Commodity Markets, Long-Run Predictability and Intertemporal Pricing

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Review of Finance (forthcoming)

Abstract

This paper shows that commodity portfolios that capture the backwardation and contango phases exhibit in-sample and out-of-sample predictive power for the first two moments of the distribution of long-horizon aggregate equity market returns, and for the business cycle. It also demonstrates that a pricing model based on the corresponding backwardation and contango risk factors explains relatively well a wide cross-section of equity portfolios. The cross-sectional "hedging" risk prices are economically consistent with the direction of long-horizon predictability. Backwardation and contango thus act as plausible investment opportunity state variables in the context of Merton's (1973) intertemporal CAPM.

Keywords: Commodities; Backwardation; Contango; Long-Run Predictability; Intertemporal Pricing

JEL classifications: G13, G14

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The authors acknowledge the comments of Guiseppe Bertola, Chris Brooks, Tolga Cenesizoglu, Julien Chevallier, Jerry Coakley, Eirini Konstantinidi, Abraham Lioui, Raman Uppal, Andrew Vivian, Sjur Weestgaard, and conference participants at the 2015 Energy Finance Conference in London, 2015 Commodity Markets Workshop in Oslo, Norway, 2015 International Research Meeting in Business and Management, Nice, France, 2015 INFINITI Conference on International Finance, 2014 Conference on High Frequency Data and Derivatives Markets, Auckland, New Zealand, 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, 2014 Conference on "Modeling Macroeconomics & Financial Time-Series", Loughborough University, 2012 EDHEC-Risk Days Conference, London, 2011 CSDA Conference on Computational and Financial Econometrics, London, and seminar participants at Universidad Autonoma de Madrid, Liverpool University Management School, EDHEC Business School and Universitat de les Illes Balears. We are especially grateful to Bernard Dumas (the Editor) and an anonymous referee for their valuable comments.

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Abstract

This paper shows that commodity portfolios that capture the backwardation and contango phases exhibit in-sample and out-of-sample predictive power for the first two moments of the distribution of long-horizon aggregate equity market returns, and for the business cycle. It also demonstrates that a pricing model based on the corresponding backwardation and contango risk factors explains relatively well a wide cross-section of equity portfolios. The cross-sectional "hedging" risk prices are economically consistent with the direction of long-horizon predictability. Backwardation and contango thus act as plausible investment opportunity state variables in the context of Merton's (1973) intertemporal CAPM.

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1. Introduction

The literature on commodity futures pricing centers around the concepts of backwardation and contango as formalized in the theory of storage (Kaldor, 1939; Working, 1949; Brennan, 1958) and the hedging pressure hypothesis (Keynes, 1930; Cootner, 1960; Hirshleifer, 1988). Returns of backwardated and contangoed portfolios have been shown to explain the cross-section of commodity futures returns (e.g., Basu and Miffre, 2013; Szymanowska et al*.,* 2014; Bakshi et al*.,* 2015). The purpose of this article is to investigate whether those returns tell us anything about long-run changes in investment opportunities and intertemporal asset pricing.

The theory of storage explains the dynamics of commodity futures prices by linking the slope of their term structure (hereafter, *TS*) to agents' incentive to hold the physical commodity. With high inventories, the term structure slopes upward, futures prices are expected to fall with maturity, and markets are *contangoed*. Conversely, when inventories are depleted, the utility from holding the physical asset (convenience yield) exceeds storage and financing costs; the futures curve then slopes downward, futures prices are expected to rise with maturity, and markets are *backwardated*. Fama and French (1987) document that the basis or gap between futures and spot prices 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 is driven by the basis and inventory levels.[1]

[1] There are also competitive rational expectations models of storage in a risk-neutral setting where the non-negativity constraint on inventory is crucial to understanding the dynamics of the spot price and the shape of the forward curve (Deaton and Laroque, 1992; Routledge et al., 2000). Extensions that allow for risk premia are developed, for instance, by Casassus et al. (2009) and Baker (2014).

The hedging pressure hypothesis instead attempts to explain the behavior of commodity futures prices with reference to the net positions of hedgers and speculators. Futures prices are predicted to increase when hedgers are net short and speculators are net long; markets are then in *backwardation*. Conversely, futures prices are expected to fall when hedgers are net long and speculators net short; markets are in *contango*. Hedging pressure (hereafter, *HP*) has been shown to play a key role as driver of commodity futures risk premia (Carter et al., 1983; Bessembinder, 1992; de Roon et al., 2000; Basu and Miffre, 2013).[2]

Commodity price momentum (hereafter, *Mom*) can be linked with backwardation and contango through the theory of storage. Deviations of inventories from normal levels are likely to persist as inventories can only be replenished through new production which may take time depending on the commodity. Thus, following a negative shock to inventories which increases the spot price, a period of high expected futures risk premia will follow as inventories are gradually restored. Gorton et al. (2012) present evidence to support this view.

The returns of commodity portfolios based on backwardation and contango signals (such as *TS*, *HP* and *Mom*) can thus be interpreted as a compensation for bearing risk during times when the futures curves slope downwards, when inventories are low and/or when hedgers are net short. Using as proxy for the investment opportunity set the aggregate equity market, this article documents that backwardation and contango contain predictive information about future

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[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., 2013; Büyükşahin and Robe, 2014). Theoretical models explain the recent swings in storable commodity prices in terms of endogenous demand shocks and changes in supply fundamentals; see, e.g. Baker and Routledge (2012), Baker (2014) and Ready (2014b).

changes in investment opportunities that is not fully revealed by traditional predictors (such as the dividend yield or term spread). This aligns well with our parallel finding that the backwardation and contango portfolios can also predict economic activity as proxied by real GDP growth of the G7 economies. Our analysis confirms that the predictive power of backwardation and contango over future changes in investment opportunities is strong at long horizons. This empirical finding dovetails neatly with the low frequency (or business cycle) dynamics of expected market returns and market volatility.

These predictability findings motivate us to estimate a novel version of Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM) using as risk factors the innovations to the *TS*, *HP* and *Mom* state variables. We show that these innovations are priced risk factors in the cross-section of stock returns, and further demonstrate that the signs of the risk prices are economically consistent with the direction of long-horizon predictability. The results agree with the notion that rational investors are willing to pay a higher price on stocks that hedge intertemporal risk, and demand a lower price on stocks that are unable to hedge because they underperform when market conditions are predicted to deteriorate. The proposed commodity factor model is able to price quite well the cross-section of stock returns, compared to extant ICAPM implementations in the literature. The predictive ability of backwardation and contango thus translates into dynamic risk premia in equity markets.

Our findings are robust to various checks. The long-run predictive ability of the backwardation and contango state variables for future changes in investment opportunities is not challenged when we consider alternative statistical tests, different out-of-sample forecast evaluation periods, and rolling versus recursive forecasting schemes. The finding that innovations to the commodity state variables are priced factors in the cross-section of stock returns (with economically plausible prices according to the direction of long-run predictability) is robust to altering the set of test assets and the ICAPM formulation to account for recursive preferences à-la Epstein and Zin (1989, 1991).

Our study relates to an extensive literature on equity premium predictability that draws upon a variety of macroeconomic and equity-based variables; see recent surveys by Cochrane (2011) and Rapach and Zhou (2013). It also speaks to a new commodity markets literature that suggests that the backwardation and contango cycle plays a role as leading indicator of future economic activity (Baker and Routledge, 2012; Koijen et al., 2013; Bakshi et al., 2015).[3] Other recent studies show that commodity market variables such as the returns of commodity futures, open interest, oil supply/demand shocks or the Baltic Dry Index explain the cross-section of equity returns or predict the business cycle (Hong and Yogo, 2012; Bakshi et al., 2012; Hou and Szymanowska, 2013; Ready, 2014a; Boons et al*.,* 2014). Our paper extends these studies by showing that backwardation and contango state variables have additional predictive content (beyond traditional predictors) for long-run changes in the investment opportunity set, and that this predictive ability translates into "hedging" risk premia for the cross-section of equities.

The paper unfolds as follows. Section 2 outlines the background theory. Section 3 describes the data and methodology to construct the commodity state variables. Sections 4 and 5 report the main empirical results and robustness checks. Section 6 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 current

[3] Baker and Routledge (2012) show that bond excess returns are higher when the crude oil futures curve slopes downward. Bakshi et al. (2015) document that commodity *TS* and *Mom* portfolios forecast real GDP growth and traditional asset returns. Koijen et al. (2013) show that the *TS* strategy performs well across asset classes and that the performance tends to worsen in global recessions.

level of their invested wealth but also about the future returns on that wealth. Merton's (1973) ICAPM in discrete time and logarithmic form can be expressed as follows

$$E_t(r_{i,t+1}) = \gamma_M \sigma_{iM,t} + \gamma_z \sigma_{i\Delta z,t}, \quad i = 1, \dots, N \tag{1}$$

where $E_t(\cdot)$ is a conditional expectation, $r_{i,t+1}$ is the month t to $t+1$ excess return of asset i, M is the market portfolio that proxies the investment opportunity set, Δz is an innovation in the state variable z that predicts changes in future investment opportunities, and $\sigma_{ij,t}$ is a conditional covariance. In equilibrium, the expected excess return on asset i is dictated by its covariance with current returns on total invested wealth, $\sigma_{iM,t}$, and with news about future returns on invested wealth, $\sigma_{i\Delta z,t}$. The prices of market and intertemporal risks are captured by γ_M and γ_z, respectively.[4] If investors do not care about future long-horizon investment opportunities, $\gamma_z = 0$, or if the investment opportunity set is constant over time, $\sigma_{i\Delta z,t} = 0$, then the expected return-covariance Equation (1) becomes the static CAPM.

Merton's (1973) theory does not, however, identify the state variables and so it could be applied as a "fishing license" (Fama, 1991) for ad-hoc risk factors. Yet, as Cochrane (2005) forcefully argues, the problem is not with the theory itself but with bad habits of applying the theory. More to the point, two restrictions that emanate from the theory ought to be tested.

The first restriction concerns the time-series behavior of the state variables; namely, they must be able to predict long-horizon changes in investment opportunities. Since these changes

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[4] γ_M can be interpreted as the representative investor's relative risk aversion (RRA) in this simplified ICAPM setting that assumes time-additive expected utility and is also adopted by Hahn and Lee (2006), Petkova (2006), Bali and Engle (2010), Maio and Santa-Clara (2012) and others. However, this interpretation is not appropriate in ICAPMs built upon the recursive preferences of Epstein and Zin (1989, 1991); see e.g., Campbell (1993, 1996), Campbell and Vuolteenaho (2004) and Maio (2013).

can be driven by the first or second moments of the aggregate market return distribution, we estimate as in Maio and Santa-Clara (2012) the following pair of predictive regressions

$$r_{M,t+1:t+h} = a + \mathbf{b}'\mathbf{z}_t + u_{t+1:t+h}\ , \tag{2}$$

$$\sigma^2_{M,t+1:t+h} = c + \mathbf{d}'\mathbf{z}_t + e_{t+1:t+h}\ , \tag{3}$$

by ordinary least squares (OLS) with monthly data $t = 1, \dots, T$ where T is the effective sample size. The target variable in Equation (2) is the market portfolio excess return continuously compounded from months $t+1$ to $t+h$; namely, $r_{M,t+1:t+h} \equiv r_{M,t+1} + \cdots + r_{M,t+h}$. The target variable in Equation (3) is the sum of monthly realized variances, $\sigma^2_{M,t+1:t+h} \equiv \sigma^2_{M,t+1} + \cdots + \sigma^2_{M,t+h}$, where $\sigma^2_{M,t+1}$ is the sum of squared daily market excess returns on month $t+1$. The candidate set of predictors is collected in the state vector $\mathbf{z}_t \equiv (z_{1,t}, \dots, z_{K,t})'$.

The second restriction links the time-series behavior of the state variables and the cross-sectional behavior of the "hedging" risk factors. If a state variable $z_{j,t}$ has predictive slopes $b_j > 0$ in (2) and $d_j < 0$ in (3), then negative innovations in $z_{j,t}$ predict a deterioration in the investment opportunity set, and the intertemporal price of risk associated with $z_{j,t}$ should be positive; $\gamma_{z_j} > 0$ in (1). Intuitively, assets that perform poorly when investment opportunities are predicted to worsen are undesirable because they reduce the agent's ability to hedge intertemporal risk; those assets should command a positive risk premium in equilibrium. Likewise, the predictive slopes $b_j < 0$ and $d_j > 0$ in (2) and (3) go hand-in-hand with a negative intertemporal risk price $\gamma_{z_j} < 0$ in (1).

Following Campbell (1996), Petkova (2006), Maio (2013) and others, we construct the intertemporal risk factors through the following vector autoregressive (VAR) model

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

which is estimated by OLS with monthly data $t = 1, \dots, T$; μ_M and $\boldsymbol{\mu}_z$ are the sample means of the market portfolio excess return and state vector, respectively. The residual sequences in the vector $\hat{\mathbf{e}}_{z,t+1}$, suitably orthogonalized with respect to $r_{M,t+1}$ and standardized so that they have the same standard deviation as $\hat{e}_{M,t+1}$, are our proxies for the intertemporal risk factors.

Let the vector $\mathbf{f}_{t+1} \equiv (f_{1,t+1},\dots,f_{K,t+1})'$ denote the intertemporal risk factors thus constructed. Then we estimate the covariance risk prices in Equation (1) by the generalized method of moments (GMM) approach developed by Hansen (1982). The GMM system is

$$\boldsymbol{g}_T(\boldsymbol{\theta}) = \frac{1}{T}\sum_{t=0}^{T-1}\begin{Bmatrix} r_{i,t+1} - \gamma_M\big(r_{i,t+1}\big)\big(r_{M,t+1} - \mu_M\big) - \boldsymbol{\gamma}'\big(r_{i,t+1}\big)(\mathbf{f}_{t+1} - \boldsymbol{\mu}) \\ r_{M,t+1} - \mu_M \\ \mathbf{f}_{t+1} - \boldsymbol{\mu} \end{Bmatrix} = \mathbf{0} \qquad (5)$$

where the first N moment conditions are the pricing errors for risky portfolios $i = 1, \dots, N$, and the remaining $K + 1$ conditions account for the uncertainty associated with estimating the means of all the factors $(\mu_M, \boldsymbol{\mu}')$. The main parameters of interest in $\boldsymbol{\theta} \equiv (\gamma_M, \boldsymbol{\gamma}', \mu_M, \boldsymbol{\mu}')'$ are the market risk price γ_M and the intertemporal "hedging" risk prices $\boldsymbol{\gamma} \equiv (\gamma_1, \dots, \gamma_K)'$.

3. Variables and Data Description

The sample period is January 1987 to August 2011 ($T = 296$ months) and the start is dictated by the availability of data on large hedgers and speculators positions in the Commitment of Traders report published by the U.S. Commodity Futures Trading Commission (CFTC).

3.1 COMMODITY AND TRADITIONAL STATE VARIABLES

Our leading conjecture is that the backwardation and contango cycle present in commodity futures markets has predictive content for the first two moments of long-horizon aggregate equity market returns. To test it, we construct backwardation and contango mimicking portfolios from end-of-month settlement prices of futures contracts for 27 commodities from *Datastream*; 12 agricultural products (cocoa, coffee C, corn, cotton n°2, frozen concentrated orange juice, oats, rough rice, soybean meal, soybean oil, soybeans, sugar n°11, wheat), 5 energies (electricity, gasoline, heating oil, light sweet crude oil, natural gas), 4 livestock (feeder cattle, frozen pork bellies, lean hogs, live cattle), 5 metals (copper, gold, palladium, platinum, silver), and lumber. Returns are computed for each commodity using the front-end contract until one month before the maturity date, the positions are then rolled to the 2nd nearest contract.

The backwardation and contango mimicking portfolios systematically buy the 20% of commodity futures that are most backwardated and short the 20% of commodity futures that are most contangoed. The commodity futures in both the long and short portfolios are equally-weighted. The fully-collateralized long-short portfolios are held for one month, and the sorting is carried out again. This sequential sorting is based on a moving average of term structure (*TS*), hedging pressure (*HP*) or momentum (*Mom*) signals. We entertain a long 12-month moving average to capture the slow dynamics of inventories (Gorton et al., 2012).

The *TS* signal is the roll yield or differential between the logarithmic prices of front and second nearest contracts; thus, the *TS* portfolio buys the assets with the highest average roll-yields and shorts the assets with the lowest average roll yields. The *HP* signal for the ith commodity combines the hedging pressure of hedgers ($HP_{H,i}$) and hedging pressure of speculators ($HP_{S,i}$) defined as $HP_{H,i} \equiv \frac{Long_{H,i}}{Long_{H,i}+Short_{H,i}}$ and $HP_{S,i} \equiv \frac{Long_{S,i}}{Long_{S,i}+Short_{S,i}}$ where $Long_{H,i}$ denotes the open interest of long hedgers, $Short_{H,i}$ denotes the open interest of short hedgers, and so forth.[5] Accordingly, following the Basu and Miffre (2013) approach, the *HP* portfolio buys the backwardated contracts with the lowest average $HP_{H,i}$ values and the highest average $HP_{S,i}$ values, and it shorts the contangoed contracts with the highest average $HP_{H,i}$

[5] The CFTC classifies commodity traders as reportable or non-reportable according to the size of their positions (large or small, respectively). Reportable traders have to state whether they act as commercial hedgers or non-commercial speculators and whether they take long or short positions. These declarations are checked, summarized in the Aggregated Commitment of Traders Report and published on the CFTC website on a bi-monthly or weekly basis. The corresponding open interest time-series made available by the CFTC for each commodity i form the basis of our calculations for $HP_{H,i}$ and $HP_{S,i}$.

values and lowest average $HP_{S,i}$ values. The *Mom* signal of the *i*th commodity is its past average excess return; thus, the *Mom* portfolio buys the commodity futures contracts with the highest mean excess returns and shorts the contracts with the lowest mean excess returns.

We benchmark the predictive ability of *commodity* state variables (and the cross-sectional pricing ability of innovations to the state variables) against *traditional* predictors. The traditional state variables are inspired from extant intertemporal asset pricing models that can be grouped as follows. On the one hand, we have the multifactor models proposed by Fama and French (1993), Carhart (1997) and Pastor and Stambaugh (2003), that were not conceived as applications of Merton's (1973) theory but have been interpreted as such later on. Here the state variables are the returns of equity portfolios sorted on size (*SMB*), value (*HML*) and momentum (*UMD*), together with a liquidity risk factor (L). Then we have five popular ICAPM applications that employ traditional macroeconomic variables; e.g. the models proposed by Campbell and Vuolteenaho (2004), Hahn and Lee (2006), Petkova (2006), Bali and Engle (2010) and Koijen et al. (2014). Appendix A provides further details on the traditional state variables.

As in Maio and Santa-Clara (2012), the predictive regressions (2) and (3) employ the cumulative sums of *UMD* and L (from months t to t-59) as predictors in order to match the persistence of the target variables and the other (macroeconomic) predictors. The same transformation is made for *SMB*, *HML* and the commodity state variables; e.g. $CTS_t \equiv \sum_{j=t-59}^{t} TS_j$ where TS_j denotes the month j excess return of the *TS* factor-mimicking portfolio.

3.2 MARKET PORTFOLIO AND TEST ASSETS

The market portfolio is proxied by the U.S. value-weighted equity index from Kenneth French's library. Table I presents summary statistics for the first two moments of the distribution of monthly equity market excess returns (Panel A), and likewise for the candidate predictors (Panels B to D); all returns are logarithmic and annualized. The average equity risk premium is 6% per annum which together with an average standard deviation of 16% amounts to an annual

Sharpe ratio of 0.37. Aggregate stock market returns and variance at 24- and 60-month horizons are persistent (akin to macroeconomic variables such as the default or term spread) with first-order autocorrelation coefficients above 0.96. The cumulated empirical commodity and equity state variables show a similar degree of persistence. The correlations between the commodity state variables are positive but low (0.33 at most) which warrants their joint consideration. The test assets for the cross-sectional pricing exercise are CRSP NYSE/AMEX/NASDAQ stocks sorted on size and book-to-market (25 portfolios) from Kenneth French's library.

[Insert Table I around here]

4. Empirical Results

4.1 LONG-RUN PREDICTABILITY

Do the commodity state variables predict long-run changes in investment opportunities? This section begins by addressing this question through a standard in-sample analysis of predictability; namely, the predictive regressions are estimated by OLS using the full sample.

Table II presents estimation results for predictive regressions (2) and (3) at horizons h of 24 and 60 months. Panel A reports predictive slopes together with Newey and West (1987) significance *t*-ratios and $\bar{R}^2$ statistics for the regressions based on the commodity state vector $\boldsymbol{z}_t^{comm} \equiv (CTS_t, CHP_t, CMom_t)'$. Reassuringly, the freely estimated predictive slopes in (2) and (3) have opposite signs. The 54% $\bar{R}^2$ (*h*=24) and 64% $\bar{R}^2$ (*h*=60) for the market return equation indicates an economically large degree of predictability at long horizons; likewise for the market variance. Hence, commodity state variables are able to forecast long-run changes in investment opportunities. But do they add predictive power to traditional predictors?

[Insert Table II around here]

To address this question, the traditional predictive regressions are augmented with the commodity state vector ($\boldsymbol{z}_t^{comm}$) and we formally test the null hypothesis that traditional predictors encompass commodity predictors, $H_0\text{: } \boldsymbol{b}^{comm} = \boldsymbol{0}$ in (2) and $H_0\text{: } \boldsymbol{d}^{comm} = \boldsymbol{0}$ in (3), against the alternative hypothesis that the corresponding vector of commodity slopes is not identically zero. The Wald test statistics reported in Panel B of Table II are generally large and strongly reject this hypothesis at the 1% level or better.

Aligned with the above test results, as shown in Panel C of Table II, the commodity state variables notably enhance the predictive ability (in-sample $\bar{R}^2$) of traditional state variables for the future aggregate market return and variance, Equations (2) and (3), respectively. Specifically, by adding commodity state variables to traditional specifications of regression (2), their predictive ability rises from 25% to 66% on average. Likewise, the $\bar{R}^2$ of the variance regression (3) more than doubles from 33% to 68% on average across specifications. The regression slopes (and t-ratios) tabulated in Appendix B for the traditional state variables confirm extant evidence that they can predict long-run changes in investment opportunities (Cochrane, 2005; Maio and Santa-Clara, 2012; Rapach et al., 2010). Altogether, the results shown in Panels B and C of Table II indicate that commodity state variables contain information on future changes in investment opportunities that is not fully revealed by known predictors; untabulated results for horizons h={12, 36} confirm this novel finding.

Does the additional predictive ability of the commodity state variables (over traditional predictors) relate to their information content on macroeconomic risk? To address this question, we fit by OLS the predictive regression $\log(GDP_{t+h}/GDP_{t+1}) = a + \mathbf{b}'\mathbf{z}_t + u_{t+1:t+h}$ to quarterly G7 real GDP data (obtained from *Datastream*); the commodity and traditional predictors are sampled quarterly here and the predictive horizons are $h = \{8, 20\}$ to match those in the preceding monthly regressions. The results reported in columns three and six of Table II confirm that commodity state variables convey additional information (beyond that contained in traditional predictors) to anticipate long-run changes in future economic conditions.

Thus far the results suggest that the backwardation and contango phases of commodity markets carry predictive information content for long-horizon changes in investment opportunities. Yet in order to provide firm evidence, we should shield our predictive analysis from two caveats. One is the Stambaugh (1999) *bias* that distorts t- and Wald-tests based on standard asymptotic critical values when the predictors are highly persistent; i.e., the Type I error (probability of wrongly rejecting the null hypothesis) is inflated. We construct their empirical critical values by subsampling using the Romano and Wolf (2001) minimum-volatility block size selection method. Significance according to the subsampling (asymptotic) tests is denoted with asterisks (bold font) in Table II and Appendix B. The subsampling-based Wald test inferences still suggest that the commodity state variables proposed are not encompassed by traditional predictors.

The other potential caveat is *look-ahead bias* or the problem that in-sample predictability may not translate into predictability in real time (see, e.g. Welch and Goyal, 2008). We address this issue by estimating Equations (2) and (3) recursively over expanding windows in order to construct two sequences of $T_1 = (1/3)T$ out-of-sample (OOS, hereafter) for the future aggregate equity market return and variance, $\hat{r}_{M,t+1:t+h}$ and $\hat{\sigma}^2_{M,t+1:t+h}$, respectively.

Table III sets out the comparison of OOS predictive ability of commodity and traditional state variables. The evaluation criteria are the mean absolute error $MAE = \frac{1}{T_1}\sum_{t=1}^{T_1}|\hat{\eta}_{t+1:t+h}|$ and mean square error $MSE = \frac{1}{T_1}\sum_{t=1}^{T_1}\hat{\eta}^2_{t+1:t+h}$ where $\hat{\eta}_{t+1:t+h} \equiv y_{t+1:t+h} - \hat{y}_{t+1:t+h}$ is the OOS forecasting error and the target variable y is the aggregate market return or variance. The table reports the t-statistics of Diebold and Mariano (1995) for the null hypothesis: $H_0\colon \Delta MAE = MAE_{trad} - MAE_{comm} = 0$ (versus $H_A\colon \Delta MAE \neq 0$) and likewise for the MSE criterion. It also displays the R^2_{OOS} of Campbell and Thompson (2008) that gives the proportional reduction in mean squared errors that a given forecasting model attains versus the historical average benchmark. More specifically, $R^2_{OOS} = 1 - \frac{MSE}{MSE_{hist}}$ where $MSE_{hist} = \frac{1}{T_1}\sum_{t=1}^{T_1}(y_{t+1:t+h} - \bar{y}_{t+1:t+h})^2$ and $\bar{y}_{t+1:t+h}$ are recursive OOS forecasts obtained under the assumptions of no predictability of the first and second moment of aggregate equity market returns; these assumptions amount to imposing $\mathbf{b}' = 0$ in (2) and $\mathbf{d}' = 0$ in (3), respectively. The hypothesis that a predictive model yields smaller MSE than the historical average, $H_0\!: R^2_{OOS} \leq 0$ (against $H_A\!: R^2_{OOS} > 0$), is examined by the one-sided *t*-test of Clark and West (2007) for nested models. All tests control for autocorrelation in prediction errors à-la Newey and West (1987).[6] The results suggest that the predictive regressions (2) and (3) based on commodity state variables often yield significantly lower *MAE*, lower *MSE* and higher R^2_{OOS} than traditional regressions, particularly, at the longest horizon of 60 months.[7]

[Insert Table III around here]

The Clark and West (2007) t-statistic is also used to conduct two encompassing tests called ENC_{trad} and ENC_{comm} for brevity. ENC_{trad} is a test of the null hypothesis that forecasts from a traditional model are as accurate as forecasts from the same model augmented with commodity variables; the alternative hypothesis is that the commodity state variables add forecast accuracy ($H_0\!: MSE_{trad} - MSE_{aug} \leq 0$ against $H_A\!: MSE_{trad} - MSE_{aug} > 0$). The notation ENC_{comm} is used to denote an otherwise identical test to assess the reverse statement that commodity predictors encompass traditional predictors. Table III shows the *MSE*-adjusted *t*-statistics pertaining to these hypotheses. For the aggregate market return, Equation (2), the overall findings from both encompassing tests are that commodity state variables add significant predictive information to traditional state variables but not the other way round. The

[6] The size distortions related to the Stambaugh bias are not of concern in tests of out-of-sample predictive ability; e.g., see Busetti and Marcucci (2012).

[7] The high predictive ability R^2_{OOS} of 56% for the commodity-based predictive model is clearly linked to the long horizon as borne out by the fact that it falls to 37% at a 24-month horizon; untabulated results show that it falls notably to 6% at *h*=12 and further to -0.27% at the short one-month horizon.

evidence is inconclusive for the aggregate market variance, Equation (3); those models for which the ENC_{trad} test is insignificant, the ENC_{comm} test is also insignificant. Untabulated results for the ENC_{trad} tests applied to the out-of-sample predictions of real GDP growth at the 8 and 20 quarter-ahead horizons indicate, like the in-sample results shown in Table II, that commodity state variables add predictive information content to traditional state variables; detailed results are available from the authors upon request.

Altogether the in-sample and out-of-sample analyses suggest that the backwardation and contango state variables have long-horizon predictive ability for the first two moments of the distribution of aggregate market excess returns, and for changes in economic conditions. Next we examine whether this predictability translates into intertemporal risk premia.

4.2 CROSS-SECTIONAL INTERTEMPORAL PRICING

Using the 25 equity test portfolios outlined in Section 3.2, we estimate the expected return-covariance Equation (1) by GMM. The intertemporal risk factors are innovations to either commodity state variables or to traditional state variables. The estimation results are shown in Table IV. Are the signs of the intertemporal risk prices consistent with the signs of the long-run predictive slopes? The negative risk prices $\hat{\gamma}_{TS}$ and $\hat{\gamma}_{HP}$ reported in Panel A are aligned with the negative predictive slopes $\hat{b}_{TS}$ and $\hat{b}_{HP}$ for the long-run aggregate equity market return, and with the positive slopes $\hat{d}_{TS}$ and $\hat{d}_{HP}$ for the long-run aggregate equity market variance (c.f., Table II). This confirms that rational agents are prepared to pay higher prices on assets that hedge intertemporal risk. Likewise, the positive risk price $\hat{\gamma}_{Mom}$ is consistent with the positive (negative) link between the *Mom* state variable and the mean (variance) of the future aggregate market return distribution. This shows that rational investors require a positive premium on assets that are poor hedges against future changes in the investment opportunity set.

[Insert Table IV around here]

In contrast, the intertemporal risk prices obtained for the traditional state variables in Panels B and C of Table IV are in most cases economically incompatible with the direction of time-series predictability which reaffirms the evidence in Maio and Santa-Clara (2012). To illustrate, a decrease in term spread (*TERM*) anticipates a worsening of long-run investment opportunities as borne out by the signs of the time-series slopes reported in Appendix B. Hence, assets that covary positively with innovations to *TERM* do not hedge reinvestment risk and a positive premium is expected; conflictingly, the cross-sectional risk price $\hat{\gamma}_{TERM}$ is negative.[8]

Next we assess the ability of the various pricing models to capture the cross-sectional variation in the average excess returns of the *N* test portfolios. For this purpose, we average the pricing errors $\hat{\alpha}_i \equiv g_{T,i}(\hat{\boldsymbol{\theta}})$ and calculate the $MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{\alpha}_i|$ and $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\hat{\alpha}_i^2}$ statistics, as well as the degrees-of-freedom adjusted fraction of the cross-sectional variation in average excess returns captured by the pricing model, $\bar{R}^2 = 1 - \frac{Var_N(\hat{\alpha}_i)}{Var_N(\bar{r}_i)}$. We also deploy the test statistic $J = T[\boldsymbol{\alpha}'\hat{\mathbf{S}}_N{}^{-1}\boldsymbol{\alpha}]$ for the null hypothesis that the sum of squared pricing errors is zero where $\boldsymbol{\alpha} \equiv (\hat{\alpha}_1, \dots, \hat{\alpha}_N)'$, and $\hat{\mathbf{S}}_N$ is the first $N \times N$ block of the spectral density matrix of the moment conditions. Finally, for each pricing model Figure 1 presents a scatterplot of the portfolios' average excess return and the model-based expected excess return. As borne out by the results in Table IV and Figure 1 the commodity risk factor model compares well with

[8] The RRA levels implied by our market risk price estimates, ranging from 2.19 to 3.16 across models, are in line with those documented in previous studies; see e.g., Mehra and Prescott (1985), Cochrane (2005), Bali and Engle (2010), Maio and Santa-Clara (2012) and Campbell et al. (2015). However, they represent small RRA levels relative to the predictions stemming from expected-utility theory (see, e.g. Rabin, 2000) or from the equity premium puzzle literature (see e.g., Mehra, 2003; Cochrane, 2005).

traditional multifactor models in terms of pricing ability.[9] The commodity state variables capture relatively well the "hedging" risk premia that agents demand on equities.

[Insert Figure 1 around here]

5. Sensitivity Analysis

This section adds robustness to our findings regarding the roles of commodity state variables as predictors of changes in investment opportunities and as drivers of intertemporal risk.

First, we analyze the predictive ability of commodity and traditional state variables under a rolling (instead of recursive or expanding window) forecasting scheme that estimates the models over windows of fixed length $T_0 = (2/3)T$ months where T is the total sample size. Rolling estimation is appealing because it offers a 'shield' against structural breaks in the data. Second, we repeat the recursive predictive analysis by considering a long holdout or out-of-sample period $T_1 = (1/2)T$ beginning on May 1999, instead of $T_1 = (1/3)T$ beginning on June 2003 as until now. Table V summarizes the results of both robustness checks through a subset of the measures reported in Table III; the unreported measures do not alter the main findings. The efficacy of the commodity state variables as OOS predictors of future changes in investment opportunities is not challenged when we obtain the forecasts through rolling estimation of the predictive regressions, nor when the forecast evaluation period is lengthened.

[Insert Table V around here]

Turning now to the cross-sectional leg of our investigation, we conduct the pricing analysis for the commodity-based and traditional multifactor models using as test assets the 25 equity portfolios sorted on size and momentum available from Kenneth French's library. The results

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[9] In line with Maio and Santa-Clara (2012), the CAPM has no pricing ability as suggested by a negative $\bar{R}^2$ for the 25 size and book-to-market sorted portfolios.

presented in Appendix C confirm our earlier conclusions. In the commodity-based ICAPM specification of Panel A, the signs of the intertemporal risk prices are consistent with the direction of long-horizon predictability; in contrast, this restriction is violated for many of the traditional models (Panels B and C). This suggests that, unlike traditional predictors, the commodity factor mimicking portfolios act as economically plausible candidates for investment opportunity state variables in the Merton (1973) ICAPM theory. Moreover, in practical terms, the proposed pricing model based on commodity risk factors competes well with traditional ICAPM implementations in terms of cross-sectional pricing ability.

We implement also the ICAPM of Campbell (1993, 1996) that is formulated upon Epstein and Zin (1989, 1991) preferences together with a log-linear approximation of the representative agent's budget constraint. The expected return-covariance equation can be expressed as

$$E_t\left(r_{i,t+1}\right) + \sigma_{i,t}^2/2 = \gamma\sigma_{i1,t} + (\gamma - 1)\sum_{k=1}^{4}\lambda_k\sigma_{ik,t} \tag{6}$$

where $\sigma_{i,t}^2/2$ is a Jensen's inequality adjustment due to log-normality; γ is interpreted as the investor's RRA level; and $\sigma_{ik,t}$ denotes the *i*th asset covariance with innovations in the market portfolio returns (for $k = 1$) and with innovations in the commodity *TS*, *HP* and *Mom* state variables ($k = 2$, 3 and 4 respectively), where the latter act as proxies for news about future changes on invested wealth. The relative importance of the market return and the commodity state variables in forecasting future investment opportunities is captured by the elements of the vector $\boldsymbol{\lambda} \equiv (\lambda_M, \lambda_{TS}, \lambda_{HP}, \lambda_{Mom})'$. In this setting, the risk prices are no longer freely estimated but restricted instead to maintain a particular relation with $\boldsymbol{\lambda}$ and the RRA parameter; namely, $\gamma_M \equiv \gamma + (\gamma - 1)\lambda_M$, and $\gamma_j \equiv (\gamma - 1)\lambda_j$ for $j = \{TS, HP, Mom\}$. Using the 25 size and book-to-market value portfolios as test assets, the GMM estimation of this restricted ICAPM formulation yields significant risk prices $\hat{\gamma}_{TS}$ of -49.06 (*t*-stat of -4.03), $\hat{\gamma}_{HP}$ of -23.99 (*t*-stat of -2.71) and $\hat{\gamma}_{Mom}$ of 46.02 (*t*-stat of 4.36) whose signs remain consistent with the direction of long-horizon predictability. This confirms that the innovations to the backwardation and contango state variables act as plausible intertemporal "hedging" risk factors.[10]

6. Conclusions

Motivated by the theory of storage and the hedging pressure hypothesis, we construct backwardation and contango state variables as factor-mimicking commodity portfolio returns using term structure, hedging pressure and momentum signals. Our findings show that the commodity state variables contain predictive information for future long-run changes in investment opportunities (and for the business cycle) that is not fully revealed by traditional state variables such as the dividend yield, default spread or term spread. The results hold both in- and out-of-sample, for different forecasting schemes, horizons and evaluation periods.

These findings lead us to examine whether the innovations in the commodity state variables are priced risk factors in a novel ICAPM formulation. We show that the cross-sectional risk prices associated with innovations to the commodity state variables are significant and economically consistent with the direction of long-run predictability. An ICAPM specification based on the commodity risk factors alone can explain the cross-sectional variation in equity returns relatively well. The predictive ability of the backwardation and contango state variables for aggregate equity market returns (variance) and business-cycle fluctuations is thus shown to be consistent with the intertemporal "hedging" risk premia that rational agents demand on equities.

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[10] It is worth stressing that in our setting the basket of commodities is not intended to proxy for the "single good" consumed by the representative investor in the Epstein and Zin (1989, 1991) recursive preferences framework. The commodities allow us to construct the backwardation and contango state variables that convey information about the future returns on aggregate wealth. The RRA level implied by the Campbell (1993, 1996) ICAPM specification in our setting is 2.64.

The paper adds to a new literature that ascribes a role to commodity market variables, such as the basis and open interest, as leading indicators of economic activity and sources of priced risk in equities. Our findings could stimulate further research on the relation between the equity risk premium, the cross-section of expected equity returns and business cycle fluctuations.

APPENDIX A. Description of traditional state variables

Panel I outlines the multifactor models that have been interpreted as applications of Merton's (1973) ICAPM theory. Definitions and sources for each of the state variables are provided in Panel II. All the variables are sampled at a monthly frequency. CV2004 is an unrestricted version of Campbell and Vuolteenaho (2004).

Panel I: Multifactor models	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.* (KLVN2014)
	A. State variables from equity pricing literature			*B. State variables from predictability literature*				
SMB	√	√	√					
HML	√	√	√					
UMD		√						
L			√					
TERM				√	√	√	√	√
PE				√				
VS				√				
DEF					√	√	√	
TBILL						√		
DY						√		
FED							√	
CP								√

Panel II: Description of state variables

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
UMD	Equity momentum factor (difference in returns between winner and loser stocks)	K.R. French's website
L	Innovations in aggregate liquidity constructed 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 (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 (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. Long-run predictive regressions of future aggregate market returns and market variances using traditional state variables

The table reports OLS regression estimation results for future aggregate market returns (Panel A) and realized market variances at 24- and 60-months horizons using traditional predictors in various sets as employed in existing models; see Appendix A for details. The market portfolio is proxied by the U.S. value-weighted stock index from Kenneth French's library. All regressions include an (unreported) intercept. Bold denotes significance at the conventional 10%, 5% or 1% levels according to the asymptotic Student's *t* critical values using the Newey-West adjustment. *, **, *** denote significance at the 10%, 5% and 1% levels according to subsampling critical values computed using the Romano and Wolf (2001) minimum-volatility block selection method. The estimation period is January 1987 to August 2011.

	Panel A: Market return								Panel B: Market variance							
	FF1993	C1997	PS2003	CV2004	HL2006	P2006	BE2010	KLVN2014	FF1993	C1997	PS2003	CV2004	HL2006	P2006	BE2010	KLVN2014
Horizon *h* =24 months																
CSMB	-0.21	-0.17	-0.11						0.00	-0.02	0.00					
CHML	**0.43**	**0.49**	**0.44**						-0.04	-0.06	-0.04					
CUMD		0.25								**-0.11** **						
CL			0.13								0.00					
TERM				5.15	**10.20**	6.72	**13.35** ***	**6.82**				**-2.00**	**-2.73** **	**-2.46** ***	**-2.61** *	-0.43
PE				**-0.40**								0.01				
VS				0.00								0.00				
DEF					1.50	2.00	7.30						**5.29** **	**5.00** **	**5.52** **	
TBILL						0.90								-0.24		
DY						**0.36**								**-0.04**		
FED							3.38								0.13	
CP								**0.05**								**-0.03** **
Horizon *h* =60 months																
CSMB	-0.31	-0.35	-0.13						0.04	0.06	0.08					
CHML	0.04	0.22	0.07						0.09	0.02	0.10					
CUMD		**0.41**								**-0.18** **						
CL			0.21 ***								**0.05**					
TERM				-3.13	**16.04** ***	**9.34** ***	**32.35** ***	5.96				**-3.16** *	**-4.09**	**-5.80** ***	**-7.46** ***	**-3.00**
PE				**-1.27**								**0.07**				
VS				0.03								-0.01				
DEF					-38.37	**65.65** **	24.53						-0.90	**-15.12** **	**-13.92** *	
TBILL						**12.30** ***								**-3.30** **		
DY						**0.96** ***								-0.05		
FED							**18.46** ***								**-3.82** **	
CP								**0.12**								**-0.02**

APPENDIX C. Robustness of cross-sectional pricing results to choice of test assets

The table reports GMM estimation results for an ICAPM based on the commodity *TS*, *HP* and *Mom* factors (Panel A) and traditional ICAPM representations (Panels B and C; see Appendix A for details). The test assets are 25 equity portfolios sorted on size and momentum. γ_M is the market (covariance) risk price, and the remaining γ coefficients are the intertemporal covariance risk prices associated with the "hedging" risk factors. 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*), root mean square error (*RMSE*), degrees-of-freedom adjusted fraction of the cross-sectional variance in average excess returns explained by the model ($\bar{R}^2$), and J test statistic for the null hypothesis that the sum of squared pricing errors is zero which follows asymptotically a $\chi^2_{N-(K+1)}$ where *N* and *K*+1 are the number of testing assets and model risk factors, respectively. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The sample period is January 1987 to August 2011.

	Panel A: Commodity risk factors	Panel B: Equity risk factors			Panel C: Risk factors from predictability literature				
		FF1993	C1997	PS2003	CV2004	HL2006	P2006	BE2010	KVLN2014
γ_M	3.14 *	2.00	2.86 *	1.88	3.23 *	3.98 **	3.72 **	3.40 **	2.96
	(1.75)	(1.41)	(1.76)	(0.77)	(1.90)	(2.26)	(2.13)	(2.02)	(1.50)
γ_{TS}	-9.51 *								
	(-1.65)								
γ_{HP}	-13.91 **								
	(-2.33)								
γ_{Mom}	22.84 ***								
	(3.18)								
γ_{SMB}		2.16	0.84	1.33					
		(1.52)	(0.55)	(0.68)					
γ_{HML}		0.83	4.48 **	-3.54					
		(0.42)	(2.10)	(-0.92)					
γ_{UMD}			4.24 **						
			(2.41)						
γ_L				35.55 ***					
				(3.37)					
γ_{TERM}					-16.71 ***	-12.22 ***	-19.75 ***	-14.71 ***	-8.75 *
					(-3.84)	(-2.98)	(-4.12)	(-3.67)	(-1.92)
γ_{PE}					4.04				
					(0.82)				
γ_{VS}					9.00 **				
					(2.23)				
γ_{DEF}						-14.42 **	-15.30 **	-17.38 **	
						(-2.09)	(-2.37)	(-2.46)	
γ_{TBILL}							-14.14 **		
							(-2.66)		
γ_{DY}							6.20		
							(1.31)		
γ_{FED}								-17.57 ***	
								(-3.25)	
γ_{CP}									26.74 ***
									(4.05)
MAE (%)	0.13	0.28	0.10	0.18	0.16	0.16	0.15	0.14	0.14
RMSE (%)	0.16	0.34	0.14	0.22	0.20	0.22	0.21	0.18	0.19
$\bar{R}^2$(%)	63.32	-48.16	73.39	32.23	42.57	34.20	34.49	55.75	52.96
J test	28.98	57.20 **	47.03 **	21.24	21.57	31.32 *	33.88 **	34.02 **	27.48

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***Figure 1*. Individual pricing errors of nine candidate ICAPMs**

This figure plots the average excess return in percentage per annum (p.a.) of each test asset versus the corresponding prediction from each of nine ICAPMs. The test assets are 25 equity portfolios sorted on size and book-to-market. The sample period is January 1987 to August 2011. The commodity-based ICAPM employs as risk factors the market portfolio and innovations in the commodity *TS*, *HP* and *Mom* state variables. The remaining models are described in Appendix A.

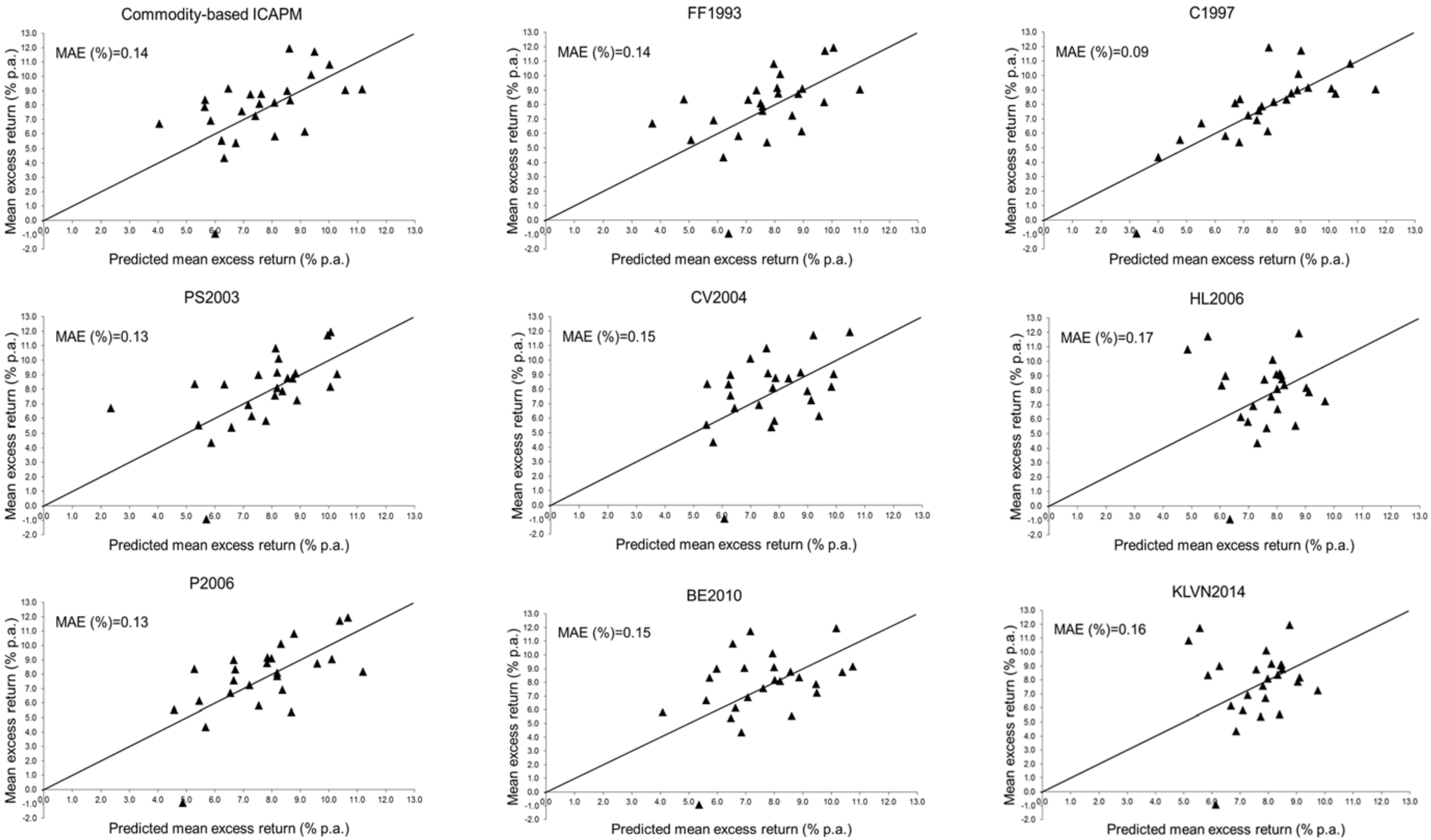

***Table I.* Summary statistics for variables in predictability regressions**

Panel A summarizes the target variables in predictive regressions (2) and (3), respectively, the aggregate excess market portfolio return and realized variance from month t+1 to t+h with h={24, 60} months. The market portfolio is proxied by the U.S. value-weighted stock index and the risk-free rate by the one-month Treasury-bill rate. The empirical state variables in Panel B and C are expressed in cumulated from month t to t-59. Panel B presents summary statistics for the backwardation and contango state variables constructed according to term structure (*CTS*), hedging pressure (*CHP*) and momentum (*CMom*) signals; Section 3.1 of the paper gives details on the construction of the commodity state variables. Panel C summarizes the equity size (*CSMB*) and value (*CHML*) portfolios of Fama and French (1993), the momentum (*CUMD*) portfolio of Carhart (1997) and the liquidity variable of Pastor and Stambaugh (2003; *CL*). Panel D reports state variables from the predictability literature. Appendix A gives details on the variables of Panels C and D. AR(1) is the first order autoregressive coefficient. All returns are annualized. The sample period is January 1987 to August 2011.

	Mean	StDev	Minimum	Maximum	AR(1)
Panel A: Market portfolio distribution (first and second moment)					
$r_M(h{=}24)$	0.0603	0.1711	-0.3023	0.3451	0.9656
$r_M(h{=}60)$	0.0629	0.1486	-0.0818	0.2069	0.9792
$\sigma_M^2(h{=}24)$	0.0325	0.0390	0.0068	0.1130	0.9912
$\sigma_M^2(h{=}60)$	0.0492	0.0458	0.0085	0.0628	0.9873
Panel B: State variables from the commodity pricing literature					
CTS	0.0417	0.0692	-0.0243	0.1000	0.9566
CHP	0.0548	0.0986	-0.0523	0.1466	0.9697
CMom	0.0796	0.0971	-0.0134	0.1630	0.9729
Panel C: State variables from the equity pricing literature					
CSMB	0.0199	0.1035	-0.0882	0.1410	0.9736
CHML	0.0398	0.0984	-0.0837	0.1870	0.9633
CUMD	0.0893	0.1479	-0.0553	0.2167	0.9729
CL	0.0020	0.0557	-0.0118	0.0134	0.9770
Panel D: State variables from the predictability literature on the equity risk premium					
TERM	0.0187	0.0118	-0.0053	0.0376	0.9778
PE	3.1513	0.2940	2.5893	3.7887	0.9869
VS	1.4945	0.6060	-1.9280	3.3411	0.8274
DEF	0.0097	0.0041	0.0055	0.0338	0.9627
TBILL	0.0390	0.0227	0.0002	0.0882	0.9901
DY	-3.8416	0.3389	-4.5282	-3.2114	0.9889
FED	0.0424	0.0251	0.0007	0.0985	0.9907
CP	0.0131	0.0160	-0.0458	0.0583	0.9611

***Table II.* Long-run predictive regressions for future aggregate market returns and variances**

Panel A reports in the first two columns of each section the OLS estimation results of regressions (2) and (3) at horizons of 24 and 60 months ahead; the predictors are the cumulated commodity factor-mimicking portfolio returns, $\boldsymbol{z}_t^{comm} \equiv (CTS_t, CHP_t, CMom_t)'$. The third column reports quarterly OLS predictive regressions for G7 real GDP growth, $\Delta GDP_{t+1:t+h} \equiv \log(GDP_{t+h}/GDP_{t+1})$, at counterpart horizons of 8 and 20 quarters ahead. All regressions include an unreported intercept. Newey-West (1987) t-test statistics are shown in parentheses. Panel B reports Wald encompassing test statistics for traditional predictive regressions augmented with $\boldsymbol{z}_t^{comm}$; the null hypothesis is that traditional predictors encompass commodity predictors, e.g., $H_0\colon b_{CTS} = b_{CHP} = b_{CMom} = 0$ in the augmented regressions. Panel C reports the adjusted R^2 (%) of traditional predictive regressions and augmented versions. The market portfolio is proxied by the U.S. value-weighted stock index from Kenneth French's library. Section 3 and Appendix A provides detailed definitions of commodity and traditional state variables. Bold denotes significance at the 10%, 5% or 1% levels according to the asymptotic distribution. *, **, *** denote significance at the 10%, 5% and 1% levels according to the subsampling distribution based on the minimum-volatility block selection method of Romano and Wolf (2001). The estimation period is January 1987 to August 2011.

	Horizon h =24 months			*Horizon h* =60 months		
	Market return	Market variance	GDP growth	Market return	Market variance	GDP growth
Panel A: Predictive models based on commodity state vector						
CTS	**-1.82** ***	**0.20** *	**-0.10** ***	**-1.23** ***	**0.08**	-0.09
	(-8.83)	(4.97)	(-3.75)	(-3.69)	(2.04)	(-1.62)
CHP	**-0.18** **	**0.10** *	**-0.02** ***	**-1.40** ***	**0.24** ***	**-0.11** *
	(-2.07)	(4.32)	(-2.09)	(-9.39)	(7.90)	(-3.30)
CMom	**1.36** ***	**-0.25** ***	**0.13** ***	**1.34** ***	**-0.21** ***	**0.11** *
	(8.68)	(-5.36)	(3.91)	(5.89)	(-6.78)	(2.44)
$\bar{R}^2$ (%)	54.69	49.91	50.55	64.41	77.56	35.47
Panel B: Encompassing tests (H$_0$: *commodity state variables do not add information to traditional predictors*)						
FF1993	**245.24** ***	**264.06** ***	**76.31** **	**303.31** ***	**549.92** ***	**61.10** ***
C1997	**220.08** ***	**173.34** ***	**37.27** **	**325.92** ***	**436.08** ***	**59.26** ***
PS2003	**232.73** ***	**277.47** ***	**74.96** ***	**289.69** ***	**507.47** ***	**79.13** ***
CV2004	**241.67** ***	**140.09** ***	**59.61** **	**127.91** ***	**269.41** ***	**51.44** **
HL2006	**284.47** ***	**80.35** *	**44.23** *	**211.92** ***	**353.90** ***	**44.93** **
P2006	**256.03** ***	**68.17** **	**48.53**	**76.85** ***	**390.82** ***	**38.35** *
BE2010	**276.41** ***	**94.26** **	**43.34** *	**143.40** ***	**349.69** ***	**43.50**
KLVN2014	**253.22** ***	**40.94**	**31.57**	**149.56** ***	**235.64** ***	**59.30** **
Panel C: $\bar{R}^2$ (%) of traditional predictive models (augmented with commodity state variables)						
FF1993	4.64 (55.72)	1.21 (55.96)	6.46 (55.33)	2.59 (64.26)	14.59 (79.39)	43.87 (72.71)
C1997	9.39 (55.55)	20.51 (56.20)	34.77 (57.07)	5.83 (67.15)	32.40 (80.70)	48.77 (74.91)
PS2003	7.43 (55.90)	0.74 (57.09)	5.74 (54.90)	6.89 (64.96)	20.11 (79.60)	51.16 (79.73)
CV2004	29.01 (66.86)	18.43 (50.74)	13.22 (53.29)	58.06 (75.64)	44.82 (78.27)	1.65 (48.16)
HL2006	20.32 (65.95)	34.50 (52.13)	17.69 (49.05)	21.82 (64.48)	41.11 (80.48)	3.64 (45.33)
P2006	31.43 (69.06)	37.24 (52.21)	18.25 (51.92)	73.53 (81.48)	60.27 (87.79)	44.69 (66.82)
BE2010	21.21 (65.87)	34.23 (54.22)	16.61 (48.24)	41.00 (67.43)	61.83 (87.29)	48.74 (70.71)
KLVN2014	28.25 (67.26)	58.28 (64.66)	35.16 (54.54)	33.96 (64.16)	49.08 (78.21)	3.86 (52.49)

***Table III.* Out-of-sample predictions for long-run future aggregate market returns and variances**

The table summarizes the out-of-sample (OOS) forecasts of predictive regressions (2) and (3) at horizons of 24 and 60 months. The state variables are described in Section 3 and Appendix A. ΔMAE (ΔMSE) refers to the Diebold and Mariano (1995) t-stat for the hypothesis of equality in mean absolute (squared) prediction errors between traditional and commodity models; e.g., $H_0: MSE_{trad} - MSE_{comm} = 0$ versus $H_A: MSE_{trad} - MSE_{comm} \neq 0$. R^2_{OOS} is the percentage reduction in *MSE* achieved by the predictive model versus the historical average benchmark; the Clark and West (2007) *MSE*-adjusted statistic is used to assess significance ($H_0: R^2_{OOS} \leq 0$ vs. $H_A: R^2_{OOS} > 0$). ENC_{trad} (ENC_{comm}) is the Clark and West (2007) *MSE*-adjusted t-stat for the null hypothesis that the forecasts from a traditional (commodity) model encompass the forecasts from the model augmented with commodity (traditional) predictors; e.g., $H_0: MSE_{trad} - MSE_{aug} \leq 0$ vs. $H_A: MSE_{trad} - MSE_{aug} > 0$ for ENC_{trad}. *, **, *** indicates significant at the 10%, 5% and 1% levels. All tests are Newey-West adjusted for autocorrelation in prediction errors. The holdout period is June 2003 to August 2011 (T_1=1/3T).

	Horizon h =24 months					*Horizon h* =60 months				
Model	ΔMAE	ΔMSE	R^2_{OOS} (%)	ENC_{trad}	ENC_{comm}	ΔMAE	ΔMSE	R^2_{OOS} (%)	ENC_{trad}	ENC_{comm}
					Panel A: Market return					
Commodity			36.7 **					56.5 ***		
FF1993	6.32 ***	5.14 ***	-154.0	2.67 ***	0.17	10.06 ***	7.73 ***	-386.1	8.10 ***	0.56
C1997	7.08 ***	5.67 ***	-360.5	6.09 ***	0.39	10.73 ***	8.29 ***	-328.1	4.16 ***	0.49
PS2003	5.65 ***	4.86 ***	-128.5	1.52 *	-0.89	8.47 ***	6.36 ***	-1650.6	6.30 ***	0.44
CV2004	1.58	1.76 *	-45.8	-1.13	-0.07	2.45 **	2.49 **	23.1 *	1.69 **	2.38 **
HL2006	2.79 ***	2.08 **	-78.6	2.79 ***	-0.67	1.66 *	1.73 *	-27.6	2.16 **	-0.42
P2006	4.58 ***	3.78 ***	-115.3	0.70	-0.89	0.40	0.57	36.1 ***	3.25 ***	3.73 ***
BE2010	2.70 ***	2.10 **	-91.4	2.75 ***	-0.60	1.38	1.40	10.7 ***	1.89 **	1.31 *
KLVN2014	-1.28	-0.31	40.0 ***	2.70 ***	2.58 ***	1.71 *	1.85 *	-19.9	2.93 ***	-2.07
					Panel B: Market variance					
Commodity			26.1 **					76.7 ***		
FF1993	-0.49	1.38	-9.2	3.40 ***	1.23	3.40 ***	3.36 ***	-23.9	2.23 **	-0.10
C1997	1.33	2.16 **	-50.6	5.01 ***	1.14	2.83 ***	2.90 ***	-2.0	1.39 *	-0.16
PS2003	-0.58	1.38	-11.2	2.62 ***	1.17	9.27 ***	6.13 ***	-970.9	5.91 ***	-0.15
CV2004	0.38	1.94 *	-25.7	-3.04	-0.75	3.16 ***	3.34 ***	11.9 *	3.62 ***	0.23
HL2006	-1.58	-0.56	30.8 ***	0.28	-0.03	3.80 ***	3.22 ***	-17.5	6.18 ***	0.33
P2006	0.18	1.68 *	-15.6	-3.45	-1.06	3.26 ***	3.80 ***	-2.8	6.24 ***	2.11 **
BE2010	-0.79	0.04	25.7 ***	0.02	-0.51	4.35 ***	3.37 ***	-33.2	5.10 ***	0.23
KLVN2014	-3.82 ***	-3.14 ***	45.0 ***	-3.65	1.66 *	2.99 ***	2.78 ***	14.4 *	7.56 ***	-0.16

***Table IV.* Cross-sectional pricing ability of commodity and traditional risk factors**

The table reports GMM estimation results for an ICAPM based on the commodity *TS*, *HP* and *Mom* factors (Panel A) and eight traditional ICAPMs (Panels B and C; see Appendix A for details). The test assets are 25 equity portfolios sorted on size and book-to-market. γ_M is the market (covariance) risk price, and the remaining γ coefficients are the intertemporal covariance risk prices associated with the "hedging" factors. 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*), root mean square error (*RMSE*), degrees-of-freedom adjusted fraction of the cross-sectional variance in average excess returns explained by the model ($\bar{R}^2$), and J test statistic for the null hypothesis that the sum of squared pricing errors is zero which follows asymptotically a $\chi^2_{N-(K+1)}$ where N and K+1 are the number of testing assets and model risk factors, respectively. *, ** and *** denote test rejection at the 10%, 5% and 1% levels, respectively. The sample period is January 1987 to August 2011.

	Panel A: Commodity risk factors	Panel B: Equity risk factors			Panel C: Risk factors from predictability literature				
		FF1993	C1997	PS2003	CV2004	HL2006	P2006	BE2010	KLVN2014
γ_M	2.43	2.27	2.74	2.19	2.83 *	3.16 **	2.95 *	2.35	3.11 *
	(1.31)	(1.51)	(1.31)	(1.29)	(1.93)	(2.02)	(1.66)	(1.11)	(2.01)
γ_{TS}	-17.00 ***								
	(-2.61)								
γ_{HP}	-16.22 ***								
	(-3.18)								
γ_{Mom}	24.89 ***								
	(4.56)								
γ_{SMB}		1.24	-0.72	1.33					
		(0.96)	(-0.39)	(1.04)					
γ_{HML}		3.64 **	6.45 ***	2.57					
		(2.38)	(3.04)	(1.43)					
γ_{UMD}			18.17 ***						
			(4.36)						
γ_L				10.62 ***					
				(2.64)					
γ_{TERM}					0.90	-12.47 ***	-5.14	-17.32 ***	-12.85 ***
					(0.24)	(-2.86)	(-0.90)	(-3.02)	(-2.98)
γ_{PE}					3.29				
					(0.89)				
γ_{VS}					-6.10 ***				
					(-2.67)				
γ_{DEF}						-0.90	-14.41 **	-17.48 ***	
						(-0.24)	(-2.08)	(-2.92)	
γ_{TBILL}							-35.11 ***		
							(-3.23)		
γ_{DY}							-11.65 ***		
							(-3.00)		
γ_{FED}								-32.24 ***	
								(-3.46)	
γ_{CP}									2.73
									(0.57)
MAE (%)	0.14	0.14	0.09	0.13	0.15	0.17	0.13	0.15	0.16
RMSE (%)	0.19	0.19	0.13	0.18	0.19	0.23	0.16	0.20	0.23
$\bar{R}^2$(%)	9.21	11.51	53.01	16.72	2.35	-35.18	25.33	-3.84	-27.43
J test	37.13 **	56.78 **	35.24 **	42.63 ***	46.52 **	45.21 ***	21.55	34.77 **	44.90 ***

***Table V*. Robustness of out-of-sample predictions for long-run future aggregate market returns and variances**

The table summarizes the out-of-sample (OOS) predictions from regressions (2) and (3) at horizons of 24 and 60 months when estimation is based on rolling windows (holdout period is June 2003 to August 2011) in Panel I, and holdout period is May 1999 to August 2011 (expanding estimation windows) in Panel II. T_1 (T) is the length in months of the holdout (total sample) period. The state variables are described in Section 3 and Appendix A. ΔMSE refers to the Diebold and Mariano (1995) t-stat for the hypothesis of equality in mean squared prediction errors between traditional and commodity models; e.g., $H_0: MSE_{trad} - MSE_{comm} = 0$ versus $H_A: MSE_{trad} - MSE_{comm} \neq 0$. R^2_{OOS} is the percentage reduction in *MSE* achieved by the predictive model versus the historical average benchmark; the Clark and West (2007) *MSE*-adjusted statistic is used to assess significance ($H_0: R^2_{OOS} \leq 0$ vs. $H_A: R^2_{OOS} > 0$). ENC_{trad} is the Clark and West (2007) *MSE*-adjusted t-stat for the null hypothesis that the forecasts from a traditional model encompass the forecasts from the model augmented with commodity predictors; e.g., $H_0: MSE_{trad} - MSE_{aug} \leq 0$ vs. $H_A: MSE_{trad} - MSE_{aug} > 0$. *, **, *** indicates significant at the 10%, 5% and 1% levels. All tests are Newey-West adjusted for autocorrelation in prediction errors.

	Panel I: Rolling scheme (Holdout period T_1 = 1/3T)						Panel II: Recursive scheme (Holdout period T_1 = 1/2T)					
	h =24 months			h =60 months			h =24 months			h =60 months		
Model	ΔMSE	R^2_{OOS} (%)	ENC_{trad}	ΔMSE	R^2_{OOS} (%)	ENC_{trad}	ΔMSE	R^2_{OOS} (%)	ENC_{trad}	ΔMSE	R^2_{OOS} (%)	ENC_{trad}
Panel A: Market return												
Commodity		40.2 ***			55.8 ***			15.6 **			38.8 ***	
FF1993	5.49 ***	-151.2	2.72 ***	7.60 ***	-375.1	7.73 ***	3.17 ***	-78.6	2.44 **	3.66 ***	-169.3	4.65 ***
C1997	5.90 ***	-355.6	6.23 ***	8.09 ***	-320.6	3.93 ***	3.54 ***	-182.3	4.12 ***	3.84 ***	-146.2	3.62 ***
PS2003	5.08 ***	-130.3	1.06	6.35 ***	-1640.6	6.29 ***	3.04 ***	-66.3	0.93	3.62 ***	-777.4	3.73 ***
CV2004	2.00 **	-50.6	-0.17	2.42 **	24.0 *	1.68 **	1.72 *	-39.9	0.96	2.83 ***	17.5 ***	3.47 ***
HL2006	1.85 *	-105.8	2.28 **	1.73 *	-28.8	2.22 **	2.70 ***	-85.1	3.65 ***	1.70 *	-5.8	1.14
P2006	3.23 ***	-89.2	0.12	0.64	32.8 ***	3.67 ***	4.10 ***	-110.3	2.42 **	2.79 ***	-60.2	2.45 ***
BE2010	1.94 *	-86.5	2.52 ***	1.34	12.8 ***	1.90 **	2.77 ***	-98.0	3.36 ***	1.40	12.0 ***	0.49
KLVN2014	-0.45	44.0 ***	1.74 **	1.84 *	-20.1	2.91 ***	0.63	5.4	2.96 ***	2.84 ***	-25.4	4.41 ***
Panel B: Market variance												
Commodity		21.9 **			76.5 ***			30.2 ***			51.4 ***	
FF1993	1.24	-10.2	3.18 ***	3.21 ***	-18.7	2.07 **	1.84 *	-17.5	3.64 ***	3.74 ***	-61.9	2.84 ***
C1997	2.02 **	-37.3	6.82 ***	2.77 ***	2.0	1.28 *	2.58 ***	-63.2	4.71 ***	2.92 ***	-36.9	1.96 **
PS2003	1.30	-14.6	2.54 ***	6.11 ***	-963.1	5.86 ***	3.00 ***	-62.7	4.08 ***	3.70 ***	-806.9	3.77 ***
CV2004	1.98 **	-34.3	-3.11	3.35 ***	12.4 *	3.64 ***	1.57	-12.4	-2.53	1.91 *	5.1 ***	2.74 ***
HL2006	-0.63	27.5 ***	0.11	3.30 ***	-19.4	6.32 ***	-0.49	34.2 ***	0.61	1.75 *	-6.3	4.99 ***
P2006	1.70 *	-22.2	1.06	3.77 ***	-1.1	6.25 ***	1.31	-2.4	-3.01	3.64 ***	-11.3	4.32 ***
BE2010	0.12	20.4 ***	-0.19	3.42 ***	-28.5	5.20 ***	0.03	29.9 ***	0.60	2.29 **	-28.9	5.28 ***
KLVN2014	-3.87 ***	46.8 ***	-3.56	2.79 ***	12.6 *	7.33 ***	-2.63 ***	46.7 ***	-3.07	0.86	28.2 ***	4.70 ***