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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, metals and energy markets depresses US economic activity and acts as an early warning signal for US recessions with a forecasting horizon ranging from one to twelve months. The results reveal that uncertainty shocks in agricultural and metals markets are more significant for the US macroeconomy when compared to 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 response to energy uncertainty shocks is significantly reduced due to either systematic policy reactions or random shocks in monetary policy.

Keywords: *Volatility*, *Commodity Prices*, *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). 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). Overall, 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 shows the negative impact of rising uncertainty on the macroeconomy (Bachman *et al*. 2013; Baker *et al.* 2016; Basu and Bundick 2017; Bloom 2009; Caggiano *et al*. 2014; Caldara *et al*. 2016; Carriere-Swallow and Cespedes 2013; Carruth *et al*. 2000; Drechsel and Tenreyro 2018; Ilut and Schneider 2014).[1] All these empirical studies show the negative macroeconomic effect of uncertainty shocks by proxying economic uncertainty using stock-market volatility, the VIX index or indexes of uncertainty about future economic policy.

[1] 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.

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. Motivated by previous theoretical and empirical findings, 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). 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 all these studies identify the negative macroeconomic impact of oil price uncertainty, there is no empirical work showing 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 energy and non-energy (agricultural and metals) commodity price uncertainty shocks.

Our results show that uncertainty shocks in agricultural, metals and energy commodity markets have a significant negative impact on US activity and its components. More specifically, using regression analysis for each individual commodity price uncertainty series on the contemporaneous change in the quarterly real GDP, we report negative and statistically significant coefficients for all commodities (except soybeans). Furthermore, when employing forecasting regressions on investment and real GDP growth, we report negative and statistically significant coefficients for all the commodity series and for forecasting horizons ranging from one to three quarters. Interestingly, the uncertainty series of agricultural and metals commodities, like wheat, gold and platinum, have higher predictive power on investment and real GDP growth when compared to the energy markets. These findings are the first to show the significantly higher predictive information power 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 (see, for example, Elder and Serletis 2010; Jo 2014; Rahman and Serletis 2011), we contribute to the literature by showing that the role of non-oil commodity uncertainty shocks are more significant for the macroeconomy when compared to oil uncertainty shocks. In order to examine the dynamic responses of economic activity to commodity price uncertainty shocks, we estimate a VAR model in which we control for various additional factors that are found to affect economic activity such as monetary policy, the rate of inflation and the slope of the yield curve.

In addition, in order to find the pure (net) recessionary impact of commodity price uncertainty shocks, we 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 many agricultural and metals commodities (like gold, wheat and platinum) have significant real effects on the macroeconomy that are completely unrelated to inflation and to any systematic monetary policy interventions. The VAR analysis shows that the estimated macroeconomic impact of uncertainty shocks in these commodity markets remains robust to the inclusion of alternative economic uncertainty measures, inflation 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, thus, are broadly in line with the findings of Bernanke *et al*. (1997) since we provide evidence that the significance of oil uncertainty shocks vanishes when we control for inflation and monetary policy shocks in the multivariate VAR model.[2] In this paper, we provide further empirical support to this argument by showing that the oil price uncertainty shocks become insignificant in our multivariate VAR setting. In simple words, our results provide further 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

[2] 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.

increase in oil prices, as opposed to the ensued tightening of monetary policy".[3] On the other hand, our VAR analysis clearly shows that this is not the case for non-oil commodities. The shocks of non-oil commodities, like corn, wheat, gold and platinum, have a significant and long-lasting negative impact on US macroeconomic activity. For example, our 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 initial shock.

Furthermore, we show that price uncertainty shocks of several agricultural and metals commodities, like corn, wheat, gold and platinum, have a larger and more persistent impact on the consumption component of US GDP. This finding is 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 this empirical finding by showing that, apart from energy price jumps, price uncertainty in energy commodities

[3] 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. Bernanke *et al.* (2004) use alternative structural VAR identification schemes and show that systematic monetary policy responses remain accountable for about half of the depressing impact of oil shocks on output. On the other hand, Hamilton and Herrera (2004) show that the Fed does not always have the ability to eliminate the recessionary consequences of oil shocks. Moreover, Carlstrom and Fuerst (2006) show that it is difficult to disentangle the recessionary impact of oil prices and of changes in the Fed fund rate, since most US economic recessions are associated with rising oil prices and a contractionary monetary policy. While the common view is that the Fed does not systematically respond to oil shocks since commodity prices are not explicit monetary policy target prices, the general consensus in the literature is in line with the more recent empirical findings of Kara (2017), who shows that the Fed includes oil prices in its policy rules, although the weight the Fed assigns to these prices is much smaller compared to their share in the US economy.

also has a persistently negative impact on consumption expenditures. In addition, our empirical findings lead to the conclusion that not only energy price uncertainty shocks, but also uncertainty shocks of various metals and agricultural commodities have an impact, of equal magnitude, on aggregate US consumption. Moreover, we show that commodity price uncertainty shocks affect negatively several other widely accepted proxies of economic activity, like the index of industrial production and the employment rate. The policy implication behind our empirical findings is that policy-makers should turn their attention to both agricultural and metals price fluctuations instead of perceiving oil uncertainty shocks as the only commodity-related threat for the macroeconomy.

Finally, our probit models indicate that a rise in the volatility of agricultural, metals and energy prices is associated with a higher probability of an economic recession in the US for horizons ranging from one to twelve months. More specifically, the energy volatility series have higher predictive information content for US recessions over short-term (up to two-month) forecasting horizons, while the agricultural and metals volatility series give significant forecasts on US recessions for longer-term forecasting horizons. The predictive power of commodity price uncertainty series for economic recession remains robust to the inclusion of various macro-factors that are used for the prediction of US economic recessions, such as the slope of the yield curve (Estrella and Hardouvelis 1991) and the economic policy uncertainty index (Baker *et al.* 2016; Karnizova and Li 2014).

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** provides robustness checks. Finally, **Section 6** concludes.

2. Methodology

2.1 Realized variance in commodity markets

Our uncertainty measure is the realized variance (RV) 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:

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

Where F_t is the nearby commodity futures price on trading day t. $RV_{t,T}$ is our estimated realized variance for each period (t,T).[4] The realized variance is then multiplied by 252 (the number of trading days for one calendar year) in order to be annualized ($COMRV = RV_{t,T} * 252$).

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

[4] 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.

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.[5]

2.2 VAR model

Following Bernanke *et al.* (1997), we estimate a multivariate VAR model in which we control also 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 (Carlstrom and Fuerst 2006; Hooker 2002; Kara 2017). In addition, we control for all the alternative proxies of macroeconomic and financial market uncertainty like the economic policy uncertainty index (Baker *et al*. 2016; Karnizova and Li 2014) 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 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 the

[5] 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. All these additional results can be provided upon request.

findings of Elder and Serletis (2010) and Jo (2014), since they do not include in their VAR identification schemes 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 the VAR modeling approach of Bekaert *et al*. (2013), we choose to place macroeconomic variables first and the financial variables (term spread, stock-market and commodity market) last in the VAR ordering due to the more sluggish response of the former compared to the latter. 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 ordering of our baseline 8-factor VAR model is as follows:

$$[\Delta GDP \;\; INFL \;\; UNEMP \;\; \Delta M2 \;\; TERM \;\; EPU \;\; SP500RV \;\; COMRV] \tag{3}$$

ΔGDP stands for the growth of real US GDP, *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 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 component of GDP (*ΔINV*) and the growth of the industrial production index (*ΔIPI*) as alternative proxies of economic activity in the US.[6]

2.3 Forecasting regression models

We complement our VAR analysis on the impact of commodity uncertainty shocks on US economic activity by using single-equation forecasting regression models. We, thus, estimate bivariate OLS forecasting regressions in which we use the realized variance of commodity prices as the only predictor of economic activity. The bivariate time-series forecasting regression model is given in **Equation (4)** below:

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

where *ΔGDP* is the growth of real US 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 investment growth (*ΔINV*) and the industrial production index growth (*ΔIPI*) of US as alternative measures of economic activity.

[6] The variables (in quarterly frequency) used in the VAR analysis cover the period from 1988 Q1 to 2016 Q4, except for the VAR model for US IPI which is employed in monthly frequency and covers the period 1988 M1 to 2017 M1.

Furthermore, and following our baseline 8-factor VAR model specification used in the VAR analysis, we estimate multivariate OLS forecasting regressions in which we include key macroeconomic and financial indicators of economic activity for the US on the left-hand side of the predictive regression equation. The multivariate time-series forecasting regression model, where we control for macroeconomic and financial fundamentals, is given in **Equation (5)** below:

$$\begin{aligned}\Delta GDP_t &= b_0 + b_1 COMRV_{t-k} + b_2 SP500RV_{t-k} + b_3 EPU_{t-k} \\ &+ b_4 TERM_{t-k} + b_5 INFL_{t-k} + b_6 \Delta M2_{t-k} + b_7 UNEMP_{t-k} + \varepsilon_t\end{aligned}, \qquad (5)$$

where *ΔGDP* is the growth of real US GDP, *COMRV* is the realized variance of agricultural, energy and metals commodity futures returns, respectively, and *SP500RV*, *EPU*, *TERM*, *INFL*, *ΔM2* and *UNEMP* are the macroeconomic and financial controls. Similarly with the bivariate models, we estimate the multivariate forecasting regression models of agricultural, energy and metals commodity volatility (**Equation (5)**) using the growth of investment (*ΔINV*) and the growth of industrial production index (*ΔIPI*) for US, respectively, as the dependent variable instead of the growth of real GDP.[7]

3. Data

3.1 Commodity prices 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

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

energy (crude oil, heating oil, gasoline, petroleum) commodity futures. Our daily commodity data covers the period from January 1988 to January 2017.[8]

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 expenditure (*CE*), investment (*INV*), Industrial Production Index (*IPI*), M2 money supply (*M2*), 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.

4. Empirical Analysis

4.1 Descriptive statistics

In this section we present the descriptive statistics for the variables used in our main analysis. **Table 1** below shows the descriptive statistics of the quarterly time-series and the correlation matrix between quarterly commodity volatility series.[9]

[8] Our quarterly dataset consists of the period from 1988 Q1 to 2016 Q4, while our monthly dataset (discussed in the online Appendix) covers the period 1988 M1 to 2017 M1.

[9] We use both quarterly and monthly time series models in our analysis. In the main body of the paper we report the descriptive statistics and the correlation matrix of the quarterly time series while in the online Appendix we additionally provide descriptive statistics for the monthly dataset and the respective correlation matrix for the commodity volatility series in monthly frequency.

[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 RV series for energy commodity prices is much higher compared to the standard deviation of non-energy RV 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 quarterly commodity RV series.

[Insert Table 2 Here]

Table 2 shows that the correlations between commodity volatility series are positive and, in most cases, greater 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 RV series of the same commodity class become even higher, a fact which indicates that the dynamics of commodity markets are being driven by common macroeconomic factors. These results are broadly in line with the findings of Bakas and Triantafyllou (2018), who show that common macro-factors drive the time-varying volatility in agricultural, energy and metals futures markets.

4.2 The impact of commodity uncertainty on the US macroeconomy

In this section we present the impact of agricultural, energy and metals commodities price uncertainty on US real GDP and investment growth. First, we estimate univariate regressions, presented in **Equation (4)**, in which we include the realized variance of commodity prices as the only explanatory variable. **Table 3** shows the regression results of our univariate regression on real GDP growth using commodity price uncertainty as our only predictor.

[Insert Table 3 Here]

The results shown in **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 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. Our results are in line with the findings of 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 univariate 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. Moreover, we additionally empirically examine the effect of commodity price volatility on US investment growth. The results of the univariate regression model are shown in **Table 4**.

[Insert Table 4 Here]

The results displayed in **Table 4** clearly show that commodity price uncertainty shocks of metals and energy commodity markets are robust indicators of depressed investment in the US economy. The negative impact of metals and energy market uncertainty on aggregate investment provides further empirical support to the theory of investment under uncertainty (Pindyck, 1991) and are in line with the findings of Elder and Serletis (2010), who find a negative impact of oil price uncertainty on US investment. Our regressions on domestic investment show that only the metals and energy commodity uncertainty series have predictive power on investment, while the coefficients of agricultural price uncertainty series are insignificant. These results were somewhat expected, since agricultural commodities are mostly linked with the consumption and not the investment side of the macroeconomy.

We additionally estimate multivariate regression models, presented in **Equation (5)**, in which we control for fundamental indicators of economic activity like inflation, monetary policy, the slope of the term structure of interest rates (Estrella and Hardouvelis 1991), stock-market volatility (Bloom 2009; Hamilton and Lin 1996) and economic policy uncertainty (Baker *et al.* 2016). **Table 5** reports the results of our multivariate OLS forecasting regression model on quarterly GDP growth using contemporaneous values of commodity uncertainty series respectively.

[Insert Table 5 Here]

From **Table 5** we observe that the contemporaneous impact of metals and energy uncertainty on economic activity is negative and statistically significant and remains robust to the inclusion of significant determinants of economic activity like inflation, monetary policy (the M2 money supply growth) and the slope of the US Treasury yield curve.

Moreover, the results displayed in **Table 5** show that energy price uncertainty has extra explanatory power when compared to popular economic uncertainty proxies that have a negative impact on the macroeconomy, such as the stock-market volatility (Bloom 2009) and the economic policy uncertainty (Baker *et al.* 2016). In simple words, the price volatility of crude oil, petroleum and gold commodity futures seems to have additional predictive information content on business cycle variability that is not captured by the other popular uncertainty proxies. Furthermore, the increased price uncertainty of some agricultural commodities, like cotton and wheat, also has a significant negative contemporaneous effect on US economic activity. Overall, our results show that, apart from energy markets, rising uncertainty in metals and agricultural markets has a significant negative contemporaneous effect on US GDP growth. Our results provide further empirical support to the findings of Elder and Serletis (2010) on oil price uncertainty, and they are broadly in line with the findings of Kang *et al.* (2017), who find that long-run shocks of commodity prices account for 11.9% of variation in US output.

In order to control for the lagged impact of commodity uncertainty on the US GDP growth, we run the same regression models in which we regress quarterly GDP growth having a one-quarter forecasting horizon (we use the lagged series of our explanatory variables). In this way, we examine the persistence of the impact of commodity uncertainty; at the same time, we implicitly make a first empirical examination of whether the impact of commodity uncertainty shocks is absorbed by inflation or by systematic monetary policy responses. **Table 6** shows the respective results of our multivariate predictive regression model on US GDP growth.

[Insert Table 6 Here]

From the results shown in **Table 6**, we observe that the coefficients of energy and metals uncertainty shocks become smaller (in absolute values) and turn from significantly negative to statistically indistinguishable from zero. The econometric interpretation of this result is that, while energy and metals commodity uncertainty shocks have a significant contemporaneous effect on GDP growth, this effect vanishes after one quarter due to the fact that these shocks either tend to be inflationary (since we now control for lagged inflation) or are offset by systematic monetary policy shocks.

Carlstrom and Fuerst (2006) and Cologni and Manera (2008) support this view for oil markets by finding that it is difficult to infer whether US 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. Our results on oil and metals uncertainty shocks are in line with those of Kang *et al.* (2017), who find that commodity price shocks account for 25.1% of variation in US consumer prices, implicitly indicating the significant inflationary pressures of commodity price shocks. Bernanke *et al.* (2004) provide additional robustness to these results by estimating a VAR framework in which they do not allow monetary policy to respond to oil shocks and find that, even under the scenario of the absence of systematic policy reactions, the impact of oil price shocks is significantly weakened when they control for monetary policy shocks (measured as surprises-innovations in the Federal fund rate) in the VAR model. Our results are in line with and provide further empirical support to the findings of Bernanke *et al.* (1997, 2004) for oil markets since we can observe (**Table 6**) that the coefficient of monetary policy (M2 money supply growth), while being insignificant for the contemporaneous regressions (**Table 5**), has now turned positive and statistically significant.[10] On the other hand, we find that the impact of the lagged (one quarter before) uncertainty shocks in corn and wheat markets remains negative and statistically significant when controlling for monetary policy and other uncertainty proxies. According to Bernanke *et al.* (1997), this means that the macroeconomic impact of agricultural uncertainty shocks cannot be attributed to systematic reactions of the monetary authority since it is unrelated to shocks in monetary policy. Our findings implicitly reveal that agricultural

[10] 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.

uncertainty gives extra predictive power on GDP growth when compared to other indicators of economic activity like US inflation and other popular economic uncertainty proxies like EPU and stock-market volatility. In addition, **Tables 7** and **8** report the regression results of our multivariate OLS regression models on quarterly US investment using contemporaneous and lagged values of commodity uncertainty series respectively.

[Insert Tables 7 and 8 Here]

From the results shown in **Tables 7** and **8**, we can conclude that the theory of investment under uncertainty remains valid when we control for macro-factors that are associated with depressing aggregate investment. Interestingly, while the results presented in **Table 7** show that there is a statistically significant contemporaneous negative impact of rising uncertainty in energy commodity markets on US aggregate investment, this impact significantly deteriorates when regressing the lagged (one quarter before) values of energy price volatility on aggregate investment (see **Table 8**). At the same time, we observe that the lagged impact of monetary variables like *ΔM2* and the *TERM* turns from insignificant (in the contemporaneous regression model given in **Table 7**) to significant (in the forecasting regression model given in **Table 8**). These results implicitly reveal that the depressing impact of energy price uncertainty is significantly offset by systematic monetary policy reactions. On the other hand, the rising volatility of corn and wheat commodity markets has a statistically significant and persistently negative impact on US aggregate investment.

We lastly report the results of our bivariate and multivariate forecasting regression models (in monthly frequency) on the US industrial production index (*IPI*) growth. **Tables 9** and **10** report the regression results of our bivariate and multivariate OLS regression models on the monthly IPI growth, respectively.

[Insert Tables 9 and 10 Here]

The results from **Tables 9-10** show that the rising commodity uncertainty has a negative effect on IPI growth. As expected, the price uncertainty in the metals markets has the most significant impact on IPI growth. When controlling for additional macroeconomic and monetary factors, we observe that energy and wheat market uncertainty contain extra predictive power which is not included in other uncertainty measures like *EPU* and stock-market volatility. On the other hand, the predictive power of metals commodity price uncertainty series is significantly reduced when adding other economic uncertainty factors, a fact which shows that stock-market volatility may include the predictive information content of the metals commodity price uncertainty series.

4.3 The responses of US economic activity to commodity price uncertainty shocks

In this section we present the dynamic responses of unexpected commodity price uncertainty shocks on US economic activity and its components. More specifically, we present the estimated generalized Impulse Response Functions (IRFs) of our baseline multivariate VAR model described in **Equations (2)** and **(3)**. **Figures 1**, **2** and **3** show the estimated IRFs for the VAR models 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.

[Insert Figures 1, 2 and 3 Here]

The IRFs 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 4 basis points four quarters after the initial volatility shock, with the effect remaining 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 5 basis points three 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 (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. The empirical studies in the literature on oil price shocks show that these price shocks do not have a pure macroeconomic (recessionary) impact since they are being followed by systematic 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). 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 (*ΔM2*) and inflation (*INFL*) in our VAR model. Thus, the estimated IRFs show the net impact of commodity price uncertainty shocks on US economic activity.[11] 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. The reduced impact of oil price shocks on US GDP growth may be attributed to the fact 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

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[11] 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 analysis can be provided upon request.

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, 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 prices.

We additionally estimate an identical VAR model given in **Equations (2)** and **(3)**, in which we use US 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 prices on US aggregate investment. **Figures 4**, **5** and **6** below show the respective IRFs of US investment based on the multivariate VAR models.

[Insert Figures 4, 5 and 6 Here]

From **Figures 4-6**, 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 variance of wheat futures prices leads to a drop of approximately 15 basis points in US investment growth in about four quarters after the initial uncertainty shock, with the effect remaining negative and statistically significant for ten 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. On the other hand, energy price uncertainty shocks have a rather small and transitory negative impact on US investment growth.

We, finally, estimate a similar VAR model in which we use the IPI growth as our proxy for economic activity (*ΔIPI* is now the first variable in the VAR ordering in **Equation (3)**) – this VAR model is estimated in monthly frequency. **Figures 7**, **8** and **9** show the estimated IRFs of our VAR model when using agricultural, energy and metals price volatility series as the commodity uncertainty measure.

[Insert Figures 7, 8 and 9 Here]

Figures 7-9 show that an unexpected positive uncertainty shock in agricultural markets like corn and wheat has a more significant and long-lasting impact on industrial production index growth 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 two months 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 IPI growth to energy price uncertainty shocks is more transitory since the negative effect disappears 3-4 months after the initial energy uncertainty shock.

5. Robustness checks

In this section we provide the results of the robustness checks, which can be found in our online Appendix. In more details, we estimate the multivariate VAR model using alternative VAR orderings. The estimated IRFs based on the alternative VAR orderings remain nearly unchanged. We additionally run the same set of OLS forecasting regressions and VAR models using alternative proxies of economic activity, like the unemployment rate (*UNEMP*), the aggregate consumption expenditure growth (ΔCE) and the capacity utilization (ΔCU). These additional results provide robustness to our main findings and conclusions since all these alternative proxies of economic activity are negatively affected by agricultural and metals price uncertainty shocks, while the respective impact from the energy uncertainty shocks is much smaller. Lastly, we estimate linear probability (OLS) and probit forecasting regression models on the NBER recession index (*NBER*), and once again our main results on forecasting economic recessions remain unaltered.

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. Unlike previous studies that use a GARCH approach to infer uncertainty shocks in oil commodity prices, we measure uncertainty in commodity markets using the realized volatility of daily returns of commodity futures prices. Our paper also 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, while the short-run (contemporaneous) impact of energy price uncertainty shocks has a significant negative impact on economic activity, this effect vanishes one quarter after the initial shock. 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 expenditure. Furthermore, when controlling for systematic monetary policy reactions and for innovations in the monetary policy stance, we find that the recessionary impact of energy shocks is significantly reduced. Regarding oil shocks, our results are in line with the findings of Bernanke *et al*. (1997, 2004), who show that the predictive power of oil is significantly reduced when controlling for monetary policy in the VAR model. On the other hand, although the non-oil price uncertainty shocks have a larger and more persistent negative impact on economic activity, our findings show that the Fed does not react to these shocks. Moreover, we find that rising uncertainty in agricultural, metals and energy markets predicts economic recessions with forecasting horizons ranging from one to twelve months ahead. In terms of policy implications, our findings suggest the inclusion of agricultural and metals price variability into the central bank information variable set when making predictions (and thus adopting proactive monetary policies) in order to ameliorate the recessionary impact of commodity market turbulence.

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Tables and Figures

Table 1. Descriptive Statistics – Quarterly Dataset

	Mean	***Std. Dev.***	***Minimum***	***Maximum***	***Skewness***	***Kurtosis***
ΔGDP	0.006	0.006	-0.021	0.019	-1.169	6.555
ΔINV	0.010	0.024	-0.096	0.058	-1.014	5.610
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
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
N	116					

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 period 1988Q1 to 2016Q4.

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

	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

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 (*GDP*) Growth with Commodity Market Uncertainty

The table presents the results of the bivariate forecasting regression model on the quarterly Gross Domestic Product growth 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 Gross Domestic Product 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:

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

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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Forecasting Investment (*INV*) Growth with Commodity Market Uncertainty

The table presents the results of the bivariate forecasting regression model on Investment growth using the volatility of agricultural, energy and metals commodity futures returns. The forecasting horizon ranges from 0 to 12 quarters. *COMRV* is the realized variance and *ΔINV* is the Investment 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:

$$\Delta INV_t = b_0 + b_1 COMRV_{t-k} + \varepsilon_t$$

Panel A: Estimated b_1 coefficients

Horizon (k)	*k=0*	*k=1*	*k=2*	*k=3*	*k=6*	*k=12*
Corn	-0.130	-0.182*	-0.126	-0.051	-0.048	0.045
Cotton	-0.196**	-0.139	-0.043	0.002	0.050	0.045
Soybeans	-0.146	-0.183	-0.146	-0.034	-0.013	-0.007
Wheat	-0.119	-0.147*	-0.121	-0.081	-0.016	0.033
Crude oil	-0.100***	-0.089**	-0.047*	-0.006	0.023	0.034**
Heating oil	-0.121***	-0.100**	-0.048	-0.006	0.015	0.029
Petroleum	-0.124***	-0.112**	-0.059*	-0.010	0.028	0.039**
Gasoline	-0.116***	-0.119***	-0.070***	-0.023	0.022	0.019
Copper	-0.133**	-0.130**	-0.095***	-0.031	-0.020	-0.005
Gold	-0.409***	-0.415*	-0.419***	-0.191	-0.001	-0.049
Platinum	-0.247***	-0.298***	-0.282***	-0.201***	0.060	0.052
Silver	-0.080	-0.097	-0.070	-0.020	0.026	-0.016

Panel B: *Adjusted R^2* values

Horizon (k)	*k=0*	*k=1*	*k=2*	*k=3*	*k=6*	*k=12*
Corn	5.2	11.4	5.0	0.1	-0.1	-0.2
Cotton	10.0	4.8	-0.4	-0.9	-0.2	-0.4
Soybeans	4.0	7.0	4.2	-0.6	-0.9	-1.0
Wheat	5.8	9.6	6.3	2.3	-0.8	-0.4
Crude oil	23.8	19.0	4.7	-0.8	0.4	1.9
Heating oil	17.7	12.2	2.1	-0.9	-0.6	0.1
Petroleum	22.8	19.1	4.7	-0.7	0.3	1.4
Gasoline	20.4	22.0	7.1	0.0	-0.2	-0.4
Copper	13.6	13.3	6.7	-0.1	-0.6	-1.0
Gold	15.0	16.0	16.3	2.7	-0.9	-0.7
Platinum	13.1	20.2	18.1	8.7	-0.1	-0.3
Silver	5.4	8.6	4.0	-0.5	-0.3	-0.7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Forecasting Gross Domestic Product (*GDP*) Growth with Commodity Market Uncertainty and Controlling for Macroeconomic and Financial Fundamentals

The table presents the results of the multivariate forecasting regression model on Gross Domestic Product growth using the volatility of commodity futures returns, in which we control for key macroeconomic and financial indicators of the US economy. We use zero quarter forecasting horizon (*k=0*). The *t*-statistics reported are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The estimated beta coefficients are based on the following regressions:

$$\Delta GDP_t = b_0 + b_1 COMRV_t + b_2 SP500RV_t + b_3 EPU_t + b_4 TERM_t + b_5 INFL_t + b_6 \Delta M2_t + b_7 UNEMP_t + \varepsilon_t$$

		Corn	*Cotton*	*Soybeans*	*Wheat*	*Crude oil*	*Heating oil*	*Petroleum*	*Gasoline*	*Copper*	*Gold*	*Silver*	*Platinum*
COMRV	*Coef.*	-0.017	-0.028***	-0.018	-0.017*	-0.015***	-0.017***	-0.019***	-0.021***	-0.007	-0.069***	-0.015**	-0.023
	t-stat	-1.45	-2.62	-1.63	-1.77	-4.82	-3.88	-4.68	-4.16	-0.57	-3.37	-2.52	-1.22
SP500RV	*Coef.*	-0.057***	-0.055***	-0.059***	-0.059***	-0.047***	-0.054***	-0.046***	-0.039***	-0.059***	-0.046***	-0.055***	-0.055***
	t-stat	-5.12	-5.50	-7.47	-6.22	-5.04	-5.32	-4.84	-3.69	-4.12	-5.25	-6.10	-4.97
EPU	*Coef.*	-0.010***	-0.009***	-0.010***	-0.009***	-0.006**	-0.007**	-0.006**	-0.007***	-0.009***	-0.008***	-0.009***	-0.008***
	t-stat	-3.42	-3.20	-3.25	-3.24	-2.20	-2.51	-2.31	-2.71	-3.05	-3.04	-3.26	-2.75
TERM	*Coef.*	0.098*	0.130**	0.118**	0.109*	0.093*	0.106*	0.099*	0.105**	0.093	0.089	0.094*	0.106*
	t-stat	1.71	2.24	2.01	1.91	1.70	1.92	1.83	1.99	1.56	1.64	1.73	1.85
INFL	*Coef.*	-0.088	-0.075	-0.074	-0.078	-0.120	-0.082	-0.113	-0.104	-0.100	-0.081	-0.103	-0.085
	t-stat	-1.00	-0.81	-0.85	-0.88	-1.52	-0.94	-1.40	-1.25	-1.06	-1.04	-1.19	-0.97
ΔM2	*Coef.*	0.127	0.138*	0.112	0.129	0.064	0.076	0.062	0.068	0.096	0.125	0.129	0.094
	t-stat	1.54	1.68	1.43	1.64	0.95	1.11	0.91	0.97	1.22	1.63	1.52	1.20
UNEMP	*Coef.*	0.041	0.026	0.013	0.030	-0.038	-0.037	-0.039	-0.037	0.018	0.022	0.038	-0.003
	t-stat	0.68	0.49	0.24	0.58	-0.77	-0.72	-0.80	-0.75	0.34	0.45	0.73	-0.06
% Adjusted R^2		37.0	38.3	37.0	37.7	41.7	40.2	41.4	41.7	36.5	40.3	38.3	37.1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Forecasting Gross Domestic Product (*GDP*) Growth with Commodity Market Uncertainty and Controlling for Macroeconomic and Financial Fundamentals

The table presents the results of the multivariate forecasting regression model on Gross Domestic Product growth using the volatility of commodity futures returns, in which we control for key macroeconomic and financial indicators of the US economy. We use a one quarter forecasting horizon (*k=1*). The *t*-statistics reported are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The estimated beta coefficients are based on the following regressions:

$$\Delta GDP_t = b_0 + b_1 COMRV_{t-1} + b_2 SP500RV_{t-1} + b_3 EPU_{t-1} + b_4 TERM_{t-1} + b_5 INFL_{t-1} + b_6 \Delta M2_{t-1} + b_7 UNEMP_{t-1} + \varepsilon_t$$

		Corn	*Cotton*	*Soybeans*	*Wheat*	*Crude oil*	*Heating oil*	*Petroleum*	*Gasoline*	*Copper*	*Gold*	*Silver*	*Platinum*
COMRV	*Coef.*	-0.042**	-0.021	-0.026	-0.030**	-0.005	-0.003	-0.006	-0.013	-0.000	-0.067	-0.015	-0.044
	t-stat	-2.24	-1.36	-1.35	-2.57	-1.11	-0.43	-0.96	-1.55	-0.01	-1.57	-1.64	-1.44
SP500RV	*Coef.*	-0.040***	-0.057**	-0.053***	-0.051***	-0.058***	-0.063***	-0.058***	-0.048*	-0.065**	-0.045***	-0.053***	-0.041***
	t-stat	-2.60	-2.47	-3.32	-2.90	-2.69	-2.83	-2.62	-1.91	-2.40	-3.48	-3.67	-2.59
EPU	*Coef.*	-0.009***	-0.006**	-0.007***	-0.006**	-0.005*	-0.006**	-0.005*	-0.005*	-0.006**	-0.005**	-0.006**	-0.005*
	t-stat	-3.29	-2.47	-2.72	-2.49	-1.75	-2.13	-1.83	-1.79	-2.39	-2.07	-2.55	-1.67
TERM	*Coef.*	0.079	0.111*	0.114**	0.102*	0.087	0.091	0.090	0.092	0.091	0.077	0.082	0.096*
	t-stat	1.46	1.76	1.96	1.94	1.48	1.54	1.52	1.60	1.51	1.34	1.38	1.82
INFL	*Coef.*	-0.192	-0.206	-0.185	-0.184	-0.231	-0.221	-0.228	-0.226	-0.224	-0.205	-0.227	-0.193
	t-stat	-1.07	-0.96	-1.01	-1.04	-1.14	-1.07	-1.12	-1.11	-1.09	-1.23	-1.16	-1.20
ΔM2	*Coef.*	0.212**	0.178**	0.166**	0.199**	0.139*	0.148*	0.139*	0.131*	0.152*	0.173**	0.178**	0.135*
	t-stat	2.49	2.12	2.13	2.49	1.83	1.91	1.84	1.77	1.94	2.08	1.98	1.77
UNEMP	*Coef.*	0.091	0.025	0.016	0.047	-0.003	0.006	-0.003	-0.016	0.013	0.025	0.042	-0.012
	t-stat	1.40	0.50	0.32	0.90	-0.06	0.11	-0.05	-0.29	0.27	0.47	0.81	-0.23
% Adjusted R^2		24.5	20.1	20.8	23.6	19.6	19.0	19.5	21.0	18.9	22.9	21.2	22.8

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Forecasting Investment (*INV*) Growth with Commodity Market Uncertainty and Controlling for Macroeconomic and Financial Fundamentals
The table presents the results of the multivariate forecasting regression model on Investment growth using the volatility of commodity futures returns, in which we control for key macroeconomic and financial indicators of the US economy. We use zero quarter forecasting horizon (*k=0*). The *t*-statistics reported are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The estimated beta coefficients are based on the following regressions:

$$\Delta INV_t = b_0 + b_1 COMRV_t + b_2 SP500RV_t + b_3 EPU_t + b_4 TERM_t + b_5 INFL_t + b_6 \Delta M2_t + b_7 UNEMP_t + \varepsilon_t$$

		Corn	*Cotton*	*Soybeans*	*Wheat*	*Crude oil*	*Heating oil*	*Petroleum*	*Gasoline*	*Copper*	*Gold*	*Silver*	*Platinum*
COMRV	*Coef.*	-0.027	-0.110*	-0.057	-0.035	-0.065***	-0.071**	-0.079***	-0.069**	-0.067	-0.156*	0.000	-0.065
	t-stat	-0.51	-1.91	-0.87	-0.94	-2.76	-2.16	-2.61	-2.22	-1.45	-1.74	0.01	-0.90
SP500RV	*Coef.*	-0.172***	-0.143***	-0.162***	-0.171***	-0.105***	-0.132***	-0.101***	-0.095**	-0.116**	-0.141***	-0.188***	-0.152***
	t-stat	-3.01	-3.17	-3.69	-4.08	-2.92	-3.73	-2.64	-2.00	-2.45	-3.46	-3.74	-3.04
EPU	*Coef.*	-0.030**	-0.029**	-0.030***	-0.028**	-0.014	-0.017	-0.016	-0.021*	-0.029**	-0.027**	-0.028**	-0.026**
	t-stat	-2.51	-2.53	-2.71	-2.50	-1.14	-1.39	-1.25	-1.72	-2.53	-2.30	-2.43	-2.13
TERM	*Coef.*	0.323	0.435*	0.380	0.343	0.288	0.342	0.314	0.336	0.242	0.298	0.330	0.338
	t-stat	1.32	1.75	1.58	1.40	1.23	1.41	1.33	1.39	0.94	1.25	1.38	1.40
INFL	*Coef.*	-0.241	-0.164	-0.175	-0.215	-0.346	-0.182	-0.314	-0.272	-0.257	-0.218	-0.261	-0.216
	t-stat	-0.63	-0.43	-0.46	-0.56	-0.99	-0.50	-0.91	-0.77	-0.67	-0.61	-0.68	-0.58
ΔM2	*Coef.*	-0.034	0.067	-0.042	-0.018	-0.235	-0.185	-0.240	-0.187	-0.127	-0.022	-0.073	-0.096
	t-stat	-0.08	0.18	-0.12	-0.05	-0.65	-0.52	-0.66	-0.50	-0.32	-0.06	-0.20	-0.25
UNEMP	*Coef.*	0.243	0.256	0.201	0.233	-0.010	-0.008	-0.013	0.036	0.267	0.221	0.193	0.156
	t-stat	0.65	0.75	0.63	0.74	-0.03	-0.02	-0.04	0.11	0.92	0.69	0.61	0.48
% Adjusted R^2		20.8	22.7	21.2	21.1	26.9	25.3	26.4	24.6	22.8	22.0	20.7	21.2

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8. Forecasting Investment (*INV*) Growth with Commodity Market Uncertainty and Controlling for Macroeconomic and Financial Fundamentals
The table presents the results of the multivariate forecasting regression model on Investment growth using the volatility of commodity futures returns, in which we control for key macroeconomic and financial indicators of the US economy. We use a one quarter forecasting horizon (*k=1*). The *t*-statistics reported are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The estimated beta coefficients are based on the following regressions:

$$\Delta INV_t = b_0 + b_1 COMRV_{t-1} + b_2 SP500RV_{t-1} + b_3 EPU_{t-1} + b_4 TERM_{t-1} + b_5 INFL_{t-1} + b_6 \Delta M2_{t-1} + b_7 UNEMP_{t-1} + \varepsilon_t$$

		Corn	*Cotton*	*Soybeans*	*Wheat*	*Crude oil*	*Heating oil*	*Petroleum*	*Gasoline*	*Copper*	*Gold*	*Silver*	*Platinum*
COMRV	*Coef.*	-0.126**	-0.055	-0.081	-0.104***	-0.035**	-0.030	-0.042*	-0.047	-0.020	-0.162	-0.037	-0.110
	t-stat	-2.16	-0.84	-1.35	-2.67	-1.97	-1.28	-1.74	-1.50	-0.53	-1.21	-1.34	-1.21
SP500RV	*Coef.*	-0.228***	-0.281***	-0.267***	-0.254***	-0.259***	-0.280***	-0.258***	-0.240***	-0.282***	-0.254***	-0.274***	-0.243***
	t-stat	-4.08	-4.29	-5.41	-5.06	-4.58	-4.79	-4.37	-3.44	-4.07	-6.62	-5.96	-5.11
EPU	*Coef.*	-0.030***	-0.022**	-0.024***	-0.023***	-0.015	-0.017*	-0.015*	-0.017*	-0.022***	-0.021**	-0.023***	-0.018**
	t-stat	-3.22	-2.56	-2.83	-2.67	-1.60	-1.95	-1.69	-1.84	-2.59	-2.42	-2.74	-2.08
TERM	*Coef.*	0.497***	0.585***	0.604***	0.570***	0.509***	0.537***	0.523***	0.536***	0.505***	0.498***	0.509***	0.543***
	t-stat	2.99	2.98	3.22	3.41	2.91	3.09	3.01	3.11	2.79	2.80	2.83	3.35
INFL	*Coef.*	-0.045	-0.092	-0.019	-0.001	-0.185	-0.107	-0.167	-0.147	-0.138	-0.095	-0.147	-0.063
	t-stat	-0.09	-0.16	-0.04	-0.00	-0.36	-0.20	-0.32	-0.28	-0.26	-0.21	-0.28	-0.14
ΔM2	*Coef.*	1.037**	0.927**	0.901**	1.022**	0.770**	0.811**	0.769**	0.779**	0.841**	0.909**	0.922**	0.816**
	t-stat	2.41	2.10	2.30	2.48	2.01	2.13	2.03	2.05	2.13	2.28	2.20	2.10
UNEMP	*Coef.*	0.523**	0.321	0.300	0.410**	0.183	0.206	0.183	0.183	0.313	0.320	0.361**	0.229
	t-stat	2.30	1.61	1.56	2.00	0.93	1.00	0.91	0.89	1.64	1.64	1.98	1.19
% Adjusted R^2		32.7	30.0	30.6	33.2	31.3	30.3	31.1	31.4	29.7	31.0	30.4	31.0

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9. Forecasting Industrial Production Index (*IPI*) Growth with Commodity Market Uncertainty

The table presents the results of the bivariate forecasting regression model on the monthly Industrial Production Index growth 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:

$$\Delta IPI_t = b_0 + b_1 COMRV_{t-k} + \varepsilon_t$$

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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10. Forecasting Industrial Production Index (*IPI*) Growth with Commodity Market Uncertainty and Controlling for Macroeconomic and Financial Fundamentals

The table presents the results of the multivariate forecasting regression model on Industrial Production Index growth using the volatility of commodity futures returns, in which we control for key macroeconomic and financial indicators of the US economy. We use a one month forecasting horizon (*k=1*). The *t*-statistics reported are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The estimated beta coefficients are based on the following regressions:

$$\Delta IPI_t = b_0 + b_1 COMRV_{t-1} + b_2 SP500RV_{t-1} + b_3 EPU_{t-1} + b_4 TERM_{t-1} + b_5 INFL_{t-1} + b_6 \Delta M2_{t-1} + b_7 UNEMP_{t-1} + \varepsilon_t$$

		Corn	*Cotton*	*Soybeans*	*Wheat*	*Crude oil*	*Heating oil*	*Petroleum*	*Gasoline*	*Copper*	*Gold*	*Silver*	*Platinum*
COMRV	*Coef.*	-0.017	-0.016	-0.017	-0.020*	-0.008**	-0.007**	-0.009**	-0.011**	-0.005	-0.018	-0.004	-0.018
	t-stat	-1.39	-1.31	-1.28	-1.88	-2.36	-2.11	-2.12	-2.17	-1.31	-1.15	-0.90	-1.28
SP500RV	*Coef.*	-0.021*	-0.023**	-0.022**	-0.020*	-0.021***	-0.025***	-0.021***	-0.018***	-0.023**	-0.024**	-0.025**	-0.021**
	t-stat	-1.73	-2.44	-1.98	-1.84	-2.94	-3.04	-2.95	-2.63	-2.42	-2.52	-2.39	-2.00
EPU	*Coef.*	-0.006***	-0.006***	-0.006***	-0.006***	-0.004**	-0.005***	-0.005**	-0.005***	-0.006***	-0.006***	-0.006***	-0.006***
	t-stat	-3.95	-3.65	-3.80	-3.83	-2.29	-2.81	-2.45	-2.74	-3.48	-3.21	-3.38	-2.90
TERM	*Coef.*	0.003	0.028	0.028	0.016	0.018	0.022	0.021	0.023	0.011	0.011	0.013	0.020
	t-stat	0.08	0.86	0.92	0.54	0.54	0.64	0.63	0.69	0.31	0.33	0.38	0.62
INFL	*Coef.*	-0.030	-0.025	-0.022	-0.027	-0.024	-0.020	-0.023	-0.023	-0.020	-0.021	-0.022	-0.019
	t-stat	-0.78	-0.65	-0.62	-0.77	-0.73	-0.58	-0.70	-0.69	-0.55	-0.60	-0.61	-0.57
ΔM2	*Coef.*	0.024	0.041	0.003	0.056	0.021	0.016	0.017	0.013	0.003	0.011	0.015	0.014
	t-stat	0.30	0.47	0.04	0.66	0.28	0.21	0.23	0.17	0.04	0.13	0.18	0.19
UNEMP	*Coef.*	0.114***	0.099***	0.089***	0.115***	0.064*	0.071*	0.066*	0.065*	0.096***	0.091***	0.096***	0.081**
	t-stat	3.16	2.99	2.60	3.29	1.72	1.89	1.73	1.70	2.74	2.60	2.68	2.21
% Adjusted R^2		14.4	13.7	14.1	16.2	16.2	14.1	15.6	16.4	13.1	13.3	13.0	13.9

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1. Response of Real GDP Growth to Agricultural Commodity Price Volatility Shocks

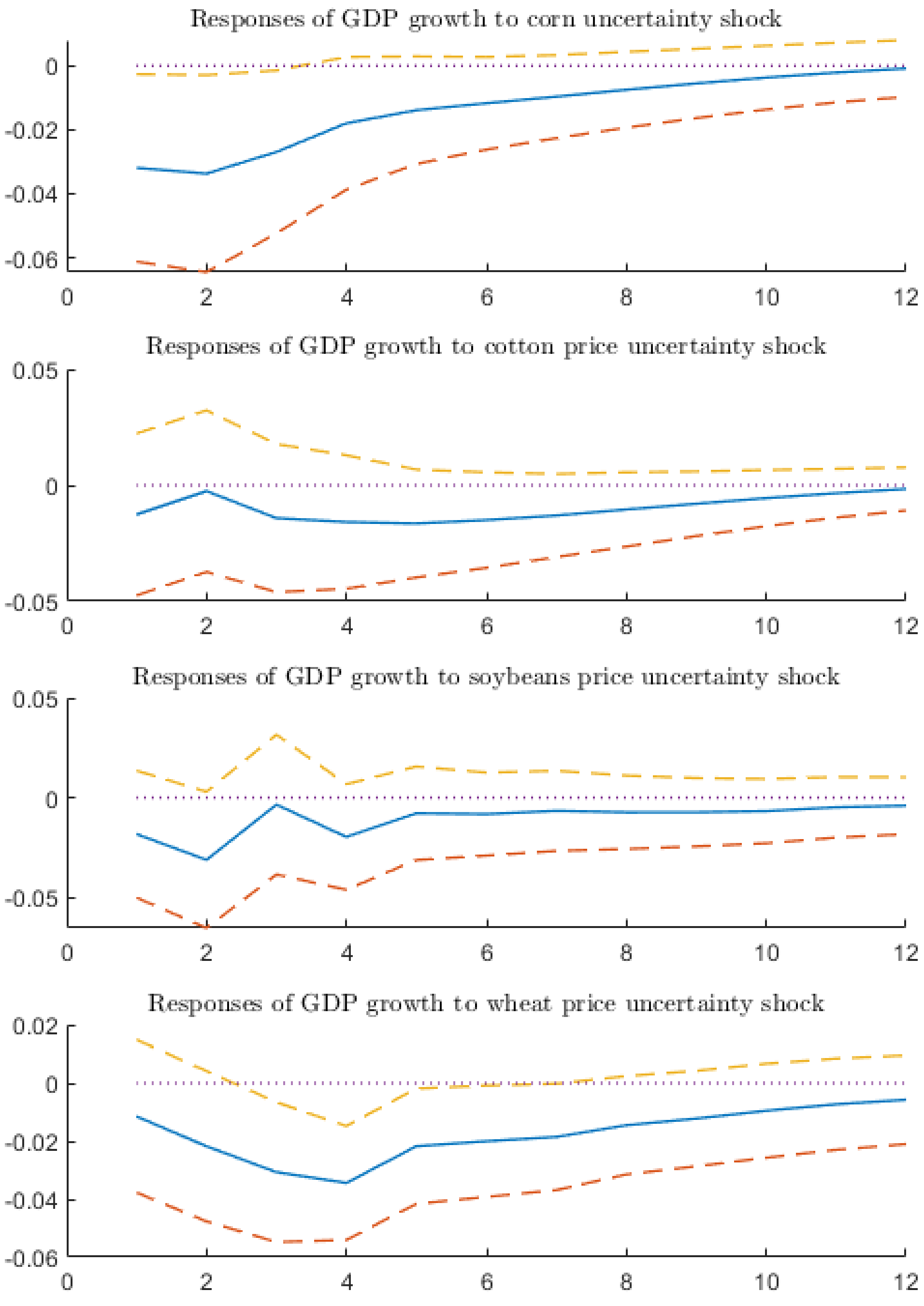

Figure 2. Response of Real GDP Growth to Energy Commodity Price Volatility Shocks

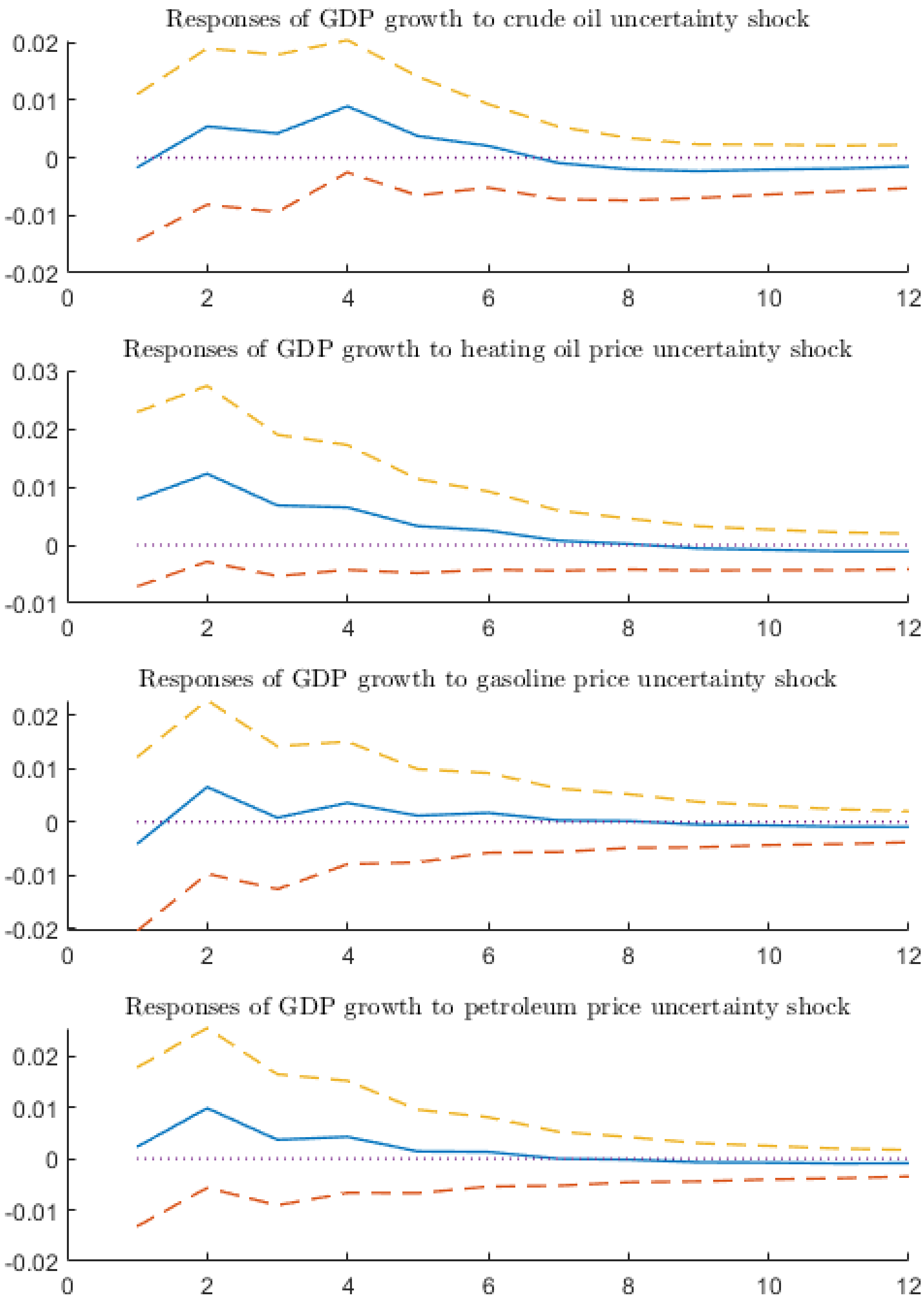

Figure 3. Response of Real GDP Growth to Metals Commodity Price Volatility Shocks

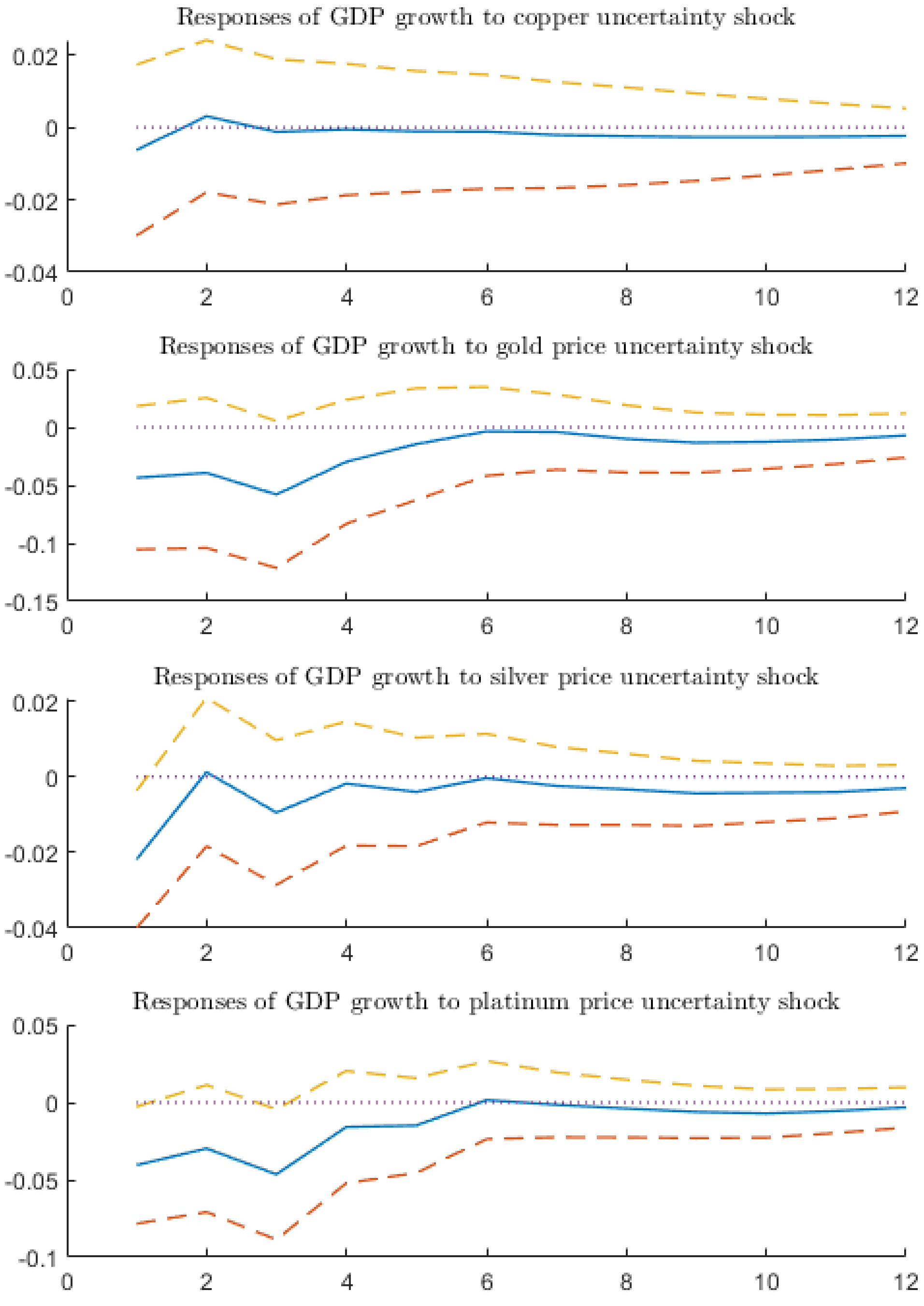

Figure 4. Response of Investment Growth to Agricultural Commodity Price Volatility Shocks

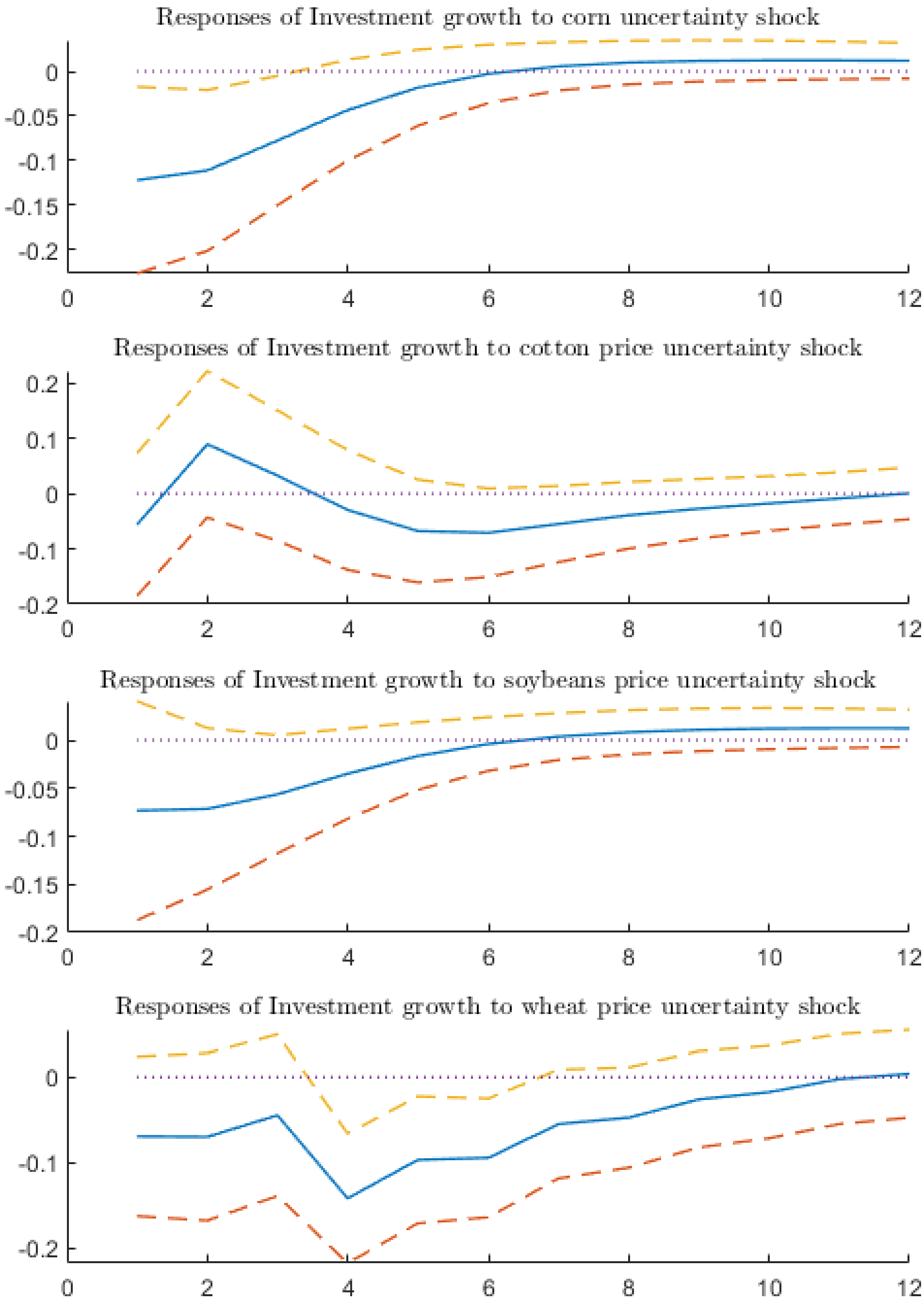

Figure 5. Response of Investment Growth to Energy Commodity Price Volatility Shocks

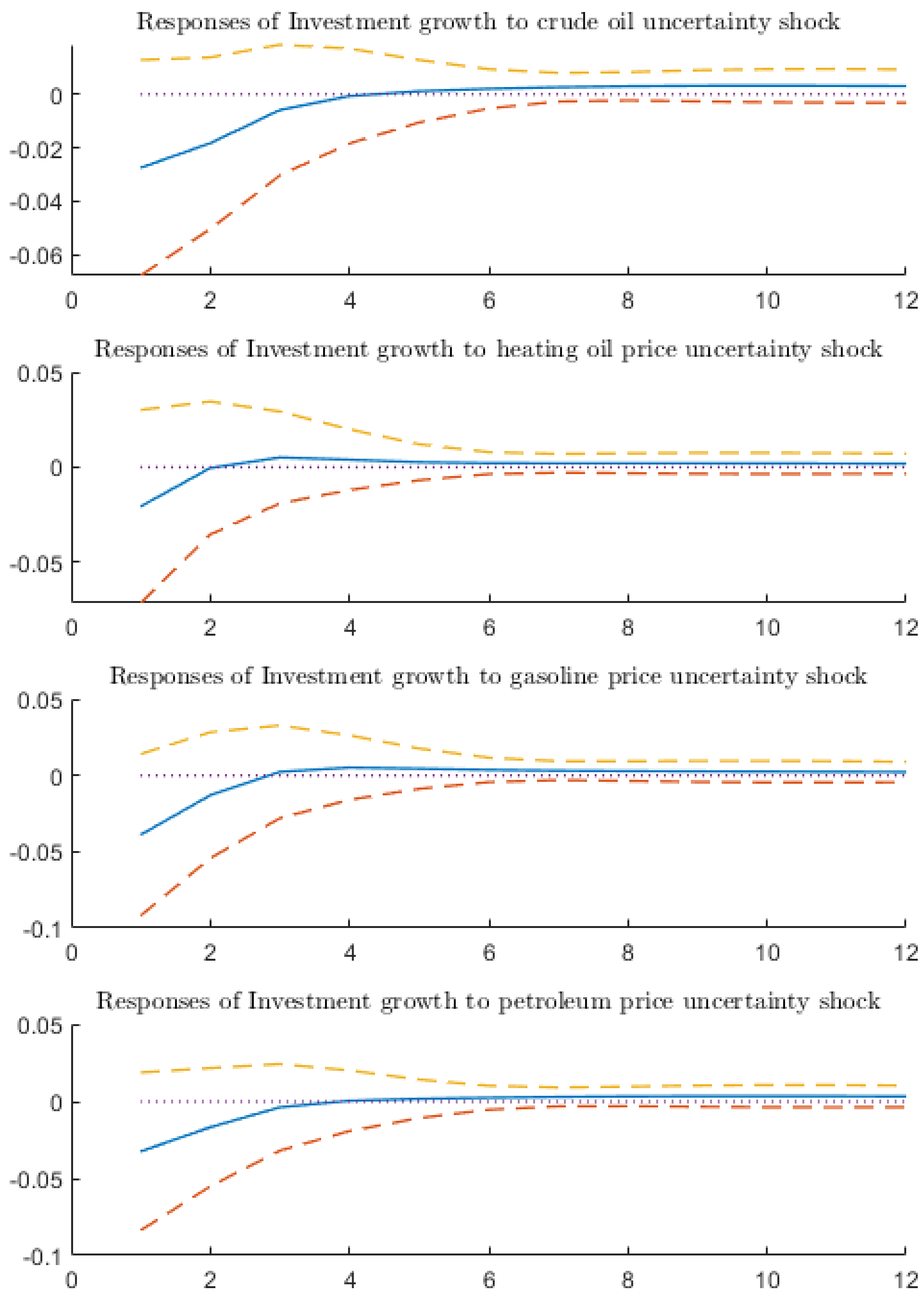

Figure 6. Response of Investment Growth to Metals Commodity Price Volatility Shocks

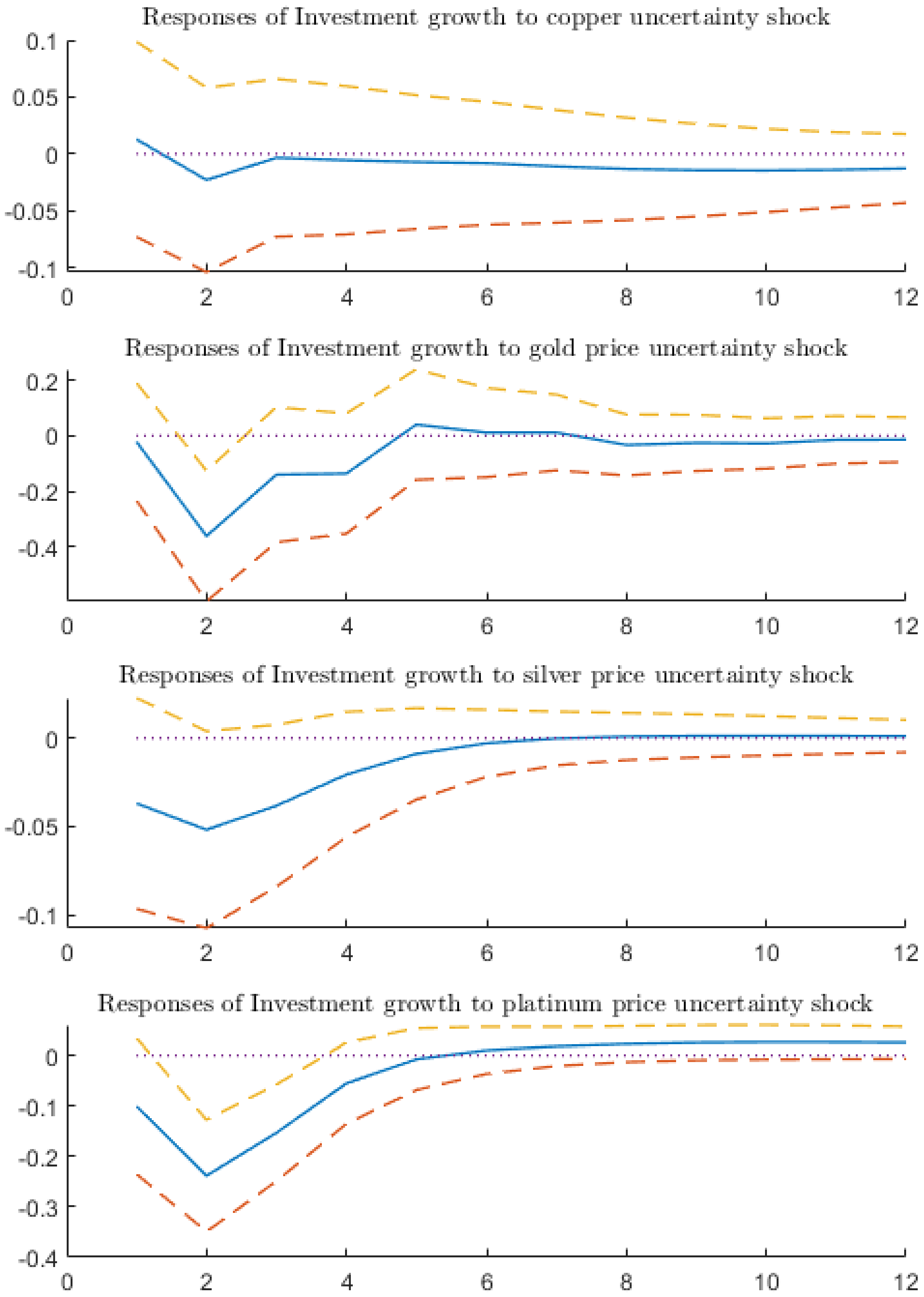

Figure 7. Response of IPI Growth to Agricultural Commodity Price Uncertainty Shocks

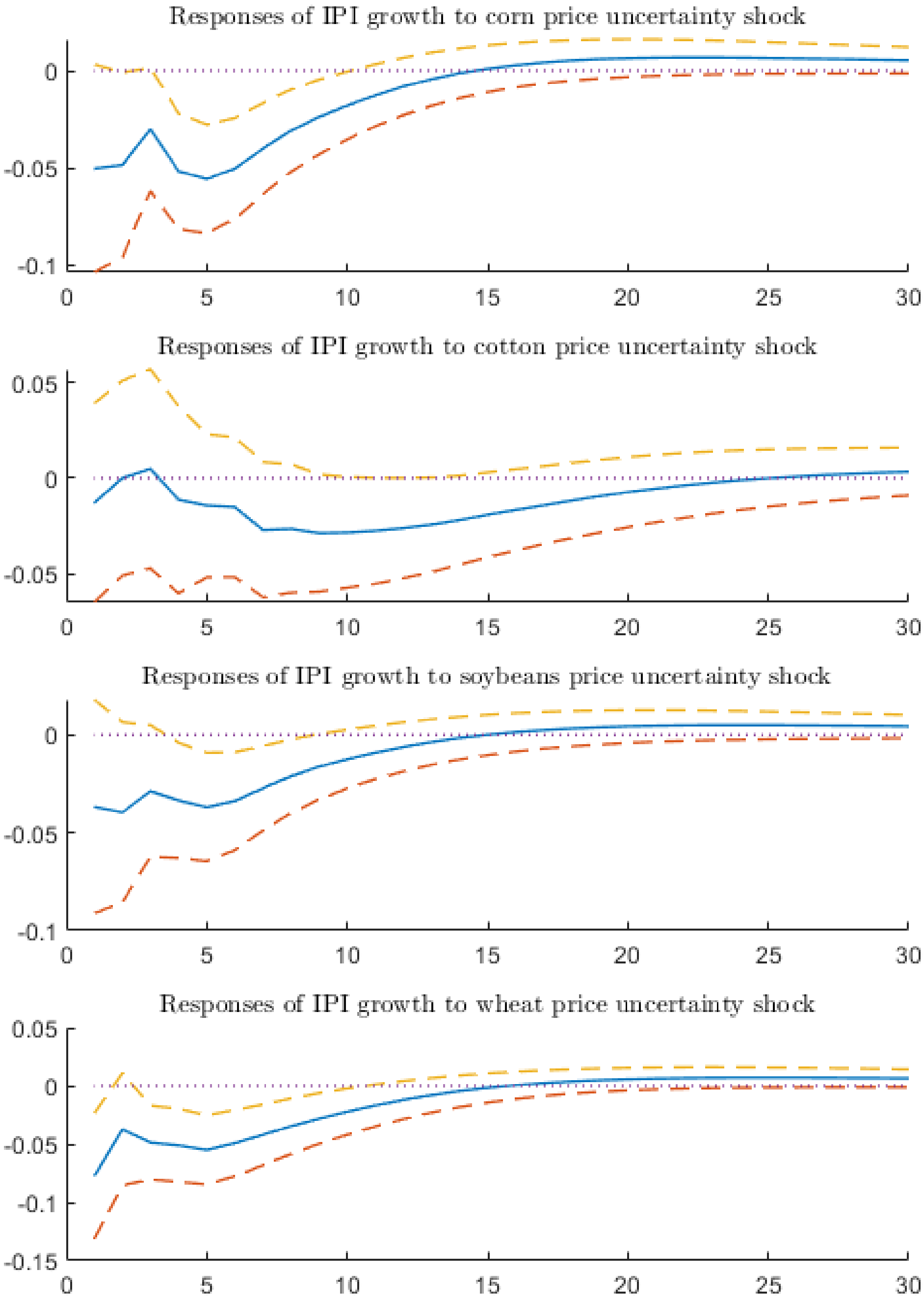

Figure 8. Response of IPI Growth to Energy Commodity Price Uncertainty Shocks

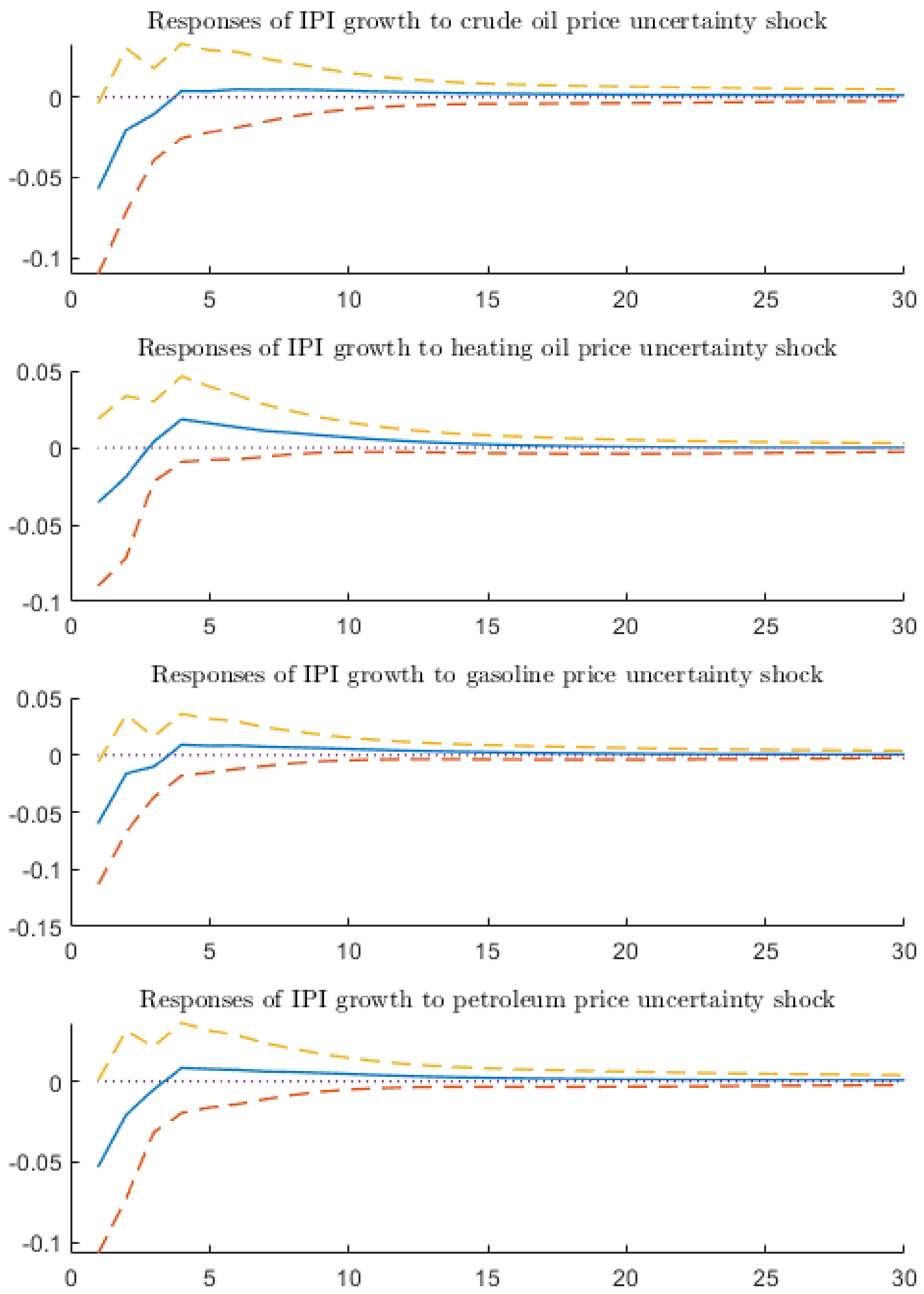

Figure 9. Response of IPI Growth to Metals Commodity Price Uncertainty Shocks