Commodity Return Predictability: Economic Value and Links to the Real Economy

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Abstract

This paper finds statistically significant out-of-sample excess commodity return predictability using forecast combinations of 28 potential predictors. Such gains in forecast accuracy translate into economically significant improvements in certainty equivalent returns and Sharpe ratios for a mean-variance investor. Commodity return forecasts are closely linked to the real economy. Return predictability is countercyclical, and the combinations of individual predictors has strong predictive power for future economic activity. By using forecast combination methods which provide insurance against model instability and model uncertainty, we reconcile our findings with the literature that documents the poor out-of-sample performance of individual return prediction models.

Keywords: Commodity futures; Return predictability; Out-of-sample forecasts; Asset allocation; Real economy

JEL classification: C52, C53, G11, G13, Q02

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1. Introduction

Compared to the vast literature on aggregate stock, bond, and currency return predictability,[1] aggregate commodity return predictability has received only little attention. This is despite the fact that commodity futures play an important role in explaining fluctuations in and projecting macroeconomic activity (Hamilton, 2009), and interest in commodities as an alternative investment asset class has grown tremendously in recent years (Fuertes, Miffre & Rallis, 2010; Erb & Harvey, 2016).

In this paper, we provide a comprehensive study of the time-series predictability of aggregate excess commodity returns–the return on the S&P Goldman Sachs commodity index (S&P GSCI) less the return on the one-month T-bill rate. To examine this issue, we consider return-forecasting models that differ in the way they assume predictability in the mean based on 28 potential predictors. In addition to individual predictive model forecasts, we also consider forecast combinations to account for model instability and model uncertainty that typically plague individual return-forecasting models leading to their poor out-of-sample performance. We implement 16 combination forecasts ranging from simple averaging schemes of individual forecasts to more sophisticated ones for a total 44 time-varying expected return models. As a benchmark model, we consider a simple no-predictability (historical average) return model and compare its performance to our time-varying models.

To measure the statistical performance the return forecasts, we use the out-of-sample (OOS) R^2 which measures the proportional reduction in mean square forecast error (MSFE) between the time-varying forecasts relative to the historical average forecast. We measure the statistical significance of the OOS R^2 using the p-value of the MSFE-adjusted statistic of Clark & West (2007). Consistent with the evidence in Welch & Goyal (2008), we find that majority of the individual predictive model forecasts generate negative and statistical insignificant OOS R^2 implying that the historical average forecast generates a lower OOS MSFE. On the other hand, we find positive out-of-sample R^2 values of 0.30–4.96% which are statistically significant for all the combination forecasts. We reconcile our findings with the evidence in Welch & Goyal (2008) by testing the stability of individual predictive models using the t-statistic from the Giacomini & Rossi (2009) forecast breakdown test. Evidence of forecast breakdown between returns and the predictors will confirm why the individual models perform poorly. It will also provide support for the superior performance of the combination forecasts as it provides insurance against model instability and model uncertainty. Our findings show strong evidence of instability between commodity returns and the predictors.

We evaluate the economic significance of return predictability by examining the port-

[1] see, for example, Cochrane, 2011, and the references therein.

folio benefits for an investor. We consider a mean-variance investor with a relative risk aversion of three who exploits this predictability when forming optimal portfolios composed of commodities and risk-free T-bills. Portfolio performance is measured using Sharpe ratio and certainty equivalent return gain. We find that the gains in predictive accuracy from combination forecasts of commodity returns translate into higher Sharpe ratios and certainty equivalent return gains. For example, the investor who uses the combination forecasts would have realized an annualized Sharpe ratio of 0.38 compared to 0.02 for the historical average benchmark forecast, and annualized certainty equivalent return gain 3.46. However, we realise lower Sharpe ratios and certainty equivalent return losses for optimal portfolios based on the majority of the individual forecasts compared to portfolios constructed using the historical average forecast.

We further examine the drivers of commodity return predictability. First, we interpret the sources of predictability by analysing the extent to which commodity return predictability is related to the business-cycle. Using the NBER-dated business-cycle indicator, we find that commodity return predictability is largely concentrated in economic recessions, with R^2 values as high as 18.18 percent, relative to expansions. Second, and in the spirit of Cochrane (2008), we test whether our predictor variables forecast economic activity. If time-varying excess commodity return forecasts are more plausibly related to macroeconomic risk, then the predictors used to forecast commodity returns should also have forecasting power for macroeconomic activity. We find that forecasts of economic activity variables such as growth in industrial production based on combinations of the individual predictors display statistically significant predictability. These results show that combination forecasts for commodity returns are closely linked to the real economy.

As a final contribution, we attempt to improve the forecasting performance of our models by implementing the conditional forecasting procedure of Giacomini & White (2006) that augments forecast selection by conditioning on a set of monitoring instruments. It is a decision-rule that tracks forecast performance over time by selecting the best forecast between the benchmark historical average and the individual (combination) forecasts. Using money stock (M2) as a monitoring instrument,[2] we find only marginal improvement in forecast performance. That is the individual forecasts continue to display statistically and economically insignificant degree of predictability. However, there is marginal improvement in the performance of the combination forecasts.

Our study is related to a strand of literature that investigate the time series predictability of commodity returns. Based on the classical theories of storage (Kaldor, 1939; Brennan, 1958) and normal backwardation (Keynes, 1930; Hicks, 1939), many articles have provided evidence of the forecasting ability commodity market variables such as

[2]We experiment with other monitoring instruments including growth in consumer price index, the VIX, and the macroeconomic uncertainty measure of Jurado, Ludvigson & Ng (2015) and find that M2 performs best in forecasting the squared error loss differential.

basis, hedging pressure, and inventory. For example, Gorton, Hayashi & Rouwenhorst (2013) find that individual commodity futures risk premium is driven by basis and inventory levels. Other studies also examine the relationship between commodity returns and macroeconomic variables. Because of short-term mismatches between the demand and supply of commodities, the general state of the economy is expected to influence commodity prices (see, for example, Bessembinder & Chan, 1992). For example, Gargano & Timmermann (2014) show that macroeconomic variables such as the 3-month treasury bill rate, term spread, the growth rate of consumer price index, money supply, among others have forecasting power for raw industrials and metals commodity index returns. Our study does not seek to test a specific theory of commodity futures returns but instead we seek to examine the forecasting power of these variables for commodity returns.

Our study departs along the following dimensions. First, we examine commodity return predictability using a much broader and comprehensive set of predictors. Second, whereas previous studies examine the predictability of either individual commodities, commodity spot indices, or an equally-weighted portfolio of individual commodity futures (see, for example, Hong & Yogo, 2012; Gorton et al., 2013; Ahmed & Tsvetanov, 2016, and the references therein), we examine the predictability of aggregate commodity returns by focussing on an investable commodity index, namely the S&P Goldman Sachs commodity index (S&P GSCI). The S&P GSCI is the benchmark commodity index used by investor to gain broad exposure to commodities through investment vehicles such as commodity-linked exchange traded products. For example, the study of Gargano & Timmermann (2014) examine the predictability of commodity spot indexes. Because of the high storage, transportation and insurance costs associated with holding the physical commodities, investors have traditionally relied on commodity futures to gain exposure to commodities (Edwards & Park, 1996; Jensen, Johnson & Mercer, 2000). Similarly, the equally-weighted portfolio of individual commodity futures studied by Hong & Yogo (2012) and Ahmed & Tsvetanov (2016) are not truly investable.

Another difference between our study and prior studies is that we address the impact of model instability and model uncertainty on predictive regression. We do implementing several forecast combination models. The exception, however, is the study of Gargano & Timmermann (2014). Our study also address concerns raised by previous studies that find that the statistical evidence of predictability does not translate into portfolio benefits benefits for an investor(Ahmed & Tsvetanov (2016)). Finally, our study extends prior studies by examining whether predictability has links to the real economy, offer an explanation for the superior performance of our forecast combination models, and implement a forecast decision rule designed to improve our return forecasts.

The rest of the paper is as follows: Section 2 describes the return prediction models we consider and the approach for evaluating out-of-sample return predictability. Section 3 describes the commodity returns data and predictor variables, and presents the empirical results. In Section 4, we analyse the link between commodity return predictability, portfolio performance and the business-cycle. Section 5 examines the economic drivers of commodity return predictability based on the combination forecasts. In Section 6, we discuss the conditional predictability ability tests that track forecast performance over time and implement forecast decision-rule designed to improve upon our forecasts. Section 7 concludes.

2. Methodology for Predicting Commodity Returns

We next introduce the individual predictive models that condition on each of the 28 predictors at a time to generate a forecast, the forecast combination methods that combine the individual predictive model forecasts using different weights, and the statistical and economic performance measures that we use in evaluating out-of-sample commodity return forecasts.

2.1. Individual Predictive Model Forecasts

Consider the following bivariate predictive regression model for excess commodity returns,

$$r_{t+1} = \alpha + \beta x_{i,\,t} + \varepsilon_{i,t+1}, \tag{1}$$

where r_{t+1} is the realized log excess return on commodity futures index from time $t-1$ to t, $x_{i,\,t}$ is a predictor available at time t, and $\varepsilon_{i,t+1}$ is a zero-mean error term. The step-ahead forecast of log excess returns is given by

$$\hat{r}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t x_{i,\,t}, \tag{2}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of α and β in Equation (1), respectively.

2.2. Combination Forecasts

A potential issue that arises when studying return predictability, however, is what economic variables have predictive power for asset returns, especially when the set of possible predictors is large. One possibility is to use financial theory to guide the selection of the relevant variables. The difficulty is that economic theory alone does not provide enough guidance and so one is likely to ignore potentially important predictors. Welch & Goyal (2008), for example, show that the poor out-of-sample forecasting performance of individual predictive model forecasts of the equity risk premium may be the result of structural instability of the underlying models. Combination forecasts incorporate information from many predictors and therefore should hedge model uncertainty and parameter instability of the individual predictive models. Our combination forecasts differ in the way we compute weights assigned to the individual predictive model forecasts. Forecast combination methods has been shown in studies such as Stock & Watson (2004), Timmermann (2006), Rapach, Strauss & Zhou (2010), among others, to lead to improved forecasts. As noted by Timmermann (2008), which combination method is ex ante optimal is an empirical question and justifies why we consider different forecast combination methods.

Let $\hat{r}_{i,\,t+1}$ denote the pseudo out-of-sample forecast of the realization r_{t+1} computed at time t based on the ith predictor variable as given by Equation (2). Most of the forecast combination methods we consider take the following form:

$$\hat{r}^{\text{CF}}_{t+1} = \sum_{i=1}^{N} w_{i,\,t}\hat{r}_{i,\,t+1}, \tag{3}$$

where $\hat{r}^{\text{CF}}_{t+1|t}$ is the combination forecast and $w_{i,\,t}$ is the weight assigned to the ith forecast with $\sum_{i=1}^{N} w_{i,\,t} = 1$.

The first set of combining methods we consider use simple averaging schemes: mean, trimmed mean, median, and weighted-mean forecasts. Rapach et al. (2010), for example, find that simple methods work well for forecasting US equity risk premium. The mean combination forecast, $\hat{r}^{\text{Mean}}_{t+1}$, is the average of the N individual forecasts that assign equal weights, $w_{i,\,t} = 1/N, i = 1, ..., N$, to each forecast defined in Equation (2):

$$\hat{r}^{\text{Mean}}_{t+1} = \frac{1}{N}\hat{r}_{1,\,t+1} + \frac{1}{N}\hat{r}_{2,\,t+1} + ... + \frac{1}{N}\hat{r}_{N,\,t+1}. \tag{4}$$

The trimmed mean forecast, $\hat{r}^{\text{Trimmed mean}}_{t+1}$, sets the $w_{i,\,t} = 0$ for the smallest and largest forecasts, and $w_{i,\,t} = 1/(N-2)$ for the remaining individual forecasts in Equation (3). The median combination forecast, $\hat{r}^{\text{Median}}_{t+1}$, is the sample median of the N individual predictive model forecasts. The weighted-mean forecast ($\hat{r}^{\text{Weighted-mean}}_{t+1}$) proposed by Bates & Granger (1969) specifies the combination weights to be proportional to the inverse of the estimated residual variance, $\sigma^2_{i,\,t}$, for the individual predictive regression models given by Equation 1,

$$\hat{r}^{\text{Weighted mean}}_{t+1} = \frac{1/(\hat{\sigma}^2_{1,\,t})}{\sum_{i=1}^{N} 1/(\hat{\sigma}^2_{i,\,t})}\hat{r}_{1,t+1} + \frac{1/(\hat{\sigma}^2_{1,\,t})}{\sum_{i=1}^{N} 1/(\hat{\sigma}^2_{i,\,t})}\hat{r}_{2,t+1} + ... + \frac{1/(\hat{\sigma}^2_{1,\,t})}{\sum_{i=1}^{N} 1/(\hat{\sigma}^2_{i,\,t})}\hat{r}_{N,t+1}, \tag{5}$$

The second set consist of various performance-based combination forecasts. First, we compute the discounted mean squared forecast error (DMSFE) combination forecast following Stock & Watson (2004). Here, the combining weights are specified as functions of the historical performance of the individual predictive model forecasts over a holdout

out-of-sample period,

$$w_{i,t}^{\text{DMSFE}} = \frac{\phi_{i,t}^{-1}}{\sum_{j=1}^{N} \phi_{j,t}^{-1}}, \quad \phi_{i,t} = \sum_{s=1}^{t-1} \theta^{t-1-s} \left(r_{s+1} - \hat{r}_{i,s+1} \right) \tag{6}$$

where θ is the discount factor.[3] When $\theta < 1$, greater importance is attached to the individual predictive model forecast with lower mean square forecast error (MSFE). That is, the individual predictive model that generates the least MSFE is assigned a greater weight because it signals better forecasting performance. In the special case where there is no discounting ($\theta = 1$) and forecasts are uncorrelated leads to the optimal combination weights proposed by Bates & Granger (1969) given by Equation (5). We consider θ values of 0.7 and 0.9. Rapach et al. (2010) also show that the DMSFE combination forecasts of US equity risk premium consistently outperforms a constant expected return benchmark forecast. Second, we consider Approximate Bayesian Model Averaging (ABMA) combination forecast following Garratt, Lee, Pesaran & Shin (2003) and choose the combining weights as follows:

$$w_{i,t}^{\text{ABMA}} = \frac{\exp(\triangle_{i,t})}{\sum_{j=1}^{N} \exp(\triangle_{i,t})}, \tag{7}$$

where $\triangle_{i,t} = \text{AIC}_{i,t} - \max_j(\text{AIC}_{j,t})$ and $\text{AIC}_{i,t}$ is the Akaike Information Criterion of model i. The ABMA thus gives higher weight to models with better historical fit as measured by the AIC. The BAyesian model has the advantage that, in addition to dealing with structural instability and model uncertainty, it also deals with estimation errors surrounding the parameters of the predictive models. Third, Elliott, Gargano & Timmermann (2013, 2015) propose a new class of combination forecast which they call Subset regression forecast. Their approach uses equally weighted combination of forecasts based on all possible predictive regression models that include a subset of the predictor variables. As noted by the authors, by keeping the number of predictors to be included in the predictive model fixed, they are able to control estimation error by trading off the bias and variance of the forecast errors similarly to generating the mean-variance efficient frontier of individual assets in portfolio theory. Suppose the number of potential predictors that enter a regression is K. A subset regression is then defined by the set of regression models that include a specified number of regressors, $k \leq K$. The $k \leq K$ dimensional subset forecasts are then averaged to generate the forecasts. In our analysis, we use a maximum K value of 7. Given K regressors in full and k regressors chosen for short models, one has to average over $C_k^K = K!/(k!(K-k)!)$ subset regression forecasts. As a special case, when $k = 1$

[3]The DMSFE combination forecast require a holdout evaluation period to estimate the combining weights. However, note that the first out-of-sample forecast of this method is simply calculated as the mean combination forecast because there is no past individual forecast used to form the DMSFE weight at this time point.

results in the mean combination forecast given by Equation (4). Generally, the subset regression forecast is given by

$$\hat{r}_{t+1}^{\text{Subset}} = \frac{1}{C_k^K} \sum_{i=1}^{C_k^K} \hat{\beta}_{i,\,t} x'_{i,\,t}, \tag{8}$$

where $\dim(x_{i,\,t}) = k$.

As our finally combination method, we generate out-of-sample forecast by estimating a predictive regression based on diffusion index that assumes a latent factor structure following Stock & Watson (2002*a*,*b*):

$$\hat{r}_{t+1}^{\text{PC}} = \hat{\alpha} + \sum_{k=1}^{K} \hat{\beta}_{k,\,t} F_{k,\,t}, \tag{9}$$

where $F_{k,\,t}$ is the kth principal component extracted from the 28 predictor variables. Diffusion indices provide a convenient way of extracting common factor from a large number of potential predictor variables. Neely, Rapach, Tu & Zhou (2014), for example, show that this approach improves US equity premium forecasting. We consider models where the principal components are selected via the Akaike information criterion (AIC),[4] the Bayesian information criterion, and the adjusted R^2 statistical model selection criterion. We set the maximum number of principal components to 4.

2.3. Historical Average Return Benchmark Forecast

The historical average return (HA) forecast is a popular benchmark forecast that has been used widely in studies of return predictability (see, for example, Welch & Goyal, 2008; Rapach & Zhou, 2013; Ahmed & Tsvetanov, 2016; and the references therein). The use of the HA return forecast as the benchmark is consistent with the hypothesis that commodity futures prices follow a random walk so returns are unpredictable (Alquist & Kilian, 2010; Chinn & Coibion, 2014). Under the null hypothesis of no predictability, the model assumes a constant expected excess commodity returns:

$$r_{t+1} = \alpha + \varepsilon_{t+1}, \tag{10}$$

[4] The Akaike information criterion (similarly the adjusted R^2 selection criterion), unlike the Bayesian information criterion (BIC) is not statistically consistent, in the sense, of selecting the "true" model, as the sample size increases without bounds. However, Pesaran & Timmermann (1995) note that in the context of forecasting asset returns where the correct list of regressors is unknown and may be changing over time, the consistency property of a model selection criterion is not as important as it may first appear. They suggest that of greater importance is to select a forecasting model that could be viewed at the time as being a reasonable approximation to the data generating process. Although AIC is statistically inconsistent, it has the property of yielding an approximate model. Shibata (1976), for example, shows that AIC strikes a good balance between giving biased estimates when the order of the model is too low, and the risk of increasing the variance when too many regressors are included.

We use the forecast from this model as the benchmark forecast against which all other forecasts are compared to in assessing commodity return predictability.

2.4. Statistical Evaluation of Commodity Return Predictability

We generate the out-of-sample forecasts using a recursive (expanding window) estimation scheme as follows. Suppose T observations are available for r_t and $x_{i,t}$. To initialize our parameter estimates for the individual predictive model forecasts, we use the first $n = 167$ observations (February 1976 to December 1989)[5] as the in-sample estimation period and the remaining $T - n = 312$ observations (beginning in January 1990) as the out-of-sample forecast evaluation period. The parameters are updated recursively as new data becomes available. Meaning that the estimation sample always starts in 1976:02 and we expand the estimation window by one month as additional observations become available. Only data up to the previous month is therefore used to estimate the model parameters and generate the pseudo out-of-sample forecast of excess commodity returns corresponding to each predictor variable for the month, $t + 1$, as

$$\hat{r}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t \, x_{i,t}, \tag{11}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of α and β in Equation (1), respectively, from regressing $\{r_s\}_{s=2}^{n}$ on a constant and $\{x_{i,s}\}_{s=1}^{n-1}$.

Following the convention in the return predictability literature, we evaluate the out-of-sample performance of the individual and combination forecasts relative to the benchmark HA return forecast using the Campbell & Thompson (2008) out-of-sample R^2 statistic, R^2_{OOS}, given by:

$$R^2_{\text{OOS}} = 1 - \frac{\text{MSFE}(\hat{r}_t)}{\text{MSFE}(\bar{r}_t)} = 1 - \frac{\sum_{t=n+1}^{T} (r_t - \hat{r}_t)^2}{\sum_{t=n+1}^{T} (r_t - \bar{r}_t)^2}, \tag{12}$$

where r_{n+1} is the realized log return at time $n + 1$ and $\hat{r}_{n+1}(\bar{r}_{n+1})$ is an alternative (HA forecast), individual predictive regression or the combination forecast, forecast. The R^2_{OOS} statistic measures the proportional reduction in mean square forecast error (MSFE) for an alternative forecast relative to the HA forecast. A positive R^2_{OOS} implies the alternative forecast, becasue it has a lower MSFE, outperforms the HA forecast.

We evaluate the statistical significance of the R^2_{OOS} statistic using the p-value of the MSFE-adjusted statistic of Clark & West (2007). The statistic tests the null hypothesis of equal out-of-sample predictive ability of the alternative model forecasts against the benchmark HA model forecast. That is, $R^2_{\text{OOS}} \leq 0$ against the alternative hypothesis that

[5] The choice of length of the in-sample estimation period enables us to have a sufficiently long out-of-sample forecasts evaluation period. Hansen & Timmermann (2012), for example, show that using a relatively large proportion of the available sample for forecast evaluation provides better size properties of the test statistics of predictive ability.

$R^2_{\text{OOS}} > 0$. Under the null of no predictability, the HA return forecast is expected to have a lower MSFE. The Clark & West (2007) procedure accounts for the fact that under the null of equal predictive accuracy, the MSFE of the HA model is expected to be lower compared to the alternative models. This is because the alternative model introduces noise into its forecasts by attempting to estimate parameters whose population values are zero. As such, finding that the HA model forecast has a lower MSFE is not clear evidence against the alternative model. Clark & West propose to adjust the MSFE to account for the noise associated with the alternative models' forecast as follows:

$$\text{MSFE-adjusted} = \frac{1}{F} \sum_{t=n+1}^{T} (r_t - \hat{r}_t)^2 - \frac{1}{F} \sum_{t=n+1}^{T} (\bar{r}_t - \hat{r}_t)^2 , \tag{13}$$

where F is the number of forecasts. They also note that the computationally most convenient way of testing the null of equal MSFE is to define:

$$\hat{f}_t = (r_t - \bar{r}_t)^2 - [(\bar{r}_t - \bar{r}_t)^2 - (\bar{r}_t - \hat{r}_t)^2] \tag{14}$$

and to regress $\hat{f}_t$ on a constant and using the resulting t-statistic for a test of zero coefficient. Although the asymptotic distribution of this test statistic is nonnormal, the authors argue that standard normal critical values provide a good approximation. They recommend to reject the null of equal MSFE if the test statistic has critical values greater than 1.282 for a one-sided 10% test, 1.645 for a one-sided 5% test, and 2.326 for a one-sided 1% test.

In addition to our formal test of significance of the R^2_{OOS}, we also use the forecast breakdown test of Giacomini & Rossi (2009) to test the stability of the individual predictive models. This test is designed to detect forecast breakdowns by assessing whether a model that display good forecasting performance in one sample period will continue to do so in other sample periods. In our framework, the null hypothesis of the forecast breakdown test is that the out-of-sample MSFE of a model is equal to its in-sample MSFE. We test this hypothesis using a one-sided t-statistic for our recursive forecasts. The one-sided t-test focusses on the alternative hypothesis that the out-of-sample MSFE of a model is higher than its in-sample MSFE.

2.5. Economic Evaluation of Commodity Return Predictability

In this section, we detail the asset allocation framework that we use to evaluate the economic significance of commodity return predictability. We test whether any statistical evidence of commodity return predictability translates into economic gains for a risk-averse investor.[6] We are motivated by studies such as Della Corte, Sarno & Tsiakas (2008), Potì (2018) and Thornton & Valente (2012) for exchange rate and bond return predictability, respectively, who find that statistical evidence of return predictability does not always translate into economic significance. By evaluating return predictability from the economic perspective, we also address the limitations of studies on commodity return predictability that only focus on statistical tests of return predictability.

2.5.1. Dynamic Asset Allocation

Following Campbell & Thompson (2008), among others, we consider a mean-variance investor who monthly allocates her wealth between commodities and risk-free T-bills using either the individual predictive regression forecasts (combination forecasts) or HA forecast of excess commodity returns. The investor optimally allocates the following share of her portfolio to commodities during the subsequent month $t+1$

$$w_t = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}}\right), \tag{15}$$

where γ is the investor's relative risk aversion coefficient, $\hat{r}_{t+1}$ is the simple excess return forecast[7] and $\hat{\sigma}^2_{t+1}$ is the excess return variance.[8] The share of wealth $1 - w_t$ is allocated to risk-free T-bills. The month $t+1$ portfolio returns is given by

$$r_{p,t+1} = r_{f,t} + w_t \hat{r}_{t+1}. \tag{16}$$

As in Campbell & Thompson (2008), Cooper & Priestley (2009), and Rapach et al. (2010), we consider γ value of three. Since we use futures, we avoid short sale restrictions but limit leverage to 50% of wealth to avoid excessive risk taking.

2.5.2. Performance Measures

We evaluate the performance of the portfolio strategies generated by our forecasting models using the realized average utility or certainty equivalent return (CER) defined as:

$$\text{CER}(r_p) = \hat{\mu}_p - \frac{1}{2}\gamma\hat{\sigma}^2_p, \tag{17}$$

[6] The R^2_{oos} statistical evaluation metric does not take into account the risk that an investor would have to bear over the out-of-sample forecast evaluation period. Leitch & Tanner (1991) in the context of studying why firms purchase professional forecasts of economic and financial variables argue that the profitability of a forecast is a more relevant metric for assessing forecasts. They show that using such a metric explains the value of forecasts to firms even when forecasts fail to beat simple models in terms of MSFE.

[7] We implement the portfolio strategy using simple (instead of log) excess returns so that the resulting portfolio returns are given by the sum of the product of portfolio weights and commodity excess returns.

[8] Following Campbell & Thompson (2008), we assume that the investor uses a five-year rolling-windows of past returns to estimate the variance of commodity futures excess return.

where $\hat{\mu}_p$ and $\hat{\sigma}_p$ are the mean and standard deviation, respectively, of portfolio excess returns over the forecast evaluation period. We compare the performance of our dynamic portfolios generated by our forecasting models to that of the HA benchmark model by computing the average utility or CER gain, $\triangle$, given by

$$\triangle = \mathrm{CER}(r_p^*) - \mathrm{CER}(r_p), \tag{18}$$

where r_p^* are the portfolio returns generated by the individual or combination forecasts (dynamic strategy) and r_p is the portfolio returns generated by the HA return forecast (static strategy). Our direct measure of economic value of return predictability is the annualized utility gain. The utility gain measure can be interpreted as the portfolio management fee that the investor would be willing to pay to have access to the dynamic portfolio strategy relative to the static strategy. Positive values indicate that the time-varying predictability models perform better the HA model. A $\triangle$ of 2% or more is usually considered to be economically significant (see, for example, Rapach et al. (2010) and the references therein.). We also report the annualized Sharpe ratio, SR, computed as the ratio of the mean of portfolio excess returns to its standard deviation.

2.5.3. Transaction Costs

A realistic assessment of the profitability of any dynamic asset allocation strategy should take into account the effect of transaction costs. With sufficiently high costs of trading, we should expect the dynamic portfolio strategies to be costly to implement relative to the static strategy because of fluctuations in their portfolio weights. We account for the effect of transaction costs in two ways. First, we compute our performance measures for the investor's realized portfolio returns net of transaction costs as

$$r_{p,\,t+1}^{\mathrm{net}} = r_{f,\,t} + w_t \hat{r}_{t+1} - \tau_{t+1} \tag{19}$$

$$\tau_{t+1} = \tilde{\tau}_{t+1}(w_{t+1} - w_{t+1}^{-}), \tag{20}$$

where τ_{t+1} is the total proportional transaction cost for the portfolio at time $t+1$, $\tilde{\tau}_{t+1}$ is the proportional transaction cost, and $w_{t+1}^{-} = w_t(1 + r_{t+1})/(1 + r_{p,t+1})$. We set the proportional transaction cost to 20 basis points per dollar of trading.

Second, we calculate the break-even proportional transaction costs, τ^{BE}, that will render the investor indifferent between two competing portfolio strategies following Della Corte et al. (2008) as

$$\tau^{\mathrm{BE}} = \frac{\bar{r}_p^{\mathrm{FC}} - \bar{r}_p^{\mathrm{HA}}}{TO^{\mathrm{FC}} - TO^{\mathrm{HA}}}, \tag{21}$$

where $\bar{r}_p^{\mathrm{FC}}$ and $\bar{r}_p^{\mathrm{HA}}$ are the portfolio mean returns of the dynamic and static portfolio strategies, respectively, and TO^{FC} and TO^{HA} are their respective average turnover. In comparing a dynamic strategy with a static strategy, an investor who pays actual transaction costs lower than the break-even cost will prefer the dynamic strategy. We report the τ^{BE} in basis points, and to facilitate the interpretability of our results, do so only when utility gain, $\triangle$, in Equation (18) is positive.

3. Empirical Results

This section describes our empirical results. We first describe and provide descriptive statistics for the data and predictor variables. Next, we report results based on full-sample estimates, and the out-of-sample analysis of the statistical and economic evidence on commodity return predictability.

3.1. Data on Commodity Futures and Predictor Variables

The dataset used for our empirical analysis is based on end-of-month total return index data on the S&P Goldman Sachs Commodity Index (S&P GSCI) downloaded from Bloomberg. We compute excess return as the log return on S&P GSCI less the log return on a one-month T-bill.[9] The sample period is January 1976 to December 2016.

Panel A of Table 1 presents descriptive statistics of monthly simple returns on the S&P GSCI for the full sample period. The table shows that the mean excess return was 0.143% with volatility close to 6%. On a risk-adjusted basis, the index recorded annualized Sharpe ratio of 0.089. The low mean return and high standard deviation suggests that commodities would be unattractive as a stand-alone investment strategy on a risk-adjusted basis. The commodity futures index returns are quite persistent with first order sample autocorrelations is 0.16.

[Insert Table 1 about here]

3.2. Predictor Variables

We consider a set of 28 predictors that have been studied in the commodity return predictability literature (see, for example, Gargano & Timmermann, 2014; Hong & Yogo, 2012; Groen & Pesenti, 2011; Chen, Rogoff & Rossi, 2010). They include commodity market, stock market, treasury and corporate bond markets, macroeconomic, and currency market variables. The predictors and their associated studies are detailed in the Appendix.

[9]The T-bill rate is downloaded from the webpage of Amit Goyal's website, `http://www.hec.unil.ch/agoyal/`.

Panel B of Table 1 presents the summary statistics for the predictor variables. Except for the commodity currencies, LTR, DFR, M1, and UNRATE, the other predictor variables are strongly positively autocorrelated with first-order autocorrelation of around 0.28 to 0.99.

3.3. In-Sample Predictability

To test whether the individual predictors have forecasting power for commodity excess returns, we run bivariate predictive regression of log commodity excess returns on each of the lagged values of predictors at a time for the full sample period (1976:02-2016:12). Table 2 report estimates of slope coefficient, β, the associated Newey & West (1987) autocorrelation and heteroskedasticity-consistent t-statistics, and the R^2 statistic. From the table, we can see that of the 28 predictor variables, only nine namely LTR, CDFP, DFR, INDPRO, CUTIL, CFNAI, CLI, BCI, and CCI display statistically significant predictive power for excess commodity futures returns at conventional levels.[10] The R^2 statistics for the nine variables range from 1.20% to 6.35%. The CLI and BCI predictors display substantial predictive ability at the 1% level with R^2 statistics of 3.65% and 6.35%, respectively.

The last two columns of Table 2 report R^2 statistics separately for the National Bureau of Economic Research (NBER)-dated business-cycle expansions and recessions. To gauge the strength of predictability during the business cycle, we compute the following version of the conventional R^2 statistic for business-cycle expansions (EXP) and recessions (REC):

$$R^2_{\text{C}} = 1 - \frac{\sum_{t=1}^{T} I_t^c \hat{\varepsilon}_{i,t}^2}{\sum_{t=1}^{T} I_t^c (r_t - \bar{r})^2} \quad \text{for} \;\; c = \text{EXP}, \; \text{REC}, \tag{22}$$

where I_t^{EXP} (I_t^{REC}) is an indicator function that takes a value of one when month t is an expansion (recession) and zero otherwise, $\hat{\varepsilon}_{i,t}$ is the fitted error based on the full estimate of the predictive regression model in Equation (1), $\bar{r}$ is full sample mean of r_t, and T is the full sample observations. The table shows that commodity return predictability is stronger in recessions relative to expansions for twenty four out of the 28 predictors. For example, the R^2_{REC} for the DFR, INDPRO, CLI, and BCI more than quadruple during recessions compared to the expansions. In-sample statistical evidence of predictability, while useful, forms only a small part of the story. The true extent of predictability can only be assessed in formal out-of-sample tests and the economic value of such predictability for investor's asset allocation decisions.

[Insert Table 2 about here]

[10]We also examined the forecasting power of additional predictor variables, namely hedging pressure, open interest and the Baltic dry. The results for these variables are not reported as they do not have sufficiently long data record.

3.4. Statistical Evaluation of Commodity Return Forecasts

The in-sample tests of predictability reported in Table 2 are not based on truly ex-ante measures of future expected commodity futures returns as the predictions would not have been available to an investor in real time because we use the full sample data for estimation. Further, there is the concern of in-sample overfitting which could overstate the true extent of predictability resulting in unusually high Sharpe ratios of the returns on trading strategies. To circumvent this problem and guard against overfitting, Table 3 reports R^2_{oos} for each of the individual predictive regression model and the combination forecasts relative to the benchmark HA forecast. The statistical significance of $R^2_{\text{oos}} > 0$ is assessed using the p-value of the MSFE-adjusted statistic of Clark & West (2007).

Panel A of Table 3 report results for the individual predictive regression forecasts. Most of the individual predictors fail to beat the HA forecast in terms of MSFE similarly to the evidence reported in many of the return predictability studies. Only twelve out of the 28 predictors have positive R^2_{oos}. Four of the positive R^2_{oos} statistics for CDFP, DFR, CUTIL, and CFNAI range from 1.13% to 3.15% with MSFEs significantly less than the MSFE of the HA forecast at the 5% level. The impressive R^2_{oos} statistics of 3.80% and 6.92% recorded for CLI and BCI, respectively, are significantly greater than zero at the 1% level. Panel B of Table 3 report results for the combination forecasts. The R^2_{oos} generated by each of the combination forecasts are impressive ranging from 0.30% for the Mean combination forecast to 4.96% for the PC (IC = BIC) combination forecasts, and outperform the HA benchmark forecast. All the combination forecasts have R^2_{oos} that are significantly greater than zero at the 1% level except the Median and PC (IC=BIC) forecasts that have R^2_{oos} significantly greater than zero at the 5% level.

[Insert Table 3 about here]

Table 4 reports the t-statistics and the associated p-values of the forecast breakdown test of Giacomini & Rossi (2009) for a quadratic loss function and a recursive estimation scheme to produce the one-step ahead out-of-sample forecast beginning in January 1990. The null hypothesis of the out-of-sample MSFE of a model is equal to its in-sample MSFE error is rejected at the 1% level for all the individual predictors. This represents a strong evidence of forecast breakdown and attests to the structural instability of the individual predictive model forecasts.

[Insert Table 4 about here]

3.5. Economic Evaluation of Commodity Return Forecasts

In this section, we test whether the statistical evidence of aggregate commodity return predictability translates into economic gains for a risk-averse investor. We consider a mean-variance investor with a relative risk aversion of three who monthly allocates wealth between commodities and risk-free T-bills using the individual (combination) forecast or the historical average forecast. Table 5 reports monthly percent Sharpe ratio (SR), Sharpe ratio net of transaction costs (SR_τ), annualized percent utility gain ($\triangle$), annualized percent utility gain net of transaction costs ($\triangle_\tau$). TO ratio in the table is the ratio of the average turnover of the static portfolio srategy (portfolio based on the HA forecast) to the average turnover of the dynamic portfolio strategy (portfolio based on individual (combination) forecasts). τ^{BE}, the breakeven transaction costs that will render the investor indifferent between the dynamic portfolio strategy and the static portfolio strategy, are reported in basis points. Transaction costs is set to 20 basis point per dollar of trading. Positive utility gain, $\triangle$, indicate that the CER of the dynamic portfolio strategy is greater than that of the static strategy. $\triangle$ of 2% or more is usually considered significant.

Column 6 Panel A in Table 5 reports $\triangle$ for the individual predictive model forecasts. Almost all the individual predictor realize negative $\triangle$ in accord with the R^2_{OOS} statistical significance results reported in Table 3. Positive number well above the 2% significance level are documented for four predictors, namely CDFP, CUTIL, CLI and BCI, out of the 28 predictors, and provide support for the out-of-sample statistical evidence of return forecasts for the same predictors reported in Table 3.

The $\triangle$ associated with the combination forecasts are reported in Panel B of Table 5. We realize positive $\triangle$ gains for all forecast combination methods. The Subset ($k = 2, ..., 7$) and the PC, $\text{IC} = R^2$ forecasts all record CER gains well above the 2% significance level. The results for the combination forecasts are also in accord with the statistical evidence of predictability reported in Table 3.

Similarly to the results for the $\triangle$ gain portfolio performance measure, SRs of the commodity portfolio generated by the individual predictive model forecasts are lower, for almost all predictors, than the portfolio that relies on the historical average return forecast. This is also consistent with the poor statistical performance of the individual predictors which has translated into bad economic performance. Turning to the results based on the forecast combination methods, a commodity portfolio that exploits predictability using any of the combining forecasts would have generated SRs that are substantially higher than those generated by the historical average forecast.

[Insert Table 5 about here]

Column 7 of Panel A in Table 5 reports the utility gain net of transaction costs results for the individual predictive model forecasts. From the table, we observe that just as in the portfolio performance without transaction costs, almost all the individual predictors realize negatiuve $\triangle_\tau$. Accounting for the effect of transaction costs does not erode the performance of the combination models as they continue to deliver $\triangle_\tau$ well above the

2% significance level. This performance, however, comes at the cost of higher average turnover. For example, the Subset ($k = 2, ..., 7$) delivers $\triangle_\tau$ of 2.2% compared to 2.6% without transaction costs. The τ^{BE} are also much higher than the actual proportional transaction cost for the combination forecasts meaning that investors would prefer the forecast combination portfolio strategy. SR_τ results are consistent with the $\triangle_\tau$ results.

4. Commodity Return Forecasts and the Macroeconomy

In this section, we conduct further analysis to shed more light on the economic drivers of commodity return predictability and portfolio performance. We investigate the link between return forecasts and the real economy. Such links should provide additional support for the performance of the forecasts based on the CLI and BCI predictors, and the forecast combination methods, and the economic rationale for the portfolio performance.

4.1. Commodity Return Forecasts and the Business-cycle

Studies such as Rapach et al. (2010), Henkel, Martin & Nardari (2011) and Gargano & Timmermann (2014) show that the predictability of stock and commodity returns is stronger during business-cycle recessions compared to expansions. These findings suggest a link between return predictability and cyclical variation of expected returns. To test this hypothesis, we use the version of the conventional R^2 statistic for business-cycle expansions (EXP) and recessions (REC) defined in Equation 22 using the the NBER-dated recession indicator.

Table 6 reports the out-of-sample R^2, the Clark & West (2007) MSFE-adjusted statistic and associated p-values separately for NBER-dated business-cycle expansions (R^2_{EXP}) and recessions R^2_{REC}. Panel A of the table report results for the individual predictive model forecasts. Almost all the individual predictive model forecasts fail to outperform the historical average forecast in terms of MSFE during both recessions and expansions. DFR, CLI and BCI predictors, however, continue to show significant levels of predictability with significantly greater than zero R^2 statistic at the 5% level during recessions and expansions.

Panel B of Table 6 report results for the combination forecasts. None of the forecasts has statistically greater than zero R^2_{OOS} statistics during expansions. However, during business-cycle recessions, the combination forecasts deliver R^2 values ranging 0.73% to 18.18% which are statistically greater than zero at the 5% level. The results show that predictability is stronger in recessions relative to expansions and confirm the findings in Gargano & Timmermann (2014).

[Insert Tables 6 about here]

4.2. Economic Performance of Commodity Portfolios and Links to the Macroeconomy

In Section 4.1, we showed that time-variation in commodity futures returns tracks the business-cycle. In this section, we examine whether the portfolios generated by the commodity return forecasts are also related to the business-cycle. We use the same asset allocation exercise detailed in Section 2.5.1, and report results separately for the NBER-dated business cycle expansions and recessions.

4.2.1. Variation in Risk Premia

In this section, we test whether the documented statistical evidence of commodity return predictability is countercyclical and related to time-variation in risk premia. Asset pricing models featuring habit persistence such as Campbell & Cochrane (1999) suggest that risk premia move countercyclically and that the Sharpe ratio of the aggregate stock market should be higher during recessions relative to expansions due to a reduced surplus consumption ratio. Wachter (2006) derives implications for bond risk premia and the term structure of interest rates in a setting with habit persistence. If risk premia varies with the business-cycle, then the portfolios generated by the return forecasts should perform better in recessions relative to expansions.

Table 7 reports SR and SR_{τ} results computed separately for NBER-dated business cycle expansions and recessions. We use the full out-of-sample forecast evaluation period so as to ensure that there are enough observations for the separate analysis of recessions. The Sharpe ratio performance results for the individual forecasts reported in Panel A are mixed. For example, the SR (SR_{τ}) of the portfolio based on CLI and BCI predictors have substantially high Sharpe ratios in recessions relative to expansions.

The Sharpe ratio results for the combination forecasts provide strong support for the suggestion of Campbell & Cochrane (1999). We can see that Sharpe ratios of portfolios based on all the forecasts from the combination methods are substantially higher in recessions relative to expansions.

4.2.2. Business-cycle phases and Economic Performance of Commodity Portfolios

Table 7 reports results of economic significance as measured by CER gains (CER gains net of proportional transaction costs of 20 basis points), $\triangle$ ($\triangle_{\tau}$), separately for business-cycle expansions and recessions. The out-of-sample portfolio performance analysis demonstrates the economic value of commodity return predictability with results concentrated in the recessionary phases of the business-cycle relative to expansions, especially for all the combination forecasts. The results for the individual predictive model forecasts are mixed.

However, this is not surprising considering their poor performance as demonstrated in Section 3.

[Insert Tables 7 about here]

Our results taken together show that predictability tracks business conditions so that expected returns, and for that matter portfolio performance, are high when business conditions are weak and vice-versa.

5. What Drives Commodity Return Predictability?

Cochrane (2008, 2017) suggests that time-varying equity risk premium forecasts are more likely related to macroeconomic risk if the predictors used to forecast returns also have predictive power for the business-cycle. Stock & Watson (2003, 2004), for example, show that forecasts of the output growth and inflation based on individual predictor variables are highly unstable over time compared to combination of forecasts. This provides a potential explanation for the poor forecasting performance of the individual predictors and the impressive performance of the combination forecasts. Since the individual predictors produce return forecasts that are highly unstable overtime as indicated by the forecast breakdown test results of Giacomini & Rossi (2009), we should observe a lack of forecasting power when the same predictors are used to predict macroeconomic activity. In contrast, the significant performance of the combination forecasts means that we should expect significant combination forecasts of macroeconomic activity. We provide support for this explanation by examining whether combination forecasts combining individual predictors can predict economic activity.

Consider the following autoregressive distributed lag model:

$$y_{t+1} = \alpha + \beta y_t + \gamma x_t + \varepsilon_{t+1}, \tag{23}$$

where y_t is either industrial production growth, Chicago Fed National activity index, yield on three-month Treasury bill rate, and Default yield spread (the difference between the yield on Moody's Baa-rated bond and Aaa-rated bond), and x_t is a predictor. We generate out-sample forecast of y_t using the same recursive estimation procedure described in Section 2.4 and use the historical average as the benchmark model. Statistical significance of R^2_{OOS} is tested using the MSFE-adjusted statistic of Clark & West (2007).

Panel A of Table 8 reports results for the individual predictors. The results show that many of the individual predictors fail to outperform the HA benchmark across the four macroeconomic activity variables with mostly negative R^2_{OOS}.

The results for the combination forecasts are reported in Panel B of Table 8. We can see that almost all the R^2_{OOS} values are positive and statistically significant at the 1% level. These results mirror those reported for the combination models in Tables 3.

Taken together, these findings provide another explanation, in addition to structural instability, for the poor performance of the individual predictive model forecasts and the gains associated with the combination forecasts which deal with model unceratinty and structural instability.

[Insert Tables 8 about here]

6. Can we Improve Forecasts by Monitoring Performance

In this section, we implement the conditional forecasting approach of Giacomini & White (2006) who develop a framework for out-of-sample predictability testing and forecast selection when the forecasting model is subject to misspecification. Their framework aids forecast selection by linking them to instruments that tell us something about current economic conditions, which should lead to improved forecasting performance.

Timmermann & Zhu (2017) extend the work of Giacomini & White (2006) and develop conditions under which the expected predictive accuracy of a set of competing forecasts can be ranked conditionally based on a set of monitoring instruments. They characterize properties that monitoring instruments should possess and show that these reflect both the accuracy of the predictors used and the strength of the monitoring instruments. Timmermann & Zhu (2017) further show that in an environment with weak predictors, selecting between a benchmark forecast and an alternative forecast based on instruments that track their forecasting performance overtime should leading to better forecasts than relying solely a single forecast.

Let $\hat{r}_{1,t+1}$ and $\hat{r}_{2,t+1}$ be two individual one-step ahead forecast of r_{t+1} generated using information up to time t. Define the square error loss

$$L(\hat{r}_{t+1}, r_{t+1}) = (r_{t+1} - \hat{r}_{t+1})^2. \tag{24}$$

Under square error loss, the loss differential between the two forecasts is

$$\triangle L_{t+1} = e^2_{1,t+1} - e^2_{2,t+1}, \tag{25}$$

where $e_{j,t+1} = r_{j,t+1} - \hat{r}_{j,t+1}$ for $j = 1, 2$ are individual forecast errors.

Following Giacomini & White (2006), the null hypothesis of conditional predictive ability is given by

$$H_0 : \mathbb{E}\left[\triangle L_{t+1} | Z_t\right] = 0, \tag{26}$$

where Z_t are monitoring instruments. We test this hypothesis using the linear regression

$$\triangle L_{t+1} = \theta_0 + \theta_1 z_t + \varepsilon_t, \tag{27}$$

where $\mathbb{E}[\varepsilon_t] = 0$, and $z_t \in Z_t$. Under the null of equal conditional predictive ability, $\theta = 0$ and $\theta_1 = 0$ in Equation (27). Non-zero values of $\theta_1 = 0$ suggests that the monitoring instrument, z_t, can help forecast differences in predictive accuracy across the two forecasts.

Using Equation (27), the expected future loss is given by $\mathbb{E}\left[\triangle L_{t+1}|Z_t\right] = \theta_0 + \theta_1 z_t$. Following Giacomini & White (2006), we consider a forecasting switching rule that chooses forecast 1 if $\mathbb{E}\left[\triangle L_{t+1}|Z_t\right] \leq 0$ or otherwise choose forecast 2:

$$r_{t+1}^{\text{SW}} = \hat{r}_{1,t+1}\mathbf{1}\{\mathbb{E}\left[\triangle L_{t+1}|Z_t\right] \leq 0\} + \hat{r}_{2,t+1}\mathbf{1}\{\mathbb{E}\left[\triangle L_{t+1}|Z_t\right] > 0\} \tag{28}$$

where $\mathbf{1}\{\mathbb{E}\left[\triangle L_{t+1}|Z_t\right] > 0\}$ is an indicator variable that takes the value one if the $r_{1,t+1}$ has the highest expected loss on $Z_t = z_t$ and zero otherwise. In our analysis, $r_{1,t+1}$ is always the HA return forecast and $r_{2,t+1}$ is either an predictive or combination forecast. As monitoring instruments, we consider growth in US consumer price index (CPI), US money stock (M2), a measure of macroeconomic uncertainty of Jurado et al. (2015), and the CBOE volatility index (VIX). The choice of the variables are motivated by the fact that they are drivers of commodity prices in general.

Table 9 reports results for the test of conditional predictability based on the four instruments. As shown in Panel A for the individual predictive model forecasts, the GW test fails to reject the null of equal predictive ability at the 5% level for all the monitoring instruments. However, there is some evidence that the monitoring instruments have predictive power for the future loss differential $\triangle L_{t+1}$ based on the t-statistic of the significance of θ_1 term in Equation (27).

The results for the combination forecasts are reported in Panel B of Table 8. We can see that the GW test rejects the null of conditional predictive ability for the M2 instrument whereas we fail to reject the null for the other monitoring instruments. Interestingly, the rejection of the null is driven solely by the significance of the information content of M2 as indicated by the significant slope coefficient, θ_1, in Equation (27). Based on this result, we use the M2 instrument to implement the forecast switching decision-rule in Equation (28).

[Insert Tables 9 about here]

Table 10 reports portfolio performance results for the forecasting switching rule. As can be see from the table, monitoring forecasting performance results in only marginal improvement in portfolio performance for the individual predictive models. However, the individual forecasts still underperformance the HA return forecast as we continue to realize low and negative SR and utility gains. The forecasting strategy benefits the combination forecast leading to improved portfolio performance.

[Insert Tables 10 about here]

7. Conclusion

In this paper, we provide a comprehensive study of aggregate commodity return predictability based on individual predictive regression models, and forecast combination methods that pool information from a large set of individual predictors. While almost all of the individual predictive regression model forecasts fail to outperform the benchmark historical average return forecast, we find that all forecast combination methods delivers statistically significant predictive ability using standrad statistical evaluation metrics. Forecasts based on commodity-specific variables, such as commodity basis, fail to outperform the historical average forecast. Of the individual predictors, the OECD Composite leading indicator (CLI) and the Business confidence index (BCI) variables contain useful information for forecasting commodity futures return. These variables display statistically significant levels of predictability. The superior forecasting performance of the combination forecasts is their ability to hedge model uncertainty and structural instability of the individual predictive models. Forecast breakdown test shows strong evidence of instability between excess commodity returns and the individual predictors, and provides an explanation for the inconsistent performance of the individual predictive models.

Commodity return predictability is also found to be countercyclical with predictability stronger during business-cycle recessions relative to expansions similarly to the findings in studies such as Gargano & Timmermann (2014), Henkel et al. (2011), Rapach et al. (2010), and Lin, Wu & Zhou (2017) for commodities spot, stocks and bond returns, respectively. We show that the combination forecasts are related to macroeconomic activity variables such as growth in industrial production, growth in consumer price index, changes in 3-month Treasury bill rate, changes in default spread, and changes in the Chicago Fed National activity index and we explain their out-of-sample gains as a result of picking up genuine variation in discount rates.

Economic significance, as measured by Sharpe ratio and utility gains gains, of commodity return forecasts indicates that the statistically significant evidence of commodity return predictability translates into economic significance in asset allocation exercise for a risk-averse investor. We find that recession is the main economic driver of these results. The investor realizes substantially high Sharpe ratio and utility gains in recessions compared to losses in expansions. The results contrast with Ahmed & Tsvetanov (2016) who find that commodity return predictability based on commodity risk factors fail to outperform the historical average benchmark.

In an attempt to improve the forecasting performance of the individual models, we implement a forecast monitoring strategy that selects either the individual (combination) forecast or the HA benchmark based on whether a monitoring instrument such as US money stock predicts positively their square error loss differential. We show that whereas this strategy does not improve the individual models, it leads to marginal increases in portfolio performance for the combination forecasts.

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Table 1: Summary Statistics for Returns and Predictor Variables

Variable	Obs	Mean	Standard deviation	Min	Max	Auto correlation	Sharpe ratio
Panel A: Index							
S&P GSCI	491	0.143	5.57	−28.29	22.31	0.16	0.089
Panel B: Predictor Variables							
Panel B1: Predictors from the commodity predictability literature							
Basis	491	0.52	1.05	−3.83	4.04	0.70	
INV	491	100.70	4.98	86.40	120.95	0.83	
PROD	491	0.09	1.46	−9.49	6.50	−0.07	
Panel B2: Predictors from the equity and bond risk premium predictability literature							
DP	491	−365.60	43.90	−452.36	−275.33	0.99	
SP500	491	0.63	4.30	−24.54	12.38	0.04	
TBL	491	4.68	3.58	0.01	16.30	0.99	
CTBL	491	−0.01	0.46	−4.62	2.61	0.36	
LTR	491	0.73	3.19	−11.24	15.23	0.05	
TMS	491	2.21	1.45	−3.65	4.55	0.95	
CTMS	491	0.00	0.47	−3.28	4.23	0.10	
YS	491	2.99	1.52	−2.28	5.93	0.97	
CDFP	491	0.00	0.30	−1.20	1.39	−0.12	
DFR	491	0.00	1.48	−9.75	7.37	−0.03	
INFL	491	0.30	0.37	−1.92	1.52	0.62	
Panel B3: Predictors related to economic activity							
M1	491	0.49	0.87	−3.20	4.93	0.12	
UNRATE	491	−0.73	17.23	−70.00	60.00	0.12	
INDPRO	491	0.17	0.61	−3.98	2.01	0.27	
CUTIL	491	0.00	0.76	−3.55	2.53	0.28	
REA	491	−0.02	55.19	−163.74	187.66	0.96	
CFNAI	491	−3.51	92.67	−466.00	273.00	0.62	
CLI	491	0.00	0.15	−0.78	0.60	0.96	
BCI	491	0.00	0.16	−0.85	0.52	0.88	
CCI	491	0.00	0.13	−0.44	0.45	0.82	
Panel B4: Exchange rates of major commodity exporting countries							
AUS	491	−0.11	3.30	−18.68	9.92	0.03	
CAN	491	−0.06	2.00	−13.03	8.85	−0.06	
NZ	491	−0.08	3.49	−24.89	18.01	−0.03	
SA	491	−0.56	4.22	−24.82	14.05	0.02	
IND	491	−0.41	2.11	−19.89	7.05	0.05	

Notes. This table reports the summary statistics of the returns on the S&P GSCI and the 31 predictor variables. We report the number of observations (Obs), the mean, standard deviation, minimum and maximum values, first-order autocorrelation and the annualized Sharpe ratio. All values are in percent. The sample period is from February 1976 to December 2016.

Table 2: In-sample Evaluation of Commodity Return Predictability

Predictor Variable	Slope Coefficient	t-stats	R^2 (%)	R^2_{EXP} (%)	R^2_{REC} (%)
Basis	−0.12	−0.49	0.05	−0.12	0.47
INV	−0.07	−1.27	0.43	1.12	−1.19
PROD	−0.04	−0.22	0.01	−0.04	0.13
DP	0.00	−0.12	0.00	0.02	−0.03
SP500	0.02	0.26	0.02	−0.28	0.75
TBL	0.02	0.33	0.02	−0.05	0.19
CTBL	0.27	0.47	0.05	0.02	0.13
LTR	−0.22	−2.44**	1.52	0.91	2.94
TMS	0.02	0.10	0.00	0.03	−0.06
CTMS	0.70	1.33	0.34	0.41	0.19
YS	−0.12	−0.68	0.11	−0.21	0.86
CDFP	−3.22	−3.56***	2.97	−0.04	10.07
DFR	0.79	2.61***	4.30	0.15	14.12
INFL	0.54	0.63	0.13	−0.36	1.27
M1	−0.45	−1.33	0.49	−0.55	2.94
UNRATE	−0.02	−0.97	0.26	−0.37	1.74
INDPRO	1.01	1.96**	1.20	−0.69	5.67
CUTIL	1.05	2.18**	2.04	−0.67	8.46
REA	0.00	0.82	0.22	0.36	−0.10
CFNAI	0.01	2.34**	2.29	0.45	6.62
CLI	7.00	3.33***	3.69	0.07	12.23
BCI	9.06	3.81***	6.35	1.17	18.57
CCI	4.91	1.86*	1.22	0.55	2.79
AUS	0.08	0.77	0.21	−0.93	2.91
CAN	0.08	0.51	0.09	−0.44	1.34
NZ	0.07	0.76	0.16	−0.60	1.96
SA	0.05	0.70	0.14	−0.52	1.70
IND	0.19	1.37	0.53	−0.38	2.69

Notes. This table reports the in-sample estimation results for the bivariate predictive regression model of log commodity excess returns and the predictor variables individually. The immediate right of slope coefficients report the Newey & West (1987) heteroskedasticity-consistent t-statistics. The R^2 statistics are computed for the full sample period 1976:02-2016:12. The R^2_{EXP} (%) (R^2_{REC} (%)) statistics in the last two columns are computed separately for the National Bureau of Economic Research (NBER)-dated business cycle expansions (recessions). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Statistical Evaluation of Commodity Return Forecasts

Predictor	MSFE	R^2_{OOS} (%)	MSFE-adjusted	Predictor	MSFE	R^2_{OOS} (%)	MSFE-adjusted
HA	38.46			HA	38.46		
Panel A: Individual predictive forecasts				Panel B: Combination forecasts			
Basis	38.69	−0.59	−0.53	Mean	38.00	1.19	2.51***
INV	38.44	0.05	0.50	Median	38.34	0.30	2.20**
PROD	38.57	−0.28	−1.20	Trimmed mean	38.07	1.01	2.52***
DP	38.72	−0.68	−0.91	Weighted mean	38.00	1.21	2.51***
SP500	38.72	−0.67	−0.23	DMSFE, 0.9	37.97	1.26	2.49***
TBL	38.95	−1.27	−1.33	DMSFE, 0.7	37.96	1.30	2.48***
CTBL	38.47	−0.03	−0.47	ABMA	38.01	1.16	2.51***
LTR	38.03	1.13	1.58*	Subset (k=2)	37.66	2.08	2.50***
TMS	38.57	−0.27	−0.85	Subset (k=3)	37.40	2.75	2.49***
CTMS	38.50	−0.10	0.05	Subset (k=4)	37.20	3.27	2.49***
YS	38.52	−0.15	−0.61	Subset (k=5)	37.06	3.64	2.48***
CDFP	37.52	2.44	2.07**	Subset (k=6)	36.96	3.90	2.46***
DFR	37.25	3.15	1.83**	Subset (k=7)	36.90	4.07	2.44***
INFL	38.63	−0.44	−0.67	PC (ic=AIC)	36.64	4.73	2.49***
M1	38.43	0.07	0.74	PC (ic=BIC)	37.01	3.76	2.29**
UNRATE	38.55	−0.24	−0.09	PC (ic=R2)	36.55	4.96	2.50***
INDPRO	38.23	0.61	1.25				
CUTIL	37.73	1.89	1.85**				
REA	38.68	−0.57	−0.48				
CFNAI	37.66	2.08	1.56*				
CLI	37.00	3.80	2.43***				
BCI	35.80	6.92	2.86***				
CCI	38.26	0.52	1.06				
AUS	38.62	−0.42	−0.42				
CAN	38.76	−0.77	−0.93				
NZ	38.63	−0.45	−0.35				
SA	38.65	−0.49	−0.66				
IND	38.37	0.23	0.90				

Notes. This table reports out-of-sample results for the individual and combination forecasts of log excess commodity returns. HA is the historical average benchmark forecast. MSFE is the mean squared forecast error. The R^2_{oos} statistic measures the proportional reduction in MSFE for the competing forecasts given in the first column relative to the HA forecast. Statistical significance for the R^2_{oos} statistic is based on the p-value for the Clark & West (2007) MSFE-adjusted statistic. This statistic tests the null hypothesis that the HA forecast MSFE is less than or equal to the competing forecast MSFE against the alternative hypothesis that the HA forecast MSFE is greater than or equal to the competing forecast MSFE. Results are reported for the full out-of-sample forecast evaluation period 1990:01-2016:12. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Results of Forecast Breakdown Test

Predictor	t-stats	p-value	Predictor	t-stats	p-value
Basis	3.23	0.001	M1	3.07	0.002
INV	3.12	0.002	UNRATE	3.11	0.002
PROD	3.09	0.002	INDPRO	3.13	0.002
DP	3.15	0.002	CUTIL	3.11	0.002
SP500	3.00	0.003	REA	3.07	0.002
TBL	3.15	0.002	CFNAI	3.11	0.002
CTBL	3.10	0.002	CLI	3.10	0.002
LTR	3.04	0.002	BCI	3.21	0.001
TMS	3.10	0.002	CCI	3.25	0.001
CTMS	3.08	0.002	AUS	3.09	0.002
YS	3.09	0.002	CAN	3.14	0.002
CDFP	3.03	0.002	NZ	3.17	0.002
DFR	3.33	0.001	SA	3.24	0.001
INFL	3.07	0.002	IND	3.08	0.002

Notes. This table reports the t-statistics and associated p-values for the forecast breakdown tests of Giacomini & Rossi (2009) using a quadratic loss function. Similarly to our out-of-sample forecasting tests, we use a recursive window estimation approach where the step-ahead forecast starts in January 1990 till the end of the sample December 2016. p-values lower than 0.1,0.05 and 0.01 denotes significance at the 10%, 5% and 1%, respectively.

Table 5: Economic Evaluation of Commodity Return Forecasts

Strategy	μ_p	σ_p	SR	SR_τ	$\triangle$	$\triangle_\tau$	TO	τ^{BE}
HA benchmark	0.002	0.09	0.02	0.02				
Panel A: Individual predictive forecasts								
Basis	−0.006	0.13	−0.05	−0.08	−1.97	−2.40	12	—
INV	−0.001	0.11	−0.01	−0.05	−0.82	−1.18	10	—
PROD	−0.011	0.08	−0.14	−0.16	−1.04	−1.23	6	—
DP	0.002	0.14	0.01	0.00	−1.93	−2.05	4	—
SP500	0.013	0.15	0.09	0.02	−1.23	−2.27	29	—
TBL	−0.003	0.16	−0.02	−0.02	−2.93	−2.98	2	—
CTBL	0.000	0.09	0.00	−0.01	−0.14	−0.18	2	—
LTR	0.033	0.15	0.22	0.12	0.73	−0.66	37	45
TMS	−0.003	0.09	−0.04	−0.05	−0.51	−0.55	2	—
CTMS	0.002	0.12	0.02	−0.03	−0.79	−1.36	16	—
YS	−0.001	0.09	−0.01	−0.02	−0.27	−0.31	2	—
CDFP	0.064	0.16	0.40	0.30	3.65	2.07	43	77
DFR	0.101	0.28	0.37	0.30	−0.24	−2.06	49	—
INFL	−0.002	0.11	−0.02	−0.05	−0.99	−1.24	8	—
M1	0.011	0.13	0.09	0.03	−0.43	−1.19	21	—
UNRATE	−0.009	0.11	−0.08	−0.13	−1.70	−2.19	14	—
INDPRO	0.015	0.12	0.13	0.05	0.34	−0.54	24	30
CUTIL	0.033	0.12	0.28	0.22	2.17	1.57	17	103
REA	−0.003	0.13	−0.02	−0.04	−1.91	−2.09	6	—
CFNAI	0.035	0.14	0.24	0.20	1.44	0.84	17	109
CLI	0.097	0.18	0.54	0.52	5.83	5.59	8	689
BCI	0.123	0.21	0.59	0.56	6.74	6.35	12	557
CCI	−0.006	0.11	−0.05	−0.09	−1.34	−1.73	11	—
AUS	−0.004	0.09	−0.04	−0.10	−0.66	−1.16	14	—
CAN	−0.012	0.09	−0.12	−0.18	−1.51	−2.03	14	—
NZ	0.005	0.12	0.04	−0.03	−0.65	−1.41	21	—
SA	−0.003	0.10	−0.03	−0.09	−0.72	−1.26	15	—
IND	0.006	0.09	0.07	0.02	0.40	0.07	10	23
Panel B: Combination forecasts								
Mean	0.019	0.09	0.21	0.18	1.66	1.46	6	106
Median	0.006	0.09	0.06	0.05	0.44	0.35	3	22
Trimmed mean	0.017	0.09	0.19	0.16	1.46	1.28	6	93
Weighted mean	0.020	0.09	0.21	0.19	1.69	1.48	6	108
DMSFE ($\theta = 0.9$)	0.020	0.09	0.22	0.19	1.75	1.54	6	112
DMSFE ($\theta = 0.7$)	0.021	0.09	0.23	0.20	1.82	1.61	7	117
ABMA	0.019	0.09	0.21	0.18	1.64	1.44	6	104
Subset (k = 2)	0.033	0.11	0.31	0.27	2.60	2.21	11	192
Subset (k = 3)	0.046	0.13	0.36	0.31	3.16	2.61	16	267
Subset (k = 4)	0.054	0.14	0.38	0.33	3.46	2.75	19	322
Subset (k = 5)	0.062	0.16	0.39	0.34	3.50	2.66	23	367
Subset (k = 6)	0.068	0.17	0.39	0.34	3.35	2.39	26	405
Subset (k = 7)	0.073	0.19	0.39	0.33	3.07	1.99	29	436
PC (IC = AIC)	0.106	0.25	0.43	0.35	2.56	0.73	49	636
PC (IC = BIC)	0.080	0.21	0.39	0.35	2.59	1.80	22	480
PC (IC = R^2)	0.115	0.25	0.45	0.38	2.91	1.03	50	691

Notes. This table reports portfolio performance results for a mean-variance investor with relative risk aversion of three who monthly allocates his wealth between commodities and risk-free T-bills using either the HA benchmark forecast (static portfolio strategy) or the individual predictive regression (combination) forecasts (dynamic portfolio strategy). The forecasts in Panel A are based on one each of the 28 predictor variables. The forecasts in Panel B are based on 28 predictors using the different combination methods outlined in Section 2.2. For each portfolio strategy, we report the annualized mean realized return (μ_p), annualized realized volatility (σ_p), annualized realized Sharpe ratio (net of cost), SR (SR_τ), annualized utility gain (net of cost), $\triangle$ ($\triangle_\tau$), the portfolio management fee that the investor would be willing to pay in order to have access to the dynamic strategy relative to the static strategy, the turnover ratio (TO) ratio, the ratio of the average turnover of the dynamic strategy relative to that of the static strategy, and the break-even transaction costs, τ^{BE}, that will render the investor indifferent between the dynamic and static portfolio strategies. We set proportional transaction costs of 20bps per dollar of trading. Since we use commodity futures, we avoid short sales restrictions but limit leverage to 50% of wealth to avoid excessive risk taking. Results are reported for the full out-of-sample forecast evaluation period 1996:01-2016:12.

Table 6: Statistical Evaluation of Commodity Return Forecasts during Business-cycles

	Expansion			Recession		
Predictor	MSFE	R^2_{OOS} (%)	MSFE-adjusted	MSFE	R^2_{OOS} (%)	MSFE-adjusted
HA	29.32			109.37		
Panel A: Individual predictive model forecasts						
Basis	29.65	−1.14	−1.11	108.75	0.56	0.72
INV	29.32	0.01	0.41	109.23	0.13	0.29
PROD	29.34	−0.07	−0.49	110.17	−0.73	−1.10
DP	29.66	−1.15	−1.15	109.04	0.30	0.89
SP500	29.15	0.57	1.25	112.93	−3.25	−1.32
TBL	29.55	−0.80	−0.39	111.82	−2.24	−1.54
CTBL	29.35	−0.12	−1.81	109.20	0.16	1.27
LTR	29.36	−0.14	0.70	105.24	3.78	1.55*
TMS	29.32	0.00	0.24	110.30	−0.85	−1.81
CTMS	29.36	−0.15	−0.02	109.36	0.01	0.08
YS	29.32	−0.02	0.06	109.84	−0.43	−0.89
CDFP	29.43	−0.37	0.54	100.31	8.28	2.12**
DFR	29.18	0.48	1.56*	99.86	8.70	1.32
INFL	29.46	−0.48	−0.92	109.76	−0.36	−0.21
M1	29.76	−1.50	−0.62	105.71	3.35	2.18**
UNRATE	29.47	−0.52	−0.94	109.00	0.34	0.37
INDPRO	29.30	0.06	0.58	107.47	1.74	1.10
CUTIL	29.50	−0.61	−0.02	101.61	7.10	2.14**
REA	29.44	−0.40	−0.22	110.40	−0.94	−0.44
CFNAI	29.42	−0.35	−0.10	101.58	7.12	1.64*
CLI	29.41	−0.32	1.28	95.86	12.35	2.21**
BCI	29.06	0.89	1.94**	88.08	19.46	2.50**
CCI	29.32	0.00	0.63	107.63	1.59	0.85
AUS	29.42	−0.36	−0.27	109.97	−0.55	−0.32
CAN	29.48	−0.55	−0.47	110.73	−1.24	−0.85
NZ	29.80	−1.64	−2.08	107.16	2.02	2.05**
SA	29.38	−0.20	0.05	110.57	−1.09	−1.24
IND	29.31	0.03	0.49	108.67	0.64	0.88
Panel B: Combination forecasts						
Mean	29.26	0.21	0.88	105.85	3.22	2.49**
Median	29.29	0.10	0.82	108.57	0.73	2.26**
Trimmed mean	29.27	0.15	0.74	106.32	2.79	2.58***
Weighted mean	29.26	0.21	0.88	105.79	3.27	2.50**
DMSFE ($\theta = 0.9$)	29.26	0.20	0.83	105.56	3.48	2.48**
DMSFE ($\theta = 0.7$)	29.26	0.20	0.82	105.43	3.61	2.48**
ABMA	29.26	0.20	0.87	105.91	3.16	2.49***
Subset (k = 2)	29.24	0.28	0.85	103.00	5.82	2.50**
Subset (k = 3)	29.24	0.25	0.84	100.67	7.95	2.50**
Subset (k = 4)	29.27	0.17	0.82	98.75	9.71	2.49**
Subset (k = 5)	29.31	0.03	0.81	97.19	11.14	2.49**
Subset (k = 6)	29.36	−0.14	0.78	95.94	12.28	2.48**
Subset (k = 7)	29.42	−0.34	0.76	94.89	13.24	2.47**
PC (IC = AIC)	29.71	−1.32	0.86	90.43	17.32	2.48**
PC (IC = BIC)	29.73	−1.39	0.50	93.53	14.49	2.40**
PC (IC = R^2)	29.73	−1.40	0.85	89.49	18.18	2.50**

Notes. This table reports out-of-sample results for the individual and combination forecasts of log excess commodity returns using the NBER-dated recession indicator. HA is the historical average benchmark forecast. MSFE is the mean squared forecast error. The R^2_{OOS} statistic measures the proportional reduction in MSFE for the competing forecasts given in the first column relative to the HA forecast. Statistical significance for the R^2_{OOS} statistic is based on the p-value for the Clark & West (2007) MSFE-adjusted statistic. This statistic tests the null hypothesis that the HA forecast MSFE is less than or equal to the competing forecast MSFE against the alternative hypothesis that the HA forecast MSFE is greater than or equal to the competing forecast MSFE. Results are reported for the full out-of-sample evaluation period 1990:01-2016:12. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Economic Evaluation of Commodity Return Forecasts during the Business-cycle

	Expansion						Recession					
Strategy	SR	SR_τ	$\triangle$	$\triangle_\tau$	TO	τ^{BE}	SR	SR_τ	$\triangle$	$\triangle_\tau$	TO	τ^{BE}
HA benchmark	0.01	0.01					0.06	0.06				
Panel A: Individual predictive model forecasts												
Basis	−0.12	−0.16	−2.31	−2.74	11	—	0.22	0.20	0.59	0.16	8	168
INV	−0.03	−0.07	−0.97	−1.32	9	—	0.09	0.06	0.33	−0.15	9	18
PROD	−0.01	−0.05	−0.08	−0.26	5	—	−0.65	−0.67	−8.37	−8.61	5	—
DP	−0.05	−0.06	−2.33	−2.47	4	—	0.28	0.27	1.18	1.09	3	1064
SP500	0.28	0.18	1.94	0.92	25	57	−0.34	−0.38	−25.90	−27.04	19	—
TBL	0.02	0.01	−1.47	−1.52	2	—	−0.14	−0.15	−14.41	−14.54	3	—
CTBL	−0.03	−0.04	−0.22	−0.26	2	—	0.09	0.09	0.44	0.41	1	342
LTR	0.07	−0.04	−0.86	−2.24	34	—	0.79	0.74	13.38	12.02	22	312
TMS	0.01	0.00	0.04	0.00	2	3	−0.22	−0.23	−4.72	−4.77	2	—
CTMS	−0.04	−0.11	−0.55	−1.11	14	—	0.17	0.14	−2.76	−3.35	11	—
YS	0.00	−0.01	−0.05	−0.08	2	—	−0.07	−0.08	−2.03	−2.09	2	—
CDFP	0.12	−0.02	0.13	−1.46	39	17	1.41	1.37	32.84	31.43	25	582
DFR	0.22	0.12	0.12	−1.66	43	42	0.91	0.87	−1.10	−3.12	36	—
INFL	−0.04	−0.07	−0.72	−0.95	7	—	0.02	−0.01	−3.12	−3.54	8	—
M1	−0.07	−0.14	−2.13	−2.90	19	—	0.79	0.75	13.09	12.32	13	404
UNRATE	−0.12	−0.18	−1.20	−1.68	13	—	−0.01	−0.04	−5.73	−6.21	8	—
INDPRO	0.05	−0.06	0.03	−0.83	22	8	0.38	0.34	2.67	1.85	14	211
CUTIL	0.00	−0.07	−0.54	−1.13	15	—	1.26	1.23	23.99	23.41	10	915
REA	−0.06	−0.08	−1.36	−1.53	5	—	0.07	0.05	−6.36	−6.62	5	—
CFNAI	−0.02	−0.09	−0.64	−1.23	15	—	0.96	0.93	18.44	17.72	13	824
CLI	0.34	0.32	2.66	2.45	6	337	1.34	1.32	33.19	32.55	15	1284
BCI	0.41	0.37	3.48	3.08	11	226	1.41	1.40	36.36	35.91	14	1720
CCI	0.04	0.00	−0.25	−0.60	9	—	−0.44	−0.47	−9.75	−10.34	10	—
AUS	0.02	−0.04	0.04	−0.41	12	3	−0.26	−0.30	−6.15	−6.87	12	—
CAN	−0.08	−0.14	−0.69	−1.16	12	—	−0.30	−0.34	−7.90	−8.57	12	—
NZ	−0.16	−0.25	−1.99	−2.76	19	—	0.65	0.63	9.97	9.41	10	501
SA	0.08	0.01	0.26	−0.29	14	21	−0.45	−0.49	−8.24	−8.67	8	—
IND	0.03	−0.02	0.11	−0.22	9	10	0.20	0.18	2.65	2.46	4	207

Table 7 continued

Strategy	Expansion						Recession					
	SR	SR_τ	$\triangle$	$\triangle_\tau$	TO	τ^{BE}	SR	SR_τ	$\triangle$	$\triangle_\tau$	TO	τ^{BE}
HA benchmark	0.01	0.01					0.06	0.06				
Panel B: Combination forecasts												
Mean	0.07	0.04	0.44	0.24	6	29	0.74	0.73	11.31	11.11	4	1193
Median	0.03	0.02	0.19	0.10	3	9	0.19	0.18	2.38	2.31	2	197
Trimmed mean	0.07	0.04	0.39	0.21	5	25	0.66	0.65	9.92	9.75	4	1047
Weighted mean	0.08	0.04	0.45	0.25	6	29	0.75	0.74	11.48	11.28	4	1214
DMSFE ($\theta = 0.9$)	0.07	0.04	0.43	0.23	6	28	0.79	0.77	12.16	11.94	4	1293
DMSFE ($\theta = 0.7$)	0.08	0.04	0.44	0.24	6	29	0.82	0.80	12.72	12.50	5	1356
ABMA	0.07	0.04	0.43	0.24	6	28	0.73	0.72	11.14	10.95	4	1172
Subset (k = 2)	0.10	0.04	0.50	0.11	10	42	1.08	1.06	19.37	18.98	7	2304
Subset (k = 3)	0.11	0.04	0.49	−0.06	14	53	1.21	1.19	24.87	24.29	10	3277
Subset (k = 4)	0.12	0.04	0.42	−0.28	18	63	1.29	1.26	28.40	27.66	13	3965
Subset (k = 5)	0.12	0.04	0.25	−0.58	21	70	1.31	1.28	30.48	29.60	15	4551
Subset (k = 6)	0.11	0.03	0.02	−0.94	24	74	1.31	1.28	31.38	30.35	17	5058
Subset (k = 7)	0.11	0.02	−0.28	−1.35	26	—	1.30	1.27	31.63	30.46	19	5511
PC (IC = AIC)	0.15	0.04	−0.99	−2.91	46	—	1.38	1.36	34.65	33.47	23	7491
PC (IC = BIC)	0.09	0.04	−1.36	−2.18	20	—	1.42	1.40	36.49	35.86	14	6132
PC (IC = R^2)	0.16	0.05	−0.79	−2.74	47	—	1.44	1.41	37.19	35.77	26	8210

Notes. This table reports portfolio performance results for a mean-variance investor with relative risk aversion of three who monthly allocates his wealth between commodities and risk-free T-bills using either the HA benchmark forecast (static portfolio strategy) or the individual predictive regression (combination) forecasts (dynamic portfolio strategy). The forecasts in Panel A are based on one each of the 28 predictor variables. The forecasts in Panel B are based on 28 predictors using the different combination methods outlined in Section 2.2. For each portfolio strategy, we report the annualized realized Sharpe ratio (net of cost), SR (SR_τ), annualized utility gain (net of cost), $\triangle$ ($\triangle_\tau$), the portfolio management fee that the investor would be willing to pay in order to have access to the dynamic strategy relative to the static strategy, the turnover ratio (TO) ratio, the ratio of the average turnover of the dynamic strategy relative to that of the static strategy, and the break-even transaction costs, τ^{BE}, that will render the investor indifferent between the dynamic and static portfolio strategies. We set proportional transaction costs of 20bps per dollar of trading. Since we use commodity futures, we avoid short sales restrictions but limit leverage to 50% of wealth to avoid excessive risk taking. Results are reported separately for NBER-dated business-cycle expansions and recessions. The out-of-sample forecast evaluation period is 1990:01-2016:12.

Table 8: Macroeconomic Variable Out-of-Sample Forecasting Results for Individual Forecasts

	Economic activity variables					Economic activity variables			
Predictor	INDPRO	CFNAI	TBL	DFY	Predictor	INDPRO	CFNAI	TBL	DFY
Basis	0.40	−0.36	−0.57	−0.33	Mean	7.27***	3.87***	13.08***	6.76***
INV	1.08**	−0.49	0.66**	−0.25	Median	5.82***	2.33***	11.49***	5.78***
PROD	0.50*	0.00	−0.23	−0.09	Trimmed mean	1.46***	0.35***	2.77***	2.16***
DP	−2.55	−0.94	−6.46	−2.16	Weighted mean	8.35***	4.86***	13.94***	7.06***
SP500	1.98**	1.13*	1.63**	9.85***	DMSFE, 0.9	10.78***	4.21***	17.28***	8.29***
TBL	−2.59	−0.91	−17.66	−4.66	DMSFE, 0.7	10.42***	4.43***	15.32***	7.93***
CTBL	3.28***	−0.24	20.52***	−3.02	ABMA	6.36***	3.08***	12.25***	6.47***
LTR	0.29	−0.68	−78.68***	2.32**	Subset (k=2)	13.03***	7.74***	19.49***	11.86***
TMS	−1.43	−0.20	−6.23	−1.22	Subset (k=3)	17.69***	11.55***	21.17***	15.73***
CTMS	0.70	0.27	1.29*	−2.86	Subset (k=4)	21.47***	15.21***	19.51***	18.73***
YS	−0.56	−0.46	−1.50	−1.71	Subset (k=5)	24.53***	18.72***	15.64***	20.91***
CDFP	0.80	0.90	−30.36***	16.25***	Subset (k=6)	27.03***	21.94***	10.31***	22.63***
DFR	−0.85	−3.92	2.32***	25.18***	Subset (k=7)	29.05***	24.96***	4.06***	23.94***
INFL	0.09	−0.34	−10.03	−4.05	PC (ic=AIC)	33.12***	0.28**	−57.11***	25.23***
M1	0.80	−0.84	−18.74	0.20	PC (ic=BIC)	33.12***	0.94**	−56.06***	25.97***
UNRATE	2.86**	−0.33	2.97***	−1.10	PC (ic=R2)	31.53***	1.14***	−59.44***	25.16***
INDPRO	14.16***	−1.05	2.17***	−1.92					
CUTIL	11.28***	21.83***	−1.68***	−1.94					
REA	−1.40	−0.55	−7.20	−0.07					
CFNAI	17.35***	13.21***	−2.94***	−1.62					
CLI	34.95***	−0.75	−17.24***	5.43**					
BCI	29.82***	0.76	−73.03***	18.78***					
CCI	9.71***	−0.21**	−25.42***	9.76***					
AUS	−0.20	−1.41	−0.26	10.60***					
CAN	−0.64	−0.55	−0.74	10.05***					
NZ	0.62	−0.48	−0.62	5.97***					
SA	−0.38	−0.25	0.57*	4.60***					
IND	−0.82	−2.96	−6.21	4.04***					

Notes. This table reports out-of-sample results for the individual forecast of macroeconomic activity variables: growth in industrial production, growth in consumer price index, changes in 3-month T-bill rate, changes in chicago Fed National Activity index, and changes in default yield spread. HA is the historical average benchmark forecast. MSFE is the mean squared forecast error. The R^2_{oos} statistic measures the proportional reduction in MSFE for the competing forecasts given in the first column relative to the HA forecast. Statistical significance for the R^2_{oos} statistic is based on the p-value for the Clark & West (2007) MSFE-adjusted statistic. This statistic tests the null hypothesis that the HA forecast MSFE is less than or equal to the competing forecast MSFE against the alternative hypothesis that the HA forecast MSFE is greater than or equal to the competing forecast MSFE. Results are reported for the full out-of-sample forecast evaluation period 1990:01-2016:12. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Statistical Evaluation of Monitoring Commodity Return Forecasts Performance

	Panel A: Individual Predictive model forecast							
	CPI				M2			
Predictor	t_0	t_1	R^2	GW t-stat	t_0	t_1	R^2	GW t-stat
Basis	0.12	−1.46	0.66	3.91	−2.27**	2.14**	1.40	5.98
INV	1.60	−2.56	2.00	1.48	−1.16	1.53	0.72	3.42
PROD	−0.24	−1.21	0.45	1.59	−1.39	0.80	0.20	1.86
DP	−1.75*	1.16	0.42	1.68	−0.89	0.09	0.00	4.18
SP500	−4.92***	7.09***	13.55	0.84	0.40	−1.09	0.37	0.52
TBL	−11.03***	14.92***	40.95	3.71	0.05	−1.61	0.80	4.59
CTBL	1.69*	−3.52***	3.71	4.02	−2.25**	2.44**	1.82	2.20
LTR	−0.89	2.49**	1.90	0.98	1.22	−0.95	0.28	1.05
TMS	−3.14***	3.79***	4.27	3.14	1.45	−2.71***	2.23	2.80
CTMS	−3.30***	5.14***	7.60	0.13	2.21**	−3.01***	2.74	0.04
YS	−0.50	−0.12	0.00	1.73	−0.62	0.22	0.02	2.23
CDFP	2.19**	−1.74*	0.93	2.22	−0.94	2.35**	1.69	2.29
DFR	3.72***	−4.98***	7.17	0.96	−0.04	0.72	0.16	1.07
INFL	−3.79***	5.10***	7.48	1.87	−0.24	−0.38	0.04	1.63
M1	−0.47	0.88	0.24	2.36	−1.44	1.91*	1.13	3.38
UNRATE	1.70*	−3.37***	3.42	2.09	−1.57	1.67*	0.86	3.94
INDPRO	2.69***	−3.71***	4.11	2.86	−2.24**	3.31***	3.30	3.14
CUTIL	5.02***	−6.32***	11.05	2.24	−0.52	1.81*	1.01	2.38
REA	−4.66***	6.54***	11.76	1.04	−0.46	−0.07	0.00	0.74
CFNAI	6.19***	−8.68***	19.01	2.07	−2.01*	3.43***	3.54	4.27
CLI	5.60***	−7.15***	13.75	2.91	−2.39**	4.28***	5.39	5.02
BCI	5.79***	−6.41***	11.33	5.22	−1.34	3.57***	3.82	5.68
CCI	2.21**	−3.06***	2.83	2.34	−0.01	0.37	0.04	1.34
AUS	−1.32	1.22	0.46	0.77	−0.23	−0.29	0.03	0.62
CAN	−1.82*	1.29	0.52	2.12	1.32	−2.74	2.29	1.81
NZ	0.80	−2.32**	1.65	1.80	−2.02*	1.97*	1.20	1.26
SA	−2.58**	2.98***	2.69	4.74	−0.06	−0.69	0.15	1.00
IND	2.05**	−2.67**	2.17	1.23	−2.07**	3.10***	2.90	0.88

Table 9 continued

	Panel A: Individual Predictive model forecast							
	VIX				Macroeconomic uncertainty			
Predictor	t_0	t_1	R^2	GW t-stat	t_0	t_1	R^2	GW t-stat
Basis	−1.91*	1.67*	0.86	3.91	−2.55**	2.45**	1.83	5.98
INV	−2.19**	2.37**	1.72	1.48	−0.23	0.24	0.02	3.42
PROD	2.11**	−2.73***	2.26	1.59	1.37	−1.54	0.73	1.86
DP	−0.94	0.51	0.08	1.68	−0.77	0.60	0.11	4.18
SP500	2.09**	−2.51**	1.92	0.84	5.16***	−5.30***	8.06	0.52
TBL	2.95***	−3.91***	4.54	3.71	4.36***	−4.66***	6.33	4.59
CTBL	−2.32**	2.28**	1.59	4.02	−3.83***	3.79***	4.29	2.20
LTR	−1.93*	2.36**	1.71	0.98	−2.22**	2.34**	1.68	1.05
TMS	3.94***	−4.63***	6.25	3.14	4.50***	−4.68***	6.39	2.80
CTMS	1.23	−1.40	0.61	0.13	1.74*	−1.78*	0.98	0.04
YS	2.66**	−3.12***	2.95	1.73	2.86***	−2.98***	2.70	2.23
CDFP	−3.07***	3.83***	4.37	2.22	−5.24***	5.48***	8.55	2.29
DFR	−2.36**	2.85***	2.47	0.96	−2.85***	2.99***	2.71	1.07
INFL	1.99*	−2.46**	1.84	1.87	1.63	−1.75*	0.95	1.63
M1	−1.87*	2.03**	1.27	2.36	−3.59***	3.63***	3.94	3.38
UNRATE	−3.58***	3.67***	4.03	2.09	−3.21***	3.18***	3.05	3.94
INDPRO	−3.03***	3.44***	3.56	2.86	−3.83***	3.94***	4.62	3.14
CUTIL	−6.27***	7.28***	14.18	2.24	−8.24***	8.52***	18.44	2.38
REA	1.71*	−2.15**	1.42	1.04	3.34***	−3.48***	3.64	0.74
CFNAI	−5.68***	6.50***	11.63	2.07	−6.50***	6.71***	12.29	4.27
CLI	−5.89***	6.90***	12.92	2.91	−7.49***	7.77***	15.82	5.02
BCI	−6.18***	7.54***	15.06	5.22	−9.51***	9.93***	23.51	5.68
CCI	−2.04**	2.35**	1.69	2.34	−3.85***	3.94***	4.61	1.34
AUS	3.22***	−3.73***	4.15	0.77	1.18	−1.29	0.52	0.62
CAN	2.26**	−2.92***	2.59	2.12	3.17***	−3.37***	3.43	1.81
NZ	−2.74***	2.63***	2.12	1.80	−3.00***	2.92***	2.59	1.26
SA	3.92***	−4.57***	6.10	4.74	2.65***	−2.81***	2.39	1.00
IND	−0.54	0.79	0.19	1.23	−2.18**	2.27**	1.58	0.88

Table 9 continued

	Panel B: Combination forecast							
	CPI				M2			
Predictor	t_0	t_1	R^2	GW t-stat	t_0	t_1	R^2	GW t-stat
Mean	5.12***	−5.20***	7.76	5.77	−1.04	3.26***	3.21	6.72**
Median	3.45***	−2.83***	2.44	4.58	−1.24	3.34***	3.36	6.81**
Trimmed mean	4.76***	−4.59***	6.17	5.99	−0.95	3.17***	3.03	6.77**
Weighted mean	5.09***	−5.15***	7.64	5.78	−1.04	3.27***	3.22	6.73**
DMSFE ($\theta = 0.9$)	5.04***	−5.11***	7.51	5.62	−1.10	3.32***	3.32	6.64**
DMSFE ($\theta = 0.7$)	5.12***	−5.25***	7.91	5.56	−1.14	3.36***	3.40	6.62**
ABMA	5.15***	−5.24***	7.88	5.76	−1.03	3.26***	3.21	6.72**
Subset (k = 2)	4.84***	−4.90***	6.96	5.18	−1.10	3.25***	3.19	6.47**
Subset (k = 3)	4.68***	−4.79***	6.67	4.69	−1.17	3.26***	3.21	6.28
Subset (k = 4)	4.56***	−4.74***	6.53	4.28	−1.24	3.27***	3.22	6.13
Subset (k = 5)	4.44***	−4.67***	6.36	3.92	−1.31	3.28***	3.23	6.01
Subset (k = 6)	4.34***	−4.63***	6.26	3.62	−1.38	3.29***	3.26	5.92
Subset (k = 7)	4.24***	−4.60***	6.18	3.37	−1.45	3.30***	3.28	5.87
PC (IC = AIC)	4.16***	−4.85***	6.82	2.56	−1.22	2.76***	2.32	4.70
PC (IC = BIC)	4.44***	−5.39***	8.30	2.61	−1.79	3.45***	3.57	4.56
PC (IC = R^2)	4.49***	−5.35***	8.19	2.61	−1.13	2.66***	2.15	5.04

	VIX				Macroeconomic uncertainty			
Predictor	t_0	t_1	R^2	GW t-stat	t_0	t_1	R^2	GW t-stat
Mean	−6.34***	7.77***	15.82	5.77	−9.39***	9.83***	23.15	6.72
Median	−3.99***	5.11***	7.53	4.58	−6.81***	7.18***	13.83	6.81
Trimmed mean	−6.39***	7.83***	16.04	5.99	−9.42***	9.86***	23.26	6.77
Weighted mean	−6.33***	7.75***	15.76	5.78	−9.38***	9.82***	23.10	6.73
DMSFE ($\theta = 0.9$)	−6.34***	7.75***	15.76	5.62	−9.41***	9.84***	23.18	6.64
DMSFE ($\theta = 0.7$)	−6.41***	7.83***	16.03	5.56	−9.44***	9.88***	23.32	6.62
ABMA	−6.36***	7.78***	15.88	5.76	−9.40***	9.84***	23.19	6.72
Subset (k = 2)	−6.24***	7.61***	15.28	5.18	−9.13***	9.55***	22.11	6.47
Subset (k = 3)	−6.14***	7.46***	14.76	4.69	−8.88***	9.28***	21.16	6.28
Subset (k = 4)	−6.05***	7.31***	14.29	4.28	−8.66***	9.04***	20.29	6.13
Subset (k = 5)	−5.95***	7.17***	13.79	3.92	−8.44***	8.80***	19.44	6.01
Subset (k = 6)	−5.85***	7.02***	13.31	3.62	−8.23***	8.58***	18.65	5.92
Subset (k = 7)	−5.77***	6.89***	12.90	3.37	−8.03***	8.36***	17.89	5.87
PC (IC = AIC)	−5.53***	6.52***	11.69	2.56	−7.63***	7.91***	16.30	4.70
PC (IC = BIC)	−5.98***	6.97***	13.16	2.61	−8.62***	8.91***	19.81	4.56
PC (IC = R^2)	−5.53***	6.52***	11.70	2.61	−7.68***	7.96***	16.49	5.04

Notes. This table reports te results of the conditional test of equal predictive ability of the HA forecast (benchmark, B) relative to the individual and combination forecasts (alternative, A) of log excess commodity. Using the loss differential, $\triangle L_{t+1} = e^2_{B,t+1} - e^2_{A,t+1}$ we test the null $\mathbb{E}[\triangle L_{t+1}|z_t] = 0$ against the two-sided alternative using each of the monitoring instrument growth in consumer price index (CPI), US money stcok (M2), the VIX, and the macroeconomic uncertainty measure of Jurado et al. (2015). The numbers shown are t-statistics of θ_0 and θ_1 from the regression $\triangle L_{t+1} = \theta_0 + \theta_1 z_t + \varepsilon$, the R^2 from this regression and the Giacomini & White (2006) (GW t-stat) test of conditional predictability. In all cases the ne Results are reported for the full out-of-sample forecast evaluation period 1990:01-2016:12. **, and *** indicate significance at the 5%, and 1% levels, respectively.

Table 10: Economic Evaluation of Monitoring Commodity Return Forecasts

Strategy	μ_p	σ_p	SR	SR_τ	$\triangle$	$\triangle_\tau$	TO	τ^{BE}
HA benchmark	−0.003	0.06	−0.05	−0.05				
Panel A: Individual predictive forecasts								
Basis	−0.007	0.07	−0.10	−0.13	−0.49	−0.74	17	—
INV	−0.002	0.09	−0.03	−0.07	−0.47	−0.83	24	—
PROD	−0.004	0.06	−0.06	−0.06	−0.04	−0.04	1	—
DP	−0.007	0.06	−0.11	−0.12	−0.38	−0.41	3	—
SP500	−0.024	0.13	−0.18	−0.23	−4.02	−4.66	43	—
TBL	−0.005	0.06	−0.08	−0.08	−0.16	−0.18	2	—
CTBL	−0.003	0.06	−0.05	−0.05	0.01	0.01	1	39
LTR	0.011	0.13	0.09	−0.01	−0.58	−1.90	85	—
TMS	−0.011	0.07	−0.15	−0.16	−0.85	−0.90	4	—
CTMS	−0.007	0.06	−0.11	−0.13	−0.29	−0.38	6	—
YS	−0.004	0.06	−0.07	−0.07	−0.07	−0.09	2	—
CDFP	0.053	0.14	0.38	0.30	3.39	2.19	79	92
DFR	0.104	0.29	0.36	0.31	−1.07	−2.44	94	—
INFL	−0.013	0.09	−0.16	−0.16	−1.49	−1.53	4	—
M1	0.022	0.08	0.27	0.21	2.16	1.63	36	95
UNRATE	−0.001	0.07	−0.01	−0.04	0.07	−0.12	13	26
INDPRO	0.030	0.10	0.31	0.27	2.52	2.12	27	166
CUTIL	0.015	0.10	0.15	0.08	0.92	0.16	50	49
REA	−0.007	0.09	−0.08	−0.09	−0.88	−0.94	5	—
CFNAI	0.062	0.14	0.44	0.40	4.16	3.57	40	219
CLI	0.132	0.20	0.66	0.64	8.09	7.68	31	576
BCI	0.169	0.24	0.71	0.68	9.27	8.69	43	527
CCI	0.005	0.09	0.06	0.01	0.13	−0.31	30	39
AUS	−0.012	0.07	−0.17	−0.19	−1.04	−1.19	11	—
CAN	−0.009	0.07	−0.12	−0.15	−0.76	−0.94	13	—
NZ	−0.004	0.06	−0.07	−0.08	−0.15	−0.21	5	—
SA	−0.003	0.07	−0.04	−0.06	−0.07	−0.22	11	—
IND	0.008	0.07	0.11	0.06	0.95	0.60	23	65
Panel B: Combination forecasts								
Mean	0.020	0.06	0.33	0.30	2.35	2.17	13	134
Median	0.002	0.06	0.04	0.02	0.62	0.54	6	33
Trimmed mean	0.016	0.06	0.27	0.24	1.99	1.84	11	112
Weighted mean	0.020	0.06	0.33	0.30	2.39	2.21	13	136
DMSFE ($\theta = 0.9$)	0.021	0.06	0.35	0.31	2.49	2.31	13	143
DMSFE ($\theta = 0.7$)	0.023	0.06	0.36	0.33	2.61	2.42	13	151
ABMA	0.019	0.06	0.32	0.29	2.32	2.14	12	132
Subset (k = 2)	0.039	0.08	0.51	0.46	3.97	3.63	23	248
Subset (k = 3)	0.058	0.10	0.58	0.53	5.20	4.71	33	354
Subset (k = 4)	0.073	0.12	0.60	0.54	5.98	5.35	41	443
Subset (k = 5)	0.085	0.14	0.59	0.54	6.32	5.58	49	512
Subset (k = 6)	0.092	0.16	0.56	0.51	6.11	5.27	55	555
Subset (k = 7)	0.110	0.18	0.62	0.57	7.23	6.35	59	662
PC (IC = AIC)	0.074	0.21	0.35	0.28	1.69	0.22	96	450
PC (IC = BIC)	0.081	0.18	0.45	0.39	4.19	3.18	66	489
PC (IC = R^2)	0.121	0.25	0.48	0.42	3.37	1.89	99	724

Notes. This table reports portfolio performance results for a mean-variance investor with relative risk aversion of three who monthly allocates his wealth between commodities and risk-free T-bills using either the HA benchmark forecast (static portfolio strategy) or the individual predictive regression (combination) forecasts (dynamic portfolio strategy). The forecasts in Panel A are based on one each of the 28 predictor variables. The forecasts in Panel B are based on 28 predictors using the different combination methods outlined in Section 2.2 using the forecast monitoring decision rule in Giacomini & White (2006). The monitoring instrument we use is broad money, M2. For each portfolio strategy, we report the annualized mean realized return (μ_p), annualized realized volatility (σ_p), annualized realized Sharpe ratio (net of cost), SR (SR_τ), annualized utility gain (net of cost), $\triangle$ ($\triangle_\tau$), the portfolio management fee that the investor would be willing to pay in order to have access to the dynamic strategy relative to the static strategy, the turnover ratio (TO) ratio, the ratio of the average turnover of the dynamic strategy relative to that of the static strategy, and the break-even transaction costs, τ^{BE}, that will render the investor indifferent between the dynamic and static portfolio strategies. We set proportional transaction costs of 20bps per dollar of trading. Since we use commodity futures, we avoid short sales restrictions but limit leverage to 50% of wealth to avoid excessive risk taking. Results are reported for the full out-of-sample forecast evaluation period 1996:01-2016:12.

A. Appendix

A.1. Construction of predictor variables

In this appendix, we provide further details and motivation for considering the predictor variables defined in Section 3.2 for commodity futures returns.

Table A1: Monthly Predictor Variables for Commodity Futures Returns

Predictor	Article(s)	Variable definition and motivation for their consideration
Basis	Fama & French (1987), Hong & Yogo (2012), Gorton et al. (2013).	To construct our monthly aggregate measure of commodity basis, we first collect futures prices of 32 individual commodities. Most of these individual commodities make up the constituents of the S&P GSCI. We then compute the basis for each individual commodity futures as the difference in log prices between two nearest-to-maturity futures prices: $$\text{Basis}_t^i = \frac{\log(f_t^{i,T_1}) - \log(f_t^{i,T_2})}{T_2 - T_1},$$ where f_t^{i,T_1} and f_t^{i,T_1} are the nearby and next-to-nearby futures prices of commodity i, respectively. Next, we compute the mean basis across commodities for each commodity sector, namely agriculture, energy, livestock, and metals. Finally the aggregate basis variable is computed as an equally weighted average of the basis across the four commodity sectors similarly to Hong & Yogo (2012). The data on 32 individual commodities futures are downloaded from Bloomberg. details of the individual commodities are provided in Table A2. The theory of storage of Brennan (1958) posits that the benefit of holding the physical commodity (convenience yield) should decline with rising inventory levels. The convenience yield is therefore closely linked to basis since it is benefit that accrues to inventory holders and not to holders of futures contract. The information content of basis could be used as a signal for inventories since commodities with low inventories have higher basis which means higher prior futures prices. As such, basis should be important for forecasting commodity returns.
Log growth of global crude oil production ($PROD$)	Groen & Pesenti (2011), Baumeister & Kilian (2012), Baumeister & Kilian (2014), Baumeister & Kilian (2015)	Log growth in global crude oil production is calculated as log(global crude oil production(t)) $-$ log(global crude oil production($t-1$)). Data on global crude oil production is downloaded from the database of the EIA. Supply is one the most important determinants of crude oil prices. For example, if crude oil production should drop whiles demand remains constant, prices would be pushed upwards. Therefore and should influence prices negatively. Considering that energy commodities, and more especially crude oil, are heavily weighted in the S&P GSCI, crude oil production should affect the return on the index.
Log growth of global crude oil inventory (INV)	Ye, Zyren & Shore (2005), Groen & Pesenti (2011), Gorton et al. (2013), Kilian & Murphy (2014)	Log growth of global crude oil inventory is defined as log(global crude oil inventory(t))$-$$log$(global crude oil inventory($t-1$)). The inventory data used in calculating this variables is constructed by multiplying U.S. crude oil inventories by the ratio of OECD petroleum inventories to U.S. petroleum inventories. Petroleum inventories are defined to include both stocks of crude oil and stocks of refined products. The theories of storage and normal backwardation of Brennan (1958) and Keynes (1930) imply that the fundamental determinants of expected commodity returns is inventory. For example, rising crude oil inventories should signal speculative demand in the commodities market. Speculators receive compensation for taking long positions since commodity producers hedge the future spot price by taking short positions in the futures market. Also, since the S&P GSCI is more heavily weighted towards energy commodities, and more especially crude oil, we should expect the level of crude oil inventory to partly drive movements in the returns of the index.

Table A1: *continued*

Predictor	Article(s)	Variable definition and motivation for their consideration
Log dividend-price ratio (*DP*)	Bessembinder & Chan (1992), Gargano & Timmermann (2014)	Log dividend-price ratio is the difference between the log of the 12-month moving sum of the dividends paid on the S&P 500 index and the log price of the S&P 500 index. The consideration of this variable as a predictor for commodity returns is motivated by studies such as Tang & Xiong (2012) and Hamilton & Wu (2015) who show that the commodities market has become more integrated with the stock and bond markets. As such, state variables that drive stock and bond returns should partly be responsible for movements in commodity returns.
S&P 500 index return (*SP500*)	Jones & Kaul (1996), Sadorsky (1999), DeRoon & Nijman (2001)	*SP500* is the log return on the S&P 500 computed as log(S&P 500 (t))-log(S&P 500 (t-1)). S&P 500 is the price level of the S&P 500 stock market index. Jones & Kaul (1996) and Sadorsky (1999) find that the stock market and oil prices tend to move together in the same direction as a response to global aggregate demand factors. Shifts in aggregate demand influence both corporate profits and the demand for oil. The S&P GSCI is heavily weighted towards energy commodities, particularly crude oil. Hence, we should expect stock index returns to partly drive movements in commodity returns.
3-month Treasury bill rate (*TBL*)	Bessembinder & Chan (1992), Sadorsky (2002) Bessembinder (1992), Bjornson & Carter (1997), Hong & Yogo (2012), Gargano & Timmermann (2014)	*TBL* is the yield on U.S. 3-month Treasury bill (secondary market). According to the theory of storage, interest rate determines the storage cost of storable commodities. For example, a commodity markets participant's expectation of the futures price of a storable commodity will depend on prevailing interest rate and the cost of storage if borrowed funds are used to purchase the commodity. Short-term interest rates should therefore be informative about future prices. The *TBL* is also known to predict common variation in stock and bond returns. It is also negatively correlated with the business-cycle; expected returns are high when business conditions are weak and low when business conditions are strong. If assume markets integration, then we should also expect the same variable to forecast commodity returns. Again the monetary policy regime of the US could impact commodity prices through currency valuation and interest rates.
Change in 3-month T-bill rate (*CTBL*)	Bessembinder & Chan (1992), Bessembinder (1992), Bessembinder (1993), Hong & Yogo (2012)	*CTBL* is defined as *TBL* (t) - *TBL* (t-1). Similarly to the 3-month T-bill rate, changes in the T-bill rate is also an economic activity variable and therefore tracks changes in business condition. The same motivation therefore applies.
Long term return (*LTR*)	Gargano & Timmermann (2014)	*LTR* is the return on long-term government bonds. The motivation for considering this variable is same as the motivation given for considering the log dividend-price ratio predictor variable.
Term spread (*TMS*)	Bessembinder & Chan (1992), Bessembinder (1993), Groen & Pesenti (2011), Gargano & Timmermann (2014)	The term spread is defined as long term government bond yield minus the yield of T-bills. *TMS* is an economic activity variable and therefore tracks changes in business condition. It is known to predict returns on stocks and bonds (Fama & French (1989)) and is positively related to expected returns on stocks and bonds. That is, expected returns are high when business conditions are weak and low when business conditions are strong. If one should take an integrated market view, then we should expect the same variable to forecast commodity returns.
Change in term spread (*CTMS*)	Bessembinder (1992), Bessembinder (1993)	*CTMS* is defined as *TMS*(t) - *TMS*(t-1). Similarly to the term spread, changes in term spread is also an economic activity variable and therefore tracks changes in business condition. Similar motivations for considering this variable therefore applies.
Yield spread (*YS*)	Fama & French (1989), Bessembinder & Chan (1992), Hong & Yogo (2012)	The yield spread is defined as the yield on Aaa-rated bond minus the yield on the 3-month treasury bill rate. *YS* is also an economic activity variable and therefore should track changes in business condition. This variable is negatively correlated with the business-cycle (Hong & Yogo (2012). We should expect commodity returns on commodities to be high when business conditions are weak and low when business conditions are strong.

Table A1: *continued*

Predictor	Paper(s)	Variable definition and motivation for their consideration
Change in default premium (*CDFP*)	Bessembinder (1992)	Change in default premium is defined as yield on Baa-rated bond minus yield on long-term government bond. *CDFP* is an economic activity variable and therefore tracks changes in business condition. This variable is negatively related to the business-cycle (Fama & French, 1989). We should expect commodity returns on commodities to be high when business conditions are weak and low when business conditions are strong.
Default return spread (*DFR*)	Bessembinder & Chan (1992), Gargano & Timmermann (2014)	*DFR* is defined as long-term corporate bond returns minus long-term government bond returns. The motivation for considering this variable is same as the motivation given for considering the log dividend-price ratio predictor variable.
Inflation (*INFL*)	Bessembinder (1993), Groen & Pesenti (2011), Gargano & Timmermann (2014)	*INFL* is defined as the log growth in U.S. consumer price index. This an economic activity variable and therefore tracks changes in business condition, and signal fluctuations in economic activity. This variable is negatively correlated with the business-cycle (Hong & Yogo (2012)). We should expect commodity returns on commodities to be high when business conditions are weak and low when business conditions are strong. Commodity futures prices are also of interest to central banks and policy-makers because they provide forecasts for key commodities, and play an important role in explaining fluctuations in and projecting macroeconomic activity.
Money stock (*M1*)	Groen & Pesenti (2011), Gargano & Timmermann (2014)	*M1* is the log growth in log growth in monthly M1 money stock. The motivation for considering this variable is same as the motivation given for considering the log dividend-price ratio predictor variable.
Unemployment rate (*UNRATE*)	Groen & Pesenti (2011), Gargano & Timmermann (2014)	*UNRATE* is the monthly unemployment rate from the website of the Archival Federal Reserve Bank of St. Louis Economic Data (ALFRED). As measure of economic activity, *UNRATE* variables also signal fluctuations in economic activity.
Log industrial production (*INDPRO*)	Bessembinder (1993), Bjornson & Carter (1997), Pagano & Pisani (2009), Groen & Pesenti (2011), Gargano & Timmermann (2014)	*INDPRO*) is the monthly log growth in OECD aggregate industrial production obtained from OECD data website, `https://data.oecd.org/`. As measure of economic activity, *INDPRO* also signal fluctuations in economic activity.
Log capacity utilization in US manufacturing (*CUTIL*)	Pagano & Pisani (2009)	*CUTIL* is the log growth in degree of capacity utilization in US manufacturing. As measure of economic activity, *CUTIL* also signal fluctuations in economic activity.
Global real economic activity index (*REA*)	Alquist, Kilian & Vigfusson (2013), Baumeister & Kilian (2014)	The global real activity index is constructed from data on global dry cargo ocean shipping freight rates as described in Kilian (2009). Global economic activity drives demand for oil and other industrial commodities in global markets. The index is based on dry cargo single voyage ocean freight rates and is explicitly designed to capture shifts in the demand for industrial commodities in global business markets. It exploits the positive correlation between ocean freights rate and economic activity. Commodities are traded globally as such the state of the global economy will partly impact movements in commodity prices. This variable has been shown to forecast movement in crude oil returns.
Chicago Fed National Activity index (*CFNAI*)	Hong & Yogo (2012)	The *CFNAI* is a monthly summary statistic for U.S. economic growth. As a measure of economic activity, the index is designed to gauge overall economic activity and related inflationary pressure. Commodity prices form a key component of inflation expectations. High economic activity is negatively correlated with inflation (Stock & Watson, 1999). As such we should expect the index to drive movement in commodity prices.
OECD composite leading indicator (*CLI*), business confidence index (*BCI*), consumer confidence index (*CCI*)	Pagano & Pisani (2009), Groen & Pesenti (2011)	These variables are measures of global economic activity similarly to the global index of real economic activity. They are designed to provide signals of turning points in the business cycle and fluctuations in economic activity.
Commodity currencies: Australia (*AUS*), Canada (*CAN*), New Zealand (*NZ*), South Africa (*SA*) & India (*IND*)	Chen et al. (2010), Gargano & Timmermann (2014), Groen & Pesenti (2011)	Chen et al. (2010) exploit the notion that changes in commodity currencies are correlated with commodity prices. These countries are major commodity exporters where commodities represent a quarter to one-half of their total export earnings, and also have a sufficiently long history of market-based floating exchange rates. Therefore movements in their exchange rate against the US dollar should be informative future commodity returns.

Table A2: Individual Commodity Futures Data

Sector/Commodity	Exchange	Bloomberg Ticker	CFTC code(s)
Agriculture			
Corn	CBOT	C	002601, 002602
Rough Rice	CBOT	RR	039601, 039781
Soybean Meal	CBOT	SM	026603
Soybean Oil	CBOT	BO	007601
Soybeans	CBOT	S	005601, 005602
Wheat	CBOT	W	001601, 001602
Ethanol	CME	DL	025601
Lumber	CME	LB	058641, 058643
Cocoa	ICE	CC	073732
Coffee	ICE	KC	083731
Cotton	ICE	CT	033661
Orange Juice	ICE	JO	040701
Sugar	ICE	SB	080732
Energy			
Brent Crude Oil	ICE	CO	—
Gasoil	ICE	QS	—
Gasoline	NYMEX	HU/XB	11659
Heating Oil	NYMEX	HO	022651
Natural Gas	NYMEX	NG	023651
WTI Crude Oil	NYMEX	CL	067651
Livestock			
Feeder Cattle	CME	FC	061641
Lean Hogs	CME	LH	054641, 054642
Live Cattle	CME	LC	057642
Metals			
Palladium	COMEX	PA	075651
Platinum	COMEX	PL	076651
Aluminium	LME	LA	NA
Copper	LME	LP	085691, 085692
Lead	LME	LL	NA
Nickel	LME	LN	NA
Tin	LME	LT	NA
Zinc	LME	LX	NA
Gold	COMEX	GC	061641
Silver	COMEX	SI	084691

Notes. This table lists all the 32 individual commodities used to construct the commodity market predictor variables grouped by sectors, the exchanges they are traded on, the corresponding Blomberg tickers, and the corresponding code in the Commitment of Traders report. The commodity futures are traded on the Chicago Board of Trade (CBOT), the Chicago Mercantile Exchange (CME), the London Metal Exchange (LME), Intercontinental Exchange (ICE), the New York Commodities Exchange (COMEX), and the New York Mercantile Exchange (NYMEX). NA means data is not available.