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Predictability in Commodity Markets: Evidence from More Than a Century*

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Abstract

Using more than 140 years of data, we comprehensively analyze the predictive power of a broad set of business cycle variables for risk and return in commodity spot markets. We find that industrial production growth and inflation are the strongest predictors for future commodity excess returns. Several further variables help predict future commodity volatilities. The introduction of derivatives generally reduces the predictability in the most active commodity markets but increases the predictability in others. Thus, derivatives likely make markets more efficient, but also attract most of the price discovering activity. Commodity spot volatilities generally rise after futures introduction.

JEL classification: G10, G11, G17

Keywords: Commodities, Return Predictability, Derivatives Introduction, Business Cycle, Volatility Predictability

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I Introduction

Commodities are highly sensitive to economic cycles. Based on this insight, a growing literature has analyzed the predictability of commodity spot excess returns and/or volatilities, mostly using variables that are known to predict equity excess returns (e.g., Gorton & Rouwenhorst, 2006; Gargano & Timmermann, 2014). The growing number of predictor variables raises several questions: Which variables known to predict stock excess returns can also predict commodity excess returns? Do the variables that predict commodity excess returns also forecast commodity return volatilities? Does predictability vary over the business cycle? Did the introduction of derivatives trading impact the degree of predictability? These are some of the questions we seek to answer.

The interest in commodity markets has grown rapidly over recent decades. Although commodities have been traded on exchanges for more than 100 years in the U.S., commodities as an asset class are still relatively unexplored. Due to the poor performance of stocks and bonds, however, investors have turned to commodities as a new investment class (e.g., Bessembinder & Chan, 1992; Gorton & Rouwenhorst, 2006; Kogan et al., 2009). Erb & Harvey (2006) show that commodities and equities have similar average returns. Because their correlations with stocks and bonds are typically low, commodities are useful to achieve a high degree of portfolio diversification, while also serving as a good hedge against inflation (e.g., Sadorsky, 2002; Gorton & Rouwenhorst, 2006; Lien & Yang, 2008; Symeonidis et al., 2012).

Being able to predict the prices (or returns) of commodities is very important for physical market traders and commodity market researchers among others. Related thereto, it is of great interest to be able to accurately model the expected return on commodity prices. Studying volatility predictability is no less important than that of the first moment. First, knowledge about the future volatility is essential for risk management in the physical markets. Second, volatility is important for inventory management. Third, the valuation of real options crucially depends on accurate volatility forecasts. Finally, studying volatility predictability helps in gaining a basic understanding of the effects of the macroeconomy on commodity markets beyond just the first moment.

The main goal of this paper is to provide the most comprehensive evidence on the predictive power of business cycle variables for commodity excess returns and volatilities to date. In doing so, we make three contributions to the literature.

First, in contrast to the existing literature, we analyze a very long sample period of more than 140 years of data and use a comprehensive set of commodity markets and predictor variables. Our sample spans the period from January 1871 to December 2015 and covers 30 commodities and 16 predictor variables. Using this dataset, we study both in-sample and out-of-sample predictability.

Second, we do not only analyze the predictability of excess returns, which is the focus of most existing studies, but also the predictability of volatilities. In doing so, we use the same time periods and techniques as for the excess returns to ensure a comparable analysis.

Third, in contrast to previous studies, our data allow us to get new insights from analyzing a long sample period as well as the strength of the predictability around economically important events such as the introduction of derivatives trading. Our long sample also enables us to analyze the predictability of both excess returns and volatilities for different states of the economy. Based on Cujean & Hasler (2017), we examine expansions and recessions separately.

We start by studying return predictability. We use lagged predictor variables to forecast the future 1-month commodity excess returns. We find that industrial production growth and inflation are the strongest predictors of future commodity excess returns. These variables perform well both in-sample and out-of-sample. Forecast combination methods also perform well out-of-sample. On the other hand, most dividend- or earnings-related equity variables have very little predictive power for future commodity excess returns.

We also study volatility prediction, where we augment the benchmark AR(1) model by our predictor variables. Interestingly, many of the variables that do not predict future excess returns perform well for volatility prediction. A forecast combination approach also yields good out-of-sample forecasts for many commodities.

Our long sample also enables us to analyze the impact of the introduction of derivatives trading on the excess return predictability. For most of the biggest commodity markets, the futures introduction decreases excess return predictability. This is consistent with futures making overall markets more efficient. On the other hand, for some commodities, excess returns are more predictable after the introduction of derivatives trading, suggesting that for these the price discovery shifts from spot markets to take place primarily in the derivatives markets, which may make future spot excess returns more predictable. Alternatively, it could be that the risk premia become more strongly time-varying. Studying the impact of the global financial crisis, we find that commodity excess returns and volatilities are substantially more predictable on average after than before its beginning.

In addition, we study the time-variation in volatility around these breakpoints. Capital constraints and the limitations to hedging after the introduction of derivatives markets could make the commodity spot excess returns more volatile. Indeed, we observe that, for most commodities, the introduction of futures increases the volatility. In addition, for most commodities, the volatility is higher in the period after the start of the financial crisis than it is before.

We also study the predictability in different stages of the business cycle. We find that industrial production growth and inflation predict future commodity excess returns both in expansions and in recessions. Overall, commodity excess returns appear to be somewhat more predictable in expansions. Interestingly, though, the past equity excess return has much stronger predictive power for future commodity excess returns in recessions. For volatility predictability, the results are even clearer: volatilities are substantially more predictable in expansions than they are in recessions.

Our study relates to the literature on commodity return predictability. Table 1 provides a detailed overview of the most relevant papers dealing with commodity spot or futures return predictability. The list is necessarily incomplete. We focus mainly on studies covering a substantial part of the commodity market rather than just single commodities, as well as on studies that broadly use business cycle variables as predictors.

We contribute to the literature on commodity spot return predictability. Fama & French (1987) use the futures basis to predict future commodity spot returns, with mixed results. Bailey & Chan (1993) document that the default yield spread and the dividend yield are significant in-sample predictors in some markets. Pagano & Pisani (2009) document that capacity utilization and inventory variables help predict future WTI oil prices. Chen et al. (2010) demonstrate the predictive power of commodity currency exchange rates, while Groen & Pesenti (2011) find that the gains from using these variables are modest and "by no means overwhelming". Gargano & Timmermann (2014) use commodity spot indices to examine the predictive ability of several variables over a somewhat longer sample period than typically analyzed in the existing literature. They find that industials, metals, and the broad index are most predictable. Furthermore, analyzing different states of the economy, they find stronger evidence for predictability during recessions. As opposed to the three aforementioned studies, we focus on individual commodities rather than aggregated indexes. Thus, we are able to analyze commodity-specific effects and those within the different commodity sectors.

Bessembinder & Chan (1992) and Bjornson & Carter (1997) use several business cycle variables to forecast commodity futures returns. Bessembinder & Chan (1992) find that the Treasury Bill rate is the strongest in-sample predictor of commodity futures returns. For metals, also the dividend yield seems to have some predictive power. Bjornson & Carter (1997) show that interest rates, inflation, and industrial production growth are the strongest in-sample predictors of agricultural futures returns. De Roon et al. (2000) find that hedging pressure forecasts commodity futures returns. Hong & Yogo (2012), Acharya et al. (2013), and Etula (2013) show that open interest, oil and gas producers' risk aversion, and broker-dealer risk aversion, respectively, also affect commodity futures returns. Hammerschmid

(2018) documents the predictability of an aggregated commodity futures index by, among others, industrial production and global trade variables. We extend these studies by analyzing the predictability of spot returns of a broad set of commodities. Furthermore, we jointly examine numerous predictor variables that have been studied in isolation (or not at all) in the existing literature.

Our study also contributes to the commodity volatility predictability literature. Table 1 also summarizes relevant studies concerned with commodity volatility predictions with business cycle variables. Pierdzioch et al. (2016) use macroeconomic and financial variables to predict the volatility of gold-price fluctuations, while Prokopczuk et al. (2019) and Hollstein et al. (2020) analyze the drivers of commodity variance. Collectively, these studies find that business cycle variables can help explaining and predicting commodity volatilities. We contribute to this literature with a systematic analysis of volatility predictability by a large set of business cycle variables. In addition, we extend the previous studies by analyzing the linkage between return and volatility predictability and business cycle stages as well as the introduction of derivatives trading.

The remainder of this paper proceeds as follows. Section II introduces the data and describes the variables. Section III presents the main empirical results. Section IV discusses the time-variation analysis. Section V provides the business cycle analysis. Finally, Section VI concludes.

II Data and Methodology

This section introduces the data used for the empirical analysis. It then explains the main variables in detail.

A Data

We obtain our data from three distinct sources. First, we retrieve the monthly time series of spot prices for 30 different commodities from the Global Financial Database (GFD). Our sample period extends from January 1871 to December 2015, covering almost 150 years. All commodity price time series are denominated in United States Dollar (USD). Table A1 of the Online Appendix provides detailed information about the commodity markets we analyze. Our aim in selecting the commodities is to have the most comprehensive coverage possible regarding commodities of different sectors while having long time series. We focus on spot prices rather than on futures prices since we can obtain a much longer history for the former. Using futures prices has the advantage that one can more easily analyze the profitability of a trading strategy from the perspective of a financial investor. Although interesting, this is not our main goal. Our objective is to analyze the spot market to identify potential economic linkages between business cycle variables and commodity excess returns and volatilities. Second, we consider most of the predictor variables employed by Goyal & Welch (2008), which they use to predict the equity premium. Third, since our focus is on commodity rather than equity markets, the Goyal & Welch (2008) list of predictor variables is likely incomplete. Therefore, we follow Gargano & Timmermann (2014) and augment the set of predictor variables with industrial production, money supply, and the unemployment rate from the Federal Reserve Bank of St. Louis (FRED).

B Variables

Commodity Excess Return Since some commodity markets are known to exhibit seasonal patterns, we deseasonalize the commodity returns by running the following regression using the full sample period:

$$R_{t+1} = \sum_{j=1}^{12} \delta_j D_{j,t+1} + \epsilon_{t+1}, \tag{1}$$

where $R_{t+1} = \left(\frac{P_{t+1}-P_t}{P_t}\right)$ is the simple return on the commodity at the end of month $t+1$. P_{t+1} and P_t denote the price at the end of months $t+1$ and t, respectively. $D_{j,t+1}$ are monthly dummy variables to account for different monthly mean returns, and δ_j and ϵ_{t+1} are the coefficients associated with the dummy variables $D_{j,t+1}$, and the error term, respectively.

We then compute the excess return on a commodity as the difference between the monthly deseasonalized simple return on the commodity and the monthly risk-free rate from the corresponding period:

$$ER_{t+1} = R^d_{t+1} - Rf_{t+1}, \tag{2}$$

where ER_{t+1} is the monthly excess return on the specific commodity at the end of month $t+1$. R^d_{t+1} denotes the deaseasonalized monthly commodity return. Rf_{t+1} refers to the risk-free rate observed at the end of month t. Following Goyal & Welch (2008), we use the 1-month Treasury bill rate to proxy for the risk-free rate.[1]

Commodity Volatility To compute a measure of dispersion on the basis of monthly excess return data, we follow Schwert (1989) and Prokopczuk et al. (2019).[2] First, we estimate a 12th-order autoregression for the commodity excess returns, i.e.:

$$ER_t = \sum_{i=1}^{12} \eta_i \, ER_{t-i} + \epsilon_t, \tag{3}$$

where ER_t is the monthly deseasonalized commodity excess return, η_i are the regression coefficients, and ϵ_t is the realized error term. Second, we use the absolute value of the realized error terms $\mid \hat{\epsilon}_t \mid$ to estimate a 12th-order autoregression, i.e.:

$$\mid \hat{\epsilon}_t \mid = \sum_{i=1}^{12} \rho_i \, \mid \hat{\epsilon}_{t-i} \mid + u_t, \tag{4}$$

[1] We obtain similar results when directly using excess returns rather than returns for deaseasonalization. The risk-free rate does not exhibit a seasonal component and thus does not influence the results.

[2] In the case of daily excess returns, we would compute the monthly variance as the sum of the squared daily excess returns. Due to our long sample period there are no daily excess returns available. Thus, we compute the monthly volatility on the basis of monthly excess returns, following the procedure suggested by Schwert (1989).

where ρ_i are the regression coefficients and u_t the realized error terms. The absolute of the fitted values represents the conditional monthly standard deviation, which we denote by σ_t, and serves as measure of volatility.

Predictor Variables To analyze whether business cycle variables carry information about future commodity excess returns and volatilities, we follow the literature and use 16 predictor variables that are usually considered to have predictive power for stock or commodity excess returns. The variables are related to the equity market, to the fixed income market, and to the overall economy.

In particular, we consider the dividend–payout ratio (de) computed as the difference between the log of 12-month moving sums of dividends and the log of 12-month moving sums of earnings. The dividends (earnings) are computed as the trailing sum of dividends (earnings) paid on the S&P 500 index over the past year. Further, we use the dividend–price ratio (dp) as the difference between the log of 12-month moving sums of dividends and the log of current prices on the S&P 500 stock index, the dividend yield (dy) as the difference between the log of 12-month moving sums of dividends and the log of the S&P 500 stock index lagged by 1 month, the earnings–price ratio (ep) as the difference between the log of monthly earnings and the log of monthly prices, the market risk premium (erp) as the difference between the change in the monthly log prices of the S&P 500 total return index and the monthly continuously compounded 1-month Treasury bill rate, and the monthly stock variance ($svar$) computed as the sum of squared daily returns on the S&P 500.

As interest-rate-related variables, we use the default return spread (dfr) computed as the difference between monthly long-term U.S. corporate bond returns on AAA- and BAA-rated bonds and monthly long-term U.S. government bond returns, the default yield spread (dfy) as the difference between monthly U.S. BAA- and AAA-rated corporate bond yields, the monthly long-term U.S. government bond returns (ltr), the monthly long-term U.S. government bond yields (lty), the monthly 3-month Treasury bill rate (tbl), and the term spread (tms) as the difference between the monthly long-term yield on U.S. government bonds and the monthly 3-month Treasury bill rate.

As variables that are related to the overall economy, we use the growth of industrial production ($\Delta indpro$) computed as the change in the logarithm of the monthly industrial production, the growth of the money stock M1 ($\Delta M1$) as the change in the logarithm of the monthly money stock, the monthly inflation rate ($infl$) calculated as the simple return on the U.S. consumer price index (CPI), and the monthly unemployment rate ($unrate$).[3] To account for non-immediate data release, we lag the variables $\Delta indpro$, $infl$, and $unrate$ by 1 month.[4]

Forecast Combination Approaches We also analyze two forecast combination approaches for out-of-sample forecasts: a simple mean forecast combination (*comb*) and a forecast combination based on an adaptive elastic net regression (*c-enet*).[5] For the mean forecast combination, we simply average all out-of-sample forecasts of different predictors (Rapach et al., 2010). For the combination adaptive elastic net of Rapach & Zhou (2019), we first obtain the single-variable out-of-sample forecasts. In a second step, for a so-called holdout out-of-sample period with similar length as the in-sample period, we regress the realized excess returns (or volatilities) on the out-of-sample forecasts. This regression is es-

[3]The monthly data of the dividends on the S&P 500 index, earnings on the S&P 500, prices on the S&P 500, U.S. BAA- and AAA-rated corporate bond returns, U.S. BAA- and AAA-rated corporate bond yields, long-term U.S. government bond returns, long-term U.S. government bond yields, 1-month Treasury bill rate, and 3-month Treasury bill rate are obtained from the extended dataset provided by Goyal & Welch (2008). The monthly data for industrial production, money supply M1, and unemployment rate with tickers "INDPRO", "M1", and "UNRATE" are obtained from FRED. The monthly U.S. consumer price index (ticker: "CPUSAM") and the monthly prices of the S&P 500 total return index (ticker: "_SPXTRD") are retrieved from the GFD.

[4]The variance risk premium, used to predict equity returns by Bollerslev et al. (2009) and Hollstein & Wese Simen (2020), holds further promise as a predictor variable. However, the time series for this and other option-implied variables (as studied by Hollstein et al., 2019) do not start before the 1990s. Therefore, we do not consider these variables in this study.

[5]The major alternative would be a kitchen sink approach, as in Goyal & Welch (2008), which makes forecasts based on a simple multivariate OLS regression. Consistent with their results, we find that this approach works well in-sample, but very poorly out-of-sample, with very low R^2s. The forecast combination approaches outlined in this section are considerably more suitable for out-of-sample predictions.

timated with the adaptive elastic net regression.[6] Finally, all variables that yield a strictly positive slope coefficient in the adaptive elastic net estimation are selected for a simple mean forecast combination. Note that the main difference between *comb* and *c-enet* is that the latter tries to pre-select in order to focus on the best forecasts only.

III Empirical Analysis

A Summary Statistics

Before turning to our main analysis, it is instructive to look at the summary statistics and correlation matrices of our variables. We classify the commodities into three groups: Agriculturals, Energies, and Metals.

Table 2 reports (monthly) summary statistics of the returns and volatilities. We observe that the average monthly returns vary between 0.24 % for *Wool* and 2.34 % for *Oranges*, 0.28 % for *Coal* and 0.84 % for *Unleaded Regular Gas*, and 0.20 % for *Aluminum* and 0.97 % for *Palladium* in the Agriculturals, Energy, and Metals sectors, respectively. These numbers are in line with former studies of, e.g., Gorton et al. (2013), although they analyze futures returns.[7] The average monthly volatilities range from 2.79 % for *Milk* to 12.03 % for *Oranges* in the Agriculturals sector, 1.87 % for *Natural Gas* to 6.90 % for *Unleaded Regular Gas* in the Energy sector, and from 1.59 % for *Gold* to 5.78 % for *Palladium* in the Metals sector. The high first-order autoregressive coefficients for volatilities are noteworthy, indicating a higher persistence and thus a potentially better predictability on the basis of their own current values, compared to commodity returns.

[6]The adaptive elastic net regression minimizes the following objective function $\min_{\beta}\left[\sum_{t=0}^{T-1}(Y_{t+1}-\alpha-\beta' X_t)^2+\lambda\left(0.5\,(1-\delta)\sum_{m=1}^{M}|\beta_m|+\delta\sum_{m=1}^{M}\beta_m^2\right)\right]$, where Y is the predicted variable, X is a set of predictor variables, β denotes a vector of M regression coefficients (of which β_m is one element), and λ is the regularization parameter for the lasso and ridge penalty terms. Following Rapach & Zhou (2019) we set $\delta = 0.5$. Based on the results of Flynn et al. (2013), we select λ using the corrected Akaike Information Criterion (AIC) of Hurvich & Tsai (1989), rather than by cross-validation.

[7]The high average monthly return of *Oranges* is due to sharp changes in the monthly price level during certain, isolated, periods. The geometric mean return for *Oranges* is 0.09% per month.

Table A2 of the Online Appendix reports (monthly) summary statistics of the predictor variables. In particular, the classical predictors *de*, *dp*, *dy*, and *ep* are characterized by high monthly standard deviations between 31.58 % and 43.11 %, respectively. Most predictors also exhibit high first-order autoregressive coefficients, indicating that they might be predictable themselves.

Tables A3, A4, and A5 of the Online Appendix report the correlation matrices between the commodity returns and volatilities, as well as among the predictor variables. In Table A3, we see that in the Agriculturals sector, *Soybean Oil*, *Soybeans*, *Soybean Meal*, and *Yellow Corn* are notably correlated. Within the Energy sector, we observe co-movements across *Heating Oil*, *Unleaded Regular Gas*, and *WTI Oil*. In the Metals sector all commodities exhibit moderate correlations. However, there is a high degree of correlation between *Silver* and *Gold* (0.62), which is also consistent with previous studies.

In Table A4 of the Online Appendix, we observe similar patterns for volatilities within the sectors. In Table A5 of the Online Appendix, we see high correlations between the interest rate-related variables, namely, *ltr* and *dfr* of –0.47 and *tbl* and *lty* of 0.90; also between *unrate* and *tms* of 0.55, and *unrate* and *dfy* of 0.67. We also observe similar information content in the related variables *ep* and *dp* (0.70) and *ep* and *dy* (0.70). Finally, *dp* and *dy* exhibit a correlation of 0.99.

B Return Predictability

In-Sample Analysis To assess the in-sample predictability of commodity excess returns, we follow the methodology of Rapach & Wohar (2006). We estimate the following regression model of the 1-month-ahead excess return on a constant and the predictor variable:

$$ER_{t,t+1} = \alpha + \beta X_t + \epsilon_{t,t+1}, \tag{5}$$

where $ER_{t,t+1}$ is the commodity excess return from month t to $t+1$, α and β are the intercept and slope parameters, respectively. X_t is the predictor variable observed at the end of month t and $\epsilon_{t,t+1}$ represents the regression error term.

Based on the regression model, we examine whether the expected commodity excess return is time-varying or constant. Under the null hypothesis that the future commodity excess return cannot be predicted using X_t, we would expect that the slope is not significantly different from zero, i.e., $\beta = 0$. Thus, the expected commodity excess return would simply be constant, and we would conclude that the best estimate of the future expected excess return is simply its recursive mean. Under the alternative hypothesis, we would expect to see that the slope loading is statistically significant, indicating evidence of predictability. We use the bootstrapped distribution proposed by Rapach & Wohar (2006) to obtain reliable statistical inferences. Following this approach, we preserve the serial correlation of the predictor variables and avoid a small-sample bias (Stambaugh, 1999).[8]

Table 3 visualizes the main results for each predictor variable and commodity. We find that $\Delta indpro$, dfr, erp, $infl$, tbl, and tms are significant in-sample predictors in many commodity markets. In particular $\Delta indpro$ and $infl$ are the strongest predictors. $\Delta indpro$ predicts future excess returns for all Agriculturals except for *Oranges*. The variable performs less well for Energy, being a significant predictor only for *WTI Oil*. In addition, $\Delta indpro$ is a significant predictor for 6 out of the 9 Metals. For $infl$, the results are even stronger. The variable significantly predicts all but 2 Agriculturals, all Energies, and 6 out of 9 Metals.

The result that future commodity excess returns are related to industrial production and inflation appears natural from an economic viewpoint. The change in industrial production

[8] First, we set up the following null hypothesis: $ER_{t,t+1} = a_0 + \epsilon_{1,t+1}$ and $X_t = b_0 + b_1\, X_{t-1} + \epsilon_{2,t}$, where a_0, b_0, and b_1 are the regression coefficients and $\epsilon_{1,t+1}$ and $\epsilon_{2,t}$ are the error terms, respectively. We then estimate the process under the null hypothesis of no predictability via OLS and bias-adjust the b_1 coefficient following Shaman & Stine (1988). Second, we use the series of error terms and set up our pseudo sample by drawing from the residuals in tandem (with replacement). For the pseudo sample, we calculate both the in-sample and the out-of-sample statistics (described in the following section). We repeat this procedure (starting with the second step) 1,000 times. This procedure controls for the Stambaugh (1999) bias because the residuals are drawn in tandem, which preserves their contemporaneous correlation structure.

is an important business cycle indicator. Since the demand for most commodities is higher in expansions than it is in recessions, the variable likely carries important information about future commodity prices. Even more naturally, inflation is also important because it carries information on the business cycle (Chen et al., 1986; Ferson & Harvey, 1991). On top of that, past price changes in commodities are an important determinant of current inflation. To the extent that these past price changes are autocorrelated, inflation is a natural predictor of future commodity excess returns. All other variables that significantly predict part of the commodity excess returns are also related to the state of the business cycle.

The detailed regression results can be found in Table A6 of the Online Appendix. Furthermore, Table 4 provides an overview of the main results. Consistent with the previous results, these tables show that the R^2s are also economically meaningful, exceeding 1% on average for $\Delta indpro$ for Agriculturals and Metals, for dfr for Energies, and for $infl$ for Agriculturals and Energies.

Part of the commodity markets are rather small and illiquid, for example *Butter*, *Corn Oil*, *Milk*, and *Coal*. These could bias our overall results. However, we find that the results for these markets are not systematically different from those of the "biggest" markets, neither in this nor in any of the ensuing analyses. Thus, it is unlikely that the inclusion of these commodities in our sample has a material impact on our main conclusions.

Out-of-Sample Results We analyze the out-of-sample results in the spirit of Goyal & Welch (2008). To obtain the first out-of-sample forecast, we estimate the forecasting model presented in Equation (5), using an initial estimation window of 10 years. We then generate the first excess return forecast by using the parameter estimates and the most recent observation of the predictor variable in the estimation period. For the following month, we roll the estimation period on by one observation month and re-estimate the forecasting model. With the new parameter estimates, we forecast the commodity excess return for the next month. The out-of-sample analysis is based on a rolling window to capture the potential time-varying relationship. To address the average length of a common business cycle, we follow Çakmaklı & van Dijk (2016) and use a 10-year rolling window.[9]

To be able to compare the out-of-sample performance of different models, we use the out-of-sample R^2 (R^2_{oos}), proposed by Campbell & Thompson (2008), which is given by:

$$R^2_{oos} = 1 - \frac{MSE_u}{MSE_r}, \tag{6}$$

where MSE_u and MSE_r are the mean squared errors of the unrestricted and restricted model, respectively. The unrestricted model is presented in Equation (5), whereas in the restricted model we impose the null hypothesis that excess returns are unpredictable (setting $\beta = 0$). Thus, based on the R^2_{oos} we answer the question: Could the predictability have been exploited in real time? How large is the additional predictive power using the variable X_t in excess of the predictive power using the historical mean? An increasing predictive power is associated with a positive R^2_{oos}.

To be able to make a statement whether the improvement is statistically significant, we compute the $MSE - F$ statistic of McCracken (2007):

$$MSE - F = (N - k + 1) \times \left(\frac{MSE_r - MSE_u}{MSE_u}\right), \tag{7}$$

where N denotes the number of out-of-sample forecasts, and k the forecast window ($k = 1$ in the case of this study). All other variables are as previously defined. The null hypothesis is that the restricted model performs at most as well as the unrestricted model, i.e., $MSE_r \leq MSE_u$. Thus, the alternative is that the unrestricted model provides smaller forecast errors than the restricted model. The statistical inference is based on a bootstrapped distribution as described above.

We summarize the main results in Tables 3 and 4 and provide detailed regression results in Table A6 of the Online Appendix. We find that the main in-sample predictors also

[9] We analyze the time series for structural breaks and our findings suggest the use of a rolling window.

perform well for out-of-sample excess return prediction. $\Delta indpro$ is a significant out-of-sample predictor for 7 of the Agriculturals and 4 Metals. $infl$ is a significant predictor for 7 Agriculturals, 4 Energies, and 1 Metal. For part of the commodities, also $\Delta M1$, dfr, and *erp* perform well out-of-sample. The remaining variables, however, seem to have very little to no out-of-sample predictability for commodity markets. Most notably, these variables include earnings- and dividends-related variables (*de*, *dp*, *dy*, *ep*). The stock variance (*svar*) and the unemployment rate also seem to be largely unrelated to future commodity excess returns.

In particular the forecast combination approaches perform well for out-of-sample predictions. Even though there are many seemingly irrelevant predictor variables included, *comb* and *c-enet* both yield a significant positive out-of-sample R^2s for 12 commodities. Turning to the magnitude of the out-of-sample R^2s, we find that these are positive on average for $\Delta indpro$ for Agriculturals and Metals, for $infl$ for Agriculturals and Energies, for *c-enet* for Energies, and for *comb* for all sectors.

The negative univariate out-of-sample R^2s observed for many predictors indicate that using the respective predictors alone, on average, one could not have benefited from the observed predictability in real time. The positive out-of-sample R^2s for the comb and c-enet approaches, in contrast, indicate that an investor could have benefited in real time when she aggregated the information in different variables. Thus, it seems that several of the variables contain some information about future commodity returns. However, when used alone, this information may be too noisy to exploit in real time. The aggregation to comb and c-enet reduces this noise, seemingly providing a better signal.

C Volatility Predictability

We now turn our attention to the predictability of the commodity volatility. In particular, we ask the question: Can any of the forecasting variables considered for returns be used to predict the volatilities over the following month?

In-Sample Analysis Using all the sample information, we estimate the following regression model:

$$\sigma_{t,t+1} = \xi + \gamma X_t + \delta \sigma_t + u_{t,t+1}, \tag{8}$$

where $\sigma_{t,t+1}$ is the monthly (average) volatility from month t to $t+1$. ξ, γ, and δ are the intercept and slope parameters, respectively. X_t represents the forecasting variable observed at the end of month t. $u_{t,t+1}$ is the regression error term. To account for the persistence in volatility, we include the lagged volatility, σ_t, as an additional predictor variable. Accordingly, we use a fitted AR(1) process as naive benchmark to address this property.[10] Thus, to examine whether a variable has significant in-sample predictability, we use the following version of an R^2:

$$R^2 = 1 - \frac{MSE_u}{MSE_r}, \tag{9}$$

where MSE_u is the average of the squared residuals from Equation (8) and MSE_r is the average of the squared residuals from a regression that sets $\gamma = 0$ in Equation (8).

Table 5 visualizes and Table A7 of the Online Appendix presents the detailed results. Table 6 provides an overview of the main results. We find that commodity volatilities are also predictable by business cycle variables. Although volatility is known to be strongly persistent, business cycle variables are able to enhance the predictability beyond that afforded by its own lag. Second, the variables that best predict commodity volatilities are generally different from those that best predict excess returns. $\Delta indpro$ only yields significant R^2s for 4 Energies and 1 Metal. $infl$ yields significant in-sample R^2s for 8 commodities in total. Better commodity volatility predictors include dfy, dp, dy, ep, lty, $svar$, and $unrate$. Interestingly, this list contains many of the variables that have very little predictive power for commodity excess returns.

[10] The strong persistence of commodity volatilities is indicated by their high AR(1) coefficients, shown in Table 2, in comparison to commodity excess returns that are only marginally autocorrelated. Thus, the best predictor for future volatility is mainly its current value. Accordingly, a fitted AR(1) process represents a more natural naive benchmark than the historical average volatility.

Out-of-Sample Results We perform our out-of-sample volatility prediction analysis just as we do for excess returns. We use the first 10 years of observations to initially estimate the model parameters (see Equation (8)). Then we predict the next month's volatility. We roll the training window by one observation month and repeat all steps. We account for the possibility of structural breaks by using a 10-year rolling window. This procedure is analogous to the return predictability analysis; however, we forecast volatility rather than the excess return. Importantly, we use the AR(1) forecast as a benchmark.

Again, we visualize the main results in Table 5, provide detailed regression results in Table A7 of the Online Appendix, and provide an overview of the main results in Table 6. We find that part of the good in-sample predictors of future commodity volatility perform poorly in an out-of-sample setting. Most notably, *svar* only yields a significant positive out-of-sample R^2 for 1 commodity. On the other hand, a notable fraction of the in-sample significant R^2s for other variables also translates into significant out-of-sample R^2s. In particular the forecast combination from the *c-enet* performs very well, with significant positive R^2s for 7 Agriculturals, 4 Energies, and 6 Metals. It seems that, despite the high degree of persistence, commodity volatilities are predictable out-of-sample.

IV Time-Variation in Predictability

To further analyze the effects of important changes in commodity markets on the predictability of commodity excess returns and volatilities, we examine the variation of predictability around specific events on the basis of a kitchen sink approach.[11] In particular, we seek to answer the question: Does the introduction of derivatives trading systematically affect the predictability of commodity excess returns and volatilities?

To do so, we first investigate the global introduction dates of commodity futures and

[11] We run a multiple regression in which we include all predictor variables. *dy*, *ep*, and *tbl* have been excluded due to high correlations and thus multicollinearity. In the case of volatility predictability, we again use an AR(1) model as a benchmark.

futures options contracts. We provide this information, as well as our information sources, in Table A1 of the Online Appendix. We separately present the futures and futures options introduction dates on the Chicago Mercantile Exchange (CME) and (if earlier) also those of other exchanges. We use the earlier of the two to determine the first global futures and futures options introduction dates. Moreover, we follow Guidolin & Tam (2013) and additionally use the beginning of the global financial crisis in 2007 as a further breakpoint. We define the start of the global financial crisis as July 2007, following the near collapse of two Bear Stearns hedge funds. We use 10 years of data (120 observations) before and after the breakpoints and compare the predictability for those windows.[12] In the case of the global financial crisis, we use 101 observations since our sample ends in 2015.

It is unclear what effect of futures and futures options introduction we should expect. On the one hand, the futures and futures options introductions could reduce the predictability since the additional trading possibilities make the market more complete. The commodities become easier to trade with lower transaction costs. In addition, the availability of futures prices may make the market more transparent. On the other hand, informed trading might take place primarily on futures and options markets after introduction. The price discovery in commodity spot markets could be slower and excess returns more predictable after the introduction of futures and futures options. For the financial crisis, we might expect a decrease in the excess return and volatility predictability after the breakpoint. Lettau & Van Nieuwerburgh (2008) and Pettenuzzo & Timmermann (2011) argue that such breakpoints are associated with model instability and increase investment risk.[13]

[12] For some of the commodities, we were only able to retrieve information on the introduction year. In this case, we end the 10-year window before introduction at the end of the previous year and start the window after introduction at the beginning of the following year.

[13] Note that in this discussion, we take a market-inefficiency view of return predictability. According to Fama (1991), return predictability can be either due to market inefficiency or time-variation in risk premia. We chose to focus on the former interpretation in relation with futures and options introduction dates since it is unclear why these events should affect the degree of time-variation in risk premia. Nevertheless, such an effect is certainly possible, in particular for the financial crisis break date.

A A History of Commodity Futures Options Trading

Since our analysis also considers the introduction of commodity futures options, it is useful to briefly outline some important historic events regarding these contracts. While trading in futures contracts was permanently allowed in the U.S., there was a ban on domestic commodity futures options between 1936 and 1981.

The ban was part of the Commodity Exchange Act 1936, which also imposed new regulations for futures trading and the prohibition of fictitious and fraudulent transactions, e.g., wash sales and accommodation trades. It aimed to prevent market manipulation, as option contracts were mainly associated with gambling and speculation rather than hedging needs. For the U.S. market before the ban, options were used by traders as an additional instrument to trade at the grain futures market. Early option-like contracts, called "Privileges", were established in the 19th and early 20th century to bet on expected price changes. Options disappeared from the exchanges between 1921 and 1926 due to a prohibitive tax and new regulations in the Futures Trading Act of 1921 and the Grain Futures Act of 1922. However, trading picked up again when the Futures Trading Act of 1921 was found unconstitutional in 1926. The interest in option contracts was very high, such that regulators regarded the trading as "frenetic", until options were finally banned in 1936.

The Commodity Exchange Act, although it was occasionally amended to extend the list of regulated commodities, stood undisturbed for thirty-five years until in the early 1970s hybrid forms of trading in commodity options began. These were mainly options traded on foreign exchanges, primarily in London ("London Options"), which were bought through American brokerage firms. However, these also included the so-called "naked" or "dealers" options, which were not covered by the 1936 regulations. Because these option contracts were used for widespread fraud, after attempts at regulation, transactions were suspended by the Commodity Futures Trading Commission (CFTC) in June 1978. Further information on the legal details of the commodity futures options regulations up to 1978 can be found in

Lower (1978).

Thereupon, rather than completely banning all options, authorities re-evaluated the economic benefit of option trading and the CFTC started a controlled and monitored 3-year pilot program with new regulations under which the first options on futures contracts were approved in 1982. The pilot program was considered successful and the authority continued to allow options on futures contracts from there on. As can be seen from Table A1 of the Online Appendix, soon after 1982, options were introduced for many commodity contracts, starting with *Sugar* and *Gold* in October 1982; 15 other commodity markets followed suit until the end of the 1980s. Today, commodity futures options are very important for traders. The total open interest in commodity futures options in 2018 was 11 million contracts, compared with an open interest of 19 million contracts in commodity futures.[14]

B Time-Variation in Return Predictability

We continue by assessing the time-variation in return predictability. We present the results in Table 7.

Starting with futures introduction, the results are overall mixed. For most commodities, we detect significant excess return predictability both before and after the futures introduction. For Agriculturals, there are 4 commodities for which the in-sample R^2 increases significantly after the introduction of futures. On the other hand, there are also 4 commodities for which the in-sample R^2 decreases. For Energies, the R^2 is significantly higher after the futures introduction in 3 and lower in 2 cases. For Metals, the R^2s tend to decrease after the futures introduction; for 5 out of 7 commodities this is the case.

For Agriculturals and Metals, the option introduction results are overall unclear. The R^2s increase and decrease for similar numbers of commodities. For Energies the R^2s increase in 3 out of 4 cases.

[14] These numbers are from the 2018 Derivatives Report of the World Federation of Exchanges: https://www.world-exchanges.org/storage/app/media/statistics/WFE%202018%20IOMA%20Derivatives%20Report%20FINAL%2010.04.19.pdf.

For *Soybeans* and *Silver*, both the introduction of futures and that of futures options decreases the return predictability. Thus, the spot markets of these commodities appear to benefit from increased transparency and additional investment possibilities and become more efficient (or risk premia become less time-varying). On the other hand, for *Milk* (same date for both), *Natural Gas*, and *Unleaded Regular Gas*, the introduction of both futures and futures options leads to enhanced predictability. In these markets, the price discovery appears to shift from the spot to the derivatives market, making the spot markets less efficient. It is notable that for the some of the most liquid commodity markets, *Soybeans*, *WTI Oil*, *Gold*, and *Silver*, the R^2s decrease after the futures introduction.

For the financial crisis, the results are rather clear. For 19 out of the 30 commodities, the predictability is significantly stronger after the financial crisis breakpoint than before it. Thus, this result is somewhat contrary to what one might expect because the crisis notably provides a breakpoint in most financial time series. However, one has to bear in mind that we examine the in-sample predictability. Thus, any change in the statistical relationship between excess returns and predictor variables can be fully captured because we run an entirely new regression after the breakpoint. Furthermore, the crisis has induced strong comovement in the returns of many assets (first a sharp decrease in prices in the recession, then an increase in the ensuing recovery), and, with this may have rendered risk premia more strongly time-varying. The increase in predictability might reflect this comovement.

C Time-Variation in Volatility Predictability

For volatility predictability (also presented in Table 7), we also obtain mixed results for the futures and futures options introduction. The R^2s increase significantly for 6 out of 10 Agriculturals and 3 out of 5 Energies, but only for 2 out of 7 Metals. For the introduction of futures options, the general patterns in results for the volatility predictability are overall similar to those for the excess return predictability: for the majority of Agriculturals there is less predictability after the futures options introduction while for Energies and Metals the

R^2s increase in most markets.

After the futures introduction, the volatility predictability decreases in some of the most liquid commodity markets (e.g., *Soybeans* and *Gold*) but it increases in others (e.g., *WTI Oil* and *Silver*). An interpretation of volatility predictability, however, is also much less strongly related to market efficiency than that of return predictability: it is unclear whether volatility should be less predictable in more efficient markets. Similarly, it is unclear whether volatility is mainly driven by time-variation in risk premia or mostly determined by noise.

After the financial crisis breakpoint, we also detect enhanced volatility predictability. For 20 out of the 30 commodities, the R^2s increase after the breakpoint. This increase in predictability is also consistent with stronger comovement in volatilities for many assets during and after the financial crisis.

D Time-Variation in Volatility

To further exploit the information content of our long sample, we analyze the volatility variation before and after the introduction of derivatives trading and the beginning of the global financial crisis.[15] In particular, we ask the question: Does the introduction of derivatives trading systematically affect the volatility of commodity excess returns?

Since the introduction of commodity derivatives trading, these markets have exhibited a steadily increasing trading volume (Gorton & Rouwenhorst, 2006; Gorton et al., 2013). The increase in trading volume reflects the rise in the hedging demand on the futures market.[16] Acharya et al. (2013) show that speculators face restrictions by investing their capital in the futures market. On the other hand, due to these capital constraints the hedging demand of commodity producers cannot be satisfied. Consequently, both the capital constraints and the limitations to hedging affect the spot prices. Thus, we expect an increase in the volatility

[15]Note that we focus here on the level of volatility and not on the predictability of volatility, as in the previous subsection.

[16]In detail, assume that a specific fraction of trading volume reflects the hedging demand of a given number of investors. Accordingly, an increase in trading volume is associated with a rise in the number of investors who look for hedging possibilities. Thus, the hedging demand increases.

after these breakpoints. Further, since the global financial crisis represents a shock to the economy, we also expect an increase in the volatility after that breakpoint.

The results of the previous literature on the effect of commodity futures trading on spot volatilities are not entirely consistent with this reasoning. Kamara (1982) provides a survey of early empirical studies, which document that the introduction of futures trading generally did not increase spot volatilities. Antoniou & Foster (1992) confirm this for the crude oil market, while Gulen & Mayhew (2000) obtain a similar finding for most international stock markets. Yang et al. (2005) find that increases in futures trading volume Granger-cause increases in spot volatilities in agricultural commodity markets. Slade & Thille (2006) also detect a positive relation between futures trading volume and spot volatility in metals markets. However, they argue that both are likely driven by a common factor.

Table 8 reports the results for the different events.[17] We use an F-test to examine whether there are significant differences in the volatilities.

We start by analyzing the effect of derivatives trading on the return volatility. For Agriculturals, our results are consistent with the previous literature. There is no clear evidence of an increase in spot volatility after futures introduction. For three commodities, we observe a significant increase, while for two there seems to be a decrease in the spot volatility. On the other hand, in the case of Energies and Metals, we obtain more evidence that the introduction of futures trading increases the spot volatility. The F-test confirms that there are significant differences in the volatilities. We detect the strongest increase for *Nickel*. Other commodities showing notable increases are *Sugar*, *Coal*, *Heating Oil*, *Unleaded Regular Gas*, *WTI Oil*, and *Aluminum*.

With the introduction of commodity futures options, the evidence is more mixed. In particular for Agriculturals and Energies, the volatilities increase more often than they decrease. However, for all Metals, the volatilities decrease after the introduction of futures options.

Analyzing the time periods around the global financial crisis, we also observe a general

[17] Analogous to the previous subsection, we use 120 observations (101 after the start of the financial crisis).

increase in the volatility across commodity markets. For 20 out of the 30 commodities, the volatility is higher in the period after than in that before the crisis.

V Predictability and Business Cycle Stages

In this section, we analyze the return predictability over business cycle stages. Based on Cujean & Hasler (2017), we separately examine expansions and recessions. To determine these, we follow the classification of the National Bureau of Economic Research (NBER) for U.S. business cycle stages.[18]

A Return Predictability

We start by analyzing the return predictability. The results are visualized in Table 9. We find that the two main unconditional predictor variables, $\Delta indpro$ and $infl$, perform well in predicting future commodity excess returns in both business cycle stages. Thus, these two variables can predict excess returns throughout the business cycle. On the other hand, we find that the lagged equity excess return (erp) has much more predictive power in recessions than in expansions. This finding is consistent with the fact that excess returns comove much more strongly in recessions. It seems that part of this comovement happens in commodity markets only with 1-month delay.

Overall, we detect a notably stronger predictability in expansions than in recessions. In particular variables like dfy, lty, $svar$, and tbl appear to have much more predictive power for future commodity excess returns in expansions than they do in recessions. The findings support those of previous studies that these variables are related to business cycle stages (e.g., Fama & French, 1989; Chen, 1991; Cochrane, 1999). Part of the differences in predictability can likely be traced back to the fact that there are more expansion months than recession

[18] To obtain meaningful results, we impose the following conditions: We report the out-of-sample results when there are at least 30 out-of-sample observations available. Further, at least 10 years of in-sample observations must be available.

months in our sample. However, 500 months out of our total 1740-month sample period are recessions. Thus, the recession sample can still be fairly large and the statistical tests should be sufficiently powerful.[19]

B Volatility Predictability

We now turn our attention to the volatility predictability over business cycle stages. Analogous to Table 9, Table 10 visualizes the results for volatility predictability in different economic stages. These are overall very similar to those for return predictability: volatility is substantially more predictable in expansions than it is in recessions. Only a few variables help predict volatilities in recessions while all variables help predict volatilities for part of the commodities during expansions. A potential explanation for this finding could be that volatility is likely even more strongly autocorrelated during recessions, making the AR-component crowd out most of the further predictability due to business cycle variables.

VI Conclusion

This paper provides comprehensive evidence on the predictability of future commodity excess returns and volatilities. We find that industrial production growth and inflation are the strongest predictors of future commodity excess returns. On the other hand, several other variables are also useful for volatility prediction. Appropriate forecast combinations provide good out-of-sample forecasts for both commodity excess returns and volatilities.

Studying the impact of the introduction of derivatives trading on the return predictability, we find that the introduction of futures decreases excess return predictability in most of the biggest markets. However, it also increases the predictability for other markets, suggesting that there are two main forces at play: enhanced market efficiency after the introduction of

[19]Note also that we do not rely on asymptotic critical value but obtain bootstrapped distributions of the same sample size as in the original time series.

derivatives, but price discovery shifts from spot to derivatives markets.

The introduction of derivatives trading generally increases the volatility in commodity markets. Furthermore, we find that excess returns and volatilities are in most cases more predictable after the start of the financial crisis. Finally, we find that commodity excess returns – and, in particular, volatilities – are more predictable in expansions than they are in recessions.

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Table 1: Literature Overview

This table presents an overview of the literature on commodity spot return, futures return, and volatility predictability. "Paper" denotes the bibliographic reference. "# Comm." and "Markets" indicate the number of commodities used in the different studies as well as the market segments covered. "Time Frame" provides the paper sample period. "Main Predictors" denotes the main predictor variables used in the different studies. "Methodology" indicates the main forecasting methodology employed and "IS/OOS" shows whether in-sample (IS) or out-of-sample (OOS) approaches (or both) are employed to analyze the forecasts. The predictor acronyms are defined in Section II. Furthermore, ik denotes the investment to capital ratio, $\Delta M2$ is the growth rate of the money stock M2, ADS is the business conditions index of Aruoba et al. (2009), CFNAI denotes the Chicago Fed National Activity Index, VIX is the volatility index, and VRP is the equity variance risk premium. OLS stands for ordinary least squares, PLS denotes partial least squares, and GMM stands for the generalized method of moments.

Paper	# Comm.	Markets	Time Frame	Main Predictors	Methodology	IS/OOS
Spot Return Predictability						
Fama & French (1987)	21	All	1967 – 1984	basis	OLS	IS
Bailey & Chan (1993)	21	All	1966 – 1987	dfy, dy	OLS	IS
Pagano & Pisani (2009)	1	WTI Oil	1990 – 2007	capacity utilization, inventories	OLS	Both
Chen et al. (2010)	1	Index	1973 – 2008	USDAUD, USDCAD, USDCLP, USDNZD, USDZAR exchange rates	Granger causality	Both
Groen & Pesenti (2011)	10	Indexes	1973 – 2009	exchange rates as in Chen et al. (2010), large set of macro variables	PLS	OOS
Gargano & Timmermann (2014)	7	Indexes	1947 – 2010	Δgdp, $\Delta indpro$, $\Delta M1$, dfr, dp, $infl$, ik, ltr, tbl, tms, $unrate$, USDAUD and USDINR exchange rates, commodity futures index, open interest	OLS	Both
This Paper	30	All	1871 – 2015	see Section II	OLS	Both
Futures Return Predictability						
Bessembinder & Chan (1992)	8	All	1975 – 1989	dfy, dy, tbl	OLS	IS
Bjornson & Carter (1997)	8	Agriculture	1969 – 1994	$\Delta indpro$, dy, dfy, erp, tbl, tms	GMM	IS
De Roon et al. (2000)	10	All	1986 – 1994	hedging pressure	OLS	IS
Hong & Yogo (2012)	30	All	1965 – 2008	dfy, tbl, open interest	OLS	IS
Acharya et al. (2013)	4	Energy	1979 – 2010	oil and gas producers' default risk	OLS	IS
Etula (2013)	14	All	1990 – 2009	broker-dealer risk aversion	OLS	Both
Hammerschmid (2018)	1	Index	1975 – 2015	$\Delta indpro$, basis, business confidence index, exports, forward rate, imports, leading indicator, open interest, spot change, volatility, volume	OLS	Both
Volatility Predictability						
Pierdzioch et al. (2016)	1	Gold	1987 – 2015	$\Delta indpro$, $\Delta M2$, dfy, erp, $infl$, tbl, tms, exchange rate index	Boosting approach	OOS
Prokopczuk et al. (2019)	25	All	1970 – 2015	$\Delta indpro$, $\Delta M2$, dfr, dfy, $infl$, tms, ADS, bond volatility index, CFNAI, exchange rate index, TED spread, VIX, VRP	OLS	IS
Hollstein et al. (2020)	11	All	1996 – 2015	volatility term structure principal components large set of macro variables	Granger causality	Both
This Paper	30	All	1871 – 2015	see Section II	OLS	Both

Table 2: Summary Statistics – Commodity Returns and Volatilities

This table presents monthly summary statistics of the simple commodity returns and the volatilities. "Mean", "SD", "Skew", "Kurt", and "AR(1)" denote the mean, standard deviation, skewness, kurtosis, and the AR(1) coefficient, respectively. The returns and volatilities presented are in percentage points. "Nobs" denotes the number of monthly observations and "First" indicates the first month and year for which data on a given commodity are available. All data are monthly and sampled at the monthly frequency.

	Returns					Volatilities						
	Mean	*SD*	*Skew*	*Kurt*	*AR*(1)	*Mean*	*SD*	*Skew*	*Kurt*	*AR*(1)	*Nobs*	*First*
Agriculturals												
Butter	0.473	7.995	0.226	9.652	0.108	4.474	2.899	1.683	7.409	0.903	1,512	Jan-1890
Cocoa	0.419	7.813	1.422	13.31	0.056	4.382	2.732	0.734	3.740	0.847	1,740	Jan-1871
Coffee Arabica	0.433	7.192	1.317	9.618	0.289	4.446	2.264	1.003	5.085	0.862	671	Feb-1960
Corn Oil	0.475	8.576	0.899	9.436	0.208	5.212	3.122	1.543	6.605	0.789	1,097	Aug-1924
Cotton	0.279	6.245	0.159	14.65	0.161	3.601	2.239	1.980	11.69	0.747	1,737	Jan-1871
Live Cattle	0.336	5.342	0.996	13.41	0.193	3.234	1.493	1.730	9.134	0.776	1,740	Jan-1871
Lean Hog	0.563	9.719	1.671	13.99	0.039	5.866	2.490	2.091	10.78	0.893	1,740	Jan-1871
Milk	0.360	6.351	0.612	7.855	0.399	2.788	2.035	1.526	6.448	0.807	1,511	Feb-1890
Oranges	2.341	23.39	4.757	72.55	0.018	12.03	7.932	4.340	38.96	0.814	1,180	Feb-1914
Soybean Oil	0.458	8.465	1.076	8.764	0.076	5.309	3.238	1.490	6.349	0.841	1,259	Feb-1911
Soybeans	0.439	8.008	0.661	10.11	0.121	4.781	2.845	1.873	9.074	0.784	1,225	Dec-1913
Soybean Meal	0.644	10.25	1.499	17.25	−0.110	6.321	3.233	1.768	8.902	0.858	1,034	Nov-1929
Sugar	0.402	9.181	1.932	14.64	0.158	5.208	3.572	1.111	3.659	0.948	1,738	Jan-1871
Wheat	0.429	8.447	0.492	8.492	−0.034	5.331	2.525	1.321	5.647	0.855	1,740	Jan-1871
Wool	0.238	5.134	0.797	17.10	0.322	2.559	1.894	2.257	11.93	0.715	1,512	Jan-1890
Yellow Corn	0.490	8.688	0.700	9.902	−0.018	5.515	2.603	1.137	5.524	0.770	1,740	Jan-1871
Energies												
Coal	0.278	5.157	2.279	35.05	0.139	2.436	2.092	3.147	19.80	0.559	1,008	Jan-1932
Heating Oil	0.802	9.329	0.899	11.28	0.030	5.771	3.473	1.052	4.889	0.830	587	Feb-1967
Natural Gas	0.593	7.386	12.76	250.2	0.024	1.872	3.022	10.92	189.7	0.078	671	Feb-1960
Unleaded Regular Gas	0.842	11.49	1.643	14.24	−0.025	6.897	3.706	1.306	5.995	0.707	506	Nov-1973
WTI Oil	0.466	8.352	1.676	15.19	0.178	4.225	3.623	1.396	5.166	0.902	1,740	Jan-1871
Metals												
Aluminum	0.203	4.702	1.208	19.58	0.024	2.212	2.345	1.894	7.882	0.889	1,272	Jan-1910
Gold	0.278	3.455	1.878	20.13	0.085	1.594	1.954	1.827	6.591	0.912	1,740	Jan-1871
High Grade Copper	0.336	6.951	2.112	32.92	0.002	3.249	2.646	2.105	10.18	0.856	1,740	Jan-1871
Nickel	0.476	7.511	5.145	72.08	0.226	3.345	3.724	2.886	19.74	0.811	1,071	Oct-1926
Palladium	0.970	10.19	1.077	10.85	−0.060	5.783	2.659	0.816	3.833	0.752	576	Jan-1968
Platinum	0.462	6.365	1.777	18.31	0.126	3.105	2.439	1.635	6.580	0.859	1,271	Feb-1910
Silver	0.312	6.036	1.127	21.02	0.071	3.110	2.876	2.080	10.07	0.852	1,740	Jan-1871
Tin	0.331	5.734	0.782	12.71	0.214	3.296	1.841	0.914	3.810	0.877	1,740	Jan-1871
Zinc	0.309	6.153	1.308	15.36	0.156	3.240	2.452	2.246	13.12	0.852	1,740	Jan-1871

Table 3: Return Predictability Heatmap

This table presents a heatmap to summarize information about the in-sample and out-of-sample R^2s of all predictor variables and forecast combinations. We sample the data at the monthly frequency and predict the future 1-month USD excess returns. We present the results for the in-sample R^2s (“R^2_{IS}”) and the out-of-sample R^2s (“R^2_{OOS}”). ■, ■, and ■ denote statistical significance at the 10%, 5%, and 1% levels, respectively. White space indicates that a variable does not yield a statistically significant R^2. For all single variables, statistical significance is determined relative to a bootstrapped distribution, while for the forecast combinations, we use the MSPE-adjusted test statistic of Clark & West (2007). “de” denotes the dividend–payout ratio, “Δindpro” the growth of industrial production, and “ΔM1” the growth of money supply M1. “dfr” is the default return spread, defined as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. “dfy” is the default yield spread, defined as the difference between U.S. BAA- and AAA-rated corporate bond yields. “dp” is the dividend–price ratio, “dy” the dividend yield, “ep” the earnings–price ratio, “erp” the market risk premium, “infl” the inflation rate, “ltr” the long-term U.S. government bond returns, “lty” the long-term U.S. government bond yields, “svar” the stock variance, and “tbl” the 3-month Treasury bill rate. “tms” is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. “unrate” is the monthly U.S. unemployment rate. “comb” and “c-enet” are a simple mean forecast combination and one based on the adaptive elastic net, respectively.

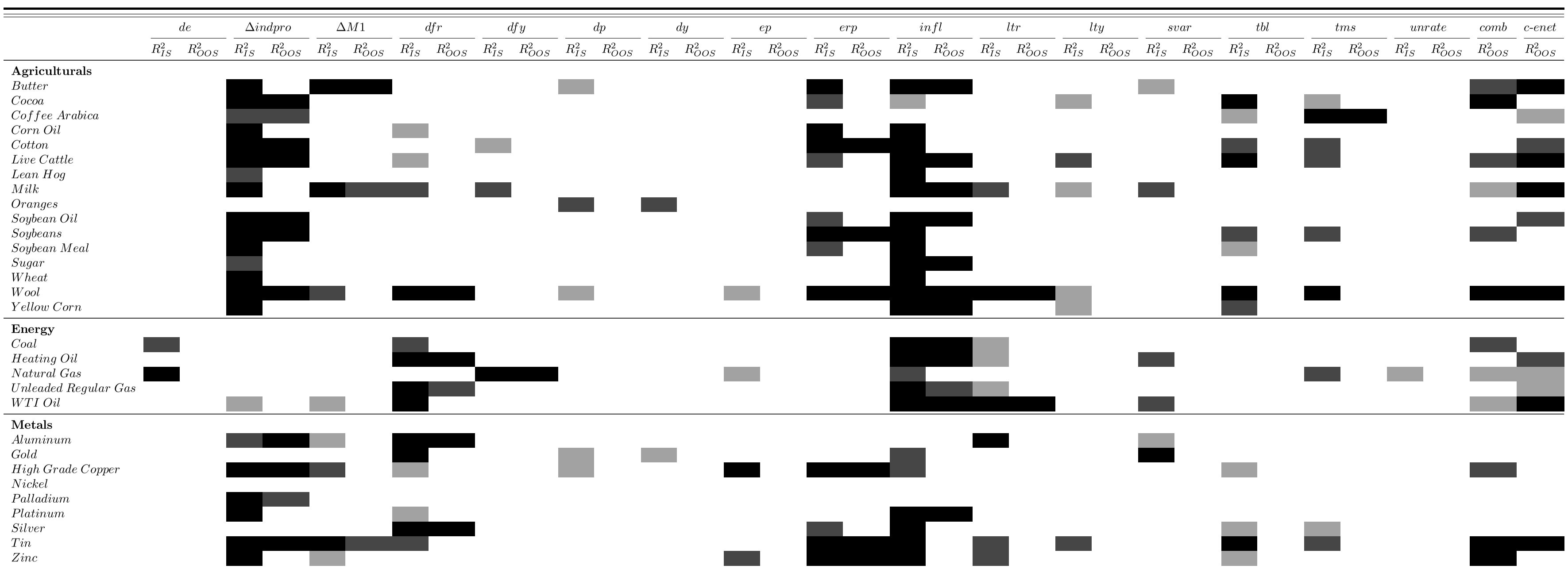


Table 4: Return Predictability – Summary Results

This table summarizes the in-sample and out-of-sample return predictability of Agriculturals, Energy, and Metals commodities. We sample the data at the monthly frequency and predict the future 1-month USD excess returns. "R^2_{IS}" and "R^2_{OOS}" denote the average in-sample R^2 and out-of-sample R^2, respectively. In parentheses, we present the share of commodities for which the respective R^2s are significantly positive at the 10% level. For all single variables, statistical significance is determined relative to a bootstrapped distribution, while for the forecast combinations, we use the MSPE-adjusted test statistic of Clark & West (2007). "de" denotes the dividend–payout ratio, "$\Delta indpro$" the growth of industrial production, and "$\Delta M1$" the growth of money supply M1. "dfr" is the default return spread, defined as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread, defined as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the monthly U.S. unemployment rate. "comb" and "c-enet" are a simple mean forecast combination and one based on the adaptive elastic net, respectively.

	Agriculturals				Energy				Metals			
	R^2_{IS}	(Shr)	R^2_{OOS}	(Shr)	R^2_{IS}	(Shr)	R^2_{OOS}	(Shr)	R^2_{IS}	(Shr)	R^2_{OOS}	(Shr)
de	0.043	(0.00)	−2.554	(0.00)	0.499	(0.40)	−2.537	(0.00)	0.043	(0.00)	−1.975	(0.00)
$\Delta indpro$	1.856	(0.94)	0.347	(0.44)	0.199	(0.20)	−1.391	(0.00)	1.440	(0.67)	0.114	(0.44)
$\Delta M1$	0.228	(0.19)	−0.986	(0.13)	0.175	(0.20)	−1.584	(0.00)	0.252	(0.44)	−1.140	(0.11)
dfr	0.221	(0.25)	−0.985	(0.06)	1.122	(0.80)	−0.300	(0.40)	0.441	(0.67)	−0.788	(0.22)
dfy	0.070	(0.06)	−1.816	(0.00)	0.334	(0.20)	−1.623	(0.20)	0.081	(0.00)	−1.595	(0.00)
dp	0.073	(0.19)	−1.800	(0.00)	0.143	(0.00)	−1.707	(0.00)	0.112	(0.22)	−1.728	(0.00)
dy	0.059	(0.06)	−1.866	(0.00)	0.154	(0.00)	−1.834	(0.00)	0.085	(0.11)	−1.780	(0.00)
ep	0.068	(0.06)	−2.485	(0.00)	0.237	(0.20)	−3.295	(0.00)	0.169	(0.22)	−1.772	(0.00)
erp	0.571	(0.56)	−0.753	(0.19)	0.038	(0.00)	−0.588	(0.00)	0.346	(0.44)	−0.517	(0.33)
$infl$	1.350	(0.88)	0.311	(0.44)	1.503	(1.00)	1.658	(0.80)	0.524	(0.67)	−0.775	(0.11)
ltr	0.234	(0.13)	−0.904	(0.06)	0.562	(0.60)	−0.386	(0.20)	0.218	(0.33)	−1.152	(0.00)
lty	0.157	(0.31)	−1.825	(0.00)	0.066	(0.00)	−1.300	(0.00)	0.142	(0.11)	−1.713	(0.00)
$svar$	0.055	(0.13)	−4.476	(0.00)	0.339	(0.40)	−3.532	(0.00)	0.090	(0.22)	−10.47	(0.00)
tbl	0.342	(0.50)	−1.817	(0.00)	0.041	(0.00)	−1.361	(0.00)	0.246	(0.44)	−1.510	(0.00)
tms	0.358	(0.38)	−1.439	(0.06)	0.205	(0.20)	−0.753	(0.00)	0.166	(0.22)	−1.380	(0.00)
$unrate$	0.052	(0.00)	−1.881	(0.00)	0.181	(0.20)	−1.125	(0.00)	0.027	(0.00)	−1.660	(0.00)
$comb$			0.118	(0.38)			0.414	(0.60)			0.215	(0.33)
c-$enet$			−0.184	(0.44)			0.622	(0.80)			−2.101	(0.11)

Table 5: Volatility Predictability Heatmap

This table presents a heatmap to summarize information about the in-sample and out-of-sample R^2s of all predictor variables and forecast combinations.. We sample the data at the monthly frequency and predict the future 1-month volatilities. We present the results for the in-sample R^2s ("R^2_{IS}") and the out-of-sample R^2s ("R^2_{OOS}"). The benchmark for the in-sample and out-of-sample R^2s is an AR(1) model forecast. ▇, ▇, and ▇ denote statistical significance at the 10%, 5%, and 1% levels, respectively. White space indicates that a variable does not yield a statistically significant R^2. For all single variables, statistical significance is determined relative to a bootstrapped distribution, while for the forecast combinations, we use the MSPE-adjusted test statistic of Clark & West (2007). "de" denotes the dividend–payout ratio, "Δindpro" the growth of industrial production, and "$\Delta M1$" the growth of money supply M1. "dfr" is the default return spread, defined as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread, defined as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the monthly U.S. unemployment rate. "comb" and "c-enet" are a simple mean forecast combination and one based on the adaptive elastic net, respectively.

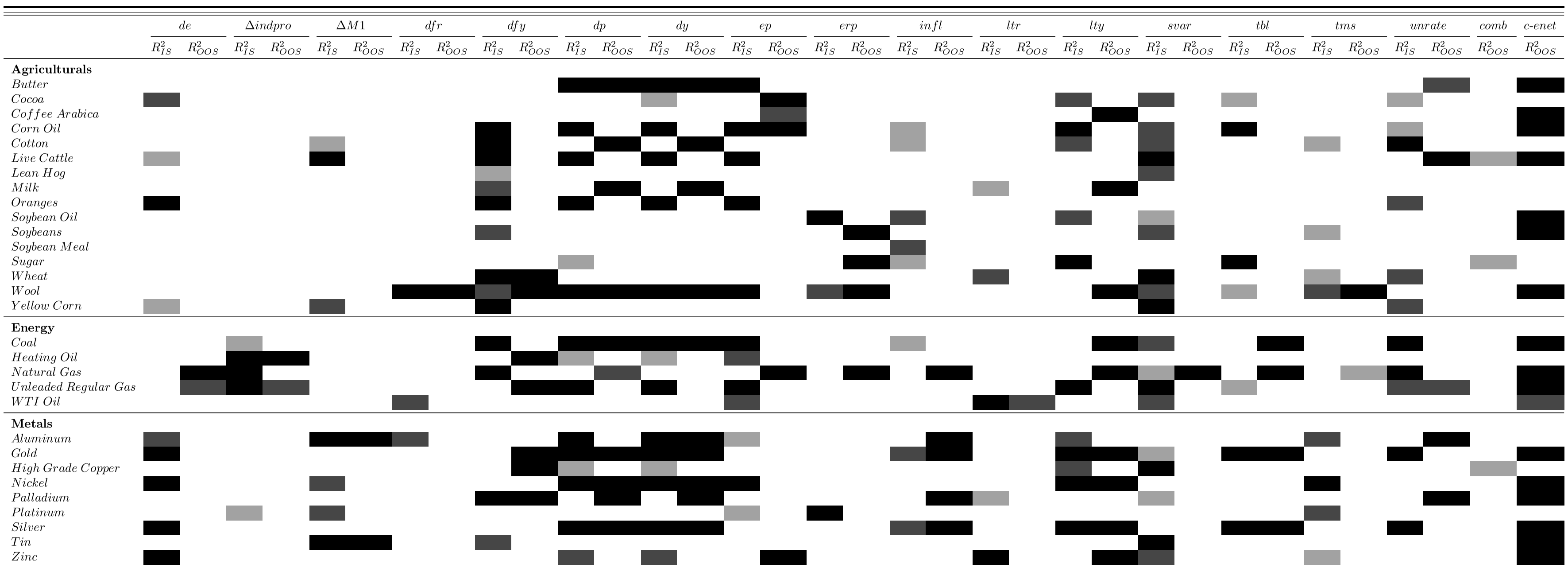


Table 6: Volatility Predictability – Summary Results

This table summarizes the in-sample and out-of-sample volatility predictability of Agriculturals, Energy, and Metals commodities. We sample the data at the monthly frequency and predict the future 1-month USD excess returns. "R^2_{IS}" and "R^2_{OOS}" denote the average in-sample R^2 and out-of-sample R^2, respectively. The benchmark for the in-sample and out-of-sample R^2s is an AR(1) model forecast. In parentheses, we present the share of commodities for which the respective R^2s are significantly positive at the 10% level. For all single variables, statistical significance is determined relative to a bootstrapped distribution, while for the forecast combinations, we use the MSPE-adjusted test statistic of Clark & West (2007). "de" denotes the dividend–payout ratio, "$\Delta indpro$" the growth of industrial production, and "$\Delta M1$" the growth of money supply M1. "dfr" is the default return spread, defined as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread, defined as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the monthly U.S. unemployment rate. "comb" and "c-enet" are a simple mean forecast combination and one based on the adaptive elastic net, respectively.

	Agriculturals				Energy				Metals			
	R^2_{IS}	(Shr)	R^2_{OOS}	(Shr)	R^2_{IS}	(Shr)	R^2_{OOS}	(Shr)	R^2_{IS}	(Shr)	R^2_{OOS}	(Shr)
de	0.127	(0.25)	−1.354	(0.00)	0.136	(0.00)	0.365	(0.40)	0.431	(0.56)	−2.049	(0.00)
$\Delta indpro$	0.046	(0.00)	−1.258	(0.00)	1.306	(0.80)	0.118	(0.40)	0.074	(0.11)	−0.917	(0.00)
$\Delta M1$	0.151	(0.19)	−1.340	(0.00)	0.024	(0.00)	−1.785	(0.00)	0.584	(0.44)	−0.569	(0.22)
dfr	0.249	(0.06)	−1.009	(0.06)	0.188	(0.20)	−1.383	(0.00)	0.081	(0.11)	−1.422	(0.00)
dfy	0.561	(0.63)	−1.635	(0.13)	0.408	(0.40)	−2.642	(0.40)	0.255	(0.22)	−0.942	(0.33)
dp	0.437	(0.38)	−0.797	(0.25)	0.986	(0.60)	−1.241	(0.40)	0.851	(0.67)	0.150	(0.44)
dy	0.431	(0.38)	−0.757	(0.25)	1.014	(0.60)	−1.570	(0.20)	0.841	(0.67)	0.130	(0.56)
ep	0.313	(0.31)	−1.429	(0.19)	1.461	(0.80)	−1.997	(0.20)	0.267	(0.33)	−1.044	(0.11)
erp	0.140	(0.13)	−0.676	(0.19)	0.056	(0.00)	−0.637	(0.20)	0.081	(0.11)	−1.095	(0.00)
$infl$	0.180	(0.31)	−1.309	(0.00)	0.134	(0.20)	−0.733	(0.20)	0.114	(0.22)	−0.028	(0.44)
ltr	0.123	(0.13)	−0.906	(0.00)	0.308	(0.20)	−0.939	(0.20)	0.231	(0.22)	−0.999	(0.00)
lty	0.276	(0.31)	−1.005	(0.19)	0.621	(0.20)	−1.582	(0.40)	0.764	(0.56)	−0.028	(0.44)
$svar$	0.317	(0.63)	−3.524	(0.00)	0.802	(0.80)	−1.603	(0.20)	0.298	(0.56)	−10.85	(0.00)
tbl	0.250	(0.19)	−2.084	(0.00)	0.258	(0.20)	−0.755	(0.40)	0.384	(0.22)	−0.967	(0.22)
tms	0.154	(0.25)	−1.822	(0.06)	0.210	(0.00)	−1.182	(0.20)	0.260	(0.44)	−1.717	(0.00)
$unrate$	0.277	(0.38)	−1.192	(0.13)	1.013	(0.60)	−1.669	(0.20)	0.541	(0.22)	−1.234	(0.22)
$comb$			−0.863	(0.13)			−2.100	(0.00)			−1.482	(0.11)
c-$enet$			−0.299	(0.44)			2.122	(0.80)			1.796	(0.67)

Table 7: Time-Variation in Predictability

*This table summarizes the results about the time-variation in the in-sample return and volatility predictability. We predict the next month excess return and volatility. We report the R^2s of a kitchen sink approach. The benchmark for return predictability is the trailing mean and for the volatility predictability it is an AR(1) model forecast. We consider three different events. First, the introduction of futures. Second, the introduction of futures options. Third, the beginning of the global financial crisis in July 2007. "R^2_{bef}" and "R^2_{aft}" denote the R^2s before and after the event. We use 120 observations to compute the R^2s. Statistical significance is based on a bootstrapped distribution. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. If the R^2 before or after the event is significantly (at 10%) larger than its counterpart (based on the bootstrapped distribution), we print the corresponding figure in **bold** font.*

	Return Predictability						Volatility Predictability					
	Futures Introduction		Options Introduction		Financial Crisis		Futures Introduction		Options Introduction		Financial Crisis	
	R^2_{bef}	R^2_{aft}	R^2_{bef}	R^2_{aft}	R^2_{bef}	R^2_{aft}	R^2_{bef}	R^2_{aft}	R^2_{bef}	R^2_{aft}	R^2_{bef}	R^2_{aft}
Agriculturals												
Butter			**14.66*****	5.486**	6.041**	**28.99*****			**20.57*****	11.47***	13.27***	**20.13*****
Cocoa	3.818**	**17.69*****	**17.76*****	9.717***	11.50***	**14.99*****	4.790**	**16.33*****	14.75***	**22.11*****	21.42***	**24.84*****
Coffee Arabica			14.67***	**18.10*****	**19.65*****	11.14***			**23.48*****	5.947**	**23.02*****	17.76***
Corn Oil					16.56***	**43.60*****					28.04***	**41.17*****
Cotton			**15.47*****	8.253***	**15.43*****	9.631***			**19.00*****	13.19***	20.50***	21.40***
Live Cattle	**13.37*****	8.135***	8.273***	7.427***	6.003***	**16.15*****	11.10***	**37.62*****	**21.46*****	12.47***	22.05***	**39.22*****
Lean Hog					10.21***	9.599***					10.86***	**16.04*****
Milk	8.969***	**13.57*****	8.969***	**13.57*****	12.82***	**34.25*****	17.09***	17.15***	17.09***	17.15***	7.578***	9.506***
Oranges	5.419***	6.776***	4.225**	5.794***	**10.57*****	5.372**	16.52***	**18.81*****	**16.38*****	14.15***	16.50***	**19.39*****
Soybean Oil	**16.80*****	5.092**	7.546***	**19.97*****	12.28***	11.22***	17.46***	**28.32*****	17.84***	15.92***	11.69***	**30.12*****
Soybeans	**33.54*****	11.25***	**14.96*****	6.366***	10.53***	**13.55*****	**19.16*****	16.12***	**25.95*****	21.15***	19.39***	**22.66*****
Soybean Meal	**15.93*****	7.836***	11.94***	11.25***	5.363**	7.307***	9.672***	**19.00*****	11.90***	**14.76*****	**22.51*****	11.05***
Sugar	1.255	**19.90*****	**17.04*****	7.795***	**15.18*****	11.17***	3.195	**6.881****	7.309***	**19.07*****	7.622**	**29.00*****
Wheat			**14.56*****	8.892***	8.986***	11.04***			17.89***	18.97***	**13.66*****	9.882***
Wool	29.26***	**48.86*****			**27.45*****	24.97***	**21.35*****	19.12***			20.82***	**32.70*****
Yellow Corn			**15.29*****	8.194***	**13.40*****	6.786***			15.50***	13.87***	**13.58*****	11.27***
Energy												
Coal	13.33***	**21.23*****			25.32***	27.00***	20.56***	**36.09*****			25.19***	**45.75*****
Heating Oil	**18.66*****	9.881***	12.78***	**16.18*****	10.34***	**33.17*****	**37.77*****	17.17***	9.976***	**25.12*****	6.962***	**29.66*****
Natural Gas	5.443***	**23.35*****	7.087***	**15.60*****	13.08***	**27.50*****	12.71***	**18.21*****	20.99***	**23.91*****	16.21***	**20.06*****
Unleaded Regular Gas	6.276***	**9.345*****	7.268***	**13.05*****	7.489***	**27.51*****	**33.54*****	19.71***	19.88***	**29.88*****	14.70***	**34.68*****
WTI Oil	**27.18*****	12.55***	**15.80*****	12.76***	11.74***	**34.12*****	14.64***	**24.51*****	20.04***	17.29***	10.23***	**36.81*****
Metals												
Aluminium	**17.75*****	5.074**			11.74***	**23.00*****	**23.43*****	10.70***			15.33***	**28.83*****
Gold	**21.21*****	14.82***	14.39***	14.77***	13.72***	**27.32*****	**52.04*****	20.90***	27.97***	**40.80*****	22.36***	20.79***
High Grade Copper	4.937**	**18.76*****	**17.58*****	14.91***	14.75***	**31.83*****	8.177***	**17.92*****	14.12***	**17.20*****	13.72***	**37.14*****
Nickel	**11.17*****	7.380***			12.14***	**16.77*****	**9.835*****	6.308***			28.83***	**36.59*****
Palladium			13.65***	**30.74*****	6.726***	**17.46*****			15.63***	**36.99*****	18.08***	19.56***
Platinum	11.57***	13.08***	5.008***	**10.56*****	10.92***	**24.18*****	**9.781*****	7.146***	8.431***	**14.53*****	15.40***	14.94***
Silver	**15.95*****	8.509***	**15.03*****	10.17***	10.02***	**18.01*****	16.94***	**21.67*****	**14.44*****	9.094***	8.533***	10.40***
Tin					16.07***	**18.79*****					9.252***	**23.42*****
Zinc	**24.98*****	11.09***			17.38***	**22.41*****	**39.80*****	22.91***			18.23***	**34.81*****

Table 8: Time-Variation in Volatility

*This table summarizes the results about the time-variation in the volatility of commodity returns. We consider three different events. First, the introduction of futures. Second, the introduction of futures options. Third, the beginning of the global financial crisis in July 2007. "SD_{bef}" and "SD_{aft}" indicate the standard deviations prior to and after the events, respectively. "ΔSD" is the difference between the volatility after and before the respective events. We use 120 observations to compute the volatility. We use the $F-$test of Snedecor & Cochran (1989) to determine whether the difference in volatilities is significantly different from zero. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively.*

	Futures Introduction			Options Introduction			Financial Crisis		
	SD_{bef}	SD_{aft}	ΔSD	SD_{bef}	SD_{aft}	ΔSD	SD_{bef}	SD_{aft}	ΔSD
Agriculturals									
Butter				6.965	15.57	8.609***	14.48	8.456	−6.027***
Cocoa	7.690	6.886	−0.804	9.759	6.264	−3.496***	8.089	7.444	−0.645
Coffee Arabica				7.776	9.289	1.513*	6.671	6.405	−0.266
Corn Oil							5.986	7.307	1.321**
Cotton				5.937	8.814	2.877***	5.629	7.214	1.585***
Live Cattle	4.502	4.735	0.234	5.973	4.429	−1.543***	3.558	4.278	0.720*
Lean Hog							12.44	10.15	−2.295**
Milk	3.088	5.573	2.485***	3.088	5.573	2.485***	6.405	5.871	−0.535
Oranges	19.57	18.42	−1.155	12.65	26.71	14.06***	47.11	18.60	−28.50***
Soybean Oil	11.05	6.051	−5.000***	9.151	6.348	−2.804***	8.301	8.507	0.206
Soybeans	9.572	8.561	−1.011	6.396	5.512	−0.884	8.025	8.456	0.431
Soybean Meal	10.56	8.256	−2.307***	8.060	6.592	−1.469**	8.951	12.19	3.236***
Sugar	5.082	10.53	5.444***	14.51	14.71	0.198	8.606	8.621	0.014
Wheat				7.105	6.729	−0.376	7.681	12.83	5.145***
Wool	3.618	6.314	2.696***				7.494	8.147	0.653
Yellow Corn				6.138	7.607	1.469**	8.350	10.18	1.827**
Energy									
Coal	3.254	8.195	4.941***				5.086	8.117	3.031***
Heating Oil	3.734	9.440	5.707***	8.808	11.70	2.890***	10.62	9.272	−1.347
Natural Gas	5.157	4.363	−0.794*	5.552	4.484	−1.067**	4.488	5.918	1.430***
Unleaded Regular Gas	6.073	10.57	4.502***	9.159	11.22	2.064**	15.60	11.36	−4.242***
WTI Oil	6.398	10.26	3.859***	7.512	8.611	1.099	9.459	9.962	0.503
Metals									
Aluminum	2.688	7.633	4.945***				4.848	7.069	2.222***
Gold	5.788	8.067	2.279***	9.011	4.497	−4.514***	4.086	5.700	1.614***
High Grade Copper	8.326	8.423	0.097	8.753	6.740	−2.013***	7.246	8.125	0.879
Nickel	3.609	14.59	10.98***				10.52	9.733	−0.783
Palladium		9.449		11.43	7.370	−4.057***	11.30	9.722	−1.583
Platinum	4.976	3.611	−1.365***	7.068	4.598	−2.471***	5.064	7.578	2.513***
Silver	3.730	4.430	0.700*	12.48	6.531	−5.954***	6.947	10.28	3.334***
Tin							5.813	8.005	2.193***
Zinc	4.006	6.827	2.822***				7.887	8.730	0.843

Table 9: Return Predictability Heatmap: Business Cycle Stages

This table presents a heatmap to summarize the predictability in different business cycle stages. We distinguish expansion and recession states, as defined by the NBER. We sample the data at the monthly frequency and predict the future 1-month USD excess returns. We present the results for the in-sample R^2s. , , and denote statistical significance at the 10%, 5%, and 1% levels, respectively. White space indicates that a variable does not yield a statistically significant R^2 and "–" means that there is not a sufficient amount of data available. Statistical significance is determined relative to a bootstrapped distribution. "de" denotes the dividend–payout ratio, "Δindpro" the growth of industrial production, and "ΔM1" the growth of money supply M1. "dfr" is the default return spread, defined as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread, defined as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the monthly U.S. unemployment rate.

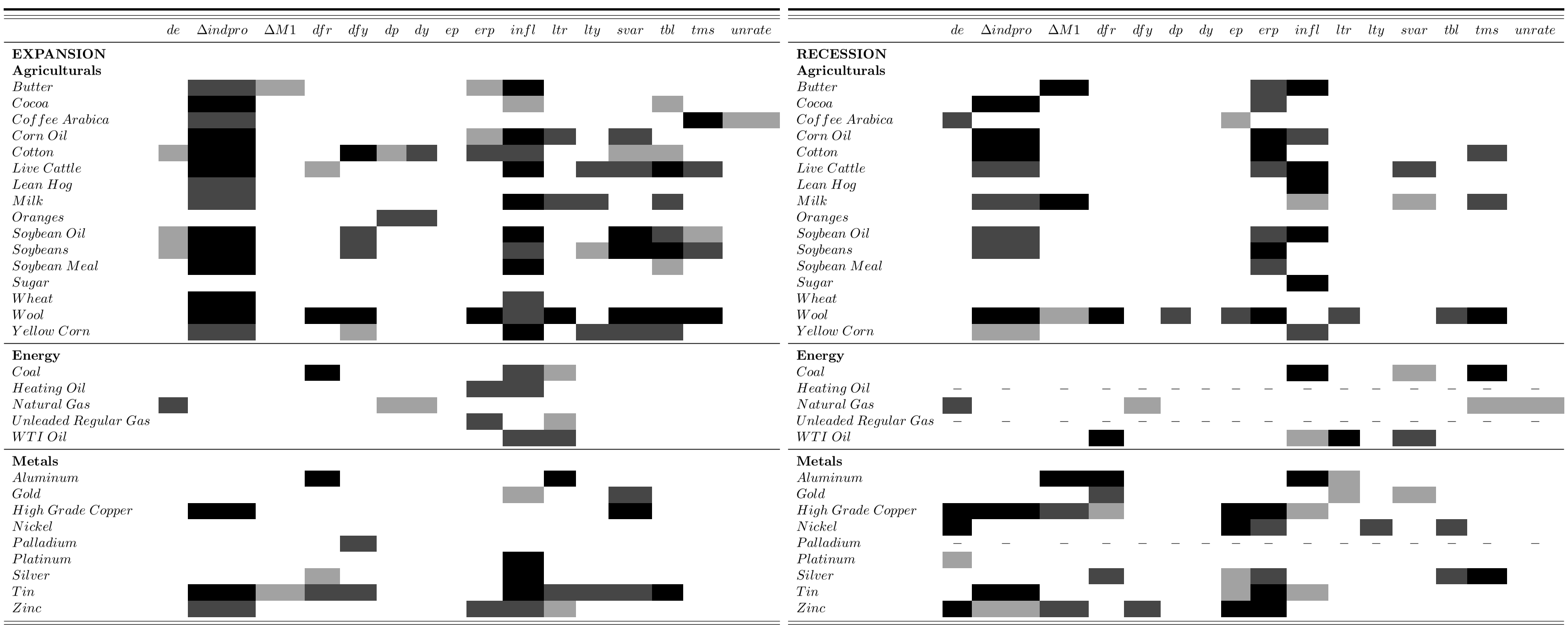
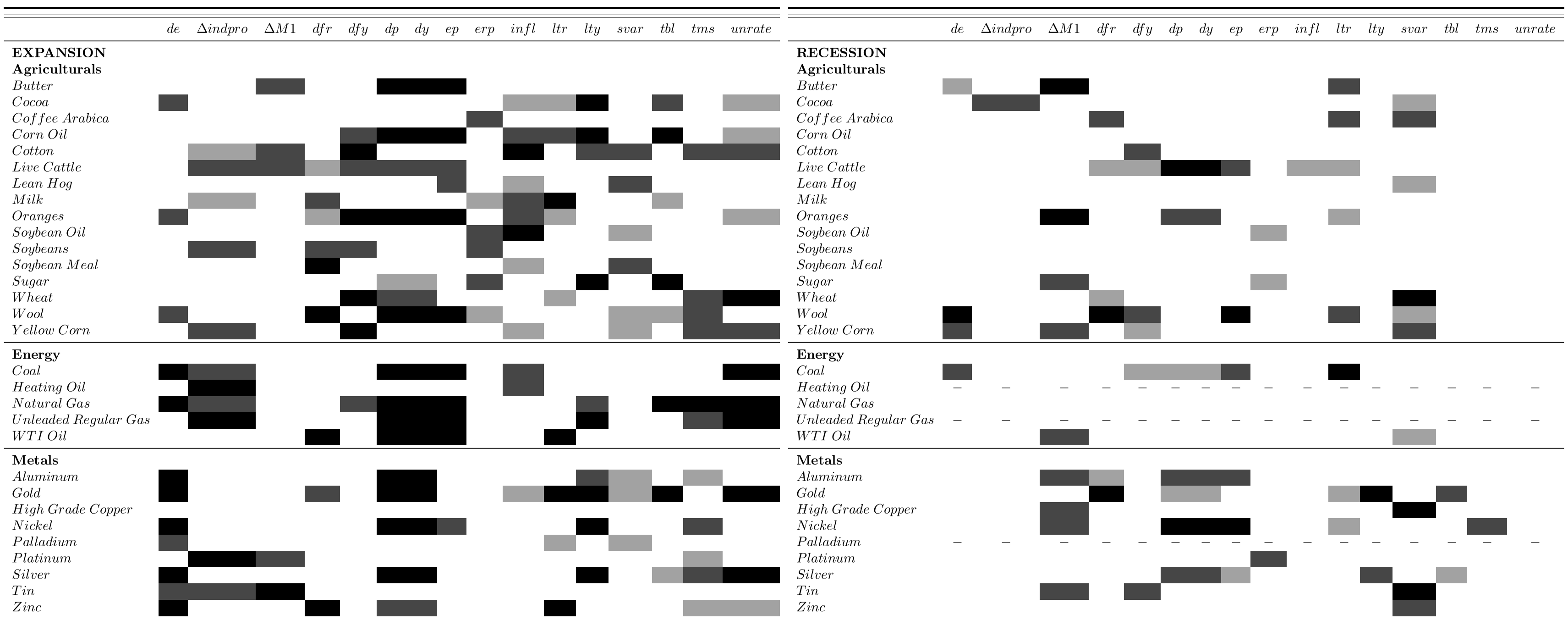


Table 10: Volatility Predictability Heatmap: Business Cycle Stages

This table presents a heatmap to summarize the predictability in different business cycle stages. We distinguish expansion and recession states, as defined by the NBER. We sample the data at the monthly frequency and predict the future 1-month volatilities. We present the results for the in-sample R^2s. The benchmark is an AR(1) model forecast. ▒, ▓, and █ denote statistical significance at the 10%, 5%, and 1% levels, respectively. White space indicates that a variable does not yield a statistically significant R^2 and "–" means that there is not a sufficient amount of data available. Statistical significance is determined relative to a bootstrapped distribution. "de" denotes the dividend–payout ratio, "Δindpro" the growth of industrial production, and "$\Delta M1$" the growth of money supply M1. "dfr" is the default return spread, defined as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread, defined as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the monthly U.S. unemployment rate.



Predictability in Commodity Markets: Evidence from More Than a Century

Online Appendix

JEL classification: G10, G11, G17

Keywords: Commodities, Return Predictability, Derivatives Introduction, Business Cycle, Volatility Predictability

Table A1: Information About the Commodities

This table provides detailed information about the commodities used in this study. We provide information on the tickers in the GFD database, a more detailed contract description, as well as the main data source of the GFD. For most commodities, the data sources are not constant over time. We indicate the respective sources that cover most of our sample period.[a] *For further information, please check the GFD data descriptions. The remainder of the table presents the futures and futures options introduction dates at the CME and, if an earlier introduction date is available at another exchange group, we also present that (sources in the footnotes). For our empirical tests, we use the earliest of the respective introduction dates presented in this table.*

[a] Several of the very old data are from Bezanson (1954).

Commodity Information				Introduction Dates (CME)[b]		Introduction Dates (Other)		Details (Other)	
Name	**GFD Ticker**	**Description**	**Main Data Source GFD**	**Futures**	**Options**	**Futures**	**Options**	**Source Other (Futures)**	**Source Other (Options)**
Agriculturals									
Butter	CMBUTD	Butter Average Price	Economic Research Service, U.S. Department of Agriculture	Sep-1996	Sep-1996	1872		CFTC[c]	
Cocoa	_CO1599D	Cocoa	New York Cocoa Exchange	–	–	Oct-1925	1986	New York Cocoa Exchange[d]	NBOT flyer[e]
Coffee Arabica	CMWCFAM	Coffee Arabica	Average New York and Bremen/Hamburg market	–	–	Mar-1882	1986	NY Coffee and Sugar Exchange[f]	
Corn Oil	CMCORNOM	Corn Oil	Economic Research Service, U.S. Department of Agriculture	–	–				
Cotton	COT_AFRD	Cotton	NBER	–	–	1870	1984	CFTC[c]	NBOT flyer[e]
Live Cattle	_ICXD	Live Cattle	US Dept. of Agriculture	Nov-1964	Oct-1984				
Lean Hog	_IHXD	Live Hog	IHX Hog Index	–	–				
Milk	CMMILKM	Milk Average Price to Farmers	Economic Research Service, U.S. Department of Agriculture	Jan-1996	Jan-1996				
Oranges	CMORANGM	Oranges Average Price to Farmers	Economic Research Service, U.S. Department of Agriculture	–	–	Oct-1966	1985	NY Times[g]	NBOT flyer[e]
Soybean Oil	_BO1599D	Soybean Oil	Chicago Board of Trade	Jul-1950	Feb-1987				
Soybeans	__SYB_TD	Soybeans	Soybeans in Southeast Iowa	Oct-1936	Oct-1987				
Soybean Meal	__SYM_4D	Soybean Meal	Soybean Meal in Kansas City	Aug-1951	Feb-1987				
Sugar	_SU1599D	Sugar	New York Board of Trade	–	–	1914	Oct-1982		NY Times[h]
Wheat	__W_USSD	Wheat	Anne Bezanson, James E. Boyle	Jan-1877	Nov-1986				
Wool	CMWOOLM	Wool 56s Staple 2 3/4 and Up	Bureau of Labor Statistics Bulletins	–	–	May-1931		U.S. Department of Agriculture[i]	
Yellow Corn	__C_US2D	Chicago Yellow Corn No. 2	Chicago Board of Trade	Jan-1877	Feb-1985				
Energy									
Coal	CMCOALM	Coal	Historical Statistics of the United States	Jul-2001	–				
Heating Oil	HO_USGD	Heating Oil No. 2 Gulf Coast FOB	No Information	Nov-1978	Jun-1987				
Natural Gas	CMWNGEM	Natural gas Europe	Average import border price	Apr-1990	Oct-1992				
Unleaded Regular Gas	RU_NYHD	Unleaded Regular Gas New York FOB	New York Harbor conventional gasoline regular	Dec-1984	Mar-1989				
WTI Oil	__WTC_D	West Texas Intermediate Oil	National Bureau of Economic Research, Bureau of Labor Statistics	Mar-1983	Nov-1986				
Metals									
Aluminum	CMALSD	Aluminum	London Metal Exchange	–	–	Dec-1978		LME[j]	
Gold	__XAU_D	Gold Bullion Price-New York	Commodity Research Bureau, Commodity Yearbook	Dec-1974	Oct-1982				
High Grade Copper	__CU_NYD	High Grade Copper	American Metal Market	Jul-1988	Jul-1988	Nov-1981		LME[j]	
Nickel	CMNISD	Nickel	London Metal Exchange	–	–	Apr-1979		LME[j]	
Palladium	XPD_D	Palladium	No Information	Jan-1968	Aug-2010				
Platinum	__PL_NYD	Platinum	American Metal Market	Dec-1956	Oct-1990				
Silver	__XAG_HD	Silver	Commodity Research Bureau, Commodity Yearbook	Jul-1933	Oct-1984				
Tin	__SN_NYD	Tin (Straits, Pigs)	London Metal Exchange	–	–	1877		LME[j]	
Zinc	__MZN2MD	Zinc Special High Grade	London Metal Exchange	–	–	Jun-1986		LME[j]	

[b] https://www.cmegroup.com/media-room/historical-first-trade-dates.html

[c] https://www.cftc.gov/About/HistoryoftheCFTC/history_precftc.html

[d] See Canalizo (1931).

[e] http://farrfutures.com/pdfs/sugar-futures-options.pdf

[f] See Brunn (1931).

[g] https://www.nytimes.com/1966/10/30/archives/citrus-group-adds-bit-of-lemon-to-new-orangejuice-trading-some.html?searchResultPosition=10

[h] https://www.nytimes.com/1982/09/27/business/commodities-at-last-options-on-futures.html?searchResultPosition=5

[i] https://books.google.de/books?id=QtnXubUP16wC&pg=PA23&lpg=PA23&dq=wool+tops+++1938&source=bl&ots=6JSQT35fHv&sig=ACfU3U2ehBCzBW1j2orEqIQ0QScJzC1gCA&hl=de&sa=X&ved=2ahUKEwjm-4_j9qjmAhXSDewKHcgDBbYQ6AEwDHoECAcQBA#v=onepage&q=wool%20tops%20%20%201938&f=false

[j] https://www.lme.com/en-GB/About/History

Table A2: Summary Statistics – Predictor Variables

This table presents monthly summary statistics about the predictor variables. "de" denotes the dividend–payout ratio, "Δindpro" the growth of industrial production, and "$\Delta M1$" the growth of money supply M1. "dfr" is the default return spread, defined as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread, defined as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the monthly U.S. unemployment rate. "Mean", "SD", "Skew", and "Kurt" denote the mean, standard deviation, skewness, and kurtosis, respectively. The next three columns show the first-order autoregressive coefficient and the p-value of the Jarque–Bera and Augmented Dickey–Fuller test, respectively. "First" and "Nobs" denote the first observation of the time series and the number of observations. All data are sampled at the monthly frequency.

Variable	**Mean**	**SD**	**Skew**	**Kurt**	**AR(1)**	**JB p-value**	**ADF p-value**	**First**	**Nobs**
de	-0.5424	0.3158	0.8124	6.4439	0.9931	<0.01	<0.01	Jan-1871	1740
$\Delta indpro$	0.0026	0.0193	0.2794	13.9795	0.5076	<0.01	<0.01	Feb-1919	1163
$\Delta M1$	0.0040	0.0065	1.7852	17.3614	0.2514	<0.01	<0.01	Feb-1947	827
dfr	0.0003	0.0135	-0.3897	11.0916	-0.1268	<0.01	<0.01	Jan-1926	1080
dfy	0.0119	0.0071	2.0854	9.7171	0.9767	<0.01	<0.01	Jan-1919	1164
dp	-3.2088	0.4311	-0.7092	3.3307	0.9941	<0.01	<0.05	Jan-1871	1740
dy	-3.2054	0.4284	-0.7395	3.3522	0.9940	<0.01	<0.05	Feb-1871	1739
ep	-2.6663	0.3745	-0.7048	6.4535	0.9884	<0.01	<0.01	Jan-1871	1740
erp	0.0040	0.0477	-0.4122	11.7655	0.1117	<0.01	<0.01	Jan-1871	1740
$infl$	0.0020	0.0072	0.5630	18.4577	0.3031	<0.01	<0.01	Jan-1875	1691
ltr	0.0048	0.0243	0.6032	7.8052	0.0379	<0.01	<0.01	Jan-1926	1080
lty	0.0512	0.0269	1.1556	3.8979	0.9966	<0.01	0.87	Jan-1919	1164
$svar$	0.0025	0.0049	6.5792	60.9568	0.6201	<0.01	<0.01	Feb-1885	1571
tbl	0.0349	0.0300	1.0576	4.4489	0.9932	<0.01	0.25	Feb-1920	1151
tms	0.0163	0.0131	-0.1532	2.9822	0.9625	0.10	<0.01	Feb-1920	1151
$unrate$	0.0582	0.0165	0.5723	3.0451	0.9905	<0.01	0.53	Jan-1948	816

Table A3: Correlations – Commodity Returns

This table reports the pairwise correlations among all commodity returns (not deseasonalized). We split the commodities into Agriculturals, Energies, and Metals. All data are sampled at the monthly frequency.

Commodity	Butter	Cocoa	Coffee Arabica	Corn Oil	Cotton	Live Cattle	Lean Hog	Milk	Oranges	Soybean Oil	Soybeans	Soybean Meal	Sugar	Wheat	Wool	Yellow Corn	Coal	Heating Oil	Natural Gas	Unleaded Regular Gas	WTI Oil	Aluminum	Gold	High Grade Copper	Nickel	Palladium	Platinum	Silver	Tin	Zinc
Cocoa	0.012																													
Coffee Arabica	0.005	0.086																												
Corn Oil	0.086	0.142	0.087																											
Cotton	0.037	0.036	0.026	0.195																										
Live Cattle	0.049	0.107	-0.019	0.142	0.039																									
Lean Hog	0.050	0.063	-0.022	0.106	0.069	0.198																								
Milk	0.357	0.006	-0.029	0.087	-0.026	-0.016	-0.046																							
Oranges	0.089	0.007	-0.017	0.003	-0.016	0.072	-0.007	-0.010																						
Soybean Oil	0.058	0.186	0.084	0.364	0.188	0.114	0.138	0.065	-0.028																					
Soybeans	0.005	0.188	0.119	0.235	0.212	0.109	0.090	-0.042	-0.043	0.540																				
Soybean Meal	0.021	0.139	0.086	0.103	0.107	0.147	0.028	0.030	-0.045	0.339	0.693																			
Sugar	0.036	0.078	0.072	0.075	0.062	0.002	0.011	0.030	-0.003	0.138	0.104	0.079																		
Wheat	-0.009	0.088	0.061	0.098	0.097	0.008	0.040	0.071	-0.005	0.287	0.265	0.286	0.096																	
Wool	0.053	0.096	0.136	0.117	0.101	0.088	0.065	0.027	-0.011	0.149	0.094	0.035	0.038	0.084																
Yellow Corn	-0.006	0.096	0.053	0.098	0.119	0.030	0.087	-0.052	-0.008	0.314	0.405	0.456	0.094	0.416	0.072															
Coal	0.045	0.025	0.051	0.115	0.012	0.077	0.059	0.120	-0.058	0.082	0.032	0.028	0.059	0.007	0.052	0.007														
Heating Oil	0.022	0.084	0.042	0.067	-0.046	0.117	0.060	0.090	0.013	0.075	0.033	0.028	-0.008	0.030	0.118	0.005	0.120													
Natural Gas	-0.060	-0.039	0.039	0.073	-0.024	0.074	0.001	0.009	-0.001	0.073	0.045	-0.016	0.106	0.003	0.005	0.051	0.276	-0.010												
Unleaded Regular Gas	0.049	0.095	0.070	0.078	-0.043	0.074	0.069	-0.003	0.007	0.042	0.021	0.008	-0.018	-0.046	0.156	0.017	0.136	0.628	-0.023											
WTI Oil	0.063	0.052	0.061	0.067	-0.004	0.001	0.005	0.067	0.017	0.064	0.027	0.003	-0.008	0.020	0.078	-0.037	0.151	0.722	0.116	0.668										
Aluminum	-0.034	0.007	0.114	0.041	0.046	0.062	0.022	0.004	-0.055	0.069	0.043	0.032	0.068	0.011	0.065	-0.012	0.114	0.183	-0.006	0.147	0.144									
Gold	-0.022	0.107	0.069	0.050	0.010	0.044	0.026	0.018	-0.020	0.105	0.142	0.108	0.106	0.084	0.080	0.071	0.061	0.130	0.116	0.082	0.122	0.070								
High Grade Copper	0.016	0.092	0.121	0.112	0.106	0.060	0.029	0.015	-0.054	0.164	0.130	0.116	0.116	0.084	0.066	0.053	0.084	0.167	0.028	0.154	0.057	0.242	0.157							
Nickel	-0.027	0.020	0.124	0.037	0.055	0.064	0.037	-0.069	-0.076	0.054	0.081	0.075	-0.009	0.025	0.114	0.072	0.082	0.161	-0.028	0.142	0.116	0.405	0.062	0.213						
Palladium	0.042	0.063	0.097	0.076	0.090	-0.031	-0.004	0.028	-0.016	0.082	0.128	0.077	0.115	0.078	0.014	0.128	0.111	0.076	0.039	0.114	0.119	0.175	0.161	0.215	0.153					
Platinum	0.062	0.072	0.114	0.058	0.034	0.059	0.025	0.089	0.007	0.099	0.080	0.064	0.034	0.086	0.103	0.109	0.089	0.144	0.029	0.154	0.111	0.177	0.191	0.168	0.152	0.386				
Silver	0.028	0.118	0.084	0.081	0.044	0.076	0.055	0.021	0.016	0.138	0.126	0.100	0.111	0.104	0.092	0.123	0.054	0.137	0.086	0.114	0.123	0.104	0.618	0.177	0.117	0.232	0.238			
Tin	0.061	0.109	0.051	0.170	0.114	0.038	0.053	0.007	-0.032	0.173	0.100	0.027	0.109	0.097	0.135	0.084	0.144	0.193	-0.035	0.182	0.128	0.206	0.114	0.264	0.203	0.172	0.139	0.176		
Zinc	0.018	0.086	0.079	0.092	0.041	0.082	0.054	0.046	-0.055	0.119	0.042	0.025	0.113	0.061	0.098	0.047	0.074	0.142	0.028	0.156	0.033	0.229	0.089	0.283	0.271	0.178	0.196	0.130	0.261	

Table A4: Correlations – Commodity Volatilities

This table reports the pairwise correlations among all commodity volatilities. We split the commodities into Agriculturals, Energies, and Metals. All data are sampled at the monthly frequency.

Commodity	*Butter*	*Cocoa*	*Coffee Arabica*	*Corn Oil*	*Cotton*	*Live Cattle*	*Lean Hog*	*Milk*	*Oranges*	*Soybean Oil*	*Soybeans*	*Soybean Meal*	*Sugar*	*Wheat*	*Wool*	*Yellow Corn*	*Coal*	*Heating Oil*	*Natural Gas*	*Unleaded Regular Gas*	*WTI Oil*	*Aluminum*	*Gold*	*High Grade Copper*	*Nickel*	*Palladium*	*Platinum*	*Silver*	*Tin*	*Zinc*
Cocoa	-0.082																													
Coffee Arabica	0.221	-0.081																												
Corn Oil	0.002	0.477	-0.135																											
Cotton	0.240	0.026	0.221	0.292																										
Live Cattle	0.094	0.244	0.248	0.407	0.217																									
Lean Hog	0.386	0.209	0.165	0.249	0.233	0.276																								
Milk	0.403	-0.304	0.055	-0.069	0.303	0.040	0.117																							
Oranges	0.219	0.025	-0.064	-0.097	-0.076	-0.230	-0.060	0.090																						
Soybean Oil	0.138	0.510	0.040	0.612	0.233	0.409	0.338	0.024	0.016																					
Soybeans	0.197	0.407	0.098	0.424	0.189	0.335	0.334	0.020	-0.016	0.589																				
Soybean Meal	0.138	0.338	0.117	0.385	0.241	0.389	0.307	0.160	-0.059	0.508	0.676																			
Sugar	-0.188	0.304	-0.273	0.253	0.173	0.035	0.048	-0.143	0.089	0.276	0.085	0.032																		
Wheat	0.324	0.190	0.180	0.236	0.315	0.279	0.256	0.312	-0.105	0.318	0.404	0.399	0.097																	
Wool	0.197	0.131	0.073	0.054	0.291	0.044	0.142	0.185	0.066	0.155	0.219	0.184	0.130	0.331																
Yellow Corn	0.370	0.001	0.197	0.220	0.413	0.337	0.352	0.334	-0.072	0.305	0.382	0.459	-0.016	0.467	0.248															
Coal	0.091	0.151	-0.122	0.111	0.094	-0.027	0.078	0.334	0.098	0.230	0.193	0.154	0.217	0.330	0.236	0.188														
Heating Oil	0.274	-0.111	0.127	-0.099	0.196	-0.105	0.186	0.243	0.107	-0.074	-0.047	-0.017	-0.084	0.172	0.122	0.209	0.091													
Natural Gas	0.168	0.132	0.067	0.094	0.105	0.123	0.128	0.176	-0.006	0.194	0.151	0.169	-0.024	0.285	0.160	0.220	0.297	0.147												
Unleaded Regular Gas	0.272	-0.138	0.166	-0.207	0.148	-0.204	0.284	0.270	0.119	0.031	0.028	0.069	-0.101	0.187	0.235	0.274	0.225	0.671	0.129											
WTI Oil	0.434	0.019	0.308	0.032	0.226	0.248	0.146	0.346	0.156	0.141	0.129	0.106	-0.020	0.409	0.324	0.332	0.265	0.774	0.240	0.673										
Aluminum	0.193	-0.065	0.188	-0.064	0.278	-0.094	0.059	0.292	0.181	0.050	0.054	0.068	0.206	0.277	0.336	0.195	0.282	0.400	0.143	0.229	0.519									
Gold	0.001	0.382	0.197	0.317	0.170	0.086	0.168	-0.160	0.061	0.368	0.315	0.234	0.497	0.251	0.222	0.034	0.259	-0.008	0.143	-0.064	0.098	0.254								
High Grade Copper	0.078	0.138	0.162	0.125	0.214	-0.004	0.117	0.049	-0.011	0.208	0.096	0.057	0.241	0.150	0.293	0.109	0.224	0.219	0.119	0.180	0.026	0.419	0.375							
Nickel	0.314	0.016	0.147	-0.099	0.209	-0.110	0.078	0.444	0.220	0.043	0.097	0.067	0.189	0.236	0.346	0.183	0.339	0.373	0.085	0.199	0.545	0.734	0.351	0.445						
Palladium	0.248	0.254	-0.035	0.191	0.190	0.026	0.042	0.217	0.154	0.153	0.233	0.121	0.111	0.288	0.036	0.179	0.222	0.134	0.070	0.012	0.153	-0.021	0.253	0.086	0.104					
Platinum	0.190	0.128	0.319	0.082	0.361	0.281	0.152	0.220	-0.039	0.192	0.100	0.202	0.071	0.316	0.162	0.436	0.124	0.299	0.076	0.205	0.325	0.282	0.125	0.266	0.252	0.189				
Silver	0.084	0.219	0.022	0.213	0.269	0.067	0.189	0.058	0.015	0.284	0.194	0.166	0.449	0.281	0.250	0.167	0.320	-0.012	0.131	0.039	0.074	0.291	0.763	0.383	0.355	0.180	0.236			
Tin	0.176	0.131	0.169	0.152	0.306	0.052	0.083	0.283	0.027	0.221	0.208	0.227	0.144	0.371	0.378	0.267	0.274	0.283	0.196	0.270	0.242	0.371	0.179	0.319	0.336	0.232	0.307	0.220		
Zinc	0.199	0.025	0.210	-0.010	0.317	-0.052	0.100	0.363	0.082	0.049	0.125	0.165	0.127	0.329	0.339	0.228	0.316	0.397	0.180	0.381	0.201	0.539	0.144	0.447	0.536	0.124	0.323	0.233	0.497	

Table A5: Correlations – Predictor Variables

This table reports the pairwise correlations among all predictor variables. "de" denotes the dividend–payout ratio, "Δindpro" the growth of industrial production, and "ΔM1" the growth of money supply M1. "dfr" is the default return spread, defined as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread, defined as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the monthly U.S. unemployment rate. All data are sampled at the monthly frequency.

$Variable$	de	$\Delta indpro$	$\Delta M1$	dfr	dfy	dp	dy	ep	erp	$infl$	ltr	lty	$svar$	tbl	tms	$unrate$
$\Delta indpro$	0.020															
$\Delta M1$	0.107	0.003														
dfr	0.093	0.047	-0.013													
dfy	0.550	-0.053	0.275	0.024												
dp	0.534	-0.031	0.015	0.000	0.458											
dy	0.531	0.000	0.011	0.017	0.453	0.994										
ep	-0.229	-0.050	-0.054	-0.074	0.075	0.701	0.697									
erp	-0.038	0.264	-0.039	0.143	-0.045	-0.089	0.020	-0.071								
$infl$	-0.230	0.183	-0.014	0.033	-0.217	-0.054	-0.049	0.133	0.036							
ltr	-0.031	-0.060	0.023	-0.465	0.070	-0.026	-0.016	-0.004	0.080	-0.075						
lty	-0.283	-0.042	0.102	-0.004	0.030	-0.119	-0.119	0.093	-0.048	0.191	0.052					
$svar$	0.284	-0.112	0.196	-0.070	0.519	0.125	0.096	-0.096	-0.250	-0.141	0.076	-0.102				
tbl	-0.317	-0.062	-0.035	-0.040	-0.061	-0.022	-0.023	0.231	-0.060	0.210	0.047	0.900	-0.162			
tms	0.143	0.053	0.288	0.086	0.205	-0.194	-0.192	-0.333	0.038	-0.064	0.001	0.001	0.162	-0.435		
$unrate$	0.085	-0.025	0.314	0.059	0.665	0.049	0.056	-0.008	0.066	0.022	0.110	0.407	0.099	0.123	0.549	

Table A6: Return Predictability – Detailed Results

*This table presents the detailed results on the in-sample and out-of-sample return predictability of Agriculturals, Energy, and Metals commodities. We sample the data at the monthly frequency and predict the future 1-month USD excess returns. "R^2_{IS}" and "R^2_{OOS}" denote the in-sample R^2 and out-of-sample R^2, respectively. In parentheses, "t-stat" presents the t-statistic of the in-sample slope coefficient. For all single variables, statistical significance is determined relative to a bootstrapped distribution, while for the forecast combinations, we use the MSPE-adjusted test statistic of Clark & West (2007). *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively. In addition, we print all significant observations in **bold**. "de" denotes the dividend–payout ratio, "Δindpro" the growth of industrial production, and "ΔM1" the growth of money supply M1. "dfr" is the default return spread, defined as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread, defined as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the monthly U.S. unemployment rate. "comb" and "c-enet" are a simple mean forecast combination and one based on the adaptive elastic net, respectively.*

	de	*Δindpro*	*ΔM1*	*dfr*	*dfy*	*dp*	*dy*	*ep*	*erp*	*infl*	*ltr*	*lty*	*svar*	*tbl*	*tms*	*unrate*	*comb*	*c-enet*
Agriculturals																		
Butter																		
R^2_{IS}	0.096	**0.642*****	**1.283*****	0.001	0.110	**0.185***	0.117	0.051	**0.664*****	**3.027*****	0.000	0.109	**0.205***	0.198	0.111	0.000		
R^2_{OOS}	−1.524	−0.102	**0.402*****	−0.662	−1.335	−2.050	−2.087	−1.661	−0.529	**2.880*****	−1.694	−2.128	−1.037	−1.816	−1.195	−1.761	**0.432****	**0.562*****
(t-stat)	−1.000	2.837	−2.619	0.091	−0.936	−1.137	−0.904	−0.754	3.051	5.250	−0.003	−1.573	−1.432	−1.882	1.239	0.022		
Cocoa																		
R^2_{IS}	0.012	**2.067*****	0.091	0.000	0.106	0.040	0.025	0.104	**0.222****	**0.210***	0.054	**0.306***	0.013	**0.566*****	**0.323***	0.004		
R^2_{OOS}	−1.858	**2.729*****	−1.600	−0.322	−1.956	−1.733	−1.798	−2.499	−0.917	−0.110	−0.791	−1.269	−10.23	−1.830	−0.922	−1.394	**0.743*****	−0.475
(t-stat)	0.476	4.127	−0.688	−0.021	−1.058	−0.833	−0.658	−1.278	1.789	1.323	0.742	−1.725	−0.351	−2.301	1.913	−0.183		
Coffee Arabica																		
R^2_{IS}	0.068	**0.800****	0.008	0.340	0.000	0.001	0.002	0.051	0.000	0.138	0.131	0.009	0.000	**0.434***	**1.523*****	0.275		
R^2_{OOS}	−1.778	**0.031****	−2.251	−0.383	−1.493	−2.261	−2.358	−2.635	−0.902	−1.291	−1.067	−1.809	−8.610	−1.006	**0.921*****	−0.664	0.322	**0.020***
(t-stat)	0.749	2.598	0.228	1.654	0.006	−0.086	−0.101	−0.547	−0.012	0.897	−0.963	−0.270	0.065	−1.743	2.872	1.469		
Corn Oil																		
R^2_{IS}	0.092	**2.591*****	0.000	**0.301***	0.013	0.000	0.033	0.051	**2.116*****	**3.548*****	0.239	0.114	0.001	0.143	0.029	0.011		
R^2_{OOS}	−2.962	−1.005	−0.877	−0.313	−2.285	−1.725	−1.476	−2.641	−2.569	−0.837	−1.571	−1.934	−7.862	−3.111	−3.067	−2.648	−0.068	−0.811
(t-stat)	0.788	4.180	−0.003	1.575	0.248	0.038	0.531	−0.620	3.672	3.827	−1.300	−0.888	0.048	−1.048	0.525	0.271		
Cotton																		
R^2_{IS}	0.001	**2.427*****	0.178	0.021	0.230	0.001	0.011	0.000	**1.585*****	**0.578*****	0.048	0.188	0.008	**0.470****	**0.465****	0.148		
R^2_{OOS}	−2.558	**0.961*****	−1.169	−2.128	−1.796	−2.079	−1.885	−2.652	**0.362*****	−0.887	−1.601	−0.805	−2.465	−1.313	−1.910	−1.151	0.086	**0.081****
(t-stat)	−0.123	4.230	−0.817	−0.354	1.029	−0.083	0.375	0.015	4.041	2.353	0.627	−1.501	0.268	−2.280	2.055	1.249		
Live Cattle																		
R^2_{IS}	0.016	**2.285*****	0.059	**0.321***	0.060	0.011	0.002	0.000	**0.394****	**2.939*****	0.136	**0.366****	0.070	**0.744*****	**0.505****	0.102		
R^2_{OOS}	−2.172	**1.007*****	−0.776	−0.267	−1.856	−2.005	−2.141	−2.541	−0.563	**4.304*****	−1.452	−1.726	−4.586	−2.294	−1.434	−1.329	**0.463****	**1.249*****
(t-stat)	−0.438	3.571	0.765	2.046	−0.524	−0.370	−0.164	−0.048	2.366	4.706	−1.275	−1.876	−0.677	−2.619	2.154	0.809		
Lean Hog																		
R^2_{IS}	0.071	**0.356****	0.001	0.024	0.011	0.047	0.039	0.001	0.033	**0.603*****	0.027	0.064	0.012	0.167	0.167	0.018		
R^2_{OOS}	−1.473	−0.726	−1.086	−0.493	−2.601	−1.889	−1.693	−2.121	−1.394	−0.746	−0.621	−2.530	−1.726	−1.702	−1.393	−1.379	−0.546	−0.718
(t-stat)	−1.025	1.902	−0.072	0.557	0.298	−0.811	−0.764	−0.098	0.548	2.827	−0.635	−0.910	−0.398	−1.402	1.517	−0.405		
Milk																		
R^2_{IS}	0.108	**1.814*****	**1.108*****	**0.340****	**0.378****	0.000	0.000	0.061	0.129	**2.211*****	**0.715****	**0.227***	**0.342****	0.185	0.000	0.000		
R^2_{OOS}	−1.084	−0.544	**0.227****	−0.872	−0.461	−1.715	−2.050	−1.914	−0.983	**3.227*****	−0.182	−1.337	−5.526	−1.791	−1.749	−1.712	**0.278***	**1.065*****
(t-stat)	−0.995	3.577	−2.147	1.815	−1.887	−0.057	0.043	0.841	1.499	4.388	−2.451	−1.916	−2.669	−1.460	−0.045	0.022		
Oranges																		
R^2_{IS}	0.141	0.070	0.003	0.015	0.149	**0.449****	**0.487****	0.204	0.050	0.123	0.056	0.001	0.125	0.002	0.002	0.098		
R^2_{OOS}	−2.177	−1.409	−1.015	−1.774	−1.376	−1.795	−2.109	−1.392	−1.781	−0.987	−0.772	−1.519	−2.597	−1.626	−1.791	−1.547	−0.804	−0.414
(t-stat)	−0.992	1.511	−0.154	0.401	−1.731	−1.356	−1.367	−1.327	−0.833	1.840	−0.891	−0.127	−1.871	−0.199	0.130	−0.887		
Soybean Oil																		
R^2_{IS}	0.005	**3.347*****	0.014	0.019	0.025	0.011	0.002	0.029	**0.345****	**2.550*****	0.003	0.076	0.009	0.200	0.209	0.006		
R^2_{OOS}	−3.133	**1.370*****	−1.547	−1.787	−2.384	−2.063	−1.873	−3.292	−0.322	**0.737*****	−0.414	−1.954	−4.971	−1.952	−2.563	−2.699	0.193	**0.193****
(t-stat)	0.239	4.616	0.340	0.389	−0.441	−0.376	−0.168	−0.557	1.558	4.568	−0.200	−0.837	−0.262	−1.378	1.517	0.205		
Soybeans																		
R^2_{IS}	0.007	**3.609*****	0.048	0.000	0.002	0.046	0.016	0.091	**0.771*****	**0.590****	0.011	0.173	0.006	**0.415****	**0.389****	0.038		
R^2_{OOS}	−3.148	**2.514*****	−0.975	−1.127	−1.558	−1.176	−1.429	−2.895	**1.005*****	−0.860	−1.073	−1.469	−2.765	−1.716	−0.795	−1.747	**0.465****	−1.869
(t-stat)	0.229	4.050	0.626	−0.003	−0.099	−0.734	−0.424	−1.015	1.869	2.596	−0.349	−1.368	0.168	−2.016	2.063	0.598		
Soybean Meal																		
R^2_{IS}	0.018	**1.027*****	0.217	0.005	0.008	0.040	0.014	0.107	**0.531****	**1.730*****	0.014	0.137	0.007	**0.263***	0.202	0.051		
R^2_{OOS}	−3.528	−0.442	−0.891	−1.084	−1.047	−1.789	−1.790	−3.596	−0.611	−0.587	−0.929	−1.872	−2.756	−1.407	−0.827	−1.335	−0.404	−1.217
(t-stat)	0.430	3.724	1.266	−0.190	0.314	−0.752	−0.442	−1.081	2.552	2.851	−0.412	−1.320	0.234	−1.756	1.577	0.816		

to be continued on the next page

Table A6: **Return Predictability – Detailed Results (continued)**

	de	*Δindpro*	*ΔM1*	*dfr*	*dfy*	*dp*	*dy*	*ep*	*erp*	*infl*	*ltr*	*lty*	*svar*	*tbl*	*tms*	*unrate*	*comb*	*c-enet*
Sugar																		
R^2_{IS}	0.000	**0.426****	0.015	0.003	0.017	0.068	0.063	0.087	0.014	**1.159*****	0.231	0.040	0.054	0.050	0.012	0.039		
R^2_{OOS}	−2.391	−0.778	−1.128	−1.601	−1.740	−1.282	−1.355	−1.498	−1.911	**0.364*****	−1.030	−1.238	−2.839	−1.663	−1.493	−1.903	0.148	−0.683
(*t-stat*)	−0.022	2.317	−0.329	0.163	−0.475	−1.091	−1.054	−1.038	0.513	3.766	1.218	−0.535	1.251	−0.575	0.286	−0.465		
Wheat																		
R^2_{IS}	0.020	**1.105*****	0.009	0.015	0.005	0.003	0.009	0.004	0.087	**0.397****	0.006	0.131	0.018	0.212	0.095	0.006		
R^2_{OOS}	−2.137	−0.256	−1.393	−2.246	−1.915	−1.425	−1.360	−2.144	−0.851	−0.599	−1.432	−2.116	−4.902	−1.714	−1.368	−2.331	−0.641	−1.319
(*t-stat*)	−0.474	3.247	0.196	−0.273	0.205	−0.205	−0.373	0.214	−1.072	2.056	0.233	−1.394	0.378	−1.549	0.944	0.199		
Wool																		
R^2_{IS}	0.006	**6.109*****	**0.611****	**2.073*****	0.001	**0.253***	0.114	**0.245***	**2.123*****	**0.776*****	**2.026*****	**0.281***	0.004	**1.060*****	**1.625*****	0.027		
R^2_{OOS}	−6.857	**3.817*****	−0.408	**0.664*****	−3.560	−2.462	−2.987	−4.401	**1.338*****	**0.183*****	**0.645*****	−3.560	−6.924	−2.591	−1.792	−4.058	**1.578*****	**2.984*****
(*t-stat*)	−0.155	6.135	2.300	2.383	−0.050	−1.390	−0.915	−1.069	3.860	2.914	−3.386	−2.042	0.148	−3.665	3.689	0.390		
Yellow Corn																		
R^2_{IS}	0.022	**1.025*****	0.009	0.059	0.000	0.013	0.007	0.000	0.070	**1.020*****	0.044	**0.291***	0.000	**0.361****	0.067	0.003		
R^2_{OOS}	−2.075	−1.613	−1.284	−1.361	−1.696	−1.344	−1.466	−1.880	−1.416	**0.185*****	−0.474	−1.927	−1.821	−1.550	−1.650	−2.435	−0.361	−1.586
(*t-stat*)	−0.547	2.327	0.211	−0.752	−0.026	−0.450	−0.345	−0.013	0.933	2.259	0.772	−2.102	0.038	−2.215	0.912	0.141		
Energy																		
Coal																		
R^2_{IS}	**0.434****	0.001	0.105	**0.703****	0.129	0.033	0.028	0.095	0.013	**1.772*****	**0.343***	0.008	0.230	0.002	0.087	0.072		
R^2_{OOS}	−2.009	−0.713	−1.240	−2.772	−2.002	−2.249	−2.213	−2.880	−0.405	**2.929*****	−0.695	−0.970	−0.831	−1.643	−0.789	−2.044	**0.943****	−1.727
(*t-stat*)	−1.638	−0.129	−0.689	1.603	−1.189	−0.546	−0.496	0.752	0.328	3.928	−1.906	−0.285	−0.842	0.104	−0.667	−0.651		
Heating Oil																		
R^2_{IS}	0.043	0.445	0.207	**1.847*****	0.243	0.135	0.165	0.036	0.127	**2.787*****	0.458	0.013	**0.675****	0.015	0.218	0.103		
R^2_{OOS}	−1.922	−1.578	−1.556	**0.885*****	−2.054	−1.831	−1.974	−2.005	−0.373	**3.064*****	−0.655	−1.234	−0.016	−0.987	−0.789	−0.761	0.621	**1.176****
(*t-stat*)	−0.414	1.615	−0.943	2.923	−1.118	−0.891	−0.976	−0.424	−0.729	2.978	−1.602	−0.301	−1.601	0.296	−1.159	−0.949		
Natural Gas																		
R^2_{IS}	**1.998*****	0.054	0.193	0.026	**1.219*****	0.104	0.101	**0.545***	0.001	**0.686****	0.127	0.012	0.023	0.078	**0.620****	**0.469***		
R^2_{OOS}	−3.934	−1.107	−0.973	−0.395	**1.222*****	−0.901	−1.193	−6.768	−0.264	−1.179	−0.902	−0.712	−8.816	−1.810	−0.528	−0.589	**0.161***	**0.239***
(*t-stat*)	−3.542	−0.490	−1.149	−0.479	−2.993	−0.959	−0.935	1.594	0.125	1.551	−1.246	−0.441	−0.402	0.741	−1.641	−2.134		
Unleaded Regular Gas																		
R^2_{IS}	0.020	0.253	0.033	**1.920*****	0.015	0.375	0.404	0.429	0.048	**1.592*****	**0.599***	0.298	0.486	0.106	0.071	0.180		
R^2_{OOS}	−2.830	−1.492	−3.016	**0.790****	−3.212	−2.199	−2.244	−2.010	−1.287	**0.745****	−1.082	−2.373	−6.969	−0.696	−0.512	−1.325	−0.244	**2.228***
(*t-stat*)	0.253	1.137	−0.248	2.348	−0.233	−1.432	−1.484	−1.443	−0.438	2.321	−1.570	−1.427	−1.233	−0.844	−0.668	−1.028		
WTI Oil																		
R^2_{IS}	0.000	**0.242***	**0.338***	**1.116*****	0.063	0.066	0.071	0.082	0.001	**0.677*****	**1.285*****	0.001	**0.280****	0.003	0.027	0.081		
R^2_{OOS}	−1.990	−2.063	−1.135	−0.009	−2.069	−1.355	−1.547	−2.814	−0.609	**2.733*****	**1.404*****	−1.208	−1.027	−1.667	−1.145	−0.907	**0.592***	**1.192*****
(*t-stat*)	−0.035	1.601	−1.207	2.204	−0.692	−0.887	−0.907	−1.024	0.087	2.407	−2.839	−0.096	−1.282	0.148	−0.457	−0.929		
Metals																		
Aluminum																		
R^2_{IS}	0.005	**0.387****	**0.351***	**1.184*****	0.169	0.047	0.034	0.087	0.081	0.155	**0.855*****	0.003	**0.288***	0.057	0.184	0.007		
R^2_{OOS}	−1.883	**0.378*****	−0.708	**0.013*****	−1.550	−2.071	−1.725	−2.091	−0.797	−0.635	−0.113	−2.026	−3.782	−1.161	−0.544	−1.543	0.468	−0.003
(*t-stat*)	0.191	2.601	−1.161	2.645	−1.731	−0.757	−0.637	−0.818	1.102	1.204	−2.661	−0.204	−1.414	−0.922	1.352	−0.259		
Gold																		
R^2_{IS}	0.030	0.017	0.074	**0.727*****	0.051	**0.198***	**0.176***	0.134	0.061	**0.261****	0.032	0.082	**0.427*****	0.175	0.133	0.026		
R^2_{OOS}	−2.886	−0.525	−1.211	−0.411	−0.285	−2.383	−2.895	−2.707	−1.217	−1.750	−1.273	−0.646	−29.48	−1.608	−2.137	−1.860	−0.018	−7.155
(*t-stat*)	−0.561	0.403	0.623	2.124	0.848	−1.737	−1.590	−1.113	0.881	1.984	0.471	−0.648	2.036	−0.789	0.794	0.449		
High Grade Copper																		
R^2_{IS}	0.012	**4.402*****	**0.518****	**0.315***	0.060	**0.206***	0.141	**0.377****	**0.561*****	**0.316****	0.041	0.151	0.000	**0.282***	0.160	0.038		
R^2_{OOS}	−1.653	**1.720*****	−1.324	−1.322	−1.629	−1.035	−1.604	−1.142	**0.666*****	−0.246	−1.840	−1.652	−5.791	−1.782	−1.372	−1.514	**0.489****	−0.903
(*t-stat*)	0.377	6.644	−1.522	1.231	−0.744	−1.877	−1.502	−2.385	2.304	1.841	−0.582	−1.307	−0.024	−1.742	1.278	−0.560		
Nickel																		
R^2_{IS}	0.070	0.061	0.049	0.030	0.008	0.043	0.031	0.195	0.079	0.035	0.003	0.008	0.000	0.075	0.213	0.031		
R^2_{OOS}	−1.527	−0.778	−0.804	−1.137	−1.290	−1.035	−1.033	−0.720	−0.823	−1.043	−1.420	−0.587	−5.320	−0.574	−0.329	−1.462	−0.105	−0.069
(*t-stat*)	0.653	1.984	−0.524	0.481	−0.429	−0.672	−0.562	−1.230	1.087	0.860	0.123	−0.246	−0.050	−0.902	1.315	−0.572		
Palladium																		
R^2_{IS}	0.000	**1.284*****	0.007	0.077	0.358	0.154	0.163	0.132	0.007	0.076	0.118	0.191	0.057	0.144	0.004	0.001		
R^2_{OOS}	−2.907	**0.406****	−1.999	−1.960	−4.066	−2.638	−2.783	−1.520	−0.901	−1.497	−1.089	−2.618	−15.44	−1.979	−2.499	−3.476	−0.731	−1.295
(*t-stat*)	0.013	2.258	−0.187	0.672	−1.162	−0.822	−0.837	−0.795	−0.215	0.601	−0.977	−1.011	−0.732	−0.802	0.132	0.069		
Platinum																		
R^2_{IS}	0.034	**0.925*****	0.066	**0.304***	0.031	0.046	0.045	0.146	0.002	**0.870*****	0.048	0.042	0.025	0.066	0.030	0.079		
R^2_{OOS}	−2.210	−1.672	−2.168	−0.080	−1.545	−1.084	−1.161	−0.995	−1.432	**0.445*****	−1.382	−1.675	−8.021	−1.584	−1.365	−1.160	−0.107	−0.851
(*t-stat*)	0.597	2.597	−0.519	1.614	−0.501	−0.783	−0.764	−1.320	0.126	2.015	−0.832	−0.739	−0.568	−0.887	0.612	−0.958		
Silver																		
R^2_{IS}	0.060	0.116	0.015	**0.798*****	0.001	0.118	0.081	0.036	**0.345****	**0.691*****	0.000	0.159	0.005	**0.335***	**0.260***	0.046		
R^2_{OOS}	−2.001	−1.069	−1.703	**0.245*****	−1.252	−2.339	−2.293	−2.461	−0.686	−0.924	−1.178	−2.435	−15.72	−1.774	−1.894	−1.507	−0.194	−9.077
(*t-stat*)	−0.751	1.116	0.239	2.337	0.105	−1.319	−1.086	−0.586	2.665	2.742	−0.031	−0.941	0.267	−1.145	1.160	0.557		
Tin																		
R^2_{IS}	0.055	**4.076*****	**0.785****	**0.347****	0.037	0.124	0.063	0.043	**1.071*****	**1.388*****	**0.427****	**0.489****	0.002	**0.846*****	**0.416****	0.002		
R^2_{OOS}	−1.295	**3.611*****	**0.247****	−0.577	−0.903	−1.872	−1.385	−2.686	**0.143*****	−0.512	−1.367	−1.777	−4.100	−1.320	−0.863	−0.870	**1.376*****	**1.666*****
(*t-stat*)	−0.705	3.791	−1.914	1.256	0.413	−1.292	−0.891	−0.691	2.878	2.916	−1.820	−2.216	−0.087	−2.703	1.936	−0.105		
Zinc																		
R^2_{IS}	0.122	**1.693*****	**0.405***	0.187	0.012	0.075	0.035	**0.374****	**0.904*****	**0.927*****	**0.434****	0.149	0.009	**0.231***	0.098	0.017		
R^2_{OOS}	−1.411	−1.048	−0.587	−1.863	−1.837	−1.091	−1.143	−1.626	**0.390*****	−0.813	−0.704	−1.999	−6.598	−1.812	−1.421	−1.551	**0.757*****	−1.220
(*t-stat*)	1.159	4.083	−1.199	0.846	0.332	−0.987	−0.659	−2.160	3.588	3.326	−2.060	−1.356	−0.349	−1.626	0.994	0.353		

Table A7: Volatility Predictability – Detailed Results

This table presents the detailed results on the in-sample and out-of-sample volatility predictability of Agriculturals, Energy, and Metals commodities. We sample the data at the monthly frequency and predict the future 1-month volatilities. "R^2_{IS}" and "R^2_{OOS}" denote the in-sample R^2 and out-of-sample R^2, respectively. The benchmark for the in-sample and out-of-sample R^2s is an AR(1) model forecast. In parentheses, "t-stat" presents the t-statistic of the in-sample slope coefficient. For all single variables, statistical significance is determined relative to a bootstrapped distribution, while for the forecast combinations, we use the MSPE-adjusted test statistic of Clark & West (2007). *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively. In addition, we print all significant observations in ***bold***. *"de" denotes the dividend–payout ratio, "Δindpro" the growth of industrial production, and "ΔM1" the growth of money supply M1. "dfr" is the default return spread, defined as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread, defined as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the monthly U.S. unemployment rate. "comb" and "c-enet" are a simple mean forecast combination and one based on the adaptive elastic net, respectively.*

	de	*Δindpro*	*ΔM1*	*dfr*	*dfy*	*dp*	*dy*	*ep*	*erp*	*infl*	*ltr*	*lty*	*svar*	*tbl*	*tms*	*unrate*	*comb*	*c-enet*
Agriculturals																		
Butter																		
R^2_{IS}	0.027	0.004	0.000	0.017	0.032	**0.793*****	**0.806*****	**0.711*****	0.002	0.022	0.067	0.026	0.077	0.070	0.080	0.072		
R^2_{OOS}	−0.231	−1.583	−3.444	−0.741	−1.444	**0.316*****	**0.442*****	−0.929	−1.759	−1.150	−0.933	−0.046	−3.870	−2.630	−1.707	**0.162****	−1.179	**1.963*****
(t-stat)	(−0.586)	(0.246)	(0.023)	(−0.455)	(0.606)	(−2.989)	(−2.971)	(−3.656)	(−0.147)	(0.591)	(0.795)	(−0.779)	(1.299)	(−1.068)	(1.039)	(−0.951)		
Cocoa																		
R^2_{IS}	**0.245****	0.020	0.025	0.176	0.003	0.164	**0.179***	0.003	0.015	0.042	0.174	**0.482****	**0.272****	0.236	0.089	**0.391***		
R^2_{OOS}	−0.784	−1.001	−1.076	−2.148	−2.922	−0.766	−0.928	**0.071*****	−1.165	−1.341	−1.187	−4.545	−3.470	−4.850	−3.991	−2.256	−0.778	−1.578
(t-stat)	(−1.962)	(−0.424)	(0.508)	(1.306)	(−0.203)	(−1.703)	(−1.800)	(−0.214)	(−0.532)	(0.656)	(−1.400)	(2.315)	(1.694)	(1.656)	(1.119)	(1.892)		
Coffee Arabica																		
R^2_{IS}	0.200	0.142	0.008	0.116	0.002	0.036	0.015	0.021	0.362	0.301	0.022	0.094	0.000	0.000	0.255	0.017		
R^2_{OOS}	−1.363	−0.936	−0.720	−0.487	−0.431	−0.479	−0.429	**0.155****	−0.408	−1.003	−0.834	**0.782*****	−5.310	−0.395	−1.656	−0.638	−0.994	**0.364*****
(t-stat)	(−1.625)	(1.141)	(0.306)	(1.091)	(−0.128)	(−0.579)	(−0.375)	(0.488)	(1.524)	(1.421)	(0.389)	(1.053)	(−0.038)	(0.053)	(1.539)	(0.485)		
Corn Oil																		
R^2_{IS}	0.088	0.004	0.011	0.135	**0.819*****	**0.984*****	**0.925*****	**0.701*****	0.075	**0.337***	0.127	**1.046*****	**0.420****	**1.046*****	0.062	**0.357***		
R^2_{OOS}	−0.023	−0.096	−0.921	−1.249	−0.445	−0.316	−0.209	**0.514*****	−0.478	−0.806	−0.943	−1.297	−1.737	−2.718	−2.607	−0.485	−2.040	**0.088*****
(t-stat)	(1.048)	(−0.145)	(−0.370)	(1.038)	(2.956)	(3.569)	(3.444)	(2.647)	(−0.792)	(1.348)	(0.974)	(3.293)	(2.026)	(3.071)	(−0.699)	(1.802)		
Cotton																		
R^2_{IS}	0.016	0.010	**0.373***	0.051	**1.554*****	0.044	0.043	0.018	0.002	**0.199***	0.033	**0.478****	**0.421****	0.143	**0.323***	**0.846****		
R^2_{OOS}	−0.679	−1.721	−0.961	−1.719	−3.127	**0.179*****	**0.386*****	−2.279	−1.213	−0.544	−1.013	−3.503	−2.881	−4.175	−1.541	−1.487	−1.293	−0.011
(t-stat)	(0.472)	(0.256)	(1.413)	(0.555)	(3.997)	(0.895)	(0.879)	(0.581)	(−0.152)	(1.750)	(−0.468)	(2.627)	(2.313)	(1.450)	(1.978)	(2.692)		
Live Cattle																		
R^2_{IS}	**0.215***	0.035	**0.857*****	0.003	**1.416*****	**1.247*****	**1.184*****	**0.739*****	0.078	0.123	0.150	0.199	**0.528*****	0.200	0.007	0.165		
R^2_{OOS}	−0.695	−1.347	−1.263	−0.782	−1.199	−4.737	−5.619	−1.048	−0.897	−0.582	−1.229	−0.135	−7.214	−1.980	−1.440	**0.628*****	**0.091***	**1.405*****
(t-stat)	(2.256)	(0.637)	(3.343)	(−0.165)	(4.162)	(5.738)	(5.616)	(5.130)	(−1.106)	(−1.358)	(−1.339)	(1.839)	(2.798)	(1.783)	(−0.366)	(1.385)		
Lean Hog																		
R^2_{IS}	0.018	0.078	0.022	0.003	**0.315***	0.046	0.046	0.129	0.001	0.085	0.016	0.050	**0.462****	0.086	0.044	0.074		
R^2_{OOS}	−1.267	−1.066	−1.712	−0.822	−2.922	−0.664	−0.771	−2.362	−0.592	−1.141	−1.013	−1.663	−1.489	−2.768	−1.754	−0.419	−0.166	−1.313
(t-stat)	(0.517)	(−0.912)	(−0.434)	(0.211)	(1.448)	(−0.740)	(−0.749)	(−1.401)	(0.145)	(1.116)	(0.474)	(−0.855)	(1.976)	(−1.037)	(0.777)	(−0.906)		
Milk																		
R^2_{IS}	0.110	0.023	0.008	0.022	**0.506****	0.001	0.000	0.092	0.116	0.152	**0.310***	0.116	0.003	0.154	0.047	0.058		
R^2_{OOS}	−2.288	−1.321	−1.186	−1.380	−5.831	**0.560*****	**1.084*****	−2.933	−0.110	−4.387	−0.610	**1.430*****	−2.701	−1.499	−3.629	−1.943	−1.284	−3.912
(t-stat)	(1.162)	(0.431)	(0.203)	(−0.373)	(2.532)	(−0.113)	(−0.005)	(−1.095)	(1.465)	(0.980)	(1.765)	(−2.123)	(0.278)	(−1.825)	(0.758)	(0.695)		
Oranges																		
R^2_{IS}	**0.607*****	0.008	0.288	0.163	**0.828*****	**2.429*****	**2.626*****	**1.052*****	0.176	0.223	0.028	0.047	0.007	0.038	0.000	**0.505****		
R^2_{OOS}	−3.256	−0.611	−2.025	−1.321	−1.769	−0.464	−0.576	−0.623	−0.045	−0.088	−1.021	−0.281	−2.900	−2.531	−2.476	−2.628	−0.691	−2.568
(t-stat)	(−2.416)	(−0.557)	(0.893)	(−1.543)	(−4.660)	(−4.280)	(−4.377)	(−3.740)	(−1.940)	(−2.525)	(0.587)	(1.030)	(0.453)	(0.813)	(−0.024)	(−2.346)		
Soybean Oil																		
R^2_{IS}	0.072	0.019	0.044	0.041	0.073	0.000	0.007	0.051	**0.717*****	**0.518****	0.005	**0.355****	**0.238***	0.178	0.063	0.121		
R^2_{OOS}	−1.309	−0.845	−1.389	−1.647	−1.266	−0.253	−0.964	−0.171	−1.200	−0.855	−1.132	−0.534	−8.590	−0.121	−0.346	−1.342	−1.619	**0.772*****
(t-stat)	(−0.885)	(−0.356)	(−0.605)	(−0.628)	(0.901)	(0.065)	(−0.322)	(0.764)	(−2.561)	(2.074)	(−0.201)	(1.857)	(1.732)	(1.355)	(0.871)	(1.044)		
Soybeans																		
R^2_{IS}	0.027	0.133	0.080	0.068	**0.371****	0.004	0.008	0.003	0.068	0.118	0.122	0.024	**0.497****	0.011	**0.306***	0.159		
R^2_{OOS}	−0.401	−0.994	−0.625	−1.096	−0.521	−1.335	−1.383	−2.689	**0.570*****	−3.043	−0.610	−1.014	−3.682	−2.057	−0.178	−1.249	−0.757	**0.209*****
(t-stat)	(−0.483)	(0.722)	(−0.940)	(0.817)	(1.631)	(−0.236)	(−0.349)	(0.210)	(−0.617)	(0.925)	(−1.180)	(0.529)	(1.520)	(−0.327)	(1.901)	(1.268)		
Soybean Meal																		
R^2_{IS}	0.037	0.152	0.020	0.176	0.073	0.001	0.001	0.015	0.006	**0.490****	0.246	0.009	0.262	0.004	0.002	0.006		
R^2_{OOS}	−1.194	−1.774	−1.294	−1.301	−2.666	−2.027	−1.780	−4.605	−1.405	−0.839	−0.600	−1.812	−2.539	−1.911	−2.136	−2.392	0.095	−0.006
(t-stat)	(−0.587)	(1.394)	(0.459)	(1.126)	(−1.048)	(−0.094)	(−0.136)	(0.382)	(−0.241)	(1.908)	(−1.920)	(−0.330)	(1.843)	(−0.223)	(−0.155)	(0.265)		

to be continued on the next page

Table A7: **Volatility Predictability – Detailed Results (continued)**

	de	*Δindpro*	*ΔM1*	*dfr*	*dfy*	*dp*	*dy*	*ep*	*erp*	*infl*	*ltr*	*lty*	*svar*	*tbl*	*tms*	*unrate*	*comb*	*c-enet*
Sugar																		
R^2_{IS}	0.155	0.019	0.047	0.056	0.000	**0.200***	0.163	0.032	0.037	**0.185***	0.009	**1.340*****	0.001	**1.346*****	0.058	0.108		
R^2_{OOS}	−2.680	−2.671	−1.520	−1.035	−1.744	−3.146	−2.367	−2.412	**0.022*****	−1.602	−0.176	−2.902	−5.842	−2.073	−1.795	−1.610	**0.185***	−0.129
(*t-stat*)	(−1.876)	(0.551)	(−0.583)	(0.679)	(0.043)	(−2.212)	(−2.008)	(−0.743)	(0.763)	(1.766)	(−0.232)	(3.466)	(0.151)	(3.806)	(−0.813)	(0.959)		
Wheat																		
R^2_{IS}	0.006	0.063	0.005	0.066	**1.115*****	0.047	0.052	0.098	0.022	0.037	**0.548****	0.035	**0.833*****	0.002	**0.247***	**0.691****		
R^2_{OOS}	−2.631	−1.036	−0.600	−1.243	**0.868*****	−0.750	−0.800	−1.513	−1.346	−2.058	−0.347	−0.152	−0.213	−1.684	−0.523	−0.079	−0.211	−1.389
(*t-stat*)	(0.282)	(0.738)	(0.184)	(0.753)	(2.950)	(−0.897)	(−0.935)	(−1.303)	(−0.502)	(0.784)	(−2.194)	(0.812)	(2.435)	(−0.155)	(1.674)	(2.405)		
Wool																		
R^2_{IS}	0.007	0.001	0.007	**2.667*****	**0.357****	**0.946*****	**0.802*****	**1.320*****	**0.445****	0.018	0.109	0.042	**0.437****	**0.277***	**0.651****	0.107		
R^2_{OOS}	−1.261	−1.280	−1.632	**2.049*****	**1.392*****	**1.350*****	**1.926*****	−1.440	**0.191*****	−0.187	−1.813	**1.492*****	−2.518	−0.285	**0.212*****	−2.522	−2.487	**3.498*****
(*t-stat*)	(0.141)	(0.061)	(0.197)	(2.646)	(1.796)	(−3.932)	(−3.564)	(−2.361)	(2.037)	(−0.586)	(−0.790)	(−1.060)	(2.308)	(−2.240)	(2.492)	(0.747)		
Yellow Corn																		
R^2_{IS}	**0.202***	0.017	**0.626****	0.232	**1.515*****	0.044	0.031	0.019	0.113	0.029	0.001	0.076	**0.616*****	0.210	0.235	**0.751****		
R^2_{OOS}	−1.605	−1.845	−1.074	−1.226	−2.133	−0.216	−0.122	−0.604	−0.986	−1.310	−1.036	−1.897	−1.422	−1.672	−3.588	−0.818	−0.673	−2.176
(*t-stat*)	(1.786)	(0.310)	(2.459)	(−1.749)	(3.388)	(0.929)	(0.786)	(−0.599)	(−1.357)	(0.541)	(0.082)	(−1.109)	(2.588)	(−1.757)	(1.945)	(2.732)		
Energy																		
Coal																		
R^2_{IS}	0.001	**0.332***	0.058	0.035	**0.704*****	**2.034*****	**2.053*****	**2.298*****	0.006	**0.352***	0.020	0.102	**0.803****	0.007	0.256	**1.556*****		
R^2_{OOS}	−1.665	−0.595	−1.796	−2.151	−0.611	**1.732*****	**1.607*****	−3.792	−1.117	−0.703	−1.581	**0.496*****	−1.400	**1.188*****	−0.830	−1.745	−2.300	**0.346*****
(*t-stat*)	(0.033)	(−2.149)	(0.636)	(0.324)	(1.750)	(−4.930)	(−5.050)	(−3.264)	(−0.228)	(−2.050)	(−0.276)	(1.005)	(2.205)	(0.249)	(1.527)	(3.168)		
Heating Oil																		
R^2_{IS}	0.117	**1.845*****	0.000	0.034	0.014	**0.678***	**0.658***	**1.069****	0.014	0.029	0.314	0.297	0.156	0.071	0.142	0.385		
R^2_{OOS}	−0.543	**1.028*****	−1.872	−1.122	**0.746****	−2.909	−3.423	−1.008	−0.351	−0.660	−0.548	−2.908	−2.847	−1.804	−2.357	−1.188	−1.168	−0.420
(*t-stat*)	(0.803)	(−3.230)	(−0.019)	(−0.416)	(0.310)	(−1.923)	(−1.904)	(−2.342)	(0.292)	(0.296)	(1.446)	(−1.631)	(0.775)	(−0.715)	(−0.970)	(−1.726)		
Natural Gas																		
R^2_{IS}	0.013	**1.338*****	0.001	0.380	**1.059****	0.206	0.238	0.112	0.091	0.170	0.006	0.176	**0.371***	0.283	0.148	**1.534*****		
R^2_{OOS}	**6.198*****	−0.050	−0.809	−0.304	−9.023	**0.646****	−0.628	**0.876*****	**1.173****	**2.245*****	−0.780	**4.506*****	**4.052*****	**4.957*****	**0.056***	−2.018	−6.118	**3.753*****
(*t-stat*)	(−0.252)	(−1.724)	(−0.118)	(−1.114)	(1.857)	(−0.889)	(−0.986)	(−0.553)	(−0.919)	(1.306)	(0.300)	(−1.710)	(1.344)	(−1.510)	(0.903)	(2.515)		
Unleaded Regular Gas																		
R^2_{IS}	0.482	**2.979*****	0.007	0.027	0.064	**1.965*****	**2.068*****	**3.603*****	0.131	0.003	0.006	**2.386*****	**2.362*****	**0.827***	0.500	**1.588****		
R^2_{OOS}	**0.416****	**0.339****	−2.227	−2.385	**1.322*****	−1.360	−1.600	−5.784	−0.998	−3.519	−1.859	−4.071	−5.666	−4.353	−0.307	**0.114****	−0.652	**6.812*****
(*t-stat*)	(1.440)	(−2.921)	(−0.177)	(−0.309)	(0.486)	(−3.335)	(−3.432)	(−4.175)	(−0.717)	(0.078)	(0.157)	(−4.509)	(3.418)	(−2.796)	(−1.830)	(−3.034)		
WTI Oil																		
R^2_{IS}	0.069	0.037	0.052	**0.465****	0.198	0.044	0.054	**0.222***	0.036	0.117	**1.194*****	0.146	**0.319****	0.099	0.003	0.002		
R^2_{OOS}	−2.581	−0.132	−2.223	−0.954	−5.641	−4.314	−3.808	−0.273	−1.889	−1.030	**0.074****	−5.931	−2.154	−3.765	−2.470	−3.507	−0.261	**0.118****
(*t-stat*)	(1.036)	(−0.698)	(0.501)	(−1.679)	(1.551)	(−0.862)	(−0.952)	(−2.009)	(−0.805)	(−1.287)	(3.145)	(1.747)	(1.806)	(1.308)	(0.199)	(0.149)		
Metals																		
Aluminum																		
R^2_{IS}	**0.300****	0.002	**0.726*****	**0.411****	0.029	**0.781*****	**0.816*****	**0.273***	0.059	0.014	0.038	**0.454****	0.147	0.106	**0.377****	0.142		
R^2_{OOS}	−1.194	−0.783	**0.428*****	−0.899	−0.292	−0.141	**0.353*****	−1.391	−1.895	**0.470*****	−0.762	−0.568	−2.518	−1.508	−1.358	**0.501*****	−2.182	−0.328
(*t-stat*)	(−1.921)	(0.276)	(2.287)	(−1.836)	(−1.103)	(−3.429)	(−3.520)	(−1.922)	(−0.919)	(0.355)	(−0.623)	(2.977)	(1.271)	(1.564)	(2.810)	(1.398)		
Gold																		
R^2_{IS}	**0.918*****	0.004	0.083	0.060	0.000	**0.690*****	**0.693*****	0.025	0.000	**0.309****	0.088	**2.997*****	**0.226***	**1.807*****	0.038	**1.610*****		
R^2_{OOS}	−2.034	−1.436	−1.476	−2.027	**0.896*****	**3.626*****	**3.172*****	−0.195	−1.079	**1.346*****	−0.820	**5.194*****	−28.21	**2.057*****	−1.034	−2.357	−4.370	**9.909*****
(*t-stat*)	(−3.329)	(−0.283)	(0.846)	(0.691)	(−0.025)	(−4.027)	(−3.955)	(−0.662)	(−0.072)	(3.039)	(0.712)	(6.159)	(1.485)	(4.582)	(0.665)	(4.413)		
High Grade Copper																		
R^2_{IS}	0.117	0.028	0.274	0.025	0.029	**0.177***	**0.177***	0.037	0.001	0.057	0.041	**0.360***	**0.520*****	0.167	0.101	0.006		
R^2_{OOS}	−2.152	−0.505	−0.659	−1.232	**0.998*****	−1.424	−1.386	−1.394	−0.858	−1.795	−1.699	−1.993	−5.897	−2.514	−2.589	−3.426	**0.096***	−3.517
(*t-stat*)	(−1.318)	(0.479)	(1.526)	(0.443)	(0.551)	(−1.856)	(−1.832)	(−0.758)	(0.154)	(0.822)	(−0.548)	(1.867)	(2.309)	(1.328)	(1.015)	(0.181)		
Nickel																		
R^2_{IS}	**1.093*****	0.029	**0.595****	0.016	0.056	**3.955*****	**3.977*****	**1.305*****	0.000	0.001	0.242	**0.662*****	0.025	0.125	**0.782*****	0.268		
R^2_{OOS}	−1.349	−1.015	−0.935	−0.757	−1.147	**0.510*****	**0.406*****	−2.196	−0.704	−0.521	−0.330	**0.555*****	−2.143	−0.060	−0.202	−2.055	−1.634	**0.729*****
(*t-stat*)	(−2.525)	(−1.273)	(2.474)	(0.373)	(−1.464)	(−5.756)	(−5.725)	(−3.780)	(0.014)	(0.125)	(−1.640)	(3.121)	(0.784)	(1.484)	(3.197)	(2.136)		
Palladium																		
R^2_{IS}	0.000	0.050	0.468	0.047	**1.519*****	0.458	0.415	0.372	0.118	0.256	**0.539***	0.053	**0.512***	0.074	0.039	0.272		
R^2_{OOS}	−1.883	−0.228	−1.715	−2.813	**0.682*****	**1.447*****	**1.913*****	−0.712	−0.767	**0.911****	−1.096	−1.460	−10.88	−1.591	−1.482	**2.384*****	−2.001	**5.381*****
(*t-stat*)	(−0.036)	(−0.463)	(1.542)	(0.429)	(2.379)	(−1.438)	(−1.344)	(−1.162)	(0.775)	(1.117)	(1.796)	(−0.497)	(1.272)	(−0.542)	(0.423)	(1.099)		
Platinum																		
R^2_{IS}	0.000	**0.287***	**0.751****	0.000	0.144	0.217	0.157	**0.262***	**0.501*****	0.056	0.114	0.002	0.107	0.046	**0.348****	0.109		
R^2_{OOS}	−2.476	−0.614	−0.481	−0.537	−2.033	−1.476	−2.007	−0.905	−0.729	−0.730	−0.216	−2.428	−8.123	−2.632	−2.140	−0.456	−0.149	−0.621
(*t-stat*)	(−0.028)	(1.467)	(2.145)	(0.015)	(1.125)	(−1.880)	(−1.591)	(−1.910)	(1.821)	(0.819)	(−1.389)	(0.133)	(0.871)	(−0.743)	(2.180)	(1.145)		
Silver																		
R^2_{IS}	**0.961*****	0.002	0.136	0.000	0.063	**1.073*****	**1.028*****	0.117	0.037	**0.309****	0.037	**2.243*****	0.098	**1.121*****	0.239	**1.899*****		
R^2_{OOS}	−4.385	−1.520	−1.779	−1.201	−1.245	**0.458*****	**0.327*****	−0.666	−0.942	**2.747*****	−2.074	**1.933*****	−22.00	**1.607*****	−1.509	−0.184	−1.887	**2.675*****
(*t-stat*)	(−3.565)	(−0.241)	(1.135)	(0.056)	(1.297)	(−4.621)	(−4.451)	(−1.321)	(0.794)	(2.511)	(0.434)	(4.706)	(1.417)	(3.147)	(1.485)	(4.507)		
Tin																		
R^2_{IS}	0.046	0.159	**2.051*****	0.024	**0.403****	0.057	0.052	0.009	0.005	0.001	0.024	0.003	**0.802*****	0.006	0.080	0.191		
R^2_{OOS}	−1.967	−1.175	**2.435*****	−2.161	−0.893	−1.539	−1.506	−2.554	−1.324	−1.562	−1.862	−1.671	−0.539	−1.529	−0.657	−1.148	−0.254	**0.633*****
(*t-stat*)	(−0.828)	(0.814)	(4.515)	(0.304)	(2.072)	(−1.087)	(−1.048)	(−0.382)	(0.237)	(0.082)	(0.463)	(0.193)	(3.085)	(−0.269)	(1.096)	(1.232)		
Zinc																		
R^2_{IS}	**0.448*****	0.106	0.174	0.146	0.055	**0.250****	**0.250****	0.000	0.004	0.024	**0.958*****	0.101	**0.249****	0.002	**0.335***	0.371		
R^2_{OOS}	−1.000	−0.979	−0.939	−1.169	−5.441	−0.117	−0.106	**0.614*****	−1.559	−1.119	−0.137	**0.187*****	−17.34	−2.530	−4.484	−4.368	−0.957	**1.302*****
(*t-stat*)	(−2.616)	(−1.027)	(1.041)	(0.927)	(0.759)	(−2.298)	(−2.197)	(−0.080)	(−0.190)	(−0.608)	(−2.909)	(1.535)	(1.094)	(0.193)	(2.243)	(1.956)		