

# *Commodity Price Uncertainty and International Trade*

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## **Abstract**

We empirically investigate the impact of commodity price uncertainty on the US and Euro Area trade flows. The findings indicate a negative and long-lasting effect of commodity uncertainty on the US and Euro Area imports and exports. The response of US and Euro Area imports and exports to structural commodity price uncertainty shocks is more than two times larger in magnitude and persistence when compared with the respective impact of structural supply shocks, global demand and commodity specific demand shocks. Moreover, our SVAR analysis shows that the commodity price uncertainty has a more dampening effect on international trade when compared with the impact of trade volatility, geopolitical uncertainty and exchange rate shocks. When examining the impact of the rising price uncertainty of individual commodities on international trade, we find that a positive price uncertainty shock in agricultural and metals commodity markets has a more significant and long-lasting negative impact on US and Euro Area trade flows when compared to the respective impact of energy price uncertainty shocks.

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## 1. Introduction

A large and growing body of the literature has empirically verified the macroeconomic impact of commodity price fluctuations (Arezki and Bruckner, 2012; Drechsel and Tenreyro, 2018; Fernandez *et al.*, 2017; Fernandez *et al.*, 2018). Fernandez *et al.* (2017) find that shocks in global commodity prices account for more than one third of global output fluctuations. Moreover, commodity price fluctuations are positively correlated with the floating exchange rates of many commodity exporting countries (Cashin *et al.*, 2004; Chen and Rogoff, 2003; Ferraro *et al.*, 2015; Singh *et al.*, 2018; Ricci *et al.*, 2013). For example, Singh *et al.* (2018) find that the crude oil implied volatility is a key driver of nine currency pairs including the EUR-USD currency pair<sup>1</sup>. Dauvin (2014) identifies the existence of oil currencies by showing that energy prices are key drivers of the exchange rates of energy exporting countries. Bodart *et al.* (2012) show that the commodity price booms have a significant impact on the currencies of small commodity exporting countries. More specifically, they show that the price change of the primary exporting commodity (the commodity that has at least 20% export share of the countries' total exports) has a significant long-run impact on the exchange rate of the respective commodity-producing country. Moreover, Coudert *et al.* (2015) find that the currencies of major oil exporting countries are more sensitive to changes in terms of trade in times of high commodity price volatility. Chen and Rogoff (2003) attribute this long-run cointegrating relationship between commodity prices and exchange rates attributing to the fact that primary commodities constitute a major component of their exports and, consequently, of their terms of trade fluctuations.

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<sup>1</sup> Chen *et al.* (2010) identify the reverse channel of causality, according to which the 'commodity currency' exchange rates are significant predictors of commodity prices for both in-sample and out-of-sample forecasts.

Some recent empirical studies provide further empirical support on the hypothesis of commodity currencies (according to which commodities are a major component of terms of trade fluctuations) by showing that commodity price shocks have a significant impact on the terms of trade (Bodenstein *et al.*, 2011; Fernández *et al.*, 2018; Giovannini *et al.*, 2019; Kilian *et al.*, 2009). For example, Fernández *et al.* (2018) find that commodity price fluctuations are significant drivers of macroeconomic fluctuations in small emerging market economies, while Giovannini *et al.* (2019) show that commodity price shocks are major drivers for the Euro Area (EA) and US trade balances. Drechsel and Tenreyro (2018) show that booms and bursts in internationally traded commodities have a dampening effect on the trade balances of emerging economies, while Kilian *et al.* (2009) and Bodenstein *et al.* (2011) show that the oil price shocks result to significant drops in oil and non-oil trade balances.

Moreover, the theory of investment under uncertainty indicates that firms postpone their investment decisions when uncertainty about future costs and profitability rises. The real options approach indicates that firms have some significant ‘option value’ to delay their investment decisions until the time uncertainty reduces significantly (Bernanke, 1983; Pindyck, 1993). On aggregate level, this postponement of investment at firm level due to higher uncertainty, leads to economic downturns and to sudden drops in economic activity (Baker *et al.*, 2016; Basu and Bundick, 2017; Bloom, 2009; Carriero, Clark and Marcellino, 2018; Fernández *et al.*, 2018; Jurado *et al.*, 2015; among others). The recent findings in the literature have identified the negative impact of commodity price uncertainty on economic activity (Elder and Serletis, 2010; Elder, 2018; Jo, 2014; Ferderer, 1996; Fernández *et al.*, 2018). For example, Elder and Serletis

(2010) and Ferderer (1996) find that rising oil price volatility leads to sudden drops in US GDP growth and US Industrial production.

Motivated by the previously mentioned empirical findings which show the existence of commodity currencies, the significance of commodity price shocks on international trade, and the dampening effect of uncertainty shocks on the US macroeconomy, we empirically examine the impact of commodity price uncertainty shocks on US and Euro Area trade flows. To the best of our knowledge, there are no previous studies examining the effect of commodity price uncertainty on international trade. While some recent findings in the literature show that the firm level uncertainty and uncertainty about aggregate demand conditions has a significant negative effect on international trade (De Sousa *et al.*, 2016; Gervais, 2018), there are no empirical findings showing the direct impact of rising uncertainty in commodity markets on international trade. In this paper, we attempt to fill this gap in the literature. Since trade flows are heavily dependent on global economic activity,<sup>2</sup> and as global economic activity is significantly affected by heightened uncertainty in commodity markets (Elder, 2018; Jo, 2014), we postulate that price uncertainty in internationally traded commodities is a key driver of fluctuations in trade flows. In this paper, we empirically test this hypothesis for the EA and the US trade, according to which higher commodity price uncertainty will lead to dampening effects on trade flows.

More specifically, following the approach of Kilian (2009) and Kilian *et al.* (2009), we estimate a Structural VAR model in which we measure the dynamic response of US and Euro Area trade flows commodity price shocks to structural shocks in global supply, global demand, commodity specific demand and commodity price uncertainty. Our SVAR analysis shows that the dynamic

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<sup>2</sup> For example, Ratnaike (2012) shows that world demand is the key driver of export performance.

response of US and Euro Area trade flows to commodity price uncertainty shocks is more than two times higher and more long-lasting when compared with the dynamic response of trade flows to structural shocks in global demand, commodity specific demand and global supply of commodities. More specifically, we find that rising commodity price uncertainty predicts a drop in both US and Euro Area imports and exports growth that remains negative and statistically significant for six months after the initial shock, while the response of US and Euro Area trade flows to positive global demand (global economic activity) and commodity specific demand (commodity price shocks) is positive and remains significant for two months after the initial shock only for the case of US exports only for US trade flows. On the other hand, our SVAR analysis shows that the Euro Area trade flows are relatively immune to global and commodity specific demand shocks. Overall, our econometric analysis shows that the most significant shock for both US and Euro Area trade flows is the commodity price uncertainty shock. The dynamic impact of commodity price uncertainty remains robust to the inclusion of variables which are close related to trade, like the real effective exchange rate and the global real economic activity into the information variable set. Moreover, our OLS predictive models show that commodity price uncertainty is a robust predictor of US and Euro Area trade flows for forecasting horizons ranging for one up to three months, and that it contains statistically and economically differentiated predictive information content when compared to the information content of the traditional macroeconomic predictors of international trade, like exchange rates, global demand and supply conditions and popular economic uncertainty proxies.

Furthermore, we examine which commodity markets are the key drivers of the negative relationship between commodity uncertainty shocks and international trade, by estimating

uncertainty in the most liquid agricultural, metals and energy commodity futures markets and examining its dynamic impact on international trade. Interestingly, our VAR analysis shows that the time varying uncertainty in some agricultural and metals commodity markets like corn, wheat and platinum has the most dampening effect on US and Euro Area trade flows, while the energy and oil uncertainty shocks have a much smaller and transitory effect on trade flows. While the relevant oil-macroeconomics literature has extensively shown the negative response of US economic activity and terms of trade to oil price and uncertainty shocks (Backus and Crucini, 2000; Elder, 2018; Elder and Serletis, 2010; Kilian *et al.*, 2009; Kilian and Vigfusson, 2017; Hamilton, 2003; Jo, 2014; Ferderer, 1996), we show that the non-oil uncertainty shocks are the key drivers of falling international trade instead.

Our contribution to the literature is twofold. Firstly, we show that commodity price uncertainty is a significant determinant of the dynamics in US and EA trade flows, while trade flows are relatively immune to the impact of trade volatility, exchange rates, commodity prices and global demand and supply shocks. Secondly, we find that, unlike with what the oil-macroeconomics literature suggests, the non-oil uncertainty shocks have a more long-lasting and negative impact on international trade when compared with the respective impact of oil uncertainty shocks. Our results are useful for trade policy since we suggest that the commodity price uncertainty shocks have played a significant role in creation of sudden drops in international trade. Moreover, our analysis indicates that trade policy makers, when trying to assess the possible determinants of the future state of international trade, should turn their attention, not only to oil price and uncertainty shocks, but also to non-oil uncertainty shocks.

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 Commodity price uncertainty

Our proxy for commodity price uncertainty (*COMRV*) is the realized variance of the daily returns of the S&P GSCI index, following the methodology of Bakas and Triantafyllou (2018). More specifically, we use the daily excess returns of the S&P GSCI broad commodity futures market index as our proxy for the daily price of commodities. Using the daily prices of the GSCI commodity futures index we estimate the monthly Realized Variance ( $RV_{t,T}$ ) for the broad commodity market index and for all individual commodities, according to Equation (1):

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

where  $F_t$  is the GSCI commodity futures price the trading day  $t$  and the time interval  $(t, T)$  is the number of trading days during each monthly period.  $RV_{t,T}$  is our estimated realized variance for each monthly period. Our monthly estimate of the annualized realized variance ( $RV$ ) is the monthly variance of the daily returns of commodity prices (for each monthly period), multiplied by 252 in order to be annualized.

## 2.2 Structural VAR model

We follow the identification strategy of Kilian (2009) and Kilian *et al.* (2009) and estimate a structural VAR model in which we decompose commodity price uncertainty shocks into three components driven by aggregate supply (global oil production growth)<sup>3</sup>, aggregate demand (global real economic activity growth) and commodity specific demand (the return of the GSCI commodity price index). More specifically, we estimate the following SVAR model allowing for 6-month worth of lags<sup>4</sup>. The structural VAR model representation is given in Equation (2):

$$A_0 Z_t = a + \sum_{i=1}^6 A_i Z_{t-i} + \varepsilon_t \quad (2)$$

The vector  $Z_t$  is the vector with the endogenous variables with the following VAR ordering given in Equation (3) below:

$$Z_t = [IMP_t \ PROD_t \ GACT_t \ \text{COMPR}_t \ \text{COMRV}_t] \quad (3)$$

Where  $IMP_t$  is the monthly growth of US and Euro Area imports,  $PROD_t$  is the percentage change of the global level of crude oil production (our proxy for aggregate supply),  $GACT$  is the Kilian and Murphy (2014) index of real global economic activity which is our proxy for global

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<sup>3</sup> In this paper we assume that the global crude oil production is a good proxy for the aggregate production of all commodities, since the oil production represents more than 40% of the production of all industrial commodities.

<sup>4</sup> The SVAR model of Kilian (2009) uses 24 lags in order to allow for enough dynamics in the system, but by this way he sacrifices 2 years of data for the estimation of the model. We follow his approach and choose 6 lags for the SVAR to allow for enough dynamics in the system and control for the persistence of commodity price and uncertainty shocks. Our findings remain unchanged when using 12 or 24 lags for the estimation of the SVAR. Moreover, our results remain robust when using more parsimonious VARs which are selected by the Akaike and Hanna-Quinn optimal lag-length criteria (e.g. the Akaike and Hanna-Quinn lag-length criteria propose a VAR model with 2 lags).

demand, COMPR is the percentage change of the GSCI commodity price index (our proxy for the commodity-specific demand shock) and the COMRV is the monthly realized variance of the daily returns of the GSCI commodity price index (our proxy for commodity price uncertainty). The variable  $\varepsilon_t$  denotes the vector of serially and mutually uncorrelated structural innovations. The matrix  $A_0$  in Equation (2) has the recursive form such that the vector of the reduced-form errors  $e_t$  of the SVAR model can be decomposed according to  $e_t = A_0^{-1}\varepsilon_t$  as follows:

$$e_t = \begin{pmatrix} e_t^{trade} \\ e_t^{prod} \\ e_t^{gact} \\ e_t^{compr} \\ e_t^{comrv} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{trade\ shock} \\ \varepsilon_t^{supply\ shock} \\ \varepsilon_t^{demand\ shock} \\ \varepsilon_t^{com\ demand\ shock} \\ \varepsilon_t^{com\ uncert\ shock} \end{pmatrix} \quad (4)$$

The restrictions imposed in our model are in line with those of Kilian (2009), and Kilian *et al.* (2009) and Kilian and Murphy (2014), according to which commodity producers can respond to instantaneous shocks in commodity prices, commodity price uncertainty and to global demand shocks in order to decide the quantity of their global supply of commodities, while on the other hand commodity specific demand shocks cannot affect global economic activity during the same month. Lastly, commodity price and uncertainty shocks cannot be affected (or explained) by changes in global demand and supply conditions, since they can only be affected by changes (shocks) in commodity specific demand. We additionally estimate two identical SVAR models for US and Euro Area export growth respectively.

### 2.3 Reduced-form VAR model

We additionally estimate a 6-factor reduced-form VAR model for the US and EA imports and exports.<sup>5</sup> The reduced form VAR model is given as:

$$Y_t = A_0 + A_1 Y_{t-1} + \dots + A_k Y_{t-k} + \varepsilon_t \quad (5)$$

Where  $A_0$  is a vector of constant terms,  $A_1$  to  $A_k$  are coefficients vectors and  $\varepsilon_t$  is an *iid* vector of error terms.  $Y_t$  is the vector of the endogenous variables. Following Bekaert *et al.* (2013), the variables of the more flexible markets, like the exchange rate and the commodity price uncertainty, are placed last in the VAR ordering. Hence, the ordering of the endogenous variables for our VAR models is given as:

$$Y_t^1 = [IMP_t, IMPV_t, GACT_t, GRISK_t, EXCH_t, COMRV_t] \quad (6)$$

$$Y_t^2 = [EXP_t, EXPV_t, GACT_t, GRISK_t, EXCH_t, COMRV_t] \quad (7)$$

where  $IMP$  and  $EXP$  are the growth rates of EA imports and exports and  $IMPV$  and  $EXPV$  are the EA imports and exports volatility measures respectively. The rest of the variables are common for both VAR models.

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<sup>5</sup> We include two lags following the optimal-lag length criterion of Frechet and Akaike.

## 2.4 OLS predictive regression models

In this section we present the specification of our bivariate and multivariate OLS predictive regression models on US and Euro Area import and export growth. Equation (8) below shows the univariate predictive regression model on US and Euro Area trade flows.

$$IMP_t = b_0 + b_1 COMRV_{t-k} + \varepsilon_t \quad (8)$$

We estimate the above regression model given in (8) for both US and Euro Area imports (IMP) and for US and Euro Area exports (EXP) using 1 up to 6 month forecasting horizon. In order to provide robustness on the predictive power of commodity price uncertainty we additionally estimate the following multivariate predictive regression models in which we control for additional predictors of US and Euro Area trade flows, as shown in Equation (9) below:

$$IMP_t = b_0 + b_1 COMRV_{t-k} + b_2 IMPV_{t-k} + b_3 EXCH_{t-k} + b_4 GACT_{t-k} + b_5 GRISK_{t-k} + \varepsilon_t \quad (9)$$

In equation (9), EXCH represents the US and the Euro Area effective exchange rate (when forecasting the US and Euro Area trade flows respectively), COMRV is the commodity price uncertainty, IMPV is the estimated GARCH(1,1) volatility of the respective trade flows, GACT is the real global economic activity index of Kilian and Murphy (2014) and GRISK is the geopolitical risk index of Caldara and Iacoviello (2018). Moreover, in order to examine whether the predictive power of commodity price uncertainty on international trade remains robust to the inclusion of oil prices, Economic Policy Uncertainty (EPU) and exchange rate volatility, we additionally estimate the following multivariate forecasting model given in Equation (10).

$$IMP_t = b_0 + b_1 COMRV_{t-k} + b_2 IMPV_{t-k} + b_3 EXCH_{t-k} + b_4 GACT_{t-k} + b_5 GRISK_{t-k} + b_6 COM_{t-k} + b_7 EXCHV_{t-k} + b_8 EPU_{t-k} + b_9 OIL_{t-k} + \varepsilon_t \quad (10)$$

Where EPU is the logarithm of Economic Policy Uncertainty, EXCHV is the monthly realized variance of the daily percentage change of US and Euro Area effective exchange rates and OIL is the monthly percentage change of WTI crude oil prices.

### 3. Data

We obtain daily data for the S&P GSCI commodity price index and for individual agricultural, metals and energy commodity futures prices from Datastream. In addition, we obtain the individual daily time series of agricultural, energy and mineral (metals) commodity of the S&P GSCI commodity futures indices. Our cross-section of agricultural commodities includes cocoa, corn, cotton, soybeans, sugar and wheat, while the cross-section of energy commodities includes crude oil, heating oil, petroleum and unleaded gasoline, and lastly, the cross-section of metals commodities includes gold, silver, copper and platinum. We additionally obtain data for the monthly WTI crude oil prices from the FRED database.

The global real economic activity index (*GACT*) is based on the work of Kilian (2009) and Kilian and Murphy (2014). This index is highly related to trade since it measures shifts in the global use of industrial commodities.<sup>6</sup> The geopolitical risk index (*GRISK*) is based on the empirical approach of Caldara and Iacoviello (2018) and measures the uncertainty related to geopolitical tensions as reflected in leading international newspapers.<sup>7</sup> The series for the EA imports (*IMP*) and exports (*EXP*) and real effective exchange rate (*EXCH*) are downloaded from the Federal Reserve Bank of St. Louis FRED database. The volatility measures of EA imports

<sup>6</sup> The global real economic activity index is downloaded from <http://www-personal.umich.edu/~lkilian>.

<sup>7</sup> The geopolitical risk index is downloaded from <https://www2.bc.edu/matteo-iacoviello/gpr.htm>.

(*IMPV*) and exports (*EXPV*) are estimated as the conditional variance of the monthly growth of the respective series using a GARCH (1,1) model. The dataset covers the period from January 1994 to January 2017<sup>8</sup>.

## 4. Empirical Analysis

### 4.1 Descriptive statistics

In this section we present some descriptive statistics of our time series sample. The Table 1 below presents the descriptive statistics for our time series sample.

[Table 1 Here]

From **Table 1** we observe that the Euro Area and the US import and export growth rates have the nearly the same mean and volatility, a fact which shows some commonality in the time series of US and Euro Area trade flows. **Figures 1** and **2** show the synchronous time series variation of commodity price uncertainty and the US and Euro Area imports and exports respectively.

[Figure 1 and 2 Here]

We observe that significant spikes in the commodity volatility series are followed by significant drops in both Euro Area and US imports and exports. In particular, the rising commodity price volatility during 2008 is being followed by falling EA and US imports and exports in 2009 and

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<sup>8</sup> We choose our time series dataset to cover the period from January 1994 to January 2017 because this is the maximum possible common sample for US and Euro Area trade flows. While available data for US trade exist before 1994, the monthly data for Euro Area trade flows start from January 1994. For this reason, we choose to use the common sample for our findings for US and Euro Area to be comparable.

the significant rebound of EA trade during the post-2010 is accompanied by lesser commodity market turbulence.

#### **4.1 Structural VAR Impulse Responses**

We measure the dynamic response of US and Euro Area trade import and export growth to the structural shocks of supply, demand, commodity specific demand and commodity price uncertainty as shown in our our SVAR model presented in Equations (2) and (3) and (4). Figure 3 shows the responses of US Import and Exports growth to a one standard deviation structural innovation to global crude oil production growth (aggregate supply shock), real global economic activity (aggregate demand shock), monthly growth in the commodity price index (commodity specific demand shock) and to realized variance of commodity price returns (commodity price uncertainty shock).

**[Figure 3 and 4 Here]**

The estimated Structural Impulse Response Functions shown in Figures 3 and 4 show that US imports and exports respond positively to unexpected aggregate demand shocks with the response being positive and statistically significant for 2 to 3 months after the initial shock, with the effect becoming statistically indistinguishable for zero after the 5<sup>th</sup> month of the initial demand or supply shock. Our findings reveal that the impact of demand shocks is larger and more persistent on US exports than US imports. This results implicitly show that an unexpected positive shock in aggregate demand for commodities has a positive effect in US trade balances since it increases the trade surplus. Our findings are in line with those of Kilian *et al.* (2009) who

show that the structural aggregate and commodity-specific demand shocks have a positive impact in the trade balance of oil and non-oil trade surplus in oil-exporting countries. On the other hand, our estimated impulse response functions show that there is no significant effect of oil supply shocks to US trade flows. On the other hand, the dynamic response of US trade flows to commodity price uncertainty shocks is negative. More specifically, a one standard deviation shock in commodity price uncertainty reduces US import growth by almost 0.5% two months after the initial shock with the effect remaining negative and statistically significant for 5 months after the initial uncertainty shock. On the other hand, a positive commodity uncertainty shock reduces US import growth by almost 0.5% one month after the initial shock with the effect remaining negative and statistically significant for two months after the initial uncertainty shock. The more persistent negative impact of US imports when compared to US exports to commodity price uncertainty shocks leads to the conclusion that the US trade balance is negatively affected when uncertainty in commodity markets rises unexpectedly<sup>9</sup>. Unlike commodity price shocks, which, according to our analysis and to the findings of Kilian *et al.* (2009), have a positive effect on US imports and exports, the commodity price uncertainty shocks have a negative and statistically significant impact on US trade flows and trade balance. Our analysis is the first to show the large and highly persistent negative impact of commodity price uncertainty on US import and export growth. Our findings are in line with the findings of Elder and Serletis (2010), Ferderer (1996), Jo (2014) and Elder (2018) who find that the rising oil price uncertainty has a negative impact on US economic activity and Industrial Production. What we additionally show, is that, the global commodity price uncertainty has a significant dampening effect, not only on US economic activity and aggregate industrial production, but also on US trade flows. The rising

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<sup>9</sup> We additionally estimate an identical SVAR model using instead of US export growth, the percentage change of US trade balance as the first variable in our VAR ordering, and we show that the trade balance is negatively affected by positive shocks in commodity price uncertainty. These results can be found in our on-line Appendix.

commodity price uncertainty, which, according to the findings of Elder and Serletis (2010), reduces aggregate investment since it postpones investment and production for later stage when the uncertainty in commodity markets is reduced, it also postpones, according to our analysis, the US aggregate international trade activity. Our findings are also in line and provide further empirical support to the results of Calvacanti *et al.* (2015) who find that the time varying volatility in the commodity terms of trade has a negative impact in economic growth.

In order to examine the dynamic effects of commodity price uncertainty (while controlling for commodity supply and demand shocks), we estimate an identical SVAR model (as shown in equations 2 to 4) for the Euro Area. The **Figures 5** and **6** show the responses of the Euro Area import and export growth to commodity supply, demand and uncertainty shocks.

[Insert **Figure 5** and **6** Here]

The responses of Euro Area trade flows to the structural shocks of our SVAR model show that, unlike US trade flows, the US imports and exports are relatively immune to aggregate demand and commodity specific demand shocks. For example, the response of Euro Area exports to a one standard deviation shock in global demand (global economic activity) is positive but insignificant. More specifically, a positive aggregate demand shock increases Euro Area imports by approximately 0.3% five months after the initial shock. On the other hand, our analysis shows that the most significant shock for the Euro Area imports and exports (in terms of both persistence and magnitude) is the commodity price uncertainty shock. A positive commodity price uncertainty shock causes a highly significant and long-lasting reduction in Euro Area imports and exports growth. More specifically, a positive uncertainty shock reduces EA imports

by approximately 0.6% one month after the initial shock with the negative effect remaining negative and statistically significant for 5 months after the initial uncertainty shock. The same uncertainty shock reduces EA exports by 0.5% two months after the initial shock with the effect remaining negative and statistically significant for 3 months after the initial price uncertainty shock. Overall, our analysis clearly shows that EA imports are more heavily impacted by commodity uncertainty shocks when compared to EA exports. This result implicitly reveals that the trade balance in the Euro Area lowers after the occurrence of large commodity price uncertainty episodes<sup>10</sup>. Moreover, our analysis is the first to show that the magnitude of the impact of commodity price uncertainty shocks is more than two times larger when compared with the magnitude of aggregate demand and supply shocks. While the maximum response of Euro Area trade flows to aggregate demand and supply shocks ranges between 0.2% and 0.3%, the maximum response of EA trade flows to commodity uncertainty shocks ranges between 0.5% and 0.6%.

#### **4.1 Reduced-form 6-factor VAR Impulse Responses**

We continue our analysis by estimating a reduced-form 6-factor VAR model in which we additionally include as endogenous variables some well-known determinants of international trade like the exchange rates, the geopolitical risk and trade volatility. We base our analysis on the orthogonalized impulse response functions (OIRFs) of the 6-factor VAR models for the EA imports and exports given in **Equations (5), (6) and (7)**. The estimated OIRFs of US trade flows are shown in **Figures 7 and 8** respectively.

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<sup>10</sup> We also estimate an identical SVAR model using the Euro Area trade balance as the first variable of our VAR ordering and we show that EA trade balance is reduced after the occurrence of shocks to commodity price uncertainty. These additional VAR results can be found on our on-line Appendix.

[**Figures 7 and 8** Here]

The estimated responses of the US trade flows in this alternative VAR specification, show that the negative impact of commodity price uncertainty shocks remains negative and statistically significant when controlling for the possible dynamic interactions between aggregate demand, exchange rates, geopolitical risk and commodity price uncertainty<sup>11</sup>. Under this VAR identification scheme, the unanticipated commodity uncertainty shock has an instantaneous and persistently negative effect on US trade flows. More specifically, a one standard deviation commodity uncertainty shock reduces US import growth by 0.4% two months after the initial shock and export growth by 0.5% one month after the uncertainty shock. The effects remain negative and statistically significant for 7 months and 5 months after the initial uncertainty shock for US imports and exports respectively. The dynamic response of US exports and imports growth to commodity uncertainty shocks is larger in magnitude and persistence when compared with responses of US trade flows to US effective exchange rate, geopolitical uncertainty and global demand (global economic activity) shocks<sup>12</sup>.

We also estimate an identical 6-factor VAR model using Euro Area imports and exports growth as the first variable in the VAR ordering as shown in Equations (4), (5) and (6). **Figures 9 and 10** show the estimated Orthogonalized Impulse Response Functions (OIRFs) for this model.

[**Figures 9 and 10** Here]

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<sup>11</sup> We must state at this point that, in this reduced-form unrestricted VAR model, we do not impose any restriction between the interaction of our endogenous variables, thus, we allow the variables to interact freely and contemporaneously with each other.

<sup>12</sup> The dynamic response of US trade flows to US import and export volatility shocks is also insignificant, but we choose not to report it for brevity issues. These additional results can be provided upon request.

The OIRFs given in **Figures 9** and **10** clearly show that the impact of commodity price uncertainty on EA imports and exports growth is significantly negative and more long-lasting when compared to the respective impact of the other endogenous variables of our VAR models. Our analysis shows that a one standard deviation shock in the commodity price uncertainty results to a 50 basis points drop (-0.5%) in EA exports two months after the initial uncertainty shock, with the effect remaining negative and statistically significant for seven months after the initial commodity uncertainty shock. In addition, a positive one standard deviation shock in commodity price volatility reduces EA import growth by almost 0.6% one month after the initial volatility shock with the effect remaining negative and significant for 7 months after the initial shock. Unlike commodity uncertainty shocks, trade flows volatility (*IMPV* and *EXPV*) shocks have insignificant and transitory effect on EA trade.<sup>13</sup> Our findings are the first to show that commodity price volatility has a more dampening effect on international trade when compared to the volatility of trade flows and the exchange rate. Overall, the estimated responses of our reduced-form VAR model show that the more significant shock for US and Euro Area trade flows (in terms of both magnitude and persistence) is the commodity price uncertainty shock.

### **4.3 Predictive regression results**

Moreover, to complement our VAR evidence, we estimate OLS forecasting regressions for the EA trade flows using commodity price uncertainty as the main predictor and controlling for the same variables with the VAR models. **Tables 2** and **3** report the results of our bivariate

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<sup>13</sup> We explore various robustness checks to show that the impact of commodity price uncertainty shocks remains robust to alternative VAR orderings and to the inclusion of other macro-variables and uncertainty proxies in the model. We, thus, estimate alternative VAR identifications using other measures of economic uncertainty like the EPU index (Baker *et al.*, 2016) and the stock-market volatility (Bloom, 2009). For brevity we do not report these results here, but they can be provided upon request.

forecasting OLS regression models presented in Equation (8) using only the commodity price uncertainty (COMRV) as our only predictor of US trade flows.

[**Tables 2 and 3** Here]

The regression results of **Tables 2 and 3** show the negative impact of the commodity price uncertainty on EA imports and exports growth since the estimated COMRV coefficients are negative and statistically significant for one up to three month forecasting horizon. The contemporaneous regressions (having 0 month forecasting horizon) show that the time variation of commodity price uncertainty explains a large part of time variation in US and Euro Area trade flows with the  $R^2$  values reaching almost 13% when regressing the COMRV on US export growth. Moreover, when forecasting US and Euro Area trade flows having 1 and 2-month forecasting horizon, estimated COMRV coefficients remain negative and statistically significant. These results clearly indicate that rising uncertainty in commodity markets be an early warning signal of a reduction in international trade in the following months. In order to provide robustness to our regression results showing the predictive power of COMRV, we estimate a multivariate forecasting regression model using some additional well-known predictors of international trade flows in the right-hand side of our regression equation, like exchange rates, trade volatility, real global economic activity and geopolitical uncertainty as shown in Equation (9). The **Tables 4 and 5** below show the respective regression results of our multivariate forecasting regression model on US and Euro Area trade flows respectively.

[**Tables 4 and 5** Here]

The regression results of Tables 4 and 5 show that the forecasting power of the commodity price uncertainty remains statistically significant for horizon up to 3 months and is robust to additional trade-related factors in the right-hand side of the forecasting regressions. These results provide support on the robustness of our VAR analysis since they show that commodity price uncertainty contains some extra predictive information content on international trade which is not included in exchange rates, trade flow volatility or on the time variation of global business cycles. Moreover, motivated by the empirical findings which show a significant impact of Economic Policy Uncertainty (Handley, 2014; Handley and Limao, 2015, Rodrik, 1991) and exchange rate volatility (Byrne *et al.*, 2008; Franke, 1991; Koray and Lastrapes, 1989) on international trade, we include the realized variance of exchange rate volatility (for US and EA respectively) and the Economic Policy Uncertainty (for US and EA respectively) as additional predictors in our multivariate regression model. We finally include oil prices in our information variable set, since oil prices have been also proven to affect the terms of trade (Backus and Crucini, 2000; Kilian *et al.*, 2009). Equation (10) shows our multivariate regression model and **Tables 6** and **7** present the respective regression results under this multivariate regression specification.

[**Tables 6** and **7** Here]

The regression results of **Tables 6** and **7** show that the predictive power of commodity price uncertainty on US and Euro Area trade flows remains robust to the inclusion of oil price returns, Economic Policy Uncertainty and exchange rate volatility and provides statistically and

economically differentiated predictive power when forecasting trade flows in the Euro Area and in the US economy.

#### **4.4 Which commodities drive the uncertainty-trade relationship?**

In order to examine which commodities drive the commodity price uncertainty and international trade relationship, we estimate the dynamic impact of agricultural, metals and energy price uncertainty shocks on US and Euro Area trade. More specifically, we estimate using equation (1) the Realized Variance of the most liquid commodity futures which are the agricultural (corn, cotton, soybeans, wheat), energy (crude oil, heating oil, petroleum and gasoline) and the metals (copper, gold, silver and platinum). **Figures 11, 12 and 13** below show the estimated OIRFs (derived by our 6-factor reduced-form VAR model) of US import growth to agricultural, energy and metals volatility shocks respectively<sup>14</sup>. The estimated VAR models are the same ones with the previous section (the only difference is that we now use the individual commodity volatility series instead of the volatility of the GSCI commodity futures index as the first variable in our 6-factor reduced form VAR model).

[**Figures 11, 12 and 13** Here]

The estimated OIRFs shown in **Figures 11, 12 and 13** show that the impact of the price uncertainty of agricultural and metals commodity markets has more long-lasting negative impact when compared with the impact of energy price uncertainty shocks. More specifically, among

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<sup>14</sup> Our findings remain unchanged when using our SVAR model presented in the previous section to examine the impact of agricultural, metals and energy price uncertainty shocks on international trade. These additional VAR results can be found in our on-line Appendix.

agricultural commodities, corn and wheat and soybeans price uncertainty has the more pronounced negative impact on US import growth, while, for metals commodity class, the platinum and gold price uncertainty shocks have the most dampening and long-lasting negative effect on US imports. Unlike metals and agricultural price uncertainty shocks, the price uncertainty in energy markets has a rather transitory negative effect in US import growth. For example, while a positive uncertainty shock in the platinum commodity market results to a 0.4% drop in US imports 3 months after the initial uncertainty shock, with the effect remaining negative and statistically significant for 7 months after the platinum uncertainty shock, the respective impact of an oil uncertainty shock is much less in magnitude and statistically insignificant. Overall, our VAR analysis shows that the commodities which drive the commodity uncertainty-trade nexus, surprisingly, do not belong to the group of energy and oil-related commodity class. While the relevant literature so far has identified the significant dampening effect of oil uncertainty on US economic activity (Elder and Serletis, 2010; Elder, 2018; Ferderer, 1996), we show that the uncertainty of non-oil commodity markets like corn, wheat and platinum has a more dampening effect on US import growth.

We additionally estimate the impact of rising volatility in different commodities on US exports.

**Figures 14, 15 and 16** below show the impact of a positive shock in price volatility of agricultural, metals and energy commodities on US import growth.

[**Figures 14, 15 and 16** Here]

From **Figures 14, 15 and 16** we show that the volatility of some metals and agricultural commodities like soybeans, wheat and platinum has a more dampening and long-lasting effect on

US exports compared to the impact of the rising volatility of energy commodities like crude oil and petroleum. For example, a positive shock in wheat price volatility reduces US export growth by almost 0.3% two months after the initial shock while the effect remains negative and statistically significant for 6 months after the initial agricultural volatility shock. On the other hand, the positive volatility shocks in energy commodity prices like crude oil and petroleum have a dampening effect on US exports which remains negative and statistically significant for 2 months after the initial energy price volatility shock. Among metals commodities, the most significant one is platinum: a one standard deviation positive shock in platinum price volatility reduces US export growth by 0.4% with the effect remaining negative and statistically significant for 7 months after the initial platinum volatility shock.

We perform the same VAR analysis by estimating identical reduced-form VAR model for Euro Area trade flows. **Figures 17 to 22** below show the estimated OIRFs of Euro Area import and export growth to agricultural, metals and energy price uncertainty shocks respectively.

[**Figures 17, 18, 19, 20, 21 and 22** Here]

The estimated OIRFs shown in Figures 17 to 22 we observe that agricultural and metals uncertainty shocks have a more negative and persistent effect on Euro Area imports and exports compared to the energy uncertainty shocks. Thus, what holds for the US, it holds for the Euro Area as well: uncertainty in agricultural and metals commodity markets (and not the uncertainty in oil markets) is the key driver of fluctuations in Euro Area trade flows. More specifically, corn, wheat and platinum price uncertainty shocks appear to be the most significant shocks affecting Euro Area imports and exports, while the energy uncertainty shocks are less in magnitude and

statistically insignificant. Interestingly, we find a significant negative response of Euro Area exports to a positive uncertainty shock in the gasoline commodity market.

## **5. Robustness**

In this section we provide additional robustness to our findings by adding some already empirically verified predictors of trade flows in our information variable set. In more detail, we estimate the SVAR model which is analytically described in Subsection 2.2, using, instead of the overall GSCI commodity price index, the WTI nominal and real crude oil prices (as shown in Kilian, 2009) and we show that the dynamic responses of international trade flows to uncertainty shocks remain robust and larger in magnitude compared to oil price shocks. Moreover, we estimate the reduced-form version of the SVAR model described in Subsection 2.2 and we find that our main results remain unaltered. These results show that commodity price uncertainty has a significant response on US and Euro Area trade even when we allow for possible interactions between global supply and demand shocks in the VAR model. Moreover, motivated by the findings of the literature which show the impact of exchange rate volatility (Chowdhury 1993; Pick, 1990) on trade flows, we estimate an additional VAR model using exchange rate volatility as an additional variable in our VAR model and our findings remain robust to this VAR identification scheme. We also perform the VAR analysis allowing for 12 and 24 lags in our SVAR model and our findings remain unaltered. We additionally estimate a more parsimonious SVAR model (as suggested by the Akaike and Schwartz optimal lag length criteria) allowing for only two lags and the results remain unaltered. Finally, we control for alternative proxies for real global economic activity, for different proxies for Economic uncertainty (e.g. stock market volatility, see Bloom, 2009) and for different proxies of aggregate supply (e.g. global inventory

level of crude oil) and our main findings remain unaltered. All the robustness results can be found in our on-line Appendix.

## **6. Conclusions**

In this paper, we empirically show the negative impact of commodity price uncertainty shocks on US and Euro Area trade flows. EA trade is significantly damaged when uncertainty about future commodity prices rises, with the effect remaining negative and statistically significant for six months after the uncertainty shock. Our SVAR analysis shows that the dampening effect of rising commodity price uncertainty on US and Euro Area trade is larger and more persistent when compared with the respective impact of the global demand, global supply, trade volatility, the exchange rate shocks. Moreover, when examining the dynamic impact of the rising uncertainty of individual commodity markets, we find that the non-oil commodity uncertainty shocks have a more long-lasting impact on US and EA exports and imports when compared to the respective impact of oil-related commodities. Our findings are significant for trade policy makers since we show that rising uncertainty in oil and non-oil commodity futures markets is associated with falling international trade. Our paper is the first clear empirical evidence showing that the commodity uncertainty shocks are more significant determinants of international trade flows, when compared with commodity price shocks. We believe that the further exploration of the effect of time varying uncertainty which is derived from forward-looking commodity option markets (e.g. option-implied volatility) on international trade, can be a fruitful area for future research.

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**Table 1: Descriptive Statistics**

	<i>Mean</i>	<i>Std. Dev.</i>	<i>Minimum</i>	<i>Maximum</i>	<i>Skewness</i>	<i>Kurtosis</i>
<i>IMP<sub>EU</sub></i>	0.005	0.030	-0.122	0.077	-0.380	4.092
<i>IMPV<sub>EU</sub></i>	0.001	0.000	0.001	0.002	3.537	20.143
<i>EXP<sub>EU</sub></i>	0.005	0.028	-0.114	0.085	-0.532	4.830
<i>EXPV<sub>EU</sub></i>	0.001	0.000	0.000	0.003	3.324	17.188
<i>IMP<sub>US</sub></i>	0.005	0.024	-0.146	0.070	-1.257	9.311
<i>IMPV<sub>US</sub></i>	0.001	0.001	0.000	0.007	6.269	49.208
<i>EXP<sub>US</sub></i>	0.004	0.023	-0.106	0.104	-0.449	6.334
<i>EXPV<sub>US</sub></i>	0.001	0.000	0.000	0.003	4.083	21.563
<i>EXCH<sub>EU</sub></i>	-0.000	0.014	-0.051	0.052	0.221	3.677
<i>EXCHV<sub>EU</sub></i>	0.004	0.003	0.000	0.028	2.931	16.082
<i>EXCH<sub>US</sub></i>	0.000	0.012	-0.040	0.055	0.096	4.413
<i>EXCHV<sub>US</sub></i>	0.004	0.003	0.000	0.026	3.086	16.544
<i>COMRET</i>	-0.002	0.066	-0.351	0.178	-0.777	5.454
<i>COMRV</i>	0.047	0.047	0.004	0.378	3.721	21.856
<i>GACT</i>	0.028	0.305	-1.332	0.666	-0.256	3.991
<i>GRISK</i>	0.824	0.646	0.251	5.362	3.628	21.096
<i>EPU<sub>EU</sub></i>	1.306	0.607	0.477	4.333	1.676	7.398
<i>EPU<sub>US</sub></i>	1.055	0.353	0.572	2.451	1.099	3.617
<i>OIL</i>	0.005	0.085	-0.337	0.214	-0.697	4.382
<i>N</i>	277					

The dataset covers the period January 1994 to January 2017.

**Table 2. Bivariate Forecasting Regressions for US Imports and Exports**

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

	(1)	(2)	(3)	(4)	(5)
<i>Horizon (k)</i>	<i>IMP</i> <i>0m</i>	<i>IMP</i> <i>1m</i>	<i>IMP</i> <i>2m</i>	<i>IMP</i> <i>3m</i>	<i>IMP</i> <i>6m</i>
<i>COMRV</i>	-0.172** (-2.35)	-0.189*** (-2.84)	-0.183*** (-2.78)	-0.116* (-1.77)	-0.009 (-0.19)
<i>N</i>	276	276	275	274	271
<i>Adj R2 (%)</i>	11.42	13.98	13.04	5.043	-0.339
<i>RMSE</i>	0.0221	0.0218	0.0219	0.0229	0.0235

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

	(1)	(2)	(3)	(4)	(5)
<i>Horizon (k)</i>	<i>EXP</i> <i>0m</i>	<i>EXP</i> <i>1m</i>	<i>EXP</i> <i>2m</i>	<i>EXP</i> <i>3m</i>	<i>EXP</i> <i>6m</i>
<i>COMRV</i>	-0.175*** (-3.90)	-0.153*** (-2.76)	-0.096 (-1.42)	-0.058 (-1.03)	0.003 (0.06)
<i>N</i>	276	276	275	274	271
<i>Adj R2 (%)</i>	12.58	9.528	3.562	1.199	-0.368
<i>RMSE</i>	0.0213	0.0217	0.0222	0.0218	0.0219

*Notes:* *t* statistics in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . The *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The forecasting horizon ranges from 1 to 6 months.

**Table 3. Bivariate Forecasting Regressions for EA Imports and Exports**

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

	(1)	(2)	(3)	(4)	(5)
<i>Horizon (k)</i>	<i>IMP</i> <i>0m</i>	<i>IMP</i> <i>1m</i>	<i>IMP</i> <i>2m</i>	<i>IMP</i> <i>3m</i>	<i>IMP</i> <i>6m</i>
<i>COMRV</i>	-0.184*** (-3.03)	-0.181*** (-3.26)	-0.136** (-2.11)	-0.097 (-1.49)	0.019 (0.46)
<i>N</i>	276	276	275	274	271
<i>Adj R2 (%)</i>	7.80	7.54	4.10	1.89	-0.29
<i>RMSE</i>	0.029	0.029	0.030	0.030	0.031

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

	(1)	(2)	(3)	(4)	(5)
<i>Horizon (k)</i>	<i>EXP</i> <i>0m</i>	<i>EXP</i> <i>1m</i>	<i>EXP</i> <i>2m</i>	<i>EXP</i> <i>3m</i>	<i>EXP</i> <i>6m</i>
<i>COMRV</i>	-0.186*** (-3.39)	-0.147** (-2.25)	-0.133** (-2.12)	-0.069 (-1.05)	0.052 (1.47)
<i>N</i>	276	276	275	274	271
<i>Adj R2 (%)</i>	9.35	5.72	4.60	0.96	0.39
<i>RMSE</i>	0.027	0.027	0.027	0.028	0.028

*Notes:* *t* statistics in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . The *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The forecasting horizon ranges from 1 to 6 months.

**Table 4. Multivariate Forecasting Regressions for US Imports and Exports**

$$IMP_t = b_0 + b_1 COMRV_{t-k} + b_2 IMPV_{t-k} + b_3 EXCH_{t-k} + b_4 GACT_{t-k} + b_5 GRISK_{t-k} + \varepsilon_t$$

	(1)	(2)	(3)	(4)	(5)
	<i>IMP</i>	<i>IMP</i>	<i>IMP</i>	<i>IMP</i>	<i>IMP</i>
<i>Horizon (k)</i>	<i>0m</i>	<i>1m</i>	<i>2m</i>	<i>3m</i>	<i>6m</i>
<i>COMRV</i>	-0.114 (-1.35)	-0.170*** (-2.69)	-0.200*** (-2.73)	-0.139** (-2.18)	-0.061* (-1.90)
<i>N</i>	276	275	274	273	270
<i>Adj R2 (%)</i>	17.21	17.43	15.33	5.862	2.655
<i>RMSE</i>	0.0212	0.0212	0.0214	0.0226	0.0231

$$EXP_t = b_0 + b_1 COMRV_{t-k} + b_2 EXPV_{t-k} + b_3 EXCH_{t-k} + b_4 GACT_{t-k} + b_5 GRISK_{t-k} + \varepsilon_t$$

	(1)	(2)	(3)	(4)	(5)
	<i>EXP</i>	<i>EXP</i>	<i>EXP</i>	<i>EXP</i>	<i>EXP</i>
<i>Horizon (k)</i>	<i>0m</i>	<i>1m</i>	<i>2m</i>	<i>3m</i>	<i>6m</i>
<i>COMRV</i>	-0.176*** (-4.12)	-0.168*** (-3.25)	-0.081 (-1.33)	-0.064 (-1.35)	-0.014 (-0.35)
<i>N</i>	276	275	274	273	270
<i>Adj R2 (%)</i>	17.98	16.71	7.268	2.545	1.689
<i>RMSE</i>	0.0205	0.0205	0.0209	0.0214	0.0215

*Notes:* *t* statistics in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . The *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The forecasting horizon ranges from 1 to 6 months. For brevity we report only the  $b_1$  coefficients of the commodity price uncertainty (*COMRV*) of the multivariate regression model.

**Table 5. Multivariate Forecasting Regressions for EA Imports and Exports**

$$IMP_t = b_0 + b_1 COMRV_{t-k} + b_2 IMPV_{t-k} + b_3 EXCH_{t-k} + b_4 GACT_{t-k} + b_5 GRISK_{t-k} + \varepsilon_t$$

	(1)	(2)	(3)	(4)	(5)
	<i>IMP</i>	<i>IMP</i>	<i>IMP</i>	<i>IMP</i>	<i>IMP</i>
<i>Horizon (k)</i>	<i>0m</i>	<i>1m</i>	<i>2m</i>	<i>3m</i>	<i>6m</i>
<i>COMRV</i>	-0.161*** (-3.05)	-0.208*** (-2.95)	-0.163** (-2.02)	-0.173* (-1.93)	-0.043 (-0.88)
<i>N</i>	276	275	274	273	270
<i>Adj R2 (%)</i>	35.57	8.53	4.85	3.18	-0.13
<i>RMSE</i>	0.024	0.029	0.029	0.030	0.030

$$EXP_t = b_0 + b_1 COMRV_{t-k} + b_2 EXPV_{t-k} + b_3 EXCH_{t-k} + b_4 GACT_{t-k} + b_5 GRISK_{t-k} + \varepsilon_t$$

	(1)	(2)	(3)	(4)	(5)
	<i>EXP</i>	<i>EXP</i>	<i>EXP</i>	<i>EXP</i>	<i>EXP</i>
<i>Horizon (k)</i>	<i>0m</i>	<i>1m</i>	<i>2m</i>	<i>3m</i>	<i>6m</i>
<i>COMRV</i>	-0.227*** (-5.59)	-0.203*** (-2.69)	-0.217*** (-3.33)	-0.149** (-2.01)	0.028 (0.63)
<i>N</i>	276	275	274	273	270
<i>Adj R2 (%)</i>	42.03	7.34	7.84	3.15	-0.083
<i>RMSE</i>	0.021	0.027	0.027	0.027	0.028

*Notes:* *t* statistics in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . The *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The forecasting horizon ranges from 1 to 6 months. For brevity we report only the  $b_1$  coefficients of the commodity price uncertainty (*COMRV*) of the multivariate regression model.

**Table 6. Multivariate Forecasting Regressions with Additional Controls for US Imports and Exports**

$$IMP_t = b_0 + b_1 COMRV_{t-k} + b_2 IMPV_{t-k} + b_3 EXCH_{t-k} + b_4 GACT_{t-k} + b_5 GRISK_{t-k} + b_6 COM_{t-k} + b_7 EXCHV_{t-k} + b_8 EPU_{t-k} + b_9 OIL_{t-k} + \varepsilon_t$$

	(1)	(2)	(3)	(4)	(5)
	<i>IMP</i>	<i>IMP</i>	<i>IMP</i>	<i>IMP</i>	<i>IMP</i>
<i>Horizon (k)</i>	<i>0m</i>	<i>1m</i>	<i>2m</i>	<i>3m</i>	<i>6m</i>
<i>COMRV</i>	-0.094 (-1.29)	-0.085* (-1.89)	-0.164** (-2.41)	-0.104** (-2.11)	-0.081* (-1.73)
<i>N</i>	276	275	274	273	270
<i>Adj R2 (%)</i>	25.63	26.90	15.94	7.381	1.670
<i>RMSE</i>	0.0199	0.0198	0.0212	0.0223	0.0230

$$EXP_t = b_0 + b_1 COMRV_{t-k} + b_2 EXPV_{t-k} + b_3 EXCH_{t-k} + b_4 GACT_{t-k} + b_5 GRISK_{t-k} + b_6 COM_{t-k} + b_7 EXCHV_{t-k} + b_8 EPU_{t-k} + b_9 OIL_{t-k} + \varepsilon_t$$

	(1)	(2)	(3)	(4)	(5)
	<i>EXP</i>	<i>EXP</i>	<i>EXP</i>	<i>EXP</i>	<i>EXP</i>
<i>Horizon (k)</i>	<i>0m</i>	<i>1m</i>	<i>2m</i>	<i>3m</i>	<i>6m</i>
<i>COMRV</i>	-0.177*** (-5.29)	-0.132*** (-2.97)	-0.043 (-0.70)	-0.005 (-0.11)	-0.035 (-0.63)
<i>N</i>	276	275	274	273	270
<i>Adj R2 (%)</i>	18.42	20.07	7.055	3.097	2.512
<i>RMSE</i>	0.0203	0.0200	0.0208	0.0212	0.0212

*Notes:* *t* statistics in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . The *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The forecasting horizon ranges from 1 to 6 months. For brevity we report only the  $b_1$  coefficients of the commodity price uncertainty (*COMRV*) of the multivariate regression model.

**Table 7. Multivariate Forecasting Regressions with Additional Controls for EA Imports and Exports**

$$IMP_t = b_0 + b_1 COMRV_{t-k} + b_2 IMPV_{t-k} + b_3 EXCH_{t-k} + b_4 GACT_{t-k} + b_5 GRISK_{t-k} + b_6 COM_{t-k} + b_7 EXCHV_{t-k} + b_8 EPU_{t-k} + b_9 OIL_{t-k} + \varepsilon_t$$

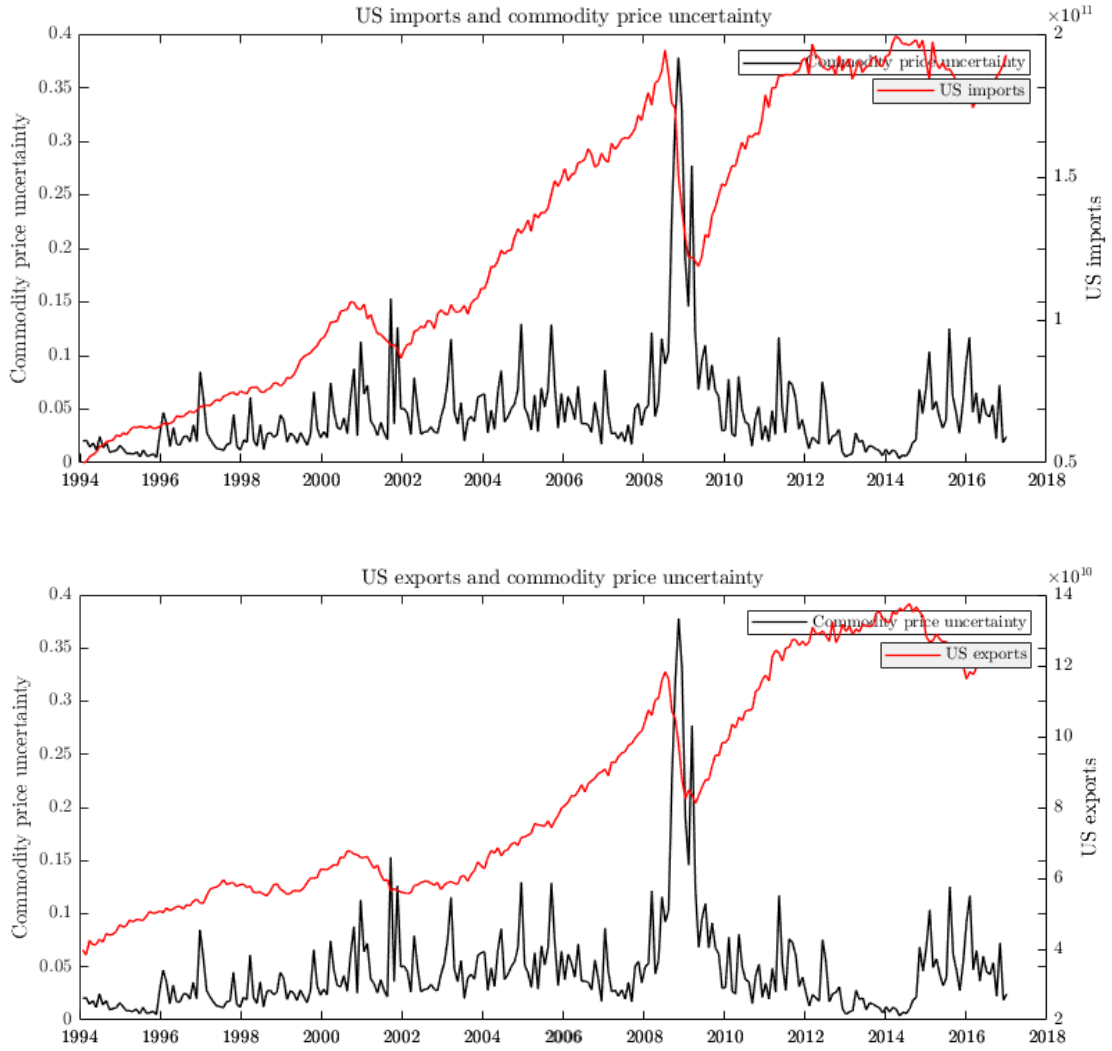
	(1)	(2)	(3)	(4)	(5)
	<i>IMP</i>	<i>IMP</i>	<i>IMP</i>	<i>IMP</i>	<i>IMP</i>
<i>Horizon (k)</i>	<i>0m</i>	<i>1m</i>	<i>2m</i>	<i>3m</i>	<i>6m</i>
<i>COMRV</i>	-0.106*** (-2.59)	-0.135** (-2.31)	-0.129 (-1.59)	-0.123 (-1.41)	-0.046 (-0.87)
<i>N</i>	276	275	274	273	270
<i>Adj R2 (%)</i>	41.22	13.46	4.298	4.133	-0.921
<i>RMSE</i>	0.0229	0.0278	0.0292	0.0293	0.0299

$$EXP_t = b_0 + b_1 COMRV_{t-k} + b_2 EXPV_{t-k} + b_3 EXCH_{t-k} + b_4 GACT_{t-k} + b_5 GRISK_{t-k} + b_6 COM_{t-k} + b_7 EXCHV_{t-k} + b_8 EPU_{t-k} + b_9 OIL_{t-k} + \varepsilon_t$$

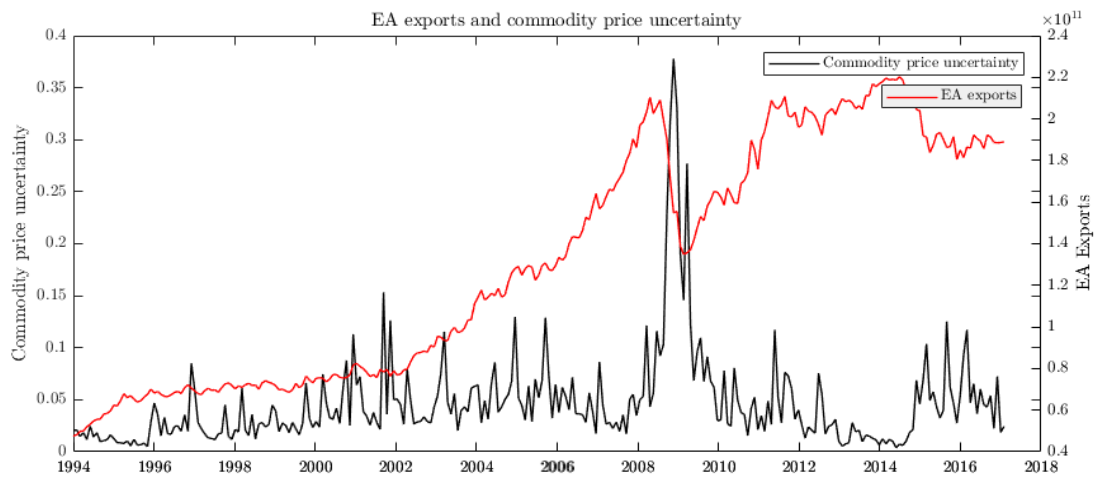
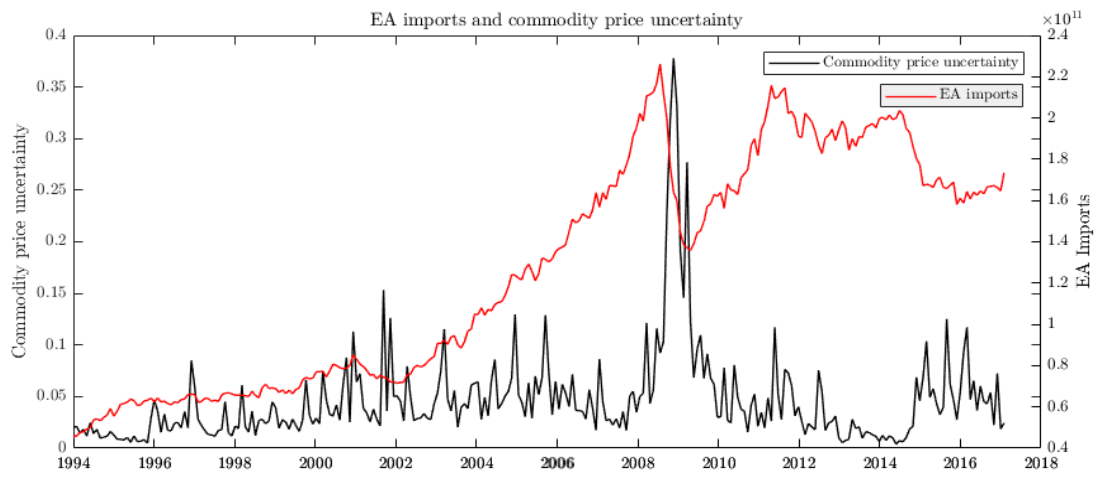
	(1)	(2)	(3)	(4)	(5)
	<i>EXP</i>	<i>EXP</i>	<i>EXP</i>	<i>EXP</i>	<i>EXP</i>
<i>Horizon (k)</i>	<i>0m</i>	<i>1m</i>	<i>2m</i>	<i>3m</i>	<i>6m</i>
<i>COMRV</i>	-0.185*** (-4.94)	-0.137** (-1.99)	-0.196*** (-2.87)	-0.110 (-1.50)	0.017 (0.33)
<i>N</i>	276	275	274	273	270
<i>Adj R2 (%)</i>	43.65	9.692	6.972	3.815	-0.843
<i>RMSE</i>	0.0207	0.0262	0.0266	0.0271	0.0278

Notes: *t* statistics in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . The *t*-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. The forecasting horizon ranges from 1 to 6 months. For brevity we report only the  $b_1$  coefficients of the commodity price uncertainty (*COMRV*) of the multivariate regression model.

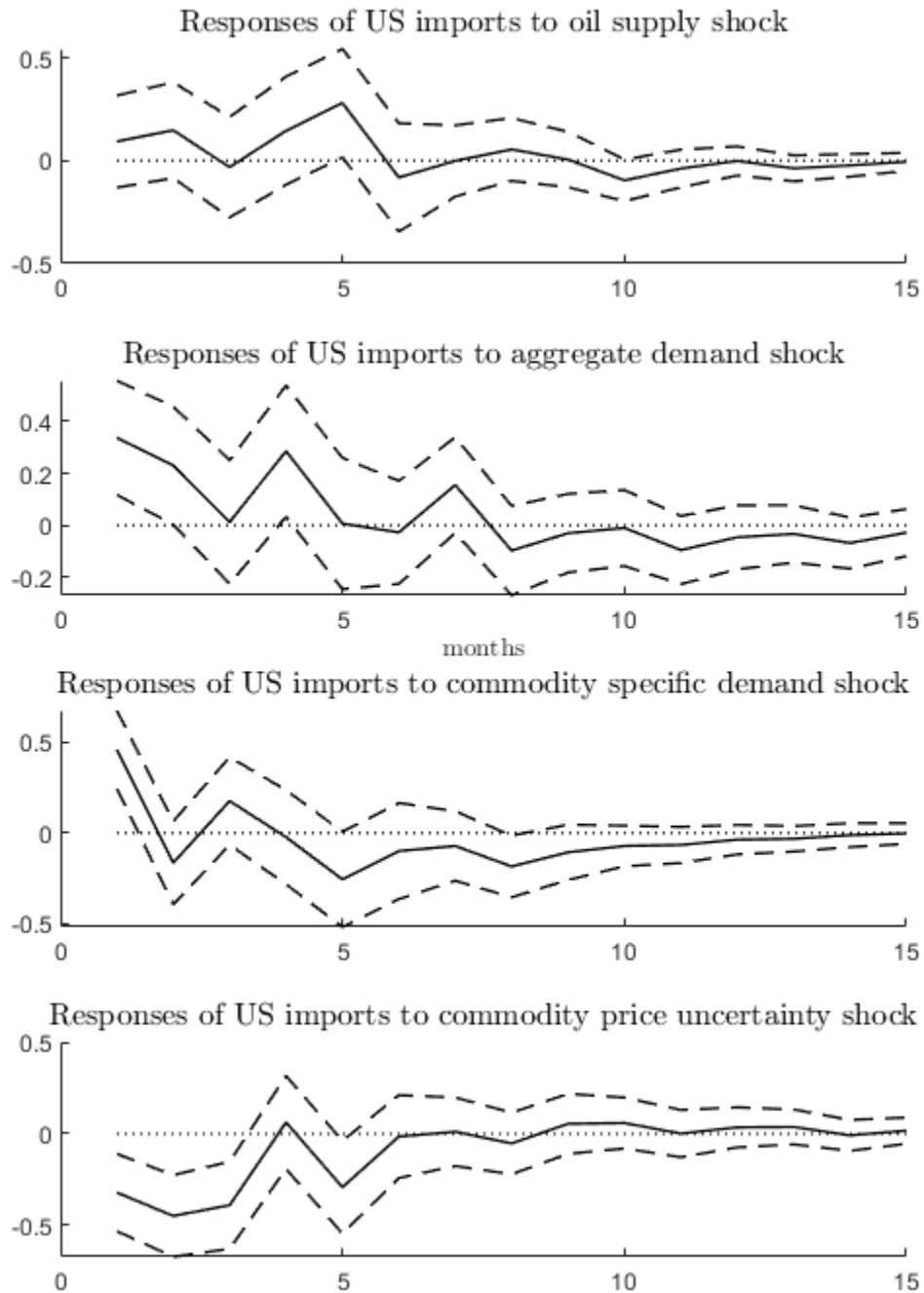
**Figure 1. US Imports & Exports and Commodity Price Uncertainty**



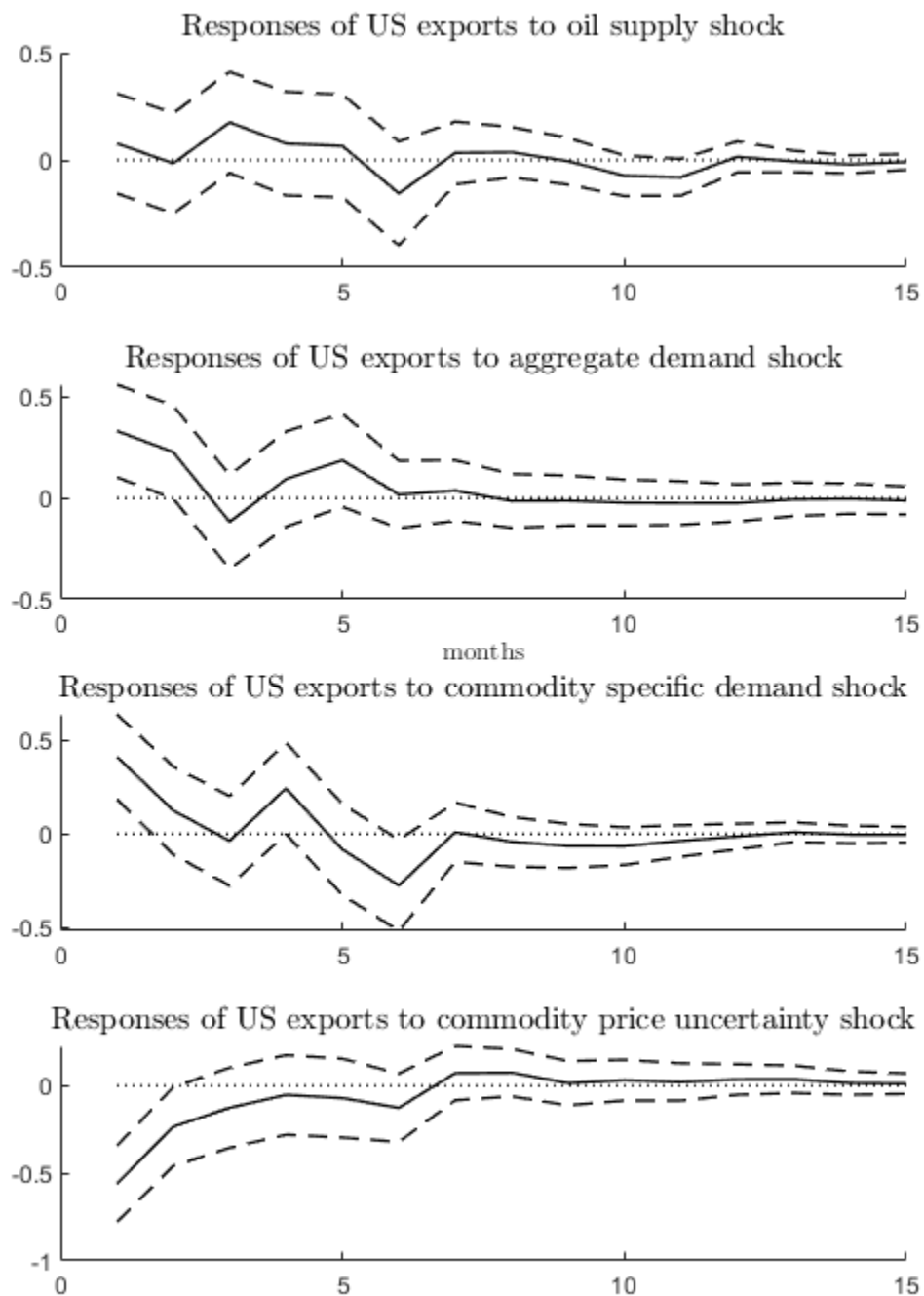
**Figure 2. Euro Area (EA) Imports & Exports and Commodity Price Uncertainty**



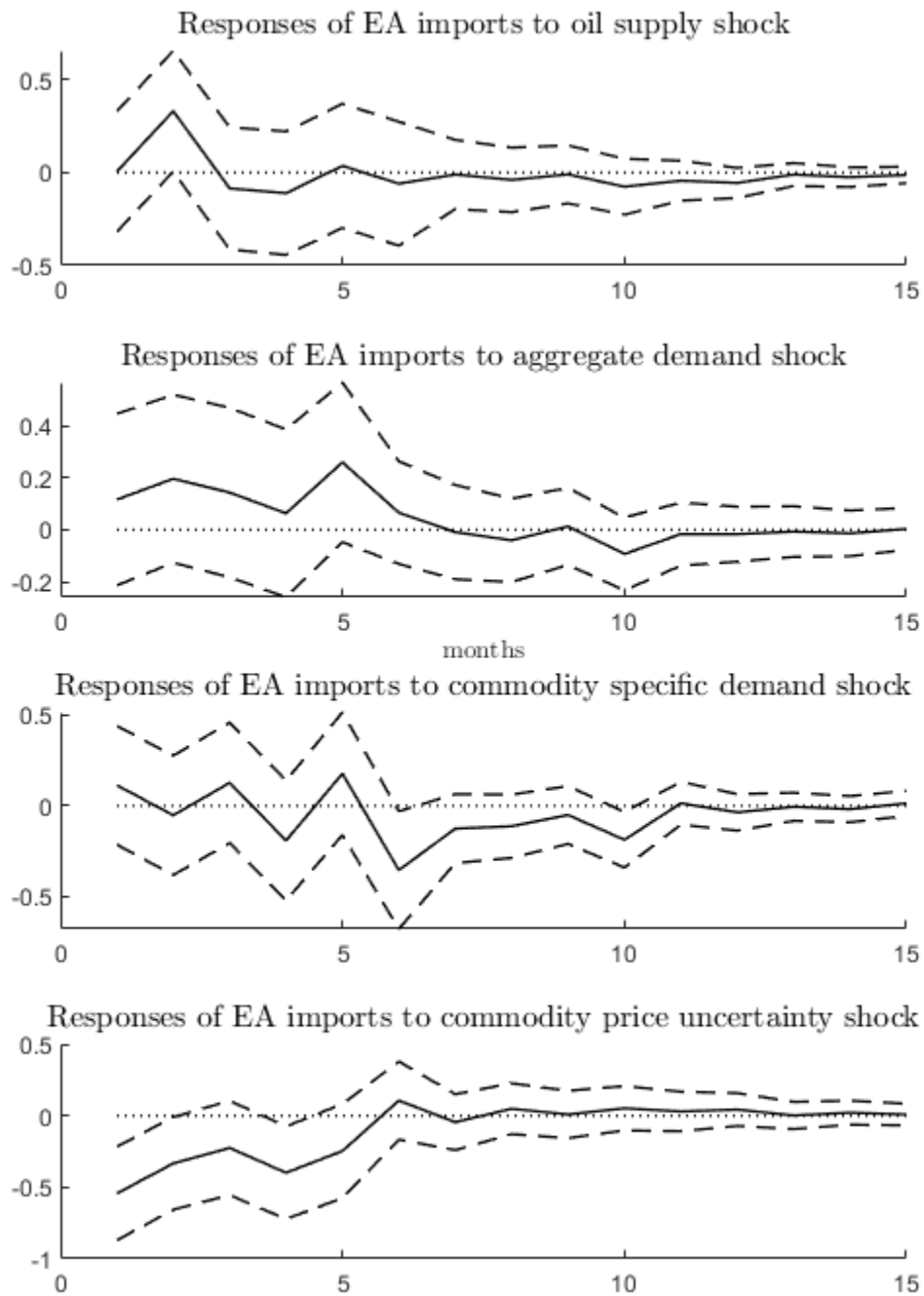
**Figure 3. Structural-form Impulse Response Functions (SIRFs) of US imports to commodity supply, demand and commodity price uncertainty shocks**



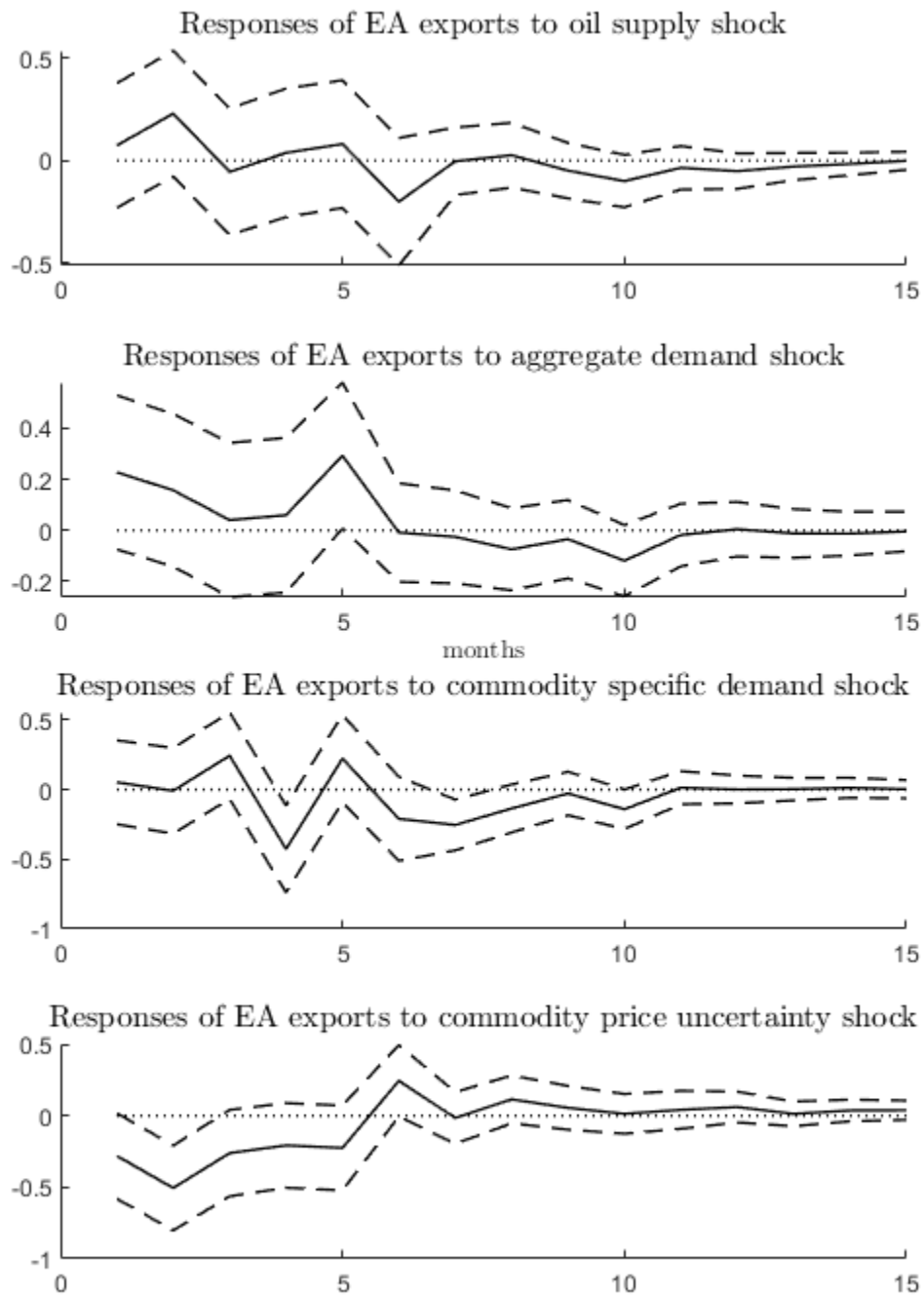
**Figure 4. Structural-form Impulse Response Functions (SIRFs) of US exports to commodity supply, demand and commodity price uncertainty shocks**



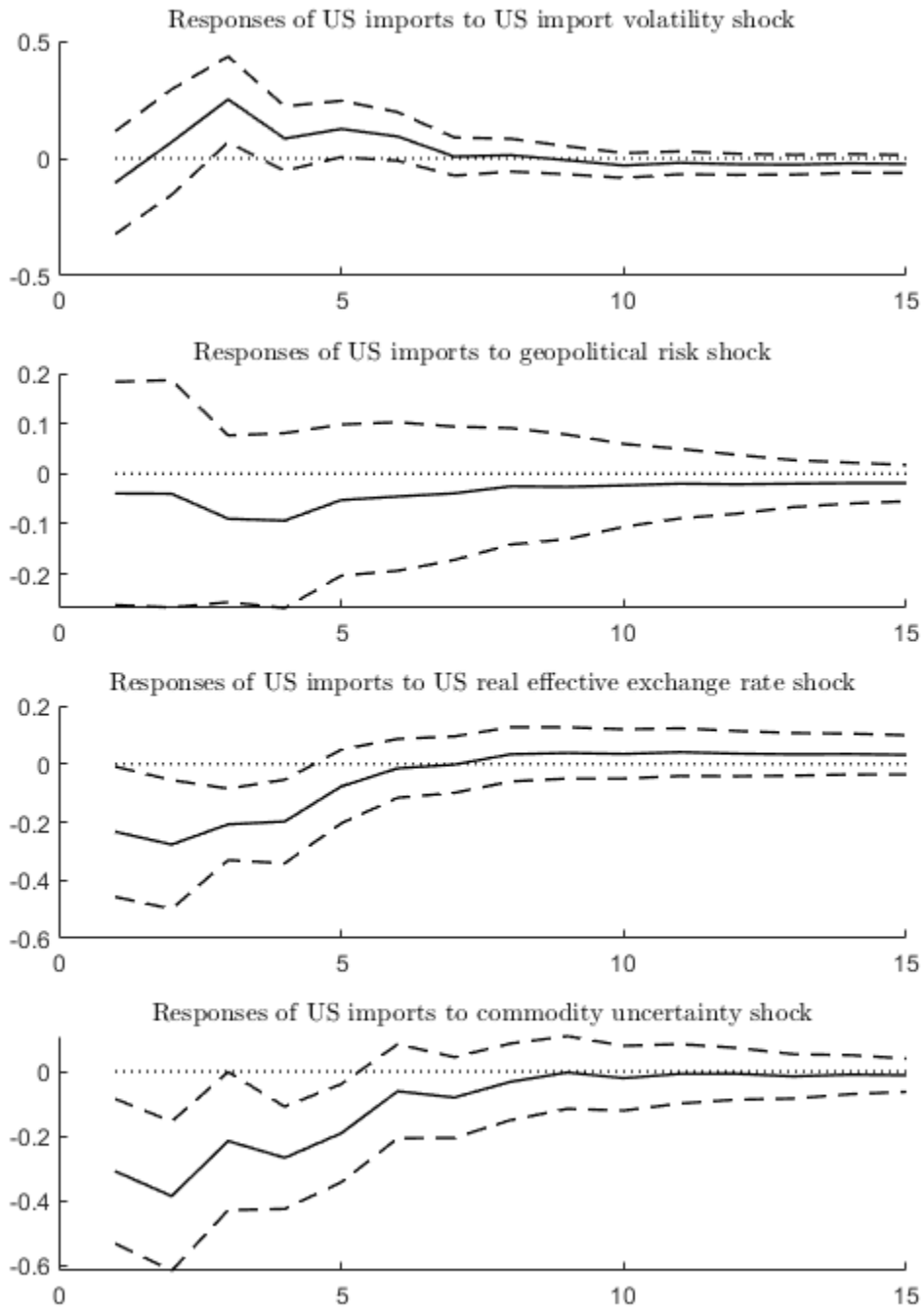
**Figure 5. Structural-form Impulse Response Functions (SIRFs) of Euro Area imports to commodity supply, demand and commodity price uncertainty shocks**



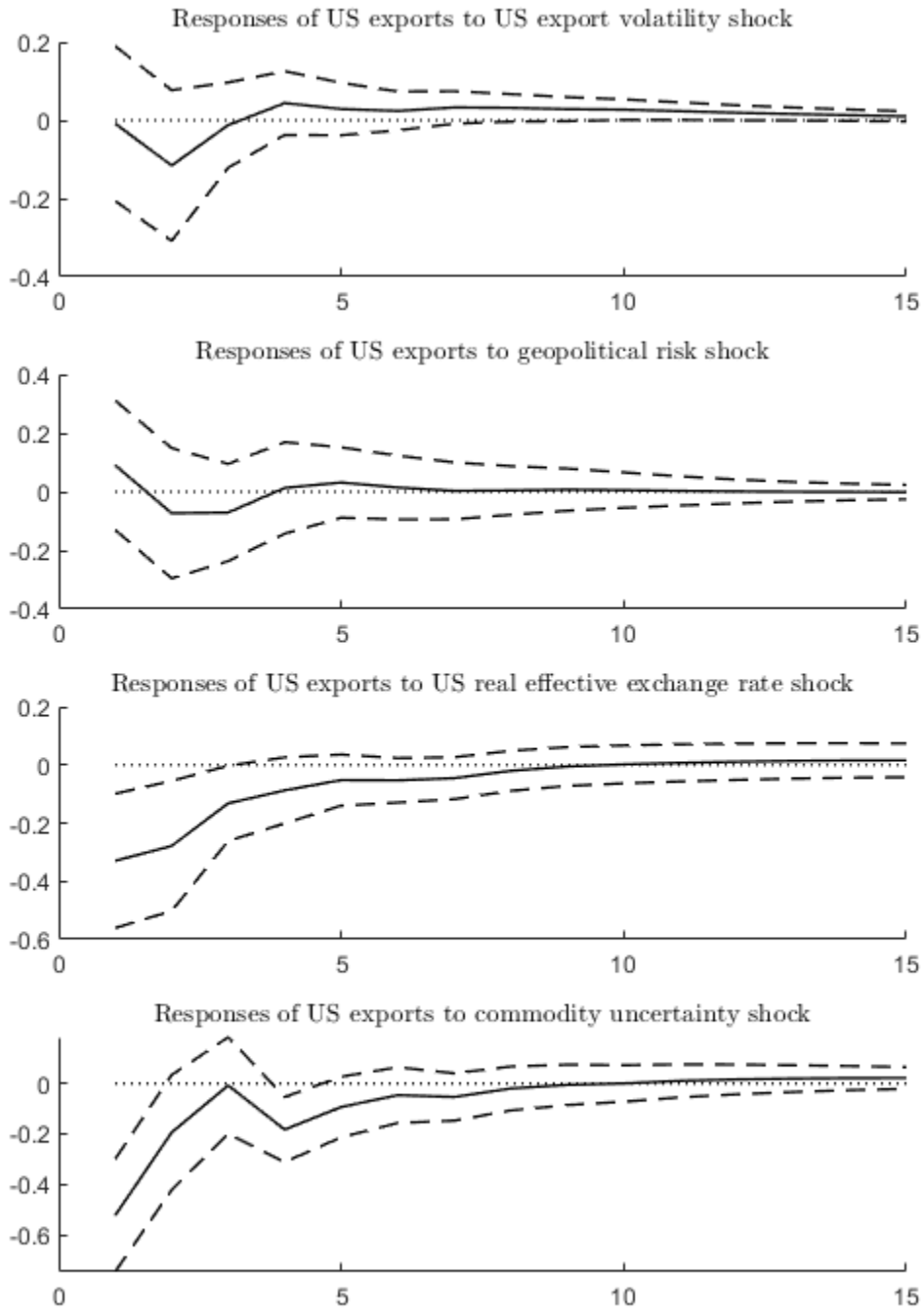
**Figure 6. Structural-form Impulse Response Functions (SIRFs) of Euro Area exports to commodity supply, demand and commodity price uncertainty shocks**



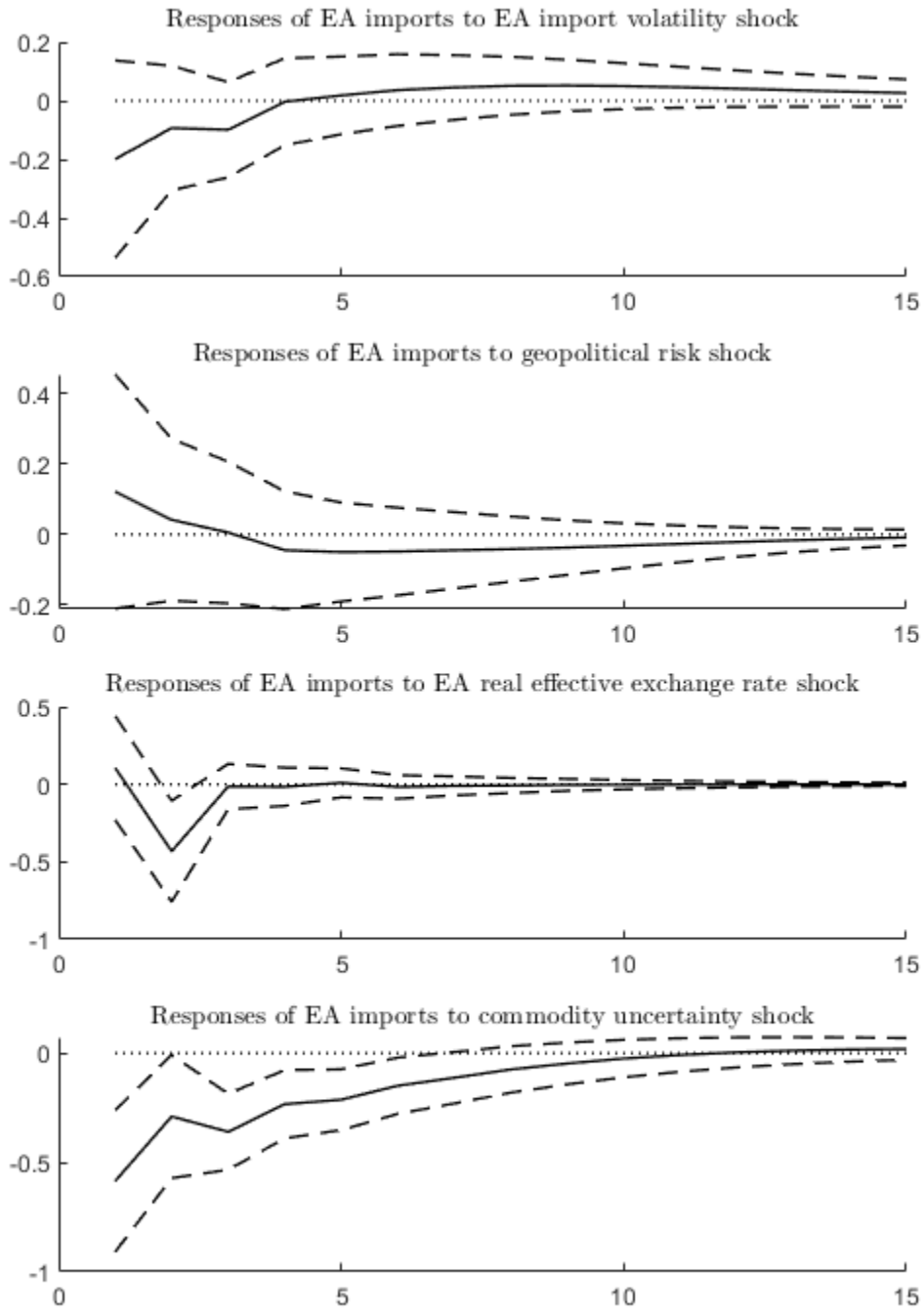
**Figure 7. OIRFs of US Imports Growth**



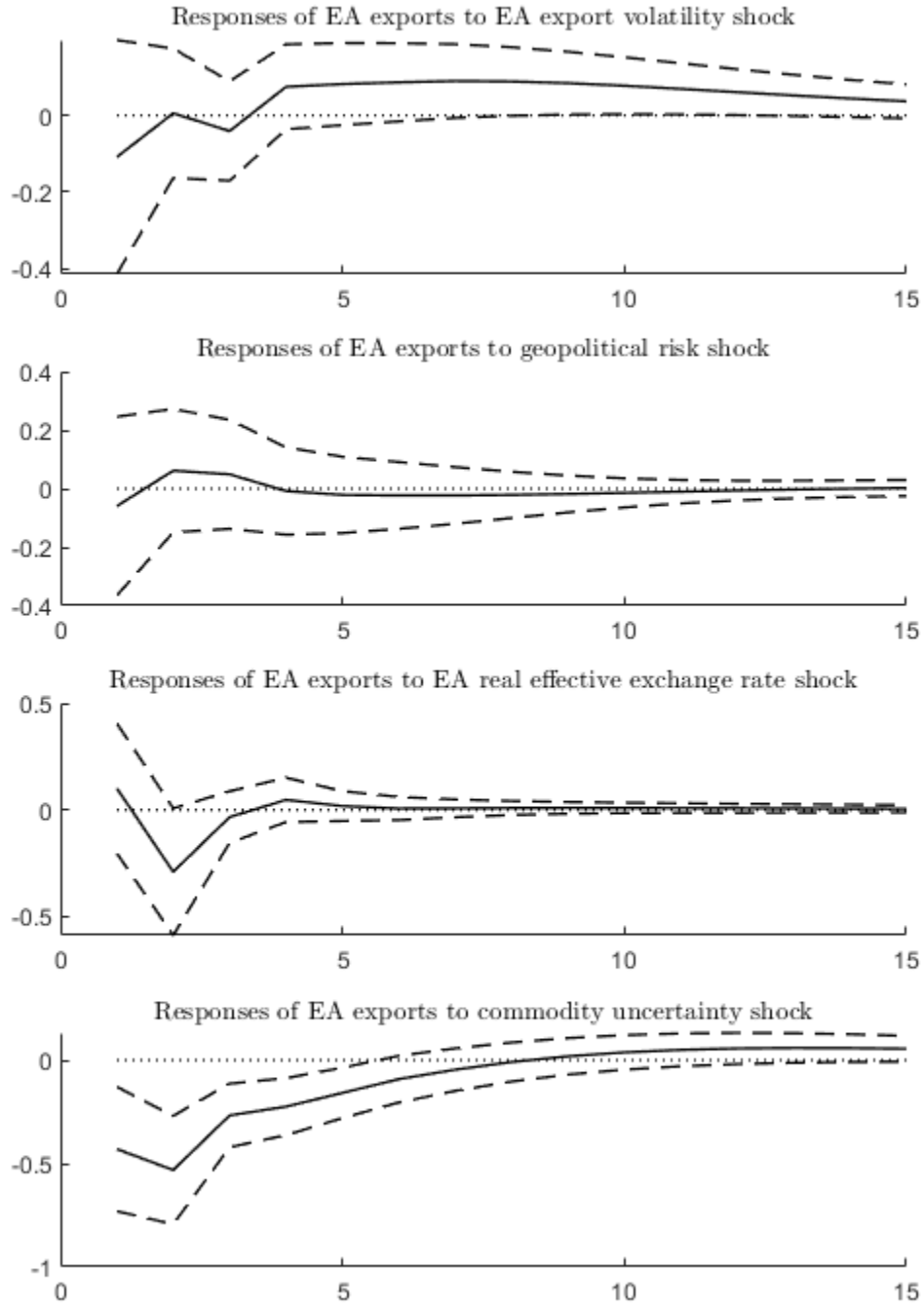
**Figure 8. OIRFs of US Exports Growth**



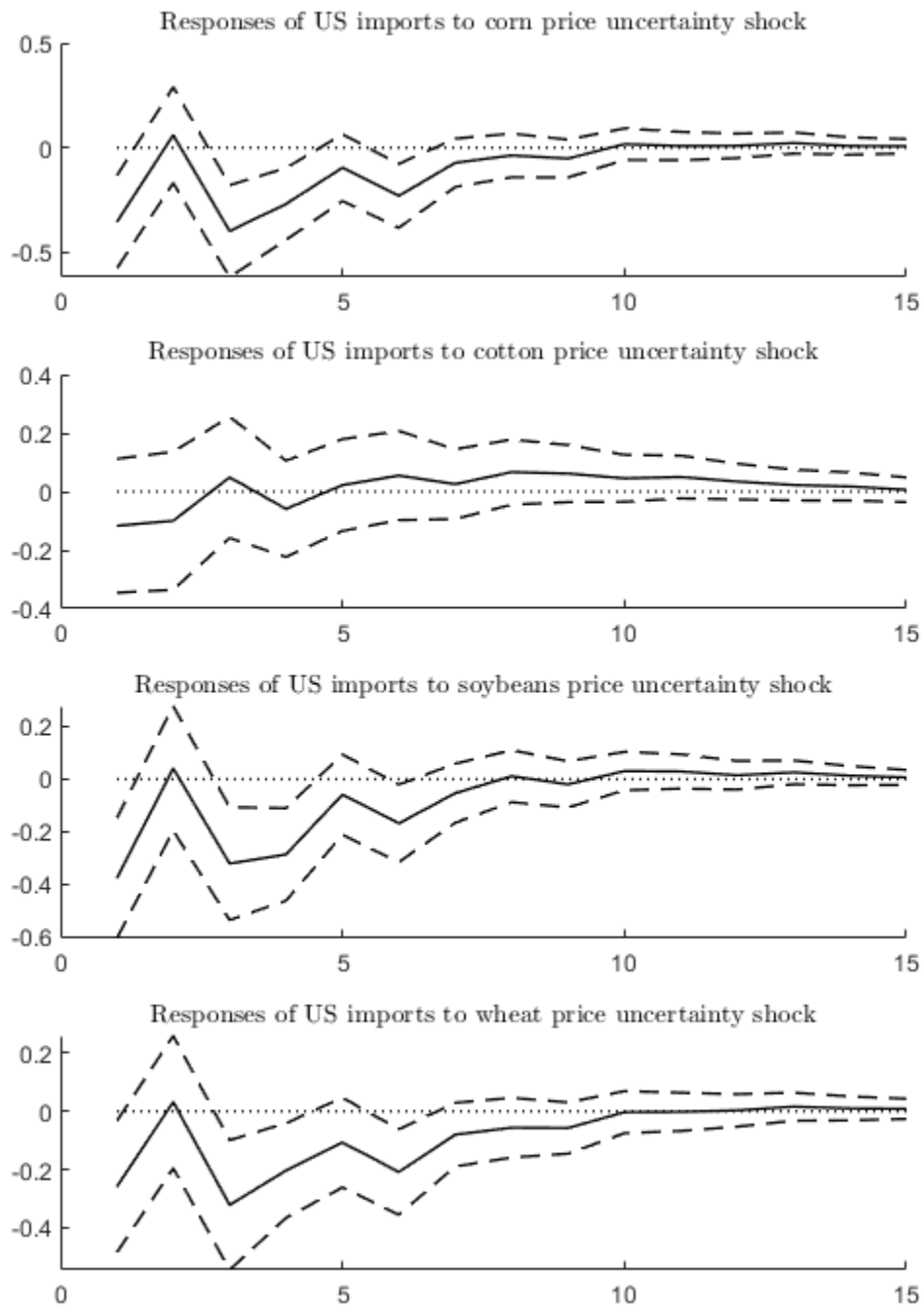
**Figure 9. OIRFs of EA Imports Growth**



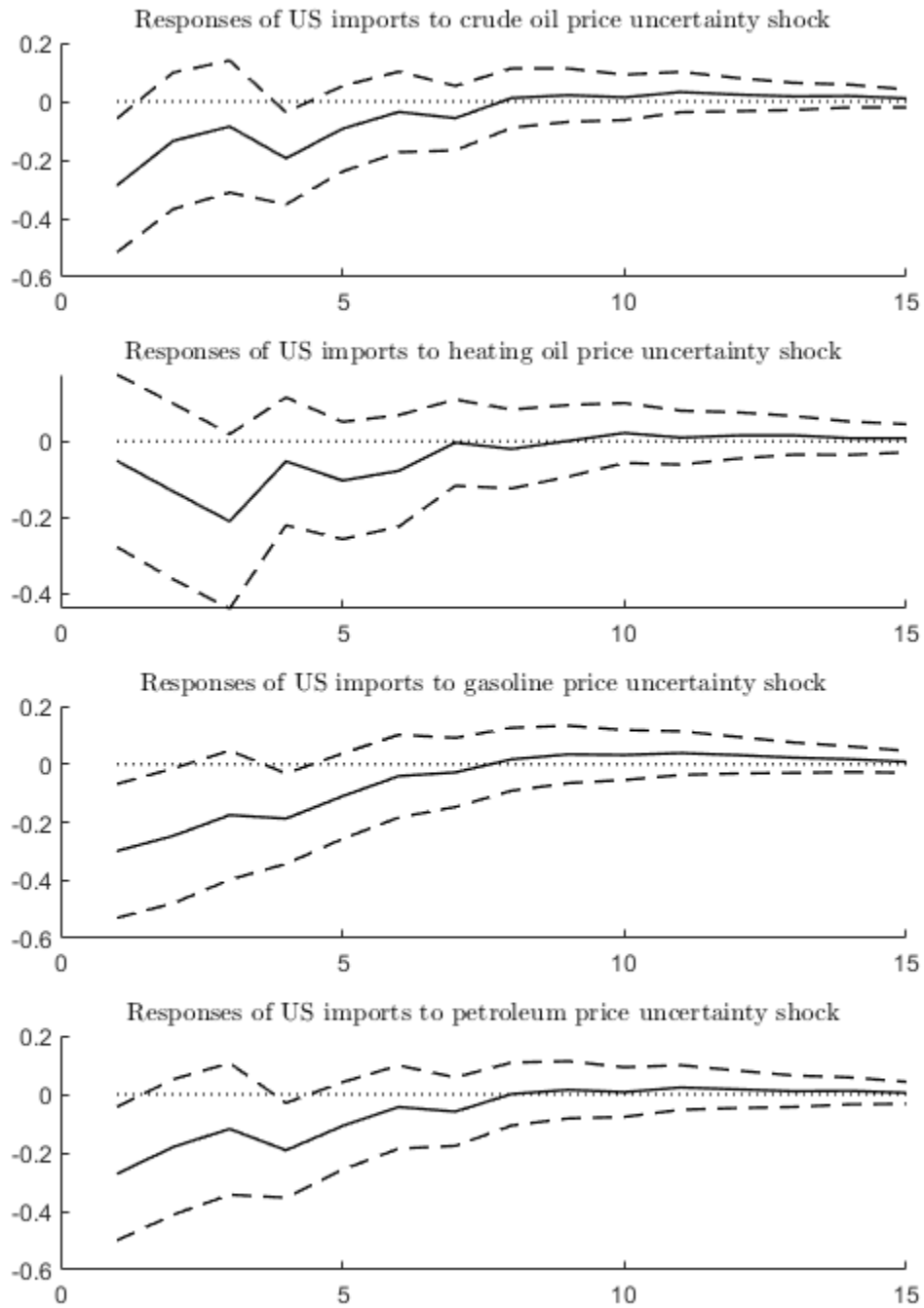
**Figure 10. OIRFs of EA Exports Growth**



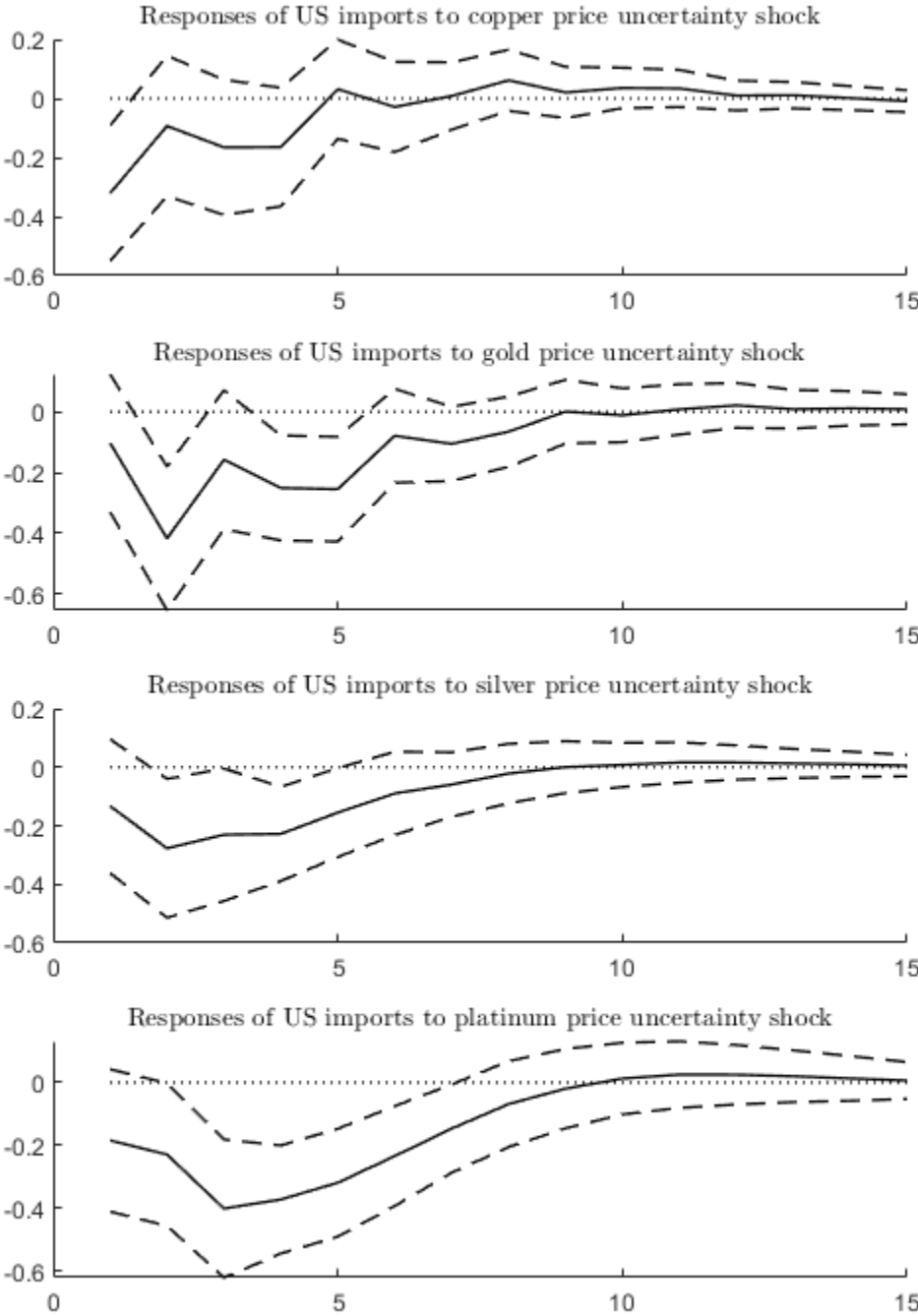
**Figure 11. OIRFs of US Imports Growth to agricultural price uncertainty shocks**



**Figure 12. OIRFs of US Imports Growth to energy price uncertainty shocks**



**Figure 13. OIRFs of US Imports Growth to metals price uncertainty shocks**



**Figure 14. OIRFs of US Exports Growth to agricultural price uncertainty shocks**

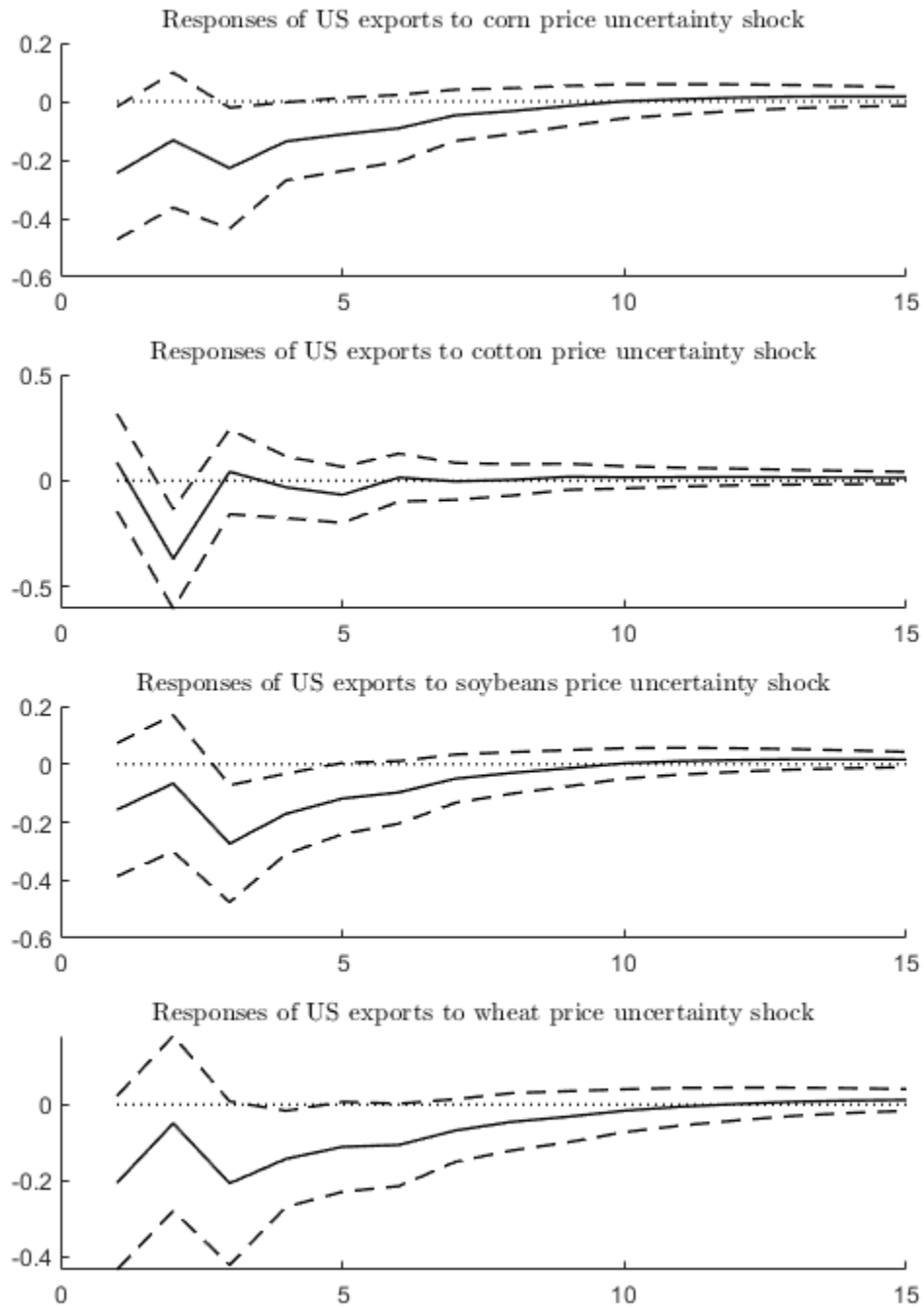
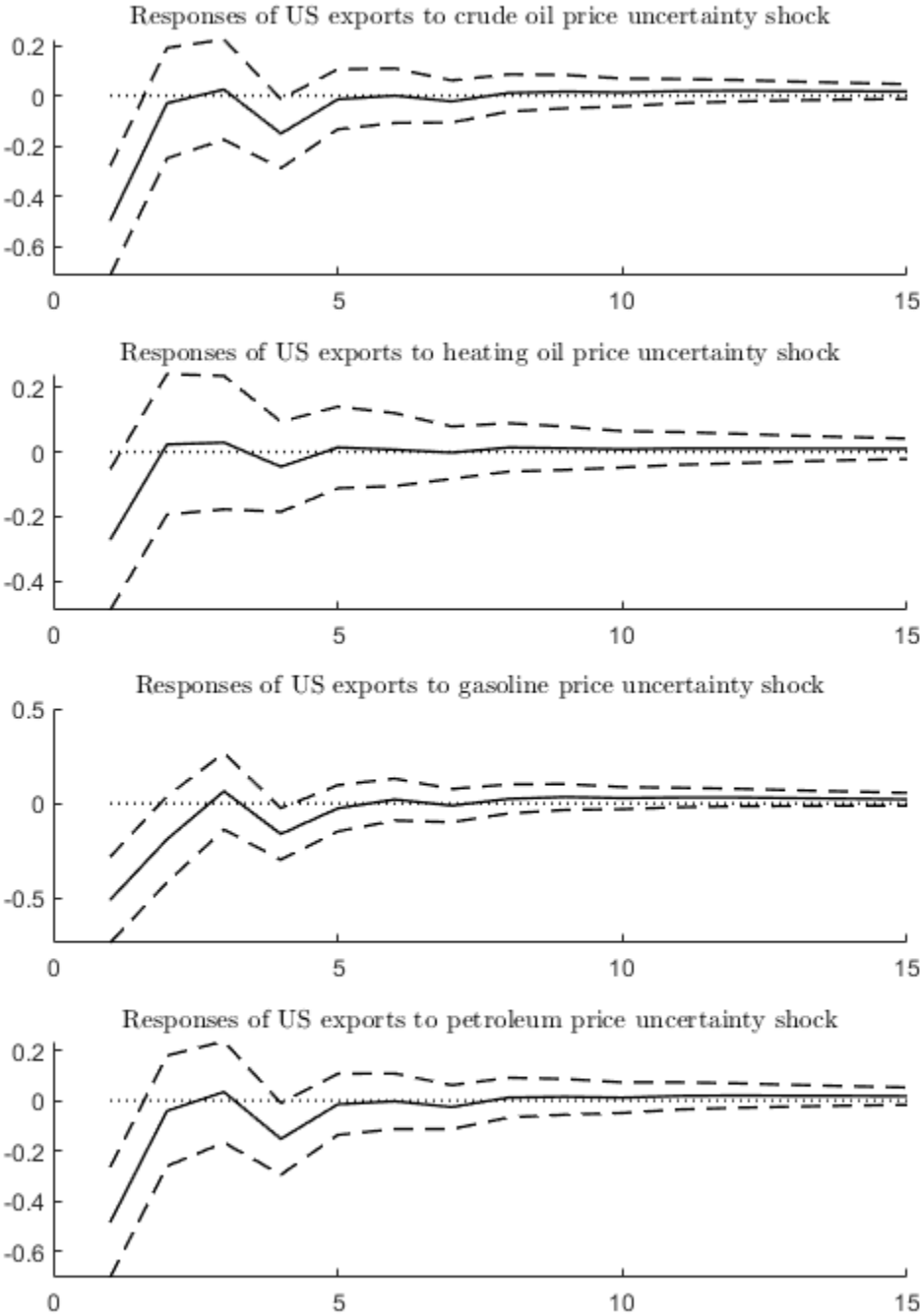
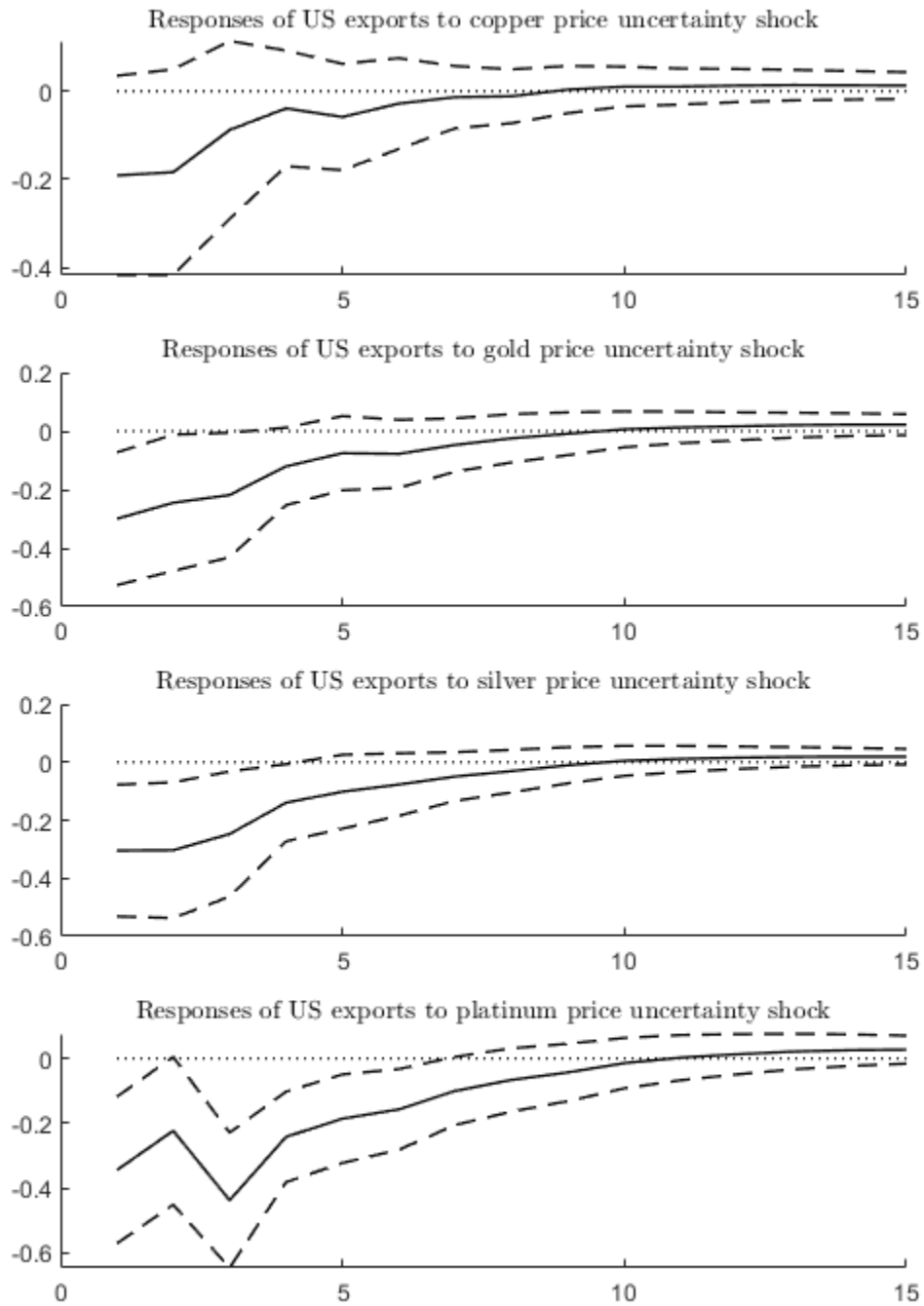


Figure 15. OIRFs of US Exports Growth to energy price uncertainty shocks



**Figure 16. OIRFs of US Exports Growth to metals price uncertainty shocks**



**Figure 17. OIRFs of EA Imports Growth to agricultural price uncertainty shocks**

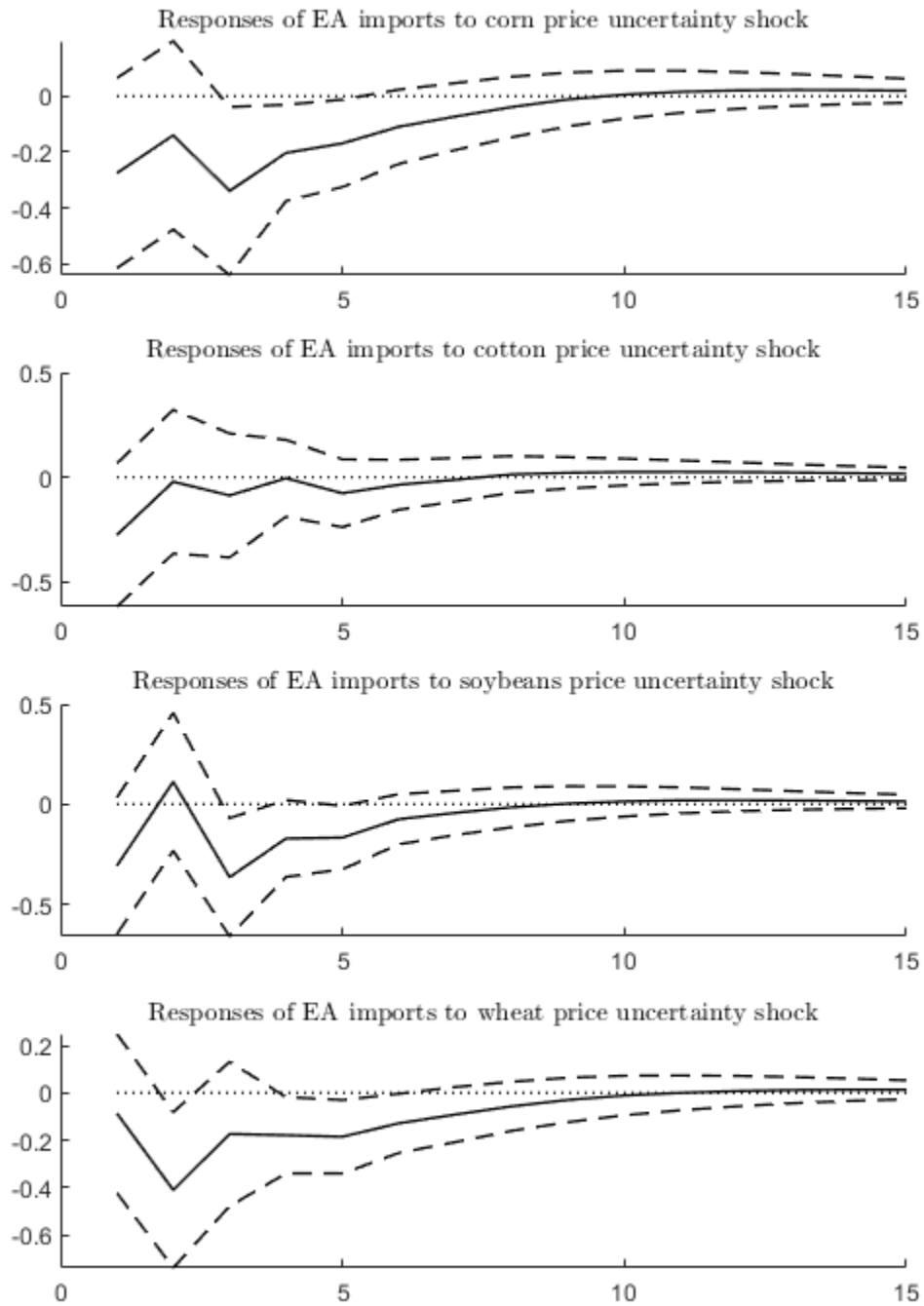
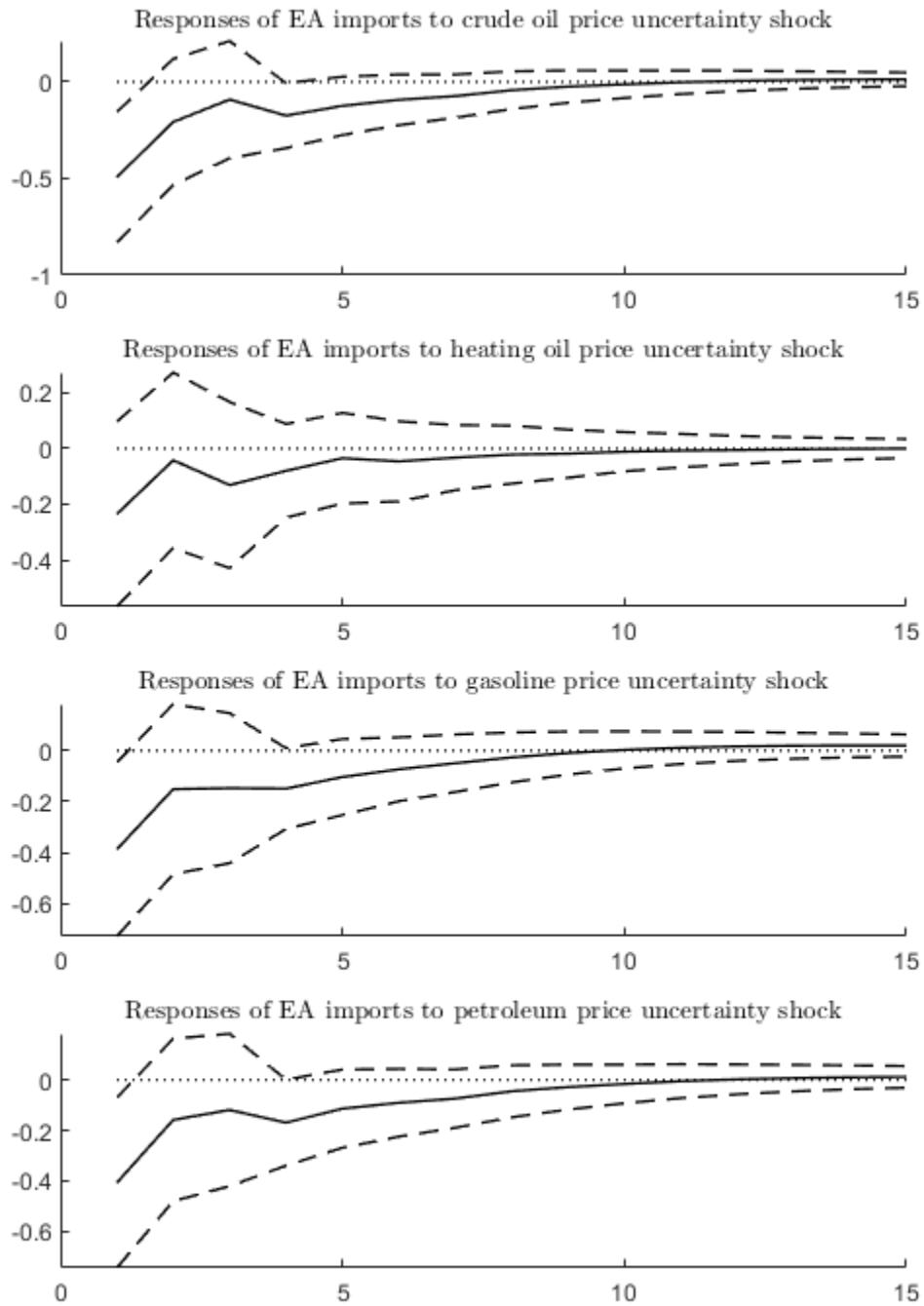
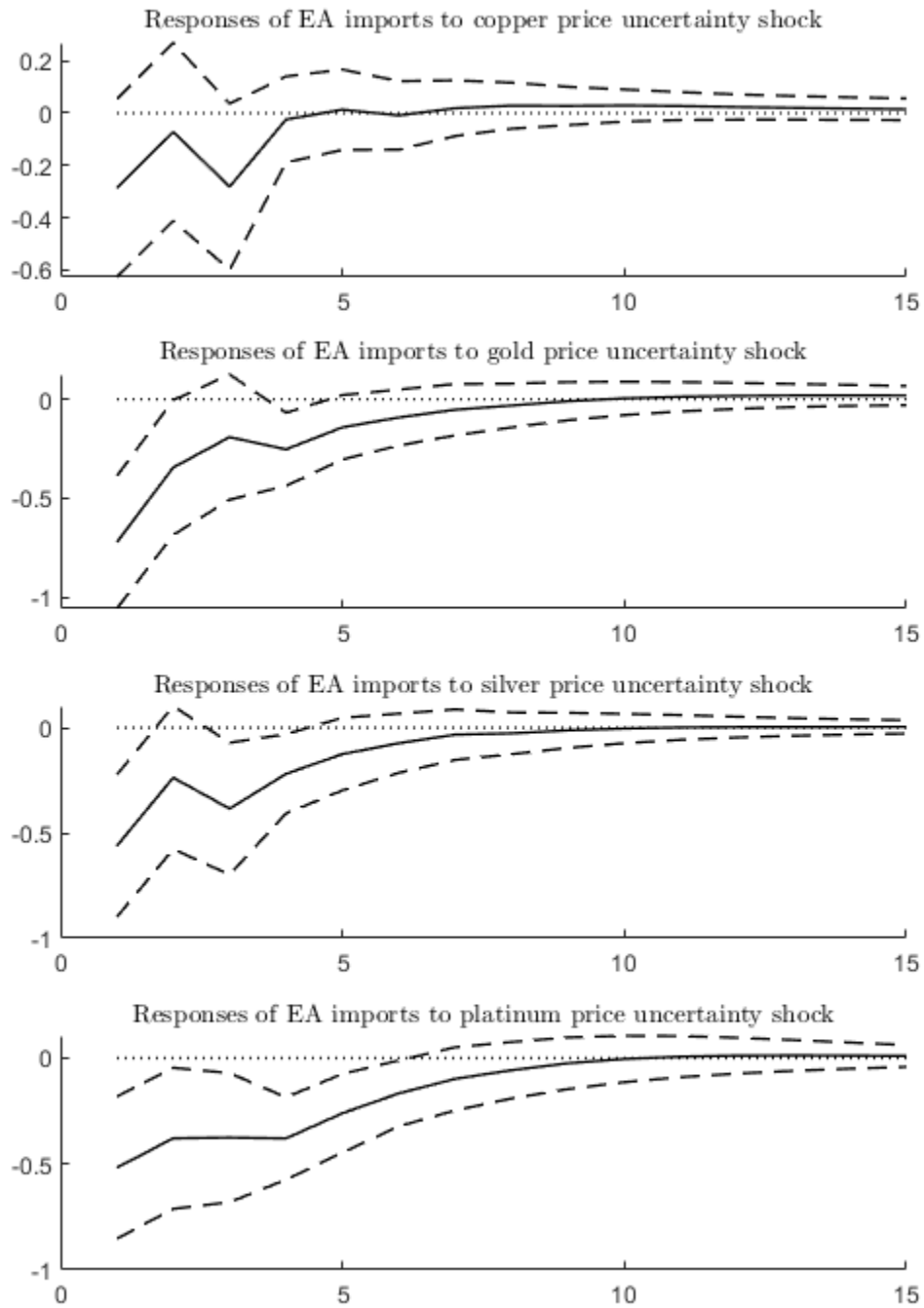


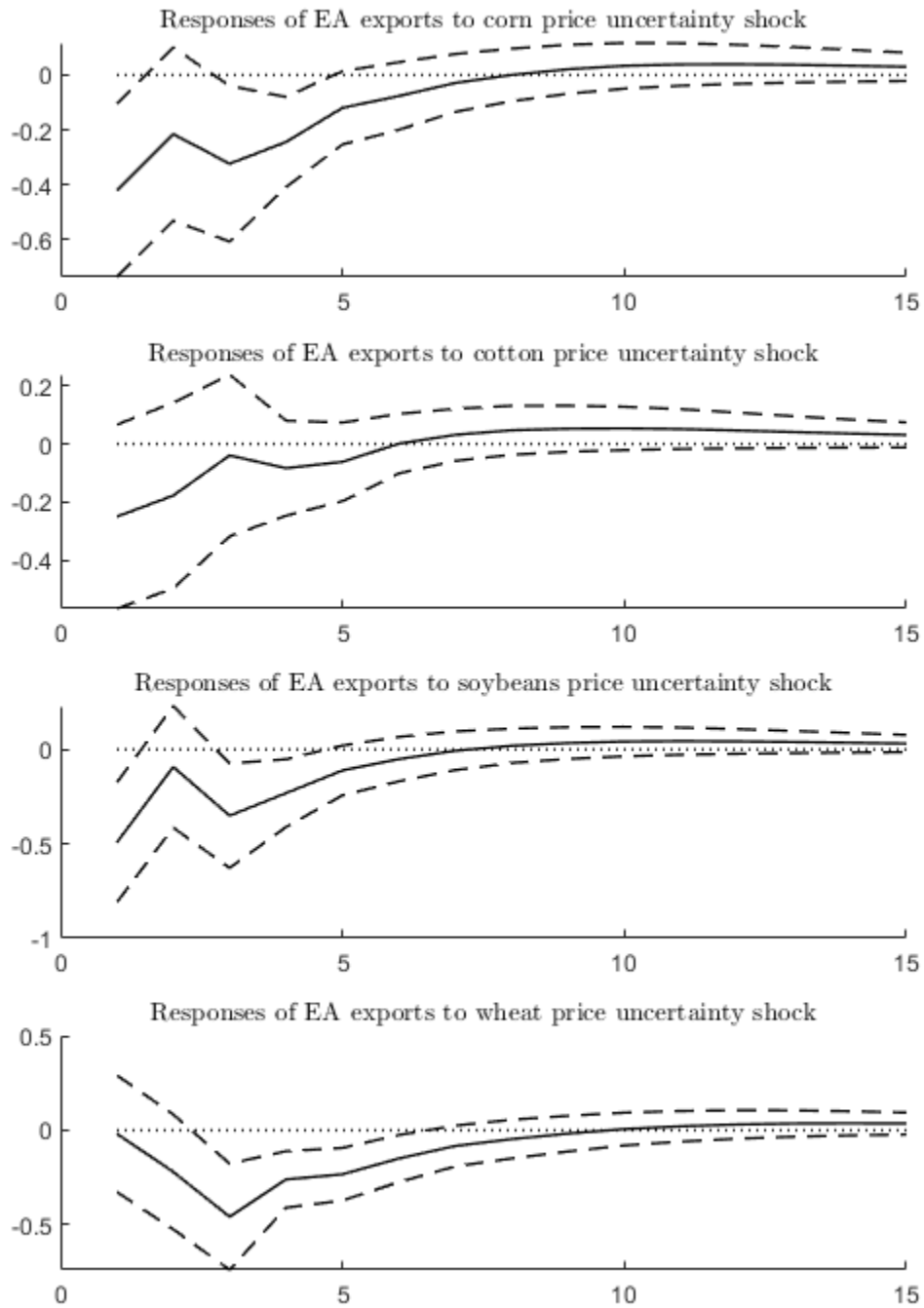
Figure 18. OIRFs of EA Imports Growth to energy price uncertainty shocks



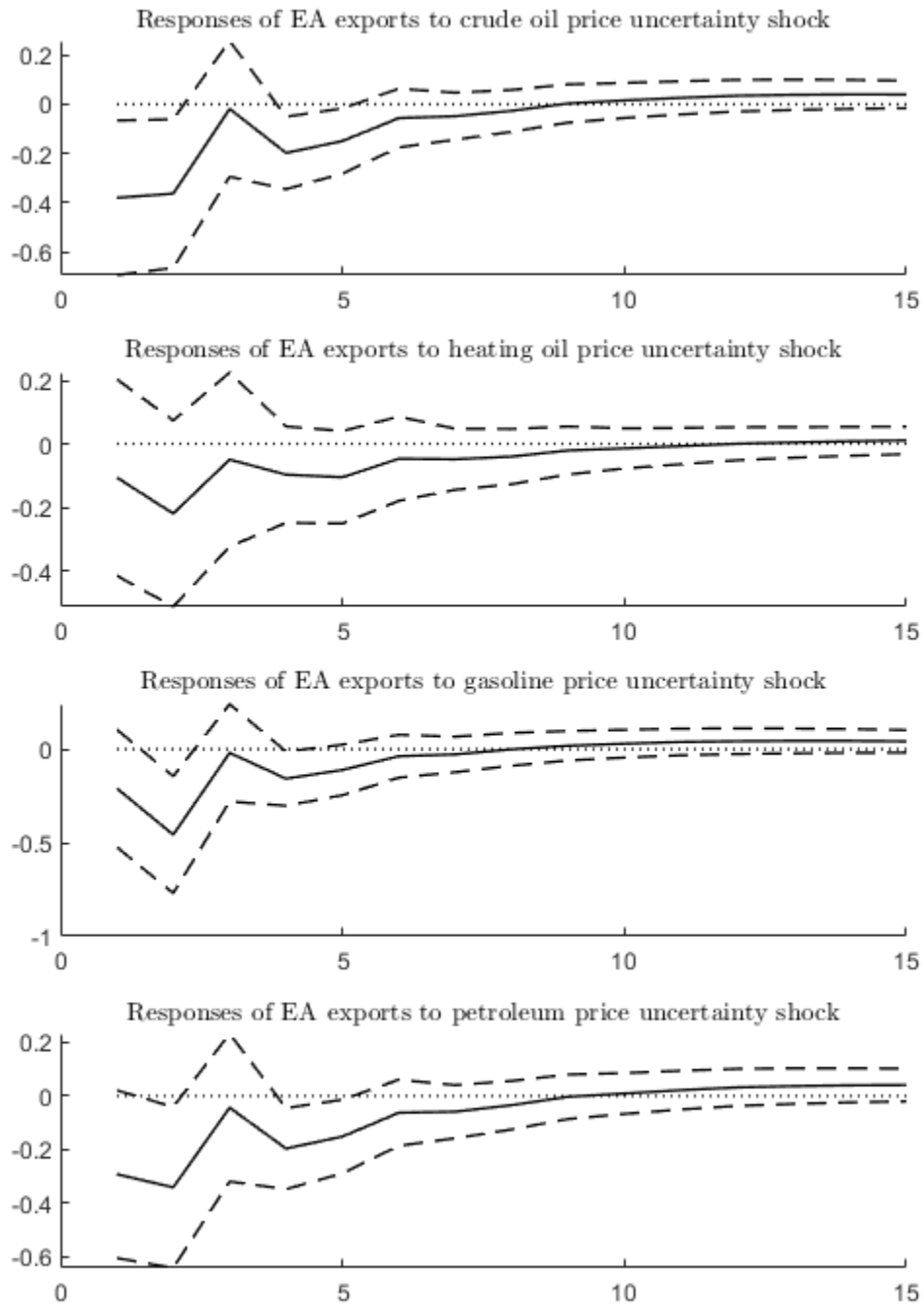
**Figure 19. OIRFs of EA Imports Growth to metals price uncertainty shocks**



**Figure 20. OIRFs of EA Exports Growth to agricultural price uncertainty shocks**



**Figure 21. OIRFs of EA Exports Growth to energy price uncertainty shocks**



**Figure 22. OIRFs of EA Exports Growth to metals price uncertainty shocks**

