Uncertainty diffusion across commodity markets

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This version: September 2022

Abstract

While numerous studies investigate volatility transmission across commodity markets, particularly oil and agricultural markets, uncertainty diffusion across commodity markets remains absent from the literature. This circumstance is primarily related to the lack of appropriate measures of commodity price uncertainty, which differs from volatility. This study focuses on measuring commodity price uncertainty and how it is transferred from one commodity market to another. Our contributions are twofold. (i) We construct an aggregate predictability-based measure of uncertainty for each group of commodity markets and different maturities, and (ii) we analyze uncertainty diffusion across different commodity markets using a vector autoregressive model. Our findings clearly demonstrate a bi-causal uncertainty transfer between agriculture, energy, and industrial markets, excluding precious metals markets. Additionally, the industrial commodity market is assumed to be the transmission channel of commodity uncertainty spread, given its close link with global economic activity. Notably, we validate the efficacy of using industrial uncertainty as a proxy for macroeconomic uncertainty. Finally, our confirmation of precious metals' insensitivity to other markets' shocks reinforces its nature as a safe haven.

Classification JEL: Q02, C32, E32

Keywords: Commodity uncertainty, vector autoregressive model, macroeconomic uncertainty.

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1. Introduction

The new landscape of commodity markets shaped by the financialization phenomenon is characterized by high price volatility.[1] Given the centrality of commodities in human activity, this ubiquitous volatility changes economic agents' behavior and has consequences on economic activity. Additionally, the pandemic, which affected the global economic context, led to the resurgence of an already uncertain environment on international markets; particularly in the commodity markets that are of interest to this study. Kyle and Xiong (2001) and the United Nations Conference on Trade and Development in 2009 detail the implications of the rising use of commodities assets amid higher volatility and the correlation between commodity prices. This suggests that countries' commodity-based financial indices are linked, and commodity price sensitivity is subject to international market conditions, exhibiting a contagious phenomenon. In a deeper way, the financialization of commodities since 2004 has led to more integrated markets, including the synergy of energy, industrial, agriculture, and precious metals commodities. According to Diebold et al. (2017), energy market has higher degree of financialization so that its shocks are transmitted to other commodity groups. The degree of integration has considerably increased between energy, metals and agriculture commodity markets (Tang and Xiong, 2012; Nazlioglu et al., 2013; Yang et al., 2021). However, the linkages including spillover effects and transmission mechanism among commodity prices are more complex and require further explorations.

This study considers uncertainty shocks as an important driving factor of the dynamic connectedness between commodity markets. Uncertainty shocks on commodity and stock markets are diverse and can arise from the economic uncertainty (Güngör and Taştan, 2021; Huang et al., 2021; Wen et al., 2022), health crisis (Jeris and Nath, 2021) or geopolitical events (Gong and Xu, 2022; Wang et al., 2022). In recent years, this last source of uncertainty shocks appears to be crucial in commodity interconnections since geopolitical threatens are more frequent and tend to occur in areas rich in energy and mineral resources. For instance, the war between Ukraine and Russia is a clear illustration. In fact, Russia being one of the world's largest producers of energy and food grains, the incident causes the prices of crude oil (as well as its by-products), natural gas, wheat and safe-havens assets (such as gold and silver) to rise sharply. Moreover, geopolitical tensions often imply adjustments and shifts in government policies, which generate broad implications for investors' sentiment on both commodity and financial markets (Asai et al., 2020). Thereby, assets pricing take into account investors' inflation expectations under time-frequency dynamics of volatility spillovers among commodity markets (Aybar et al., 2020). Therefore, extreme events resulting from geopolitical risk favor investor panic under uncertainty, that afterwards drive anomalous market volatility and ultimately affects the long-term stability of commodity markets (Tiwari et al., 2021). Commodity markets are inherently volatile because they are purely governed by expectations wherein agents are unable to determine the market equilibrium in advance. Given that economic activity is highly dependent on commodities, this context leads to reexamining the sufficiency of the common

[1] Commodity financialization is defined as the increase in the volume of transactions on financial instruments, such as "Futures" contracts on commodity markets. For more details about see Silvennoinen and Thorp (2013), Chari and Christiano (2017).

reliance on commodity price volatility when analyzing economic recessions.

Existing research investigates the concepts of volatility and uncertainty in an interchangeable manner, and volatility-based uncertainty measures have recently emerged (such as the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models, implied volatility index). Since Jurado et al. (2015) proposed definition of uncertainty as the volatility of an unpredictable disturbance on some macroeconomic and financial factors, this subsequently created a major distinction in modeling volatility and uncertainty in various empirical works. Likewise, relying on this distinction when investigating the oil market, Joëts et al. (2018) conclude that volatility and uncertainty in prices are not alike. Diebold and Kilian (2001) proposed a predictability approach on economic variables that contributes more to uncovering agents' decision-making process than examining a simple dispersion degree on some interest variables. Since volatility and uncertainty are conceptually different, it is illogical to claim that volatility spillover is roughly equivalent to uncertainty diffusion. Commodity price volatility may or may not generate uncertainty, which could have macroeconomic implications. This assertion is not only related to the clarification regarding the distinction between volatility and uncertainty, but also confirmed by empirical literature, which has widely investigated price volatility spillovers among commodity markets; oil and agriculture markets in particular (Busse et al., 2010; Zhang et al., 2010; Serra, 2011; Serra et al., 2011; Hassouneh et al., 2012; Kristoufek et al., 2012).

This paper aims at exploring a new insight of commodity markets' instability. We focus on the diffusion of unpredictable shocks (such as COVID-19 outbreak or Ukraine-Russia war), involving markets' disturbances. Therefore, this paper goes beyond the empirical literature on volatility in two ways: First, we propose a practical measure of commodity price uncertainty based on predictability, as opposed to volatility. For that purpose, we develop a price uncertainty aggregate measure for 21 commodity markets using a moving average stochastic volatility model on price forecasting error.[2] By employing this perspective, we note that unlike the volatility measure, which relies on a backward-looking approach, the uncertainty measure includes agents' anticipation through forecasting based on financial or economic events (Joëts et al., 2017). In this sense, measuring uncertainty looks forward at financial or economic disturbances. Second, we emphasize the transmission mechanism of uncertainty shocks across different commodity markets by examining impulse response functions through a multivariate time-series model. We also present macroeconomic perspectives of uncertainty transmission mechanisms across markets.

Our investigation uncovers two notable findings. (i) The predictability-based uncertainty indicator outperforms the volatility indicator when considering the 2007-2008 financial crisis, suggesting that reasoning in terms of uncertainty, rather than volatility, could present a tool for investors for gauging economic expectations. (ii) A bi-causal effect is evident between agriculture, energy, and industrial markets' uncertainties, with the exception of precious metals markets. Moreover, we show that industry uncertainty could serve as a proxy for macroeconomic uncertainty, as it functions similarly to global demand uncertainty that ensures uncertainty diffusion

[2]The aggregate measure of uncertainty is computed using weights provided by World Bank data.

across heterogeneous markets. The latter aspect is more observable in the energy market during economic turmoil than in other markets. In the same vein, one might argue that industry uncertainty as a proxy for macroeconomic uncertainty, captures the geopolitical uncertainty. It is notable that these results can be considered original, as such an aggregate measure of uncertainty in commodity markets has not yet been explored, including the resultant cross-market uncertainty transmission. Our outcomes shed light on some implications for both investors and policymakers. On the one hand, our paper provides investors an at-hand instrument to appraise price uncertainty in various commodity markets, which may give perspective for the development of hedging strategies to rule out, as much as possible, uncertainty spillover effects across commodity markets. On the other hand, when formulating effective macroeconomic policies, policymakers should consider heterogeneous uncertainty transfer effects between markets. Notably, actions to promote energy and agriculture security in an economic cooperation framework could help reducing, at the country level, uncertainty spillover effects on markets with strong diffusion (energy, agriculture, and industry).

The remainder of the study is organized into five sections. Section 2 presents discussion of volatility versus uncertainty. Section 3 describes the construction of our aggregate uncertainty index for commodity markets. Section 4 presents the empirical strategy and results on commodity uncertainty shock transmission. Section 5 examines industry uncertainty as a potential proxy of macroeconomic uncertainty, presenting a vehicle through which the latter could spill over into other markets. Section 6 concludes the study.

2. Discussion on volatility versus uncertainty

This section presents some background on the concepts of volatility (or risk) and uncertainty in economic literature for preliminary orientation.

2.1. Theoretical debate

From the microeconomic perspective, it is necessary to reference Knight (1921), the first author to highlight the distinction between risk (commonly volatility) and uncertainty, which then entered the lexicon of economics and decision theory. The difference between risk and uncertainty is generally interpreted as being related to whether agents can be assumed to function as if they possess well-defined probabilities for possible outcomes. If so, the situation is one of risk; if not, it is one of uncertainty. While the distinction between risk and uncertainty, so defined, is often encountered in the literature, until recently its role enables some economists (particularly those working in the neoclassical tradition) to rule out uncertainty (Hirshleifer, 1970). Indeed, the main reasons for doing so are found in the modern theory of choice wherein subjective probabilities are derived from agents' orderings over lotteries; therefore, most economists have more willingness to do this with the assumption of consistent choice.

In the neoclassical macroeconomics literature, the debate on risk-uncertainty has resurfaced. In his famous critique, Lucas (1976) reveals that monetary policy intertemporal choices are based on discretion bypass agents'

rational anticipations in the risk-uncertainty environment. In that sense, agents' behavior adapts to economic policies structural changes. Keynes also set out exactly the distinction commonly assigned to Knight (1921). Whatever the merits of this contention, it has acquired considerable currency in recent years, leading to renewed interest in the risk-uncertainty distinction. LeRoy and Singell (1987) argue that the common interpretation of Knight's risk-uncertainty distinction concerning whether agents possess subjective probabilities constitutes a misreading of Knight. On the contrary, Knight clearly shared the modern view that agents can always be assumed to act as if they possess subjective probabilities, even in the case of uncertainty. Knight's theory refers to risk situations where insurance markets exist and uncertainty situations where they do not. In that sense, uncertainty means a situation in which insurance markets collapse because of moral hazard and adverse selection. This latter view of uncertainty suggests a striking anticipation of the modern treatment of market failure. The economic outlook we can cast on this distinction is relative to entrepreneurship, as highlighted by LeRoy and Singell (1987). According to these authors, Knight's risk, uncertainty, and profit are properly read as an analysis of the consequences of entrepreneurship being uninsurable for economic institutions and economic theory. The central assumption of Knight's risk, uncertainty, and profit is the presence or absence of insurance markets and not necessarily the applicability or inapplicability of probabilistic calculus, as clearly established.

The macroeconomic perspective presents a similar interpretation to the Knightian risk approach in the sense that volatility (risk) measures the extent to which a macroeconomic aggregate fluctuates around its expected long-term value. Hence, economic uncertainty can be defined as a circumstance wherein the economic future is unreadable, agents' behavior becomes unpredictable, and projects become unreliable. Based on this definition, uncertainty is related to a lack of reliable forecasting of interest variables. Therefore, following this reasoning, volatility cannot always be accompanied by uncertainty, as part of the volatility can be captured using modern forecasting models (Joëts et al., 2018).

2.2. Empirical debate

To the best of our knowledge, the literature predominantly focuses on volatility and uncertainty measurement.

Uncertainty has a crucial role in many studies in terms of sources, measurement, potential effect on agents' behavior (Dixit, 1989), and economic activity (Bloom et al., 2007; Bloom, 2009; Bachmann et al., 2013; Jurado et al., 2015).[3] Among studies regarding the real implications of uncertainty, Bloom (2009) and Bloom et al. (2018) were the first to highlight uncertainty as the main driver of business cycle fluctuations and point out during the United States (US) recession that uncertainty goes up by almost 50% on average. Likewise, these uncertainty shocks lead to a significant temporary fall in output and productivity.

Uncertainty is tough to quantify since it is an intrinsically unobservable concept to be measured. The literature on uncertainty is primarily based on proxies due to the challenging nature of accurately measuring uncertainty.

[3] Bloom (2014) and Baker et al. (2014) provide large reviews of literature regarding uncertainty shocks.

Therefore, two approaches of observable and unobservable (latent) uncertainty measures are used. Observable measures are primarily volatility-based and rely on proxies using time-series variations of observable economic and financial indicators. Among others, we note cross-sectional dispersion of firms, industry earnings, or productivity (Bloom, 2009; Bloom et al., 2018)), and the implied volatility index also known as VIX (Bloom, 2009).[4] In the same vein, several measures have also been developed, including the variance risk premium (Zhou, 2018; Bali and Zhou, 2016), consumers' perceived uncertainty from survey data (Leduc and Liu, 2016), and the volatility of fiscal instruments estimated under time-varying volatility (Fernandez-Villaverde et al., 2015).[5] Additionally, there are previous newspapers-based uncertainty measures, such as economic policy uncertainty (Brogaard and Detzel, 2015; Baker et al., 2016; Azqueta-Gavaldón, 2017) and the geopolitical risk (Caldara and Iacoviello, 2020).

Latent or unobservable measures rely on the approach proposed by Jurado et al. (2015) for which fluctuations in observable economic indicators may vary for several reasons that are not imputed to uncertainty; hence, they define uncertainty as the volatility of an unforecastable component of a large group of macroeconomic and financial indicators. This latter approach provides predictability-based uncertainty measures (Scotti, 2016; Jurado et al., 2015; Rossi and Sekhposyan, 2015; Ludvigson et al., 2015; Bachmann et al., 2013) that are forecast-dependent.

All the measures presented above consider at least three sources of uncertainty that include macroeconomics, financial markets, and economic policy. Among studies investigating the impact of each source of uncertainty on the economic activity, Jurado et al. (2015) find that macroeconomic uncertainty shock has a sustained and adverse effect on industrial production and employment, as opposed to implied volatility or economic policy-based uncertainty. Other studies investigate the possibility of an aggregate measure of uncertainty based on several proxies: Haddow et al. (2013) use principal component analysis to extract an uncertainty index based on four indicators (financial and survey data), and Charles et al. (2018) use a dynamic factor model (Doz et al., 2012) to construct an uncertainty composite index (UCI). The former study is implemented for the UK in the 1985-2013 period. The latter study, conducted for the US, includes economic policy uncertainty source along with six uncertainty proxies used in the literature, including two macroeconomic and financial uncertainty factors based on unpredictability proposed by Jurado et al. (2015) and Ludvigson et al. (2015),a measure of microeconomic uncertainty with the forecast disagreement index proposed by Bachmann et al. (2013), the "former" implied volatility index, corporate bond spreads, and an index of economic policy uncertainty proposed by Baker et al. (2016).[6] Charles et al. (2018) compared the sensitivity of macroeconomic variables

[4]The VIX is a stock market-based option-implied volatility that can be decomposed into two components, a proxy of the risk aversion and expected stock market volatility. VIX represents the option-implied expected volatility of the S&P500 index with a horizon of 30 calendar days (22 trading days). It is an implied or "risk-neutral" volatility, as opposed to actual or physical expected volatility. If we consider a discrete state economy, physical volatility will intuitively use actual state probabilities to arrive at the physical expected volatility, whereas risk-neutral volatility would make use of probabilities adjusted for the pricing of risk.

[5]Several Studies of uncertainty shocks use either VAR models or Dynamic Stochastic General Equilibrium (DSGE) models (Bloom et al., 2018; Leduc and Liu, 2016).

[6]Baker et al. (2016) construct an economic policy-related uncertainty measure based on newspaper analysis and its impact on financial and macroeconomic variables.

(S&P500 stock market index, inflation, nominal wage, manufacturing production, employment, hours worked, and federal fund rate) to the UCI and six other individual standard proxies of uncertainty from VAR models. Following their results, an increase in the UCI leads to a significant drop in all macroeconomic variables, and only uncertainty measures based on predictability and corporate bond spreads are important, but not dominant, sources of macroeconomic variables' volatility.

Finally, previous literature presents different sources and measures of uncertainty. In this study, we are interested in the macroeconomic side of uncertainty in commodity markets. To this end, it is beneficial to use Jurado et al. (2015)'s idea of predictability and the appropriate methodology corresponding to commodity markets' characteristics. The following section presents the construction of the aggregate uncertainty index in commodity markets.

3. Commodity markets' aggregate uncertainty index

3.1. Data description

Our sample consists of 21 world commodity markets classified into four main groups of energy, industry, agriculture, and precious metals. Commodity price data for all markets monthly in frequency and are extracted from the World Bank website. The period ranges from January 1995 to December 2018 (see Table 1 in Appendix A).[7]

Figure 1 (in Appendix B) illustrates the evolution of agricultural commodity prices. An upward trend occurs in the early 2000s for most agricultural markets (cocoa, maize, lumber, coffee, soybeans, sugar, and wheat). Figure 2 (in Appendix B) presents the price dynamic of industrial commodities (aluminum, lead, tin, copper, nickel, zinc, and iron). These markets also experienced a significant upward trend in the early 2000s. Historically, China's entry into the World Trade Organization could justify this price increase. During that period, driven by the industrial production above 10%, a world growth cycle led to economic growth of 4.5%. Conversely, during the 2008 economic crisis, most industrial commodities experienced a considerable drop in prices before a slight rebound after the crisis. Oil, gas, and coal represent our energy markets. At first glance, Figure 3 (in Appendix B) presents a bullish trend from the 2000s before slight drops in 2008, in late 2014, and early 2015 for oil and gas. The fall in coal price was more premature in 2011-2012. Finally, gold, platinum, and silver markets represent the precious metals markets. Figure 4 (in Appendix B) shows gold and platinum series with a steady upward trend in the early 2000s. These prices slow down after 2011. Note that these markets have particular specificities related to their components that are safe havens. Due to the stationarity issue, we log-differentiate the seasonally adjusted series at the first order to obtain returns. These data are used to obtain the uncertainty index, as described in the following subsection.

[7]World Bank Commodity Markets: Commodity-prices-pinksheets. The data are seasonally adjusted using a deterministic log-additive decomposition method with values close to those obtained with seasonal-trend decomposition using LOESS.

3.2. Methodology

The predictability-based uncertainty of Jurado et al. (2015) is defined as the conditional volatility of an unpredictable disturbance. In the same vein, we construct our aggregate uncertainty measure in commodity markets using the data described and based on the concept of predictability. Following Joëts et al. (2017), we compute the uncertainty measure of each market in three steps. (i) Estimation of an AR (1) process on a fixed rolling window for each market series of price returns; (ii) The h-step-ahead forecast and the extraction of the forecast error associated with the corresponding forecast horizon; and (iii) Estimation of the stochastic conditional volatility of the forecast error.[8] Unlike recent empirical studies using AR terms and exogenous predictors to construct oil price uncertainty (Nguyen et al., 2019; Cross et al., 2020), in this study, we choose a large number of heterogeneous markets and for methodological convenience, to specify the forecasting model for each commodity market with the AR(1) process.

Note that the final step, referencing Chan and Jeliazkov (2009) and Chan and Hsiao (2014), relies on a moving average stochastic volatility (MASV) model that accounts for the volatility specifications over time and clustering phenomena that remain a characteristic of commodity markets. More specifically, it assumes that the forecast error w_t can be defined by the following equation:

$$w_t = \mu + v_t \tag{1}$$

where μ is a constant and represents the mean of the forecast error. The variable v_t is assumed to be serially dependent and follows the MA (q) of the form:

$$v_t = \varepsilon_t + \psi_1 \varepsilon_{t-1} + ... + \psi_q \varepsilon_{t-q} \tag{2}$$

$$h_t = \mu_h + \phi_h(h_{t-1} - \mu_h) + \varsigma_t \tag{3}$$

where $\varepsilon_t \sim N(0, e^{h_t})$ and $\varsigma_t \sim N(0, \sigma_h^2)$ are independent of each other.[9] The variable h_t is the log-volatility of ε_t and is assumed to follow an AR (1) process, μ_h is the level of the log-variance and $\mid \phi_h \mid < 1$ represents the persistence of the log-variance. Note that this variance is not allowed to vary unrestrictedly with time. The feature of this model fundamentally differs from GARCH-type models where the time-varying volatility is assumed to follow a deterministic, rather than stochastic, evolution. The stochastic volatility model is thus conveniently expressed in hierarchical form and is center-parameterized. According to **?**, under the assumption of moving average extension, the conditional variance of the series w_t is given by:

$$V(w_t|\mu, \psi, h) = e^{h_t} + \psi_1^2 e^{h_{t-1}} + ... + \psi_q^2 e^{h_{t-q}} \tag{4}$$

[8] In this study, we use one-month horizon uncertainty. For interested readers, an uncertainty for each market and different forecast horizon h is available upon request.

[9] $\varepsilon_0 = \varepsilon_1 = ... = \varepsilon_{-q+1} = 0$. The roots of the characteristic polynomial associated with the coefficients of the MA process, $\psi = (\psi_1, .., \psi_q)'$ are outside the unit circle, which ensures the stability of the model.

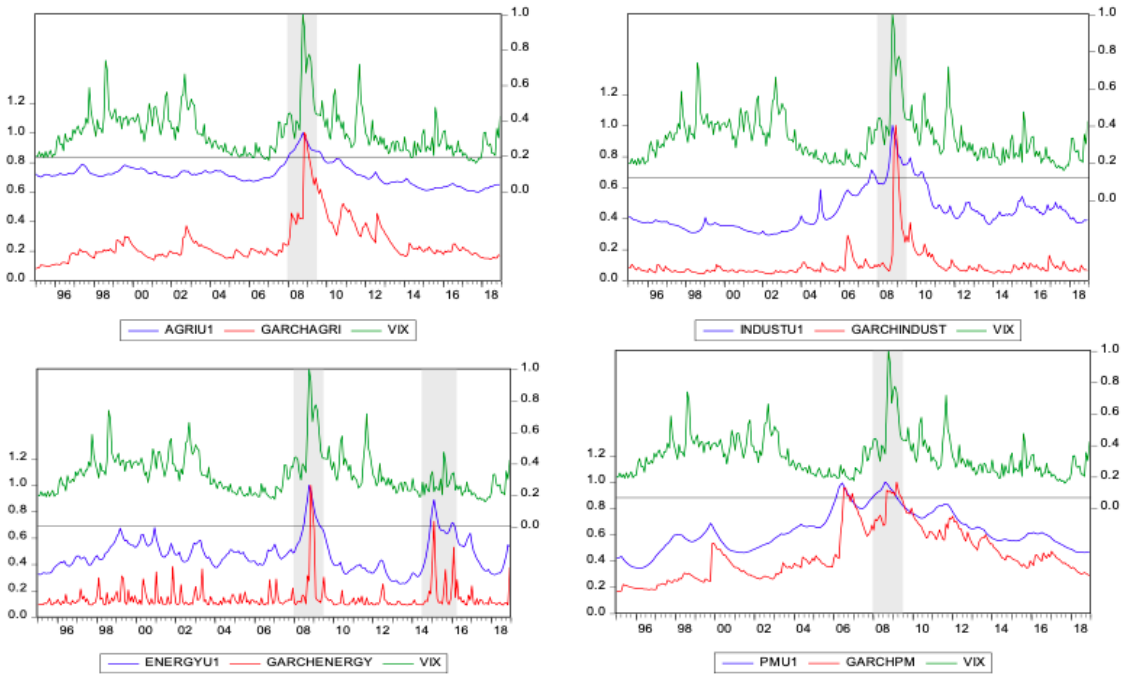
The estimates of this stochastic volatility make it possible to capture both moving average and log-volatility effects, as shown in equations (2) and (3), respectively.[10] From equation (4), an aggregate index of uncertainty for each group of commodity markets (agriculture, industry, energy, and precious metals) is obtained by computing a simple weighted average of individual price uncertainties noted as $V(w_t|\mu, \psi, h_t) = U_{i,h}$. Formally, we note $U_{m,h}$ our aggregate uncertainty index defined as follows:

$$U_{m,h} = \sum_{i=1}^{n} \alpha_i U_{i,h} \tag{5}$$

where m indicates a given group of commodity markets, i an individual commodity market that belongs to group m, and h the horizon. Notice that α_i represents the weight of the individual market i.[11]

For each group of commodity markets, Figure 1 presents the one-month commodity price uncertainty (blue line) we computed above in comparison to GARCH (1,1) volatility measure (red line), and VIX (green line). Simultaneous presentation of these measures allows us to emphasize the relevance of our predictability-based measure of uncertainty with respect to other indicators based on volatility. Table 2 (in Appendix A) gives an overview of variables' labels and description. [12]

Figure 1 – **Uncertainty versus Volatility.**



Note: These figures depict one-month uncertainty, labeled AGRIU1, INDUSTU1, ENERGYU1, and PMU1 for agriculture, industry, energy, and precious metals markets (blue line scaled on the left axis), respectively (Table 2, in Appendix A). The volatility is based on the estimation of a GARCH(1,1) on market groups (red line scaled on the left axis) labeled GARCHAGRI, GARCHINDUST, GARCHENERGY, and GARCHPM. The VIX is the green line scaled on the right axis.

[10] See Chan and Jeliazkov (2009) and **?** The MATLAB code used to estimate the MASV model is freely available from Joshua Chanâs website. For each variable, we obtain 20000 loops or draws from the posterior distribution using the Gibbs sampler after a burn-in period of 1000.

[11] Markets weights are available on the World Bank Commodity Markets website: Commodity-pricespinksheets.

[12] GARCH stands for Generalized Autoregressive Conditional Heteroskedasticity model. For each group of commodity markets, we compute a GARCH (1,1) volatility measure of commodity price returns. In turn, the VIX represents implied volatility.

The vertical gray bands correspond to heightened uncertainty episodes that are generally associated with economic turmoil, such as the great recession of 2008. We consider a given period to correspond to an episode of heightened uncertainty for a commodity market when the measure of uncertainty exceeds the horizontal bar that represents 1.65 standard deviation above the unconditional mean of the commodity price uncertainty. During these periods of heightened uncertainty, different measures of uncertainty and volatility have reached a peak; however, the upward slope before the peak began earlier for our measure of uncertainty compared to other measures. This indicates that the predictability-based measure of uncertainty captures the slope a few months earlier economic turmoil episodes, whereas volatility-based measures, such as VIX and GARCH, react a few months later. For instance, analyzing the recent financial crisis, which lasted 19 months (December 2007-June 2009, represented by the gray band) according to the NBER recession dates disclosure, market price volatility (red line) is accompanied by uncertainty (blue line). Agriculture, industry, and to a lesser extent, energy markets' uncertainties start an upward trend around June 2007 (three months before the crisis), before VIX and GARCH volatility indices (July and August 2008, respectively), reaching their peak in October 2008 at almost the same time as VIX, but two months prior to GARCH. Furthermore, the timing gap is also observable in the precious metals market where the uncertainty upward dynamic begins earlier, reaching a peak in July 2008, along with implied volatility in October 2008, and GARCH in March 2009. Therefore, compared with volatility, predictability-based uncertainty can be considered a leading indicator that reflects investors' expectations and a forthcoming economic turmoil signal at a significant level. This early warning signal of global economic recession indicates the potential negative effects of uncertainty in agricultural, energy, and metals markets on economic activity for a given forecasting horizon, as highlighted by Jurado et al. (2015), Joëts et al. (2017), and Triantafyllou et al. (2019). Moreover, for reasons already discussed in the introduction and emphasized in section 2, it is less surprising that volatility measures seem more unstable before 2008; thereby, it permits the exposure of a clear distinction between patterns of episodes of volatility and uncertainty. While periods of significant uncertainty amplify volatility, periods of high volatility are not necessarily accompanied by heightened uncertainty. Having constructed uncertainty indices, the next consideration is whether interactions between markets' uncertainties exist.[13]

4. Uncertainty diffusion within commodity markets

4.1. Empirical strategy

Thus far, this commodity markets analysis has captured the diffusion of volatility, but not uncertainty. Some studies have highlighted volatility diffusion within commodities using either conditional variance or implied volatility measures. For instance, Nazlioglu et al. (2013) conduct an empirical analysis to examine the volatility transmission of oil to common agricultural commodity prices (wheat, corn, soybeans, and sugar). They specified a GARCH model for each market and performed a variance causality test analysis for the 2005 pre-crisis

[13]Table 4 (in appendix A) displays the descriptive statistics of uncertainty variables.

and post-crisis period, demonstrating the spillover effects of oil market volatility on the agricultural markets during the 2005 post-crisis period except for sugar. Gozgor et al. (2016) replicate this analysis on the same commodity markets using a GJR-GARCH approach, finding a higher correlation of oil market volatility with the four agricultural markets. Liu et al. (2013) analyze short- and long-run volatility transmission between crude oil implied volatility and other important volatility indices, including stock market volatility (VIX), the euro/dollar exchange rate volatility index, and the gold price volatility index. They argued that only short-run relationships exist among these indices, and oil market volatility is influenced by the other indices in terms of volatility expectations in the oil market becoming sensitive to other marketsâ volatility shocks when global economic activity is extremely unstable.

This study endeavors to fill the literature gap on the issue of uncertainty diffusion between commodity markets.[14] For that purpose, we propose to assess the transmission of one-month (very short term) aggregate uncertainty across markets. Table 3 (in Appendix A) presents the markets' uncertainties correlation matrix and the level of significance. Positive relationships notably arise from the interconnections among markets. For instance, industry and precious metals record the highest correlation coefficient of 72%. To conduct our analysis, we rely on a vector autoregressive (VAR) modeling, which allows us to capture each variable's response to any change in another variable. This property is suitable to capture uncertainty diffusion across commodity markets once a measure of uncertainty is available. The reduced form of the VAR model is defined as follows:

$$U_t = C + \Phi_1 U_{t-1} + ... + \Phi_p U_{t-p} + D_m + V_t \tag{6}$$

where U_t corresponds to a vector of four endogenous variables of uncertainty for each commodity markets' group; namely, the one-month uncertainty in agriculture, energy, industry, and precious metals markets. However, the way we manage the variables' classification order will be presented later. C is a vector of constants, and Φ_p is the matrix of autoregressive coefficients corresponding to a lag p of the system.[15] V_t is the vector of orthogonal error terms. D_m represents time dummies specific to each group of markets and structural breaks that are identified by the Zivot-Andrews unit root test (see Table 5, in Appendix A).[16]

To assess the uncertainty diffusion across commodity markets, we use Generalized Impulse Response Functions (GIRFs) to avoid ordering uncertainty variables. Indeed, it seems to be difficult to intuitively determine which uncertainty variable is more exogenous than others to establish the ordering in the Cholesky factorization; therefore, we reference Koop et al. (1996)'s GIRFs using the following equation:

$$GIRF_u\left(h, I_{t-1}, V_t\right) = E\left[U_{t+h}|I_{t-1}, V_t\right] - E\left[U_{t+h}|I_{t-1}\right] \tag{7}$$

[14]We are thankful towards an anonymous referee also highlighting as an insightful point implications for commodity of cryptocurrency markets.

[15]The lag length criteria retained is two, following standard information criteria. We use different lag specifications to test the robustness of our results. The qualitative results of our study are not affected by the choice of the lag specification.

[16]The test reveals that our uncertainty variables are all stationary at a 5% significance level. Moreover, structural break dates identified by the test are agriculture (08/2012), industry (05/2010), energy (06/2009, 08/2014), precious metals (09/2011).

where I_{t-1} is the information set at time $t-1$ and V_t is a realization of exogenous shocks (that comes from the vector of the orthogonal error terms). The response of each variable in U_t at the horizon h is computed by simulating the evolution of the model conditionally to the initial condition I_{t-1} and to a given realization V_t. Having described the estimation strategy and the way we capture uncertainty diffusion among markets, we will present the results in the next section.

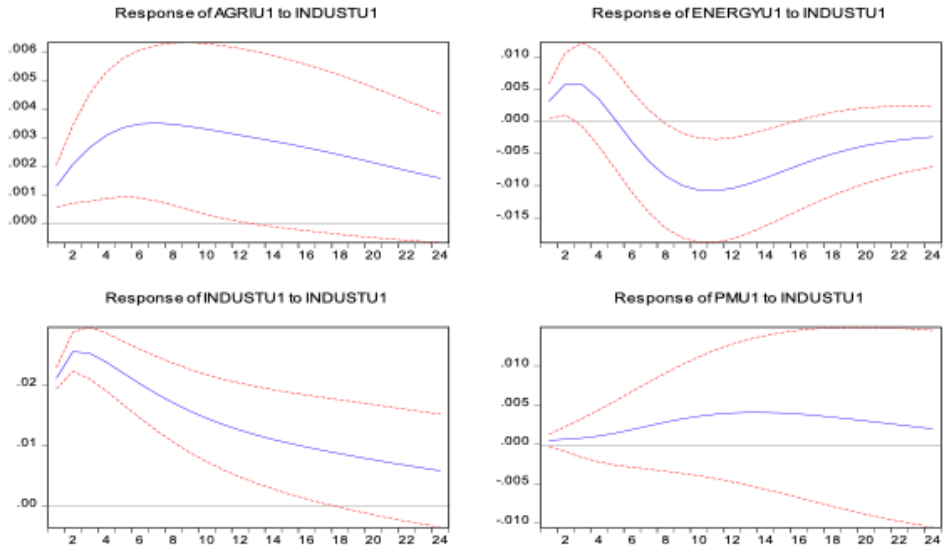
4.2. Results discussion

In the following GIRFs, a given uncertainty shock in one commodity market is helpful for evaluating how this uncertainty can be transferred to other markets. The explanation of the aggregate uncertainty diffusion mechanism between markets relies on prior identification of main components in each commodity group. We consider the main factors or drivers of aggregate uncertainty in each commodity group as those that register the highest weight. For instance, the crude oil market accounts for 84% of the total share of the aggregate energy market uncertainty and is considered as its leading component.

Figure 2 presents the transmission of industry uncertainty shock to other markets. The industrial market is strongly represented by copper (38% of the total share), which is one of the most important nonferrous metals in the modern industry.[17] Uncertainty in the industrial market is transmitted to energy and agriculture markets for two and six months, respectively. Concerning industrial and energy markets, it is necessary to highlight the close link between industrial commodities and global demand to understand the diffusion of the industry uncertainty to the energy market. Copper is the most used for industrial purposes, for infrastructure renewal, construction projects, and telecommunications. Thus, copper is considered a leading indicator of global economic health. More than any other base metal, copper is closely tied to manufacturing, electrical engineering, industrial production, information technology, construction, and the medical sector. In general, rising copper prices indicate strong demand and a global economic strength, whereas lower copper prices indicate a weaker economy; therefore, the diffusion of uncertainty from industry to the energy market is primarily conveyed through the demand channel. For instance, it appears that the 2008 economic crisis generated overall uncertainty in the industrial market, and in the copper market in particular, which was also reflected in the energy market. Copper is one of the main components of renewable energy systems, which uses more metal than traditional energy sources. Concerning industrial and agricultural markets, diffusion of uncertainty between these markets is also linked with global demand. Joëts et al. (2017) argue that beyond traditional supply and demand shocks, the macroeconomic uncertainty constitutes another key channel through which economic fundamentals may impact commodity prices.

[17] Despite aluminum and iron have considerable weights, we insist on copper and its prominent role in the industry sector.

Figure 2 – **Responses to one-month industry uncertainty shock.**



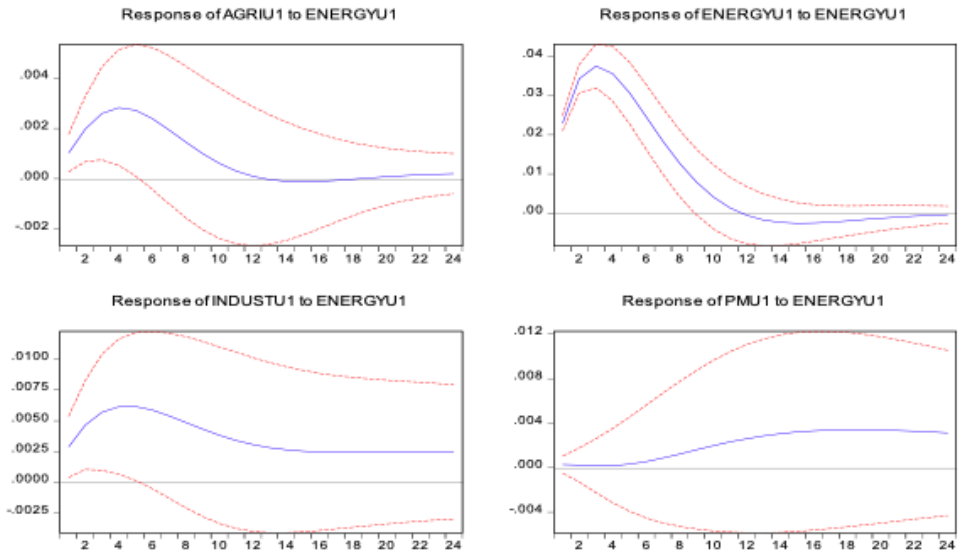
Note: AGRIU1 (one-month agriculture market uncertainty), INDUSTU1 (one-month industry market uncertainty), ENERGYU1 (one-month energy market uncertainty), and PMU1 (one-month precious metals market uncertainty).

Figure 3 illustrates the uncertainty transmission from the energy market to agriculture, industry, and precious metals markets. A positive and significant impact of energy uncertainty on agriculture and industry occurs for four and five months, respectively. It is sufficient to say that the spread of uncertainty occurs in the short-run from energy to both agricultural and industrial markets. Knowing that the oil market accounts for 84% of the energy market, thus has the same proportion in energy market uncertainty construction, oil market uncertainty is considered to be the main driver of this sector.

The energy market was strongly influenced by the discovery of coal in the 18th century (1797), which became a primary energy source until the advent of oil in the 19th century (1859). With oil exploration and the establishment of the oil industry that has developed making derivatives, oil has become the dominant component of the global energy market. Among many other natural resources, oil remains an object of covetousness among states to the point of generating geopolitical and strategic interests. This circumstance was compounded by the wars in Kuwait (1990), Afghanistan (2001), and Iraq (2002-2003). Due to the wars, a sharp increase in oil prices was followed by uncertainty that was linked to a rise in the precautionary demand with the establishment of reserves. During the recession of 2008-2009, there was a downward trend of prices, as in most sectors of the economy. Historically, there have been oil shortages with price spikes and high volatility in 1996, 2001, and 2005, but these have not led to much uncertainty (Kilian, 2010). Nazlioglu et al. (2013) investigate the transmission of volatility from oil to agricultural markets (corn, soybeans, and wheat) revealing a dynamic transfer of volatility after the food crisis in 2005. Following the food price crisis, a risk transmission dimension of the dynamic interrelationships between energy and agricultural markets emerged, as the latter are increasingly used as inputs in the former for biofuel production. Indeed, several studies analyze the link between oil and agricultural prices in terms of biofuels; for instance, Busse et al. (2010), Zhang et al. (2010), Serra (2011), Serra et al. (2011), Hassouneh et al. (2012), and Kristoufek et al. (2012). The common conclusion of these

empirical investigations is that there is at least a direct short-run volatility transmission between oil and some agricultural commodities. Notably, according to our global uncertainty diffusion analysis, we also found a similar relationship, wherein uncertainty on the energy market spills over to the agriculture market and vice-versa, since oil derivatives are obtained from several crops' agricultural commodities.[18] Uncertainty in the energy market is transmitted onto the industrial market for up to five months. It is notable that energy costs are high for copper extraction, smelting, and refining processes. Copper and oil demonstrate a positive correlation at 84% since 2002. Ji and Fan (2012) find that there is significant volatility spillover effect from oil to nonenergy commodities of industrial metals (copper, aluminum, and nickel). According to this study, the dynamic correlation strengthened after the 2008 crisis, indicating that the consistency of market price trends was affected by the economic recession; therefore, if oil price fluctuates in the long-run, so too does copper price. Likewise, both commodities are the main sources of uncertainty in the energy and industry markets and are strongly correlated to the same fundamental economic factors.

Figure 3 – **Responses to one-month energy uncertainty shock.**

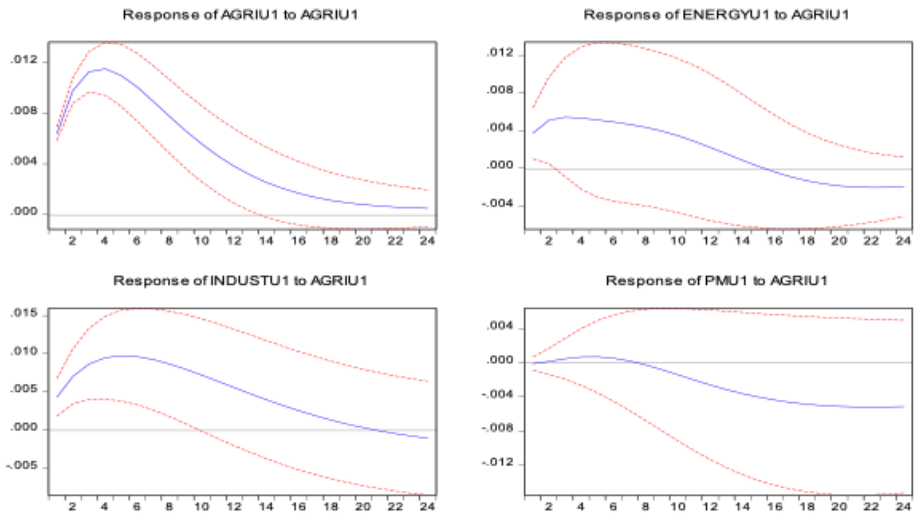


Note: AGRIU1 (one-month agriculture market uncertainty), INDUSTU1 (one-month industry market uncertainty), ENERGYU1 (one-month energy market uncertainty), PMU1 (one-month precious metals market uncertainty), and MACROU1 (one-month macroeconomic uncertainty).

Figure 4 presents the responses of various markets' uncertainties to agriculture uncertainty shocks. The impact is significant for industrial and energy markets. This finding indicates that an increase in agriculture uncertainty leads to an increase of uncertainty in the energy and industry markets, which reach a peak after two and five months, respectively. Regarding the agricultural and energy markets, unlike studies based on volatility, which only demonstrate the one-way effect of volatility spillover from oil to some agricultural markets, our findings determine two-way uncertainty diffusion between the two markets, particularly during crisis periods.

[18]The reverse causality of uncertainty diffusion from agricultural to energy markets is confirmed in Figure 4.

Figure 4 – **Responses to one-month agriculture uncertainty shock.**



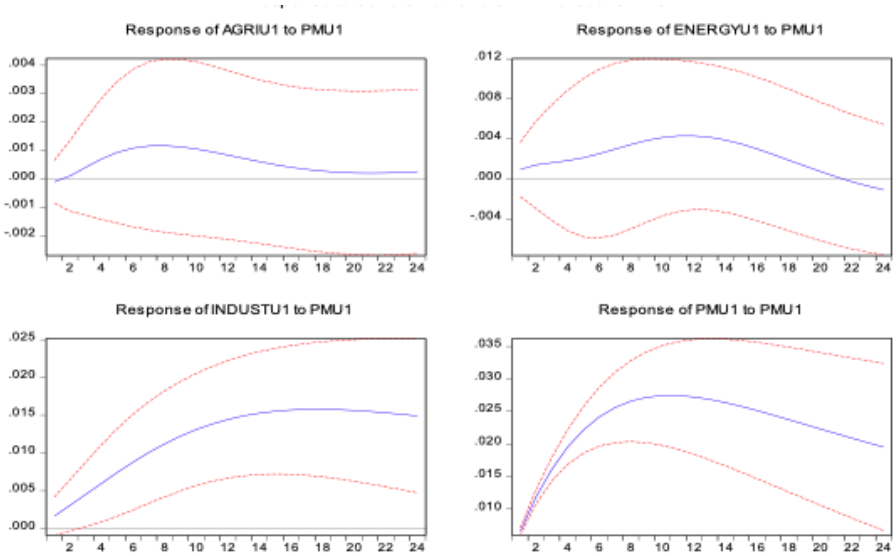
Note: AGRIU1 (one-month agriculture market uncertainty), INDUSTU1 (one-month industry market uncertainty), ENERGYU1 (one-month energy market uncertainty), and PMU1 (one-month precious metals market uncertainty).

Figure 5 depicts the precious metals uncertainty effect on other commodity markets. According to this graph, precious metals do not affect any other commodity market except the industrial commodity market, where the effect is persistent, vanishing within 36 months after the initial shock. This is not surprising since the correlation between both sectors' uncertainties is high and significant. Regarding the industry-precious metals relationship, the price of copper has historically been highly correlated with the price of gold, Chinese economy, world trade, and more commonly, with oil price. Also, the close connection between industrial and precious metals volatility may be related to the increasing importance of different metals in financial markets and their competitive role as hedging tools during market turmoil, such as gold and silver in traditional precious metals, and copper in industrial metals (Sakemoto, 2018; Baur and Smales, 2020; Sikiru and Salisu, 2021). Note that from Figure 2 to 4, precious metals remain insensitive to all other market shocks. This is less surprising, as long as they are considered safe havens used by investors with high-risk aversion as hedging strategies. This market is strongly dominated by gold (78% of the total share) and has a countercyclical pattern.

Biatkowski et al. (2015), use a Markovian regime-change model with an Augmented Dickey-Fuller (ADF) test to calculate the fundamental value of gold and capture the explosive trajectories of the price of gold, finding the most significant historical boom to be in the early 1980s. The explanation is related to the fact that there is an increase in inflation caused by the oil crisis between 1979 and 1982, coupled with US accommodative monetary policy and expansive budget. This spiral has led financial market participants to turn to precious metals. It is also notable that commodity prices increased, and the influx of funds into gold-listed indices likely contributed to this price dynamic. Uncertainty in the precious metals market in the 1980s also coincides with the 1981-1982 recession. The fight against inflation by a contraction of the money supply initiated by Volker, the then president of the Fed, in response to Reagan's decision to oppose a return to the gold-standard monetary system, led to the crisis from 1981 to 1982. The uncertainty on the silver (19% of the total share) is more

related to the different political crises between the United States, Iran, and Afghanistan. The price of silver rose sharply following the Hunt Brothers' affair, which made a fortune in the oil and silver financial markets between 1970 and 1990 (Bredin et al., 2022); however, the crisis of 2008 did not extend to the precious metals markets. While gold and silver prices rose slightly, platinum (3% of the total share) more easily accommodated to the industrial metals cycle. This suggests that agents' anticipation of this price increase as uncertainty in these markets has remained very low. In contrast to the recent financial crisis of 2008, the spillover mechanism of the 1981-1982 crisis is linked to the precious metals markets through Federal inflation targeting and interest rate policy.

Figure 5 – **Responses to one-month precious metals uncertainty shock.**



Note: AGRIU1 (one-month agriculture market uncertainty), INDUSTU1 (one-month industry market uncertainty), ENERGYU1 (one-month energy market uncertainty), and PMU1 (one-month precious metals market uncertainty).

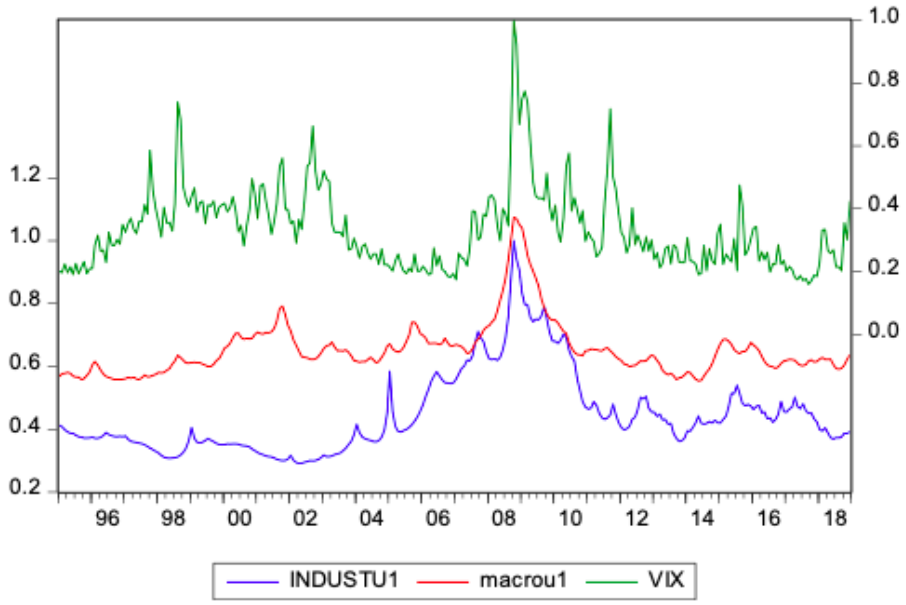
The results demonstrate a reciprocal effect in uncertainty diffusion between commodity markets other than the precious metal market; however, the industrial market is the only one that reacts in a persistent way to precious metals uncertainty shocks. Therefore, industrial uncertainty has links with all other commodity markets that must be addressed, particularly in terms of interactions between heterogeneous markets.[19]

5. Analysis of industry and macroeconomic uncertainties

Our findings present the uncertainty in commodity markets and the role of demand in the interaction between different markets. Figure 6 presents the comovement between industry market uncertainty, macroeconomic uncertainty, and the VIX, revealing that the evolution of industrial and macroeconomic uncertainties have been strongly linked since 2005, due to the intensification of international trade and commodity financialization.

[19]Tables on variance decomposition of endogenous variables are available upon request.

Figure 6 – **Macroeconomic uncertainty, VIX, and industry uncertainty.**



Note: On the left axis, this figure depicts both macroeconomic (red line) and industry (blue line) uncertainty, labeled MACROU1 and INDUSTU1, respectively. The VIX (green line) represents the implied volatility index scaled on the right axis.

This section is geared toward interpreting industry uncertainty diffusion. First, we present the impact of macroeconomic uncertainty and stock market volatility on commodity markets to compare with industrial uncertainty. Second, we examine industry and macroeconomic uncertainty contributions in agriculture and energy markets during the financial crisis of 2008. This helps to determine whether industry uncertainty could be considered a proxy for the macroeconomic uncertainty.

5.1. Comparative impact of the predictability-based and volatility-based uncertainty measure on commodity markets

This section presents the comparative impact of the predictability-based uncertainty measure and the volatility-based measure on commodity markets. This is accomplished by removing industry uncertainty and adding the volatility (VIX) and macroeconomic uncertainty variables into the previously estimated VAR model to analyze their effects on commodity market uncertainty. The macroeconomic uncertainty constructed by Jurado et al. (2015) relies on 132 macroeconomic and financial time series extracted from the FRED-MD monthly database.[20] Both macroeconomic and financial indicators are unbalanced to avoid the over-representation of financial variables and prioritize macroeconomic variables.[21] Jurado et al. (2015) emphasize that macroeconomic uncertainty proxy fluctuates countercyclically with global economic activity and business cycles.[22]

Figures 5 and 6 (in Appendix B) show the effect of one-month VIX and one-month macroeconomic uncertainty

[20]This includes: real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization indices, price indices, bond and stock market indices, and foreign exchange rate measures.

[21]A brief overview of the technical construction of macroeconomic uncertainty is presented in Appendix A.

[22]The implied volatility measure (VIX) is available on Bloomberg or Yahoo Finance website. Macroeconomic uncertainty is free to access on Ludvigson homepage: macroeconomic-uncertainty.

on commodity markets, respectively. The response of energy and agriculture uncertainties following a VIX index shock is very low compared to that obtained with macroeconomic uncertainty. The magnitude is larger when the shock comes from the one-month macroeconomic uncertainty than from the implied volatility index. While the effect of macroeconomic uncertainty on energy uncertainty is more protracted (seven months), the response of energy market uncertainty after the VIX shock is more transient (two months). This confirms that the effect of the predictability-based uncertainty measure, whether related to overall economic activity (macroeconomic uncertainty) or individual sectors (commodity markets), is more persistent than the common implied volatility index. While agriculture uncertainty is slightly more sensitive to macroeconomic uncertainty shock (five months), the effect of the volatility shock in the agriculture market is not significant. This is especially true as financial markets, with dynamics that are replicated by the implied volatility, have a closer link with energy than with agriculture. To stick with the previous results, we recall that the effect of the industry uncertainty on the agriculture market reaches a peak within five months, whereas the effect on the energy market occurs within two months after the initial shock (Figure 2). We also observe that the timing effect of the industry uncertainty on commodity markets follows the pattern of the macroeconomic uncertainty on the agriculture market. Consequently, given that industry uncertainty affects both agriculture and energy markets, as does macroeconomic uncertainty, there appears to be a correlation that we will further investigate through the historical decomposition.

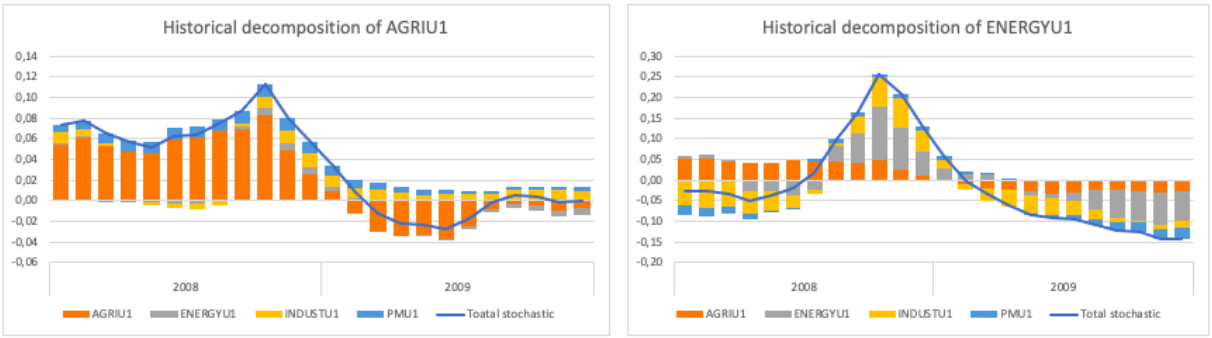
5.2. Historical decomposition of agriculture and energy markets shocks in terms of industry and macroeconomic uncertainty

We strongly established throughout this study that industry uncertainty is a special vehicle of global demand uncertainty to commodity markets. Central to this insight, the role of industrial metals in the global economic activity fluctuations must be explored. For centuries, and more particularly over the past two decades, demand has gradually connected with the industrial sector. From then on, the increase in sensitivity of industry uncertainty to other markets' shocks also clearly reflects global demand uncertainty to the same shocks. Based on economic intuition, this reasoning helps to overcome the issue of explaining the diffusion of uncertainty across heterogeneous markets. The historical decomposition analysis is an alternative method of variance decomposition that considers the different contributions of structural shocks to system components in the historical variation of a variable (Burbidge and Harrison, 1985).The purpose here is to compare the magnitude of the relative shares of macroeconomic and industrial uncertainties in agricultural and energy markets. This allows a better understanding of our proxy thesis.

We rely on Figure 6, presenting higher comovements between industry and macroeconomic uncertainty from January 2005 to December 2009, to scrutinize the historical decomposition from January 2008 to December 2009 with a focus on the 2008 financial crisis period. Figures 7 and 8 illustrate the relative contributions of

uncertainty shocks in various markets to the decomposition of the agriculture and energy sectors.[23] Agriculture contribution accounts for a large portion of its historical decomposition for the given period. This is primarily due to specific agriculture factors that have an indirect relationship with the economy. In fact, agricultural commodities often face weather conditions (seasonality) and producers often hold harvest stocks to smooth the supply chain until the following season. Moreover, crops' quality depends on how much they are protected from health disasters, such as plagues and insects that damage plants. Beyond those factors, due to permanent storage activity, the agricultural market is more resilient to economic shock; therefore, the contributions of other markets' uncertainty are limited in agriculture due to its low sensitivity. This insight holds for both industry and macroeconomic uncertainty shares in the agriculture market. The historical decomposition of energy, industry, and macroeconomic uncertainties' shares become more observable in relatively equivalent proportions for the second part of the 2008 financial crisis. In addition, with regard to energy, the contributions of both macroeconomic and industry uncertainties are, on average, more or less equal over the given period and follow the same trend, particularly in the second half of the crisis (from September 2008 to June 2009). This is less surprising, as unlike the agricultural market, which has an indirect link with economic activity and is less affected by exogenous shock, the energy market remains very sensitive. Likewise, due to the low-income elasticity of demand for agricultural commodities, these markets are less sensitive to global economic recession. Since it is established that the energy sector is sensitive to economic activity shock, using industry uncertainty as a proxy of the global demand uncertainty presents a viable method of shock replication.

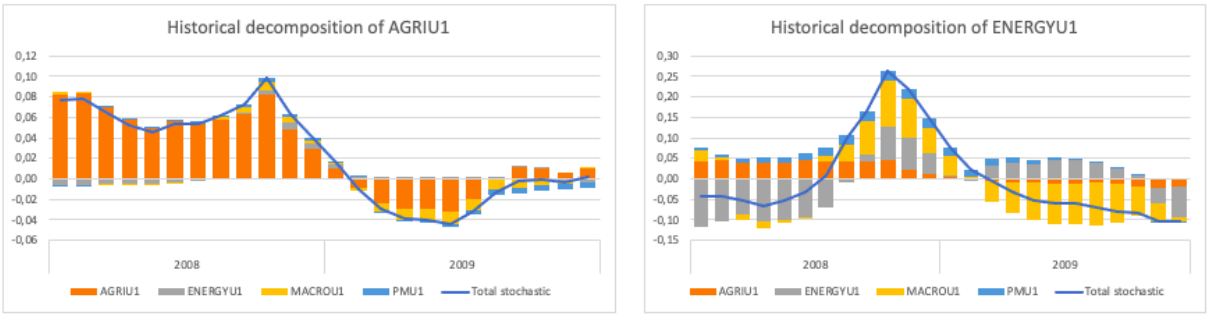
Figure 7 – **Historical decomposition of the energy and agriculture markets with respect to industry uncertainty.**



Note: Total stochastic (the demeaned one-month agriculture and energy uncertainty), AGRIU1 (one-month agriculture uncertainty contribution), ENERGYU1 (one-month energy uncertainty contribution), INDUSTU1 (one-month industry uncertainty contribution), and PMU1 (one-month precious metals uncertainty contribution).

[23] Regarding industry and precious metals historical decomposition graphs, more details are available upon request.

Figure 8 – **Historical decomposition of the energy and agriculture markets with respect to macroeconomic uncertainty.**



Note: Total stochastic (the demeaned one-month agriculture and energy uncertainty), AGRIU1 (one-month agriculture uncertainty contribution), ENERGYU1 (one-month energy uncertainty contribution), MACROU1 (one-month macroeconomic uncertainty contribution), and PMU1 (one-month precious metals uncertainty contribution).

In summary, our analysis demonstrates that industry uncertainty is a valid proxy for macroeconomic uncertainty. For practical purposes, we can argue, in addition to being an indicator of the macroeconomic uncertainty, our measure of industry uncertainty has the advantage of being easier to compute, as it uses only prices and not several factors as in Jurado et al. (2015).

6. Conclusion

This study endeavored to analyze uncertainty transmission between various commodity markets. To conduct our analysis, we construct an aggregate uncertainty measure for each commodity market category (agriculture, industry, energy, and precious metals). To assess the extent to which market uncertainty diffusion is possible, we estimate a standard VAR model that considers market-specific characteristics linked to structural breaks by incorporating dummy variables and GIRFs. Our results demonstrate a bi-causal relationship among agriculture, energy, and industry markets; however, the precious metals market does not react to any market uncertainty exogenous shock, due to their well-identified safe haven role during economic turmoil. Moreover, the industrial market is simultaneously sensitive to agriculture, energy, and precious metals market shocks; thus, we assert that industrial commodity uncertainty is an indicator of macroeconomic uncertainty, and has a predominant role in uncertainty diffusion across commodity markets. Additionally, we compared the contributions of industry and the macroeconomic uncertainty shocks in agriculture and energy markets. Unlike the agriculture market, we particularly observe during the 2008 crisis that the contribution of the industry uncertainty is almost the same as that of the macroeconomic uncertainty in the energy market. It is also noteworthy that we clearly differ from studies on commodity volatility not only on the assessment of prices disturbances but also the diffusion mechanisms through the resulting findings.

Regarding the context of the COVID-induced economic uncertainty, our analysis may also shed light. In fact, beyond endogenous uncertainty diffusion across markets, the COVID-19 outbreak as an exogenous shock, has

affected global economic activity by crippling many interconnected business sectors. For instance, oil price fell by two- thirds in January 2020, combined with a 24% decrease after the OPEC+ agreement failure (in March 2020). Agricultural price decline has been on the order of 9% since January 2020. The industrial red metal (copper) slowdown reached 4,684$ a ton in mid-March 2020, its annual lowest value. This context creates a global uncertainty environment that lowers economic activity and reinforces uncertainty diffusion across markets. Thereby, uncertainty over several agricultural commodities that are experiencing a fall in prices has large negative repercussions on oil and oil derivatives prices and vice-versa. Furthermore, copper uncertainty is tied to its price plunge, reflecting a slowdown in economic activity. The contagion effect that arises from this crisis could generate uncertainty within markets; thus, the consolidation of the uncertainty diffusion analysis across markets. Once more, the illustration of the health crisis' effects on specific markets indicates that the global demand channel driven by industry is the means through which uncertainty diffuses to agriculture and energy markets. Therefore, an exogenous shock such as the health crisis does not alter the mechanism. On the contrary, it passes through an induced-macroeconomic shock. In the same vein, the Russia-Ukraine conflict as a geopolitical event involving high macroeconomic uncertainty, has triggered turmoil in the financial markets and drastically increased uncertainty about the recovery of the global economy. The conflict threatens to squeeze energy and other commodity markets. Russia is among top 5 producers of oil, natural gas, steel, nickel aluminum, and wheat. On its side, Ukraine is the key producer of corn, wheat, sunflowers, sugar beet, barley, soybeans and rapeseed. Higher commodity prices intensify the threat of high long-lasting inflation which increases the risk of stagflation and social unrest. Other sectors such as automotive, transport, and chemicals are likely more vulnerable. The exposure to imported inflation and trade disruptions varies across regions. For instance, European economies are more at risk due to its high dependence on Russian oil and natural gas.

Our study has policy implications for investors and authorities. From the investors' perspective, they have at disposal a reliable instrument to appreciate price uncertainty in global commodity markets as well as the macroeconomic mechanisms of diffusion. More specifically, an appropriate portfolio diversification strategy for risk-averse investors might consist of mitigating the uncertainty spillover effects with a combination of precious metals and one of other assets' groups. From the authorities' perspective, we could draw both short and long-term challenges: Short-term challenges would involve policymakers to cushion price increases that could create an inflationary spiral in order to protect households with low income. Long-term challenges would consist of promoting a supply diversification strategy to reduce the dependence for net importers. For instance, while northern countries are more concerned by energy security, southern countries are betting for food security. Hence, governments could rely on trade and storage policies to insulate their domestic markets from external commodity shocks. This fosters price stability through transaction costs. Moreover, regional trade agreements might prevent the exposure to global commodity markets' linkages.

Finally, this article is not devoid of possible improvements since they might set path to future research works,

such as macroeconomic drivers of commodity price uncertainty.

Acknowledgments

We would like to thank Fabien Rondeau, Louise Narbonne, Thibaut Arpinon, Martina Dattilo and Roberto Brunetti for the careful reading of the manuscript. We are also grateful to anonymous reviewers for the insightful and constructive suggestions to greatly improve the quality of the manuscript. Finally, we acknowledge the contributions of participants at international conferences, workshops and seminars that helped divulging the paper.

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A Appendix A

A1. Tables

Table 1A – **Commodity monthly prices data from January 1995 to December 2018.**

Markets	Description	Units	Weights	Source
Energy				
Oil	Average oil price	$/bbl	0.84	World Bank
Gas	Average gas price	$/mmbtu	0.05	World Bank
Coal	Average coal price	$/mt	0.11	World Bank
Precious Metals				
Gold	Gold spot price	$/troy oz	0.78	World Bank
Platinum	Platinum spot price	$/troy oz	0.03	World Bank
Silver	Silver spot price	$/troy oz	0.19	World Bank
Agriculture				
Cocoa	Cocoa spot price	$/kg	0.10	World Bank
Coffee	Average coffee price	$/kg	0.12	World Bank
Maize	Maize spot price	$/mt	0.14	World Bank
Cotton	Cotton spot price	$/kg	0.06	World Bank
Lumber	Average Logs price	$/cubic meter	0.26	World Bank
Soybeans	Soybeans spot price	$/mt	0.12	World Bank
Sugar	Sugar spot price	$/kg	0.12	World Bank
Wheat	Average wheat price	$/mt	0.08	World Bank
Industry				
Aluminum	Aluminum spot price	$/mt	0.27	World Bank
Copper	Copper spot price	$/mt	0.38	World Bank
Lead	Lead spot price	$/mt	0.02	World Bank
Nickel	Nickel spot price	$/mt	0.08	World Bank
Tin	Tin spot price	$/mt	0.02	World Bank
Zinc	Zinc spot price	$/mt	0.04	World Bank
Iron	Iron spot price	$/mt	0.19	World Bank

Source: World Bank.

Table 2A – **Variables description.**

Variables	Labels	Description
Agriculture	AGRIU1	one-month agriculture uncertainty
Industry	INDUSTU1	one-month industry uncertainty
Energy	ENERGYU1	one-month energy uncertainty
Precious Metals	PMU1	one-month precious metals uncertainty
Volatility	VIX	one-month implied volatility index
Uncertainty	MACROU1	one-month macroeconomic uncertainty

Table 3A – **Market uncertainty - Correlation matrix.**

	AGRIU1	INDUSTU1	ENERGYU1	PMU1	VIX	MACROU1
AGRIU1	1.000					
	(0.000)					
INDUSTU1	0.550	1.000				
	(0.000)					
ENERGYU1	0.349	0.349	1.000			
	(0.000)	(0.000)				
PMU1	0.487	0.728	0.222	1.000		
	(0.000)	(0.000)	(0.000)			
VIX	0.631	0.263	0.460	0.222	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)		
MACROU1	0.662	0.703	0.644	0.583	0.566	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Note: AGRIU1 (one-month agriculture market uncertainty), INDUSTU1 (one-month industry market uncertainty), ENERGYU1 (one-month energy market uncertainty), PMU1 (one-month precious metals market uncertainty), VIX (implied volatility), and MACROU1 (one-month macroeconomic uncertainty). The probability values are in parenthesis.

Table 4A – **Market uncertainty - Descriptive statistics.**

	AGRIU1	INDUSTU1	ENERGYU1	PMU1	VIX	MACROU1
Mean	0.717	0.446	0.473	0.629	0.333	0.654
Median	0.713	0.407	0.452	0.603	0.306	0.632
Max	1.000	1.000	1.000	1.000	1.000	1.074
Min	0.598	0.291	0.251	0.344	0.159	0.554
Std dev	0.074	0.132	0.131	0.155	0.130	0.089
Jarque-Berra	0.000	0.000	0.000	0.000	0.000	0.000
Obs	288	288	288	288	288	288

Note: AGRIU1 (one-month agriculture market uncertainty), INDUSTU1 (one-month industry market uncertainty), ENERGYU1 (one-month energy market uncertainty), PMU1 (one-month precious metals market uncertainty), VIX (implied volatility), and MACROU1 (one-month macroeconomic uncertainty). The probability values are in parenthesis.

Table 5A – **Zivot-Andrews unit root test with structural breaks.**

One-month uncertainty	P_{value}	Break dates
Agriculture	0.013	08/2012
Industry	0.001	05/2010
Energy	0.041	06/2009, 08/2014
Precious Metals	0.002	09/2011

A2. A brief technical construction of the macroeconomic uncertainty index

Like commodity market uncertainty, Jurado et al. (2015)'s macroeconomic uncertainty is linked to predictability but differs in its estimation methodology. To present the empirical approach, we denote y_{jt} a single time series in a set of variables $Y_t(y_{jt} \in Y_t = (y_{1t}, ..., y_{Nyt}))$, the h-period uncertainty in that series is defined as the conditional volatility $U_{jt}^{y}(h)$ of the purely unforecastable component of the future value of the series.

$$U_{jt}^{y}(h) = \sqrt{E\left[\left(Y_{jt+h} - E\left(Y_{jt+h}|J_t\right)\right)^2 |J_t\right]} \tag{8}$$

where $j = 1, ., N_y$ and $E(.|J_t)$ is the conditional expectation of the variable. The variable J_t is the set of information available at date t. The uncertainty linked to the variable Y_{jt+h} is therefore defined as the expectation of the squared error forecast. If we consider j individual measures of uncertainty, then we can proceed to an equally weighted aggregation (w_j being the weight) of the latter and obtain the following expression of macroeconomic uncertainty:

$$U_t^{y}(h) = p \lim_{N_y \to \infty} \sum_{i=1}^{N_y} w_j U_{jt}^{y}(h) \equiv E_w\left[U_{jt}^{y}(h)\right] \tag{9}$$

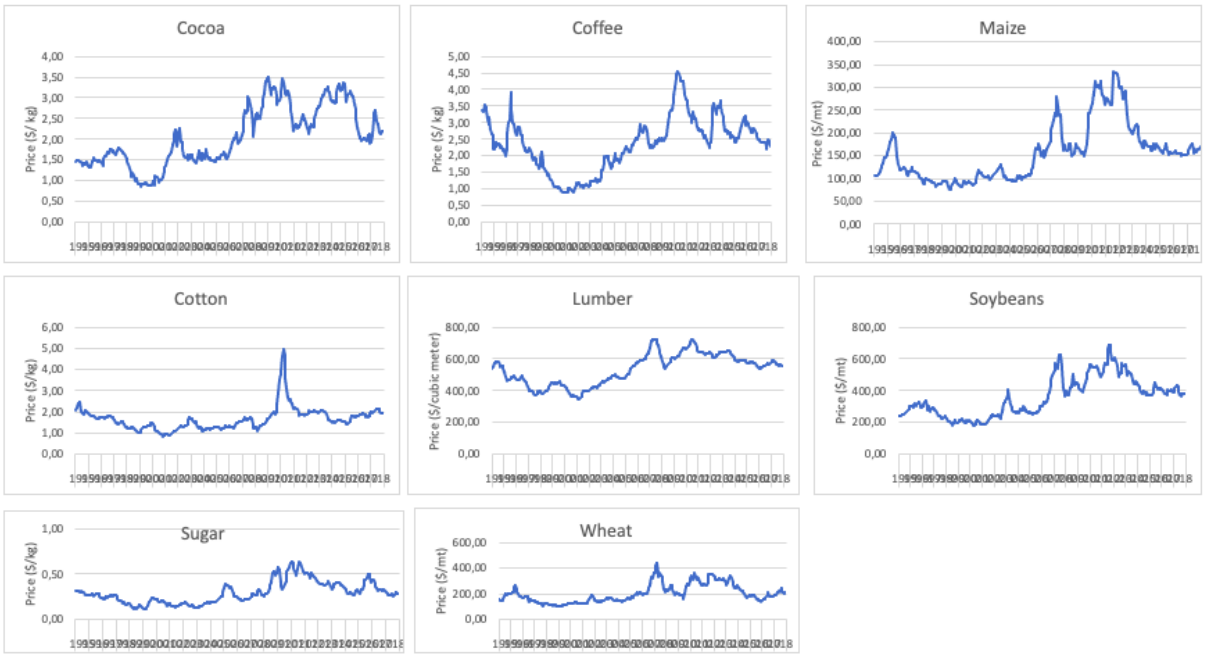
Jurado et al. (2015) propose the estimation of equations (8) and (9) in three steps. The first step is to substitute the conditional expectation $E(Y_{jt+h}|J_t)$, in equation (8), by a forecast in order to compute forecast errors. To do so, they used a factors model with large N predictors X_{it} , $j = 1, ., N$ that takes the approximated form:

$$X_{it} = \Lambda_i^{F'} F_t + e_{it}^{X} + V_t \tag{10}$$

where F_t is a $r_f \times 1$ is a vector of latent common factors, Λ_i^F is the vector latent factor loadings and e_{it}^X is the vector of idiosyncratic errors that co,siders some cross-sectional correlations. The second step is defining the h-step ahead forecast $V_{jt+h}^{y} = Y_{jt+h} - E(Y_{jt+h}|J_t)$, and estimating the associated conditional volatility, notably $E\left[\left(V_{t+h}^{y}\right)^2 |J_t\right]$ with $h \geq 1$. In the final step, macroeconomic uncertainty $U_t^y(h)$ is constructed from individual uncertainty measures, $U_{jt}^{y}(h)$ through an equally weighted average.

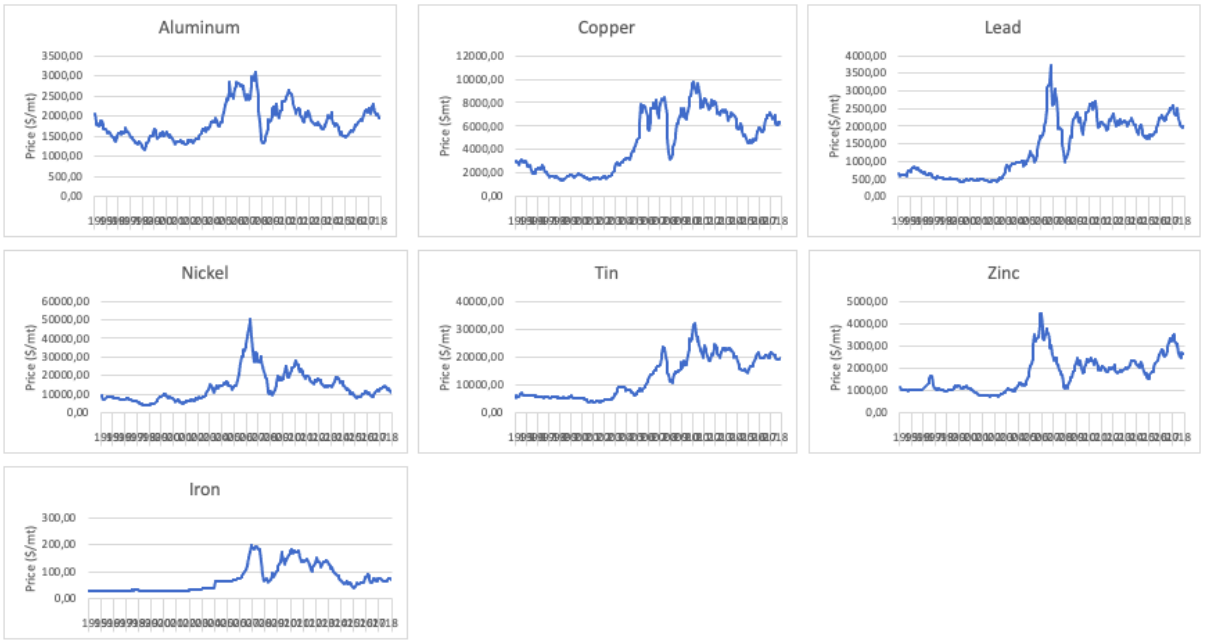
B Appendix B

Figure 1B – **Agriculture markets (monthly seasonally adjusted prices).**



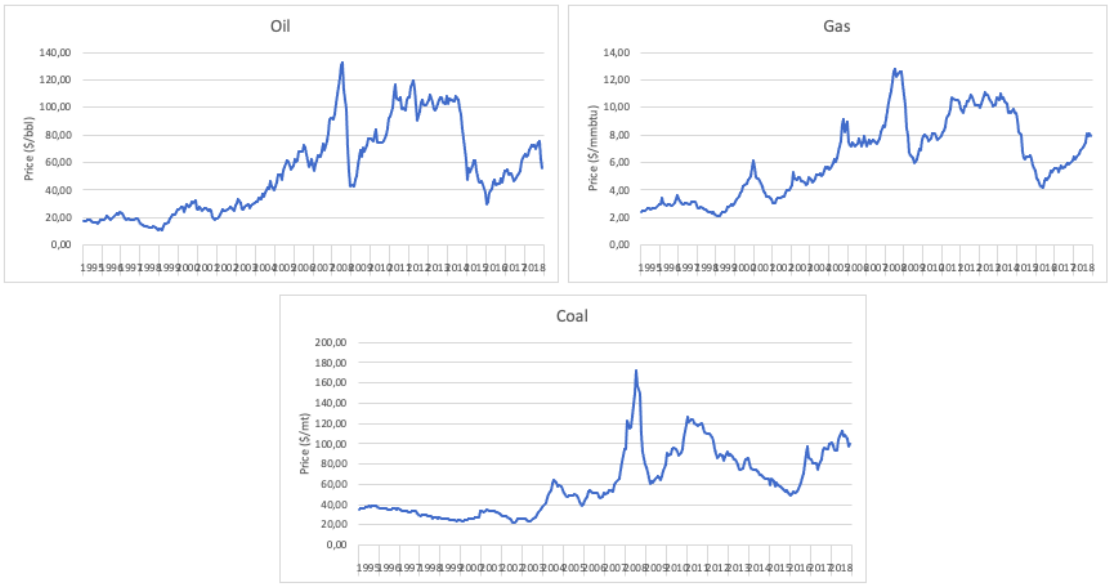
Source: World Bank from January 1995 to December 2018.

Figure 2B – **Industry markets (monthly seasonally adjusted prices).**



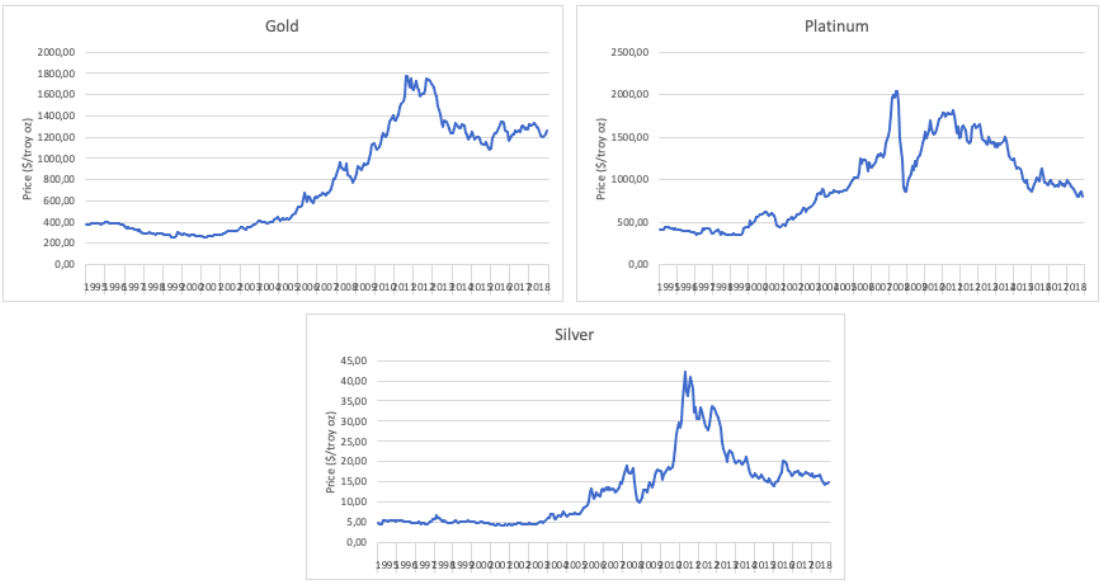
Source: World Bank from January 1995 to December 2018.

Figure 3B – **Energy markets (monthly seasonally adjusted prices).**



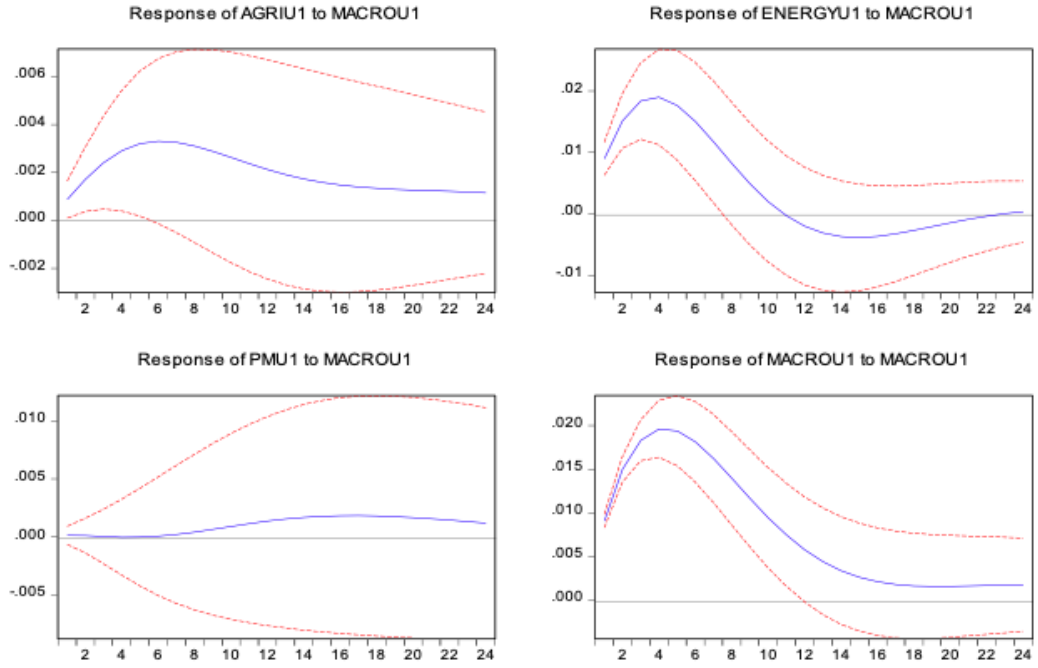
Source: World Bank from January 1995 to December 2018.

Figure 4B – **Precious metals markets (monthly seasonally adjusted prices).**



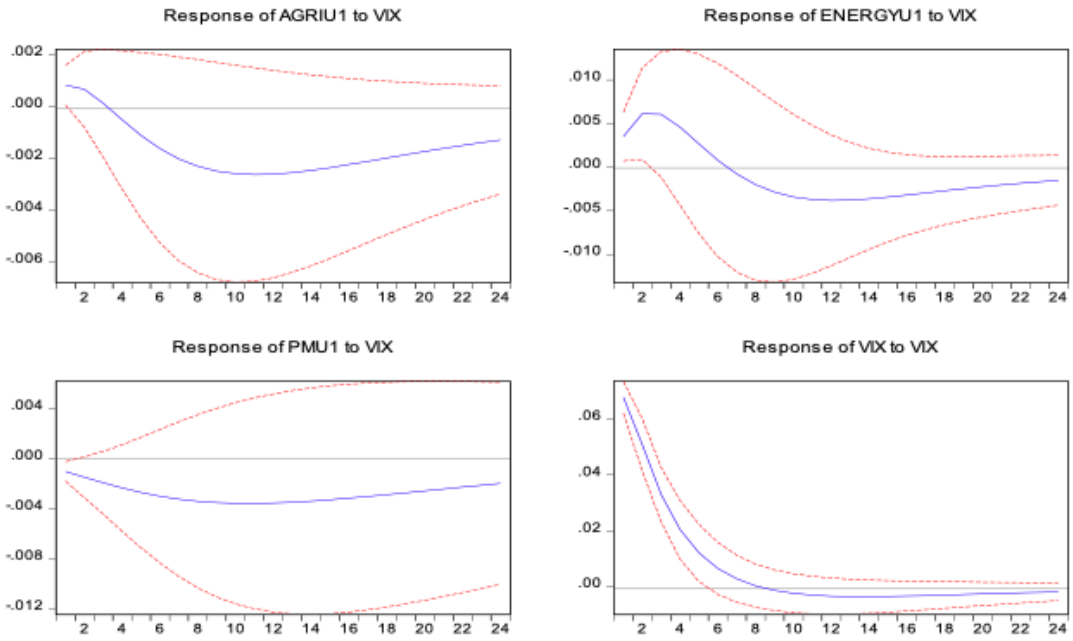
Source: World Bank from January 1995 to December 2018.

Figure 5B – **One-month macroeconomic uncertainty effect on commodity markets uncertainty.**



Note: AGRIU1 (one-month agriculture market uncertainty), ENERGYU1 (one-month energy market uncertainty), PMU1 (one-month precious metals market uncertainty), and MACROU1 (one-month macroeconomic uncertainty).

Figure 6B – **One-month VIX effect on commodity markets uncertainty.**



Note: AGRIU1 (1-month agriculture market uncertainty), ENERGYU1 (1-month energy market uncertainty), PMU1 (1-month precious metals market uncertainty), VIX (1-month implied volatility index).