Predictability in carry and momentum strategies across asset classes
Preliminary version

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March 15, 2012

Abstract In this paper we study the predictability of carry and momentum returns in different asset classes. We examine whether predictors related to macroeconomics variables, liquidity conditions and uncertainty can explain these strategies' returns in asset classes such as equities, bonds, currencies and commodities. The performance of a forecasting model based on lagged business cycle, liquidity and uncertainty predictors indicates that while uncertainty does not explain the returns, business cycle predictors as well as liquidity variables have a strong explanatory power for strategies that combine carry and momentum across asset classes. Furthermore, we uncover interesting dynamic correlation and return structures that can be related to the recent increase in trading activity by certain investors, namely hedge funds.

Keywords: carry trades, momentum, predictability, business cycles, uncertainty, liquidity, hedge funds

JEL Classification Numbers: C53, G11, G12, G13, F44, D84.

1 Introduction

This paper offers new evidence on the relative importance of predictive variables in explaining the returns to carry and momentum strategies across commodity, bond, currency and equity futures. Predictability in (cash) equity and bond markets has been studied extensively, for example by Fama and French (1989), Ilmanen (1995) and Chen et al. (1986), but less work has been carried out on predictability in futures markets[1]. Carry strategies relate the current spread between futures and spot prices to the return on an asset, while momentum strategies relate an asset's return to it's own past returns. We study these two phenomena in a unifying framework. The economically and statistically significant positive returns to those strategies have proven to be a challenge to financial economists, as most traditional risk factor explanations have not been successful. We find that the combined profitability of momentum and carry strategies can be predicted by common macroeconomic variables that are related to business cycles and funding liquidity and is therefore related to rational risk based explanations.

The key feature of our analysis is to examine the average returns on carry and momentum strategies across a wide set of markets and asset classes together. The power of looking at all assets together greatly improves the ability to identify common factor structures (see Asness et al. (2011)). The predictability for the individual strategies is only weak and only marginally statistically significant. On the other hand by combining the carry and momentum strategy the predictability becomes highly statistically and economically significant. These results give rise to dynamic portfolio allocations using the predictability results within carry and momentum strategies, which is left for future work. Furthermore, we uncover interesting time variations in the returns and correlation dynamics that we argue can be linked to the recent increase in trading activity of hedge funds in futures markets.

The aim of the paper is to go beyond previous research in carry and momentum and (1) extend and study in depth the performance of momentum and carry strategies in, (2) study the comovement of the strategies within and across asset classes, (3) understand their common economic drivers by examining these phenomena simultaneously across asset classes, including the role certain investors such as hedge funds which are known to implement these strategies.

[1] A notable example is Bessembinder and Chan (1992)

For our study we make use of various futures markets across multiple asset classes. In general, futures markets provide an excellent laboratory for studying strategies that take long and short positions. In contrast to stock markets, most futures markets are very liquid and feature high transaction volumes and very low transaction costs. By the very nature of futures contracts, taking long or short positions is a natural process for investors. Furthermore, these markets are mainly populated by sophisticated institutional investors such as hedge funds and investment banks who do not face short selling constraints which would prevent market participants fully exploring the momentum and carry profits, as in Stambaugh et al. (2011). Finally, futures markets are excellent candidates to study out of sample predictability since the timing of buy and sell orders can be carefully specified by observing the predictors signal.

We start our investigation by forming portfolios of futures contracts in commodity, currency, equity and bond markets based on the carry and momentum signals. This approach contrasts with most previous studies, which construct portfolios *within* asset classes. Furthermore, most of the momentum and carry trade literature constructs cross sectional portfolios only focusing on the relative performance of securities, finding that securities that recently outperformed their peers or had a stronger carry signal than their peers will generate higher excess returns. Recently, Moskowitz et al. (2010a) and Baltas and Kosowski (2011) demonstrate that positive alpha can be generated based on signals derived purely from a securities own past returns. This trading strategy is related to, but different from, the cross sectional finding and has been termed time series momentum. We apply and extend this differentiation to the carry signal.

We find that carry and momentum strategies have high and statistically significant returns across asset classes and strategies. The Sharpe ratios vary between 0.3 for equity carry to 1.09 for commodity carry. Furthermore, all asset classes outperform the long only benchmark. Surprisingly, given the perception of commodities to be very risky, commodity markets outperformed in terms of Sharpe ratios. Our results also confirm the stylized facts within the asset classes that have been observed by other authors, such as the negative skewness of carry returns in currencies.

Next we investigate the correlation of the trading strategies across asset classes. We find that the correlation is low which leads us to implement volatility weighted portfolios of the trading strategies. Portfolio strategies across asset classes perform even better than the individual strategies with Sharpe ratios of above 1. Given these high returns we examine whether the payoffs of the volatility weighted portfolios are correlated to various forms of risk factors, but find no evidence. We then investigate the dynamic properties of the strategies' performance and correlation. Interestingly we find that the correlation within the trading strategies increased over the sample period and the mean returns decreased and even became insignificant. This leads to the conjecture that the trading strategies are affected by limits to arbitrage and delegated portfolio management, as in Vayanos and Woolley (2011). We test if capital flows of hedge funds are related to the increasing correlation and find indeed a positive relation.

Finally, we consider predictability using three classes of indicators covering business cycle, liquidity, and uncertainty effects. For each of these measures we demonstrate high levels of predictability in the monthly returns for carry and momentum ranging between 1% and 3% percent for the individual portfolios.

Testing predictability by means of multiple predictive regressions we determine the relative importance of the different regressors. We find that uncertainty, measured with the sentiment index of Baker and Wurgler (2006) is subsumed by liquidity and business cycle predictors. These factors remain significant, demonstrating that business cycle predictors have an orthogonal predictive element to liquidity risk for carry and momentum returns. Furthermore, supporting our analysis of correlation dynamics we show that the returns of the combined carry and momentum portfolio have greater predictability than the constituent strategies, for each of the considered classes of predictors. In this parsimonious regression we are able to predict 7% of the monthly variance in the combined portfolio.

Throughout our predictability analysis we find hedge fund flows represent the strongest predictor of returns, with t-statistics over 3 in all but one case. This supports our findings in the correlation dynamics and the hypothesis that carry and momentum returns are affected by limits to arbitrage and delegated portfolio management.

Our paper relates to three streams of literature: predictability of carry and momentum, performance of trading strategies across asset classes, and the effects of limits to arbitrage on market dynamics. In the last decade there have been a number of attempts to explain momentum profits ubiquitous in stock markets. Chordia and Shivakumar (2002) find that macroeconomic factors known to predict stock returns (Chen et al. (1986)) also explain momentum profits. Griffin et al. (2003) provide global analysis of momentum in equity markets. They find little correlation between momentum profits of different stock markets, and limited predictability of macroeconomic factors internationally. An emerging stream of work relates momentum profits to uncertainty. Wang and Xu (2010) use market volatility as a proxy for uncertainty, finding it to be a better predictor of momentum returns than traditional macroeconomic variables. Stambaugh et al. (2011) relate uncertainty to market sentiment, defined by Baker and Wurgler (2006), which they argue drives short selling risk. This in turn leads to overpricing of stocks held on the short leg of momentum portfolios, therefore generating momentum profits. Predictability in carry strategy returns has received less attention, one notable exception is Bakshi and Panayotov (2011) who demonstrate carry returns relate to a commodity index, volatility and liquidity measures.

The second stream of literature we draw from studies well known equity market anomalies across multiple asset classes. Asness et al. (2011) find that a strong common factor structure emerges for value and momentum strategies when performance is aggregated across asset classes. Moskowitz et al. (2010a) consider time-series momentum across equities, fixed income, foreign exchange and commodities, and demonstrate abnormal returns of time-series momentum are driven by the activities of speculators and hedgers. Koijen and Vrugt (2011) show the carry trade performs well for equity fixed income, foreign exchange and commodities.

The last theme relates asset returns to limits to arbitrage and hedge fund flows. Brunnermeier and Pedersen (2009) demonstrate that speculator capital is a driver of market liquidity and risk premiums. Jylhä and Suominen (2011) describe a model which endogenously generates carry strategies traded by hedge funds.

The rest of the paper is structured as follows. Section 2 describes the data and introduces the construction of momentum and carry portfolios. Section 3 analyzes the risk and return profile of the trading strategies, examines their risk exposure to traditional risk factors, and considers the dynamics of the strategy returns and correlations. Section 4 introduces and presents our methodology and results to investigate the predictability of business cycle, uncertainty and liquidity predictors.

2 Data and portfolio construction

In this section we describe our data sources and lay out the methodology for constructing momentum and carry portfolios. We also present the summary statistics of the individual futures contracts.

2.1 Asset data and summary statistics

The data we use covers a cross section of 66 futures contracts across the asset classes commodities, currencies, bonds, and equities, over the sample period from January 1977 to January 2012. The analysis is carried out on a monthly frequency, although we collect daily data to construct proxies for futures market volatility. We obtain daily settlement prices for the first and second nearest to maturity futures contract from different futures exchanges via TickData. It is important to note that some asset classes have futures contracts expiring every month, others have contract months that are regularly spaced (every 3 months, for example) or irregularly spaced (7 months out of the year). We acknowledge this fact by conducting robustness tests with different specifications of the carry measure. Furthermore, while spot data is available for most futures contracts, we follow the literature, e.g. Moskowitz et al. (2011), and use near-month futures prices instead of spot prices. This is particulary important for commodity futures contracts. Using the near month futures price as a measure of spot price allows us to focus on the change in futures price over time, unclouded by other differences between futures and cash prices such as differences in transaction or transportation costs, delivery cost, or delivery location and also mitigates problems of low liquidity and irregular price behavior. One weakness in using near month prices is that due to the irregular spacing of futures expiry, for a given futures contract the near month price may reflect a contract that expires after a few months, rather than within a few days. In order to remain consistent we apply this to all asset classes.

Individual futures contract have a finite life defined by the contractual delivery date and no initial cash payments, besides margins which constitute only a fixed percentage, take place. Therefore in order to calculate returns in futures markets some further assumptions have to be made. We assume as in Bessembinder (1992), deRoon et al (2000) and Moskowitz et al (2011) that futures positions are fully collateralized and positions are opened in the most liquid futures contract, which is typically the nearest or next nearest to delivery contract[2]. Each day, we compute the daily return of each individual futures contract and then compound the daily returns to a monthly return series.

Commodities: Our total commodity sample consists of grain, metal, animals, and energy classes, including the following 27 contracts ranging from January 1977 to January 2011: Copper, Gold, Palladium, Platinum , Silver, Feeder Cattle, Live Cattle, Live/Lean Hogs, Pork Bellies, Brent Crude Oil NY, Heating Oil NY, Natural Gas, NY Light Sweet Crude Oil, Unleaded Gasoline, Cocoa, Coffee, Cotton, Lumber, Sugar, Corn, Oats, Soybeans, Soybean Oil, Soybean Meal, and Wheat.

Currencies: We use 9 currency futures contracts, all denominated in US Dollars, ranging from January 1977 to January 2011. These contracts include: Australian Dollar, British Pound, Canadian Dollar, Deutsche Mark, Euro FX, Japanese Yen, Mexican Peso,Swiss Franc, and US Dollar Index.

Equities: Our total equity sample contains 22 international equity indices. Some of futures contracts have been available since 1982 while others have only become available in the 2000s. Included contracts are: AEX Index, ASX SPI 200 Index, CAC 40 Index, DAX Index, DJ Stoxx 50 Index, DJ Euro Stoxx 50 Index, BIG Dow, DJIA FTSE 100 Index, FTSE/MIB Index, Hang Seng Index, IBEX 35 Index, MSCI Taiwan Index, NASDAQ 100 Index, Nikkei 225 Index, NYSE Composite Index, Russell 2000 Index, S&P 400 MidCap Index, S&P 500 Index, S&P Asia 50 Index, S&P Canada 60 Index, Swiss Market Index, and Tokyo Price Index.

Bonds: We use 18 bond futures contracts ranging from January 1982 to January 2012 including: Australian 90-day, Australian 3-year, Australian 10-year, Canadian Govt Bond, Euro Bobl 5-year, Euro Bund 10-year, Euro Schatz 2-year, Euro Euribor 3-month, Eurodollar, Long Gilt, Japanese 10-year Bond, LIBOR 1-month Municipal Bonds, Sterling 3-month, T-Bills, T-Notes 2-year, T-Notes 5-year, T-Notes 10-year, and T-Bond 30-year.

Descriptive statistics: Descriptive statistics for the individual futures contracts are presented in Table 1. The first column shows the name of the contracts, while the next four columns present the mean, standard deviation, skewness and sharpe ratios of the returns sorted by asset class, commodity, currency, bond and equity. The table highlights the stylized facts of the individual asset classes: First, the annualized mean returns differ significantly for the individual contracts. Equities, bonds and currencies yield predominantly positive returns, while commodities yield negative and

[2]It is important to note that we appropriately adjust for rollovers in order to reflect a tradable return series

positive returns. More striking are the differences in volatilities across asset classes. Equities and commodities have much larger volatilities than bond and currency futures. This is particularly important for the across asset class strategies. We discuss below how we deal with this issue in our analysis.

2.2 Trading strategies

In this section we define and describe the construction of time series strategies based on the carry and momentum signal as well as the construction of volatility weighted strategies across asset classes. We define time series strategies, following Moskowitz et al (2011), as strategies that focus purely on a security's *own* signal. In contrast cross-sectional strategies focus on the *relative* strength of securities 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. We are not interested in coming up with the best predictors in each asset class and a holding period that maximizes the potential profits. Rather, our goal is to maintain a simple and fairly uniform approach that is consistent across asset classes and thus minimizes the pernicious effects of data snooping. By applying this we first fix the holding period to be one months and do not consider different specification of overlapping periods. Second, we consider the past 12-month cumulative raw return as the momentum signal which is standard in the literature. Third, the carry signal is the normalized past one month difference between front month futures contract and second to maturity contract defined as $\frac{F_t^{T+1}}{F_t^T} - 1$, where F_t^{T+1} and F_t^T are the time t front and second to maturity futures contracts, respectively. The summary statistics for the carry signal are presented in Table 1.

The trading strategy based on the carry signal is well known in the currency literature (Burnside et al. 2011), where it is motivated by the failure of uncovered interest parity (UIP) documented by Bilson (1981) and Fama (1984). The currency carry trade can be equivalently stated in terms of borrowing low-interest-rate currencies and lending high-interest-rate currencies. Furthermore, the profitability of carry trades has been documented in commodity markets (Gorten et al. (2007)) and recently in equity and bond markets (Koijen et al (2011)).

The rest of this section lays out the technical details of the different trading strategies. It is important to note that we implement the trading strategies for each asset class separately and use a volatility weighted approach to aggregate them across asset classes.

Time Series Carry and Momentum strategy: Time series strategies consist of longing assets that have a positive carry and momentum signal, respectively, and shorting assets with a negative carry and momentum signal. We use the same construction as in Burnside et al. (2011) or Moskowitz et al (2011) and define the time series carry return for any asset $i = 1, ..., N$ within each asset class, as,

$$z^i_{t+1} = sign\left(\frac{F^{T+1}_{t,i}}{F^T_{t,i}} - 1\right) r^i_{t,t+1}, \tag{1}$$

while the time series momentum return is defined as,

$$z^i_{t+1} = sign\left(r^i_{t-12,t}\right) r^i_{t,t+1}. \tag{2}$$

$r^i_{t,t+1}$ is the one month return, $r^i_{t-12,t}$ the past 12 month cumulative return, and $\frac{F^{T+1}_{t,i}}{F^T_{t,i}} - 1$ the carry signal of asset i. The portfolio time series strategy combines all the individual momentum or carry returns in an equally-weighted portfolio, which is defined as,

$$R^j_{t+1} = \frac{1}{N}\sum_{i=1}^{N} z_{t+1}, \tag{3}$$

where N is the total number of assets within each asset class j. In total we get 8 time series trading strategies. One carry and one momentum strategies for each of the four asset classes, commodities, currencies, bonds, and equities.

Combo strategies: We define time series combo strategies as the equally weighted average of carry and momentum strategies within an asset class.

Volatility weighted trading strategies : In line with Moskowitz et al. (2011) and Asness et al. (2011) we construct inverse volatility weighted return portfolios *across* asset classes for time series carry, momentum and combo portfolios. We chose to volatility weight the strategies due to the very different volatilities across asset classes. The volatility weighting does not optimize the performance of the strategies which is in line with our objective to choose a general method to construct the portfolios. The returns to the volatility weighted portfolios are then defines as,

$$R^{Vol}_{t+1} = \frac{1}{4}\sum_{i=1}^{4} \frac{10\%/\sqrt{4}}{\sigma_i} R^j_{t+1} \tag{4}$$

where the scaling factor $\frac{10\%/\sqrt{4}}{\sigma_i}$ is chosen in such a way that the ex-ante performance of the portfolios is approximately equal to 10 %.

3 Characterizing Momentum and Carry returns

In this section, we present our main empirical results regarding the profitability and characteristics of carry and momentum strategies within and across asset classes, the exposure of the trading returns to traditional risk factors and the dynamics of the trading returns and correlations over time.

3.1 Returns to carry and momentum strategies

Within asset classes: Table 2, Panel A, shows the average annualized mean returns, standard deviations, kurtosis, skewness and sharpe ratios of the carry and momentum strategies within the asset classes commodities, currencies, bonds and equities. We report the carry and momentum returns individually and also report the returns to the combo strategies which is an equally weighted average of the portfolios. In addtion, we report the returns of an equally weighted long only portfolio within asset classes for comparison.

Turning to mean returns we find that commodities have the highest returns of 0.094 and 0.098 for momentum and carry, respectively. Currency and Bonds have similar means of 0.034 and 0.023 for momentum and 0.032 and 0.021 for carry. The biggest differences between momentum and carry returns are for equities with 0.076 for momentum and only 0.031 for the carry strategy.

The higher moments of the return distributions displays some interesting facts as well. First, the standard deviation of the momentum and carry strategies is highest for equities. Even higher then for commodities. Bonds have the lowest standard deviation, while currencies have standard deviations just in between bonds and commodities.The kurtosis is above 4 for all trading strategies and does not display any clear pattern. More interestingly are the patterns for the skewness. While the momentum and carry returns are positively skewed for Bonds and Equities they are negatively skewed for currencies. This is consistent with the literature, e.g. Menkhoff et al. (2011). The results for commodities are mixed. The momentum returns are negatively skewed while the carry returns are positively skewed.

In order to get a first measure of risk-adjusted returns we investigate the Sharpe ratios of the strategies. We find that commodities achieve the highest sharpe ratios of 0.98 for momentum and 1.09 for carry strategies both annualized. Currencies, bonds and equities return sharpe ratios of 0.49, 0.64 and 0.55 for momentum strategies and 0.62, 0.69. and 0.31 for carry strategies, respectively. It is interesting that commodities achieve the highest performance as they are regarded as the most risky asset class. Maybe this can be explained by their very low sharpe ratios of only 0.15 for long only strategies.

Table 2, Panel B, shows the correlations of the individual strategies within and across asset classes. First, the table shows that the correlation between carry and momentum strategies within asset class is relatively low. Commodity, currency and equity strategies display correlations of 0.12, 0.26 and 0.11. Only the bond strategies have a higher correlation of 0.62. This low correlation gives rise to combined portfolios of carry and momentum within asset classes. Table 2, Panel B, shows the summary statistics of the combo strategies. It is interesting to note that for all asset classes the combo strategies have a higher sharpe ratio than the individual strategies.

Figure 1 displays the cumulative returns of the carry, momentum and combo strategies for the individual asset classes. Commodities display the highest cumulative returns, followed by currencies and equities. Bonds have the lowest returns. These results are consistent with the mean returns in Table 2. An interesting observation from Figure 1 is how the curve of commodities and currencies flattens after December 2000 and August 2002, respectively. We will explore this feature further in section 3.3.

Across asset classes: Table 2 Panel B shows that the correlations of the strategies across asset classes are close to zero or even negative. For example, the carry strategy of commodities is negatively correlated with the momentum and carry strategy of currencies or the carry in currencies is negatively correlated to the carry and momentum strategies of equities. These findings give rise to a potential diversification benefit across asset classes. Table 3 shows the results of volatility weighting the strategies across asset classes. We find that all strategies have sharpe ratios of above 1. Furthermore, the negative skewness in many strategies is reduced significantly and close to zero in all cases. We will explore the dynamic structure of the correlation of the strategies in section 3.3. In the rest of the paper we will focus on examining the properties of the volatility weighted portfolios instead of examining the individual asset classes.

3.2 Risk factor exposure

Given the high returns of the strategies, we examine in this section whether the payoffs of carry, momentum and combo portfolios can be explained by traditional risk factors. In particular, we consider the following risk factors: in the first setting use the traditional CAPM with the S&P 500 and MSCI world as proxies for the market returns. Second, we consider the Fama and French (1993) factors, the excess return to the MSCI, the size premium (SMB), and the value premium (HML). In addition to those tradeable risk factor we also consider macro economic risk factors, namely the term spread, the short rate, the dividend yield and the default spread, and liquidity risk factor which consist of the TED spread, the Stambaugh market liquidity measure and a measure of total hedge fund capital.

Table 4 reports the estimates of the time series regression

$$r_t = \alpha + f_t'\beta + \epsilon_t \tag{5}$$

where r_t are the returns to the volatility weighted momentum, carry and combo portfolios and the $f_t's$ are the respective risk factors. We find that the CAPM model is not able to explain the returns to the trading portfolios. No strategy loads statistically significant on the S&P 500 index returns, while the carry strategy loads negatively on the MSCI World index. This results in highly significant alphas. The strategies load negatively or statistically insignificant on the Fama and French factors. Again this results in highly significant alphas. The second set of variables are non traded macroeconomic and liquidity risk factors. We find only one risk factor, the dividend yield, is statistically significant related to the combo strategy. Secondly, we find only weak results for the liquidity risk factors. Momentum is significantly related to the TED spread and the carry strategy to the hedge fund capital variable.

3.3 Dynamics of carry and momentum strategies

Finally, rather than looking at the static returns and correlations among carry and momentum strategies across asset classes, we study the dynamics of the strategy returns over time as well as the dynamic correlations.

We start by examining the stability of momentum, carry and combo strategies over time. Figure

3 plots the average returns to the three across asset class portfolios over rolling windows of 18 months. It can be seen that the profitability of the strategies is time-varying and that the highest returns were generated in the early period from 1976 to 1980 and in two later periods from the early 2000's to 2004 and during the financial crisis around 2008. In those time periods the trading strategies have reached average returns of above 2% per month. Also, the figure illustrates that the returns are far from being constant even over intermediate time intervals of several years. This is important for investors seeking to profit from those strategies because they need to have a long enough investment horizon and may induce limits to arbitrage. The second important observation is that carry, momentum and their combination seem to be highly correlated. This suggests a common factor structure across asset classes. The only time the high positive correlation decreased is during the recent financial crisis.

To get a better idea of the dynamic structure of the trading strategies, investigate the dynamics of the returns and correlations for each asset class individually, and to compare them we split our sample into two periods. Our first period is 1994-2002 and the second is 2002-2012. We start this investigation only in 1994 because this is the first time that all asset classes were traded. We report the annualized mean, the standard deviation and the sharpe ratio for each strategy and asset class for these two periods. For all strategies and asset classes there is a tendency for higher returns in the first half of the sample and lower returns in the second. The same holds for the sharpe ratios. This effect is particularly pronounced for commodities and currencies. The Sharpe ratios of momentum strategies decrease from 1.44 to 0.49 for commodities and 1.30 to 0.87 for currencies. The effect is also observable for the carry strategy. Here the sharpe for commodities decreased from 1.3 to 0.87 and for currencies from 1.00 to an insignificant sharpe ratio of 0.04. All these results remain valid for the combo strategies.

Next we examine the correlation dynamics across asset classes and trading strategies. Figure 4 plots the rolling two-year average correlation across asset classes for carry and momentum strategies. As the figure shows, there appears to be a time trend where momentum strategies have become more correlated over time. The opposite holds for carry strategies that appear to become less correlated. Consequently, we find that the correlation across momentum and carry strategies does not display any time trend. Table 5 Panel B reports the correlation within carry and momentum strategies across asset classes for the two time period mentioned earlier. We find, identical to Figure

4, that the correlation within momentum strategies increases from 0.07 to 0.20 and the correlation within carry strategies decreases from 0.07 to -0.01. The correlation across momentum and carry strategies remains constant at 0.11.

All previous results are interesting in light of the general growth in hedge fund assets and the financial sector in general. The increase in correlation of momentum strategies as well as the reducing returns to the trading strategies might be related to the increased participation of those financial institutions which implement the trading strategies across asset classes. To test more formally how carry and momentum correlations change over time, and are related to hedge fund activity and liquidity we run time series regressions that look at these effects simultaneously. To proxy for time-varying correlations, the dependent variable is the cross product of the carry and momentum strategy within and across the different asset classes (see Asness et al. (2011)).

Table 5 Panel C shows the resulting t-stats of regressing the time-varying correlation of the strategies on the liquidity, the hedge fund and the trend variable. We observe that the trend variable is indeed positively and statistically significant related to the correlation of the momentum strategies. On the other hand, the trend variable is negatively related to the correlation of the carry returns. This confirms the findings of the previous paragraph. Another interesting result is the relation of hedge fund capital flows and the time-varying correlations. For all correlations, within trading strategy and across, the flow variable is positively correlated and statistically significant. This indicates, that hedge funds do indeed have an effect on the performance of the carry and momentum strategies.

4 Predictability of Carry and Momentum Returns

In this section we consider the theoretical basis for predictability in carry and momentum strategies embedded in business cycle, liquidity and uncertainty indicators. For each of these classes of predictors we compare our empirical findings across assets classes to relevant studies for individual asset classes, predominately based in the equity cross-sectional momentum literature.

At the end of the section we present a parsimonious regression and discuss the relevant importance of predictors.

4.1 Business cycle predictors

To study the common drivers of carry and momentum strategies we investigate whether their excess returns are attributable to the predictable component of market returns derived from business cycle predictors. We conjecture that macroeconomic variables shown by previous studies to predict stock market returns will predict excess returns in our carry and momentum portfolios. We first consider the theoretical framework for this approach, and then discuss the empirical motivations and implications of each factor.

The theoretical basis for business cycle predictability stems from asset pricing models which relate expected returns to the conditional covariance of returns with the pricing kernel; defined as the marginal utility of consumption of a representative agent. Conjecturing a linear multivariate proxy for the pricing kernel yields a time varying multibeta model with K expected risk premiums, $\lambda_{kt}(\mathbf{X_{t-1}})$, where $k = 1, ...K$. Here, $\mathbf{X_{t-1}}$ is our information set conditional on time $t-1$. Now we define expected returns as,

$$E[R_{it}|\mathbf{X_{t-1}}] = \lambda_{0t} + \sum_k c_{ik}\lambda_{kt}(\mathbf{X_{t-1}}). \tag{6}$$

Here c_{ik} denotes the component of expected return derived from the kth conditional risk premium. Following the work of Ferson and Harvey (1991) and He et al. (1996) we postulate the conditional risk premium at time t can be written as a linear function of lagged macroeconomic variables; dividend yield (DIV), the short rate (YLD), the slope of the risk free term structure ($TERM$), the default spread (DEF), which are each defined in detail below. The kth conditional time t risk premium is therefore,

$$\lambda_{kt} = a_{k0} + a_{k1}DIV_{t-1} + a_{k2}\,YLD_{t-1} + a_{k3}\,TERM_{t-1} + a_{k4}DEF_{t-1}. \tag{7}$$

Rewriting equation 4.1 with equation 7 we obtain the one-period-ahead forecast of returns,

$$R_{it} = d_{i0} + d_{i1}DIV_{t-1} + d_{i2}\,YLD_{t-1} + d_{i3}\,TERM_{t-1} + d_{i4}DEF_{t-1} + e_{it}. \tag{8}$$

where $d_{i0} = \lambda_0 + \sum_k c_{ik}a_{k0}$ and $d_{ij} = \sum_k c_{ik}a_{kj}$ for $j > 0$. This provides a framework to study predictability embedded within the returns of carry and momentum, based on business cycle indicators; dividend yield, short rate, term spread and default spread.

We define the dividend yield (DIV) as the total dividend payments accruing over the previous 12 months to stocks in the CRSP value weighted index. The dividend yield has been shown to predict long term mean reversion in stock prices over several economic cycles (Keim and Stambaugh (1986) and Campbell and Shiller (1988)) and is considered a proxy for the risk premium embedded in equity prices (Fama and French (1988)), since a high dividend yield implies dividends are being discounted at a higher rate. Therefore, if the equity risk premium is embedded in carry and momentum portfolios we expect a high dividend yield to predict positive excess returns, and a significant positive regression coefficient.

The second factor we use is the short rate (YLD), defined as the yield on the three-month T-bill. Fama (1981) and Fama and Schwert (1977) demonstrate this rate is inversely related to future stock returns, suggesting that it serves as a proxy for expected economic growth.

We include the term spread ($TERM$), 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.

The final business cycle indicator in equation 8 is the default spread (DEF), 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 (1988) 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.

Table 5 shows the results of equation 8, alongside liquidity and uncertainty factors. We demonstrate that macroeconomic factors in isolation are able to predict 1.1% of in sample variance for cross asset momentum portfolio and 1.1% of the carry portfolio. We find the strongest predictability for the combined carry and momentum portfolio, where our indicators predict 2.8% of the monthly variance.

Across the macro forecasting regression we find that the short rate only significantly predicts returns for our carry portfolio. Interestingly, however, we report a positive sign, opposite to that reported in the equity literature where a low short rate is taken as a predictor of economic expansion and positive stock returns. This relation is consistent with the finding of Chordia and Shivakumar (2002) who report a significant positive coefficient in a predictive regression of equity cross-sectional momentum returns.

In our analysis of the term spread we find predictability in carry strategies in agreement with single stock equity risk premium literature, supporting the hypothesis that a high term spread forecasts economic expansion, generating a positive coefficient on the $TERM$ regressor in our predictive regression. An analogous result is also reported for the combined portfolio.

However, contrary to the findings of Chordia and Shivakumar (2002) who demonstrate the term spread to strongly predict cross-sectional momentum in equities, we find no evidence for an equivalent relationship when momentum strategies are taken across asset classes.

For default spreads we find the drivers of future returns in cross asset class trading strategies diverge from cross-sectional equity momentum demonstrated in Chordia and Shivakumar (2002). We find the lagged default spread has a positive coefficient for momentum returns across asset classes, in contrast to the positive coefficient found by Chordia and Shivakumar (2002)

The last macroeconomic predictor we consider is dividend yield. For both the individual portfolios and the combined portfolio we find a negative relation, opposite to the observations of stock returns and equity risk premia, as well as the equity cross section findings of Chordia and Shivakumar (2002). Notably, we find a very significant negative loading for the combined carry and momentum portfolios, suggesting a joint factor structure of carry and momentum portfolios when taken across asset classes.

In general, we find that incorporating additional asset classes to portfolios when studying carry and momentum portfolios dramatically alters the dynamics of predictability of momentum returns. In some cases the loading on macroeconomic factors even changes sign to that reported in the equity momentum literature.

Importantly, we find comparable dynamics in cross asset carry and momentum strategies, suggesting a common factor structure driving predictability. This common structure is emphasized in the combined carry and momentum portfolio where we find significant predictability using default spread, dividend yield and term spread.

4.2 Predictability using liquidity measures

In this section we consider whether liquidity acts as a predictor for returns of carry and momentum strategies. Previously, in section 3.2 we found that liquidity fails to account contemporaneously for time series momentum or carry across asset classes, in agreement with the results of Moskowitz et al. (2010b). In contrast for cross-sectional momentum Asness et al. (2011) find liquidity is a contemporaneous risk factor. In light of these results we consider whether liquidity factors predict returns in our time series carry and momentum portfolios across asset classes.

We motivate the inclusion of liquidity factors from the limits to arbitrage literature. Acharya et al. (2011) show in futures markets, comprised of speculators and hedgers, limits on speculators ability to meet hedging demand in the market lead to a risk premium. For instance, in a market where hedgers are net long, we would expect longer dated futures to trade above near dated, generating positive returns for speculators who take the short position. In this setting periods of illiquidity lead to speculators requiring a greater compensation for taking risk from the hedgers, generating higher returns. This mechanism will affect momentum and carry returns since both are related to the slope of futures term structure in our analysis.

Based on this methodology we regress the performance of our carry and momentum portfolios on lagged liquidity factors. These are 3 month LIBOR (B3M), TED spread, market liquidity, defined for our risk factors analysis in section 3.2. The results are given in table 5.

Intriguingly, despite finding little contemporaneous relation between our portfolios and liquidity measures, we find that liquidity measures have significant predictive power over all three of our strategies. We demonstrate that liquidity factors are able to explain more of the variance of returns for each carry, momentum and the combined portfolios.

4.3 Predictability using uncertainty measures

The third class of predictor for carry and momentum returns we consider is uncertainty. In a recent study Stambaugh et al. (2011) use the sentiment index of Baker and Wurgler (2006), derived from the first principle component of a number of sentiment factors, to proxy for macroeconomic uncertainty. Stambaugh et al. (2011) demonstrate the sentiment measure significantly predicts returns of a number of market anomalies including equity cross sectional momentum.

They argue that in periods where sentiment is high there will exist greater short selling risk. These generate restrictions on the short selling of assets, which in turn leads to over pricing of assets. This over pricing of certain assets then yields returns on the short legs of momentum trades.

In regressions of strategy performance on the lagged sentiment index of Baker and Wurgler (2006) we find highly significant predictability. However, the measure fails to explain as much of the variance as either liquidity or macroeconomic factors, and is subsumed in group regressions, reported in the next section.

4.4 Comparison of predictability measures

In the last section of table 5 we regress the performance of our strategies on all of the predictive factors, providing a comparison of the relative performance of the different predictors. We find that hedge fund flows significantly, with t-statistics greater than 3 for momentum and the combined portfolios, predict strategy returns even when controlling for macroeconomic factors and uncertainty measures. Furthermore, for uncertainty, we show that any predictability is subsumed by the liquidity and macroeconomic factors.

Looking at the explanatory power of the collective regression we see that a combination of liquidity, macroeconomic and uncertainty factors improves the adjusted R-squared compared to regressions within the predictor classes for all three strategies. This implies an orthogonal predictive component between liquidity and macroeconomic measures for momentum and carry returns. The combined portfolio of carry and momentum is particularly revealing; we find 7% of the variance of the combined monthly returns is explained using our predictors. This suggests a common factor structure between carry and momentum.

5 Conclusion

Taken individually, and within asset class, carry and momentum both produce abnormal returns. For each strategy we demonstrate a significant diversification benefit when combing volatility weighted returns across asset classes. Studying the correlation dynamics between asset classes within the strategies we find cross asset correlation over the last 20 years has increased for momentum and has decreased (if anything) for carry. Between the two strategies we find no evidence of a time trend in correlation, although the correlation between and within the strategies co-moves. In all cases we also find that correlation is closely related to hedge fund flows. With times of higher carry-momentum correlation coinciding with positive fund flows. On account of their low correlation, when collecting cross asset carry and momentum strategies into a combined portfolio we demonstrate significant diversification benefits.

To understand the origins of carry and momentum profits we examine to what extent their returns relate to common risk factors used throughout the literature, including Fama and French, macroeconomic and liquidity factors. We find that the strategies can not be explained with these traditional risk factors, retaining significant alpha in all cases.

Intriguingly, in one month forecasting regressions we find liquidity factors - most prominently hedge fund flows - strongly predict individual carry and momentum returns. We find a marked increased in this predictability when the carry and momentum are combined, suggesting liquidity risk is a common factor. In addition to a liquidity story the combined portfolio also demonstrates the influence of time varying risk premia. This is implied as the predictive regression is enhanced with the addition of business cycle predictors. These results provide an intriguing platform from which to relate fund flows, predictability and trading strategy returns.

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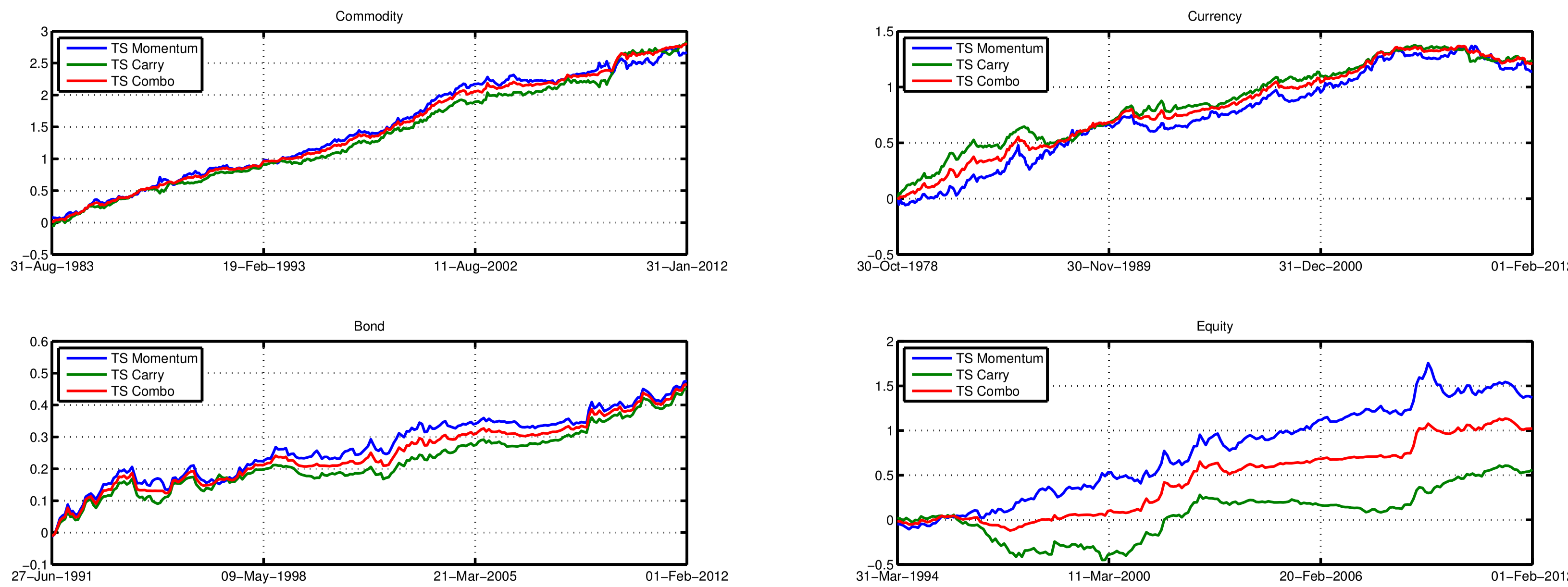

Figure 1: **Cumulative returns of momentum, carry and combo strategy within asset classes:** The figure displays the cumulative return of the carry, momentum and combo strategies for the four asset classes, commodities, currencies, bonds and equities. The sample period differ from one to the other asset class.

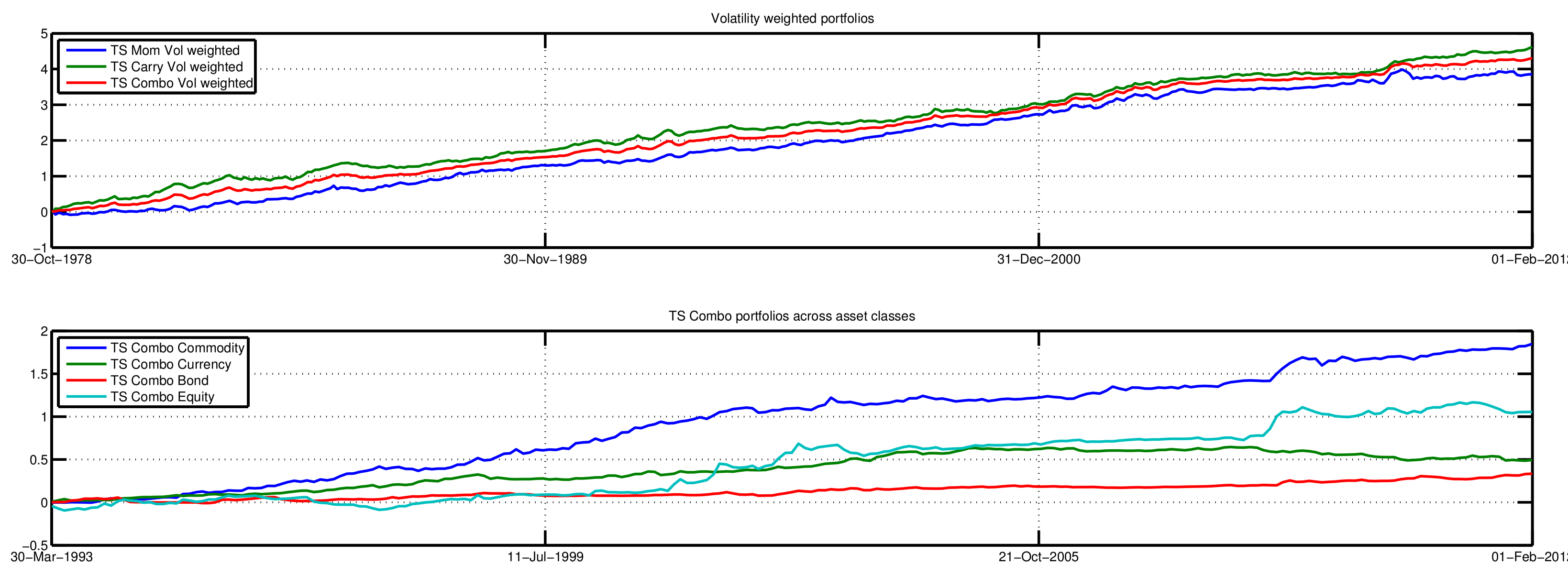

Figure 2: **Cumulative returns of volatility weighted momentum, carry and combo strategy across asset classes:** The figure displays the cumulative return of the volatility weighted momentum, carry and combo strategies as well as the cumulative returns of the combo strategies by asset class.

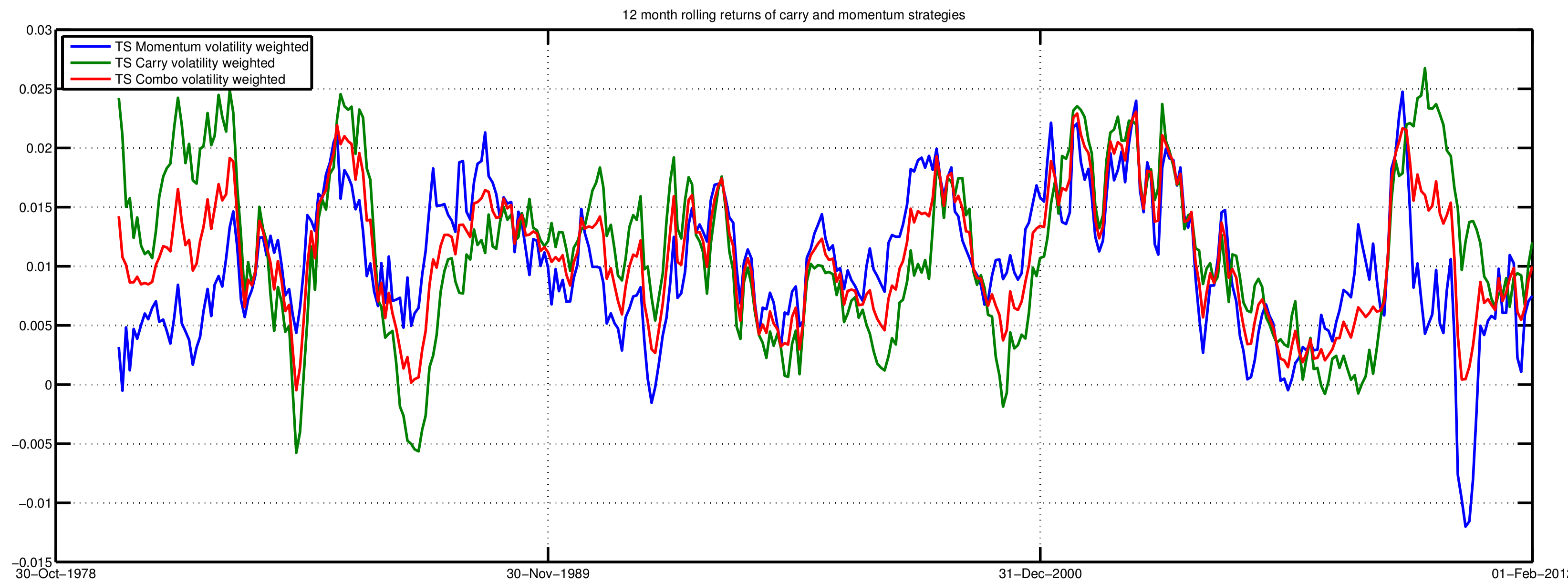

Figure 3: **Rolling 18 month average returns of volatility weighted momentum, carry and combo strategy across asset classes:** The figure displays the 18-month rolling moving average of the volatility weighted momentum, carry and combo portfolios.

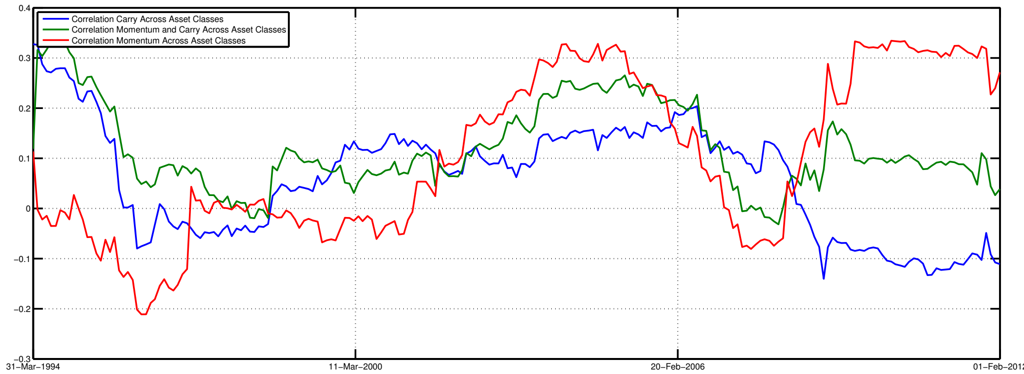

Figure 4: **Correlation of individual momentum and carry strategies across asset classes:** This figure displays the rolling 18-month correlation within momentum and carry strategies. Furthermore, we report the correlation across momentum and carry strategies.

Table 1: **Individual summary statistics:** Panel A, B, C, and D in this Table presents the summary statistics for the individual commodities, currencies, bonds and equities, respectively. The table presents the name of the contract, the period of availability, mean excess returns, standard deviations, skewness and Sharpe ratios. The next columns show the mean and standard deviation of the individual carry signals. All statistics are annualized.

Panel A: Commodities								
Contract	**Period**		**Excess Return**				**Carry**	
	Start	End	Mean	Vol.	Skew	Sharpe	Mean	Vol.
Soybean Oil	Jul 82	Jan 12	-0.020	0.264	0.056	-0.075	-0.080	0.050
Cocoa	Jul 86	Jan 12	-0.080	0.292	0.236	-0.275	-0.074	0.117
NY Light Sweet Crude Oil	Jan 87	Jan 12	0.083	0.341	-0.171	0.243	0.013	0.072
Corn	Jul 82	Jan 12	-0.063	0.253	0.039	-0.250	-0.242	0.122
Brent Crude Oil ICE	Aug 03	Jan 12	0.105	0.334	-1.185	0.315	-0.058	0.044
Cotton	Jan 87	Jan 12	-0.044	0.270	-0.118	-0.165	-0.134	0.164
Feeder Cattle	Jan 78	Jan 12	0.031	0.146	-0.378	0.211	0.010	0.063
ICE Gasoil	Jan 10	Jan 12	0.224	0.235	-0.779	0.953	-0.019	0.021
Copper COMEX	Dec 89	Jan 12	0.076	0.272	-0.538	0.279	0.039	0.066
Unleaded Gasoline	Sep 87	Dec 06	0.168	0.353	0.148	0.477	0.134	0.159
TOCOM Platinum	Jul 03	Jan 12	0.058	0.286	-1.773	0.203	0.038	0.019
TOCOM Gold	Jul 03	Jan 12	0.127	0.187	-1.524	0.677	-0.012	0.012
Orange Juice	Jul 87	Jan 12	-0.011	0.310	0.288	-0.034	-0.093	0.115
Coffee	Jan 87	Jan 12	-0.073	0.372	0.427	-0.195	-0.119	0.141
Lumber	Dec 74	Jan 12	-0.099	0.300	-0.004	-0.332	-0.273	0.175
Live Cattle	Dec 74	Jan 12	0.036	0.167	-0.392	0.214	0.042	0.131
NY Natural Gas	Jan 93	Jan 12	-0.185	0.603	0.238	-0.307	-0.229	0.205
Oats	Jul 82	Jan 12	-0.084	0.315	0.991	-0.268	-0.247	0.170
Sugar	Jul 86	Jan 12	0.043	0.331	-0.065	0.129	0.026	0.195
Soybean Meal	Jul 82	Jan 12	0.051	0.255	-0.190	0.200	0.026	0.090
Silver COMEX	Dec 83	Jan 12	-0.006	0.278	-0.125	-0.020	-0.080	0.059
Soybeans	Jul 82	Jan 12	0.004	0.240	-0.371	0.016	-0.063	0.071
Wheat CBOT	Jul 82	Jan 12	-0.069	0.257	-0.056	-0.270	-0.187	0.136
ICE WTI Light Sweet Crude Oil	Jan 10	Jan 12	0.044	0.285	-0.563	0.156	-0.095	0.024
Unleaded Gasoline (RBOB)	Oct 06	Jan 12	0.119	0.397	-1.399	0.300	0.045	0.085
Panel B: Bonds								
Australian 90-day SFE	Jul 01	Jan 12	-0.000	0.008	1.960	-0.048	0.003	0.009
Australian 10-year SFE	Jul 01	Jan 12	0.003	0.009	0.115	0.363	-0.001	0.009
Australian 3-year SFE	Jul 01	Jan 12	0.005	0.011	0.345	0.455	-0.000	0.011
Euro Bobl 5-year	Jan 97	Jan 12	0.026	0.033	-0.016	0.804	0.046	0.018
Euro Bund 10-year	Jan 97	Jan 12	0.039	0.053	0.068	0.751	0.056	0.015
Buxl 30yr	Sep 05	Jan 12	0.046	0.119	1.062	0.387	0.006	0.063
Euro Schatz 2-year	Mar 97	Jan 12	0.010	0.014	0.045	0.729	0.021	0.008
Canadian Govt Bond	Apr 90	Jan 12	0.047	0.059	-0.115	0.796	0.053	0.060
LIBOR 1-month	Sep 90	Dec 01	0.008	0.007	0.523	1.125	0.002	0.009
T-Notes 5-year	Jul 88	Jan 12	0.032	0.043	-0.020	0.754	0.061	0.032
Long Gilt LIFFE	Jul 98	Jan 12	0.027	0.059	0.125	0.459	0.053	0.067
Japanese 10-year Bond TSE	Jul 03	Jan 12	0.016	0.032	-0.725	0.511	0.057	0.022
T-Notes 2-year	Jan 91	Jan 12	0.017	0.018	0.221	0.963	0.031	0.013
T-Notes 10-year	Jan 83	Jan 12	0.047	0.070	0.052	0.669	0.091	0.038
T-Bond 30-year	Oct 82	Jan 12	0.055	0.105	0.079	0.522	0.104	0.060

Panel C: Currencies								
Contract	**Period**		**Excess Return**				**Carry**	
	Start	End	Mean	Vol.	Skew	Sharpe	Mean	Ann.Vol.
Australian Dollar	Jan 87	Jan 12	0.046	0.118	-0.605	0.388	0.081	0.024
British Pound	Sep 77	Jan 12	0.013	0.108	-0.138	0.117	0.046	0.019
Canadian Dollar	Jan 77	Jan 12	0.008	0.069	-0.529	0.116	0.018	0.013
US Dollar Index	Jul 89	Jan 12	-0.020	0.088	0.318	-0.228	-0.032	0.030
Euro FX	Jan 99	Jan 12	0.008	0.110	-0.156	0.074	-0.007	0.013
Japanese Yen	Mar 77	Jan 12	0.006	0.119	0.327	0.046	-0.096	0.022
Swiss Franc	Dec 74	Jan 12	-0.001	0.126	-0.099	-0.011	-0.086	0.027
Panel D: Equities								
DAX Index	Jan 97	Jan 12	0.024	0.245	-0.815	0.099	-0.082	0.016
AEX Index	Jan 08	Jan 12	-0.057	0.249	-0.919	-0.230	0.024	0.015
FTSE 100 Index	Jul 98	Jan 12	-0.010	0.156	-0.656	-0.067	-0.019	0.065
Hang Seng Index	Feb 01	Jan 12	0.045	0.231	-0.608	0.196	0.018	0.015
IBEX 35 Index	Jul 03	Jan 12	0.041	0.190	-0.685	0.218	0.007	0.032
FTSE/MIB Index	Oct 04	Jan 12	-0.061	0.220	-0.541	-0.279	0.069	0.045
KOSPI 200	Sep 03	Jun 11	0.148	0.222	-0.651	0.666	-0.026	0.025
NASDAQ 100 Index	Apr 96	Jan 12	0.053	0.295	-0.589	0.180	-0.104	0.097
Nikkei 225 Index	Sep 90	Jan 12	-0.054	0.221	-0.299	-0.247	-0.008	0.139
S & P Canada 60 Index	Oct 99	Jan 12	0.035	0.166	-0.845	0.213	0.016	0.200
Russell 2000 Index	Feb 93	Dec 08	0.019	0.191	-0.934	0.098	-0.006	0.122
S & P 500 Index	Apr 82	Jan 12	0.056	0.158	-0.850	0.357	-0.078	0.033
Swiss Market Index	Oct 98	Jan 12	-0.002	0.152	-0.618	-0.014	0.023	0.032
Tokyo Price Index	Jul 03	Jan 12	-0.011	0.187	-1.042	-0.060	0.088	0.156
MSCI Taiwan Index	Apr 97	Jan 12	0.007	0.285	-0.043	0.024	0.031	0.051
DJ Stoxx 50 Index	Jul 03	Jan 12	0.016	0.150	-0.695	0.109	0.061	0.105
DJ Euro Stoxx 50 Index	Jul 98	Jan 12	-0.023	0.213	-0.593	-0.110	0.017	0.043
NYSE Composite Index	Jan 84	May 03	0.057	0.149	-1.098	0.381	-0.066	0.075

Table 2: **Summary statistics of time series (TS) strategies within and across asset classes based on momentum (mom) and carry signals:** This Table reports mean, standard deviations (both annualized), skewness, and kurtosis of timeseries (TS) portfolios based on the momentum (mom) and carry signals for the asset classes, commodity, currency, bond and equity. Numbers in the brackets show Newey and West (1987) adjusted t-statistics. Returns are monthly and the sample period is 01/1982 to 01/2012.

Panel A: Summary statistics

	Commodity				**Currency**				**Bond**				**Equity**			
	Mom	Carry	Combo	long	Mom	Carry	Combo	long	Mom	Carry	Combo	long	Mom	Carry	Combo	long
mean	0.094	0.098	0.097	0.020	0.034	0.032	0.032	0.011	0.023	0.021	0.021	0.031	0.076	0.031	0.056	0.038
(t-stat)	5.151	5.940	7.524	0.800	2.875	3.631	3.799	0.963	2.991	3.220	3.289	3.790	2.392	1.346	2.667	0.994
stdev	0.099	0.089	0.070	0.135	0.070	0.052	0.049	0.068	0.036	0.030	0.030	0.039	0.139	0.101	0.091	0.166
kurtosis	5.233	4.830	4.936	7.024	4.805	4.918	4.865	4.116	4.220	4.547	5.096	3.445	5.325	6.108	9.086	4.507
skewness	-0.241	0.570	0.182	-0.652	-0.567	-0.634	-0.603	-0.001	0.228	0.069	0.244	-0.027	0.583	0.915	1.647	-0.894
Sharpe	0.948	1.094	1.385	0.147	0.491	0.620	0.648	0.164	0.641	0.690	0.705	0.813	0.550	0.309	0.613	0.228

Panel B: Correlations

		Commodity		**Currency**		**Bond**		**Equity**	
		tsmom	tscarry	tsmom	tscarry	tsmom	tscarry	tsmom	tscarry
Commodity	tsmom	1.000	0.119	0.256	0.105	0.059	0.024	0.251	0.163
	tscarry		1.000	-0.044	-0.152	0.130	0.123	0.126	0.058
Currency	tsmom			1.000	0.262	0.078	0.023	0.307	0.077
	tscarry				1.000	0.081	0.042	-0.069	-0.037
Bond	tsmom					1.000	0.619	0.131	0.139
	tscarry						1.000	0.054	0.012
Equity	tsmom							1.000	0.114
	tscarry								1.000

Table 3: **Summary statistics of volatility weighted trading strategies across asset classes on momentum (mom) and carry signals:** This Table reports mean, standard deviations (both annualized), skewness, and kurtosis of timeseries (TS) and cross sectional (CS) portfolios based on the momentum (mom) and carry signals for the asset classes, commodity, currency, bond and equity. Furthermore, summary statistics of volatility weighted portfolios across asset classes are presented. Numbers in the brackets show Newey and West (1987) adjusted t-statistics. Returns are monthly and the sample period is 01/1982 to 01/2012.

Panel A: Summary statistics				
	Across asset classes			
	Mom	Carry	Combo	long
mean	0.116	0.127	0.118	0.021
(t-stat)	5.968	6.876	7.523	0.827
stdev	0.114	0.109	0.092	0.096
kurtosis	5.316	3.431	4.303	5.122
skewness	-0.285	-0.056	-0.062	-0.012
Sharpe	1.018	1.173	1.284	0.21

Table 4: **Risk exposure:** This table reports the estimates of the equation $z_t = a + f_t'\beta + \epsilon_{t+1}$, where z_t is the monthly volatility weighted carry, mom and combo strategy, respectively and f_t is a vector of risk factors. We divide the table into trade able risk factors and non trade able risk factors. Tradable risk factors are the CAPM factors and Fama-French factors, while non trade able factors are macro risk factors and liquidity risk factors. Heteroscedasticity-consistent standard errors are in parentheses.

Traded risk factors							
		MSCI	S&P 500			alpha	R^2
CAPM	**mom**	0.000	-0.006			0.010	0.027
		(0.118)	(-1.4185)			(7.639)	
	carry	-0.011	0.004			0.011	0.055
		(-2.164)	(0.901)			(7.545)	
	combo	-0.006	-0.000			0.010	0.05
		(-1.648)	(-0.040)			(7.833)	
		HML	SMB	MSCI		alpha	R^2
Fama-French	**mom**	-0.007	-0.006	0.001		0.010	0.058
		(-2.299)	(-3.172)	(0.121)		(7.413)	
	carry	0.001	-0.004	-0.009		0.010	0.011
		(0.840)	(-1.712)	(-1.62)		(6.585)	
	combo	-0.002	-0.005	-0.005		0.010	0.033
		(-1.537)	(-3.179)	(-1.685)		(7.522)	
Non traded risk factors							
		tspread	short	dyield	dspread		R^2
Macro Risk	**mom**	-0.000	-0.001	-0.002	0.004		0.006
		(-0.309)	(-0.378)	(-0.713)	(1.717)		
	carry	0.002	0.004	-0.005	0.003		0.008
		(0.984)	(1.190)	(-1.690)	(1.197)		
	combo	0.002	0.003	-0.005	0.005		0.021
		(0.813)	(0.976)	(-2.233)	(1.752)		
		TED	STLiq	HFAUM	BBSRB3M		R^2
Liquidity riskk	**mom**	0.003	-0.002	0.001	0.000		0.004
		(1.843)	(-1.028)	(0.359)	(0.169)		
	carry	-0.000	-0.000	-0.004	0.000		-0.000
		(-0.051)	(-0.340)	(-1.832)	(0.580)		
	combo	0.001	-0.001	-0.001	0.000		0.001
		(1.202)	(-0.868)	(-0.547)	(0.541)		

Table 5: **Dynamics of momentum and carry strategies:** Panel A reports the mean, standard deviation and Sharpe ratio of momentum, carry and combo strategies for the time period 04/1994 to 08/2002 and 08/2002 to 01/2012 for the individual asset classes commodities, currencies, bonds and equities. Furthermore, results for the volatility weighted portfolios are reported. Panel B reports the average correlation within momentum strategies, carry strategies and across the strategies for the same two time periods as before. Panel C investigates the dynamics of the correlation. The panel reports the t-stats of regressing instantaneous correlation on liquidity measures and a time trend.

Panel A: Risk/Return										
		Momentum			**Carry**			**Combo**		
		Mean	Std	Sharpe	Mean	Std	Sharpe	Mean	Std	Sharpe
Commodity	04/1994-08/2002	0.12	0.08	1.44	0.11	0.09	1.30	0.118	0.07	1.54
	08/2002-1/2012	0.06	0.12	0.49	0.09	0.11	0.87	0.08	0.07	1.09
Currency	04/1994-08/2002	0.05	0.05	0.93	0.04	0.04	1.00	0.05	0.04	1.15
	08/2002-1/2012	0.00	0.07	0.01	0.01	0.04	0.04	0.00	0.04	0.03
Bond	04/1994-08/2002	0.02	0.03	0.49	0.01	0.03	0.42	0.01	0.03	0.55
	08/2002-1/2012	0.02	0.03	0.62	0.02	0.03	1.01	0.02	0.03	0.84
Equity	04/1994-08/2002	0.09	0.14	0.65	0.02	0.12	0.14	0.06	0.10	0.60
	08/2002-1/2012	0.07	0.14	0.48	0.04	0.07	0.60	0.06	0.08	0.69
All	04/1994-08/2002	0.12	0.10	1.45	0.14	0.11	1.23	0.14	0.09	1.54
	08/2002-1/2012	0.08	0.13	0.60	0.12	0.08	1.40	0.10	0.08	1.20
Panel B: Correlations										
		$\rho(M,M)$	$\rho(C,C)$	$\rho(C,M)$						
	04/1994-08/2002	0.07	0.07	0.11						
	08/2002-1/2012	0.20	-0.01	0.11						
Panel C: Dynamics of correlations										
		BBSR	TED	Miq	Flows	trend				
	$\rho_t(M,M)$	2.52	-0.81	0.26	2.16					
	$\rho_t(C,C)$	-0.32	-2.09	-0.44	2.08					
	$\rho_t(C,M)$	0.93	-1.22	-0.87	3.15					
	$\rho_t(M,M)$					2.30				
	$\rho_t(C,C)$					-1.92				
	$\rho_t(C,M)$					0.39				

Table 6: **Predictive regressions:** This table tests the predictability of monthly volatility weighted momentum and carry portfolios across asset classes. The table presents the results of regressing volatility weighted momentum and carry portfolios onto business cycle, liquidity and uncertainty predictor variables, respectively. All predictor variables are lagged one month. The table reports Newey-West adjusted t-statistics.

	General Macro				**Liquidity exposure**				**Uncertainty**	
	dspread	dyield	short	tspread	B3M	TED	Mliq	HFFlow	Uncertainty	R^2
tsmom	0.005	-0.005	0.002	0.002						0.011
tstat	2.162	-2.003	0.822	1.316						
tscarry	0.002	-0.005	0.006	0.004						0.011
tstat	0.962	-1.766	1.996	2.278						
comboall	0.004	-0.006	0.005	0.004						0.029
tstat	1.953	-3.016	1.991	2.499						
tsmom					0.003	0.002	-0.000	0.007		0.032
tstat					2.443	1.836	-0.184	3.440		
tscarry					0.002	0.000	0.003	0.007		0.027
tstat					1.614	0.076	2.163	3.963		
comboall					0.002	0.002	0.002	0.007		0.041
tstat					2.442	1.342	1.273	3.893		
tsmom									0.006	0.014
tstat									3.705	
tscarry									0.005	0.010
tstat									2.094	
comboall									0.007	0.028
tstat									3.593	
tsmom	0.002	-0.003	0.004	0.003	0.003	0.004	-0.000	0.006	0.004	0.040
tstat	0.959	-1.108	1.348	1.678	1.797	3.214	-0.169	2.378	1.778	
tscarry	-0.000	-0.004	0.007	0.005	0.003	0.001	0.003	0.007	0.001	0.037
tstat	-0.158	-1.097	2.133	2.313	1.767	0.861	2.260	3.577	0.266	
comboall	0.001	-0.004	0.006	0.004	0.003	0.003	0.002	0.006	0.002	0.068
tstat	0.429	-1.680	2.545	2.657	2.235	2.646	1.331	3.380	1.137	