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Commodity Price Uncertainty as a Leading Indicator of Economic Activity

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Abstract

In this paper we examine the impact of commodity price uncertainty on US economic activity. Our empirical analysis indicates that uncertainty in agricultural, energy and metals markets depresses US economic activity and acts as an early warning signal for US recessions. Our VAR analysis shows that uncertainty shocks in agricultural and metals markets have a more long-lasting dampening effect on US economic activity and its components, when compared to the effect of oil price uncertainty shocks. Finally, we show that when accounting for the effects of macroeconomic and monetary factors, the negative dynamic response of economic activity to agricultural and metals price uncertainty shocks remains unaltered, while the respective macroeconomic response to energy uncertainty shocks is significantly reduced due to either systematic policy reactions or random shocks in monetary policy.

Keywords: *Volatility, Commodity Markets, Economic Recession, Economic Activity*

JEL Classification: *C32, E27, F37, G17, Q02, Q43*

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1. Introduction

The real options approach to the theory of investment under uncertainty indicates that firms postpone their investment decisions, or they exercise their real option to wait to invest in highly uncertain times, due to the irreversible nature of investment decisions. This 'irreversibility' property of investment raises firms' 'option value' to delay or postpone their investment decisions for less uncertain times (Aguerrevere, 2009; Bernanke, 1983; Brennan and Schwartz, 1985; Henry, 1974; Pindyck, 1991; 1993; Triantis and Hodder, 1990; among others). In a similar way, uncertainty may lead to a reduction in employment and consumption due to a precautionary savings effect by economic agents (Caggiano *et al*., 2014; Edelstein and Killian, 2009; Schaal, 2017; Skinner, 1988). Hence, the overall consensus in the literature is that rising economic uncertainty results to a drop in aggregate investment, consumption and employment, which, in turn, leads to economic recessions.[1]

A large and growing body in the literature shows the negative impact of rising uncertainty on the macroeconomy (Bachman *et al*., 2013; Baker *et al*., 2016; Basu and Bundick, 2017; Bloom, 2009; Bonciani and Van Roye, 2016; Caggiano *et al*., 2014; Caldara *et al*., 2016; Carriere-Swallow and Cespedes, 2013; Drechsel and Tenreyro, 2018; Ferrara and Guérin, 2018; Ilut and Schneider, 2014; Popp and Zhang, 2016; Saijo, 2017; among others).[2] For example, Bloom (2009) shows that when uncertainty shock is defined as an increase in stock-market volatility, then this type of shock has a persistently negative impact on US economic activity, while Popp and Zhang (2016) show that economic uncertainty shocks, proxied by shocks in the VXO index, have negative effects on the US macroeconomy and the financial markets, with the impact of the uncertainty shock being higher in magnitude during recessionary periods. All these empirical studies show the negative macroeconomic effect of uncertainty shocks

[1] While the general consensus in the literature on investment under uncertainty is that rising uncertainty results to a drop in firm-level and aggregate investment, and therefore in economic activity, there are some studies which identify a positive effect of uncertainty shocks on investment and real output under specific macroeconomic conditions (Lence and Hayes, 1998; Marmer and Slade, 2018).

[2] Bloom (2009) shows that the negative impact of uncertainty shocks, which are proxied by the US stock-market volatility, occurs because higher uncertainty leads firms to 'temporarily pause their investment and hiring process'. Bachmann and Bayer (2013) find that the 'wait-and-see' factor in German firms is a key factor that affects the business cycle in the German economy. Bloom *et al*. (2007) empirically verify this evidence by showing that higher uncertainty increases firms' real option values to wait and reduces their responsiveness to aggregate demand shocks.

by proxying economic uncertainty using stock-market volatility, the VIX index, or measures of uncertainty about future economic policy.

In this paper, we move the current research a step further by modeling uncertainty as the volatility of primary agricultural (corn, cotton, soybeans, wheat), metals (copper, gold, platinum, silver) and energy (crude oil, heating oil, petroleum, gasoline) commodity prices. Commodities are highly homogeneous products that are used as primary inputs for the production of manufacturing products. Therefore, their price volatility is a significant source of uncertainty for economic agents, hence, according to the real options theory of investment under uncertainty, the rising commodity market volatility should be associated with a subsequent drop in investment, consumption, production and, ultimately, economic activity. Moreover, the general consensus in the literature is that commodity prices are driven by the forces of aggregate supply and demand conditions (Borensztein and Reinhart, 1994; Kilian, 2009; Roberts and Schlenker, 2013; among others). Therefore, a higher commodity price uncertainty could signal higher uncertainty about aggregate supply and demand conditions in the economy. This uncertainty, about aggregate demand and supply, is typically followed by sudden drops in economic activity (Basu and Bundick, 2017; Caggiano *et al.*, 2014; Leduc and Liu, 2016; among others). The relevant literature has identified a significant linkage between commodity price fluctuations and the macroeconomy (Alquist *et al.*, 2019; Fernández *et al.*, 2018; Fernandez-Perez *et al.*, 2017; Ferraro and Peretto, 2018; Frankel and Rose, 2010; Gilbert, 2010; Karali and Power, 2013; Nocetti and Smith, 2011; Ready, 2018; among others). For example, Ferraro and Peretto (2018) using an endogenous growth model show that commodity price changes are strongly correlated with short-run economic growth, while Fernández *et al*. (2018) show that a common factor, capturing co-movement in global commodity prices, explains more than one third of real output fluctuations of emerging market economies. Another strand of the empirical literature identifies significant linkages between monetary policy, inflation and commodity prices (Anzuini *et al.*, 2013; Frankel, 1984; Frankel and Rose, 2010; Frankel and Hardouvelis, 1985; Gilbert, 2010; Gospodinov and Ng, 2013; Han *et al.*, 1990; Orden and Fackler, 1989; Scrimgeour, 2015).

Motivated by the previous findings of the literature on the effects of uncertainty shocks and the literature which identifies the significant linkages between commodity prices and the macroeconomy, we empirically examine the impact of commodity price uncertainty on US economic activity. To the best of our knowledge, the empirical literature showing the effect of commodity price uncertainty on macroeconomic fluctuations is limited. Previous empirical studies identify the well-known oil-macroeconomy relationship according to which rising prices and volatility in the crude oil market result in depressing investment, a fall in GDP growth and economic recession (Elder, 2018; Elder and Serletis, 2010; Ferderer, 1996; Hamilton, 1983; 1996; 2003; Jo, 2014; Kilian, 2009; Kilian and Vigfusson, 2011; 2013; 2017; Lee *at al*., 1995; Rahman and Serletis, 2011; Ravazzolo and Rothman, 2013; Ready, 2018). For example, Hamilton (1983, 1996, 2003) finds an asymmetric relationship between oil price changes and economic activity by showing that oil price increases have a more negative impact on US GDP growth when compared to the positive impact of oil price decreases. Lee *et al*. (1995) and Ferderer (1996) were among the first to identify the role of the conditional second moment of oil price (i.e., variability) on forecasting macroeconomic activity. More specifically, they find that the conditional volatility of crude oil prices explains significantly better GNP growth variability when compared to the forecasting ability of crude oil prices. The recent empirical findings of Elder (2018), Elder and Serletis (2010) and Jo (2014) provide further insights into the significant forecasting power of oil price uncertainty on economic activity.

Although the studies mentioned above identify the negative macroeconomic impact of oil price uncertainty, there is no empirical work showing what is the macroeconomic impact of uncertainty in agricultural and metals commodity markets. In this paper, therefore, we attempt to fill this gap in the literature by examining and comparing the macroeconomic impact of agricultural, metals and energy commodity price uncertainty shocks. Our results show that uncertainty shocks in agricultural, metals and energy commodity markets have a significant negative impact on US economic activity and its components. More specifically, by examining the forecasting power of commodity price uncertainty using the bivariate regressions on real GDP and industrial production growth, we report negative and statistically significant coefficients for all commodity series and for forecasting horizons ranging from one to six quarters. Interestingly, the uncertainty series of agricultural and metals commodities, like wheat, gold and platinum, have higher predictive power on the measures of economic activity when compared to the energy markets. These findings are the first to show the significantly higher predictive information content of agricultural and metals commodities as opposed to energy commodities on US economic activity. While the previous findings in the literature identify the role of oil price uncertainty shocks (Elder and Serletis, 2010; Jo, 2014; Rahman and Serletis, 2011), we contribute to the literature by showing that non-oil commodity market uncertainty shocks have a more dampening effect on real output when compared to oil uncertainty shocks. Our evidence is in line with the previous findings of Karali and Power (2013) and Gilbert (2010) according to which agricultural prices and volatility are better explained by macroeconomic factors like the industrial production growth, inflation and short-term interest rates.

Interestingly, while we report a significant causal relationship running from agricultural and metals commodity price uncertainty to economic activity, we do not find the same evidence for oil market uncertainty. On the contrary, we provide evidence of a reverse channel of causality for energy commodity markets. While the relevant literature so far has identified the recessionary impact of oil price uncertainty shocks (Elder and Serletis, 2010; Elder, 2018; Kilian and Vigfusson, 2017), our analysis identifies the reverse channel of causality according to which changes in US real output affect oil price uncertainty. These results are in line with the recent empirical findings of Van Robays (2016) and Bakas and Triantafyllou (2018), who empirically examine the impact of macroeconomic uncertainty on agricultural, metals and energy markets and find that macro-uncertainty shocks have the highest and more long-lasting dynamic effect on the volatility of energy markets.

Furthermore, in order to examine the dynamic responses of economic activity to commodity price uncertainty shocks, we estimate a multivariate VAR model in which we control for various factors, suggested by the literature to affect economic activity, such as the slope of the US Treasury yield curve and measures of macroeconomic and financial uncertainty. Moreover, a number of empirical studies have shown that oil price shocks are inflationary and thus have attributed a large part of the recessionary impact of oil price shocks to the systematic monetary policy responses of the Fed, after the occurrence of unexpected shocks in oil prices in the fear of inflationary pressures (Beckerman and Jenkinson, 1986; Bernanke *et al.*,1997; Kara, 2017; among others).[3]

[3] There is still an ongoing lively debate in the literature about whether the recessionary impact of oil price shocks is genuine or it can be (at least partially) attributed to systematic reactions of the monetary authority in order to offset the inflationary pressures of rising oil prices. For example, while Bernanke *et al.* (1997) show that the oil shocks have been followed by contractionary monetary policy (which ultimately lowers output growth), Hamilton and Herrera (2004) and Kilian and Lewis (2011) find that the Fed does not respond (at least not so aggressively as Bernanke *et al.* (1997) imply) to rising oil price shocks, and hence the effect of rising oil prices is purely recessionary. In our multivariate VAR model,

Hence, in order to find the pure (net) recessionary impact of commodity price uncertainty shocks, we also control for endogenous interactions between commodity price fluctuations and monetary policy by including the money supply and the inflation rate as endogenous variables in our VAR model. We find that price uncertainty shocks of some agricultural and metals commodities (like corn, wheat, gold and platinum) have significantly negative effects on real GDP growth that are unrelated to inflation and monetary policy. The VAR analysis shows that the estimated macroeconomic impact of uncertainty shocks in these commodity markets remains robust to the inclusion of economic uncertainty measures and monetary policy instruments.

In addition, we show that unlike the metals and agricultural uncertainty shocks, oil price uncertainty shocks become insignificant when we control for inflation and monetary policy. Our results are also broadly in line with the findings of Bernanke *et al.* (1997), since we show that the dampening effect of oil uncertainty shocks vanishes when we control for inflation and monetary policy shocks.[4] In this way, our results provide new empirical support to the findings of Bernanke *et al*. (1997), who show that 'it is not possible to determine how much of the decline in output is the direct result of the increase in oil prices, as opposed to the ensued tightening of monetary policy'.[5] On the other hand, our VAR analysis clearly shows that this is not the case for non-oil commodities. The uncertainty shocks of non-oil commodities, like corn, wheat, gold and platinum, have a significant and long-lasting negative impact on US macroeconomic activity irrespectively of whether we control (or not) for monetary policy in the VAR system. Our multivariate VAR analysis reveals that a positive one-standard-deviation shock in wheat price volatility results in four basis points drop in GDP growth four quarters after the initial uncertainty shock, with the impact remaining negative and statistically significant from the second until the sixth quarter after the

we control for both monetary policy shocks and inflation, in order to account for possible interactions between commodity price uncertainty, inflation and monetary policy, and thus to identify the pure recessionary impact of commodity price uncertainty shocks.

[4] Bernanke *et al.* (1997) additionally find that the recessionary impact of oil shocks is also reduced even when they restrict monetary policy not to have systematic reactions to oil shocks. This means that the recessionary impact of oil price uncertainty shocks is either inflationary or can be attributed to systematic (or random) shocks-responses of the monetary authority.

[5] The relevant literature has extensively shown that on many occasions the monetary policy authority reacts (at some degree) to oil price shocks by raising the Fed fund rate in order to control the inflationary pressures of these shocks. Bernanke *et al.* (1997) are the first to show that oil shocks may not be the primary cause of US economic recessions since the monetary authority most of the time reacts to these shocks by raising short-term interest rates. Thus, it is difficult to attribute economic recessions solely to oil price shocks.

initial uncertainty shock. Our results, also, show that commodity price uncertainty shocks affect negatively several other widely accepted proxies of economic activity, like the industrial production index, investment, consumption, capacity utilization and the unemployment rate. Our results are broadly in line with the findings of Bellemare *et al*. (2013) who show that rising agricultural price volatility has a negative effect on economic welfare in developing countries. Here, we additionally show that rising agricultural price volatility (or uncertainty) has a negative effect on aggregate consumption and investment of developed economies like US.

Overall, we empirically verify the real options theory of 'investment under uncertainty' when modeling uncertainty as the realized variance of the daily returns of commodity markets. More specifically, our VAR analysis shows that aggregate investment is the component of GDP which is more heavily impacted by commodity price uncertainty shocks, hence we provide further empirical support to the real options theory of investment under uncertainty (Henry, 1974; Pindyck, 1991) by modeling uncertainty as the volatility of major agricultural, metals and energy prices. Finally, our findings showing the negative effects of volatility of storable commodities like corn and wheat, are in line with the previous empirical evidence which shows the economic significance of convenience yields and inventory levels for aggregate production and consumption (Milonas and Thomadakis, 1997; Pindyck, 2004; Williams and Wright, 1982; Wright, 2011). The policy implication behind our empirical findings is that policy-makers should turn their attention to both agricultural and metals commodity price fluctuations instead of perceiving oil market uncertainty shocks as the only commodity-related threat for the macroeconomy.[6]

The rest of the paper is organized as follows. **Section 2** outlines the empirical methodology. **Section 3** describes the data. **Section 4** presents the empirical analysis, and **Section 5** discusses our robustness checks. Finally, **Section 6** concludes.

[6] According to this strand of the literature, the rising price volatility of storable commodities coincides with higher convenience yields for holding physical inventory (Milonas and Thomadakis, 1997), and thus lowers commodity inventory levels and results to de-stabilizing production and consumption in the economy (Williams and Wright, 1982). Hence, our results showing that rising volatility of corn and wheat prices result to a drop in US industrial production and consumption expenditures, provide further insights to this literature.

2. Methodology

2.1 Uncertainty in Commodity Prices

Our uncertainty measure (*COMRV*) is the realized variance of the daily returns of commodity futures. Following Ferderer (1996), we construct both quarterly and monthly volatility series for each commodity futures contract by computing for each period (quarter/month) the standard deviation of the daily returns. We calculate the realized variance using daily closing prices of the nearby futures contract, according to **Equation (1)** below:

$$COMRV_{t,T} = \frac{252}{T}\sum_{i=1}^{T}\left(\frac{F_{t+i}-F_{t+i-1}}{F_{t+i-1}} - \overline{\frac{F_{t+i}-F_{t+i-1}}{F_{t+i-1}}}\right)^2, \quad (1)$$

Where F_t is the nearby commodity futures price on trading day t and $\overline{(F_{t+i}-F_{t+i-1})/F_{t+i-1}}$ is the average futures returns for each period *(t,T)*. $COMRV_{t,T}$ is our estimated realized variance for each period (quarter/month).[7,8] Our approach of estimating the realized variance using the standard deviation of daily returns is found to be preferable since it relies on all the information contained in the daily observations as compared to the approach of estimating unobservable GARCH measures of volatility based on quarterly or monthly commodity price series (see for example, Andersen *et al.*, 2003). In simple words, the realized volatility is the actual variation that market participants and firms observe in the market and that, based on that variation, they take investment decisions and exercise (or not) their option to wait until the price variability reduces significantly.[9]

2.2 Multivariate VAR Model

Following Bernanke *et al.* (1997), we estimate a multivariate VAR model in which we control for inflation and monetary policy as endogenous variables. In this way, we implicitly account for the inflationary impact of commodity prices and for possible

[7] The time period for the estimation of realized variance is either quarterly or monthly depending on the frequency of the time-series used in our econometric model.
[8] The realized variance is multiplied by 252 (the number of trading days for one calendar year) in order to be annualized.
[9] Our main findings remain unaltered when we use the GARCH approach of Elder and Serletis (2010) for the estimation of oil price uncertainty as the conditional standard deviation of a one-step ahead forecast error. In addition, our main findings remain unaltered when we use the GARCH (1,1) model for the measurement of commodity price uncertainty, although the predictability of the uncertainty series is slightly reduced under this methodology. These additional results can be provided upon request.

monetary policy reactions to commodity market turbulence (Beckerman and Jenkinson, 1986; Carlstrom and Fuerst, 2006; Hooker, 2002; Kara, 2017; Kilian and Lewis, 2011). In addition, we control for proxies of macroeconomic and financial market uncertainty using the economic policy uncertainty (EPU) index (Baker *et al*., 2016) and the volatility of the S&P500 stock-price index (Bloom, 2009; Caggiano *et al*., 2017; Hamilton and Lin, 1996; Schwert, 1989). Moreover, in the VAR model we control for the slope of the US Treasury yield curve which is also a significant predictor of US economic activity (Estrella, 2005; Estrella and Hardouvelis, 1991). The major advantage of our VAR identification scheme is that we control for the major determinants of economic activity in the VAR setting. Thus, our VAR estimates give a more robust estimation compared to that of Elder and Serletis (2010) and Jo (2014), since these works do not include in the VAR identification any variable that controls for monetary policy or other proxies of macroeconomic and financial uncertainty that have already been proven significant indicators of US economic recessions. Following Bekaert *et al*. (2013), we choose to place the macroeconomic variables first and the financial variables last in the VAR ordering due to the more sluggish response of the former compared to the latter, while we follow Jurado *et al.* (2015) and place the uncertainty measures last in the VAR ordering.

Our reduced form VAR model is given in **Equation (2)** below:

$$Y_t = A_0 + A_1 Y_{t-1} + ... + A_k Y_{t-k} + \varepsilon_t \tag{2}$$

Where A_0 is a vector of constants, A_1 to A_k are matrices of coefficients and ε_t is the vector of serially uncorrelated disturbances, with zero mean and variance-covariance matrix $E(\varepsilon_t, \varepsilon_t^{'}) = \sigma_{\varepsilon}^2 I$. Y_t is the vector of endogenous variables. The lag-length (*k*) in the VAR model is selected using the Schwarz (*SBIC*) optimal lag-length information criterion.[10] To recover orthogonal shocks, we use a Cholesky decomposition with the following ordering in our baseline 8-factor VAR model:

[10] Our IRFs estimates remain robust to the choice of lags that are included in the VAR. More specifically, we have estimated alternative versions of the baseline multivariate VAR model using the Akaike and the Hannan-Quinn information criteria for selecting the optimal lag-length (*k*). Moreover, following Elder and Serletis (2010) and Jo (2014), we have also estimated the VAR model using a full year of lags (i.e. *k=4*) for all variables. The evidence from all these alternative versions of the VAR model shows that our main results remain unaltered, and that our findings are stable to the choice of lags used in the VAR. These additional results can be available upon request.

$$[\Delta GDP \;\; INFL \;\; UNEMP \;\; \Delta M2 \;\; TERM \;\; EPU \;\; SP500RV \;\; COMRV] \qquad (3)$$

ΔGDP stands for the growth of real GDP (the proxy of US economic activity), *COMRV* is the realized variance of daily returns of the commodity futures prices, *SP500RV* is the realized variance of daily returns of the S&P 500 stock-market index, *EPU* is the economic policy uncertainty index, *UNEMP* is the unemployment rate, *ΔM2* is the growth of M2 money supply, *INFL* is the inflation rate (the quarterly growth of consumer price index (CPI) using a rolling fixed window of four quarters) and *TERM* is the slope of the term structure of US interest rates (namely, the difference between the 10-year US Treasury Bond yield and the 3-month US Treasury Bill rate). We additionally estimate our baseline 8-factor VAR model where, instead of *ΔGDP*, we use the growth of the investment and consumption components of GDP (*ΔINV* and *ΔCONS*), and the growth of the industrial production index (*ΔIPI*), the capacity utilization growth (*ΔCU*) and the unemployment rate (*UNEMP*) as alternative proxies of economic activity in the US.[11]

3. Data

3.1 Commodity Data

We obtain daily time-series data for the prices of the major S&P GSCI commodity futures indices from DataStream. More specifically, we obtain data for the prices of agricultural (corn, cotton, soybeans, wheat), metals (copper, gold, silver, platinum) and energy (crude oil, heating oil, gasoline, petroleum) commodity futures. Our daily commodity data covers the period from 1st January 1988 to 31st January 2017.

3.2 Macroeconomic and Financial Data

We obtain quarterly and monthly (where available) US data for real gross domestic product (*GDP*), consumer price index (*CPI*), unemployment rate (*UNEMP*), consumption expenditures (*CONS*), investment (*INV*), industrial production index

[11] The variables (in quarterly frequency) used in the VAR analysis cover the period from 1988Q1 to 2016Q4, except for the VAR model for the IPI which is employed in monthly frequency and covers the period 1988M1 to 2017M1. In the robustness section we additionally examine multivariate VAR models, in quarterly frequency, for the two main components of GDP; investment growth (*ΔINV*) and consumption expenditures growth (*ΔCONS*), and analogous multivariate VAR models, in monthly frequency, for the capacity utilization growth (*ΔCU*) and the unemployment rate (*UNEMP*), as alternative proxies of economic activity.

(*IPI*), capacity utilization (*CU*), M2 money supply (*M2*), economic policy uncertainty index (*EPU*), the 10-year US treasury bond rate and the 3-month US treasury bill rate from the Federal Reserve Bank of Saint Louis (FRED). We also obtain data for the S&P 500 stock-market index from DataStream. The slope of the yield curve (*TERM*) is estimated as the difference between the 10-year US government bond yield and the 3-month maturity US treasury bill rate. All the macroeconomic and financial data series cover the period from January 1988 to January 2017.[12]

3.3 Descriptive Statistics

Table 1 shows the descriptive statistics of the variables and the correlation matrix between commodity volatility series in the quarterly frequency.[13]

[Insert **Table 1** Here]

From **Table 1** we observe that energy commodity volatility series, such as the crude oil and petroleum, exhibit a higher mean compared to agricultural and metals commodity volatility series. In addition, the standard deviation of the realized variance series for energy commodity prices is much higher compared to the standard deviation of non-energy realized variance series. This indicates that the time variation and the sudden swings in time-varying volatility are much higher in energy commodity markets when compared to agricultural and metals commodity markets. Moreover, **Table 2** displays the correlation matrix of our commodity realized variance series.

[Insert **Table 2** Here]

Table 2 shows that the correlations between commodity volatility series are positive and, in most cases, larger than 40%. These results are a first indication of significant co-movements in the volatility of commodity prices. Furthermore, we observe that the correlations between commodity realized variance series of the same commodity class

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[12] All variables have been tested for stationarity and the null hypothesis of unit root have been rejected using both the Augmented Dickey-Fuller and the Philips-Perron unit root tests. The results of the unit root tests can be provided upon request.

[13] We use both quarterly and monthly time-series models in our empirical analysis. Our quarterly dataset consists of the period 1988Q1-2016Q4, while our monthly dataset covers the period 1988M1-2017M1. Here, we report the descriptive statistics for the quarterly dataset and the respective correlation matrix for the commodity volatility series in quarterly frequency. The descriptive statistics and correlation matrix for the monthly data exhibit a similar behavior with the quarterly sample. The tables for the monthly dataset can be provided upon request.

become even higher, which indicates that co-movement is stronger for commodity markets in the same class.

4. Empirical Analysis

4.1 OLS Predictive Regressions Results

For an initial investigation of the impact of agricultural, energy and metals commodity markets uncertainty on US economic activity we use single-equation forecasting regression models. Following the output forecasting approach of Estrella and Hardouvelis (1991), we estimate bivariate OLS forecasting regressions in which we use the realized variance of commodity prices as the only predictor of economic activity, as follows:

$$\Delta GDP_t = b_0 + b_1 COMRV_{t-k} + \varepsilon_t \ , \tag{4}$$

where ΔGDP is the growth of real GDP and $COMRV$ is the realized variance of agricultural, energy and metals commodity futures returns, respectively. The forecasting horizon ranges from 0 to 12 quarters. We additionally estimate the bivariate forecasting regressions of **Equation (4)** using the IPI growth (ΔIPI) as an alternative measure of economic activity in US.[14]

Table 3 shows the regression results of our bivariate regression on real GDP growth using commodity price uncertainty as our only predictor.

[Insert **Table 3** Here]

The results from **Table 3** indicate that rising uncertainty in agricultural, metals and energy prices is associated with a significant drop in GDP growth. The estimated coefficients of the commodity price uncertainty series remain negative and statistically significant for forecasting horizons ranging from one up to six quarters ahead. When regressing the contemporaneous time-series of commodity price volatility on GDP

[14] The variables (in quarterly frequency) used in the regression analysis cover the period from 1988Q1 to 2016Q4, except for the regressions for IPI which are employed in monthly frequency and cover the period 1988M1 to 2017M1.

growth, we find that the volatility of metals and energy commodity prices are the most significant indicators of economic activity with adjusted R^2 values reaching 29.8%, 30.0% and 28.6% for the case of crude oil, gasoline and gold, respectively.

These results, reinforce the previous evidence on the predictive ability of financial variables, and especially of the various measures of financial volatility, for economic activity (Schwert, 1989; Ferrara *et al.*, 2014; Chauvet *et al.*, 2015; among others). Furthermore, our findings are in line with Elder and Serletis (2010), Elder (2018) and Jo (2014), according to which oil uncertainty shocks are significant indicators of economic activity. On the other hand, our empirical analysis is the first to show that rising uncertainty in metals and in some agricultural markets (like wheat) are equally important indicators of falling economic activity. However, when we lengthen the forecasting horizon, we observe that the volatility of energy commodities like crude oil, petroleum and gasoline have a poorer forecasting ability when compared with the explanatory power of agricultural and metals commodities. For example, the adjusted R^2 value of the bivariate regression falls from 10.2% (one quarter forecasting horizon) to 1.3% (two quarters forecasting horizon) when forecasting GDP growth using the realized variance of crude oil futures as a predictor, while the respective adjusted R^2 falls from 18.7% to 9.8% when using the realized variance of gold futures instead. Our results on the macroeconomic information content of commodity price volatility are broadly in line with findings of Kang *et al.* (2017) and Fernández *et al.* (2018), who find that fluctuations in commodity prices are a significant driver of macroeconomic fluctuations in US output and in small emerging market economies output.

We additionally examine the effect of commodity price volatility on the industrial production index growth (ΔIPI), in monthly frequency. **Table 4** report the regression results of the bivariate OLS forecasting regression models for the monthly IPI growth.

[Insert **Table 4** Here]

The results from **Table 4** confirm the findings for GDP growth, and show that commodity uncertainty has a negative effect on industrial production growth. As expected, the price uncertainty in the metals markets has the most significant impact on IPI growth.[15]

4.2 Commodity Price Uncertainty and US Economic Recessions

In this section, we follow the econometric approach of Estrella and Mishkin (1998) on the prediction of US recessions, using our measures of commodity price uncertainty. More specifically, we present the results based on the bivariate linear probability and probit models in which we predict the probability of US economic recessions (i.e. the right-hand-side variable in **Equation (4)** for these models is a binary (0-1) variable that indicates the NBER based US economic recessions (*NBER*)). **Tables 5** and **6** show the results based on the bivariate linear probability and probit regression models respectively.

[**Tables 5** and **6** Here]

The results, presented in **Tables 5-6**, clearly show the strong and significant predictive power of commodity price uncertainty for US economic recessions in both short- and long-term forecasting horizons. More specifically, our bivariate linear probability and probit regressions report positive and statistically significant coefficients for all commodity realized variance series in the short-term (for one- and two-month forecasting horizons). We additionally observe that the short-term predictive power of crude oil and petroleum price uncertainty is significantly higher compared to other non-oil commodity volatility series. Our regression analysis clearly shows that oil price uncertainty is more closely associated with subsequent US economic recessions when compared to non-oil price uncertainty. Our results on the significant predictive power of oil price uncertainty (for short-term forecasting horizons) are broadly in line with the evidence in Hamilton (1983, 2003) and the recent empirical findings of Killian and Vigfusson (2017), who show that oil price shocks can act as leading indicators for US economic recessions. On the other hand, we observe that the predictive power of oil price uncertainty is significantly deteriorated for medium-term (three-month and six-month) forecasting horizons, while the respective predictive power of some agricultural

[15] Following our baseline 8-factor model, used in the VAR analysis, we have estimated multivariate OLS predictive regressions in which we include these key macroeconomic and financial determinants of economic activity on the left-hand side of the predictive regression equation. The main findings, using this multivariate regression model, remain unaltered. These results are available upon request.

and metals commodities such as wheat, gold and platinum is significantly increased and thus these series can act as better indicators of US economic recessions for medium-term forecasting horizons.[16] In addition, **Figure 1** shows the estimated recession probability based on the bivariate probit models when using agricultural, energy and metals price uncertainty as predictors of NBER recessions respectively.

[**Figure 1** Here]

From **Figure 1** we can easily observe that the rising probabilities of our probit models are associated with economic recessions in the US. More specifically, the estimated probabilities from the bivariate probit models corresponds to the observed episodes of US economic recessions. **Figure 1** shows the high predictive power of crude oil and petroleum price uncertainty on US economic recessions when compared to the non-oil price uncertainty. The increased predictive power of oil price uncertainty on economic activity does not contrast our findings and the previous evidence by Bernanke et al. (1997, 2004), since this increased predictive power of oil price uncertainty on economic recessions may partially be due to increased monetary policy interventions.

4.3 Multivariate VAR Results

In this section we present the results of the baseline multivariate VAR model (as described in **Equations (2)** and **(3)**). We begin our analysis with the results from the Granger causality tests between commodity price uncertainty and economic activity derived from our baseline multivariate VAR model. The results of the Granger causality tests for the commodity uncertainty-GDP growth pair is shown in **Table 7**.[17]

[Insert **Table 7** Here]

[16] This outcome is a first indication of our basic conclusions from our VAR analysis, according to which the recessionary impact of non-oil commodity markets uncertainty is found to be more long-lasting compared to the impact of uncertainty in oil commodity markets.

[17] Here we provide the results of the Granger causality tests for the main variables of interest (i.e. the commodity uncertainty-GDP growth pair). The full set of results for the Granger causality tests for all remaining variables in our VAR model can be provided upon request. In addition, we have also estimated the Granger causality tests for the commodity uncertainty-IPI growth pair as well as for the two components of GDP (ΔINV and $\Delta CONS$). Our main findings are qualitatively similar. These additional results are provided upon request.

The results of Granger causality tests presented in **Table 7** show that price uncertainty in the agricultural and metals markets like corn, wheat, silver and gold Granger cause GDP growth. So, these tests identify a unidirectional causality from the majority of agricultural and metals markets to US economic activity. On the other hand, we do not find any significant causality running from energy commodity markets to US economic activity (i.e., we fail to reject the hypothesis of no causality from energy markets to GDP growth). In addition, when examining the reverse channel of causality, our tests show that the only significant causal relationship is from US economic activity to energy price uncertainty. Hence, according to these tests, the changes in US economic activity, do Granger cause oil price uncertainty, while they do not (Granger) cause uncertainty in agricultural and metals commodity markets. Our results are the first to identify this reverse channel of causality between oil price uncertainty and the macroeconomy. The findings of the relevant literature so far have shown that oil price uncertainty shocks have a significant negative impact on US macroeconomy (Elder and Serletis, 2010; Elder, 2018; Jo, 2014; Ferderer, 1996). Our evidence here, is that the causal relationship is not from oil uncertainty shocks to macroeconomic fluctuations, but from US economic activity to oil and, in general, energy price uncertainty. Our results are broadly in line with the more recent empirical findings which show that macro-uncertainty shocks have a significant effect in uncertainty in oil and energy markets (Bakas and Triantafyllou, 2018; Joets *et al.*, 2017; Van Robays, 2016).

We continue our VAR analysis by estimating the dynamic responses of unexpected commodity price uncertainty shocks on US economic activity and its components. More specifically, we present the estimated orthogonalized impulse response functions (IRFs), in which the shocks are identified using a Cholesky decomposition, for our baseline multivariate VAR model described in **Equations (2)** and **(3)**.[18,19] **Figure 2** shows the estimated IRFs for the VAR models of GDP growth in which we use the agricultural (corn, cotton, soybeans, wheat), energy (crude oil, heating oil, gasoline,

[18] Here we provide the estimated IRFs of commodity uncertainty shocks on the measure of economic activity in the VAR model (GDP growth). The full set of the estimated IRFs for all the variables included in our VAR model can be provided upon request.

[19] For robustness purposes, we have also estimated orthogonalized IRFs, using a Cholesky decomposition with alternative orderings for the variables in our VAR model. Furthermore, for additional robustness, we have estimated the generalized IRFs which do not require orthogonalization of shocks and, unlike the impulse responses on orthogonalized shocks, are insensitive to the choice of the ordering of variables in the VAR model (see Pesaran and Shin, 1998). Our main findings remain unaltered when we estimate either the generalized IRFs, or the orthogonalized IRFs with alternative VAR orderings. The set of these additional results can be provided upon request.

petroleum) and metals (copper, gold, silver, platinum) price volatility series as proxies for commodity price uncertainty.

[Insert **Figure 2** Here]

The IRFs, from **Figure 2**, show that agricultural and metals commodity price uncertainty shocks have a negative and long-lasting impact on US GDP growth. Specifically, our VAR analysis shows that rising volatility in some precious metals and agricultural prices, like platinum, gold and wheat, has a more negative and long-lasting impact on US GDP growth when compared with the respective macroeconomic effects of energy price uncertainty shocks. The results of our VAR model show that a positive one-standard-deviation shock in the volatility of wheat prices reduces GDP growth by almost 10 basis points one quarter after the initial volatility shock, with the effect remaining negative and statistically significant for five quarters after the initial shock. In addition, our VAR analysis shows that a positive one-standard-deviation shock in the realized variance of platinum futures prices reduces GDP growth almost 12 basis points two quarters after the initial uncertainty shock, with the effect remaining significant for four quarters after the initial platinum uncertainty shock. On the other hand, the estimated response of US GDP growth to energy price uncertainty shock is statistically insignificant (statistically indistinguishable from zero) for all energy commodity markets considered. In our multivariate VAR model, we control for monetary policy (money supply - *M2*) and inflation, so we are able to control for any possible interactions between monetary policy, inflation and commodity price volatility. In addition, we control for both macroeconomic and financial uncertainty (*EPU* and *SP500RV*) and thus we are able to account for possible interactions between commodity price volatility and uncertainty that stems from the broader macroeconomic and financial environment.[20]

Our findings are line with those of Bernanke *et al*. (2004), Carlstrom and Fuerst (2006) and Cologni and Manera (2008) who show that it is difficult to infer whether US

[20] Following the work of Bakas and Triantafyllou (2018), which shows that unobserved macroeconomic uncertainty have a stronger effect on the volatility of commodity prices compared to observable measures of economic uncertainty, we additionally estimate the baseline multivariate VAR model where we replace *EPU* with the unobservable macroeconomic uncertainty measure (*MU*) of Jurado *et al.* (2015). Our main findings do not change when we control for the unobserved macroeconomic uncertainty in the VAR model. These results can be provided upon request.

economic recessions have occurred because of oil prices or subsequent monetary policy reactions and that a significant part of the recessionary effects of oil price shocks is due to the systematic monetary policy reaction function. Oil shocks are frequently being followed by reactions of monetary policy and that overall, it is difficult to disentangle the recessionary impact of oil price shocks and monetary policy changes, which many times occur simultaneously (Bernanke *et al.*, 1997; 2004; Carstrom and Fuerst, 2006; Kara, 2017). Our results are also in line and provide further insights to the findings of Ferraro and Peretto (2018) who show that commodity prices are associated with short-run growth of commodity-rich economies. Here, we additionally show that commodity price volatility shocks are significantly (negatively) associated and also have a negative dynamic effect on US real GDP growth. Assuming the same type of endogeneity between commodity price uncertainty and monetary policy, we control for possible interactions between monetary policy and commodity price uncertainty by including as endogenous variables the money supply growth ($\Delta M2$) and inflation (*INFL*) in our VAR model. Thus, the estimated IRFs show the net impact of commodity price uncertainty shocks on US economic activity.[21]

Unlike the empirical analysis of Elder and Serletis (2010) and Jo (2014), who do not control for inflation and systematic monetary policy shocks, in our VAR model we control for the possible interactions between monetary policy, inflation and commodity price uncertainty in order to measure the net real macroeconomic impact of unexpected random shocks in commodity price uncertainty. Our VAR estimates are broadly in line with the findings of Bernanke *et al.* (1997; 2004) and Kara (2017) since we find that the impact of oil price uncertainty shocks on US economic growth is significantly deteriorated when we control for monetary policy and inflation in our VAR model; thus, we implicitly allow for possible interactions between commodity price uncertainty shocks and monetary policy changes.[22] Our analysis implicitly reveals that the reduced impact of oil price uncertainty shocks on US GDP growth may be attributed to the fact

[21] We additionally estimate a structural VAR (SVAR) model in which we restrict monetary policy to have no systematic reaction to commodity price uncertainty shocks. Even under this VAR identification scheme, our basic findings remain unaltered. The impact of agricultural and metals commodity price uncertainty shocks remains negative and statistically significant irrespective of the systematic (or random) interactions of monetary policy with commodity price fluctuations. These additional results based on the SVAR model can be provided upon request.

[22] Our results remain robust to the inclusion of alternative monetary policy instruments like the Federal funds rate and the 3-month US Treasury Bill rate. These additional results can be provided upon request.

that these shocks are either inflationary and, as a consequence, do not pass to the real economy, or they result in a systematic reaction of the monetary authority (through contractionary monetary policy), which in turn reduces output. Thus, our analysis implicitly shows that oil shocks primarily affect the monetary (nominal) and not the real part of the macroeconomy. On the other hand, the impact of non-oil price uncertainty shocks, such as shocks in wheat, gold and platinum price variability, remains robust to the inclusion of inflation, monetary policy and other macroeconomic factors directly related to economic activity. These results clearly show that, in sharp contrast to oil shocks, the agricultural and metals commodity price uncertainty shocks have a purely macroeconomic (recessionary) impact and, thus, they can act as leading indicators of economic activity. The policy implication of our empirical findings is that monetary authorities should consider to target also the commodity price uncertainty of non-oil commodity market uncertainty. This policy may be feasible since commodity prices are significantly affected by changes in interest rates and monetary policy (Anzuini *et al*., 2013; Frankel and Hardouvelis, 1985; Gubler and Hertweck, 2013; Hammoudeh *et al.*, 2015). Moreover, according to the empirical findings of Triantafyllou and Dotsis (2017), US monetary policy is capable of affecting the option-implied uncertainty on agricultural commodity markets.

We also estimate a similar VAR model (as given in **Equations (2)** and **(3)**) in which we use the industrial production growth as our proxy for economic activity (ΔIPI is now the first variable in the VAR ordering) – this VAR model is estimated in monthly frequency. **Figure 3** shows the estimated orthogonalized IRFs of our VAR model when using agricultural, energy and metals price volatility series as the commodity uncertainty measure.

[Insert **Figure 3** Here]

Figure 3 shows that an unexpected positive uncertainty shock in agricultural markets like corn and wheat has a long-lasting impact on the IPI growth in the US when compared to the respective effect of energy and metals price volatility. For example, a one-standard-deviation shock in wheat price uncertainty reduces IPI growth by almost 8 basis points one month after the initial shock with the effect remaining negative and statistically significant for ten months after the initial shock. On the other hand, the response of industrial production growth to energy price uncertainty shocks is more transitory since the negative effect disappears 2-3 months after the initial energy uncertainty shock.[23] Overall, the results based on the monthly frequency VAR model are in line with our quarterly VAR. Our findings show that, albeit in line with the oil-macroeconomy literature, according to which energy price shocks have a negative impact on economic activity in US (Elder and Serletis, 2010; Elder, 2018; Jo, 2014), the effect of energy markets is transitory and vanishes after a 3-months period, that is one quarter after the initial shock. These results are also in line with the findings of our forecasting regression models, according to which, the predictive power of oil price uncertainty is significant and relatively higher for short-term forecasting horizon, while it vanishes for medium and long-term forecasting horizon. On the other hand, the negative impact of agricultural and metals price uncertainty shocks remains significant for about one year after the initial shock.

5. Robustness Checks

In this section we provide the results of our robustness checks. In specific, we estimate the same multivariate VAR models for the two main components of GDP; that is investment growth (*ΔINV*) and consumption expenditures growth (*ΔCONS*), and for the growth of capacity utilization (*ΔCU*) and the unemployment rate (*UNEMP*) as alternative proxies of economic activity. We start by estimating an identical VAR model, given in **Equations (2)** and **(3)**, in which we use investment growth (*ΔINV*) instead of GDP growth as the first variable in the VAR ordering. Using this VAR model, we measure the impact of random shocks in the time-varying uncertainty of commodity markets on the investment component of the US output. **Figure 4** shows the respective orthogonalized IRFs of investment growth based on the multivariate VAR models.

[Insert **Figure 4** Here]

From **Figure 4**, we observe that a positive shock in the realized variance of corn, wheat, gold and platinum results to significant drops in US investment growth. More specifically, an unexpected positive one-standard-deviation shock in the realized

[23] The results based on the VAR model in monthly frequency, where we use IPI growth as proxy of economic activity, reaffirm our previous evidence, which are based on the VAR model in quarterly frequency using the measure of real GDP growth as proxy, and furthermore shows that our findings are robust to the estimation of the VAR model in different frequencies (quarterly/monthly).

variance of corn and wheat futures leads to a drop of approximately 40 basis points in US investment growth in one quarter after the initial uncertainty shock, with the effect remaining negative and statistically significant for six quarters after the initial shock. In addition, a positive price uncertainty shock in the gold futures market reduces US investment growth by nearly 40 basis points two quarters after the initial shock, while a platinum uncertainty shock results to a reduction of investment of about 50 basis points two quarters after the platinum shock, with both effects remaining significantly negative for five quarters after the initial metals uncertainty shocks. On the other hand, energy price uncertainty shocks have a rather small and transitory negative impact on US investment growth.

We also estimate the baseline VAR model in which we use consumption expenditures growth (*ΔCONS*) as the first variable in the VAR ordering (**Equation (3)**). **Figure 5** shows the estimated orthogonalized IRFs for agricultural, energy and metals uncertainty shocks respectively.

[**Figure 5** Here]

The estimated IRFs (**Figure 5**) clearly show that the impact of agricultural volatility shocks in US consumption growth is larger in magnitude and more persistent as opposed the impact of energy volatility shocks. We observe that a positive shock in the realized variance of corn, cotton and wheat results to significant drops in consumption growth. For example, a one-standard-deviation shock in corn price uncertainty leads to a drop of 10 basis points in consumption growth in about three quarters after the initial shock. These results reinforce the evidence that agricultural commodities are largely related with consumption. However, we also find that metals commodity markets, like gold and platinum, have also a negative dynamic effect on US consumption growth. These findings are in line with Edelstein and Killian (2009), who show that energy price shocks result in a reduction in consumer spending, since they can create sudden shifts in precautionary savings and changes in the cost of energy-usage durables. We extend here this empirical finding by showing that, apart from energy price spikes, price uncertainty in both energy and non-energy commodity markets has persistently negative impact on aggregate consumption expenditures.

In addition, we estimate the baseline VAR model with capacity utilization growth (*ΔCU*) as the first variable in the VAR ordering (**Equation (3)**) – this VAR model is also estimated in monthly frequency. **Figure 6** shows the estimated orthogonalized IRFs for agricultural, energy and metals uncertainty shocks respectively.

[**Figure 6** Here]

The estimated IRFs (**Figure 6**) provide a similar evidence with that from the other measures of economic activity; that the impact of agricultural volatility shocks in US capacity utilization growth are larger in magnitude and more persistent as opposed to the impact of energy volatility shocks.

Finally, we estimate the baseline VAR model, in monthly frequency, where we explore the dynamic responses of commodity price uncertainty shocks on the unemployment rate (*UNEMP*) - as another proxy for the US economic activity.[24] **Figure 7** shows the estimated orthogonalized IRFs for agricultural, energy and metals uncertainty shocks respectively.

[**Figure 7** Here]

The estimated IRFs (**Figure 7**) clearly show that the impact of agricultural volatility shocks is larger in magnitude and more persistent as opposed the impact of energy volatility shocks. For example, a shock in corn price uncertainty increases US unemployment rate by approximately 8 basis points with the effect remaining positive and statistically significant for almost 35 months after the initial shock. On the other hand, except from platinum, the energy and metals commodity price uncertainty has a lower effect (in magnitude and persistence) on US unemployment rate.

These additional results provide further robustness to our main findings and conclusions from the main VAR analysis since all alternative proxies of economic activity are found to be negatively affected by agricultural and metals markets

[24] The VAR model used here is the baseline 8-factor VAR (described in Equation (3)) in monthly frequency in which the industrial production growth (*ΔIPI*) is placed first and the unemployment rate (*UNEMP*) is placed third in the VAR ordering. For robustness purposes, we have also estimated a VAR model where we reverse the ordering of these two variables, and our findings remain qualitatively the same. These additional results can be provided upon request.

uncertainty shocks, while the respective impact from the energy uncertainty shocks is found to be much smaller.

6. Conclusions

Motivated by the real options approach of the theory of investment under uncertainty, we empirically examine the impact of commodity price uncertainty on US economic activity. Our paper differentiates from the previous literature since we empirically examine the impact of both oil and non-oil commodity price uncertainty shocks on US macroeconomy using a class of agricultural, metals and energy commodities. Our empirical analysis reveals that uncertainty in agricultural, energy and metals markets has significant predictive information content on economic activity. Rising uncertainty in all commodity markets is associated with slumps in US GDP and its components and with economic recessions. However, our VAR analysis for the first time shows that the causality between oil price uncertainty and US macroeconomy is unidirectional and runs from output fluctuations to oil price uncertainty and not the opposite. On the other hand, the dynamic effects of uncertainty in many agricultural and metals commodities have a long-lasting negative impact on US economic activity and its components, such as investment and consumption expenditures. Our VAR analysis shows that aggregate investment is the component of GDP which is more sensitive to agricultural and metals commodity price uncertainty shocks, hence, we implicitly verify the real options model of investment under uncertainty when the uncertainty shock is modeled as the rising volatility in commodity markets. Furthermore, when controlling for the monetary policy stance, we find that the recessionary impact of energy shocks is significantly reduced. Our results are in line with the findings of Bernanke *et al*. (1997; 2004) who show that the predictive power of oil shocks is significantly reduced when controlling for monetary policy in the VAR model. Although the non-oil price uncertainty shocks have a larger and more persistent negative impact on economic activity, our findings implicitly reveal that these types of uncertainty shocks have not been taken into consideration by policy-makers. Hence, our findings implicitly reveal as policy implications the need of the inclusion of agricultural and metals markets uncertainty into the central bank information variable set when making predictions on future economic activity, and thus adopting proactive monetary policies by monitoring variables which could act as non-standard indicators of future macroeconomic downturns (Woodford, 1994). The more careful consideration of non-oil commodity fluctuations and rising uncertainty in agricultural and metals futures markets might be another non-conventional monetary policy in order to ameliorate the recessionary impact of commodity market turbulence.

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Tables and Figures

Table 1. Descriptive Statistics

	Mean	*Std. Dev.*	*Minimum*	*Maximum*	*Skewness*	*Kurtosis*
ΔGDP	0.006	0.006	-0.021	0.019	-1.169	6.555
ΔIPI	0.004	0.012	-0.056	0.025	-2.017	9.306
ΔINV	0.010	0.024	-0.096	0.058	-1.014	5.610
ΔCONS	0.012	0.006	-0.026	0.026	-2.040	13.438
ΔCU	-0.001	0.012	-0.059	0.026	-1.629	8.446
SP500RV	0.030	0.047	0.004	0.441	6.386	54.028
EPU	4.627	0.287	4.083	5.288	0.403	2.422
TERM	0.018	0.011	-0.006	0.036	-0.223	1.952
INFL	0.006	0.005	-0.023	0.017	-1.763	11.941
ΔM2	0.013	0.007	-0.003	0.046	0.652	5.638
UNEMP	0.061	0.015	0.039	0.101	0.999	3.207
COMRV						
Corn	0.059	0.046	0.006	0.311	2.039	10.011
Cotton	0.057	0.040	0.012	0.271	2.439	10.920
Soybeans	0.050	0.036	0.006	0.212	1.925	7.251
Wheat	0.071	0.052	0.009	0.305	1.827	7.005
Crude oil	0.119	0.119	0.016	0.769	3.383	16.460
Heating oil	0.104	0.086	0.015	0.652	3.174	17.686
Petroleum	0.099	0.095	0.012	0.633	3.499	18.099
Gasoline	0.112	0.096	0.014	0.742	3.584	20.829
Copper	0.065	0.069	0.012	0.522	3.745	21.350
Gold	0.025	0.023	0.002	0.143	2.552	10.923
Platinum	0.044	0.036	0.006	0.249	3.257	17.331
Silver	0.078	0.075	0.009	0.479	2.924	13.419
T = 116 *Quarters*						

Notes: The descriptive statistics are based on the balanced dataset of the 12 agricultural, energy and metals commodities and the macroeconomic and financial time-series for the quarterly dataset over the period 1988Q1 to 2016Q4.

Table 2. Correlation Matrix for the Agricultural, Energy and Metals Commodity Markets

	Corn	*Cotton*	*Soybeans*	*Wheat*	*Crude oil*	*Heating oil*	*Petroleum*	*Gasoline*	*Copper*	*Gold*	*Platinum*	*Silver*
Corn	1.000											
Cotton	0.619	1.000										
Soybeans	0.763	0.548	1.000									
Wheat	0.751	0.623	0.591	1.000								
Crude oil	0.260	0.268	0.241	0.219	1.000							
Heating oil	0.140	0.220	0.193	0.126	0.928	1.000						
Petroleum	0.269	0.292	0.265	0.227	0.991	0.956	1.000					
Gasoline	0.364	0.396	0.361	0.284	0.912	0.906	0.942	1.000				
Copper	0.555	0.387	0.422	0.428	0.413	0.300	0.421	0.502	1.000			
Gold	0.584	0.404	0.452	0.499	0.463	0.366	0.468	0.538	0.628	1.000		
Platinum	0.568	0.412	0.560	0.466	0.484	0.387	0.498	0.532	0.530	0.719	1.000	
Silver	0.619	0.510	0.436	0.539	0.346	0.218	0.351	0.423	0.672	0.806	0.587	1.000

Notes: The agricultural commodities consist of corn, cotton, soybeans and wheat, while the energy commodities consist of crude oil, heating oil, petroleum and gasoline, and finally, the metals commodities consist of copper, gold, platinum and silver.

Table 3. Forecasting Gross Domestic Product Growth with Commodity Price Uncertainty

Panel A: Estimated b_1 coefficients

Horizon (k)	*k=0*	*k=1*	*k=2*	*k=3*	*k=6*	*k=12*
Corn	-0.049**	-0.050**	-0.034**	-0.021*	-0.038*	-0.005
Cotton	-0.063**	-0.042**	-0.026*	-0.018	-0.006	-0.001
Soybeans	-0.047	-0.047	-0.040	-0.013	-0.029*	-0.017
Wheat	-0.045**	-0.042**	-0.039**	-0.035	-0.021*	-0.008
Crude oil	-0.028***	-0.017***	-0.007**	-0.004	0.007**	0.004
Heating oil	-0.032***	-0.018*	-0.008	-0.006	0.006	0.001
Petroleum	-0.035***	-0.021**	-0.009**	-0.006*	0.008*	0.003
Gasoline	-0.035***	-0.025***	-0.011***	-0.007**	0.004	-0.003
Copper	-0.036**	-0.024**	-0.012**	-0.011	-0.014	-0.006
Gold	-0.139***	-0.109**	-0.085***	-0.062***	-0.030	-0.034
Platinum	-0.077***	-0.073***	-0.053***	-0.041***	-0.002	-0.005
Silver	-0.035**	-0.027*	-0.013	-0.009	-0.004	-0.005

Panel B: *Adjusted R^2* values

Horizon (k)	*k=0*	*k=1*	*k=2*	*k=3*	*k=6*	*k=12*
Corn	13.0	13.6	5.9	1.7	7.6	-0.8
Cotton	17.3	7.3	2.2	0.6	-0.8	-1.0
Soybeans	7.5	7.2	5.1	-0.3	2.1	0.1
Wheat	14.3	12.6	10.7	8.4	2.4	-0.5
Crude oil	29.8	10.2	1.3	-0.2	0.8	-0.3
Heating oil	20.6	5.6	0.4	-0.3	-0.2	-1.0
Petroleum	29.1	10.2	1.3	-0.1	0.7	-0.7
Gasoline	30.0	14.6	2.4	0.6	-0.5	-0.7
Copper	16.0	7.0	1.0	0.8	1.6	-0.4
Gold	28.6	17.2	10.2	5.1	0.5	1.0
Platinum	21.4	18.7	9.8	5.6	-0.9	-0.9
Silver	19.1	10.4	1.7	0.5	-0.7	-0.6

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table presents the results of the bivariate forecasting regression model on gross domestic product growth (*ΔGDP*) using the realized variance series of agricultural, energy and metals commodity futures returns. The forecasting horizon ranges from 0 to 12 quarters. *COMRV* is the realized variance and *ΔGDP* is the GDP growth. The standard errors are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The estimated beta coefficients are based on the following bivariate regressions: $\Delta GDP_t = b_0 + b_1 COMRV_{t-k} + \varepsilon_t$.

Table 4. Forecasting Industrial Production Growth with Commodity Price Uncertainty

Panel A: Estimated b_1 coefficients

Horizon (k)	*k=0*	*k=1*	*k=2*	*k=3*	*k=6*	*k=12*
Corn	-0.027**	-0.024	-0.025*	-0.029**	-0.013	-0.008
Cotton	-0.030**	-0.027	-0.026	-0.022	-0.019	-0.002
Soybeans	-0.027*	-0.028	-0.031*	-0.033*	-0.022	-0.008
Wheat	-0.023**	-0.025*	-0.020**	-0.026**	-0.028**	-0.012
Crude oil	-0.014**	-0.014***	-0.012***	-0.011**	-0.004	-0.001
Heating oil	-0.015**	-0.014**	-0.014**	-0.011*	-0.004	-0.003
Petroleum	-0.017**	-0.016***	-0.015**	-0.013**	-0.005	-0.002
Gasoline	-0.019***	-0.018***	-0.016***	-0.015***	-0.006*	-0.002
Copper	-0.010	-0.017**	-0.021**	-0.016*	-0.004	0.000
Gold	-0.082***	-0.054**	-0.064**	-0.074***	-0.041*	-0.010
Platinum	-0.053***	-0.040***	-0.042***	-0.048***	-0.037***	-0.004
Silver	-0.014*	-0.013*	-0.015	-0.014	-0.008	0.003

Panel B: *Adjusted R^2* values

Horizon (k)	*k=0*	*k=1*	*k=2*	*k=3*	*k=6*	*k=12*
Corn	5.1	4.3	4.7	6.3	1.1	0.2
Cotton	4.6	3.7	3.4	2.4	1.6	-0.3
Soybeans	3.5	3.9	4.7	5.4	2.2	0.0
Wheat	5.4	6.2	3.8	6.9	7.8	1.1
Crude oil	12.2	11.5	8.9	7.0	0.5	-0.2
Heating oil	7.7	6.5	6.3	4.5	0.3	0.0
Petroleum	10.9	10.5	8.5	6.6	0.6	-0.1
Gasoline	13.6	12.1	9.5	8.8	1.3	-0.1
Copper	1.4	4.5	7.1	3.9	0.0	-0.3
Gold	14.2	6.0	8.5	11.6	3.3	-0.1
Platinum	14.6	8.2	8.7	11.8	6.7	-0.2
Silver	3.8	3.4	4.6	3.9	1.0	-0.1

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table presents the results of the bivariate forecasting regression model on the industrial production index growth (*ΔIPI*) using the realized variance series of agricultural, energy and metals commodity futures returns. The forecasting horizon ranges from 0 to 12 months. *COMRV* is the realized variance and *ΔIPI* is the industrial production index growth. The standard errors are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The estimated beta coefficients are based on the following bivariate regressions: $\Delta IPI_t = b_0 + b_1 COMRV_{t-k} + \varepsilon_t$.

Table 5. Forecasting US Economic Recessions with Commodity Price Uncertainty

Panel A: Estimated b_1 coefficients

Horizon (k)	*k=0*	*k=1*	*k=2*	*k=3*	*k=6*	*k=12*
Corn	1.341*	1.202	1.226	1.272	0.948	0.223
Cotton	1.799**	1.621*	1.390	1.288	0.825	-0.338
Soybeans	1.874**	1.794*	1.841**	1.827**	1.286	0.092
Wheat	1.532**	1.463**	1.435**	1.436**	1.179*	0.526
Crude oil	0.979***	0.925***	0.911***	0.636**	0.316	-0.107
Heating oil	1.109***	1.049***	1.010***	0.616*	0.352	-0.051
Petroleum	1.166***	1.095***	1.082***	0.727**	0.404	-0.101
Gasoline	1.166***	1.104***	1.110***	0.811**	0.529*	-0.056
Copper	0.991**	0.946**	0.951**	0.912**	0.638*	0.106
Gold	4.064***	4.122***	4.321***	3.798***	2.646**	0.134
Platinum	3.135***	2.942***	2.814***	2.520***	1.671*	0.322
Silver	0.838*	0.769	0.761	0.663	0.426	-0.315

Panel B: *Adjusted R^2* values

Horizon (k)	*k=0*	*k=1*	*k=2*	*k=3*	*k=6*	*k=12*
Corn	5.8	4.6	4.8	5.1	2.7	-0.1
Cotton	7.4	5.9	4.3	3.6	1.3	0.0
Soybeans	7.6	7.0	7.3	7.2	3.4	-0.3
Wheat	10.4	9.4	9.1	9.1	6.0	1.0
Crude oil	25.4	22.6	21.9	10.5	2.4	0.0
Heating oil	19.0	16.9	15.7	5.7	1.6	-0.3
Petroleum	23.9	21.1	20.6	9.1	2.6	-0.1
Gasoline	22.5	20.2	20.4	10.7	4.4	-0.2
Copper	6.9	6.3	6.3	5.8	2.7	-0.2
Gold	15.2	15.6	17.2	13.2	6.3	-0.3
Platinum	22.1	19.5	17.7	14.2	6.1	-0.1
Silver	6.2	5.1	5.0	3.7	1.4	0.6

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table presents the results of the bivariate linear probability forecasting regression model on US economic recessions (*NBER*) using the realized variance series of agricultural, energy and metals commodity futures returns. The forecasting horizon ranges from 0 to 12 months. *COMRV* is the realized variance and *NBER* is the US economic recessions index. The standard errors are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The estimated beta coefficients are based on the following linear probability bivariate regressions: $NBER_t = b_0 + b_1 COMRV_{t-k} + \varepsilon_t$.

Table 6. Forecasting US Economic Recessions with Commodity Price Uncertainty

Panel A: Estimated b_1 coefficients

Horizon (k)	*k=0*	*k=1*	*k=2*	*k=3*	*k=6*	*k=12*
Corn	5.661**	5.080*	5.197*	5.417**	4.053	1.251
Cotton	7.548**	6.794**	5.836*	5.404*	3.530	-2.202
Soybeans	7.812**	7.482**	7.716**	7.660**	5.361	0.516
Wheat	6.103**	5.812**	5.677**	5.657**	4.659*	2.305
Crude oil	5.497***	4.911***	4.767***	2.096	1.196	-1.129
Heating oil	6.840***	6.213***	5.797***	2.125	1.376	-0.386
Petroleum	6.879***	6.061***	5.913***	2.382	1.484	-0.956
Gasoline	6.010***	5.392***	5.455***	2.799*	1.923*	-0.411
Copper	3.943**	3.747**	3.772**	3.602**	2.561**	0.610
Gold	16.389***	16.736***	17.648***	15.270***	10.712***	0.804
Platinum	13.682***	12.393***	11.528***	10.069***	6.225**	1.590
Silver	3.230**	2.951*	2.912*	2.529	1.668	-3.199

Panel B: *Pseudo R^2* values

Horizon (k)	*k=0*	*k=1*	*k=2*	*k=3*	*k=6*	*k=12*
Corn	6.8	5.5	5.7	6.2	3.5	0.3
Cotton	8.7	7.0	5.2	4.4	1.9	0.5
Soybeans	8.8	8.1	8.6	8.4	4.2	0.0
Wheat	11.1	10.2	9.8	9.7	6.6	1.5
Crude oil	28.7	24.8	23.9	10.0	2.9	0.7
Heating oil	24.0	20.9	18.9	5.9	2.2	0.1
Petroleum	27.9	23.8	23.0	8.7	3.0	0.4
Gasoline	24.1	21.0	21.3	10.4	4.7	0.1
Copper	7.2	6.6	6.7	6.1	3.2	0.1
Gold	16.1	16.6	18.3	14.1	7.1	0.0
Platinum	23.3	20.1	18.0	14.4	6.2	0.3
Silver	6.7	5.6	5.5	4.2	1.8	2.1

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table presents the results of the bivariate probit forecasting regression model on US economic recessions (*NBER*) using the realized variance series of agricultural, energy and metals commodity futures returns. The forecasting horizon ranges from 0 to 12 months. *COMRV* is the realized variance and *NBER* is the US economic recessions index. The standard errors are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The estimated beta coefficients are based on the following probit bivariate regressions: $P(NBER_t = 1) = F(b_0 + b_1 COMRV_{t-k})$.

Table 7. Granger Causality Tests between Gross Domestic Product Growth and Commodity Price Uncertainty

Panel A

Dependent variable	***Independent variable***	***Chi-square***	***p-value***
ΔGDP	*Corn*	29.831***	0.008
ΔGDP	*Cotton*	0.972	0.615
ΔGDP	*Soybeans*	2.738	0.254
ΔGDP	*Wheat*	8.725**	0.013
ΔGDP	*Crude oil*	2.216	0.330
ΔGDP	*Heating oil*	2.858	0.240
ΔGDP	*Petroleum*	1.935	0.380
ΔGDP	*Gasoline*	0.692	0.707
ΔGDP	*Copper*	0.275	0.871
ΔGDP	*Gold*	4.555*	0.100
ΔGDP	*Silver*	4.817*	0.090
ΔGDP	*Platinum*	5.097*	0.078

Panel B

Dependent variable	***Independent variable***	***Chi-square***	***p-value***
Corn	*ΔGDP*	0.314	0.843
Cotton	*ΔGDP*	0.979	0.613
Soybeans	*ΔGDP*	0.509	0.775
Wheat	*ΔGDP*	0.485	0.785
Crude oil	*ΔGDP*	5.779*	0.056
Heating oil	*ΔGDP*	10.875***	0.004
Petroleum	*ΔGDP*	7.385**	0.025
Gasoline	*ΔGDP*	8.633**	0.013
Copper	*ΔGDP*	0.257	0.859
Gold	*ΔGDP*	2.507	0.285
Silver	*ΔGDP*	3.627	0.163
Platinum	*ΔGDP*	0.568	0.753

Notes: The table shows the results of the Granger causality tests between commodity price uncertainty and gross domestic product growth (*ΔGDP*). The tests refer to the baseline multivariate VAR model presented in Equation (3). The optimal lag-length is based on the Schwarz criterion. The null hypothesis is that the independent variable does not Granger cause the dependent variable. *, ** and *** denotes the rejection of the null hypothesis of no causality at the 10%, 5% and 1% level respectively.

Figure 1. Estimated Recession Probability from the Bivariate Probit Model for Commodity Markets

Agricultural Markets | **Energy Markets** | **Metals Markets**

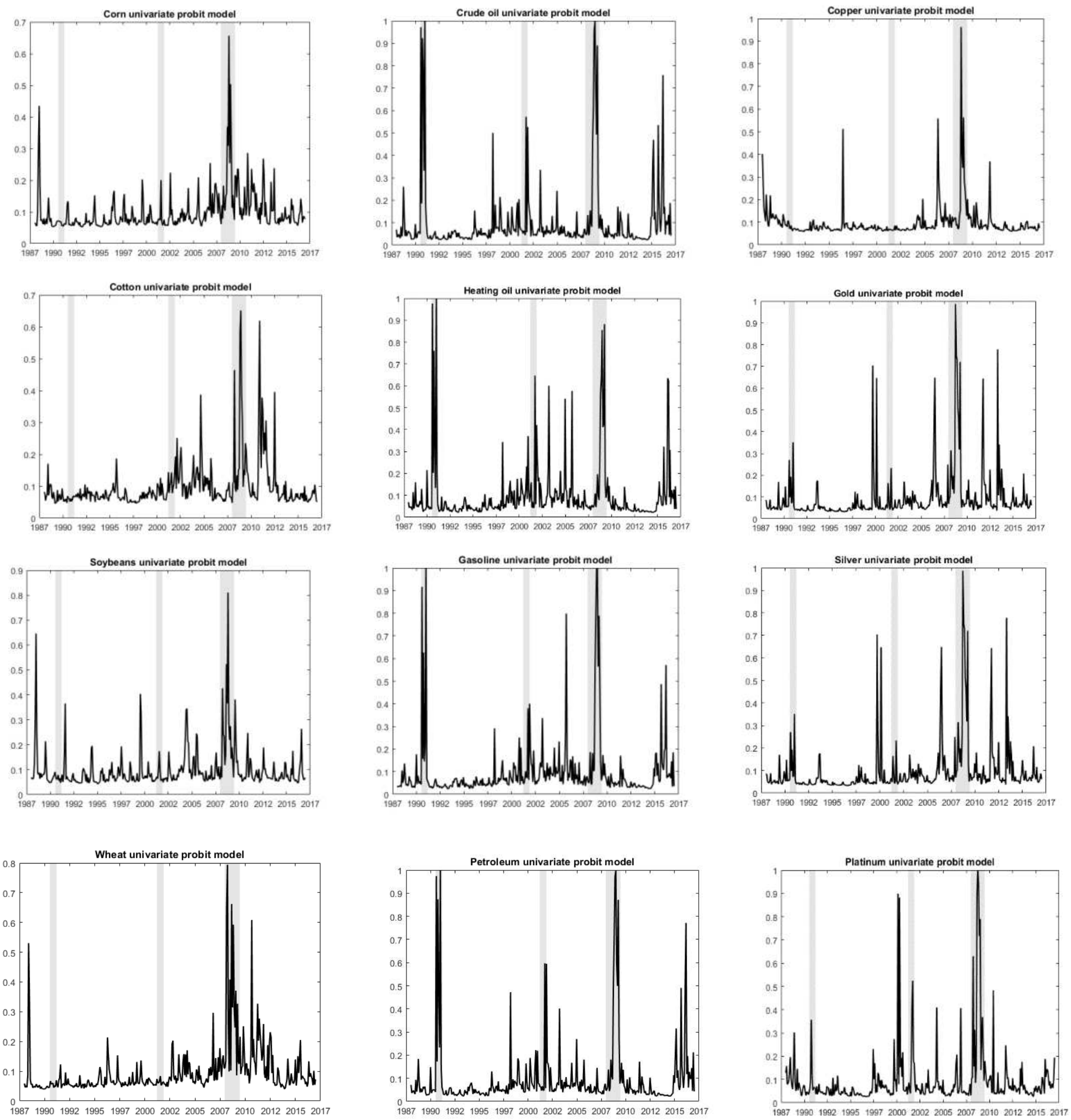
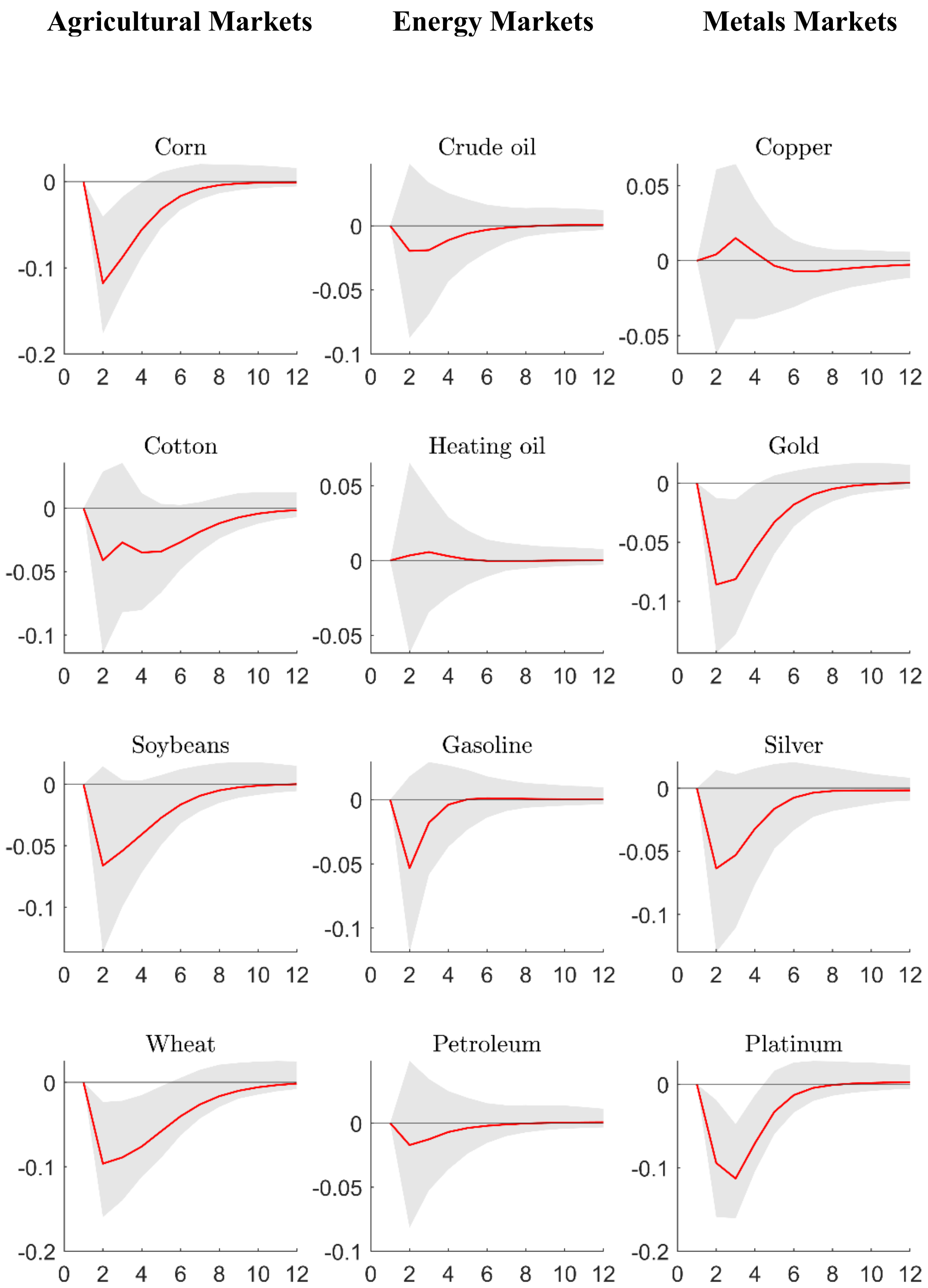


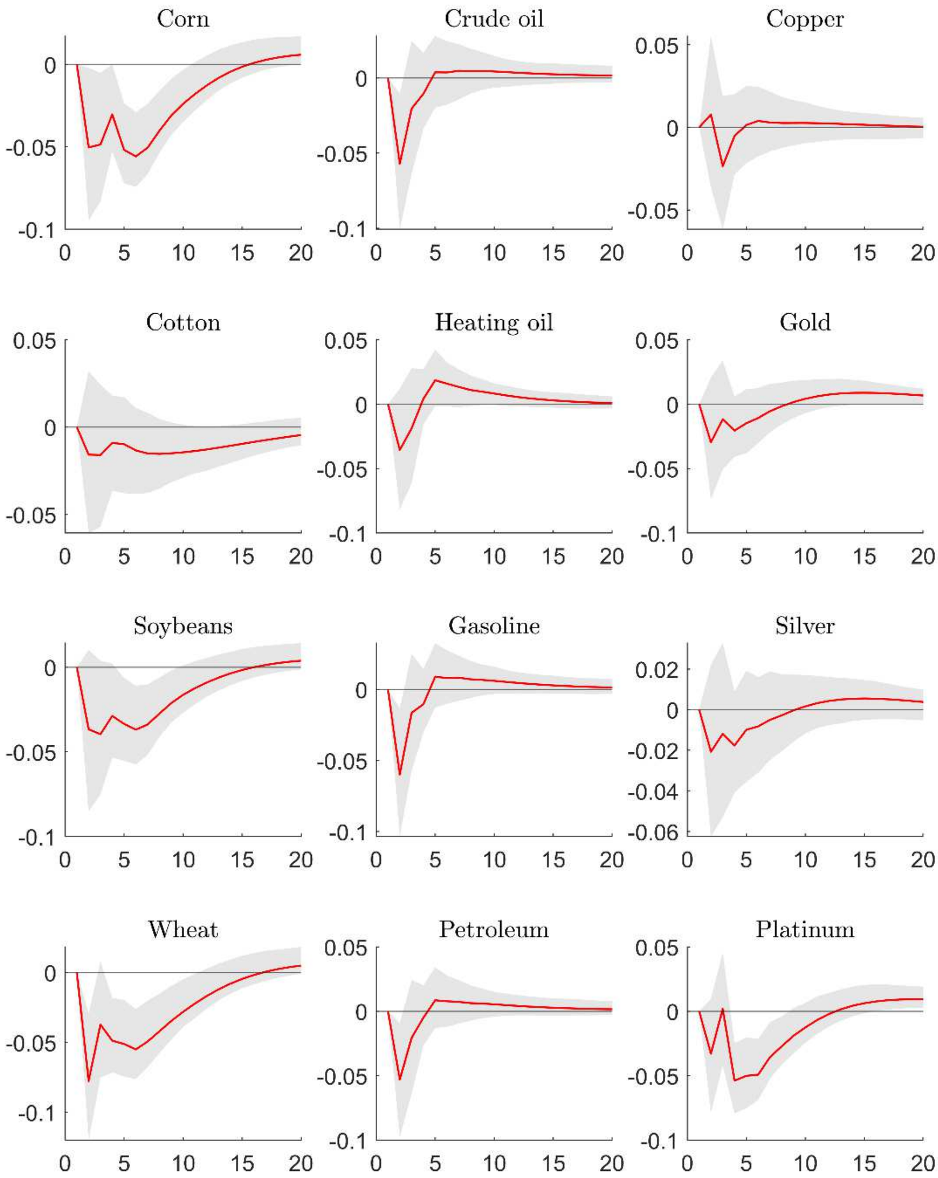
Figure 2. Response of GDP Growth to Commodity Price Uncertainty Shocks



Notes: The solid red line shows the estimated IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1,000 replications. The estimated orthogonalized IRFs are expressed in percentages (%).

Figure 3. Response of IPI Growth to Commodity Price Uncertainty Shocks

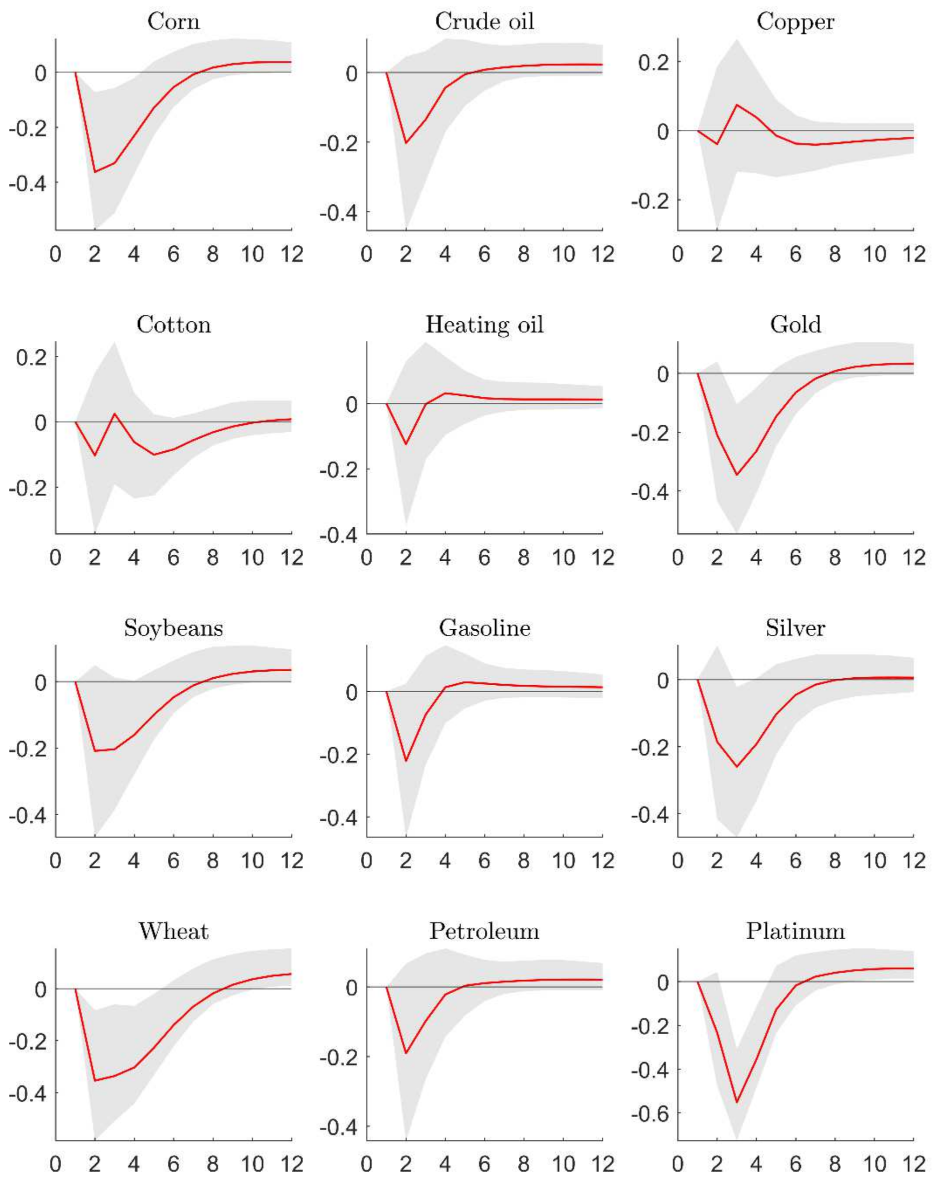
Agricultural Markets **Energy Markets** **Metals Markets**



Notes: The solid red line shows the estimated IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1,000 replications. The estimated orthogonalized IRFs are expressed in percentages (%).

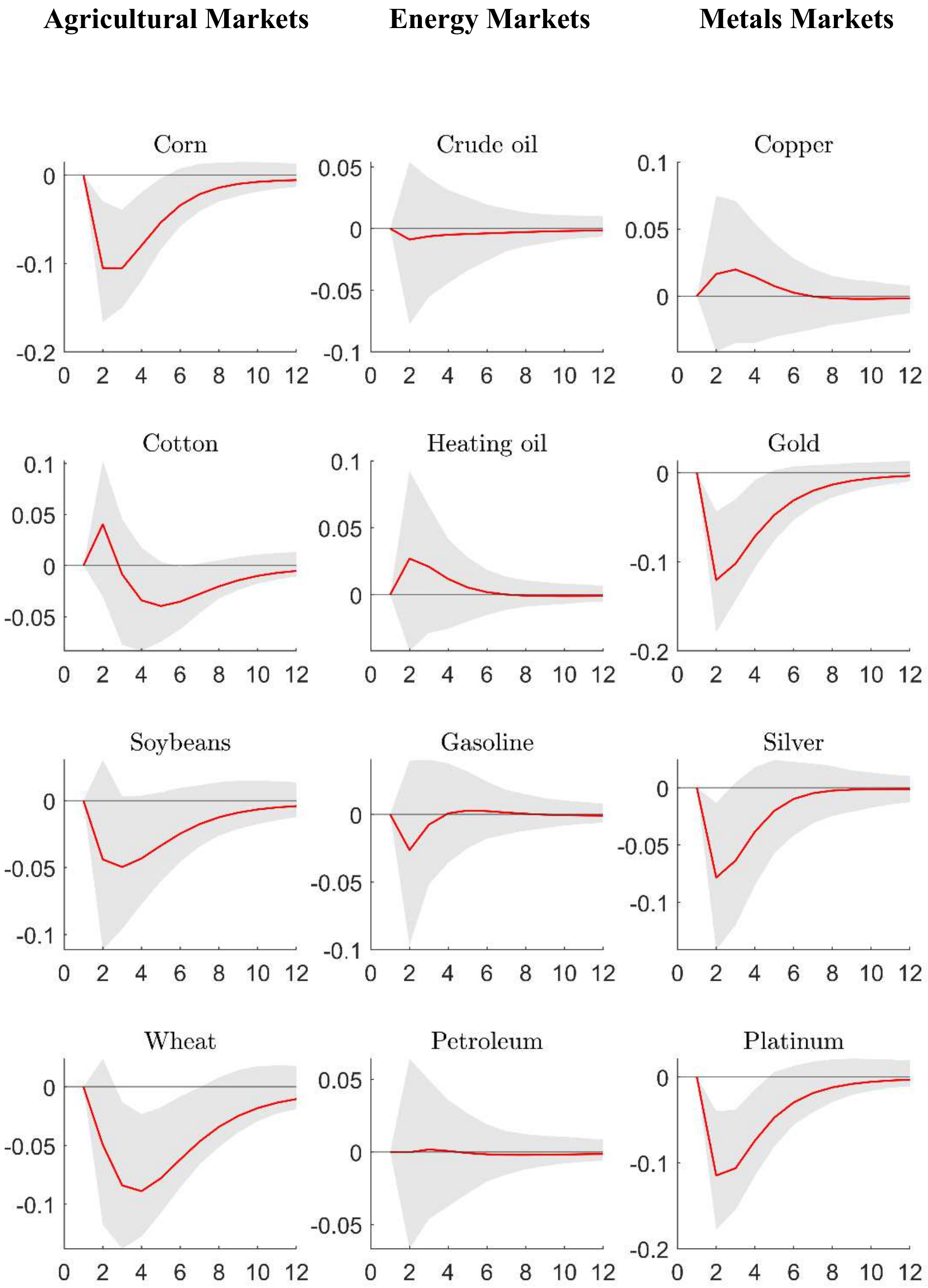
Figure 4. Response of Investment Growth to Commodity Price Uncertainty Shocks

Agricultural Markets **Energy Markets** **Metals Markets**



Notes: The solid red line shows the estimated IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1,000 replications. The estimated orthogonalized IRFs are expressed in percentages (%).

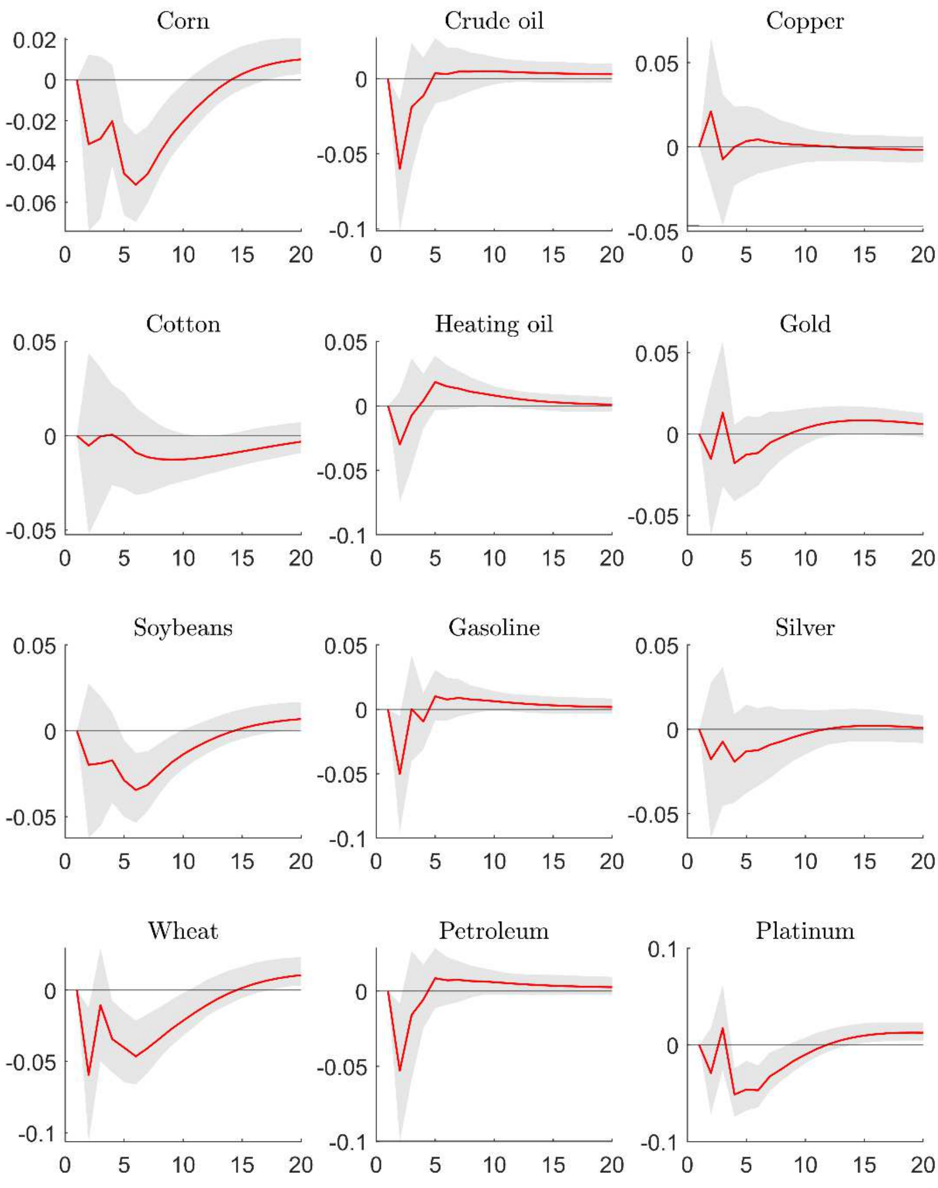
Figure 5. Response of Consumption Growth to Commodity Price Uncertainty Shocks



Notes: The solid red line shows the estimated IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1,000 replications. The estimated orthogonalized IRFs are expressed in percentages (%).

Figure 6. Response of Capacity Utilization to Commodity Price Uncertainty Shocks

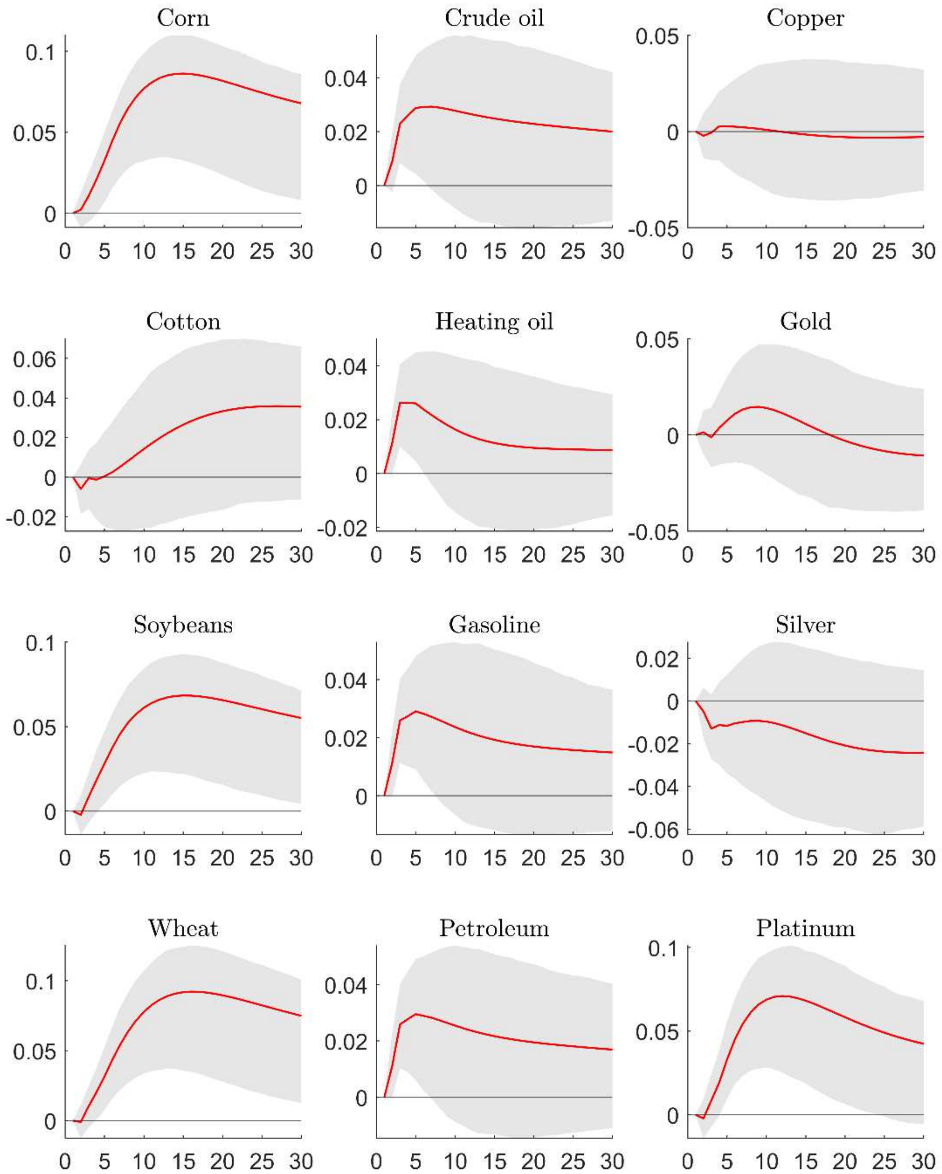
Agricultural Markets **Energy Markets** **Metals Markets**



Notes: The solid red line shows the estimated IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1,000 replications. The estimated orthogonalized IRFs are expressed in percentages (%).

Figure 7. Response of Unemployment Rate to Commodity Price Uncertainty Shocks

Agricultural Markets **Energy Markets** **Metals Markets**



Notes: The solid red line shows the estimated IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1,000 replications. The estimated orthogonalized IRFs are expressed in percentages (%).