentum strategies were highly co-moving with carry strategies and therefore business cycle predictors between 1994 and 2002, when hedge fund assets under management (AUM) was low, the correlation has since decreased. The decrease in correlation has coincided with significant increases in hedge fund AUM, providing evidence that limits to arbitrage have become more relevant in explaining momentum returns.

The key feature of our analysis is to examine the returns to carry and momentum strategies across a wide set of markets and asset classes together. The power of looking at all asset classes and strategies together greatly improves the ability to identify common factor structures (see Asness, Moskowitz, and Pedersen (2013)). Carry strategies relate the directly observable current spread between futures and spot price to the expected return on an asset (Koijen, Moskowitz, Pedersen, and Vrugt (2013)), while momentum strategies resort to a purely statistical measure that relates an asset's expected return to its own past returns (Moskowitz, Ooi, and Pedersen (2012)). From an

[1]The work in this chapter appears in Ahmerkamp and Grant (2013b)

efficient markets perspective momentum strategies are a direct test of the random walk hypothesis, while carry strategies are a direct measure of expected return or risk premia when expected price appreciation is assumed a random walk. Observing the returns of both strategies together provides an avenue for identification strategies to disentangle the role of behavioral limits to arbitrage effects on futures returns from systematic risks associated with time-varying expected returns.

We start our empirical analysis by forming portfolios of futures contracts in commodity, currency, equity, bond and metals markets based on carry and momentum signals. We choose to study asset returns related to an asset's *own* signal (referred to as time-series carry or time-series momentum) rather than constructing portfolios by ranking securities based on the *relative* strength of the security's respective trading signal (referred to as cross-sectional carry or cross-sectional momentum). Traditionally, studies of carry or momentum have focused on the cross-sectional methodology, however, more recently Moskowitz, Ooi, and Pedersen (2012) and Baltas and Kosowski (2015) have investigated time-series momentum. In this paper we extend the time-series concept to carry, leading to several significant empirical contributions. For the sake of brevity, unless otherwise stated references henceforth to carry or momentum indicate time-series carry or time-series momentum, respectively.

We find ubiquitous evidence of carry and momentum return premia across all asset classes we study. Global strategies, that are volatility weighted averages across asset classes, generate Sharpe ratios of above 1.2 for the momentum signal and up to 1.3 for carry strategies. Surprisingly, the average correlation between carry and momentum strategies is almost zero - though highly time varying - which generates a diversification benefit when combining carry and momentum strategies into one portfolio. Combined strategies generate a Sharpe ratio of above 1.4. Even though futures markets do not present any natural short selling constraints, with respect to transaction cost or accessibility, we find that the returns to the short side of the strategies relative to a benchmark or market portfolio contribute to the majority of the profitability of momentum and carry strategies. This might be explained by constrained market participants who are restricted in trading short positions. The reduced arbitrage activity and arbitrage capital could lead to market frictions and therefore higher returns, see e.g. Stambaugh, Yu, and Yuan (2012). Furthermore, we show that the profitability of carry and momentum strategies varies significantly over time, which might induce limits to arbitrage for hedge funds or other major market participants, who often have short investment horizons and thus may act myopically.

To investigate the source of the abnormal strategy returns, we focus on the relative importance of common systematic sources of risk premia and institutional investment in the form of arbitrage capital deployed by hedge funds. First, following the methodology of Chordia and Shivakumar (2002), we test whether carry and momentum returns are explained by common macroeconomic variables known to be related to business cycles, as noted by Bessembinder and Chan (1992). Using the lagged values of the dividend yield, default spread, three-month T-bill yield and term spread to predict one month ahead returns, we show that the predicted component of carry returns is the primary cause of the observed carry returns. This finding extends the analysis of Koijen, Moskowitz, Pedersen, and Vrugt (2013), who show that carry return dynamics are related to recession and expansion periods, and confirms carry strategies are compensation for time varying risk premia. Our analysis uncovers interesting dynamics and time variation in the return premia that seem at odds with current financial economic theories. The fitted risk premia behave procyclically, in that they are high when economic activity is high and are low when economic activity is low. The returns to momentum strategies behave similarly to carry strategies but are statistically insignificant - or at best weakly significant - related to macroeconomic variables. Furthermore, the variation does not explain the observed return premia. For comparison, we investigate the time varying risk premia for long only strategies and find that they behave counter cyclically, confirming and updating the findings of Bessembinder and Chan (1992) for an extended dataset over a wider number of futures contracts.

Second, we study the relation between hedge fund returns and capital flows with carry and momentum strategy returns. Interestingly, carry and momentum strategies explain on average a larger fraction of returns to hedge funds than the factors of Fung and Hsieh (2004). Given the importance of carry and momentum in explaining hedge fund returns, we next investigate the relation between capital flows and strategy returns. We find that momentum strategies are significantly related to lagged variables of hedge fund capital, with increases in hedge fund capital followed by reduced strategy returns. This effect is consistent with the predictions of limited arbitrage capital (see e.g. Jylhä and Suominen (2011)). These findings suggest: an increase in hedge fund capital reduces constraints to arbitrage for inefficiencies in futures markets and therefore reduces expected returns. We next investigate the relation between hedge fund capital and momentum returns over time. We find that the effects of limited arbitrage capital are stronger in the second half of the sample, which coincides with higher hedge fund capital flows. However, carry strategies are not related to capital flows.

We also uncover interesting dynamics with respect to carry and momentum returns, their correlation across markets, and the relation to hedge fund capital over time. Momentum returns across markets are less profitable and more correlated over time, while the profitability and correlation of carry strategies remains constant. At the same time, the correlation between carry and momentum strategies across markets decreases. We report that carry strategies are particularly profitable during periods of high S&P 500 returns, while momentum strategies are more profitable during S&P 500 downturns. In addition, we find that the correlation of carry and momentum strategies is highly related to hedge fund capital with decreased correlation when capital flows are high. This effect is more pronounced in the second half of the sample. In a final investigation we combine all results and find that, while momentum is highly correlated with carry strategies and therefore with macroeconomic variables; when the total hedge fund capital was low the correlation between the strategies becomes negligible, with the capital of hedge funds explaining most of the momentum return variation in the second half of the sample when total hedge fund AUM became high.

Our study is related to the growing literature on global asset pricing that analyzes multiple trading strategies in a variety of markets and asset classes jointly. Studying different markets and trading strategies together helps to identify and rule out various explanations for the return premia that could not have been found in isolation. Asness, Moskowitz, and Pedersen (2013) study cross-sectional momentum and value strategies within and across individual equity markets, country indices, government bonds, currencies, and commodities simultaneously. They find that the strategies are globally affected by market and funding liquidity risk and are consistently positively correlated within strategy and negatively correlated across value and momentum. Fama and French (2012) study their three factor model consisting of size, value, and momentum factors across global asset markets and find that a global version of their model does not explain global returns. Israel and Moskowitz (2013) examine if shorting, firm size, and time has an effect on the profitability of size,value and momentum strategies.

Our study is also related to the literature that studies individual strategies across asset classes. Koijen, Moskowitz, Pedersen, and Vrugt (2013) study cross-sectional carry strategies within and across the same asset classes we study. They find that the carry strategies across asset classes underperform simultaneously, with times of poor performance coinciding with periods of global recessions and liquidity crises. Moskowitz, Ooi, and Pedersen (2012) document significant risk adjusted returns for time series momentum strategies across equity index, currency, commodity, and bond futures and link them to the trading behavior of speculators in futures markets. Baltas and Kosowski (2015) extend their study by increasing the frequency of the strategy rebalancing from a monthly to weekly and daily frequencies and present evidence that trend following fund returns are indeed exposed to those factors.

In addition to studies across asset classes, a large literature studies individual strategies in individual asset classes. First, carry strategies in currency markets have been studied by Brunnermeier, Nagel, and Pedersen (2008), Lustig and Verdelhan (2008), Gabaix (2008) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), who explain the return premia with macroeconomic risk explanations such as consumption risk, liquidity risk, crash risk or volatility risk. Momentum strategies in currency markets have been studied by Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), who argue that limits to arbitrage have an effect on the profitability of these strategies. Carry and momentum strategies have also been studied individually in commodity markets by Gorton and Rouwenhorst (2004). The literature on momentum in equity markets is exhaustive. We refer to Moskowitz (2003) for an excellent review.

The remainder of this paper proceeds as follows: Section II details our data, the assumptions made in constructing returns and the carry and momentum portfolio construction; Section III characterizes the returns to carry and momentum in terms of returns and alpha generation, and the influence of long and short positions; Section IV discusses the results of our tests seeking to explain the high returns to carry and momentum strategies by comparing the relative value of systematic factors and institutional ownership; Section V explores what we can learn from momentum by observing carry; and Section VI concludes.

II. Returns, Leverage and Trading Strategies

This section describes our data, the computation of excess returns in futures markets and the construction of carry and momentum portfolios across asset classes.

A. Data Set and Sample Contracts

Our dataset consists of closing prices of first and second to maturity futures contracts for 55 assets, spanning the asset classes: commodities (17 contracts), currencies (9 contracts), bonds (12 contracts), equities (10 contracts) and metals (7 contracts) from Bloomberg. Our analysis is carried out at monthly frequency, although we collect daily price data to construct volatility estimates. To avoid issues around price irregularities between cash and futures price such as transaction and delivery costs we focus our study on futures prices and avoid the use of spot prices entirely.

The first column of Table 1.1 lists all 55 futures used in this study. The second column displays the earliest date of available data for each futures contract. We note that our effective sample size of available contracts for the analysis varies over time. The start dates range from January 1980 for many commodities to March 2004 for the equity index FTSE MIB. To illustrate this point further, Figure 1.1 displays the number of assets available over time distinguished by asset class. The sample starts with 12 futures contracts, mostly commodities, the size then increases monotonically, reaching 55 futures contracts in March 2004 spread across all asset classes.

B. Excess Futures Returns

Individual futures contracts have a finite life defined by the contractual delivery date. Contracts require no cash payments before maturity besides margin payments that constitute a fixed percentage of the notional value[2]. Therefore, in contrast to calculating equity returns, calculating futures returns requires some further assumptions. We construct and define returns by assuming that an investor allocates $M_{i,t}$ dollars of capital today, denoted by time t, to finance a futures contract on asset i[3]. The current futures contract at time t of asset i that expires in period T is denoted as $F_{i,t}^{T}$ where $t < T$. Furthermore, we assume that the investor opens a futures position in the most liquid futures contract, which is typically the nearest or next nearest to delivery contract, and is not within the delivery month. At time $t + 1$ the value of the initial dollar allocation $M_{i,t}$, assuming it can be invested in a risk free money account, yielding r^f, and the price change in the

[2]Here we abstract from infrequent margin changes by futures exchanges (Daskalaki and Skiadopoulos (2013))

[3]$M_{i,t}$ must be at least as big as the margin requirement set by the respective futures exchanges

futures contract results in a total value of $M_{i,t}(1+r_t^f)+F_{i,t+1}^T-F_{i,t}^T$, is given by,

$$R_{i,t+1}=\frac{M_{i,t}(1+r_t^f)+F_{i,t+1}^T-F_{i,t}^T-M_{i,t}}{M_{i,t}}=\frac{F_{i,t+1}^T-F_{i,t}^T}{M_{i,t}}+r_t^f. \tag{1.1}$$

Consequently, the return in excess of the risk free rate is

$$r_{i,t+1}=\frac{F_{i,t+1}^T-F_{i,t}^T}{M_{i,t}}. \tag{1.2}$$

The third and fourth columns of Table 1.1 present summary statistics for the fully collateralized futures returns for all asset classes. These statistics are calculated by setting $M_{i,t}=F_{i,t}^T$ in equation 1.2. In agreement with the recent literature on futures markets (e.g. Koijen, Moskowitz, Pedersen, and Vrugt (2013), Moskowitz, Ooi, and Pedersen (2012), De Roon, Nijman, and Veld (2000) and Baltas and Kosowski (2014)) we find a large variation in sample mean returns across the different contracts. Bonds and currencies generate consistent positive excess returns on average over the sample, while for commodities and metals only half of the contracts have positive average excess returns. In equities most series have positive excess returns with the exception of TOPIX and FTSE MIB which are negative.

More striking, and important for the comparability and construction of a diversified portfolio across asset classes, is the cross-sectional variation in volatilities. Commodities and metals consistently display the highest volatilities, followed by equities and currencies. Not surprisingly, bonds have the lowest annual standard deviations. Even between assets of the same class, sample variation in volatility can be significant. For example, within commodities Cattle displays a volatility of 15 percent, while Natural Gas is three times as volatile at 48 percent. To account for the different volatilities within the cross-section of assets we introduce the concept of a leverage factor.

C. Leverage Factor

The generalized definition of the return process in Equation 1.2 allows adjustment of the leverage factor, $M_{i,t}$, in both the cross-section and the time series of futures returns. We set $M_{i,t}=\sigma_{i,t}F_{i,t}^T$, where $\sigma_{i,t}$ is the ex-ante volatility of asset i, estimated as the mean absolute value[4] of daily returns over the previous 3 months[5]. The volatility weighting of the leverage factor follows the method of Moskowitz, Ooi, and Pedersen (2012) and Baltas and Kosowski (2014), and addresses the disparity in volatility across assets, effectively setting the ex-ante volatility of each leveraged futures return to unity. The alternative would be to equally weight assets as is often done in cross-sectional studies within asset class (For instance, Burnside, Eichenbaum, and Rebelo (2011)

[4]Using the absolute value, instead of the squared returns, reduces the impact of a few extreme returns on the volatility estimator.

[5]For robustness, Appendix IX reports Sharpe ratios for trading strategies based on different possible volatility measures.

in currencies). However, in our case this would lead the higher volatility commodity based assets to dominate portfolio returns and swamp the lower volatility bonds returns, effectively reducing the diversification benefit.

The use of a rolling 3 month window for dynamic volatility estimation means that the leverage factor varies in the time series for each asset as well as in the cross-section across assets. Therefore, ceteris paribus, when a particular asset has high volatility its notional value in the portfolio will be reduced. Since futures markets contain many idiosyncratic risk factors, it is possible for one asset to experience high volatility whilst another is unaffected. Assuming the well recognised persistence of volatility (Chen, Daigler, and Parhizgari (2006)), dynamic volatility adjustment would respond by reducing exposure on the first asset during its higher risk period.

D. *Trading signals*

We next define the trading signal of the time series carry and momentum strategies. In general, we define time series strategies - following Moskowitz, Ooi, and Pedersen (2012) - as strategies that focus purely on a security's *own* signal. In contrast, cross-sectional strategies focus on the *relative* strength of signal in the cross-section. For each asset class we consider the simplest and - to the extent a standard exists - most standard carry and momentum measures. Our aim is not to identify the best predictors in each asset class or a holding period that maximizes the potential profits. Rather, our goal is to maintain a simple and uniform approach that is consistent across asset classes and thus minimizes the pernicious effects of data snooping.

With this methodology in mind, we first fix the holding period to be one month and do not consider different specifications for overlapping periods. Second, we consider the past 12-month cumulative raw return as the momentum signal which is common in the literature (see Moskowitz, Ooi, and Pedersen (2012)). Third, the carry signal is defined as the 12 month average of the futures basis calculated as the proportional difference between the first futures contract and second to maturity contract defined as $\frac{F_{i,t}^{T}}{F_{i,t}^{T+1}} - 1$. With $F_{i,t}^{T+1}$ and $F_{i,t}^{T}$ denoting the price of the time t front and second to maturity futures contracts, respectively. Mean and standard deviation summary statistics for the futures basis of each asset are reported in columns five and six of Table 1.1, respectively. Taking the 12 month average of the futures basis is particularly important for commodities, which feature strong seasonal variations in the term structure (Crain and Lee (1996) is a good example for wheat futures). Furthermore, we believe that a 12-month carry signal is easier to compare to the 12-month momentum signal.

In contrast to the momentum signal, which is a pure statistical measure to detect a trending time series, Koijen, Moskowitz, Pedersen, and Vrugt (2013) show that the carry signal can be interpreted with help of no-arbitrage arguments across all asset classes considered. The most prominent carry signal that has been widely studied in the literature is the currency carry. It is well known that the slope of the futures term structure in currency markets is related to the interest rate differential between foreign and local risk free interest rate (classically, Meese and Rogoff (1983), Hansen and Hodrick (1980) and Fama (1984), and more recently Eichenbaum, Burnside, and Rebelo (2007)) . Second, the equity carry can be rewritten as the expected dividend yield minus the local risk free rate, while the commodity and metals carry is the convenience yield in excess of storage costs. For bonds the definition of carry is more vague but is related to the bond yield plus the "roll down", which captures the price increase due to the fact that the bond rolls down the yield curve. For more details we refer to Koijen, Moskowitz, Pedersen, and Vrugt (2013) for an excellent exposition.

E. Trading Rules and Portfolio Construction

Having defined the trading signals we will now define the trading rules and portfolio construction. The trading strategies are implemented by taking long positions in assets that have a positive carry and momentum signal, respectively, and shorting assets with a negative carry and momentum signal, respectively. The construction is the same as in Burnside, Eichenbaum, and Rebelo (2011) or Moskowitz, Ooi, and Pedersen (2012). In addition to the separate trading strategies, we explore the returns of a trading strategy that takes a long position in an asset if and only if the momentum and the carry signal are positive and a short position if and only if both signals are negative. We call this strategy a combo strategy. The combo strategy is equivalent to a 50/50 combination of a carry and momentum strategy, analogous to the combo strategy in Asness, Moskowitz, and Pedersen (2013). In mathematical terms the trading rule for the momentum signal is defined as

$$x_{i,t}^{Mom} = \begin{cases} +1, & r_{t-12,t}^{i} > 0 \\ -1, & r_{t-12,t}^{i} < 0 \end{cases} \tag{1.3}$$

where $r_{t-12,t}^{i}$ are the past 12-month cumulative returns. The trading rule for the carry signal is defined as

$$x_{i,t}^{Carry} = \begin{cases} +1, & \frac{1}{12}\sum_{j=0}^{12} \frac{F_{i,t-j}^{T}}{F_{i,t-j}^{T+1}} - 1 > 0 \\ -1, & \frac{1}{12}\sum_{j=0}^{12} \frac{F_{i,t-j}^{T}}{F_{i,t-j}^{T+1}} - 1 < 0 \end{cases} \tag{1.4}$$

Finally, the trading rule for the combo signal is defined as

$$x_{i,t}^{Combo} = \begin{cases} +1, & \frac{1}{12}\sum_{j=0}^{12} \frac{F_{i,t-j}^{T}}{F_{i,t-j}^{T+1}} - 1 > 0 \; and \; r_{t-12,t}^{i} > 0 \\ -1, & \frac{1}{12}\sum_{j=0}^{12} \frac{F_{i,t-j}^{T}}{F_{i,t-j}^{T+1}} - 1 < 0 \; and \; r_{t-12,t}^{i} < 0 \\ 0, & else \end{cases} \tag{1.5}$$

The signal of a combo strategy is equivalent to an equally weighted position in a carry and momentum strategy but has the benefit that no money has to be invested if the carry and momentum signal have opposite signs. The realized payoff of the carry and momentum strategies for each individual asset i are then given by

$$z_{i,t+1}^{Mom} = x_{i,t}^{Mom} \frac{F_{i,t+1}^T - F_{i,t}^T}{\sigma_{i,t} F_{i,t}} = x_{i,t}^{Mom} r_{i,t+1} \tag{1.6}$$

for the momentum strategy,

$$z_{i,t+1}^{Carry} = x_{i,t}^{Carry} \frac{F_{i,t+1}^T - F_{i,t}^T}{\sigma_{i,t} F_{i,t}} = x_{i,t}^{Carry} r_{i,t+1} \tag{1.7}$$

for the carry strategy and

$$z_{i,t+1}^{Combo} = x_{i,t}^{Combo} \frac{F_{i,t+1}^T - F_{i,t}^T}{\sigma_{i,t} F_{i,t}} = x_{i,t}^{Combo} r_{i,t+1} \tag{1.8}$$

for the combo strategy. In all three cases we assume the leverage factor $M_{i,t} = \sigma_{i,t} F_{i,t}$.

In order to remain simple and uniform in our analysis, we construct the portfolios of carry and momentum strategies following Moskowitz, Ooi, and Pedersen (2012) and Baltas and Kosowski (2014) as an equally weighted average of the inverse volatility leveraged assets. Specifically, the portfolio return of the momentum strategy is defined as

$$R_{t+1}^{Mom} = \frac{1}{N_t} \sum_{i=1}^{N_t} x_{i,t}^{Mom} 0.2 r_{i,t+1} = \frac{1}{N_t} \sum_{i=1}^{N_t} x_{i,t}^{Mom} 0.2 \frac{F_{i,t+1}^T - F_{i,t}^T}{\sigma_{i,t} F_{i,t}} \tag{1.9}$$

of the carry strategy as

$$R_{t+1}^{Carry} = \frac{1}{N_t} \sum_{i=1}^{N_t} x_{i,t}^{Carry} 0.2 r_{i,t+1} = \frac{1}{N_t} \sum_{i=1}^{N_t} x_{i,t}^{Carry} 0.2 \frac{F_{i,t+1}^T - F_{i,t}^T}{\sigma_{i,t} F_{i,t}}, \tag{1.10}$$

and of the combo strategy as

$$R_{t+1}^{Combo} = \frac{1}{N_t} \sum_{i=1}^{N_t} x_{i,t}^{Combo} 0.2 r_{i,t+1} = \frac{1}{N_t} \sum_{i=1}^{N_t} x_{i,t}^{Combo} 0.2 \frac{F_{i,t+1}^T - F_{i,t}^T}{\sigma_{i,t} F_{i,t}}, \tag{1.11}$$

where N_t is the number of assets available at time t. The scaling factor of 0.2 is chosen to target an ex-ante volatility equal to approximately 20 percent. The choice of scaling factor is arbitrary and is only made to simplify comparison of our strategies with those popular in the market(see Moskowitz, Ooi, and Pedersen (2012)).

To compare the performance of the trading strategies relative to a benchmark, we construct equally weighted portfolios of the volatility adjusted futures returns. These are the long only counterpart to our strategies and are called risk parity portfolios (Asness, Frazzini, and Pedersen (2012)). These portfolios provide a benchmark upon which to compare the relative performance of our trading strategies. We define the long only portfolio as

$$R_{t+1}^{Long} = \frac{1}{N_t}\sum_{i=1}^{N_t} 0.2 r_{i,t+1} = \frac{1}{N_t}\sum_{i=1}^{N_t} 0.2 \frac{F_{i,t+1}^T - F_{i,t}^T}{\sigma_{i,t} F_{i,t}}. \tag{1.12}$$

Even though the volatility weighting in the portfolio construction is only used to make the performance of the different asset classes comparable, it is important to evaluate the returns to the carry, momentum, and combo strategy against a risk parity portfolio. Frazzini and Pedersen (2014) show that if some investors are averse to leverage, low-beta assets will offer higher risk-adjusted returns and high-beta assets lower risk-adjusted returns. Leverage aversion breaks the standard CAPM since it implies the highest risk-adjusted return is not achieved by the market but by a portfolio that overweights safer assets. Thus, an investor who is less leverage averse (or less leverage constrained) than the average investor can benefit by overweighting low-beta assets underweighting high-beta assets, and applying some leverage to the resulting portfolio. Therefore, volatility adjusting portfolio weights may lead to excess returns due to leverage aversion. By comparing our trading strategies to the risk parity portfolio, we focus on the performance of carry and momentum signals, rather than returns from overweighting assets with higher volatility.

Lastly we note that all momentum, carry, combo and long only portfolios are constructed across and within the asset classes currencies, bonds, equities, commodities and metals. We denote the portfolio across all asset classes as the "Global" portfolio.

F. Market, Macroeconomic and Hedge Fund Data Sources

To understand the performance of our trading strategies we use a variety of additional data sources. For risk factor regressions we use; (1) the Fama and French Factor times series taken from Eugene Fama's website[6], (2) the Value and Momentum Everywhere Factor data of Asness, Moskowitz, and Pedersen (2013) taken from the AQR website[7]; (3) a market factor based on the monthly MSCI index taken from Bloomberg; (4) a funding liquidity factor based on the TED spread, the difference between the interbank rate and T-bills, calculated with data taken from Federal Reserve Economic Data (FRED) website[8]; and (5) the liquidity factor of Pastor and Stambaugh (2001) downloaded from Lubos Pastor's website[9]. To calculate macroeconomic price based factors; the rate on T-bills is downloaded from the FRED website, the total dividend payments accruing to the CRSP value-weighted index is taken from Center for Research in Security Prices (CRSP) database, yield rate on US 10 year treasury and 3 month T-bills are taken from the FRED website. Industrial production data is taken from the FRED website. Data for the average yield for Moodys BAA and AAA rated bonds was taken from Bloomberg. Hedge fund style factors (Fung and Hsieh

[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[7] http://www.aqr.com
[8] http://research.stlouisfed.org/fred2/
[9] http://faculty.chicagobooth.edu/lubos.pastor/research/

(2004)) were downloaded from David A. Hsieh's Data Library[10]. Returns for the S&P index were calculated using the S&P total return index downloaded from Bloomberg. Recession indicators were downloaded from Nation Bureau of Economic Research(NBER)'s website[11]. Data for total hedge fund capital available and capital flow to the hedge fund industry was taken from the Barclay Hedge Fund Database. Hedge fund index data was taken from the Credit Suisse hedge fund database.

III. Characterizing Carry and Momentum Returns

Table 1.2 and Table 1.3 show the consistent performance of carry and momentum strategies as well as their combination (combo) within and across (global) the asset classes bonds, commodities, currencies, equities and metals. While Moskowitz, Ooi, and Pedersen (2012) study time series momentum across asset classes we are, to the best of our knowledge, the first to study time series carry strategies across asset classes and a combination of carry and momentum strategies. Furthermore, while most previous studies, such as Koijen, Moskowitz, Pedersen, and Vrugt (2013) and Asness, Moskowitz, and Pedersen (2013), resort to cross-sectional trading strategies, we focus purely on an asset's own carry and momentum signal. In doing so, we hope to understand the time series behavior of an asset instead of its cross-sectional difference to other assets.

A. Return Premia of Global Strategies

We start by characterizing the return premia to global carry, momentum, and combo. Each global strategy is defined as the returns of the respective strategy type aggregated across bonds, commodities, currencies, equities and metals.

A.1. Return Premia

The first 5 rows of Table 1.2 Panel A report the annualized mean return, standard deviation, Sharpe ratio as well as skewness and kurtosis for global momentum, carry, combo and the long only. Over the full sample - from 1980 to 2012 - returns to momentum strategies are highest, with a mean of 8.6%, in contrast with carry, which had a mean return of 6.1%. At the same time, however, the standard deviation of carry is significantly lower at 4.7% annualized, in contrast to 6.7% for momentum strategies. This leads to risk adjusted Sharpe ratios of 1.3 and 1.2 for carry and momentum, respectively. Interestingly, we find the risk adjusted returns of our time-series global carry strategies compare closely with the global cross-sectional carry strategies of Koijen, Moskowitz, Pedersen, and Vrugt (2013), who find a Sharpe ratio of 1.2 for a similar dataset and sample period. Global momentum is negatively skewed, which is consistent with the findings of Daniel and Moskowitz (2013), and indicates that momentum returns are affected by occasional

[10] http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm
[11] http://www.nber.org

large negative returns or market crashes. This feature of momentum returns is illustrated in Panel B of Figure 1.3, which shows that the momentum strategy has a number of draw-downs, defined as a peak to trough decline in cumulative returns, of over 8%. In contrast, global carry has fewer and smaller draw-downs. Brunnermeier, Nagel, and Pedersen (2008) show that currency carry trades are affected by market crashes which leads to a negative skewness. However, this argument does not hold for the carry trade across asset classes. The excess kurtosis for both strategies is only marginally larger than the mean return and does therefore not indicate heavy tails.

Figure 1.2 Panel A plots the cumulative sum of log returns of global carry and momentum strategies over the time period 1980 to 2012. In addition to the previous results we observe that the returns to carry strategies behave in an S-shape over the sample. After consistent positive returns from 1980 to 1990, the cumulative performance flattened briefly in the early 1990s, then became strong again until 2002, when the performance noticeably flattened. The performance increased again after 2005. In contrast, the momentum strategy does not feature this S-shape but displays higher volatility.

The combined carry and momentum (combo) strategy outperforms the individual momentum and carry strategies in terms of risk adjusted returns, with a Sharpe of 1.4. In terms of absolute mean returns, the combo strategy is in between the returns to carry and momentum with a premium of 6.5%, but has a very low volatility of only 4.5%. Figure 1.3 illustrates the combo strategy is more stable than either the carry or the momentum strategy, with more consistent returns (seen in Panel A) and fewer and smaller draw-downs (pictured in Panel B), with a sample maximum draw-down of only 6.8% in August 2003, comparable to the annual return premium. Figure 1.2 Panel A illustrates this observation. Furthermore, the combo strategy does not display any skewness and only a marginal kurtosis.

Given that time series momentum strategies outperform cross-sectional strategies, as shown by Moskowitz, Ooi, and Pedersen (2012), it is remarkable that carry strategies further outperform the time series momentum strategies. Tests of asset pricing models, which struggle to explain time series momentum strategies, will have difficulty accounting for the returns to carry strategies, and even more so the combo strategies. We next examine the applicability of the popular capital asset pricing model (CAPM).

A.2. CAPM Alphas and Betas

Rows 6-9 of Table 1.2 Panel A report the CAPM alphas and betas as well as their t-statistics of carry, momentum, and combo. The CAPM betas are estimated unconditionally over the entire sample period by performing a time-series regression of each portfolio's monthly returns on the global long only portfolio. Setting the global long only portfolio as the 'market portfolio' is important for two reasons. First, most studies use the S&P 500 or the global MSCI index to test for alpha generation in trading strategies. We, however, believe that this benchmark is not adequate in futures markets, which span a variety of asset classes and geographical regions. Second, since the carry and momentum strategies are dynamically volatility weighted, there is the possibility that the abnormal returns, when considered in isolation, are driven by leverage aversion risk premia. This mechanism is demonstrated by Frazzini and Pedersen (2014), who find volatility weighting or leveraging of asset classes can lead to risk adjusted returns due to leverage aversion. By setting the volatility weighted long only performance as the market portfolio in our CAPM regressions, we remove any excess return component originating from leverage aversion in the CAPM alpha.

In the final column of Table 1.2, Panel A we find the summary statistics of the volatility weighted long only strategy. We can see that the long only strategy already exhibits a Sharpe ratio of 0.8, far higher than the Sharpe ratios to the S&P or MSCI indices.

The CAPM alphas of momentum, carry and combo strategies are all highly significant. Carry exhibits an alpha of 6.7 percent annually that is statistically different from zero with a t-statistic of 7.8. This compares closely to the findings of Koijen, Moskowitz, Pedersen, and Vrugt (2013) who report a cross-sectional carry alpha of 8.7 percent for a similar sample period, set of assets and benchmark strategy. Interestingly, we find the carry alpha is even higher than the unconditional return due to the negative beta with the risk parity benchmark portfolio, indicating carry has particularly attractive properties for investors with long only futures portfolios. The alphas for momentum and combo strategies are significant and produce an annual return of 7.0 and 6.1 percent that is 1.7 and 0.4 percent lower than the unconditional returns, respectively. We find an alpha t-statistic for momentum of 5.9, closely agreeing with the 6.6 reported by Moskowitz, Ooi, and Pedersen (2012). The reported beta estimates show that the carry strategy is statistically significant and negatively related to the long only strategy with an estimate of -0.1. On the other hand, the momentum strategy is statistically significant and positively related to the long only portfolio. By combining the two strategies, the resulting beta estimate for the combo portfolio is statistically insignificant from zero.

Figure 1.2 Panel B plots the cumulative CAPM alphas to the momentum, carry and combo strategies. We can see that the cumulative alpha returns to momentum strategies reduced significantly, while the returns to the carry strategies increased. On the other hand, the cumulative returns to combo strategies remain almost unchanged.

Taken together, the results reveal that carry and momentum strategies seem to have different sources of return premia. We explore this hypothesis in the next section.

A.3. Long/Short Return Premia and Number of Assets

To understand better the origin of the global portfolio performance, we separate strategy returns into those derived from long and short futures positions within the portfolio, referred to as the long and short leg, respectively. This approach is based on the findings of papers such as Stambaugh, Yu, and Yuan (2012) and Hong, Lim, and Stein (2000) who argue that trading strategy returns to long/short portfolios equity can be disproportionately be attributed to short positions. Table 1.2 Panel B and Panel C report the summary statistics of the long and the short leg of the trading strategies.

Before discussing the origin of strategy returns, it is important to note that for the time series strategies we study, the ratio of short to long positions can vary with time. It is even feasible for the portfolio to contain only long or only short positions. This is in contrast to cross-sectional strategies, in which portfolios are comprised of an equal number of long and short positions, therefore forcing a constant one to one ratio between the number of long and short positions. To diminish concerns that the number of long or short assets play a role in the return generation, Figure 1.4 shows the relative number of long assets (number of long assets divided by the total number of assets) against the returns of the carry, momentum, and combo strategies. For all three strategies the scatter plot does not display any significant trends. Most points are centered around the 0.5 line, which corresponds to an equal amount of long and short positions. The concentration of centered points is highest for carry strategies, while momentum returns do have some outliers. The combined returns have a large variation in the proportion of assets long but have a low dispersion of returns, indicating the diversification originates from the interaction of the risk premia of the strategies, rather than simply a reduction in the market exposure of the portfolio. The last two lines of Table 1.2 Panel A report the average number of short and long positions over time. For momentum strategies on average 56 percent of the assets are long and 44 percent are in the short portfolio. For carry strategies 43 percent are long and 56 percent are short positions. The combo portfolio is almost equally weighted. These results alleviate the concern that the returns are related to the relative number of long or short positions in the portfolios.

Comparing Panels B and C in Table 1.2 we can infer that three-quarters of the individual momentum and carry profitability results from the long positions in the portfolio. For the combo portfolio two-thirds of the returns are from the long and one third from the short side. For the long positions the skewness is consistently negatively skewed while the short side displays a positive skew. Since the long-only portfolios are dominated by general market exposure, we also report the CAPM alpha and beta of the carry, momentum, and combo strategies. We find that for momentum, carry, and combo strategies the resulting CAPM alphas from the long side are all statistically significantly different from zero, with annual returns of 2.8%, 2.4% and 2.6%, respectively. Hence, for an investor constrained to hold long-only investments, all strategies still offer additional return premia above the risk parity portfolio. Next we examine the CAPM alphas from the short portfolios. We find that the alphas are highly significant with annual returns of 4.1%, 4.3% and 3.5% for momentum, carry and combo returns. This suggests that the short side of the portfolio is on a risk adjusted basis double as profitable as the long side. From a theoretical perspective this result is troubling. While this result is consistent with the findings of Stambaugh, Yu, and Yuan (2012) and Hong, Lim, and Stein (2000), who argue that short sale impediments and higher transaction costs for shorting stocks leads to higher short side returns, it seems difficult to accept this argument for futures markets. Taking a long or a short position in futures is virtually equivalent and the transaction costs do not differ. This raises the question as to why there is such a large dispersion between the long and the short side of the trading portfolios.

Figure 1.5 plots the long and the short cumulative returns, as well as the long and short CAPM alpha cumulative returns. The plots illustrate the observations in Panels B and C of Table 1.2. The cumulative returns of the CAPM alpha long side decrease significantly in contrast to the long only portfolio, while the cumulative returns of the CAPM alpha short side increase. It also appears that the long returns are a lot more volatile compared to the long/short portfolio or the short side returns.

B. Return Premia within Asset Classes

To understand the origin of returns to the global portfolio, in this section we analyze the returns to carry, momentum, and combo portfolios separately within the asset classes bonds, commodities, currencies, equities and metals. Our main concern is that the global results are driven by one of the asset classes only, which would make the global analysis redundant. Furthermore, we want to examine whether the characteristics within asset class match the previous literature and to compare features to the global portfolios.

B.1. Return Premia

Table 1.3 reports the summary statistics for momentum, carry and combo strategies across the asset classes bonds, commodities, currencies, equities and metals. The first observation is that all mean returns or return premia across asset classes and strategies are positive. However, the returns vary cross-sectionally from 1.6% annually for equity carry strategies to 10.4% annually for bond momentum strategies. At the same time, the risk adjusted returns, expressed as Sharpe ratios, vary from 0.1 for equity carry to 1.1 for commodity momentum. Even though there are cross-sectional differences in mean and Sharpe ratio, no clear pattern emerges for the sources of the cross-sectional differences. For example, while equity carry Sharpe ratios are lower than currency carry Sharpe's, equity momentum Sharpe ratios are higher than currency momentum Sharpe ratios. We can therefore remove the concern that the returns to the global portfolios are driven by the performance of one or two asset classes only.

Comparing our results to those in the literature, we find our time-series carry returns are broadly inline with the cross-sectional carry performance described by Koijen, Moskowitz, Pedersen, and Vrugt (2013). One notable exception is the equity portfolio, where our time-series carry performs considerable worst with a Sharpe of 0.1, compared to 0.9 reported by Koijen, Moskowitz, Pedersen, and Vrugt (2013) for cross-sectional carry. For momentum across asset classes, our results compare qualitatively with those of Moskowitz, Ooi, and Pedersen (2012), with commodities performing around twice that of currencies on a risk adjusted basis.

Figure 1.6 plots the cumulative sum of log returns as well as of the CAPM alphas for each asset class individually. As with the global strategies, momentum strategies perform best across asset classes, followed by combo and carry strategies. Within asset class the diversification benefit of the combined strategy is still clear, with combo returns more stable than individual carry or momentum. The behaviour of the cumulative CAPM alphas in the time series is analogous to that of the global portfolios. Explicitly, we see that the alpha to momentum strategies reduces over time, the alpha to carry strategies increases and the combo portfolio remains stable.

The skewness for momentum strategies is negative across asset classes, which is consistent with the findings of Daniel and Moskowitz (2013) and matches the results from the global strategies. The skewness across carry strategies does, however, display cross-sectional variation. While the skewness of commodity, equity and metal portfolios is positive, the skewness of currency carry strategies is highly negative, consistent with Brunnermeier, Nagel, and Pedersen (2008) and indicates that the returns to currency carry trades are a compensation for crash risks. The global carry strategy, on the other hand, is positively skewed, suggesting crash risk cannot explain global carry returns.

Table 1.3 reports the CAPM alpha and beta with respect to the long only portfolio for strategies in each asset class. For momentum and carry strategies we observe significant alphas for commodities, currencies, equities and metals. Only bonds have insignificant alphas, though they are still positive. For the combo strategy all alphas are significantly different from zero when controlling for the long only strategy. These observations match the global portfolios. The beta exposure of the strategies is consistently positive for momentum strategies across asset classes and mostly negative for carry strategies.

Figure 1.7 plots the long and short contribution for mean excess returns and mean CAPM alphas of carry, momentum, and combo strategies across all asset classes. The contribution of the long mean excess returns is higher than the short side across strategies and asset classes. The short profits for bond momentum and equity and bond carry are even negative. The long and short mean CAPM alphas, however, change this picture. For all trading strategies and asset classes, but bonds, the short profits are significantly higher than the long profits. This is most significant for the commodity and metals classes. Again, this is analogous to the global portfolios.

In summary, when studying the returns to strategies for each asset class, we find remarkably consistent characteristics, with only small asset specific differences. This confirms that global portfolio returns are not driven solely by a single asset class and establishes the diversification benefit of a global portfolio.

B.2. The Effect of Recessions on Return Predictability

In their recent paper Kacperczyk, Nieuwerburgh, and Veldkamp (2014) test whether the skill of asset managers changes between recession and boom periods. They find that some managers possess a persistent skill which allows them to predict stock returns, and that this is more evident in times of recessions when it is displayed as an improved ability to time the markets. For these managers predictability increases during recessions. To test whether recession periods affect predictability of carry and momentum strategies in futures markets, rows 12-15 of Table 1.2 compare the CAPM alpha for each studied global strategy. We find that the alpha remains significant for each strategy in and out of recessions, apart from the momentum alpha, which is insignificant for during recessions. This result suggests that the findings of Kacperczyk, Nieuwerburgh, and Veldkamp (2014) relating to managerial skill in stock markets are unlikely to be mistaken for managerial skill amongst commodity trading advisors (CTAs) following time-series carry or momentum strategies.

C. Comovement Structure Globally and within Asset Classes

In the previous sections we examine carry and momentum strategies simultaneously across asset classes to better identify the sources of profitability among these strategies. In this section we study the correlation within and across trading strategies and asset classes. Evidence in favor of or against common sources of variation in carry and momentum strategies may support or challenge theoretical explanations for their existence and may ultimately point to underlying economic drivers of their returns.

C.1. Full Sample Correlation

Table 1.4 and Table 1.5 report the full sample correlation of the global strategies and correlation within and across asset classes and strategies, respectively. Table 1.4 reports the correlation of the global total returns, the CAPM alpha, the long leg only, and the short leg only strategy returns. The correlation between momentum and carry total returns is 0.28. This value suggests at least a partial common source of returns for momentum and carry. The correlation of carry and momentum with the long only portfolio is particularly revealing. Long and momentum have a positive correlation of 0.24 whereas long and carry have a negative correlation of -0.21. We therefore conclude that the correlation between carry and momentum is not explained by a common exposure of carry and momentum to the passive asset, but rather a feature of the dynamic asset allocation behind each strategy.

The findings for strategy co-movement are qualitatively similar for the alpha returns. The correlation between momentum and carry only increases slightly to 0.35. For the long strategy returns and the short strategy returns we find that momentum and carry strategies are highly correlated for both sides of the portfolio. The similarity of the correlation structure for alpha and excess returns suggests strategy co-movement is not driven by a market component.

Table 1.5 examines the correlation structure within and across asset classes and strategies. Panel A of Table 1.5 reports the average pair-wise correlation of momentum, carry, combo, long and across carry and momentum among individual contracts within the same asset class. The correlations within momentum, carry and combo strategies and asset classes are all positive, ranging from 0.13 for commodity combo and carry strategies to 0.43 for equity momentum and bond combo. In general, the correlations are highest for bonds and lowest for commodities. To some extent the correlation within asset classes is expected, in the case where a given asset class strategy is net long or net short systematic risk within the market will generate positive correlation.

Interestingly, the correlation between the individual momentum and carry returns is the lowest. Consistent with the findings of Moskowitz, Ooi, and Pedersen (2012) for momentum strategies, we find that all strategy correlations are lower than the correlation of the pure long portfolios. These results indicate that a diversified portfolio across all assets of carry, momentum, and combo strategies provides a greater diversification benefit than a portfolio of passive long positions across all assets, consistent with the findings of the previous sections.

Panel B of Table 1.5 reports the return correlation between asset classes for each of the carry, momentum, combo and long only strategy types. Here, consistent with Moskowitz, Ooi, and Pedersen (2012), we find that momentum correlations across asset classes are all positive, ranging from 0.01 to 0.33. The same is true for combo strategies, where the correlations range from 0.02 to 0.16. This result is striking in that these are totally different asset classes, yet there is common movement in the momentum and combo strategies. At this point, it is interesting to note that Asness, Moskowitz, and Pedersen (2013) report a similar consist correlation for both value and cross-sectional momentum strategies across asset classes. In contrast to our findings for momentum and combo, carry strategies do not exhibit consistent co-movement. While all correlations are relatively low, some asset class pairs show a mix of positive and negative correlations for carry strategies. This distinction leads to a diversification benefit to carry strategies in comparison to momentum strategies. We find the structure of correlation amongst long only strategies opposite to that of carry strategies: asset pairs with positive correlation for carry are negative for long only, and visa versa.

Panel C of Table 1.5 presents the correlation across the trading strategies momentum and carry as well as across asset classes. The correlation between carry and momentum within asset class ranges from -0.02 to 0.69, where the 0.69 for bonds is significantly higher than the rest of the correlations. For currency strategies we find 0.29 correlation between carry and momentum, substantively higher than Burnside, Eichenbaum, and Rebelo (2011)'s estimate for cross-sectional strategies on forward markets between 1976-2010 of 0.10. Without a longer available data set it is difficult to determine whether the reduced correlation in our analysis, compared to that of Burnside, Eichenbaum, and Rebelo (2011) is related to differences between time-series and cross-sectional strategies or is due to decreased strategy correlation between 1976-1986. Correlations across asset classes and strategies are all indistinguishable from zero. This feature is good news for a diversified portfolio across asset classes and strategies and substantiates the higher Sharpe ratio for global combo strategies. It is also interesting to note that the correlation seen between the global strategies is due to correlation within asset class, rather than due to inter-asset class correlation.

IV. Understanding the Return Premia to Carry and Momentum

In this section we try to understand the origin of the exceptional carry, momentum, and combined portfolio returns. To do this we compare strategy returns to common risk factors, business cycle risk and capital flows of hedge funds.

A. Risk Factor Models

We start by considering the explanatory power of standard and non-standard risk factor models. Table 1.6 reports the risk adjusted performance, the factor exposures, and the respective Newey and West (1987) adjusted t-statistics from regressing the returns to global momentum, carry and combo strategies on four model specifications.

Panel (a) of Table 1.6 reports the results from regressing global strategy returns on a version of the "Value and Momentum Everywhere" factors of Asness, Moskowitz, and Pedersen (2013). These are diversified portfolios of cross-sectional value and momentum strategies in global equities, equity indices, bonds, commodities, and currencies augmented with our global volatility weighted long only portfolio (risk parity portfolio), as a market factor. In all three cases, the strategies deliver a large and significant alpha - or intercept - with respect to these factors of 7.4%, 6.5% and 6.2% for carry, momentum, and combo strategy, respectively. The momentum and the carry strategy do exhibit significant exposure to the market factor - but with opposite signs. While momentum strategies are positively correlated, the returns to carry strategies are significantly negatively correlated, confirming the results of the previous section. As a consequence of the opposing component correlations, the combo strategies do not have a factor exposure to the market factor. All three global strategies do not exhibit significant betas on the value factor but combo and momentum strategies have a significant exposure to the momentum everywhere factor. This result confirms the finding by Moskowitz, Ooi, and Pedersen (2012) that time series momentum strategies are related to cross-sectional strategies but still exhibit positive alpha.

Panel (b) of Table 1.6 reports the results from a standard Fama and French (1992) risk factor analysis, where we regress the strategy returns on the HML and SMB portfolio factors and include the MSCI index as a market factor. We find again that all strategies deliver highly significant alphas, even above those with respect to the value and momentum factors of 6.8%, 10.4% and 7.7% for carry, momentum, and combo portfolios, respectively. In all three cases, the strategies do not exhibit significant betas with respect to the MSCI market factor. However, all strategies have significant beta exposure to the HML and SMB factors. The signs of the betas are negative, which explains the high alphas.

Panel (c) of Table 1.6 reports results using the TED spread, a proxy for funding liquidity as discussed by Brunnermeier and Pedersen (2009) and Asness, Moskowitz, and Pedersen (2013), as well as a proxy for market liquidity constructed by Pastor and Stambaugh (2001). Pastor and Stambaugh (2001) find that liquidity risk is positively correlated with expected returns of individual US stocks, suggesting stock returns are a compensation for liquidity risk. Furthermore, Pastor and Stambaugh (2001) find that a liquidity factor accounts for half of momentum profits in US stock markets. Asness, Moskowitz, and Pedersen (2013) show this relation extends to other markets. In our liquidity factor regressions, we find no significant relation between TED spread and any of the strategies. Looking across the liquidity tests, only the relationship between carry and market liquidity is even weakly significant. We therefore conclude that liquidity in itself does not play an appreciable role in the returns to carry and momentum strategies in futures markets.

Given the relatively high explanatory power of the value and momentum everywhere factors, we test in Panel (d) of Table 1.6 a combination of those factors and liquidity factors. For the combo strategy we do not find major changes in the alphas or beta exposures to the previous results. Interestingly, we find that when including the funding liquidity measure to the value and momentum factors, the alpha of the time series strategy becomes insignificant. This suggests that the difference between cross-sectional momentum strategies and time series momentum strategies can be explained by funding liquidity. The carry strategy is also significantly related to funding liquidity but with the opposite sign to the beta exposure of momentum strategies. The opposing signs of beta exposure to funding liquidity is similar to the results of Asness, Moskowitz, and Pedersen (2013). Analogous to their findings, we find that liquidity exposure does not fully explain the returns to carry and momentum.

B. Time Varying Expected Returns and Business Cycles

A large and growing literature, of which good examples are Lustig, Roussanov, and Verdelhan (2014) and Chordia and Shivakumar (2002), links currency carry strategies and momentum strategies to macroeconomic business cycle risk. The ubiquitous carry and momentum returns that are profitable in diverse asset classes such as bonds, commodities, currencies, equities and metals suggest that common systematic factors could be the source of these high average returns. Another hint of a macroeconomic relationship is given in Table 1.11, which suggests that correlation between carry and momentum returns are related to expansion and recession periods.

In this section we investigate whether the common variation in returns of carry and momentum strategies can be explained by common macroeconomic variables that are related to the business cycle. Practically, we test whether returns are predicted by a set of lagged macroeconomic variables, known to predict stock and bond returns. These variables include: (1) the three month T-bill (*ShortRate*), which is negatively related to future stock market returns and serves as a proxy for expectations of future economic activity (Fama and Schwert (1977)). (2) The dividend yield (*DivYield*) on the market, defined as the total dividend payments accruing to the CRSP value-weighted index over the previous 12 months divided by the current level of the index, which has been shown to be associated with slow mean reversion in stock returns across several economic cycles (Fama and French (1988b) and Campbell and Shiller (1988)). (3) The term spread (*TermSpread*), measured as the difference between the average yields of 10 year Treasury bonds and 3 month T-bills, based on the findings of Fama and French who provide evidence that this measure forecasts short-term business cycles. (4) The final business cycle indicator is the default spread (*DefSpread*), defined as the difference in yield between the highest and lowest rated investment grade bonds. Specifically, we calculate the default spread as the average yield of bonds rated BAA by Moodys minus bonds rated AAA by Moodys. Fama and French (1988a) demonstrate that the spread tracks long term business cycles. They find that it is higher in recessions and lower in expansions, and therefore proxies for the unobservable default risk premium embedded in corporate debt.

We use the predictive regression within the context of a multi-beta framework with linear time-varying risk premia. This follows the work of Chordia and Shivakumar (2002) and Bessembinder and Chan (1992) who show that, assuming a linear multivariate proxy for the pricing kernel, the expected return is the one-period-ahead forecast from the following regression:

$$R_t = \alpha + \beta_1 DivYield_{t-1} + \beta_2 ShortRate_{t-1} + \beta_3 TermSpread_{t-1} + \beta_4 DefSpread_{t-1} + \epsilon \quad (1.13)$$

As in Chordia and Shivakumar (2002) and Bessembinder and Chan (1992) we do not test whether the payoff from the strategy is related to its covariation with risk factors. Nevertheless, the regression framework does allow us to test whether strategy payoffs are captured by a common set of standard macroeconomic variables.

Table 1.7 Panel A presents the regression coefficients and the Newey and West (1987) adjusted t-statistics from regressing the momentum, carry and combo strategy returns on the lagged set of macroeconomic variables. The estimated coefficients for the dividend yield are statistically significant and negatively related to the future strategy returns for all strategies. The default spread is positively related to expected returns, though only with marginal significance for carry strategies. The short rate is again statistically significant and positively related to strategy returns, albeit only marginally for momentum returns. Finally, the term spread is positively related to the carry and combo strategy, however not significantly for momentum. The adjusted R^2 of the predictive regressions is highest for the combo and carry strategy with 3.7% and 3.0%, respectively. Whereas the adjusted R^2 for the momentum strategy is only 1.4%. Table 1.7 Panel A also reports the coefficient estimates for the intercept of the predictive regression, which can be interpreted as the residual return premium not explained by the business cycle variation. The first column in Table 1.7 Panel B also reports the annualized version of the coefficient estimate. For momentum and combo strategies, the residual return premia estimates remain significant. For momentum, this result is contrary to Chordia and Shivakumar (2002)'s finding that cross-sectional stock equity momentum profits are insignificant after business cycle predictors are considered.

In contrast to momentum and combo, for carry strategies the alpha is only insignificantly different from zero, suggesting that global carry strategies are predicted by business cycle factors. However, the carry returns can not be explained by business cycle risk, as even though the significant coefficient estimates are consistent with the notion of time-varying risk premia or expected returns, the sign of the coefficients are troubling. The coefficient estimates from Chordia and Shivakumar (2002) and Bessembinder and Chan (1992) have exactly the opposite sign from the coefficient estimates we obtain. This finding is puzzling, essentially it suggests that the carry strategy has both positive abnormal returns whilst also providing insurance against downturns. To determine whether the peculiarity originates from the futures contracts we use or from the implementation of the trading strategy we test the risk parity portfolio in the same predictive regression framework. The last two rows of Table 1.7 Panel A present the results: All regression coefficients have the opposite sign to the regression coefficient for the trading strategies. Though the coefficients' estimates are mostly insignificant, the signs correspond to the findings by Chordia and Shivakumar (2002) and Bessembinder and Chan (1992), and suggest the risk premia of the risk parity portfolios behave counter cyclically, analogous to equity and bond markets. These findings suggest that the risk premia in global carry strategies are strongly pro-cyclical, while momentum strategies are only weakly pro-cyclical. The risk premia of the long only strategy on the other hand are counter cyclical, which corresponds to the findings of Ludvigson and Ng (2009) for bonds or Lustig, Roussanov, and Verdelhan (2014) for currencies.

Figure 1.8 and Table 1.7 Panel B further investigate the cyclical variation of the risk premia. Figure 1.8 displays estimated carry, momentum, and combo risk premia over time, which are the fitted values from the predictive regression. The estimated premia are non-trivial in economic terms, with absolute premia of up to 1% a month for carry strategies. The estimated risk premia also display considerable time series variation and change sign over time. While they are mostly negative in the 1980's and early 1990's, they become highly positive in the mid 1990's to mid 2000's and become negative in the final years of the sample. The top chart of Figure 1.8 also displays the 12 month rolling average of industrial production growth. It appears that industrial production growth and the variation of the risk premia is positively correlated. The bottom chart of Figure 1.8 demonstrates the risk premia to the risk parity portfolio are negatively correlated to the risk premia of carry, momentum, and combo strategies. To assess the correlation more formally, Table 1.7 Panel A reports the correlations of the expected returns with the industrial production growth and the return premia to carry, momentum, combo and long only strategies. The correlation is indeed significantly positive with industrial production and significantly negative with respect to the long only return premia. These results support the finding that the counter cyclical strategy risk premia are not accounted for due to the underlying futures contracts premia.

Asness, Moskowitz, and Pedersen (2013) show that funding liquidity has significant explanatory power for value and momentum strategies. The same result holds for carry and momentum strategies as Panel (d) of Table 1.6 shows. To account for the possibility that the previous results are driven by funding liquidity instead of the business cycle variables, we include the TED spread into the predictive regressions. Table 1.7 Panel C reports the results of the regression. When including the TED spread, the predictive power of the macroeconomic variables does not decrease. In fact, the inclusion increases the statistical significance of the coefficient estimates and increases the R^2 for carry strategies. We therefore conclude the countercyclical carry performance is robust to funding liquidity. The last two rows of Table 1.7 Panel C test for statistically significant coefficient estimates of the TED spread for the long only strategy. Here we do find that the TED spread has statistical power in explaining the long only portfolio. This result is consistent with the finding of Frazzini and Pedersen (2014), who relate the profitability of risk parity portfolios to leverage averse agents, rather than macroeconomic factors.

C. Hedge Funds and Limits to Arbitrage

Having found only partial explanations for the abnormal returns to carry, momentum and combo strategies, in this section we investigate whether institutional ownership and limited arbitrage capital are related to strategy risk premia. Our approach is twofold: first, we demonstrate a significant proportion of strategy returns are explained by hedge fund indices; then second, we uncover relations between hedge fund capital flows and assets under management and our strategy returns.

C.1. Hedge Fund Indices and Carry and Momentum Returns

We first test whether hedge funds or particular hedge fund styles follow carry or momentum strategies. Table 1.8 presents regression coefficients obtained from regressing the net-of-fee monthly returns of five asset under management weighted hedge fund indices on various factor combinations. The table considers an index covering all hedge fund styles (HF Index), an event driven style index (Even Driven), a fixed income arbitrage style index (FixedInc.Arb.), a macro index (Macro), a long/short index (Long Short) and a managed futures or CTA index (CTA). We choose these styles to represent a large cross-section of hedge fund categories.

For each hedge fund index, column (1) reports the regression coefficients, their statistical significance and the adjusted R^2 for carry, momentum, and the long only strategies. We also include S&P 500 index returns for completeness. For robustness and comparison, column (2) reports the regression results when using the Fung and Hsieh (2004) hedge fund factors and column (3) combines the Fung and Hsieh (2004) with the carry, momentum, and long only strategy returns.

The results from column (1) show that the carry, momentum, and long only strategy do indeed have a high explanatory power for each of the hedge fund indices. The adjusted R^2 vary between 19% for macro strategies to 51% for long and short strategies. Our strategies even explain 43% of the global hedge fund index returns across all styles. Furthermore, all coefficient estimates for the long only and momentum strategies are highly significantly different from zero, while three out of five hedge fund indices are statistically significant related to the carry strategy. The highest significance of the carry strategies is with respect to the fixed income arbitrage index, which corresponds to the findings of Jylhä and Suominen (2011) for pure currency carry strategies.

For comparison we regress the hedge fund indices on the Fung and Hsieh (2004) hedge fund factors in column (2). Unsurprisingly, these factors have a high explanatory power as well, however, they do have lower adjusted R^2 in four out of six hedge fund styles in comparison to our strategies. This effect is particularly interesting for the macro and CTA style, where the Fung and Hsieh (2004) factors have an adjusted R^2 of 8 and 18 percent, respectively, while the carry, momentum, and long strategies explain 19 and 43 percent, respectively. This is surprising because the Fung and Hsieh (2004) factors were constructed to mimic risks in trend following strategies, which are exactly the strategies that CTAs employ. Bhardwaj, Gorton, and Rouwenhorst (2008) make a similar observation. For a final comparison, column (3) presents the results of a combined regression of carry, momentum, and long returns as well as the Fung and Hsieh (2004) factors. The adjusted R^2 do increase in most cases, however, not significantly. Furthermore, the coefficient estimates of the carry, momentum, and long strategies remain statistically significant or even increase while the significance for most Fung and Hsieh (2004) factors decreases.

The first two rows of Table 1.8 present the alphas (in percent) with t-statistics. Consistent with their usual definition, the alphas represent the average residual return that cannot be explained by the factor model in question. For all hedge fund strategies the alphas are significantly lower for the momentum, carry and long strategies, than when including the Fung and Hsieh (2004) factors. Even though the alphas remain significant for most of the strategies, we find that the CTA alpha completely disappears. This result is consistent with the findings of Baltas and Kosowski (2014). The results indicate that the carry, momentum, and long factor might help to disentangle the sources of hedge fund alpha that have received a lot of attention in the academic literature.

C.2. Hedge Fund Capital and Strategy Returns

Given that the returns of momentum, carry and long strategies are highly correlated with returns of strategies employed by hedge funds, we next examine the relation between the returns to trading strategies with capital available to hedge funds and the flow of capital to hedge funds.

A large and growing literature (for instance, Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), Jylhä and Suominen (2011) and Akbas, Armstrong, Sorescu, and Subrahmanyam (2013)) argue that the limited availability of arbitrage capital can have an effect on the profitability of trading strategies and, therefore, induce time varying returns. To test this mechanism for carry, momentum and combo returns, Table 1.9 Panel A reports the results from regressing strategy returns on lagged measure of changes in hedge fund arbitrage capital (HF Capital) and a measure of contemporaneous capital flow (HF Flow). Changes in hedge fund arbitrage capital are proxied by changes in the total asset under management of hedge funds times the TED spread, a measure of funding liquidity or available leverage. HF Flow is proxied for using the total capital flow to hedge funds. The data was obtained from the Barclay Hedge Fund Database. The construction of the variables we use as measures for hedge fund activity are similar to those used by Jylhä, Rinne, and Suominen (2014), Jylhä and Suominen (2011) and Baltas and Kosowski (2014).

Theory suggests that when constraints on arbitrage capital are released the next period strategy returns should be diminished. At the same time, the contemporaneous capital inflow should increase prices, and therefore generate lower next period returns. In our case, this is equivalent to hedge funds having more capital available to arbitrage and reduce market inefficiencies. In Table 1.9 Panel A we observe exactly this effect. Following increases in the capital available to hedge funds, returns decrease in the next period for momentum strategies. The same effect can be observed for combo strategies. Carry strategies, in contrast, are not affected by hedge fund capital increases(Contrary to the findings of Jylhä and Suominen (2011) for cross-sectional currency carry). Our findings for momentum and combo agree with Naik, Ramadorai, and Stromqvist (2007), who show lagged increases in hedge fund AUM coincide with decreases in next period strategy alpha. In contrast, Baltas and Kosowski (2014) studying explicitly time series momentum in futures markets, find no relation between systematic CTA AUM and time series momentum performance. We note, it is surprising that the we find a relation between the wider hedge fund market and time series momentum futures strategies, but this pattern is not reflected in the class of funds where it should be most prevalent(as in Baltas and Kosowski (2014)). Together, these findings point to counter-intuitive relations between the labelled objectives of strategies and the characteristics of their performance.

The second conjecture of the theories, that hedge fund flows are contemporaneously positively related to returns, does not appear in the data for momentum, carry or combo strategies. Long only strategies, though, are significantly positively related to capital inflows.

In order to show that this effect is indeed related to the hedge fund capital, and not related to the funding liquidity channel we tested earlier, we repeat the same regression in Table 1.9 Panel A with the inclusion of the TED spread as a proxy for funding liquidity and the market liquidity variable in the regression. We find that the results remain robust even when including the two liquidity variables.

Finally, Table 1.9 Panel B splits the full sample into two subsamples from 31/03/1994 to 31/07/2002 and from 31/07/2002 to 31/12/2011 and repeats the regression from Panel A. The hypothesis is that, given the very large capital flows into the hedge fund sector starting in the early 2000's, the effect of limited arbitrage is amplified in the second half of the sample. Supporting this conjecture, we find the regression coefficients for the growth in hedge fund capital for the momentum strategies are very significant in the second half of the sample, whilst they become insignificant in the first half. Furthermore, we find that in the first half of the sample, only the hedge fund capital has a significant effect for the long strategy, the other results remain unchanged. Figure 1.9 illustrates time variation in the relationship between strategy Sharpe and HF Capital. It is clear that risk adjusted returns of the long portfolio are significantly negatively related to changes in hedge fund capital following the dot-com crash and during the 2008 financial crisis, however, since 2009 the relation has turned positive. There is also some time variation in the regression t-statistic with momentum Sharpe ratio on HF Capital, with a pronounced decrease during recession periods.

In summary, our findings suggest that momentum and combo next period returns are lowered by hedge funds deploying arbitrage capital which causes a reduction in the market inefficiencies underlying strategy returns. Furthermore, this effect has become more pronounced since 2000 and is highest during recessions. In contrast, carry returns show no significant relation to hedge fund capital.

V. What Can We Learn About Momentum by Observing Carry?

In this final section we investigate the co-movement structure and joint profitability of carry and momentum strategies over time. This section serves as a preliminary investigation, highlighting possible identification methods to disentangle the role of limited arbitrage or behavioural effects on futures returns and systematic risks that are associated with time-varying expected returns, in explaining the omnipresent returns to momentum strategies.

A. Time Trend

Figure 1.10 plots the rolling three year average strategy correlation within global momentum, global carry, and global combo and between global carry and momentum strategies. The figure indicates there is a time trend among momentum strategies with correlation increasing over the sample, particularly since 2002. In contrast, correlation between carry strategies appears to be decreasing with time over the full sample, with a notable decrease in correlation after 2002, but has a positive relationship in the first part of the sample.

The increase in correlation between momentum strategies coincides with a general growth in the financial sector and hedge fund assets under management, suggesting a mechanism relating to increased market participation of quantitative arbitrageurs such as hedge funds or index investors. Indeed, Tang and Xiong (2010) argue that the significant increase in correlation amongst commodity futures returns over the last 20 years is due to the rise of commodity index investing. For our combo strategies, the increasing correlation of momentum appears to be countered by the decreasing correlation of the carry component, leading to no significant time trend in combination strategy correlation. Throughout the sample period, correlation between carry and momentum strategies is significantly lower than correlation within strategies, demonstrating a diversification benefit to holding the combined strategies.

To quantitatively investigate mechanisms behind strategy performance Table 1.10 Panel A reports Sharpe ratios and correlations for the dataset split by different regimes. The first 3 rows report results for the dataset split into thirds of approximately 10 years each. The increased correlation among momentum strategies during the sample period seen in Figure 1.10 coincides with a decrease in Sharpe ratio from 1.6 in the first period, covering March 1982 to March 1992, to 1.0 for the last period, spanning March 2002 to March 2012. For carry strategies, where we report a decrease in correlation, there is a small increase in Sharpe ratio from 1.1 to 1.3 between the first and last sample splits, respectively. The results hint at the importance of diversification and that over the examined sample period increased (decreased) correlation has decreased (increased) performance in momentum (carry). We also note that the increasing correlation amongst assets in the long portfolio supports the findings of Tang and Xiong (2010).

Panels B and C of Table 1.10 breakdown the performance of the strategies into the returns relating to their constituent long and short legs for different sample periods. We find that, for the global carry and momentum strategies, the contribution of volatility adjusted returns, summarized by the Sharpe ratio, is consistently lower for the short leg of the returns and is lowest for the latest period, from 2002 to 2012. Over this period, global carry and momentum short leg Sharpe ratios were 0.23 and -0.10, respectively. The contribution of the long leg to momentum strategies shows no significant trend, whilst for carry strategies it appears that the increase in strategy Sharpe ratio is generated by the short leg performance, with an increase in Sharpe ratio from 1.0 to 1.6 between the first and last split of the data. For combination strategies, long leg returns have a small increase in Sharpe ratio through the sample, while we find a significant decrease in Sharpe ratio in the last period for short leg returns.

B. Recessions and Hedge Fund Liquidity

The second set of rows in Table 1.10 Panel A report the summary statistics for returns conditioned on recessions and non-recessions. We find that during recessions the momentum Sharpe ratio is lower (1.1 verses 1.4). In results not reported, the decrease is caused by increased volatility during recessions, rather than a decrease in returns. Higher adjusted momentum returns in expansions is at odds with cyclical risk premia arguments (Chordia and Shivakumar (2002) for momentum in stock markets), however, it agrees with the findings of Baltas and Kosowski (2014) for futures markets, and confirms the relation to business cycles previously discussed in Table 1.7. For carry strategies the Sharpe ratio is higher (1.6 verses 1.2) during recessions, as the increase in returns subsumes a small increase in strategy volatility. We report consistent relationships for the returns conditioned on the top and bottom quintile of S&P 500 month performance. For the combination strategy, the opposing Sharpe ratios of the constituent carry and momentum strategies and low correlation between carry and momentum strategies (5% for recessions) lead to higher and more consistent Sharpe ratios between recessionary and non-recessionary periods(1.3 and 1.5, respectively). The same pattern is seen in the Sharpe ratios conditioned on S&P 500 returns.

Table 1.11 examines more formally the dynamics of carry and momentum returns over time, in recessions, and with changes in hedge fund liquidity. This is conducted by running time-series regressions with correlation as the dependent variable regressed on to a time trend, a recession dummy, and a measure of hedge liquidity, to indicate the marginal influence and statistical significance of each factor. To calculate time-varying correlations we take the cross product of monthly returns across assets, following the methodology of Asness, Moskowitz, and Pedersen (2013). For instance, the correlation time-series $\rho(\text{mom}, \text{mom})_t$ is defined as the average across-assets at time t of $r_{i,t}^{\text{mom}} \times r_{k,t}^{\text{mom}}$ where $r_{i,t}^{\text{mom}}$ is the return to the momentum strategy for asset i at time t. The correlations $\rho(\text{mom}, \text{car})$, $\rho(\text{car}, \text{car})$ and $\rho(\text{long}, \text{long})$ are defined similarly. These time series are regressed on a linear time trend, a recession indicator (defined by the NBER) and the product of the monthly change in hedge fund assets under management and the TED spread, lagged by one month, as a measure of changes in hedge fund liquidity. The upper section of Table 1.11 reports regressions for the full sample over which all time series are available, from January 1994 to August 2011. The middle and lower section of the table report analogous regressions for the first and second halves of the data, respectively.

Over the full sample we find that correlation between momentum strategies is significantly increasing over time when controlling for recessions and hedge fund liquidity. Splitting the sample before and after December 2002, we observe this trend is only significant for the second period. In contrast to momentum strategies, we find over the full sample period that the correlation among carry strategies is significantly decreasing with time for the full period and second half. Yet, it is significantly increasing for the first half of the sample, controlling for recessions and hedge fund liquidity.

Correlation between carry and momentum strategies has a similar profile to the correlation among momentum, with a positive relationship in the first part of the sample, a negative in the second, and an overall decrease with time once recessions and changes in hedge fund liquidity are controlled for. This trend indicates that the diversification benefit to holding carry and momentum strategies has increased over time, particularly since 2002.

Once time trends and liquidity effects are controlled for, the recession indicator has nearly no significant relation to our strategy correlation. The only exception is the positive relation for momentum strategy correlation in the last half of the sample, not seen among carry strategies or between carry and momentum strategies.

We find a number of interesting relations between strategy correlation and the one month lagged monthly change in hedge fund liquidity. For the full sample regression, correlation between momentum strategies has a strong inverse dependence on our hedge fund liquidity measure, indicating that correlation between time series momentum strategies follows decreases in hedge fund liquidity. In contrast, amongst carry strategies we find no evidence that liquidity affects correlation for the first half, second half or full sample once recessions and time trend are controlled for. Interestingly, the correlation between carry and momentum strategies has a strong dependence on liquidity over the full sample, with increases in correlation following decreases in liquidity. When splitting the sample at December 2002, we find no evidence for liquidity driving correlation before 2002 but a particularly strong relationship in the second half of the sample.

A possible explanation for the reduced correlation among momentum and between carry and momentum strategies following increases in liquidity could be that increased market participation of arbitrageurs reduces opportunities relating to a risk factor common to momentum, and between carry and momentum strategies. We leave a detailed investigation of this mechanism for future work.

To investigate further the empirical relation between carry and momentum returns and hedge fund liquidity, Table 1.12 reports results for a regression of momentum returns on to hedge fund capital (HF capital), whilst controlling for carry returns. This allows us to determine whether the component of momentum returns that is not explained by carry returns is related to hedge fund liquidity. For the full sample we find that momentum returns are significantly driven by HF

Capital when carry is controlled for. For the first half of the sample, January 1994 to December 2002, we observe that after carry returns are controlled for there is no significant relationship between momentum and HF capital. However, for the second period, January 2003 to August 2011, we find a significant proportion of momentum returns are explained by liquidity effects, with a t-statistic of -4.0 on HF capital, once carry returns are controlled for.

Going forward, the relation of strategy returns to hedge fund liquidity provides an interesting avenue for future research into the role of arbitrageurs in futures markets, mechanisms effecting the correlation structure and risk premia embedded in carry and momentum strategies.

VI. Conclusion

We provide comprehensive evidence on the return premia to carry and momentum futures strategies across asset classes. For momentum, we find a common factor structure of returns, with high strategy correlation between asset classes. This strong correlation across such diverse asset classes is difficult to reconcile with behavioral theories and hints at the treatment of futures as an asset class in of itself. Furthermore, the considerable diversification benefit of combining carry and momentum strategies across asset classes presents a daunting task for rational risk-based pricing models that have so far struggled to explain individual strategies on a single asset class.

We find the highly significant returns to carry and momentum strategies are robust to a number of factor models, however, we find significant, but opposite covariation between a risk parity portfolio of futures contracts and both the global carry and momentum portfolios. Momentum has a positive relation and carry has a negative relation with portfolio returns - indicating at least part of the source of diversification benefit seen in the combined portfolio. For practitioners, these findings suggest carry and momentum portfolios provide an attractive investment opportunity.

Although we have studied a wide set of asset classes over both carry and momentum, we have limited our study to traditional choices of trading rules and volatility estimators and have avoided pairwise correlation adjustment. We have chosen this approach to focus our study on diversification benefit across strategies and asset classes. However, the optimization of these parameters provides an exciting avenue for further research, particularly for practitioners. Baltas and Kosowski (2015) provides an excellent exposition of this nascent topic for momentum strategies.

Investigating other possible sources of abnormal strategy returns, we find carry returns are explained by business cycle risk. However, momentum returns cannot be explained by business cycle risk but are significantly influenced by hedge fund capital flows, suggesting momentum risk premia are related to limits to arbitrage of hedge funds. Splitting our sample in half, we find momentum has only been significantly influenced by hedge fund capital flows after 2002, when hedge fund assets under management (AUM) were significantly higher. We argue that the rise of hedge fund AUM and activity in momentum strategies has increased connectivity between hedge fund liquidity and momentum strategies. Therefore, since 2002, hedge fund capital inflows have been deployed as arbitrage capital in momentum strategies, reducing next period strategy returns.

Supporting this hypothesis we find since 2002 increases in hedge fund capital are followed by a reduction in correlation between momentum strategies.

For policy makers, the impact of hedge fund capital on momentum returns and strategy correlation point to a positive influence that hedge funds have on futures markets. If increases in hedge fund capital decrease inefficiencies manifested in momentum, then policy makers restricting hedge fund capital, or central banks increasing capital costs, should be wary of causing an increase in market inefficiency and associated strategy correlation.

VII. Appendix: Tables

Table 1.1. Summary statistics for individual futures contracts
The table presents summary statistics for the 55 futures contracts across the asset classes bonds, commodities, currencies, equities and metals. From left to right the summary statistics are the instruments' name, the start date of the price series, the annualized fully collateralized excess return, its annualized standard deviation, the mean of the futures basis as well as its standard deviation. All series end in September 2012.

Underlying	Start	Returns		Basis		Underlying	Start	Returns		Basis	
		Mean	Std	Mean	Std			Mean	Std	Mean	Std
Bond						**Currency**					
Canadian Bill	Aug-90	0.8	1.3	0.1	3.0	AUD/USD	Jan-87	4.5	12.1	0.6	7.9
Canadian 10Yr	Sep-89	4.1	6.4	0.8	18.6	CAD/USD	Apr-86	2.0	7.5	0.2	5.6
Euro Bobl	Oct-91	3.1	3.5	0.4	5.4	CHF/USD	Apr-86	1.4	11.9	-0.4	8.0
Euro Bund	Nov-90	4.1	5.5	0.4	4.8	EUR/USD	May-98	0.6	10.3	-0.1	5.0
Euro Buxl	Oct-98	4.2	11.1	0.3	5.1	GBP/USD	May-86	2.2	10.0	0.4	7.0
Euro Schatz	Mar-97	1.1	1.4	0.2	2.1	JPY/USD	May-86	0.4	11.2	-0.7	8.2
Japan 10Yr	Oct-85	3.4	5.2	0.5	4.7	NOK/USD	May-02	4.7	13.7	0.2	6.9
Long Gilt	Nov-82	2.8	7.6	0.5	22.3	NZD/USD	May-97	3.6	13.9	0.6	6.0
US Govt Long	Jan-80	4.8	11.6	0.8	15.2	SEK/USD	May-02	4.4	13.5	0.0	6.1
US Govt 10Yr	May-82	5.3	7.0	0.8	9.5	**Equity**					
US Govt 2Yr	Jun-90	1.8	1.7	0.6	16.0	ASX SPI 200	May-00	1.8	16.8	-0.2	3.6
US Govt 5Yr	May-88	3.3	4.2	0.5	8.4	AEX	Jan-89	0.8	25.1	-0.2	15.5
Commodity						CAC 40	Dec-88	2.4	22.9	-0.1	4.0
Cattle, Live	Jan-80	4.2	14.8	0.2	27.8	DAX Index	Nov-90	4.2	23.6	-0.8	6.2
Cocoa	Jan-80	-5.6	30.7	-1.5	23.4	FTSE 100	Mar-88	2.5	18.7	-0.6	11.3
Coffee, 'C'	Jan-80	-2.6	36.0	-0.9	48.3	FTSE MIB	Mar-04	-3.5	24.8	0.4	4.8
Corn	Jan-80	-5.9	23.6	-1.9	33.7	IBEX 35	Jul-92	5.2	24.7	-0.1	4.3
Cotton, No. 2	Jan-80	-3.4	24.6	-0.4	54.5	S&P 500	Apr-82	6.0	19.9	-0.6	8.8
Crude, Brent	Jun-88	12.2	33.8	0.2	18.3	Toronto 60	Sep-99	3.4	21.0	-0.2	4.4
Crude, WTI	Apr-83	6.9	34.4	0.2	21.9	TOPIX	May-90	-5.8	23.8	-0.0	11.4
Gasoil	Jul-89	12.2	32.3	0.1	18.5	**Metals**					
Gasoline	Oct-05	5.1	37.8	-0.2	10.2	Copper	Jul-97	8.3	28.0	0.0	9.1
Heating Oil	Jul-86	8.3	33.8	0.1	19.8	Gold, 100 oz	Jan-80	-0.7	19.4	-0.9	8.5
Lean Hogs	Apr-86	-0.4	22.8	-1.6	57.4	Nickel	Jul-97	8.0	38.5	0.1	7.9
Natural Gas	Apr-90	-24.2	48.4	-1.5	40.5	Platinum	Jan-84	3.2	23.3	0.3	15.1
Soybean	Jan-80	0.7	22.7	-0.6	18.1	Aluminum	Jul-97	-3.1	21.8	-0.4	4.2
Soybean Meal	Jan-80	5.4	24.5	0.1	26.4	Silver	Jan-80	-4.6	31.6	-1.0	10.4
Soybean Oil	Jan-80	-2.5	23.8	-0.7	19.3	Zinc	Jul-97	-3.4	31.1	-0.4	5.2
Sugar, #11	Jan-80	-5.5	38.6	-0.7	58.2						
Wheat	Jan-80	-7.2	26.4	-1.5	41.9						

Table 1.2. Performance of global carry and momentum strategies

This table presents the performance statistics for global momentum, carry, combo and long strategies. Global strategies are inverse volatility weighted strategies across the asset classes bonds, commodities, currencies, equities and metals. Panel A, B and C report the summary statistics for the total returns, the returns of the long side and the returns to the short side of the strategies, respectively. Reported are the mean, the standard deviation (both annualized), the Sharpe ratio, the skewness and the kurtosis. We also report the CAPM alpha and beta as well as the t-statistics of the strategies relative to the long only benchmark portfolio. Finally, we report the average relative number of long and short positions in the strategy portfolios. The dataset covers the period January 1980 to September 2012.

Panel A:	**Long/Short**	Momentum	Carry	Combo	Long
	Mean	8.6	6.1	6.5	5.8
	Std Dev	6.7	4.7	4.5	7.4
	Sharpe	1.2	1.3	1.4	0.8
	Skewness	-0.3	0.1	-0.0	-0.3
	Kurtosis	8.8	6.2	7.3	6.8
	CAPM alpha	7.0	6.7	6.1	
	t-stat	5.9	7.8	7.4	
	CAPM beta	0.2	-0.1	0.0	
	tstat	4.8	-4.3	1.0	
	% Long positions	56.0	43.4	50.4	
	% Short positions	44.0	56.6	49.6	
	Recession CAPM alpha	8.3	6.7	6.2	
	t-stat	1.4	2.2	1.7	
	Non-recession CAPM alpha	5.8	6.7	5.6	
	t-stat	5.2	7.4	6.9	
Panel B:	**Long only**				
	Mean	6.4	4.8	4.3	5.8
	Std Dev	5.5	3.8	3.2	7.4
	Sharpe	1.1	1.2	1.3	0.8
	Skewness	-0.6	-0.1	-0.2	-0.3
	Kurtosis	8.7	6.9	7.8	6.8
	CAPM alpha	2.8	2.4	2.6	
	t-stat	4.7	5.6	5.6	
	CAPM beta	0.6	0.4	0.3	
	tstat	28.8	28.1	18.0	
Panel C:	**Short only**				
	Mean	2.0	1.2	2.2	5.8
	Std Dev	4.3	4.8	3.1	7.4
	Sharpe	0.5	0.2	0.7	0.8
	Skewness	0.2	0.5	0.3	-0.3
	Kurtosis	20.2	7.9	11.2	6.8
	CAPM alpha	4.1	4.3	3.5	
	t-stat	6.8	9.3	7.7	
	CAPM beta	-0.4	-0.5	-0.3	
	tstat	-18.8	-34.2	-16.2	

Table 1.3. Performance of carry and momentum strategies within asset classes
This table presents the performance statistics of carry, momentum, and combo strategies within the asset classes bonds, commodities, currencies, equities and metals. Reported are the mean, the standard deviation (both annualized), the Sharpe ratio, the skewness and the kurtosis. Also we report the CAPM alpha and beta as well as the t-statistics of the strategies relative to the long only benchmark portfolio. Finally, we report the average relative number of long and short positions in the strategy portfolios. The dataset covers the period January 1980 to September 2012 for commodities, bonds, metals and equities and April 1985 to September 2012 for currencies.

		Bond	Commodity	Currency	Equity	Metals
Momentum	Mean	10.4	10.1	5.8	7.2	8.9
	Std Dev	13.5	9.1	13.1	13.7	11.9
	Sharpe	0.7	1.1	0.4	0.5	0.7
	Skewness	-0.2	-0.2	-0.4	-0.2	-0.5
	Kurtosis	7.7	6.6	7.3	11.2	8.5
	CAPM alpha	2.4	9.6	4.4	5.3	8.2
	t-stat	1.3	5.8	1.8	2.3	4.0
	CAPM beta	0.6	0.0	0.2	0.2	0.1
	tstat	19.8	0.9	5.1	5.2	1.4
	% Long positions	70.9	49.5	60.2	62.5	44.0
	% Short positions	29.1	50.5	39.8	37.5	56.0
Carry	Mean	10.0	7.1	5.9	1.6	5.1
	Std Dev	12.4	8.9	10.3	11.8	11.1
	Sharpe	0.8	0.8	0.6	0.1	0.4
	Skewness	-0.0	0.1	-0.5	0.6	0.3
	Kurtosis	7.2	6.4	8.5	14.2	7.9
	CAPM alpha	1.8	8.2	4.7	2.8	5.7
	t-stat	1.4	5.5	2.3	1.6	4.5
	CAPM beta	0.6	-0.4	0.2	-0.4	-0.5
	tstat	30.5	-11.9	5.7	-10.5	-22.7
	% Long positions	77.6	35.3	57.0	19.7	15.2
	% Short positions	22.4	64.7	43.0	80.3	84.8
Combo	Mean	9.9	7.4	5.6	3.7	6.1
	Std Dev	11.0	7.1	9.4	9.2	8.5
	Sharpe	0.9	1.0	0.6	0.4	0.7
	Skewness	-0.1	-0.0	-0.6	0.2	-0.1
	Kurtosis	9.3	7.6	8.6	20.8	7.6
	CAPM alpha	2.2	7.8	4.3	3.4	6.2
	t-stat	1.8	6.5	2.5	2.3	4.6
	CAPM beta	0.6	-0.2	0.2	-0.1	-0.2
	tstat	29.4	-6.6	6.7	-2.0	-9.8
	% Long positions	58.4	26.1	39.4	12.3	11.4
	% Short positions	10.2	41.4	22.6	29.1	53.2

Table 1.4. Correlation of global carry and momentum

This table presents the correlation of global carry, momentum, combo and long only strategies. The table documents the correlation amongst strategies using four different versions or components of strategy return: (1) total return, (2) CAPM alpha return, (3) long leg return, and (4) short leg return. All correlations are calculated from monthly returns over the sample period January 1980 to September 2012

	Long/Short				**Alpha**			
	Mom	Carry	Combo	Long	Mom	Carry	Combo	Long
Mom	1.00	0.28	0.86	0.24	1.00	0.35	0.87	0.00
Carry		1.00	0.72	-0.21		1.00	0.75	-0.00
Combo			1.00	0.05			1.00	0.00
Long			0.05	1.00				1.00
	Long				**Short**			
	Mom	Carry	Combo	Long	Mom	Carry	Combo	Long
Mom	1.00	0.78	0.87	0.82	1.00	0.73	0.91	-0.69
Carry		1.00	0.87	0.82		1.00	0.79	-0.87
Combo			1.00	0.67			1.00	-0.63
Long				1.00				1.00

Table 1.5. Correlation within and across asset classes and strategies

Panel A reports by asset class the average pair-wise correlation of each instruments momentum, carry, combo and long only return series. It also reports the average pairwise cross correlation between the individual momentum and carry returns. Panel B reports the correlation of the volatility weighted momentum, carry, combo and long only portfolios across asset classes. Panel C reports the correlation across trading strategies (carry and momentum) and asset classes. Correlations are calculated from monthly returns over the period January 1982 to December 2009.

Panel A: Within asset classes

	Bond	Commodity	Currency	Equity	Metals
$\rho(Mom, Mom)$	0.39	0.15	0.39	0.43	0.31
$\rho(Carry, Carry)$	0.38	0.13	0.25	0.27	0.25
$\rho(Mom, Carry)$	0.23	0.03	0.10	0.03	0.02
$\rho(Combo, Combo)$	0.43	0.13	0.35	0.38	0.26
$\rho(Long, Long)$	0.55	0.24	0.52	0.55	0.42

Panel B: Across asset classes

	Momentum					Carry				
	Bond	Commodity	Currency	Equity	Metals	Bond	Commodity	Currency	Equity	Metals
Bond	1.00	0.01	0.08	0.08	0.09	1.00	0.05	-0.02	-0.06	0.12
Commodity		1.00	0.16	0.14	0.14		1.00	-0.12	-0.06	0.21
Currency			1.00	0.24	0.33			1.00	0.04	-0.14
Equity				1.00	0.32				1.00	-0.09
Metals					1.00					1.00

	Combo					Long				
	Bond	Commodity	Currency	Equity	Metals	Bond	Commodity	Currency	Equity	Metals
Bond	1.00	0.02	0.05	-0.04	0.11	1.00	-0.09	0.08	-0.23	-0.19
Commodity		1.00	0.07	0.08	0.06		1.00	0.40	0.22	0.40
Currency			1.00	0.16	0.10			1.00	0.14	0.46
Equity				1.00	0.15				1.00	0.31
Metals					1.00					1.00

Panel C: Across trading strategies

	Carry				
Momentum	Bond	Commodity	Currency	Equity	Metals
Bond	0.69	-0.00	0.06	-0.04	0.04
Commodity	-0.01	0.13	-0.03	0.06	-0.08
Currency	0.03	0.15	0.29	0.01	0.06
Equity	-0.05	0.04	0.05	-0.02	0.05
Metals	0.10	-0.13	-0.07	0.02	0.16

Table 1.6. Risk factor exposure

This table reports the regression coefficients (alpha as annualized percent) and the respective Newey and West (1987) adjusted t-statistics from regressing the returns to momentum, carry and combo strategies on four model specifications: (a) a version of Asness, Moskowitz, and Pedersen (2013) "Value and Momentum everywhere" model that uses a volatility weighted cross-sectional momentum portfolio across asset classes (Mom. Every.) and a volatility weighted cross-sectional value portfolio across asset classes (Value Every.) as factors which we augment with the volatility weighted long only portfolio as a market proxy; (b) a version of the Fama and French (1992) model that uses the high minus low (FF HML) and the small minus big (FF SMB) portfolios as factors and includes the MSCI index as a market proxy; (c) a liquidity risk model that includes the TED spread (Funding Liq.) as a funding liquidity proxy and the Pastor and Stambaugh (2001) market liquidity proxy (Market Liq.); and (d) a combination of (a) and (c). The last row reports the adjusted R^2's of the regressions. The sample is from January 1980 to September 2012.

	(a)			(b)			(c)			(d)		
	Carry	Mom	Combo	Carry	Mom	Combo	Carry	Mom	Combo	Carry	Mom	Combo
Alpha	7.38	6.48	6.15	6.84	10.36	7.66	8.96	6.70	7.18	11.93	2.55	6.78
tstat	(5.21)	(3.93)	(5.04)	(5.35)	(6.01)	(6.37)	(3.90)	(2.13)	(3.30)	(4.89)	(0.89)	(3.17)
Long	-0.12	0.15	0.01							-0.13	0.17	0.02
tstat	(-2.70)	(2.89)	(0.36)							(-3.02)	(3.28)	(0.39)
Value Every.	-0.59	-0.26	-0.46							-0.74	-0.22	-0.51
tstat	(-1.46)	(-0.56)	(-1.32)							(-1.85)	(-0.46)	(-1.45)
Mom. Every.	0.60	2.73	1.56							0.53	2.69	1.51
tstat	(1.78)	(6.99)	(5.38)							(1.58)	(6.88)	(5.19)
MSCI				-0.01	-0.02	-0.01						
tstat				(-0.62)	(-0.48)	(-0.62)						
FF HML				0.00	-0.00	-0.00						
tstat				(0.56)	(-3.31)	(-1.96)						
FFSMB				-0.00	-0.00	-0.00						
tstat				(-2.72)	(-2.01)	(-2.77)						
Funding Liq.							-0.00	0.00	0.00	-0.13	0.17	0.02
tstat							(-1.23)	(1.26)	(0.10)	(-3.02)	(3.28)	(0.39)
Market Liq							-0.04	-0.02	-0.03	-0.74	-0.22	-0.51
tstat							(-2.38)	(-0.92)	(-1.67)	(-1.85)	(-0.46)	(-1.45)
R^2	0.07	0.32	0.22	0.03	0.05	0.22	0.02	0.00	0.00	0.10	0.32	0.22

Table 1.7. Business cycle risk in carry and momentum strategies

Panel A of this table presents the coefficients and Newey and West (1987) adjusted t-statistics when carry, momentum, combo and long strategies are regressed against lagged values of the macroeconomic predictor variables dividend yield (Div Yield), default spread (Def Spread), short rate (Short Rate) and term spread (Term Spread). The last column reports the R^2 of the regression. The first column of Panel B represents the residual or average unexplained returns of the predictive model. The residual columns present the correlations of the fitted values of the model or estimated time-varying risk premia. Panel C presents the same regressions as in Panel A including the TED spread as a proxy for funding liquidity.

Panel A:	Intercept	Div Yield	Def Spread	Short Rate	Term Spread	R^2
Momentum	0.009	-0.006	0.001	0.002	0.002	1.367
	(2.513)	(-2.304)	(0.243)	(1.969)	(1.548)	
Carry	0.004	-0.007	0.004	0.002	0.003	2.999
	(1.355)	(-3.673)	(1.838)	(2.950)	(2.894)	
Combo	0.005	-0.006	0.003	0.002	0.003	3.675
	(2.140)	(-3.812)	(1.310)	(3.250)	(2.782)	
Long	0.012	0.003	-0.002	-0.002	-0.001	1.422
	(2.666)	(1.040)	(-0.602)	(-2.079)	(-0.627)	
Panel B:	Adj. returns	Momentum	Carry	Combo	Long	Ind Prod
Momentum	0.110	1.000	0.862	0.963	-0.193	0.418
	(2.513)					
Carry	0.043		1.000	0.963	-0.089	0.129
	(1.355)					
Combo	0.063			1.000	-0.208	0.282
	(2.140)					
Long	0.141				1.000	-0.191
	(2.666)					
Panel C:	TED Spread	Div Yield	Def Spread	Short Rate	Term Spread	R^2
Momentum	0.006	-0.006	-0.002	0.001	0.003	1.759
	(1.793)	(-2.192)	(-0.419)	(1.156)	(1.613)	
Carry	-0.004	-0.007	0.007	0.003	0.004	3.249
	(-1.400)	(-3.703)	(2.342)	(3.008)	(2.895)	
Combo	0.001	-0.007	0.003	0.002	0.003	3.315
	(0.372)	(-3.747)	(1.114)	(2.659)	(2.798)	
Long	-0.011	0.002	0.004	-0.000	0.000	2.047
	(-2.601)	(0.607)	(0.799)	(-0.172)	(0.024)	

Table 1.8. Hedge fund styles and strategy returns

This table reports the regression coefficients and the respective t-statistics from regressing a cross-section of hedge fund indices on various combinations of factors. The hedge fund indices include an all strategy index, an event driven strategy index, a fixed income arbitrage strategy index, a macro strategy index, an equity long and short strategy index and a managed futures index (CTA), these are taken from the Credit Suisse hedge fund database. The factors included are the S&P 500 index, the equally volatility weighted long strategy, the momentum strategy, the carry strategy and the five Fung and Hsieh (2004) factors. The last row reports the adjusted R^2 of the regression. The sample is from 1994 to 2011.

	HF Index			Event Driven			FixedInc.Arb.			Macro			Long Short			CTA		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Alpha	0.42	0.69	0.50	0.65	0.62	0.63	0.29	0.43	0.34	0.56	1.06	0.64	0.49	0.70	0.60	-0.25	0.87	-0.05
tstat	(3.32)	(5.45)	(3.66)	(6.22)	(6.43)	(5.86)	(2.60)	(4.06)	(2.88)	(2.87)	(5.29)	(2.94)	(3.18)	(4.49)	(3.53)	(-1.25)	(3.86)	(-0.25)
SandP	0.22	0.26	0.20	0.21	0.22	0.17	0.06	0.08	0.03	0.11	0.15	0.11	0.34	0.40	0.32	-0.13	0.02	-0.06
tstat	(6.90)	(9.44)	(6.27)	(7.91)	(10.54)	(6.67)	(2.30)	(3.57)	(1.20)	(2.28)	(3.56)	(2.09)	(8.82)	(11.99)	(8.07)	(-2.63)	(0.32)	(-1.22)
Long	0.15		0.13	0.09		0.07	0.24		0.21	0.16		0.15	0.16		0.13	0.31		0.29
tstat	(2.98)		(2.46)	(2.21)		(1.84)	(5.27)		(4.77)	(2.06)		(1.84)	(2.65)		(2.13)	(3.99)		(3.85)
Mom	0.21		0.21	0.08		0.11	-0.17		-0.15	0.36		0.34	0.22		0.24	0.74		0.70
tstat	(3.91)		(3.77)	(1.82)		(2.57)	(-3.52)		(-3.12)	(4.29)		(3.89)	(3.38)		(3.48)	(8.90)		(8.52)
Carry	-0.11		-0.13	-0.18		-0.21	0.16		0.15	-0.03		-0.04	-0.24		-0.29	0.07		0.04
tstat	(-1.50)		(-1.71)	(-2.86)		(-3.44)	(2.33)		(2.22)	(-0.23)		(-0.29)	(-2.59)		(-3.03)	(0.62)		(0.36)
PTFSbd		-0.02	-0.02		-0.03	-0.03		-0.01	-0.01		-0.02	-0.01		-0.02	-0.01		0.03	0.04
tstat		(-2.95)	(-2.77)		(-4.61)	(-4.33)		(-1.38)	(-1.98)		(-1.34)	(-1.16)		(-1.91)	(-1.54)		(2.40)	(3.52)
PTFScom		0.02	0.00		0.00	-0.01		0.01	0.01		0.02	0.01		0.01	-0.01		0.05	0.01
tstat		(1.94)	(0.45)		(0.27)	(-1.17)		(0.92)	(1.23)		(1.57)	(0.36)		(1.03)	(-0.58)		(2.75)	(0.91)
PTFSfx		0.01	0.01		0.01	0.01		-0.01	-0.02		0.01	0.01		0.01	0.01		0.04	0.03
tstat		(1.57)	(1.38)		(1.20)	(1.23)		(-2.53)	(-2.98)		(1.14)	(0.83)		(1.36)	(1.30)		(3.20)	(3.24)
PTFSir		-0.02	-0.01		-0.01	-0.01		-0.02	-0.01		-0.01	-0.01		-0.02	-0.01		-0.02	-0.00
tstat		(-3.61)	(-2.82)		(-3.23)	(-2.91)		(-4.79)	(-3.64)		(-1.88)	(-0.99)		(-3.04)	(-2.52)		(-1.97)	(-0.36)
PTFSstk		0.02	0.01		-0.00	-0.01		0.00	0.00		0.02	0.01		0.02	0.01		0.04	0.01
tstat		(1.68)	(0.83)		(-0.41)	(-0.86)		(0.34)	(0.39)		(1.62)	(0.65)		(1.49)	(0.84)		(2.64)	(1.03)
R^2	0.43	0.39	0.47	0.46	0.49	0.54	0.22	0.25	0.32	0.19	0.08	0.18	0.51	0.47	0.53	0.43	0.18	0.51

Table 1.9. Hedge fund capital and strategy returns

This table presents the estimated coefficients and respective t-statistics of regressing momentum, carry, combo and long only strategies on measures of hedge fund capital. The proxies for hedge fund capital are the total hedge fund asset under management times the TED spread and changes thereof. The table also presents a proxy for capital flow into the hedge fund industry. As control variables the table includes the TED spread and the market liquidity. Panel A presents the regression results over the whole sample from 1994 to 2011 and Panel B splits the sample into two equal parts.

	Panel A:	Intercept	HF Capital	HF Flow	Fund.Liq.	Market Liq	R^2
(1)	Momentum	0.009	-0.454	-0.191			1.757
		4.536	-2.987	-0.220			
(2)	Momentum	0.008	-0.450	-0.146	0.001	-0.030	1.614
		2.108	-2.045	-0.164	0.110	-1.511	
(1)	Carry	0.007	0.046	-0.625			-0.267
		5.223	0.542	-1.337			
(2)	Carry	0.008	-0.033	-0.664	-0.003	-0.046	2.128
		3.406	-0.265	-1.344	-0.805	-2.724	
(1)	Combo	0.007	-0.198	-0.377			0.851
		5.524	-2.234	-0.772			
(2)	Combo	0.008	-0.245	-0.388	-0.001	-0.037	2.257
		3.294	-1.843	-0.805	-0.490	-2.452	
(1)	Long	0.004	-0.080	2.349			3.246
		1.607	-0.372	1.915			
(2)	Long	0.005	-0.111	2.244	-0.002	0.051	4.052
		1.092	-0.420	1.750	-0.330	1.438	

	31/03/1994-31/07/2002				31/07/2002-31/12/2010			
Panel B:	Intercept	HF Capital	HF Flow	R^2	Intercept	HF Capital	HF Flow	R^2
Momentum	0.009	-2.029	1.274	-1.054	0.008	-0.452	-0.211	2.059
	4.800	-0.992	0.567		2.294	-2.981	-0.207	
Carry	0.007	0.804	1.481	-1.603	0.005	0.003	-0.487	-0.796
	3.970	0.370	0.578		2.991	0.040	-1.042	
Combo	0.008	-0.623	1.461	-1.380	0.006	-0.226	-0.283	1.766
	4.988	-0.372	0.732		2.810	-2.575	-0.523	
Long	0.006	-5.747	-4.357	3.436	0.008	0.005	2.162	3.257
	2.418	-2.041	-1.580		1.612	0.023	1.407	

Table 1.10. Dynamics of carry and momentum returns

Reported are Sharpe ratios and correlations among global carry, global momentum, and global combined strategies across different economic environments. Statistics for the equivalent equally volatility weighted long only strategy are also shown for comparison. The first four columns report the Sharpe ratio of the all-asset-class global momentum, global carry and global combination strategies, alongside the equal volatility weighted long only strategy. The last four columns report the average pair-wise correlation for assets within global momentum (1), within global carry (2), between global momentum and global carry (3), and within long only (4). These statistics are reported for three parts of sample period split at March 1982 and March 1992, during recessionary and non-recessionary periods (as defined as the NBER), and for months with the top 20th and bottom 20th percentile of S&P 500 returns. Panel A reports statistics for strategy net return, Panel B and C report analogous statistics for the returns of constituent long and short legs, respectively.

	Sharpe ratios				Correlations			
	Mom.	Carry	Combined	Long	(1)	(2)	(3)	(4)
Panel A: Net Returns								
Mar-82 to Mar-92	1.621	1.141	1.496	0.630	0.252	0.223	0.080	0.240
Mar-92 to Mar-02	1.769	1.343	1.794	0.556	0.246	0.226	0.085	0.238
Mar-02 to Mar-12	1.015	1.273	1.260	1.194	0.358	0.175	0.031	0.322
Recession	1.048	1.570	1.280	-0.580	0.394	0.189	0.112	0.309
Non-recession	1.369	1.197	1.511	1.158	0.297	0.197	0.045	0.285
Best 20% S&P rets.	1.599	0.536	1.228	2.969	0.327	0.198	0.088	0.275
Worst 20% S&P rets.	1.328	2.738	2.260	-1.509	0.322	0.189	0.057	0.283
Panel B: Long Leg Returns								
Mar-82 to Mar-92	1.215	1.032	1.320		0.231	0.200	0.118	0.240
Mar-92 to Mar-02	1.424	1.305	1.512		0.232	0.202	0.124	0.238
Mar-02 to Mar-12	1.221	1.591	1.484		0.329	0.249	0.233	0.322
Recession	0.148	0.017	0.379		0.325	0.283	0.174	0.309
Non-recession	1.372	1.580	1.561		0.304	0.227	0.213	0.285
Best 20% S&P rets.	2.971	2.778	2.382		0.275	0.234	0.165	0.275
Worst 20% S&P rets.	-0.266	0.260	0.860		0.300	0.233	0.194	0.283
Panel C: Short Leg Returns								
Mar-82 to Mar-92	0.921	0.538	0.814		0.257	0.244	0.182	0.240
Mar-92 to Mar-02	0.939	0.573	1.090		0.244	0.244	0.172	0.238
Mar-02 to Mar-12	-0.098	-0.228	0.166		0.363	0.279	0.195	0.322
Recession	1.188	1.309	1.324		0.354	0.248	0.213	0.309
Non-recession	0.222	-0.078	0.471		0.269	0.272	0.176	0.285
Best 20% S&P rets.	-0.834	-1.637	-0.446		0.324	0.254	0.200	0.275
Worst 20% S&P rets.	2.139	2.439	2.289		0.310	0.253	0.181	0.283

Table 1.11. Dynamics of correlation within and across strategies

Reported are monthly time-series regressions of conditional correlations among global carry, momentum, and combined strategies on to a time trend and economic variables. The conditional correlations used as the dependent variables are estimated as the average of correlations among momentum strategies globally, carry strategies globally, and between carry and momentum strategies globally. These are regressed on a time trend, a recession dummy (as defined by the NBER) and a measure of hedge fund liquidity defined as the product of the monthly change in hedge fund assets under management and the TED spread. The conditional correlations used as the dependent variables are calculated as the month average correlation between daily strategy returns. Analysis of the full sample is reported in Panel A. Panels B and C report the equivalent analysis for the first and second half of the available sample split at December 2002.

Dependent variable =	$\rho(\text{mom}, \text{mom})_t$	$\rho(\text{car}, \text{car})_t$	$\rho(\text{mom}, \text{car})_t$	$\rho(\text{long}, \text{long})_t$
Full Period				
Time trend	0.0073	-0.0043	-0.0073	0.0088
(t-stat)	(4.55)	(-3.68)	(-4.59)	(8.16)
Recession	0.0473	0.0076	0.0323	-0.0215
(t-stat)	(1.85)	(0.41)	(1.26)	(-1.25)
HF Capital	-3.3381	0.3417	-3.9995	-1.0392
(t-stat)	(-3.08)	(0.43)	(-3.69)	(-1.43)
Jan-1994 to Dec-2002				
Time trend	0.0004	0.0112	0.0163	-0.0037
(t-stat)	(0.12)	(3.66)	(3.87)	(-1.44)
Recession	-0.0140	-0.0360	0.0368	0.0143
(t-stat)	(-0.42)	(-1.29)	(0.95)	(0.61)
HF Capital	-9.4742	-8.7801	-27.5238	9.6809
(t-stat)	(-0.72)	(-0.80)	(-1.82)	(1.05)
Jan-2003 to Aug-2011				
Time trend	0.0128	-0.0168	-0.0221	0.0119
(t-stat)	(2.45)	(-5.39)	(-5.43)	(3.53)
Recession	0.0893	0.0230	0.0062	-0.0289
(t-stat)	(2.38)	(1.03)	(0.21)	(-1.20)
HF Capital	-2.4157	0.1598	-4.9306	-1.0024
(t-stat)	(-1.88)	(0.21)	(-4.94)	(-1.21)

Table 1.12. Momentum predictability given carry returns and hedge fund capital

This table reports the coefficient estimates and t-statistics of regressing momentum returns on carry returns, a measure of Hedge Fund capital, and macroeconomic variables (dividend yield, default spread, short rate, and term spread). The table reports the regression results split into three samples. The first sample for the full period, the second from January 1994 to December 2002 and the final sample from January 2003 to August 2011.

	int.	Carry	HF Capital	Div Yield	Def Spread	Short Rate	Term Spread	R^2
Full Period								
Mom	0.025	0.430	-0.801	-0.002	-0.010	-0.001	-0.002	12.999
t-stat	(2.455)	(3.843)	(-4.167)	(-0.651)	(-1.816)	(-0.694)	(-0.704)	
Jan-1994 to Dec-2002								
Mom	0.043	0.546	-3.583	-0.005	-0.031	-0.002	0.001	29.879
t-stat	(1.771)	(5.432)	(-1.851)	(-0.979)	(-2.288)	(-0.438)	(0.216)	
Jan-2003 to Aug-2011								
Mom	0.037	0.296	-0.785	-0.019	0.003	0.001	0.001	6.891
t-stat	(0.847)	(1.194)	(-4.049)	(-0.981)	(0.196)	(0.200)	(0.094)	

VIII. Appendix: Figures

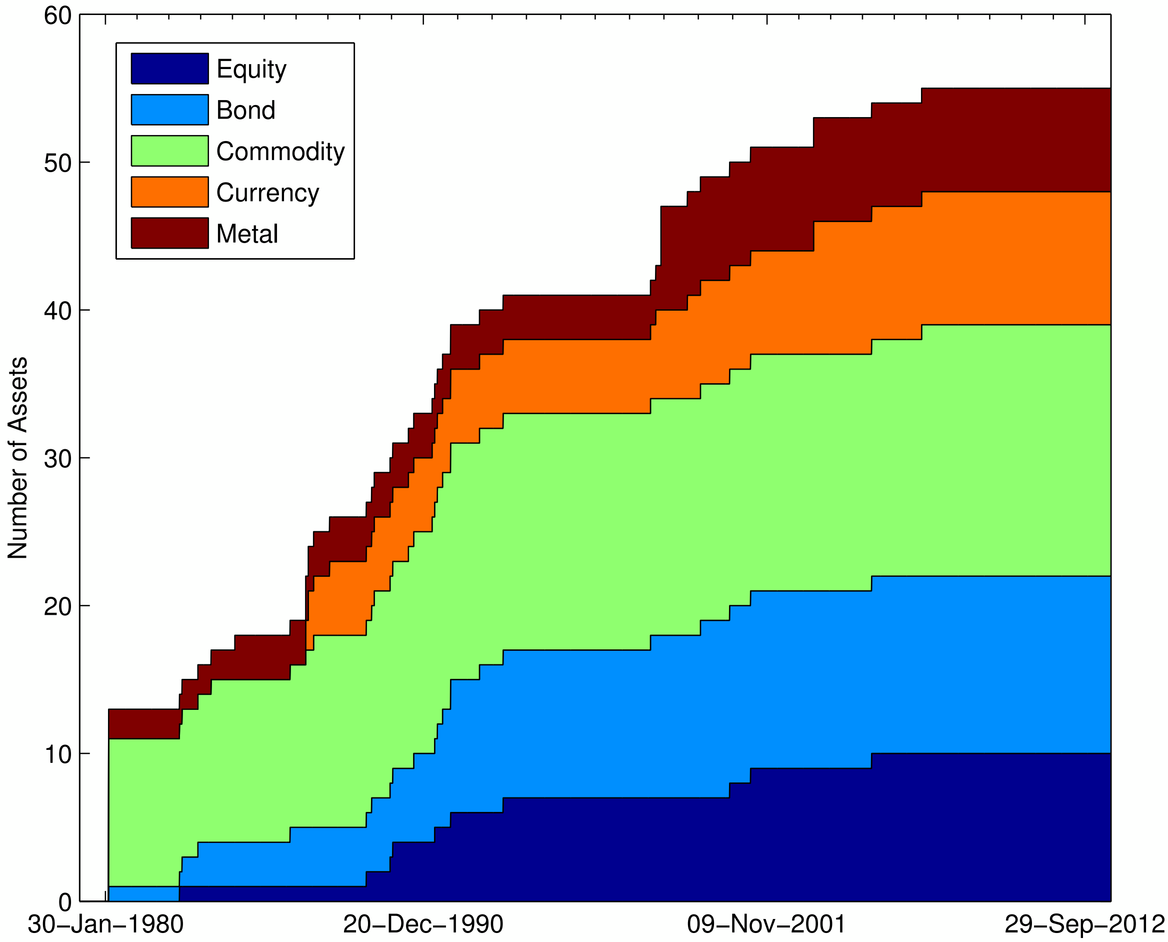
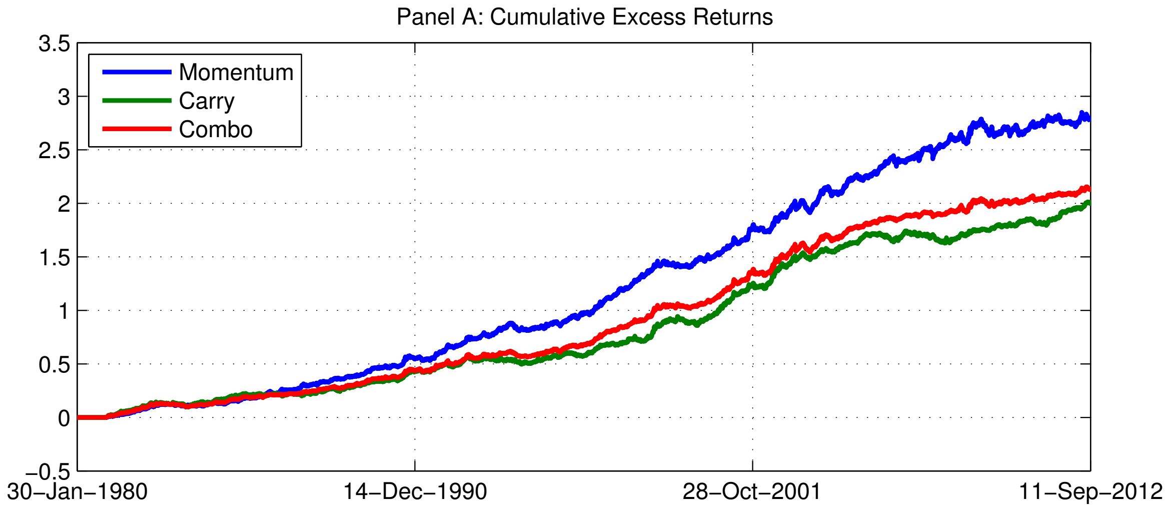


Figure 1.1. Number of available contracts by asset class
This figure presents the number of available assets categorized by asset class into equities, bonds, commodity, currency and metals. The sample runs from January 1980 to September 2012.



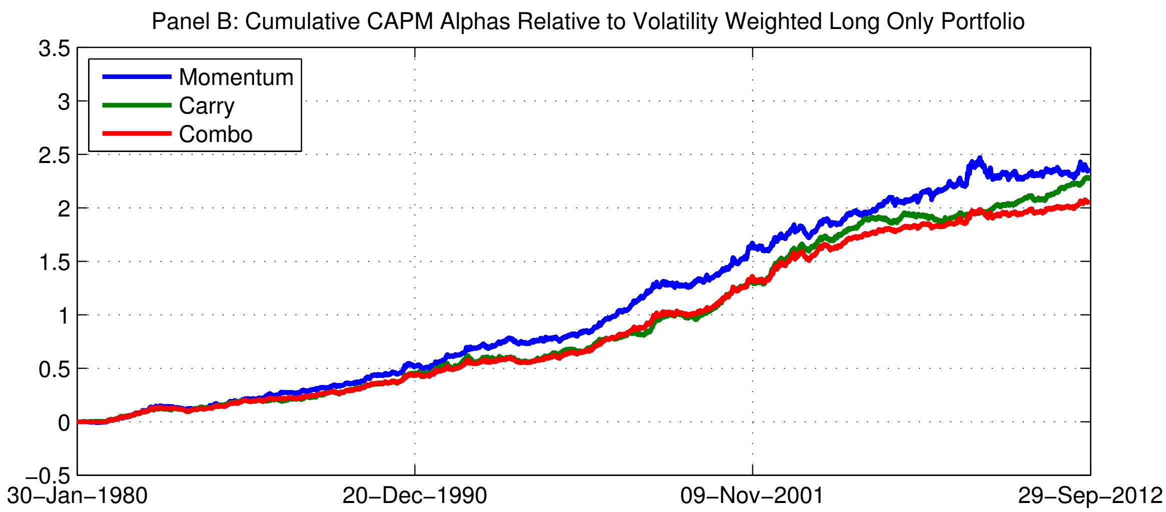


Figure 1.2. Cumulative returns to global carry, momentum, and combo strategies
Plotted are the daily cumulative sum of log returns on carry, momentum, and combo global portfolios for the period January 1981 to September 2012. Each global strategy is constructed as an equal weighted portfolio of asset class strategy returns for equities, bonds, commodities, currencies and metals. Panel A and Panel B show the cumulative excess returns and the cumulative CAPM alphas, respectively. The CAPM alphas are calculated relative to the equal volatility weighted long only strategy.

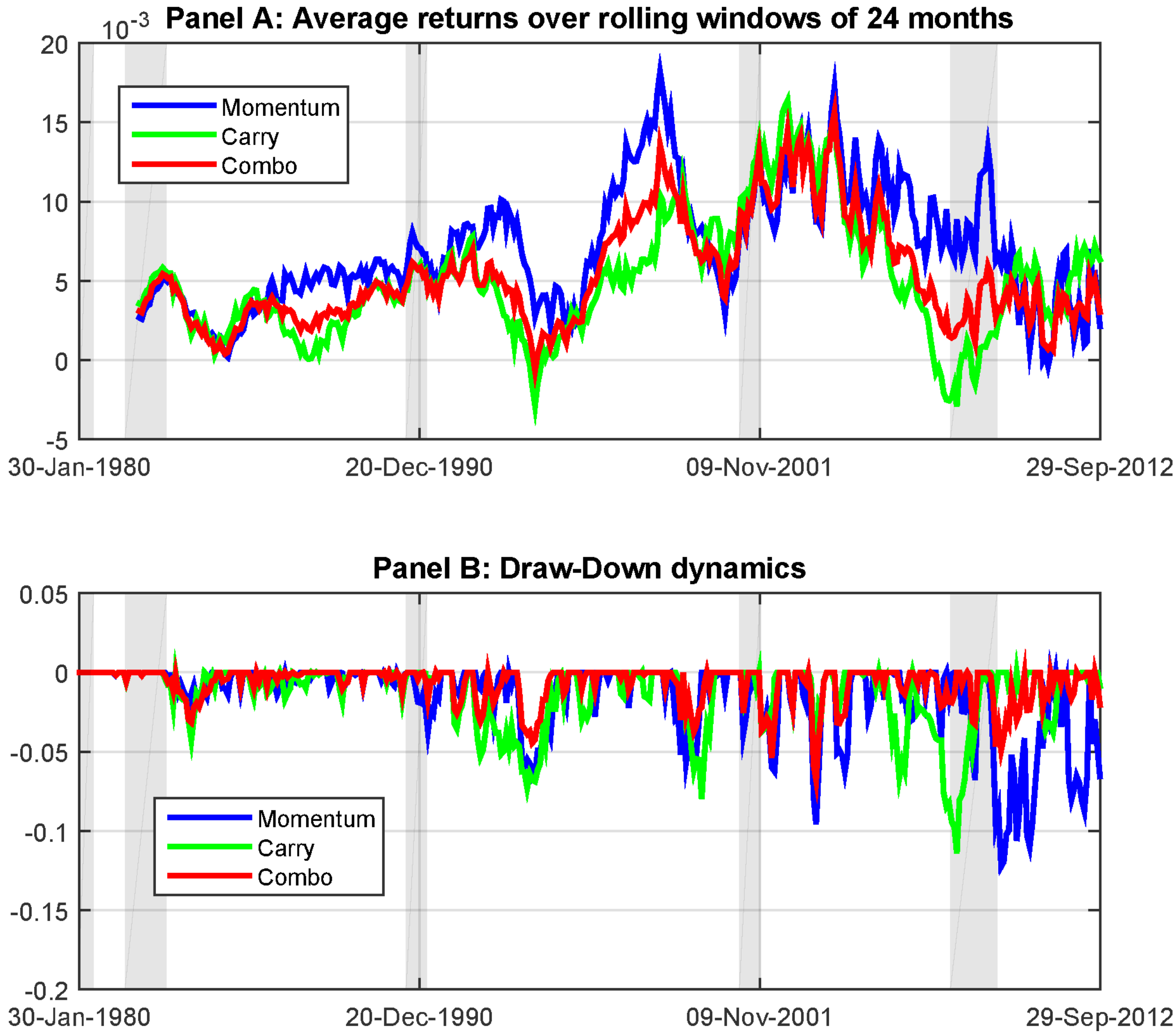


Figure 1.3. Rolling average return dynamics and draw-down dynamics of global carry, momentum,

This figure shows the draw-down dynamics and rolling average return dynamics for global carry, momentum, and combo strategies. Panel A shows average monthly returns over rolling windows of 24 months for the individual strategies. Panel B shows the maximum draw-down dynamics of the global strategies. We define the maximum draw down as $D_t = \sum_{s=1}^{t} r_s - \max_{u\epsilon(1,\ldots,t)} \sum_{s=1}^{u} r_s$, where r_s denotes the return on the global trading strategies. The sample period is Jan 1980 to Sep 2012. The grey bands refer to recessions as defined by the NBER.

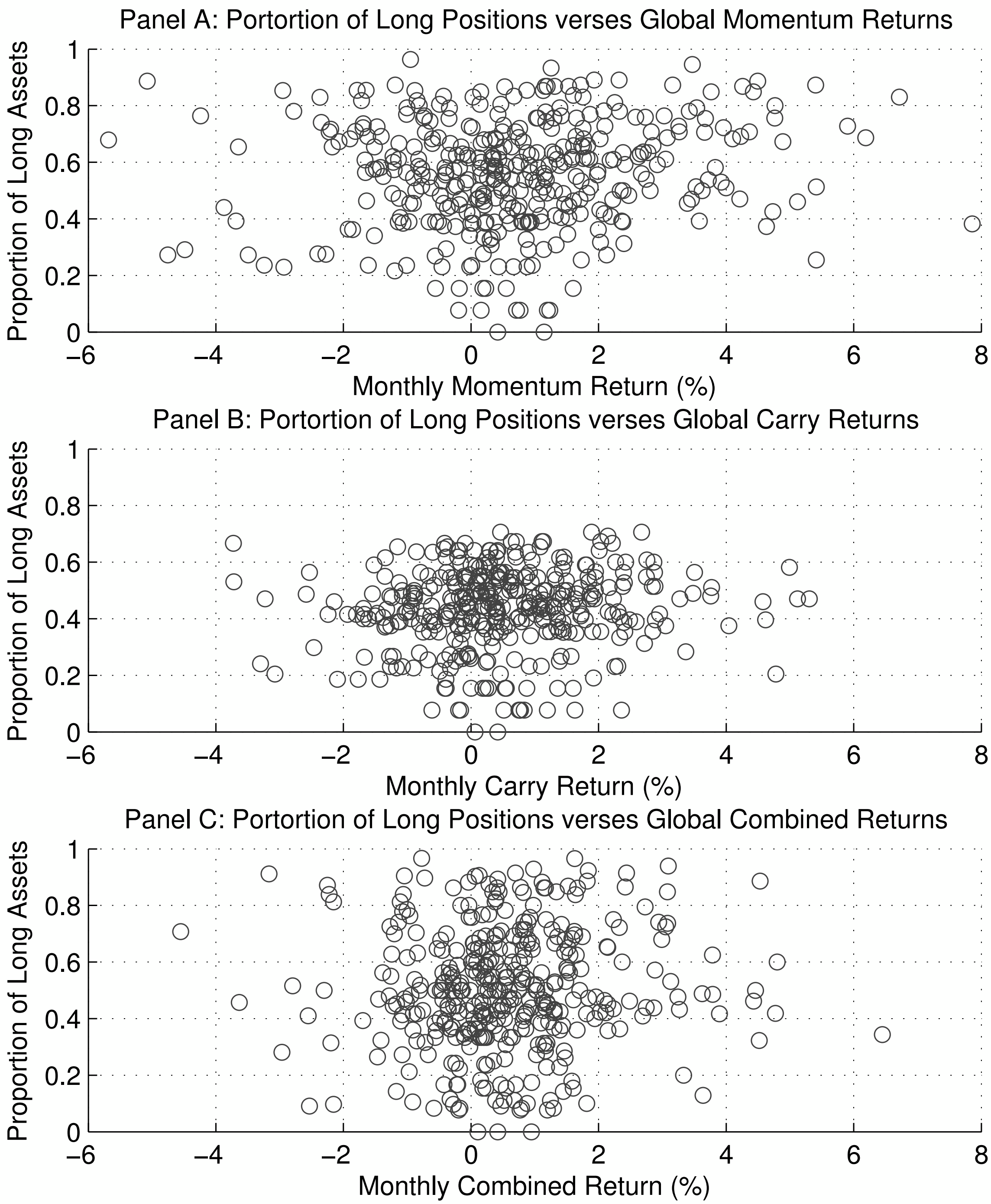


Figure 1.4. Proportion of long assets verses monthly return

The figure presents scatter plots of the proportion of long assets within each strategy verses monthly return for global portfolios. Plots for global carry, global momentum, and global combo strategies are shown in Panel A, Panel B and Panel C, respectively.

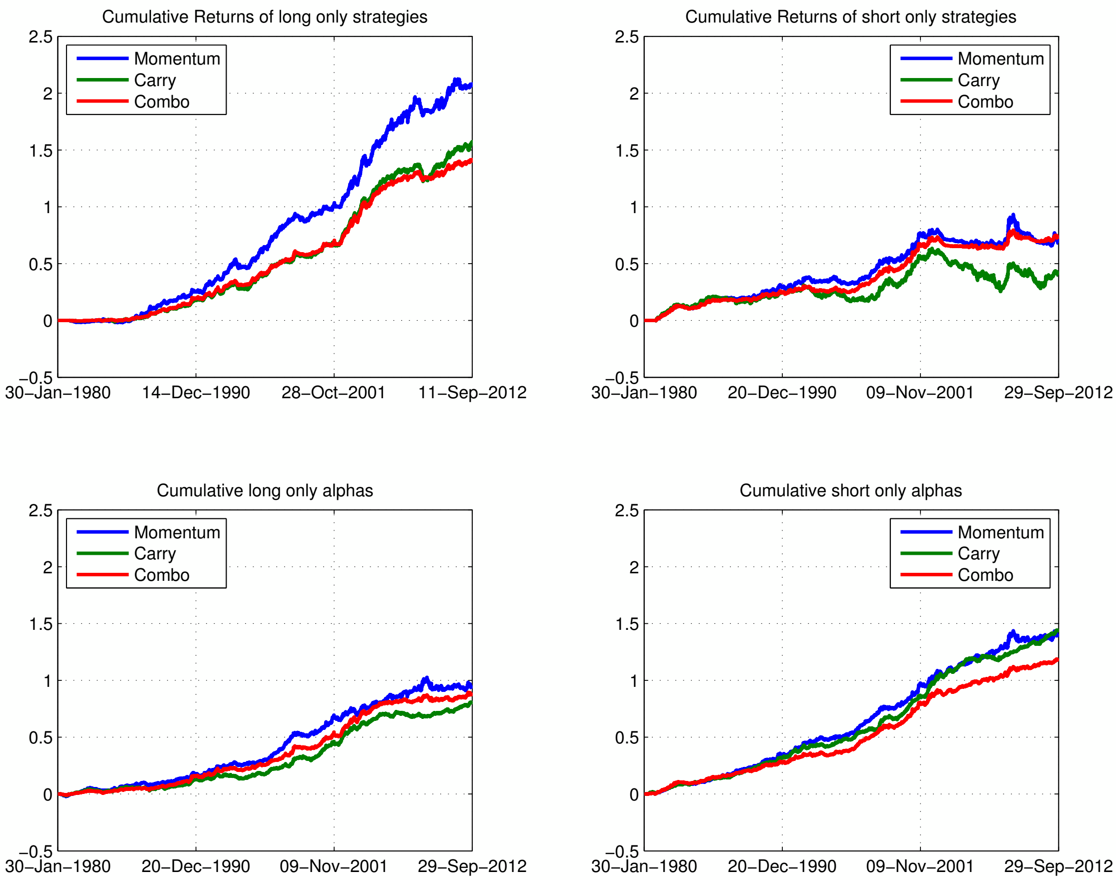
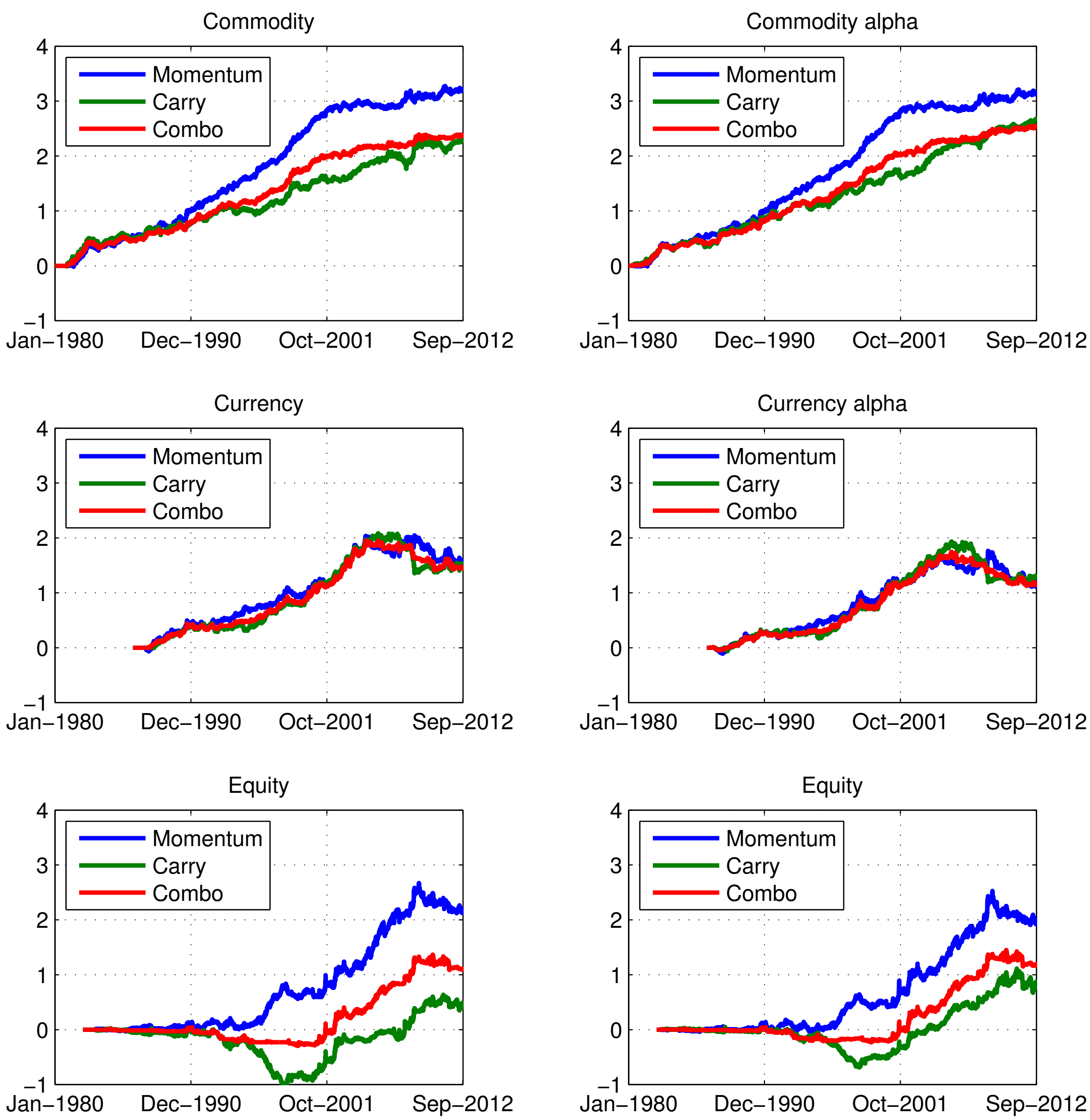


Figure 1.5. Cumulative returns for long and short legs of global carry, momentum, and combo

This figure presents the daily cumulative sum of excess returns and CAPM alphas (relative to a long only volatility weighted portfolio) for the long only and short only legs of global carry, momentum, and combo portfolios for the period January 1981 to September 2012. Each global strategy is constructed as an equal weighted portfolio of asset class strategy returns for equities, bonds, commodities, currencies and metals.


Commodity
Commodity alpha
Currency
Currency alpha
Equity
Equity
Momentum
Carry
Combo
4
3
2
1
0
−1
Jan−1980
Dec−1990
Oct−2001
Sep−2012

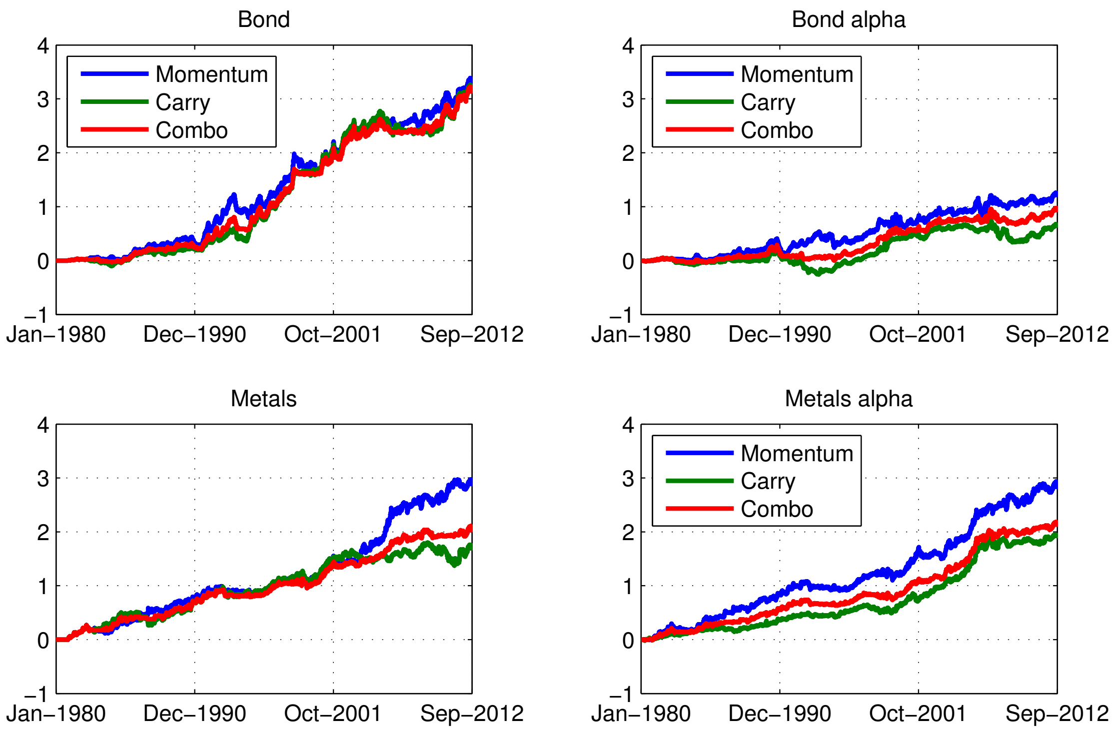


Figure 1.6. Cumulative returns to carry, momentum, and combo strategies within asset classes This figure presents the daily cumulative sum of log excess returns and daily cumulative sum of CAPM alphas on carry, momentum, and combo portfolios decomposed by asset class for commodities, bonds, currencies, equities and metals, over the period January 1981 to September 2012. For each asset class the CAPM alphas are calculated relative to the long only equal volatility weighted portfolio of assets within the class. The daily excess returns are displayed on the left hand side, whilst on the right hand side are the CAPM alphas.

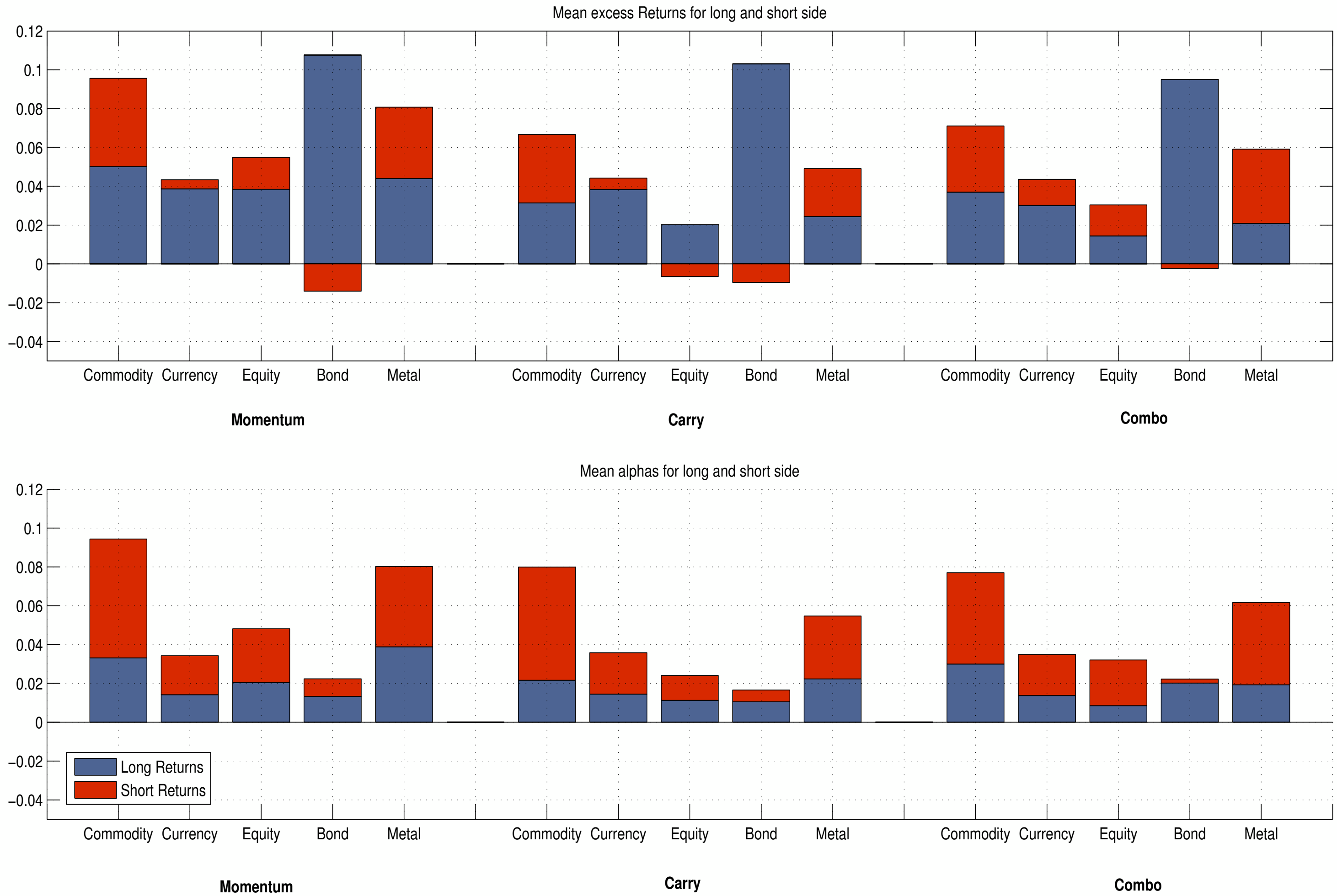
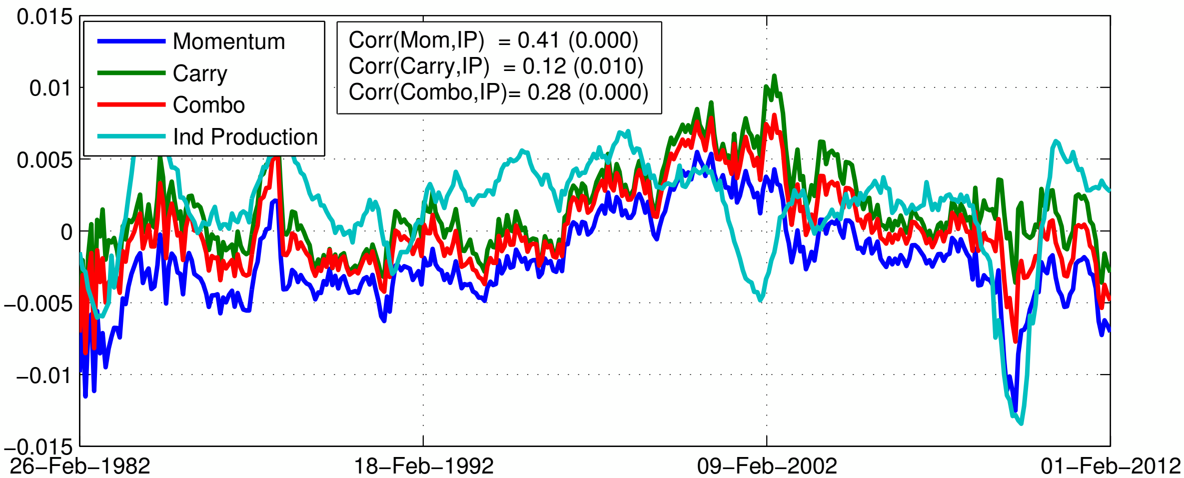


Figure 1.7. Long and short contribution for mean excess returns and mean CAPM alphas of carry, momentum, and combo

This figure presents the long and short contribution for mean excess returns and mean CAPM alphas of carry, momentum, and combo strategies across the asset classes commodities, currencies, equities, bonds and metals.



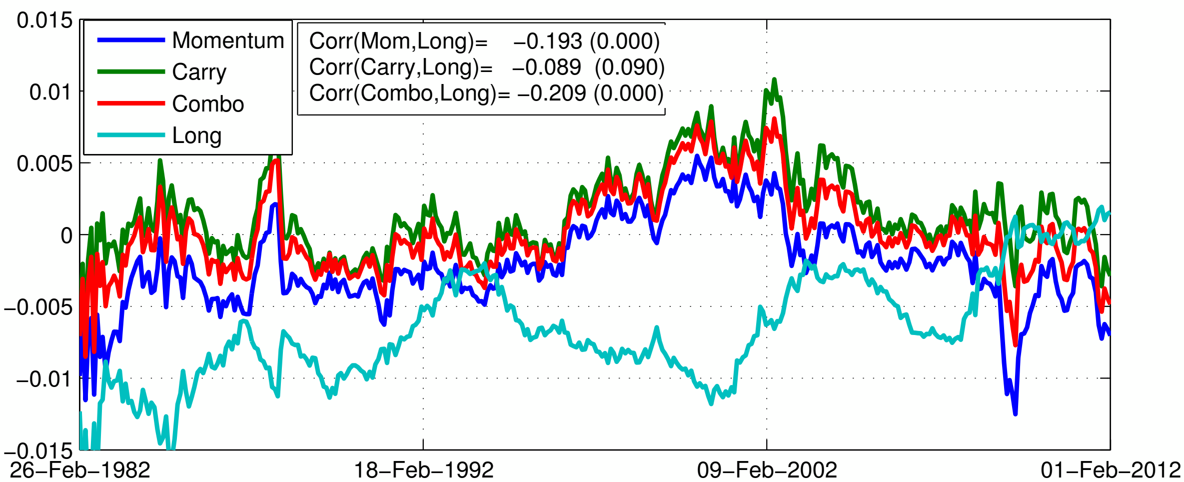


Figure 1.8. Global momentum, carry and combo returns adjusted for macroeconomic predictor

Panels A and B show the global momentum, carry and combo monthly strategy returns after adjusting for returns predicted by the business cycle model. Adjusted returns are measured as the unexplained portion (intercept plus residual) of the following model: $R_t = \alpha + \beta X_{t-1} + \epsilon_t$, where X is a vector representing the predictor variables dividend yield, default spread, term spread, and the yield on the three-month T-bill. Panel A also shows the 12 month average growth of an industrial production index, while Panel B shows the volatility weighted long only portfolio.

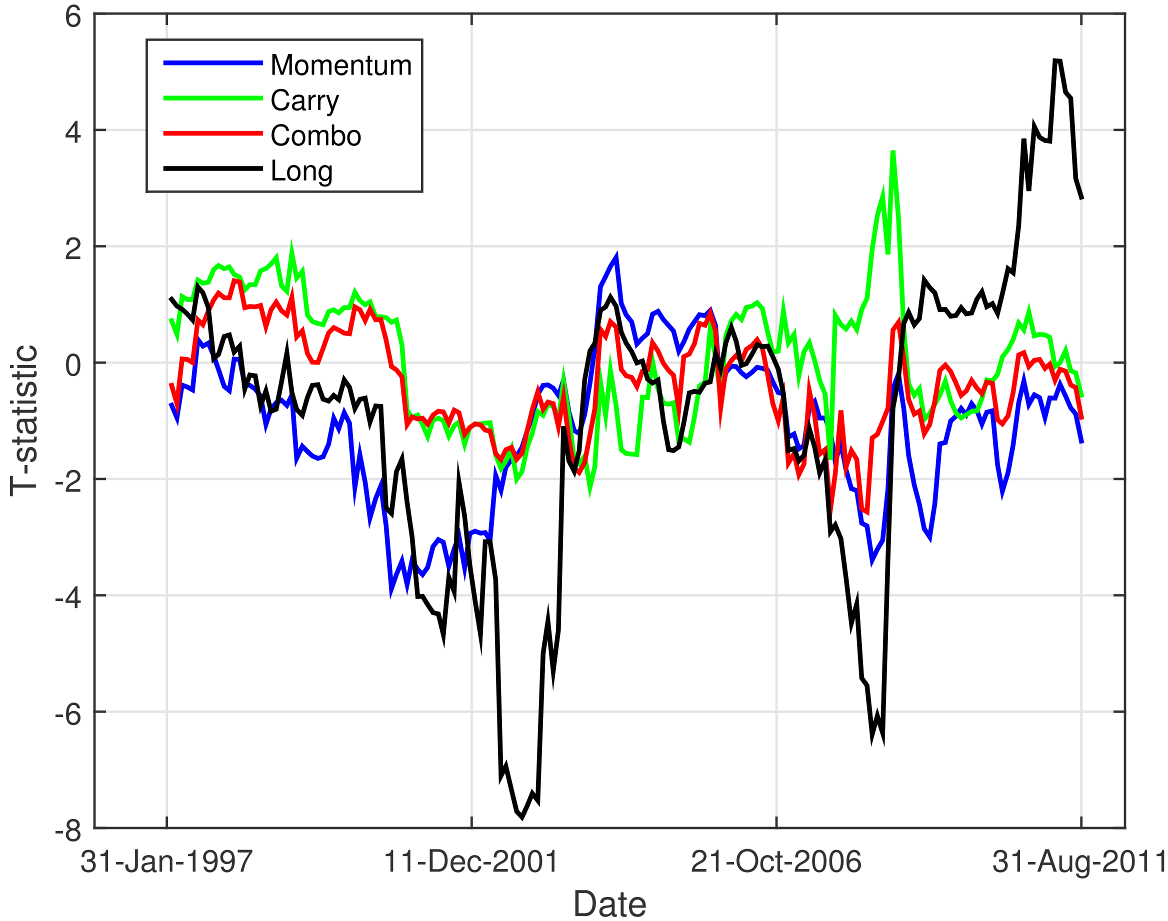


Figure 1.9. Rolling regression of strategy Sharpe on changes in hedge fund capital
Plotted are t-statistics for 3 year rolling regressions of monthly strategy Sharpe ratio on to lagged difference of hedge assets under management (HF Capital). The daily Sharpe ratio is calculated as the monthly return divided by the standard deviation of returns in that month.

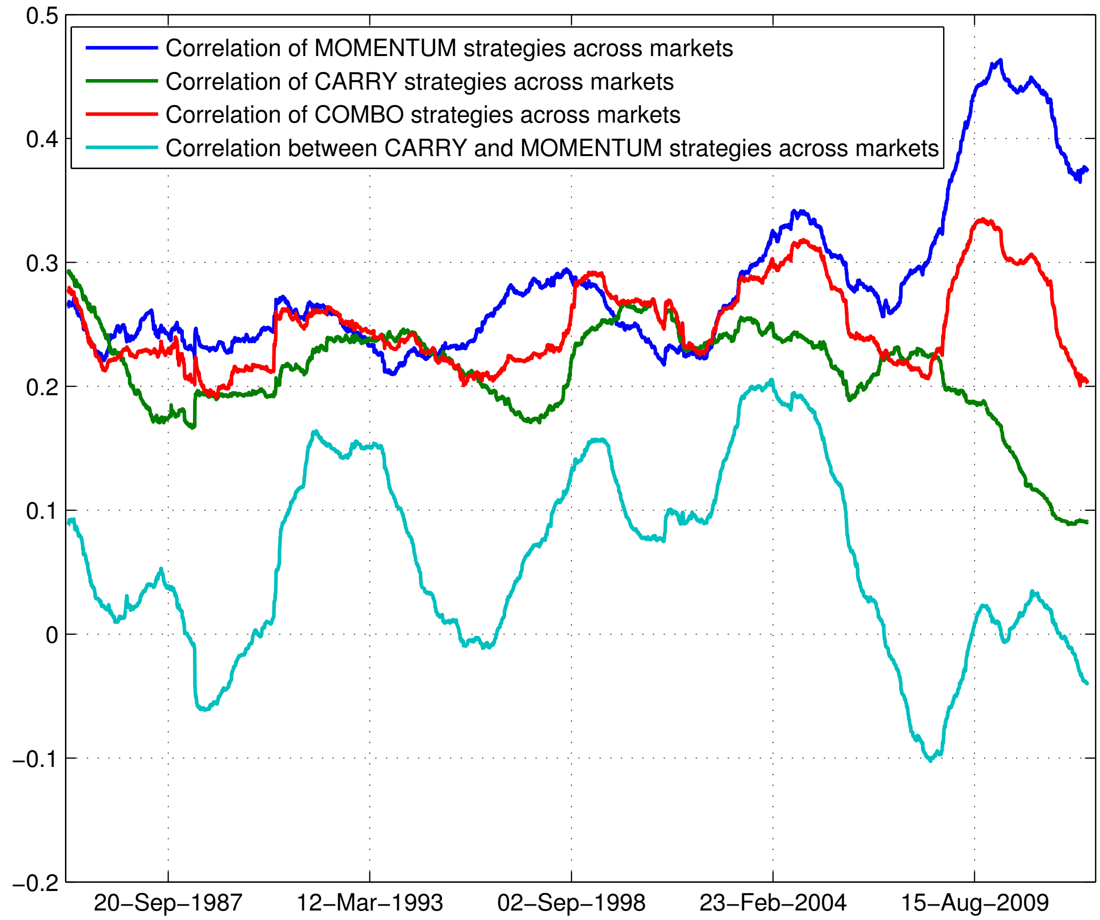


Figure 1.10. Time-varying correlation between global portfolios
Plotted are rolling three year average correlations between asset class portfolios among carry strategies, among momentum strategies, among combination strategies, and between carry and momentum strategies.

IX. Appendix A

Table 1.13. Comparison of volatility measures

The table shows the strategy Sharpe ratio for different variants of the scaling volatility estimator, $\hat{\sigma}_{i,t}$ where i is the asset and t is the month, as defined in equations 1.6, 1.7 and 1.8. The three estimators considered are; mean absolute difference (denoted 'MAD'); standard deviation (denoted 'SD'), an exponentially-weighted lagged squared daily returns univariate GARCH model (denoted 'GARCH') as used by Moskowitz, Ooi, and Pedersen (2012). For each estimator type mean estimates are reported for 20 and 60 business day estimation windows. The body of this chapter uses a 20 day mean absolute deviation volatility estimator.

	20 days			60 days		
	MAD	SD	GARCH	MAD	SD	GARCH
Momentum	1.236	1.223	1.202	1.236	1.217	1.208
Carry	1.062	1.043	1.029	1.066	1.050	1.030
Combo	1.429	1.417	1.382	1.433	1.419	1.392
Long	0.749	0.759	0.724	0.753	0.762	0.733

Chapter 2

Optimal futures portfolios and hedge fund capital[1]

I. Introduction

Futures contracts have become an integral part in many diversified portfolios. In particular, dynamic trading strategies that exploit the predictable variation of futures returns such as carry and momentum strategies have attracted the interest of a variety of institutional investors. Carry strategies relate the directly observable current spread between futures and spot price to the expected return on an asset (Koijen, Moskowitz, Pedersen, and Vrugt (2013)), while momentum strategies resort to a purely statistical measure that relates an asset's expected return to its own past return (Moskowitz, Ooi, and Pedersen (2012)). Moskowitz, Ooi, and Pedersen (2012) and Koijen, Moskowitz, Pedersen, and Vrugt (2013) show that carry and momentum signals predict expected returns in futures markets consistently across asset classes leading to significant trading profits. The high profitability of carry and momentum strategies has generated a wide debate as to the underlying explanations for the significant return premia and presents a strong challenge to standard finance theory.

In this chapter we contribute to the literature by studying the economic anatomy of optimal portfolios based on carry and momentum signals in a unifying framework. We take the viewpoint of a risk averse investor, who maximizes his expected utility of a portfolio of futures contracts across equities, bonds, currencies, commodities and metals. We model the portfolio weights of each asset as a function of the asset's momentum and carry characteristics using the parametric portfolio approach by Brandt, Santa-Clara, and Valkanov (2009). The asset characteristics are similar to the concept of signals common in the literature but modified accordingly for the parametric portfolio. Our data covers the period from January 1980 to January 2012, and we study the cross-section of up to 54 futures contracts spanning across the asset classes of currencies, commodities, equity indices and bonds.

Besides using the parametric portfolio choice framework, we go beyond previous research in carry and momentum strategies by (a) providing an in-depth analysis of the performance of the optimal portfolios, including a detailed description of the characteristics of the strategy returns

[1]The work in this chapter appears in Ahmerkamp and Grant (2013a)

and portfolio weights, the sensitivity of the returns to changes in risk aversion levels and the return profile over time, (b) studying the relative contribution of carry and momentum signals for the return attribution in a statistical framework, (c) studying the diversification benefit of including optimal futures portfolios in traditional and non-traditional equity and bond portfolios, (d) quantifying the importance of transaction costs, (e) studying the relation to standard and non-standard risk factors and investigating the performance over the business cycle, and (f) studying the influence of institutional investors, in particular hedge funds, on the profitability of the trading strategies.

We find large and significant return premia to optimal futures portfolios based on carry and momentum, when estimating the parametric portfolio policy in- and out-of-sample. The certainty-equivalent (CE) gain from investing in optimal carry and momentum strategies relative to the risk-free rate is 15% per annum and has a Sharpe ratio of 1.2. The CE and Sharpe ratio are 8% and 0.5 higher than the performance of a volatility weighted long-only portfolio, respectively. Therefore a large part of the optimal futures additional return premia can be attributed to the predictable variation of excess futures returns due to the carry and momentum signals. We find that the optimal out-of-sample portfolio policy coefficient of the momentum is 1.5 times the carry, nevertheless, both characteristics contribute statistically significantly to the performance of optimal carry and momentum strategies. Increasing the level of risk aversion reduces the allocation to carry and momentum strategies, however, the relative importance of carry and momentum characteristic in the portfolio remains constant. Furthermore, we find that the diversification benefit of including optimal carry and momentum strategies in portfolios of stock market factors and bonds, as in Barroso and Santa-Clara (2013) and Eichenbaum, Burnside, and Rebelo (2007), is highly desirable from an investors perspective. We find that including optimal carry and momentum strategies in a traditional portfolio increases the Sharpe ratio on average by 0.7 out-of-sample. Even more important: the inclusion reduces the skewness and kurtosis of the original portfolios and therefore minimizes the overall risk.

In order to understand the high returns to optimal futures portfolios, we investigate if they can be explained by (i) the inclusion of transaction costs, (ii) traditional risk factors, business cycle and liquidity risk, and (iii) institutional investors influences related to segmented markets.

First, we find that transaction costs do not play a significant role in explaining the significant return premia. Even though the inclusion of transaction costs marginally reduces the Sharpe ratio of the optimal futures portfolios, they cannot account for the full return premia. The result is not surprising given that transaction costs in futures markets are much smaller than in equity and currency markets.

Second, we test if time variation in optimal futures portfolios can be explained by traditional risk factors (e.g., Fama and French (1992)), business cycles (e.g., Cooper and Priestley (2009), Ludvigson and Ng (2009) and Chordia and Shivakumar (2002)) and liquidity risk (e.g., Brunnermeier, Nagel, and Pedersen (2008)). While traditional risk factors such as Fama and French

(1992)'s three factor model, the value and momentum "everywhere" factors of Asness, Moskowitz, and Pedersen (2013) and liquidity risk (Pastor and Stambaugh (2001)) do not explain the full extent of the return premia, we do find that macroeconomic and common systematic variables predict the returns to optimal carry and momentum portfolios. The relation between macroeconomic variables and optimal futures returns is pro-cyclical, consistent with the findings of Chordia and Shivakumar (2002) but inconsistent with the traditional macro finance view that asset risk premia are counter-cyclical (Cochrane (2011)).

Recently, the literature in financial economics has started to investigate the influence of segmented markets on the return generating process, e.g. Brunnermeier (2009), Gabaix, Krishnamurthy, and Vigneron (2007), Duffie and Strulovici (2012) and Vayanos and Vila (2009). Segmented markets have an effect on expected returns because financial agents, who are active in a particular market, have only limited risk sharing abilities. Most theoretical models predict that expected returns are related to capital and capital flows deployed in the asset classes. The limited risk bearing capacity of speculators generate downward sloping demand curves that result in a positive relation between capital flows and contemporaneous returns. Consequently, expected returns are negatively correlated with the total capital committed within an asset class. We view the returns of optimal carry and momentum strategies through the lens of segmented markets, exploring the relation between speculative capital and the profitability of the trading strategies.

Consistent with the theoretical predictions of segmented market models, we lastly find that speculative capital of hedge funds is a strong determinant of the time-varying profitability of optimal carry and momentum strategies. We first show that the returns to carry and momentum strategies account for a large fraction of aggregated hedge fund returns with 40% of hedge fund return variance across styles explained by market and optimal carry and momentum factors. Where we note that the optimal carry and momentum strategies explain on average a larger fraction of hedge funds returns, and further reduce the statistical significance of the residual alpha, than the factors of Fung and Hsieh (2004). This finding suggests a possible avenue to enhance their dynamic risk factor approach could be to incorporate parametric futures portfolios. We next regress optimal carry and momentum returns on contemporaneous capital flows and lagged total assets under management (AUM) in the hedge fund industry. We show that hedge fund capital flows are positively related to the strategy returns, while total AUM negatively predicts expected returns.

To understand the relative contribution of business cycle risk and hedge fund capital flows, we run regressions of strategy returns on hedge fund variables together with macroeconomic business cycle indicators. We find that the hedge fund variables completely drive out the predictability of the macroeconomic variables. This suggests that the strategy return and business cycle relation is due to pro-cyclical capital flows into the hedge fund industry. For robustness we re-run all regressions on a long-only portfolio. Here, we find that expected returns are counter-cyclically related to business cycle conditions, consistent with macroeconomic theory, and are not related to speculative capital of hedge funds.

Our investigation differs from the recent literature in four main aspects. First, we study the returns of optimal dynamic futures portfolios conditioned on carry and momentum signals from the perspective of a utility maximizing risk averse investor. Most studies on trading strategies focus on simple equally or cross-sectionally weighted portfolios. This choice is guided by evidence that simple allocation rules tend to outperform more complex optimized portfolios (e.g., DeMiguel, Garlappi, and Uppal (2009)). However, this simplified framework ignores uncertainties that investors face. Namely, investors have to deal with the signal choice, the weighting of each signal and their risk preferences and be aware of changing cross and inter asset class correlation changes. In the setting of Brandt, Santa-Clara, and Valkanov (2009) we can accommodate preference structures other than simple mean-variance utility functions. The main advantage of using a preference structure such as utility with constant relative risk aversion (CRRA) is that it incorporates preferences to higher-order moments in a parsimonious manner. This feature is particularly desirable when studying momentum and carry strategies that are exposed to crash risks leading to negatively skewed return distributions, e.g., Brunnermeier, Nagel, and Pedersen (2008) and Daniel and Moskowitz (2013). Second, the parametric portfolio approach avoids the need to model all the moments of the conditional return distribution. The methodology makes the portfolio estimation computationally tractable and avoids the estimation of a high dimensional parameter space. Third, our framework allows us to study the joint contribution of carry and momentum signals to the return process together in a unifying framework. Most recent studies of carry and momentum have focused on the strategies individually, however, there are indications that the correlation between carry strategies and momentum strategies is very low, e.g., Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) and Koijen, Moskowitz, Pedersen, and Vrugt (2013). Analogous to Asness, Moskowitz, and Pedersen (2013), who combine value and momentum strategies, combining carry and momentum strategies can not only add to the diversification benefit from a portfolio allocation perspective, but also helps us to understand the common drivers of strategies from an asset pricing perspective. Fourth, we study the predictable variation of futures returns across a wide range of asset classes: commodities, currencies, bonds, and equities. Most previous studies on momentum and carry strategies resort to individual asset classes. Studying return variation across asset classes reduces the influence of idiosyncratic asset class specific sources of risk and helps us to identify systematic sources of variation. We therefore contribute to the recent asset pricing literature that attempts to develop financial theories that are applicable to a variety of asset classes, markets and strategies together in a unifying framework, see Asness, Moskowitz, and Pedersen (2013), Koijen, Moskowitz, Pedersen, and Vrugt (2013) and Moskowitz, Ooi, and Pedersen (2012).

The remainder of this paper proceeds as follows. In Section II we describe the construction of optimal parametric portfolios by Brandt, Santa-Clara, and Valkanov (2009) that we adapt to accommodate asset classes with various levels of volatility. In Section III we discuss the data we use, how we construct futures returns and our construction of the momentum and carry characteristics.

In Section IV we discuss optimal carry and momentum portfolios in terms of profitability, changing risk aversion, risk exposure, transaction costs and diversification benefit. Section V presents the empirical results of the theoretical explanations for time variation in returns and Section VI concludes.

II. Portfolio Construction

In this section we describe the general framework of parametric portfolio construction introduced by Brandt, Santa-Clara, and Valkanov (2009) and adapt it to futures markets that feature different levels of contract specific volatility. We then provide details on the data we use and the construction of tradable futures return series as well as the construction of carry and momentum characteristics.

A. *Optimal Futures Portfolios with Predictable Returns*

We optimize futures portfolios from the perspective of a risk averse utility maximizing investor, who has access to futures markets across a range of asset classes. The investor's problem is to maximize conditional expected utility of the portfolio return, $r_{p,t+1}$, by choosing portfolio weights $w_{i,t}$ for N_t futures contracts, where each futures contract, i, has a return of $r_{i,t+1}$ from date t to $t+1$,

$$\max E_t\left[u(r_{p,t+1})\right] = \max_{\{w_{i,t}\}_{i=1}^{N_t}} E_t\left[u\left(r_t^f + \sum_{i=1}^{N_t} w_{i,t} r_{t+1}^i\right)\right]. \tag{2.1}$$

We assume the investor has constant relative risk aversion (CRRA) utility, with risk aversion factor γ. The main advantage of CRRA utility is that it incorporates preferences to higher-order moments. In contrast to standard mean variance utility, which focuses purely on preferences in the first two moments of the distribution of portfolio returns, CRRA utility penalizes kurtosis and skewness (Brandt, Santa-Clara, and Valkanov (2009)).

The alternative traditional portfolio optimization approach requires the investor to model the joint distribution of returns and characteristics. Here, the investor is required to estimate the conditional means, variances, and covariances of all asset returns as a function of their characteristics. DeMiguel, Garlappi, and Uppal (2009) provide an excellent exposition of the mean-variance (quadratic) optimization literature. Due to estimation difficulties, they demonstrate the mean-variance methodology and several of its variants fail to improve on a simple equally weighted portfolio allocation. If the investor uses a utility function other than the quadratic one the required parameter estimation for the skewness, kurtosis and even higher moments by portfolio optimization becomes extremely challenging and robust estimates are difficult to obtain.

We proceed by following Brandt, Santa-Clara, and Valkanov (2009) to parameterize the optimal portfolio weights as a linear function of asset's characteristics. In this setting the portfolio weight on asset i at time t is defined by

$$w_{i,t} = \theta^\top \frac{x_{i,t}}{\sigma_{i,t} N_t}, \tag{2.2}$$

where $x_{i,t}$ is a vector of characteristics of futures contract i at time t. The portfolio policy, θ, is a vector of parameters to be estimated. In addition to scaling the weights by N_t as in Brandt, Santa-Clara, and Valkanov (2009), which allows us to optimize the portfolio with an arbitrary and time varying number of assets without changing the characteristics of the allocation, we scale the weights and therefore the returns by their respective volatilities. The volatility scaling parameter $\sigma_{i,t}$, which is defined as the past 3 months absolute value of daily returns[2], ensures that the performance of the optimal portfolio is not dominated by the returns of higher volatility assets (Moskowitz, Ooi, and Pedersen (2012)). It is important to note that we do not scale the individual returns to optimize the portfolio returns, but rather to take into account the very different levels of volatility across diverse asset classes such as bonds, equities, currencies and commodities. To obtain a meaningful comparison between, and portfolio allocation across, the different asset classes the dynamic volatility scaled weights reduce the leverage of assets with a high volatility and increase the leverage of assets with low volatility to reach an equal level of volatility for all asset classes. For the choice of characteristics, $x_{i,t}$, we restrict ourselfs to the use of carry and momentum that have previously been shown to be related to expected futures returns (e.g. Koijen, Moskowitz, Pedersen, and Vrugt (2013) and Moskowitz, Ooi, and Pedersen (2012)). Carry for asset i at time t is typically defined as the relative difference between the front month futures contract and second to maturity contract, $\frac{F_{i,t-j}^{T+1}}{F_{i,t-j}^{T}} - 1$, where $F_{i,t}^{T}$ and $F_{i,t}^{T+1}$ are the prices of the time t front and second to maturity futures contracts, respectively. This definition is often labelled futures basis and can be interpreted as a risk premium paid in compensation for holding the futures contract (Gorton, Hayashi, and Rouwenhorst (2012)). We adapt the definition of the carry characteristic to make it suitable for the presented portfolio optimization framework. We require that the measure is (1) proportional to the strength of the futures basis, (2) comparable across the cross-section of futures contracts for assets across investment classes, and (3) considered in isolation for each asset rather ranked over the cross-section. To generate the measure we take the monthly futures basis of each asset divided by mean absolute deviation of the futures basis in the previous 12 months,

$$x_{i,t}^{carry} = \frac{F_{i,t}^{T} - F_{i,t}^{T+1}}{\sigma_t^{255}(F_{i,t}^{T} - F_{i,t}^{T+1})}. \tag{2.3}$$

where $\sigma^{255}(F_{i,t}^{T} - F_{i,t}^{T+1})$ is defined as the annualized daily mean absolute deviation of the futures basis for the previous 255 days. This normalization is an important feature that ensures that for a given carry portfolio policy, our returns are not dominated by assets with high carry volatility.

The momentum characteristic is constructed using a similar method to Brandt, Santa-Clara, and Valkanov (2009) and Moskowitz, Ooi, and Pedersen (2012) using the 12 month average of the excess return. However, for our framework, due to the range in volatility of excess returns between futures contracts, we normalise the average excess return by the annualized mean absolute

[2]Using the absolute value instead of the squared returns reduces the impact of extreme realization on the volatility estimator.

deviation of the past 255 days excess returns. This ensures that higher volatility futures do not have disproportionately large characteristics that would dominate the portfolio weighting. The momentum characteristic for the contract i at time t is therefore

$$x_{i,t}^{\text{mom}} = \frac{1}{12} \sum_{s=1}^{12} \frac{r_{i,t-s}}{\sigma^{255}(r_{i,t})}, \tag{2.4}$$

where $\sigma^{255}(r_{i,t})$ is the annualised daily standard deviation of excess returns of the i-th futures contract for the past 255 days.

By scaling the futures basis and the 12 month excess return for individual carry and momentum characteristics, we ensure that no one asset has disproportionately large characteristic, and therefore excessive extreme portfolio weights. However, although this re-scaling ensures characteristics are consistent in the cross-section of assets for each portfolio parameter, the necessary and fundamentally different scaling methods between carry and momentum characteristics lead to dissimilar variation over all assets between characteristics. To ensure that portfolio coefficients are comparable, we re-normalize over all assets for each portfolio coefficient, dividing each characteristic by its respective standard deviation measured across all assets-months. We label the re-normalized characteristics $\hat{x}_{i,t}$. It is important to realize that this has no effect on optimal portfolio weights, or performance metrics, but simplifies the interpretation of portfolio policy coefficients to allow the comparison of their relative magnitudes. This methodology differs from that of Brandt, Santa-Clara, and Valkanov (2009) since it allows for time-variation in the cross-sectional mean and standard deviation of weights.

B. Portfolio Estimation

The parametric structure of portfolio weights introduced in the previous section implies that we can rewrite the conditional portfolio optimization with respect to the portfolio weights $w_{i,t}$ as the unconditional optimization with respect to the coefficient θ, as

$$\max_{\theta} E\left[u(r_{p,t+1})\right] = E\left[u\left(r_t^f + \sum_{i=1}^{N_t} \theta^\top \frac{\hat{x}_{i,t}}{\sigma_{i,t} N_t} r_{t+1}^i\right)\right], \tag{2.5}$$

which can be estimated by maximizing the corresponding sample analog with respect to θ, given by

$$\max_{\theta} \frac{1}{T} \sum_{t=0}^{T-1} u(r_{p,t+1}) = \frac{1}{T} \sum_{t=0}^{T-1} u\left(r_t^f + \sum_{i=1}^{N_t} \theta^\top \frac{\hat{x}_{i,t}}{\sigma_{i,t} N_t} r_{t+1}^i\right). \tag{2.6}$$

To obtain our estimate of the optimal parametric portfolio we therefore reach the optimization problem,

$$\hat{\theta} = \arg\max_{\theta} \sum_{t=0}^{T-1} u\left(r_t^f + \sum_{i=1}^{N_t} \theta^\top \frac{\hat{x}_{i,t}}{\sigma_{i,t} N_t} r_{t+1}^i\right). \tag{2.7}$$

The chosen parametrization of the optimal portfolio problem has several main advantages over the traditional Markowitz approach, particularly when applied to optimal futures portfolios. First, the parameter space to be estimated is reduced to the dimension of θ, which is only as high as the number of characteristics included in the problem. Second, the constant coefficient θ implies that the portfolio weight in each asset depends only on the futures's characteristics and not its historic return. This is important as we are not interested in which asset class or individual asset performed best, but only on the relative contribution of momentum and carry characteristic. Third, the parametric portfolio policy optimizes a utility function and not a measure of the distance between forecasted and realized return. Therefore, θ conveys information about all the moments, not only the first. Fourth, we can easily embed the volatility scaling as in Moskowitz, Ooi, and Pedersen (2012) and Baltas and Kosowski (2014) that makes the returns in each asset class comparable. Finally, by posing the portfolio problem as an estimation problem, we can conduct statistical inference for the estimated parameters $\hat{\theta}$ using simple generalized methods of moments (GMM) procedure. More details on the statistical inference are in Appendix A and Brandt, Santa-Clara, and Valkanov (2009).

C. Construction of Tradable Futures Return Series

We calculate the excess returns on futures contracts based for fully collateralized positions following the methodology described in Chapter 1. Explicitly,

$$r_{i,t+1} = \frac{F_{i,t+1}^{T} - F_{i,t}^{T}}{F_{i,t}}. \tag{2.8}$$

Where $F_{i,t}^{T}$ is the price at time t of the i-th futures contract expiring at time T.

D. Transaction Costs

For each underlying asset, contract positions must be 'rolled' before expiry in order to calculate a continuous return series. Rolling futures contracts requires closing the full futures position in advance of each maturity, whilst simultaneously opening a position in the next nearest maturity contract. For the majority of futures contracts this requires monthly trading of the whole position, suggesting a monthly cost equal to that of the bid-ask spread. However, Gârleanu and Pedersen (2013) argue that trading costs from rolling are negligible, due to a separate roll market which entails smaller costs than independently selling the old contract and buying the new one. Consequently, although in implementation the entire portfolio is traded before each maturity, we only consider the *difference* in monthly allocation when calculating trading costs. Analogous to Brandt, Santa-Clara, and Valkanov (2009) we therefore calculate costs based on monthly turnover defined as

$$T_t = \sum_{i=1}^{N_t} |w_{i,t} - w_{i,t-1}|, \tag{2.9}$$

where $w_{i,t}$ refers to the monthly weighting of assets defined above. The optimal portfolio equation is now,

$$\hat{\theta} = \arg\max_{\theta} \sum_{t=0}^{T-1} u \left(r_t^f + \sum_{i=1}^{N_t} \theta^\top \frac{\hat{x}_{i,t}}{\sigma_{i,t} N_t} r_{t+1}^i - \sum_{i=1}^{N_t} c_{i,t} \theta^\top \left| \frac{\hat{x}_{i,t}}{\sigma_{i,t} N_t} - \frac{\hat{x}_{i,t-1}}{\sigma_{i,t-1} N_{t-1}} \right| \right), \tag{2.10}$$

where $c_{i,t}$ is the fractional cost of buying (or selling) asset i at time t, defined as

$$c_{i,t} = \frac{F_{i,t,T}^{\text{Bid}} - F_{i,t,T}^{\text{Ask}}}{2(F_{i,t,T}^{\text{Bid}} + F_{i,t,T}^{\text{Ask}})} \tag{2.11}$$

for futures contracts on the i-th asset at time t with maturity T. The factor of two in Equation 2.11 corresponds to the one-way transaction cost incurred when the weighting is changed for buying and selling, as defined in Equation 2.10. For a given time-series and cross section of transaction costs we can therefore find optimal portfolio characteristics by optimizing the average utility of returns net of transaction costs.

III. Data

In this section we first describe the price data we use, including preliminary descriptive statistics for the derived characteristics, then discuss the intuition and construction of the macroeconomic and hedge fund series.

A. Price Data

We use the same price data as used in Chapter 1 with exception of the removal of the Amsterdam Equity Index (AEX). The AEX data was removed from the dataset due to anomalies in the return series. Summary statistics for price data are given in Table 1.1. Unlike Chapter 1, we do not distinguish our analysis by asset class, since some of the asset classes have very few contracts, which would lead to an unstable estimate of optimal portfolio policy.

Figure 2.1 reports the cross-sectional means and standard deviations of the carry and momentum characteristics across time. The carry and momentum characteristics are time varying and display episodes of high and low volatilities. The cross sectional standard deviation of the carry characteristic is higher than for the momentum characteristic. Figure 2.1 also displays the cross sectional correlation of the characteristics. We can observe that the correlation is mostly positive but highly time varying. The correlation varies mostly between 0 and 0.5. Interestingly, the correlation decreased since the early 2000's with a short interruption during the Lehman Brothers crisis. This hints that including carry and momentum characteristics in an optimal portfolio portfolio framework might add a substantial diversification benefit.

B. Macroeconomic and Liquidity Data

B.1. Macroeconomic Proxies

As proxies for the state of the economy we choose three sets of macroeconomic variables. First, we follow Cooper and Priestley (2009) and choose the output gap as an empirical proxy for business cycles. The output gap (IP Gap) is measured as the deviation of the logarithm of total industrial production from a trend that includes both a linear component and a quadratic component, the raw industrial production data is taken from the FRED website. Cooper and Priestley (2009) show that the output gap is a prime business cycle indicator and predicts stock and bond risk premia counter-cyclically, consistent with theoretical predictions.

Second, we use a set of four common systematic price-based variables that are related to the business cycle, described at length in Section 1.B. These variables include the three month T-bill (Yield), dividend yield (Div Yield), the term spread (TSpread), and default spread (Def).

Finally, we use business cycle indicators from the National Bureau of Economic Research (NBER), who publish a range of ex-post information on business cycles. Notably, they report the dates that are related to an economic expansion, defined from trough to peak, and economic recession, defined from peak to trough. We further subdivide the expansion and recession periods into equal halves and denote them early as late expansions/recessions. These indicators are not used for forecasting regressions as they are only reported ex-post by NBER.

B.2. Liquidity Proxies

As a state variable for changing liquidity environments we use the TED spread (Brunnermeier and Pedersen (2009)). The TED spread is defined as the difference between the 3 month LIBOR Eurodollar rate and the 3 month T-Bill rate. The LIBOR rate reflects uncollateralized lending in the interbank market, which is subject to default risk, while the T-Bill rate is assumed risk-less since it is guaranteed by the U.S. government. When banks face liquidity problems the TED spread typically increases, as bank funding cost increase whilst the T-Bill yield falls due to a "flight-to-liquidity" or "flight-to-quality".

C. Hedge Fund Data

We construct proxies for the total capital available and capital flow to the hedge fund industry as measures for arbitrage capital similar to Jylhä, Rinne, and Suominen (2014), Jylhä and Suominen (2011), Della Corte, Ramadorai, and Sarno (2013) and Naik, Ramadorai, and Stromqvist (2007). For both measures we use monthly return and total asset under management (AUM) data from a large cross-section of hedge funds and funds-of-funds from January 1994 to December 2012 obtained from Barclay-Hedge databases. We select the subset of funds from this data, that are self reporting global macro funds and commodity trading advisors (CTAs) to construct the aggregate measures.

C.1. *Total Arbitrage Capital*

We define total arbitrage capital for each time t as the sum of AUM across N global macro funds and commodity trading advisors. Furthermore, we scale the aggregate number by the M2 money supply of the US to get a relative measure of hedge fund/arbitrage capital,

$$HFAUM_t = \frac{\sum_{i=1}^{N} AUM_{i,t}}{M2}. \tag{2.12}$$

C.2. *Total Arbitrage Flows*

We measure the total arbitrage flow as the AUM-weighted net flow of CTA and global macro funds scaled by lagged AUM. For each fund i, we construct time t net flows as,

$$Flow_{i,t} = AUM_{i,t} - AUM_{i,t-1}(1 + r_{i,t}). \tag{2.13}$$

Then we define the AUM-weighted net flow scaled by lagged AUM as

$$Flow_t = \sum_{i=1}^{N} w_{i,t-1} \frac{Flow_{i,t}}{AUM_{i,t-1}}, \tag{2.14}$$

where $w_{i,t-1} = \frac{AUM_{i,t-1}}{\sum AUM_{i,t-1}}$. Having described the portfolio allocation and the data we use, we will continue with the main empirical results.

IV. Characterising Optimal Futures Portfolios

In this section we analyze the performance of optimal futures portfolios based on the carry and momentum characteristics across all asset classes. We then study the role of changing risk aversion on the profitability of the optimal portfolios and investigate the diversification benefit of optimal futures for classical stock and bond portfolios.

A. *Carry and Momentum Portfolio Returns Across Asset Classes*

Table 2.1 presents summary statistics for the parameter estimates, portfolio weights and returns of four base-case portfolio parameterizations, which are estimated in and out of sample. The in-sample exercise uses all available data to estimate the parameters of the model. The out-of-sample methodology uses a recursive procedure by first estimating the parameters in an initial configuration period of 120 months and then re-estimating the model every month, using an expanding window of data until the end of the sample is reached. The out-of-sample estimation is less prone to look ahead biases and resembles the parameter estimation of a real-time investor. The first three portfolio parameterizations are formulated by including either the futures contract's carry characteristic and momentum characteristic in isolation or a combination of carry and momentum characteristics, using the portfolio policy function in Equation 2.2. These parameterizations are compared to a long only benchmark portfolio[3]. The table is split into three sections: The first set of rows report parameter estimates and associated student t-statistics, the following set describes the distribution of portfolio weights and the remaining rows report summary statistics of the optimized portfolio returns. The sample period is from January 1982 to September 2012.

In Table 2.1 the first 4 rows of the first column present the estimates of the in-sample policy parameters, θ, and the corresponding t-statistics for a combined parametric portfolio including both the carry and momentum characteristics. Without imposing any ex-ante relation between characteristics and future returns, we find that the θ estimates for both characteristics are positive and significant, with a GMM t-stat of 2.65 and 4.29 for the carry and momentum characteristic, respectively. The positive relation confirms the general findings of the literature: a positive carry signal, defined as when the near contract trades above the far contract, predicts positive next month return (Koijen, Moskowitz, Pedersen, and Vrugt (2013)) and a positive momentum signal, defined as positive performance over the previous 12 months predicts positive next month return(Moskowitz, Ooi, and Pedersen (2012)). The relation between futures returns and trading characteristics is a result of the estimation procedure and was not assumed ex-ante, as most cross-sectional sorts resort to. For comparison, we also report the results of the portfolio parametrization using only individual characteristics in the second and third column. For each characteristic we find positive coefficient estimates with highly significant t-statistics (4.65 and 5.39 for the carry and momentum characteristic, respectively). The fourth column reports the summary statistics of the long only portfolio. This portfolio policy is nested in the parametric function of Equation 2.2 by removing the momentum and carry characteristic and introducing a characteristic of unity across all assets and months. The reported θ_{long} of 2.86 demonstrates that ex-post allocation to an equally weighted portfolio of futures over the sample period is 2.86 times the initial wealth for an investor with power utility of risk aversion five. The t-statistics are based on errors calculated using the covariance estimator of Equation 2.18.

As a consequence of re-normalizing the portfolio characteristics, the magnitudes of the coefficients can be compared to each other. In-sample we find the optimal futures portfolio has a momentum characteristic larger than carry, 3.157 compared to 2.036. Nevertheless, both coefficients are highly significant. Here again, the comparable magnitudes support the inclusion of both characteristics in an optimal futures portfolio.

Compared to the momentum only and carry only parameterizations, the sum of coefficients for the optimal carry and momentum portfolio is bigger, indicating that a diversification benefit leads

[3]For the long only portfolio we still estimate the θ parameter but set the characteristics to $x_i = 1$. We therefore estimate the optimal weights for an inverse volatility weighted portfolio of futures contracts, that is a popular investment strategy denoted as risk parity portfolios.

the optimal portfolio to have larger net exposure. This feature is reflected in the next six rows of Table 2.1, which characterize the distribution of the portfolio weighting.

For portfolios based on carry and momentum characteristics, we find that the time series average absolute volatility adjusted weight[4] of futures contracts is 0.072, slightly larger than that for the individual carry and momentum characteristics of 0.055 and 0.062. The next two rows report the time series average of the maximum and minimum volatility-adjusted contract weighting. The range of weights describes the average maximum exposure the strategy has to any one contract. For the in-sample carry and momentum portfolio we find the maximum and minimum allocation are 0.308 and −0.301, respectively. On first inspection, these values seem high compared to Brandt, Santa-Clara, and Valkanov (2009). However, we have far fewer assets, 54 futures contracts compared to over 5500 stocks, and in the beginning of our sample we have only 13 available assets as can be seen in Figure 1.1. As such, the limits of the optimal portfolio weight is only three times that of the equally weighted portfolio, and therefore we can conclude that the portfolio remains well diversified given the number of available assets.

The next two rows of Table 2.1 report the time series average of the sum of negative volatility-adjusted weights and time series average fraction of short positions, respectively. We find that the combined characteristics portfolio has a smaller fraction of short positions compared to that of the individual characteristics portfolios. However, the magnitude of the difference in negative weights is negligible.

The last weighting statistic is the average monthly turnover for each contract. We use this measure to calculate the transaction costs from modifying contract weighting. We find a turnover of 1.119 for the in-sample optimal carry and momentum portfolio[5]. Although such a turnover would be high for a stock portfolio, this value is less than the inherent turnover of a futures trading strategy or that required for the long-only futures strategy.

The last 6 rows of Table 2.1 present summary statistics for portfolio returns of the optimal strategies. The four left hand columns demonstrate the in-sample portfolio to have very impressive performance. The leveraged optimal futures portfolio based on the carry and momentum characteristic has an annualized return of 36.8% with a Sharpe ratio of 1.162. The last row of Table 2.1 reports the certainty equivalent return (CE) - the annualized risk free return at which the investor would be indifferent to the strategy return. The CE measure provides a parsimonious perspective from which to understand the return distribution, since it takes into account the entire distribution of returns and is monotonic with our objective function. As a result, the CE penalizes large values in the higher moments of the distribution of returns. The certainty equivalent of the optimal carry and momentum portfolio is 15.1% above the risk-free rate. Here, we can also see the benefit of combining both carry and momentum characteristics to form the optimal

[4]For each weighting statistic we report the product of the actual futures weight and the annualized 3 months absolute mean deviation, $\sigma_i w_i$, to compare the economic significance of the futures weights within the optimal portfolio for contracts over a wide range of volatilities.

[5]In results not reported in the table, this is found as 29.0% of the mean absolute weight.

portfolio. The carry-only portfolio has a high excess kurtosis of 2.097, which is reflected in a lower CE return of 7.5%. In the combined portfolio this is reduced to 1.097 leading to a 6.7% increase in CE. Our in-sample results confirm the importance of carry and momentum characteristics in policy selection, with significantly higher Sharpe and CE returns for policies including carry and momentum compared to the long portfolio. By construction the optimiser is targeting maximum CE and therefore the strong in-sample performance in of itself is not entirely surprising. However, it is important to note that the performance has been achieved with only one or two optimisation parameters. This bodes well for the out-of-sample performance.

The four right hand side columns of Table 2.1 repeat the summary statistics of the in-sample estimation for the out-of-sample exercise. The first rows of Table 2.1 report the average out-of-sample coefficient estimates. We use the first ten years of data, from January 1982 to September 1992, to estimate the coefficients of the initial portfolio policy. Each month, we then re-estimate the parameters using an expanding window of data until the end of the sample is reached. Figure 2.2 displays the θ estimates and the corresponding confidence bands for the carry and momentum coefficients over time. The coefficients of the characteristics are roughly similar to the in-sample estimates and do not display much time variation. Furthermore, the confidence bands show that the coefficient estimates are statistically significant, most of the time, for both characteristics. In contrast to the in-sample results, we find a slight widening of the difference between the carry and momentum coefficients, with the ratio of momentum-to-carry coefficient increasing from 1.6 in-sample to 2.1 for out-of-sample estimates.

The strong performance of the in-sample optimized portfolio is to some extent unsurprising, since the coefficients are chosen ex-post to maximize the CE return. What is surprising is the similarity to the out-of-sample results. For all portfolio configurations, we report a smaller than 1% difference in CE, when returns are calculated based on out-of-sample portfolio characteristics. Figure 2.3 Panel A displays the cumulative returns of the optimal out-of-sample carry and momentum strategies over time and compares it to the optimal carry only, momentum only and long only portfolios. We find that the optimal carry and momentum portfolio has a significantly higher performance than the individual carry and momentum portfolios. This again indicates a diversification benefit of including both characteristics. Furthermore, all strategies have better performance than the long only strategy which is consistent with their statistically significant θ estimates and reinforces the importance of both carry and momentum characteristics for policy selection.

Comparing the distribution of adjusted portfolio weights between in- and out-of-sample results, we find out-of-sample metrics to be generally more conservative. For instance, for combined characteristics the monthly mean absolute adjusted out-of-sample weight is 0.05 compared to 0.07 in-sample. The difference is stark when we consider the extremes of the distribution. Going from in- to out-of-sample, we find the maximum and minimum weights halved from 0.308 to 0.174 and from -0.301 to -0.158, respectively. These findings give us confidence that the strong performance of the out-of-sample portfolio is not dependent on a few lucky trades; although the time series average of portfolio turnover is smaller, we find that the turnover as percentage of total absolute portfolio weight remains nearly unchanged at 32%. We report analogous results when the in- and out-of-sample carry-only and momentum-only portfolios are compared.

Finally, we study the dynamic behaviour of the out-of-sample carry and momentum returns from 1992 to 2012. Figure 2.3 Panel B presents the 24 months rolling Sharpe ratio for carry and momentum strategies. The Sharpe ratio is highly time-varying: even though it is positive for the entire period, a negative trend is observable. While the Sharpe ratio varied around 2 and 3 in the period from 1997 to 2005, it deteriorated to a level of around 1 or lower since then. The same effect can be observed for the rolling 12 months average return of the carry and momentum strategy in Figure 2.4. While the returns are highly time varying in the early sample, they deteriorate towards the end. The plots on the right side of Figure 2.4 report the draw-down dynamics of the strategy. While a clear trend is not observable, we consider two sample events and their effect on the optimal portfolio. Looking at the optimal momentum portfolio, we find the largest draw-down from December 1993 to August 1994, losing 31.3%. In Figure 2.2, we see the policy response to this event: we observe a small but sharp decrease of the momentum coefficient around the same period. The second event we consider is the dramatic draw-down of the carry strategy in the run-up to the sub-prime crisis of 2008[6], where it suffered a loss of 38.1% between April 2005 and December 2007. However, for the carry event we observe a different portfolio response. The carry event estimation sample was nearly double the size of the momentum event. As a consequence of this and its occurrence towards the end of the sample, we observe a smaller magnitude and more gradual reduction in theta estimate compared to the earlier momentum event.

B. *Effects of Changing Risk Aversion*

The optimal portfolio policy depends critically on the preferences of the investor. Following Brandt, Santa-Clara, and Valkanov (2009), throughout this paper we optimize a portfolio for an investor with a CRRA utility function with relative risk aversion of $\gamma = 5$. In this section, to give a better sense of the role of the utility function in the portfolio allocation, we present the in- and out-of-sample results for varying degrees of risk aversion. In addition to the base-case coefficient $\gamma = 5$, we report the estimation results for a CRRA risk aversion coefficient of $\gamma = 2$, corresponding to an investor with a low risk aversion and a risk aversion of $\gamma = 100$, corresponding to an investor who is very sensitive to even small loses.

The results for varying relative risk aversion are reported in Table 2.2. Panel A of Table 2.2 reports statistics for the optimal carry and momentum portfolio, Panel B reports analogous results for an optimal allocation to an equal volatility-weighted long-only portfolio, which serves as a benchmark for comparison.

Looking first at the optimal portfolio for the momentum and carry characteristics for small

[6] a closely timed draw-down is reported by Koijen, Moskowitz, Pedersen, and Vrugt (2013) for their carry factor.

values of γ, we find that the coefficients of both characteristics are large. As we increase risk aversion, a higher γ gives lower portfolio coefficients and therefore allocations. These observations demonstrate that the allocation is related to both risk and return, since for larger levels of risk aversion the utility cost of risk subsumes benefits with associated returns until the allocation, and thus the portfolio coefficients, are reduced.

Note that the tilt towards the momentum characteristic is maintained with the ratio of momentum-to-carry coefficients of around 1.5 and 2.0 for in-sample and out-of-sample, respectively, across the three levels of risk aversion. The portfolio weighting statistics paint the same picture: The weights are scaled down equally with increasing levels of risk aversion. This effect is seen for both time-series averages of the mean absolute weight, minimum weight, maximum weight and the portfolio turnover metric. Accordingly, the time series average faction of short positions is nearly unchanged over the different γ levels maintaining approximately 0.43 and 0.270 for in- and out-of-sample, respectively. We therefore conclude that the relative importance of the carry and momentum characteristics in the investors optimal portfolio remains independent of varying degrees of risk aversion.

The last 6 rows of Table 2.2 Panel A report performance statistics. As we would expect from its higher characteristic coefficients, the $\gamma = 2$ case generates very high returns - with an annualized return of 57% in-sample and 119% out-of- sample. These returns are accompanied by similarly high annualized standard deviations of 36% and 67%. With increasing γ, the coefficients, the portfolio weights, and therefore portfolio return and volatility, are reduced towards zero. Indeed, with $\gamma = 100$ annualized return is reduced to 6.4% in-sample and 4.8% out-of-sample. The associated annualized standard deviations of returns are less than 1.5% for both sampling methodologies.

The last row of Table 2.2 Panel A reports the CE return in excess of the risk-free rate. The CE cannot be compared across levels of risk aversion. However, we note that for each level of risk aversion the CE is at least improved for the out-of-sample methodology. This feature suggests that not only is the portfolio policy performance not a result of data mining, as discussed above, but there may be circumstances where the ability of the out-of-sample policy to adapt to market conditions can generate superior returns compared to what would be achieved with a fixed policy.

C. Diversified Investor with Optimal Futures Portfolio

Given the recent trend of including dynamic futures portfolios in diversified portfolios of institutional investors, we next investigate the diversification benefit of including optimal futures portfolios based on the carry and momentum characteristics in such allocations. Explicitly, we test the hypothesis that a diversified investor, who already has an optimal allocation to popular tradable risk factors or asset classes, would benefit out of sample from the inclusion of an optimal carry and momentum strategy in his portfolio. This relatively unexplored topic of including dynamic trading strategies in traditional asset allocation mixes - notable exceptions include Barroso and Santa-Clara (2013) and Eichenbaum, Burnside, and Rebelo (2007) - is not only important from an investors perspective, but will give us an indication of the economic value of higher moments of the return distribution with respect to the standard risk factors that cannot be observed in the linear regression framework.

To introduce other tradable assets into our portfolio parameterization, we modify our return on wealth, $r_{p,t+1}$, in Equation 2.6 to incorporate classes of risk factor returns containing M tradable assets. The return on the wealth of the investor is now given by

$$r_{p,t+1} = rf_t^{US} + \sum_{j=1}^{M} w_j F_{j,t+1} + \sum_{i=1}^{N_t} w_{i,t} r_{i,t+1}, \tag{2.15}$$

where w_j is the portfolio weight on the tradable factor $F_{j,t+1}$, expressed as excess returns, and $w_{i,t}$ depends on the carry and momentum characteristics through θ policy coefficients, as previously described. We estimate the optimal portfolio by maximizing the CRRA utility of returns from Equation 2.15 for θ and w_j setting $\gamma = 5$.

Table 2.3 reports comparative return statistics for out-of-sample optimal allocations to four popular risk factor classes: a passive index investment in the S&P 500, Fama and French factors taken from Fama and French (1992), equity value and momentum factors of Asness, Moskowitz, and Pedersen (2013) and a portfolio containing the S&P 500 and the 10 year US government treasury bond. To provide a benchmark case, for each risk factor class we first consider performance of an out-of-sample allocation to just the tradable risk factor(s) in that class, effectively forcing θ coefficients to be zero.

The first and second columns of Table 2.3 report return statistics for our optimal carry and momentum strategy base case, and the optimal carry and momentum with long-only, respectively. The remaining columns are in pairs and report performance statistics of each class of risk factors for the benchmark case, on the left, and diversified portfolio case, on the right.

The opportunity to invest in futures is clearly of significant value to investors. Figure 2.5 displays performance metrics for each risk factor class, without and then with the addition of the carry and momentum optimal futures strategy. The inclusion of futures in the optimal portfolio enhances performance for nearly all reported metrics, analogous to Barroso and Santa-Clara (2013)'s finding that currency optimal portfolio returns are improved when combined with a range of market factors. Amongst our benchmark portfolios the highest out-of-sample certainty equivalent was the equity value and momentum factors of Asness, Moskowitz, and Pedersen (2013) with 4.9% above the risk free rate. In contrast, when futures are included in the diversified portfolios even the lowest CE, the diversified value and momentum portfolio, is 16.4%.

Looking across Table 2.3 we can see the CE gains of including futures dwarfs the CE increase of popular risk factors over the stock market. The highest certainty equivalent gain amongst our benchmark factor portfolios is the one based on the value and momentum factors of Asness, Moskowitz, and Pedersen (2013), corresponding to 2.7% gain over the stock market. Interestingly, we observe that, although the Fama and French factors have a higher-than-market Sharpe ratio, the inclusion of the HmL and SmB factors actually decreases CE due to the higher kurtosis of these factors. This finding highlights the impact of high moments embedded in the Fama and French Factors on a risk averse investor (As also noted by Chung, Johnson, and Schill (2006)).

In summary, we find that including optimal carry and momentum portfolios into the asset allocation of a diversified investor is optimal, both from the perspective of increasing Sharpe ratios and decreasing higher moments such as kurtosis and skewness.

V. Business Cycles, Limits to Arbitrage and Hedge Fund Capital

The impressive performance of optimal futures portfolios across asset classes and the significant diversification benefit of including optimal futures portfolios in traditional portfolio allocations presents yet another challenge to existing financial economic theories. The performance of the optimal portfolios is driven to a large extent by the significant predictable variation in excess returns of futures contracts conditioned on the price-based asset characteristics carry and momentum. Optimal futures portfolios improve the Sharpe ratio of the long-only benchmark, which is by itself a dynamic strategy due to the volatility adjustment, by almost 0.5. Furthermore, the diversification benefit of including optimal carry and momentum portfolios within a stock and bond portfolio are highly desirable from an investors perspective. They increase the Sharpe ratios of the total portfolios on average by 0.6 and reduce skewness and kurtosis. In this section, we contribute to the understanding of dynamic trading strategies by exploring the role of transaction costs, traditional risk factors, business cycle, liquidity risk and the role of institutional investment - in particular hedge fund activity - on the profitability of optimal futures portfolios based on carry and momentum characteristics.

A. Optimal Futures Returns with Transaction Costs

Transaction costs have been shown to significantly reduce (Korajczyk and Sadka (2004)) or even remove (Lesmond, Schill, and Zhou (2004)) abnormal profits. For carry strategies, Eichenbaum, Burnside, and Rebelo (2007) find the inclusion of costs substantially reduces excess returns, although they remain significant. Therefore, it is a natural starting point to introduce transaction cost adjusted portfolio returns. However, futures markets do have low transaction costs compared to equity markets and currency forwards, so ex-ante we expect their effect to be small. Furthermore, due to a separate roll market (Gârleanu and Pedersen (2013)) transaction costs are only apposite when the portfolio is modified. Thus, with a typical one-way trading cost of 0.05% (Gârleanu and Pedersen (2013)) combined with monthly turnover of approximately 25% (see Table 2.1), annual costs would be expected of the order 0.1%, small compared to strategy returns in excess of 35%.

Table 2.4 reports statistics for optimal portfolios where the portfolio policy is determined by optimizing the utility of net returns, given in Equation 2.10 for two different cost specifications alongside the zero cost case for comparison. The first specification considers a conservative estimate for one-way transaction costs of 0.05%, constant across time series and cross-section. The second specification measures transaction costs directly from the futures bid-ask spread of monthly close prices.

The difference in optimal portfolio policy with transaction costs is negligible, even with the introduction of conservative costs. For the in-sample methodology, the addition of a flat cost across all contracts in the utility maximisation leads to a minor increase in the magnitude of the carry characteristic, from 2.036 to 2.090, and a slight decrease in the momentum characteristic, from 3.137 to 3.135. Due to the similarity in portfolio characteristics, the futures weighting dynamics, reported in rows five to ten of Table 2.4, are virtually identical between the three cost cases.

The last seven rows of the table report return statistics. As conjectured, the return of the flat transaction cost optimal portfolio is reduced the most, albeit still small compared to overall return, with a reduction of 1.6% from 36.8% to 35.2%. The new portfolio policy leads the bid-ask cost specification to have a slight increase in returns of 0.4% over the zero cost base case. The consistency of the last three rows demonstrates changes in certainty equivalent due to transaction costs are only related to the reduction in returns, ceteris paribus, and not the impact of costs on the optimal portfolio policy. Taking costs into account, we find a 1.4% and 0.6% reduction in certainty equivalent net return for the flat cost and bid-ask specification, respectively, compared to the no cost case. Columns four to seven of Table 2.4 show differences in portfolios and returns are further reduced for the out-of-sample methodology. Given these results, we conclude that transaction costs play only a minor role in explaining the performance of optimal futures portfolios.

B. Risk Factor Exposure

To better understand the sources of the risk-return profile, we next evaluate the risk-adjusted performance of optimal carry and momentum portfolios within the framework of standard and non-standard linear risk-factor models typically used in the asset pricing literature. Table 2.5 reports results from regressing individual optimal carry and momentum returns, as well as a combination of the two, on various model specifications.

The first three columns of Table 2.5 report the results from regressing the optimal strategy returns on factors from the Value and Momentum Everywhere model by Asness, Moskowitz, and Pedersen (2013). The value and momentum factors are diversified, volatility weighted portfolios of cross-sectional value and momentum strategies in global equities, equity indices, bonds, commodities and currencies. We add the optimal long-only portfolio as a benchmark market factor to the model. In all three cases, the strategies deliver a large and highly significant alpha, or intercept, with respect to the value and momentum factors of about 19%, 14% and 21% for optimal carry, momentum, and combined strategies, respectively. This suggests that whether individually or jointly, the returns to our portfolios are not explained by the Value and Momentum Everywhere factors. However, both the value and momentum factors are statistically significant and positively related to all optimal strategies. The factor exposure of the long-only benchmark shows some cross-sectional differences. While it is negatively and insignificantly related to carry strategies, it is highly significantly and positively related to the optimal momentum strategy. This high positive significance carries over to the combination of optimal carry and momentum strategies. These findings confirm the results by Moskowitz, Ooi, and Pedersen (2012), who show that time-series momentum strategies are related to cross-sectional strategies, although it is in contrast to Koijen, Moskowitz, Pedersen, and Vrugt (2013), who do not find significant exposure of carry strategies with respect to value and momentum factors.

The next three columns in Table 2.5 present results from regressing the optimal strategy returns on Fama and French (1992)'s market, high-minus-low and small-minus-big factors. With the exception of the momentum strategy, we find that all factors have a significant negative relation with optimal carry, momentum, and carry and momentum returns. The negative factor exposure explains the highly significant alphas of 21%, 31% and 37% for optimal carry, momentum and carry and momentum portfolios, respectively. Due to the negative beta coefficients these alpha estimates are higher than the average excess return for the respective portfolio. Therefore, rather than explaining the returns, the Fama and French results raise another anomaly to be explained, and support the inclusion of optimal futures portfolios alongside a traditional equity portfolio.

The fourth set of regressions in Table 2.5 reports the exposure of optimal carry, momentum, and carry and momentum returns to the market liquidity risk factor by Pastor and Stambaugh (2001). In all three strategy cases the beta coefficient estimates remain statistically insignificant. In the last three columns of Table 2.5 we repeat the exercise but include the Value and Momentum Everywhere factors. While the coefficient estimates of the Asness, Moskowitz, and Pedersen (2013) factors remain almost unchanged from the first regression exercise, we find that the market liquidity risk factor is now highly positive and significantly related to optimal momentum and optimal carry and momentum returns. The coefficient for optimal carry strategies remains unchanged.

Even though we find some exposure of optimal carry and momentum returns to standard and non-standard risk factors, a large proportion of the returns remains unexplained, as measured by alpha. In particular, the negative correlation of optimal carry and momentum returns with market factors is difficult to reconcile with standard risk-based explanations. However, these findings may be masked by significant dynamic exposure of these factors driven by changing economic environments that are related to time-varying beta estimates or market frictions. We explore this possibility in the next two sections.

C. Macroeconomic Influences and Funding Liquidity

In this section we test whether theoretical conjectures on the effect of macroeconomic risk and liquidity risk on optimal carry and momentum portfolios are reflected in the data. Even though the literature in financial economics has provided evidence of time variation in risk premia due to changing business cycle and liquidity environments in a variety of asset classes, it is not clear ex-ante if these sources of time-varying risk also explain, or are related to, the returns of optimal carry and momentum strategies in futures markets. Equilibrium models based on the assumption that all claims, including futures contracts, are costlessly marketable, e.g., Richard and Sundaresan (1981), indicate that risk premia in both futures and other asset markets are sensitive to the same sources of economic uncertainty. This similarity implies that state variables that possess forecast power in stock and bond markets should also forecast expected futures returns for other assets. Imposing macroeconomic theories of discount rate variation would therefore imply that the returns to optimal carry and momentum strategies are counter-cyclically related to macroeconomic state variables.

C.1. Macroeconomic and Liquidity Risk in Optimal Carry and Momentum Portfolios

Table 2.6 Panel A reports the performance of the optimal carry and momentum strategy across different economic environments and serves as a preliminary test for our economic analysis. The first three columns report the Sharpe ratios of the trading strategy in three different time periods. The first time period ranges from 1982 to 1992, the second from 1992 to 2002, and the final and most recent time period ranges from 2002 to 2012. We find that the Sharpe ratios in the first two time periods remain almost unchanged at 1.51 and 1.53, respectively. However, in the third period the performance deteriorates significantly to 1.07. While this is still an impressive Sharpe ratio, it is almost one third smaller than in the previous twenty years. This suggests that significant time variation in the performance of the trading strategies exists. We compare these results to the long-only strategy and find that the effect is exactly the opposite. The Sharpe ratios are lower in the early sample but increase steadily.

Next, we relate the performance of the optimal carry and momentum strategy to variations in business cycle conditions. In particular, we study the Sharpe ratios during the early and late phases of recessions and expansions. If strategy return is due to business cycle risk, then returns should be higher in expansionary periods when the marginal utility of returns is lower(Chordia and Shivakumar (2002)). However, we observe the opposite dynamics, Sharpe ratios are substantially higher during recessions, averaging 2.2, than in expansions, averaging 1.3. Second, the difference between the Sharpe ratios during the early and late stage of recession and expansion periods, respectively, is only significant during expansions. While early expansions have an average Sharpe ratio of 1.07 this value increases to 1.53 in late expansions. Comparing our findings for the long-only strategy, we find the expected trend, with higher returns during expansionary periods and negative returns during recessions.

Finally, we test how changing liquidity environments affect the performance of the optimal carry and momentum strategy. We find that during worsening liquidity environments, proxied for by negative changes in the TED spread[7], the Sharpe ratios are higher than during improving

[7] Improving and worsening liquidity environments are defined as positive and negative changes in the TED spread, respectively.

liquidity conditions. In particular, we find that the Sharpe ratio is 1.59 on average during worsening conditions and 1.18 during improving liquidity conditions.

All these preliminary results indicate that expected returns are time-varying and the time variation is related to macroeconomic state variables. We now investigate if the findings are consistent with theoretical predictions. Panel B of Table 2.6 examines more formally how optimal carry and momentum returns are related to macroeconomic and liquidity risk. We use predictive regressions within the context of a multi-beta framework with linear time-varying risk premia. We follow the approach by Chordia and Shivakumar (2002) and Bessembinder and Chan (1992), who show that, assuming a linear multivariate proxy for the pricing kernel, the expected return is the one-period-ahead forecast from the regression,

$$R_t = \alpha + \beta Z_{t-1} + \epsilon, \tag{2.16}$$

where Z_{t-1} is a vector of economic state variables and R_t are the portfolio returns. By following this approach, we do not test whether the payoff of the optimal strategies are related to their covariation with risk factors. Instead, the regression framework allows us to test whether strategy payoffs are captured by a common set of standard macroeconomic variables. As mentioned earlier, we use two sets of macroeconomic variables. First, we use the US industrial production gap (IP gap) for which Cooper and Priestley (2009) show a strong relation to business cycles and to have strong predictive power for expected bond and stock returns. Second, we use the common systematic price-base factors, dividend yield, term spread, yield and default spread, as measures for macroeconomic conditions.

Panel B of Table 2.6 presents the regression coefficients and the Newey and West adjusted t-statistics from regressing the optimal carry and momentum returns on the lagged sets of macroeconomic variables. In the macroeconomic model, the estimated coefficient for the IP gap is positively and statistically significant related to the strategy returns. The adjusted R^2 value of the predictive regression is 2%. From the results for the common systematic risk factors, we find that coefficients for the dividend yield are statistically negative related to the future strategy returns. The default spread is positively related to expected returns, however, not statistically significant. The short-rate is again statistically significant and positively related to the strategy returns. Finally, the term spread is positively and marginally significantly related to the optimal carry and momentum strategy. The adjusted R^2 value is only 1.3%.

When interpreting these results, we note that the two ex-ante stock and bond variables, default spread and dividend yield, are counter-cyclical: when real activity is expected to be high, these variables take low values. Conversely, the term spread and yield are pro-cyclical: high values coincide with high expected real activity. Examining the data, we find that the IP gap is positively related to expected optimal carry and momentum returns. This relationship suggests that the variation of the expected returns is pro-cyclical. The same result is applicable when observing the common systematic factors. While the dividend yield is negatively related to expected returns, the yield and the term spread are positively related to future returns. Again, this suggests that the return premia are pro-cyclical. These findings, however, are inconsistent with macroeconomic theories of discount rate variation(For instance, Chordia and Shivakumar (2002) or Bessembinder and Chan (1992)), which predict counter-cyclical variation of risk premia. These results may be interpreted as investors using futures trading strategies as a source of hedging, or as a misspecification due to the macroeconomic variable being related to variables that are pro-cyclically correlated.

D. Hedge Fund Activity and Capital Flows

Recently, a large stream of literature in financial economics emphasizes segmented markets and frictions as a source of predictable variation in asset prices. Segmented markets are important for expected returns because financial agents, who are active in a particular market, have only limited risk-sharing abilities. Theoretical examples of segmentation in diverse asset classes are given by Brunnermeier (2009), Gabaix, Krishnamurthy, and Vigneron (2007), Duffie and Strulovici (2012) and Vayanos and Vila (2009). Most of the theoretical models predict that expected returns are related to capital and capital flows deployed in the asset classes. The limited risk-bearing capacity of speculators generates downward sloping demand curves that result in a positive relation between capital flows and contemporaneous returns. Consequently, expected returns are negatively correlated with the total capital committed within an asset class. Jylhä and Suominen (2011) show theoretically and empirically, in a similar vain to our study, that returns to carry strategies in currency markets are predicted by the speculative capital of hedge funds active in these markets.

In this section we test if financial market frictions, in particular speculative capital flows of hedge funds, are related to the returns of optimal carry and momentum portfolios. We proceed as follows: First, we test if hedge funds indeed trade in carry and momentum strategies within the framework of a linear factor model; second, we test if speculative capital by hedge funds is related to optimal carry and momentum returns.

D.1. Hedge Fund Returns and Optimal Carry and Momentum Strategies

Table 2.7 presents the results from regressing the net-of-fee monthly returns of three asset-under-management weighted hedge fund indices on the returns of the optimal futures portfolios, and various combinations of factor benchmark models. We include a hedge fund return index that covers all hedge fund styles and two sub-indices: one macro hedge fund index and a managed futures hedge fund index. We choose the Fung and Hsieh (2004) 7-factor model (FH7, hereafter) and a simple CAPM model based on the returns of the MSCI as benchmark models. The FH7 incorporates five primitive trend-following factors for bonds, commodities, currencies, interest rates and equity classes. Furthermore, we include the term spread and the default spread as control variables for changing macroeconomic environments, given the results of the previous section. For each hedge fund index or subindex, columns (1)-(4) of Table 2.7 report the alpha, which can be interpreted as the proportion of returns that cannot be explained by the factors, and the beta coefficients denoting the factor loadings. In brackets we report the statistical significance in terms of Newey-West adjusted t-statistics for each coefficient. In the last row we report the adjusted R^2 values.

Column (1) and (2) of Table 2.7 report the results of regressing the hedge fund index returns, first on the MSCI returns, and then on a combination of MSCI returns and the optimal carry and momentum returns. In agreement with the literature, we observe that all factor coefficient estimates are positive and highly significantly related to hedge fund index returns. However, a surprising feature is the explanatory power of the factors measured by adjusted R^2 values. We find that, while the MSCI explains around 28% of the variation in all hedge fund returns, this value increases by almost 10% to a total of 40% when including the optimal carry and momentum factor. For robustness, we report in column (3) and (4) the benefit of including the optimal carry and momentum factor into the FH7 model. The FH7 model already explains 35% of variation in hedge fund returns. When including the optimal carry and momentum factor this value increases again by almost 8% to a total of 43%.

In the next four columns we repeat the exercise but use global macro hedge fund returns as the dependent variable. In this setting the MSCI only explains 3% and the FH7 factors account for only 5% variability of global macro returns. When including the optimal carry and momentum returns into the regression the R^2 values increase in both cases to more than 19%. A similar finding emerges for the last four columns. Here, we present the results for the managed futures index. In these regressions the MSCI is almost unrelated, or even negatively related, to the managed futures returns. Including the optimal carry and momentum factor raises the explanatory power to 30%. Even more unexpected are the results for the FH7 factors. The FH7 factors are constructed to resemble the risk in trend-following strategies, which is exactly what managed futures invest in. While these factors indeed explain 18% of the variance, the inclusion of the optimal carry and momentum factor raises this by 25% to a total of 42%.

In summary, the presented results suggest that hedge fund returns can be better proxied for using optimal futures strategies than the popular dynamic factors of Fung and Hsieh (2004). This suggests the trading behaviour of hedge funds, and by association capital flow to hedge funds, could have an effect on the profitability of optimal carry and momentum strategies as conjectured earlier. We explore this hypothesis further in the following section.

D.2. Hedge Fund Capital and Optimal Carry and Momentum Strategies

Table 2.8 tests if optimal carry and momentum returns are related to financial frictions and, in particular, to speculative capital of hedge funds. Panel A of Table 2.8 reports the performance of the optimal carry and momentum strategy conditioning on different hedge fund related states and serves as a preliminary investigation. First, the Sharpe ratios are reported during times of capital flows, into and out of the hedge fund sector. We find that the Sharpe ratios of optimal carry and momentum strategies are higher during times of capital outflows. The Sharpe ratios are 1.32 and

1.49 during times of inflows and outflows, respectively. These observations are consistent with the implications of markets with frictions. During times of capital outflows, less capital is available to arbitrage inefficiencies, which in turn implies higher returns. For comparison, we also report the performance of a long-only strategy during these states of the world. We find exactly the opposite relation: Sharpe ratios are higher for increasing than for decreasing states.

In the next columns of Table 2.8 we split the data sample into two periods, prior to and after August 1998, which roughly corresponds to the peak of the funding crisis following the collapse of Long Term Capital Management (LTCM). A variety of academic studies find a structural break in the return generating process of hedge funds during this time, e.g., Meligkotsidou and Vrontos (2008) or Sadka (2010). We find that the performance of optimal carry and momentum strategies before 1998 is significantly higher than afterwards, with Sharpe ratios of 1.67 and 1.15, respectively.

Finally, in Table 2.8 Panel A we investigate the effects of changing liquidity conditions on the performance of optimal carry and momentum before and after August 1998 (LTCM crash). Similarly to Panel A of Table 2.6, we find strategy Sharpe ratios are higher in times of worsening liquidity conditions and lower in times of improving liquidity conditions. This effect is symmetric for the time before and after August 1998. Changing liquidity conditions have the same effect on long-only strategies. These two findings suggest that, while funding liquidity is an important source of expected returns in futures markets, it is not specific to optimal carry and momentum strategies.

Table 2.8 Panel B examines more formally the relation between optimal carry and momentum strategies and speculative capital, which we define as the capital available to hedge funds. We regress the trading strategies return series' on the contemporaneous month's hedge fund flow and the previous month's hedge fund total AUM (HF AUM). This regression follows the methodology of Jylhä and Suominen (2011) and Jylhä, Rinne, and Suominen (2014). We also include a time trend variable to account for the positive trend in total AUM and the negative trend in the optimal portfolio returns. Panel B of Table 2.8 presents the coefficient estimates, the Newey-West adjusted test statistics and the adjusted R^2 values for the regression. We find that the coefficients to both HF AUM and HF Flow are statistically highly significant. Furthermore, the signs of the coefficients confirm the conjectures: the HF Flow variable is contemporaneously positive related to optimal carry and momentum returns, consistent with a downward sloping demand curve. However, this effect results in the lower than expected returns with respect to total capital committed in the next period, which is confirmed by the data; the lagged HF AUM variable is negatively related to optimal carry and momentum returns.

To disentangle the role of liquidity risk, macroeconomic risk and speculative capital, we run several control regressions. First, we add the lagged TED spread into the regression framework. As expected, and consistent with the results in Table 2.6 Panel A, the coefficient estimate for the TED spread is statistically insignificant, while the coefficients of HF AUM and HF Flow remain significant. Next we test the explanatory power of lagged macroeconomic variables used in the previous section together with the hedge fund flow variables. Panel B of Table 2.8 shows that the coefficient estimate of the IP Gap becomes insignificant once we use this variable together with the HF AUM and HF Flow variables. This influence indicates that the pro-cyclical behaviour of expected returns of optimal carry and momentum strategies documented in the previous section is not driven by changing risk preferences of economic agents, but rather due to the correlation of the HF Flow and IP Gap variable. In undocumented results we find that the correlation between HF Flow and IP Gap is 55%. Finally, we regress optimal carry and momentum returns on lagged yield and term spread. As for the IP Gap, we find that the coefficients are not significant once we include the hedge fund capital variables. For comparison, we also test the regressions for the long-only strategy. We find that the HF AUM and HF Flow variables are not significantly related to the long strategy, suggesting the relations between optimal portfolio returns and HF AUM and HF Flow are related to the carry and momentum characteristics and not price movements of the underlying futures contracts. On the other hand, we find that IP Gap variable predicts significantly counter-cyclical risk premia for the long-only strategy, which is not evident, after controlling for hedge fund flows, in the optimal portfolios. Lastly, we find that the TED spread is weakly but significantly related to the long-only strategy, consistent with liquidity risk theories.

Table 2.8 Panel C reports the results from regressing optimal carry and momentum strategies on the HF AUM and HF Flow variables conditioned on improving and weakening macroeconomic environments. First, we find that HF AUM is always negatively and statistically significantly related to optimal carry and momentum strategies regardless of the macroeconomic states. For the HF Flow variable, on the other hand, we find that a significant flow return relation is only given in weakening macroeconomic environments, while this relation is insignificant during economic upturns. For long-only strategies the relation between HF AUM and HF Flow variables and returns remains insignificant.

In summary, the results in this section suggest that a large proportion of the returns to optimal carry and momentum strategies are due to the segmentation of futures markets from other asset classes. In particular, the strong involvement of hedge funds limits the risk sharing ability of market participants with other asset classes. Consequently, only increasing capital available to hedge funds reduces the returns to the trading strategies and increases the efficiency of futures markets.

VI. Conclusion

We have empirically investigated optimal futures portfolios based on the momentum and carry characteristic across currencies, commodities, equity indices and bond futures. We adapt the optimal parametric policy methodology by Brandt, Santa-Clara, and Valkanov (2009) to include assets with varying levels of volatility. We find that the optimal carry and momentum strategy yields high Sharpe ratios and certainty equivalent returns. As a consequence of targeting the utility of the investor over the period studied the return distribution has reduced higher moments compared to equity strategies based on traditional risk factors. Accordingly, we find that adding carry and momentum predictors to an ex-ante optimal allocation to traditional risk factors generates large certainty equivalent increases in the resulting portfolios. Furthermore, we find the optimal strategy returns are very closely related to hedge fund indices, with optimal strategy returns explaining more of index variance than the factors of Fung and Hsieh (2004).

Analyzing the origin of optimal portfolio returns we find qualitatively similar results to those of the rule based carry and momentum strategies studied in Chapter 1. The returns to the optimal carry and momentum portfolios are hard to understand within a framework that relies on covariance risk with standard risk factors and cannot be explained by time varying macroeconomic or funding liquidity risk. In contrast, we find that the returns to optimal carry and momentum returns are highly related to speculative capital of hedge funds. Contemporaneously larger capital flows lead to higher optimal carry and momentum returns, implying that expected returns decrease with the total amount of assets under management of hedge funds.

These findings have important implications for investors and policy makers. First for investors, we have demonstrated the significant returns generated by optimal futures portfolios. However, investors who are active in these strategies should be aware that a large proportion of the performance relies on the size of the hedge fund industry and, in particular, the speculative capital available to arbitrage inefficiencies. The high returns of optimal carry and momentum strategies might deteriorate in the future with increasing hedge fund industry size. Second, from a policy perspective, it seems disadvantageous to restrict hedge funds in their activity in futures markets; on the contrary, the more capital hedge funds allocate to futures markets the more efficient they become. Although we concede the policy structure around hedge funds is complex, we offer our results as a possible counter argument to recent calls restricting the ability to operate of hedge funds that have emanated from the aftermath of the 2008 financial crisis.

VII. Appendix: Tables

Table 2.1. Optimal futures strategy portfolio returns

This table shows estimates of the portfolio policy for individual carry, momentum, and joint carry and momentum characteristics across all available assets. The portfolio policy is defined in Equation 2.7. The reported values are estimated by optimizing a power utility function with a relative risk aversion of five. We use futures prices from Bloomberg from January 1980 to September 2012. The first four columns report in-sample results where optimal characteristics are calibrated once for the entire sample period. The remaining columns report out-of-sample results. Here we use data from January 1982 to January 1992 (120 months) to estimate the initial coefficients and corresponding portfolio weights to generate next month returns. The coefficients are then re-estimated each subsequent month for the remainder of the sample, yielding an out-of-sample return. The first 6 rows refer to the optimal portfolio coefficients and their associated student t-statistic for the carry characteristic, momentum characteristic and long-only strategy, in descending order. The following 4 rows report weighting parameters: the average absolute portfolio weight, the maximum weight, the minimum weight, and the turnover of the portfolio. The remaining columns report the portfolio return statistics, annualized mean return, annualized standard deviation of returns, skewness of returns, excess kurtosis of returns, Sharpe ratio, and certainty equivalent return excess of the risk-free rate.

	In sample				Out of sample			
	C&M	Car.	Mom.	Long	C&M	Car.	Mom.	Long
θ_{carry}	2.036	3.195			1.714	3.073		
(t-stat)	(2.65)	(4.65)			(1.70)	(3.51)		
θ_{mom}	3.157		3.853		3.514		4.197	
(t-stat)	(4.29)		(5.39)		(3.59)		(4.61)	
θ_{long}				2.862				2.572
(t-stat)				(4.13)				(3.00)
$\lvert w_i \rvert$	0.072	0.055	0.062	0.082	0.050	0.038	0.046	0.052
$\max(w_i)$	0.308	0.305	0.239	0.082	0.174	0.171	0.141	0.052
$\min(w_i)$	-0.301	-0.381	-0.197	0.082	-0.158	-0.230	-0.100	0.052
$\sum w_i I(w_i < 0)$	-1.658	-1.686	-1.173	0.000	-1.002	-1.133	-0.752	0.000
$\sum I(w_i < 0)/N_t$	0.427	0.534	0.375	0.000	0.271	0.351	0.241	0.000
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	1.119	0.743	1.163	0.000	0.825	0.511	0.865	0.001
$\bar{r}$	0.368	0.202	0.307	0.179	0.364	0.190	0.307	0.171
$\sigma(r)$	0.232	0.166	0.210	0.150	0.239	0.160	0.224	0.131
Skewness	0.105	0.256	0.084	-0.218	0.061	0.364	-0.119	-0.421
Excess kurtosis	1.097	2.097	1.237	0.627	1.059	2.674	0.671	1.114
Sharpe	1.162	0.821	1.056	0.779	1.110	0.791	0.993	0.838
CE	0.151	0.074	0.123	0.064	0.151	0.085	0.119	0.087

Table 2.2. Varying risk aversion

Reported are estimates of futures portfolio policy with the characteristic carry, momentum, carry and momentum combined, and long-only optimized for different power utility functions with a relative risk aversion of 1, 5 (used in previous tables), and 100. Policy estimates and associated return statistics are reported for in-sample and out-of-sample portfolios. For the in-sample section, we estimate an optimal portfolio policy based on data from January 1982 to September 2012. Out-of-sample optimisation is calibrated over the period from January 1982 to January 1992. We then form out-of-sample monthly portfolios by enlarging the sample period and re-estimating the portfolio policy for each subsequent month until the end of the sample. In the upper panel, the first 4 rows refer to the optimal portfolio characteristics and their associated bootstrapped student t-statistic for the carry, and momentum, in descending order. The following 4 rows report weighting parameters, the average absolute portfolio weight, the maximum weight, the minimum weight, and the turnover of the portfolio. In these measures, each weighting parameter is multiplied by its respective futures volatility to ensure comparability. The remaining rows report portfolio the return statistics: annualized mean return, annualized standard deviation of returns, skewness of returns, excess kurtosis of returns, Sharpe ratio, and certainty equivalent return excess of the risk-free rate. The lower panel reports analogous statistics for the long-only portfolio.

	In sample			Out of sample		
Variable	$\gamma = 2$	$\gamma = 5$	$\gamma = 100$	$\gamma = 2$	$\gamma = 5$	$\gamma = 100$
Panel A: Carry and Momentum						
θ_{carry}	3.542	2.043	0.106	4.855	1.713	0.083
(t-stat)	(3.63)	(2.66)	(0.52)	(2.25)	(1.70)	(1.73)
θ_{mom}	4.528	3.147	0.154	9.793	3.515	0.172
(t-stat)	(4.27)	(4.28)	(0.80)	(4.77)	(3.59)	(3.58)
$\lvert w_i \rvert$	0.111	0.071	0.004	0.139	0.050	0.002
$\max(w_i)$	0.491	0.308	0.016	0.488	0.174	0.009
$\min(w_i)$	-0.493	-0.301	-0.015	-0.445	-0.158	-0.008
$\sum w_i I(w_i < 0)$	-2.649	-1.658	-0.084	-2.814	-1.002	-0.049
$\sum I(w_i < 0)/N_t$	0.436	0.427	0.430	0.271	0.271	0.270
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	1.689	1.117	0.055	2.312	0.825	0.041
$\bar{r}$	0.572	0.368	0.064	1.194	0.364	0.048
$\sigma(r)$	0.356	0.231	0.015	0.670	0.240	0.013
Skewness	0.120	0.105	0.264	0.052	0.065	-0.139
Excess kurtosis	1.084	1.097	1.413	1.024	1.068	0.632
Sharpe	1.161	1.162	0.892	1.141	1.110	-0.118
CE	0.371	0.151	0.003	0.481	0.151	0.005
Panel B: Long only						
θ_{long}	8.098	2.862	0.162	7.351	2.572	0.156
(t-stat)	(5.37)	(4.13)	(0.16)	(3.92)	(3.00)	(3.63)
$\lvert w_i \rvert$	0.233	0.082	0.005	0.149	0.052	0.003
$\max(w_i)$	0.233	0.082	0.005	0.149	0.052	0.003
$\min(w_i)$	0.233	0.082	0.005	0.149	0.052	0.003
$\sum w_i I(w_i < 0)$	0.000	0.000	0.000	0.000	0.000	0.000
$\sum I(w_i < 0)/N_t$	0.000	0.000	0.000	0.000	0.000	0.000
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.001	0.000	0.000	0.002	0.001	0.000
$\bar{r}$	0.453	0.179	0.057	0.469	0.171	0.042
$\sigma(r)$	0.426	0.150	0.011	0.374	0.131	0.009
Skewness	-0.229	-0.218	-0.056	-0.380	-0.421	-0.598
Excess kurtosis	0.573	0.627	0.889	0.992	1.114	1.223
Sharpe	0.777	0.779	0.568	0.916	0.838	-0.834
CE	0.195	0.064	0.000	0.269	0.087	0.003

Table 2.3. Diversification benefit of the optimal futures portfolio

Reported are out-of-sample performance statistics for optimal portfolios containing popular classes of tradable risk factors. For each class of risk factors we compare out-of-sample portfolio performance with and without the inclusion of the carry and momentum futures portfolio. Optimal portfolios are calculated by incorporating traditional strategy performance into the portfolio return as described in Equation 2.15. The first column reports performance of our base case optimal carry and momentum strategy. The second column reports the same strategy with the inclusion of an equally weighted long only futures return. The remaining columns display statistics for the four strategy classes we consider; a passive index strategy represented by the excess return of the S&P 500 index, the Fama-French factors (Market Excess Return, High minus Low, Big minus Small) taken from Eugene Fama's website, equity value and momentum factors taken from Tobias Moskowitz's website, and a portfolio consisting of S&P 500 excess return and the excess return on the 10 year treasury bill. For each class we report a 'benchmark' case, where we force all futures weights to zero, so that the reported performance is the optimal allocation for that risk factor class in isolation. This is reported in the left hand column of each class. On the right hand column of each class we include the optimal carry and momentum strategy. For each strategy class out-of-sample optimisation is calibrated over the period from January 1982 to January 1992. The reported performance is then calculated using optimised weights and characteristics for an expanding window for each subsequent month. Performance statistics are in rows, reporting in descending order: maximum monthly return, minimum monthly return, annualised mean return, annualised standard deviation, monthly excess skewness, monthly kurtosis, annualised Sharpe ratio, and the certainty equivalent return in excess of the risk free rate.

	Optimal Futures		Risk Factor Classes							
	Long only		Stocks		Fama & French		Value & Mom.		Stocks & Bonds	
	w/o	w	w/o	w	w/o	w	w/o	w	w/o	w
$\max(r)$	0.276	0.285	0.075	0.267	0.206	0.295	0.573	0.314	0.165	0.259
$\min(r)$	-0.188	-0.234	-0.129	-0.194	-0.162	-0.210	-0.306	-0.193	-0.117	-0.205
$\bar{r}$	0.364	0.529	0.086	0.406	0.162	0.462	0.258	0.420	0.094	0.403
$\sigma(r)$	0.239	0.301	0.106	0.246	0.204	0.265	0.253	0.265	0.132	0.241
Skewness	1.059	0.928	1.323	1.242	0.800	1.402	16.538	1.037	1.707	1.437
Ex. Kurtosis	0.060	-0.026	-0.568	0.086	0.154	0.106	1.829	0.092	-0.025	0.121
Sharpe	1.110	1.276	0.318	1.209	0.502	1.275	0.724	1.163	0.310	1.224
CE	0.151	0.186	0.021	0.179	0.016	0.198	0.049	0.164	0.013	0.184

Table 2.4. Optimal futures returns with transaction costs

This table shows estimates of portfolio policy for joint carry and momentum characteristics across all available assets for the utility function specified in Equation 2.7. Average utility of return is maximized for a gamma five power utility function for two cost specifications. In the first specification transaction costs are a constant 0.1% across assets and time. In the second, costs are based on the monthly close bid-ask spread for the corresponding asset. For comparison, statistics for zero transaction costs are also reported. The first three columns report "in-sample" results where optimal characteristics are calibrated once for the entire sample period. The remaining columns report "out-of-sample" results, here we use data from January 1982 to January 1992 to estimate the initial coefficients and corresponding portfolio weights to generate next month return. The coefficients are then re-estimated each subsequent month for the reminder of the sample, generating an out of sample return series. The first 4 rows refer to the optimal portfolio coefficients and their associated student t-statistic for the carry characteristic and momentum characteristic, in descending order. The following 6 rows report weighting parameters, the average absolute portfolio weight, the maximum weight, the minimum weight, and the turnover of the portfolio. Each weighting parameter is multiplied by volatility to ensure comparability. The remaining rows report the portfolio return statistics, annualized mean return, annualized standard deviation of returns, skewness of returns, excess kurtosis of returns, Sharpe ratio, and certainty equivalent return excess of the risk free rate. The certainty equivalent return is reported for returns net-of-costs for each of the three cost specifications.

	In sample			Out of sample		
	$c_{i,t} =$			$c_{i,t} =$		
	0.000	0.001	$f(me_{i,t}, t)$	0.000	0.001	$f(me_{i,t}, t)$
θ_{carry}	2.036	2.090	2.074	1.714	1.714	1.714
(t-stat)	(2.65)	(2.75)	(2.75)	(1.70)	(1.68)	(1.68)
θ_{mom}	3.157	3.135	3.297	3.514	3.514	3.514
(t-stat)	(4.29)	(4.21)	(4.46)	(3.59)	(3.54)	(3.54)
$\|w_i\|$	0.072	0.072	0.074	0.050	0.050	0.050
$\max(w_i)$	0.308	0.311	0.317	0.174	0.174	0.174
$\min(w_i)$	-0.301	-0.305	-0.309	-0.158	-0.158	-0.158
$\sum w_i I(w_i < 0)$	-1.658	-1.675	-1.709	-1.002	-1.002	-1.002
$\sum I(w_i < 0)/N_t$	0.427	0.428	0.426	0.271	0.271	0.271
$\sum \|w_{i,t} - w_{i,t-1}\|$	1.119	1.120	1.161	0.825	0.825	0.825
$\bar{r}$	0.368	0.352	0.372	0.364	0.346	0.358
$\sigma(r)$	0.232	0.231	0.238	0.239	0.238	0.238
Skewness	0.105	0.103	0.099	0.061	0.033	0.037
Excess kurtosis	1.097	1.098	1.093	1.059	1.001	1.008
Sharpe	1.162	1.115	1.145	1.110	1.058	1.101
CE$\|c_{i,t} = 0.000$	0.152	0.152	0.152	0.084	0.084	0.084
CE$\|c_{i,t} = 0.001$	0.138	0.138	0.138	0.072	0.072	0.072
CE$\|c_{i,t} = f(me_{i,t}, t)$	0.146	0.146	0.146	0.080	0.080	0.080

Table 2.5. Risk factors and optimal futures portfolios

This table reports the regression coefficients (alpha is reported as annualized percent) and the respective Newey and West (1987) adjusted t-statistics from regressing the returns to optimal out-of-sample momentum, carry and combined carry and momentum (Car&Mom) strategies on four factor model specifications: (a) A version of Asness, Moskowitz, and Pedersen (2013) "Value and Momentum Everywhere" model that is a volatility weighted cross-sectional momentum portfolio across asset classes (Mom. Every.) and a volatility weighted cross-sectional value portfolio across asset classes (Value Every.) which we augment with the volatility weighted long only portfolio as a market proxy, (b) a version of the Fama and French (1992) model that uses the high minus low (FF HML) and the small minus big (FF SMB) portfolios as factors and includes the MSCI index as a market proxy, (c) a liquidity risk model that includes the Pastor and Stambaugh (2001) market liquidity proxy (Market Liq.) and (d) a combination of (a) and (c). The last row reports the adjusted R^2's of the regressions. The sample is from January 1992 to September 2012.

	Carry	Mom	Car& Mom	Carry	Mom	Car&Mom	Carry	Mom	Car&Mom	Carry	Mom	Car&Mom
Alpha	19.272	14.412	21.698	21.353	31.472	37.012	20.016	29.965	34.946	19.273	14.412	21.699
tstat	(4.89)	(3.14)	(4.12)	(6.09)	(6.64)	(7.17)	(5.40)	(6.24)	(6.66)	(4.89)	(3.14)	(4.12)
Long	-0.169	1.001	0.729							-0.151	1.013	0.748
tstat	(-1.34)	(6.80)	(4.32)							(-1.19)	(6.82)	(4.40)
Value Every.	0.336	0.269	0.410							0.335	0.268	0.409
tstat	(3.96)	(2.73)	(3.62)							(3.94)	(2.71)	(3.60)
Mom. Every.	0.259	0.468	0.535							0.252	0.463	0.528
tstat	(3.67)	(5.71)	(5.69)							(3.56)	(5.62)	(5.59)
MSCI				-0.281	-0.006	-0.167						
tstat				(-4.51)	(-0.07)	(-1.82)						
FF HML				0.002	-0.003	-0.002						
tstat				(2.07)	(-3.04)	(-1.57)						
FFSMB				-0.002	-0.003	-0.004						
tstat				(-2.42)	(-2.21)	(-2.68)						
Market Liq							-0.071	-0.023	-0.057	-0.151	1.013	0.748
tstat							(-1.46)	(-0.37)	(-0.83)	(-1.19)	(6.82)	(4.40)
R^2	0.061	0.238	0.160	0.118	0.035	0.160	0.004	-0.003	-0.001	0.062	0.236	0.160

Table 2.6. Macroeconomic and funding liquidity influences on optimal carry and momentum portfolios

This table reports the performance of optimal carry and momentum portfolios across different economic environments (Panel A) and the results from regressing optimal carry and momentum portfolios on economic predictor variables (Panel B). The first three columns of Panel A show the Sharpe ratios of the trading strategies across the total sample period divided in three subperiods (1982-1992, 1992-2002, and 2002-2012). The next four columns report the Sharpe ratios across different business cycle states. Early expansions and late expansions are defined as the first half and second half, respectively, of an expansion period as defined by NBER (from trough to peak). Early recessions and late recessions are defined as the first half and second half, respectively, of an recession period as defined by NBER (from peak to trough). The final two columns report the Sharpe ratios of improving and worsening liquidity environment, defined as positive and negative changes in the TED spread, respectively. Panel B presents the coefficients and Newey and West autocorrelation consistent standard errors when optimal carry and momentum returns are regressed against lagged values of macroeconomic and funding liquidity variables. First, optimal carry and momentum returns are regressed on lagged values of the industrial production gap (IP Gap) as a measure of business cycle conditions. IP Gap is the deviation of the logarithm of total industrial production from a trend that includes both a linear component and a quadratic component. Second, trading returns are regressed on lagged values of common systematic variables including the dividend yield (Div Yield), the short yield (yield), the default spread (Def) and the term spread (TSpread). Third, trading returns are regressed on a measure of funding liquidity, the TED spread (TED). In all specifications adjusted R^2's are reported. In all panels the table also reports the results for a long only, carry only and momentum only optimized portfolio.

Panel A: Sharpe Ratios across Different Economic Environments

	Timeperiod			Business Cycle				Liq. Environment	
				Expansion		Recession			
	82-92	92-02	02-12	Early	Late	Early	Late	Worse.	Improv.
Carry & Mom	1.51	1.53	1.07	1.07	1.53	2.12	2.37	1.59	1.18
Long	0.95	1.02	1.35	1.43	1.26	-0.14	-0.43	1.47	1.13
Mom	1.46	1.50	0.92	0.96	1.60	1.58	2.10	1.56	1.09
Carry	1.15	1.32	0.87	1.08	0.88	2.71	2.84	1.24	1.01

Panel B: Statistical Significance

	Macro			Common Factors						Liquidity		
	α	IP Gap	$\bar{R}^2$	α	Div Yield	Yield	Def	TSpread	$\bar{R}^2$	α	TED	$\bar{R}^2$
Carry & Mom	0.022	0.149	0.021	0.012	-0.025	0.009	0.013	0.012	0.013	0.025	-0.013	-0.002
(t-stat)	(4.59)	(2.63)		(0.41)	(-2.09)	(1.96)	(0.82)	(1.82)		(5.23)	(-0.75)	
Long	0.014	-0.022	-0.003	0.031	0.003	-0.003	-0.014	-0.001	-0.004	0.022	-0.016	0.023
(t-stat)	(4.69)	(-0.62)		(1.52)	(0.47)	(-0.89)	(-1.34)	(-0.19)		(3.94)	(-1.48)	
Carry	0.014	0.033	-0.001	-0.023	-0.019	0.009	0.015	0.017	0.042	0.015	-0.016	0.003
(t-stat)	(4.73)	(0.91)		(-1.30)	(-2.76)	(3.43)	(2.14)	(3.71)		(4.73)	(-1.26)	
Momentum	0.022	0.119	0.014	0.012	-0.012	0.007	0.003	0.007	0.003	0.023	-0.005	-0.004
(t-stat)	(4.99)	(2.22)		(0.40)	(-1.24)	(1.53)	(0.21)	(1.12)		(5.36)	(-0.31)	

Table 2.7. Return decomposition of hedge fund indices

This table reports the results of regressing the returns of hedge fund indices on various return factors. The hedge fund indices include an index across all strategies (HF Index), a macro strategy sub index (HF Macro), and a managed futures sub index (HF CTA). For each hedge fund index return regression we use three factor specifications: (1) includes the returns to the MSCI; (2) the returns to the MSCI and the optimal carry and momentum strategy (Car & Mom); (3) corresponds to an extended Fung and Hsieh (2004) model using all primitive trend-following Fung and Hsieh (2001) factors, the S&P500, the term spread (TSpread), which is the difference between a 10 year and a 3 month bond yield, and the default spread (DefSpread), and (4) which is a combination of (3) including the optimal carry and momentum strategy (Car & Mom). The data period used for the regressions is restricted by the data availability of the Fung and Hsieh (2004) factors, from January 1994 to December 2011.

	HF Index				HF Macro				HF CTA			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Alpha	0.01	0.00	0.00	-0.00	0.01	0.01	0.01	0.01	0.01	-0.00	0.02	0.01
tstat	(4.87)	(3.13)	(0.35)	(-0.10)	(4.89)	(2.61)	(1.25)	(0.64)	(2.46)	(-0.73)	(1.10)	(0.56)
MSCI	0.25	0.26	0.23	0.24	0.11	0.14	0.10	0.12	-0.03	0.01	0.05	0.08
tstat	(6.39)	(7.06)	(5.61)	(6.36)	(2.05)	(2.67)	(1.82)	(2.38)	(-0.59)	(0.32)	(0.95)	(2.11)
Car&Mom		0.10		0.09		0.17		0.16		0.28		0.26
tstat		(4.03)		(4.52)		(5.04)		(5.14)		(7.48)		(7.93)
PTFSbd			-0.03	-0.03			-0.02	-0.02			0.04	0.04
tstat			(-2.36)	(-2.22)			(-1.21)	(-1.13)			(2.39)	(2.75)
PTFScom			0.02	0.01			0.02	0.00			0.05	0.02
tstat			(1.73)	(0.98)			(1.20)	(0.33)			(3.03)	(1.51)
PTFSfx			0.01	0.01			0.01	0.01			0.04	0.04
tstat			(1.03)	(1.08)			(0.78)	(0.81)			(2.89)	(3.03)
PTFSir			-0.02	-0.01			-0.02	-0.01			-0.02	-0.00
tstat			(-3.58)	(-3.18)			(-1.85)	(-1.12)			(-2.14)	(-0.72)
PTFSstk			0.02	0.01			0.02	0.01			0.05	0.02
tstat			(1.66)	(0.92)			(1.35)	(0.42)			(2.99)	(1.75)
TSpread			-0.00	-0.00			-0.00	-0.00			0.00	0.00
tstat			(-1.90)	(-1.44)			(-1.47)	(-1.00)			(0.01)	(0.81)
DefSpread			0.00	0.00			0.00	0.00			-0.00	-0.00
tstat			(0.84)	(0.95)			(0.07)	(0.11)			(-0.59)	(-0.68)
R^2	0.29	0.38	0.36	0.43	0.03	0.19	0.05	0.19	-0.00	0.30	0.18	0.42

Table 2.8. Hedge funds, speculative capital and the optimal carry and momentum strategy This table reports the performance of optimal carry and momentum portfolios across different hedge fund related economic environments (Panel A), the results from regressing optimal carry and momentum portfolios on proxies for speculative capital of hedge funds (Panel B), the interaction of macroeconomic environments and speculative capital in explaining optimal carry and momentum returns (Panel C). The first two columns of Panel A present the performance, measured as Sharpe ratio, of optimal carry and momentum portfolios during increasing and decreasing hedge fund flow (HF Flow) environments. HF Flow is measured as the sum of the past 12 months capital flows into the hedge fund industry. The next two columns report the Sharpe ratios before and after the LTCM crisis and the last four columns interact improving and worsening liquidity environments before and after the LTCM crisis. Panel B provides statistical evidence of optimal carry and momentum returns regressed on total hedge fund asset under management scaled by M2 (AUM), HF Flow and a time trend variable. The table only reports the coefficient estimates as well as Newey-West adjusted test statistics for the total AUM and HF Flow variables. The table also presents regression results when including combinations of TED, IP Gap, Yield and TSpread. Panel C presents the coefficient estimates and test statistics of optimal carry and momentum returns regressed on HF AUM and HF Flow interacted with growing and decreasing business conditions measured by IP Gap growth and NBER recession periods. In all panels the results for long only, carry only and momentum only are presented for comparison.

Panel A: Sharpe Ratios in Different Hedge Fund States								
	HF Flow		LTCM		LTCM and Liq.			
					pre 08/98		post 08/98	
	Incr.	Decr.	pre 08/98	post 08/98	Wors.	Impr.	Wors.	Impr.
Carry & Mom	1.32	1.49	1.67	1.15	1.83	1.49	1.33	0.95
Long	1.13	1.35	1.41	1.10	1.73	1.27	1.23	0.96
Mom	1.16	1.49	1.60	1.04	1.76	1.49	1.34	0.80
Carry	1.12	1.14	1.51	0.92	1.58	1.18	0.92	0.92
Panel B: Speculative Capital and Optimal Carry and Momentum Returns								
	α	HF AUM_{t-1}	HF $Flow_t$	TED	IP Gap	Yield	TSpread	$\bar{R}^2$
(1)	0.043	-0.178	0.402					0.026
(t-stat)	(5.86)	(-3.97)	(3.24)					
(2)	0.038	-0.194	0.431	0.010				0.026
(t-stat)	(4.75)	(-4.16)	(3.83)	(1.17)				
(3)	0.043	-0.182	0.417		-0.006			0.022
(t-stat)	(5.45)	(-3.03)	(2.05)		(-0.09)			
(4)	0.021	-0.178	0.462			0.002	0.005	0.015
(t-stat)	(0.50)	(-2.50)	(2.13)			(0.35)	(0.61)	
Long	0.027	-0.068	0.31	-0.024	-0.104			0.036
(t-stat)	(4.21)	(-1.13)	(1.52)	(-1.81)	(-2.38)			
Carry	0.031	-0.189	0.40	0.003	-0.0852			0.029
(t-stat)	(4.50)	(-2.3)	(1.86)	(0.33)	(-1.23)			
Mom	0.029	-0.146	0.43	0.012	0.006			0.061
(t-stat)	(-1.75)	(-1.98)	(1.86)	(1.55)	(0.07)			
Panel C: Macro Environments and Speculative Capital								
		HF AUM×		HF Flow×				
	α	$I_{(IPGap>0)}$	$I_{(IPGap<0)}$	$I_{(IPGap>0)}$	$I_{(IPGap<0)}$			$\bar{R}^2$
Carry and Mom	0.043	-0.159	-0.224	0.134	0.776			0.025
(t-stat)	(5.08)	(-2.58)	(-2.48)	(0.62)	(1.92)			
Long	0.016	0.007	-0.046	0.086	0.132			-0.010
(t-stat)	(3.63)	(0.11)	(-0.85)	(0.43)	(0.61)			
Carry and Mom	0.045	-0.188	-0.188	0.255	0.898			0.027
(t-stat)	(5.27)	(-3.06)	(-1.98)	(1.19)	(1.88)			
Long	0.014	0.037	-0.093	0.021	0.075			0.020
(t-stat)	(3.46)	(0.93)	(-1.18)	(0.14)	(0.19)			

VIII. Appendix: Figures

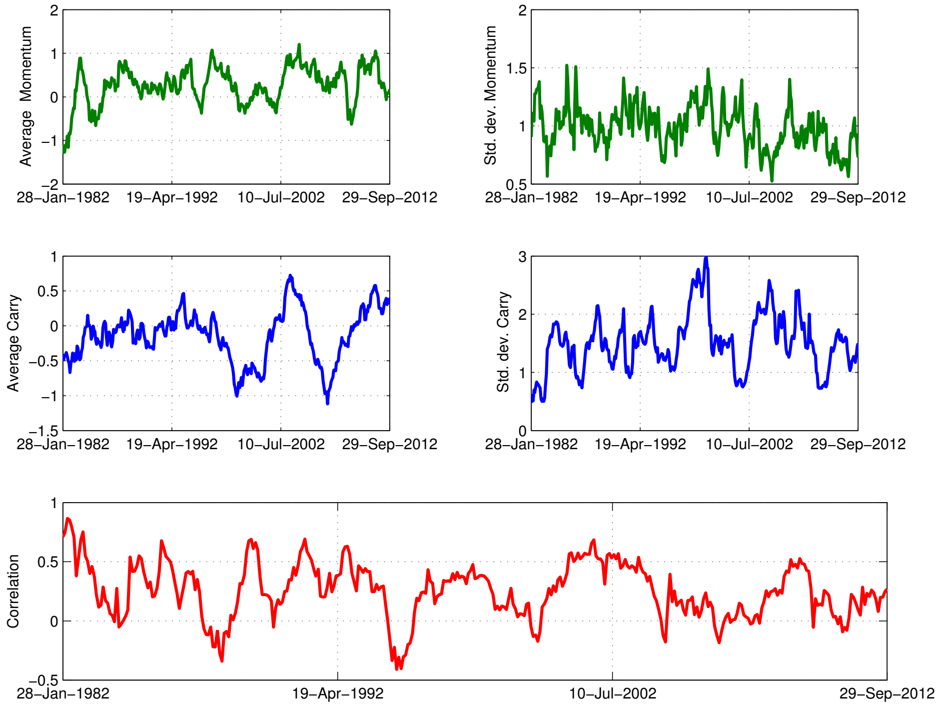


Figure 2.1. Cross sectional summary statistics of carry and momentum characteristics
The figure displays cross-sectional means and standard deviations of the carry and momentum characteristics every month from January 1982 to September 2012. The raw carry characteristic is calculated as the basis of the asset divided by the 255 day annualized basis volatility. The raw momentum characteristic is the 12 month excess return divided by the 255 day annualized return. For a given characteristic type, the reported characteristics are calculated by dividing the raw characteristic values by the standard deviation of all asset-months. We also report the cross-sectional correlation of carry and momentum characteristics.

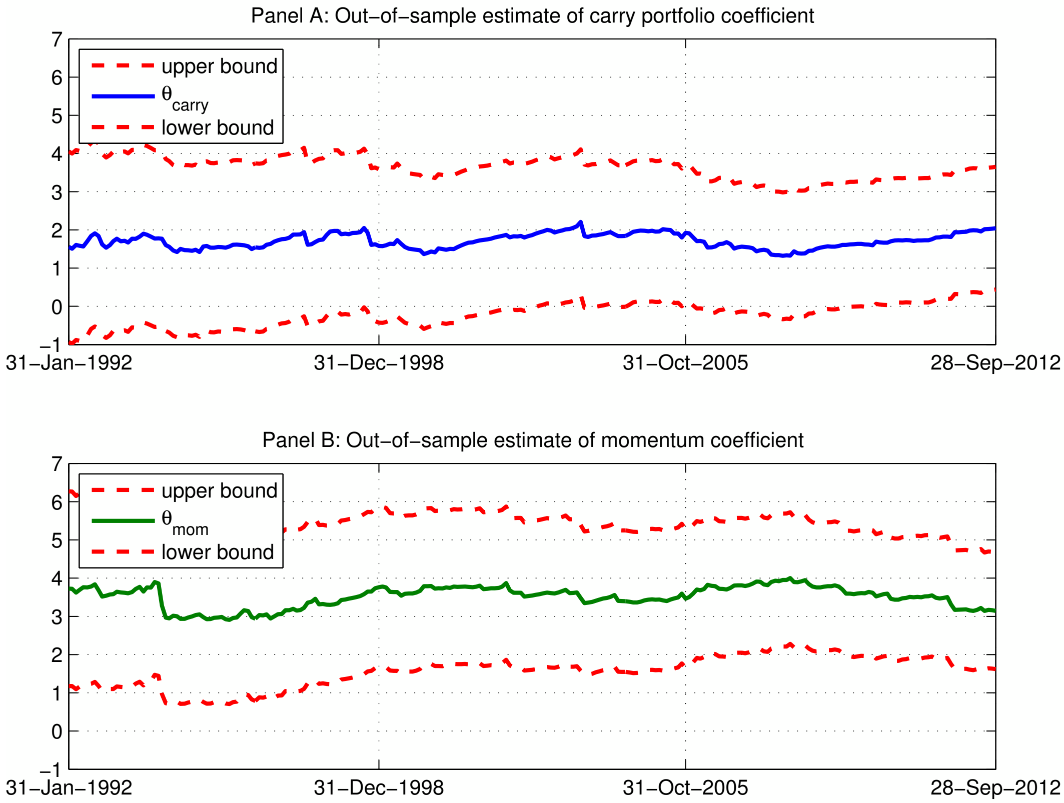


Figure 2.2. Out-of-sample parametric policy estimates

These figures display the θ estimates for the out of sample parametric portfolio choice problem. The displayed parameters are estimated for all futures assets and both signals in the portfolio optimization of Equation 2.7. Panel A reports the estimates for the carry signal (θ_{carry}), Panel B reports for the momentum signal (θ_{mom}). We also report the upper and lower 95 percentile confidence bands for each parameter. The standard errors are estimated form the asymptotic covariance matrix within the framework of general methods of moment (GMM) by Hansen (1982). The model is calibrated for the in-sample period from January 1980 to December 1990 and then the θ's are re-estimated every month, using an expanding window of data until September 2012.

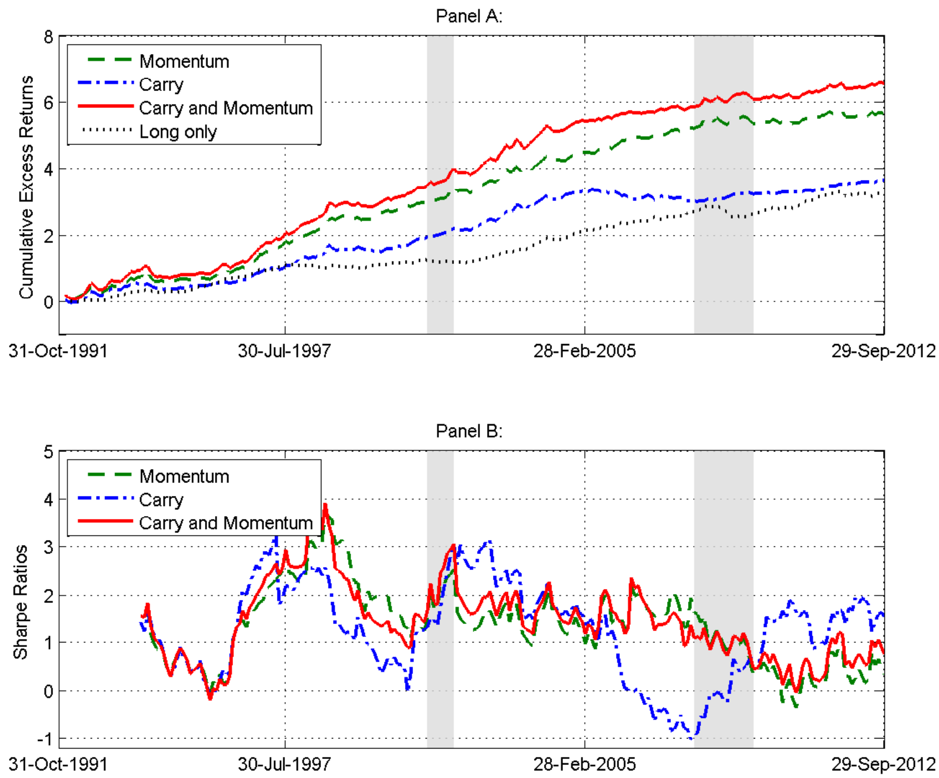


Figure 2.3. Historical performance of carry, momentum, and carry and momentum
These plots present the cumulative logarithmic returns and rolling Sharpe ratios for the out of sample estimation from January 1990 to September 2012. The portfolios are optimized for a power utility function with a relative risk aversion of $\gamma = 5$. Panel A presents the cumulative returns for the carry, momentum, and the combined carry and momentum portfolio. For comparison, Panel A includes the cumulative return series of an optimized long only portfolio. Panel B presents the 24 month rolling Sharpe ratios of the return series for carry, momentum, and the combined carry and momentum portfolio. The grey bands in both panels indicate the NBER recession periods (business cycle peak to trough).

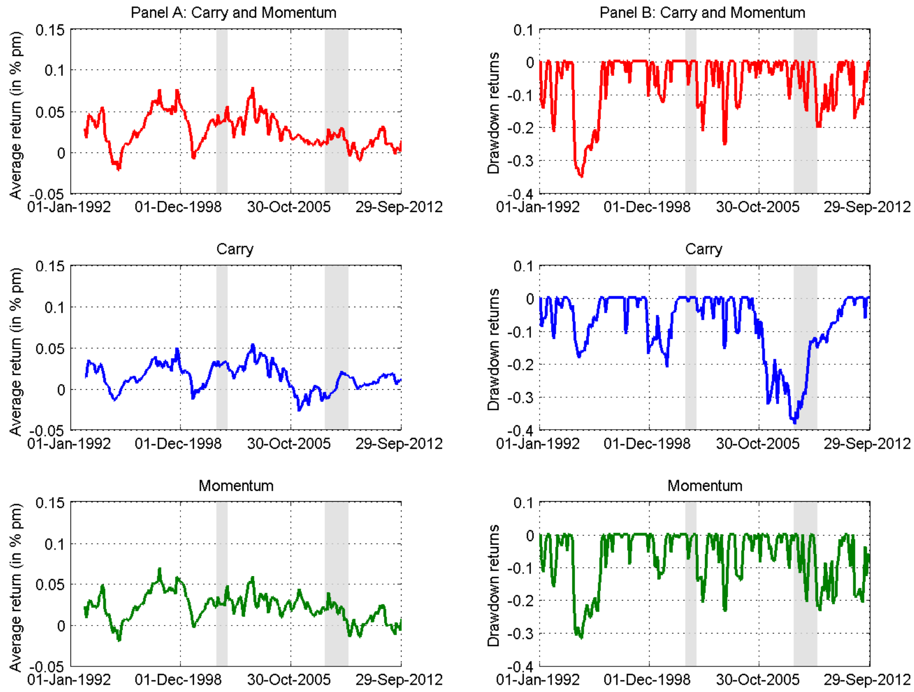


Figure 2.4. Rolling average returns and draw-down dynamics
These figures show average monthly excess returns over rolling windows of 12 months and the maximum draw-down dynamics for the optimal portfolios. The portfolios are optimized out of sample for the estimation from January 1990 to September 2012 and a power utility function with a relative risk aversion of $\gamma = 5$. Panel A reports the rolling averages for momentum and carry as well as for carry and momentum separately. Panel B reports the draw-downs for the same set of trading strategies. Draw-down is defined as $D_t := \sum_{s=1}^{t} r_s - \max_{u \epsilon \{1,\ldots,t\}} \sum_{s=1}^{u} r_s$ where r_t are the returns to the trading strategies.

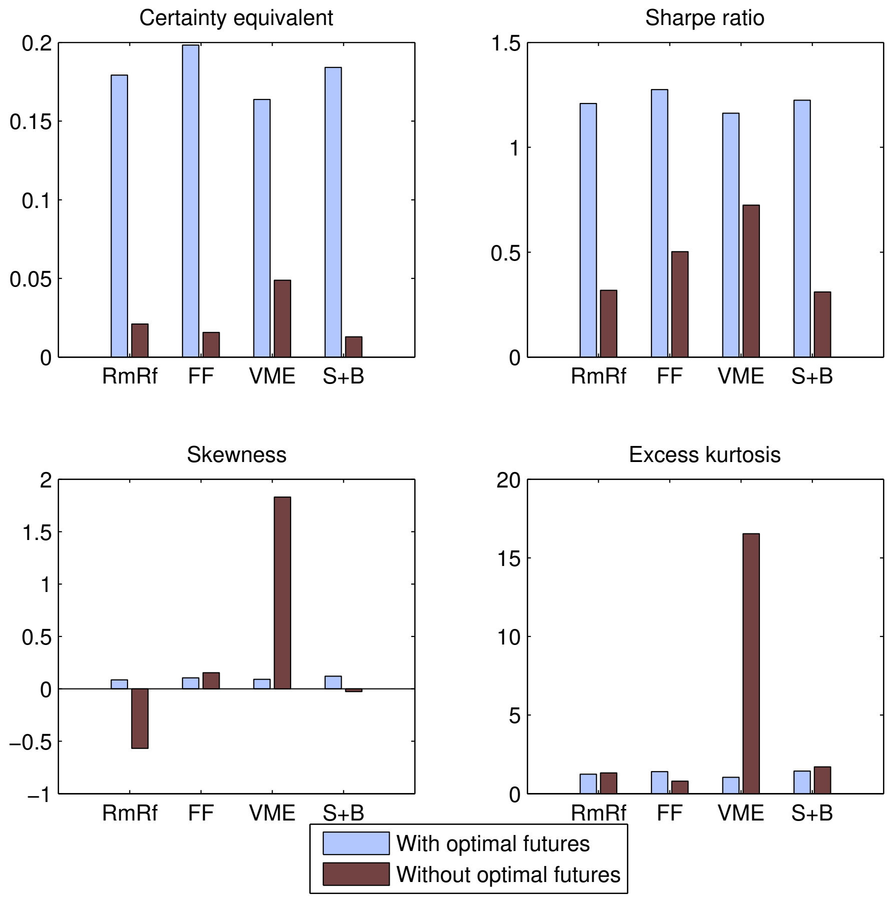


Figure 2.5. Diversified investor

Reported are out-of-sample performance statistics for optimal portfolios containing popular classes of tradable risk factors. For each class of risk factors we compare out-of-sample portfolio performance with and without the inclusion of the carry and momentum futures portfolio. Optimal portfolios are calculated by incorporating traditional risk factor performance into the portfolio return as described in Equation 2.15. The figure contains four plots of performance measures, clockwise from the upper left depicting, certainty equivalent, Sharpe ratio, skewness and excess kurtosis. Each plot displays statistics for the four strategy classes we consider: (1) a passive index strategy represented by the excess return of the S&P 500 index, denoted "RmRf"; (2) the Fama-French factors (Market Excess Return, High minus Low, Big minus Small),"FF", taken from Eugene Fama's website; (3) equity value and momentum factors,"VME", taken from Tobias Moskowitz's website; and (4) a portfolio consisting of S&P 500 excess return and the excess return on the 10 year treasury bill, "S+B". For each class we report a 'benchmark' case, where we force all futures weights to zero, so that the reported performance is the optimal allocation for that risk factor class in isolation. This is displayed by the red bars in the plots, blue bars show performance statistics when we include the optimal carry and momentum strategy.

IX. Appendix A

A. Statistical Inference

By posing the portfolio problem as an estimation problem, we can conduct statistical inference for the estimated parameters $\hat{\theta}$. In particular, the optimization problem (2.7) with the parametric and linear portfolio policy (2.2) satisfies the first-order conditions,

$$\frac{1}{T}\sum_{t=0}^{T-1} h(r_{t+1}, x_t; \theta) \equiv \frac{1}{T}\sum_{t=0}^{T-1} u'(r_{p,t+1}) \left(\frac{1}{N_t \sigma_{i,t}} \hat{x}_t^\top r_{t+1}\right) = 0. \tag{2.17}$$

Interpreting this relation in terms of the general method of moments estimator (GMM) by Hansen (1982), we have the asymptotic covariance matrix of $\hat{\theta}$ as,

$$\Sigma_\theta = \mathrm{AsyVar}[\hat{\theta}] = \frac{1}{T}\left[G^\top V^{-1} G\right]^{-1} \tag{2.18}$$

where

$$G \equiv \frac{1}{T}\sum_{t=0}^{T-1} \frac{\partial(r_{t+1}, x_t; \theta)}{\partial \theta} = \frac{1}{T}\sum_{t=0}^{T-1} u''(r_{p,t+1}) \left(\frac{1}{N_t \sigma_{i,t}} \hat{x}_t^\top r_{t+1}\right) \left(\frac{1}{N_t \sigma_{i,t}} \hat{x}_t^\top r_{t+1}\right)^\top \tag{2.19}$$

and V is a consistent estimator of the covariance matrix of $h(t, x; \theta)$. If we assume that the portfolio policy is correctly specified and implements an unconstrained optimization then, by construction, the marginal utilities are uncorrelated and we can consistently estimate V by,

$$\frac{1}{T}\sum_{t=0}^{T-1} h(r_{t+1}, x_t; \hat{\theta}) h(r_{t+1}, x_t; \hat{\theta})^\top. \tag{2.20}$$

To accommodate for a misspecified portfolio policy or weighting constraints, this estimator can be substituted for an autocorrelation adjusted estimator, such as that of Newey and West (1987).

As an alternative to asymptotic estimators altogether, the covariance matrix can be estimated using a bootstrap method. This approach consists of taking a large number of randomized samples (with replacement) of price and signal data. For each sample, the θ coefficients are re-estimated, collectively yielding a distribution of coefficients to compute the covariance matrix. This method has the advantage of not being subject to difficulties associated with asymptotic results, and accommodates any non-normal features of the data. We use the bootstrapped covariance matrix for all reported characteristic errors.

Using the covariance matrix, we test individual and joint hypotheses on the portfolio policy estimates to determine whether an investor finds it optimal to assign portfolio weights according to historical characteristics of each futures contract.

It is important to recognise that the significance of the portfolio coefficients does not correspond to whether a characteristic is cross-sectionally related to the conditional moments of excess futures returns. Instead, significance implies that optimized portfolio characteristic generates a statistically significant increase in the investors utility of wealth. Therefore, if the contribution of two moments are correlated such that their effects offset each other in the investor utility function, the optimal portfolio will be found to be independent of that characteristic.

Chapter 3

Assessing the Economic Significance of Commodity Futures Price Predictors

I. Introduction

The aim of this chapter is to establish whether six characteristics of commodities found in the literature to predict commodity returns are in fact economically significant. The characteristics we study fall into two categories: first, commodity specific, where the characteristic varies in the cross-section and time-series of commodities; second, market wide, where the characteristic is macroeconomic, varying only in the time-series of returns. We argue that if the information encoded in these characteristics is indeed of economic value, then practitioners can exploit these relations in realtime to develop market timing portfolios and enhance profits.

To test this argument we use a similar parametric portfolio approach to Chapter 2, based on the findings of Brandt, Santa-Clara, and Valkanov (2009) for characteristics portfolios in stock markets. As noted in Chapter 2, the parametric portfolio of Brandt, Santa-Clara, and Valkanov (2009) conveniently avoids difficulties associated with estimating the moments of the expected return distribution by focusing on the metric we are primarily interested in: the historical average utility of the investor. Furthermore, the model replicates the realtime capital allocation perspective of an investor, as a result, providing an out of sample return series free from look ahead bias. In this setting, we identify economic significance of predictors as a statistically significant increase in investor wealth when switching from a benchmark portfolio to a parametric commodity portfolio, following the methodology applied by DeMiguel, Garlappi, and Uppal (2009) to assess the economic benefit of optimal mean-variance equity portfolios.

The three commodity specific characteristics we study are carry, momentum and hedging pressure. Carry and momentum are defined as the futures basis and 12 month return, respectively, described at length in Chapter 1. Hedging pressure is defined as the net position of market participants denoted as 'hedgers' (De Roon, Nijman, and Veld (2000)). The three market wide characteristics are: aggregate open interest (Hong and Yogo (2012)), defined as constant in the cross-section of commodities as the aggregated 12 month open interest growth; the Baltic Dry Index, based on quotes for booking vessels on various routes (Bakshi, Panayotov, and Skoulakis (2011)); and the industrial output gap, calculated as the departure of industrial production growth from its trend (Cooper and Priestley (2009)).

These six predictors, combined with the futures price, give us a consistent set of 19 contracts measured at monthly frequency spanning from April 1991 to December 2013, inclusive. To ensure our portfolio performance is measured out of sample, we split the dataset into an in-sample period, from April 1991 to April 2001, and an out-of-sample period, from May 2001 to December 2013. For the in-sample period, we estimate the parameters once at the end of the period, then record the associated portfolio performance metrics. For the first month of the out-of-sample period we record the portfolio parameters of the previous month. Based on the estimated parameters portfolio weights are derived and performance is calculated. The sample is then extended and the process is repeated for each successive month for the out-of-sample period.

For our all characteristic in-sample portfolio we report statistically significant portfolio estimates for the momentum, open interest, Baltic Dry Index and output gap growth characteristics. However, we fail to find - even in sample - the expected portfolio policy parameter relation for carry or hedging pressure. This is surprising given the relations found by Koijen, Moskowitz, Pedersen, and Vrugt (2013) for carry and De Roon, Nijman, and Veld (2000) for hedging pressure in commodity markets. It is also in contrast to our findings for time-series volatility scaled carry for commodities in Chapter 1 and the results in Chapter 2 for volatility scaled carry in parametric futures portfolios. The relationship for carry is all the more surprising as it is negative and significant, opposite to the value predicted by the literature. The in-sample carry portfolio parameter is found to have a student t-statistic of (-2.1), derived from bootstrapped covariance matrix of the parameter estimator, in the all characteristic portfolio. On closer inspection, we find when individually estimating carry in-sample, the carry portfolio coefficient becomes insignificant. We therefore conclude the loading of carry in the joint portfolio suggests an interaction with the momentum characteristic.

During the in-sample period we report very strong performance for the commodity parametric portfolio. Over the 10 year period the annualized excess return is a huge 81%, albeit with a large annualized volatility of 38%. These moments generate a highly attractive Sharpe ratio of 2.16. Furthermore, the third and fourth moments are relatively benign, with skewness and excess kurtosis measured as 0.58 and 0.66, respectively.

To assess the economic significance of the in-sample performance we first benchmark our parametric strategy performance to that of an equally-weighted portfolio of commodity futures. We then compare portfolio returns over a range of measures to test whether the parametric portfolio performance is statistically superior to that of the benchmark. During the in-sample period the parametric portfolio performance exceeds that of the equally-weighted benchmark over a range of metrics. The most notable metric is that of the opportunity cost to an investor of holding the benchmark portfolio rather than switching to the parametric portfolio. Such an investor would have to be paid 34% annually to remain holding the benchmark portfolio over the parametric portfolio. The performance of the in-sample portfolio is stellar. Over the 10 year in-sample period a dollar invested in April 1991 in the parametric commodity portfolio would have grown to over 377 dollars by April 2001.

The out-of-sample findings are in sharp contrast to our in-sample results. Over the 12 year out-of-sample period the Sharpe ratio for the all characteristic portfolio is only 0.16, slightly less than the equally-weighted strategy over the same period (0.20). However, the first and second moments mask the true issue with the parametric commodity portfolio - the extremely high third and fourth moments. The skewness is 0.89 and the excess kurtosis is a staggering 6.16. The kurtosis is severely penalized in the objective function of the representative investor, leading to an opportunity cost of switching investment from the optimal strategy to the equally-weighted strategy of -34%, annualized. Therefore an investor would pay 34% a year to hold the naive equally-weighted portfolio rather than the optimal parametric commodity portfolio.

The dismal performance of the out-of-sample parametric portfolios leads us to the conclusion that for the studied predictors between 2001 and 2013 the six predictors have no economic significance. For robustness, we test whether the poor out-of-sample performance holds over (1) different market regimes, (2) for varying levels of risk aversion and for (3) across commodity sub asset classes.

To attempt to understand the effect of market regimes on portfolio performance, we first consider whether the parametric commodity portfolio was adversely affected by the commodity boom, which we define as the period between December 2005 and June 2008. We argue that this period represents a regime change, leading to the possibility that optimal portfolio parameters could have changed and therefore estimates, mainly based on the previous period, are inappropriate for the new market structure.

To test this hypothesis we break the sample into three periods, corresponding to before, during and after the commodity boom in our out-of-sample analysis. For a policy based on all the studied commodity characteristics we do not find convincing evidence that the poor out-of-sample performance is caused by a regime shift. For each of the studied sub samples the opportunity cost to holding the all characteristic portfolio compared to the benchmark is negative. For our portfolio based on commodity specific characteristics (carry, momentum and hedging pressure) the last regime does have a positive opportunity cost of investment of 12%. Comparing this to the previous regimes, the discrepancy can be attributed to the low kurtosis of the commodity specific portfolio in the post-boom period. However, despite the positive opportunity cost, the figure itself is found to be insignificant in bootstrapping tests.

To determine the robustness of the poor out-of-sample performance, we also investigate the effect of changing the representative investor's relative risk aversion (CRRA). For both our portfolio optimization and performance analysis we assume a representative investor with a constant relative risk aversion of five. This choice follows the parametric equity portfolios of Brandt, Santa-Clara, and Valkanov (2009) and Barroso and Santa-Clara (2013). One of the key factors in the poor performance of the out-of-sample parametric portfolio is the particularly high kurtosis in the out-of-sample period, hinting that results might be improved if the impact of the kurtosis was lessened by reducing risk aversion. To assess the impact of changing risk aversion, we estimate parametric portfolio policy for three different levels of risk aversion: 3, 5 and 10. For the all characteristic and macroeconomic parametric portfolios we report findings consistent with the main analysis: the out-of-sample performance remains negative at each level of risk aversion. For the commodity specific portfolio we do find a positive opportunity cost when the CRRA is 10, however, the estimate is not found to be significant in bootstrap analysis.

To test whether the poor performance is related to a single asset class we re-run our analysis with each of the commodity classes considered (energy, grains, livestock, metals, softs) removed. For each of these subsets of commodities we find a negative opportunity cost, suggesting that the poor out-of-sample performance is consistent across asset classes.

These results show that, although parametric portfolios can work well for stocks (Brandt, Santa-Clara, and Valkanov (2009)) and futures (Chapter 2), the methodology breaks down when commodity futures are considered in isolation, even when the set of characteristics is expanded to include known predictors in the commodity market. This finding holds for varying portfolio settings, for subsets of commodity assets and for subsets of characteristics. Our results present an important warning for market practitioners when assessing the role of commodity predictors in their portfolio allocation decisions. Combined with the findings of Chapters 1 and 2, the results hint at the importance of more complex predictors and the benefit of aggregating strategy returns across asset classes.

II. Methodology

To determine the economic benefit of commodity predictors to an investor we proceed in two steps. First, we calculate out-of-sample parametric portfolio returns based on the commodity predictors; building on the work of Brandt, Santa-Clara, and Valkanov (2009) for equities, Barroso and Santa-Clara (2013) for currencies and Chapter 2 for futures. Then, we assess whether a representative investor would prefer the out-of-sample portfolio to that of a simple equally-weighted benchmark portfolio using the performance measures detailed in DeMiguel, Garlappi, and Uppal (2009).

A. Parametrization of portfolio weights

Following Barroso and Santa-Clara (2013)'s application of parametric portfolios to forward contracts in currency markets, we examine strategies that consist of 100% investment in the risk-free asset, yielding r_t^f, and a portfolio of commodity futures with the i-th commodity weighted $w_{i,t}$ with excess return $r_{i,t}$ at time t. This yields a portfolio period return,

$$r_{t+1}^p = r_{t+1}^f + \sum_{i=1}^{N} w_{i,t} r_{i,t+1}. \tag{3.1}$$

The investor's problem is then to choose portfolio weights, $w_{i,t}$, so as to maximize their utility of wealth,

$$\max_{\{w_{i,t}\}_{i=1}^{N_t}} E_t[u(r_{p,t+1})] = E_t\left[\sum_{i=1}^{N_t} w_{i,t} r_{i,t+1}\right]. \tag{3.2}$$

To simplify the portfolio choice problem we parameterize the portfolio weights as a linear function of each asset's characteristics to give,

$$w_{i,t} = \frac{\theta^T \hat{x}_{i,t}}{N}, \tag{3.3}$$

where $\hat{x}_{i,t}$ is a $k \times 1$ vector of asset characteristics and θ is a vector of coefficients to be estimated. Alternative parametrization methods include: volatility weighting (studied in Chapter 2) and weighting relative to a benchmark portfolio (Brandt, Santa-Clara, and Valkanov (2009)). We choose not to volatility adjust portfolio weights as, now we are concerned only with commodities, the cross-sectional volatility variation is reduced rendering the added portfolio construction complexity unnecessary. We do not weight assets relative to a benchmark portfolio, since we model the investment choices of a hedge fund manager targeting absolute returns. As such, in our framework setting $\theta = 0$ leads the investor to hold only the risk free asset. This contrasts Brandt, Santa-Clara, and Valkanov (2009) parametric portfolio weighting, defined relative to a benchmark portfolio, which replicates the investment choices active portfolio manager aiming to beat the benchmark portfolio.

The asset characteristics, $\hat{x}_{i,t}$, are standardized depending on the nature of the underlying predictors. For commodity characteristics (such as the futures basis and past 12 month returns), we follow Brandt, Santa-Clara, and Valkanov (2009) and cross-sectionally standardize the raw characteristic values, $\hat{x_{i,t}}$, to have zero mean and unit standard deviation across all commodities at time t. Considering a single commodity specific characteristic in isolation, this setting ensures that the net weight of assets are always zero, and that the standard deviation of portfolio weights has a one to one relation with θ, the characteristic portfolio coefficient. In this sense, the commodity specific characteristics generate portfolio allocations similar to trading strategies which form long-short portfolios based on the difference in the cross-section of assets. Examples for commodity markets include: Miffre and Rallis (2007) for momentum and Koijen, Moskowitz, Pedersen, and Vrugt (2013) for carry. The difference is that in our portfolios every asset is weighted proportional to its relative signal, compared to traditional long-short strategies which typically form a portfolio by equally weighting assets long in the top quintile and short in the bottom for a given trading signal.

For commodity characteristics that are constant in the cross-section (such as the Baltic Dry Index and output gap growth) we divide the raw characteristics by their time series standard deviation across the entire sample. Dividing through by the sample standard deviation to calculate $\hat{x}_{i,t}$ does not introduce a look ahead bias, since the constant is absorbed by the optimizer, but ensures that our θ estimates are comparable across characteristics and we can easily assess the relative economic significance. This methodology is similar to that applied in Chapter 2 because it allows time-series variation in portfolio weights based on a given characteristic.

The $1/N$ in Equation 3.3 follows the parameterization of Brandt, Santa-Clara, and Valkanov (2009) and Barroso and Santa-Clara (2013), and ensures that our θ estimates are comparable to these studies. Both Brandt, Santa-Clara, and Valkanov (2009) and Barroso and Santa-Clara (2013) have a varying number of assets within their sample and argue that by scaling weights by $1/N_t$ they avoid the optimal portfolio being overweight in the latter part of the sample where there are more assets. In our analysis we avoid this issue by studying a fixed number of commodities.

An important aspect of the parametrization is that the θ coefficients are constant across assets and through time. Fixing θ constant in the cross-section of commodities ensures the performance of the optimal portfolio is based on each of the characteristic's association with historical returns across all commodities, rather than the historical returns of a particular commodity. Defining θ to be constant through time implies that the coefficients that optimize an investors conditional expected utility for any given date will maximize the investors unconditional expected utility (Brandt, Santa-Clara, and Valkanov (2009)).

To estimate the optimal portfolio coefficients, we use the fact that the θ estimates are constant across assets and through time to take the sample analog of Equation 3.2;

$$\hat{\theta} = \max_{\theta} \frac{1}{T} \sum_{t=0}^{T-1} u \left(r_t^f + \sum_{i=1}^{N} \frac{\theta^\top \hat{x}_{i,t} r_{i,t}}{N_t} \right). \tag{3.4}$$

Where we define u as a utility function with constant relative risk aversion (CRRA). The variable $\hat{\theta}$ is our estimate of the optimal portfolio policy. To determine the associated error in $\hat{\theta}$ we follow Brandt, Santa-Clara, and Valkanov (2009) and estimate the covariance matrix using a bootstrapping technique. After estimating the optimal portfolio policy we compute in-sample portfolio returns based on Equation 3.1.

B. Out-of-sample parametric portfolios

To test the out-of-sample performance of optimal commodity portfolios we replicate the information set of a realtime investor. To do this, we first split our sample into an in-sample estimation period, from May 1991 to April 2001, and an out-of-sample allocation period, from May 2001 to December 2013. For each month in the out-of-sample estimation period we estimate $\hat{\theta}$ on all available data. Based on this policy, portfolio weights and calculated on contemporary characteristics, then the performance of the portfolio is recorded for the following month. This process is repeated for each subsequent month until the end of the sample, resulting in an out-of-sample optimal portfolio return series and a varying $\hat{\theta}_t$ estimate.

C. Performance Evaluation

To assess the economic significance of the returns to the commodity parametric portfolio, we evaluate its value to a representative investor who has a choice between a benchmark portfolio and the optimal strategy returns. In this section we discuss our choice of benchmark portfolios and metrics to compare performance.

C.1. Benchmark Portfolios

To benchmark the performance of our strategies we primarily use a static allocation to an equally-weighted portfolio of commodity futures. For robustness we also consider consider an optimal allocation to an equally-weighted portfolio and the Goldman Sachs Commodity Index. For the equally-weighted benchmark portfolio we calculate returns as,

$$r_t^{\mathrm{ew}} = \frac{1}{N} \sum_i^N r_{i,t}. \tag{3.5}$$

The use of an equally-weighted portfolio as a benchmark is common in both the optimal strategy literature and commodity literature. For the optimal strategy literature examples include: DeMiguel, Garlappi, and Uppal (2009)'s evaluation of mean-variance portfolio allocation and extensions; Guidolin and Timmermann (2008)'s portfolio allocation based on higher order moments for international stock indices and Brandt, Santa-Clara, and Valkanov (2009)'s parametric equity portfolio. Examples in the commodity literature include Bodie and Rosansky (1980) and Fama and French (1987) who use an equally-weighted portfolio to demonstrate the benefits of adding commodities to a stock portfolio and to study the difference between the theory of storage and risk premia for commodities, respectively.

The second benchmark we consider is an equally weighted portfolio with dynamic optimal leverage (EWOL). Defining leverage as $L_t = \sum_i^N |w_{i,t}|$ we see how higher $\hat{\theta}_t$ estimates lead to larger magnitude of weights and higher leverage. The EWOL portfolio allows us to test whether any performance benefit of the optimal characteristic portfolio compared to the equally-weighted portfolio is in fact a consequence of the time varying leverage of the characteristic portfolios, rather than the predictive properties of the characteristics (a concern noted by Barroso and Santa-Clara (2013)).

To calculate the EWOL portfolio returns we use a similar approach to the characteristic portfolios, with the same in-sample estimation period and out-of-sample allocation period. At the end of the estimation period we estimate the equally-weighted portfolio leverage, θ_{long}, to maximize ex-ante utility. We then use the optimal leverage to calculate the portfolio weights and record returns for the following month. We repeat the process for each subsequent month until the end of the sample.

Conveniently, the implementation of the EWOL portfolio can be nested within our parametric portfolio model by optimizing a parametric portfolio with a single characteristic type, where all assets have characteristic values equal to unity throughout time. Explicitly, $x_{i,t} = 1$ for all i and t. For the EWOL portfolio the single coefficient, θ_{long}, is equal to the leverage of the portfolio, $L_t = \hat{\theta}_t$. Therefore, an EWOL portfolio with $\theta_{long} = 1$ for all t exactly replicates the equally-weighted benchmark portfolio.

For robustness we also compare strategy returns to those of the Goldman Sachs Commodity Index (GSCI). The index weights constituent commodities based on their global production and relative amount of trading activity, respectively. For a modern investor indices present one of the easiest methods to gain exposure to commodities, however, at the beginning of our out-of-sample period they were still in their infancy with only \$6.8 billion of investment (Masters (2008)), justifying our choice of the equally-weighted portfolio as our primary benchmark.

Possible alternative benchmarks from the commodity literature include dynamically volatility weighting contracts and popular commodity indices. We choose not to dynamically weight contracts in the portfolio (as used to weight futures strategies by Moskowitz, Ooi, and Pedersen (2012) and Baltas and Kosowski (2014)) to avoid complicating our analysis with the choice of volatility estimators and due to the relative homogeneity of volatilities within the commodity asset class.

C.2. Performance Measures

Having decided on the benchmarks from which to assess optimal commodity returns, we now consider the performance measures to differentiate the economic significance of the return series.

Share ratio The Sharpe ratio is calculated as the sample mean of out-of-sample excess portfolio returns, $\hat{\mu}$, divided by their sample standard deviation, $\hat{\sigma}$:

$$\hat{\mathrm{SR}} = \frac{\hat{\mu}}{\hat{\sigma}}. \tag{3.6}$$

Turnover To understand the amount our portfolio weightings change each month, we follow DeMiguel, Garlappi, and Uppal (2009) to calculate portfolio turnover. Turnover is defined as the time series average of the sum of the absolute value of trades over N available assets:

$$\mathrm{Turnover} = \frac{1}{T-1} \sum_{t=1}^{T-1} \sum_{i=1}^{N} \left(|w_{i,t+1} - w_{i,t+}| \right), \tag{3.7}$$

in which $\hat{w}_{i,t+}$ is defined as the portfolio weights at time $t+1$ before rebalancing,

$$\hat{w}_{i,t+} = (1 + r_{i,t})\hat{w}_{i,t}. \tag{3.8}$$

The turnover quantity represents the average percentage of wealth traded each month to maintain the strategy.

Opportunity cost To assess the benefit to an investor of holding optimal strategies we calculate the opportunity cost, defined as the additional return above that of the benchmark portfolio that makes the investor indifferent to switching to the proposed strategy.

In keeping with our parametric portfolio estimation, we calculate the opportunity cost for a CRRA utility investor who considers an equally-weighted portfolio of commodity futures as the benchmark portfolio. Explicitly, we calculate opportunity cost, c,

$$E[u(1 + r^{ew} + c)] = E[u(1 + r^{p})]. \tag{3.9}$$

Where u is the same utility function from Equation 3.2 used for optimal portfolio parameter estimation and r^{ew} is the return to the equally-weighted portfolio. If c is found to be positive, then we conclude that an investor would have to be offered a premium (equal to c) on top of the benchmark in order to switch from holding the optimal strategy. Conversely, in the case where c is negative, the investor holding the optimal strategy would pay a fee to switch to the benchmark strategy.

Our approach is taken from Simaan (1993) and is similar to West, Edison, and Cho (1993)'s analysis. The choice of utility function to calculate investor preferences varies amongst previous studies, but it is always chosen to be commensurate with the portfolio optimization studied. For instance, studies focusing on mean-variance allocation strategies, and their extensions, use the related quadratic utility (Fleming, Kirby, and Ostdiek (2001), Fleming, Kirby, and Ostdiek (2003) and DeMiguel, Garlappi, and Uppal (2009)). For studies analyzing the effect of higher moments on returns utility functions are either extended to include these higher moments (Jondeau and Rockinger (2012)) or a CRRA utility function is used (Jondeau and Rockinger (2006) and Brandt, Santa-Clara, and Valkanov (2009)).

Return-loss To understand the benefit of an optimal strategy compared to the benchmark strategy after transaction costs are considered, we compute the *return-loss*, defined as the additional net return, taking into account transaction costs, needed for strategy k to perform as well as the benchmark strategy in terms of Sharpe ratio. To calculate the strategy return net of transaction costs we first determine the evolution of net wealth when portfolio rebalancing incurs a cost,

$$W_{k,t+1} = W_{k,t}(1 + r_t^{k,p}) \left(1 - c \times \sum_{j=1}^{N} |\hat{w}_{k,j,t+1} - \hat{w}_{k,j,t+}|\right), \tag{3.10}$$

where c is the fractional cost of rebalancing a futures contract. Based on discussions with market practitioners we fix c in the time-series and cross-section at 35 basis points. From Equation 3.10 the return net of transaction costs given by $\frac{W_{k,t+1}}{W_{k,t}} - 1$. The return-loss is computed as,

$$\text{return-loss}_k = \frac{\mu_{ew}}{\sigma_{ew}} \times \sigma_k - \mu_k, \tag{3.11}$$

where μ and σ refer to the monthly mean and standard deviation of returns of the denoted strategy and ew indicates the equally-weighted benchmark strategy.

C.3. Bootstrapping

To determine the statistical significance of our estimates for Sharpe, certainty equivalent and return-loss we use the block bootstrapping technique of Politis and Romano (1994). The true distribution for each performance estimator is approximated with the empirical distribution of 10,000 bootstraps. Each bootstrap consists of block samples of total length T. The starting point for each block is randomly selected from the sample and the length of the block is taken from a geometric distribution with expectation l, the block length. The block length was selected using the approach of Politis and White (2004) with the correction pointed out by Patton, Politis, and White (2009).

III. Data Description

For our analysis we use two types of data set. Firstly, time series' that relate to each commodity: price, return, basis, momentum, and hedging pressure. The summary statistics and meta data for these series are reported in Table 3.1. Secondly, macroeconomic times series' that are aggregated across commodities or taken from external sources: aggregated open interest, Baltic Dry Index and the Industrial production gap. Summary statistics for these series are reported in Table 3.2. In this section we detail the method of construction and reasoning behind the inclusion for each of these series.

A. Futures Returns

The futures dataset we use consists of monthly sampled close prices for 19 commodity contracts taken from Bloomberg. For each commodity the listed exchange and commodity class is reported in Table 3.1. The dataset starts in June 1990, the first month that the 19 assets are available, and ends in December 2013. Since in rare circumstances contracts for certain assets are not traded for a whole month, there are three price-months out of a sample of 5168 where the required contract was not found. For these cases we forward fill prices (following, for example, Pesaran, Schleicher, and Zaffaroni (2009)).

For each month, the daily close price is recorded for the first traded day of the month. Monthly returns are then calculated for the nearest available contract with more than one month before maturity. The nearest contract is labelled T, the next nearest contract is labelled $T+1$ and so on. Monthly returns for asset i at month t are therefore,

$$r_{i,t} = \frac{F_{i,t}^{T} - F_{t-1,i}^{T}}{F_{t-1,i}^{T}}. \tag{3.12}$$

By construction, $r_{i,t}$ is the fully collateralised *excess* return on a futures position in contract i at time t.

B. Commodity Characteristics

In this section we describe the construction of the commodity specific characteristics, $x_{i,t}$ for carry, momentum, and hedging pressure.

Carry Our carry characteristic is based on the price spread between the nearest and next nearest contract. The predictive properties of the spread have been studied for a number of different asset classes. Traditionally, studies have focused on currencies markets, of which Engel (1996) provides a good survey, with more recent extensions to futures markets (Koijen, Moskowitz, Pedersen, and Vrugt (2013) and our findings in Chapter 1). We define our raw carry characteristic as the relative price difference between the two nearest contracts,

$$carry_{i,t} = \frac{F_{i,t}^{T} - F_{i,t}^{T+1}}{F_{i,t}^{T+1}}. \tag{3.13}$$

Momentum Previous returns have been shown to predict future returns in both the cross-section of stocks (Jegadeesh and Titman (1992)), and the time-series for individual stocks (Moskowitz, Ooi, and Pedersen (2012)) with analogous findings across asset classes (Asness, Moskowitz, and Pedersen (2013)). Following the consensus within the literature, we calculate our momentum characteristic as the average of previous 12 month futures excess returns,

$$momentum_{i,t} = \frac{1}{12} \sum_{s=t-11}^{t} r_{s,i}. \tag{3.14}$$

Hedging pressure Hedging pressure is calculated using data from the U.S. Commodity Futures Trading Commission (CFTC). The CFTC reports the weekly commitments of traders where open interest is categorised, for reporting traders, into positions held by *commercials* and *non-commericials*. The CFTC regulations define *commercial* traders as "[entities] involved in the product, processing or merchandising of a commodity"[1], who use futures contracts in a given commodity for hedging purposes. In contrast, *non-commercial traders* do not own the underlying asset or its financial equivalent; they hold only positions in futures contracts. Following De Roon, Nijman, and Veld (2000), hedging pressure is defined as the relative net short position of commercials,

$$hedging\ pressure_{i,t} = \frac{\text{Commercial short}_{i,t} - \text{Commercial long}_{i,t}}{\text{Commercial long}_{i,t} + \text{Commercial short}_{i,t}}. \tag{3.15}$$

[1] See `http://www.cftc.gov`

The CFTC reports the commitments of traders every Tuesday, therefore, to ensure the characteristics are always calculated previous to any trading decision, the characteristic for month t is defined as the relative net short position reported in the last week of month $t-1$. To calculate each of the variables in equation 3.15, we aggregate data across all exchanges for commodities by their CFTC commodity code.

C. Macroeconomic Characteristics

In the following we describe the estimation and construction of the macroeconomic variables that are used in the economic assessment of return predictability. We use the U.S. industrial production (IP) output gap as a measure of local U.S. specific demand, the Baltic Dry Index growth rates as a measure for global demand and the geometric average of open interest as a market specific measure of commodity hedging demand. We limit ourselves to these three macroeconomic characterises to avoid overspecifying the optimization. Other possible predictors could include a measure of funding liquidity or measures of hedge fund capital. We decide to not include these predictors as they are found in Chapter 2 to not have more explanatory power for futures returns than the IP gap (See Table 2.8 Panel B). Summary statistics for the three chosen time series are reported in Table 3.2.

Industrial production output gap We measure the output gap using the out-of-sample construction method introduced by Cooper and Priestley (2009). The technique to measure the output gap is widely applied in the economic literature and allows for a slowly changing trend by employing a quadratic trend as well as a linear trend,

$$y_t = a + b * t + c * t^2 + \nu_t. \tag{3.16}$$

Where y_t is the log of industrial production, t is a time trend and ν_t is the error term, which defines the output gap. We use an expanding estimation window to estimate the ν_t out-of-sample. We run the regression (3.16) first from 1970:1 to 1973:1 and store the residual value at time 1973:1, ν as the first output gap observation at that time. Then we repeat the regression from 1970:1 to 1973:2 and store the last residual value at time 1973:2. We continue this procedure until we reach the end of the sample. Our starting point is chosen to be 1970:1 to account for the well-known slowdown in economic growth in the early 1970s (see, for example,Perron (1989) and Taylor (1993)).

Baltic Dry Index (BDI) growth rate Bakshi, Panayotov, and Skoulakis (2011) show that growth rates of the BDI are leading indicators for stock market returns, economic growth, and commodities. The BDI has been published daily by the Baltic Exchange in London since May 1985. The index is based on daily quotes for booking vessels of various sizes and across multiple maritime routes, and therefore is an indicator of transportation costs for raw materials shipped by sea. Based on the premise that the supply structure of the shipping industry is generally predictable and relatively inflexible, changes in shipping costs have been seen largely as due to changes in the worldwide demand for raw materials. We obtain quotes for the BDI from Bloomberg. To calculate BDI growth rates, we follow Bakshi, Panayotov, and Skoulakis (2011) and compute log changes in the BDI index over the preceding three months, defining the corresponding BDI growth rate as,

$$g_t = \ln\left(\frac{BDI_t}{BDI_{t-3}}\right). \tag{3.17}$$

Following Bakshi, Panayotov, and Skoulakis (2011), a three month lag length is chosen to reduce noise in the predictor.

Aggregate open interest growth rate Hong and Yogo (2012) find the aggregate open interest in futures contracts predicts commodity returns. Hong and Yogo (2012) argue that open interest rises due to increased hedging demand, and prices react with a delay due to limited risk absorption capacity. Futures open interest therefore predicts returns to a range of asset classes, including commodities.

Following Hong and Yogo (2012) we construct the aggregate open interest growth predictor variable by computing the dollar open interest for each commodity as the spot price times the quantity of futures contracts outstanding. We then follow four steps detailed by Hong and Yogo (2012): (1) we aggregate dollar open interest within the commodity sectors gains/oilseeds, livestock, metals, softs, and energy; (2) we determine the sector monthly growth rate; (3) we compute the monthly aggregate growth rate of open interest as an equally weighted average of the growth rate for each of the five sectors and finally, (4) take the 12-month geometric average. Hong and Yogo (2012) argue that it is necessary to take the 12 month average to handle noise and seasonal effects in raw open interest data.

IV. Results

A. *In-sample optimal portfolio performance*

Table 3.3 displays the performance of the commodity parametric portfolios during the estimation period, from May 1991 to April 2001 inclusive, alongside the performance of the equally-weighted (EW) and equally-weighted with optimal leverage (EWOL) benchmark portfolios for the same time frame. The first 14 rows of Table 3.3 report the estimates for the optimal portfolio policy coefficients, $\hat{\theta}$, at the end of the estimation period. Looking at the rightmost column we see the policy estimates for the parametric portfolio using all six characteristics. By construction, each characteristic should have a positive and significant portfolio coefficient. However, surprisingly, this is not the case for the carry and hedging pressure coefficient.

The failure of hedging pressure to predict returns contradicts the relation reported by De Roon, Nijman, and Veld (2000), who find a positive Fama-Macbeth style regression coefficient when commodity returns are regressed onto hedging pressure for bimonthly data between January 1986 and December 1994. With the exception of the carry characteristic, the characteristics coefficients found to be significant are positive as predicted by their respective literatures.

The second surprise is the negative and significant sign for the carry coefficient, which appears to be contrary to Koijen, Moskowitz, Pedersen, and Vrugt (2013)'s findings for carry strategies. Sorting commodity portfolios using the futures spread, Koijen, Moskowitz, Pedersen, and Vrugt (2013) demonstrate the rank of a commodity's futures basis versus its peers positively predicts its future returns. Given the similarities of our framework we would therefore expect a positive value for the carry coefficient. The discrepancy is perhaps due to our choice of estimation period, defined between 1990 and 2000, where in Chapter 1 we saw relatively poor performance for the similar time-series carry strategies for commodities and metals. We investigate this later in our robustness analysis.

The columns 3 to 8 of Table 3.3 report results for the individual commodity specific characteristics (carry, momentum, and hedging pressure), the combination of the three specific characteristics, and a combined portfolio of all the macroeconomic characteristics (open interest, Baltic Dry Index and output gap growth). With the exception of carry, for each of these portfolio configurations we find qualitatively the same results as for the joint portfolio. For carry we find that the negative relation disappears. This implies that the significant negative relationship documented in the combined portfolio is not due to the traditional carry mechanism, but seems to be related to an interaction with the momentum characteristic.

The two leftmost columns of Table 3.3 report statistics for our two benchmark portfolios. These portfolios serve as a reference point from which we judge the performance of the combined portfolio. The left column details the performance of the equally weighted (EW) portfolio of commodities, which we find to have an annualized return and standard deviation of 2% and 8%, respectively, giving a Sharpe ratio of 0.28. The next column reports the same metrics for the equally-weighted with optimal leverage portfolio. This portfolio is estimated by finding the weight of the equally-weighted portfolio that maximizes the utility of wealth for the investor. For our estimation period we determine θ_{long} to be 0.61, implying that the optimal allocation of the equally-weighted portfolio is 0.61. Importantly, we find this value to be insignificant, suggesting that there is no benefit to holding this portfolio over the simple equally-weighted portfolio. This finding justifies our use of the simple equally-weighted portfolio as the benchmark for performance analysis.

The lower 11 rows in Table 3.3 report performance metrics for each portfolio. The all characteristic portfolio has very attractive in-sample returns. The annualized mean return and standard deviation are 81% and 38%, respectively. Furthermore, the portfolio has a small positive skewness and low excess kurtosis, 0.58 and 0.66, respectively. The returns have a high Sharpe ratio, 2.16, which bootstrap analysis demonstrates to be significantly greater than the equally weighted portfolio (Sharpe 0.28), with the null hypothesis that EW returns is greater than parametric portfolio returns rejected at the 0.5% level. Due to its strong performance, we find that an investor would have to be paid 34% a year (defined as the opportunity cost) in addition to the equally-weighted portfolio to switch away from the parametric portfolio. The strong performance of the in-sample all characteristic portfolio can be seen in Figure 3.2, where over the in-sample period, from April 1991 to March 2001, a \$1 investment would have grown to over \$310.

Inspecting the performance metrics for the macroeconomic and commodity specific portfolios allows us to disentangle the origins of the joint portfolio returns. We find both parametric portfolios perform well and have an opportunity cost of 15% and 12%, respectively. These values are broadly inline with the findings for the in-sample optimal futures parametric portfolio studied in Chapter 2. The commodity specific portfolio is also preferable considered on most of the other return metrics, with higher returns, higher risk adjusted returns and lower kurtosis than the macroeconomic parametric portfolio. The excess kurtosis of the macroeconomic portfolio is particularly high at 4.74. Based on these findings we conclude the parametric commodity portfolio performs well in-sample, and this performance can be attributed to both the macroeconomic and commodity specific components. In the next section we see whether this performance continues in the out-of-sample allocation period.

B. Out-of-sample optimal portfolio performance

Table 3.4 reports results for the out-of-sample optimal portfolio allocation based on the 6 studied predictors and combinations thereof. For each portfolio, policy coefficients are estimated based on the estimation period, initially from May 1991 to Apr 2001, then weights are calculated and corresponding returns are recorded for the following month. The estimation period is then expanded and the coefficients estimated for each subsequent month until the end of the sample. The reported θ estimates and associated test statistics are the time-series average of the monthly values.

Looking across Table 3.4 we see that our out-of-sample results are dramatically different to those in-sample. The estimates of θ are of smaller magnitude and, with the exception of momentum, all insignificant. From an investors perspective, the exceptional returns of the in-sample analysis are now non-existent. This finding holds for every one of the considered portfolios. None of the portfolios show a significant opportunity cost of investment compared to the equally-weighted portfolio, indicating that our representative investor would see no gain in holding the optimal portfolio over the equally-weighted benchmark. The positive return-loss metric in the last row confirms this story. Figure 3.2 illustrates the step change in performance from the in-sample to the out-of-sample period. The stellar in-sample performance stagnates as soon as we enter the out-of-sample period, with the portfolio having a small positive return but with high volatility, particularly during the 2007 and 2008 commodity boom and following financial crisis.

The rightmost column of portfolio 3.4 reports policy averages for the all characteristic portfolio in the top 12 rows, associated performance metrics are reported below. For every characteristic, with the exception of the momentum characteristic, the θ estimates are insignificant. The insignificant policy estimates are also associated with poor return performance. Rows 15 to 19 of Table 3.4 report the moments of the excess return distribution. The out-of-sample all characteristic portfolio does have a positive mean annualized excess return of 8%, however, it has a high standard deviation, 44% annualized, and particularly high excess kurtosis, 6.16.

The first and second moment lead to a low Sharpe ratio, 0.18, which is similar to that of the equally-weighted benchmark, 0.20. The higher moments of the all characteristic portfolio reveal an even worse picture, particularly the excess kurtosis, reported as 6.16. The large kurtosis clearly generates some very poor performing months with respect to utility, generating an opportunity cost of holding the equally-weighted portfolio of -36% per annum. This implies that an investor with $\gamma = 5$ risk aversion would pay 36% a year to hold the equally-weighted benchmark portfolio, rather than hold the all characteristic strategy. Using the GSCI as a benchmark portfolio, as reported in Table 3.5 slightly reduces this figure to 25% per annum.

The impact of the financial crisis on the estimates of θ for the all characteristic portfolio is illustrated in Figure 3.1. Each subplot in the figure depicts the θ estimate for a certain characteristic, along with associated error estimates. Looking across the different characteristics we see that there is trend for the magnitude of each characteristic to decrease over the out-of-sample period. Interestingly, the coefficient for open interest and Baltic Dry Index drop dramatically between December 2007 and July 2009.

To benchmark the performance of the parametric portfolios, the first and second leftmost columns of Table 3.4 report results for the equally-weighted (EW) and equally-weighted with optimal leverage (EWOL) benchmark portfolios. For the 2001-2013 sample period we find both benchmark portfolios offer poor return for risk, yielding Sharpe ratios of 0.20 and 0.14, respectively, with the dynamic optimal leverage of the equally-weighted portfolio performing worse than a static equally-weighted allocation. Although the EWOL does have a lower Sharpe ratio, it has positive and significant opportunity cost of 2%, annualized. This implies that our representative investor would pay up to 2% to switch from the EW strategy to the EWOL. The EWOL has a θ_{long} of 0.59, indicating that the optimal allocation of the equally weighted strategy is on average 59%, suggesting that the equally-weighted strategy is too volatile for the investor.

Given the poor performance of the benchmark portfolios, the failure of any of the optimal strategies to have statistically significant performance relative to the benchmark is all the more damning.

The third column of Table 3.4 reports results for a parametric portfolio calibrated using only the carry characteristic. Over the out-of-sample period, we find the average portfolio θ estimate for the carry characteristic is small and insignificant. This finding is the same when the characteristic is considered as part of the all characteristic and commodity specific portfolios. Furthermore, the portfolio returns are poor: The carry only portfolio, although low in volatility (1% annualized), has a small negative performance leading to a negative Sharpe ratio. The opportunity cost is also negative, suggesting an investor would rather hold the equally-weighted benchmark portfolio than the optimal carry portfolio. In Table 3.5 the strategy performance is compared to the GSCI. In this case we find the carry only portfolio has a significant and positive opportunity cost because of its low volatility, skew and kurtosis compared to the GSCI. For both benchmarks we find a small (but insignificant) negative return loss, showing there is a small but insignificant benefit to holding the carry portfolio over the respective benchmarks. These findings are in contrast to those of Koijen, Moskowitz, Pedersen, and Vrugt (2013), who find significant predictability for the carry signal amongst commodities. The difference could be due to their longer sample or on the dynamic inclusion of assets based on availability.

The fourth column of Table 3.4 reports results for the parametric portfolio with only the momentum characteristic. As with the all characteristic portfolio, over the sample the average estimated portfolio parameter, $\hat{\theta}$, is found to be significant and positive, for the individual momentum portfolio having a test statistic of 2.8. This finding is in keeping with the literature for momentum in commodity markets (for instance, Miffre and Rallis (2007)). Despite the significant portfolio parameter estimate, the momentum only portfolio has poor performance compared to the equally-weighted strategy. The Sharpe is slightly lower, 0.16 compared to 0.20, and the opportunity cost is negative, at -1%. Due to the GSCI's high volatility, the opportunity cost of holding the GSCI rather than momentum strategy is 10% per annum and highly significant. This indicates the parametric momentum portfolio is preferable to the GSCI index, confirmed as statistically significant to 1% in bootstrap analysis.

The last commodity specific characteristic we consider is hedging pressure, shown in the fifth column of Table 3.4. Here again, the individual characteristic portfolio has a qualitatively equal portfolio coefficient and test statistic to its respected values in the all characteristic portfolio. Similar to the in-sample results, we find no significant predictability for hedging pressure out-of-sample. The averaged characteristic parameter estimate, $\hat{\theta}_{\mathrm{hp}}$, though positive, is insignificant and the Sharpe is only 0.03. Due to the low volatility of the portfolio returns there is a positive opportunity cost to holding the portfolio (annualized 3% and 15% for EW and GSCI, respectively), but this cost is insignificant in both cases. Looking across to the benchmark sample statistics, the small positive opportunity cost is primarily caused by the poor performance of the benchmarks, rather than the strong performance of the portfolio. Indeed, the investor would rather hold the risk free rate than the GSCI over our sample period. The return-loss metric demonstrates analogous results.

The sixth column of Table 3.4 combines the three commodity specific characteristics together. For each characteristic in this combined portfolio the results are qualitatively the same as the respective individual portfolios. Carry and hedging pressure remain insignificant and momentum is strongly positive. There is no apparent diversification benefit to the portfolio. The Sharpe is small, 0.12, and the opportunity cost to holding the equally-weighted portfolio is -4%.

The seventh column reports results for the open interest, Baltic Dry Index (BDI) and Industrial Production Gap growth (IP) macroeconomic characteristics considered together. In contrast to the in-sample analysis, where each of the characteristics had significant policy coefficients, we find only the open interest predictor has a significant θ estimate, in agreement with the findings of Hong and Yogo (2012). The lack of a significant θ estimate for BDI and IP is contrary to the findings of Bakshi, Panayotov, and Skoulakis (2011) and Cooper and Priestley (2009), respectively. Although insignificant, the signs of each coefficient are consistent with those predicted by the literature.

Looking at the performance of the macroeconomic portfolio, we find some very odd features, with very high volatility and extremely high kurtosis. Despite a stronger return, 5% annualized, than the equally-weighted benchmark, 3% annualized, and commodity specific combined portfolio, 2% annualized, the performance of the macroeconomic portfolio is negatively impacted by the high volatility (36% annualized) and extremely high excess kurtosis (11.25). These sample moments lead to a very negative opportunity cost of -24%, implying the returns to the macroeconomic optimal portfolio are so bad that an investor would rather pay 24% a year to hold the equally-weighted strategy. The large higher moments are likely a feature of the equal weighting of $x_{i,t}$ across commodities in the characteristics construction. This means that at any time the portfolio is either net long or net short. Therefore, times of high market correlation are likely to produce high volatility. This is illustrated in Figure 3.2, where we see the macroeconomic strategy has extremely large volatility during the financial crisis when commodities were highly correlated (Tang and Xiong (2010)).

V. Robustness

In the previous section we have seen how the commodity specific and macroeconomic predictors fail to generate economically significant returns in an out-of-sample parametric commodity portfolio. In this section we test the robustness of this result over sub-samples of data, varying levels of risk aversion and for different subsets of commodities.

A. Sub-sample Analysis

The period between January 2005 and June 2008 saw an unprecedented and simultaneous rise in commodity prices (Tang and Xiong (2010)), often labelled the 'commodity boom' (Conceição and Marone (2008) or Helbling (2012)), followed by a crash in late 2008 as global demand fell due to the sub-prime crisis. Therefore, our sample covers three distinct regimes: (1) before the commodity boom (April 2001 to December 2004), (2) the commodity boom (January 2005 to June 2008) and (3) a post-boom period (July 2008 to December 2013). To understand the effects of the three periods in Table 3.6 we analyze the parametric portfolio performance for each of these periods.

Starting with the commodity specific portfolio, over the three sub-samples, we find only a small difference in the portfolio parameter estimates, $\hat{\theta}$. However, we do find that for each period the carry parameter estimate is negative and is marginally significant. This is puzzling given previous findings by Koijen, Moskowitz, Pedersen, and Vrugt (2013), which suggest the opposite sign. For the momentum and hedging pressure characteristics we find the sub-samples reflect the findings of the full sample portfolio parameter estimates, with a significant positive relation for momentum (predicted by the literature, Baltas and Kosowski (2014), among others) and an insignificant relation for hedging pressure for each of the sample periods.

In the pre-boom period the excess mean return of the commodity specific portfolio is a positive 6% a year, mirroring the strong performance of the benchmark portfolios. However, since 2005 the performance of the optimal commodity strategy has been opposite to the benchmarks; first having poor performance in the boom period, then outperforming during the post-boom crash. For both the pre-boom and boom periods the opportunity cost of holding the equally-weighted benchmark portfolio is a significantly negative -14% and -15% for pre-boom and post-boom period, respectively. However, the poor performance of the benchmark during the post-boom period gave a positive opportunity cost which was marginally significant.

The macroeconomic portfolio behaves very differently to the commodity specific portfolio. First, the macroeconomic character estimates vary across the sub-samples, with all three θ estimates monotonically decreasing, both in magnitude and significance, over the three samples. Interestingly, the pre-boom period demonstrates the relations held in the respective literature, which only considers pre-2005 periods; all three macroeconomic characteristics having positive and significant estimates, albeit marginally significant in the case of IP Gap. During the pre-boom period the macroeconomic parametric portfolio yielded high excess returns compared to the benchmark, 19% versus 3% annualized. This increase in returns is accompanied by an increase in volatility, but the optimal portfolio Sharpe ratio is still greater than the benchmark, 0.62 versus 0.38. Despite the higher Sharpe ratio, the prospect of holding the optimal macroeconomic portfolio has a negative opportunity cost to an investor holding the benchmark portfolio of -10%. This last finding suggests that even for periods where the macroeconomic characteristics are significant and generate positive returns, their high kurtosis makes them undesirable to investors. During the boom period the macroeconomic portfolio has negative mean excess return of -1% and an extremely high annualized volatility, 44%, and excess kurtosis, 9.48. These large higher moments of the optimal macroeconomic portfolio return distribution result in our representative investor willing to pay 53% per annum to hold the equally-weighted portfolio rather than the optimal portfolio. In the post-boom period the optimal strategy excess kurtosis is higher (15.87) but, due to poor performance of the benchmark, the opportunity cost of holding the benchmark is still negative, but much reduced in magnitude at -5%.

The last column for each period reports results for the all characteristic optimal portfolio. The estimated parameters for this portfolio are similar to the constituents, however, the performance is dominated by the macroeconomic characteristics. This feature results in large second, third and fourth moments and leads to a negative opportunity cost to holding the benchmark portfolio of -31%, -64% and -9% for the pre-boom, boom, and post-boom periods, respectively.

In summary, we find variations in portfolio policy estimates and associated return metrics for different sample periods corresponding to different market regimes. However, except in a few isolated cases where market performance is particulary poor, there is no significant economic benefit to parametric commodity portfolios.

B. Varying Risk Aversion

So far we have assumed that our representative investor has a constant relative risk aversion (CRRA) of $\gamma = 5$. This assumption is based on optimal parametric portfolios of Brandt, Santa-Clara, and Valkanov (2009) and Barroso and Santa-Clara (2013). Our results with this level of CRRA have suggested that optimal allocation based on established predictors fails to beat an equally-weighted portfolio of commodities, and in many cases the GSCI, benchmarks. For robustness we now test whether our results hold for varying levels of CRRA.

Table 3.7 reports the portfolio parameter estimates and performance for the commodity specific, macroeconomic, and all characteristic parametric portfolios for three levels of CRRA, increasing from left to right. As we would expect, increasing CRRA leads to lower θ estimates, seen for each portfolio configuration. The smaller portfolio parameters generate smaller portfolio weights and reduced mean excess returns. Accordingly, the higher moments are also reduced. For each of the considered portfolios the first and second moment of the return distribution scales (nearly) proportionally, leading to the Sharpe ratio for each portfolio considered being qualitatively unchanged across the different portfolio levels of CRRA.

Although portfolio Sharpe ratio is consistent across varying CRRA, the same cannot be said for the opportunity cost of holding the equally-weighted portfolio over the parametric portfolios. For low γ the opportunity cost of holding the equally-weighted portfolio is highly negative, -11%, -52% and -75% for the commodity specific, macroeconomic and all characteristic portfolios, respectively. The opportunity cost increases with increasing γ, and is in fact positive when $\gamma = 10$, for the commodity specific portfolio.

The positive opportunity cost for the commodity specific portfolio estimated with high CRRA might at first seem counter-intuitive; we know the parametric portfolios perform badly compared to an equally weighted strategy due to large higher moments, so lower CRRA of utility should relax the amount the higher moments are penalized. However, here we see the optimizer compensating for the high CRRA by reducing the portfolio parameters. This effect leads to a relatively small investment in the optimal portfolio, with an average monthly sum of absolute weights equal to 0.42 (not reported) compared to unity for the equally-weighted portfolio. Furthermore, the net weight of zero for the commodity specific portfolio and high correlation between commodities further reduces the optimal portfolio volatility.

Despite an exception for high CRRA and the commodity specific portfolio, we broadly conclude that the poor performance of the optimal portfolio is not dependent on the level of CRRA.

C. Strategy performance across commodity classes

Table 3.8 reports results for the optimal portfolio policies and equally-weighted with optimal leverage portfolios where types of commodities are removed from the sample. By performing the optimal portfolio analysis for these subsets of assets, we can identify whether a particular class of commodity is aversely affecting our results.

Looking across Table 3.8 we see no evidence for the adverse affects of a single class of commodity. The estimated out-of-sample policy coefficients are qualitatively the same when commodities of type energy, grains, livestock, metals or softs are removed from the dataset. Mirroring the results of the full dataset, carry has marginally significant negative coefficients; momentum has significant positive coefficients, as predicted by the literature; and hedging pressure, open interest, Baltic Dry Index, industrial production gap all have insignificant coefficients.

The lower half of the table reports performance results for each of the subsets of data. Here we see only minor variation in the excess return distributions of the portfolios. Across the 5 portfolios the annualized mean and standardized deviation of portfolio excess return varies from 5% to 7% and 37% to 45%, respectively. The Sharpe is in a range of 0.13 to 0.24. Due to greater variation across higher moments of the return distributions and the non-linearity of the utility function, the opportunity cost of investing in the all characteristic optimal portfolio is in a range from -61% and -21%, annualized. Despite the variation across the subsets of the commodities, for each subset the opportunity cost of investing in the optimal portfolio is significantly negative, indicating that an investor would pay to avoid holding any of the optimal portfolios, consistent with the out-of-sample analysis presented in Table 3.4. For each subset of commodities, the return-loss metric is positive, confirming that an investor would choose not to invest in the optimal strategies.

For each subset of commodities alongside the parametric performance, we also examine the performance of the out-of-sample equally-weighted with optimal leverage (EWOL) portfolio. The results for the EWOL portfolio indicate the time-series average optimal allocation of the equally-weighted portfolio is less than 1 for each of the subsets of commodities. This average leverage implies that the simple equally weighted portfolio, which has a leverage of 1 by construction, is overweight for our representative investor. Interestingly, we find that the opportunity cost compared to the full equally-weighted portfolio of the EWOL subsets of assets is positive and significant when each of the commodity classes are excluded from the portfolio except for softs, suggesting that softs perform poorly. The EWOL results for return-loss by asset class are inconclusive: some of the subsets of assets have a positive EWOL return loss, suggesting they are attractive to an investor versus the all asset equally weighted portfolio, but these return-loss measurements are found to be insignificant.

VI. Conclusion

In this chapter we refute the economic significance of 6 well-known predictors for commodity markets in the period from 2001 to 2013. The predictors are of two categories: First, commodity specific, where the predictor varies in the cross-section and time-series of commodities (futures basis, past returns and the net position of hedgers); second, macroeconomic, where the predictor is constant in the cross-section but varies in the time series (aggregate open interest, Baltic Dry

Index and the industrial production gap).

We measure the economic value of predictors based on their ability to predict returns in the parametric portfolio policy model of Brandt, Santa-Clara, and Valkanov (2009). The methodology reflects the realtime capital allocation problem of a representative investor and avoids look ahead bias embedded in traditional regression models of predictability. To apply Brandt, Santa-Clara, and Valkanov (2009)'s parameterization we, adapt the predictors to define asset characteristics. For commodity specific predictors we calculate characteristics by standardizing the predictor signal on a monthly basis. This approach gives similar portfolio weights to traditional sorted long-short portfolios, where assets are ranked in the cross-section based on predictors. For market wide predictors we set the characteristic constant over the cross-section of assets. For a given month, the portfolio weight is then calculated based on the parametric policy, defined as linear function of that month's characteristics. We model the optimal policy as constant and estimate it by maximizing the investor's utility of wealth.

For an initial inspection of the predictors, we first estimate the optimal portfolio policy in-sample for the estimation period, from 1991 to 2001. Here we find significant returns to the all characteristic parametric policy. We broadly find the estimated policy coefficients are inline for the relations documented in the literature, with exception of carry and hedging pressure. For carry we find an opposite relation to that predicted in the literature, however, this disappears when carry is considered on its own, rather than in the joint portfolio. For hedging pressure we fail to find a significant relationship.

We calculate out-of-sample portfolio return for the allocation period (2001 to 2013) by expanding the estimation window month by month. Each month we estimate the optimal policy, then calculate the month weights, and record the following month's returns. To assess the economic benefit of the out-of-sample parametric portfolio we compare returns to those of equally-weighted portfolio of commodities futures. We find the returns to the out-of-sample portfolio are non-existent for both the joint portfolio and when characteristics are considered individually. We also find that, with only a few minor exceptions, the poor out-of-sample performance holds for different sub-samples of data, varying levels of risk aversion and different commodity subclasses.

We believe, although our model is highly stylized interpretation of an investors portfolio choices, our findings indicate that the predictive relations reported in the commodity literature fail to deliver economic benefit in the period 2001 to 2013. This serves as a warning to commodity practitioners that who rely on in-sample predictive regressions for their portfolio allocation.

VII. Appendix: Tables

Table 3.1. Summary statistics for individual commodity contracts

The 19 commodity futures used in our analysis are listed by class of commodity. For each commodity, the first 4 rows report name, Bloomberg (BBG) code, class and exchange. The remaining 10 columns report the monthly percentage mean and standard deviation for the commodity returns, basis, momentum and hedging pressure, reported in percentage terms. Futures returns, based on price data from Bloomberg, are calculated by holding the nearest contract to expiry until the first of the month, then rolling to the next nearest. The basis is calculated as the nearest contract price less the second nearest, divided by the second nearest. Where the nearest and next nearest contracts have the same definition as the return calculation. Momentum is calculated as the average of the previous 12 months futures returns. Hedging pressure is calculated using data taken from the U.S. Commodity Futures Trading Commission (CFTC) commitments of traders (COT) reports. For the first trading day of each month hedging pressure is calculated as $\textit{hedging pressure}_{i,t} = \frac{\textit{Commercial short}_{i,t} - \textit{Commercial long}_{i,t}}{\textit{Commercial long}_{i,t} + \textit{Commercial short}_{i,t}}$, based on the previous week's COT report.

Name	BBG Code	Class	Exchange	Returns		Basis		Momentum		Hedg. Pres.	
				mean	std	mean	std	mean	std	mean	std
Crude Oil, WTI	CL	Energy	NYMEX Exchange	0.9	9.0	0.1	1.4	0.9	3.1	2.4	6.3
Heating Oil	HO	Energy	NYMEX Exchange	0.8	9.0	-0.1	1.9	0.8	3.0	7.8	7.2
Natural Gas	NG	Energy	NYMEX Exchange	-0.5	14.1	-1.0	5.4	-0.6	4.5	5.8	5.1
Corn	C	GrainsOilseeds	Chicago Board of Trade	-0.3	7.8	-1.6	3.7	-0.3	2.2	1.3	14.5
Oats	O	GrainsOilseeds	Chicago Board of Trade	0.0	8.7	-1.5	3.9	-0.0	2.9	32.7	18.3
Wheat	W	GrainsOilseeds	Chicago Board of Trade	-0.3	8.0	-1.5	3.3	-0.3	2.3	4.6	11.0
Cattle, Feeder	FC	Livestock	Chicago Mercantile Exchange	0.1	3.9	0.1	1.5	0.1	1.1	-15.7	23.0
Cattle, Live	LC	Livestock	Chicago Mercantile Exchange	-0.1	3.8	-0.1	3.3	-0.0	1.1	5.2	11.7
Lean Hogs	LH	Livestock	Chicago Mercantile Exchange	-0.4	6.7	-0.9	6.7	-0.4	2.0	-0.6	19.8
Gold, 100 oz	GC	Metals	COMEX division of NYMEX	0.3	4.6	-0.5	0.3	0.3	1.3	22.0	29.4
Copper	HG	Metals	COMEX division of NYMEX	0.8	7.6	0.5	1.6	0.8	2.6	8.4	20.5
Palladium	PA	Metals	NYMEX Exchange	1.2	9.9	-0.2	1.1	1.2	3.4	36.5	29.4
Platinum	PL	Metals	NYMEX Exchange	0.7	6.2	0.1	0.9	0.7	1.8	47.8	24.9
Silver	SI	Metals	COMEX division of NYMEX	0.7	8.5	-0.5	0.4	0.7	2.2	45.5	16.6
Kansas Wheat	KW	Softs	ICE Futures US Softs	0.2	7.8	-0.7	2.8	0.2	2.3	4.6	11.0
Cocoa	CC	Softs	ICE Futures US Softs	-0.0	8.6	-1.4	1.5	-0.1	2.3	9.5	12.5
Cotton, No. 2	CT	Softs	ICE Futures US Softs	-0.3	8.1	-1.0	3.7	-0.3	2.7	3.7	19.6
Coffee, 'C'	KC	Softs	ICE Futures US Softs	-0.1	11.2	-1.5	3.2	-0.0	3.6	12.2	14.8
Sugar, #11 World	SB	Softs	ICE Futures US Softs	0.6	8.9	0.6	4.0	0.6	2.5	12.5	14.7

Table 3.2. Benchmarks and predictors

Reported are summary statistics and correlations for the two benchmarks; the equally weighted portfolio of commodity futures (EW) and the Goldman Sachs Commodity Index (GSCI); and the three macroeconomic predictors, open interest (OI), Baltic Dry Index(BDI) and the industrial production gap (IP). the OI predictor is defined as the aggregate open interest growth rate, calculated by taking the time series 12 month geometric average of the mean monthly dollar growth in open interest for the five classes of commodity, following Hong and Yogo (2012). The BDI predictor is calculated using the monthly growth of the Baltic Dry Index, following Bakshi, Panayotov, and Skoulakis (2011). Industrial production gap is calculated following the out-of-sample approach introduced by Cooper and Priestley (2009). The first 2 columns report the monthly percentage mean and standard deviation. The last 5 columns report the correlation matrix between the time series.

Name		mean	std	Correlation				
				EW	GSCI	OI	BDI	IP
Equally weighted	EW	0.23	3.79	1.00				
Goldman Sachs Commodity Index	GSCI	0.22	6.22	0.76	1.00			
Open Interest	OI	0.77	2.65	0.27	0.25	1.00		
Baltic Dry Index	BDI	-0.47	3.87	0.19	0.16	0.06	1.00	
Industrial Prod. Gap	IP	-2.52	7.11	-0.00	0.03	-0.16	0.07	1.00

Table 3.3. In-sample commodity futures portfolio policy

In-sample portfolio estimates based on Equation 3.4 and associated return statistics are reported for the period April 1991 to March 2001 inclusive for different combinations of characteristics. The first and second columns report results for the equally-weighted benchmark (EW) and the equally-weighted with optimal leverage (EWOL) portfolios, respectively. The remaining columns report results for different optimal portfolio configurations: carry (1), momentum (2), hedging pressure (3), commodity specific (4), macroeconomic (5) and all characteristics (6). The first 14 rows report the average optimal policy estimates for different sets of characteristics. The remaining rows display average portfolio return statistics: annualised mean return, annualised standard deviation, skewness, excess kurtosis, Sharpe, Sharpe bootstrapped p-value for the null hypothesis that the strategy Sharpe is less than that of the benchmark portfolio, the opportunity cost (Simaan (1993)) of holding the benchmark portfolio versus the optimal strategy, bootstrapped p-value that the opportunity cost is negative, portfolio turnover, return-loss over the benchmark portfolio and bootstrapped p-value that the return-loss is positive.

	EW	EWOL	(1)	(2)	(3)	(4)	(5)	(6)
θ_{carry}			-0.17			-1.87		-2.56
(t-stat)			(-0.2)			(-1.7)		(-2.1)
θ_{mom}				2.52		3.27		3.57
(t-stat)				(3.1)		(3.3)		(3.5)
$\theta_{\text{hedg. pres.}}$					-0.69	-0.86		-0.21
(t-stat)					(-0.6)	(-0.7)		(-0.2)
$\theta_{\text{open int.}}$							2.57	2.66
(t-stat)							(2.6)	(2.6)
θ_{bdi}							2.75	3.42
(t-stat)							(1.5)	(1.8)
θ_{ip}							1.67	2.95
(t-stat)							(1.3)	(2.1)
θ_{long}		0.61						
(t-stat)		(0.8)						
$\hat{\mu}$	0.02	0.01	0.00	0.25	0.01	0.36	0.28	0.81
$\hat{\sigma}$	0.08	0.05	0.01	0.21	0.04	0.24	0.25	0.38
Skewness	-0.34	-0.33	-0.14	0.01	0.08	-0.06	1.59	0.58
Excess kurtosis	-0.10	-0.10	0.16	0.13	1.27	1.44	4.74	0.66
Sharpe	0.28	0.25	0.06	1.17	0.19	1.48	1.12	2.16
Sharpe p-val		0.12	0.92	0.05	0.57	0.04	0.04	0.00
CE		0.00	-0.00	0.11	0.00	0.17	0.12	0.34
CE(p-val)		0.41	0.61	0.07	0.52	0.05	0.06	0.00
Turnover	0.06	0.04	0.08	0.74	0.23	1.24	2.68	3.76
Return-loss		-0.02	-0.04	-0.10	-0.02	-0.15	-0.09	-0.30
Return-loss(p-val)		0.00	0.00	0.18	0.15	0.15	0.20	0.03

Table 3.4. Out-of-sample commodity futures portfolio policy

Out-of-sample portfolio estimates based on Equation 3.4 for the period April 2001 to December 2013, inclusive, for different combinations of characteristics are reported. The optimal portfolio policy is first estimated for the period from April 1991 to March 2001. The policy is then used to determine portfolio weights that month, and the portfolio return is recorded for April 2001. The out-of-sample return is calculated by expanding the policy estimation window and recording portfolio return for each successive month until the end of the sample in December 2013. The first and second column report results for the equally-weighted benchmark (EW) and the equally-weighted with optimal leverage (EWOL) portfolios, respectively. The remaining columns report results for different optimal portfolio configurations: carry (1), momentum (2), hedging pressure (3), commodity specific (4), macroeconomic (5) and all characteristics (6). The first 14 rows report the average optimal policy estimates for different sets of characteristics. The remaining rows display average portfolio return statistics: annualised mean return, annualised standard deviation, skewness, excess kurtosis, Sharpe, Sharpe bootstrapped p-value for the null hypothesis that the strategy Sharpe is less than that of the benchmark portfolio, the opportunity cost (Simaan (1993)) of holding the benchmark portfolio versus the optimal strategy, bootstrapped p-value that the opportunity cost is negative, portfolio turnover, return-loss over the benchmark portfolio and bootstrapped p-value that the return-loss is positive.

	EW	EWOL	(1)	(2)	(3)	(4)	(5)	(6)
θ_{carry}			-0.06			-1.28		-1.30
(t-stat)			(-0.1)			(-1.6)		(-1.6)
θ_{mom}				1.65		2.16		2.07
(t-stat)				(2.8)		(3.0)		(2.8)
$\theta_{\text{hedg. pres.}}$					0.30	-0.20		-0.15
(t-stat)					(0.5)	(-0.2)		(-0.1)
$\theta_{\text{open int.}}$							1.19	0.92
(t-stat)							(1.8)	(1.2)
θ_{bdi}							1.13	1.36
(t-stat)							(1.1)	(1.3)
θ_{ip}							0.35	0.44
(t-stat)							(0.2)	(0.3)
θ_{long}		0.59						
(t-stat)		(1.2)						
$\hat{\mu}$	0.03	0.02	-0.01	0.03	0.00	0.02	0.05	0.08
$\hat{\sigma}$	0.16	0.11	0.01	0.17	0.04	0.19	0.36	0.44
Skewness	-0.51	-0.14	-0.09	-0.17	-0.08	-0.25	1.33	0.89
Excess kurtosis	1.96	6.53	1.65	2.07	1.84	1.13	11.25	6.16
Sharpe	0.20	0.14	-0.73	0.16	0.03	0.12	0.15	0.18
Sharpe p-val		0.86	1.00	0.64	0.71	0.60	0.62	0.61
CE		0.02	0.03	-0.01	0.03	-0.04	-0.24	-0.36
CE(p-val)		0.00	0.32	0.30	0.31	0.69	0.97	1.00
Turnover	0.07	0.03	0.04	0.29	0.07	0.48	0.66	0.92
Return-loss		-0.00	-0.01	0.00	-0.01	0.02	0.03	0.03
Return-loss(p-val)		0.47	0.10	0.46	0.32	0.59	0.63	0.63

Table 3.5. Out-of-sample commodity futures portfolio policy with GSCI benchmark

Out-of-sample portfolio estimates based on Equation 3.4 for the period April 2001 to December 2013, inclusive, for different combinations of characteristics are reported. The optimal portfolio policy is first estimated for the period from April 1991 to March 2001. The policy is then used to determine portfolio weights that month, and the portfolio return is recorded for April 2001. The out-of-sample return is calculated by expanding the policy estimation window and recording portfolio return for each successive month until the end of the sample in December 2013. The first and second column report results for the Goldman Sachs Commodity Index (GSCI) benchmark and the equally-weighted with optimal leverage (EWOL) portfolios, respectively. The remaining columns report results for different optimal portfolio configurations: carry (1), momentum (2), hedging pressure (3), commodity specific (4), macroeconomic (5) and all characteristics (6). The first 14 rows report the average optimal policy estimates for different sets of characteristics. The remaining rows display average portfolio return statistics: annualised mean return, annualised standard deviation, skewness, excess kurtosis, Sharpe, Sharpe bootstrapped p-value for the null hypothesis that the strategy Sharpe is less than that of the benchmark portfolio, the opportunity cost (Simaan (1993)) of holding the benchmark portfolio versus the optimal strategy, bootstrapped p-value that the opportunity cost is negative, portfolio turnover, return-loss over the benchmark portfolio and bootstrapped p-value that the return-loss is positive.

	GSCI	EWOL	(1)	(2)	(3)	(4)	(5)	(6)
θ_{carry}			-0.06			-1.28		-1.30
(t-stat)			(-0.1)			(-1.6)		(-1.6)
θ_{mom}				1.65		2.16		2.07
(t-stat)				(2.8)		(3.0)		(2.8)
$\theta_{\text{hedg. pres.}}$					0.30	-0.20		-0.15
(t-stat)					(0.5)	(-0.2)		(-0.1)
$\theta_{\text{open int.}}$							1.19	0.92
(t-stat)							(1.8)	(1.2)
θ_{bdi}							1.13	1.36
(t-stat)							(1.1)	(1.3)
θ_{ip}							0.35	0.44
(t-stat)							(0.2)	(0.3)
θ_{long}		0.59						
(t-stat)		(1.2)						
$\hat{\mu}$	0.03	0.02	-0.01	0.03	0.00	0.02	0.05	0.08
$\hat{\sigma}$	0.25	0.11	0.01	0.17	0.04	0.19	0.36	0.44
Skewness	-0.60	-0.14	-0.09	-0.17	-0.08	-0.25	1.33	0.89
Excess kurtosis	1.30	6.53	1.65	2.07	1.84	1.13	11.25	6.16
Sharpe	0.13	0.14	-0.73	0.16	0.03	0.12	0.15	0.18
Sharpe p-val		0.56	1.00	0.50	0.63	0.52	0.54	0.54
CE		0.13	0.14	0.10	0.15	0.07	-0.15	-0.28
CE(p-val)		0.00	0.09	0.01	0.10	0.28	0.80	0.96
Turnover		0.03	0.04	0.29	0.07	0.48	0.66	0.92
Return-loss		-0.01	-0.01	-0.01	-0.01	0.00	0.01	0.00
Return-loss(p-val)		0.26	0.07	0.36	0.27	0.50	0.55	0.56

Table 3.6. Portfolio policy for different sample periods

Out-of-sample portfolio estimates based on Equation 3.4 for the three sample periods: April 2001 to December 2005, January 2005 to June 2008 and July 2008 to June 2011, corresponding to before, during and after the commodity boom, respectively. The optimal portfolio policy is first estimated based on data from April 1991 to March 2001, optimal parameters and corresponding portfolio weights are calculated, and returns reported for the following month, April 2001. The sample is then expanded for each successive month until the end of the sample. The first, second and third columns report sample estimates for the equally weighted benchmark portfolio (EW), the Goldman Sachs Commodity Index (GSCI), and the equally-weighted with optimal leverage (EWOL) portfolios, respectively, for the pre-boom period. The next three columns report pre-boom sample estimates for commodity specific (1), macroeconomic (2) and all characteristic (3) optimal portfolio configurations, respectively. Columns 7-12 and 13-18 report results for the boom and post-boom periods in the same format, respectively. The first 14 rows report the average optimal policy estimates for different sets of characteristics. The remaining rows display average portfolio return statistics: annualised mean return, annualised standard deviation, skewness, excess kurtosis, Sharpe, Sharpe bootstrapped p-value for the null hypothesis that the strategy Sharpe is less than that of the benchmark portfolio, the opportunity cost (Simaan (1993)) of holding the benchmark portfolio versus the optimal strategy, bootstrapped p-value that the opportunity cost is negative, portfolio turnover, return-loss over the benchmark portfolio and bootstrapped p-value that the return-loss is positive.

	Pre-boom						Boom						Post-boom					
	EW	GCSI	EWOL	(1)	(2)	(3)	EW	GCSI	EWOL	(1)	(2)	(3)	EW	GCSI	EWOL	(1)	(2)	(3)
θ_{carry}				-1.69		-1.84				-1.27		-1.17				-1.00		-1.00
(t-stat)				(-1.7)		(-1.8)				(-1.6)		(-1.4)				(-1.5)		(-1.5)
θ_{mom}				2.86		2.82				2.18		1.96				1.66		1.63
(t-stat)				(3.3)		(3.1)				(3.1)		(2.7)				(2.8)		(2.7)
$\theta_{\text{hedg. pres.}}$				-0.61		-0.32				-0.36		-0.30				0.19		0.06
(t-stat)				(-0.5)		(-0.3)				(-0.4)		(-0.3)				(0.3)		(0.1)
$\theta_{\text{open int.}}$					2.14	1.85					1.45	1.12					0.39	0.15
(t-stat)					(2.5)	(2.0)					(2.1)	(1.6)					(1.2)	(0.4)
θ_{bdi}					2.63	3.16					1.03	1.24					0.17	0.20
(t-stat)					(1.8)	(2.0)					(1.0)	(1.1)					(0.7)	(0.9)
θ_{ip}					0.90	1.20					0.34	0.33					-0.02	-0.01
(t-stat)					(0.8)	(1.0)					(0.4)	(0.3)					(-0.3)	(-0.3)
θ_{long}			0.56						0.92						0.40			
(t-stat)			(0.9)						(1.7)						(1.1)			
$\hat{\mu}$	0.03	0.04	0.04	0.06	0.19	0.27	0.11	0.16	0.10	-0.01	-0.01	-0.05	-0.04	-0.09	-0.04	0.02	0.01	0.05
$\hat{\sigma}$	0.09	0.18	0.07	0.25	0.30	0.47	0.14	0.23	0.14	0.20	0.44	0.50	0.19	0.28	0.10	0.14	0.33	0.37
Skewness	-0.40	0.19	-1.06	-0.47	0.21	0.28	0.45	-0.02	0.43	0.17	0.81	0.70	-0.55	-0.83	-1.30	-0.16	2.62	1.96
Excess kurtosis	0.07	0.32	2.18	0.33	1.41	1.04	3.24	-0.64	4.81	0.59	9.48	7.13	0.72	1.63	3.18	-0.27	15.87	11.03
Sharpe	0.38	0.24	0.51	0.24	0.62	0.56	0.78	0.67	0.66	-0.07	-0.03	-0.11	-0.20	-0.32	-0.44	0.16	0.03	0.14
Sharpe p-val		0.75	1.00	1.00	0.94	0.96		0.54	0.99	0.92	1.00	1.00		0.66	0.96	0.27	0.40	0.33
CE		-0.05	-0.02	-0.15	-0.10	-0.31		-0.04	-0.02	-0.16	-0.53	-0.64		-0.17	0.07	0.12	-0.07	-0.09
CE(p-val)		0.92	1.00	1.00	0.99	0.99		0.58	0.99	0.95	0.99	1.00		0.96	0.10	0.14	0.66	0.69
Turnover	0.06	0.64	0.02	0.29	0.58	0.74	0.09	0.69	0.07	0.89	1.05	1.42	0.08	0.70	0.04	0.70	0.59	0.98
Return-loss		0.06	0.00	0.13	0.04	0.11		0.05	0.01	0.19	0.48	0.63		0.03	0.02	-0.05	-0.08	-0.12
Return-loss(p-val)		0.94	0.97	1.00	0.95	0.97		0.57	0.95	0.94	1.00	1.00		0.64	0.95	0.24	0.39	0.33

Table 3.7. Portfolio policy for different levels of risk aversion

Out-of-sample portfolio estimates based on Equation 3.4 for the three levels of risk aversion; $\gamma = 3$, $\gamma = 5$ and $\gamma = 10$: For each level of risk aversion the optimal portfolio policy is first estimated based on data from April 1991 to March 2001, optimal parameters and corresponding portfolio weights are calculated, and returns reported for the following month, April 2001. The sample is then expanded for each successive month until the end of the sample. The first and second columns report sample estimates for the equally-weighted (EW) and Goldman Sachs Commodity Index (GSCI) benchmark portfolios, respectively. The next four columns report estimates for the equally-weighted with optimal leverage strategy (EWOL), commodity specific (1), macroeconomic (2) and optimal portfolio configurations (3), respectively, based on the estimation of the optimal portfolio for an investor with CRRA utility of $\gamma = 3$. The next four columns report $\gamma = 5$ results, and the last four report $\gamma = 10$ results. The first 14 rows report the average optimal policy estimates for different sets of characteristics. The remaining columns report results for different optimal portfolio configurations: carry, momentum, hedging pressure, commodity specific, macroeconomic and all characteristics. The first 14 rows report the average optimal policy estimates for different sets of characteristics. The remaining rows display average portfolio return statistics: annualised mean return, annualised standard deviation, skewness, excess kurtosis, Sharpe, Sharpe bootstrapped p-value for the null hypothesis that the strategy Sharpe is less than that of the benchmark portfolio, the opportunity cost (Simaan (1993)) of holding the benchmark portfolio versus the optimal strategy, bootstrapped p-value that the opportunity cost is negative, portfolio turnover, return-loss over the benchmark portfolio and bootstrapped p-value that the return-loss is positive.

				$\gamma = 3$				$\gamma = 5$				$\gamma = 10$		
	EW	GCSI	Long	(1)	(2)	(3)	Long	(1)	(2)	(3)	Long	(1)	(2)	(3)
θ_{carry}				-2.11		-2.13		-1.28		-1.30		-0.65		-0.65
(t-stat)				(-1.6)		(-1.6)		(-1.6)		(-1.6)		(-1.6)		(-1.6)
θ_{mom}				3.55		3.41		2.16		2.07		1.08		1.04
(t-stat)				(3.1)		(2.8)		(3.0)		(2.8)		(3.0)		(2.8)
$\theta_{\text{hedg. pres.}}$				-0.31		-0.22		-0.20		-0.15		-0.10		-0.08
(t-stat)				(-0.2)		(-0.1)		(-0.2)		(-0.1)		(-0.2)		(-0.1)
$\theta_{\text{open int.}}$					1.98	1.53			1.19	0.92			0.59	0.45
(t-stat)					(1.8)	(1.2)			(1.8)	(1.2)			(1.8)	(1.2)
θ_{bdi}					1.91	2.30			1.13	1.36			0.56	0.67
(t-stat)					(1.1)	(1.3)			(1.1)	(1.3)			(1.1)	(1.3)
θ_{ip}					0.57	0.74			0.35	0.44			0.17	0.21
(t-stat)					(0.2)	(0.3)			(0.2)	(0.3)			(0.2)	(0.2)
θ_{long}			0.98				0.59				0.30			
(t-stat)			(1.2)				(1.2)				(1.2)			
$\hat{\mu}$	0.03	0.01	0.03	0.04	0.09	0.13	0.02	0.02	0.05	0.08	0.01	0.01	0.03	0.04
$\hat{\sigma}$	0.16	0.11	0.18	0.32	0.59	0.73	0.11	0.19	0.36	0.44	0.05	0.10	0.18	0.22
Skewness	-0.51	-0.35	-0.14	-0.25	1.24	0.85	-0.14	-0.25	1.33	0.89	-0.13	-0.25	1.39	0.92
Excess kurtosis	1.96	0.85	6.52	1.10	10.94	6.18	6.53	1.13	11.25	6.16	6.55	1.15	11.51	6.15
Sharpe	0.20	0.10	0.14	0.12	0.14	0.18	0.14	0.12	0.15	0.18	0.14	0.11	0.15	0.17
Sharpe p-val		0.55	0.86	0.59	0.62	0.61	0.87	0.59	0.62	0.61	0.86	0.61	0.61	0.62
CE		0.02	-0.02	-0.11	-0.52	-0.75	0.02	-0.04	-0.24	-0.36	0.11	0.08	-0.02	-0.08
CE(p-val)		0.13	0.94	0.87	0.99	1.00	0.00	0.70	0.97	1.00	0.00	0.14	0.60	0.85
Turnover	0.07	0.68	0.04	0.79	1.12	1.54	0.03	0.48	0.66	0.92	0.01	0.24	0.33	0.46
Return-loss		0.00	0.01	0.04	0.07	0.07	-0.00	0.02	0.03	0.03	-0.01	0.00	0.01	0.01
Return-loss(p-val)		0.44	0.81	0.62	0.66	0.65	0.47	0.59	0.64	0.64	0.10	0.51	0.60	0.61

Table 3.8. Portfolio policy by type of commodity

Out-of-sample portfolio estimates based on Equation 3.4 are reported for analysis when commodities of a given class are removed from the dataset. For each subset of commodities the optimal portfolio policy is first estimated based on data from April 1991 to March 2001, optimal parameters and corresponding portfolio weights are calculated, and returns reported for the following month, April 2001. The sample is then expanded for each successive month until the end of the sample. The first and second columns report sample estimates for the equally-weighted (EW) benchmark portfolio and Goldman Sachs Commodity Index (GSCI), respectively. The next two columns report estimates for the equally-weighted with changing leverage optimal leverage strategy (EWOL) and all characteristic portfolio, respectively, based on a subset of commodities excluding energy commodities. The remaining 4 pairs of columns report results for a data set excluding commodities classed as grains, livestock, metals, and softs, respectively. The first 14 rows report the average optimal policy estimates for different sets of characteristics. The remaining rows display average portfolio return statistics: annualised mean return, annualised standard deviation, skewness, excess kurtosis, Sharpe, Sharpe bootstrapped p-value for the null hypothesis that the strategy Sharpe is less than that of the benchmark portfolio, the opportunity cost (Simaan (1993)) of holding the benchmark portfolio versus the optimal strategy, bootstrapped p-value that the opportunity cost is negative, portfolio turnover, return-loss over the benchmark portfolio and bootstrapped p-value that the return-loss is positive.

			Ex. Energy		Ex. Grains		Ex. Livestock		Ex. Metals		Ex. Softs	
	EW	GCSI	EWOL	(1)	EWOL	(1)	EWOL	(1)	EWOL	(1)	EWOL	(1)
θ_{carry}				-1.19		-1.79		-0.99		-1.74		-1.31
(t-stat)				(-1.4)		(-1.9)		(-1.0)		(-1.9)		(-1.3)
θ_{mom}				1.92		2.15		2.02		2.22		1.78
(t-stat)				(2.4)		(2.6)		(2.6)		(2.5)		(2.1)
$\theta_{\text{hedg. pres.}}$				0.08		-0.10		-0.04		-1.66		0.31
(t-stat)				(0.2)		(-0.1)		(-0.0)		(-1.2)		(0.3)
$\theta_{\text{open int.}}$				0.85		1.40		0.85		1.35		1.01
(t-stat)				(0.9)		(1.5)		(1.0)		(1.4)		(1.2)
θ_{bdi}				2.08		1.27		1.40		1.64		0.84
(t-stat)				(1.3)		(1.0)		(1.3)		(1.2)		(0.8)
θ_{ip}				0.09		0.96		0.47		0.44		0.58
(t-stat)				(-0.1)		(0.5)		(0.3)		(0.5)		(0.4)
θ_{long}			0.47		0.93		0.63		0.37		0.74	
(t-stat)			(0.9)		(1.5)		(1.3)		(0.6)		(1.3)	
$\hat{\mu}$	0.03	0.03	0.00	0.07	0.02	0.11	0.02	0.07	-0.01	0.07	0.02	0.05
$\hat{\sigma}$	0.16	0.25	0.08	0.45	0.13	0.45	0.11	0.45	0.05	0.38	0.11	0.37
Skewness	-0.51	-0.60	-0.10	0.74	-0.46	0.59	0.17	1.35	-0.57	0.67	-0.34	1.37
Excess kurtosis	1.96	1.30	9.57	9.72	2.55	4.46	6.59	9.11	6.56	4.22	5.04	8.18
Sharpe	0.20	0.13	0.04	0.16	0.18	0.24	0.17	0.16	-0.10	0.18	0.17	0.13
Sharpe p-val		0.66	0.98	0.58	0.59	0.52	0.68	0.61	1.00	0.60	0.64	0.56
CE		-0.10	0.02	-0.61	0.02	-0.36	0.02	-0.39	0.02	-0.24	0.02	-0.21
CE(p-val)		0.96	0.01	0.99	0.00	1.00	0.00	1.00	0.02	0.99	0.21	1.00
Turnover	0.07		0.02	1.06	0.03	0.82	0.02	0.75	0.02	0.85	0.02	0.60
Return-loss		0.02	0.00	0.04	-0.00	0.01	-0.00	0.04	0.01	0.03	-0.00	0.04
Return-loss(p-val)		0.68	0.73	0.61	0.30	0.50	0.25	0.63	0.96	0.66	0.39	0.57

VIII. Appendix: Figures

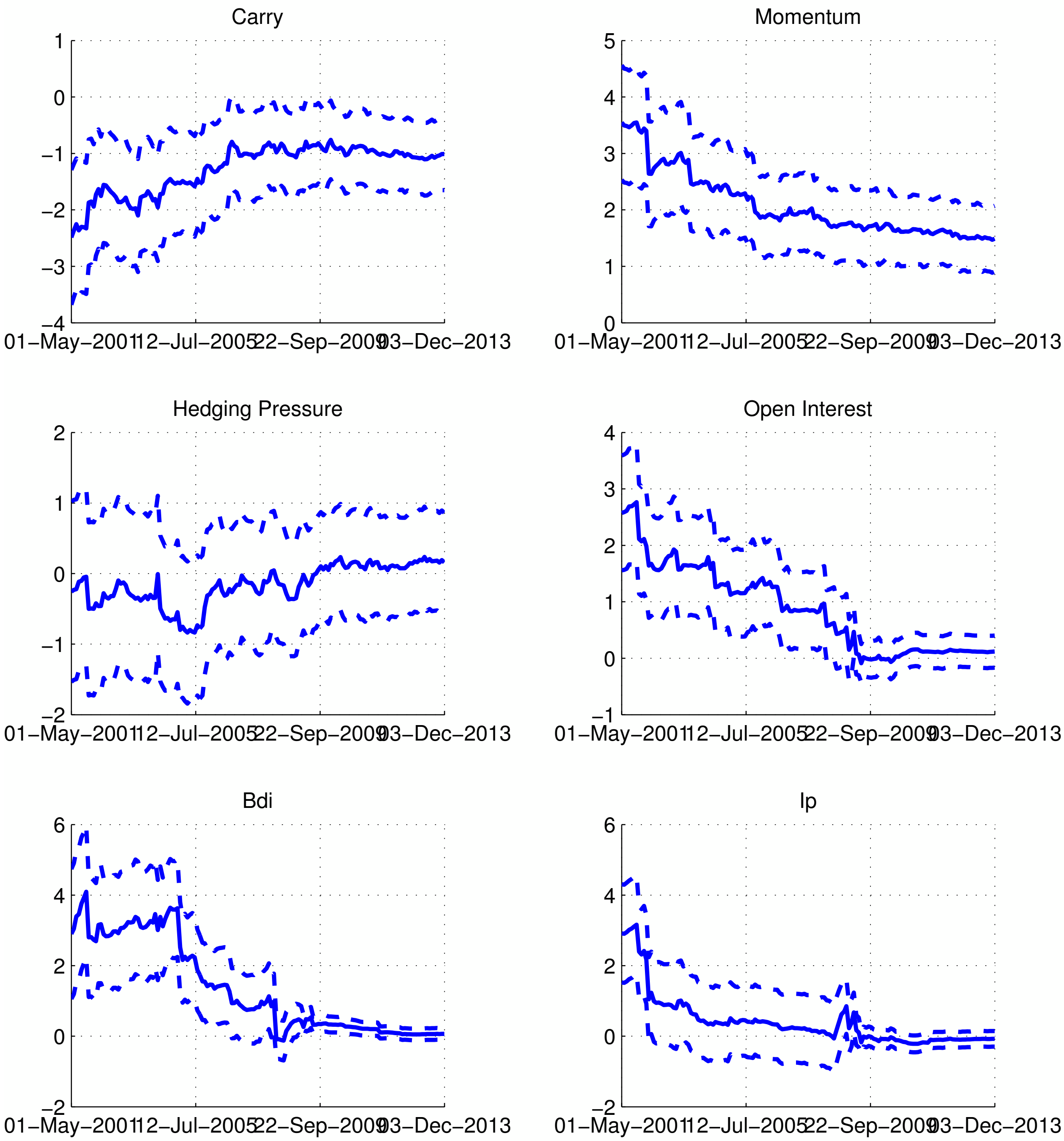


Figure 3.1. Optimal portfolio parameter estimates
For the combined strategy, containing all 6 characteristics, portfolio estimates of optimal characteristic weightings, $\hat{\theta}$, are shown. For each plot the monthly estimate of $\hat{\theta}$ is shown as a solid line for each characteristic. Dashed lines of the same color indicate one sigma estimation error.

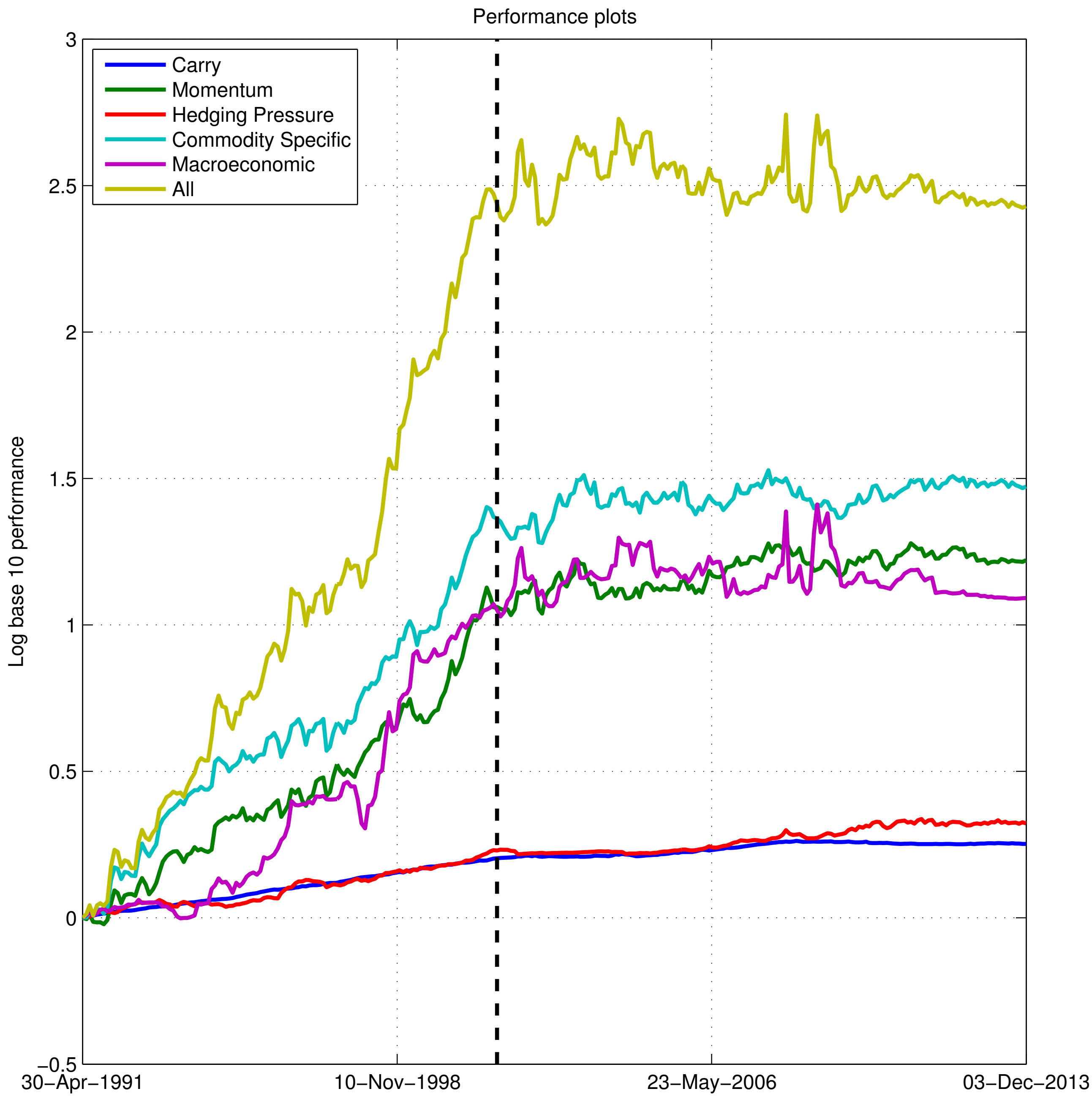


Figure 3.2. Portfolio performance

For individual and combined characteristics portfolio estimates return series are shown. In-sample and out-of-sample returns to each portfolio are concatenated. In-sample returns are reported before April 2001 and out-of-sample thereafter, the change in regime is indicated with a vertical dashed line. The y-axis is the log base 10 portfolio value from one dollar invested in the respective portfolio in April 1991.

Chapter 4

Conclusions

This thesis examines carry and momentum trading strategies in futures markets (Chapter 1 and Chapter 2) and a variety of trading strategies in commodity markets (Chapter 3). Chapter 1 studies the individual and joint performance of carry and momentum strategies over the asset classes bonds, commodities, currencies, equities, and metals. Within each asset class we find significant strategy returns for both carry and momentum strategies, with the exception of bond momentum. Combining strategies across asset classes we form global carry and momentum portfolios. We find the correlation between global carry and global momentum returns to be small and time-varying. The resulting diversification benefit leads to an increase in Sharpe ratio and reduced draw-downs in the combined portfolio. To attempt to understand the exceptional returns of the individual and combined global portfolio, we consider a number of risk factors, but fail to explain portfolio returns using stock market momentum, funding or liquidity measures. However, we do find that lagged macroeconomic variables explain carry returns, suggesting the role of business cycle risk. On the other hand, momentum strategies are only weakly affected by macroeconomic variables, but are significantly related to measures of hedge fund capital. Capital outflows predict momentum returns, suggesting the limits to arbitrage of capital constrained hedge funds lead to market inefficiencies.

The findings of Chapter 1 have important implications for both investors and policy makers. First investors, who trade in carry and momentum strategies should be aware that a significant proportion of strategy performance depends on the ability of hedge fund industry to arbitrage inefficiencies. For policy makers, our findings add to the debate whether hedge funds distort markets and their activities should be restricted. Our results refute this logic: capital inflows and high hedge fund AUM lead to a reduction of carry and momentum inefficiencies. However, we concede that policy decisions must take into account a far wider set of market inefficiencies than those attributed to the returns of trading strategies.

Given the impressive performance of carry and momentum strategies, Chapter 2 demonstrates that the predictive power of the carry and momentum signals has economic significance. To test for the economic significance of strategy returns we measure the increase in wealth for a representative investor who uses a parametric portfolio policy, which specifies each asset's portfolio weight as a linear function of the asset's carry and momentum predictor, to make real-time capital allocation choices. Using the same data set as Chapter 1, we first estimate the portfolio policy for an in-sample period from 1982 to 1992. Here, without assuming a relationship ex-ante, we confirm that the carry and momentum signals predict expected returns.

We then analyze the properties of the optimal futures portfolio out-of-sample from 1992 to 2012. The out-of-sample returns have a number of similar features to the rule based strategy studied in Chapter 1: We find that strategy returns are not compensation for traditional risk factors, funding risk, liquidity risk, or business cycle risk. Also similar to momentum for the rule based carry and momentum, we find that optimal carry and momentum is highly related to speculative capital of hedge funds.

In Chapter 3 we use a parametric portfolio policy framework to show that six well-known predictors of commodity returns are unable to forecast returns out of sample. This is an important finding, as it suggests that the six predictors, which have received significant attention in the academic literature, are not economically significant. The six predictors we consider are three cross-sectional predictors (carry, momentum, and hedging pressure) and three market wide predictors (aggregate open interest, Baltic Dry Index, and the output gap). For our in-sample estimation period, from 1991 to 2001, we find momentum and the three market wide predictors are significant. However, we fail to report the expected relation for the carry and hedging pressure. During the in-sample period we report highly significant returns, with an opportunity cost to an investor of holding an equally weighted benchmark portfolio versus the returns of the optimal policy equal to 34%, annualized, with a Sharpe of 2.2. Despite the incredible performance in sample, the parametric commodity portfolio fails miserably out of sample. In the out-of-sample allocation period the Sharpe reduces to 0.18, similar to the benchmark equally-weighted portfolio Sharpe of 0.20. However, the Sharpe ratio hides the true issue with the out-of-sample portfolio returns: the extremely high excess kurtosis of 6.2. As a result, the opportunity cost of a representative investor of holding the portfolio becomes negative. For robustness, we test our findings for different sample periods, levels of risk aversion and asset classes, however, we find the portfolio performance remains qualitatively unchanged. In contrast to the first two chapters, Chapter 3 serves as a warning to practitioners that in-sample relations, particularly market-wide macroeconomic predictors, generate poor returns out-of-sample for commodity portfolios. Going forward, we hope the approach provides a framework for future studies to assess the economic benefit of other commodity predictors.

Trading strategies in futures markets provide a means of portfolio allocation for investors, a test of theory for academics and a manifestation of market inefficiency for policy makers. Our hope is that this thesis contributes to the understanding of this fascinating topic.

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