Commodity Strategies Based on Momentum, Term Structure and Idiosyncratic Volatility

Ana-Maria Fuertes*, Joëlle Miffre **, Adrian Fernandez-Perez***

First version: February 2013

This version: January 2014

* Professor of Financial Econometrics, Cass Business School, City University, London, ECIY 8TZ, England; Tel: +44 (0)20 7040 0186; E-mail: a.fuertes@city.ac.uk.

** Professor of Finance, EDHEC Business School, 392 Promenade des Anglais, Nice, France; Tel: +33 (0)4 9318 3255. E-mail: Joelle.Miffre@edhec.edu. *Corresponding author.*

*** Research Fellow, Auckland University of Technology, Private Bad 92006, 1142 Auckland, New Zealand; Tel: +64 9921 9999. E-mail: adrian.fernandez@aut.ac.nz.

The research was supported by funding from INQUIRE UK which we gratefully acknowledge. The article represents the views of the authors and not of INQUIRE UK. We would like to thank two anonymous referees, Katja Ahoniemi, Chris Brooks, Jerry Coakley and George Skiadopoulos for useful suggestions. We also acknowledge the comments from seminars participants at the Universitat de Illes Ballears, Universidad de las Palmas de Gran Canaria, 2012 EDHEC-Risk Days Conference and 2011 CSDA Conference on Computational and Financial Econometrics.

Commodity Strategies Based on Momentum, Term Structure and Idiosyncratic Volatility

Abstract

This article demonstrates that momentum, term structure and idiosyncratic volatility signals in commodity futures markets are not overlapping which inspires a novel triple-screen strategy. We show that simultaneously buying contracts with high past performance, high roll-yields and low idiosyncratic volatility, and shorting contracts with poor past performance, low roll-yields and high idiosyncratic volatility yields a Sharpe ratio over the 1985 to 2011 period which is five times that of the S&P-GSCI. The triple-screen strategy dominates the double-screen and individual strategies and this outcome cannot be attributed to overreaction, liquidity risk, transaction costs or the financialization of commodity futures markets.

Keywords: Commodity futures, Momentum, Term structure, Idiosyncratic volatility.

JEL classifications: G13, G14

1. Introduction

The recent literature on commodity futures pricing has shown that long-short portfolios based on various signals can capture the risk premium of commodity futures, although their ability to explain the cross-section variation in returns is still subject to debate (Daskalaki *et al.,* 2012; Bakshi *et al.*, 2013; Szymanowska *et al.,* 2013). These signals are based on momentum (Erb & Harvey, 2006; Miffre & Rallis, 2007; Shen *et al.*, 2007; Szakmary *et al.*, 2010), the slope of the term structure of commodity futures prices (Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006), inventory levels (Gorton *et al.*, 2012), hedging pressure (Basu & Miffre, 2013; Dewally *et al*., 2013) or idiosyncratic volatility (Miffre *et al.*, 2013).

This article is concerned with three of those signals, term structure, momentum and idiosyncratic volatility, labeled hereafter as TS, Mom and IVol, respectively. The TS signal consists of taking long positions in commodities with downward-sloping term structures (or positive roll-yields) and short positions in commodities with upward-sloping term structures (or negative roll-yields), and relates to the theory of storage (Working, 1949; Brennan, 1958) and thus to inventory considerations (Gorton *et al.*, 2012).[1] The other two signals, Mom and IVol, originated in the equity pricing literature with Jegadeesh & Titman (1993) proposing the long-short Mom strategy that buys recent winners and shorts recent losers[2] and Ang *et al.* (2006, 2009) bringing forward the IVol strategy that buys stocks with low idiosyncratic

[1] When inventories are high, the TS is upward-sloping which encourages inventory holders to buy the physical commodity at a cheap price and sell it forward at a premium that exceeds the cost of storing and financing the commodity. The TS strategy recommends selling such contangoed commodities as their price tends to decline with contract maturity. When inventories are low, the TS is downward-sloping because the convenience yield derived from owning the commodity spot then exceeds the costs of storage and financing incurred in the spot market. The TS strategy recommends buying such backwardated commodities as their price tends to rise with contract maturity.

[2] While the profitability of momentum strategies is undisputed, there is still some debate regarding the reasons behind the profits. While Lesmond *et al.* (2004) and Chordia & Shivakumar (2002) attribute them to transaction costs or time-variation in expected returns, behavioral models such as Barberis *et al.* (1998), Daniel *et al.* (1998) and Hong & Stein (1999) relate the abnormal returns to cognitive errors that investors make when incorporating information into prices (see also Cooper *et al.*, 2004).

volatility and sells stocks with high idiosyncratic volatility, where the latter is modeled relative to the three-factor model of Fama & French (1993).[3]

The present article demonstrates that, when applied to commodities, the Mom, TS and IVol signals are non-overlapping which motivates the design of a new triple-screen strategy. Consistently buying commodity futures with high past performance, high roll-yields and low IVol and shorting contracts with poor past performance, low roll-yields and high IVol generates a sizeable Sharpe ratio that compares favorably to the one obtained when using the signals either in isolation or in pairs. Over the same period, the Sharpe ratio of the Standard & Poor's Goldman Sachs Commodity Index (S&P-GSCI) is also notably smaller. In formal statistical tests, we demonstrate that the profitability of the long-short triple-screen portfolios is driven neither by liquidity risk, nor by overreaction, and is robust to transaction costs. We also show that the above findings are not purely an artifact of the recent financialization observed in commodity futures markets. Last but not least, the long-short portfolios formed via the triple-screening of signals are better able to diversify equity risk than the long-only S&P-GSCI portfolio. The added performance and increased diversification benefits come at the cost of losing the inflation hedge provided by long-only positions in commodities.

The remainder of the paper unfolds as follows. Section 2 presents the dataset and Section 3 discusses the extent to which the Mom, TS and IVol signals overlap as predictors of commodity futures returns. Section 4 outlines our triple-screen strategy and analyzes its performance. Section 5 presents various robustness checks before concluding in Section 6.

[3] A large literature tests whether IVol is priced in equity markets. Some articles advocate the presence of a zero relationship between IVol and equity returns as investors should not request a premium for holding a risk that is easy to diversify (e.g., Sharpe, 1964; Bali & Cakici, 2008; Huang *et al.,* 2010; Han & Lesmond, 2011). Other papers show that the relationship is either positive (Merton, 1987; Goyal & Santa-Clara, 2003; Malkiel & Xu, 2004; Fu, 2009) or negative (Ang *et al.*, 2006, 2009).

2. Data

The analysis is based on the daily settlement prices of 27 commodity futures contracts over the period January 2, 1979 to August 31, 2011 which are downloaded from *Datastream.* The cross-section includes various styles such as agriculture (cocoa, coffee C, corn, cotton n°2, frozen concentrated orange juice, rough rice, oats, soybean meal, soybean oil, soybeans, sugar n° 11, wheat), energy (electricity, gasoline, heating oil n° 2, light sweet crude oil, natural gas), livestock (feeder cattle, frozen pork bellies, lean hogs, live cattle), metals (copper, gold, palladium, platinum, silver) and random length lumber. Daily settlement prices on the S&P-GSCI over the same period are obtained from *Bloomberg*.

In designing our commodity trading strategies, we make sure that the most liquid futures contracts (*i.e.*, nearest or second-nearest to maturity) are held in the long-short portfolios. This is achieved by using the prices of the nearest contract until the last day of the month prior to maturity, when we roll then to the prices of the second-nearest contract.

To establish robust evidence, we measure the performance of our strategies after factoring in the risk premium that investors may demand for holding illiquid assets. Since contracts located in the mid- to far-end of the term structure are less liquid, we model the liquidity risk premium, following Pastor & Stambaugh (2003), using *all* contracts available in the term structure of the 27 commodities over the period from January 1979 to August 2011. Thus we construct a liquidity risk premium series that spans the period from January 1985 to August 2011. The latter implies that, effectively, January 1985 represents the beginning of the timeframe over which the performance of the strategies is studied.

The long-short commodity portfolios are fully collateralized meaning that half of the trading capital is invested in risk-free interest bearing accounts for the both the long and short portfolios. Thus investors earn half of the returns of the ‘longs’ minus half of the returns of the 'shorts'. Unless we explicitly refer to total (*i.e.*, excess plus collateral) returns, the empirical results presented in the paper are based on excess (*i.e.*, total minus collateral) returns and will be simply referred to as returns. Proxying the risk-free rate by the 3-month US Treasury-bill rate implies that the collateral mean return over our effective sample period (1985-2011) stands at 4.10%. Thus, assuming no margin calls, the gross performance of the unlevered portfolios reported hereafter is understated by that amount.[4]

3. Individual Momentum, Term Structure and Idiosyncratic Volatility Signals

Recent papers suggest that Mom, TS and IVol signals have predictive content for commodity futures returns (see *e.g.*, Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006; Miffre & Rallis, 2007; Miffre *et al.*, 2013). This section discusses the three individual signals.

3.1 Benchmark model for idiosyncratic volatility

Unlike the momentum and term structure signals, the idiosyncratic volatility signal has to be defined on the basis of a chosen benchmark model which can be formalized as

$$r_{i,d} = \alpha_i + \boldsymbol{\beta}_i^{'}\boldsymbol{F_d} + \varepsilon_{i,d}, \qquad d = 1, \ldots, D \text{ days} \tag{1}$$

where $r_{i,d}$ is the day d return of the i^{th} commodity futures contract, $\boldsymbol{F_d}$ is a vector of systematic risk premia, $\varepsilon_{i,d}$ is an innovation, and $(\alpha_i, \boldsymbol{\beta}_i^{'})$ are parameters estimated by OLS iteratively over the days spanned by a rolling window of R ={1, 3, 6 or 12} months. As in Ang *et al.* (2006, 2009), the IVol strategy buys (sells) the assets with the lowest (highest) IVol signal which is obtained as the residual standard deviation of the above time-series model.

[4] This is the approach adopted in Szakmary *et al.* (2010) and Basu & Miffre (2013). Others opt for levered portfolios (Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006; Miffre & Rallis, 2007; Shen *et al.*, 2007; Fuertes *et al.*, 2010). Note that the choice of fully-collateralized long-short portfolios, as opposed to levered ones, is purely an "accounting" choice that affects means and standard deviations but has no influence on statistical significance or Sharpe ratios.

Which risk factors are plausible candidates for inclusion in the above equation? Two types of risk factors have been used in the commodities literature. On the one hand, there are factors inspired by *traditional* asset pricing models such as the equity market risk premium (Rm-Rf), the size and value risk premia of Fama & French (1993, SMB and HML), the S&P-GSCI or an equally-weighted portfolio of all commodity futures (EW). On the other hand, there are factors purposely designed to capture the *fundamentals* of backwardation and contango as modeled via long-short Mom, TS and hedging pressure portfolios.[5] We consider all of them and, as the main task of this article is to demonstrate that combining Mom, TS and IVol signals is more useful than deploying the individual strategies, we select the benchmark model that gives the best performance for the IVol strategy. Thus, the task of improving upon the IVol strategy by overlaying Mom and TS signals to it becomes more challenging.

Bearing the above rationale in mind, we extract the IVol signal from various traditional and fundamental benchmarks. The *traditional* benchmarks treat as risk factors the S&P-GSCI portfolio, an equally-weighted (EW) portfolio of all 27 commodities[6], the equity market excess return (Rm-Rf), and the size (SMB) and value (HML) factors of Fama & French (1993). The *fundamental* benchmarks consider as risk premia long-short portfolios based on Mom, TS and hedging pressure. In each of the long-short strategies, we average the sorting signal over the past 12 months and hold the long-short positions for a month; for further details on the design of the hedging pressure portfolio, see Basu & Miffre (2013).

[5] Unlike the theory of storage of Working (1949) and Brennan (1958) and the hedging pressure hypothesis of Cootner (1960), the momentum strategy is not grounded in theory. But empirical studies have shown that winners exhibit backwardated characteristics such as positive roll-yields, low standardized inventories and net short hedging, while losers present contangoed features (Miffre & Rallis, 2007; Gorton *et al.,* 2012; Dewally *et al.,* 2013). Despite the fact that roll-yield, hedging pressure and past performance can be used as signals to capture the risk premium of commodity futures, there is an ongoing debate on whether these factors are priced cross-sectionally (see Daskalaki *et al.,* 2012; Bakshi *et al.*, 2013; Szymanowska *et al.,* 2013).

[6] The use of an equally-weighted portfolio of the commodities in our sample instead of the S&P-GSCI is motivated by the fact that the latter is heavily tilted towards energy commodities.

For a given benchmark, the IVol strategy then buys the quintile of commodities with the lowest IVol over the past *R* (=1, 3, 6 or 12) months, sells the quintile with the highest IVol and holds the fully-collateralized long-short portfolio for a month. Table 1 summarizes the performance of different IVol portfolios obtained according to various traditional benchmarks (Models A to D) and fundamental benchmarks (Models E to H). Almost all benchmarks are deployed over the period from 1985 to 2011. The exceptions are those that include the hedging pressure factor which, due to data availability at the CFTC (Commodity Futures Trading Commission), cover the slightly shorter period from 1987 to 2011.

[Table 1 around here]

The best performing IVol portfolios, based on benchmarks that use the S&P-GSCI as risk factor, earn a Sharpe ratio of 0.38 on average across the different ranking periods. The strategies that rely on *fundamental* benchmarks generate lower Sharpe ratios (0.21 across Models E and H of Table 1) than those obtained using *traditional* benchmarks (0.35 across Models A to D). These results are consistent with those reported in Miffre *et al.* (2013) who argue 1. that the IVol strategy works in commodity futures markets only when the IVol signal is extracted relative to a traditional version of Merton's (1973) ICAPM and 2. that the decrease in Sharpe ratios obtained in Table 1 while moving from traditional to fundamental benchmarks relates to the pricing of contangoed portfolios.

In the paper, according to the above rationale, we employ as IVol signal the residual standard deviation from the benchmark model based on the S&P-GSCI as single risk factor.[7] We are

[7] One could argue that our IVol strategy is, effectively, buying commodities with low total volatility and shorting commodities with high total volatility. In order to address this concern, we compute the returns and corresponding Sharpe ratios of long-short fully-collateralized portfolios formed according to the total volatility signal (*i.e.*, standard deviation of commodity returns) and contrast them with those reported in Table 1, Panel A. The Sharpe ratios of the total-volatility strategy are far less attractive ranging from a low of 0.1320 (R=6) to a high of 0.2120 (R=3), which are roughly half those of our chosen IVol strategy based on the S&P-GSCI. Hence, the two signals are not identical.

mindful that the term *idiosyncratic volatility* is a misnomer given that those residuals are not white noise but, nevertheless, we adopt it like other studies such as Ang *et al.* (2006, 2009) who also recognize that IVol might proxy for the risk of a yet-to-be-specified missing factor.

3.2 Design and Performance of Individual Strategies

We deploy three strategies based on Mom, TS or IVol, respectively. At the time of portfolio formation we extract the signals over various ranking windows (R=1, 3, 6 or 12 months) and sort the available cross-section of commodities accordingly. The sorting signal for Mom is the past performance of each commodity over the past R months. The sorting signal for TS is the roll-yield of each commodity measured as the log price differential between front and second nearest contracts and averaged out over the past R months. As detailed above, the sorting signal for IVol is the residual standard deviation from (1) using S&P-GSCI as risk factor.

In each of them, the long portfolio is the quintile that is expected to outperform based on the corresponding signal; *i.e.*, the 20% of commodities with best past performance, highest average roll-yields or lowest levels of IVol. The short portfolio is the quintile that is expected to underperform based on the signal; *i.e.*, the 20% of commodities with the worst past performance, the lowest average roll-yields or the highest levels of IVol. As we employ four ranking periods, we have four individual long-short Mom, TS or IVol strategies. Following Erb & Harvey (2006) and Ang *et al*. (2006, 2009), the long-short portfolios are held for one month, at the end of which the portfolio formation process is repeated again and so forth.

Our choice of percentile to form the long and short portfolios (*i.e.,* top and bottom quintiles) follows from the strategy for equities promoted in Ang *et al.* (2006, 2009) and also from the literature on commodity futures markets (*e.g.*, Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006). The sensitivity of the results to the percentile of choice is examined in Section 4.1. In order to avoid portfolio concentration on specific commodities and thus ensure better diversification, equal weights are given to the constituents of each (top and bottom) quintile. However, the equal-weighting scheme could exacerbate illiquidity problems, making it difficult for investors to open or close positions. We examine in Section 5.2 the extent to which the performance of our triple-screen portfolios relates to a liquidity risk premium.

Table 2 summarizes the performance of long-short fully-collateralized Mom, TS and IVol portfolios alongside the performance of the long-only S&P-GSCI portfolio.

[Insert Table 2 around here]

The Sharpe ratios of the long-short portfolios range from 0.19 to 0.47 with an average at 0.37, whereas that of the S&P-GSCI merely stands at 0.14. Likewise, the Sortino ratio and Omega ratio of the long-short portfolios are consistently higher than those of the S&P-GSCI, averaging 0.17 and 1.33, respectively, versus 0.06 and 1.11 for the S&P-GSCI. This reinforces the widely-held view that investors benefit from taking long positions in backwardated markets and short positions in contangoed markets.

3.3 Disentangling the Three Signals

In order to motivate the triple-screen strategy we need to provide evidence that the three signals do not contain identical information. For this purpose, we employ two distinct approaches based on correlations and cross-section regressions, respectively.

We begin by computing pairwise correlations between the long-short Mom, TS and IVol portfolio returns – each portfolio is formed by equally-weighting the corresponding strategies corresponding to the ranking periods of 1, 3, 6 and 12 months. The return correlations are indeed low ranging from 10% (p-value of 0.08) between the Mom and IVol portfolios, to 21% (p-value of 0.00) between the TS and IVol portfolios. As highlighted in Miffre & Rallis (2007), Gorton *et al.* (2012) and Dewally *et al.* (2013) inter alios, all these portfolios are deemed to capture the fundamentals of backwardation and contango, so it is not surprising to see that their returns are positively correlated. Yet, the correlations are small, suggesting that the allocations do not fully overlap. In simple words, when we buy a past winner, we are not necessarily buying a commodity with high roll-yield or low IVol. Likewise, when we sell a past loser, we are not necessarily selling a commodity with low roll-yield or high IVol.

The second approach builds on the methodology proposed by George & Hwang (2004) also used by Park (2010). Each month *t* we run the following cross-sectional regression

$$r_{i,t} = b_{0,t} + b_{1,t} ln\left(OI_{i,t-1}\right) + b_{2,t} MomL_{i,t-1} + b_{3,t} MomS_{i,t-1} + b_{4,t} TSL_{i,t-1} + b_{5,t} TSS_{i,t-1} + b_{6,t} IVolL_{i,t-1} + b_{7,t} IVolS_{i,t-1} + e_{i,t} \qquad (2)$$

where $r_{i.t}$ is the i^{th} commodity futures return, $OI_{i.t-1}$ is the lagged dollar value of open interest as control for illiquidity effects, and the remaining regressors are dummy variables. $MomL_{i.t-1}$ takes value 1 if the i^{th} commodity is included in the *long* Mom portfolio formed at time *t*-1 using information over the previous *R* months, and 0 otherwise; $MomS_{i,t-1}$ is defined similarly with reference to the *short* Mom portfolio. $TSL_{i,t-1}$ equals 1 if the i^{th} commodity is included in the *long* TS portfolio formed at time *t*-1 based on average roll-yields over the previous *R* months, and 0 otherwise; $TSS_{i,t-1}$ is defined similarly with reference to the *short* TS portfolio. $IVolL_{i,t-1}$ and $IVolS_{i,t-1}$ are defined likewise but based on each commodity's IVol over the previous *R* months. The model error is denoted $e_{i,t}$, and $(b_{0,t}, b_{1,t}, \dots, b_{7,t})'$ are unknown parameters that can be consistently estimated by OLS.

Given the ranking periods of 1, 3, 6 and 12 months, we end up with four sets of cross-section regressions whose coefficients are averaged in order to compute $\left(\hat{b}_{2,t} - \hat{b}_{3,t}\right)/2$, $\left(\hat{b}_{4,t} - \hat{b}_{5,t}\right)/2$ and $\left(\hat{b}_{6,t} - \hat{b}_{7,t}\right)/2$. These differentials can be interpreted as the excess returns of fully-collateralized pure strategies. For example, $\left(\hat{b}_{2,t} - \hat{b}_{3,t}\right)/2$ measures the monthly mean excess return that investors demand for taking on the risk of momentum trading after controlling for the risks embedded in the term structure and idiosyncratic volatility signals. Table 3 shows the average coefficients in Panel A and the annualized mean excess returns of the pure strategies in Panel B. The results are reported over the full sample period from February 1985 to August 2011, and over two non-overlapping subsamples of roughly equal length (February 1985 to August 1997, and September 1997 to August 2011).

[Insert Table 3 around here]

The results in Panel A show over the whole sample that for a given signal either the long or short dummy is significantly priced cross-sectionally which suggests that each of the three signals has its own merit and hence, investors could extract profits from their combination.[8] Consistent with the negative relationship between liquidity and expected returns found elsewhere (Brennan *et al*., 1998), the coefficient on open interest is negative. These cross-sectional regressions provide evidence, *prima facie*, that the profitability of the long-short strategies is not merely a compensation for illiquidity; this issue is revisited in Section 5.2. The results over the two sub-periods in Table 3 reveal that there is some time variation in the relative importance of the factors that command a risk premium in commodity futures markets. In fact, some of the results over the full period appear largely driven by one of the subperiods. But overall we can conclude that the signals do not fully overlap.

The results in Panel B over the full sample period suggest that the pure Mom and IVol signals earn an average return of 3.87% and 4.66%, respectively, versus a lower 2.20% for the pure TS signal.[9] The sub-sample analysis reveals that the relative strength of the three pure signals

[8] The results are not sensitive to the inclusion of $R_{i,t-1}$, as in George & Hwang (2004). The coefficient of the lagged monthly return is very small at 0.0107 and insignificant (*t*-statistic =0.77).

[9] We also deployed the two-step methodology of Fama & McBeth (1973) and, reassuringly, the findings do not qualitatively challenge our main inferences based on George & Hwang (2004). The long and long-short (short) TS and IVol portfolios are found to command positive (negative) risk premiums that are significant at conventional levels. The risk premium associated with the long-short momentum portfolio, albeit positive, is found to be non-significant. The coefficient on open interest is negative and significant. More details are available from the authors upon request.

varies over time but all of them yield attractive returns; exceptions are the TS signals and Mom signals in the first and second sub-periods, respectively.

4. Combined Momentum, Term Structure and Idiosyncratic Volatility Signals

4.1 Design and Performance of Triple-Screen Strategy

Having shown that the predictive power of Mom, TS and IVol signals for commodity futures returns is not tantamount, we now design a triple-screen (or combined) strategy. Our main task is then to demonstrate in a robust way that such a combined strategy is worthwhile in the sense that it provides a superior risk-return profile than that afforded by the individual signals.

Over each month of the sample period we deploy the following screening approach which builds on Achour *et al.* (1998). Three scores are assigned to each of the N commodities at the time of portfolio formation according to past performance (Mom), roll-yields (TS) and IVol over the previous R-months window. The highest score of N is given to the commodity with the best past performance, and the lowest score of 1 is given to the commodity with the worst past performance. Likewise, the highest score of N is given to the commodity with the highest average roll-yield, and the lowest score of 1 is given to the commodity with the lowest average roll-yield. Finally, the highest score of N is given to the commodity with the lowest IVol, and the lowest score of 1 is given to the commodity with the highest IVol. We sort the commodities based on their total score, buy the quintile with the highest total score, sell the quintile with the lowest total score and hold the long-short portfolio for one month.

Figure 1 plots the future value of $1 invested in the long-only S&P-GSCI portfolio, and the long-short portfolios based on: *i*) Mom, *ii*) TS, *iii*) IVol, and *iv*) all three signals (triple-screen). Since four signal lengths R are considered for the long-short portfolios, for simplicity, the figure plots the future value of a fully-collateralized portfolio that equally-weights the four long-short portfolios arising from the four signal lengths. The graph suggests that combining the three signals adds value relative to exploiting them individually. All the long-short portfolios are more profitable than the long-only S&P-GSCI for most of the period.

[Insert Figure 1 around here]

Table 4 shows the performance of long, short and long-short (fully-collateralized) triple-screen portfolios. The long portfolios earn positive and significant mean returns that average 8.34% per annum while the short portfolios earn negative mean returns that average -6.44% per annum. Thus the long-short triple-screen strategies yield positive mean returns that are strongly significant both statistically and economically, ranging from 5.80% to 8.27% per annum with an average at 7.39%. This represents a substantial improvement in performance relative to the S&P-GSCI and the individual strategies that we studied earlier on.

[Insert Table 4 around here]

By comparing the risk measures in Panels B of Tables 2 and 4, it is noticeable that the triple-screen strategies are to some extent less risky than the single-screen counterparts or the S&P-GSCI. For example, the maximum drawdown of the triple-screen portfolios ranges from -30.75% and -14.97% with an average at -23.57%, while the maximum drawdown of the single-screen strategies ranges from -58.64% to -19.94% with an average at -34.41%, suggesting that the later are more risky. Likewise, the skewness of the triple-screen strategies often exceeds that of the S&P-GSCI or that of the single-screens. In fact, as Table 4 shows, the percentage of positive months and the maximum 12-month rolling returns are higher for the triple-screen strategies (59.23% and 38.42%, respectively) than for any of the individual strategies (54.56% and 34.52%, respectively).

Table 4, Panel C, shows that the triple-screen portfolios improve substantially upon the individual counterparts in terms of risk-adjusted performance. For example, the Sharpe ratios of the triple-screen portfolios, ranging from 0.52 to 0.77 and averaging at 0.69, show a substantial improvement over that of individual strategies (that range from 0.19 to 0.47 in Table 2). The average Sharpe ratio of the triple-screen strategies is also five times higher than that of the S&P-GSCI that merely stands at 0.14 over the same time period (c.f., Table 2).

Table 5 summarizes the performance of the strategies in various settings: I) full sample period from February 1985 to August 2011; II) two sub-periods of roughly equal length from February 1985 to August 1997, and from September 1997 to August 2011; III) two sub-periods, respectively, preceding and reflecting the financialization of commodity futures markets roughly dated January 2006 as suggested, *e.g*. in Stoll and Whaley (2010); IV) two sub-periods pre and post January 2000 on the basis of the dynamics shown in Figure 1 for the triple-screen strategy; and V*)* two sub-periods, respectively, preceding and reflecting the late 2000s financial crisis using July 2007 as approximate date, see *e.g.*, Brunnermeier (2009).

[Insert Table 5 around here]

Examining the performance of the triple-screen strategy over time (Panel A in Table 5), we conclude that it is time-varying, as one would expect; in fact, the strategies perform better over the recent past. However, almost over *all* the sub-periods considered, the Sharpe ratios of the triple-screen strategies are fairly high (above 0.5) and hence, attractive to commodity investors. Moreover, for most of the sub-periods the Sharpe ratios of the triple-screen strategies exceed those of the individual strategies. The sub-sample analysis therefore confirms the results presented earlier; namely, investors are better off combining the signals.

Next we examine the sensitivity of the results reported in Table 4 to the number of commodities included in the long and short portfolios out of those available.[10] Accordingly,

[10] Our baseline triple-screen strategy is based on the most extreme quintiles, *i.e.* the top or first quintile (long portfolio) and the bottom or fifth quintile (short portfolio). The performance of the triple-screen strategy based on the second and fourth quintiles deteriorates as one would expect – the average Sharpe ratio averages 0.33 across ranking periods versus the 0.69 reported in Table 4 for the top and bottom quintiles. This confirms that investors are better off trading the most extreme quintiles.

we analyze the performance of triple-screen strategies that include in the long and short portfolios, respectively: (A) the single commodity ranked top and the single commodity ranked bottom according to the triple score measure; (B) the top and bottom 10% of commodities, also called deciles, and (C) the top and bottom 30% of commodities. The results show that the triple-screen portfolios with zero diversification, strategy (A) above, earn more at 11.76% on average across all four ranking periods than the best diversified counterpart portfolios, strategy (C) above, whose average performance stands at 5.97% on average. However, on a risk-adjusted basis as captured by the Sharpe ratios, the triple-screen strategies performance improves with the diversification, ranging from an average of 0.54 for the least-diversified portfolios that contain 1 commodity in the long and short portfolios to an average of 0.71 for the most diversified portfolios with 30% of the available cross-section in the long and short portfolios. Detailed results on this sensitivity analysis are available upon request.

Finally, in order to offer more intuition on the triple-screen strategy, Appendix A reports the frequency with which each commodity enters the long and short portfolios. We also present the beta of each commodity relative to S&P-GSCI and the corresponding R^2 statistic of equation (1) estimated over the whole sample period 1985-2011. The results indicate that the triple-screen strategy primarily buys cattle and energy contracts (that rank high in terms of exposure to the S&P-GSCI), sells agricultural commodities such as cocoa, coffee and oats, and ignores commodities in the soy complex, rough rice or electricity.

4.2 Risk Diversification and Inflation Hedging

Performance, risk diversification and inflation hedging are the three main motives of investors to consider commodities in their strategic asset allocation (Bodie & Rosansky, 1980; Bodie, 1983; Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006). Our analysis thus far has established evidence that the triple-screen portfolios meet the first objective of delivering good performance. The next question is then whether or not they are appropriate risk diversification and inflation hedging tools. To address this issue, we examine the extent to which the total returns of the long-short commodity portfolios correlate with the total returns of traditional assets (Standard & Poor's 500 and Barclays bond index) and with inflation shocks.[11] We then compare the diversification and inflation hedging properties of our long-short portfolios to those provided by a long-only commodity portfolio such as the S&P-GSCI. The pairwise correlations and significance *p*-values are reported in Table 6.

[Insert Table 6 around here]

The long-short portfolio returns are essentially uncorrelated with the S&P 500 index returns and with Barclays bond index returns. The same qualitative evidence is obtained when the signals are exploited individually and when they are combined. Likewise, the correlation between the S&P-GSCI returns and Barclays bond index returns is insignificant. In contrast, the correlation between the S&P-GSCI returns and the S&P 500 index returns is significantly positive at 13%. This analysis shows that, while both long-only and long-short commodity portfolios act as good diversifiers of fixed income risk, investors interested in diversifying equity risk should opt for a long-short approach to commodity investing.

Figure 2 plots the mean total returns per annum of the S&P 500 and S&P-GSCI indices, the triple-screen portfolios and the individual strategies. The time period is from July 2007, which roughly marks the beginning of the recent financial crisis, as suggested by Brunnermeier (2009) among others, until August 2011. Consistent with our previous correlation analysis, both the S&P 500 and the S&P-GSCI index lose on average a total of -5.03% and -3.11% per annum, respectively. Meanwhile, the long-short portfolios gain something between 3.76% and

[11] Inflation shocks are calculated as residuals of an ARMA model fitted to logarithmic monthly changes in the U.S. Consumer Price Index obtained from the Federal Reserve Bank of St. Louis.

11.46% per annum. Thus, the value of long-short commodity portfolios as diversifiers of equity risk is especially attractive since the beginning of the recent financial crisis.

[Insert Figure 2 around here]

In terms of inflation hedging, the S&P-GSCI ranks first, with the long-short portfolios offering little or no hedge. The enhanced diversification benefit and superior performance of long-short versus long-only investing come thus at the cost of an inferior inflation hedge.

5. Robustness Analysis

We now conduct some additional tests in an attempt to establish robust conclusions on the superiority of the long-short portfolios that jointly exploit the Mom, TS and IVol signals.

5.1 Double-Screen versus Triple-Screen Strategies

In order to provide convincing evidence on the merit of the proposed triple-screen strategy, it remains to be shown that it outperforms the simpler double-sort strategies that exploit either Mom and TS, IVol and TS or IVol and Mom signals. For this purpose, we form double-screen portfolios that long (short) the 20% of commodities with the highest (lowest) scores according to the signal pair at hand. We should stress that, so as to ensure that the comparison is as informative as possible, the current double-screen strategies are also based on the most extreme *quintiles* as grouping criteria, namely, they include the same number of commodities in their long and short portfolios as the single and triple-screen strategies previously analyzed (Tables 2 and 4). The summary statistics for the double-sort strategies are shown in Table 7.

[Insert Table 7 around here]

The average performance stands at 6.28% a year on average for the double-screen in Table 7 versus 7.39% a year for the triple-screen in Table 4. Likewise, the average Sharpe, Sortino and Omega ratios of 0.69, 0.33 and 1.69 for the triple-screen strategies (Table 4) are more attractive than the corresponding 0.59, 0.28 and 1.57 for the double-screen strategies (Table 7). Finally, we observe that combining signals in a double-screen strategy enhances performance relative to the individual strategies or to a long-only position in the S&P-GSCI.

5.2 Liquidity Risk

There remains the important concern of whether the outperformance of the triple-screen strategy is merely a manifestation of the risk premium that investors demand for holding illiquid commodities. This concern is directly confronted in two ways.[12] First, we measure the portfolio's alpha using a two-factor model that includes the S&P-GSCI and a liquidity risk premium (LRP) constructed *à-la* Pastor & Stambaugh (2003) using commodity futures data[13]

$$r_{P,t} = \alpha + \beta_{S\&P\_GSCI} S\&P\_GSCI_t + \beta_{LRP} LRP_t + \nu_{P,t} \qquad (3)$$

The significant alphas reported in Table 8 (Panel A), ranging from 5.35% to 7.36%, indicate that the outperformance of the triple-screen strategy is not an artifact of liquidity risk.

[Insert Table 8 around here]

We should stress that the interpretation of the alphas is intrinsically linked to the benchmark of choice, namely, in the present context all we can say is that the alphas represent the abnormal return of the strategy over and above what would be expected as compensation for taking systematic commodity market risk (S&P-GSCI) and liquidity risk.

Thus, to provide more robust evidence we confront the liquidity issue in a different manner by re-applying the same strategies now to a restricted cross-section that only includes the 90%

---

[12] Moreover, the cross-sectional analysis presented in Table 3 indicated that the pure Mom, TS and IVol strategies are profitable even after the inclusion of lagged $OI as regressor which represents indirect evidence that the profitability of the signals is not merely a compensation for illiquidity.

[13] To construct long-short liquidity risk mimicking portfolios the ranking period is fixed at 60 months, the holding period at 12 months, and each portfolio (long or short) contains 20% of all the contracts available at the time of portfolio formation along the entire term structure for each commodity. Further details on the liquidity risk mimicking portfolio construction are available from the authors.

most liquid commodity futures contracts. More specifically, at the time of portfolio formation we systematically filter out the 10% of commodities with the lowest average $OI over the preceding R months. Summary statistics are presented in Table 8, Panel B. A comparison of these results with those reported in Table 4 shows that differences in performance are negligible. For example, the average Sharpe ratios of the triple-screen portfolios are 0.69 in Table 4 when the asset allocation is based on the entire cross-section of commodities, and 0.67 in Table 8, Panel B when the least liquid assets are filtered out. This confirms that the performance of the triple-screen strategies is not merely a compensation for liquidity risk. Reassuringly, the liquidity analysis does not challenge our main conclusion that the triple-screen strategies improve upon the performance of each of the individual strategies

The previous liquidity robustness check was addressed over the entire sample period. We now turn attention to the abnormal performance of the strategies in 'tranquil' versus 'crisis' times. This is done by augmenting the benchmark model formalized as equation (3) with a dummy variable equal to 1 from July 2007 onwards and 0 elsewhere. The abnormal performance of the strategies pre- and post-July 2007 is shown in Table 8, Panel C, where $\alpha_{tranquil}$ is the intercept of the model, and α_{crisis} is the sum of the latter and the coefficient of the crisis dummy. In line with our previous findings, the alphas of the triple-screen strategy are more prominent in crisis (α_{crisis} = 12.30% on average) than in tranquil periods ($\alpha_{tranquil}$ = 5.68% on average) but the strategy is worthwhile throughout with a lowest alpha of 3.96% a year. Although time-dependent, the outperformance is sustained.

5.3 Transaction Costs

The triple-screen portfolios are rebalanced monthly and draw upon a small cross-section of commodities that are often liquid, relatively cheap and easy to sell short. It is thus unlikely that their abnormal performance will be totally wiped out by the costs of implementing the strategies. To formally assess this issue, we re-construct the portfolios applying transaction costs of 0.033% and 0.066% per commodity trade. These figures are quite conservative, *e.g.* Locke & Venkatesh's (1997) estimates for futures trading costs range between 0.0004% and 0.033% of notional value. These trading costs are employed each time that a commodity is bought or sold in the portfolio, in addition of the small amount of commodities that are bought or sold each month because of the monthly rebalancing to 1/*N*. Table 9 presents the gross and net performance of the triple-screen and individual strategies. Net of reasonable transaction costs (TC), the triple-screen strategies generate mean return of 7.10% (TC=0.033%) and 6.82% (TC=0.066%) per annum on average, which are similar in magnitude to the average gross returns of 7.39% (TC=0%). The decline in abnormal performance is thus negligible.

[Insert Table 9 around here]

To conduct this robustness check in a different manner, we resort now to a *break-even transaction cost* approach and calculate the required level of cost per commodity trade that makes the mean return of the strategy not larger than zero. Greater break-even costs correspond with less trading-intensive strategies. The results are reported on the right-hand side of Table 9. The pattern of break-even transaction costs observed over ranking periods is as one would expect: the asset allocation signals are more stable as the ranking period increases, thus we rebalance less frequently, and accordingly, the break-even costs increase uniformly. The break-even cost levels for triple-screen strategy equal to 1.11% on average, ranging from 0.40% to 1.82%, and are substantially higher than Locke & Venkatesh's (1997) ceiling estimate at 0.033% per commodity trade. Hence, significant mean returns remain after plausible levels of transaction costs. Last but not least, after accounting for transaction costs the superior performance of the triple-screen versus the individual strategies still prevails.

5.4 Short-Term Overreaction and Mean Reversion

This section tests the hypothesis that the performance of the triple-screen portfolios is not driven by short-term overreaction and a subsequent market correction. For this behavioral explanation to hold, the triple-sort strategies ought to become unprofitable as the holding period lengthens. Figure 3 presents average Sharpe ratios over holding periods from 1 to 72 months (i.e., 6 years) of the individual and triple-screen strategies considered.

[Insert Figure 3 around here]

Although the evolution in the observed Sharpe ratios is non-monotonic, there is a clear contrast regarding the long-term trend in performance between the IVol strategy, on the one hand, and the Mom and TS strategies, on the other hand. We can see that, in line with Jegadeesh & Titman (2001), the Mom portfolios perform poorly as the holding period rises. A similar observation applies to the TS portfolios whose performance tends to mean revert. These gradual long-term declines in performance are not borne out, however, by the Sharpe ratio of the individual IVol strategies.[14] The contrast can partly explain why the performance of the triple-screen strategy deteriorates with the holding period but only by a negligible amount compared, for instance, to the Mom strategy. Altogether, this represents reasonable evidence to conclude that the risk-adjusted performance of the triple-screen strategies applies to long, as well as short, horizons, ruling out a behavioral explanation based on overreaction and subsequent mean reversion.

5.5 Can the Financialization of Commodity Futures Markets Explain Performance?

The flow of cash into commodity markets and its potentially destabilizing role on prices are the subject of an intense and on-going debate both in political and regulatory circles and amongst academics (for a recent review of the literature see, *e.g.* Cheng & Xiong, 2013). We

[14] This is consistent with the findings in Ang *et al*. (2006) who conclude that behavioral explanations are unlikely to account for the performance of equity-based IVol portfolios.

observed in the results shown in Figure 1 and Table 5 that the triple-screen strategies perform particularly well in the recent past; namely, at the time of the financialization of commodity futures markets. Hence, one may hypothesize that large speculators, by increasing their long and short positions in commodity futures markets, influence the performance of the triple-screen strategies. Using the notion of causality proposed by Granger (1969), the above hypothesis is tested by estimating the following regression model using monthly data:

$$r_{P,t} = \delta_0 + \delta_1 \Delta OI_{i,t-1} + \delta_2 r_{P,t-1} + \nu_{P,t} \tag{4}$$

where $r_{P,t}$ is the triple-screen portfolio return and $\Delta OI_{i,t}$ is the change in the long (or short) open interest of large speculators for the i^{th} commodity. The hypothesis that the change in the long (or short) open interest of large speculators does not Granger-cause the performance of the strategies is formulated as $H_0: \delta_1 = 0$. The results can be found in Appendix B. Since only 4% of the significance *t*-ratios for δ_1 fall outside the 95% confidence bands, we can conclude that the change in speculators' positions has no impact on performance.

6. Conclusions

This article focuses on momentum, term structure and idiosyncratic volatility signals that have been shown to predict commodity futures returns in the recent literature. Idiosyncratic volatility is defined with respect to the S&P-GSCI as benchmark. We expand upon the extant literature by showing that the three signals are independent enough which legitimates the design of a triple-screen strategy that combines all three signals. Over the period from 1985 to 2011, investors who systematically buy commodities with high past performance, high average roll-yields and low idiosyncratic volatility, on the one hand, and short commodities with poor past performance, low average roll-yields and high idiosyncratic volatility, on the other hand, obtain an average Sharpe ratio of 0.69. Instead the average Sharpe ratio of long-short portfolios based on the individual signals merely stands at 0.37, and that of the S&P-GSCI is even lower at 0.14. Robustness tests confirm that the triple-screen strategies also outperform double-screen strategies and their superior performance cannot be attributed to liquidity risk or transaction costs. Moreover, the superior profitability of the triple-screen strategies is neither driven by short-term overreaction and subsequent mean reversion, nor by the recent financialization of commodity futures markets. Finally, the triple-screen portfolios are found useful at diversifying equity risk but not as inflation hedge.

The main scope of this article has been to investigate the effectiveness of combining momentum, term structure and idiosyncratic volatility signals. An open question is whether overlaying other signals based on inventory levels or hedging pressure (Gorton *et al.*, 2012; Basu & Miffre, 2013) could yield better performance. This is an avenue for future research.

References

Achour, D., Harvey, C. R., Hopkins, G., & Lang, C. (1998). Stock selection in emerging markets: Portfolio strategies for Malaysia, Mexico and South Africa. Emerging Markets Quarterly, 2, 38-91.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. Journal of Finance, 61, 259-299.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further U.S. evidence. Journal of Financial Economics, 91, 1–23.

Bali, T. G., & Cakici N. (2008). Idiosyncratic volatility and the cross-section of expected returns. Journal of Financial and Quantitative Analysis, 43, 29-58.

Bakshi, G., Gao, X., & Rossi, A. (2013). Asset pricing models that explain the cross-section and time-series of commodity returns. Working paper, University of Maryland.

Basu, D., & Miffre, J. (2013). Capturing the risk premium of commodity futures: The role of hedging pressure. Journal of Banking and Finance, 37, 2652-2664.

Barberis, N, Schleifer, A., & Vishny, R. (1998). A model of investor sentiment. Journal of Financial Economics, 49, 307-343.

Bodie, Z. (1983). Commodity futures as a hedge against inflation. Journal of Portfolio Management, 12-17.

Bodie, Z., & Rosansky, V. (1980). Risk and return in commodity futures. Financial Analysts Journal, 36, 27-39.

Brennan, M. (1958). The supply of storage. American Economic Review, 47, 50-72.

Brennan, M.J., Cordia, T., & Subrahmanyam, A. (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. Journal of Financial Economics, 49, 345–373.

Brunnermeier, M. (2009). Deciphering the liquidity and credit crunch 2007-2008. Journal of Economic Perspectives, 23, 77-100.

Chordia T, & Shivakumar, L. (2002). Momentum, business cycle and time-varying expected returns. Journal of Finance, 57, 985-1018.

Cheng, I-H., & Xiong, W. (2013). The financialization of commodity markets. NBER Working paper No. 19642, http://www.nber.org/papers/w19642.

Cooper, M. J., Gutierrez, R. C., & Hameed, A. (2004). Market states and momentum. Journal of Finance, 59, 1345-1366.

Cootner, P. (1960). Returns to speculators: Telser vs. Keynes. Journal of Political Economy, 68, 396-404.

Daniel, K, Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. Journal of Finance, 53, 1839-1885.

Daskalaki, C., Kostakis, A., & Skiadopoulos, G. (2012). Are there common factors in commodity futures returns? Working Paper, University of Piraeus.

Dewally, M., Ederington, L., & Fernando, C., (2013). Determinants of trader profits in commodity futures markets. Review of Financial Studies, 26, 2648-2683.

Erb, C., & Harvey, C. (2006). The strategic and tactical value of commodity futures. Financial Analysts Journal, 62, 69-97.

Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33, 3-56.

Fama, E., & MacBeth, J. D. (1973). Risk, returns, and equilibrium: Empirical tests. Journal of Political Economy, 81, 607-636.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. Journal of Financial Economics, 91, 24-37.

Fuertes, A.M., Miffre, J., & Rallis, G. (2010). Tactical allocation in commodity futures markets: Combining momentum and term structure signals. Journal of Banking and Finance, 34, 2530–2548.

George, T.J., & Hwang, C. (2004). The 52-week high and momentum investing. Journal of Finance, 59, 2145-2176.

Gorton, G., & Rouwenhorst, G. (2006). Facts and fantasies about commodity futures. Financial Analysts Journal, 62, 47-68.

Gorton, G., Hayashi, F., & Rouwenhorst, G. (2012). The fundamentals of commodity futures returns. Review of Finance, 17, 35-105.

Goyal, A., & Santa-Clara, P. (2003). Idiosyncratic risk matters! Journal of Finance, 58, 975-1007.

Granger, C. W. J. (1969). Investigating causal relations by econometric models. Econometrica, 37, 424-438.

Han, Y., & Lesmond, D. (2011). Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. Review of Financial Studies, 24, 1590-1629.

Hong, H., & Stein, J. (1999). A unified theory of underreaction, momentum trading and overreaction in asset markets. Journal of Finance, 54, 2143-2184.

Huang, W., Liu, Q., Rhee, S. G., & Zhang, L. (2010). Return reversals, idiosyncratic risk, and expected returns. Review of Financial Studies, 23, 147-168.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance, 48, 65-91.

Jegadeesh, N. & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. Journal of Finance, 56, 699-720.

Lesmond, D. A., Schill, M. J., & Zhou, C. (2004). The illusory nature of momentum profits. Journal of Financial Economics, 71, 349-380.

Locke, P., & Venkatesh, P. (1997). Futures market transaction costs. Journal of Futures Markets, 17, 229-245.

Malkiel, B., & Xu, Y. (2004). Idiosyncratic risk and security returns. Working Paper, University of Texas at Dallas

Merton, R.C. (1973). An intertemporal capital asset pricing model. Econometrica, 41, 867-887.

Merton, R.C. (1987). A simple model of capital market equilibrium with incomplete information. Journal of Finance, 42, 483-510.

Miffre, J., & Rallis, G. (2007). Momentum strategies in commodity futures markets. Journal of Banking and Finance, 31, 1863-1886

Miffre, J., Fuertes, A.M., & Fernandez-Perez, A. (2013). Commodity futures returns and idiosyncratic volatility. Working paper.

Park, S. (2010). The moving average ratio and momentum. Financial Review, 45, 415–447

Pastor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. Journal of Political Economy, 111, 642-685.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance, 19, 425-442.

Shen, Q., Szakmary, A., & Sharma, S. (2007). An examination of momentum strategies in commodity futures markets. Journal of Futures Markets, 27, 227-256.

Stoll, H. & Whaley, R. (2010). Commodity index investing and commodity futures prices. Journal of Applied Finance, 20, 7-46

Szakmary, A., Shen, Q., & Sharma, S. (2010). Trend-following strategies in commodity futures: A re-examination. Journal of Banking and Finance, 34, 409-426.

Szymanowska, M., De Roon, F., Nijman, T., & Van Den Goorbergh, R. (2013). An anatomy of commodity futures risk premia. Journal of Finance, forthcoming.

Working, H. (1949). The theory of the price of storage. American Economic Review, 39, 1254-1266.

Table 1. Idiosyncratic volatility signal and benchmark model.

The table presents summary statistics for individual idiosyncratic volatility (IVol) strategies where the signal is modeled relative to *traditional* benchmarks in Models A to D that consider as risk factors: *i*) the S&P-GSCI, *ii*) the equally-weighted portfolio of all commodity futures (EW), *iii*) the equity market excess returns (Rm-Rf), and the size and value premia of Fama & French (1993, SMB and HML), or *fundamental* benchmarks in Models E to H that treat as risk factors: *i*) the commodity-based momentum (Mom), *ii*) term structure (TS) and *iii*) hedging pressure portfolios. The ranking period over which the IVol signals are modeled is denoted *R* and is expressed in months. Mean stands for annualized mean excess return, SD stands for annualized standard deviation. *t*-statistics are in parentheses. All but one model are estimated over the period from February 1985 to August 2011, the exception being the model with hedging pressure risk (Models G and H) that is only feasible over the period January 1987 to August 2011 due to data constraints.

	Traditional benchmarks						Fundamental benchmarks				
	R = 1	R = 3	R = 6	R = 12	Average		R = 1	R = 3	R = 6	R = 12	Average
Model A: S&P-GSCI factor						**Model E: Mom factor**					
Mean	0.0454	0.0437	0.0399	0.0500	0.0448	Mean	0.0291	0.0234	0.0189	0.0213	0.0232
	(2.00)	(1.93)	(1.78)	(2.16)			(1.36)	(1.04)	(0.88)	(1.03)	
SD	0.1171	0.1162	0.1148	0.1176	0.1164	SD	0.1107	0.1165	0.1103	0.1069	0.1111
Sharpe ratio	0.3878	0.3759	0.3478	0.4255	0.3843	Sharpe ratio	0.2628	0.2005	0.1711	0.1997	0.2085
Model B: EW factor						**Model F: TS factor**					
Mean	0.0375	0.0362	0.0262	0.0378	0.0344	Mean	0.0303	0.0144	0.0098	0.0133	0.0169
	(1.82)	(1.73)	(1.28)	(1.91)			(1.29)	(0.64)	(0.44)	(0.62)	
SD	0.1063	0.1075	0.1053	0.1002	0.1048	SD	0.1211	0.1167	0.1156	0.1106	0.1160
Sharpe ratio	0.3526	0.3366	0.2493	0.3774	0.3290	Sharpe ratio	0.2501	0.1238	0.0844	0.1200	0.1446
Model C: Rm-Rf, SMB, HML and S&P-GSCI factors						**Model G: Hedging Pressure factor**					
Mean	0.0389	0.0423	0.0431	0.0514	0.0440	Mean	0.0435	0.0298	0.0199	0.0281	0.0303
	(1.77)	(1.88)	(1.92)	(2.23)			(1.99)	(1.20)	(0.83)	(1.19)	
SD	0.1132	0.1157	0.1148	0.1170	0.1152	SD	0.1085	0.1223	0.1175	0.1150	0.1158
Sharpe ratio	0.3437	0.3661	0.3755	0.4396	0.3812	Sharpe ratio	0.4006	0.2435	0.1691	0.2442	0.2643
Model D: Rm-Rf, SMB, HML and EW factors						**Model H: Mom, TS and Hedging Pressure factors**					
Mean	0.0311	0.0356	0.0269	0.0338	0.0318	Mean	0.0225	0.0159	0.0302	0.0313	0.0250
	(1.54)	(1.72)	(1.33)	(1.73)			(1.08)	(0.69)	(1.36)	(1.43)	
SD	0.1043	0.1062	0.1034	0.0992	0.1033	SD	0.1031	0.1136	0.1089	0.1064	0.1080
Sharpe ratio	0.2985	0.3347	0.2596	0.3408	0.3084	Sharpe ratio	0.2177	0.1401	0.2776	0.2941	0.2324

Table 2. Performance of momentum, term structure and idiosyncratic volatility strategies.

The table presents summary statistics for the excess returns of the S&P-GSCI and fully-collateralized long-short momentum, term structure and idiosyncratic volatility (IVol) portfolios. Past performance and average roll-yields are measured over ranking periods *R* spanning 1 to 12 months. IVol is measured as the standard deviation from regressions of daily commodity futures returns on the S&P-GSCI over the same ranking periods. The long portfolio buys the quintile with either the best past performance, the highest average roll-yields or the lowest IVol and the short portfolio sells the quintile with either the worst past performance, the lowest average roll-yields or the highest IVol. *t*-statistics are in parentheses. The sample covers the period from February 1985 to August 2011.

	Momentum					Term structure					Idiosyncratic Volatility					S&P-GSCI
	R = 1	R = 3	R = 6	R = 12	Average	R = 1	R = 3	R = 6	R = 12	Average	R = 1	R = 3	R = 6	R = 12	Average	
Panel A: Excess returns																
Annualized arithmetic mean	0.0476	0.0596	0.0255	0.0614	0.0485	0.0206	0.0445	0.0447	0.0369	0.0367	0.0454	0.0437	0.0399	0.0500	0.0448	0.0281
	(1.93)	(2.38)	(1.08)	(2.36)		(0.98)	(2.24)	(2.21)	(1.74)		(2.00)	(1.93)	(1.78)	(2.16)		(0.71)
Annualized geometric mean	0.0397	0.0514	0.0182	0.0528	0.0405	0.0146	0.0393	0.0394	0.0311	0.0311	0.0385	0.0369	0.0334	0.0431	0.0380	0.0069
Panel B: Risk measures																
Annualized volatility	0.1271	0.1284	0.1207	0.1320	0.1270	0.1087	0.1021	0.1035	0.1075	0.1054	0.1171	0.1162	0.1148	0.1176	0.1164	0.2043
Annualized downside volatility (0%)	0.0734	0.0676	0.0726	0.0762	0.0725	0.0754	0.0660	0.0676	0.0765	0.0714	0.0884	0.0743	0.0682	0.0795	0.0776	0.1438
Skewness	0.3291	0.4253	0.0353	0.2237	0.2533	-0.2599	0.1081	0.0089	-0.3257	-0.1172	-0.7679	-0.2317	-0.0721	-0.2674	-0.3348	-0.2740
Kurtosis	4.3205	3.8344	3.1141	3.5672	3.7090	6.3463	4.5211	3.8663	4.4598	4.7984	7.2079	3.7478	3.2926	4.2937	4.6355	5.4066
99% VaR (Cornish-Fisher)	0.0823	0.0744	0.0790	0.0816	0.0793	0.1010	0.0729	0.0716	0.0859	0.0829	0.1197	0.0853	0.0777	0.0908	0.0934	0.1782
% of positive months	0.5486	0.5331	0.5191	0.5422	0.5358	0.5141	0.5521	0.5446	0.5487	0.5399	0.5799	0.5521	0.5605	0.5519	0.5611	0.5281
Maximum run-up (consecutive)	1.1950	1.2734	1.0308	1.1351	1.1586	1.0019	1.5474	1.0253	0.9181	1.1232	0.9958	0.8072	0.9138	1.2612	0.9945	1.7566
Run-up length (months)	7	9	7	5	7	9	10	8	12	10	8	7	9	9	8	8
Maximum drawdown	-0.5864	-0.3581	-0.3242	-0.4257	-0.4236	-0.5116	-0.3279	-0.2589	-0.1994	-0.3244	-0.3153	-0.2294	-0.2641	-0.3287	-0.2844	-0.7030
Drawdown length (months)	123	28	97	36	71	168	9	7	7	48	71	61	72	66	68	8
Maximum 12M rolling return	0.3887	0.4067	0.3088	0.4332	0.3843	0.3086	0.3313	0.2843	0.3358	0.3150	0.3821	0.3426	0.3213	0.2987	0.3362	0.5355
Minimum 12M rolling return	-0.3418	-0.3271	-0.2403	-0.2632	-0.2931	-0.2878	-0.3567	-0.1632	-0.1972	-0.2512	-0.2668	-0.2078	-0.2142	-0.2018	-0.2226	-0.9133
Panel C: Risk-adjusted performance																
Sharpe ratio	0.3748	0.4638	0.2111	0.4656	0.3788	0.1893	0.4356	0.4325	0.3433	0.3502	0.3878	0.3759	0.3478	0.4255	0.3843	0.1375
Sortino ratio (0%)	0.1723	0.2253	0.0912	0.2200	0.1772	0.0791	0.1979	0.1945	0.1460	0.1544	0.1606	0.1625	0.1528	0.1859	0.1655	0.0564
Omega ratio (0%)	1.3256	1.4134	1.1678	1.4222	1.3322	1.1585	1.4025	1.3953	1.3051	1.3154	1.3468	1.3154	1.2872	1.3802	1.3324	1.1127

Table 3. Pure momentum, term structure and idiosyncratic volatility signals.

The table reports in Panel A the coefficient estimates of cross-sectional regressions of commodity futures returns on lagged dollar open interest and 6 dummy variables as formalized in equation (2). Long Mom dummy equals 1 (0) for commodity *i* if it is included in (excluded from) the long momentum portfolio; Short Mom dummy equals 1 (0) for commodity *i* if it included in (excluded from) the short momentum portfolio. Long TS (IVol) and Short TS (IVol) dummies are similarly defined with respect to the term structure (idiosyncratic volatility) portfolios. The coefficient estimates reported are averages over ranking periods of 1, 3, 6 and 12 months, and *t*-statistics for the significance of the averages are reported in the next column. Panel B reports the annualized mean returns of fully-collateralized long-short strategies based on pure Mom, TS and IVol signals and significance *t*-statistics. The results are for the full sample period from February 1985 to August 2011 and two non-overlapping periods of approximately equal length.

	Feb 1985 to Aug 2011		Feb 1985 to Aug 1997		Sept 1997 to Aug 2011	
	Coeff.	***t-stat***	**Coeff.**	***t-stat***	**Coeff.**	***t-stat***
Panel A: Coefficients of cross-section regressions						
Intercept	0.0168	(3.10)	0.0448	(6.27)	-0.0062	(-0.79)
Open interest	-0.0009	(-3.20)	-0.0024	(-6.17)	0.0003	(0.72)
Long Mom dummy	0.0038	(2.27)	0.0047	(2.02)	0.0030	(1.25)
Short Mom dummy	-0.0026	(-1.59)	-0.0046	(-1.99)	-0.0008	(-0.35)
Long TS dummy	0.0006	(0.38)	-0.0009	(-0.46)	0.0017	(0.74)
Short TS dummy	-0.0031	(-2.06)	0.0001	(0.04)	-0.0057	(-2.80)
Long IVol dummy	0.0016	(1.21)	-0.0026	(-1.59)	0.0051	(2.63)
Short IVol dummy	-0.0062	(-3.44)	-0.0091	(-3.56)	-0.0037	(-1.49)
Panel B: Pure strategy						
Momentum	0.0387	(2.86)	0.0558	(3.10)	0.0228	(1.16)
Term structure	0.0220	(1.87)	-0.0062	(-0.39)	0.0444	(2.67)
Idiosyncratic volatility	0.0466	(3.73)	0.0388	(2.18)	0.0531	(3.06)

Table 4. Performance of triple-screen momentum, term structure and idiosyncratic volatility strategies.

The table presents summary statistics for the returns of fully-collateralized long, short and long-short portfolios. The asset allocation is based on triple-screen strategies that exploit momentum, term structure and idiosyncratic volatility signals. The signals are measured over ranking periods *R* ranging from 1 to 12 months. Significance *t*-statistics are in parentheses. The sample covers the period from February 1985 to August 2011.

	Long Portfolios					Short Portfolios					Long-Short Portfolios				
	R = 1	R = 3	R = 6	R = 12	Average	R = 1	R = 3	R = 6	R = 12	Average	R = 1	R = 3	R = 6	R = 12	Average
Panel A: Excess returns															
Annualized arithmetic mean	0.0620	0.0793	0.0847	0.1078	0.0834	-0.0539	-0.0758	-0.0702	-0.0576	-0.0644	0.0580	0.0775	0.0774	0.0827	0.0739
	(2.04)	(2.38)	(2.67)	(3.12)		(-1.47)	(-2.15)	(-2.04)	(-1.65)		(2.68)	(3.63)	(3.85)	(3.91)	
Annualized geometric mean	0.0497	0.0646	0.0714	0.0923	0.0695	-0.0717	-0.0920	-0.0857	-0.0732	-0.0807	0.0518	0.0715	0.0722	0.0770	0.0681
Panel B: Risk measures															
Annualized volatility	0.1570	0.1712	0.1625	0.1749	0.1664	0.1887	0.1814	0.1759	0.1770	0.1808	0.1117	0.1098	0.1030	0.1071	0.1079
Annualized downside volatility (0%)	0.1031	0.1154	0.1153	0.1234	0.1143	0.1188	0.1084	0.1115	0.1059	0.1111	0.0695	0.0714	0.0586	0.0672	0.0667
Skewness	0.0029	-0.1656	-0.2796	-0.5254	-0.2419	0.1783	0.5543	0.1932	0.2499	0.2939	0.0560	-0.1206	0.2279	-0.0418	0.0304
Kurtosis	5.6208	6.5070	6.3005	6.9362	6.3411	4.5469	5.3478	3.4674	3.4050	4.1918	5.1952	5.2559	3.5096	3.5406	4.3753
99% VaR (Cornish-Fisher)	0.1279	0.1544	0.1465	0.1692	0.1495	0.1431	0.1295	0.1216	0.1179	0.1280	0.0854	0.0866	0.0607	0.0698	0.0756
% of positive months	0.5455	0.5647	0.5796	0.5682	0.5645	0.4702	0.4132	0.4331	0.4416	0.4395	0.5768	0.5931	0.6019	0.5974	0.5923
Maximum run-up (consecutive)	0.9077	1.7494	1.5868	1.7494	1.4983	1.5594	2.1533	1.8823	1.6744	1.8173	0.9104	1.2415	1.1805	1.1068	1.1098
Run-up length (months)	8	8	10	10	9	6	7	6	5	6	7	9	20	10	12
Maximum drawdown	-0.5011	-0.4913	-0.5028	-0.5825	-0.5194	-0.8986	-0.9512	-0.9329	-0.9067	-0.9224	-0.3075	-0.2884	-0.1970	-0.1497	-0.2357
Drawdown length (months)	24	8	10	15	14	263	263	287	263	269	43	36	13	5	24
Maximum 12M rolling return	0.5734	0.5727	0.5636	0.5334	0.5608	0.3398	0.3363	0.3715	0.3010	0.3372	0.4002	0.3845	0.3769	0.3751	0.3842
Minimum 12M rolling return	-0.5203	-0.5379	-0.5949	-0.7577	-0.6027	-0.8324	-0.6980	-0.5272	-0.6013	-0.6647	-0.1787	-0.2293	-0.1935	-0.1490	-0.1876
Panel C: Risk-adjusted performance															
Sharpe ratio	0.3950	0.4631	0.5212	0.6163	0.4989	-0.2857	-0.4178	-0.3990	-0.3252	-0.3569	0.5190	0.7062	0.7517	0.7722	0.6873
Sortino ratio (0%)	0.1756	0.2089	0.2346	0.2798	0.2247	-0.1105	-0.1632	-0.1522	-0.1277	-0.1384	0.2386	0.3362	0.3775	0.3710	0.3308
Omega ratio (0%)	1.3550	1.4390	1.5172	1.6194	1.4826	0.8080	0.7289	0.7401	0.7852	0.7656	1.4786	1.7202	1.7642	1.7781	1.6852

Table 5. Stability analysis of performance of triple-screen and individual strategies.

The table reports Sharpe ratios of the individual and triple-screen strategies over the: I) whole sample period from February 1985 to August 2011, II) two approximately equal-length periods from February 1985 to August 1997, and from September 1997 to August 2011, III) the financialization of commodity futures markets period and preceding period using January 2006 as approximate cutoff point, IV) the periods before and after January 2000, and V*)* the late 2000s financial crisis period and preceding period using July 2007 as approximate break date.

	I	II		III		IV		V	
Start period	Feb 1985	Feb 1985	Sep 1997	Feb 1985	Jan 2006	Feb 1985	Jan 2000	Feb 1985	Jul 2007
End period	Aug 2011	Aug 1997	Aug 2011	Dec 2005	Aug 2011	Dec 1999	Aug 2011	Jun 2007	Aug 2011
Panel A: Momentum, Term Structure and Idiosyncratic Volatility									
R = 1	0.5190	0.4536	0.5745	0.4556	0.7627	0.2874	0.8045	0.4283	1.1060
R = 3	0.7062	0.4954	0.8723	0.5945	1.1144	0.4836	0.9504	0.6195	1.1063
R = 6	0.7517	0.6085	0.8648	0.7474	0.7615	0.5864	0.9334	0.7354	0.8340
R = 12	0.7722	0.7668	0.7749	0.7319	0.9045	0.6999	0.8498	0.7272	0.9965
Average	0.6873	0.5811	0.7716	0.6324	0.8858	0.5143	0.8845	0.6276	1.0107
Panel B: Momentum									
R = 1	0.3748	0.8167	0.0462	0.2863	0.6933	0.5393	0.1925	0.2857	0.9776
R = 3	0.4638	0.4996	0.4356	0.3490	0.8840	0.3915	0.5460	0.3900	0.7631
R = 6	0.2111	0.0931	0.2992	0.1004	0.5798	0.0695	0.3611	0.0841	0.9031
R = 12	0.4656	0.5191	0.4265	0.3714	0.8104	0.4523	0.4799	0.4131	0.6719
Average	0.3788	0.4821	0.3019	0.2768	0.7419	0.3632	0.3949	0.2932	0.8289
Panel C: Term Structure									
R = 1	0.1893	-0.3162	0.6459	0.1805	0.2254	-0.2623	0.7526	0.1297	0.4734
R = 3	0.4356	0.0005	0.8207	0.3980	0.5948	0.1341	0.8245	0.3632	0.7998
R = 6	0.4325	0.2952	0.5462	0.4768	0.2690	0.3416	0.5376	0.4218	0.4462
R = 12	0.3433	0.1902	0.4784	0.2902	0.5483	0.2432	0.4644	0.2805	0.7591
Average	0.3502	0.0424	0.6228	0.3364	0.4094	0.1142	0.6448	0.2988	0.6196
Panel D: Idiosyncratic volatility									
R = 1	0.3878	0.1101	0.6700	0.3171	0.6515	0.0576	0.8479	0.3480	0.5380
R = 3	0.3759	0.1959	0.5316	0.4130	0.2484	0.2191	0.5667	0.4347	0.0790
R = 6	0.3478	0.0693	0.5848	0.3371	0.3813	0.0732	0.6767	0.4377	-0.1192
R = 12	0.4255	0.0576	0.7236	0.3399	0.7077	0.0776	0.8353	0.4183	0.4597
Average	0.3843	0.1082	0.6275	0.3518	0.4973	0.1069	0.7317	0.4097	0.2394

Table 6. Diversification and inflation hedge of triple-screen and individual strategies.

The table reports pairwise correlation coefficients between the total returns of commodity portfolios and the S&P 500 index returns (first column), Barclays bond index returns (second column) and inflation innovations (third column). Significance *p*-values are in parentheses. The sample covers the period from February 1985 to August 2011.

	S&P 500		Barclays		Inflation shocks	
Panel A: Momentum, Term Structure and Idiosyncratic Volatility						
R = 1	-0.08	(0.17)	0.02	(0.69)	0.06	(0.30)
R = 3	-0.04	(0.53)	0.03	(0.58)	0.13	(0.02)
R = 6	-0.04	(0.45)	0.08	(0.20)	0.13	(0.02)
R = 12	-0.06	(0.30)	0.05	(0.39)	0.19	(0.00)
Average	-0.05		0.05		0.13	
Panel B: Momentum						
R = 1	-0.05	(0.37)	0.05	(0.43)	-0.01	(0.90)
R = 3	-0.03	(0.60)	0.02	(0.69)	0.08	(0.15)
R = 6	-0.06	(0.29)	0.08	(0.18)	0.02	(0.74)
R = 12	-0.04	(0.48)	0.07	(0.28)	0.11	(0.05)
Average	-0.04		0.05		0.05	
Panel C: Term Structure						
R = 1	-0.12	(0.03)	-0.04	(0.47)	0.12	(0.04)
R = 3	-0.11	(0.04)	-0.02	(0.71)	0.13	(0.02)
R = 6	-0.01	(0.87)	0.01	(0.85)	0.13	(0.02)
R = 12	0.07	(0.24)	0.00	(0.96)	0.14	(0.01)
Average	-0.05		-0.01		0.13	
Panel D: Idiosyncratic volatility						
R = 1	0.03	(0.61)	-0.04	(0.50)	0.07	(0.25)
R = 3	-0.03	(0.65)	-0.01	(0.81)	0.09	(0.11)
R = 6	-0.03	(0.64)	-0.02	(0.72)	0.11	(0.04)
R = 12	-0.03	(0.55)	-0.04	(0.50)	0.13	(0.02)
Average	-0.01		-0.03		0.10	
Panel E: S&P-GSCI	0.13	(0.02)	-0.01	(0.85)	0.30	(0.00)

Table 7. Performance of double-screen strategies

The table presents summary statistics for the returns of fully-collateralized long-short portfolios. The asset allocation is based on double-screen strategies that exploit two of the following three signals: momentum (Mom), term structure (TS) and/or idiosyncratic volatility (IVol). The signals are measured over ranking periods *R* ranging from 1 to 12 months. Significance *t*-statistics are in parentheses. The sample covers the period from February 1985 to August 2011.

	Mom-TS Strategy					**IVol-TS Strategy**					**IVol-Mom Strategy**					**Double-Screen**
	R = 1	R = 3	R = 6	R = 12	Average	R = 1	R = 3	R = 6	R = 12	Average	R = 1	R = 3	R = 6	R = 12	Average	**Average**
Panel A: Excess returns																
Annualized arithmetic mean	0.0627	0.0904	0.0616	0.0541	0.0672	0.0460	0.0713	0.0667	0.0561	0.0600	0.0616	0.0785	0.0479	0.0561	0.0610	0.0628
	(2.99)	(4.52)	(3.08)	(2.52)		(2.27)	(3.65)	(3.37)	(2.69)		(2.89)	(3.50)	(2.20)	(2.64)		
Annualized geometric mean	0.0570	0.0852	0.0565	0.0482	0.0617	0.0405	0.0663	0.0616	0.0505	0.0547	0.0556	0.0719	0.0418	0.0504	0.0549	0.0571
Panel B: Risk measures																
Annualized volatility	0.1080	0.1028	0.1024	0.1090	0.1056	0.1043	0.1003	0.1012	0.1057	0.1029	0.1100	0.1154	0.1113	0.1077	0.1111	0.1065
Annualized downside volatility (0%)	0.0638	0.0565	0.0655	0.0697	0.0639	0.0710	0.0582	0.0647	0.0738	0.0669	0.0664	0.0649	0.0607	0.0639	0.0639	0.0649
Skewness	0.4756	0.3877	0.0538	0.0542	0.2428	-0.2854	0.1579	-0.0627	-0.3916	-0.1455	-0.1695	0.2453	0.3094	0.0274	0.1032	0.0668
Kurtosis	6.3559	4.4026	3.9366	3.9291	4.6561	6.0917	3.3144	3.9217	3.5930	4.2302	4.0462	3.8961	4.0359	3.1508	3.7822	4.2228
99% VaR (Cornish-Fisher)	0.0782	0.0611	0.0689	0.0743	0.0706	0.0933	0.0599	0.0700	0.0776	0.0752	0.0801	0.0711	0.0700	0.0681	0.0723	0.0727
% of positive months	0.5549	0.5962	0.5701	0.5714	0.5731	0.5611	0.5804	0.5828	0.5877	0.5780	0.5893	0.5804	0.5478	0.5487	0.5666	0.5726
Maximum run-up (consecutive)	0.7907	0.8961	0.7463	1.1424	0.8939	1.2673	1.1410	1.3539	0.7531	1.1288	0.9604	1.2063	1.2452	1.0549	1.1167	1.0465
Run-up length (months)	6	10	8	8	8	8	8	8	12	9	7	6	6	9	7	8
Maximum drawdown	-0.3237	-0.1605	-0.1456	-0.3437	-0.2434	-0.3083	-0.2152	-0.2463	-0.2805	-0.2626	-0.3013	-0.1684	-0.2410	-0.2182	-0.2322	-0.2460
Drawdown length (months)	28	9	7	62	27	36	9	8	74	32	54	47	29	12	36	31
Maximum 12M rolling return	0.3633	0.3837	0.3381	0.4533	0.3846	0.4075	0.3613	0.3663	0.3355	0.3676	0.3178	0.3238	0.3467	0.3347	0.3307	0.3610
Minimum 12M rolling return	-0.2658	-0.1272	-0.1281	-0.1966	-0.1794	-0.1969	-0.2103	-0.2294	-0.2088	-0.2113	-0.1409	-0.1236	-0.1396	-0.2386	-0.1607	-0.1838
Panel C: Risk-adjusted performance																
Sharpe ratio	0.5808	0.8794	0.6023	0.4965	0.6398	0.4408	0.7108	0.6594	0.5307	0.5854	0.5599	0.6805	0.4307	0.5213	0.5481	0.5911
Sortino ratio (0%)	0.2829	0.4629	0.2853	0.2273	0.3146	0.1949	0.3511	0.3086	0.2307	0.2713	0.2554	0.3364	0.2046	0.2432	0.2599	0.2819
Omega ratio (0%)	1.5663	1.9418	1.5979	1.4628	1.6422	1.4058	1.7061	1.6408	1.4853	1.5595	1.5022	1.6629	1.3807	1.4721	1.5045	1.5687

Table 8. Liquidity risk analysis and tranquil- versus crisis-period analysis of triple-screen and individual strategies.

Panel A presents coefficient estimates from regressions of the returns of long-short portfolios on the S&P-GSCI and a liquidity risk premium obtained *à-la* Pastor & Stambaugh (2003). Panel B reports annualized mean, annualized standard deviation (SD) and Sharpe ratio of returns of the long-short portfolios that exclude the 10% of commodities with lowest $OI at the time of portfolio formation. Panel C reports the 'tranquil' period alpha ($\alpha_{tranquil}$) and the 'crisis' period alpha (α_{crisis}) obtained by adding to the model reported in Panel A a dummy variable equal to one from July 2007 onwards and zero elsewhere. R is the ranking period over which the signals are modeled. Newey-West significance t-statistics are reported in parentheses. The sample covers the period from February 1985 to August 2011.

	Panel A. Liquidity-robust alpha						Panel B. Restricted cross-section with 90% of most liquid				Panel C. Tranquil versus crisis period liquidity-robust alpha			
	α		$\beta_{S\&P\text{-}GSCI}$		β_{LRP}		Mean		SD	Sharpe	$\alpha_{tranquil}$		α_{crisis}	
Momentum, Term Structure and Idiosyncratic Volatility														
R = 1	0.0535	(2.61)	0.0671	(1.93)	0.1616	(1.69)	0.0534	(2.61)	0.1057	0.5054	0.0396	(1.76)	0.1309	(3.36)
R = 3	0.0713	(3.89)	0.1142	(3.41)	0.1630	(1.80)	0.0689	(3.36)	0.1055	0.6530	0.0569	(2.87)	0.1406	(3.94)
R = 6	0.0716	(4.24)	0.1009	(2.55)	0.1149	(1.49)	0.0819	(4.38)	0.0956	0.8566	0.0665	(3.56)	0.0983	(2.85)
R = 12	0.0736	(4.31)	0.1467	(3.60)	0.1350	(1.80)	0.0653	(3.40)	0.0973	0.6707	0.0641	(3.46)	0.1222	(3.26)
Average	0.0675		0.1072		0.1436		0.0674			0.6714	0.0568		0.1230	
Momentum														
R = 1	0.0467	(1.86)	0.0264	(0.51)	0.0139	(0.16)	0.0288	(1.25)	0.1184	0.2432	0.0346	(1.27)	0.1208	(2.37)
R = 3	0.0557	(2.16)	0.0943	(1.83)	0.0511	(0.59)	0.0605	(2.55)	0.1221	0.4956	0.0432	(1.58)	0.1133	(1.61)
R = 6	0.0236	(1.18)	0.0479	(0.97)	0.0069	(0.08)	0.0394	(1.69)	0.1193	0.3302	0.0072	(0.37)	0.1153	(2.11)
R = 12	0.0568	(2.46)	0.1078	(1.63)	-0.0281	(-0.25)	0.0647	(2.77)	0.1185	0.5463	0.0485	(1.92)	0.0911	(1.74)
Average	0.0457		0.0691		0.0109		0.0484			0.4038	0.0334		0.1101	
Term Structure														
R = 1	0.0156	(0.75)	0.1214	(2.85)	0.1021	(0.97)	0.0335	(1.58)	0.1092	0.3073	0.0054	(0.25)	0.0601	(1.10)
R = 3	0.0411	(2.26)	0.0777	(1.92)	0.0609	(0.73)	0.0585	(2.97)	0.1015	0.5770	0.0324	(1.60)	0.0751	(2.33)
R = 6	0.0412	(2.33)	0.0926	(2.20)	0.0185	(0.24)	0.0422	(2.19)	0.0986	0.4277	0.0384	(2.02)	0.0515	(1.19)
R = 12	0.0328	(1.76)	0.1137	(2.74)	-0.0182	(-0.22)	0.0470	(2.24)	0.1063	0.4420	0.0253	(1.25)	0.0747	(1.67)
Average	0.0326		0.1013		0.0408		0.0453			0.4385	0.0254		0.0654	
Idiosyncratic volatility														
R = 1	0.0400	(2.14)	0.0381	(0.96)	0.2738	(2.63)	0.0536	(2.43)	0.1136	0.4717	0.0296	(1.42)	0.0877	(2.17)
R = 3	0.0379	(2.09)	0.0438	(1.10)	0.2719	(2.75)	0.0476	(2.22)	0.1101	0.4326	0.0391	(1.98)	0.0337	(0.71)
R = 6	0.0332	(1.73)	0.0717	(1.88)	0.2632	(2.63)	0.0367	(1.77)	0.1064	0.3452	0.0373	(1.82)	0.0111	(0.22)
R = 12	0.0405	(2.08)	0.0879	(2.66)	0.3417	(4.02)	0.0417	(1.94)	0.1090	0.3828	0.0317	(1.49)	0.0865	(1.87)
Average	0.0379		0.0604		0.2876		0.0449			0.4081	0.0344		0.0547	

Table 9. Transaction costs of triple-screen and individual strategies.

The table reports the annualized gross and net mean returns of the triple-screen and individual strategies, where the net performance is modeled relative to two levels of transaction cost (TC). The last column presents the break-even cost of the long-short portfolios defined as the transaction cost that would yield zero net returns. Significance *t*-statistics are in parentheses. *R* is the ranking period over which the signals are modeled. The sample covers the period from February 1985 to August 2011.

	TC = 0%		**TC = 0.033%**		**TC = 0.066%**		**Break-even cost**
Panel A: Momentum, Term Structure and Idiosyncratic Volatility							
R = 1	0.0580	(2.68)	0.0537	(2.49)	0.0488	(2.26)	0.40%
R = 3	0.0775	(3.63)	0.0738	(3.44)	0.0709	(3.31)	0.92%
R = 6	0.0774	(3.85)	0.0754	(3.74)	0.0734	(3.64)	1.29%
R = 12	0.0827	(3.91)	0.0810	(3.83)	0.0795	(3.76)	1.82%
Average	0.0739		0.0710		0.0682		1.11%
Panel B: Momentum							
R = 1	0.0476	(1.93)	0.0336	(1.37)	0.0196	(0.80)	0.13%
R = 3	0.0596	(2.38)	0.0554	(2.22)	0.0513	(2.05)	0.50%
R = 6	0.0255	(1.08)	0.0229	(0.97)	0.0203	(0.86)	0.33%
R = 12	0.0614	(2.36)	0.0596	(2.29)	0.0577	(2.22)	1.12%
Average	0.0485		0.0429		0.0372		0.52%
Panel C: Term Structure							
R = 1	0.0206	(0.98)	0.0179	(0.85)	0.0152	(0.72)	0.26%
R = 3	0.0445	(2.24)	0.0426	(2.14)	0.0407	(2.05)	0.79%
R = 6	0.0447	(2.21)	0.0434	(2.14)	0.0420	(2.08)	1.09%
R = 12	0.0369	(1.74)	0.0362	(1.71)	0.0355	(1.67)	1.68%
Average	0.0367		0.0350		0.0333		0.96%
Panel D: Idiosyncratic volatility							
R = 1	0.0454	(2.00)	0.0412	(1.81)	0.0381	(1.68)	0.50%
R = 3	0.0437	(1.93)	0.0425	(1.88)	0.0409	(1.81)	0.96%
R = 6	0.0399	(1.78)	0.0390	(1.73)	0.0380	(1.69)	1.35%
R = 12	0.0500	(2.16)	0.0495	(2.13)	0.0489	(2.11)	2.90%
Average	0.0448		0.0430		0.0415		1.43%

Figure 1. Future value of $1 invested in commodity portfolios

The figure plots the future value of $1 invested in January 1985 in the S&P-GSCI, the novel triple-screen strategy proposed, and each of the three individual strategies based on momentum, term structure or idiosyncratic volatility.

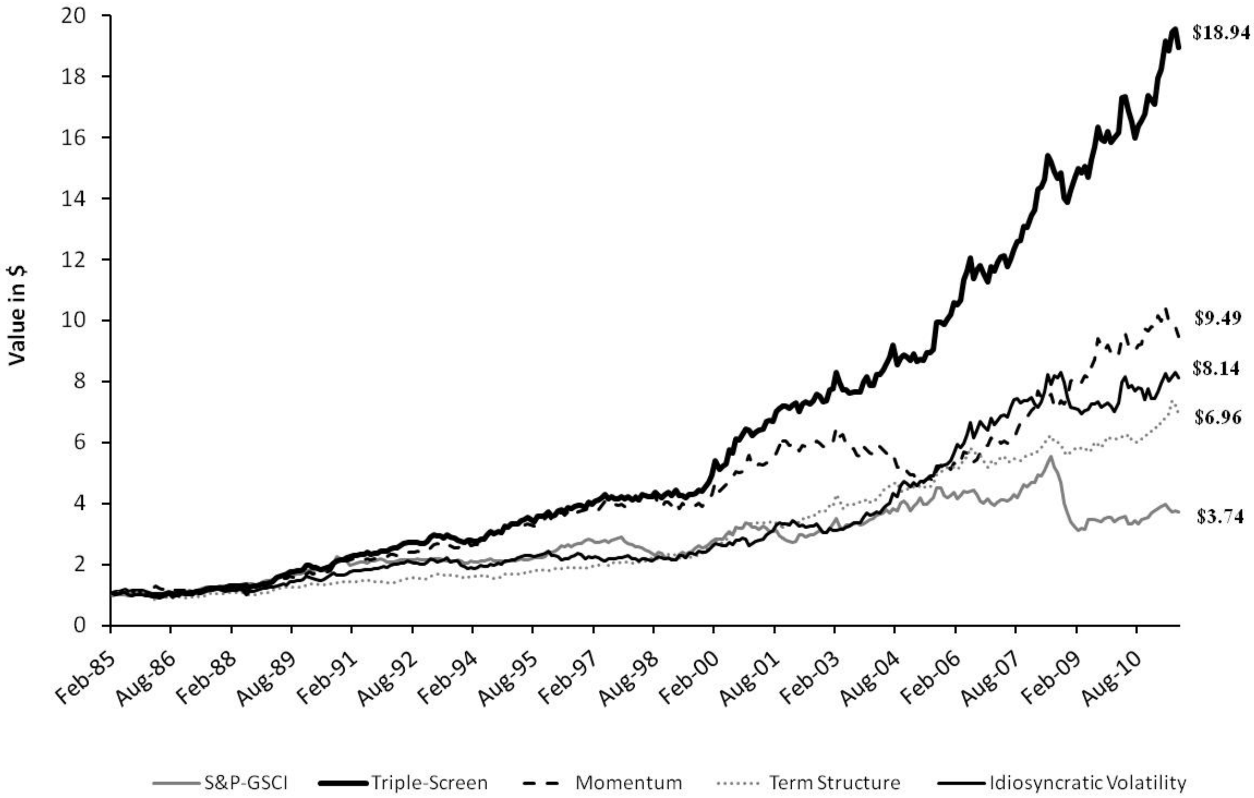


Figure 2. Total mean returns per annum over the period July 2007 - August 2011.

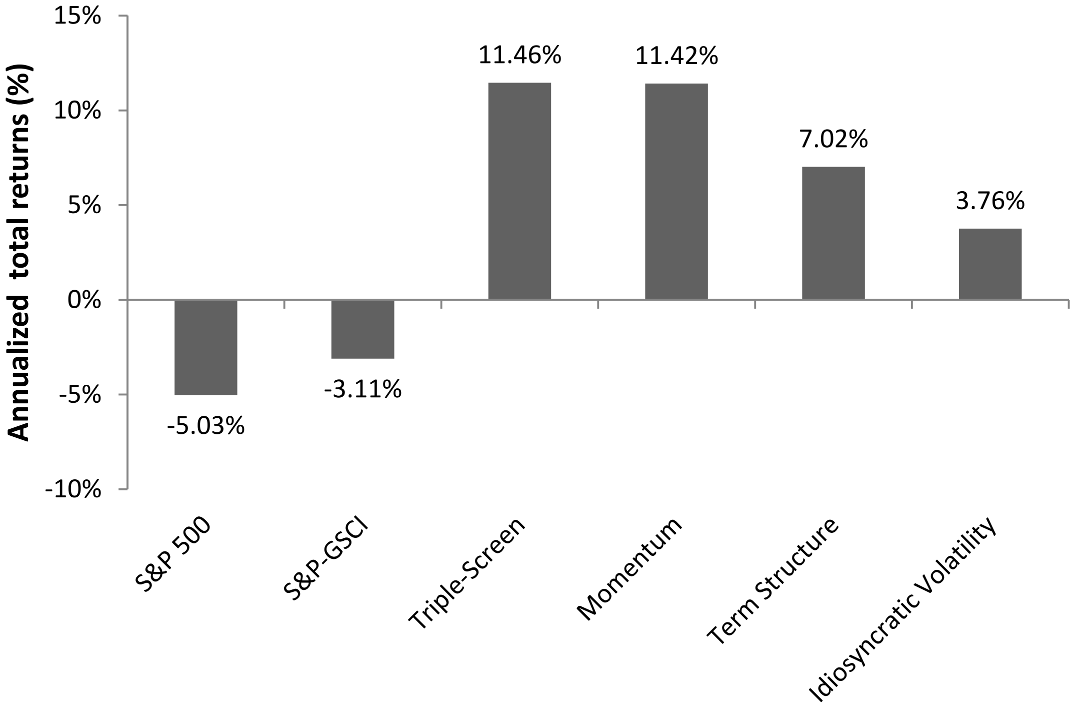
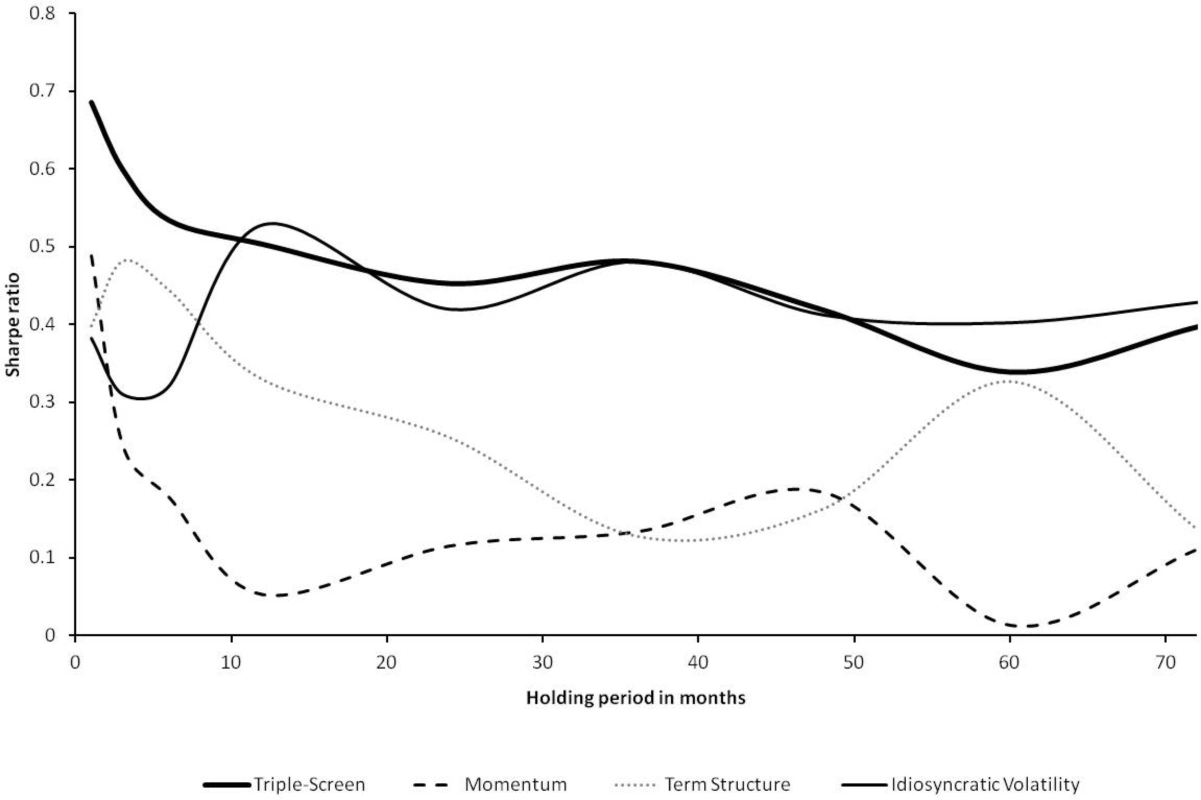


Figure 3. Sharpe ratio versus holding period.



APPENDIX A
Constituents of triple-screen portfolios

The appendix presents the frequency of each commodity futures contract in entering the long and short triple-screen portfolios, alongside the OLS estimates of the slope coefficient, Newey-West significance *t*-statistics and adjusted R^2 of equation (1) which regresses each commodity futures returns onto the excess returns of the S&P-GSCI. The estimation is conducted over the entire sample period from 1985 to 2011.

	Long (%)	Short (%)	$\beta_{\text{S\&P-GSCI}}$	t-stat	Adj-R^2
Cocoa	3.27%	43.94%	0.15	(7.11)	2.24%
Coffee	3.75%	49.92%	0.22	(8.34)	3.69%
Copper	16.99%	5.66%	0.31	(9.86)	9.31%
Corn	6.38%	25.28%	0.35	(14.22)	8.03%
Cotton	16.11%	26.08%	0.22	(9.30)	3.71%
Crude oil	50.32%	3.19%	1.55	(50.05)	77.40%
Electricity	1.99%	10.61%	0.63	(12.41)	17.42%
Feeder cattle	61.32%	1.04%	0.10	(5.48)	3.12%
Gasoline	51.28%	2.31%	1.42	(69.79)	69.46%
Gold	27.43%	0.72%	0.20	(13.80)	8.39%
Heating oil	40.27%	2.87%	1.49	(47.90)	74.43%
Hogs	25.60%	24.08%	0.26	(9.26)	4.34%
Live cattle	47.53%	1.36%	0.19	(9.68)	5.63%
Lumber	15.23%	39.79%	0.05	(3.54)	0.30%
Natural gas	2.71%	40.27%	1.10	(17.71)	24.22%
Oats	5.58%	47.77%	0.33	(11.54)	4.99%
Orange	10.85%	31.18%	0.11	(5.84)	0.71%
Palladium	13.00%	18.18%	0.27	(10.05)	5.61%
Platinum	29.67%	6.86%	0.26	(11.73)	6.82%
Pork bellies	11.40%	28.47%	0.29	(6.17)	2.61%
Rough rice	1.67%	12.76%	0.14	(7.61)	4.11%
Silver	4.70%	19.62%	0.39	(13.34)	8.10%
Soybean meal	29.43%	0.64%	0.33	(13.57)	8.92%
Soybean oil	7.02%	5.98%	0.30	(12.27)	5.51%
Soybeans	13.16%	11.08%	0.31	(13.13)	9.94%
Sugar	10.69%	28.15%	0.33	(10.90)	4.15%
Wheat	12.36%	31.98%	0.37	(12.19)	7.35%

APPENDIX B
Causality tests of financialization of commodity markets.

The appendix reports *t*-statistics for the null hypothesis that change in the long or short open interest (OI) of large speculators do not Granger-cause the returns of long-short triple-screen portfolios. *R* is the ranking period over which the signals are modeled. The sample covers the period from February 1985 to August 2011.

	R=1		R=3		R=6		R=12	
	Long OI	Short OI	Long OI	Short OI	Long OI	Short OI	Long OI	Short OI
Cocoa	-0.93	-0.12	0.04	-0.81	1.10	-0.50	0.70	-0.78
Coffee	-0.56	-1.29	-0.25	-1.70	0.15	-1.17	0.41	-1.63
Copper	-0.72	-1.04	0.07	-0.42	-0.44	-0.55	0.25	-1.85
Corn	0.57	-0.50	1.30	-0.17	0.61	-0.53	0.43	-0.10
Cotton	0.01	0.35	0.56	-0.23	0.70	-0.81	0.61	-0.61
Crude oil	-0.09	-0.28	0.87	-1.21	0.61	0.10	1.01	-1.06
Electricity	1.86	-0.28	0.73	-0.45	0.76	-0.39	-0.68	-0.35
Feeder cattle	1.12	-0.40	1.17	1.00	0.42	-0.53	0.60	-0.47
Gasoline	1.79	2.68	1.66	2.23	2.19	2.28	1.99	1.80
Gold	0.46	-0.59	0.92	0.30	0.09	0.29	0.45	-0.07
Heating oil	-0.08	-1.56	-0.07	-0.26	0.30	0.34	-0.89	0.13
Hogs	-0.26	-0.06	0.71	0.08	-0.20	0.76	-0.02	0.85
Live cattle	-0.20	1.02	-0.74	1.04	-0.99	0.16	-0.43	-0.20
Lumber	0.78	0.95	0.20	0.93	-0.01	0.28	0.18	-0.49
Natural gas	-0.42	-0.79	-0.75	-0.71	-0.68	-0.27	-1.07	-0.40
Oats	1.27	-0.58	0.05	-1.16	-0.40	-1.22	0.12	-0.23
Orange	0.27	0.54	0.35	0.62	0.83	1.28	0.18	1.30
Palladium	0.12	-1.15	-0.34	-0.60	-0.47	0.06	-0.04	-0.76
Platinum	0.21	0.38	-0.11	1.23	-0.70	0.65	0.09	1.09
Pork bellies	0.28	-1.16	-0.13	-1.05	0.62	-1.38	0.79	-1.12
Rough rice	-0.01	-0.26	0.40	-0.34	-0.60	-0.95	-0.26	-0.66
Silver	-0.97	-0.31	-0.36	-0.40	-0.69	-0.36	-0.67	-0.59
Soybean meal	-0.03	0.15	-0.16	0.32	-0.06	1.01	0.70	1.92
Soybean oil	0.52	-0.62	1.33	-0.56	0.84	-0.40	1.41	-1.51
Soybeans	0.61	-2.16	0.54	-1.65	-0.03	-1.98	-0.55	-0.32
Sugar	1.38	-2.43	1.20	-1.12	0.95	-0.82	0.80	-0.64
Wheat	-0.45	-0.84	-0.75	-0.64	-0.72	-1.51	-0.69	-1.13