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We investigate whether and to what extent macroeconomic uncertainty predicts the volatilities of commodity futures. By examining 15 commodities in 5 categories, we find that the measure of aggregate macroeconomic uncertainty based on a large dataset has sizable predictive effects for commodity volatility. The predictive relationship holds both in-sample and out-of-sample after controlling for lagged volatility. However, the extent of predictability differs across commodities, with energy and metals futures exhibiting the most significant effects. For all commodities, the improvement in forecasting is more pronounced after 2005 and during recession periods.

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1. INTRODUCTION

Since the financialization of commodity markets starting in the early 2000s, commodity futures have emerged as a popular asset class for speculation and asset management purposes (Basak and Pavlova, 2016; Christoffersen et al., 2017; Tang and Xiong, 2012). This prompts interest in the volatility predictability of commodity futures markets because commodity volatility is a determinant of portfolio allocation (Singleton, 2014; Büyükşahin and Robe, 2014), risk management (Conover et al., 2010), derivatives pricing (Cortazar et al., 2016), and core macroeconomic quantities (Kilian, 2009).

In this paper, we investigate whether macroeconomic uncertainty predicts commodity volatility. Our study contributes to two strands of literature. The first is the literature on commodity volatility predictability by macroeconomic variables. Christiansen et al. (2012) show that interest rate is a useful predictor when forecasting the volatility of Standard & Poor's GSCI commodity index. Hammoudeh and Yuan (2008) find that rising interest rates tend to reduce the volatilities of gold, silver, and copper. Foreign exchange variables play an important role in influencing commodity volatilities as well. The U.S. dollar impacts gold volatility (Tully and Lucey, 2007). The exchange rates of small commodity exporters possess predictive power for global commodity prices, this relationship holds both in-sample and out-of-sample (Chen et al., 2010). Shang et al. (2016) claim that foreign exchange variable prices commodity futures and contains information about future movements in commodity markets. Variables relevant to inflation and industrial production may also affect commodity return and volatility. For example, Bailey and Chan (1993) give evidence that inflation and industrial production risk earn risk premiums in commodity markets.

Another strand of the literature has examined the impact of macroeconomic uncertainty on commodity markets. The channels vary across commodity categories. For industrial inputs, price fluctuations are driven mainly by demand shocks triggered by uncertainty about the future. Take crude oil as an example. Precautionary demand shocks caused by uncertainty drive price fluctuations (Kilian, 2009). Macroeconomic uncertainty may be transmitted to the prices of precious metals, which are commonly regarded as hedge investments against foreign exchange or reserve assets, via exchange rates and portfolio rebalancing. As an important precious metal, gold has been a reserve asset for centuries, particularly in times of economic uncertainty (Aggarwal and Lucey, 2007). Capie et al. (2005) find that gold serves as a hedge against the dollar and that the extent to which gold acts as an exchange hedge depends heavily on the unpredictable political events. In addition to USD, gold also serves as a hedge investment against GBP exchange rates (Ciner et al., 2013). In terms of portfolio rebalancing, economic uncertainty makes stock returns more volatile, leading investors to rebalance their portfolios in favor of a safe-haven like gold, which results in an increase in the price of gold. As uncertainty leads to an increase in current gold volatility, future gold volatility increases because the volatility of gold is highly persistent (Fang et al., 2017). Reboredo and Uddin (2016) and Joëts et al.

(2017) provide evidence of the safe-haven role of gold when facing economic uncertainty.

The empirical literature has used several measures of economic uncertainty to investigate the impact of economic uncertainty on commodity futures. The S&P 500 turnover, a common proxy for dispersion in opinion (Scheinkman and Xiong, 2003) and hence a potential indicator of uncertainty about future market valuation, is a useful predictor of commodity volatilities (Christiansen et al. 2012). The economic policy uncertainty (EPU) index, proposed by Baker et al. (2016), has predictive power for commodity returns (Wang et al., 2015; Reboredo and Wen, 2015). Yin and Han (2014) find that the relationship between uncertainty and commodity prices varies over time, with a large change occurring after the 2008-2009 global financial crisis. Antonakakis et al. (2014) find a negative relationship between the EPU index and oil price shocks. The GEPU index, proposed by Davis (2016) and based on the EPU index, measures a GDP-weighted average of national economic policy uncertainty. Fang et al. (2017) suggest that the GEPU index has a positive influence on gold volatility, which is significant in both the statistical and the economic sense. The aggregate macroeconomic uncertainty, put forth by Jurado et al. (2015), affects commodity price returns and the impact of macroeconomic uncertainty is more pronounced in volatile times (Joëts et al., 2017; Tan and Ma, 2017). Studies on the impact of the aggregate macroeconomic uncertainty in commodity futures markets focus on return predictability, however, the literature is silent on the ability of aggregate macroeconomic uncertainty to predict commodity volatility. In addition, the out-of-sample forecasting performance of aggregate macroeconomic uncertainty is usually ignored in the existing work. Our study fills this gap.

In this paper, we use the aggregate uncertainty index of Jurado et al. (2015) to measure macroeconomic uncertainty. The aggregate macroeconomic uncertainty index, abbreviated as MacUnc, measures the conditional volatility of the purely unforecastable components of the future values of macroeconomic variables. Jurado et al. (2015) rely on a comprehensive dataset that includes 132 monthly macroeconomic series and 147 financial series to generate both the aggregate macroeconomic uncertainty index and the financial uncertainty index (FinUnc)[2]. We choose the aggregate macroeconomic uncertainty index for its two distinguishing features. Firstly, MacUnc measures the purely unforecastable components of macroeconomic variables, which makes it an indicator of uncertainty about economic fundamentals rather than economic fluctuations. Secondly, MacUnc measures the common variation in uncertainty across many macroeconomic variables, which is a superior measurement of macroeconomic uncertainty than the uncertainty in any single macro variable.

We study whether MacUnc predicts the volatility of commodities in five classes, namely, energy, metals, grains, softs and livestock. Our main finding is that macroeconomic uncertainty significantly increases the forecasting power for

[2] Financial uncertainty is used for comparison.

commodity volatility even after controlling for lagged volatility. This holds both in-sample and out-of-sample. However, the predictability improvement is not the same for all commodity classes and sample periods. Macroeconomic uncertainty is more powerful in forecasting the volatilities of energy products and metals and its predictive power is stronger after 2005 for all commodity categories.

Specifically, full-sample analysis provides evidence that macroeconomic uncertainty helps to predict future volatility for all commodity categories. In general, a 1% rise in MacUnc results in a 22.1% increase in commodity volatility for the full sample and a 31.0% volatility increase when restricting the sample to after 2005. For energy products and metals, the two most affected commodity categories, a 1% increase in MacUnc increases volatility by 21.0% and 17.2%, respectively. These numbers go up to 31.2% and 29.7% in the years after 2005. Looking at the out-of-sample performance, a model that includes macroeconomic uncertainty beats the AR(1) benchmark for every commodity category and brings an overall improvement in accuracy of 9.59%. The augmented model achieves an even more pronounced improvement of 10.989% after 2005.

The remainder of this paper is organized as follows. Section 2 describes the data sample, principal components and uncertainty indexes. Section 3 outlines the econometric framework. Section 4 presents the empirical results and Section 5 presents our conclusions.

2. DATA DESCRIPTION

2.1. Measuring Commodity Futures Volatility

The primary interest of our study is the prediction of the volatility of commodity futures. However, the integrated volatility series are unobservable. According to Andersen et al. (2003), if the number of intra-period observations is large enough, the realized volatility is an appropriate proxy for the latent integrated volatility. Thus, we use realized volatilities as the dependent variables in our predictive regressions.

Following the notation in Christiansen et al. (2012), for each commodity, $r_{t,\tau}$ denotes the τth daily continuously compounded return in month t and M_t is the number of trading days in month t, then the realized variance in month t is computed as the sum of the squared daily returns, $\sum_{\tau=1}^{M_t} r_{t,\tau}^2$. Thus we proceed by computing the monthly realized volatility as the log of the square root of the realized variance:

$$RV_t = ln\sqrt{\sum_{\tau=1}^{M_t} r_{t,\tau}^2}.$$

We obtain daily trade data on commodity futures from Norgate Data[3]. Our dataset includes all available time periods for each commodity. The way we choose

[3] https://www.premiumdata.net

commodity futures follows Christoffersen et al. (2017). Specifically, we focus on the three most heavily traded commodities in energy, metals, grains, softs, and livestock[4]. This results in a total of 15 commodities for our study: crude oil, natural gas, and heating oil for energy; gold, silver, and copper for metals; soybeans, corn, and wheat for grains; sugar, coffee, and cotton for softs; and live cattle, lean hogs, and feeder cattle for livestock. See Table I for the sample periods of the realized volatilities and other details on the selected 15 commodities.

TABLE I

Summary of Commodity Futures

Category	Commodity	Symbol	Exchange	Start	End	Obs.
Energy	Crude Oil	CL	NYMEX/CME	198701	201603	351
	Natural Gas	NG	NYMEX/CME	199301	201603	279
	Heating Oil	HO	NYMEX/CME	198401	201603	387
Metals	Gold	GC	COMEX/CME	198401	201603	387
	Silver	SV	COMEX/CME	198312	201603	388
	Copper	HG	COMEX/CME	198912	201603	316
Grains	Soybeans	SY	CBOT/CME	198207	201603	405
	Corn	CN	CBOT/CME	198207	201603	405
	Wheat	WC	CBOT/CME	198207	201603	405
Softs	Sugar #1	SB	ICE	198607	201603	357
	Coffee "C"	KC	ICE	198701	201603	351
	Cotton #2	CT	ICE	198701	201603	351
Livestock	Live Cattle	LC	CME	197412	201603	496
	Lean Hogs	LH	CME	198104	201603	420
	Feeder Cattle	FC	CME	197801	201603	459

Note. This table shows the selected commodities in each category. For each commodity, the sample period is reported. We also report the symbol, exchange and number of observations for each commodity.

2.2. Principal Component Analysis

While it is essential to study the predictive power of macroeconomic uncertainty for the volatility of a single commodity, it is also important to identify the overall impact of macroeconomic uncertainty on a commodity category and on all commodities investigated. To this end, we compute the first principal component for the three commodity volatility series in each category, obtaining five principal components (denoted as PC. Energy, PC. Metals, PC. Grains, PC. Softs and PC. Livestock). We

[4] These five commodity categories are proposed by Gorton et al. (2012).

also compute the first principal component for all 15 commodity volatility series (denoted as PC. All), resulting in six principal components in total. See Table II for the variance proportions and eigenvectors of the principal components. The principal components explain 67.4%, 66.2%, 74.2%, 46.0%, 73.6% and 30.7% of the cross-sectional variation in the volatilities of the selected energy, metal, grain, soft, and livestock commodities and all 15 commodities, respectively.

TABLE II

Variance Proportion and Eigenvector for Principal Component Analysis

	First Principal Component					
	Energy	Metals	Grains	Softs	Livestock	All
Panel A: Proportion						
	0.674	0.662	0.742	0.460	0.736	0.307
Panel B: Eigenvector						
Crude Oil	0.647					0.293
Natural Gas	0.362					0.045
Heating Oil	0.671					0.247
Gold		0.579				0.246
Silver		0.619				0.256
Copper		0.530				0.293
Soybeans			0.544			0.292
Corn			0.621			0.324
Wheat			0.564			0.337
Sugar #1				0.706		0.219
Coffee "C"				-0.226		-0.053
Cotton #2				0.672		0.265
Live Cattle					0.623	0.286
Lean Hogs					0.490	0.215
Feeder Cattle					0.610	0.294

Note. The table shows the variance proportions and eigenvectors for the first principal component of energy, metal, grain, soft, livestock commodities and all 15 commodities. Panel A gives the variance proportion explained by each principal component. The eigenvectors in Panel B describe the series of uncorrelated linear combinations of the commodity volatilities that contain the most cross-sectional variance in the volatilities of the corresponding category.

2.3. Macroeconomic and Financial Uncertainty Indexes

Our main predictive variable is the aggregate macroeconomic uncertainty index proposed by Jurado et al. (2015). We also use their financial uncertainty index for comparison. Both indexes are obtained from their website and cover the period from July 1960 to June 2017, which completely covers all available periods of the 15 realized commodity volatilities. Thus, the sample periods for empirical study equal to the time spans of realized commodity volatilities, as shown in Table I. Motivated by the logarithmic form of the realized volatility, we take a natural logarithm of the uncertainty indexes.

Table III reports summary statistics for the uncertainty indexes, realized commodity volatilities and principal components. The realized volatility series are highly persistent, as indicated by their large autocorrelation coefficients. Both uncertainty series show an even stronger persistence, with their autocorrelation coefficients approaching 1. To test for normality, we employ Jarque-Bera (henceforth JB) statistics. We also check the stationary of each series by applying the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Both the ADF and PP statistics reject the null hypothesis of a unit root for every series.

TABLE III

Summary Statistics

Note. The table reports summary statistics for two logarithmic uncertainty indexes, 15 log realized commodity volatilities and 6 principal components. We report the mean, standard deviation, skewness, kurtosis, the first order autocorrelation coefficient, JB statistic, ADF statistic, PP statistic and the number of observations. ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively.

Variables	Mean	Std. Dev.	Skewness	Kurtosis	AR(1)	JBstat	ADFstat	PPstat	Obs.
Panel A: Logarithmic Uncertainty Indexes									
MacUnc	-0.417	0.128	1.252	4.338	0.985	166.594***	-3.167***	-3.055**	496
FinUnc	-0.114	0.177	0.442	2.712	0.979	17.866***	-3.798***	-3.544***	496
Panel B: Logarithmic Realized Volatilities									
Crude Oil	-2.483	0.419	0.311	3.823	0.683	15.564***	-4.662***	-8.250***	351
Natural Gas	-2.035	0.363	0.277	2.611	0.590	5.317*	-8.276***	-8.278***	279
Heating Oil	-2.508	0.416	0.214	3.427	0.664	5.910**	-5.554***	-8.895***	387
Gold	-3.254	0.468	-0.249	3.401	0.623	6.563**	-5.208***	-9.629***	386
Silver	-2.669	0.429	0.162	3.052	0.611	1.751	-5.382***	-9.912***	388
Copper	-2.747	0.382	0.375	4.126	0.628	24.107***	-4.780***	-8.650***	316
Soybeans	-2.898	0.395	0.061	3.075	0.672	0.346	-7.286***	-8.819***	405
Corn	-2.868	0.447	-0.121	2.942	0.706	1.048	-5.968***	-8.263***	405
Wheat	-2.728	0.379	0.235	2.884	0.710	3.953	-5.003***	-8.035***	405
Sugar #1	-2.473	0.368	-0.135	2.943	0.666	1.136	-5.431***	-8.462***	357
Coffee "C"	-2.417	0.375	0.151	4.825	0.555	50.061***	-6.756***	-10.176***	351
Cotton #2	-2.751	0.343	0.124	2.846	0.628	1.251	-5.445***	-9.123***	351
Live Cattle	-3.235	0.363	0.142	2.754	0.715	2.923	-5.970***	-8.860***	496
Lean Hogs	-2.804	0.283	0.456	3.764	0.591	24.796***	-6.899***	-10.510***	420
Feeder Cattle	-3.310	0.367	-0.140	2.701	0.688	3.192	-5.642***	-9.114***	458
PC. Energy	0	1.422	-0.109	3.000	0.728	0.547	-4.137***	-6.497***	279
PC. Metals	0	1.409	0.569	3.880	0.700	27.255***	-4.081***	-7.421***	316
PC. Grains	0	1.492	0.192	2.931	0.739	2.582	-5.718***	-7.600***	405
PC. Softs	0	1.174	-0.133	3.179	0.715	1.502	-4.803***	-7.551***	351
PC. Livestock	0	1.485	0.127	2.809	0.666	1.764	-5.971***	-9.162***	420
PC. All	0	2.146	0.466	4.334	0.788	30.772***	-3.876***	-5.453***	279

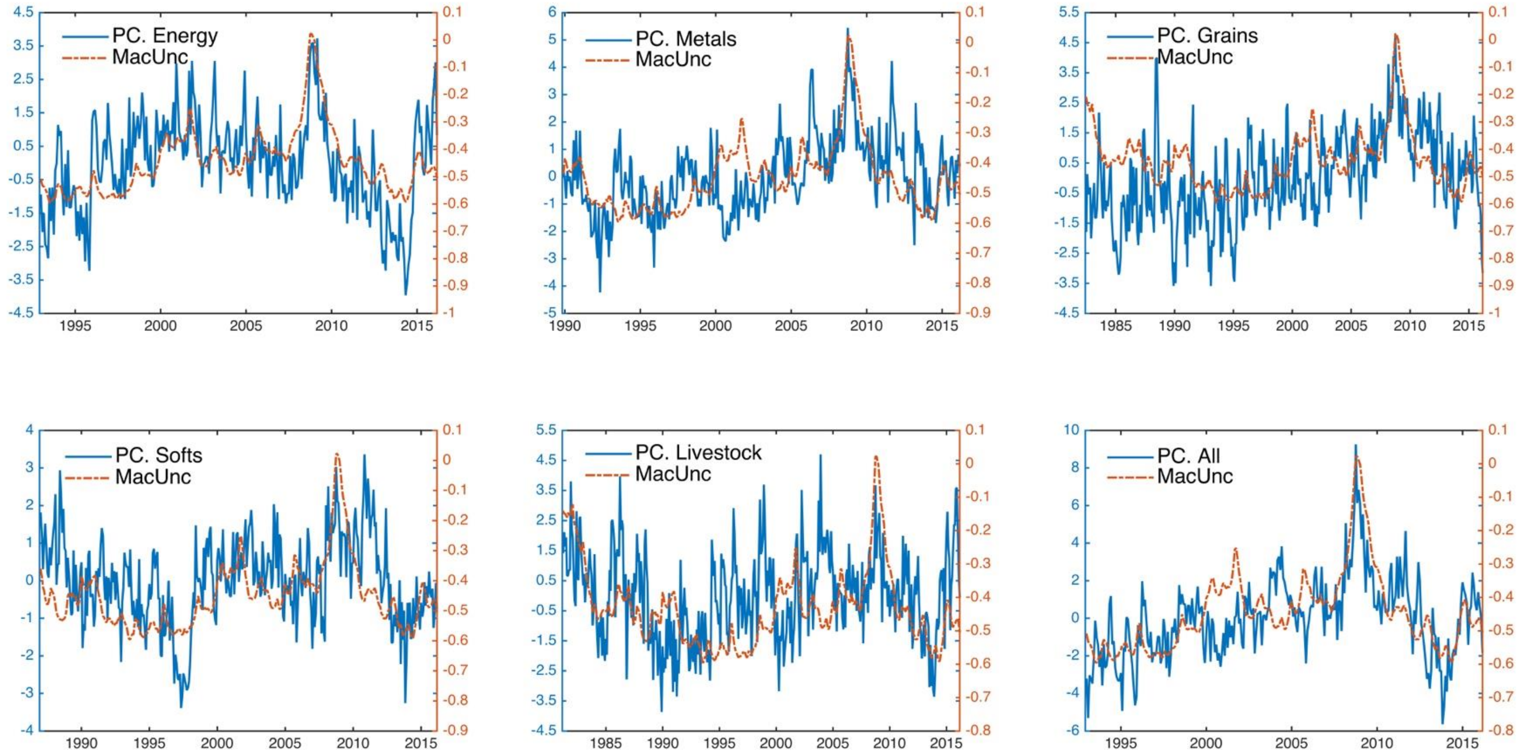
PC. Energy
MacUnc
PC. Metals
MacUnc
PC. Grains
MacUnc
PC. Softs
MacUnc
PC. Livestock
MacUnc
PC. All
MacUnc

Figure 1 shows the time trend of the macroeconomic uncertainty index (MacUnc) and the six principal components. We can see a lead-lag relationship between MacUnc and the principal components clearly, especially between MacUnc and PC. All and between MacUnc and PC. Energy. We can therefore infer that macroeconomic uncertainty may contain predictive information for commodity volatility. In addition, the forecasting performance of MacUnc is better after 2005, particularly for PC. Metals and PC. Grains. Thus, the predictive power of MacUnc may be heterogeneous across different classes of commodities and vary over time. We verify these conjectures in the following section.

FIGURE 1

Time Series Data for Principal Components and Macroeconomic Uncertainty Index

Note. Figure 1 plots the macroeconomic uncertainty index (MacUnc) with six principal components: PC. Energy, PC. Metals, PC. Grains, PC. Softs, PC. Livestock, and PC. All. For each subfigure, the principal component is the solid line and MacUnc is the dashed line.

3. Econometric Framework

We apply standard univariate predictive regressions for the realized volatility of commodity i:

$$RV_{i,t} = \alpha + \beta RV_{i,t-1} + \gamma U_{t-1} + \varepsilon_{i,t}.$$

$RV_{i,t}$ denotes the monthly realized volatility of commodity i in month t (we also use principal components as dependent variables in latter analysis). Our forecasting variable, U_{t-1}, is the lagged macroeconomic uncertainty index. The financial uncertainty index is used as the forecasting variable in section 4.4. for comparison. Our primary interest is the magnitude and significance of β. All variables are standardized before regression so that we can compare the magnitude of β across different commodities directly.

Volatility is persistent, which makes it important to include an autoregressive term in the predictive regression when investigating whether macroeconomic uncertainty possesses additional predictive power beyond the information contained in the lagged volatility. Many studies apply similar approaches to investigate variable predictability. See, among others, Avramov (2002), Ludvigson and Ng (2009) and Christoffersen et al. (2017).

Compared with in-sample predictability, out-of-sample forecasting performance is a more accurate measure to evaluate the predictive power of macroeconomic uncertainty index. The out-of-sample forecast is similar to in-sample analysis, but now we conduct the predictive regression recursively. To be more specific, we start with an initial window consisting of 120 observations (ten years). We regress our predictive model on this initial sample and obtain a one-step-ahead forecast. We then expand our window by adding an observation and repeat the exercise. By doing this, we get a forecast sequence. We proceed until the expanded sample equals the full sample.

We evaluate the resulting out-of-sample forecasts against the benchmark forecasts of an AR(1) model by calculating the mean of the squared forecast errors (MSFE) of the two forecast sequences. Then we compute the out-of-sample R-square (henceforth R^2_{OOS}) (Campbell and Thompson, 2008), the percentage variation in MSFE of our forecasts relative to benchmark AR (1) forecasts. The CW statistic (Clark and West, 2007) is adopted to test the significance of R^2_{OOS} . Given our sample size, a R^2_{OOS} of 0.5% is sufficient to mark an economically significant improvement in forecast accuracy.

4. Empirical Results

4.1. Full-Sample Analysis

The baseline results for the 15 commodity volatilities obtained by predictive regressions are reported in Table IV. The financialization of commodity markets has had important consequences for the behavior of commodities (Adams and Glück, 2015; Tang and Xiong, 2012). To investigate the potential change after financialization, we also run the regressions on two subsamples (before and after 2005) in addition to the full sample. The results for the subsamples are reported in Panels B and C, respectively. To account for potential serial correlation, Newey-West standard errors are used and presented in parentheses. We display the variation in adjusted R-square (hereafter $\Delta\bar{R}^2$) relative to a benchmark univariate AR(1) model in the last line of each panel to show the improvement of forecasting power brought by including the macroeconomic uncertainty index.

TABLE IV

Predictive Regression of the Monthly Log Realized Commodity Volatility on Macroeconomic Uncertainty

	Energy			Metals			Grains			Softs			Livestock		
	CL	NG	HO	GC	SV	HG	SY	CN	WC	SB	KC	CT	LC	LH	FC
Panel A: Full Sample															
β	0.587***	0.562***	0.578***	0.529***	0.590***	0.543***	0.651***	0.680***	0.678***	0.623***	0.547***	0.569***	0.690***	0.564***	0.649***
	(0.044)	(0.043)	(0.040)	(0.056)	(0.053)	(0.050)	(0.041)	(0.039)	(0.039)	(0.044)	(0.066)	(0.056)	(0.030)	(0.063)	(0.037)
γ	0.196***	0.107**	0.181***	0.206***	0.090*	0.200***	0.083**	0.092***	0.108***	0.138***	-0.068*	0.161***	0.092***	0.110***	0.116***
	(0.041)	(0.044)	(0.032)	(0.045)	(0.046)	(0.055)	(0.037)	(0.034)	(0.031)	(0.047)	(0.038)	(0.040)	(0.028)	(0.036)	(0.028)
Obs.	350	278	386	384	387	315	404	404	404	356	350	350	495	419	456
$\bar{R}^2$	0.494	0.354	0.463	0.420	0.378	0.424	0.453	0.499	0.512	0.462	0.309	0.412	0.520	0.358	0.482
$\triangle\bar{R}^2$	0.027	0.008	0.024	0.032	0.007	0.031	0.005	0.006	0.010	0.015	0.002	0.021	0.007	0.009	0.011
Panel B: Sample before 2005															
β	0.560***	0.503***	0.540***	0.496***	0.529***	0.476***	0.653***	0.619***	0.577***	0.603***	0.548***	0.573***	0.718***	0.591***	0.677***
	(0.057)	(0.065)	(0.052)	(0.065)	(0.059)	(0.081)	(0.054)	(0.053)	(0.057)	(0.061)	(0.078)	(0.060)	(0.031)	(0.072)	(0.037)
γ	0.178***	0.138**	0.163***	0.191***	-0.077	-0.066	0.002	0.009	0.005	0.155***	-0.079	0.132**	0.088***	0.075**	0.113***
	(0.046)	(0.066)	(0.050)	(0.066)	(0.050)	(0.061)	(0.043)	(0.044)	(0.031)	(0.055)	(0.051)	(0.054)	(0.030)	(0.037)	(0.028)
Obs.	215	143	251	249	252	180	269	269	269	221	215	215	360	284	321
$\bar{R}^2$	0.423	0.309	0.387	0.358	0.293	0.229	0.421	0.378	0.327	0.453	0.314	0.377	0.557	0.366	0.519
$\triangle\bar{R}^2$	0.024	0.013	0.019	0.027	0.003	0.000	-0.003	-0.002	-0.003	0.018	0.003	0.014	0.006	0.003	0.010
Panel C: Sample after 2005															
β	0.598***	0.540***	0.568***	0.429***	0.456***	0.436***	0.528***	0.539***	0.580***	0.611***	0.503***	0.563***	0.537***	0.473***	0.516***
	(0.088)	(0.056)	(0.090)	(0.091)	(0.102)	(0.094)	(0.076)	(0.098)	(0.078)	(0.068)	(0.082)	(0.099)	(0.078)	(0.082)	(0.111)
γ	0.248***	0.191***	0.297***	0.229***	0.223***	0.388***	0.223***	0.183**	0.195***	0.166**	-0.027	0.171**	0.150*	0.214***	0.143*
	(0.087)	(0.064)	(0.079)	(0.084)	(0.072)	(0.082)	(0.066)	(0.070)	(0.062)	(0.069)	(0.065)	(0.077)	(0.089)	(0.076)	(0.084)
Obs.	135	135	135	135	135	135	135	135	135	135	135	135	135	135	135
$\bar{R}^2$	0.603	0.403	0.634	0.309	0.330	0.558	0.451	0.398	0.473	0.478	0.243	0.417	0.360	0.344	0.325
$\triangle\bar{R}^2$	0.035	0.026	0.044	0.039	0.037	0.081	0.030	0.023	0.026	0.019	-0.005	0.020	0.015	0.033	0.013

Note. The table reports in-sample predictability results for the 15 commodity volatilities. Results are listed by commodity category. The intercept is omitted for each regression because all variables are standardized before estimation. Newey-West standard errors are presented in parentheses. The number of observations and adjusted R-square ($\bar{R}^2$) are also reported. $\Delta\bar{R}^2$ represents variation in $\bar{R}^2$ relative to a benchmark univariate AR(1) model. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Macroeconomic uncertainty is a useful predictor of realized commodity volatility. The forecasting effect we find in the full sample implies that higher macroeconomic uncertainty is followed by a period of higher commodity volatility for almost all commodities.[5] More specifically, for every commodity, the coefficient of MacUnc is significant and the $\Delta\bar{R}^2$ is positive, indicating the robustness and significance of the predictive power of the macroeconomic uncertainty index. As expected, the autoregressive component also plays an important role in predicting the realized volatility.

The predictive power of macroeconomic uncertainty varies by category. It is noteworthy that the forecasting power of MacUnc is most pronounced for four commodity volatilities, those of crude oil and heating oil in the energy class and of gold and copper in metals. Variation in macroeconomic uncertainty predicts a large fraction of variation in RV series for the above four commodities. More precisely, the coefficients of MacUnc are 0.196, 0.181, 0.206 and 0.200 for these commodities, respectively. This means, for example, that a 1% increase in MacUnc leads to a 20.6% increase in the subsequent RV of gold. These four coefficients are all significant at the 1% level. Moreover, adding MacUnc to our predictive specification results in a significant improvement in forecasting power, as shown by the increase of 0.027 (5.782%), 0.024 (5.467%), 0.032 (8.247%), and 0.031 (7.888%)[6] in $\bar{R}^2$ for CL, HO, GC and HG, respectively.

There are major differences in the predictive power of MacUnc between the samples of before 2005 observations (Panel B) and after 2005 observations (Panel C). There is a noteworthy change in the significance of the coefficients of MacUnc before and after 2005 for metals and grains. Before 2005, macroeconomic uncertainty has little predictive content for the realized volatilities of five commodities, silver, copper, soybean, corn, and wheat[7], as indicated by the insignificant coefficients of MacUnc. However, after 2005, macroeconomic uncertainty shows a strong forecasting effect on the realized volatilities of these five commodities. For instance, a 1% increase in MacUnc causes a 38.8% increase in the subsequent RV of copper. In addition, $\Delta\bar{R}^2$ is around zero for each of the five commodities in Panel B, suggesting MacUnc contains minor predictive content for the RVs of these five commodities before 2005. After 2005, however, $\Delta\bar{R}^2$ ranges from 0.026 (5.817%) to 0.081 (16.981%) for these five commodities, indicating a significant increase in forecasting power.

For the other commodities, the predictive power of macroeconomic uncertainty also shows a great improvement after 2005, reflected in larger coefficients on MacUnc and larger $\Delta\bar{R}^2s$ in Panel C. In particular, for crude oil, natural gas, heating oil, and gold, the coefficients of MacUnc are so large that a 1% rise in

[5] Higher MacUnc predicts higher subsequent realized volatility for all commodities except coffee.
[6] For space concerns, the $\bar{R}^2$ of the AR(1) benchmark is omitted.
[7] The five commodities mentioned consist of two metals and all three grains. Noting this will be helpful for later analysis.

macroeconomic uncertainty leads to an around 20% increase in these four realized volatilities. The percentage increases in $\bar{R}^2$s for the above four regressions range from 6.162% to 14.444%, which also marks a significant improvement in the predictive power of MacUnc. According to Tang and Xiong (2012), considerable index investments began to flow into commodity markets after 2004, resulting in an integration of commodity markets with other financial markets. Meanwhile, portfolio rebalancing of index investors leads to volatility spillovers into commodity markets. This process, known as financialization, might be the main driving force behind the notable improvement in MacUnc's predictive power after 2005. Because macroeconomic uncertainty has become an important predictor of volatilities of almost all commodities after 2005, it is useful to rely on its information content when forecasting commodity market volatilities.

To identify the overall impact of macroeconomic uncertainty on a commodity category, we resort to principal components. Table V presents evidence that the macroeconomic uncertainty index can help to predict the principal components. We consider five principal components for five commodity categories and a principal component extracted from all 15 realized commodity volatility series as well.

TABLE V

Predictive Regression of Principal Component on Macroeconomic Uncertainty

	Dependent Variable: Principal Component					
	Energy	Metals	Grains	Softs	Livestock	All
Panel A: Full Sample						
β	0.608***	0.619***	0.706***	0.645***	0.634***	0.650***
	(0.053)	(0.053)	(0.036)	(0.053)	(0.035)	(0.046)
γ	0.210***	0.172***	0.099***	0.164***	0.109***	0.221***
	(0.042)	(0.050)	(0.033)	(0.040)	(0.029)	(0.051)
Obs.	278	315	404	350	419	278
$\bar{R}^2$	0.556	0.510	0.548	0.533	0.452	0.652
$\triangle\bar{R}^2$	0.028	0.022	0.008	0.021	0.009	0.028
Panel B: Sample before 2005						
β	0.470***	0.535***	0.638***	0.662***	0.660***	0.688***
	(0.089)	(0.060)	(0.054)	(0.060)	(0.034)	(0.066)
γ	0.304***	-0.014	0.008	0.151***	0.085***	0.111**
	(0.064)	(0.055)	(0.042)	(0.042)	(0.032)	(0.049)
Obs.	143	180	269	215	284	143
$\bar{R}^2$	0.479	0.278	0.402	0.534	0.464	0.522
$\triangle\bar{R}^2$	0.055	-0.004	-0.002	0.017	0.005	0.009
Panel C: Sample after 2005						
β	0.555***	0.493***	0.594***	0.610***	0.544***	0.567***
	(0.100)	(0.099)	(0.097)	(0.092)	(0.113)	(0.075)
γ	0.312***	0.297***	0.205***	0.193**	0.182**	0.310***
	(0.087)	(0.082)	(0.070)	(0.080)	(0.085)	(0.081)
Obs.	135	135	135	135	135	135
$\bar{R}^2$	0.641	0.492	0.527	0.519	0.406	0.672
$\triangle\bar{R}^2$	0.048	0.056	0.026	0.025	0.023	0.041

Note. This table reports in-sample predictability results for six principal components, containing the first principal components of the realized volatilities of commodities in energy, metals, grains, softs, livestock, and the principal component of all 15 realized commodity volatilities. Panels A, B and C report results obtained from the full sample, the sample of observations before 2005, and the sample of observations after 2005, respectively. For each regression, the intercept is omitted as before. Newey-West standard errors are presented in parentheses. $\Delta\bar{R}^2$ represents variation in $\bar{R}^2$ relative to a univariate AR(1) model. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A shows that macroeconomic uncertainty helps to predict future volatility for all commodity categories. Specifically, all coefficients of MacUnc are significant at the 1% level and there is positive variation in $\bar{R}^2$ relative to a univariate AR(1) model for every regression. In general, a 1% rise in MacUnc results in a 22.1% increase in commodity volatility. The inclusion of MacUnc increases $\bar{R}^2$ by 0.028. However, the improvements brought by MacUnc do not hold uniformly for all commodity classes. The most affected classes are energy products and metals, as indicated by the large coefficients of MacUnc and significant improvements in $\bar{R}^2s$. This finding makes economic sense because energy products and metals are indispensable industrial materials whose prices are more sensitive to macroeconomic environments. This echoes results by Joëts et al. (2017) that industrial markets are highly sensitive to the level of macroeconomic uncertainty.

Comparing Panels B and C, we find a significant improvement in the forecasting power of macroeconomic uncertainty after 2005. The macroeconomic uncertainty index shows up as a powerful predictive variable for all commodity categories after 2005. Importantly, it seems that MacUnc contains little predictive content before 2005 for metals and grains, as indicated by their insignificant coefficients and close-to-zero $\Delta\bar{R}^2$s. In sharp contrast, after 2005, a 1% rise in MacUnc causes a volatility increase of 29.7% and 20.5% for metals and grains, respectively, which marks MacUnc a powerful predictor. Also, the $\Delta\bar{R}^2$s of these two classes climb to 0.056 and 0.026, as another evidence of predictability enhancement. The rest of commodity categories experienced improvement of volatility predictability by MacUnc after 2005, as seen in the larger coefficients in Panel C. In general, a 1% rise in MacUnc leads to an overall increase of 11.1% in commodity volatility before 2005 and the percentage increase goes up to 31.0% after 2005. The forecasting power of the predictive model relative to an AR(1) model increases from 0.009 to 0.041 between the pre- and post-2005 periods, measured by variations in $\bar{R}^2$s.

In sum, in-sample results show that macroeconomic uncertainty has significant forecasting power for commodity volatility even after controlling for lagged volatility. However, the predictability does not hold uniformly for all commodity classes and sample periods. Macroeconomic uncertainty is more powerful in forecasting volatilities of energy products and metals and is more pronounced after 2005 for all commodity categories.

4.2. Out-of-Sample Analysis

The out-of-sample forecasts are generated recursively with an expanding window, as discussed in section 3. We evaluate the forecast results by R_{OOS}^2 and CW statistics. The CW statistic tests the null hypothesis of equal forecast performance against the alternative of superior performance by the model augmented by macroeconomic uncertainty relative to the benchmark AR(1) model. The MSFEs of the augmented model and the benchmark model are provided for comparison.

TABLE VI

Out-of-sample Forecasting Results for 15 Commodities

	Energy			Metals			Grains			Softs			Livestock		
	CL	NG	HO	GC	SV	HG	SY	CN	WC	SB	KC	CT	LC	LH	FC
Panel A: Full Sample															
MSFE. AR(1)	0.081	0.079	0.075	0.139	0.107	0.090	0.084	0.101	0.067	0.072	0.083	0.077	0.064	0.057	0.074
MSFE	0.075	0.079	0.071	0.132	0.106	0.084	0.083	0.100	0.065	0.071	0.085	0.075	0.063	0.056	0.073
$R^2_{OOS}(\%)$	6.974**	-0.209	5.514***	4.986***	0.952*	7.064**	0.685	1.545*	2.492*	1.607***	-2.608	3.733**	1.810***	0.460*	1.841***
CWstat	2.172	0.931	2.541	2.974	1.369	2.166	1.084	1.426	1.592	3.161	0.576	1.908	2.877	1.414	2.687
Panel B: Sample before 2005															
MSFE. AR(1)	0.079	0.115	0.081	0.153	0.094	0.075	0.090	0.100	0.053	0.066	0.121	0.067	0.066	0.061	0.083
MSFE	0.074	0.114	0.078	0.147	0.093	0.075	0.091	0.101	0.054	0.064	0.125	0.065	0.065	0.062	0.082
$R^2_{OOS}(\%)$	6.810**	1.529	4.007**	3.414***	0.767	0.035	-1.405**	-0.741	-0.691	2.722***	-3.587	2.880	2.015***	-1.337	1.900***
CWstat	2.186	0.871	1.956	2.657	1.174	0.496	-2.210	-1.014	-1.267	2.696	0.051	1.210	2.849	0.467	2.410
Panel C: Sample after 2005															
MSFE. AR(1)	0.081	0.072	0.069	0.125	0.120	0.097	0.077	0.103	0.082	0.077	0.056	0.085	0.061	0.051	0.060
MSFE	0.076	0.073	0.064	0.116	0.118	0.088	0.074	0.098	0.078	0.076	0.057	0.081	0.060	0.050	0.059
$R^2_{OOS}(\%)$	7.087*	-0.703	7.250**	6.855**	1.095	9.515**	3.396**	4.030**	4.792**	0.880**	-1.118*	4.213*	1.412*	3.094**	1.716*
CWstat	1.609	0.725	1.910	2.085	1.042	2.117	1.715	1.675	1.826	1.975	1.307	1.636	1.355	2.060	1.373

Note. This table shows out-of-sample forecast results for 15 realized commodity volatilities. Panel A reports statistics computed from full-sample forecasts, Panel B reports statistics obtained from forecasts before 2005, and Panel C presents results for forecasts after 2005. The reported statistics include the mean of the squared forecast errors of the benchmark AR (1) model, denoted as MSFE. AR (1), the MSFE of the macroeconomic uncertainty augmented model, the out-of-sample R-square of Campbell and Thompson (2008), presented as a percentage, and the CW statistics put forth by Clark and West (2007). The R^2_{OOS} s and CW statistics test the null hypothesis of equal forecasting performance by the model augmented by macroeconomic uncertainty and an AR(1) benchmark model against the alternative hypothesis of superior predictive performance by the augmented model. ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively.

Table VI reports the out-of-sample forecast results for the 15 commodities. As shown in Panel A, the model augmented by macroeconomic uncertainty generally outperforms a simple autoregressive benchmark. This is corroborated by the positive and significant R^2_{OOS} s, indicating a superior predictive performance by the augmented model relative to the benchmark model. The model that includes macroeconomic uncertainty performs well in forecasting the realized volatilities of crude oil, heating oil, gold, and copper, as indicated by the R^2_{OOS} of 6.974, 5.514, 4.986, and 7.064, respectively. This finding makes sense economically since those four commodities are closely related to industrial production and their prices are more vulnerable to macroeconomic variations.

Compared to Panel B, Panel C shows more out-of-sample success for the macroeconomic uncertainty augmented model, implying that macroeconomic uncertainty is more powerful in forecasting commodity volatilities after 2005. In particular, for copper, soybeans, corn, wheat, cotton, and lean hogs, the R^2_{OOS} s are insignificant or negative in Panel B, indicating a worse or equal predictive performance by the model including macroeconomic uncertainty relative to a simple autoregressive benchmark. However, the R^2_{OOS} s of these six commodities turn positive and significant after 2005. Also, the post-2005 R^2_{OOS} s are sizable, ranging from 3.094 to 9.515. Moreover, for crude oil, heating oil, and gold, the R^2_{OOS} s experience a significant increase after 2005, from 6.810, 4.007 and 3.414 in Panel B to 7.087, 7.250 and 6.855 in Panel C. These results indicate that the macroeconomic uncertainty augmented model performs much better than the AR(1) benchmark model after 2005.

TABLE VII

Out-of-sample Forecasting Results for Principal Components

	Dependent Variable: Principal Component					
	Energy	Metals	Grains	Softs	Livestock	All
Panel A: Full Sample						
MSFE. AR(1)	0.948	1.108	0.973	0.697	1.156	1.944
MSFE	0.926	1.046	0.953	0.663	1.151	1.758
$R^2_{OOS}(\%)$	2.318**	5.665**	2.124*	4.784***	0.366**	9.590**
CWstat	1.726	2.106	1.523	2.874	1.828	2.218
Panel B: Sample before 2005						
MSFE. AR(1)	0.726	0.850	0.949	0.601	1.227	1.404
MSFE	0.682	0.869	0.957	0.564	1.246	1.430
$R^2_{OOS}(\%)$	6.055*	-2.255	-0.791*	6.157***	-1.576	-1.848
CWstat	1.570	-1.087	-1.429	3.043	0.965	-0.129
Panel C: Sample after 2005						
MSFE. AR(1)	0.988	1.225	1.000	0.765	1.068	2.040
MSFE	0.969	1.125	0.948	0.734	1.035	1.816
$R^2_{OOS}(\%)$	1.830*	8.148**	5.197**	4.018**	3.093*	10.989**
CWstat	1.609	2.204	1.787	2.054	1.622	2.235

Note. This table reports out-of-sample predictive results for six principal components. Panel A reports statistics computed from the full-sample forecasts, Panel B reports statistics obtained from forecasts before 2005, and Panel C presents results for forecasts after 2005. The reported statistics include the mean of the squared forecast errors of the benchmark AR(1) model, denoted as MSFE. AR (1), the MSFE of the macroeconomic uncertainty augmented model, the out-of-sample R-square of Campbell and Thompson (2008), presented in percentage, and the CW statistics put forth by Clark and West (2007). The R_{OOS}^2 s and CW statistics test the null hypothesis of equal forecasting performance by the model augmented by macroeconomic uncertainty and an AR(1) benchmark model against the alternative hypothesis of superior predictive performance by the augmented model. ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively.

Table VII presents the out-of-sample forecasting results for six principal components. Panel A shows that the model augmented by macroeconomic uncertainty beats the AR(1) benchmark model for every commodity category. The augmented model preforms best in forecasting the volatility of metals, among the five commodity classes, supported by the largest R_{OOS}^2 of 5.665. In terms of out-of-sample forecast accuracy, the model including macroeconomic uncertainty brings an overall improvement of 9.59% relative to the AR (1) benchmark model, which indicates that the MacUnc is a powerful predictor.

The model augmented by macroeconomic uncertainty performs better after 2005. Particularly, for metals, grains, and livestock, the R_{OOS}^2 s are insignificant or negative in Panel B, indicating a worse or equal predictive performance by the model including macroeconomic uncertainty relative to a simple autoregressive benchmark. However, the R_{OOS}^2 s of these three commodity classes turn positive and significant after 2005, ranging from 3.093 to 8.148. In general, there is little difference between the predictive performances of the macroeconomic uncertainty augmented model and the univariate AR(1) benchmark before 2005 but a large difference after 2005, as indicated by the R_{OOS}^2 of 10.989.

To sum up, the model augmented by macroeconomic uncertainty generally outperforms a univariate AR (1) benchmark, particularly after 2005. Admittedly, the univariate AR (1) benchmark is quite simple and a more sophisticated predictive model could capture more features of the data and thus may perform better. We still consider it encouraging that macroeconomic uncertainty generally performs well in these simple out-of-sample forecast comparisons.

4.3. Improvements in Forecast Performance Over Time

We study the improvements in the out-of-sample performance after 2000 for energy, metals, and grains. For each category, we select typical commodities and report the results in Figure 2. The figure shows the time series of the squared forecast errors of the macroeconomic uncertainty augmented model minus the squared forecast errors of the AR (1) benchmark, denoted ΔSFE. Thus a negative value of ΔSFE signifies a superior performance by the augmented model relative to the benchmark at a particular point in time. According to Christiansen et al. (2012), macro-finance variables provide predictive content beyond autoregressive benchmarks during the 2007-2009 financial crisis. To identify potentially different dynamics during recessions, we mark the NBER-dated business-cycle recession periods with shadows.

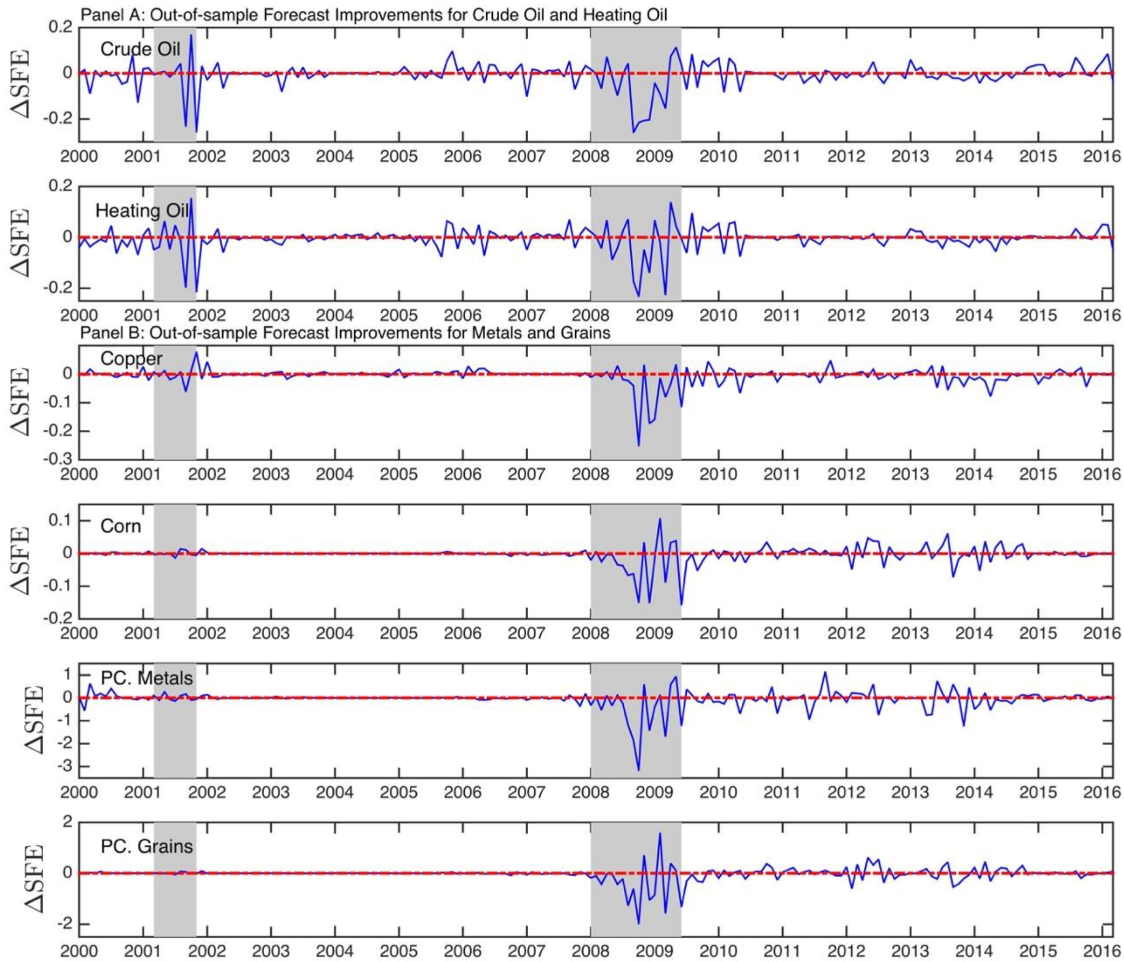

FIGURE 2

Improvements of Out-of-sample Performance for Energy, Metals and Grains

Note. This figure shows the time variation in the out-of-sample performance of MacUnc in predicting the monthly realized volatilities of energy, metals, and grains. We report results for typical commodities in each category. Specifically, we use crude oil and heating oil to represent energy products, copper for metals, and corn for grains. Results of principal components of metals and grains are also displayed. ΔSFE is the difference between the squared forecast errors of the macroeconomic uncertainty augmented model and the AR(1) benchmark. Hence, a negative value signifies a superior performance by the augmented model against the benchmark model at a particular point in time. The shadow regions indicate NBER-dated business-cycle recessions and the red line marks the value of 0.

As documented in section 3.2.2, the model augmented by macroeconomic uncertainty generally outperforms a univariate AR(1) benchmark, and Figure 2 provides evidence on the time periods when the augmented model performs better. For energy products, the augmented model beats the autoregressive benchmark in every recession[8]. However, the same does not hold for metals and grains. Before financialization, the ΔSFE line almost coincides with the zero line for metals and grains, indicating an equal performance by the macroeconomic uncertainty augmented model and the AR (1) model. In the post-financialization period, the augmented model beats the benchmark model over the most recent 2008-2009 recession. In short, for energy products, significant improvements in forecasting accuracy happen during each recession, while both financialization and recessions are required to generate a sizable forecasting improvement for metals and grains.

4.4. Using the Financial Uncertainty Index

In addition to macroeconomic uncertainty, Jurado et al. (2015) also propose a financial uncertainty index (FinUnc) based on 147 financial variables. These financial indicators are expected to respond immediately to genuine news contained in data releases and disaster events. Considering the close relationship between the financial uncertainty index and the aggregate state upon which investors' decisions depend, it is worthwhile to investigate the predictive content of the financial uncertainty index in forecasting commodity volatilities. Moreover, as documented in Jurado et al. (2015), financial variables are far more volatile than macro indicators and thus may dominate the macro series. This claim prompts an interest in exploring the relative importance of MacUnc and FinUnc in predicting commodity volatilities.

TABLE VIII

Using Financial Uncertainty Index

[8] This finding is in line with Antonakakis et al. (2014), which shows that spillovers between economic policy uncertainty and changes in oil prices reached an unprecedented height during the Great Recession of 2007-2009.

	Dependent Variable: Principal Component					
	Energy	Metals	Grains	Softs	Livestock	All
Panel A: Full Sample						
β	0.633***	0.690***	0.724***	0.660***	0.659***	0.749***
	(0.052)	(0.052)	(0.036)	(0.061)	(0.032)	(0.037)
γ	0.188***	0.050	0.050	0.145***	0.045	0.097**
	(0.045)	(0.052)	(0.033)	(0.037)	(0.035)	(0.041)
Obs.	278	315	404	350	419	278
$\bar{R}^2$	0.553	0.489	0.542	0.529	0.443	0.630
$\triangle\bar{R}^2$	0.025	0.001	0.002	0.017	0.000	0.006
Panel B: Sample before 2005						
β	0.504***	0.535***	0.633***	0.695***	0.677***	0.704***
	(0.079)	(0.060)	(0.055)	(0.071)	(0.032)	(0.071)
γ	0.267***	-0.015	0.038	0.100**	0.018	0.060
	(0.083)	(0.062)	(0.044)	(0.039)	(0.042)	(0.059)
Obs.	143	180	269	215	284	143
$\bar{R}^2$	0.470	0.278	0.404	0.524	0.457	0.513
$\triangle\bar{R}^2$	0.046	-0.004	0.000	0.007	-0.002	0.000
Panel C: Sample after 2005						
β	0.704***	0.570***	0.612***	0.552***	0.576***	0.666***
	(0.060)	(0.107)	(0.108)	(0.079)	(0.097)	(0.066)
γ	0.150***	0.198***	0.175***	0.262***	0.132***	0.200***
	(0.055)	(0.102)	(0.077)	(0.070)	(0.060)	(0.068)
Obs.	135	135	135	135	135	135
$\bar{R}^2$	0.609	0.463	0.519	0.536	0.394	0.652
$\triangle\bar{R}^2$	0.016	0.027	0.018	0.042	0.011	0.021

Note. This table reports results of using a model augmented by financial uncertainty index to predict six principal components. Panels A, B and C report results obtained from the full sample, the sample of observations before 2005, and the sample of observations after 2005, respectively. For each regression, the intercept is omitted as before. Newey-West standard errors are presented in parentheses. $\Delta\bar{R}^2$ represents variation in $\bar{R}^2$ relative to a benchmark univariate AR(1) model. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table VIII reports results for a predictive regression with the financial uncertainty index included. The results for commodity volatility predictability are similar to those for principal components and so are omitted. Panels A and B show that financial uncertainty only significantly improves forecasts for energy products. However, financial uncertainty becomes an important predictor for every commodity category after 2005, as indicated by the significant coefficients of FinUnc in Panel C and the notable increases in $\bar{R}^2$s relative to the AR(1) benchmark. Overall, in the years after 2005, a 1% rise in financial uncertainty causes a 20% increase in commodity volatility. The model augmented by the financial uncertainty index improves forecasting power by 0.021 relative to an AR(1) benchmark, as measured by the variation in $\bar{R}^2$.

To investigate the relative importance of macroeconomic uncertainty and financial uncertainty in forecasting commodity volatilities, we use both uncertainty indexes simultaneously. The predictive regression for the principal component of commodity class j now becomes:

$$PC_{j,t} = \alpha + \beta PC_{j,t-1} + \gamma_1 U_{t-1} + \gamma_2 F_{t-1} + \varepsilon_{i,t}.$$

$PC_{j,t}$ denotes the principal component of realized volatilities of commodity class j in month t. Our predictors, U_{t-1} and F_{t-1}, are the lagged macroeconomic uncertainty and the lagged financial uncertainty, respectively. Our primary interest is the relative magnitude of γ_1 and γ_2. To this end, all variables are standardized before regression so that we can compare the magnitudes of γ_1 and γ_2 directly.

TABLE IX

Using Both Uncertainty Indexes

	Dependent Variable: Principal Component					
	Energy	Metals	Grains	Softs	Livestock	All
Panel A: Full Sample						
β	0.584***	0.608***	0.706***	0.633***	0.634***	0.650***
	(0.056)	(0.051)	(0.036)	(0.058)	(0.035)	(0.046)
γ_1	0.149***	0.230***	0.102***	0.119**	0.114***	0.223***
	(0.046)	(0.058)	(0.038)	(0.048)	(0.034)	(0.053)
γ_2	0.118**	-0.081	-0.006	0.082*	-0.011	-0.003
	(0.046)	(0.053)	(0.031)	(0.045)	(0.042)	(0.042)
Obs.	278	315	404	350	419	278
$\bar{R}^2$	0.563	0.512	0.547	0.536	0.451	0.650
$\triangle\bar{R}^2$	0.035	0.024	0.007	0.024	0.008	0.026
Panel B: Sample before 2005						
β	0.441***	0.535***	0.629***	0.663***	0.660***	0.691***
	(0.088)	(0.060)	(0.056)	(0.061)	(0.034)	(0.065)
γ_1	0.215**	-0.007	-0.021	0.144**	0.093***	0.137**
	(0.084)	(0.076)	(0.044)	(0.062)	(0.035)	(0.069)
γ_2	0.147	-0.010	0.051	0.010	-0.019	-0.035
	(0.100)	(0.091)	(0.051)	(0.063)	(0.048)	(0.083)
Obs.	143	180	269	215	284	143
$\bar{R}^2$	0.486	0.274	0.402	0.532	0.462	0.519
$\triangle\bar{R}^2$	0.062	-0.008	-0.002	0.015	0.003	0.006
Panel C: Sample after 2005						
β	0.554***	0.488***	0.574***	0.543***	0.543***	0.541***
	(0.103)	(0.103)	(0.108)	(0.089)	(0.112)	(0.073)
γ_1	0.319***	0.265***	0.156*	0.073	0.163	0.261***
	(0.114)	(0.099)	(0.087)	(0.099)	(0.111)	(0.087)
γ_2	-0.009	0.047	0.086	0.215***	0.028	0.094
	(0.056)	(0.112)	(0.096)	(0.080)	(0.069)	(0.067)
Obs.	135	135	135	135	135	135
$\bar{R}^2$	0.638	0.489	0.527	0.535	0.402	0.674
$\triangle\bar{R}^2$	0.045	0.053	0.026	0.041	0.019	0.043

Note. This table reports results of a predictive regression that includes both macroeconomic uncertainty and financial uncertainty for six principal components.

Panels A, B and C report results obtained from the full sample, the sample of observations before 2005, and the sample of observations after 2005, respectively. For each regression, the intercept is omitted as before. Newey-West standard errors are presented in parentheses. $\Delta\bar{R}^2$ represents the variation in $\bar{R}^2$ relative to a benchmark univariate AR(1) model. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Results of the predictive regression including both uncertainty indexes are presented in Table IX. Importantly, macroeconomic uncertainty dominates financial uncertainty in the whole sample period. Panel A provides evidence for this claim, as the coefficients of MacUnc are significant for every commodity category, while the coefficients of FinUnc are smaller or insignificant. After 2005, MacUnc maintains its dominance over FinUnc and the forecasting power of MacUnc becomes stronger for energy products, metals, and grains. Moreover, it is noteworthy that the overall impact of MacUnc dominates FinUnc in every sample period under investigation, as shown in the last column of the table.

In brief, financial uncertainty possesses information content when forecasting commodity volatility and its predicting power is more pronounced after 2005. However, financial uncertainty generally loses its significance when macroeconomic uncertainty is included, implying a dominating role of macroeconomic uncertainty in predicting commodity volatility.

5. CONCLUSIONS

This study investigates to what extent macroeconomic uncertainty predicts volatility in commodity futures markets. We find that macroeconomic uncertainty contains predictive power for future volatility of energy, metal, grain, soft, and livestock commodities. Importantly, macroeconomic uncertainty has significant forecasting power for commodity volatility even after controlling for the lagged volatility. Our out-of-sample results show that the inclusion of macroeconomic uncertainty enhances the forecasting performance relative to an autoregressive benchmark. However, the predictability does not hold uniformly for all commodity classes and sample periods. Macroeconomic uncertainty is more powerful in forecasting the volatilities of energy products and metals and its predictive power is more pronounced after 2005 for all commodity categories.

Though the model augmented by macroeconomic uncertainty generally outperforms the AR(1) benchmark, improvements in forecasting accuracy vary strongly over time. For energy products, significant improvements in forecasting accuracy happen during each recession, while both financialization and recessions are required to generate a sizable forecasting improvement for metals and grains. Our results also support the dominating role of macroeconomic uncertainty in predicting commodity volatility over financial uncertainty.

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