Forecasting Commodity Futures Returns with Stepwise Regressions: Do Commodity-Specific Factors Help?

Massimo Guidolin†
Bocconi University and Baffi-CAREFIN Centre

Manuela Pedio
Bocconi University and Baffi-CAREFIN Centre

Abstract

We test whether three well-known commodity-specific variables (basis, hedging pressure, and momentum) may improve the predictive power for commodity futures returns of models otherwise based on macroeconomic factors. We compute recursive, out-of-sample forecasts for fifteen monthly commodity futures return series, when estimation is based on a stepwise model selection approach under a probability-weighted regime-switching regression that identifies different volatility regimes. Comparisons with an AR(1) benchmark show that the inclusion of commodity-specific factors does not improve the forecasting power. We perform a back-testing exercise of a mean-variance investment strategy that exploits any predictability of the conditional risk premium of commodities, stocks, and bond returns, also taking into account transaction costs caused by portfolio rebalancing. The risk-adjusted performance of this strategy does not allow us to conclude that any forecasting approach outperforms the others. However, there is evidence that investment strategies based on commodity-specific predictors outperform the remaining strategies in the high-volatility state.

Keywords: stepwise regression, commodity returns, predictability, portfolio back-testing.

1. Introduction

Recently, in the academic literature a debate has raged on the role played and the alleged distortions induced by speculative investors in commodity markets. For instance, Tang and Xiong (2012) have reported a surge from \$15 to \$200 billion of capital flows in commodity futures markets between 2003 and 2008 from institutional investors. Irwin and Sanders (2011), Tang and Xiong (2012), and Hamilton and Wu (2015) have traced the start of the process of financialization of commodity markets back to 2004. In this context, a literature has developed that has investigated the risk sources driving commodity futures returns. In this

† Corresponding author. Address: Bocconi University, Finance dept., via Roetgen 1, 20136 Milan, Italy. E-mail: massimo.guidolin@unibocconi.it. Tel.: +39-02-5836.3556. Pedio: Bocconi University, Finance dept., via Roetgen 1, 20136 Milan, Italy. E-mail: manuela.pedio@unibocconi.it.

context, in this paper we formally test—both using standard statistical criteria and resorting to economically grounded loss (portfolio trading) functions—whether such a process of financialization may have shifted the balance of the predictive relationships involving commodity returns from being dominated by variables that describe the dynamics and state of (dis-)equilibrium in the very commodity markets to the more classical variables that relate asset prices to business cycles and macroeconomic conditions. We perform such an analysis by exploiting the flexible predictive power of stepwise regressions, a tool that allows some or all of the variables in a standard linear multivariate regression to be chosen automatically, using various statistical criteria, from a set of variables (see, e.g., Sharma and Yu, 2015).

In fact, it is possible to identify different strands in the literature on commodity returns. The first strand argues that the expected return of any given commodity futures is driven by factors which are specific to each market. This group of papers is based on two main classical theories, which assume that the level of inventories and the relative positions of short vs. long hedgers in the futures markets (hedging pressure) are the key determinants of futures returns. First, the theory of storage (Kaldor, 1939; Brennan, 1958) is based on the assumption that producers and inventory holders receive implicit benefits from inventories deriving from the possibility to manage any temporary shortages (the “convenience yield”). However, due to the presence of costs of carrying such inventories, these benefits decline as inventories increase. Because inventories influence spot and futures price relative movements, the convenience yield turns out to be related to the *basis*, i.e., the difference between spot and futures prices. Second, the theory of normal backwardation in Keynes (1930) and Hicks (1939) is based on the assumption that, to induce risk-averse speculators to take long positions, current futures prices must be set at a discount vs. expected future spot prices at maturity, i.e., in ordinary times, the market would be in backwardation. The size of the discount is the future risk premium and it depends on the interplay between hedgers and speculators.

Many papers have provided empirical evidence on the forecasting power of commodity-specific factors related to these classical theories (basis and hedging pressure, besides momentum that may be associated to speculative herding behavior). For example, Gorton, Hayashi, and Rouwenhorst (2012), exploiting the Theory of Storage, identify a linkage between the basis and individual commodity futures return. Building on the theory of hedging pressure, Stoll (1979), Hirshleifer (1988) and de Roon, Nijman, and Veld (2000) found that hedging pressure affects individual commodity futures premiums. A second strand of literature has tested the relationship between macroeconomic variables and commodities. These papers are mainly based on the assumption that storage costs and convenience yields are expected to be influenced by the general state of the economy through short-term mismatches between the demand and supply of commodities (see e.g., Bessembinder and Chan, 1992). However, only a small portion of the literature studies the predictive power of macroeconomic variables that have been proven to carry a relation with commodity futures returns. For instance, Gargano and Timmermann (2014) examine the predictability of commodity returns from some macroeconomic variables and find that bond spreads, the growth rate of money supply, and industrial production are better predictors of raw industrials and metals index returns, than for foods and textiles commodities. They also observe that the predictability of commodity futures returns based on inflation, industrial production, and money supply is stronger during economic recessions than during expansions. Giampietro et al. (2018) test whether flexible specifications of pricing kernels that jointly price the cross section of commodities, equities, and government bonds can be specified to reflect standard macroeconomic variables or else it needs to be extended to include commodity-specific variables; they find evidence that commodity market information would be required.

In this paper we compare the predictive power of macro-economic variables for commodity returns with that of popular models, extended to include three commonly used aggregate commodity-specific factors (i.e., basis, hedging pressure, and momentum), which may improve the predictive power of models based on the lagged values of 138 macroeconomic-based factors, as in Ludvigson and Ng (2009) and Welch and Goyal (2008). Because we would like to capture broad categories of economic activity indicators, we use variables in a wide set of macroeconomic variables, such as output and income, prices, employment, new orders, housing construction and selling activity variables, money, credit, and exchange rates.

Our question is of considerable importance to both practitioners (arguably, investors, including both hedgers and speculators) and academics: under the null hypothesis that commodity returns have come to be mostly driven by macroeconomic factors, this would make of commodities just another asset class—say, similar to stocks, corporate and government bonds—and possibly deny commodities of the appeal often deriving from being considered as an “alternative class”; however, if the null were to be rejected showing that accurate and economically valuable predictions can be derived only from the information in commodity-specific variables, this would confirm that commodities remain “special” and are worth being considered as a separate asset class, as it seems to be currently the case if one pays attention to the way in which graduate teaching curricula as well as trading desks are organized.

We conduct our analysis on 15 continuous commodity futures series, i.e., Brent Crude Oil, Gasoline, Corn, Soybeans, Wheat, Coffee, Cocoa, Sugar, Cotton, Gold, Silver, Platinum, Orange

Juice, Lumber, and Live Cattle. We examine the sample period January 1989 - December 2012. As You and Daigler (2013), we focus on individual futures contracts. To assess out-of-sample (henceforth, OOS) predictability, we split our data and use information for the period January 1989 - December 2003 for in-sample estimation of the models, and data for the period January 2004 - December 2012 to test the recursive out-of-sample forecasting performance of a range of models. In addition, we take into account the different regimes of market volatility and investigate whether the predictive power of the models may depend on such regimes. To test the conjecture of a strong dependence, we split both the in-sample and OOS windows in high- and low-volatility periods (differently from Jensen et al., 2000, who have instead emphasized monetary policy regimes). We use the VIX index as a “proxy” of market volatility. In order to select the macroeconomic variables to consider, we adopt a principal components analysis, as suggested by Stock and Watson (2006): we therefore identify a limited number of linearly uncorrelated variables which effectively summarize a large part of the sample variation of a set of potentially correlated variables. We include in our analysis the first ten principal components, which explain 60% of the variance of the initial information set.

Because we study a heterogeneous set of commodities, it is plausible to assume that each of them may be predicted by different macroeconomic variables. For this reason, we apply a variable selection methodology to each commodity. This approach aims at finding a well-specified model for each commodity futures return, starting from the same set of predictors. Filtering the variables and getting the “best” subset of variables for each commodity series avoids statistically irrelevant predictors which would just add noise to the forecasting exercises, uselessly reducing the degrees of freedom. In particular, we use forward and backward stepwise selection methods, two common tools to select variables in linear regression analysis. These are methods for selecting variables from a large dataset, starting with no variables in the model and with a model including all the available predictors, respectively. An automatic procedure then identifies the most significant variables at each step of the selection, based on given criteria. Lastly, to account for the effects of commodity-specific factors, we add them to the models previously obtained.[2] From the estimation of the resulting predictive regressions, we find that the models that include commodity-specific variables perform better than those that do not in the high-volatility regime, yielding significant regression coefficients and higher R-squares and adjusted R-squares. However, the regression coefficients associated to

[2] For each commodity series, we investigate a total of eight variable selection procedures and volatility state-combinations models, based on principal components of macroeconomic variables, and eight variable selection procedures and volatility state-combinations models based on principal components of macroeconomic variables augmented by commodity-specific factors.

commodity-specific factors are not significant, both in the high- and low-volatility states. Hence, the inclusion of the commodity-specific factors does not bring any positive effects to the in-sample predictive power of the models as both the R-squared and adjusted R-squared of the models fail to show any substantial improvements.

We calculate low- and high-volatility recursive, OOS forecasts with backward and forward predictive regressions that include principal components of macroeconomic variables only vs. forecasts which also include the commodity-specific factors. At this point, we perform a probability-weighted model averaging by calculating the forecasts of futures returns as the weighted average of the low- and high-volatility forecasts, where the weights are represented by the predicted probabilities derived from a Markov switching model applied to the VIX index series. To evaluate the forecasting accuracy of the models, we adopt two measures: the mean absolute prediction error (MAPE) and the root-mean-square prediction error (RMSPE). Both MAPE and RMSPE lead us to conclude that neither the models that include only principal components of macroeconomic variables nor models that comprise commodity-specific factors yield better OOS performances than a simple, naïve first-order autoregressive benchmark.

Finally, extending previous work by Jensen et al. (2000), Erb and Harvey (2006), and Fuertes, Miffre, and Rallis (2010), we turn to a mean-variance framework in which the asset menu includes both commodities and traditional assets (equities and bonds). Following DeMiguel et al. (2007), we recursively build static one-period optimal mean-variance portfolios, considering both rolling and expanding windows of data starting in January 2004 and that ends in December 2012. For each optimal set of portfolio weights, we compute the corresponding average realized return, realized mean-variance utility, and Sharpe ratio for the back-testing period. In order to make our analysis robust, we repeat calculations afresh for a range of values of the risk aversion coefficient (between 0.10 and 2.5). In addition, we account for the transaction costs of rebalancing the portfolio over time. We consider, as a general rule, that an investor may want to rebalance her portfolio only if she can achieve, at least in ex-ante terms, an increase in expected utility, i.e., if at time t only if the costs implied by the rebalancing decision are less than the increase in portfolio risk-adjusted expected returns at $t + 1$.

The back-testing of optimal portfolios is performed both for the case in which we predict futures returns only with macroeconomic variables and when we consider instead models that include commodity-specific factors. Although such a OOS portfolio back-testing may seem not justified by the in-sample and statistical OOS results, a recent literature in portfolio management (see, e.g., Dal Pra, Guidolin, Pedio, and Vasile, 2018) has shown that—because the typical loss functions employed are deeply different—it is possible for statistical back-testing to reveal a distorted, downward-based picture of the amount of economic value that instead a OOS portfolio back-test may disclose. In fact, our results suggest that portfolios resulting from the joint use of macroeconomic and commodity specific factors perform better (in the case of models built by forward selection) than models driven by macroeconomic variables only. We compare the results between the scenarios with and without transaction costs and find that under transaction costs, the portfolios associated with regressions based on forward selection algorithms but involving both macro and commodity-specific factors are characterized by better performance than the macroeconomic variables-only models; the contrary happens in the case of regressions built using backward selection stepwise methods. Interestingly, the asset allocations are dominated by long exposures to bonds and the residual is structured as a long/short strategy with an almost perfect zero net exposure to commodities and equities. The empirical result that even going beyond standard mean-variance analysis, it may be difficult to obtain evidence in favour of multi-asset portfolios including long positions in individual commodities, has recently echoed in the literature (see, e.g., Henriksen, Pichler, Westgaard, and Frydenberg, 2018; Lean, Nguyen, and Uddin, 2018).

We repeat these analyses separately with reference to commodity futures returns predicted from optimally selected models (through stepwise regression methods), with reference to low- vs. high-volatility regimes. We construct low- and high-volatility portfolios for all models and risk aversion coefficient combinations and for both the positive vs. the zero transaction costs scenarios. We find that the optimal portfolios obtained with reference to the high-volatility regime imply more accurate forecasts, higher realized Sharpe ratios, and higher mean-variance realized utility values than the low-volatility regime portfolios, coherently with the regression results commented above. These results appear novel: You and Daigler (2013) have examined the diversification benefits of using individual futures contracts in a Markowitz framework and investigated the differences between ex-ante, in-sample results and ex-post, realized performances. However, our focus is distinctively devoted to the differential predictability of commodity-specific vs. variables that capture the state of the business cycle.

The rest of the paper is organized as follows: Section 2 describes the methodology. Section 3 contains a description of the data. Section 4 reports the results of the estimation of the models and their OOS performances. Section 5 reports the back-testing results from the mean-variance back-testing exercises. Section 6 summarizes the main results.

2. Research design

2.1. Definition of volatility regimes

It is nowadays notorious in the literature that different regimes of market volatility should be featured in factor models, based on the evidence that financial markets may change dramatically (see, e.g., Rapach and Zhou, 2013). Portfolio managers, risk arbitrageurs, and corporate treasurers closely monitor volatility trends, because changes in prices could have a major impact on their investment and risk management decisions. We adopt the VIX index provided by the Chicago Board Options Exchange (CBOE) from January 1989 to December 2012 as a proxy of market volatility. Given that the VIX index is characterized by the presence of different states (or regimes), we introduce a regime switching framework in order to disentangle the different levels of market volatility. In particular, we adopt a two-state regime switching model to feature the existence of a high-volatility and a low-volatility state, where the transition between the two regimes is governed by a Markov process:[3]

$$VIX_t = c_{s_t} + \phi VIX_{t-1} + \varepsilon_t, \tag{1}$$

with $\varepsilon_t \sim N(0, \sigma^2)$. The variable s_t is a Markov state variable, that follows the transition matrix

$$P = \begin{bmatrix} P(s_t = 0|s_{t-1} = 0) & P(s_t = 1|s_{t-1} = 0) \\ P(s_t = 0|s_{t-1} = 1) & P(s_t = 1|s_{t-1} = 1) \end{bmatrix} = \begin{bmatrix} p_{00} & p_{10} \\ p_{01} & p_{11} \end{bmatrix}, \tag{2}$$

where p_{ij} (i, j = 0,1) denotes the transition probability of $s_t = j$, given $s_{t-1} = i$ and the transition probabilities satisfy $p_{i0} + p_{i1} = 1$. The transition matrix governing the behaviour of the state variable, contains only two parameters p_{00} and p_{11}. Hence, we assume the variable s_t is not directly observable, but that it can be inferred from the past behaviour of y_t.

Figure 1 plots the estimated filtered probabilities that the VIX was in a low-volatility regime (clearly the plot for high-volatility state is just specular). From an inspection of the figure, it seems that the entire sample period could be divided into four different sub-periods. In particular, January 1989-December 1997 and January 2004-December 2007 can be considered as low-volatility periods, while January 1998- December 2003 and January 2008-December 2012, as high-volatility periods.

2.2. Forecasting with many macroeconomic predictors: principal components

Stock and Watson (2006) surveyed the literature concerning methods to forecast economic time series variables using many predictors. Among all the methodological solutions analysed, the authors showed that forecasts based on principal components of a large number of predictors are first-order asymptotically efficient given that both the number of predictors and the number of observations are very large, and this is particularly true when we consider a

[3] Jensen et al. (2000) provide evidence on the role of commodity futures in mean-variance portfolios. They find that in periods of restrictive monetary policy, commodity futures carry an important weight and yield a considerable performance enhancement. However, since their paper, it has become common to classify financial market regimes on the basis of the level of volatility.

large set of macroeconomic variables (Stock and Watson, 2002). The core idea of principal component analysis (PCA) is to identify a limited number of linearly uncorrelated variables, the so-called principal components (PCs), which summarize the largest part of the variation of a sample set of potentially correlated variables.

The PCA approach is based on a well-known result, the *singular value decomposition theorem*, that states that any symmetric matrix $X \in S^n$ can be decomposed through the symmetric eigenvalue decomposition as

$$X = \sum_{i=1}^{n} \lambda_i u_i u_i = U \Lambda U', \quad (3)$$

where Λ is a diagonal matrix and the U is orthogonal, so that $UU' = U'U = I_n$. Given n variables, we obtain the principal components starting from the decomposition of the covariance (or correlation) matrix, $\Sigma = \sum_{i=1}^{n} \lambda_i u_i u_i = U \Lambda U'$, such that:

$$PC_k = \sum_{i=1}^{n} u_{ki} U_i, \quad (4)$$

where U_1, U_2, ..., U_n represent the vectors of the original variable, u_k is the *k*th eigenvector of Σ and u_{k1}, u_{k2}, ..., u_{kn} are its *n* elements.

Using principal component analysis to summarize a large set of macroeconomic factors (see Section 3), we estimate the following model for the returns of each commodity *j*, $R_{t+1,j}$:

$$R_{t+1,j} = \alpha + \sum_{i=0}^{N} \beta_{ij} PC_{t,ij} + D_{t,j}\left(\sum_{k=1}^{K} \gamma_{kj} C_{t,kj}\right) + \epsilon_{t,j}, \quad (4)$$

where α is the model's intercept, β_{ij} is the factor loading of the *i*th principal component, γ_{kj} represents the regression coefficients of the *k*th commodity-specific factor, $C_{t,kj}$ and $D_{t,j}$ is a dummy variable, which is equal to 1 when the model also contains commodity-specific factors, and 0 if otherwise. $\epsilon_{t,j}$ represents the error term, assumed to be white noise and such that $Corr\left(\epsilon_j, \epsilon_i\right) = 0$, for all pairs *i* and *j*.

Figure 2 reports the graph of the cumulative variance explained by principal components. To reduce the number of parameters to be estimated, we decide to include only the first ten components resulting from the PCA performed, which explain 60% of the total variance of the initial informational set (the dotted line in the Figure 2 represents the tenth principal component). In addition, Table 1 provides a representation of the scale of the factor loadings. They range from -1 to 1; loadings close to -1 or 1 indicate that the factor strongly affects the variable, while loadings close to zero indicate that the factor has a weak effect.

2.3. Variables selection method: stepwise regressions

Starting from the set of principal components computed previously, we apply a variable selection methodology to select the variable to be included as regressors to estimate futures returns of each commodity in the sample. To this purpose we rely on stepwise regression, an automatic variable selection procedure, which chooses from a set of candidate regressors the explanatory variables that are, jointly, the most relevant. Different stepwise regression procedures are available, but we decided to use the unidirectional forward and backward methods. Forward selection starts with no variables in the model, testing the inclusion of each variable with a chosen model-fit criterion, adding the variable (if any) whose inclusion gives the most statistically significant improvement of the fit, and repeating this process until none of the remaining variables improves the model to a statistically significant extent. Backward elimination starts with all candidate variables, testing the deletion of each variable using a chosen model-fit criterion, deleting the variable (if any) whose exclusion gives the less statistically significant deterioration of the model fit, and repeating this process until no further variables can be deleted without a statistically significant loss of fit.

Stepwise regression procedures admit different selection criteria for variables to be included or excluded from the models; for instance, it may rely on a sequence of F-tests or on an information criterion, that is, a measure that trades-off in-sample fit with parsimony of the mole, such as the Akaike information criterion (henceforth, AIC). In line with the recent literature, we adopt the AIC as a selection criterion, $AIC = 2k - 2\ln(\hat{L})$, where $\hat{L}$ is the maximum value of the likelihood function of the model and k is the number of parameters to be estimated. Given a set of models, the preferred one is that with the smallest AIC value.[4]

In total, we estimated four different models for each commodity using backward procedures and four using forward procedures: a model that regresses futures returns on the principal components only (potentially a subset of the initial set, according to the selection procedure) in periods of low volatility and in periods of high volatility; a model that regresses futures returns on principal components and on commodity-specific factors, both in time of high and low volatility. We then compute out-of-sample forecasts for models that include and exclude commodity-specific factors using the weighted average of low-volatility and high-volatility estimates, where weights are represented by the filtered probability obtained from the application of the Markov switching model described earlier.

3. The data

3.1. Commodity futures returns

We consider time series of monthly returns computed using settlement prices of futures contracts on 15 commodities, collected from *Thomson Reuters Datastream,* for a period

[4] The original algorithm that includes the AIC criterion in forward and backward selection was developed by Efroymson (1960). AIC is known to be an asymptotically unbiased selection criterion.

spanning from January 1989 to December 2012. The dataset contains two energy commodities (Brent Crude Oil and Gasoline), seven agricultural commodities (Corn, Soybeans, Wheat, Coffee C, Cocoa, Sugar No.11, and Cotton No.2), three metals commodities (Gold 100Oz, Silver 5000Oz, and Platinum), two general commodities (Orange Juice and Lumber), and one livestock commodity (Live Cattle).[5]

Following a common practice of both practitioners and academics we consider investors to assume fully collateralised positions in commodity futures. This implies two consequences. First, investors are not allowed to operate on margin, thus using leverage; while this approach limits the size of the return that could be reached, it has the advantage to make investments in commodities directly comparable with the investments in other asset classes, which usually require an initial money outflow. Second, the lack of a margin system limits the possibility of any unintentional liquidation (due to insufficient collateral) of the position before the end of the investor's holding period.

We compute the return on a future position on commodity *j* at time *t* as:

$$R_{j,t+1} = \frac{F_{j,t+1}^{(1)}}{F_{j,t}^{(1)}} - 1 + R_t^f, \tag{5}$$

where R_t^f is the risk-free rate between time t and t + 1, here proxied by the 1-month T-bill rate. Naturally, the computation of the time series of futures returns is complicated by the fact that the front-end contract (typically the most liquid and used by the trades) has to be rolled over before expiry in order to maintain a long-term position (while at the same time avoiding taking a delivery). In case of physically settled contracts, to avoid the delivery, traders shall close their position before the "*First Notice Day*", which is the first day from which the exchange may assign the delivery of the underlying asset, before the "*Last Trading Day*". In order to identify the First Notice Day for each contract, we have considered the official trading calendar of the relevant exchange. In addition, to forecast when actually (before the First Notice Day) the majority of the investors are likely to roll over their positions, we adopted a methodology proposed by Bakshi, Gao, and Rossi (2017) and widely consistent with the intuition of Gorton et al. (2012) and Hong and Yogo (2012). Because the investor wants to avoid delivery, we assume that she takes position in the futures contract with the second closest maturity on the last business day of each month t, when the contract's First Notice Day occurs after the end of month t+1.

In Table 2 we report the summary statistics of the commodity futures returns. We notice

[5] As recently shown by Aslan, Yozgatligil, and Iyigun (2018), with reference to commodity returns, it may be possible to group different commodity returns series on the basis of commonalities in the estimated linear autoregressive and non-linear threshold autoregressive feautures to further reduce the dimension of the cross-section.

that the commodities in the sample have similar volatility, except for Corn, Cotton, Live Cattle, Gold 100Oz, and Soybeans. We also find that the time series of commodities futures returns have platykurtic tails (kurtosis lower than 3) and positive skew, except for Corn, Live Cattle and Soybeans, which display a negative skew. We also notice that Brent Crude Oil and Gasoline have a higher average return during the sample period than the other commodities.

3.2. Macroeconomic-based factors

Since we want to represent broad categories of economic activity, we consider the 125 macroeconomic-based factors by Ludvigson and Ng (2009), adding some series by Welch and Goyal (2008). We obtain a set of 139 variables, spanning from January 1989 to December 2012, and we group the variables into eight main categories: output and income, labour market, housing, consumption, orders and inventories, money and credit, stock market, bond and exchange rate, and prices series. A Reader may find a detailed description of the variables and of the sources from which they were collected in Appendix A.

Since previous literature has highlighted that most macroeconomic series are not stationary, in the sense that they contain one (or more) unit roots, we perform the Augmented Dickey-Fuller (ADF) test on the series. The null hypothesis of this test is that the series contains unit roots, thus we decide to maintain the original values of the variables if the null hypothesis is rejected at a significance level of 5%. Otherwise, we differentiate the variables and test them again. Again, we maintain the first difference of the variables if the null hypothesis is rejected at a significance level of 10%. On the contrary, we exclude the variables if the null hypothesis cannot be rejected in the second application of the Dickey Fuller test. At the end of this process, we obtain a set of 128 macroeconomic variables.

3.3. Commodity-specific factors

Commodity-specific factors considered are the hedging pressure factor (HP), the basis factor, and the momentum factor, and are defined exactly as in Daskalaki, Kostakis, and Skiadopoulos (2014). The hedging pressure factor is represented by the difference between positive and negative hedging pressure positions. The hedging pressure of a commodity j at time t is calculated as the ratio between the number of short hedging positions minus the number of long hedging positions, divided by the total number of hedgers in the commodity market:

$$HP_{j,t} = \frac{\#shorthedgeposition_{j,t} - \#longhedgeposition_{j,t}}{Total\#hedgeposition_{j,t}}. \tag{6}$$

The basis factor is defined as the difference of the return of a portfolio of commodity futures with positive basis and a portfolio with negative basis. For a commodity *j* at time *t*, basis is calculated as

$$Basis_{j,t} = \frac{F_{j,t} - F_{j,t+1}}{F_{j,t}}, \tag{7}$$

where $F_{j,t}$ is the price of the nearest available futures contract on *j*, while $F_{j,t+1}$ is the price of the next nearest available futures contract on *j*.

Finally, the momentum factor is the difference between the return of a portfolio of commodity futures with positive prior 12-month return and the return of a portfolio of futures with negative prior 12-month return. Gorton et al. (2012), Shen, Szakmary, and Sharma (2007) and Narayan, Ahmed, and Narayan (2015) have documented robust momentum effects in commodity futures returns. Table 3 reports summary statistics for the commodity-specific factors from January 1989 to December 2012.

4. Empirical results

In this Section we first discuss the model estimated. Then, we provide a detailed analysis of the out-of-sample predictability power of the models, using the mean absolute error and root-mean-square error and comparing the forecast performances of the models that includes only macroeconomic variables to models based on both macroeconomic and commodity-specific factors.

4.1. Results from in-sample estimation

We also estimate a first order autoregressive model for each commodity futures return series, to be used as a benchmark to assess the forecast performances of the other models. First, we report results of the linear regression models for the commodity futures returns. In Table 4 we report the regression coefficients, the R-squares, and adjusted R-squares for the best models: the regression results for low- and high-volatility states are reported separately. Low-volatility models are estimated on the period starting from January 1989 and ending in December 1997; the high-volatility models, instead, are estimated on the period from January 1998 to December 2003. The estimation periods fail to exhaust the sample because they simply form the basis for the subsequent backtesting exercise. Panels A and B of Table 4 are dedicated to backward and forward stepwise regessions that include macroeconomic variables only. Panel C and D, instead, show results for backward and forward algorithms that employ both macroeconomic and commodity specific factors as predictors in a stepwise algorithm. Finally, Panel E reports the regression coefficients for the first-order autoregressive benchmark.

First, in panels A and B, backward and forward stepwise algorithms lead to the specification of rather similar models. In general, for most commodities, there is evidence of considerably more macroeconomic predictors being selected in the high volatility regime than in the low one, consistently with our brief literature review. For instance, silver futures returns are predicted by PC3 and PC7 under both backward and forward variable inclusion algorithms in the low volatility state, and by PC1, PC2, PC5, and PC10 under both stepwise rules in the high volatility regime. The resulting adjusted R-squares are included between an approximate 2% (for gold) and 15% (platinum) in the low volatility regime, and 2% (for coffee) and a remarkable 26% (for gasoline) in the high-VIX one.[6]

In panels C and D of Table 4, when commodity-specific predictors are added, the general insights on when and which macroeconomic factors are included as predictors remain intact. This is already an indication that the predictive power of the latter is approximately independent of the power of the former set of variables. In fact, the improvement in forecasting accuracy brought about by the basis, hedging pressure, and momentum is modest: in both panels, they are hardly ever significant in terms of t-tests, while the resulting adjusted R-square generally declines! For instance, comparing panels A and C, we find that in the latter the adjusted R-squares range now between -2 and 12 percent (down from a range +2 to 15 percent) in the low-volatility regime, and between -4 and 20 percent (down from a range +2 to 26 percent) in the high volatility regime.

In panel E of Table 4, we report on the performance of the AR(1) benchmark, finding that the autoregressive coefficient is hardly ever significant independently of the volatility regime. Therefore this appears to be a weak benchmark. Yet, the adjusted R-square, that we do not report because they would be hardly meaningful being based on a autoregressive structure, tended to generally exceed (although by a modest spread) those in panels A-D of the table.

4.2. Comparison of out-of-sample performances

The existing literature abounds with results in which relatively rich predictive models offer a rather accurate in-sample fit that however fails to be met by a similarly accurate out-of-sample (henceforth, OOS) performance, presumably due to over-fitting problems (see, for instance, Rapach and Wohar, 2006). In addition, empiricists have been aware at least since Bossaerts and Hillion's (1999) work on equity return forecastability, that even predictive regressions specified on the basis of information criteria that penalize over-fitting (such as the AIC that we employ), may in any case lead to poor OOS performance. Therefore, the goal of this section is to

[6] The fact that the number and nature of the principal components included in the "optimized" predictive regressions is highly sensitive to whether the data are drawn from a low- vs. a high-volatility regime provides indirect confirmation of the presence of regime switching dynamics in the data.

investigate the OOS power of the models estimated in Section 4.1, when parameter estimates are held fixed to those in Table 4 and therefore are obtained with reference to data for a 1989-2003 sample. As a result, the OOS period is Jan. 2004 – Dec. 2012 and appears to be long in terms of number of observations spanned and to also include two different volatility "cycles/regimes": 2004-2007 and then 2011-2012 characterized by low volatility, and 2008-2010 characterized by a high volatility regime.

In particular, we compute the one-month ahead forecasts of futures commodity returns under both low- and high-volatility predictive regressions (specified using either backward or forward stepwise methods). This is performed from models that include macroeconomic predictors only (using the parameter estimates in panels A and B of Table 4) but also models expanded to include commodity factors (using the estimates in panels C and D). At each point in time of the OOS period, the forecasts are also (i.e., in addition to forecasts that simply classify the t+1 regime as either low- or high-volatility, according to whether the time t filtered probability of a low-volatility regime exceeds or not 0.5) obtained as (filtered, one-step forward-iterated, real-time) probability-weighted averages of the forecasts that refer to the low- vs. the high-volatility state. Under a MSE loss function, such weighting by predicted regime probabilities of regime-specific forecasts can be shown to be optimal under the assumption that the Markov states are independent of all other shocks in the model.

To evaluate the accuracy of the different combination between stepwise predictor selection techniques and whether the selection set includes or not the commodity-specific factors, we use two standard summary measures, the mean absolute prediction error (MAE) and the root mean square prediction error (RMSE). The MAE is the average of the absolute forecast errors of the models over the OOS period, say between i = 1 and T,

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|\widehat{y_t} - y_t| = \frac{1}{n}\sum_{t=1}^{T}|\hat{e}_t|, \quad (8)$$

where $|\hat{e}_t|$ is the the absolute error, $\widehat{y_t}$ is the prediction from a given model/selection method, and y_t is the true value of a variable. Clearly, the smallest the MAE, the highest is the forecasting power of a model. Panel A of Table 5 reports the realized OOS values of MAE for the backward and forward stepwise methodologies. The upper portion of the table shows the values of MAE for backward and forward stepwise regressions that only include macroeconomic factors, when we do not average-weight the low- and high-volatility regime forecasts; next, we report similar, unweighted forecasts when the set of predictors also includes the basis, hedging pressure, and momentum; the last two sections of the Table report, in the same order, similar information when we weight-average the forecasts from different regimes on the basis of their one-step ahead predicted probability of being in either a low- or in a high-volatility regime.[7] The very bottom of the table reports theMAE of the AR(1) benchmark. We prefer to comment on MAE first because this forecast accuracy measures is obviously less sensible to outliers and is therefore more robust.

In Table 5, there is no stark result, apart from the fact the *grand* average of MAE values with and without commodity-specific factors are approximately the same. However, this just applies to the average of the MAEs (both unweighted and probability-weighted), as for some commodities there is evidence of the inclusion of the basis, hedging pressure, and momentum lowering MAE (this happens for crude oil, lumber, soybeans, gold, and platinum), for some others increasing MAE (wheat, gasoline, orange juice, coffee, and sugar). For the remaining five commodity futures returns series, the evidence is indeed mixed. In any event, all such differences are modest. For instance, the largest reduction occurs in the case of the Brent crude oil futures returns series, when the state probability-weighted MAE declines from 0.105 to 0.103 when commodity-specific predictors are included and a backward stepwise selection is applied (in the case of the forward algorithm, the declines is from 0.101 to 0.098). However, for all series, the reported MAEs are structurally lower for the low-volatility regime, even though this regimes implies stronger predictability, as one would expect from the much lower variation in realized returns of this state of the world. Finally, and crucially, for most series we observe a difficulty by predictive regressions of all types at outperforming the AR(1) benchmark that in fact implies lower MAEs for 12 series out of 15 (the only ties are obtained for corn, live cattle, and gold, but also in these cases, the solid OOS performance is attributable to commodity factors only in the case of gold).

Panel B of Table 5 reports the OOS values for the second measure of predictive accuracy, RMSE, defined as

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(\hat{y}_t - y_t)^2}{T}}, \tag{9}$$

Where the notation is the same as in equation (8). Panel B is then structured like Panel A. Also the key qualitative remarks expressed with reference to Panel A apply in this case. First, the *grand* average of the OOS RMSE values with and without commodity-specific factors are approximately the same. In some cases only (Brent crude, lumber, soybeans and especially in

[7] While the upper portion of the Table relies only on whether the state probability of a low regime exceed 0.5 or not, the bottom parts of the Table also rely on the predictions from the estimated two-state MS model for the VIX. Although one may argue that the this way of proceeding is more elegant and consistent with the framework of our paper, note that at this point we find ourselves jointly assessing the predictive power of the predictive regressions that include or not commodity-specific factors and the forecasting accuracy of a simple MS model for the VIX. The latter model, as simple and compelling as it may appear, does not represent the main object of our analysis.

the high-volatility regime, and platinum), the inclusion of basis, hedging pressure, and momentum as predictors lowers the RMSE, for others it increases it. However, for the remaining series, including commodity factors does not help. In panel B, there is some tendency for the forward stepwise algorithm to lead to lower RMSEs than the backwards algorithm, a difference that did not appear in panel A and therefore indicates that backward-type forecasts produce more large outliers than forward-type do. Second, also in this case and all series, the reported RMSEs are structurally lower for the low-volatility regime. Third, for all series but gold and live cattle futures returns, all stepwise methods and selections of predictors lead to higher RMSEs than the AR(1) benchmark does.

5. Portfolio allocation tests

Even though the OOS statistical evidence in Section 4 on the predictive power of the basis, hedging pressure, and momentum as well as on all models, even those just based on macroeconomic variables are quite grim, an investor would be more interested in the possibility to exploit the forecasts from the various models than in their MAEs or RMSEs compared to a AR(1) benchmark. Therefore, in this Section we conduct an additional OOS recursive asset allocation exercise based on the forecasts of expected futures commodity returns estimated under different combinations of model selection criteria and of types of predictors included. This exercise is particularly relevant given the increasing interest of investor in including commodities in their portfolios, as they would offer diversification opportunities with respect to other asset classes with which they tend to show modest or even negative correlations (see Daskalaki and Skiadopoulos, 2011; Giampietro et al., 2018). Recent literature, see e.g., Dal Pra et al. (2018) has shown a few cases in which a statistical model fails to outperform simple benchmarks in terms of realized OOS predictive accuracy and yet lead to a solid increase in risk-adjusted portfolio performance relative to the same benchmark.

5.1. Optimal portfolios in a mean-variance framework

Our aim is to compare the realized (risk-adjusted) OOS performance of portfolios that exploit forecasts of futures returns estimated with macroeconomic variables-based models with those that rely on forecasts produced expanding the set of predictors to include, "local" asset class-specific variables. To use a robust framework—that over short investment intervals is known to well approximate many other types of utility modes—we compute optimal portfolios in a mean-variance set up. Among the tradable assets we include the S&P 500 total return index, US 10-Year Treasuries, and 30-day T-bills to proxy for the equity market, the default risk-free bond market, and for cash investments, respectively. We include equity, bonds, and cash on top of our

15 commodity futures strategies not only for realism, to simulate the strategic asset allocation decisions of a US investor over time, but also because the literature has strongly emphasized how the decorrelation properties of commodities may make them considerably more appealing than what their Sharpe ratios reveal (see, e.g., Chong and Miffre, 2010; Daskalaki and Skiadopoulos, 2011; Henriksen et al., 2018). To retain symmetry and obtain a fair "playing field" across assets, we apply to stock and bond returns the same predictive models (for instance, in terms of whether only macro variables are to be included, as well in terms of the backward or forward stepwise approaches implemented) applied to commodity futures returns. For simplicity, we assume that instead a constant and known in advance 1-month T-bill rate.

In more detail, let $\mu_{i,t+1}$ be the predicted return with $\sigma^2_{i,t+1}$ the variance on the asset *i*. Suppose that an investor allocates her wealth at time t according to a set of weights $\boldsymbol{\omega}_t$, for which $\sum_{i=1}^{n} \omega_{i,t} = 1$ holds (n is the number of assets in the her menu of choice) and that she cares (at least locally, i.e., for a one-period investment horizon) only about the conditional mean and variance of her portfolio returns, so that she wants to maximize the functional

$$\max_{\boldsymbol{\omega}_t} \mu_{p,t+1} - \frac{\gamma}{2}\sigma^2_{P,t+1}, \tag{10}$$

where γ represents her risk aversion coefficient. If we indicate the risk-free rate as r^f_{t+1}, we have that, at any point in time, the portfolio expected return is

$$\mu_{p,t+1} = r^f_{t+1} + (\boldsymbol{\mu}_{t+1} - r^f_{t+1}{}'\mathbf{1})'\boldsymbol{\omega}_t \tag{11}$$

and the portfolio variance is

$$\sigma^2_{P,t+1} = \sum_{i,j=1}^{n} \omega_{i,t}\omega_{j,t} Cov(r_{i,t+1}, r_{j,t+1}) = \boldsymbol{\omega}_t{}'\boldsymbol{\Sigma}_{t+1}\boldsymbol{\omega}_t\ , \tag{12}$$

where $\boldsymbol{\omega}_{t+1}$ represents the vector of weights and $\boldsymbol{\Sigma}_{t+1}$ the variance-covariance matrix of asset returns predicted at time *t* for time *t*+1. This leads to classical, unconstrained program

$$\max_{\boldsymbol{\omega}_t}\ r^f_{t+1} + (\boldsymbol{\mu}_{t+1} - r^f_{t+1}{}'\mathbf{1})'\boldsymbol{\omega}_t\ - \frac{\gamma}{2}\boldsymbol{\omega}_t{}'\boldsymbol{\Sigma}_{t+1}\boldsymbol{\omega}_t \tag{13}$$

$$\boldsymbol{\omega}_{t+1}{}'\mathbf{1} = 1.$$

which, from its first order condition, implies the formulas for the optimal vector of weights:

$$\widehat{\boldsymbol{\omega}}_t = \frac{1}{\gamma}\boldsymbol{\Sigma}^{-1}_{t+1}(\boldsymbol{\mu}_{t+1} - r^f_{t+1}{}'\mathbf{1}). \tag{14}$$

No short sale constraints are imposed. We build static one-period optimal portfolios over time, considering expanding windows of data, starting from the beginning of our sample and including all the data until the time of the forecast; then we calculate the corresponding portfolio expected return for each time *t*. The recursive exercise is initialized with reference to January 1989 - December 2003 to produce a January 2004 portfolio and then iterated 107 times until the last estimation sample, January 1989-November 2012, to produce a optimal portfolio for December 2012. Because in this paper we do not compute forecast of second-order moments, we use historical data on the same expanding window describe above to estimate the sample covariance matrix.[8]

For the sake of robustness, we use three different values of the risk aversion coefficient γ (0.10, 0.25, and 0.5). To make our portfolio exercise realistic, we also take into account the transaction costs of rebalancing the portfolio at any time *t*. Additionally, we consider that an investor may want to rebalance her portfolio only if she can get an advantage in terms of the expected return of the portfolio. This means that she will decide to rebalance her portfolio at time *t* only if the transaction costs of rebalancing do not exceed the portfolio expected returns at *t+1*. Therefore, we solve the portfolio problem under the following, additional condition

$$\sum_{i=1}^{n} \left|\Delta \boldsymbol{\omega}_{i,t}\right| \times \ tc \ \geq \sum_{i=1}^{n} \boldsymbol{\mu}_{t+1} \widetilde{\boldsymbol{\omega}}_{i,t} \tag{15}$$

Where *tc* is some proportional transaction cost, $\Delta \boldsymbol{\omega}_{i,t+1}$ represents a hypothetical change in weights in case of rebalancing and $\widetilde{\boldsymbol{\omega}}_{i,t+1} \equiv \Delta \boldsymbol{\omega}_{i,t} + \Delta \boldsymbol{\omega}_{i,t+1}$ represents the hypothetical weights at *t+1* in case of rebalancing. If (15) holds, then an investor would not rebalance between *t* and *t+1*, as the implied costs are higher than the resulting expected benefits. Otherwise, we assume that the investor will rebalance her portfolio at *t*+1 and take the resulting transaction costs into account when computing realized portfolio performance. As for the imputed level of the cost *tc*, we face a need to introduce some simplification because in reality, investor willing to rebalance her portfolios would pay two types of transaction costs: costs to access the market (or infrastructure costs) and liquidity costs. While it is quite difficult to make assumptions on the first type of costs, as they are likely to depend on the exact nature of an investor (e.g., whether she is an institutional investor and of what size), we can reasonably assume the liquidity costs being close to the bid-ask spread as a percentage of the mid-price and therefore being proportional to the amount transacted. Therefore, to estimated the parameter *tc*, we have collected daily best ask and best bid prices for commodity futures contracts, for the period Jan. 1996 - Dec. 2016. For each commodity, we estimate a daily time series for *tc* as the bid-ask spread as a percentage of the mid-price. Next, we compute the average *tc* as the grand average of all such daily values. We get an average value of the transaction costs across all commodities equal to approximately 0.09%. Therefore, also because such estimates are considerably variable over time and across different commodities, to simplify we set *tc* = 0.1%. When the constraint (15) is added to the general mean-variance program in (13), the solution must be performed numerically using a non-linear optimization algorithm

[8] We have also experimented with 5-year rolling estimation windows, obtaining qualitatively similar results.

Panel A of Table 6 reports summary statistics for realized performances and recursive optimal portfolio weights obtained considering the three alternative risk aversion coefficient (0.1, 0.25, and 0.5), when the forecasts for commodity futures returns are computed from stepwise predictive regressions based on macro principal components only. Panel B reports the corresponding results when the basis, hedging pressure, and momentum are used as additional predictors. Interestingly, and almost independently of the assumed parameter γ, the largest fraction of all portfolios is allocated to 10-year Treasuries. This result seems to be plausible, given the high 10-year bond returns recorded during the 2004-2012 sample, that is in fact largely dominated by the Great Financial Crisis and the ensuing deep recession in the US, when interest rates plummeted and long-term government bonds gave extraordinarily high average returns; the demand for stocks is small but always positive. Interestingly, when commodity-specific factors are included, the share of bonds slightly declines (from 96-98% to 94-95%), the one of stocks modestly increases (from 1-2 to 2-3 percent), and residually the overall weight to commodities goes from 1-3 percent to 2-4 percent. In particular, crude oil, gold, and corn (when only macro factors are used) are the commodities in relatively high positive demand, and gasoline, wheat, cotton, and live cattle are the commodities in the largest negative demand.

The most striking results in Table 6, panel A, emerge from the upper portion devoted realized performances, especially when compared to panel C, that concerns portfolio weights under the benchmark model.[9] First, there is now a massive difference between the OOS realized performances of forward vs. backward stepwise regression methods, in the sense that while the former leads to high and appealing annualized Sharpe ratios (essentially of 0.36 independently of the selected value of γ), the former yields essentially zero or even slightly negative risk-adjusted indices. Second, such annualized Sharpe ratios are more than double vs. those obtainable under the benchmark AR(1) model (0.13 independently of γ), and this derives from both the higher realized mean returns and from lower realized portfolio standard deviations. Therefore investing in predictive technologies based on macro variables that may be though to affect the fundamental pricing kernel does pay out in a OOS back-testing exercise, but only when the selected loss function is based on the (risk-adjusted) portfolio performance, while it does not under more classical, statistical loss functions, such as the MAE and RMSE covered in Table 5.

[9] In panel C, the average allocation implied by the benchmark are even more biased towards long positions in government bonds, now exceeding 100%. The long positions in commodities are modest and now concentrated in silver, Brent crude oil, and gasoline; gold is instead massively shorted, which represents the most visible difference vs. the allocations in panels A and B.

Panel B of Table 6 answers instead the question as to whether commodity-specific factors generate economic value in a portfolio problem. Although the averages for the weights for the different asset classes and commodities that are generally similar (though not exactly identical) vs. those in panel A, unreported plots reveal that their dynamics is positively correlated but not identical. As a result, the maximum realized risk-adjusted performance in the top portion of the Table differs and it is in fact considerably higher, almost double (0.65 vs. 0.36, independently of γ), than that in panel B. This implies that accessing to the predictive power of the basis, hedging pressure, and momentum massively increases the economic value of predictive systems applied to portfolio management that includes commodity futures among the asset classes.[10] This is consistent with a recent literature that has stressed that such "local" factors may come to play a key role in making sense of the cross-section of commodity returns, e.g., de Roon et al. (2000) and Daskalaki et al. (2014). In fact, such outperformance seems to derive more from a further improvement in the mean realized portfolio returns than from a reduction of realized risk.

Table 7 repeats the comparisons performed in Table 6, when transaction costs are taken into account, which in our experiment turns out to be important also because the predictive systems that we propose end up implying a considerable degree of turnover and portfolio re-shuffling over time. Panel A is comparable to Table 6 and shows that—because an investor is allowed not to trade to rebalance her portfolio when expected cost exceeds the expected benefit—taking realistic transaction costs into account slightly improves realized portfolio performance, in risk adjusted terms. However, this remains true only for the forward predictor selection algorithm, while for very high values of γ, some instability in the ratio appears in the case of the benchmark.[11] Moreover, our earlier conclusions concerning the economic value of the commodity-specific predictors remain intact and can be quantified in a difference between annualized Sharpe ratios of 0.65 when commodity predictors are exploited vs. 0.36 when they are not, a spread of approximately 0.29.

Panels B and C of Table 7 proceed to disentangle the results under transaction costs in panel A between the periods of low- vs. high volatility.[12] Interestingly, all realized annual Sharpe ratios move up now, and the difference between the predictability regressions and the

---

[10] Also in this case, the effect can be noted only when the predictions are computed using a forward stepwise algorithm that starts out with a null model without any predictability, and progressive expands the set of predictors if and when these lower the AIC of the resulting model,

[11] In Table 7 and also as a way to check the robustness of our results, we have extended the exercise to include more values of the risk aversion coefficient γ, also exceeding 1.

[12] We have also performed this robustness check for the case without transaction costs and it gave insights qualitatively similar to those reported in the main text.

benchmark do become massive. For instance, in periods of high volatility and for $\gamma = 1$, the benchmark achieves a ratio of 0.13 to be contrasted to a stunning 2.63 from forward stepwise regressions based on macro PCs only and 2.70 from models that also include the basis, hedging pressure, and momentum; these estimates are 0.13, 0.60, and 1.08 with reference to the low-volatility period. The finding that models of predictability generate more economic value in times of distress is fully consistent with the OOS measures of forecasting accuracy commented in Section 4.

However, one implicit finding is that under transaction costs, the commodity-specific factors add more risk-adjusted performance in tranquil times (the increase in Sharpe ratio is approximately 0.48 and it exceeds the probability-weighted estimate reported above) vs. times of distress (the improvement is a modest 0.07), which implies that macroeconomic factors play a leading roles especially during the less frequent crisis periods.

6. Conclusions

In this paper, we have compared the predictive power for commodity futures returns of models based on macroeconomic variables with models augmented to include three commodity-specific factors that have received considerable attention in earlier work. Differently from previous papers, we concentrate almost entirely on the genuine OOS forecasting power of a range of regressions and a simple AR benchmark. Finally, we have assessed the relative portfolio performance of the models in a mean-variance framework.

From in-sample estimation, we conclude that neither models with macroeconomic variables alone, nor models which also include commodity-specific factors outperform the others. Both types of predictive regressions lead to modest adjusted R-squares; furthermore, all models imply the widespread appearance of non-significant coefficients for most commodity-specific factors as well as a majority of the macro principal components. Probably as a result of this, when we investigate the OOS predictive accuracy of the models over the 2004-2012 period, we find that the MAE and the RMSE scores fail to show any marked differences across models. In fact, all types of models perform worse than the benchmarks, with the exception of the predictions generated in the low volatility regime.

Against this background, the OOS results from the recursive portfolio allocations and the resulting risk-adjusted performances are instead sharp: exploiting predictive regressions—remarkably those from stepwise forward algorithms that go “simple to general”—tends to generate large increases in realized Sharpe ratios. Such ability to create economic value is further enhanced when the basis, hedging pressure, and momentum are used as predictors, especially in times of quiet financial markets and low volatility. Taking into account the implied transaction costs implied does not affect the conclusions but ,if any, makes them stronger.

Even though they can generate economic value and this should be noted by money and risk managers, it remains the case that in statistical terms, both the macroeconomic and commodity-specific factors carry limited predictive power for commodity futures returns. A potential explanation for this empirical finding is that commodities are extremely heterogeneous in terms of their economic determinants, and therefore a unique, even if detailed, set of variables may be insufficient to capture and predict futures contract returns. In future research, it may prove useful to investigate whether the inclusion of commodity factors specific *to each underlying*, individual commodity (e.g., oil inventory for oil futures, temperature levels in specific areas for orange juice output, rainfall levels in specific regions for soybean crops, etc.) may deliver further, substantial increases in forecasting power.

In this paper, we have adopted a pseudo-out of sample approach in that the predictor selection methodology implemented through stepwise regressions is only performed in the full sample and again with reference to the first date of our recursive back-testing sample (December 2003). It would be interesting to follow, among the others, Zheng, Kulkarni, and Poor (2013) to adopt online algorithms stemming from the theory of attribute distributed learning, that sequentially takes new observations and incorporates them immediately, simultaneously adjusting the way that the individual predictors are combined and providing feedback to the individual predictors for them to be retrained in order to achieve a better ensemble predictor in real time. Zheng et al. (2013) have proven that such algorithms are particularly useful when applied to financial market prediction.

Finally, although our results show that there may exist a payoff from modelling commodity futures returns (selecting the corresponding linear regressions by stepwise methods), it would seem natural to explore whether other aggregate variables (possibly also related to commodity markets) may improve the overall forecasting performance. Our set merging Ludvigson and Ng's (2009) with Welch and Goyal (2008) variables appears to be rich, but richer is always possible. Moreover, while in this paper we have classified sample dates as belonging to good and bad times and then, conditioning on that, distinguished between regimes of low- and high-volatility, it may prove interesting to develop an integrated regime switching predictive framework in which regimes and forecasting models are specified and estimated jointly, as in Giampietro et al. (2018).

References

Aslan, S., Yozgatligil, C., and Iyigun, C. (2018). Temporal clustering of time series via threshold autoregressive models: application to commodity prices. *Annals of Operations Research*, 260, 51-77.

Bakshi, G ., Gao, X., and Rossi, A. (2017). A better specified asset pricing model to explain the cross-section and time-series of commodity returns. *Management Science*, forthcoming.

Bessembinder, H., and Chan, K. (1992). Time-varying risk premia and forecastable returns in futures markets. *Journal of Financial Economics*, 32, 169-193.

Bossaerts, P., and Hillion, P. (1999). Implementing statistical criteria to select return forecasting models: what do we learn?. *Review of Financial Studies*, 12, 405-428.

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

Chong, J., Miffre, J. (2010), Conditional correlation and volatility in commodity futures and traditional asset markets. *Journal of Alternative Investments*, 12, 61-75.

Dal Pra, G., Guidolin, M., Pedio, M., and Vasile, F. (2018). Regime shifts in excess stock return predictability: an out-of-sample portfolio analysis. *Journal of Portfolio Management*, 40, 10-24.

Daskalaki, C., and Skiadopoulos, G. (2011). Should investors include commodities in their portfolios after all? New evidence. *Journal of Banking and Finance*, 35, 2606–2626.

Daskalaki, C., Kostakis, A., and Skiadopoulos, G. (2014). Are there common factors in individual commodity futures returns?. *Journal of Banking and Finance*, 40, 346–363.

DeMiguel, V., Garlappi, L., and Uppal, R. (2007). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy?. *Review of Financial studies*, 22, 1915-1953.

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

Efroymson, M. A. (1960). Multiple regression analysis. In *Mathematical Methods for Digital Computers*, A. Ralston and H. S. Wilf (eds.), pp. 191-203. Wiley, New York.

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

Fuertes, A. M., Miffre, J., and Rallis, G. (2010). Tactical allocation in commodity futures markets. *Journal of Banking and Finance*, 34, 2530–2540.

Gargano, A., and Timmermann, A. (2014). Forecasting commodity price indexes using macroeconomic and financial predictors. *International Journal of Forecasting*, 30, 825–843.

Giampietro, M., Guidolin, M., and Pedio, M. (2018). Estimating stochastic discount factor models with hidden regimes: Applications to commodity pricing. *European Journal of Operational Research*, 265, 685-702.

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

Henriksen, T. E. S., Pichler, A., Westgaard, S., and Frydenberg, S. (2018). Can commodities dominate stock and bond portfolios? *Annals of Operations Research*, forthcoming.

Hamilton, J. D., and Wu, J. C. (2015). Effects of index-fund investing on commodity futures prices. *International Economic Review*, 56, 187-205.

Hicks, J. R. (1939). *Value and Capital*. Oxford Clarendon Press, London.

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

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

Irwin, S. H., and Sanders, D. R. (2011). Index funds, financialization, and commodity futures markets. *Applied Economic Perspectives and Policy*, 33, 1-31.

Jensen, G., Johnson, R., and Mercer, J. (2000). Efficient use of commodity futures in diversified portfolios. *Journal of Futures Markets*, 20, 489-506.

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

Keynes, J. M. (1930). *A Treatise on Money*. Macmillan Press, London.

Lean, H., H., Nguyen, D., K., and Uddin, G. (2018). On the Role of Commodity Futures in Portfolio Diversification, Working Paper, Indiana University.

Ludvigson, S. C., and Ng, S. (2009). Macro factors in bond risk premia. *Review of Financial Studies*, 22, 5027-5067.

Narayan, P. K., Ahmed, H. A., and Narayan, S. (2015). Do momentum-based trading strategies work in the commodity futures markets?. *Journal of Futures Markets*, 35, 868-891.

Rapach, D., E., and Zhou, G. (2013). Forecasting stock returns. In *Handbook of Economic Forecasting* 2, Part A, 328-383.

Rapach, D. E., and Wohar, M. E. (2006). In-sample vs. out-of-sample tests of stock return predictability in the context of data mining. *Journal of Empirical Finance*, 13, 231-247.

Sharma, M. J., and Yu, S. J. (2015). Stepwise regression data envelopment analysis for variable reduction. *Applied Mathematics and Computation*, 253, 126-134.

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

Stock, J. H., and Watson, M. W. (2002). Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association*, 97, 1167-1179.

Stock, J. H., and Watson, M. W. (2006). Forecasting with many predictors. In *Handbook of Economic Forecasting*, G. Elliott, C. Granger, and A. Timmermann (eds.), 1, 515-554. Elsevier.

Stoll, H.R. (1979). Commodity futures and spot price determination and hedging in capital market equilibrium. *Journal of Financial and Quantitative Analysis*, 14, 873–894.

Tang, K., and Xiong, W. (2012). Index investment and the financialization of commodities. *Financial Analysts Journal*, 68, 54-74.

Zheng, H., Kulkarni, S. R., and Poor, H. V. (2013). A sequential predictor retraining algorithm and its application to market prediction. *Annals of Operations Research*, 208, 209-225.

You, L., and Daigler, R. T. (2013). A Markowitz optimization of commodity futures portfolios. *Journal of Futures Markets*, 33, 343-368.

Welch, I., and Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, 21, 1455-1508.

Table 1

Principal components factor loadings

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Production Index	-0.04	0.07	-0.03	0.01	-0.04	0.05	-0.02	0.14	-0.01	0.01
Production Index less transfers	-0.11	0.10	-0.02	0.07	-0.02	0.12	-0.08	0.14	0.08	-0.07
Real Consumption	-0.01	0.10	-0.10	0.05	0.02	-0.01	0.15	0.05	-0.12	0.13
Manufacturin & Trade sales	-0.06	0.09	-0.12	0.04	0.14	-0.08	0.09	-0.03	-0.11	0.22
Retail sales	0.01	0.09	-0.11	0.04	0.06	-0.06	0.15	0.10	-0.18	0.12
Internal Production : total	-0.19	0.05	-0.04	-0.03	0.20	0.03	-0.01	-0.02	0.01	-0.04
Internal Production : products	-0.17	0.04	-0.05	-0.02	0.22	0.06	-0.01	-0.05	0.05	-0.10
Internal Production : final prod	-0.15	0.04	-0.05	-0.02	0.23	0.07	0.00	-0.08	0.04	-0.11
Internal Production : consumer goods	-0.12	0.05	-0.05	-0.04	0.23	0.04	0.00	-0.13	0.06	-0.11
Internal Production : durable consumer goods	-0.12	0.07	-0.05	-0.06	0.22	0.05	-0.04	-0.11	0.00	-0.06
Internal Production : cons nondble	-0.06	0.00	-0.02	0.00	0.11	0.01	0.03	-0.08	0.09	-0.10
Internal Production : bus eqpt	-0.17	0.01	-0.05	0.01	0.15	0.09	-0.01	0.01	0.00	-0.07
Internal Production : materials	-0.18	0.05	-0.03	-0.03	0.13	-0.01	0.00	0.02	-0.04	0.06
Internal Production : durable goods materials	-0.18	0.06	-0.01	-0.01	0.14	0.01	-0.02	0.03	-0.01	0.01
Internal Production : nondurable goods materials	-0.09	0.00	-0.02	-0.07	0.05	-0.11	0.00	0.09	-0.08	0.01
Internal Production : manufacturing	-0.19	0.05	-0.04	-0.03	0.20	0.02	-0.02	0.02	0.00	-0.04
Internal Production : residential utilities	0.03	0.17	0.20	-0.02	0.05	0.04	0.16	-0.02	0.03	-0.03
Internal Production : fuels	0.00	0.00	-0.03	-0.05	0.09	-0.02	0.09	0.07	-0.03	0.04
NAPM production index	-0.19	0.04	0.08	0.00	-0.07	-0.11	-0.04	0.00	0.04	0.00
Capacity utilization	-0.12	-0.14	-0.10	0.12	-0.05	0.14	-0.05	0.06	-0.06	0.09
Index of Help-wanted advertising	-0.10	0.03	0.02	-0.01	0.03	0.02	-0.10	0.12	0.21	-0.06
Ratio of Help-Wanted Ads/No. Unemployed (AC)	-0.14	0.03	0.02	0.00	0.02	0.04	-0.10	0.10	0.19	0.00
Civilian Labor Force: Employed, Total	-0.09	-0.01	0.05	0.01	-0.05	0.03	-0.06	0.15	0.04	0.08
Civilian Labor Force: Employed, Nonagric.Industries	-0.08	0.00	0.05	0.01	-0.05	0.04	-0.05	0.15	0.04	0.08
Unemployment Rate: All Workers, 16 Years & Over	0.12	-0.02	-0.01	-0.02	0.01	-0.04	0.03	-0.01	-0.07	-0.10
Unemployment By Duration: Average Duration In Weeks	0.05	0.04	-0.02	-0.08	-0.08	-0.09	-0.05	0.05	0.01	-0.09
Unemploy By Duration: Persons Unempl Less Than 5 Wks	0.03	-0.03	-0.02	0.05	0.09	-0.03	0.09	0.00	-0.03	0.02
Unemploy By Duration: Persons Unempl 5 To 14 Wks	0.06	-0.01	0.00	-0.01	-0.03	0.02	-0.02	-0.03	-0.04	-0.09
Unemploy By Duration: Persons Unempl 15 To 26 Wks	0.08	0.01	-0.01	-0.06	-0.08	0.01	-0.05	0.01	-0.03	-0.09
Initial Claims for Unemployement Insurance	0.07	-0.07	0.07	0.04	-0.04	0.03	-0.04	-0.02	-0.03	-0.04
Employees On Nonfarm Payrolls - Goods-Producing	-0.19	-0.01	-0.01	0.09	0.01	0.09	-0.02	0.09	-0.06	0.09
Employees On Nonfarm Payrolls - Mining	-0.01	0.01	0.00	0.01	0.03	0.13	0.04	0.07	-0.03	-0.03
Employees On Nonfarm Payrolls - Manufacturing	-0.19	-0.07	-0.02	0.10	0.02	0.07	-0.06	-0.01	-0.06	0.05
Employees On Nonfarm Payrolls - Durable Goods	-0.19	-0.03	0.00	0.10	0.03	0.09	-0.05	-0.04	-0.06	0.06
Employees On Nonfarm Payrolls - Nondurable Goods	-0.14	-0.14	-0.07	0.06	-0.01	-0.03	-0.08	0.08	-0.03	-0.01
Employees On Nonfarm Payrolls - Financial Activities	-0.01	0.06	0.02	0.05	0.02	0.15	-0.01	0.03	-0.04	0.07
Employees On Nonfarm Payrolls - Government	0.01	0.02	-0.05	-0.05	-0.05	0.03	-0.02	-0.03	-0.07	-0.02
Avg Weekly Hrs of Prod - Goods-Producing	-0.05	0.04	-0.08	-0.04	0.10	-0.04	0.03	0.18	-0.02	-0.18
Avg Weekly Hrs of Prod - Mfg Overtime	-0.06	0.01	-0.04	-0.09	0.06	-0.05	0.02	0.11	-0.01	-0.17
Average Weekly Hours, Mfg.	-0.07	0.04	-0.08	-0.05	0.12	-0.04	0.02	0.13	0.02	-0.16
NAPM Employment Index	-0.18	-0.01	0.11	0.08	-0.07	0.08	0.03	0.05	0.01	0.05
Housing Starts:Nonfarm(1947-58);Total Farm&Nonfarm(1959)	0.01	0.06	-0.02	-0.01	0.00	-0.07	0.02	0.31	-0.06	-0.04
Housing Starts:Northeast	0.00	0.04	-0.02	-0.02	0.02	-0.03	0.02	0.11	-0.16	-0.02
Housing Starts:Midwest	0.02	0.04	-0.05	0.01	-0.01	-0.05	0.06	0.20	-0.08	-0.04
Housing Starts:South	0.00	0.04	-0.02	-0.03	0.02	-0.06	0.02	0.25	-0.07	0.02
Housing Starts:West	0.00	0.01	0.03	0.03	-0.03	0.01	-0.04	0.09	0.13	-0.08
Housing Authorized: Total New Priv Housing Units	0.01	0.07	-0.04	-0.02	0.03	-0.05	0.05	0.30	-0.02	0.01
Houses Authorized By Build. Permits:Northeast	-0.01	0.06	-0.05	-0.04	0.02	-0.04	0.05	0.18	-0.14	0.12
Houses Authorized By Build. Permits:Midwest	0.03	0.02	-0.01	-0.04	-0.03	-0.04	0.04	0.31	-0.07	-0.02
Houses Authorized By Build. Permits:South	0.00	0.05	-0.04	-0.02	0.05	-0.06	0.07	0.25	-0.03	-0.02
Houses Authorized By Build. Permits:West	0.00	0.04	0.00	0.05	0.01	0.01	-0.02	-0.01	0.14	0.00
Purchasing Managers' Index	-0.20	0.02	0.08	0.03	-0.09	-0.06	-0.02	0.03	0.02	0.01
Napm New Orders Index	-0.18	0.05	0.07	-0.03	-0.08	-0.11	-0.05	0.01	0.07	-0.03
Napm Vendor Deliveries Index	-0,15	0,06	0,14	0.06	-0.11	-0.10	0.06	0.01	-0.05	0.01
Napm Inventories Index	-0.12	-0.02	0.06	0.10	-0.08	0.06	0.03	0.08	0,02	0.07
Mfrs' New Orders, Consumer Goods And Materials	-0.07	0.04	-0.07	-0.03	0.10	-0.05	0.04	-0.13	0.02	0.22
Mfrs' New Orders, Durable Goods Industries	-0.06	0.04	-0.04	0.02	0.09	-0.04	0.04	-0.14	0.02	0.29
Mfrs' New Orders, Nondefense CaProduction Indextal Goods	-0.04	0.02	-0.03	0.04	0.02	-0.03	0.02	-0.09	0.07	0.24
Manufacturing And Trade Inventories	-0.11	-0.05	0.08	0.12	-0.07	0.05	-0.05	0.00	0.03	0.04
Ratio, Mfg. And Trade Inventories To Sales	0.03	-0.11	0.15	0.01	-0.15	0.09	-0.10	0.03	0.11	-0.21
Money Stock: M1	0.03	0.00	0.04	-0.15	0.03	-0.08	-0.27	0.08	0.13	0.07
Money Stock: M2	0.10	0.07	0.10	-0.06	0.09	0.21	-0.06	0.08	0.04	0.12
Money Stock: Currency held by the public	0.00	0.00	-0.01	-0.08	-0.03	-0.13	-0.12	-0.06	-0.01	0.16
Money Supply: Real M2 (AC)	0.09	0.14	0.10	-0.02	0.05	0.20	-0.13	0.06	0.02	0.11

Table 1 (Continued)

Principal components factor loadings

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Monetary Base, Adj For Reserve Requirement Changes	0.00	-0.01	0.06	-0.12	0.01	-0.07	-0.22	0.02	0.06	0.20
Depository Inst Reserves:Total, Adj For Reserve Req Chgs	0.01	-0.04	0.12	-0.14	0.04	0.03	-0.26	0.09	0.09	0.12
Depository Inst Reserves:Nonborrowed,Adj Res Req Chgs	0.02	-0.04	0.11	-0.14	0.03	0.03	-0.27	0.10	0.09	0.12
Commercial and Industrial Loans, All Commercial Banks	0.06	0.16	0.18	-0.02	0.04	0.11	0.16	-0.01	0.03	0.00
Change Commercial and Industrial Loans, All Commercial Banks	-0.01	-0.01	0.06	-0.03	-0.02	0.01	-0.09	0.08	-0.02	-0.10
Ratio, Consumer Installment Credit To Personal Income	0.01	0.04	0.09	0.06	-0.05	0.02	0.10	-0.06	-0.15	0.13
S&P 500	0.00	0.05	-0.17	0.16	-0.07	-0.01	0.08	0.05	0.29	0.08
S&P: indust	-0.01	0.05	-0.17	0.14	-0.07	-0.01	0.08	0.05	0.29	0.09
S&P div yield	0.00	-0.06	0.16	-0.15	0.07	0.01	-0.08	-0.05	-0.29	-0.08
S&P PE ratio	0.06	0.08	-0.19	0.08	-0.02	-0.06	0.04	0.01	0.27	0.04
DP	0.03	-0.03	-0.11	-0.12	0.02	-0.27	-0.16	-0.04	0.02	-0.07
b/m	-0.03	-0.03	0.05	-0.10	0.03	-0.01	0.02	-0.05	-0.01	-0.13
ntis	0.01	-0.02	-0.06	-0.09	0.05	0.02	-0.02	-0.04	0.01	-0.15
svar	0.00	-0.06	0.08	-0.02	0.05	-0.01	-0.05	0.02	-0.13	0.02
Fed Funds	-0.15	-0.08	0.07	0.09	-0.13	0.04	0.00	-0.02	-0.10	-0.05
Comm paper	-0.16	-0.03	0.01	-0.02	-0.17	0.08	0.02	-0.02	-0.10	-0.01
3 mo T-bill	-0.15	-0.03	-0.02	-0.01	-0.20	0.07	0.04	-0.01	-0.06	-0.02
6 mo T-bill	-0.15	-0.02	-0.04	-0.07	-0.20	0.09	0.04	-0.02	-0.05	-0.01
1 yr T-bond	-0.14	0.01	-0.07	-0.13	-0.20	0.11	0.06	-0.02	0.00	0.01
5 yr T-bond	-0.07	0.03	-0.10	-0.23	-0.16	0.11	0.09	-0.04	0.04	0.04
10 yr T-bond	-0.06	0.03	-0.08	-0.26	-0.14	0.10	0.09	-0.03	0.04	0.04
Aaa bond	-0.07	-0.01	-0.03	-0.26	-0.09	0.11	0.07	-0.04	-0.03	0.09
Baa bond	-0.05	0.00	-0.02	-0.26	-0.09	0.13	0.05	-0.04	-0.05	0.08
CP-FF spread	-0.14	0.10	0.01	-0.05	-0.13	-0.11	-0.01	-0.02	0.01	0.04
3 mo-FF spread	-0.10	0.14	0.02	-0.10	-0.08	-0.22	-0.02	-0.05	0.00	-0.05
6 mo-FF spread	-0.13	0.12	0.02	-0.08	-0.10	-0.22	-0.02	-0.05	-0.02	-0.03
1 yr-FF spread	-0.16	0.07	-0.01	-0.07	-0.12	-0.20	-0.03	-0.06	-0.02	-0.04
5 yr-FF spread	0.04	0.07	-0.14	-0.27	-0.06	0.07	0.06	0.00	0.07	0.06
10 yr-FF spread	0.06	0.06	-0.13	-0.27	-0.02	0.06	0.05	0.01	0.08	0.06
Aaa-FF spread	0.08	0.03	-0.09	-0.25	0.04	0.05	0.02	0.01	0.05	0.11
Baa-FF spread	-0.02	0.13	0.04	-0.14	-0.02	-0.28	-0.03	-0.06	0.03	-0.07
Nominal E§ective Exchange Rate, Unit Labor Costs (IMF)	-0.01	-0.01	-0.09	-0.09	-0.06	0.18	0.04	0.11	-0.07	-0.09
Foreign Exchange Rate: Switzerland - Swiss Franc Per U.S.$	-0.02	0.04	-0.11	-0.05	-0.08	0.17	0.05	-0.02	0.06	-0.06
Foreign Exchange Rate: Japan - Yen Per U.S.$	0.00	0.03	-0.07	-0.01	-0.01	0.19	0.01	-0.01	-0.02	-0.19
Foreign Exchange Rate: United Kingdom - Cents Per Pound	0.01	-0.01	0.10	0.05	0.05	-0.14	-0.04	0.03	-0.01	0.04
Foreign Exchange Rate: Canada - Canadian $ Per U.S.$	-0.02	-0.01	-0.04	-0.09	0.02	0.08	-0.07	0.03	-0.25	0.03
Producer Price Index: Finished Goods	-0.03	-0.18	0.13	-0.07	0.04	-0.01	0.13	0.10	0.12	0.02
Producer Price Index: Finished Consumer Goods	-0.03	-0.17	0.14	-0.07	0.04	-0.01	0.15	0.10	0.11	0.04
Producer Price Index:I ntermed Mat.Supplies & Components	-0.07	-0.16	0.16	-0.05	0.02	-0.08	0.14	0.03	0.07	0.00
Producer Price Index: Crude Materials	-0.04	-0.11	0.11	0.00	0.08	-0.06	0.13	0.02	0.12	0.00
Spot market price index: bls & crb: all commodities	-0.07	0.01	0.07	-0.05	-0.04	-0.07	0.02	-0.06	0.04	-0.09
Producer Price Index: Nonferrous Materials	-0.10	0.00	0.08	-0.06	-0.04	-0.10	0.07	-0.04	0.03	-0.02
Napm Commodity Prices Index	-0.09	-0.07	0.13	0.05	-0.11	-0.10	0.08	-0.01	-0.04	-0.05
CProduction Index-U: All Items	-0.02	-0.24	0.05	-0.09	0.07	-0.01	0.11	0.07	0.08	0.04
CProduction Index-U: Apparel & Upkeep	-0.02	-0.09	-0.10	-0.03	0.03	0.01	0.00	-0.07	0.01	0.00
CProduction Index-U: Transportation	0.02	0.20	0.20	-0.01	0.02	0.02	0.15	-0.02	0.02	0.00
CProduction Index-U: Medical Care	0.01	0.22	0.20	-0.02	0.02	0.00	0.13	-0.02	0.03	0.00
CProduction Index-U: Commodities	0.02	0.21	0.20	-0.02	0.02	0.02	0.14	-0.02	0.02	0.00
CProduction Index-U: Durables	-0.03	-0.12	-0.13	0.01	-0.06	-0.05	-0.08	-0.03	-0.10	0.05
CProduction Index-U: Services	0.05	-0.17	-0.06	0.01	0.03	-0.04	0.05	0.01	0.03	-0.04
CProduction Index-U: All Items Less Food	-0.02	-0.23	0.05	-0.09	0.07	-0.03	0.11	0.05	0.09	0.05
CProduction Index-U: All Items Less Shelter	0.02	0.21	0.20	-0.02	0.02	0.01	0.14	-0.02	0.02	0.00
CProduction Index-U: All Items Less Midical Care	-0.02	-0.23	0.06	-0.09	0.07	-0.01	0.12	0.07	0.09	0.04
Pce, Impl Pr Deflator:Pce (BEA)	-0.02	-0.22	-0.04	-0.07	0.06	-0.07	0.21	0.01	0.02	-0.02
Pce, Impl Pr Deflator:Pce; Durables (BEA)	-0.02	-0.13	-0.14	0.00	-0.04	-0.11	0.02	-0.05	-0.09	0.02
Pce, Impl Pr Deflator:Pce; Nondurables (BEA)	-0.03	-0.18	0.10	-0.12	0.07	0.00	0.13	0.07	0.10	0.07
Pce, Impl Pr Deflator:Pce; Services (BEA)	0.02	-0.10	-0.13	0.03	0.03	-0.08	0.18	-0.07	-0.05	-0.12
Avg Hourly Earnings of Prod - Goods-Prod	-0.01	-0.02	0.05	-0.02	0.02	0.12	0.00	-0.08	0.03	-0.11
Avg Hourly Earnings of Prod - Construction	0.01	-0.04	0.05	0.02	-0.09	0.09	0.04	-0.05	0.06	-0.07
Avg Hourly Earnings of Prod - Manufacturi	-0.03	-0.02	0.03	-0.05	0.08	0.08	-0.04	-0.12	0.02	-0.09
U. Of Mich. Index Of Consumer Expectations (UM)	-0.01	0.10	-0.12	0.03	-0.12	0.03	-0.02	0.02	0.10	-0.12
Baseline_overall_index	-0.01	-0.06	0.12	-0.05	0.09	0.03	-0.12	0.00	-0.10	0.05
News_Based_Policy_Uncert_Index	-0.01	-0.06	0.11	-0.04	0.10	0.03	-0.11	-0.02	-0.10	0.03
Crude oil price	-0.05	-0.10	0.10	-0.07	0.01	-0.04	0.13	-0.03	0.04	0.06

Table 2

Summary statistics for commodity futures returns

Variable	Mean	Median	SD	Skewness	Kurtosis
Brent Crude Oil	0.015	0.014	0.095	0.516	3.568
Corn	-0.003	-0.007	0.074	-0.098	0.499
Lumber	-0.006	-0.008	0.095	0.575	1.684
Live Cattle	0.002	0.001	0.039	-0.481	2.720
Soybeans	0.004	0.000	0.067	-0.083	0.952
Wheat	-0.005	-0.007	0.081	0.499	2.097
Cocoa	-0.002	-0.010	0.086	0.580	1.127
Cotton No.2	0.000	-0.004	0.076	0.375	0.863
Gold 100 Oz	0.003	-0.003	0.045	0.204	1.481
Gasoline	0.016	0.015	0.099	0.414	2.563
Orange Juice	-0.002	-0.008	0.088	0.621	1.602
Coffee C	0.001	-0.010	0.111	1.020	2.729
Platinum	0.009	0.006	0.098	0.487	3.302
Sugar No.11	0.008	0.009	0.092	0.253	0.740
Silver 5000 Oz	0.005	-0.002	0.081	0.031	1.081

Table 3

Summary statistics for commodity-specific factors

Variable	Mean	Median	SD	Skewness	Kurtosis
Hedging Pressure	0.004	0.005	0.044	-0.125	1.012
Basis	0.010	0.011	0.045	-0.009	1.393
Momentum	0.009	0.009	0.050	0.353	3.329

Table 4

Estimation of backward and forward regression models

Panel A – Results for models including only macro principal components, backward algorithm

						LOW VOLATILITY							
Commodity Return	**Intercept**	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**	**PC9**	**PC10**	**R-squared**	**Adjusted R-squared**
Brent Crude Oil	0.0194**							0.0133**		-0.0099	-0.0092	0.0914	0.0649
Corn	0.0006						0.0039*					0.0266	0.0173
Lumber	0.0052												
Live Cattle	0.0017		-0.0019*			0.0019						0.0490	0.0308
Soybeans	0.0025		0.0021		-0.0035*		0.0027					0.0654	0.0382
Wheat	-0.0018						-0.0041		0.0045*			0.0045	0.0323
Cocoa	-0.0098	-0.0032*										0.0300	0.0207
Cotton No.2	-0.0063	-0.0029*	-0.0029	-0.0043*		-0.0067***						0.1021	0.0668
Gold 100 Oz	-0.0033			0.0023								0.0246	0.0154
Gasoline	0.0122												
Orange Juice	-0.0030												
Coffee C	0.0060					-0.0095*				-0.0178**		0.0757	0.0579
Platinum	-0.0033	-0.0037**				-0.0062***	0.0038	-0.0074*		0.0082**		0.1863	0.1460
Sugar No.11	0.0078	-0.0035*								0.0091*		0.0562	0.0380
Silver 5000 Oz	-0.0015			0.0041				-0.0060				0.0425	0.0241
						HIGH VOLATILITY							
Commodity Return	**Intercept**	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**	**PC9**	**PC10**	**R-squared**	**Adjusted R-squared**
Brent Crude Oil	-0.0017	-0.0086	0.0165***									0.2137	0.1905
Corn	-0.0153**					0.0043					-0.0056*	0.0736	0,0463
Lumber	-0.0375***		0.0137***		-0.0047		0.0067		0.0111*			0.2104	0.1626
Live Cattle	0.0027												
Soybeans	-0.0319*	-0.0026	0.0087**	0.0069*	-0.0062**			0.0104***	0.0060	-0.0057*		0.2082	0.1203
Wheat	-0.0511***		0.0112***	0.0096***						-0.0080***		0.2825	0.2504
Cocoa	-0.0673**		0.0192***	0.0082		0.0098*		0.0151***		-0.0065		0.2267	0.1672
Cotton No.2	-0.0159	-0.0064***	0.0077*				-0.0069*	0.0064*		-0.0054		0.2441	0.1860
Gold 100 Oz	-0.0070		0.0040*		-0.0034*							0.1275	0.1018
Gasoline	-0.0650*	-0.0096***	0.0309***	0.01306*			0.0142**	0.0092				0.3141	0.2613
Orange Juice	0.0151		-0.0082**			-0.0047*	-0.0067*	-0.0073**		-0.0103***		0.2283	0.1689
Coffee C	-0.0174						-0.0078					0.0349	0.0209
Platinum	0.0313*	-0.0067**		-0.0073	0.0061	-0.0108**					0.0143**	0.2401	0.1816
Sugar No.11	-0.0224		0.0106**	0.0061				0.0098**				0.1357	0.0970
Silver 5000 Oz	-0.0137	-0.0033*	0.0077***			0.0051*					-0.0046	0.1631	0.1124

***significant at 1% level, **significant at 5% level, *significant at 10% level

Table 4 (Continued)

Estimated backward and forward stepwise regressions

Panel B – Results for models including only macro principal components, forward algorithm

						LOW VOLATILITY							
Commodity Return	**Intercept**	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**	**PC9**	**PC10**	**R-squared**	**Adjusted R-squared**
Brent Crude Oil	0.0212**							0.0139**				0.0573	0.0483
Corn	0.0006						0.0039*					0.0266	0.0173
Lumber	-0.0039			-0.0076*								0.0283	0.0191
Live Cattle	0.0017		-0.0019*			0.0019						0.0490	0.0308
Soybeans	-0.0012				-0.0032*							0.0282	0.0190
Wheat	-0.0018						-0.0041		0.0045*			0.0505	0.0323
Cocoa	-0.0098	-0.0032*										0.0300	0.0207
Cotton No.2	0.0063				-0.0033	-0.0055**						0.0840	0.0664
Gold 100 Oz	-0.0033			0.0023								0.0246	0.0154
Gasoline	0.0122												
Orange Juice	-0.0030												
Coffee C	0.0022	-0.0047				-0.0101**				-0.0158*			
Platinum	-0.0033	-0.0037**				-0.0062***	0.0038	-0.0074**		0.0082**		0.1863	0.1460
Sugar No.11	0.0078	-0.0035*								0.0091*		0.0562	0.0380
Silver 5000 Oz	-0.0015			0.0041				-0.0060				0.0425	0.0241
						HIGH VOLATILITY							
Commodity Return	**Intercept**	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**	**PC9**	**PC10**	**R-squared**	**Adjusted R-squared**
Brent Crude Oil	-0.0017	-0.0086***	0.0165***									0.2137	0.1905
Corn	-0.0153**					0.0043					-0.0056*		
Lumber	-0.0376***		0.0137***		-0.0047		0.0067		0.0111**			0.2104	0.1626
LiveCattle	0.0027												
Soybeans	-0.0011				-0.0053**			0.0041			-0.0064*	0.1403	0.1018
Wheat	-0.0021						-0.0057*	-0.0081***		-0.0091***		0.2466	0.2129
Cocoa	0.0182			-0.0072*		0.0064	-0.0134**			-0.0089*		0.1775	0.1276
Cotton No.2	0.0185*	-0.0063***		-0.0066*			-0.0112***			-0.0060		0.2233	0.1762
Gold 100 Oz	-0.0070		0.0040**		-0.0034**							0.1275	0.1018
Gasoline	-0.0009	-0.0108***	0.0181***		-0.0053					-0.0089*		0.3009	0.2585
Orange Juice	-0.0223**			0.0061**						-0.0092***		0.1685	0.1441
Coffee C	-0.0174						-0.0078					0.0349	0.0209
Platinum	0.03134*	-0.0067**		-0.0073	0.0061**	-0.0107**					0.0143	0.2401	0.1816
Sugar No.11	0.0214		-0.0083**		0.0059							0.0739	0.0466
Silver 5000 Oz	-0.0137	-0.0033***	0.0077*			0.0051*					-0.0046	0.1631	0.1124

***significant at 1% level, **significant at 5% level, *significant at 10% level

Table 4 (Continued)

Estimated backward and forward stepwise regressions

Panel C – Results for models including both macro principal components and commodity-specific factors, backward algorithm

Commodity Return	Intercept	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	HP	Basis	Momentum	R-squared	Adjusted R-squared
								LOW VOLATILITY								
Brent Crude Oil	0.0163							0.0116**		-0.0115*	-0.0094	-0.3885	0.1276	0.0770	0.1203	0.0675
Corn	0.0033						0.0039*					-0.0800	-0.1889	-0.0749	0.0430	0.0055
Lumber	0.0053											0.2519	0.0031	-0.0195	0.0098	-0.0190
Live Cattle	0.0005		-0.0021**			0.0019						0.0740	0.0521	0.0341	0.0620	0.0156
Soybeans	0.0037		0.0019		-0.0033*		0.0029					0.0664	-0.0585	-0.0985	0.0736	0.0180
Wheat	0.0002						-0.0039		0.0043			0.0322	-0.1588	-0.0336	0.0566	0.0099
Cocoa	-0.0120	-0.0027										0.0747	0.4010*	-0.2003	0.0665	0.0299
Cotton No.2	-0.0048	-0.0026	-0.0033	-0.0039		-0.0063***						0.1540	-0.0203	-0.0997	0.1138	0.0511
Gold 100 Oz	-0.0047			0.0026*								0.1906**	0.0965	0.0597	0.0981	0.0627
Gasoline	0.0127											-0.3510	-0.0391	0.0122	0.0287	0.0004
Orange Juice	-0.0059											0.3466	0.4232	-0.2005	0.0336	0.0054
Coffee C	0.0083					-0.0079				-0.0162*		0.5583*	-0.2175	0.0142	0.1100	0.0659
Platinum	-0.0026	-0.0036**				-0.0061**	0.0038	-0.0072*		0.0084**		0.0389*	-0.0371	-0.0180	0.1872	0.1208
Sugar No.11	0.0072	-0.0042**								0.0088*		-0.3540*	0.0011	0.0220	0.0917	0.0467
Silver 5000 Oz	-0.0014			0.004628*				-0.0050				0.3694**	-0.0252	0.1300	0.1213	0.0778
								HIGH VOLATILITY								
Commodity Return	Intercept	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	HP	Basis	Momentum	R-squared	Adjusted R-squared
Brent Crude Oil	-0.0027	-0.0088***	0.0168***									0.1808	0.2228	-0.1531	0.2268	0.1673
Corn	-0.0158**					0.0039					-0.0053	0.2434	0.0191	0.0380	0.1135	0.0453
Lumber	-0.0354**		0.0136**		-0.0042		0.0068		0.0098*			-0.2508	0.0185	-0.1449	0.2399	0.1555
Live Cattle	0.0035											0.1182	-0.0138	-0.0220	0.0098	-0.0346
Soybeans	-0.0276	-0.0028	0.0086*	0.0067*	-0.0054**			0.0095*	0.0056	-0.0057*		0.1336	0.1057	-0.2180	0.2278	0.0991
Wheat	-0.0507***		0.012***	0.0088***						-0.0071**		0.1896	0.0858	0.0430	0.3089	0.2441
Cocoa	-0.0702**		0.0192***	0.0080		0.0105**		0.0147***		-0.0064		-0.1346	0.1119	0.0739	0.2321	0.1330
Cotton No.2	-0.0200	-0.0061***	0.0078**				-0.0072*	0.0056*		0.0051		-0.0560	0.3177	-0.0434*	0.2805	0.1876
Gold 100 Oz	-0.0039		0.0040**		-0.0027*							0.1396	0.0202	-0.1651	0.1573	0.0925
Gasoline	-0.0622*	-0.0099***	0.0305***	0.0124*			0.0138**	0.0092				0.2061	0.0424	-0.0360	0.3198	0.2321
Orange Juice	0.0214*		-0.0086***			-0.0058*	-0.0078**	-0.0078**		-0.0104***		0.3409	0.0892	-0.2811	0.2683	0.1738
Coffee C	-0.0187						-0.0075					-0.3370	-0.0280	0.0644	0.0533	-0.0041
Platinum	0.0180	-0.0062*		-0.0088*	0.0038	-0.0086					0.0161**	-0.2601	0.3922	0.3876	0.2874	0.1954
Sugar No.11	-0.0253			0.0104**	0.0055			0.0101**				-0.0313	0.0579	0.1063	0.1392	0.0585
Silver 5000 Oz	-0.0127	-0.0032*	0.0078**			0.0052*					-0.0046	-0.1397	0.0077	-0.0834	0.1828	0.0920

***significant at 1% level, **significant at 5% level, *significant at 10% level

Table 4 (Continued)

Estimated backward and forward stepwise regressions

Panel D – Results for models including both macro principal components and commodity-specific factors, forward algorithm

LOW VOLATILITY																
Commodity Return	**Intercept**	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**	**PC9**	**PC10**	**HP**	**Basis**	**Momentum**	**R-squared**	**Adjusted R-squared**
Brent Crude Oil	0.0199**							0.0128**				-0.3476	0.0491	0.0195	0.0801	0.0440
Corn	0.0033						0.0040*					-0.0800	-0.1889	-0.0749	0.0430	0.0055
Lumber	-0.0038			-0.0072								0.2067	0.0124	0.0082	0.0353	-0.0025
Live Cattle	0.0005		-0.0021*			0.0019						0.0740	0.0521	0.0341	0.0620	0.0156
Soybeans	7.06E-02				-2.95E+00							0.0000	0.0000	0.0000	0.0371	-0.0008
Wheat	0.0002						-0.0039		0.0043			0.0322	-0.1588	-0.0336	0.0566	0.0099
Cocoa	-0.0120	-0.0027										0.0747	0.4010*	-0.2003	0.0665	0.0299
Cotton No.2	0.0072				-0.0032	-0.0053**						0.1632	-0.0100	-0.0988	0.0979	0.0533
Gold 100 Oz	-0.0047			0.0025*								0.1906**	0.0965	0.0597	0.0981	0.0627
Gasoline	0.0127											-0.3510	-0.0391	0.0122	0.0287	0.0004
Orange Juice	-0.0059											0.3466	0.4232	-0.2005	0.0336	0.0054
Coffee C	0.0052	-0.0041				-0.0083				-0.0145*		0.4693	-0.2798	0.0741	0.1227	0.0701
Platinum	-0.0026	-0.0036**				-0.0061**	0.0038	-0.0072*		0.0084**		0.0389	-0.0371	-0.0180	0.1872	0.1208
Sugar No.11	0.0072	-0.0042**								0.0088*		-0.3540*	0.0011	0.0220	0.0917	0.0467
Silver 5000 Oz	-0.0014			0.0046*				-0.0050				0.3694**	-0.0252	0.1300	0.1213	0.0778
HIGH VOLATILITY																
Commodity Return	**Intercept**	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**	**PC9**	**PC10**	**HP**	**Basis**	**Momentum**	**R-squared**	**Adjusted R-squared**
Brent Crude Oil	-0.0027	-0.0088***	0.0169***									0.1808	0.2228	-0.1531	0.2268	0.1673
Corn	-0.0159**					0.0039					-0.0053	0.2434	0.0191	0.0380	0.1135	0.0453
Lumber	-0.0354**		0.0136***		-0.0042		0.0068		0.00975*			-0.2508	0.0185	-0.1449	0.2399	0.1555
Live Cattle	0.0035											0.1182	-0.0138	-0.0220	0.0098	-0.0346
Soybeans	0.0004				-0.0047*			0.0034			-0.0057	0.0568	0.1418	-0.1623	0.1556	0.0765
Wheat	-0.0039						-0.0057*	-0.0078***		-0.0083***		0.2219	0.1537	-0.0426	0.2786	0.2110
Cocoa	0.0171			-0.0071		0.0067	-0.0137**			-0.0091		-0.0295	0.2237	-0.1418	0.1897	0.0997
Cotton No.2	0.0143	-0.0060***		-0.0068**			-0.0114***			-0.0058		-0.0301	0.3685*	-0.1013	0.2720	0.1911
Gold 100 Oz	-0.0039		0.0040**		-0.0027							0.1396	0.0202	-0.1651	0.1573	0.0925
Gasoline	-0.0004	-0.0111***	0.0183***		-0.0047**					-0.0086*		0.2104	0.1320	-0.1326	0.3086	0.2318
Orange Juice	-0.0199**			0.0058**						-0.0088**		0.2592	0.0498	-0.1216	0.1881	0.1256
Coffee C	-0.0187						-0.0075					-0.3370	-0.0280	0.0644	0.0533	-0.0041
Platinum	0.0180	-0.0062*		-0.0088*	0.0038	-0.0086					0.0161**	-0.2601	0.3922	0.3876	0.2874	0.1954
Sugar No.11	0.0177		-0.0081**		0.0055							-0.0300	0.1518	0.0396	0.0801	0.0093
Silver 5000 Oz	-0.0127	-0.0032*	0.0078**			0.005199*					-0.0046	-0.1397	0.0077	-0.0834	0.1828	0.0920

***significant at 1% level, **significant at 5% level, *significant at 10% level

Table 4 (Continued)

Estimated backward and forward stepwise regressions

Panel E – AR(1) Benchmark

LOW VOLATILITY			HIGH VOLATILITY		
Commodity Return	Intercept	AR(1)	Commodity Return	Intercept	AR(1)
Brent Crude Oil	0.0132	0.3068***	Brent Crude Oil	0.0197	0.0523
Corn	-0.0008	0.0474	Corn	-0.0140**	-0.0707
Lumber	0.0051	-0.0122	Lumber	-0.0061	0.0466
Live Cattle	0.0041	-0.1503	Live Cattle	0.0021	0.0334
Soybeans	-0.0023	-0.0506	Soybeans	0.0038	0.1367
Wheat	-0.0006	0.0645	Wheat	-0.0123*	-0.0667
Cocoa	-0.0074	-0.0820	Cocoa	-0.0007	-0.0509
Cotton No.2	0.0064	0.0726	Cotton No.2	-0.0071	-0.1363
Gold 100 Oz	-0.0065**	-0.1012	Gold 100 Oz	0.0027	-0.0402
Gasoline	0.0120	0.3134***	Gasoline	0.0212*	-0.0009
Orange Juice	-0.0040	0.0638	Orange Juice	-0.0103	-0.1949
Coffee C	0.0074	0.1135	Coffee C	-0.0194*	-0.0924
Platinum	0.0034	0.0151	Platinum	0.0083	0.0226
Sugar No.11	0.0090	0.0697	Sugar No.11	0.0015	-0.0121
Silver 5000 Oz	-0.0035	-0.0111	Silver 5000 Oz	-0.0016	-0.3542***

***significant at 1% level, **significant at 5% level, *significant at 10% level

Table 5

Mean absolute error (MAE) and root-mean-square error forecast (RMSE) OOS accuracy measures

Panel A – Models including only macro principal components

MAE - Backward/Forward Selection - Separated Low/High Volatility - Commodity-Specific Factors Excluded

	Brent Crude Oil	Corn	Lumber	Live Cattle	Soybeans	Wheat	Cocoa	Cotton No.2	Gold 100 Oz	Gasoline	Orange Juice	Coffee C	Platinum	Sugar No.11	Silver 5000 Oz
Backward-Low Volatility	0.0749	0.0644	0.0660	0.0336	0.0621	0.0666	0.0549	0.0613	0.0366	0.0875	0.0696	0.0725	0.0673	0.0602	0.0718
Backward-High Volatility	0.1078	0.0948	0.1214	0.0318	0.1277	0.1134	0.2254	0.1632	0.0529	0.1965	0.1002	0.0743	0.1259	0.1784	0.1179
Forward-Low Volatility	0.0820	0.0644	0.0665	0.0336	0.0635	0.0666	0.0549	0.0638	0.0366	0.0875	0.0696	0.0762	0.0673	0.0602	0.0718
Forward-High Volatility	0.1078	0.0948	0.1214	0.0318	0.1078	0.1341	0.1180	0.1212	0.0529	0.1387	0.0911	0.0743	0.1259	0.1224	0.1179

MAE - Backward/Forward Selection - Separated Low/High Volatility - Commodity-Specific Factors Included

	Brent Crude Oil	Corn	Lumber	Live Cattle	Soybeans	Wheat	Cocoa	Cotton No.2	Gold 100 Oz	Gasoline	Orange Juice	Coffee C	Platinum	Sugar No.11	Silver 5000 Oz
Backward-Low Volatility	0.0741	0.0669	0.0665	0.0337	0.0623	0.0670	0.0600	0.0630	0.0367	0.0902	0.0719	0.0795	0.0665	0.0624	0.0705
Backward-High Volatility	0.1034	0.0943	0.1131	0.0322	0.1205	0.1126	0.2224	0.1536	0.0504	0.1984	0.1057	0.0767	0.1246	0.1800	0.1188
Forward-Low Volatility	0.0818	0.0669	0.0656	0.0337	0.0632	0.0670	0.0600	0.0652	0.0367	0.0902	0.0719	0.0803	0.0665	0.0624	0.0705
Forward-High Volatility	0.1034	0.0943	0.1131	0.0322	0.0975	0.1340	0.1173	0.1177	0.0504	0.1351	0.0923	0.0767	0.1246	0.1209	0.1188

MAE - Backward/Forward Selection - Low/High Volatility weighted by Filtered Probabilities - Commodity-Specific Factors Excluded

	Brent Crude Oil	Corn	Lumber	Live Cattle	Soybeans	Wheat	Cocoa	Cotton No.2	Gold 100 Oz	Gasoline	Orange Juice	Coffee C	Platinum	Sugar No.11	Silver 5000 Oz
Backward-Weighted	0.1050	0.0775	0.0893	0.0327	0.0925	0.0911	0.1345	0.1094	0.0450	0.1386	0.0852	0.0775	0.0997	0.1158	0.1189
Forward-Weighted	0.1008	0.0775	0.0880	0.0327	0.0824	0.0993	0.0835	0.0912	0.0450	0.1125	0.0805	0.0791	0.0997	0.0917	0.1189

MAE - Backward/Forward Selection - Low/High Volatility weighted by Filtered Probabilities - Commodity-Specific Factors Included

	Brent Crude Oil	Corn	Lumber	Live Cattle	Soybeans	Wheat	Cocoa	Cotton No.2	Gold 100 Oz	Gasoline	Orange Juice	Coffee C	Platinum	Sugar No.11	Silver 5000 Oz
Backward-Weighted	0.1026	0.0788	0.0859	0.0327	0.0894	0.0913	0.1348	0.1050	0.0436	0.1404	0.0902	0.0803	0.0979	0.1176	0.1182
Forward-Weighted	0.0983	0.0788	0.0841	0.0327	0.0781	0.1000	0.0855	0.0891	0.0436	0.1117	0.0828	0.0805	0.0979	0.0919	0.1182

MAE - Low/High Volatility weighted by Filtered Probabilities - AR(1) models

	Brent Crude Oil	Corn	Lumber	Live Cattle	Soybeans	Wheat	Cocoa	Cotton No.2	Gold 100 Oz	Gasoline	Orange Juice	Coffee C	Platinum	Sugar No.11	Silver 5000 Oz
AR(1)	0.0727	0.0779	0.0740	0.0325	0.0681	0.0789	0.0693	0.0736	0.0455	0.0845	0.0743	0.0714	0.0755	0.0788	0.0902

Table 5 (Continued)

Mean absolute error (MAE) and root-mean-square error forecast (RMSE) OOS accuracy measures

Panel B – Models including both macro principal components and commodity-specific factors

RMSE - Backward/Forward Selection - Separated Low/High Volatility - Commodity-Specific Factors Excluded

	Brent Crude Oil	Corn	Lumber	Live Cattle	Soybeans	Wheat	Cocoa	Cotton No.2	Gold 100 Oz	Gasoline	Orange Juice	Coffee C	Platinum	Sugar No.11	Silver 5000 Oz
Backward-Low Volatility	0.0905	0.0833	0.0809	0.0414	0.0811	0.0831	0.0716	0.0812	0.0449	0.1096	0.0858	0.0961	0.0882	0.0772	0.0888
Backward-High Volatility	0.1406	0.1151	0.1617	0.0395	0.1787	0.1428	0.2942	0.2243	0.0637	0.2571	0.1269	0.1033	0.1659	0.2249	0.1462
Forward-Low Volatility	0.1002	0.0833	0.0840	0.0414	0.0821	0.0831	0.0716	0.0829	0.0449	0.1096	0.0858	0.0975	0.0882	0.0772	0.0888
Forward-High Volatility	0.1406	0.1151	0.1617	0.0395	0.1399	0.1693	0.1430	0.1604	0.0637	0.1906	0.1114	0.1033	0.1659	0.1471	0.1462

RMSE - Backward/Forward Selection - Separated Low/High Volatility - Commodity-Specific Factors Included

	Brent Crude Oil	Corn	Lumber	Live Cattle	Soybeans	Wheat	Cocoa	Cotton No.2	Gold 100 Oz	Gasoline	Orange Juice	Coffee C	Platinum	Sugar No.11	Silver 5000 Oz
Backward-Low Volatility	0.0871	0.0850	0.0812	0.0415	0.0815	0.0836	0.0767	0.0824	0.0451	0.1111	0.0902	0.1017	0.0873	0.0804	0.0873
Backward-High Volatility	0.1357	0.1155	0.1535	0.0396	0.1688	0.1416	0.2881	0.2039	0.0614	0.2579	0.1362	0.1034	0.1630	0.2269	0.1466
Forward-Low Volatility	0.0976	0.0850	0.0832	0.0415	0.0824	0.0836	0.0767	0.0848	0.0451	0.1111	0.0902	0.1015	0.0873	0.0804	0.0873
Forward-High Volatility	0.1357	0.1155	0.1535	0.0396	0.1246	0.1702	0.1428	0.1562	0.0614	0.1861	0.1110	0.1034	0.1630	0.1456	0.1466

RMSE - Backward/Forward Selection - Low/High Volatility weighted by Filtered Probabilities - Commodity-Specific Factors Excluded

	Brent Crude Oil	Corn	Lumber	Live Cattle	Soybeans	Wheat	Cocoa	Cotton No.2	Gold 100 Oz	Gasoline	Orange Juice	Coffee C	Platinum	Sugar No.11	Silver 5000 Oz
Backward-Weighted	0.1386	0.0988	0.1231	0.0405	0.1370	0.1162	0.2058	0.1654	0.0553	0.1934	0.1084	0.1062	0.1344	0.1651	0.1189
Forward-Weighted	0.1294	0.0988	0.1214	0.0405	0.1120	0.1312	0.1087	0.1256	0.0553	0.1540	0.0992	0.1063	0.1344	0.1171	0.1189

RMSE - Backward/Forward Selection - Low/High Volatility weighted by Filtered Probabilities - Commodity-Specific Factors Included

	Brent Crude Oil	Corn	Lumber	Live Cattle	Soybeans	Wheat	Cocoa	Cotton No.2	Gold 100 Oz	Gasoline	Orange Juice	Coffee C	Platinum	Sugar No.11	Silver 5000 Oz
Backward-Weighted	0.1339	0.0994	0.1181	0.0403	0.1312	0.1160	0.2023	0.1517	0.0540	0.1938	0.1158	0.1071	0.1314	0.1669	0.1182
Forward-Weighted	0.1243	0.0994	0.1163	0.0403	0.1037	0.1324	0.1101	0.1225	0.0540	0.1515	0.1015	0.1065	0.1314	0.1174	0.1182

RMSE - Low/High Volatility weighted by Filtered Probabilities - AR(1) models

	Brent Crude Oil	Corn	Lumber	Live Cattle	Soybeans	Wheat	Cocoa	Cotton No.2	Gold 100 Oz	Gasoline	Orange Juice	Coffee C	Platinum	Sugar No.11	Silver 5000 Oz
AR(1)	0.0916	0.0965	0.0936	0.0403	0.0869	0.1019	0.0880	0.0972	0.0586	0.1116	0.0901	0.0945	0.1055	0.1022	0.1137

Table 6

Optimal portfolio allocations and realized performances

The upper portion of the table reports summary statistics for realized, optimal portfolio performances when the predictive models for commodity futures returns include only macroeconomic variables. The bottom portion contains average weights for each asset in the asset menu.

Panel A

	Optimal Portfolio Allocations - Macroeconomic Variables Models					
	Backward Selection γ=0.1	Forward Selection γ=0.1	Backward Selection γ=0.25	Forward Selection γ=0.25	Backward Selection γ=0.5	Forward Selection γ=0.5
Average Monthly Return	-0.00003	0.00108	0.00000	0.00108	0.00000	0.00108
Monthly Standard Deviation	0.01417	0.01048	0.01401	0.01048	0.01401	0.01048
Yearly Sharpe Ratio	-0.00620	0.35763	-0.00106	0.35777	-0.00091	0.35769
Mean-Variance	-0.00004	0.00108	-0.00003	0.00107	-0.00005	0.00105
	Average Weights					
Brent Crude Oil	5.585%	3.434%	5.581%	3.435%	5.581%	3.435%
Corn	1.119%	2.718%	1.116%	2.718%	1.116%	2.718%
Lumber	0.578%	-0.682%	0.576%	-0.682%	0.576%	-0.682%
LiveCattle	-0.550%	-2.552%	-0.550%	-2.552%	-0.550%	-2.553%
Soybeans	1.414%	-1.235%	1.420%	-1.235%	1.420%	-1.235%
Wheat	-1.441%	-1.891%	-1.443%	-1.892%	-1.443%	-1.892%
Cocoa	-0.028%	-0.575%	-0.026%	-0.575%	-0.027%	-0.575%
Cotton No.2	-2.749%	0.067%	-2.745%	0.067%	-2.745%	0.067%
Gold 100 Oz	3.294%	1.063%	3.289%	1.063%	3.289%	1.063%
Gasoline	-4.359%	-2.372%	-4.353%	-2.372%	-4.353%	-2.372%
OrangeJuice	-0.457%	-0.453%	-0.459%	-0.453%	-0.459%	-0.453%
Coffee C	-0.020%	1.121%	-0.020%	1.121%	-0.020%	1.121%
Platinum	-0.184%	0.097%	-0.184%	0.097%	-0.184%	0.097%
Sugar No.11	0.731%	0.604%	0.733%	0.604%	0.732%	0.604%
Silver 5000 Oz	-1.542%	-0.052%	-1.541%	-0.052%	-1.541%	-0.052%
S&P 500	2.993%	1.807%	2.992%	1.807%	2.992%	1.807%
10Y Treasury Bond	95.616%	98.902%	95.616%	98.902%	95.616%	98.902%

Table 6 (Continued)

Optimal portfolio allocations and realized performances

The upper portion of the table reports summary statistics for realized, optimal portfolio performances when the predictive models for commodity futures returns include both macroeconomic and factor-specific variables. The bottom portion contains average weights for each asset in the asset menu.

Panel B

	Optimal Portfolio Allocations - Macroeconomic Variables and Commodity-Specific Factors Models					
	Backward Selection γ=0.1	**Forward Selection γ=0.1**	**Backward Selection γ=0.25**	**Forward Selection γ=0.25**	**Backward Selection γ=0.5**	**Forward Selection γ=0.5**
Average Monthly Return	-0.00005	0.00178	-0.00003	0.00178	-0.00003	0.00178
Monthly Standard Deviation	0.01554	0.00950	0.01536	0.00950	0.01535	0.00951
Yearly Sharpe Ratio	-0.01053	0.64782	-0.00587	0.64782	-0.00571	0.64776
Mean-Variance	-0.00006	0.00177	-0.00006	0.00177	-0.00008	0.00175
	Average Weights					
Brent Crude Oil	2.156%	3.855%	2.151%	3.855%	2.151%	3.855%
Corn	-0.449%	0.695%	-0.452%	0.696%	-0.452%	0.696%
Lumber	0.642%	-0.586%	0.641%	-0.586%	0.640%	-0.586%
LiveCattle	0.478%	0.474%	0.478%	0.473%	0.478%	0.473%
Soybeans	1.360%	0.171%	1.365%	0.171%	1.366%	0.171%
Wheat	-0.455%	-1.106%	-0.457%	-1.106%	-0.457%	-1.106%
Cocoa	-0.124%	-0.094%	-0.122%	-0.094%	-0.122%	-0.094%
Cotton No.2	-1.563%	-0.206%	-1.560%	-0.206%	-1.560%	-0.206%
Gold 100 Oz	3.435%	3.006%	3.430%	3.006%	3.430%	3.006%
Gasoline	-2.030%	-3.174%	-2.024%	-3.174%	-2.023%	-3.174%
OrangeJuice	0.269%	0.224%	0.268%	0.223%	0.268%	0.223%
Coffee C	0.186%	0.525%	0.186%	0.525%	0.186%	0.525%
Platinum	-0.353%	-0.461%	-0.353%	-0.461%	-0.353%	-0.461%
Sugar No.11	-0.074%	0.296%	-0.072%	0.296%	-0.072%	0.296%
Silver 5000 Oz	-0.241%	0.221%	-0.239%	0.221%	-0.239%	0.221%
S&P 500	1.426%	1.838%	1.425%	1.838%	1.425%	1.838%
10Y Treasury Bond	95.336%	94.321%	95.336%	94.321%	95.336%	94.321%