Commodity Price Uncertainty and International Trade

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Abstract

We empirically investigate the impact of commodity price uncertainty on US and Euro Area trade flows. Our results indicate that the response of US and Euro Area trade flows to commodity uncertainty shocks is larger, in magnitude and persistence, when compared with the respective impact of commodity supply and demand shocks. Moreover, our analysis shows that a one-standard deviation shock in commodity price volatility has a higher (in magnitude) and more persistent effect on trade when compared with the respective shocks in exchange rates and commodity prices. Finally, an uncertainty shock in various agricultural and metals markets has a similar negative impact on trade flows to that of energy uncertainty shocks.

Keywords: *Commodity Price Uncertainty, Volatility, International Trade*

JEL Classification: *C32, F14, F47, O13, Q02*

[†] ***Acknowledgments*****:** We would like to thank the Editor, Timothy Richards and two anonymous referees for their constructive comments and helpful suggestions. We also like to thank the participants of the 18th Conference on Research on Economic Theory and Econometrics (CRETE 2019), the 2nd RCEA Warsaw Money-Macro-Finance Conference (WMMFC 2019), and the 5th International Conference in Applied Theory, Macro and Empirical Finance (AMEF 2019) for their useful comments and suggestions. Any remaining errors are the responsibility of the authors. The authors declare that they have no conflict of interest.

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1. Introduction

The impact of uncertainty in commodity markets on the trade flows of the global economy is a relatively uncharted field of research. The commodity-macroeconomy literature is mainly focused on the effect of oil price uncertainty on global economic activity and international trade (Elder, 2018; Elder and Serletis, 2010; Jo, 2014; among others), with the effect of non-oil commodity price fluctuations being a relatively unexplored area. Similarly, while there is ample empirical evidence on the relation of commodity prices with international trade (Backus and Crucini, 2000; Bodenstein *et al*., 2011; Kilian *et al*., 2009; Giovannini *et al*., 2019; among others), the literature provides limited evidence on the respective impact of commodity price uncertainty on trade.

In this paper we aim to fill this gap by examining the impact of commodity uncertainty shocks on US and Euro Area (EA henceforth) trade flows. To the best of our knowledge, the literature dealing with the effects of commodity price fluctuations and uncertainty on international trade is scarce, mostly focusing on the macroeconomic effects of oil and energy price fluctuations on the economy. A number of recent findings show that firm-level uncertainty and uncertainty about aggregate demand conditions have a significant negative effect on international trade (De Sousa *et al.*, 2016; Gervais, 2018), while others show that oil price fluctuations hurt globalization and decrease bilateral trade volumes (Chen and Hsu, 2012; 2013). However, there is a lack of empirical evidence examining the dynamic responses of rising uncertainty in commodity markets on international trade. Furthermore, our contribution is also the examination of the effects of non-energy (agricultural and metals), in addition to energy, commodity price uncertainty shocks on international trade.

The closest paper to ours is the recent study of Tran (2021), who empirically examines the impact of commodity price uncertainty shocks on economic activity and trade flows for a small open economy (Australia). Our paper differs from this study in various ways. First, unlike Tran (2021), we examine the impact of commodity price uncertainty on US and EA trade flows; thus, our results on the effect of commodity uncertainty shocks are generalized for large open markets, capturing a larger portion of international trade flows. Second, further to Tran (2021) who examines the effects of commodity price uncertainty (by constructing a commodity uncertainty index capturing uncertainty in all major agricultural, metals and energy commodity markets), we additionally explore the separate effects of energy, agricultural and metals uncertainty on international trade. In this way, we also provide additional evidence on the macroeconomic effects of commodity-class specific uncertainty shocks.

For our econometric analysis we use a Structural Vector Autoregressive (SVAR henceforth) model and empirically examine the impact of commodity price uncertainty shocks on US and EA trade. More specifically, following the modeling approach of Kilian (2009), Kilian *et al*. (2009) and Chen *et al*. (2016), we estimate a SVAR model in which we measure the dynamic responses of US and EA trade flows to structural shocks in global supply, global demand, commodity-specific demand, and commodity price uncertainty. Following the standard approach in the literature, we identify uncertainty shocks as a structural one-standard deviation shock in commodity price volatility (in the spirit of Bloom, 2009; Elder and Serletis, 2010; Jo, 2014; among others).

Our analysis shows that the dynamic response of US and EA trade flows to commodity price uncertainty shocks is higher and more long-lasting when compared with the dynamic response of the trade flows to structural shocks in global demand, global supply, and commodity-specific demand. We also evidence that commodity price uncertainty shocks have a more pronounced negative effect on US and EA trade when compared to the impact of first moment commodity shocks.

Moreover, we find that non-oil uncertainty shocks have a similar, in magnitude and persistence, negative impact on international trade as compared to the impact of oil uncertainty shocks. We show that a positive commodity price uncertainty shock reduces US and EA imports and exports growth. This effect remains negative and statistically significant for up to eight months after the initial uncertainty shock, while the response of US and EA trade flows to aggregate demand (global real economic activity shock) and commodity-specific demand (commodity price shock) is positive and remains significant for up to five months after the initial shock, only for the case of US exports. Conversely, our analysis shows that the EA trade flows are relatively immune to aggregate demand and commodity-specific demand shocks.

Overall, our SVAR evidence shows that the most significant shock (in terms of both magnitude and persistence) for both the US and EA trade flows is the commodity price uncertainty shock. In addition, the results from a supplementary 5-factor SVAR model show that the negative effect of commodity price uncertainty on US and EA trade remains robust to the inclusion of variables, which are closely related to international trade, into the information variable set (like the real effective exchange rate and global economic activity). These findings contribute and provide further support to the recent evidence of Giovannini *et al.* (2019) who show that commodity price shocks are key drivers of reversals in US and EA trade.

The literature dealing with the links between commodity markets and trade shows that rising commodity (oil) prices lead to changes in exports and imports, where the sign of the change depends on whether the country is a net importer or a net exporter (of oil). For example, Backus and Crucini (2000) show that oil prices are positively correlated with the terms of trade of oil-exporting countries and negatively correlated with the terms of trade of net oil-importers. While the oil-macroeconomy literature shows that the effect of oil price shocks on trade flows depends on the 'commodity-exposure' of the country, we postulate and empirically verify that this is not the case when examining the impact of commodity price uncertainty shocks on international trade flows. Our results are the first to show that all the major agricultural, metals and energy commodity price uncertainty shocks have a negative effect on US and EA imports and exports, irrespectively of whether the US or the EA economies are major net importers or exporters of some of the agricultural, metals or energy commodities used in our analysis.

Finally, we examine whether the effect of different commodity classes on the link between commodity uncertainty and international trade varies. To do so, we estimate additional SVAR models where, instead of a broad commodity price uncertainty measure, we use the price uncertainty for the most liquid agricultural, metals and energy commodity markets and examine its dynamic impact on international trade. Interestingly, our analysis shows that rising uncertainty in some agricultural and metals commodity markets, like corn, wheat, and platinum, has a similar negative effect on the US and EA trade flows with that of energy uncertainty shocks. While the previous oil-macroeconomy literature shows the significant response of economic activity and terms of trade to oil price and uncertainty shocks (Backus and Crucini, 2000; Chen and Hsu, 2012; 2013; Elder, 2018; Elder and Serletis, 2010; Jo, 2014; Kilian *et al*., 2009), our work is the first to show that the non-oil uncertainty shocks have a similar recessionary effect on international trade.

The economic interpretation of our findings is that rising commodity price uncertainty, except from exercising firms' option to postpone investment in commodity-related projects, also exercises producers and firms' real option to postpone their decisions to import or export the commodities (and the industrial products which are produced by raw commodities) in times of lowered commodity price uncertainty. Our findings on the significant negative effects of agricultural price uncertainty shocks on US and EA trade are in line with and provide further insights on the strand of literature which identifies a significant link between commodity prices and macroeconomic fluctuations (Gilbert, 2010; Karali and Power, 2013; among others).

Our results are useful for trade policymakers since we show that commodity price uncertainty shocks play a significant role in the creation of sudden drops in international trade. Moreover, our analysis indicates that trade policymakers, when assessing the possible key determinants of the future state of international trade, should turn their attention, not only to oil price and uncertainty shocks, but also to the agricultural and metals commodity price uncertainty shocks.

The rest of the paper is organized as follows. **Section 2** provides the background literature and theoretical framework related to our work. **Section 3** outlines the econometric methodology and describes the data. **Section 4** presents the empirical analysis, while **Section 5** provides robustness checks. Finally, **Section 6** concludes.

2. Background

2.1 Related Literature

Commodity price fluctuations have a significant impact on the macroeconomy (Alquist *et al*., 2019; Arezki and Bruckner, 2012; Drechsel and Tenreyro, 2018; Fernández *et al*., 2017; Ferraro and Peretto, 2018; Gordon *et al*., 1984). For example, Fernández *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 (Bodart *et al*., 2012; Cashin *et al*., 2004; Chen and Rogoff, 2003; Coudert *et al*., 2015; Dauvin, 2014; Ferraro *et al*., 2015; among others).

Hence, a prominent channel through which commodity price fluctuations could affect international trade is the exchange rate sensitivity to commodity price shocks, often leading to the existence of 'commodity currencies' (Chen and Rogoff, 2003; Coudert *et al.*, 2015; Dauvin, 2014; Ferraro *et al*., 2015; among others). Commodity currencies are defined as the exchange rates of commodity-exporting countries whose currencies are tied with the price changes of their major exporting commodities (Cashin *et al*., 2004; Chen and Rogoff, 2003). For instance, Ferraro *et al*. (2015) show that changes in a country's major commodity export price have a statistically significant contemporaneous relationship with commodity currencies' exchange rates. Dauvin (2014) identifies the existence of 'oil currencies' by showing that energy prices are key drivers of the exchange rates of energy exporting countries, while 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.

Additionally, another strand of the commodity literature shows that commodity price shocks have a significant impact on the terms of trade (Bodenstein *et al*, 2011; Cashin *et al*., 2004; Drechsel and Tenreyro, 2018; Fernández *et al.*, 2018; Giovannini *et al.*, 2019; Kilian *et al*., 2009). For example, Giovannini *et al.* (2019) show that commodity price shocks are major drivers for the EA and US trade balances, and terms of trade, while Drechsel and Tenreyro (2018) show that booms and busts in internationally traded commodities have a negative 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 recent findings in the empirical literature provide evidence of a significant negative effect of commodity price uncertainty on economic activity (Elder 2018; Elder and Serletis, 2010; Ferderer (1996); Jo, 2014; among others). For example, Elder and Serletis (2010) and Ferderer (1996) show that rising oil price volatility leads to sudden drops in US real GDP and industrial production.

2.2 Conceptual Framework

The underlying theory and theoretical models dealing with the effects of uncertainty shocks on international trade have their roots on the real options model of investment under uncertainty (Bloom, 2009; Novy and Taylor, 2020; among others). This approach indicates that firms postpone their irreversible investment decisions when faced with a more uncertain business environment up until the time the uncertainty is resolved (Bernanke, 1983; Bloom, 2009; Hassler, 1996; Pindyck, 1991; among others). In an open economy framework, firms also adjust their inventories by cutting their orders of foreign inputs as a response to the increase in uncertainty (Novy and Taylor, 2020).

Novy and Taylor (2020) bring the real options model of irreversible investment decisions under uncertainty to the international trade context. More specifically, they introduce uncertainty in an open economy model in which firms import durable and nondurable inputs from foreign and domestic suppliers. In their model, an uncertainty shock (defined either as uncertainty about productivity or aggregate demand for final goods) changes firm's optimal inventory policy, with firms reducing their orders for foreign inputs much more compared to that of domestic inputs due to higher fixed costs. The relative drop in demand for foreign inputs (compared with that of domestic inputs) ultimately leads to a sudden drop in international trade.

Furthermore, Giovannini *et al.* (2019) develop a New Keynesian Dynamic Stochastic General Equilibrium (DSGE) model for the trade between US, EA and Rest of World (RoW) that includes a commodity sector. In their model, perfectly competitive firms, in those three regions, produce a final good using local intermediate goods, imported commodities and manufactured goods as their primary inputs for production. Moreover, in this model, only the RoW countries produce commodities, hence all the commodities used by US and EA firms are imported from the RoW countries. The model identifies the significant role of global commodity price shocks on EA and US trade balances, particularly the persistent effect on EA and US trade during the post-2008 crisis period.

Tran (2021) develops a DSGE model for the Australian economy in which he introduces global commodity price uncertainty shocks. In this model, trade takes place between the Australian economy and the RoW economies, with both parts producing commodity and non-commodity tradable goods. The DSGE model of Tran (2021) treats separately commodity price shocks and commodity price uncertainty shocks by estimating commodity uncertainty as the standard deviation of the technology shock in all sectors of the economy, including the commodity sector. The main mechanism through which trade is reduced after a commodity price uncertainty shock, is through the higher adjustment costs of firms that face higher price uncertainty. Because of the high cost of adjusting prices, firms operating in the commodity sector respond to higher commodity price uncertainty by increasing markups to avoid selling at a lower price (Bloom, 2009; Tran, 2021). This precautionary increase in markups at the firm level occurs because the commodity producing firms' losses from pricing below their profit maximizing level are larger than their losses for overpricing.

Our work builds on the aforementioned theoretical models which investigate the negative effects of uncertainty shocks on international trade. Our econometric analysis implicitly indicates that a structural DSGE model, like those presented in Tran (2021) and Giovannini *et al.* (2019), could match our SVAR estimates, and thus can provide further economic insights to our findings. More specifically, the estimation of a global DSGE model augmented with commodity price uncertainty would be capable of showing the underlying economic forces generating the uncertainty in commodity markets and ultimately leading to the contraction in international trade.

3. Methodology and Data

3.1 Commodity Price Uncertainty

Our proxy for commodity price uncertainty (*COMRV*) is the realized variance of the daily returns of the S&P GSCI broad commodity index (Bakas and Triantafyllou, 2018; Wang *et al*., 2012; among others).[1] More specifically, using the daily prices (F_t) of the GSCI broad commodity futures

[1] The realized variance is the most used proxy for uncertainty in the broad literature focusing on the effects of uncertainty in the economy (see, for example, Bloom, 2009; Caldara *et al.*, 2016; Carriere-Swallow and Cespedes, 2013; among others).

market index we estimate the monthly realized variance *($RV_{t,T}$)* for the broad commodity market index, according to **Equation (1)**:

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

where F_t is the GSCI commodity futures price on trading day t, $\overline{(F_{t+i} - F_{t+i-1})/F_{t+i-1}}$ is the average futures returns for each monthly period (t,T), and the time interval (t,T) is the number of trading days during each month. $RV_{t,T}$ is our estimated realized variance for each monthly period. The monthly estimate of the annualized realized variance *(COMRV)* is the variance of the daily returns of commodity prices (for each month), multiplied by 252 in order to be annualized.

3.2 SVAR Models

3.2.1 Baseline SVAR Model

Our SVAR modeling approach is based on the decomposition of the supply and demand shocks as shown in Kilian (2009), Kilian *et al*. (2009) and Chen *et al.* (2016). Hence, we estimate a structural VAR model in which we decompose the commodity shocks on trade into four components which are driven by aggregate supply, aggregate demand, commodity-specific demand, and commodity-specific uncertainty.

We follow the assumptions made by Kilian (2009) by postulating that commodity price changes and commodity price uncertainty are driven by structural innovations in supply and demand for commodities. While our proxy for aggregate demand is the global economic activity index of Kilian (2019) which effectively measures the global demand for commodities, our proxy for aggregate supply differs from the oil-related narrative that follows Kilian's (2009) work (namely the global crude oil production growth).

Unlike Kilian (2009), our analysis focuses on the impact of global commodity price uncertainty which is ultimately composed by the price fluctuations of both energy and non-energy (agricultural and mineral) commodities. For this reason, to estimate the global commodity supply shocks, we need to use a measure proxying for the global (aggregate) level of major energy, agricultural and metals inventories. Since there are no reliable monthly series for global production and inventories for agricultural and mineral commodities, our proxy for commodity supply shocks stems out from the implications of the Theory of Storage (Brennan, 1958; Bobenrieth *et al.*, 2013, 2021; Triantafyllou *et al.*, 2020; Working, 1948; among others). According to the Theory of Storage, the marginal convenience yield for holding physical inventories is captured by changes in the commodity futures basis. More specifically, an increasing commodity futures basis is associated with increasing convenience yield for holding commodity inventories, and with sudden drops in commodity inventory levels often leading to inventory stock-outs.

Following this approach, we estimate the commodity futures basis as the price spread between the nearby and 3-month maturity futures contracts written on a broad commodity price index. In our SVAR analysis, a positive structural shock in commodity futures basis is the proxy of global commodity supply shocks.[2] Finally, the commodity-specific demand shock is based on the returns of the GSCI broad commodity price index and commodity-specific uncertainty is proxied through the GSCI commodity price realized variance.

[2] For robustness purposes we also follow the approach of Kilian (2009) and estimate the SVAR model using the global crude oil production as the proxy of aggregate supply shocks. These additional SVAR results can be found in our online Appendix.

More specifically, we estimate the following baseline SVAR model for the cases of the US and EA trade flows respectively, allowing for 2 lags in the SVAR.[3] The structural VAR model representation is given in **Equation (2)**:

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

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

$$Z_t = [BASIS_t \quad GACT_t \quad COMPR_t \quad COMRV_t \quad TRADE_t]' \quad (3)$$

where *BASIS* is the 3-month commodity futures basis (which is our proxy for global supply), defined as the 3-month forward spread (the difference between the Thomson Reuters CRB nearby commodity futures index and the respective 3-month maturity commodity futures index). *GACT* is the Kilian (2009, 2019) index of real global economic activity (our proxy for global demand), *COMPR* is the percentage change of the GSCI broad commodity price index (our proxy for commodity-specific demand), *COMRV* is the monthly realized variance of the daily returns of the GSCI broad commodity price index (our proxy for commodity price uncertainty), and *TRADE* which contains the growth rate of US exports (*EXP*).

We additionally estimate identical SVAR models for the US imports growth (where the *TRADE* variable contains the growth rate of US imports (*IMP*)) as well as for the EA imports and exports

[3] The Akaike and Hannan-Quinn information criteria suggest 2 lags for the optimal lag-length for the SVAR model. For robustness we also follow Kilian (2009) and choose a higher number of lags in the SVAR to allow for enough dynamics in the system and control for the persistence of commodity price and uncertainty shocks. Our main findings remain unchanged when using 6, 12 or 24 lags for the estimation of the SVAR. These additional results can be found in our online Appendix.

growth, respectively. E_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:

$$e_t \equiv \begin{pmatrix} e_t^{BASIS} \\ e_t^{GACT} \\ e_t^{COMPR} \\ e_t^{COMRV} \\ e_t^{TRADE} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{aggregate\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{commodity-specific\ demand\ shock} \\ \varepsilon_t^{commodity\ uncertainty\ shock} \\ \varepsilon_t^{trade\ shock} \end{pmatrix} \qquad (4)$$

The restrictions imposed in our model are in line with the standard approach in the commodity literature according to which commodity prices and uncertainty being the outcome of supply and demand for commodities. Moreover, our assumptions are in line with those of Kilian (2009), Kilian *et al*. (2009) and Kilian and Murphy (2014) with our structural commodity supply shock having a contemporaneous effect in demand, commodity prices and uncertainty, while there is no contemporaneous effect of demand, commodity prices and uncertainty on supply, with supply reacting to demand and commodity price uncertainty at least with a monthly lag. In line with the findings of Bodenstein *et al*. (2011), Giovannini *et al.* (2019) and Kilian *et al.* (2009) who show that commodity price shocks have a significant impact on international trade, we place the international trade variable last in the VAR ordering in order to capture the instantaneous effect of commodity price and uncertainty shocks to US and EA imports and exports growth.[4]

Lastly, by placing *COMPR* before *COMRV* (i.e., controlling for the first moment shocks in commodity markets), we follow the modeling approach of Bloom (2009) and Carrière-Swallow

[4] We additionally estimate the SVAR model with alternative orderings for robustness checks. The additional results can be found in our online Appendix (based on an alternative ordering) or are available upon request from the authors (various alternative orderings).

and Céspedes (2013) and allow for first moment shocks to generate uncertainty in commodity markets. Our SVAR modeling approach, in which rising commodity prices generate increasing uncertainty in commodity markets, is also consistent with the commodity literature's findings that commodity price spikes are associated with rising convenience yields and uncertainty in respective commodity markets (Bobenrieth *et al*., 2013, 2021; Milonas and Thomadakis, 1997; Triantafyllou *et al*., 2015, 2020). We base our analysis on the estimated Impulse Response Functions (IRFs henceforth), defined as the responses to one-standard deviation structural shocks, and are recursively identified within the SVAR model.

3.2.2 Alternative SVAR Model

Furthermore, in order to provide robustness to our main SVAR results, we estimate a 5-factor SVAR model for the US and EA imports and exports in which the first and second moment shocks in global commodity markets are treated as exogenous to the US and EA economies.[5] The assumption of strict exogeneity of commodity price uncertainty shocks is standard in the uncertainty modeling literature according to which financial and macroeconomic uncertainty shocks are not the outcome of endogenous interactions between financial markets and the real economy (Bloom, 2009; Pindyck, 2004; among others). The strict exogeneity of uncertainty shocks is in line with the empirical evidence and modelling approaches of economic uncertainty shocks in the relevant literature (Caggiano *et al*., 2014; Jo, 2014; among others). The SVAR model is given as:

$$B_0 Y_t = c + B_1 Y_{t-1} + \ldots + B_k Y_{t-k} + \varepsilon_t \tag{5}$$

[5] We include 2 lags following the optimal-lag length criteria of Akaike and Hannan-Quinn.

Where B_0 is the matrix of contemporaneous variables, c is a vector of constant terms, B_1 to B_k are coefficients vectors and ε_t is the vector of structural shocks which are serially uncorrelated with zero mean and diagonal variance-covariance matrix. The shocks are orthogonalized and identified using the Cholesky identification scheme. Y_t is the vector of the endogenous variables.

Our structure in the 5-factor VAR setup follows that of Bloom (2009) and Caggiano *et al.* (2014), according to which uncertainty shocks instantaneously affect prices (commodity prices and exchange rates) and then quantities (global economic activity and international trade). Since US and some of the EA economies (like Norway, France, and Germany) are major exporters of commodities like corn, wheat, gold, and crude oil, we follow the literature on commodity currencies (Chen and Rogoff, 2003; Coudert *et al*., 2015) by allowing for possible interactions between commodity prices and exchanges rates when including them as endogenous variables in the SVAR model. More specifically, we place first the commodity market variables and then the exchange rates in the VAR ordering in order to capture the fact that shocks firstly affect commodity markets and then exchange rates (Bodart *et al*., 2012; Chen and Rogoff, 2003; Ferraro *et al*., 2015; Zhang *et al*., 2016).[6] The VAR ordering for our 5-factor SVAR model is given as:

$$Y_t^1 = [COMRV_t \ \ COMPR_t \ \ EXCH_t \ \ GACT_t \ \ EXP_t]' \tag{6}$$

$$Y_t^2 = [COMRV_t \ \ COMPR_t \ \ EXCH_t \ \ GACT_t \ \ IMP_t]' \tag{7}$$

[6] By placing first commodity prices and then exchange rates in the VAR ordering we are in line with the findings in the relevant literature which identify a significant impact and predictive power of commodity prices on exchange rates. For example, Ferraro *et al.* (2015) find a significant predictive power of commodity prices on US exchange rates for short-term horizon. Moreover, there is another strand of the literature identifying the reverse channel of causality, according to which exchange rates have significant impact and predictive power on commodity prices (Chen *et al*., 2016; among others). To test this, we estimate the SVAR model with an alternative VAR ordering in which we place exchange rates (*EXCH*) first in the ordering. These additional SVAR results provide robustness to our findings and can be found in our online Appendix.

In Equations (6) and (7), *EXP* and *IMP* are the growth rates of US imports and exports, respectively. The rest of the variables are common for both models and contain the commodity price uncertainty measure (*COMRV*), the log difference of the GSCI commodity price index (*COMPR*), the real effective exchange rate (*EXCH*) and the real global economic activity index (*GACT*) of Kilian (2009, 2019). We estimate also identical SVAR models for the EA imports and exports growth respectively.

3.3 Data

The series for the commodity price index returns (*COMPR*) and commodity price uncertainty (*COMRV*) are based on the S&P GSCI data. Specifically, we obtain monthly and daily data for the S&P GSCI broad commodity price index and 12 agricultural, metals and energy commodity futures prices from Datastream.[7] The monthly commodity price series are constructed as the average of the respective daily commodity series for each monthly period.

The series of imports (*IMP*) and exports (*EXP*) and the real effective exchange rates (*EXCH*) for the US and EA are downloaded from the Federal Reserve Bank of St. Louis FRED database. Since our series for US and EA trade flows are expressed in nominal terms, they are deflated using the US and EA consumer price indexes (downloaded also from FRED database), respectively.[8] The

[7] The cross-section of agricultural commodities includes corn, cotton, soybeans and wheat, while the energy commodities includes crude oil, heating oil, unleaded gasoline and petroleum and lastly, the metals commodities includes copper, gold, silver and platinum.
[8] The EA imports and exports series, used in our analysis, do not include intra-European trade, taking into account only the imports and exports of the EA economies to the rest of the world.

global real economic activity index (*GACT*) is based on the work of Kilian (2009, 2019). This index is highly related to trade since it measures shifts in the global use of industrial commodities.[9]

Finally, the Thomson Reuters CRB 3-month forward commodity futures price index along with the nearby commodity futures index series, which are used for the estimation of commodity futures basis (*BASIS*), are downloaded from the Refinitiv database. Our dataset covers monthly data over the period from January 1994 to May 2021 (a total of 329 observations).[10]

4. Empirical Analysis

4.1 Preliminary Empirical Evidence

In this section we provide preliminary evidence between commodity price uncertainty series and international trade by presenting the descriptive statistics for our time series. **Table 1** below presents the descriptive statistics for our sample.

[**Table 1** Here]

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

[9] The updated and corrected version of the index of global real economic activity, that is used in our analysis, is downloaded from https://www.dallasfed.org/research/igrea.

[10] Our time series dataset covers the period from January 1994 to May 2021 since this is the maximum possible common sample for both the US and EA trade flows. While available data for US trade exist before 1994, the monthly data for EA trade flows and EA exchange rates start from January 1994. For this reason, we choose to use this common sample for US and EA so that our findings to be comparable.

[**Figure 1** Here]

We observe that significant spikes in the commodity volatility series are followed by significant drops in both US and EA imports and exports growth series. In particular, the rising commodity price volatility during 2008 is followed by falling US and EA trade series in 2009 and the significant rebound of US and EA trade during the post-2010 is accompanied by lesser commodity market turbulence. Finally, the significant volatility episode in the beginning of the COVID period (May-June 2020) is followed by a major drop in US and EA trade measures.

4.2 Baseline SVAR Model Results

We measure the dynamic response of US and EA trade imports and exports growth to the structural shocks of global supply, global demand, commodity-specific demand, and commodity price uncertainty as shown in our SVAR model presented in **Equations (2)-(4)**. **Figures 2** and **3** show the estimated (ordinary and cumulative) IRFs of US and EA trade flows to various types of commodity shocks identified in the SVAR model. In more detail, the upper panel of **Figure 2** shows the responses of US imports and exports growth to a one standard deviation structural innovation to the commodity futures basis (aggregate supply shock), real global economic activity (aggregate demand shock), commodity-specific demand shock and commodity price uncertainty shock. **Figure 3**, in addition, shows the respective cumulative responses of trade flows to various commodity shocks.

[**Figure 2-3** Here]

The estimated IRFs shown in the upper panel of **Figure 2** show that US imports and exports respond positively to unexpected aggregate demand shocks with the response remaining positive and statistically significant for 5 months after the initial shock. Moreover, our SVAR analysis shows that US and EA imports reduce at around 0.8% to 1.3% three months after a global commodity supply shock.

Furthermore, from **Figure 3** we observe that the cumulative effect of commodity price uncertainty is much larger (in absolute terms) compared to that of commodity demand and supply shocks. More specifically, a one standard deviation shock leads to a permanent (without any bounce-back behavior) 2% drop of US and EA exports and to a permanent 1.7% drop in US and EA imports in three to four months after the uncertainty shock. The permanent (cumulative) effect of commodity price uncertainty shocks on international trade is much larger compared to that of commodity demand and supply shocks. For instance, a commodity supply shock results to a less than 1% permanent loss in US and EA trade flows.

Our baseline SVAR analysis shows that the dynamic response of US trade flows to commodity price uncertainty shocks is negative and remains negative and statistically significant for 5 to 10 months after the initial uncertainty shock. More specifically, a one standard deviation structural shock in commodity price uncertainty reduces US imports growth by almost 0.8% 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 exports growth by 1.3% one month after the initial shock, with the effect remaining negative and statistically significant for 5 months after the initial uncertainty shock.

The higher (in absolute value) cumulative response of US imports (when compared to the respective response of 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.[11] Unlike commodity price shocks, which, according to our analysis, and the findings of Kilian *et al*. (2009), have a positive effect on US imports and exports, 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 trade flows. Our findings are in line with the findings of Elder (2018), Elder and Serletis (2010), Ferderer (1996) and Jo (2014) who show that rising oil price uncertainty has a negative impact on US economic activity and industrial production. What we additionally show here, is that commodity price uncertainty has a significant negative effect also on US trade flows. Rising oil price uncertainty, according to the findings of Elder and Serletis (2010) and Jo (2014), reduces aggregate investment and production since it postpones firms' investment and production decisions for later stage when uncertainty in commodity markets is reduced. In addition, we find that rising commodity price uncertainty also postpones US international trade decisions, hence, it results to a reduction of the US trade flows.

[11] We additionally estimate an identical SVAR model using instead of the US exports growth, the percentage change of US trade balance as the last variable in our VAR (*TRADE*), and we show that the trade balance is negatively affected by positive shocks in commodity price uncertainty. These results can be provided by the authors upon request.

These findings are in line with the work of Chen and Hsu (2012), who show that international trade flows will be lower when oil price volatility is high.[12] Finally, our findings are in line with those of Tran (2021), who shows that rising commodity price uncertainty reduces import and exports for the Australian economy, which is a major commodity exporter. What we additionally show, is that the contractionary effects of commodity uncertainty on exports and imports, can be generalized for a set of countries (like the EA economies) which are not classified as major commodity exporters.

In order to examine the dynamic effects of commodity price uncertainty in the EA trade flows (while controlling for commodity supply and demand shocks), we estimate an identical SVAR model (as shown in **Equations (2)-(4)**) for the EA. The lower panel in **Figures 2-3** shows the (ordinary and cumulative) responses of the EA imports and exports growth to commodity supply, demand and uncertainty shocks. The IRFs in **Figure 2** reveal similar responses of the EA trade flows to shocks in aggregate demand, supply and commodity price uncertainty.

On the other hand, our analysis shows that the most significant shock for the EA imports and exports (in terms of persistence) is the commodity price uncertainty shock. A positive commodity price uncertainty shock causes a highly significant and long-lasting drop in EA imports and exports growth. More specifically, a positive uncertainty shock reduces EA exports by 1% three months after the initial shock with the effect remaining negative and statistically significant for 4 months after the initial price uncertainty shock. Similarly, the uncertainty shock reduces EA imports by approximately 0.8% three months after the initial shock with the effect remaining negative and

[12] According to Chen and Hsu (2012), oil price volatility raises importers' and exporters' uncertainty with regard to future movements of oil prices. This, in turn, causes the postponement of both corporate investment and consumption of durable goods. This leads to a decline, first in demand, and, consequently, in trade flows.

statistically significant for 5 months after the initial price uncertainty shock. Moreover, our analysis is the first to show that the negative impact of commodity price uncertainty shocks on international trade is similar in magnitude and more persistent when compared with that of the aggregate demand and supply shocks.

Furthermore, we supplement our baseline SVAR results with the forecast error variance decomposition (FEVD) estimates for the US and EA import and export growth based on the SVAR model presented in **Equations (2)-(4).** The FEVDs of the trade flows are shown in **Table 2** below.

[**Table 2** Here]

From **Table 2** we can observe that more than half of the forecast error variance of trade flows is explained by its own contributions, with commodity price uncertainty having the second most significant contribution when explaining the forecast error variance of trade flows. For instance, commodity price uncertainty explains approximately 26.4% of the forecast error variance of US exports, while the respective relative contribution of supply and demand shocks is less than 10%. This pattern remains qualitatively the same for the US imports as well as for the EA trade flows.[13] Overall, we conclude that the relative contribution of commodity price uncertainty shocks when examining the forecast error variance of international trade flows is significantly higher to that of commodity demand and supply shocks.

[13] Our findings on the estimated FEVDs remain robust to alternative SVAR orderings. The results of the FEVDs for alternative SVAR orderings can be found in our online Appendix.

4.3 Commodity Classes and the Uncertainty-Trade Nexus

In order to examine the effect of the different classes of commodities for the commodity price uncertainty and international trade nexus, we estimate the dynamic impact of agricultural, metals and energy price uncertainty shocks on US and EA trade. More specifically, we estimate, using **Equation (1)**, the realized variance of the most liquid commodity markets which consist of the agricultural (corn, cotton, soybeans, wheat), energy (crude oil, heating oil, petroleum, gasoline) and metals (copper, gold, silver, platinum) commodities.

Figure 4 shows the estimated IRFs derived from our baseline SVAR model, as shown in **Equations (2)-(4)**, for the US imports growth to agricultural, energy and metals uncertainty shocks respectively. These estimated SVAR models are identical with the model presented in the previous section (the only difference is that now we use each individual commodity - price and volatility - series instead of the measures based on the GSCI broad commodity index).

[**Figure 4** Here]

Our estimated IRFs in the upper panel of **Figure 4** show, for the first time in the literature, that the impact of price uncertainty of the agricultural and metals commodity markets is similar in magnitude and persistence with that of the energy price uncertainty shocks. More specifically, among agricultural commodities, corn, cotton and soybeans price uncertainty have the more pronounced negative impact on US exports growth, while, for the metals commodity class, platinum, silver and gold price uncertainty shocks have the most long-lasting and negative effect on US exports.

Among the commodities belonging to the energy commodity class, as expected by the previous evidence from the oil-macroeconomics literature (Elder and Serletis, 2010; Jo, 2014), crude oil uncertainty has the highest (in magnitude) negative effect on US trade flows. While the relevant literature so far has identified the significant recessionary effect of oil uncertainty on US economic activity (Elder, 2018; Elder and Serletis, 2010; Ferderer, 1996), we present here some evidence that the uncertainty of both oil and non-oil commodity markets like corn, wheat, and platinum has a more pronounced effect on US imports growth.

We additionally estimate the impact of rising uncertainty in different commodities on US imports growth. Panel B of **Figure 4** shows the impact of a positive shock in price uncertainty of agricultural, metals and energy commodities on US imports growth. We observe that the uncertainty of some metals commodities like gold and platinum has a more recessionary and long-lasting effect on US exports compared to the impact of rising uncertainty in energy and agricultural commodities. Among metals commodities, the most significant one is platinum: a one standard deviation positive shock in platinum price uncertainty reduces US exports growth by 0.6% with the effect remaining negative and statistically significant for 8 months after the initial platinum uncertainty shock.

We perform the same type of analysis by estimating identical baseline SVAR models for the EA trade flows. **Figure 5** shows the estimated IRFs for the EA imports and exports growth to agricultural, metals and energy price uncertainty shocks respectively.

[**Figure 5** Here]

From the estimated IRFs in **Figure 5**, we observe that agricultural, energy and metals uncertainty shocks have a negative and persistent effect on EA imports and exports. Thus, our previous findings for the US holds also for the EA: uncertainty in agricultural and metals commodity markets (and not only uncertainty in oil markets) is also a key driver of fluctuations for the EA trade flows. In more detail, our analysis shows that the energy uncertainty shocks have the most significantly negative effect on EA exports while the metals uncertainty shocks have the most significant negative impact on EA imports.

5. Robustness Checks

5.1 Alternative SVAR Model Results

We continue our analysis by estimating an alternative 5-factor SVAR model in which we include as endogenous variables some well-known determinants of international trade, like the exchange rate, commodity prices and global economic activity. We base our IRFs on the Cholesky identification scheme of the 5-factor SVAR model for the US imports and exports growth, respectively, as presented in **Equations (5)-(7)**. The estimated IRFs of US trade flows (imports and exports) are shown in the upper panel of **Figure 6**.

[**Figure 6** Here]

The estimated responses of the US imports and exports in this alternative SVAR specification, show that the negative effect of commodity price uncertainty shocks on US trade remains negative and statistically significant when controlling for possible dynamic interactions between aggregate demand, exchange rates, commodity prices and uncertainty. Under this VAR identification scheme, the unanticipated commodity uncertainty shock has an instantaneous and persistently negative effect on US trade flows.

More specifically, the results show that a one standard deviation commodity uncertainty shock reduces US imports growth by 0.6% three months after the initial shock and US exports growth by 0.5% two months after the uncertainty shock. These effects remain negative and statistically significant for 9 and 7 months after the initial uncertainty shock for the 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 the responses of the US trade flows to the US effective exchange rate, commodity price and global economic activity shocks.[14]

We also estimate an identical 5-factor SVAR model for the EA, using the EA imports and exports growth as the last variable in the VAR ordering presented in **Equations (6)** and **(7)**. The lower panel of **Figure 6** shows the estimated IRFs for these models. The IRFs for the EA show that the impact of commodity price uncertainty on EA imports and exports growth is significantly negative and more long-lasting when compared with the respective impact of the other endogenous variables in the SVAR model. Our analysis shows that a one standard deviation shock in the commodity price uncertainty results to a 1% drop in EA exports one month after the initial uncertainty shock, with the effect remaining negative and statistically significant for 5 months after the initial commodity uncertainty shock. In addition, a positive one standard deviation shock in

[14] Interestingly, our SVAR analysis reports a drop of US trade flows in response to US dollar appreciation. These results are broadly in line and provide further support to the recent literature on the dominant currency paradigm (Georgiadis and Schumann, 2021; Gopinath *et al*., 2020; among others). According to the findings of this literature, global trade (both imports and exports) deteriorates when a dominant currency, like the US dollar, appreciates. The decline, in both exports and imports, in response to the dominant currency appreciation comes from the fact that both exports and imports are invoiced globally in US dollars, hence, an appreciation would discourage exports and imports in the same way.

commodity price uncertainty reduces EA imports growth by almost 1.2% two months after the initial uncertainty shock with the effect remaining negative and significant for 8 months after the initial shock.

We finally estimate the same set of commodity-specific SVAR models presented in **Subsection 4.3** using this alternative SVAR identification scheme, as presented in **Equations (5)-(7)**. **Figures 7** and **8** below report the estimated orthogonalized IRFs of US and EA imports and exports growth to agricultural, metals and energy price uncertainty shocks when using this alternative SVAR identification scheme.

[**Figures 7-8** Here]

The estimated IRFs shown in **Figures 7** and **8** provide additional robustness to our baseline commodity specific SVARs, since we find that our main findings on the negative effect of major agricultural, metals and energy markets remain unaltered when using this alternative SVAR identification scheme.

5.2 Additional Robustness Checks

In this section we provide additional robustness to our main findings by using a variety of modifications over a) alternative specifications, b) lag lengths, c) the variable sets and d) causal orderings for our structural VAR setups which are described in **Subsection 3.2**. First, we estimate our baseline SVAR model shown in **Equations (2)-(4)**, using, instead of the *BASIS*, the global crude oil production growth (*PROD*) as used and described by Kilian (2009) and Kilian and Murphy (2014). Using this SVAR modeling approach, in which the supply shocks are estimated as the structural one standard deviation shocks in the global crude oil production growth, our SVAR results remain unaltered. These results show that our findings are independent of the choice of the measure used for the identification of supply shocks.

Furthermore, following the relevant literature indicating that approximately one year of lags is needed for capturing the dynamics in the VAR system (Kilian, 2009; Hamilton, 2003; among others), we estimate our baseline SVAR model allowing for additional number of lags. More specifically, we perform the analysis allowing for 6, 12 and 24 lags respectively in our baseline SVAR model and our findings remain unaffected by the number of lags.

We continue our robustness checks by using a number of alternative/additional measures in our information variable set. In more detail, we estimate the SVAR model (as presented in **Subsection 3.2.1**), using, instead of the broad GSCI commodity price index, the series of the WTI crude oil prices (as used in Kilian, 2009) and we show that the dynamic responses of the international trade flows to uncertainty shocks, using this alternative measure, remain unaltered. We, also, estimate alternative VAR orderings for the baseline as well as the alternative SVAR models, described in **Subsection 3.2**, and we find that our main results remain unchanged.

Finally, we control for additional measures, like different proxies of economic uncertainty (e.g., the US and EA economic policy uncertainty), the WTI oil prices, and a measure of geopolitical uncertainty, in a higher-dimensional SVAR model and again our main findings remain unaffected. Likewise, we examine the robustness of our results on the method of deflation used for the trade flow series. To do this, we estimate the SVAR model where we use trade price indexes instead of

CPI indexes to deflate the exports and imports series. Again, our main results remain unaltered. All the robustness check results discussed here can be found in the online **Appendix**.

6. Conclusions

In this paper, we empirically show the negative impact of commodity price uncertainty shocks on US and EA trade flows. Our SVAR analysis reveals that both US and EA trade flows are significantly reduced when uncertainty about future commodity prices rises, having an approximate 2% cumulative drop three to four months after the initial uncertainty shock. Our analysis also shows that the cumulative contractionary effect of rising commodity price uncertainty on US and EA trade is larger and more persistent when compared with the respective impact of the global supply, global demand and commodity-specific demand shocks. Moreover, when examining the dynamic impact of the rising uncertainty in individual commodity markets, we find that the non-oil commodity uncertainty shocks have a similar, in magnitude and persistence, 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 both oil and non-oil commodity markets is associated with falling international trade. Our paper is the first to show that commodity uncertainty shocks are significant determinants of international trade flows, when compared with commodity price shocks. We believe that a further exploration of the effects of time-varying uncertainty, which is derived from forward-looking commodity option markets (e.g., option-implied volatility), on international trade, will be a fruitful area for future research. Furthermore, our results are broadly in line with the theoretical models of Giovannini *et al*. (2019) and Tran (2021) which show the importance of commodity price and uncertainty shocks on international trade. We postulate that an extension and estimation of a multi-country DSGE trade model augmented with global commodity price uncertainty, would provide additional insights on this strand of literature. We also leave this proposition as another direction for further research.

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Tables and Figures

Table 1: Descriptive Statistics

	Mean	***Std. Dev.***	***Minimum***	***Maximum***	***Skewness***	***Kurtosis***
COMPR	-0.001	0.068	-0.345	0.177	-0.885	5.740
COMRV	0.047	0.054	0.004	0.475	4.428	28.103
GACT	0.021	0.652	-1.631	1.881	0.663	3.283
BASIS	-0.286	0.619	-1.289	0.705	-0.015	1.273
IMP_{US}	0.003	0.024	-0.130	0.108	-0.956	9.180
EXP_{US}	0.002	0.029	-0.283	0.134	-2.671	33.407
IMP_{EA}	0.003	0.032	-0.173	0.093	-0.732	6.219
EXP_{EA}	0.004	0.034	-0.319	0.133	-2.644	27.990
$EXCH_{US}$	0.000	0.012	-0.041	0.055	0.225	4.294
$EXCH_{EA}$	-0.000	0.014	-0.051	0.052	0.241	3.982

The table presents the descriptive statistics of all the variables used in the SVAR analyses. The dataset is at monthly frequency and covers the period January 1994 to May 2021 (a total of 329 observations). All variables are defined in the data subsection.

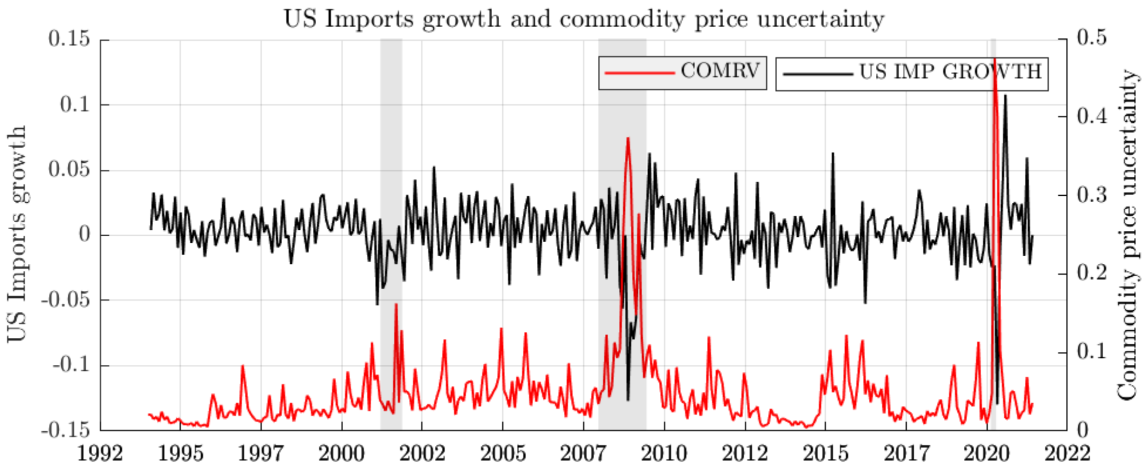
Table 2. Variance Decompositions of US and EA Trade Flows (*Baseline SVAR Model*)

Contribution From / To	SUPPLY shock	DEMAND shock	COM DEMAND shock	COM UNCERT shock	TRADE shock
US EXP	5.4%	3.2%	5.1%	26.4%	60.0%
US IMP	2.7%	4.9%	8.1%	13.6%	70.8%
EA EXP	4.0%	1.8%	3.0%	21.9%	69.4%
EA IMP	4.4%	2.1%	6.3%	15.8%	71.3%

The table shows the forecast error variance decomposition (FEVD) estimates for the US and EA import and export growth which are based on the baseline SVAR model described in Equations (2)-(4). More specifically, we present the contribution of aggregate supply, aggregate demand, commodity-specific demand, commodity price uncertainty and trade structural shocks when explaining the forecast error variance of US and EA trade flows. All rows sum to 100%.

Figure 1. US and EA Trade and Commodity Price Uncertainty
This plot shows the monthly time series for the real US and EA imports and exports growth along with the commodity price uncertainty (*COMRV*) series. The grey shaded areas represent the NBER US Recessions.

Panel A: US Imports and Exports



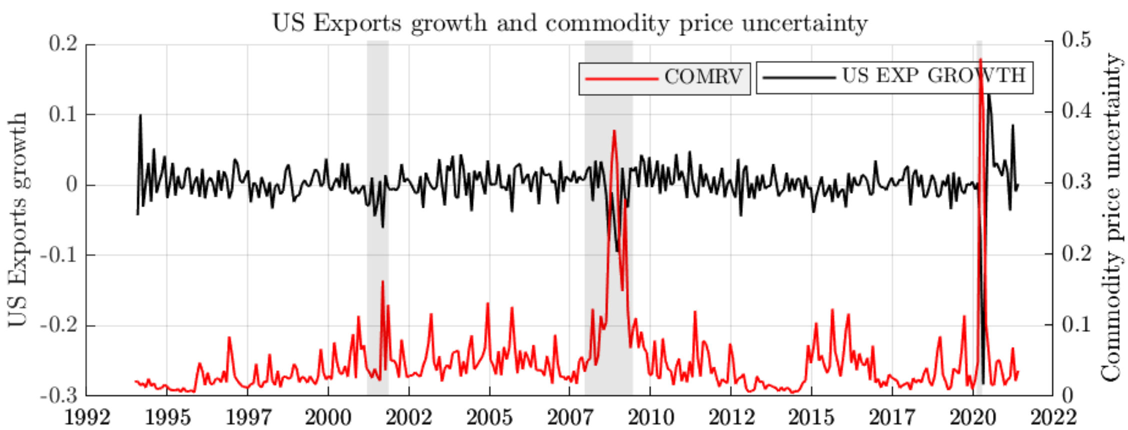
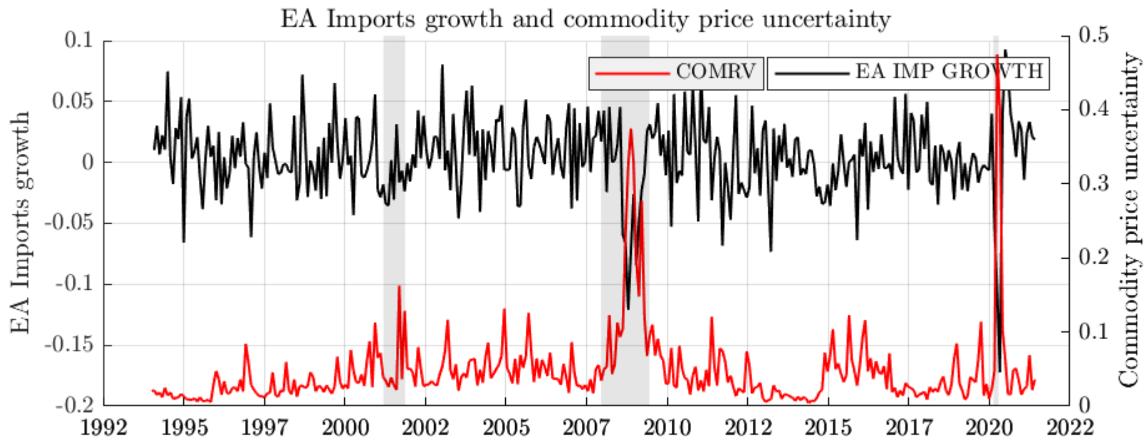


Figure 1. continued

Panel B: EA Imports and Exports



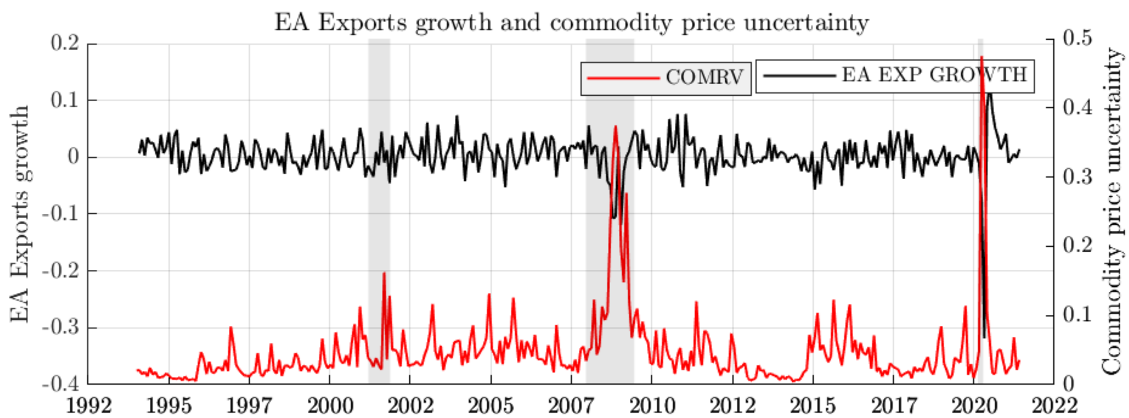


Figure 2. Responses of US and EA Trade Flows (*Baseline SVAR Model*)

The solid line shows the estimated IRFs of US and EA imports and exports growth to aggregate supply, aggregate demand, commodity-specific demand, and commodity price uncertainty structural shocks which are based on the baseline SVAR model described in Equations (2)-(4). The shaded area shows the estimated 90% bootstrapped confidence intervals using 1,000 replications.

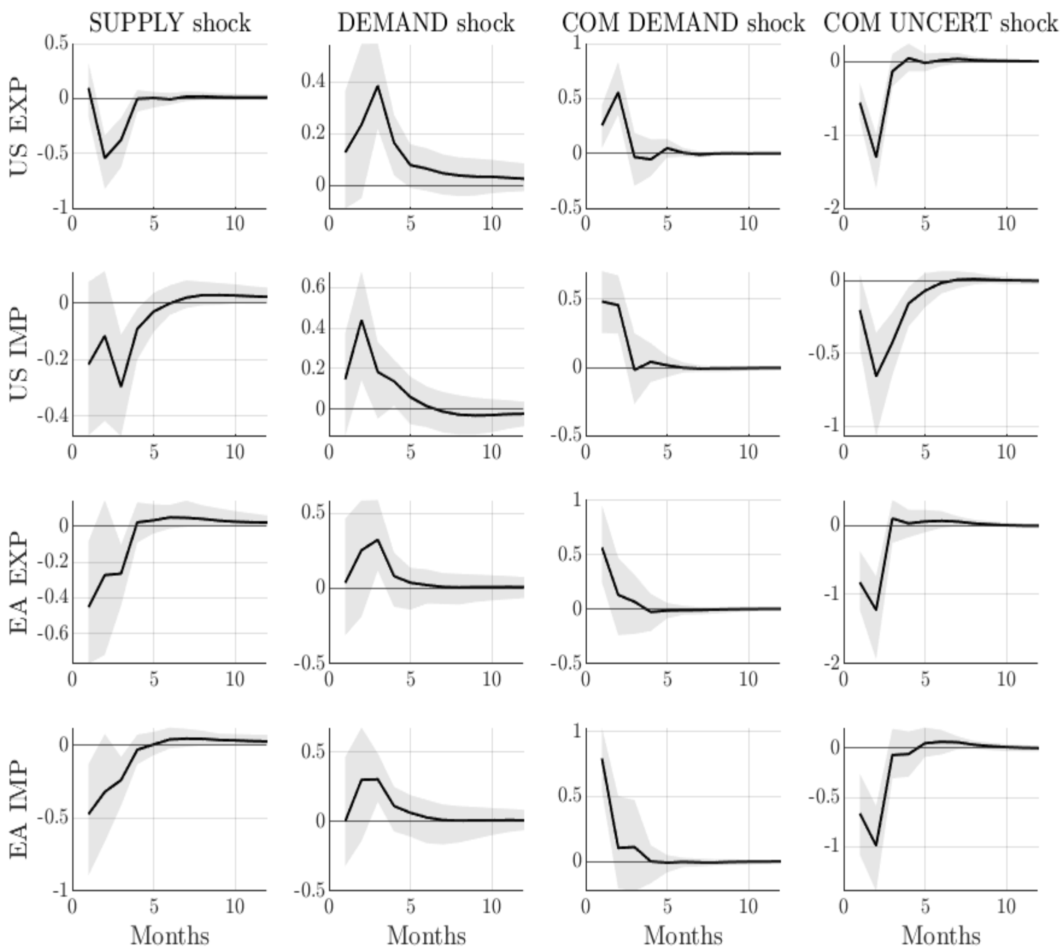


Figure 3. Cumulative Responses of US and EA Trade Flows (*Baseline SVAR Model*)
The solid line shows the estimated cumulative IRFs of US and EA imports and exports growth to aggregate supply, aggregate demand, commodity-specific demand, and commodity price uncertainty structural shocks which are based on the baseline SVAR model described in Equations (2)-(4). The shaded area shows the estimated 90% bootstrapped confidence intervals for the cumulative IRFs using 1,000 replications.

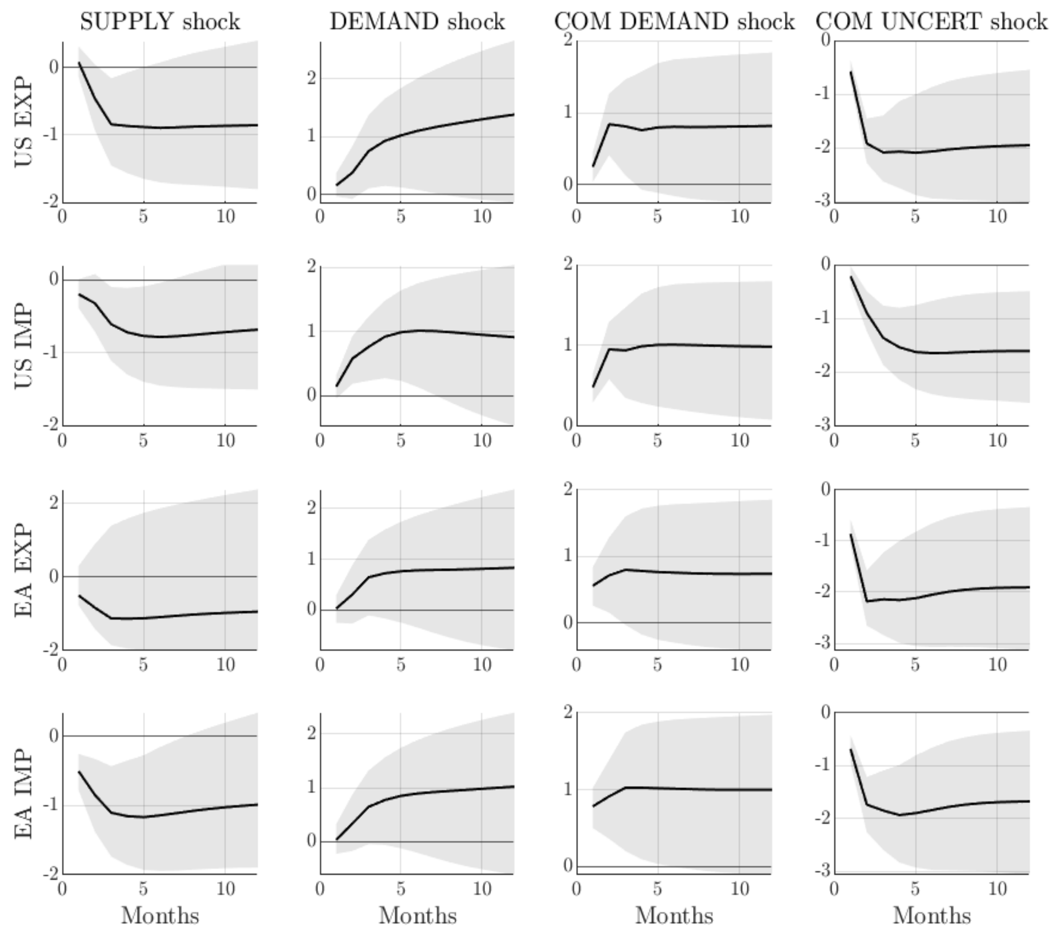
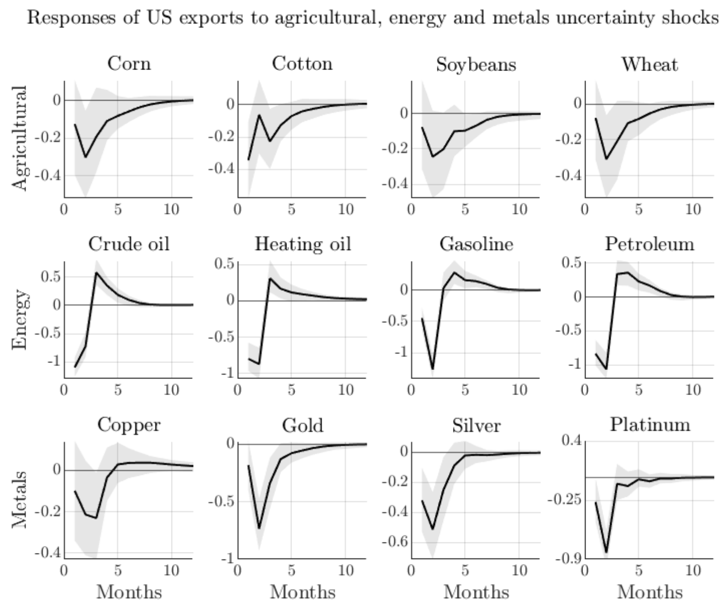


Figure 4. Responses of US Trade Flows to Agricultural, Metals and Energy Uncertainty Shocks (*Baseline SVAR Model*)

The solid line shows the estimated IRFs of US exports and imports growth which are based on the baseline SVAR model described in Equations (2)-(4) for the 12 agricultural, energy and metals commodity markets. Panel A and B reports the responses of US exports and imports to exogenous commodity price uncertainty shocks in agricultural, energy and metals commodity markets respectively. The shaded area shows the estimated 90% bootstrapped confidence intervals using 1,000 replications.

Panel A: US Exports



Panel B: US Imports

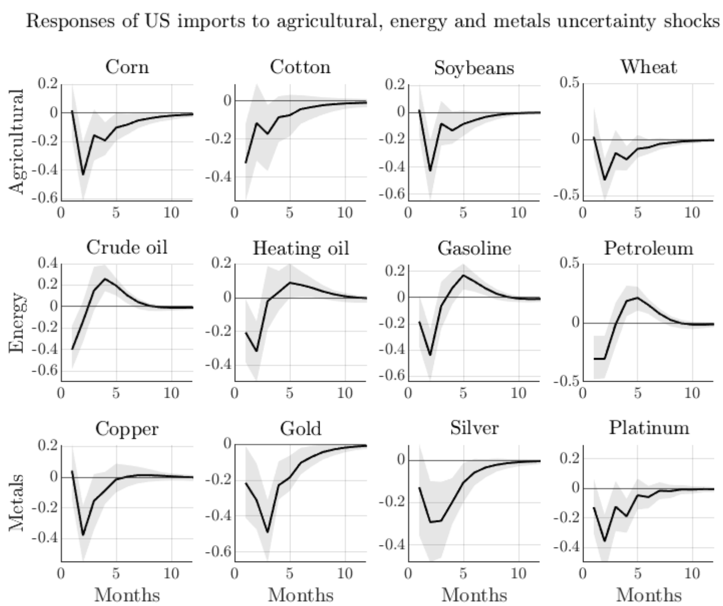
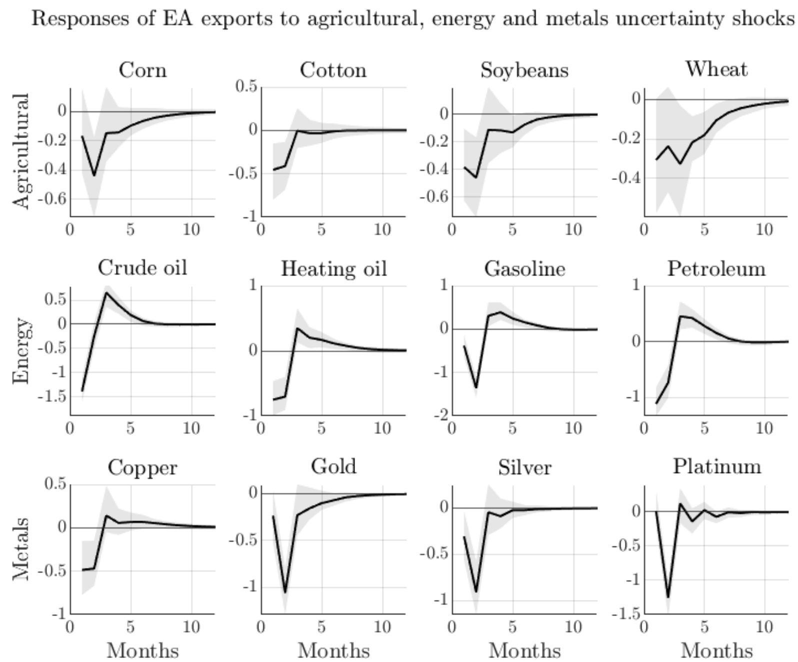


Figure 5. Responses of EA Trade Flows to Agricultural, Metals and Energy Uncertainty Shocks (*Baseline SVAR Model*)

The solid line shows the estimated IRFs of EA exports and imports growth which are based on the baseline SVAR model described in Equations (2)-(4) for the 12 agricultural, energy and metals commodity markets. Panel A and B reports the responses of EA exports and imports to exogenous commodity price uncertainty shocks in agricultural, energy and metals commodity markets respectively. The shaded area shows the estimated 90% bootstrapped confidence intervals using 1,000 replications.

Panel A: EA Exports



Panel B: EA Imports

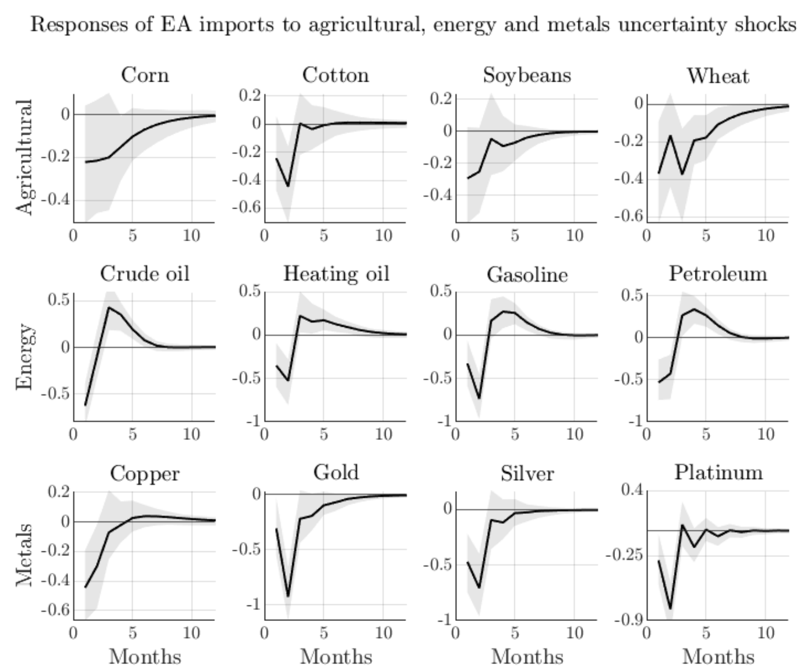


Figure 6. Responses of US and EA Trade Flows (*Alternative SVAR Model*)

The solid line shows the estimated IRFs of US and EA exports and imports growth which are based on the alternative 5-factor SVAR model described in Equations (5)-(7). The shaded area shows the estimated 90% bootstrapped confidence intervals using 1,000 replications.

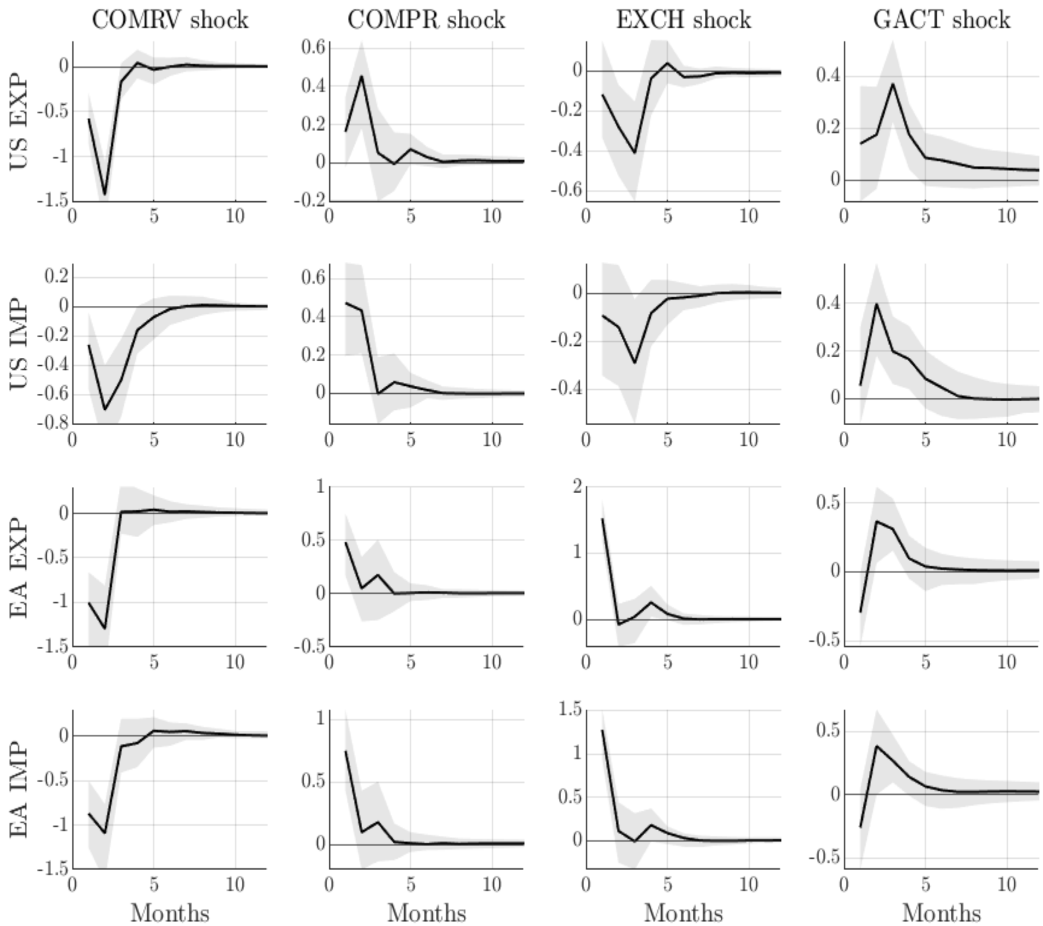
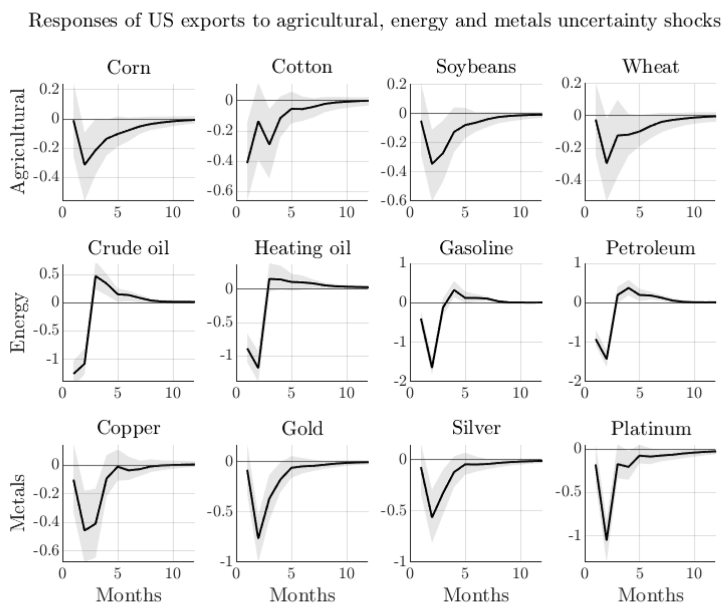


Figure 7. Responses of US Trade Flows to Agricultural, Metals and Energy Uncertainty Shocks (*Alternative SVAR Model*)

The solid line shows the estimated IRFs of US exports and imports growth which are based on the 5-factor SVAR model described in Equations (5)-(7) for the 12 agricultural, energy and metals commodity markets. Panel A and B reports the responses of US exports and imports to exogenous commodity price uncertainty shocks in agricultural, energy and metals commodity markets respectively. The shaded area shows the estimated 90% bootstrapped confidence intervals using 1,000 replications.

Panel A: US Exports



Panel B: US Imports

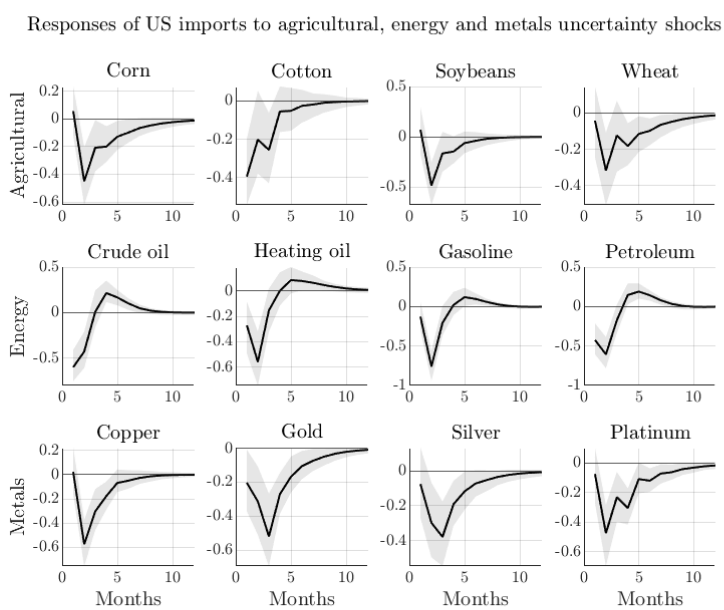
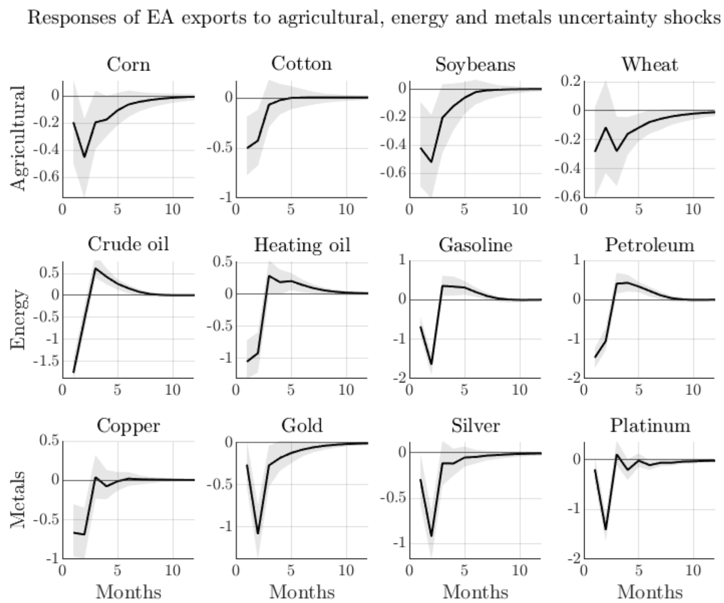


Figure 8. Responses of EA Trade Flows to Agricultural, Metals and Energy Uncertainty Shocks (*Alternative SVAR Model*)

The solid line shows the estimated IRFs of EA exports and imports growth which are based on the 5-factor SVAR model described in Equations (5)-(7) for the 12 agricultural, energy and metals commodity markets. Panel A and B reports the responses of EA exports and imports to exogenous commodity price uncertainty shocks in agricultural, energy and metals commodity markets respectively. The shaded area shows the estimated 90% bootstrapped confidence intervals using 1,000 replications.

Panel A: EA Exports



Panel B: EA Imports