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Commodity price uncertainty as a leading indicator of economic activity

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Abstract

This article examines the impact of commodity price uncertainty on the U.S. economic activity. Our analysis indicates that uncertainty in agricultural, energy and metals markets depresses economic activity in the United States. Uncertainty shocks in agricultural and metals markets have a more long-lasting dampening effect on economic activity and its components, when compared to the effect of oil 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 uncertainty shocks remains unaltered, while the respective macroeconomic response to energy uncertainty shocks is significantly reduced.

KEYWORDS

commodity markets, economic activity, economic recession, volatility

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 the firms' 'option value' to delay or postpone their investment decisions for less uncertain times (Bernanke, 1983; Henry, 1974; Pindyck, 1991; 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 & Kilian, 2009). 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. A large and growing body in the literature has shown the negative impact of rising uncertainty on the macroeconomy (Al-Thaqeb et al., 2020; Baker et al., 2016; Bloom, 2009; Caldara et al., 2016; Henzel & Rengel, 2017; Jurado et al., 2015; Prüser & Schlösser, 2020; Tiwari et al., 2020; among others). All these empirical studies show the negative macroeconomic effect of uncertainty shocks by proxying economic uncertainty using stock-market volatility, the VIX index, or measures of uncertainty about future economic policy. In addition, the empirical research at the microeconomic level has shown that uncertainty also have negative effects on the investments of various firms and industries (Alessandria et al., 2015; Ghosal & Loungani, 2000; Koetse et al., 2006; Panagiotidis & Printzis, 2020; among others).

In this article, we move the current research a step further by modelling uncertainty as the volatility of primary agricultural (corn, cotton, soybeans and wheat), metals (copper, gold, platinum and silver) and energy (crude oil, heating oil, petroleum and 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 (Gilbert, 2010; Kilian, 2009; Roberts & Schlenker, 2013; among others). In this way, higher commodity price uncertainty could signify higher uncertainty about aggregate supply and demand conditions in the economy.[1]

This uncertainty, about aggregate demand and supply, is typically followed by sudden drops in economic activity (Caggiano et al., 2014; Leduc & Liu, 2016; among others). The empirical literature has identified a significant linkage between commodity price fluctuations and the macroeconomy (Alquist et al., 2020; Fernández et al., 2018; Fernandez-Perez et al., 2017; Ferraro & Peretto, 2018; Frankel & Rose, 2010; Gilbert, 2010; Karali & Power, 2013; Moutos & Vines, 1992; among others). For example, Moutos and Vines (1992), using a closed-economy macroeconomic model, show that commodity price shocks are major drivers of inflation and real output. 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 dynamic interactions between monetary policy, inflation and commodity prices (Frankel, 1984; Frankel & Rose, 2010; Gilbert, 2010; Han et al., 1990; Moutos & Vines, 1992; Orden & Fackler, 1989; Sekine & Tsuruga, 2018; among others).

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 the U.S. 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 & Serletis, 2010; Ferderer, 1996; Hamilton, 2003; Henzel & Rengel, 2017; Jo, 2014; Kilian, 2009; Kilian & Vigfusson, 2017; Lee et al., 1995; Rahman & Serletis, 2011; Ravazzolo & Rothman, 2013; Serletis & Xu, 2019). 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), Henzel and Rengel (2017) and Serletis and Xu (2019) provide further insights into the significant forecasting power of oil price uncertainty on economic activity, with the study of Henzel and Rengel (2017) which further shows that rising uncertainty in the broad commodity price index leads to a persistent drop in real economic activity.

Although the studies mentioned above identify the negative macroeconomic impact of oil and broad commodity price uncertainty, there is no empirical work showing what is the macroeconomic impact of uncertainty in agricultural and metals commodity markets. In this article, 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 the U.S. 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, such as corn, 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 the U.S. economic activity. While the previous findings in the literature identify the role of oil price uncertainty shocks (Elder & Serletis, 2010; Jo, 2014; Rahman & Serletis, 2011; Serletis & Xu, 2019), 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 results are broadly in line with the findings of Henzel and Rengel (2017) that show the persistence negative effect of commodity price uncertainty shocks on economic activity. We provide additional evidence to their findings by showing that uncertainty in agricultural and metals commodity classes has the highest recessionary impact, when compared with that of oil price uncertainty. The substantially stronger negative impact of agricultural price uncertainty and, at the same time, the weakened recessionary impact of oil price uncertainty can be attributed to the existence of biofuels which has changed the relative macroeconomic importance and interdependence between energy and agricultural markets (De Gorter & Just, 2009; Zilberman et al., 2013). Our findings are in line with the previous evidence 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.

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 United States 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 & Jenkinson, 1986; Bernanke et al., 1997; Kara, 2017; among others). Additionally, a significant strand of the literature has identified many significant linkages between uncertainty and monetary policy.[2] Motivated by the aforementioned strand of the literature, and in order to find the pure (net) recessionary impact of commodity price uncertainty shocks, we also control for dynamic interactions between commodity price fluctuations and monetary policy by including the Fed funds rate 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 monetary policy. For example, our VAR analysis reveals that a positive one-standard-deviation shock in wheat price volatility results in eight basis points drop in GDP growth, four quarters after the initial uncertainty shock, with the impact remaining negative and statistically significant until the sixth quarter after the initial shock. 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 monetary policy shocks. In order to examine whether the recessionary effect of energy price uncertainty shocks is attributed to a systematic monetary policy reaction, we conduct a counterfactual VAR analysis by estimating an (otherwise identical) VAR model treating policy shocks as exogenous in the VAR. In this way, we shut off the policy response to commodity price uncertainty shocks, hence, we examine the recessionary impact of agricultural, metals and energy price uncertainty shocks in the absence of policy interventions to financial markets. Our counterfactual exogenous VAR analysis shows that the responses of US economic activity to energy price uncertainty shocks turn from insignificant to negative and significant when we shut off the endogenous interactions between agricultural, metals and energy commodity markets and the U.S. policy rate. On the other hand, the recessionary impact of agricultural and metals uncertainty shocks remains roughly the same, independently of whether we control (or not) for endogenous policy reactions in the VAR. 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'.[3] Moreover, our results shed more light on the literature on the risk taking and uncertainty channel of monetary policy, according to which monetary policy has a significant effect on uncertainty and risk aversion in the banking sector and the equity market (Bekaert et al., 2013; Borio & Zhu, 2012; Bruno & Shin, 2015; David & Veronesi, 2014).

Our findings, 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 United States.

Overall, we empirically verify that the real options theory of investment under uncertainty is valid when modelling uncertainty as the realized variance of the daily returns of major agricultural, metals and energy commodity markets. More specifically, our VAR analysis shows that aggregate investment is the GDP component which is more heavily impacted by commodity price uncertainty shocks, hence our results provide further empirical support to the real options theory of investment under uncertainty (Henry, 1974; Pindyck, 1991). 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 & Thomadakis, 1997; Pindyck, 2004). The policy implication behind our empirical findings is that policymakers 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.[4]

The rest of the article 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 and provides policy recommendations.

2 | METHODOLOGY

2.1 | Uncertainty in commodity prices

Our uncertainty measure (*COMRV*) is the realized variance of the daily returns of commodity futures. We follow a standard approach in the commodity volatility literature (see Ferderer, 1996; Triantafyllou et al., 2020; Wang et al., 2012; among others) and construct both quarterly and monthly volatility series for each commodity futures contract by computing for each period (quarter/month) the variance of the daily returns. We calculate the realized variance using daily closing prices of the nearby futures contract, according to Equation (1) below:

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

where F_t is the nearby commodity futures price on trading day t and is the average futures returns for each period (t,T). $COMRV_{t,T}$ is our estimated realized variance for each period (quarter/month).[5] Our approach of estimating the realized variance 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.[6]

2.2 | Baseline 8-Factor 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 monetary policy reactions to commodity market turbulence (Beckerman & Jenkinson, 1986; Bernanke et al., 1997; Kara, 2017; Kilian & 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). Moreover, in the VAR model we control for the slope of the U.S. Treasury yield curve which is also a significant predictor of US economic activity (Estrella & 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:

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

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.[7] To recover orthogonal shocks, we use a

Cholesky decomposition with the following ordering in our baseline 8-factor VAR model:

$$[\Delta GDP\ INFL\ UNEMP\ FFR\ TERM\ EPU\ SP500RV\ COMRV]. \tag{3}$$

where ΔGDP stands for the growth of real GDP (the proxy of the U.S. economic activity), *INFL* is the inflation rate (the quarterly growth of consumer price index [*CPI*] using a rolling fixed window of four quarters), *UNEMP* is the unemployment rate, *FFR* is the U.S. Fed funds rate,[8] *TERM* is the slope of the term structure of the U.S. interest rates (namely, the difference between the 10-year US Treasury Bond yield and the 3-month U.S. Treasury Bill rate), *EPU* is the economic policy uncertainty index of Baker et al. (2016), *SP500RV* is the realized variance of daily returns of the S&P 500 stock-market index and *COMRV* is the realized variance of daily returns of the commodity futures prices. 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 $\Delta CONS$), 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 United States.[9]

2.3 | 8-Factor VAR model with exogenous monetary policy shocks

In order to examine the direct effect of commodity price uncertainty shocks on the U.S. economy, without allowing for systematic (endogenous) reactions of the monetary authority, we follow the framework of Bernanke et al. (1997) who examine how much of the oil shocks had a direct effect on the U.S. output, and how much was the indirect effect stemming for the systematic response of the monetary authority (to oil shocks) in order to control the inflationary pressures. To do so, we follow their VAR modelling approach by treating policy related shocks as exogenous to commodity markets. In this way, we shut off the response of policy rates to commodity uncertainty shocks, hence we implicitly examine the recessionary effects of commodity uncertainty shocks if the monetary authority had remained unresponsive to those shocks.[10] Following Bernanke et al. (1997), we conduct a counterfactual VAR analysis in which we shut off the endogenous response of monetary policy to commodity price uncertainty shocks. What is also measured by this model is what would be the recessionary impact of agricultural, metals and energy commodity price uncertainty shocks in the absence of monetary policy interventions in order to ameliorate the inflationary and recessionary pressures of those shocks. In more details, the VAR model (with strictly exogenous) monetary policy shocks is

$$Y_t = A_0 + \sum_{i=1}^{k} A_i Y_{t-i} + \sum_{i=1}^{k} B_i X_{t-i} + e_t. \tag{4}$$

In Equation (4), we have the same variables as in our baseline 8-factor VAR model, with the only difference being that we shut off the endogenous responses of policy-related variables like the Fed funds rate (*FFR*), the slope of the U.S. treasury yield curve (*TERM*) and the economic policy uncertainty (*EPU*). More specifically, vectors Y_t and X_t are the vectors with the endogenous and exogenous variables of the VAR as follows:

$$Y_t = [COMRV\ SP500RV\ INFL\ \Delta GDP\ UNEMP]' \tag{5}$$

$$X_t = [FFR\ TERM\ EPU]'. \tag{6}$$

In this VAR model, following Bloom (2009) and Caggiano et al. (2014), we also place the commodity and stock-market uncertainty variables first in order to allow for the shocks to affect firstly the commodity markets and the stock-market, and then the consumer prices and the quantities in the economy.[11]

2.4 | 9-Factor VAR model (controlling for exchange rate)

Motivated by the strand of the literature showing the significant interdependence between commodity prices and exchange rates (Chen et al., 2010; Ferraro et al., 2015; Liu et al., 2020; Zhang et al., 2016; among others), we additionally estimate our baseline VAR model by including the U.S. effective exchange rate in the VAR. The VAR ordering of the 9-factor VAR, controlling for exchange rate, is given below:

$$[\Delta GDP\ INFL\ UNEMP\ EXCH\ FFR\ TERM\ EPU\ SP500RV\ COMRV]. \tag{7}$$

The ordering of the variables is the same as with the baseline 8-factor VAR model, where adding *EXCH* as an additional endogenous variable in the VAR.[12]

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 and wheat), metals (copper, gold, silver, platinum) and energy (crude oil, heating oil, gasoline and petroleum) commodity futures. Our daily commodity data cover the period from 1 January 1988 to 31 January 2017.

3.2 | Macroeconomic and financial data

We obtain quarterly and monthly (where available) U.S. data for real gross domestic product (*GDP*), consumer price index (*CPI*), consumption expenditures (*CONS*), investment (*INV*), industrial production index (*IPI*), capacity utilization (*CU*), unemployment rate (*UNEMP*), economic policy uncertainty index (*EPU*), the US Fed funds rate (*FFR*), the 10-year U.S. treasury bond rate and the 3-month US treasury bill rate and the U.S. effective exchange rate (*EXCH*) from the Federal Reserve Bank of Saint Louis (FRED). We also obtain data for the S&P 500 stock-market index (*SP500*) from DataStream. The slope of the yield curve (*TERM*) is estimated as the difference between the 10-year U.S. government bond yield and the 3-month maturity U.S. treasury bill rate. All the macroeconomic and financial data series cover the period from January 1988 to January 2017.[13]

4 | EMPIRICAL ANALYSIS

4.1 | Predictive regressions results

For an initial investigation of the impact of agricultural, energy and metals commodity markets uncertainty on the U.S. 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:

$$\Delta GDP_t = b_0 + b_1 COMRV_{t-k} + u_t, \tag{8}$$

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 (8) using the IPI growth (ΔIPI) as an alternative measure of economic activity in the United States.[14] Table 1 shows the regression results of our bivariate regression on real GDP growth using commodity price uncertainty as our only predictor.

The results from Table 1 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 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 (Chauvet et al., 2015). 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 Fernández et al. (2018), who find that fluctuations in commodity prices are a significant driver of macroeconomic fluctuations in the United States 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 2 report the regression results of the bivariate OLS forecasting regression models for the monthly IPI growth.

The results from Table 2 confirm the findings for GDP growth, and show that commodity uncertainty has

TABLE 1 Forecasting GDP growth with commodity Price uncertainty

Horizon (k)	$k = 0$	$k = 1$	$k = 2$	$k = 3$	$k = 6$	$k = 12$
Panel A: estimated b_1 coefficients						
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
Horizon (k)	**$k = 0$**	**$k = 1$**	**$k = 2$**	**$k = 3$**	**$k = 6$**	**$k = 12$**
Panel B: adjusted R^2 values						
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: 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: $\Delta GDP_t = b_0 + b_1 COMRV_{t-k} + u_t$.
$^*p < 0.10$. $^{**}p < 0.05$. $^{***}p < 0.01$.

a negative effect on industrial production growth. Our bivariate regression results show that agricultural and metals price uncertainty has the most significant impact on IPI growth.[15] Finally, in our online appendix, we provide some further estimations as robustness checks to these results. More specifically, we have explored both probit and linear probability bivariate predictive regression models on the *NBER* recession index (*NBER*), and we find that the probability of the U.S. recessions rises significantly after large commodity market uncertainty shocks.

4.2 | VAR results

4.2.1 | Baseline 8-Factor VAR results

In this section, we present the results of the baseline multivariate VAR model (as described in Equations (2) and (3)). We base our VAR analysis on 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

TABLE 2 Forecasting IPI growth with commodity Price uncertainty

Horizon (k)	k = 0	k = 1	k = 2	k = 3	k = 6	k = 12
Panel A: estimated b_1 coefficients						
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
Horizon (k)	**k = 0**	**k = 1**	**k = 2**	**k = 3**	**k = 6**	**k = 12**
Panel B: adjusted R^2 values						
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: 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: $\Delta IPI_t = b_0 + b_1 COMRV_{t-k} + u_t$.
*$p < 0.10$. **$p < 0.05$. ***$p < 0.01$.

identified using a Cholesky decomposition, for our baseline multivariate VAR model described in Equations (2) and (3).[16] Figure 1 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, petroleum) and metals (copper, gold, silver, platinum) price volatility series as proxies for commodity price uncertainty.

The IRFs, from Figure 1, show that agricultural and metals commodity price uncertainty shocks have a negative and long-lasting impact on the U.S. 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 the U.S. 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

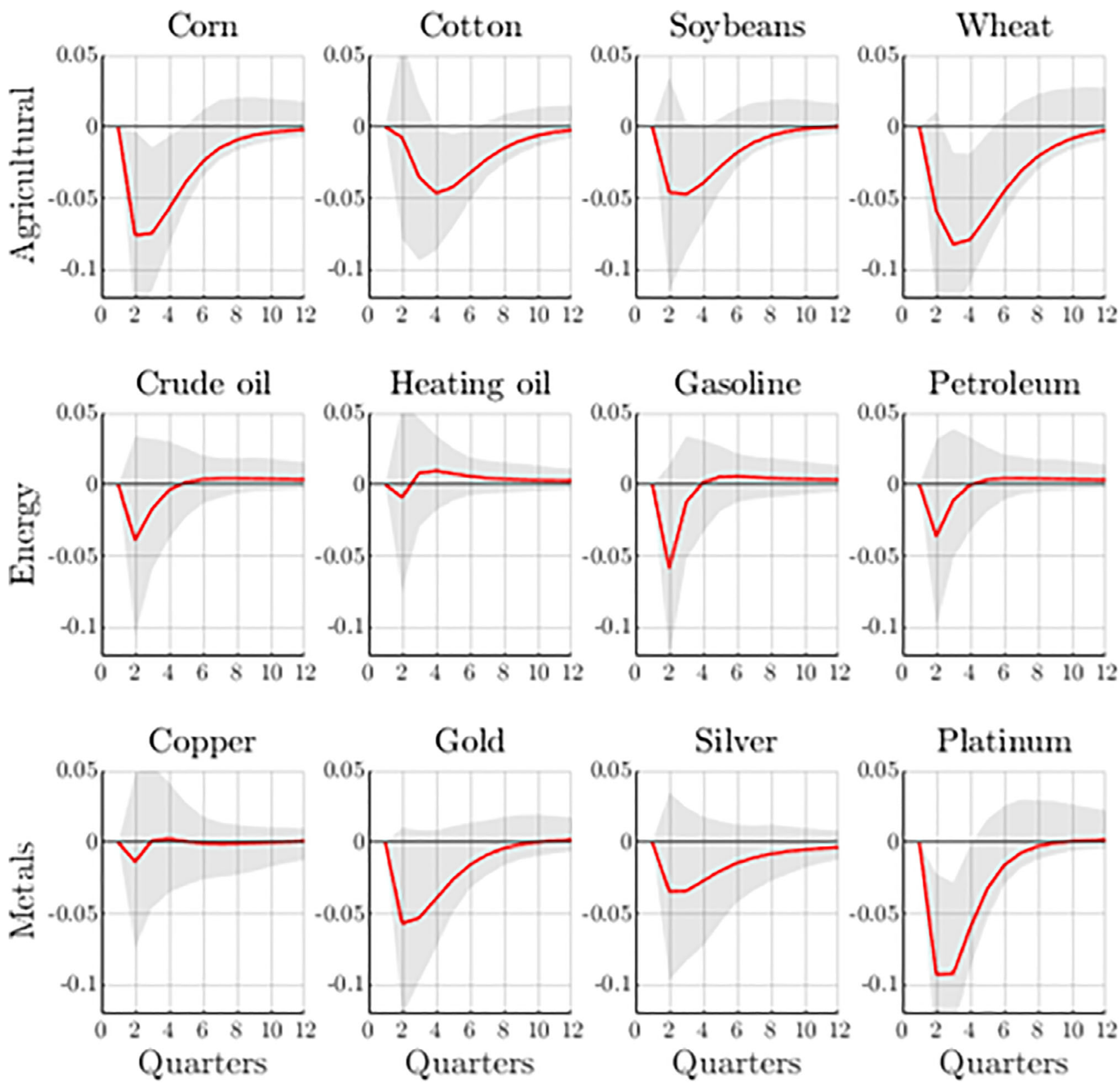

FIGURE 1 Response of GDP growth to commodity price uncertainty shocks
Notes: The solid red line shows the estimated orthogonalized IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1000 replications. The estimated orthogonalized IRFs are expressed in percentages (%). [Colour figure can be viewed at wileyonlinelibrary.com]

the realized variance of platinum futures prices reduces GDP growth almost 9 basis points one quarter after the initial uncertainty shock, with the effect remaining significant for four quarters after the initial uncertainty shock. On the other hand, the estimated response of US GDP growth to energy price uncertainty shock is statistically insignificant for all energy commodity markets considered. Interestingly, the response of GDP growth to crude oil and petroleum uncertainty shocks turns from negative to positive six quarters after the initial shocks. These results are in line with those of Bloom (2009) who shows that uncertainty shocks (proxied by the VIX index), lead to an initial drop and a subsequent rebound (overshoot) of economic activity. The economic interpretation of this result, is, according to Bloom (2009), that an uncertainty shock, results in the subsequent drops in economic activity (firms postponing investment in risky projects for less uncertain times), while in the medium term there is an overproduction and overinvestment in the economy, when eventually there is much less uncertainty-ambiguity regarding future macroeconomic outcomes.

In our multivariate VAR model, we control for both the monetary policy 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.[17]

Our findings are line with those of Bernanke et al. (2004) and Cologni and Manera (2008) who show that it is difficult to infer whether the U.S. 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; Carlstrom & Fuerst, 2006; Kara, 2017). Our results are also in line and provide further insights to the findings of Ferraro and Peretto (2018) that 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 the U.S. 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 U.S. Fed funds rate (*FFR*) and inflation (*INFL*) in our VAR model. Thus, the estimated IRFs show the net impact of commodity price uncertainty shocks on the U.S. economic activity.[18]

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 in our VAR model; thus, we implicitly allow for possible interactions between commodity price uncertainty shocks and monetary policy changes.[19] Our analysis implicitly reveals that the reduced impact of oil price uncertainty shocks on US GDP growth may be attributed to the fact that these shocks 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 targeting 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 (Gilbert, 2010; Gubler & Hertweck, 2013). Moreover, according to the empirical findings of Triantafyllou and Dotsis (2017), the U.S. 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 the monthly frequency. Figure 2 shows the estimated orthogonalized IRFs of our VAR model when using agricultural, energy and metals price volatility series as the commodity uncertainty measure.

Figure 2 shows that an unexpected positive uncertainty shock in some agricultural and metals markets like corn and wheat and platinum has a long-lasting impact on the IPI growth in the United States when compared to the respective effect of energy price volatility. For example, a one-standard-deviation shock in wheat price uncertainty reduces IPI growth by almost 7 basis points 1 month after the initial shock with the effect remaining negative and statistically significant for 10 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 and 3 months after the initial energy uncertainty shock.[20] 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 the United States (Elder, 2018; Elder & Serletis, 2010;

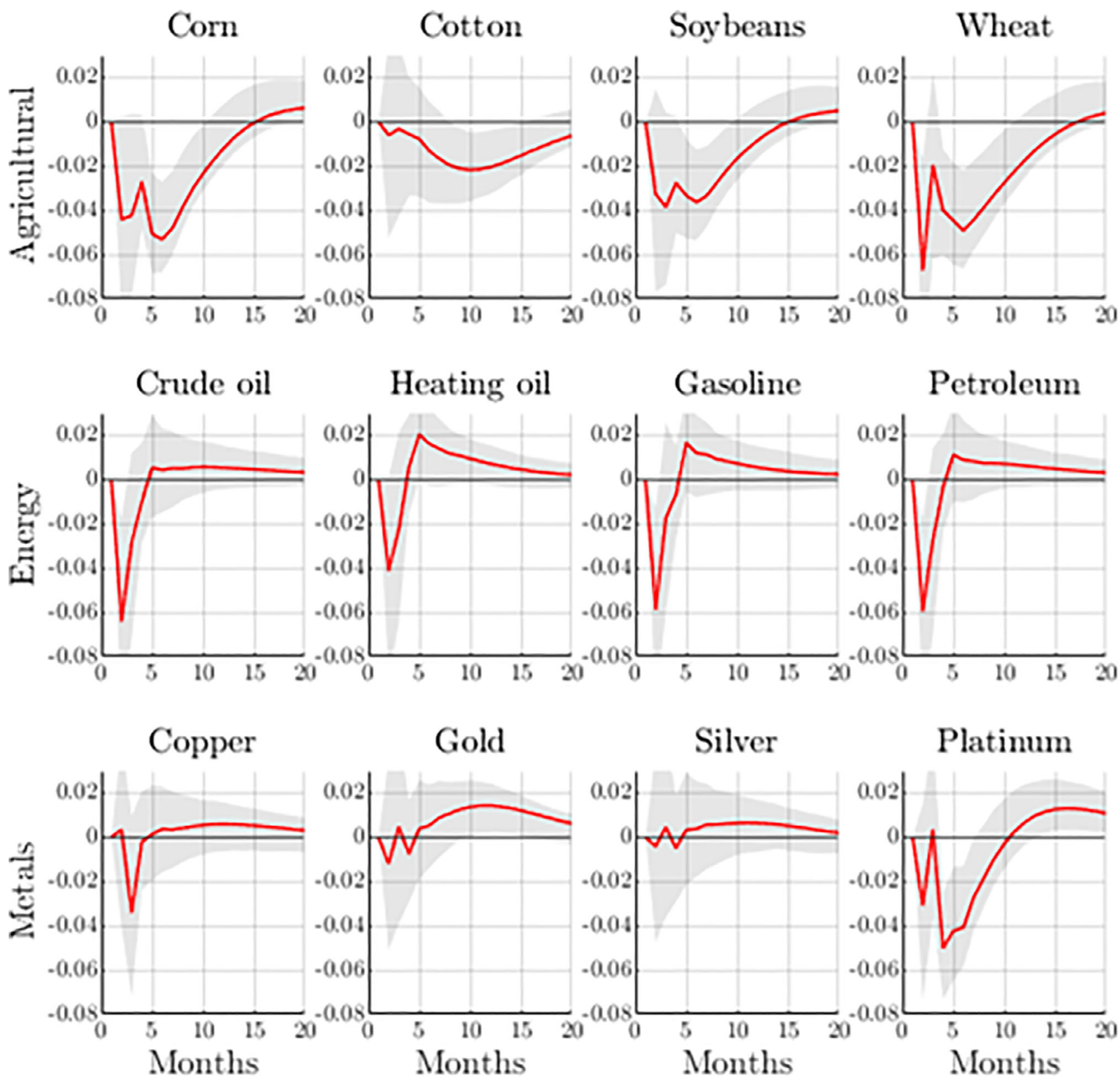

FIGURE 2 Response of IPI growth to commodity price uncertainty shocks

Notes: The solid red line shows the estimated orthogonalized IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1000 replications. The estimated orthogonalized IRFs are expressed in percentages (%). [Colour figure can be viewed at wileyonlinelibrary.com]

Jo, 2014), the effect of energy markets is transitory and vanishes after a 3-month period, which 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 1 year after the initial shock.

4.2.2 | 8-Factor VAR (with exogenous monetary policy shocks) results

In this section, we present the results of our VAR model (shown in Equations (4)–(6)) in which we shut off the endogenous response of monetary policy shocks. Figures 3 and 4 show the dynamic response of the quarterly GDP and monthly IPI growth to agricultural, metals and energy price uncertainty shocks in the VAR model in which we do not allow for dynamic interactions between commodity markets and monetary policy.

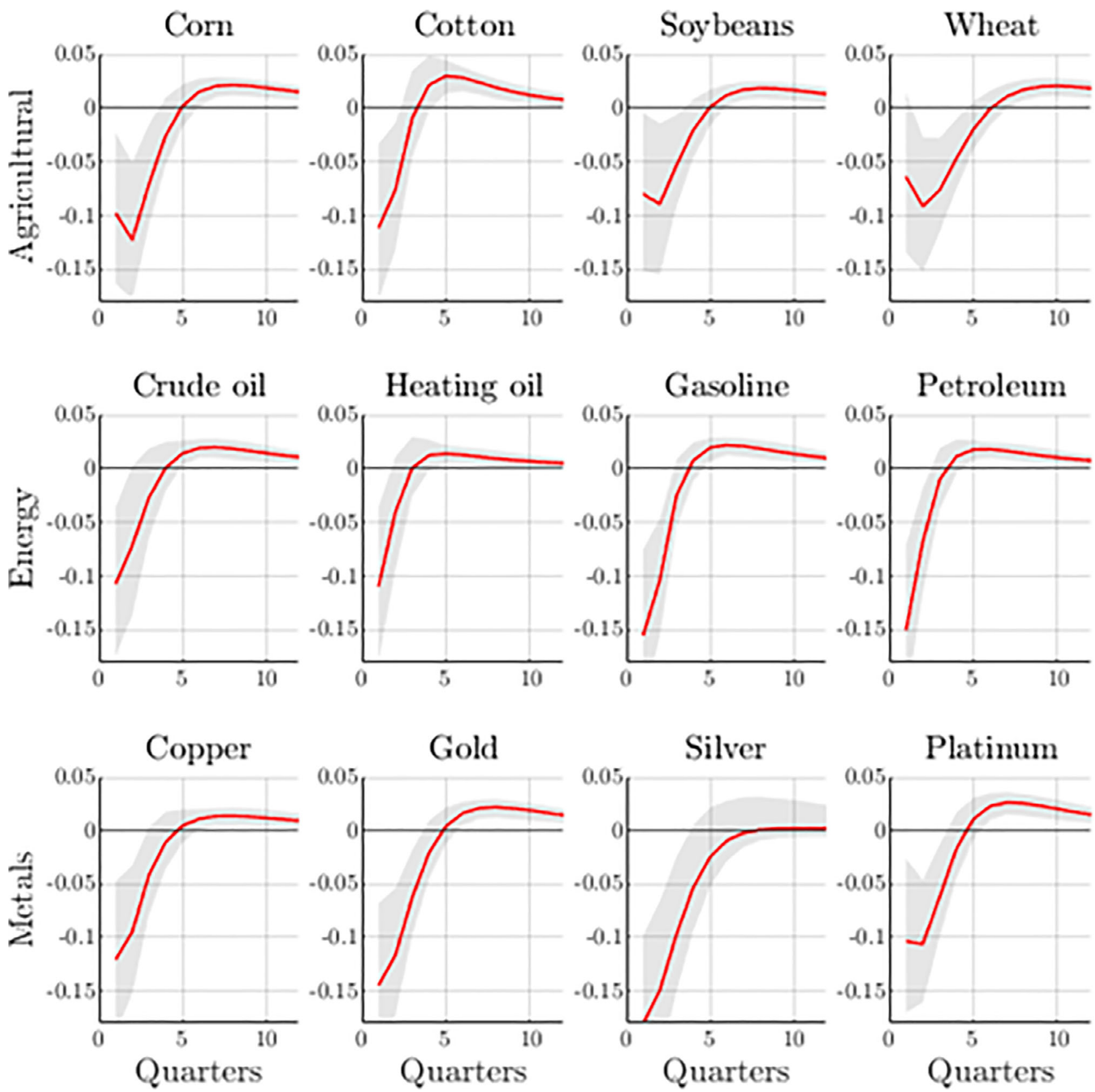

FIGURE 3 Response of GDP growth to commodity price uncertainty shocks (with exogenous monetary policy shocks)
Notes: The solid red line shows the estimated orthogonalized IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1000 replications. The estimated orthogonalized IRFs are expressed in percentages (%). [Colour figure can be viewed at wileyonlinelibrary.com]

The results in Figures 3 and 4 show that the dynamic response of the U.S. real GDP and IPI growth to oil price uncertainty shocks is significantly increased, and in this VAR identification scheme, it becomes strongly negative and statistically significant. Our results are in line with the oil-macroeconomy literature which shows that oil price uncertainty shocks have a significant negative impact on economic activity (Elder, 2018; Elder & Serletis, 2010; Ferderer, 1996; Guo & Kliesen, 2005; Jo, 2014). However, these results, when paired with our baseline VAR evidence, in which we allow for endogenous interactions between commodity markets and monetary policy, shed more light on the crucial question and on-going debate on whether the recessionary effect of oil shocks on the U.S. economy is ameliorated when allowing for systematic monetary policy reactions to oil shocks (Carlstrom and Fuerst, 2006; Bernanke et al., 1997; Hamilton & Herrera, 2004; Kara, 2017). Moreover, our results are

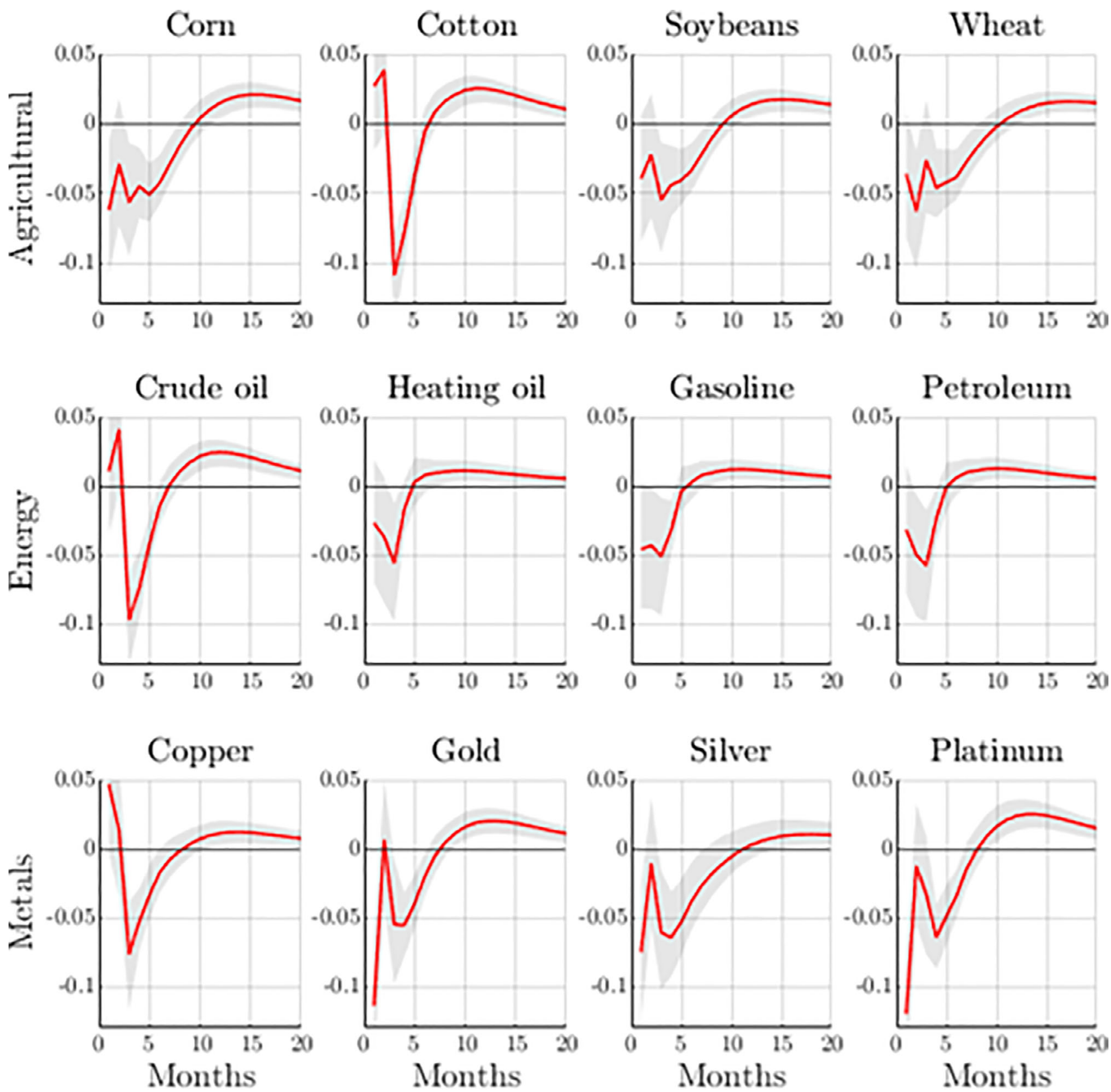

FIGURE 4 Response of IPI growth to commodity price uncertainty shocks (with exogenous monetary policy shocks)
Notes: The solid red line shows the estimated orthogonalized IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1000 replications. The estimated orthogonalized IRFs are expressed in percentages (%). [Colour figure can be viewed at wileyonlinelibrary.com]

broadly in line with the literature showing that a large part of the recessionary effect of oil shocks is the outcome of the systematic reaction of the monetary authority to oil shocks in order to avoid the inflationary or recessionary pressures which may arise because of the oil shocks (Bernanke et al., 1997, 2004; Kara, 2017).

Additionally, our findings shed more light on the literature on the risk taking and uncertainty channel of monetary policy which shows that lax monetary policy has a significant effect on uncertainty and risk aversion in the equity market (Bekaert et al., 2013; David & Veronesi, 2014), since we show that monetary policy can be effective in reducing uncertainty in commodity markets, hence, according to our analysis, contributing to both financial (commodity-related) and macroeconomic stability.

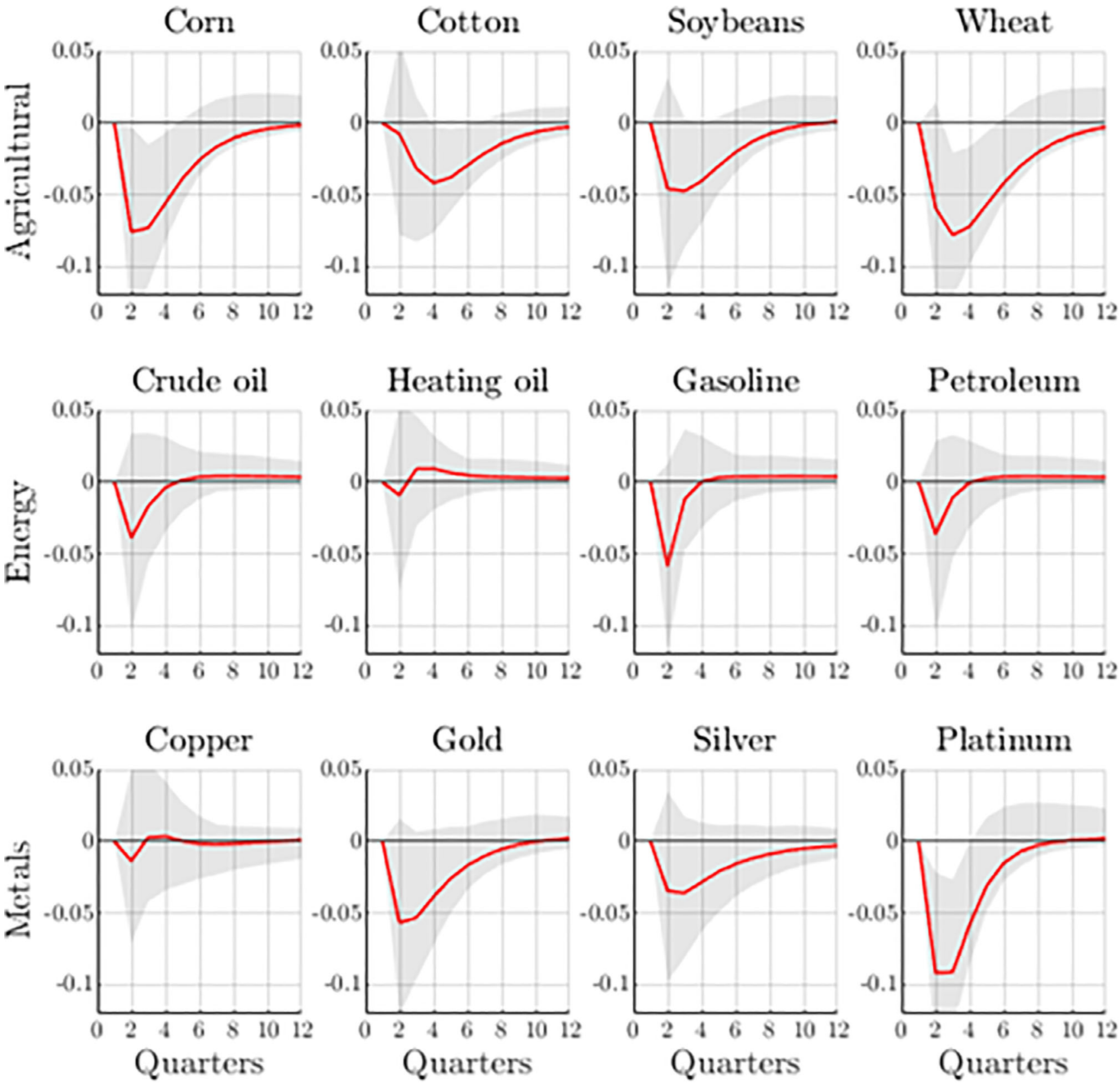

FIGURE 5 Response of GDP growth to commodity price uncertainty shocks (9-factor VAR model - controlling for exchange rate)
Notes: The solid red line shows the estimated orthogonalized IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1000 replications. The estimated orthogonalized IRFs are expressed in percentages (%). [Colour figure can be viewed at wileyonlinelibrary.com]

4.2.3 | 9-Factor VAR (with exchange rate) results

In this section, we present the VAR results of our 9-factor VAR model presented in Equation (7) in which we control also for the U.S. effective exchange rate. Motivated by the findings in the literature showing the significant dynamic interactions between commodity prices and exchange rates (e.g. Chen et al., 2010; Ferraro et al., 2015, among others), we control for the exchange rate in the VAR to examine whether the channel through which commodity price uncertainty affects the U.S. real economic activity passes through exchange rates. Figures 5 and 6 below show the response of GDP and IPI growth to commodity uncertainty shocks when controlling for dynamic interactions between commodity price uncertainty and the U.S. effective exchange rate in the VAR.

From Figures 5 and 6, we observe that the responses of GDP growth and IPI growth to agricultural, metals and energy price uncertainty shocks remain roughly

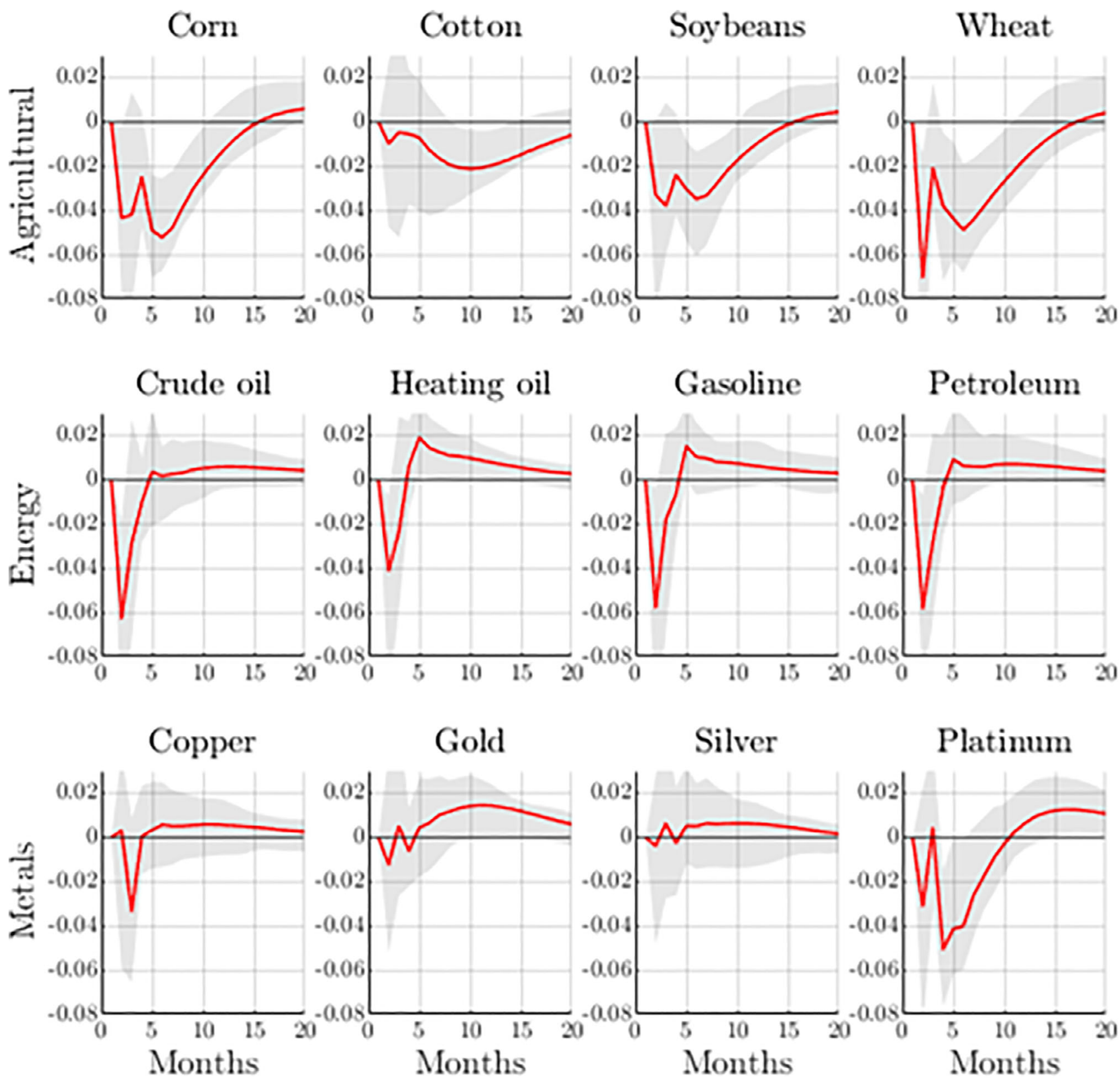

FIGURE 6 Response of IPI growth to commodity Price uncertainty shocks (9-factor VAR model - controlling for exchange rate)
Notes: The solid red line shows the estimated orthogonalized IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1000 replications. The estimated orthogonalized IRFs are expressed in percentages (%). [Colour figure can be viewed at wileyonlinelibrary.com]

unchanged when controlling for exchange rates, hence, we conclude that the transmission channel through which commodity uncertainty shocks arrive to the real economy does not pass through exchange rates.

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 ($\Delta CONS$), 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 7 shows the respective

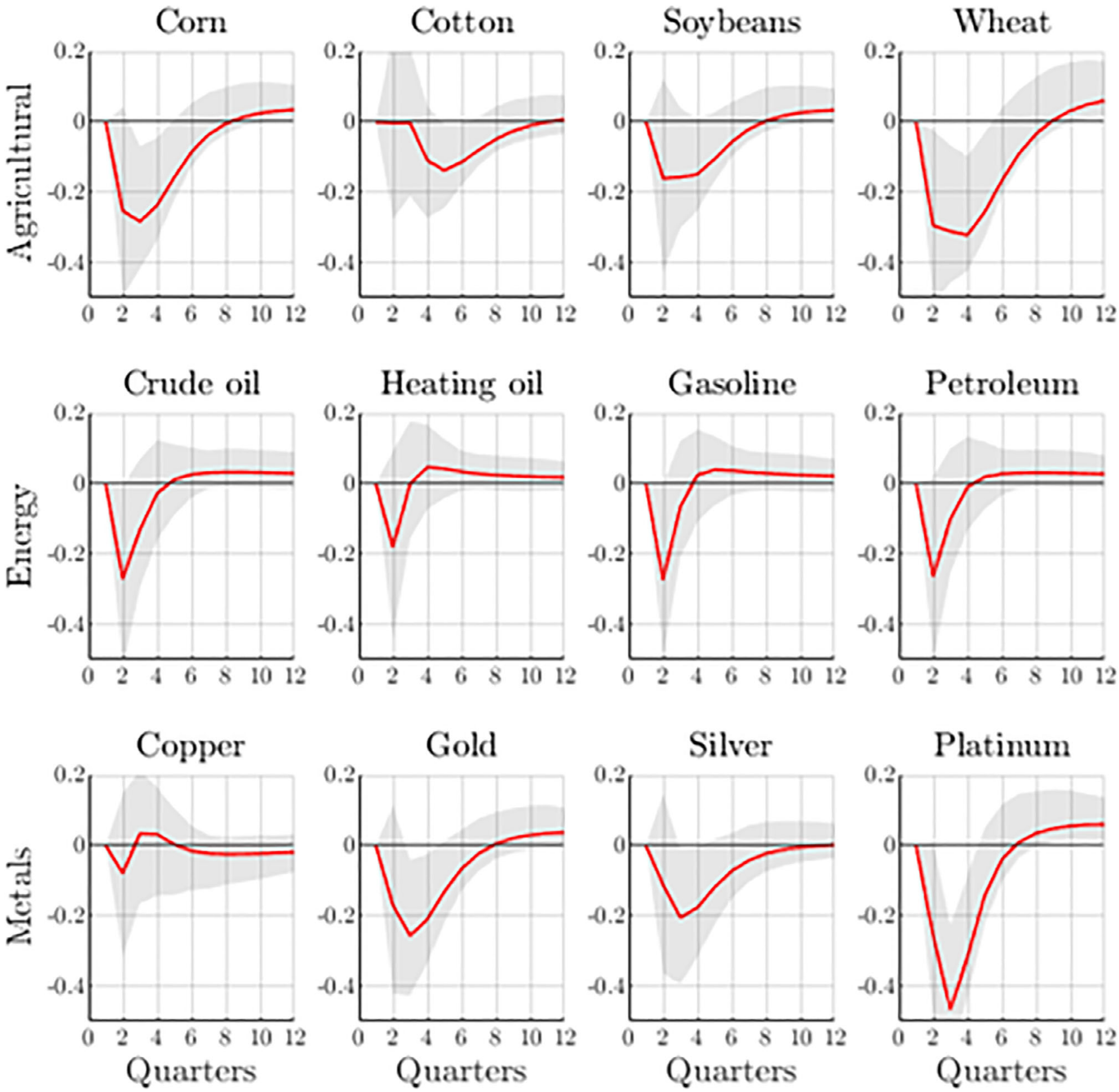

FIGURE 7 Response of investment growth to commodity Price uncertainty shocks
Notes: The solid red line shows the estimated orthogonalized IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1000 replications. The estimated orthogonalized IRFs are expressed in percentages (%). [Colour figure can be viewed at wileyonlinelibrary.com]

orthogonalized IRFs of investment growth based on the multivariate VAR models.

From Figure 7, we observe that a positive shock in the realized variance of corn, wheat, gold and platinum results to significant drops in the U.S. investment growth. More specifically, an unexpected positive one-standard-deviation shock in the realized variance of corn and wheat leads to a drop of approximately 40 basis points in the U.S. investment growth 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 market reduces the U.S. investment growth by nearly 25 basis points two quarters after the initial shock, while an uncertainty shock in the platinum market results to a reduction of investment of about 40 basis points two quarters after the platinum shock, with both effects remaining significantly negative for five quarters after the initial shock. On the other hand, energy price uncertainty shocks have a statistically insignificant effect

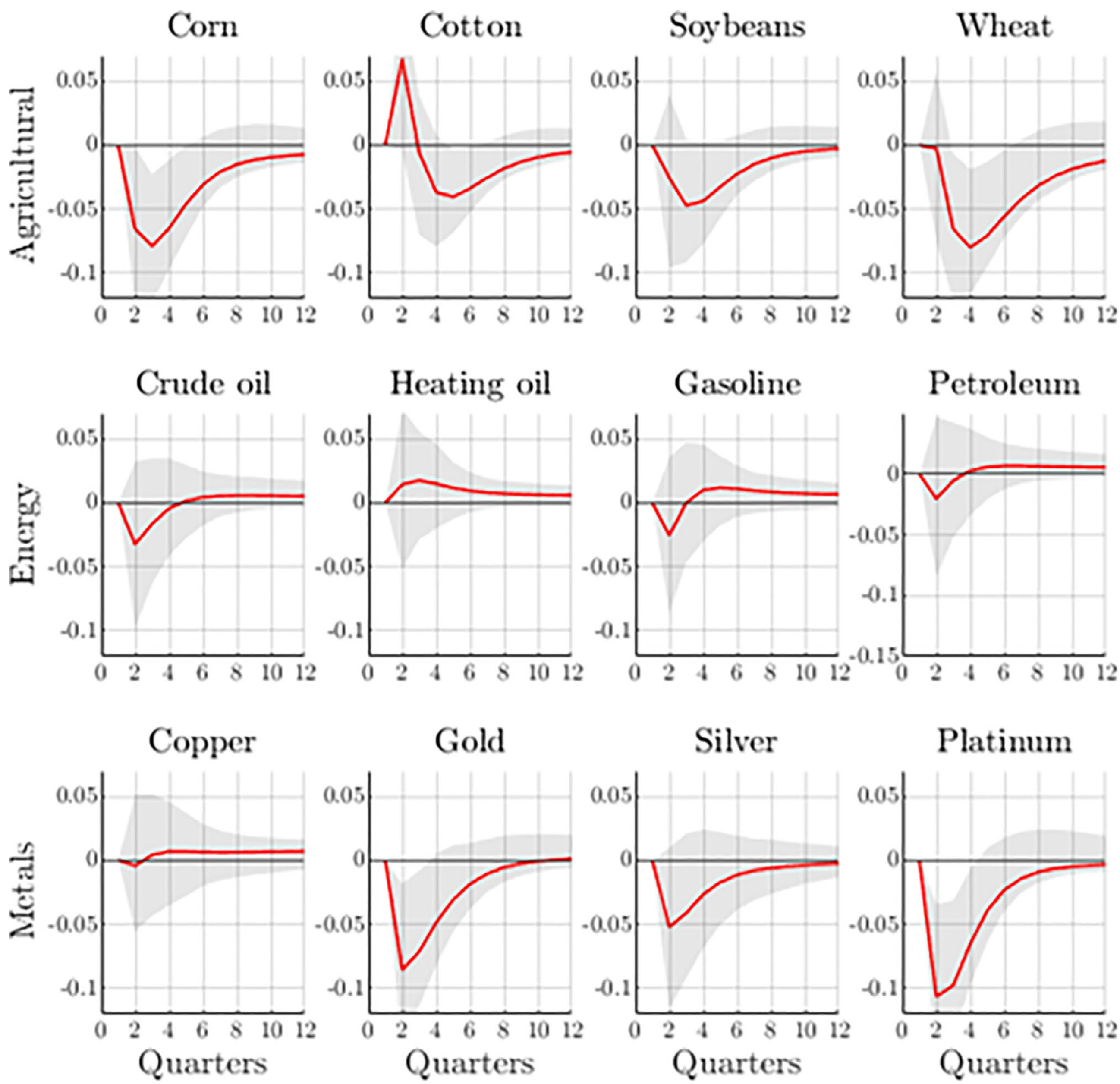

FIGURE 8 Response of consumption growth to commodity Price uncertainty shocks
Notes: The solid red line shows the estimated orthogonalized IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1000 replications. The estimated orthogonalized IRFs are expressed in percentages (%). [Colour figure can be viewed at wileyonlinelibrary.com]

on the U.S. investment growth. We also estimate the baseline VAR model in which we use consumption expenditures growth ($\Delta CONS$) as the first variable in the VAR ordering (Equation (3)). Figure 8 shows the estimated orthogonalized IRFs for agricultural, energy and metals uncertainty shocks, respectively.

The responses (Figure 8) clearly show that the impact of agricultural volatility shocks in the U.S. 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 more than 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 to consumption. However, we also find that metals commodity markets, like gold and platinum, have also a negative dynamic effect on the

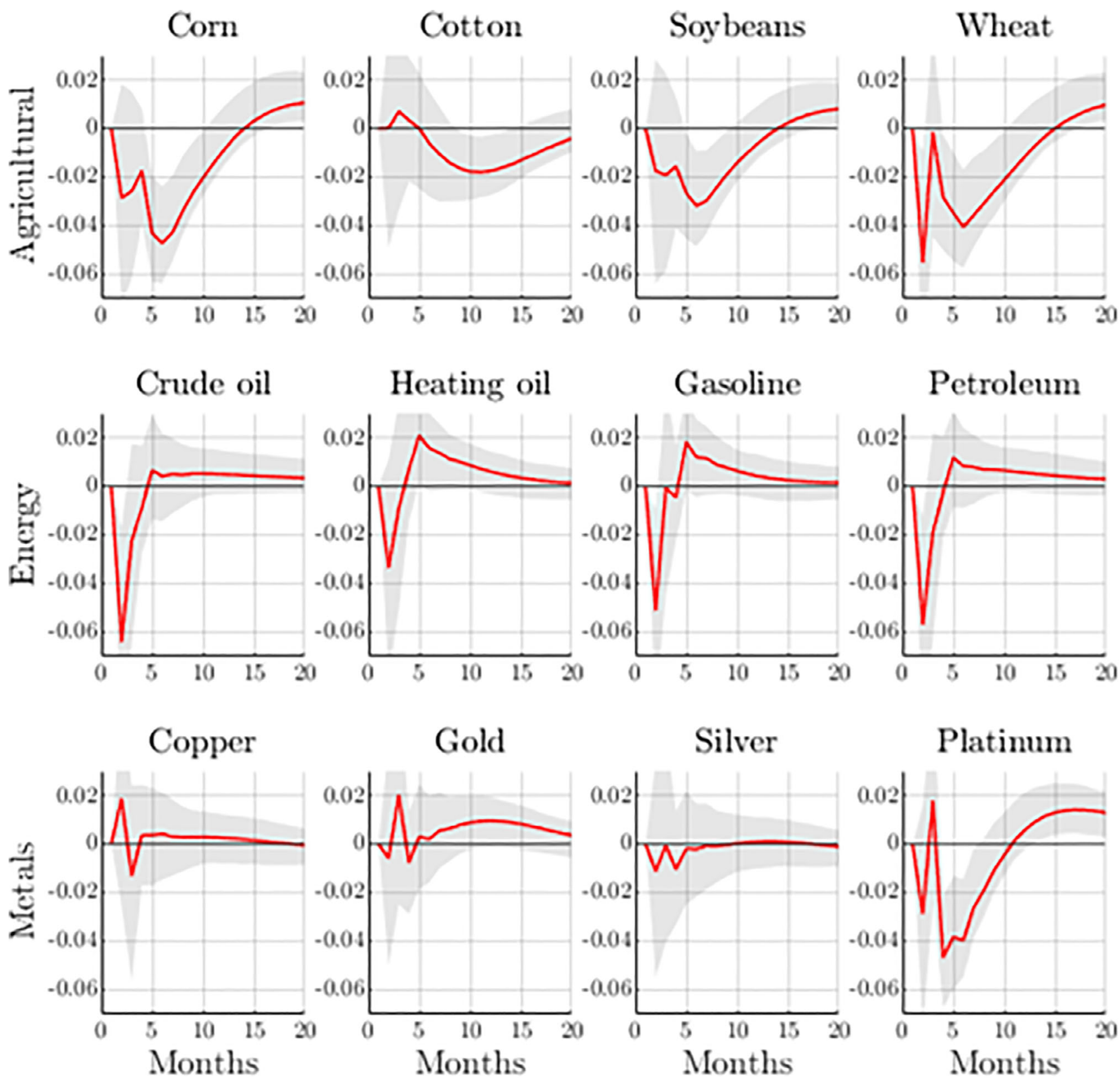

FIGURE 9 Response of capacity utilization to commodity Price uncertainty shocks
Notes: The solid red line shows the estimated orthogonalized IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1000 replications. The estimated orthogonalized IRFs are expressed in percentages (%). [Colour figure can be viewed at wileyonlinelibrary.com]

U.S. consumption growth. These findings are in line with the findings of Edelstein and Kilian (2009) that 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 show here that their empirical finding holds for agricultural and metals markets, by showing that positive uncertainty shocks in these markets reduce consumption expenditure. However, we fail to verify the same for energy markets. 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 the monthly frequency. Figure 9 shows the estimated orthogonalized IRFs for agricultural, energy and metals uncertainty shocks, respectively.

The IRFs (Figure 9) provide a similar evidence with that from the other measures of economic activity; that the impact of agricultural volatility shocks in the U.S. 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

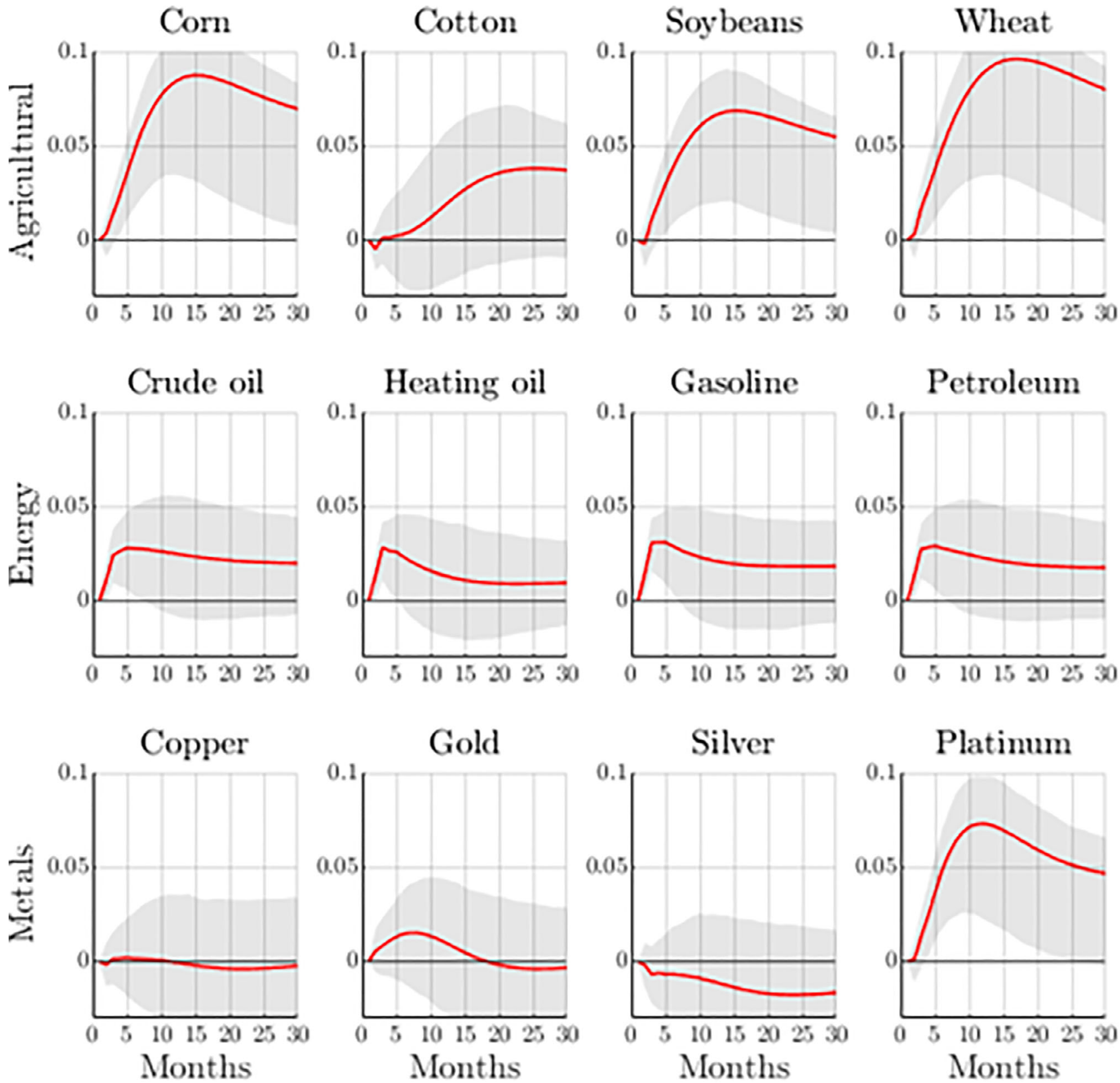

FIGURE 10 Response of unemployment rate to commodity Price uncertainty shocks

Notes: The solid red line shows the estimated orthogonalized IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1000 replications. The estimated orthogonalized IRFs are expressed in percentages (%). [Colour figure can be viewed at wileyonlinelibrary.com]

model, in the monthly frequency, where we explore the dynamic responses of commodity price uncertainty shocks on the unemployment rate (*UNEMP*) - as another proxy for the U.S. economic activity.[21] Figure 10 shows the estimated orthogonalized IRFs for agricultural, energy and metals uncertainty shocks respectively.

The estimated IRFs (Figure 10) 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 the U.S. 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 smaller effect (in both magnitude and persistence) on US unemployment. The increased significance of agricultural uncertainty shocks on US unemployment, may stem from the fact that a large percentage of global production of major globally traded agricultural commodities, like corn and wheat, takes place in US, hence, the rising uncertainty regarding future agricultural prices, postpones investment and production decisions of farmers and producers in the fear of uncertain profits due to high volatility in global corn and wheat prices. At the aggregate level, this is a possible channel explaining why higher agricultural price uncertainty results to increasing the U.S. unemployment rate.

These additional results provide further robustness to our findings and conclusions from the main VAR analysis since all alternative proxies of economic activity (industrial production, investment and consumption components of GDP, capacity utilization and the unemployment rate) are found to be adversely affected by agricultural and metals markets 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 article 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 the U.S. GDP and its components and with economic recessions, with the recessionary impact of agricultural and metals commodity markets being larger in magnitude and persistence compared to that of energy markets.

Our VAR analysis also shows that the investment and consumption component of GDP are more sensitive to agricultural and metals commodity price uncertainty shocks, with the agricultural price uncertainty shocks having the more pronounced negative effect on aggregate consumption expenditure. These findings provide further empirical insights on the literature showing the significant linkage between agricultural prices with consumer prices and demand (Dewbre et al., 2008). What we additionally show here is that uncertainty in major agricultural markets has a persistently negative impact on the U.S. aggregate consumption expenditure. Our article is the first to show that food price volatility has significant adverse effects on consumption, not only of emerging economies – as the relevant literature suggests (e.g. Fulton & Reynolds, 2015), but also on developed and industrialized economies like the United States. One possible mechanism may stem through the fact that a significant percentage (more than 30% according to the US Department of Agriculture) of global production of some major globally traded agricultural products like corn and wheat takes place in US. One pertinent variable that is sensitive to agricultural price volatility is agricultural exports, which have varied widely over the study period. For instance, figures from the US Department of Agriculture show that the U.S. exports of corn were over 60 million metric tonnes in 2007 and less than one-third that amount in 2012. Agricultural exports, in turn, have a direct effect on other important measures, including the US balance of payments. Agricultural price volatility also affects farm and farm-related employment, government farm price supports, and the food insecurity allotments of the U.S. Supplemental Nutrition Assistance Program meant to combat food insecurity. Furthermore, the greater sensitivity of the U.S. economic activity to agricultural uncertainty shocks may partly stem from the increased role of biofuels which have created more interdependence between agricultural markets, like corn and soybeans, and the crude oil market (De Gorter & Just, 2009). More research is needed to determine the mechanisms through which negative economic effects occur as a result of price uncertainty for both agricultural commodities and metals. We leave this question as a potential avenue for future research.

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 the 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.

ACKNOWLEDGEMENTS

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ENDNOTES

[1] Smith and Lapp (1993), for example, empirically verify this for the U.K. economy, by showing that the volatility in the U.K. agricultural farm prices is significantly higher in times of macroeconomic uncertainty.

[2] For example, the literature on the linkages between uncertainty and monetary policy show that the economic effects of monetary policy are less during uncertain times both in the United States (Aastveit et al., 2017) and the Euro Zone (Pellegrino, 2018). Also, after an uncertainty shock, monetary policy has been found to be more effective in stabilizing economic activity during expansions rather than recessions (Caggiano et al., 2017). Lastly, monetary policy uncertainty results in lower inflation in the short term, while long-term monetary policy uncertainty leads to higher inflation (Creal & Wu, 2017).

[3] The literature has extensively shown that in many occasions the monetary policy authority reacts (at some degree) to oil price shocks by raising the Fed funds 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 the U.S. 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.

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

[5] 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. The realized variance is multiplied by 252 (the number of trading days for one calendar year) in order to be annualized.

[6] 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.

[7] Our orthogonalized 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.

[8] We also estimate the VAR model using, instead of the Fed funds rate, the M2 money supply growth as an alternative policy instrument, and our results remain unaltered. These additional results can be provided upon request.

[9] 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 1988 M1 to 2017 M1. In the robustness section we additionally examine multivariate VAR models, in the quarterly frequency, for the two main components of GDP; investment growth (ΔINV) and consumption expenditures growth ($\Delta CONS$), 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.

[10] Moreover, we additionally estimate a structural VAR model using identifying restrictions which we allow for monetary policy to respond to changes in inflation and output with a significant lag, after the contemporaneous interrelations between commodity markets and the macroeconomy have taken place. Hence, in this SVAR identification strategy, we also restrict monetary policy to have a short-run (instantaneous) response to commodity price uncertainty shocks, while at the same time it responds to changes in output and inflation as the standard macroeconomic theory suggests (see Bloom, 2009; Bernanke et al. (1997), Caggiano et al., 2014; among others). These results are provided in our appendix.

[11] We must state that, just like our baseline endogenous VAR model, the results of the exogenous VAR model are also insensitive to the ordering of the endogenous variables. These results can be provided upon request.

[12] As with our baseline VAR model, the results of the 9-factor VAR as insensitive to the VAR ordering. These additional VAR results can be provided upon request.

[13] All variables have been tested for stationarity and the null hypothesis of unit root has 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.

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

[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 show that only agricultural uncertainty remains a significant predictor of the U.S. IPI growth on the multivariate regression setting. These results are available upon request.

[16] 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. 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 & 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.

[17] 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.

[18] In Section 4.2.2 we additionally estimate a VAR 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.

[19] Our results remain robust to the inclusion of alternative monetary policy instruments like the 3-month U.S. Treasury Bill rate and the M2 money supply growth. These additional results can be provided upon request.

[20] 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 the 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).

[21] 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.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

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APPENDIX A

In the appendix, we provide the description and results of our SVAR model with our short-run restrictions where we restrict monetary policy to have a contemporaneous response to commodity and stock-market uncertainty shocks, while, being placed last in the SVAR ordering it is allowed to respond to changes in output and inflation with a significant (one period) lag, like the standard macroeconomic literature suggest (Bernanke et al., 1997; Bloom, 2009; Caggiano et al., 2014; among others).

Hence, in this way, we estimate an SVAR model with the following VAR ordering:

$$Z_t = [COMRV\ NFL\ \Delta GDP\ UNEMP\ FFR]'. \tag{A1}$$

The ordering of the SVAR is that of Caggiano et al. (2014), hence, with this ordering we assume that commodity uncertainty shocks have a direct effect on inflation and real GDP growth, while monetary policy (*FFR*) reacts last after observing the fluctuations in output and inflation.

The SVAR model representation is given below:

$$A_0 Z_t = b + \sum_{i=1}^{h} A_i Z_{t-i} + z_t. \tag{A2}$$

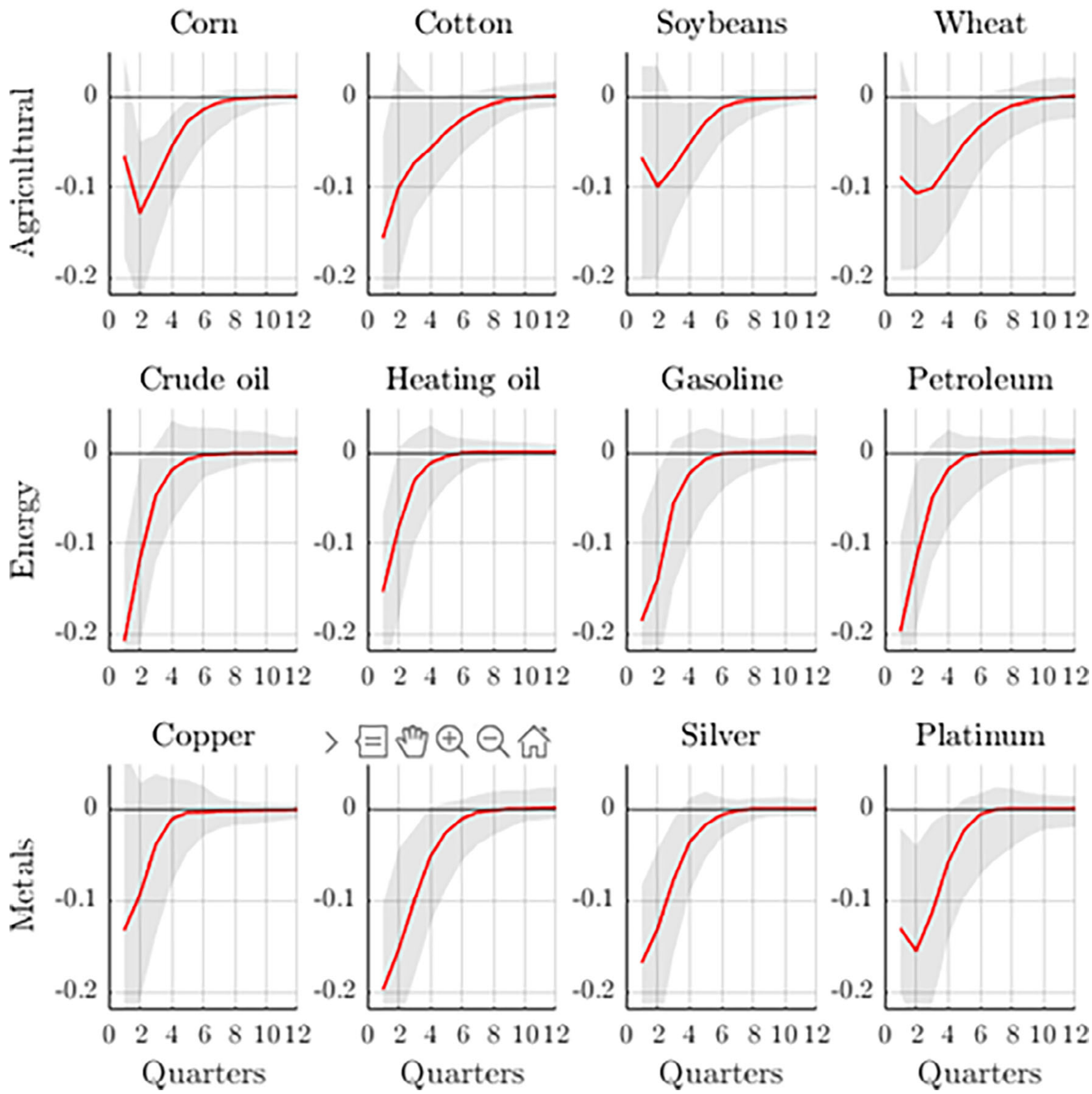

FIGURE A1 Response of GDP growth to commodity price uncertainty shocks (SVAR model)
Notes: The solid red line shows the estimated orthogonalized IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1000 replications. The estimated orthogonalized IRFs are expressed in percentages (%). [Colour figure can be viewed at wileyonlinelibrary.com]

In Equation (A2), z_t is the vector with orthogonal structural innovations and h is the lag-length of the SVAR model which is chosen based on the Akaike optimal lag-length criterion. The recursive structure of matrix A_0 identifying short-run restrictions in Equation (A2) is given below:

$$A_0 = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \tag{A3}$$

These short-run restrictions monetary policy has zero short-run effect on commodity price uncertainty and output fluctuations, and it can only respond one quarter after observing the shocks in commodity markets, inflation and output. On the other hand, commodity price uncertainty is allowed to have a short-term direct effect on both inflation and economic activity.

The results of the SVAR model are given in Figures A1 and A2 below. As we observe from the results in Figures A1 and A2, the responses of GDP and IPI growth to metals, energy and agricultural uncertainty shocks are all negative and statistically

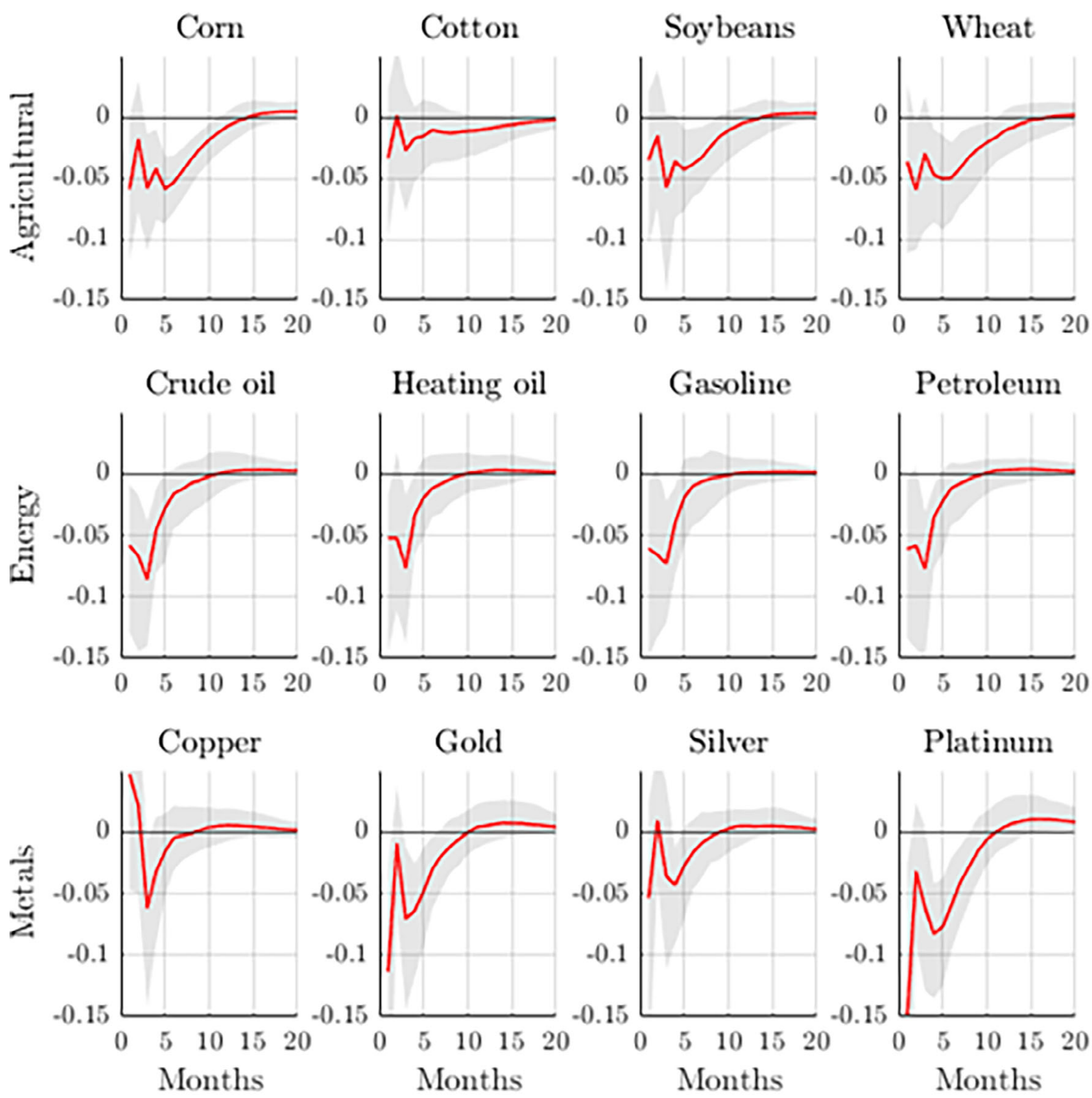

FIGURE A2 Response of IPI growth to commodity Price uncertainty shocks (SVAR model)
Notes: The solid red line shows the estimated orthogonalized IRFs and the grey shaded area show the corresponding 90% bootstrapped confidence intervals based on 1000 replications. The estimated orthogonalized IRFs are expressed in percentages (%). [Colour figure can be viewed at wileyonlinelibrary.com]

significant. Hence, in this SVAR framework, in which we restrict the monetary policy to make intervention when observing increasing uncertainty in commodity markets, the impact of agricultural, metals and energy commodity price uncertainty is negative and significant.