COMMODITY RISK FACTORS AND INTERTEMPORAL ASSET PRICING

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Abstract

This article provides a comprehensive in-sample and out-of-sample analysis of the predictive ability of commodity risk factors for future long-horizon changes in investment opportunities. Motivated by the theories of storage and hedging pressure, the factors are constructed according to signals that are linked to backwardation and contango. The encouraging findings on predictive ability lead us to propose an Intertemporal CAPM (ICAPM) implementation that utilizes the commodity risk factors as state variables. We show that the proposed model implies intertemporal "hedging" risk premiums that are theoretically consistent with rational pricing by risk-adverse investors. The model is also able to price relatively well a large cross-section of test assets that include stocks, fixed income securities and commodities.

Keywords: ICAPM; Theory of Storage; Hedging Pressure Hypothesis.

JEL classification: G13, G14.

This version: May 2014.

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The authors acknowledge the useful comments of Guiseppe Bertola, Chris Brooks, Jerry Coakley, Eirini Konstantinidi, Abraham Lioui, David Rapach, George Skiadopoulos, Raman Uppal, seminar participants at Liverpool University Management School, EDHEC Business School and Universitat de les Illes Balears, Departament d'Economia de l'Empresa, Auckland University of Technology, and conference participants at the 2014 Conference on Modelling Macroeconomic and Financial Time Series, Loughborough University, 2014 Money Macro and Finance Workshop on "Empirical Modelling of Financial Markets", Brunel University, London, 2014 Conference in Honour of Professor Ron Smith, Birkbeck College, London, 2012 EDHEC-Risk Days Conference, London, and 2011 CSDA Conference on Computational and Financial Econometrics, London.

1. Introduction

The literature on commodity futures pricing centers around the theory of storage (Kaldor, 1939; Working, 1949; Brennan, 1958) and the hedging pressure hypothesis (Cootner, 1960; Hirshleifer, 1988). The theory of storage links the slope of the term structure of commodity futures prices (hereafter, *TS*) to the incentive of agents to own the physical commodity. With high inventories, the term structure slopes upward and markets are *contangoed*. Conversely, when inventories are depleted, the utility from owning the physical asset (known as convenience yield) is likely to exceed storage and financing costs; the futures curve slopes downward and markets are *backwardated*. Fama and French (1987) show that the difference between the futures and spot price (the basis) depends on interest rates and seasonals in convenience yields. Erb and Harvey (2006), Gorton and Rouwenhorst (2006), and Gorton *et al.* (2012) also support the theory of storage by showing that the risk premium of commodity futures can be modeled as a function of either the basis or the level of inventories.[1]

The hedging pressure hypothesis relates the evolution of commodity futures prices to the net positions of hedgers and speculators. Futures prices are expected to rise when hedgers are net short and speculators are net long; this market state is known as *backwardation*. Conversely, futures prices are expected to fall when hedgers are net long and speculators net short; this is known as *contango*. Hedging pressure (hereafter, *HP*) has been shown to play a critical role as determinant of commodity futures risk premia (Carter *et al.*, 1983; Bessembinder, 1992; de Roon *et al.*, 2000; Basu and Miffre, 2013).[2]

[1] Alternatively, the behavior of commodity spot and futures prices has been studied in a risk-neutral world using competitive rational expectations models of storage (Deaton and Laroque, 1992; Routledge *et al.*, 2000). In these models, the non-negativity constraint on inventory is crucial to understanding the dynamics of the spot price and the shape of the forward curve. Extensions of storage models that allow for a risk premium can be found in Casassus *et al.* (2009) and Baker (2012).

[2] The sharp increase in commodity assets under management post-2004 revived the debate on the function of speculators as both liquidity and risk-bearing providers and on their potential influence on futures prices, volatility and cross-market linkages (Stoll and Whaley, 2010; Brunetti *et al.*, 2011; Büyükşahin and Robe, 2014). Theoretical models can rationalize the recent commodity price

Momentum (hereafter, *Mom*) can also be theoretically linked to the commodity futures cycle through the theory of storage. Deviations of inventories from normals levels are likely to be persistent as inventories can only be replenished through new production which may take some time depending on the commodity. Thus, following a negative shock to inventories (that pushes up the spot price) a period of high expected futures risk premiums will follow as inventories get gradually restored. Gorton et al. (2012) adduce evidence to support this view.

The returns on strategies that exploit *TS*, *HP* or *Mom* signals can thus be interpreted as a compensation for bearing risk during times when inventories are low or when hedgers are net short or when the commodity futures curve slopes downwards. Not surprisingly, the returns of long-short commodity *TS*, *HP* or *Mom* mimicking portfolios explain well the cross-sectional variation in commodity futures returns (Basu and Miffre, 2013; Bakshi *et al.,* 2013; Szymanowska *et al.,* 2014). Given the link between the shape of the commodity futures curve and the dynamics of commodity supply and consumption (see Ready, 2014, in the context of crude oil), commodity risk factors may predict changes in future investment opportunities.

This article provides evidence that commodity *TS*, *HP* and *Mom* risk factors contain information about future long-horizon aggregate market returns (and volatilities) that is not fully revealed by traditional predictors. The notable predictive ability of the commodity risk factors, both in-sample and out-of-sample, encourages us to attempt a novel implementation of Merton (1973)'s intertemporal CAPM (ICAPM) using them as intertemporal "hedging" factors. We validate this idea empirically by showing that the intertemporal risk prices estimated by the Generalized Method of Moments (GMM) method are consistent with the direction of predictability of the underlying commodity state variables. More specifically, the results suggest that rational investors are willing to pay a higher price on assets that hedge

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dynamics in terms of endogenous demand shocks and changes in oil supply fundamentals (Baker, 2012; Baker and Routledge, 2012; Ready, 2014).

intertemporal risk and demand a lower price on assets that underperform when future market conditions are predicted to deteriorate.[3] The model can price relatively well a cross-section of 32 test assets, including stocks, fixed income securities and commodity futures.

Further analysis confirms that both legs of our analysis, time-series predictability and cross-sectional asset pricing, are robust. The favorable findings on long-horizon predictability are unchallenged when we consider alternative inference methods, forecasting schemes (rolling versus recursive) and forecast evaluation periods. The cross-sectional asset pricing evidence is affirmed with various market portfolio proxies, test assets, estimation method and under distinct ICAPM formulations with time-additive or recursive utility.

Our study adds to a recent but fast growing literature that contends that commodity risk factors can forecast economic activity and are able to price traditional assets (Baker and Routledge, 2012; Bakshi *et al.*, 2013; Koijen *et al.*, 2013b; Yang, 2013).[4] It also relates to a literature that shows that commodity market variables such as the returns of commodity futures, open interests, oil supply/demand shocks or the Baltic Dry Index are priced risk factors that explain cross-sectional differences in expected stock returns (Boons *et al.,* 2012; Hong and Yogo, 2012; Hou and Szymanowska, 2013; Ready, 2013, 2014; Bakshi *et al.*, 2014). Our main point of departure from these studies is to contend that commodity *TS*, *HP* and *Mom* factors can play a double role. First, they are good predictors relative to known state variables, both in-sample and out-of-sample, for future investment opportunities. Second, their innovations proxy risk factors that explain the cross-sectional pattern of asset returns in a plausible manner according to the baseline Merton's (1973) ICAPM theory.

[3] These findings are broadly in line with the theoretical model of Ready (2014) which predicts that oil supplies that are unresponsive to growth expectations act as partial hedge against growth shocks, thereby lowering the risk associated with these shocks and consequently the equity premium.

[4] Baker and Routledge (2012) show that bond excess returns are higher when the crude oil futures curve slopes downward. Bakshi *et al*. (2013) document that the commodity *TS* and *Mom* factors forecast real GDP growth and traditional asset returns. Koijen *et al*. (2013b) argue that the *TS* factor relates to global recessions, while Yang (2013) links it to producers' investment shocks.

In what follows, Section 2 outlines the ICAPM theory. Section 3 describes the data and the factor-mimicking *TS*, *HP* and *Mom* portfolios. Section 4 discusses the evidence on the predictive ability of the commodity risk factors, and on their plausibility as ICAPM state variables. Section 5 provides robustness checks and Section 6 briefly concludes.

2. Market Return Predictability and Intertemporal Asset Pricing

The fundamental insight of intertemporal asset pricing theory is that, in solving their lifetime consumption decisions under uncertainty, long-term investors care not only about the level of their invested wealth but also about the future returns on that wealth. In this paper, we focus on the simplified formulation of the Merton (1973) Intertemporal Capital Asset Pricing Model (ICAPM) which, in discrete time and logarithmic form, can be expressed as follows

$$E_t\left(R_{i,t+1}\right) = \gamma_M Cov_t(R_{i,t+1}, R_{M,t+1}) + \gamma_z Cov_t(R_{i,t+1}, \Delta z_{t+1}) \tag{1}$$

for risky assets i =1,…,N, where $E_t(.)$ is the expectation operator, $R_{i,t+1}$ is the asset i return between t and t+1 in excess of the risk-free rate, $R_{M,t+1}$ is the market portfolio excess return which summarises the current investment opportunity set, and z_{t+1} is a state variable whose innovation (denoted Δz_{t+1}) signals a change in future investment opportunities. Equation (1) says that the expected excess return of asset i is determined by a weighted sum of its conditional covariances with the return on total invested wealth and with news about future returns on invested wealth; the weights γ_M and γ_z are the prices of market risk and intertemporal risk, respectively. Equation (1) collapses to the static CAPM when investors do not care about changes in future investment opportunities, $\gamma_z = 0$, when the investment opportunity set is constant, $Cov_t\left(R_{i,t+1}, \Delta z_{t+1}\right) = 0$, or when the intertemporal risk and market risk are perfectly cross-sectionally correlated. For investors with time-additive utility, the parameter γ_M can be interpreted as the relative risk aversion (RRA) coefficient.[5]

The ICAPM theory does not identify the state variables. This leads to the perverse situation where the theory can be exploited as a "fishing license" (Fama, 1991) for *ad hoc* risk factors. Yet, the problem lies in bad habits of using the theory because "one could do a lot to make sure the candidate state variables really are plausible investment-opportunity state variables" (Cochrane (2005; Ch.9). Two key restrictions ought to be tested.

The first ICAPM restriction implies that the state variables must be able to predict long-horizon changes in investment opportunities. To probe it, we estimate by OLS the following predictive equations for the first and second moment of market returns, respectively

$$RM_{t+1,t+q} = a + \mathbf{b}'\mathbf{z}_t + u_{t+1,t+q} \,, \tag{2}$$

$$VM_{t+1,t+q} = c + \mathbf{d}'\mathbf{z}_t + e_{t+1,t+q} \,, \tag{3}$$

where t=1,…,T are months and T is the effective sample size (the original number of months minus the horizon q). The target variable in (2) is the market portfolio excess log return continuously compounded from month t+1 to month t+q; formally, $RM_{t+1,t+q} = RM_{t+1} + \cdots + RM_{t+q}$. The regressand in (3) is the sum of future monthly realized variances, $VM_{t+1,t+q} = VM_{t+1} + \cdots + VM_{t+q}$, constructed from daily market portfolio returns.[6] The state variables are collected in the $K \times 1$ vector $\mathbf{z}_t \equiv (z_{1,t}, \dots, z_{K,t})'$.

The second ICAPM restriction links the direction of the long-horizon predictability with intertemporal asset pricing. If a particular state variable $z_{j,t}$ has predictive slopes $b_j > 0$

[5] This simplified ICAPM version is adopted by Maio and Santa-Clara (2012), Bali and Engle (2010), Hahn and Lee (2006), Petkova (2006) and others; see Cochrane (2005; Ch.9) for a derivation. Using the more general Epstein and Zin (1989) recursive utility which disentangles risk aversion from intertemporal substitution, Campbell (1993) derives an ICAPM specification in which the prices of market risk and intertemporal risk prices are restricted parameters parameters, and the former is no longer interpreted as RRA coefficient. Variants and extensions of Campbell's (1993) model are developed by Campbell (1996), Maio (2013), Campbell and Vuolteenaho (2004) and others.

[6] The latent market volatility on month t can be consistently estimated *ex post* as the realized variance or sum of squared daily market returns, $VM_t = \sum_{d=1}^{D} RM_{d,t}^2$ with D the number of days on month t, if the daily market returns are independent. The correlation function confirms the latter.

(market return) and $d_j < 0$ (market variance), this means that negative innovations in $z_{j,t}$ are proxy with good news about future investment opportunities. Then such a variable should have a positive risk price $\gamma_j > 0$. The intuition is that assets that do poorly when there is bad news about future market returns are undesirable because they reduce the consumer's ability to hedge changes in future investment opportunities. This positive (negative) correlation between b_j (d_j) and γ_j also holds under Campbell's (1993) ICAPM formulation with recursive preferences but it requires RRA > 1 so that the investor's desire to hedge intertemporal risk outweighs his ability to profit from higher $R_{i,t+1}$ when there is good news.

Following Campbell (1996), Petkova (2006), Maio (2013) and others, we construct the innovations to the state variables via a vector autoregressive (VAR) model

$$\begin{pmatrix} RM_{t+1} \\ \mathbf{z}_{t+1} \end{pmatrix} = \begin{pmatrix} \mu_{RM} \\ \boldsymbol{\mu}_z \end{pmatrix} + \mathbf{A} \begin{pmatrix} RM_t - \mu_{RM} \\ \mathbf{z}_t - \boldsymbol{\mu}_z \end{pmatrix} + \begin{pmatrix} e_{M,t+1} \\ \mathbf{e}_{z,t+1} \end{pmatrix}, \tag{4}$$

estimated by OLS with monthly data t=1,…,T. The innovations in the state variables, denoted $\mathbf{f}_{t+1} \equiv (f_{1,t+1},\ldots, \ f_{K,t+1})'$, are the residual sequences $\hat{\mathbf{e}}_{z,t+1}$ orthogonalized with respect to RM_{t+1}, and standardized so that they have the same standard deviation as $\hat{e}_{M,t+1}$.

The asset pricing model can be implemented by the one-step generalized method of moments (GMM) procedure developed by Hansen (1982). The first N sample moments are the pricing errors for risky assets i=1,…,N, and the remaining K+1 sample moments account for the uncertainty associated with estimating the factor means . Formally, we have

$$g_T(\mathbf{b}) = \frac{1}{T}\sum_{t=0}^{T-1} \begin{cases} R_{i,t+1} - \gamma_M\left(R_{i,t+1}\right)(RM_{t+1} - \mu_M) \\ \qquad -\boldsymbol{\gamma}_{\mathbf{z}}'\left(R_{i,t+1}\right)(\mathbf{f}_{t+1} - \boldsymbol{\mu}_{\mathbf{z}}) \\ RM_{t+1} - \mu_M \\ \mathbf{f}_{t+1} - \boldsymbol{\mu}_{\mathbf{z}} \end{cases} = \mathbf{0}, \tag{5}$$

and the parameters of interest are the market risk price γ, and the intertemporal "hedging" risk prices $\boldsymbol{\gamma}_{\mathbf{z}} \equiv (\gamma_{z_1}, \ldots, \gamma_{z_K})'$. The vector $\mathbf{b} \equiv (\gamma_M, \boldsymbol{\gamma}_{\mathbf{z}}', \mu_M, \boldsymbol{\mu}_{\mathbf{z}}')'$ collects all the parameters.

3. State Variables and Data

The analysis is based on data from January 1989 to August 2011 (T=272 months). The factor-mimicking portfolio construction, explained next, employs end-of-month prices of front-end futures contracts for N=27 commodities from *Datastream*.[7] The cross-section is dictated by the availability of data on large hedgers and speculators positions which is published by the *Commodity Futures Trading Commission* in the Commitments of Traders Report.

3.1 BACKWARDATION, CONTANGO AND INTERTEMPORAL RISK

Our leading conjecture is that factor-mimicking portfolios formed according to measures of backwardation (and contango) can predict the first two moments of aggregate market excess returns over long horizons. This conjecture is motivated by a recent literature which links the backwardation and contango dynamics of commodity futures markets with future economic activity (Baker and Routledge, 2012; Bakshi *et al.*, 2013; Koijen *et al.*, 2013b; Yang, 2013) and with commodity supply dynamics (see Ready, 2014, for crude oil)

The *TS* factor-mimicking portfolio employs as backwardation/contango signal the end-of-month *roll yield* defined as the average of the intra-month daily roll yields, $Roll_t \equiv (1/D)\sum_{d=1}^{D} lnF(d,T_1)_t - lnF(d,T_2)_t$ with $lnF(d,T_1)_t$ and $lnF(d,T_2)_t$ the futures prices of the nearby and second-nearest contracts on day d of month t. The backwardation/contango signal for the *HP* portfolio is jointly derived from two hedging pressure measures; $HP_{i,t}^{spec} \equiv \frac{OI(spec,L)_{i,t}}{OI(spec,L)_{i,t}+OI(spec,S)_{i,t}}$ where $OI(spec,L)_{i,t}$ and $OI(spec,S)_{i,t}$ are speculators' open interests pertaining to long and short positions, respectively, reported at the end of week i=1,…,4 during month t, and $HP_{i,t}^{hedg} \equiv \frac{OI(hedg,L)_{i,t}}{OI(hedg,L)_{i,t}+OI(hedg,S)_{i,t}}$ defined similarly for hedgers. These

[7] The 27 commodities include 12 agricultural products (cocoa, coffee C, corn, cotton n°2, concentrated frozen orange juice, rough rice, oats, soybean meal, soybean oil, soybeans, sugar n°11, wheat), 5 energy contracts (electricity, gasoline, heating oil, light sweet crude oil, natural gas), 4 livestock commodities (feeder cattle, frozen pork bellies, lean hogs, live cattle), 5 metals (copper, gold, palladium, platinum, silver), and lumber. The price series are obtained from *Datastream* employing front contracts up to one month before maturity.

weekly measures are averaged to define the corresponding monthly HP_t^{hedg} and HP_t^{spec} measures. The HP portfolio buys the contracts with the lowest HP_t^{hedg} and the highest HP_t^{spec}, and shorts the contracts with the highest HP_t^{hedg} and the lowest HP_t^{spec}. The *Mom* portfolio buys (sells) the contracts with the highest (lowest) past 12-month return.

The signals are averaged over a 12-month ranking period and the long-short portfolio is held for one month. All positions, long and short, are fully-collateralized. The long portfolio contains the 20% most backwardated (equally weighted) contracts according to each signal, and the short portfolio includes the 20% most contangoed (equally weighted) contracts.[8]

To illustrate the ability of the *HP*, *TS* and *Mom* signals to capture the commodity futures cycle, we plot end-of-month crude oil futures prices in Figure 1. Shaded areas signify months when the commodity futures contract is in backwardation according to a given signal; namely, when $Roll_t > 0$ in Panel A, $HP_t^{spec} > 0.5$ and $HP_t^{hedg} < 0.5$ in Panel B, and the past 12-month average return is positive in Panel C. The three panels show a good (albeit imperfect) correspondence between backwardation and rising futures prices.

3.2 TRADITIONAL STATE VARIABLES

We benchmark the predictive ability of the commodity risk factors against that of well-known state variables as employed in two groups of models. The first group comprises five popular ICAPM applications that employ traditional predictors (e.g., term spread and dividend yield) as state variables. The second group comprises three widely-used multifactor models in the equity pricing literature which were not originally conceived as ICAPM applications but whose risk factors (beyond the market) have been subsequently interpreted

[8] The 20% composition of the long and short *HP* portfolios is attained via a double-sort based, first, on hedgers' *HP* with the 50th quantile as breakpoint and, second, speculators' *HP* with the 40th quantile. We computed the fraction of the months in which each of the 27 commodities enters the long (short) portfolio. The unreported results, available upon request, did not reveal any clear pattern; namely, the *HP*, *TS* and *Mom* risk premia are not driven by specific commodities.

as intertemporal risk factors: the returns of size (*SMB*), value (*HML*), and momentum (*Eq-Mom*) sorted equity portfolios, and a liquidity risk factor. Appendix A provides details.

3.3 MARKET PORTFOLIO AND TEST ASSETS

We proxy the market portfolio by a mix of stocks, bonds and commodities with weights 50%, 40% and 10%, respectively, which broadly reflect the proportion of each asset class in total wealth: the U.S. value-weighted equity index obtained from Kenneth French's library, the Barclays bond index, and the Standard & Poor's Goldman Sachs Commodity Index (S&P-GSCI). The bond and commodity index observations are obtained from *Bloomberg*.

Table I presents summary statistics for the market portfolio (Panel A) and the state variables (Panels B to D). All returns are logarithmic and in excess of the 1-month Treasury bill rate. The pairwise return correlations between the three commodity state variables are positive but low (0.38 at most), which motivates their joint inclusion in our empirical models.

[Insert Table I around here]

The pricing models are tested over a large cross-section of assets (*N*=32) that comprise 25 equity portfolios (CRSP NYSE/AMEX/NASDAQ stocks sorted by size and book-to-market) from Kenneth French's library, 6 bond portfolios (U.S. Treasury bond indices with maturities of 1, 2, 5, 10, 20 and 30 years) from the CRSP database, and the S&P-GSCI.

Empirical Results

4.1 LONG-HORIZON PREDICTIVE ABILITY OF COMMODITY RISK FACTORS

Are the commodity risk factors able to predict future changes in investment opportunities over long horizons? To address this question, we begin by estimating equations (2) and (3) applying OLS to the full set of observations; this enables an in-sample predictability analysis. Second, we conduct an out-of-sample predictability analysis based on recursive windows.

The commodity factor-mimicking portfolio returns are cumulated over p (current and past p-1) months to define the predictor $\boldsymbol{z}_t$ in equations (2) and (3). For instance, we define $\tilde{z}_{TS,t} \equiv \sum_{j=t-(p-1)}^{t} z_{TS,j}$, where $z_{TS,j}$ is the month j excess return of the commodity *TS* factor-mimicking portfolio; we consider p={24, 36, 60} months. The empirical equity risk factors *SMB*, *HML*, *Eq-Mom* and *L* are similarly transformed into cumulative sums. This is a convenient dimensionality reduction since, by matching the persistence of predictors and predictands, it circumvents the need for adding lags of the variables.[9]

The estimation results for equations (2) and (3) using traditional state variables and commodity risk factors are shown in Tables II and III, respectively. Throughout the analysis we consider the nine pairwise combinations of horizon q and cumulative length p (for *SMB*, *HML*, *Eq-Mom* and *L*) equal to 24, 36, 48 months; for space limitations, Table II reports only the predictive regressions corresponding to p=q=60 months, but we discuss the results for all p and q combinations. The tables report OLS slope estimates together with autocorrelation and heteroskedasticity (h.a.c.) t-statistics based on Newey and West (1987).

Various features are observed in both sets of results that affirm conventional wisdom. The magnitude of the predictive slopes and the predictive power given by the $\bar{R}^2$ generally increase with the horizon (see e.g., Cochrane, 2005; Ch. 20). The second moment of the aggregate market excess return is easier to predict than its first moment, as borne out by the higher predictive power obtained for equation (3) than for equation (2). Third, for a given horizon q the predictive power of empirical risk factors (i.e., factor mimicking portfolio returns) improves with the cumulation length p which confirms that by aggregation it is possible to filter out excessive short-term fluctuations that are unrelated to the business cycle.

[9] Aggregate market returns (and variance) over long horizons of 24, 36 and 60 months are, like traditional predictors, very persistent as suggested by the first-order autocorrelation coefficient. The empirical risk factors require cumulation over at least 24 months to achieve similar persistence. Time-series plots show that the cumulated empirical risk factors have a higher 'signal-to-noise' ratio than the monthly factor-mimicking portfolio returns, namely, they can mimic better the slow changes in long-horizon investment opportunities. Detailed results are available from the authors upon request.

The results in Table II affirm the findings of what Cochrane (2005; Ch. 20) describes as a 'new generation' of empirical research that documents long-horizon predictability of aggregate market returns; see also Maio and Santa-Clara (2012) for recent evidence. The predictive power reaches 38.7% (market return) and 67.3% (market variance), respectively.

[Insert Table II and Table III around here]

The predictability results in Table III for the commodity risk factors are very encouraging. First, the predictive slopes essentially keep the same sign across specifications.[10] Second, the predictive ability of the proposed commodity risk factors is remarkable, reaching 61.4% (market return) and 77.2% (market variance). This suggests that commodity risk factors are good competitors to traditional predictors, namely, they contain at least as much information on changes in future investment opportunities as known predictors.[11] But do they contain *additional* information? To address this question, the commodity state vector $(\tilde{z}_{TS,t}, \tilde{z}_{HP,t}, \tilde{z}_{Mom,t})'$ is added to the traditional regressions, and we reassess predictive power and conduct a Wald test for the null hypothesis that the predictive coefficients of the commodity risk factors are jointly zero. The results for p=q=60 months (all other cases are available upon request) are shown in the bottom section of Table II.

The predictive power of traditional state variables for market returns is greatly enhanced by adding commodity factors from 21% on average (Table II; top panel), to 59% on average (Table II; bottom panel). For the market variance, the predictive power almost doubles from 41% to 79% on average when the commodity risk factors are added (Table II; bottom panel). The Wald test statistics for the null hypothesis that traditional predictors encompass the

[10] In the market returns equation the predictive slopes of *TS* and *HP* are negative, and those of *Mom* are typically positive; the other way round in the market variance equation. Bakshi *et al*. (2013) also document different signs for the slopes of the commodity *TS* and *Mom* factors in a regression analysis of their role as leading indicators of economic activity.

[11] Regarding market returns, the traditional state variables achieve a predictive power of 20.32% on average with range [1.47%, 38.73%] over all nine combinations of p and q; the predictive power of the commodity risk factors averages 37.25% with range [8.39%, 61.44%], which represents a notable improvement. The counterpart figures for the market variance reveal a similar improvement.

commodity risk factors, $H_0: b_{TS} = b_{HP} = b_{Mom} = 0$ in eq. (2) and $H_0: d_{TS} = d_{HP} = d_{Mom} = 0$ in eq. (3) are significant. This analysis suggests that commodity risk factors contain information on changes in future investment opportunities not revealed by known predictors.

We should note a caveat of asymptotic inference (i.e., standard t-tests and Wald tests) in predictability regressions, namely, the size distortions induced by the large persistence of the predictors. Seeking to shield our analysis from this critique we compute subsampling *p*-values for uncentered statistics using the minimum-volatility block size selection method proposed by Romano and Wolf (2001). In Tables II and III, we employ bold font (asterisks) to denote significance according to asymptotic (subsampling) inference. The significance of the predictive slopes somewhat lessens but the inferences from the Wald suggesting the traditional factors do not encompass commodity risk factors test remain unchallenged.

Another well-known critique of traditional predictive regressions is that they have performed poorly in real time. In order to produce evidence on the relative predictive ability of commodity risk factors that is free from this critique (also known as "look-ahead" bias), we assess the extent to which models estimated with data available up to time *t* are able to predict aggregate market returns and variances over an unseen (out-of-sample) future period. To this end, the total sample period comprising *T* months is divided into an estimation period (T-T_1) and a holdout or evaluation period (T_1). We obtain recursive parameter estimates $(a_t, \boldsymbol{b}'_t, c_t, \boldsymbol{d}'_t)$ for equations (2) and (3) over expanding samples starting; the first sample is 1989:01-2003:11, the second sample is 1989:01-2003:12 and so on, which implies T_1=(1/3)T. The out-of-sample predictions for q=p=60 are summarized in Table IV.

We report the mean absolute error, $MAE = \frac{1}{T_1}\sum_{t=1}^{T_1}\left|\hat{u}_{t+1,t+q}\right|$, and root mean square error, $RMSE = \sqrt{\frac{1}{T_1}\sum_{t=1}^{T_1}\hat{u}_{t+1,t+q}^2}$, where $\hat{u}_{t+1,t+q} \equiv y_{t+1,t+q} - \hat{y}_{t+1,t+q}$ with $y_{t,t+q}$ denoting the actual aggregate market return (or variance) from month t+1 to t+q, and $\hat{y}_{t+1,t+q}$ the prediction based on data up to month t. Since the historical average is the most common benchmark for evaluating forecasting models of the equity premium, we also present the out-of-sample (OOS) statistic $\bar{R}^2_{OOS,m} = 1 - \frac{MSE_m}{MSE_{hist}}$ which gives the proportional reduction in MSE for an arbitrary forecast model m relative to the historical average; $MSE_{hist} = \frac{1}{T_1}\sum_{t=1}^{T_1}(y_{t+1,t+q} - \bar{y}_{t+1,t+q})^2$ where $\bar{y}_{t+1,t+q}$ are recursive forecasts from a naive version of equations (2) and (3) with only a constant (i.e., $\mathbf{b}' = 0$ and $\mathbf{d}' = 0$).

In order to assign significance to the out-of-sample predictability results we conduct tests of various hypotheses using two tests. The null hypothesis $H_0{:}\,\Delta MSE = 0$ where $\Delta MSE = MSE_{trad} - MSE_{comm}$ versus the alternative $H_A{:}\,\Delta MSE \neq 0$ are assessed using the Diebold and Mariano (1995) t-test for non-nested models; likewise for the *MAE*. In order to assess whether a given forecasting model yields a significantly smaller *MSE* than the historical average (i.e., $H_0{:}\,\bar{R}^2_{OOS} = 0$ versus $\bar{R}^2_{OOS} > 0$) we deploy the one-sided *encompassing* t-test proposed by Clark and West (2007) for nested models. The same test is applied to evaluate the null hypothesis H_0: 'the forecasts from a traditional model encompass the forecasts from the same model expanded with the commodity risk factors' (ENC_1) versus H_A: 'the commodity risk factors add significant information to the traditional predictors', and H_0: 'the forecasts from the commodity model encompass the forecasts from the same model expanded with traditional predictors' (ENC_2) versus H_A: 'the traditional predictors add significant information to the commodity risk factors'. All tests are adjusted for serial dependence in prediction errors using the Newey-West (1987) method.

The smallest out-of-sample predictive errors (in absolute terms as borne out by the *MAE* and *RMSE,* and relative to the historical average as borne out by the $\bar{R}^2_{OOS}$) correspond with the commodity-based model which significantly outperforms all traditional models. The ENC_1 hypothesis is clearly refuted which suggests that commodity risk factors add significant information to traditional state variables. In sharp contrast, the ENC_2 hypothesis is most often not rejected which suggests that commodity risk factors encompass traditional predictors.

Are the commodity risk factors also able to predict real economic activity? To answer this question we collect quarterly real GDP data for the G7 countries from *Datastream* and estimate the predictive regression, $\ln(GDP_{t+h}/GDP_{t+1}) = a + \mathbf{b}'\mathbf{z}_t + u_{t+1,t+h}$, for the equivalent horizons h={8, 12, 20} quarters. The results are reported in the bottom panel of Table II. Reassuringly, the signs of the slopes are economically plausible as they coincide with those obtained for the market returns predictive equation and are opposite of those in the market variance predictive regression. The predictive ability reaches 70% and confirm that the three commodity risk factors have predictive ability for future economic conditions.

4.2 ARE THE FACTOR RISK PRICES CONSISTENT WITH ICAPM THEORY?

We now assess the compatibility of the time-series predictive slopes and the intertemporal risk prices obtained by GMM estimation of equation (1) using a cross-section of 32 test assets. Table VI reports the GMM estimation results. We begin by discussing the results for the commodity-based multifactor pricing model which are reported in the leftmost column.

[Insert Table V and Figure 2 around here]

The GMM estimates of the covariance risk prices γ_{TS} and γ_{HP} are negative, in line with the negative (positive) predictive slopes for market returns (variances) reported in Table II. This confirms that rational agents are prepared to pay higher prices on assets that are able to hedge intertemporal risk. The estimate for γ_{Mom} is positive which is consistent with the positive (negative) link between the *Mom* state variable and future market returns (variances) documented in the long-run predictability analysis. Hence, rational investors require a positive premium for holding assets that are poor hedges against intertemporal risk.[12]

[12] The joint predictive ability of the commodity *TS*, *HP* and *Mom* factors is greater than that obtained with pairs of (or individual) factors; *e.g.*, the $\bar{R}^2$ of predictive regressions for $RM_{t,t+q}$ with

In sharp contrast, traditional state variables generally fail to produce intertemporal risk prices whose sign is consistent with the direction of long-horizon predictability, in line with the recent evidence in Maio and Santa-Clara (2012). To illustrate with an example, a decrease in the term spread (*TERM*) anticipates a decline in investment opportunities as suggested by the predictive slopes in Table II. Hence, assets that covary positively with innovations to *TERM* do not hedge reinvestment risk and therefore a positive premium is required. However, the estimates of γ_{TERM} in Panel C of Table V are negatively signed.[13]

Finally, we compare the models' ability to capture the cross-sectional variation in the average excess returns of $N = 32$ tests assets using three criteria. The first criterion is the mean pricing error defined using the absolute or square loss function, $MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{\alpha}_i|$ or $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\hat{\alpha}_i^2}$ where $\hat{\alpha}_i \equiv g_{T,i}(\hat{\mathbf{b}})$ is the pricing error for asset *i*. The second measure is the degrees-of-freedom adjusted fraction of the cross-sectional variation in average excess returns captured by the pricing model, $\bar{R}^2 = 1 - \frac{Var_N(\hat{\alpha}_i)}{Var_N(\bar{R}_i)}$. The third criterion is a J test statistic for the null hypothesis that the sum of squared pricing errors is zero, $J = T[g_T(\hat{\mathbf{b}})'\hat{\mathbf{S}}^{-1}g_T(\hat{\mathbf{b}})]$ which follows a $\chi^2_{N-(K+1)}$ distribution asymptotically, and $\hat{\mathbf{S}}$ is the $N\times N$ spectral density matrix of the sample moments. As shown in Table V, the commodity-based pricing model achieves the lowest pricing errors (MAE and RMSE of 0.11% and 0.14%, respectively, and the largest explanatory power ($\bar{R}^2$ of 66.55%). Secondly, the *J* test does not

q=60 months reaches 19% on average with factors in pairs, which is well below the 38% obtained jointly (Table III). Likewise, the ICAPM specification based on the three state variables has much better pricing power at 66.52% (Table V; Panel A) than the nested models with paired factors at 20.27% on average. These results affirm the low correlations among the *TS*, *HP* and *Mom* risk factors.

[13] The relative risk aversion levels (γ) suggested by the multifactor models, ranging from 4.07 to 7.27, are plausible according to expected-utility theory (see e.g. Maio and Santa-Clara, 2012; Bali and Engle, 2010; Cochrane, 2005; Mehra and Prescott, 1985). Other theories challenge this interpretation, e.g., Epstein and Zin (1989) propose recursive utility functions that disentangle the relative risk aversion and elasticity of intertemporal substitution, and Rabin (2000) questions the ability of expected-utility theory to rationalize risk aversion over both small and large stakes.

reject the null for the commodity-based ICAPM, in contrast with various traditional models. Finally, Figure 2 plots for each test asset the average excess return vis-à-vis the corresponding model prediction. The points are at least as close to the 45° line for the commodity-based model as for the traditional models. For completeness, we should note that the GMM estimation of the nested CAPM equation corroborates that the intertemporal "hedging" risks play a crucial role; the CAPM equation has essentially no pricing ability as borne out by a negligible $\bar{R}^2$ of -0.97% and a strongly significant J statistic of 52.97.

Robustness Checks

5.1 TIME-SERIES PREDICTIVE ABILITY

The out-of-sample predictive analysis for alternative choices of forecasting schemes, evaluation versus estimation period ratio (T_1/T-T_1) and horizon is summarized in Appendix B. To preserve space, we focus on the (R)MSE metric since the results for MAE are very similar.

First, the predictive regressions estimated over rolling windows of fixed 15-year length lead to similar conclusions (Panel I). Second, at a 24-month horizon, the commodity-risk factor model still yields significantly better forecasts than the historical average and than most of the traditional models. Unsurprisingly, the forecast errors increase relative to the 60-month horizon (Table III). The findings are also unchallenged when we entertain a longer forecast evaluation period of T_1=1/2T months starting on May 2000 (Panel III).

5.2 CROSS-SECTIONAL PRICING

Robustness checks on the role of the commodity factor-mimicking portfolios as priced factors that proxy intertemporal risk are shown in Appendix C. Panel I, column one, shows results for a GMM system with intercept $\hat{\gamma}_0$ which is positive (but small) suggesting some misspecification. But the risk prices remain consistently signed in relation with the long-horizon predictive slopes in Table II. Panel I, column two, entertains a simpler system that excludes the K factor means. The main findings are unchallenged; including the means helps in identification as borne out by the lower MAE and higher $\bar{R}^2$ of the original N+K+1 system.

Columns three and four of Panel I pertain to two-step efficient GMM that gives less weight to the noisier moment conditions, and iterated GMM with identical asymptotic properties but potentially better finite-sample performance. Explanatory power is given by the weighted least squares (WLS) R^2 statistic, and the J statistic represents now the weighted sum of squared pricing errors.[14] The results are very similar and reveal limited efficiency gains. The penultimate column of Panel I illustrates that the signs of the OLS (beta) risk prices obtained through the two-step Fama and MacBeth (1973) approach are plausible.

The last column entertains Campbell's (1993) ICAPM version based on a representative agent model with the non-expected utility function of Epstein and Zin (1989) and a loglinear approximation of the budget constraint. Model 1 is Campbell's equation (36) which is derived by assuming that the (co)variances of lognormal asset returns and consumption are time constant, and Model 2 is equation (42) that relaxes this assumption. The signs of the commodity factor risk prices estimated by one-step GMM are unchanged.[15]

Panel II considers as test assets the 25 portfolios sorted by size and momentum (25 SMom) from Kenneth French's library alongside the same 6 U.S. Treasury-bond indices and the S&P-GSCI; the 25 portfolios sorted by size and book-to-market (25 SBM); and the 25 size and momentum sorted portfolios (25 SMom). Panel III, considers as alternative market

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[14] In two-step and iterated GMM, the weighting matrix is the first N×N block of the inverse of $\hat{\mathbf{S}}$, and $R^2_{WLS} = 1 - \bar{\widehat{\boldsymbol{\alpha}}}'\hat{\mathbf{S}}_N^{*-1}\bar{\widehat{\boldsymbol{\alpha}}}/\bar{\mathbf{R}}'\hat{\mathbf{S}}_N^{*-1}\bar{\mathbf{R}}$, where $\bar{\widehat{\boldsymbol{\alpha}}}$ and $\bar{\mathbf{R}}$ are N×1 vectors of demeaned pricing errors and demeaned excess returns, respectively, and $\hat{\mathbf{S}}_N^{*} \equiv diag_N(\hat{\mathbf{S}})$. R^2_{WLS} gives the explanatory power of models for 'repackaged' portfolios which may not be of interest to investors (Cochrane, 2005).

[15] Appendix C reports the market risk price $\gamma_M \equiv \gamma + (\gamma - 1)\lambda_M$ and intertemporal risk prices $\gamma_j \equiv (\gamma - 1)\lambda_j$ for Model 1 and $\gamma_M \equiv \gamma + (\gamma - 1 - \omega)\lambda_M$ and $\gamma_j \equiv (\gamma - 1 - \omega)\lambda_j$ for Model 2, where $j = \{TS, HP, Mom\}$; γ is the RRA whose estimate is 6.69 (Model 1) or 6.53 (Model 2), ω is a coefficient resulting from the conditional heteroskedasticity of asset returns and consumption whose estimate is a significant 20.03, and $\boldsymbol{\lambda} \equiv (\lambda_M, \lambda_{TS}, \lambda_{HP}, \lambda_{Mom})'$ is a nonlinear function of a discount coefficient ρ and the matrix $\mathbf{A}$ of our VAR equation (4) with innovations orthogonalized (and scaled) as noted in Section 2. Following Maio (2012) and Campbell and Vuolteenaho (2004) we adopt a value for ρ that implies a constant consumption to wealth ratio of about 5% per annum ($\rho = 0.95^{1/12}$).

portfolio proxies: the US value-weighted equity index; the US value-weighed equity index (60% loading) and the Barclays bond index (40% loading); and the US value-weighted equity index (90% loading) together with the S&P-GSCI (10% weight). The one-step GMM estimates obtained for these cases do not materially challenge the main findings.[16]

Conclusions

This paper studies the long-horizon predictive ability of factor-mimicking commodity portfolios based on term structure, hedging pressure or momentum signals that are motivated by the theories of storage and hedging pressure. The factors proxy the backwardation/contango risk and contain information on future changes in investment opportunities that is not fully revealed by traditional predictors. The results hold both in-sample and out-of-sample, for different forecasting schemes, horizons and evaluation periods.

Accordingly, we conjecture that commodity risk factors are plausible candidates as state variables in a novel empirical implementation of Merton's (1973) ICAPM. The findings support this conjecture in that the estimated intertemporal risk prices are consistent with the direction of time-series predictability. Moreover, the commodity-based multifactor model can price well a cross-section of equity, fixed income and commodity portfolios. The findings are robust to alternative choices of estimation method, test assets and market portfolio proxy.

Our work adds to a recent strand of the literature that ascribes a role to commodity market variables, such as the basis and open interests, as leading indicators of economic activity and as sources of priced risk. The evidence reported may inspire further research on the interactions between commodity futures, traditional assets classes and the business cycle.

[16] The in-sample and out-of-sample predictive analyses based on these market portfolio proxies are qualitatively similar to those reported earlier in Tables II to IV. Results are available upon request.

References

Baker, S. (2012) The financialization of storable commodities. Unpublished Working Paper, Carnegie Mellon University.

Baker, S., and Routledge, B. (2012) The price of oil risk. Unpublished Working Paper, Tepper School of Business

Bakshi, G., Gao, X., and Rossi, A. (2013) A better specified asset pricing model to explain the cross-section and time-series of commodity returns. Unpublished Working Paper, University of Maryland.

Bakshi, G., Panayotov, G., and Skoulakis, G. (2014) In search of explanation for the predictive ability of the Baltic Dry index for global stock returns, commodity returns, and global economic activity. Unpublished Working Paper, University of Maryland.

Bali, T., and Engle, R. (2010) The intertemporal capital asset pricing model with dynamic conditional correlations, *Journal of Monetary Economics* **57**, 377-390.

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

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

Bessembinder, H. (1992) Systematic risk, hedging pressure, and risk premia in futures markets, *Review of Financial Studies* **5**, 637-667.

Brennan, M. (1958) The supply of storage, *American Economic Review* **48**, 50-72.

Boons, M., de Roon, F., and Szymanowska, M., (2012) The stock market price of commodity risk. Unpublished Working Paper, Tilburg University.

Brunetti, C., B. Büyükşahin and Harris, J. (2011) Speculators, prices and market volatility. Unpublished Working Paper, John Hopkins University.

Büyükşahin, B. and Robe, M. (2014) Speculators, commodities and cross-market linkages, *Journal of International Money and Finance* **42**, 38-70.

Campbell, J. (1996) Understanding risk and return, *Journal of Political Economy* **104**, 298–345.

Campbell, J., and Vuolteenaho, T. (2004) Bad beta, good beta, *American Economic Review* **94**, 1249-1275.

Carhart, M., (1997) On persistence in mutual fund performance, *Journal of Finance* **52**, 57-82.

Carter, C., Rausser, G., and Schmitz, A. (1983) Efficient asset portfolios and the theory of normal backwardation, *Journal of Political Economy* **91**, 319-331.

Casassus, J., Collin-Dufresne, P., and Routledge, B. R. (2009) Equilibrium commodity prices with irreversible investment and non-linear technologies, Unpublished Working Paper, Pontificia Universidad Catolica de Chile.

Clark, T. E., and West, K. D. (2007) Approximately normal tests for equal predictive accuracy in nested models, *Journal of Econometrics* **138**, 291-311.

Cochrane, J. H., (2005) *Asset pricing, revised edition*, Princeton University Press, New Jersey, 2nd edition.

Cochrane, J. H. and Piazzesi, M. (2005) Bond risk premia, *American Economic Review* **95**, 138–160.

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

Deaton, A., and Laroque, G. (1992) On the behaviour of commodity prices, *Review of Economic Studies* **59**, 1-23.

De Roon, F. A., Nijman, T. E., and Veld, C. (2000) Hedging pressure effects in futures markets, *Journal of Finance* **55**, 1437-1456.

Diebold, F.X., and Mariano, R.S., (1995) Comparing predictive accuracy. *Journal of Business & Economic Statistics* **13**, 253-263.

Epstein, L., and Zin, S. (1989). Substitution, risk aversion and the temporal behaviour of consumption and asset returns: a theoretical framework. *Econometrica* **57**, 937-969.

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

Fama, E. (1991) Efficient capital markets: II, *Journal of Finance* **46**, 1575–1617.

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

Fama, E., and French, K. (1987) Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage, *Journal of Business* **60**, 55-73.

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

Fama, E., and French, K. (1996) Multifactor explanations of asset pricing anomalies, *Journal of Finance* **51**, 55-84.

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

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

Hahn, J., and Lee, H. (2006) Yield spreads as alternative risk factors for size and book-to-market, *Journal of Financial and Quantitative Analysis* **41**, 245-269.

Hansen, L. (1982) Large sample properties of generalized method of moments estimators. *Econometrica* **50**, 1029-1054.

Hirshleifer, D. (1988) Residual risk, trading costs, and commodity futures risk premia, *Review of Financial Studies* **1**, 173-193.

Hong, H., and Yogo, M. (2012) What does futures market interest tell us about the macroeconomy and asset prices? *Journal of Financial Economics* **105**, 473–490.

Hou, K., and Szymanowska, M. (2013) Commodity-based consumption tracking portfolio and the cross-section of average stock returns. Unpublished Working Paper, Ohio State University.

Kaldor, N. (1939) Speculation and economic stability, *Review of Economic Studies* **7**, 1-27.

Koijen, R., Lustig, H. and Van Nieuwerburgh, S. (2013a) The cross-section and time-series of stock and bond returns. Unpublished Working Paper, NYU Stern School of Business.

Koijen, R., Moskowitz, T., Pedersen, L., and Vrugt., B. (2013b) Carry. Unpublished Working Paper, London Business School.

Kwiatkowski, D., Philips, P., Schmidt, P., and Shin, Y., (1992) Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?, *Journal of Econometrics* **54**, 159-178.

Maio, P. (2013) Intertemporal CAPM with conditioning variables, *Management Science* **59**, 122-141.

Maio, P. and Santa-Clara, P. (2012) Multifactor models and their consistency with the ICAPM, *Journal of Financial Economics* **106**, 586–613.

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

Mehra, R., and Prescott, E. (1985) The equity premium: a puzzle, *Journal of Monetary Economics* **15**, 145–161.

Miffre, J., and Rallis, G. (2007) Momentum strategies in commodity futures markets, *Journal of Banking and Finance* **31**, 6, 1863-1886.

Newey, W. K., and West, K. D. (1987) Hypothesis testing with efficient method of moments estimation, *International Economic Review* **28**, 777-787.

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

Petkova, R. G. (2006) Do the Fama-French factors proxy for innovations in predictive variables? *Journal of Finance* **61**, 581-612.

Ready, R. (2013). Oil prices and the stock market. Working Paper, University of Rochester.

Ready, R. (2014). Oil consumption, economic growth, and oil futures: A fundamental alternative to financialization. Working Paper, University of Rochester.

Romano, J., and M. Wolf, 2001. Subsampling intervals in autoregressive models with linear time trend. *Econometrica*, 69, 1283-1314.

Routledge, B. R., Seppi, D. J., and Spatt, C. S. (2000) Equilibrium forward curves for commodities, *Journal of Finance* **55**, 1297-1338.

Shanken, J. (1992) On the estimation of beta-pricing models, *Review of Financial Studies* **5**, 1-33.

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

Szymanowska, M., De Roon, F., Nijman, T., and Van Den Goorbergh, R. (2014) An anatomy of commodity futures risk premia, *Journal of Finance* **69**, 453-482.

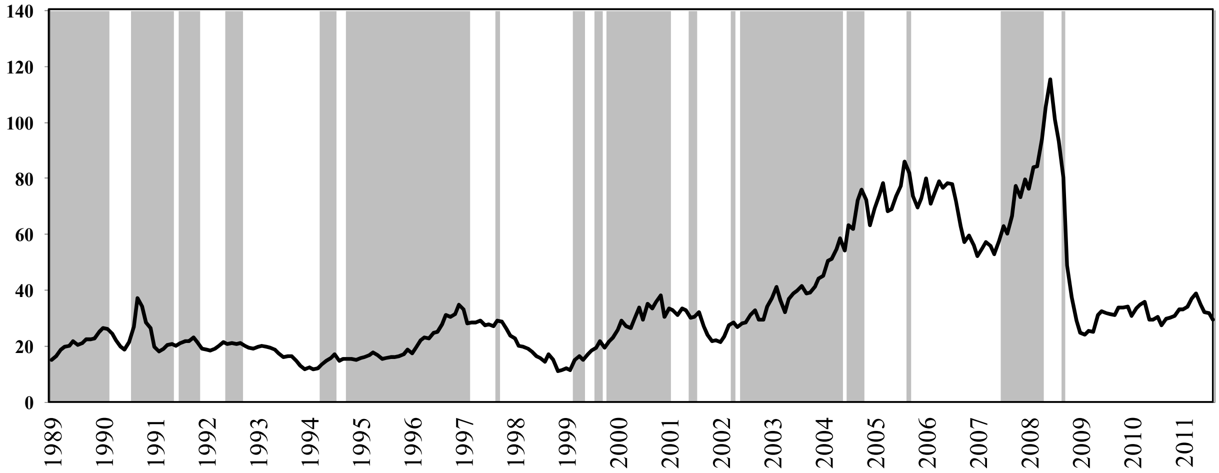
Working, H. (1949) The theory of price of storage, *American Economic Review* **39**, 1254-1262.

Yang, F. (2013) Investment shocks and the commodity basis spread, *Journal of Financial Economics* **110**, 164–184.

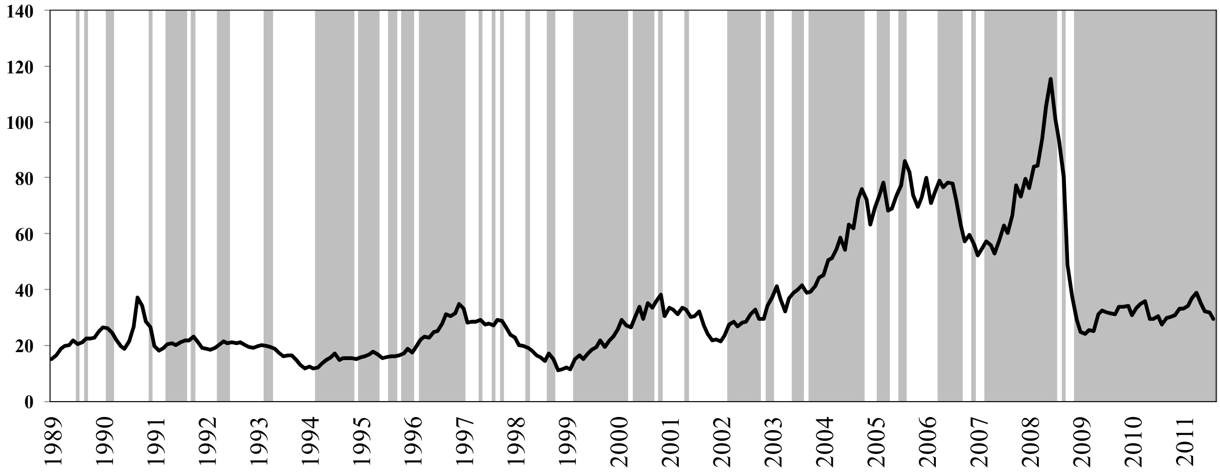
Figure 1. Historical crude oil futures prices and backwardation.

The continuous line denotes the end-of-month futures price of crude oil. Shaded areas denote months when the average of daily roll yields is positive (front-end futures curves slope downward) in Panel A, when speculators are net long and hedgers are net short in Panel B, or when the 12-month average returns are positive (Panel C). The sample period runs from January 1989 to August 2011.

Panel A: Backwardation states identified from Term Structure signal



Panel B: Backwardation states identified from Hedging Pressure signal



Panel C: Backwardation states identified from Momentum signal

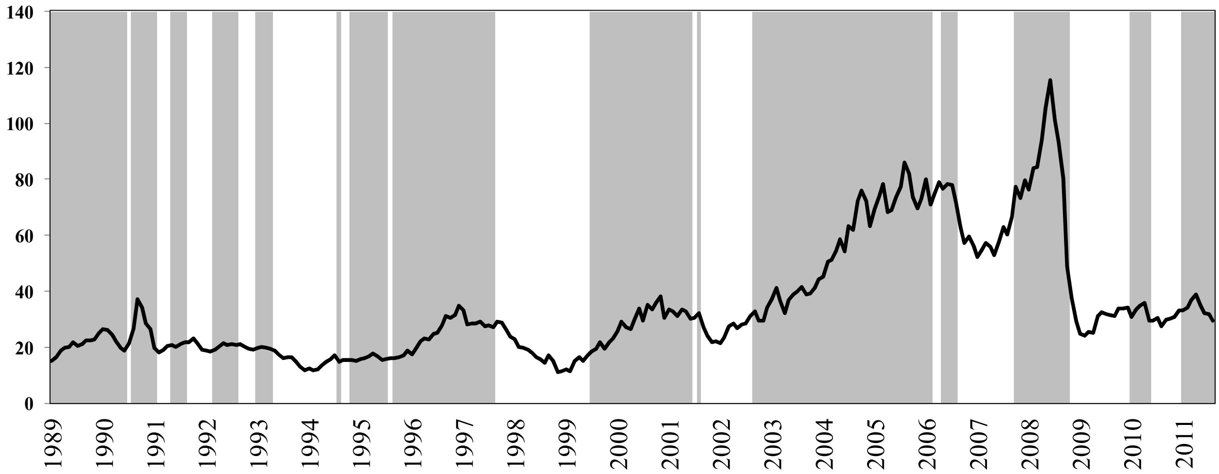


Figure 2. Individual pricing errors of nine candidate ICAPMs.

This figure plots the average excess returns in percentage per annum (p.a.) of 32 test assets against the corresponding excess returns predicted from nine ICAPM specifications. The test assets are the 25 SBM portfolios, 6 U.S. Treasury-bond indices with maturities of 1, 2, 5, 10, 20 and 30 years, and the S&P-GSCI. The sample period is January 1989 to August 2011. The commodity-based ICAPM considers as risk factors the market portfolio and the innovations in the commodity *TS*, *HP* and *Mom* state variables. The remaining models are described in Appendix A.

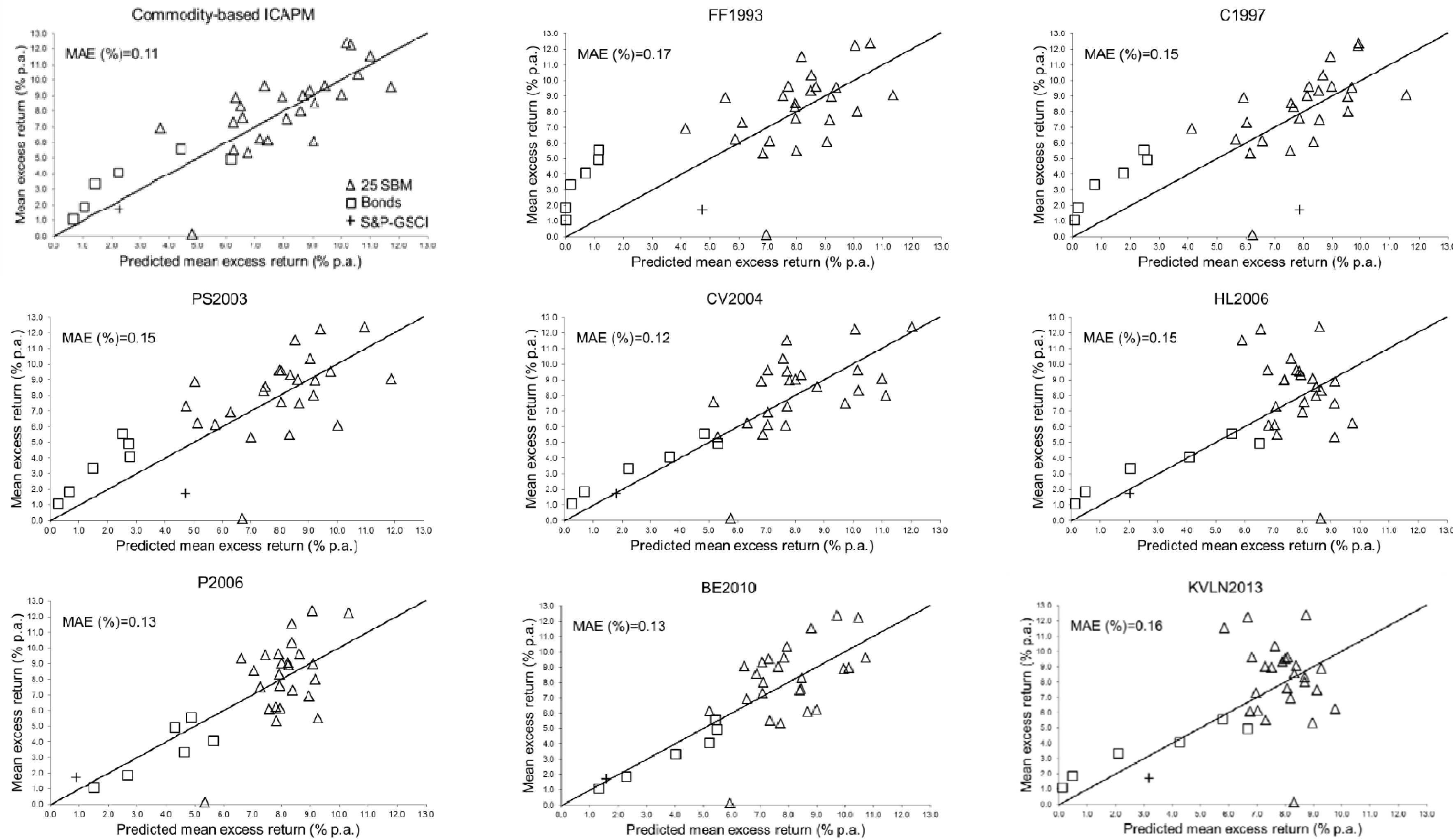


Table I. Summary statistics for market portfolio and state variables.

Panels A and B report summary statistics for the annualized excess log returns of the market portfolio and commodity-based state variables based on term structure (*TS*), hedging pressure (*HP*) and momentum (*Mom*). Panel C summarizes the excess returns of equity-based state variables based on size (*SMB*), value (*HML*), and momentum (*Eq-Mom*), all in annualized form, and for the non-traded liquidity factor of Pastor and Stambaugh (2003; *L*). Panel D pertains to state variables from the predictability literature. The market portfolio is proxied by a combination of the value-weighted CRSP stock index (50% weight), the Barclays bond index (40%) and the S&P-GSCI (10%). The risk-free rate is proxied by the one-month Treasury-bill rate. Appendix A provides detailed definitions for the state variable reported in Panels C and D.

	Mean	StDev.	Min.	Max.
Panel A: Market	0.0578	0.0869	-0.1606	0.0609
Panel B: State variables from the commodity pricing literature				
TS	0.0521	0.1044	-0.0921	0.0908
HP	0.0581	0.0896	-0.0577	0.0962
Mom	0.0802	0.1270	-0.1044	0.1256
Panel C: State variables from the equity pricing literature				
SMB	0.0198	0.1177	-0.1639	0.2202
HML	0.0264	0.1121	-0.1268	0.1387
Eq-Mom	0.0799	0.1764	-0.3472	0.1839
L	0.0022	0.0627	-0.2704	0.2874
Panel D: State variables from the predictability literature				
TERM	0.0182	0.0121	-0.0053	0.0376
PE	3.1894	0.2748	2.5893	3.7887
VS	1.4945	0.6060	-1.9280	3.3411
DEF	0.0095	0.0042	0.0055	0.0338
TBILL	0.0369	0.0224	0.0002	0.0882
DY	-3.8811	0.3231	-4.5282	-3.2114
FED	0.0399	0.0245	0.0007	0.0985
CP	0.0122	0.0162	-0.0458	0.0583

Table II. Long-horizon predictability regressions for traditional state variables.

The table presents predictive regressions for future market portfolio returns and variances at horizon of q=60 months. The state variables are dictated by extant models; see Appendix A. The empirical risk factors *SMB, HML, Eq-Mom* and L are cumulated over p=60 (current and past) months. The market portfolio is a combination of the value-weighted CRSP stock index (50% loading), Barclays bond index (40% loading) and S&P-GSCI (10% loading). The table reports the OLS predictive slopes with Newey-West (1987) t-statistics in parentheses; bold denotes significant slopes at conventional 10%, 5% or 1% levels using standard asymptotic inference. *, **, *** denote significant at 10%, 5% and 1% level using subsampling p-values based on the minimum-volatility block selection method of Politis and Wolf (2001). All regressions include an (unreported) intercept. $\bar{R}^2$ is the adjusted coefficient of determination. The bottom part of the table reports two diagnostics for the model at hand augmented with the commodity risk factors: a Wald test for the null hypothesis that the traditional predictors encompass the commodity risk factors, namely, $H_0: b_{TS} = b_{HP} = b_{Mom} = 0$ in eq. (2), Panel A, and $H_0: d_{TS} = d_{HP} = d_{Mom} = 0$ in eq. (3), Panel B, and the adjusted coefficient of determination ($\bar{R}^2_{\Delta comm}$). The sample period is 1989:01 to 2011:08.

	Panel A: Market return								Panel B: Market variance							
	FF1993	C1997	PS2003	CV2004	HL2006	P2006	BE2010	KVLN2013	FF1993	C1997	PS2003	CV2004	HL2006	P2006	BE2010	KVLN2013
SMB	-0.15	**-0.20**	-0.13						**0.03**	**0.04**	**0.04**					
	(-1.50)	(-1.95)	(-1.30)						(2.53)	(3.07)	(3.60)					
HML	-0.07	0.01	-0.06						0.02	0.00	0.02					
	(-0.62)	(0.06)	(-0.50)						(1.12)	(0.24)	(1.42)					
Eq-Mom		**0.15**								**-0.02**						
		(2.26)								(-2.44)						
L			**0.06** **								**0.02**					
			(0.94)								(3.37)					
TERM				1.82	**4.27** *	**5.18**	**10.21** ***	2.27				-0.35	**-0.56**	**-1.53** ***	**-1.69** ***	**-0.54**
				(0.92)	(2.15)	(2.25)	(6.61)	(1.02)				(-1.50)	(-2.11)	(-4.45)	(-8.15)	(-1.94)
PE				**-0.28**								**0.04**				
				(-5.20)								(5.54)				
VS				**0.03** **								0.00				
				(1.23)								(-0.63)				
DEF					1.26	1.76	2.41						**-2.85**	**-3.32** *	**-3.07** *	
					(0.12)	(0.20)	(0.26)						(-2.87)	(-4.30)	(-3.94)	
TBILL						1.99								**-0.88** **		
						(1.23)								(-3.97)		
DY						**0.17**								0.00		
						(3.11)								(-0.23)		
						[0.31]								[0.64]		
FED							**4.60** ***								**-0.87** ***	
							(4.35)								(-8.23)	
CP								**0.03**								0.00
								(2.83)								(-1.46)
$\bar{R}^2$(%)	11.23	14.22	12.89	33.56	9.47	38.73	30.52	16.65	33.74	38.58	43.15	39.82	22.31	64.02	67.28	16.35
Observations	213	213	213	213	213	213	213	213	213	213	213	213	213	213	213	213
Models augmented with commodity *TS* , *HP* and *Mom* risk factors:																
Wald test (ENC)	**171.48** ***	**191.41** ***	**161.43** ***	**88.80** ***	**179.94** ***	**57.44** **	**112.72** ***	**132.54** ***	**493.25** **	**344.30** **	**437.23** ***	**245.17** ***	**305.22** ***	**361.73** ***	**358.53** ***	**237.27** ***
$\bar{R}^2_{\Delta comm}$(%)	56.65	61.83	57.00	63.37	58.83	75.83	66.26	57.71	82.56	84.81	83.32	76.65	79.04	89.24	90.07	77.35

Table III. Long-horizon predictability regressions for commodity state variables.

The table presents predictive regressions estimated over the full sample from 1989:01 to 2011:08 for the future market portfolio return (Panel A) and market variance (Panel B) at horizons q={24, 36, 60} months. The state variables are commodity *TS, HP* and *Mom* factor-mimicking portfolio returns cumulated over the current and past $p-1$ months, for p={24, 36, 60}. The market portfolio is a combination of the value-weighted CRSP stock index (50% loading), Barclays bond index (40% loading) and S&P-GSCI (10% loading). Panel C reports predictive regressions for GDP growth of the G7 countries using quarterly data over equivalent horizons and cumulative periods of 8, 12 and 20 quarters ahead. All regressions include an (unreported) intercept. The table reports the OLS predictive slopes. Bold denotes significant slopes at conventional 10%, 5% or 1% levels using standard asymptotic inference based on Newey-West (1987) *t*-statistics reported in parentheses. *, **, *** denotes significance at 10%, 5% and 1% level based on empirical *p*-values derived by subsampling the uncentered t-statistics using the minimum-volatility block selection of Politis and Wolf (2001). $\bar{R}^2$ is the adjusted coefficient of determination.

Cumulative length:	*p* =24			*p* =36			*p* =60		
Horizon:	*q* =24	*q* =36	*q* =60	*q* =24	*q* =36	*q* =60	*q* =24	*q* =36	*q* =60
Panel A: Market return									
TS	**-0.46** **	**-0.37**	**-0.78** ***	**-0.40**	**-0.47** ***	**-0.51** **	**-0.85** ***	**-0.59** ***	**-0.45** **
	(-2.47)	(-2.09)	(-6.41)	(-2.20)	(-3.30)	(-3.11)	(-7.61)	(-4.63)	(-2.78)
HP	-0.17	-0.14	**-0.38** ***	-0.06	-0.12	**-0.35**	-0.01	-0.13	**-0.58** ***
	(-1.57)	(-1.57)	(-4.64)	(-0.70)	(-1.52)	(-5.00)	(-0.26)	(-2.59)	(-6.50)
Mom	**0.18** *	**0.46** ***	**0.64** ***	**0.34** **	**0.56** ***	**0.48** ***	**0.65** ***	**0.73** ***	**0.48** ***
	(2.65)	(4.16)	(8.96)	(5.12)	(7.33)	(6.21)	(8.13)	(8.42)	(4.42)
$\bar{R}^2$(%)	8.39	24.16	41.62	18.93	46.59	31.94	49.08	61.44	53.09
Panel B: Market variance									
TS	0.02	0.01	**0.04**	0.01	0.02	0.02	**0.05**	**0.02**	**-0.03**
	(1.53)	(0.51)	(2.86)	(0.74)	(1.02)	(1.37)	(4.21)	(2.55)	(-2.49)
HP	**0.04** **	**0.05**	**0.06** ***	**0.04**	**0.05**	**0.06** ***	**0.02**	**0.03**	**0.05** **
	(5.20)	(4.76)	(5.83)	(3.58)	(4.95)	(9.83)	(3.96)	(6.39)	(6.25)
Mom	0.01	-0.01	**-0.09** ***	-0.01	**-0.04** *	**-0.07** ***	**-0.06** ***	**-0.08** ***	**-0.05** ***
	(0.95)	(-0.95)	(-11.66)	(-1.34)	(-4.32)	(-11.68)	(-4.97)	(-9.71)	(-6.10)
$\bar{R}^2$(%)	14.83	12.41	65.93	12.61	32.64	75.69	48.24	77.15	73.22
Panel C: Real economic activity									
TS	-0.03	-0.02	**-0.12**	-0.02	-0.04	**-0.08**	**-0.10**	**-0.08**	**-0.09**
	(-0.80)	(-0.43)	(-2.54)	(-0.41)	(-0.92)	(-1.89)	(-3.75)	(-2.62)	(-1.62)
HP	-0.01	-0.01	-0.02	-0.01	-0.01	**-0.04**	**-0.02**	**-0.03**	**-0.11** *
	(-0.65)	(-0.22)	(-0.86)	(-0.34)	(-0.75)	(-1.92)	(-2.09)	(-2.83)	(-3.30)
Mom	-0.01	0.05	**0.16** ***	**0.04**	**0.10** *	**0.12**	**0.13** ***	**0.17** ***	**0.11** *
	(-0.27)	(1.51)	(3.86)	(2.31)	(3.77)	(3.62)	(3.91)	(6.60)	(2.44)
$\bar{R}^2$(%)	-1.66	3.35	42.38	2.22	29.98	32.51	50.55	70.70	35.47

Table IV. Out-of-sample predictive ability of commodity and traditional state variables.

The table reports statistics and tests to compare the out-of-sample (OOS) predictive ability of commodity risk factors and traditional predictors; see Appendix A for details on the latter. MAE is the mean absolute error, RMSE is the root mean squared error, R^2_{OOS} is the percentage reduction in MSE achieved by the model at hand relative to the historical average benchmark; asterisks denote significant reduction at the 10% (*), 5% (**) or 1% (***) levels. The first two equal-predictive-ability tests are based on the Diebold and Mariano (1995) t-statistic for the null hypothesis $H_0: \Delta MAE = MAE_{trad} - MAE_{comm} = 0$ against $H_A: \Delta MAE \neq 0$, and $H_0: \Delta MSE = 0$ against $H_A: \Delta MSE \neq 0$. The next two tests are based on the Clark and West (2007) MSE-adjusted t-statistic for H_0: 'the forecasts from a traditional model encompass the forecasts from the same model augmented with the commodity risk factors' (ENC_1), and for H_0: 'the forecasts from the commodity model encompass the forecasts from a traditional model augmented with the commodity risk factors' (ENC_2). *, **, *** denote significant at 10%, 5% and 1% level. All test statistics are corrected for autocorrelation a là Newey-West (1987). The forecasts are obtained through a recursive window scheme. The out-of-sample forecast evaluation period runs from December 2003 until the sample end on August 2011.

	Prediction errors			**Equal-predictive-ability tests**			
Model	*MAE*	*RMSE*	R^2_{OOS}(%)	H_0:ΔMAE= 0	H_0:ΔMSE= 0	H_0:ENC_1	H_0:ENC_2
Panel A: Market returns							
Commodity-based	0.1230	0.1332	74.78 ***	–	–	–	–
FF1993	0.3528	0.3677	-95.37	7.31 ***	4.91 ***	5.76 ***	-0.48
C1997	0.3690	0.3769	-105.25	11.36 ***	7.28 ***	4.00 ***	-0.60
PS2003	0.7125	0.7603	-735.09	6.71 ***	4.71 ***	4.60 ***	-0.48
CV2004	0.2114	0.2568	4.70	1.88 *	2.17 **	1.62 *	1.88 **
HL2006	0.2441	0.3068	-36.02	2.00 **	2.29 **	2.64 ***	1.39 *
P2006	0.2154	0.2473	11.67 *	2.32 **	2.52 **	2.84 ***	4.07 ***
BE2010	0.1896	0.2449	13.33 **	1.39	1.74 *	2.34 ***	2.27 ***
KVLN2013	0.2381	0.2938	-24.73	2.07 **	2.33 **	2.67 ***	-4.11
Panel B: Market variance							
Commodity-based	0.0136	0.0153	79.51 ***	–	–	–	–
FF1993	0.0221	0.0241	63.10 ***	2.42 **	2.69 ***	0.93	-5.53
C1997	0.0276	0.0303	41.39 ***	3.14 ***	3.26 ***	1.85 **	-5.52
PS2003	0.0910	0.0940	-463.45	12.17 ***	6.56 ***	5.36 ***	-4.96
CV2004	0.0336	0.0347	23.45 ***	6.35 ***	5.69 ***	4.09 ***	-5.60
HL2006	0.0418	0.0420	-12.73	10.35 ***	11.72 ***	6.71 ***	-1.72
P2006	0.0291	0.0304	41.26 ***	4.79 ***	4.43 ***	4.29 ***	-1.01
BE2010	0.0226	0.0232	65.62 ***	2.93 ***	2.85 ***	5.87 ***	4.06 ***
KVLN2013	0.0391	0.0394	0.82	13.64 ***	12.34 ***	12.58 ***	-1.66

Table V. Factor risk premia for commodity-based and traditional ICAPM specifications.

The table reports the one-step GMM estimation results for a commodity-based ICAPM implementation (Panel I) and eight traditional ICAPM implementations (Panels II and III); see Appendix A for details on the latter. CV2004 corresponds to an unrestricted version of Campbell and Vuolteenaho (2004). The test assets are 25 equity portfolios sorted by size and book-to-market (25 SBM), 6 U.S. Treasury-bond indices with maturities of 1, 2, 5, 10, 20 and 30 years, and the S&P-GSCI. γ is the market (covariance) risk price. The remaining γ_z in the table are the intertemporal (covariance) risk prices. The remaining γ_z in the table are the covariance risk associated with traditional state variables from the equity pricing and predictability literatures. Bold font denotes significant covariance risk prices at the 10% level or better. Robust GMM *t*-statistics are reported (in parentheses) based on the Bartlett kernel with Newey-West optimal bandwidth selection. The performance metrics are: mean absolute pricing error (MAE), degrees-of-freedom adjusted fraction of the cross-sectional variance in average excess returns explained by the model ($\bar{R}^2$), and the chi-squared *J* test statistic for the null hypothesis that the sum of squared pricing errors is zero. *, ** and *** denote test rejection at the 10%, 5% and 1% levels, respectively. The sample covers the period 1989:01-2011:08.

	Panel I: Commodity risk factors	**Panel II: Equity risk factors**			**Panel III: Risk factors from predictability literature**				
		FF1993	C1997	PS2003	CV2004	HL2006	P2006	BE2010	KVLN2013
γ_M	4.07	**5.21**	**5.79**	**5.56**	**6.35**	**6.93**	**7.15**	5.16	**7.27**
	(1.37)	(2.22)	(2.34)	(2.09)	(2.41)	(2.61)	(2.28)	(1.54)	(3.08)
γ_{TS}	**-40.53**								
	(-5.62)								
γ_{HP}	**-17.06**								
	(-2.27)								
γ_{Mom}	**45.52**								
	(6.37)								
γ_{SMB}		2.36	2.02	2.17					
		(1.04)	(0.83)	(0.98)					
γ_{HML}		**6.42**	**7.92**	**8.58**					
		(2.16)	(2.76)	(3.72)					
$\gamma_{Eq\text{-}Mom}$			**8.38**						
			(2.16)						
γ_L				**-24.73**					
				(-4.21)					
γ_{TERM}					**-12.47**	**-11.15**	-5.55	**-13.13**	**-12.33**
					(-3.26)	(-3.10)	(-1.17)	(-2.88)	(-3.34)
γ_{PE}					-1.77				
					(-0.35)				
γ_{VS}					**-29.82**				
					(-4.08)				
γ_{DEF}						2.78	**-34.04**	**-39.31**	
						(0.57)	(-4.04)	(-5.31)	
γ_{TBILL}							**-42.14**		
							(-9.00)		
γ_{DY}							**-9.62**		
							(-2.32)		
γ_{FED}								**-49.62**	
								(-7.50)	
γ_{CP}									-0.85
									(-0.14)
MAE (%)	0.11	0.17	0.15	0.15	0.12	0.15	0.13	0.13	0.16
RMSE (%)	0.14	0.21	0.19	0.19	0.16	0.22	0.16	0.16	0.22
$\bar{R}^2$(%)	66.52	32.49	37.97	40.80	57.73	21.27	54.37	57.17	22.89
J test	32.38	48.49 **	55.11 ***	46.79 **	47.97 **	46.51 **	34.18	33.58	45.61

APPENDIX A. Description of state variables in traditional ICAPM implementations.

Panel I outlines eight multifactor models that have been interpreted according to the ICAPM theory of Merton (1973). Definitions and sources for each of the state variables are provided in Panel II. All the variables are sampled at the monthly frequency for our empirical analysis.

Panel I: Multifactor models

	State variables from the literature on equity pricing			**State variables from the predictability literature**				
	Fama and French (FF1993)	Carhart (C1997)	Pastor and Stambaugh (PS2003)	Campbell and Vuolteenaho (CV2004)	Hahn and Lee (HL2006)	Petkova (P2006)	Bali and Engle (BE2010)	Koijen *et al.* (KVLN2013)
SMB	√	√	√					
HML	√	√	√					
Eq-Mom		√						
L			√					
TERM				√	√	√	√	√
PE				√				
VS				√				
DEF					√	√	√	
TBILL						√		
DY						√		
FED							√	
CP								√

Panel II: Description of state variables

Name	**Definition**	**Data source**
SMB	Size factor (difference in returns between small and large capitalization stocks)	K.R. French's website
HML	Value factor (difference in returns between high and low book-to-market stocks)	K.R. French's website
Eq-Mom	Equity momentum factor (difference in returns between winner and loser stocks)	K.R. French's website
L	Innovations in aggregate liquidity construced by Pastor and Stambaugh (2003)	R. F. Stambaugh's website
TERM	Slope of Treasury yield curve (yield spread between the 10 year T-bond and 3 month T-bill)	US Federal Reserve website
PE	Price earnings (log ratio of the price of the S&P 500 index to a ten-year moving average of earnings)	R. Shiller's website
VS	Value spread (difference between the log book-to-market ratios of small-value and small-growth stocks)	K.R. French's website
DEF	Default spread (difference between the yields on BAA- and AAA-rated corporate bonds)	US Federal Reserve website
TBILL	3-month T-bill rate	US Federal Reserve website
DY	Dividend yield (log ratio of the sum of annual dividends to the level of the S&P 500 index)	Bloomberg
FED	Federal reserve fund rate	US Federal Reserve website
CP	Cochrane-Piazzesi (2005) bond factor obtained as the fitted value from a regression of excess bond returns on forward rates	M. Piazzesi's website

APPENDIX B. Out-of-sample predictive ability results for alternative evaluation period, horizon and recursive scheme.

The table reports results of three robustness checks on the out-of-sample (OOS) predictive ability of commodity risk factors vis-à-vis traditional predictors; see Appendix A for details on the latter. RMSE is the root mean squared error, R^2_{OOS} is the percentage reduction in MSE achieved by the model at hand relative to the historical average benchmark. The first equal-predictive-ability test is based on the Diebold and Mariano (1995) t-statistic for the null hypothesis $H_0\colon \Delta MSE = MSE_{trad} - MSE_{comm} = 0$ against $H_A\colon \Delta MSE \neq 0$. The next two tests are based on the Clark and West (2007) MSE-adjusted t-statistic for H_0: 'the forecasts from a traditional model encompass the forecasts from the same model augmented with the commodity risk factors' (ENC_1), and for H_0: 'the forecasts from the commodity model encompass the forecasts from a traditional model augmented with the commodity risk factors' (ENC_2). *, **, *** denote significant at 10%, 5% and 1% level. All test statistics are corrected for autocorrelation a là Newey-West (1987). In Panel I the forecasts are obtained through a rolling-window estimation scheme of the model coefficients; in Panel II the horizon q is 24 months; in Panel III the out-of-sample period is half of the total sample period. In each panel all other specifications are as indicated in parenthesis in the top row.

	Panel I: Rolling scheme (p =q =60; $T_1 = 1/3T$)					Panel II: Horizon q =24 months (Recursive scheme; $T_1 = 1/3T$)					Panel III: Evaluation sample size $T_1 = 1/2T$) (Recursive scheme; p =q =60)				
	Prediction errors		Equal-predictive-ability tests			Prediction errors		Equal-predictive-ability tests			Prediction errors		Equal-predictive-ability tests		
Model	$RMSE$	$R^2_{OOS}(\%)$	$H_0: \Delta MAE = 0$	$H_0: ENC_1$	$H_0: ENC_2$	$RMSE$	$R^2_{OOS}(\%)$	$H_0: \Delta MAE = 0$	$H_0: ENC_1$	$H_0: ENC_2$	$RMSE$	$R^2_{OOS}(\%)$	$H_0: \Delta MAE = 0$	$H_0: ENC_1$	$H_0: ENC_2$
Panel A: Market returns															
Commodity-based	0.133	74.78 ***	–	–	–	0.143	32.50 **	–	–	–	0.174	40.11 ***	–	–	–
FF1993	0.383	-107.8	5.930 ***	6.790 ***	-0.477	0.241	-87.90	3.677 ***	2.788 ***	-0.484	0.285	-89.80	2.759 ***	3.601 ***	0.744
C1997	0.393	-118.4	8.407 ***	3.228 ***	-0.604	0.306	-202.9	4.921 ***	5.972 ***	-0.548	0.292	-100.2	3.304 ***	3.477 ***	0.517
PS2003	0.809	-824.4	5.641 ***	5.415 ***	-0.478	0.236	-80.79	3.786 ***	1.266	-1.088	0.554	-618.1	3.288 ***	3.324 ***	0.934
CV2004	0.278	-9.023	3.108 ***	1.510 *	1.875 **	0.153	24.37 ***	0.318	-1.982	0.293	0.285	-90.31	3.017 ***	3.063 ***	1.901 **
HL2006	0.305	-31.71	2.236 **	2.421 ***	1.393 *	0.158	19.18 ***	0.612	2.163 **	1.556 *	0.230	-23.93	1.109	2.341 ***	-0.986
P2006	0.246	14.73 **	2.612 ***	2.820 ***	4.067 ***	0.199	-28.56	1.651 *	-1.978	0.199	0.304	-117.0	3.708 ***	2.261 **	2.650 ***
BE2010	0.243	16.57 ***	1.693 *	2.249 ***	2.273 ***	0.155	22.33 ***	0.623	2.988 ***	1.519 *	0.190	15.30 ***	0.400	1.850 **	-0.061
KVLN2013	0.294	-21.99	2.296 **	2.537 ***	-4.112	0.152	25.14 ***	0.428	2.558 ***	1.801 *	0.217	-10.40	0.890	2.259 **	-2.040
Panel B: Market variance															
Commodity-based	0.015	79.51 ***	–	–	–	0.022	26.96 ***	–	–	–	0.017	48.22 ***	–	–	–
FF1993	0.026	51.36 ***	1.825 *	1.209	-5.527	0.027	-4.126	1.628	3.238 ***	0.920	0.022	34.89 ***	2.572 ***	1.518	-1.540
C1997	0.029	37.20 ***	2.211 **	1.404	-5.523	0.032	-42.35	2.208 **	3.874 ***	0.774	0.025	15.84 ***	2.792 ***	2.246 **	-2.215
PS2003	0.092	-515.3	7.360 ***	6.030 ***	-4.964	0.027	-4.008	1.652 *	3.322 ***	0.978	0.064	-433.3	3.352 ***	3.402 ***	-0.321
CV2004	0.032	27.03 ***	7.736 ***	5.689 ***	-5.596	0.028	-5.897	1.948 *	-2.980	-1.187	0.029	-10.07 ***	3.185 ***	3.662 ***	1.140
HL2006	0.038	-2.566	7.893 ***	8.201 ***	-1.720	0.025	10.28 **	1.296	2.070 **	-0.850	0.032	-34.40	4.220 ***	6.735 ***	2.106 **
P2006	0.031	28.81 ***	4.962 ***	4.742 ***	-1.009	0.029	-16.56	2.027 **	-1.224	-1.396	0.031	-24.79 ***	3.947 ***	4.574 ***	1.117
BE2010	0.026	49.28 ***	4.626 ***	7.884 ***	4.061 ***	0.025	12.42 **	1.668 *	2.061 **	-0.857	0.017	62.68 ***	-0.100	3.955 ***	-0.517
KVLN2013	0.036	6.780	4.755 ***	6.851 ***	-1.663	0.023	27.99 ***	0.148	-0.161	0.340	0.028	-0.599	2.520 ***	5.040 ***	1.613 *

APPENDIX C. Commodity-based ICAPM results with alternative estimation methodology, test assets and market portfolio proxy.

The table reports estimation results of the commodity-based ICAPM. γ_0 is a mispricing constant, γ_M is the price of market risk, $(\gamma_{TS}, \gamma_{HP}, \gamma_{Mom})'$ are the intertemporal risk prices. In Panel I, the 'GMM estimation' column reports one-step, two-step and iterative GMM estimates for systems of dimensions N+K+1 or N+1 with or without intercept; N is the number of test assets and K is the number of state variables; the 'OLS estimation' column reports two-stage Fama and MacBeth (1973) beta risk prices; the column 'ICAPM with EZ utility' reports the one-step GMM estimates of the Campbell's (1993) ICAPM formulation based on Epstein and Zin (1989) recursive preferences; the model on the left column is the formulation which imposes restrictions on risk prices assuming constant (co)variances of asset returns and consumption, the model on the right is the counterpart equation relaxing this assumption. In Panel II, the test assets are 25 equity portfolios sorted by size and book-to-market (25 SBM), 25 equity portfolios sorted by size and momentum (25 SMom), 6 U.S. Treasury-bond indices with various maturities, and the S&P-GSCI. In Panel III, the market portfolio is proxied by equity, bond and commodity indices in the specified proportions (Panel C). The results in Panel II and III are based on one-step GMM estimation of equation (5). Robust GMM t-statistics (in parentheses) are based on the Bartlett kernel with Newey-West (NW) optimal bandwidth selection. Significant coefficients at the 10%, 5% or 1% levels are in bold. In the Fama-MacBeth (1973) column, the (underlined) t-statistics are based on the Shanken (1992) covariance. The NW t-statistics for Campbell's (1993) ICAPM are based on standard errors derived using the delta method. The diagnostics are the mean absolute error (MAE), the root mean squared error (RMSE), the adjusted fraction of the cross-sectional variance in average excess returns explained by the model ($\bar{R}^2$) and its weighted least squares version (R^2_{WLS}), and the J test statistic for the null of zero (weighted) sum of squared pricing errors; *, ** and *** denote test rejection at the 10%, 5% and 1% levels. The sample period is 1989:01-2011:08.

	Panel I: Methodology								**Panel II: Testing assets**			**Panel III: Market portfolio proxy**		
	GMM estimation (covariance risk prices)				**OLS estimation (beta risk prices)**		**EZ-ICAPM** Campbell (1993)							
	One-step $N+K+1$	One-step $N+1$	Two-step $N+K+1$	Iterative $N+K+1$	Fama-MacBeth (1973)		Model 1 *homosk*	Model 2 *heterosk*	25 SMom, 6 Bonds, S&P-GSCI	25 SBM	25 SMom	100% Equity	60% Equity 40% Bonds	90% Equity 10% Comm.
γ_0	**0.002**					**0.002**								
	(14.38)					(3.77)								
						(1.26)								
γ_M	3.004	5.667	**4.814**	**4.939**	**0.004**	**0.002**	**12.40**	**8.148**	4.463	**6.050**	**7.249**	2.316	3.674	2.303
	(1.16)	(1.62)	(1.76)	(1.97)	(12.77)	(7.77)	(6.46)	(2.71)	(1.48)	(1.80)	(2.22)	(1.29)	(1.35)	(1.19)
					(1.86)	(0.96)								
γ_{TS}	**-23.94**	**-44.23**	**-32.77**	**-21.71**	**-0.018**	**-0.016**	**-20.67**	**-29.69**	**-41.89**	**-25.47**	**-22.85**	**-23.40**	**-35.47**	**-26.73**
	(-4.12)	(-4.94)	(-4.97)	(-3.82)	(-4.28)	(-3.23)	(-5.96)	(-5.06)	(-5.87)	(-2.99)	(-2.46)	(-4.91)	(-5.28)	(-5.15)
					(-1.60)	(-1.54)								
γ_{HP}	-7.618	**-18.40**	-6.987	-5.797	-0.0033	-0.0014	**-11.27**	**-8.656**	**-19.26**	**-28.20**	**-27.30**	**-12.24**	**-18.49**	**-12.27**
	(-1.28)	(-2.11)	(-1.04)	(-1.00)	(-0.91)	(-0.38)	(-5.31)	(-2.44)	(-2.55)	(-3.75)	(-3.31)	(-2.54)	(-2.58)	(-2.38)
					(-0.27)	(-0.13)								
γ_{Mom}	**24.90**	**47.54**	**39.43**	**29.06**	**0.0171**	**0.0133**	**19.01**	**29.73**	**52.11**	**48.39**	**44.74**	**28.14**	**44.24**	**30.21**
	(4.37)	(5.22)	(5.10)	(4.46)	(3.53)	(2.67)	(6.94)	(6.32)	(6.57)	(5.95)	(4.42)	(5.71)	(6.23)	(5.83)
					(1.51)	(1.25)								
MAE (%)	0.116	0.154	0.134	0.157			0.114	0.109	0.113	0.126	0.115	0.136	0.116	0.134
RMSE (%)	0.157	0.192	0.184	0.202			0.138	0.134	0.134	0.157	0.143	0.175	0.146	0.172
$\bar{R}^2$(%)	55.97	38.66	44.01	38.79	40.37	46.54	69.09	70.69	81.56	31.30	76.19	49.66	63.81	51.20
R^2_{WLS}(%)			98.64	98.80										
J test	60.70 **	33.94	33.60	37.17			30.67	47.35	29.94	30.73 *	25.81	34.76	32.85	33.83