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(PRELIMINARY)

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Commodity prices are volatile. Forecasting the volatility has been notoriously difficult. We propose using Internet search activity to forecast commodity futures price volatility. We show that Google search volume improves forecasts of volatility both in-sample and out-of-sample in all commodity categories (energy, metal and agriculture).

Keywords: Commodity, volatility, forecasting, futures markets, Internet search activity

1. Introduction

Commodity prices are volatile. For example, the average annualized realized volatility in crude oil, copper and corn futures prices over the ten-year period from 2004 to 2013 is 32%, 31% and 31%, respectively. This exceeds the realized volatility in the S&P 500 index futures over the same period by almost a factor of two. Forecasting commodity price volatility is critical for traditional hedgers who use commodities in production as well as other types of investors such as commodity index funds who increasingly include commodity futures in their portfolios.[1] Yet, this forecasting is notoriously difficult. The effort usually involves implementing a variety of generalized autoregressive conditional heteroskedasticity (GARCH) models such as Kang, Kang and Yoon (2009) and Wei, Wu and Huang (2010) for the crude oil market.

We propose a new variable to improve forecasting commodity price volatility: Internet search engine activity. We use Google search activity data available at weekly frequency since

[1] Financialization of commodity markets has been documented in numerous studies, for example, Büyükşahin, and Robe (2014) and Tang and Xiong (2012).

January 2004.[2] We include all commodities for which uninterrupted Google data series is available (gold, silver, copper, crude oil, natural gas and corn) and show that the Google search activity is a useful predictor of price volatility for these commodities.

Our results add to the growing literature on usefulness of Internet search activity data in numerous contexts including Ginsberg (2009) detecting influenza epidemics, Choi and Varian (2009) predicting automobile sales, unemployment claims and consumer confidence, D'Amuri and Marcucci (2009) forecasting unemployment rate, Wu and Brynjolfsson (2013) predicting housing market trends, etc. Several studies have shown that online search activity is associated with volatility and returns in financial markets such as Da, Engelberg and Gao (2011) and Vlastakis and Markellos (2012) for individual stocks, Dimpfl and Jank (2015) for the Dow Jones Industrial Average index, Da, Engelberg and Gao (2015) for stock indices, exchange traded funds and Treasury bonds, and Kita and Wang (2012) and Smith (2012) for exchange rates.

In the commodity markets, work with big data has been limited. Two studies focus on crude oil price *level*. Fantazzini and Fomichev (2014) use Google search data along with macroeconomic variables to forecast the level of real price of crude oil. Azar (2009) uses Google searches to study the joint dynamics between crude oil price level and interest in electric cars. Three studies analyze *volatility* of prices. Guo and Ji (2013) use Google search terms to build a "market concern" index and show its effect on crude oil price level and volatility. Ji and Guo (2015) use Google search data to study behavior of crude oil prices around oil-related events such as hurricanes. Peri, Vandone and Baldi (2014) employ Google search data along with information published in newspapers to analyze the relationship between volatility and information arrival in the corn futures market. However, all three studies are limited to in-sample

[2] Google is the most popular Internet search engine with the U.S. market share of 67.6% as of April 2014 (http://www.comscore.com/Insights/Market-Rankings/comScore-Releases-April-2014-US-Search-Engine-Rankings).

analysis, which does not show whether Internet search data is useful for out-of-sample forecasting.[3]

We contribute to this work in commodity markets in two ways. First, we analyze all commodities for which Google search activity data is available instead of focusing on one particular commodity. This alleviates potential concerns about data mining. Second, in addition to in-sample analysis, we conduct out-of-sample forecasting. This allows us to show that Google search activity is a useful predictor of price volatility not only in-sample but also out-of-sample.

In the in-sample analysis, we employ a vector autoregressive (VAR) model and Granger causality tests. For each commodity the model contains four variables: Google search volume, continuously compounded futures return, futures volatility measured as the realized standard deviation (computed using 5-minute futures returns), and futures trading volume. The results show that Google search activity predicts volatility in all six commodities.

In-sample results are often prone to pitfalls involving overfitting and spurious correlations. Therefore, we follow with out-of-sample evaluations that have been quite effective in reducing these problems. The key out-of-sample evaluation concept we use is encompassing. It argues that if model 1 contains all relevant information for forecasting a target variable over model 2, forecast errors of model 1 should be uncorrelated with forecasts from model 2. Otherwise, model 2 provides additional information in the forecasts and is not encompassed by model 1. This is especially useful in our context where we examine the marginal contribution of Google search activity in forecasting commodity price volatility while allowing other regressors.

One potential issue in the out-of-sample approach is the sensitivity of results to the estimation window size. We use Rossi and Inoue (2012) encompassing tests that are robust to

[3] Mao, Counts and Bollen (2011) include gold in their analysis of financial indices (Dow Jones stock index and VIX market volatility index) but gold is not included in their out-of-sample forecasting exercise.

window size to address this shortcoming and avoid concerns about data snooping over window sizes. The results show that Google search activity provides superior forecasts for volatilities of gold, silver, crude oil, natural gas and corn.

The remainder of this paper begins with a data description in Section 2. Section 3 presents the empirical results including robustness checks and Section 4 concludes with a brief discussion.

2. Data

This section describes the Internet search activity and futures market data followed by correlations between the two data sets.

2.1 Internet Search Activity

To measure trader attention to commodity markets, we obtain Internet search activity data from Google Trends (http://www.google.com/trends), a Google service that provides data showing how frequently search terms have been used in the Google Search engine. Market participants looking for information about commodities use many possible search terms. Instead of displaying the *number* of searches for each search term, Google Trends calculates a search volume *index* scaled by the maximum value over the time period selected for each search term. The search volume index ranges from zero to 100, with a value of 100 representing the peak of search activity for the given search term during the sample period. This normalization makes it difficult to aggregate search volume indices for multiple search terms because the number of searches differs across search terms. Fortunately, Google Trends aggregates search activity data for related searches by topic categories and regions.

We use search activity data for gold, silver, copper, crude oil, natural gas and corn from the Commodities & Futures Trading subcategory under the Finance/Investment category in the U.S. region. Specifically, we download search volume indices for the following search terms in this subcategory: 'gold', 'silver', 'copper', 'oil', 'natural gas' and 'corn'.[4] These search volume indices represent search activity data aggregated across many search terms that contain these commodity names. For example, the top five search terms containing the word 'oil' were *oil prices*, *oil price*, *crude oil*, *price of oil* and *crude oil prices*. Section 3.3 discusses robustness checks with these individual search terms.

Google Trends data is available since January 2004 at weekly frequency. We examine a sample period from January 4, 2004 to November 21, 2014. When search activity for a given search term is too low, Google Trends reports missing (zero) values of the search volume index. We have uninterrupted non-missing values for gold, silver and oil during our entire sample period. Uninterrupted non-missing values for copper, natural gas and corn begin on October 1, 2004, July 29, 2005 and January 21, 2005, respectively. We use these dates as the starting points of the respective samples.[5]

2.2 Futures Market Data

To investigate the effect of Internet search activity on the commodity markets, we use futures data for metal (gold, silver and copper), energy (crude oil and natural gas) and agriculture (corn)

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[4] Using this subcategory ensures that our data is not polluted by searches containing our search terms but not related to commodities such as 'baby oil' or 'corn dog'.
[5] We do not analyze other commodities, for example, soybeans and wheat because the Google Trends data contains too many missing values.

commodities listed in Table 1.[6] We use two measures of volatility. First, we compute the weekly realized volatility

$$RV_t = \sqrt{\sum_{i=1}^{n} r_{t,i}^2}\,, \tag{1}$$

where RV_t is the realized standard deviation during week t, and $r_{t,i}^2$ is the squared continuously compounded return in intraday interval i during week t. The returns are computed using prices of the nearby futures contract.[7] Following the existing literature (for example, Bollerslev, Tauchen and Zhou, 2009), we use 5-minute intraday intervals in the calculation. Second, we use range-based volatility estimators proposed by Garman and Klass (1980) and Rogers and Satchell (1991). The results are similar in all volatility estimators and we, therefore, report only the realized volatility results.

[Insert Table 1 about here]

Figure 1 shows the Google search volume indices for 'gold' and 'oil' and realized volatility in the nearby gold and crude oil futures from January 3, 2004 to November 21, 2014. Increases in search activity coincide with periods of high volatility. The other commodities (silver, copper, natural gas and corn) exhibit similar patterns.

[Insert Figure 1 about here]

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[6] The futures market data is obtained from Genesis Financial Technologies. We omit the weeks of November 26, 2004 and August 31, 2007 for crude oil and copper, respectively, because the futures data is missing in our data set. The resulting number of observations is shown in Table 2.

[7] We use a continuous series of the most liquid futures contract. The metal and energy commodity markets (gold, silver, copper, crude oil and natural gas) have futures contracts for all twelve calendar months. The most liquid contract is the nearby contract. It becomes relatively illiquid in its last few days of trading. Therefore, we switch to the next month contract when its daily contract volume exceeds the nearby contract volume. The corn market has only March, May, July, September and December contracts. We again use the most liquid contract and switch to the next month contract when its daily contract volume exceeds the nearby contract volume. The September contract is never the most liquid one and we, therefore, roll over from the June contract directly to the December contract.

2.3 Correlations

Table 2 shows correlations of log-differences of Google search activity with volatility, trading volume and returns in the futures markets.[8] Changes in the search activity are positively and significantly correlated with contemporaneous changes in realized volatility and trading volume in all six markets. For example, the correlation between changes in search activity and changes in volatility ranges from 0.14 for natural gas to 0.48 for crude oil. This result is consistent with trader attention reflected in the Google search queries that translates into futures trading activity. Correlation of changes in the Google search volume with contemporaneous returns is not significant. This is not surprising because our measure of Internet search activity is not directional; it simply reflects investor attention to the commodity markets.

[Insert Table 2 about here]

3. Results

We employ two complementary approaches to demonstrate that the Google search activity is a useful predictor of commodity futures price volatility: in-sample analysis and out-of-sample forecasting. We follow with robustness checks.

3.1. VAR Estimation Results

We begin by estimating a vector autoregression (VAR) for each commodity, specified as

$$\boldsymbol{x_t} = \boldsymbol{\alpha} + \sum_{j=1}^{4} \boldsymbol{\beta_j}\, \boldsymbol{x_{t-j}} + \boldsymbol{\varepsilon_t}, \tag{2}$$

where $\boldsymbol{\alpha}$ is a vector of constant terms, $\boldsymbol{\beta_j}$ is the vector of coefficients for lag j, and $\boldsymbol{x_t}$ is a vector of four variables: weekly Google Trends search volume index, realized volatility measured by

[8] We use log-differences to avoid potential spurious correlations.

the realized standard deviation, trading volume and return.[9] $\boldsymbol{\varepsilon_t}$ is a vector of random disturbances. Following Dimpfl and Jank (2015), we take the natural logs of the realized standard deviation, search volume index and trading volume. This transformation reduces skewness and excess kurtosis of these variables. We also test for stationary using the Phillips and Perron (1988) test. The null hypothesis of a unit root is strongly rejected for all variables in all commodity markets. We include four lags of variables in the VAR.[10]

For all six commodities, the coefficient estimate of the first lag of the Google search activity in the realized volatility equation is positive and statistically significant at the five percent level.[11] To examine whether Google search activity has predictive power for realized volatility, trading volume and returns, we use the VAR estimation results to perform Granger causality tests. Table 3 shows the results. In all six commodities, there is strong evidence that Google search activity Granger causes realized volatility after controlling for other variables, i.e., lags of realized volatility, trading volume and return. This is not the case in the opposite direction: realized volatility does not Granger cause Google search activity. Google search activity is also a useful predictor of trading volume for metals and crude oil. The relation between volatility and volume is bidirectional as described in previous studies, for example, Darrat, Zhong and Cheng (2007) for stocks. There is also some evidence of bidirectional relation between Google search activity and returns. Futures return is a significant predictor of search activity in four out of six commodities. In all of these cases, the relation between returns and Google search activity in subsequent weeks is positive. Google search activity is a significant predictor of returns only for copper and crude oil.

[9] We also considered including futures open interest in the model. However, the open interest of the nearby contract is driven to a large extent by periodic rollovers from the nearby to the next-to-mature contract.
[10] The Akaike criterion suggested using four lags for silver, copper and oil, five lags for gold and corn and eight lags for natural gas. Using these numbers of lags in the VAR produces results that are similar to the reported results.
[11] VAR coefficient estimates are not tabulated for brevity but are available upon request.

[Insert Table 3 about here]

An alternative way of characterizing the relative predictive content of variables in the VAR is the decomposition of the forecast error variance. The decomposition represents the relative contribution of innovations in each variable to the other variables. Table 4 shows the variance decomposition results for the log of realized volatility. The variance decomposition results depend on the ordering of variables. Placing a variable earlier in the decomposition tends to increase its contribution to the forecast error variance. Therefore, we use two alternative orderings. When the Google search activity is placed last in the ordering, its contribution to the forecast error variance of log realized volatility ranges from about 2% for corn to almost 17% for crude oil, and averages about 9% across the six markets. This can be viewed as the lower bound of the contribution of Google search activity in predicting realized volatility. When we place the Google search activity first in the ordering, its contribution in the forecast error variance of realized volatility increases and averages about 34% across the six markets. Overall, the variance decompositions suggest that Google search activity explains a significant portion of the forecast error variance of realized volatility.

[Insert Table 4 about here]

Figure 2 shows impulse responses that represent the effect of a one standard-deviation shock in a given variable on the other variables in the model. We present results only for oil to save space. Impulse responses for the other five commodities are generally similar and available upon request. The first column shows the effect of the Google search activity shock on the other variables. Unexpected increases in the Google search activity predict higher trading volume and realized volatility. The first line shows how Google search activity reacts to shocks in the other variables. Google search activity tends to rise after price increases. Although the futures trading volume and our measure of search activity do not represent trading direction or bullish sentiment, this finding could reflect positive feedback trading by uninformed speculators (i.e., trend chasing). Google search activity also reacts positively to realized volatility. This could reflect investors searching for information on the Internet as a reaction to news that caused unexpected volatility in the commodity prices.

[Insert Figure 2 about here]

3.2. Out-of-Sample Forecasting

This section takes an out-of-sample approach to evaluating the role of Google search activity in forecasting volatility. The out-of-sample approach has been quite effective in reducing the problem of in-sample overfitting with spurious regressors. However, one potential issue is the sensitivity of results to the estimation window size. To address this shortcoming, we use the Rossi and Inoue (2012) methods robust to the window size to avoid concerns about data-snooping over window sizes. Their encompassing (ENC) tests build on Clark and McCracken (2001) study that compares forecast errors in nested models. We also use a recursively estimated out-of-sample R^2 based on Campbell and Thompson (2008) to understand the size of the contribution of Google search activity to commodity price volatility.

For each commodity, our benchmark model forecasts the log of realized volatility based on commonly used variables: lags of realized volatility, returns and log of trading volumes. To be consistent with the VAR in Section 3.1, we use four lags. This will be our restricted model, model 1. Let the forecast errors from this model be denoted as u_{1t}. We add four lags of log of Google search volume to the benchmark model to form our unrestricted model, model 2. Let the forecast errors from this model be denoted as u_{2t}. Let R be the number of observations used to estimate the parameters to form the first one-step forecast. After that, the models are recursively estimated adding one observation at a time. If *T* denotes the total number of observations, there will be *T-R* forecasts from restricted and unrestricted models. The ENC test statistic is computed as follows:

$$ENC = \frac{\sum_{t=R+1}^{T} u_{1t}(u_{1t} - u_{2t})}{\sum_{t=R+1}^{T} u_{2t}^2}(T - R). \tag{3}$$

To compute the ENC tests recursively, we start at the lower end of the estimation window with R^L observations and after adding one observation at a time we go up to the upper end, R^U. We follow the Rossi and Inoue (2012) recommendation to use 15% trimming on each side of the sample for choosing R^L and R^U. Rossi and Inoue (2012) recommend using two versions of the ENC test. The tests are denoted as

$$Sup - ENC = Sup_{R \in (R^L, \ldots, R^U)}\{ENC(R)\} \tag{4}$$

and

$$Ave - ENC = \frac{1}{R^U - R^L + 1} \sum_{R=R^L}^{R^U} ENC(R). \tag{5}$$

The supremum and average of recursive encompassing tests are reported in the upper panel of Table 5. They are statistically significant at 1 percent level for all commodities. The dotted lines in Figure 3 show the recursively estimated ENC test statistics. Values above zero indicate that the unrestricted model forecast improves upon the restricted model forecast. A downward-sloping line with a constant slope would indicate that the forecast is improved by a fixed amount throughout the sample period.[12] The ENCs in Figure 3 show some variability but are generally consistent with a stable forecasting contribution of the Google search volume index.

[12] A simple example would be to assume that the forecast error of the unrestricted model is a constant fraction of the forecast error from the restricted model in equation 3. In that case, the recursive ENC statistics go down linearly as R increases and T is fixed.

[Insert Table 5 about here]

We also recursively compute the out-of-sample R^2 using the same 15% trimming to understand by what percentage the out-of-sample mean squared errors are reduced by adding the Google search volume to the model:

$$R_{OS}^2 = \frac{\frac{1}{T-R}\sum_{t=R+1}^{T}(u_{1t}^2 - u_{2t}^2)}{\frac{1}{T-R}\sum_{t=R+1}^{T}(u_{1t}^2)} \times 100 \qquad (6)$$

The out-of-sample R^2 values are reported in the bottom panel of Table 5 and solid lines in Figure 3. Adding Google search volume results in reduced mean squared errors in five out of the six commodity markets: The mean R^2 ranges from by 2 percent in gold to 4 percent in natural gas. The maximum of the R^2s ranges from 5 percent in silver to 7.5 percent in natural gas. This suggests that while the net contribution of the Google search volume in forecasting volatility is somewhat time-varying, it does provide useful information that improves volatility forecasts by reasonable amounts.

[Insert Figure 3 about here]

3.3 Robustness Checks

In this subsection, we test whether our results are robust to the choice of Google Trends search terms. As explained in Section 2.1, the search volume indices for our search terms ('gold', 'silver', 'copper', 'oil', 'natural gas' and 'corn') represent search activity data aggregated across many search terms that contain these commodity names. For example, the top five search terms containing the word 'corn' were *corn prices*, *corn price*, *corn futures*, *corn bushel* and *corn cbot*, the top five search terms containing the word 'oil' were *oil prices*, *oil price*, *crude oil*, *price of oil* and *crude oil prices*, etc. To eliminate concerns about possible data mining over the search terms, we test each of the top five search terms separately.[13] The results do not differ. This agrees with, for example, Fantazzini and Fomichev (2014) who also conclude that the results in their study of crude oil are robust to the use of basic keywords.

As an additional robustness check, we include Google search activity in the *entire* Commodities & Futures Trading subcategory to control for search activity in other commodities. This control variable was not significant.

Finally, since our main analysis uses search activity data in the U.S. region, we conduct a robustness check using the same search terms with "World" as the region. The results were generally similar but somewhat weaker, perhaps reflecting the fact that Internet searches in some countries may not be closely linked to trading in the futures market. For example, India ranks second in searches for 'silver' that Google classifies into "Commodities & Futures Trading" category. This interest in silver is, however, most likely related to purchases of silver for jewelry and storage of value in general rather than to silver futures trading.

4. Conclusion

Our paper shows that Google search activity is a useful predictor of commodity price volatility. One question that remains open is what type of traders is driving this relation. Da, Engelberg and Gao (2011) present evidence that in individual stocks Google search activity reflects attention of retail investors.

We explore this question in two ways. First, we employ the weekly Commitment of Traders (COT) report prepared by the U.S. Commodity Futures Trading Commission (CFTC)

[13] In some cases, search terms about another commodity appear. For example, the top five search terms for silver were *price silver*, *silver prices*, *gold*, *silver gold* and *price of silver*. Testing each search term separately ensures that the results are not confounded by other commodities.

that shows the breakdown of futures open interest into three trader category types.[14] There are two reportable categories (commercial traders, i.e., hedgers, and non-commercial traders, i.e., large speculators) and one non-reportable category reflecting small traders. We find that changes in the Google search activity are strongly positively correlated with changes in the non-commercial and non-reportable positions in gold, silver and oil. These correlations are insignificant in copper, natural gas and corn.

Second, instead of the commodity futures data, we use trading volume data for exchange traded funds (ETFs) for gold (ticker symbol GLD) and crude oil (ticker symbol USO). These ETFs are securities that track the commodities and trade like stocks on stock exchanges. ETFs can be used by retail investors to gain exposure to commodities with less capital and lower risk than in the futures markets. Our results indicate that Google search activity is even more strongly correlated with the ETFs trading volume than with the commodity futures trading volume, suggesting that Google search activity may be measuring attention of retail investors.

[14] We merge our data with the CFTC COT data for the same week. The COT report is issued as of Tuesday.

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Table 1
Summary Information for Futures Markets

	Contract Symbol	Exchange[a]	Trading Hours (Eastern Time)
Gold	GC	COMEX	Su 18:00 – Fr 17:15 with 45-minute breaks starting at 17:15
Silver	SI	COMEX	Su 18:00 – Fr 17:15 with 45-minute breaks starting at 17:15
Copper	HG	COMEX	Su 18:00 – Fr 17:15 with 45-minute breaks starting at 17:15
Crude oil	CL	NYMEX	Su 18:00 – Fr 17:15 with 45-minute breaks starting at 17:15
Natural gas	NG	NYMEX	Su 18:00 – Fr 17:15 with 45-minute breaks starting at 17:15
Corn	ZC	CBOT	Mo–Fr 9:30–14:15 & Su–Fr 20:00–8:45

[a] COMEX, NYMEX and CBOT stand for Commodity Exchange, New York Mercantile Exchange and Chicago Board of Trade, respectively. All commodities are traded on the Chicago Mercantile Exchange Globex electronic trading platform.

Table 2
Correlations of Google Search Activity with Volatility, Trading Volume and Returns in Futures Markets

	Gold	Silver	Copper	Crude Oil	Natural Gas	Corn
Correlation with:						
Volatility	**0.45 (0.00)**	**0.37 (0.00)**	**0.27 (0.00)**	**0.49 (0.00)**	**0.14 (0.00)**	**0.27 (0.00)**
Trading volume	**0.37 (0.00)**	**0.23 (0.00)**	**0.18 (0.00)**	**0.36 (0.00)**	**0.10 (0.03)**	**0.31 (0.00)**
Return	0.02 (0.57)	0.04 (0.30)	-0.02 (0.68)	-0.07 (0.08)	-0.01 (0.89)	0.07 (0.11)
N	567	567	527	567	486	514

The sample period is from January 3, 2004 to November 21, 2014. Log-differences are used for Google Trends search volume index, realized standard deviation and trading volume. *p*-values are shown in parentheses. Bold text indicates statistical significance at 5% level. N indicates the number of observations measured in weeks.

Table 3
Granger Causality Tests

	Gold	Silver	Copper	Crude Oil	Natural Gas	Corn
GT → RV	**25.4 (0.00)**	**26.7 (0.00)**	**13.8 (0.01)**	**32.2 (0.00)**	**20.7 (0.00)**	**11.4 (0.02)**
RV → GT	3.8 (0.44)	7.3 (0.12)	5.5 (0.24)	6.7 (0.16)	7.5 (0.11)	9.0 (0.06)
GT → Trading volume	**18.8 (0.00)**	**36.7 (0.00)**	**10.2 (0.04)**	**17.6 (0.00)**	2.6 (0.62)	6.0 (0.20)
Trading volume → GT	**11.2 (0.03)**	**10.2 (0.04)**	4.4 (0.36)	4.2 (0.38)	**10.9 (0.03)**	7.0 (0.13)
GT → Return	1.2 (0.87)	1.8 (0.78)	**17.2 (0.00)**	**18.8 (0.00)**	6.0 (0.20)	5.1 (0.28)
Return → GT	**24.6 (0.00)**	**21.6 (0.00)**	2.7 (0.61)	**9.8 (0.04)**	6.6 (0.16)	**9.8 (0.04)**
RV → Trading volume	**32.3 (0.00)**	**47.0 (0.00)**	**28.5 (0.00)**	**20.0 (0.00)**	**11.3 (0.02)**	**12.4 (0.01)**
Trading volume → RV	**18.0 (0.00)**	**10.2 (0.04)**	**16.7 (0.00)**	**31.6 (0.00)**	2.7 (0.60)	**16.0 (0.00)**

The sample period is from January 3, 2004 to November 21, 2014. The table shows Wald test statistics of VAR Granger causality tests. GT and RV stand for logs of the Google Trends search volume index and realized standard deviation, respectively. *p*-values are shown in parentheses. Bold text indicates statistical significance at 5% level.

Table 4
Variance Decomposition from the VAR

	Gold	Silver	Copper	Crude Oil	Natural Gas	Corn
Cholesky ordering: RV, Trading Volume, Return, GT						
GT	7.4	6.3	8.0	16.8	12.2	2.1
RV	80.4	87.9	89.4	81.2	78.0	95.7
Trading Volume	1.9	0.6	1.5	1.1	3.1	1.3
Return	10.3	5.3	1.1	0.9	6.7	0.9
Cholesky ordering: GT, RV, Trading Volume, Return						
GT	44.5	33.7	29.3	55.5	23.8	17.2
RV	47.0	62.4	67.8	42.4	67.5	80.1
Trading Volume	0.9	0.5	1.7	1.0	3.2	1.6
Return	7.5	3.4	1.2	1.1	5.5	1.1

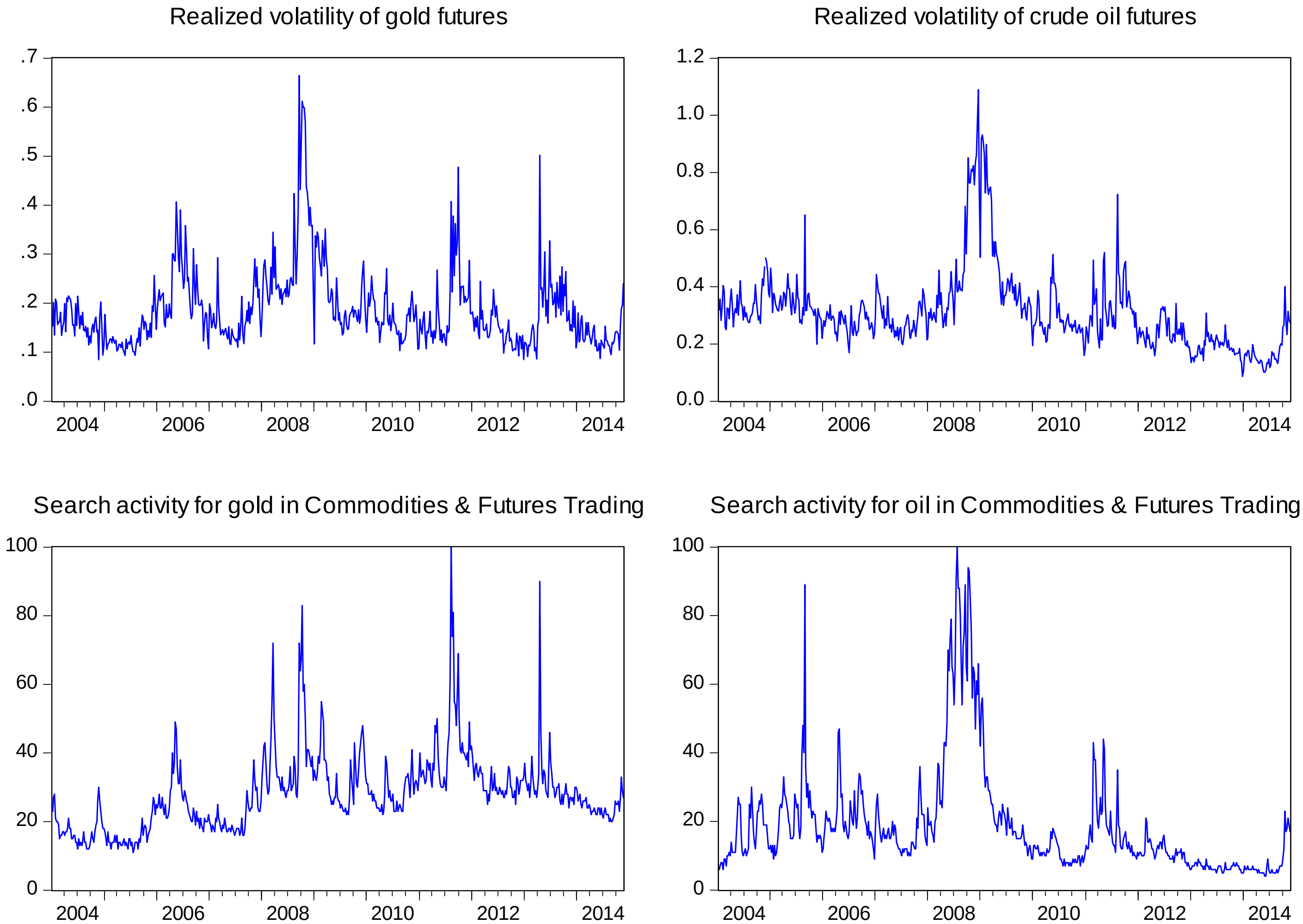
The sample period is from January 3, 2004 to November 21, 2014. The table shows the percentage of forecast error variance of the log of the realized volatility for a forecast horizon of 12 weeks explained by the variables in the relevant rows. RV and GT stand for logs of the realized standard deviation and Google Trends search volume index, respectively.

Table 5
Out-of-Sample R^2 and Encompassing Tests

	Gold	Silver	Copper	Crude Oil	Natural Gas	Corn
Sup-ENC	**21.44**	**20.42**	**18.90**	**24.53**	**13.35**	**6.59**
Ave-ENC	**9.77**	**10.46**	**5.12**	**12.47**	**8.58**	**3.16**
Max out-of-sample R^2	4.80	5.00	5.64	6.19	7.50	2.14
Mean out-of-sample R^2	1.83	2.54	-0.05	4.13	4.33	0.77

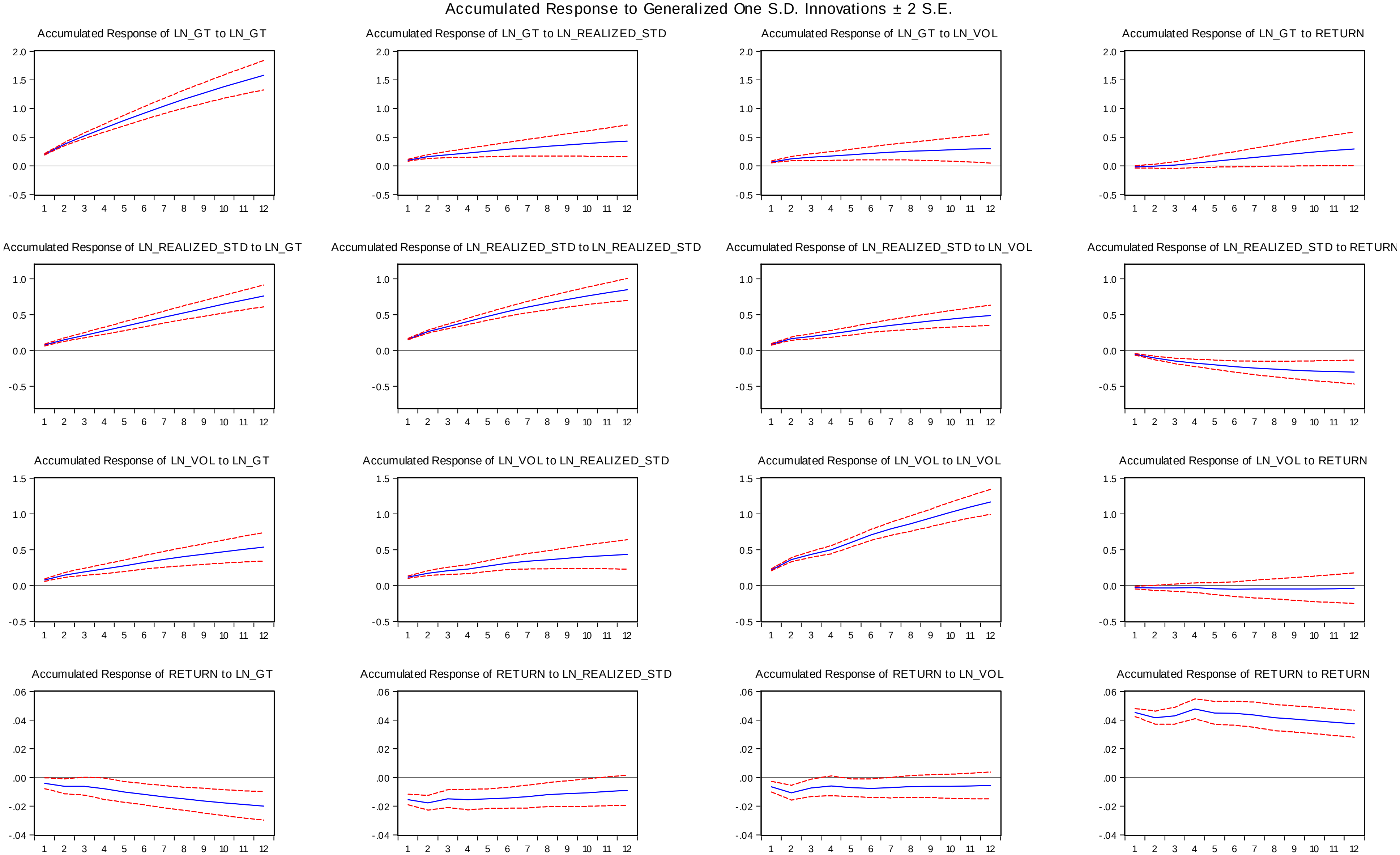
The table shows supremum and average of recursive encompassing tests on logs of the realized standard deviations of the commodities. The restricted model includes four lags of realized volatility, returns and log of volume. The unrestricted model adds four lags of Google Trends search volume index to the restricted model. 15% trimming is used on both sides of the sample. Bold text indicates statistical significance at 5% level. (Per Table 2b of Rossi and Inoue (2012), the 10%, 5% and 1% critical values for the Sup-ENC tests with four additional variables are 4.508, 5.975 and 9.501, respectively, and the 10%, 5% and 1% critical values for the Ave-ENC tests with four additional variables are 1.916, 2.790 and 4.701, respectively.)

Figure 1
Realized Volatility and Google Search Activity



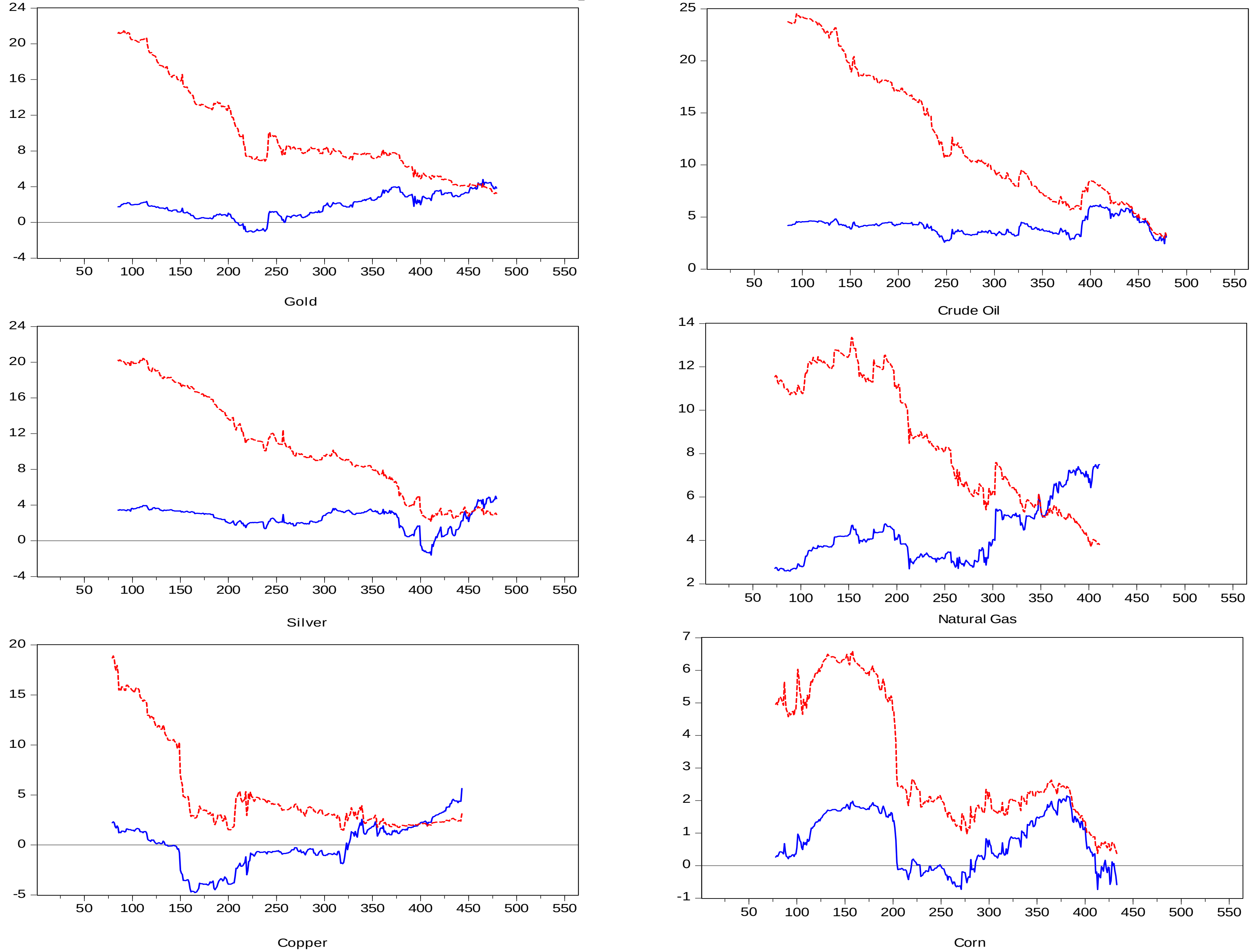
The sample period is from January 3, 2004 to November 21, 2014. The upper panels show realized volatility of gold and oil nearby futures. The bottom panels show the search volume indices for ‘gold’ and ‘oil’ in the Commodities & Futures Trading subcategory under the Finance/Investment category of Google Trends within the U.S.

Figure 2
Impulse Responses for Crude Oil



The solid (blue) lines show the accumulated responses to generalized one-standard deviation innovations. LN_GT, LN_REALIZED_STD, LN_VOL and RETURN stand for log of Google Trends search volume index, log of realized standard deviation, log of trading volume and returns, respectively. The dashed (red) lines are two-standard-error bands. The values on the horizontal axis correspond to weeks.

Figure 3
Out-of-Sample R^2 and ENC Tests



The dotted (red) lines show the recursively estimated ENC statistics. The solid (blue) lines show the recursively estimated out-of-sample R^2s.