Abstract

A novel measure of two classes of monthly commodity price uncertainty is constructed by applying mixed-frequency state-space modelling to price forecasts of six energy and fourteen metal commodities. Energy price uncertainty shocks are contractionary for the world economy, while metal price uncertainty shocks are not. Both metal and energy prices decrease following an associated price uncertainty shock, with counterfactual analysis revealing that energy price uncertainty has a mainly direct impact on energy returns while the impact of metal price uncertainty on metal returns is mediated through global financial markets. Global economic activity is a significant driver of both commodity uncertainties, while global financial uncertainty is only important for metal price uncertainty. Our results highlight the differences between metal and energy price uncertainties, both in terms of the driving forces behind them, as well as their economic impact.

Keywords: Energy prices, metal prices, uncertainty, forecast disagreement
JEL Classification: C32, E32, D80
1. Introduction

Uncertainty about energy and metals prices matters because these commodities play crucial but distinctive roles in the modern economy. Energy commodities are critical as production inputs for goods and services across most sectors, and affect both real and financial markets. The importance of metals and their prices is related to their use in the production of a narrower range of goods ranging from the relatively simple to high-tech. Further, precious metals have a special role in financial markets as hedging instruments. The volatile price movements of both metal and energy commodities\(^1\), as well as their associated uncertainties, can pose a significant threat to global supply chains, which can potentially cripple the growth of the world economy. The resulting supply shocks can generate stagflation and thus further present a significant challenge to monetary and fiscal policymakers. In addition, commodity price uncertainties can also be associated with other types of economic uncertainty and amplify them. Therefore, it is crucial to properly measure commodity price uncertainties and explore their relationship with economic activity and other types of economic and policy uncertainties.

This paper constructs novel measures of energy and metal price uncertainty for the period between January 1995 and December 2019, compares their relationships to global economic uncertainty measures, and evaluates their different effects on global economic activity and financial markets. Using disagreements of one-year ahead price forecasts for 14 metal-related and 6 energy-related commodities from Consensus Economics, we construct aggregate measures of metal price uncertainty and energy price uncertainty using a mixed-frequency state-space model (e.g. Aruoba et al. (2009) and Sheen et al. (2015)). Though disagreements amongst forecasters do not necessarily capture all dimensions of uncertainty (see Lahiri and Sheng (2010)), our measures based on multivariate forecasts are a useful contribution to the literature on commodity price uncertainty, given that existing measures are typically for a single commodity (e.g. crude oil) and are based on realized volatility or implied volatility of market prices, which may inadequately measure risk for commodities with low trading liquidity. Our measures are not dependent on trading liquidity and capture the dynamics of perceived price uncertainty for a wide range of energy and metal commodities, which make them suited to analyze the implications of commodity market uncertainty for the global economy and for countries that have an exposure to a large variety of commodity trades.

\(^1\)The substantial fluctuations of oil prices in the 1970s had severe effects on the global economy that posed a significant dilemma for monetary policy, forcing central bankers to prioritize either stabilising inflation or stabilising output. Substantial volatility in oil prices has continued to the present day—for example WTI crude oil price increased from an all time low of -US$37 US dollar a barrel in April 2020 to a nearly all time high of $119 in March 2022. With the increasing financialisation of commodity markets in the last two decades, the price movements of many other commodity prices have become increasingly correlated with oil, and nearly all major commodities have recently exhibited even wider price fluctuations. For example, prices of copper, aluminium and lithium nearly doubled within one and half years since the onset of the COVID-19 pandemic in 2020, while the London Metal Exchange three-month nickel price more than tripled between March 4 and March 8 2022, forcing the exchange to halt trading of the metal.
We investigate the nexus between our derived measures of commodity price uncertainty and existing measures of a set of global uncertainties including economic, policy and financial uncertainty. We utilize the following recently developed measures: global economic uncertainty constructed using forecast variance (Bobasu et al., 2021), global economic policy uncertainty produced by text scanning for key words in newspapers (Baker et al., 2016), global economic uncertainty and global inflation uncertainty indices constructed using stochastic volatility models (Berger et al., 2017), and a measure of global financial uncertainty (Caggiano and Castelnuovo, 2021). Bivariate Granger-causality test results indicate that metal price uncertainty is caused by measures of global economic activity and global output uncertainty but does not cause these variables; however causality is bi-directional in the case of energy price uncertainty. We find bi-directional causality between global financial uncertainty and both metal and energy price uncertainty. Finally, we find that energy price uncertainty causes global inflation uncertainty.

To understand the implications of commodity price uncertainty for global economy activity, we estimate a vector autoregression (VAR) model that contains our measures of energy or metal price uncertainty as well as the measures of global economic activity, global economic uncertainty, commodity prices, global financial market conditions and global financial uncertainty. We find that a positive shock to energy price uncertainty leads to a decrease in global economic activity consistent with the previous studies (Elder and Serletis (2010), Rahman and Serletis (2012) and Jo (2014)). However, economic activity is not significantly affected by the metal uncertainty shock. We also find energy and metal prices decrease following their associated price uncertainty shock. Counterfactual analysis shows that the impact of energy price uncertainty on energy prices is mostly direct while the impact of metal price uncertainty on metal prices is also affected by the response of the global financial market: higher metal price uncertainty induces global investors to sell metal commodities in their portfolio, causing metal prices to fall. Variance decomposition shows both uncertainties are mainly driven by their own shocks and shocks to global economic activity. However, our results indicate global financial uncertainty is only important for metal price uncertainty fluctuations. These results highlight the differences between metal and energy price uncertainties, both in terms of their driving forces and their impacts.2

Our work is related to a recent literature that focuses on measuring economic uncertainty

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2 One could construct an overall commodity price uncertainty indicator that includes both energy and metal commodities. We did this and found it is highly correlated with and behaves similarly to our metal price uncertainty indicator. This is partially due to the fact that there are 14 metal- compared to 6 energy-related commodities in the data set, so that the Kalman filter places a higher weight on metal commodities. As presented in the text, our results show that both the driving forces and the impacts on the global economy of metal and energy price uncertainty are different. By separating them, we get a better understanding of the implications of commodity price uncertainty. The results for a combined energy and metals uncertainty indicator are available upon request from the corresponding author.
and evaluating its impact on the economy. An important goal of this literature is to produce measures of uncertainty that are independent of implied market risk. These include measures based on news (e.g. Baker et al. (2016) and Husted et al. (2020)), forecast errors (e.g. Scotti (2016), Rossi and Sekhposyan (2015) and Ma and Samaniego (2019)), econometric models (e.g. Jurado et al. (2015) and Jo and Sekkel (2017)) and survey disagreement (e.g. Bachmann et al. (2013) and Sheen and Wang (2021)). Regardless of how uncertainty is measured, the consensus in this literature is that heightened uncertainty reduces economic activity.

Our work is also related to studies exploring effects of uncertainty in commodity markets. These typically focus on a single commodity and use univariate measures of uncertainty or GARCH-in-mean models to find how commodity market uncertainty affects different economic and financial indicators. There is a consensus in this literature on the contractionary effects of commodity uncertainty shocks. For example, (Elder and Serletis, 2010) and (Jo, 2014) demonstrate an increase in uncertainty about the crude oil price tends to reduce economic activity in the US and global economy. (Rahman and Serletis, 2012) and Bashar et al. (2013) find a similar effect of oil price uncertainty for Canada. However, there is no consensus on the effects of commodity price uncertainty on the stock market. Using a bivariate GARCH-in-mean VAR model Alsalmâ (2016) find no statistical significance of the effect of oil price uncertainty on U.S. stock returns, while Bams et al. (2017) find a negative effect of gold market and oil market uncertainty on stock markets. Using analyst forecast errors, Ma and Samaniego (2020) construct oil earning uncertainty and find higher uncertainty is related to future economic downturns but at the same time tends to increase stock prices.

Another related and growing literature explores the potential channels through which commodity prices themselves respond to changes in economic conditions, including uncertainty. The two primary channels are: 1) shocks to the demand and supply of commodities, which could be driven by business cycles and financial conditions (Prokopczuk et al., 2019) and more recently by global pandemic conditions (Bakas and Triantafyllou, 2020); and 2) changes in the sensitivity of commodity prices to economic shocks, for which macroeconomic uncertainty is found to be one significant contributing factor (eg: Watugala (2020) and Van Robays (2016)). Van Robays (2016) finds that higher macroeconomic uncertainty significantly increases the sensitivity of individual commodity prices to demand and supply shocks. Further, it is well recognized that price co-movements across a wide range of commodities are increasingly correlated due to the financialisation of commodity market and index trading (Tang and Xiong, 2012), and Christoffersen and Pan (2018) show that oil price volatility has become a strong predictor of returns and volatility of the overall stock market possibly due the financialisation of the commodity market. A possible mechanism is that increases in oil price uncertainty predict tighter funding constraints of financial intermediaries.

The rest of the paper is organised as follows. Section 2 describes the survey data and outlines the mixed-frequency state-space framework. Section 3 presents our measures of energy
and metal price uncertainty. Sections 4 and 5 discuss Granger-causality and the impacts of commodity price uncertainty shocks, respectively. Section 6 concludes.

2. The survey data and the mixed frequency model

2.1. Data

We use Consensus Economics individual forecast data for twenty metal and energy commodities from August 1995 to November 2019. As shown in Table 1, the metal commodities include nine non-precious metals (aluminium, cobalt, copper, lead, molybdenum, nickel, tin, uranium and zinc), iron ore and four precious metals (gold, silver, palladium and platinum). The energy commodities include crude oil, RBOB gas, gas oil, natural gas, coking coal and steaming coal. Our list of metal-related commodities matches the constituents of the IMF metal price index. We broaden the list of energy-related commodities compared to the constituents of the IMF energy price index by including gasoline and gas oil.

<table>
<thead>
<tr>
<th>Metal Commodities</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminum</td>
<td>LME cash price - high grade, 99.7% minimum purity</td>
</tr>
<tr>
<td>Cobalt</td>
<td>LME cash price - minimum 99.3% purity</td>
</tr>
<tr>
<td>Copper</td>
<td>LME cash price - grade A</td>
</tr>
<tr>
<td>Lead</td>
<td>LME cash price - 99.97% minimum purity</td>
</tr>
<tr>
<td>Molybdenum</td>
<td>Drummed molybdic oxide (57-63% molybdenum)</td>
</tr>
<tr>
<td>Nickel</td>
<td>LME cash price - 99.8% minimum purity</td>
</tr>
<tr>
<td>Tin</td>
<td>LME cash price - 99.85% minimum purity</td>
</tr>
<tr>
<td>Uranium</td>
<td>( U_3O_8 ) spot price</td>
</tr>
<tr>
<td>Zinc</td>
<td>LME cash price - 99.995% minimum purity</td>
</tr>
<tr>
<td>Iron Ore</td>
<td>Australian Fines hematite ores, 62% fe content</td>
</tr>
<tr>
<td>Precious Metals</td>
<td></td>
</tr>
<tr>
<td>Gold</td>
<td>London Bullion Market Association (LBMA) spot price</td>
</tr>
<tr>
<td>Silver</td>
<td>London Bullion Market Association (LBMA) spot price</td>
</tr>
<tr>
<td>Palladium</td>
<td>London Platinum and Palladium Market (LPPM) spot price</td>
</tr>
<tr>
<td>Platinum</td>
<td>London Platinum and Palladium Market (LPPM) spot price</td>
</tr>
<tr>
<td>Energy</td>
<td></td>
</tr>
<tr>
<td>Crude Oil</td>
<td>Brent - North Sea, Spot Price</td>
</tr>
<tr>
<td>Gasoline</td>
<td>U.S. Reformulated Blendstock for Oxygenated Blending (RBOB) - NY Harbor spot price</td>
</tr>
<tr>
<td>Gas Oil</td>
<td>low sulphur gas oil spot prices on Inter Continental Exchange (ICE)</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>US spot prices from the Henry Hub in Louisiana</td>
</tr>
<tr>
<td>Coking Coal</td>
<td>Australian seaborne benchmark premium hard coking</td>
</tr>
<tr>
<td>Steaming Coal</td>
<td>Australian thermal coal (calorific value of around 6000 kcal/kg NAR)</td>
</tr>
</tbody>
</table>

Table 1: List of metal and energy commodities from Consensus Economics used for construction of metal and energy commodity price uncertainty indices

Our data consists of individual fixed-event forecasts of the prices of 14 aforementioned metal-related and 6 energy-related commodities by different financial institutions. The frequency
of the dataset has been changing throughout our sample period: from August 1995 to the end of 2002 the data are available for four or five months per year\(^3\) with no data available in 2003; and from February 2016 to November 2019 the data became available monthly. Despite the irregularity of the months in which the data are available, the first forecast is always for the first upcoming quarter. For instance, if a forecaster reports data in May, the first forecast is made for June, and if the forecaster reports in June, the first forecast would be made for September. These fixed-event forecasts thus exhibit varying horizons, and so we follow the literature (see e.g. Dovern et al. (2012), Hubert (2015) and Siklos (2013)) in converting fixed-event forecasts into fixed-horizon forecasts. Given that we have forecasts for ‘quarter months’ March, June, September and December, we calculate the forecasts for the other months as a weighted average of forecasts for the surrounded ‘quarter months’ with a weight of 2/3 on the closest quarter month and a weight of 1/3 on the farthest quarter month (e.g. a forecast for May will be the weighted average of the forecasts for March and June with the corresponding weights of 1/3 and 2/3). Once individual forecasts for each month are obtained, we derive a measure of commodity price uncertainty by using the interquartile range (IQR) of the 12-month ahead price forecasts. Figure 1 compares the IQR and the related VIX measure for crude oil, gold and silver.\(^4\) It can be seen that our measures of gold, silver and oil price uncertainties and the corresponding VIX measures seem to closely track each other.

2.2. The mixed frequency state-space model

Having obtained the 12-month ahead forecast dispersion for each of the relevant commodities, and given that the survey data are not available in each month, we construct the aggregate metal and energy price uncertainty indices using a mixed-frequency state-space model (e.g.: Aruoba et al. (2009) and Sheen and Wang (2021)).

For each index, we denote \(u_t\) as the unobserved (general) commodity price uncertainty measure, and vector \(Y_t\) as the observed forecast dispersion variables. Assuming the unobserved state and observed variables follow AR(1) processes, our state-space model has the following form:

\[
\begin{align*}
    u_t &= \rho u_{t-1} + \epsilon_t \\
    Y_t &= \gamma Y_{t-1} + \beta u_t + \eta_t
\end{align*}
\]

where \(\rho\) measures the persistence of \(u_t\), and \(\epsilon_t\) denotes the innovation of \(u_t\) with mean zero and

\[^3\]From August 1995 to August 2002 data are available in February, May, August and November. From March 2004 to June 2007 the data are available in March, June, September and December. From October 2007 to April 2012 the data are available in January, April, July and October. From June 2012 to December 2015 the data are available in February, April, June, August and October.

\[^4\]The VIX data are sourced from Federal Reserve Bank of St Louis’ FRED database, and both dispersion and VIX measures are standardized with a zero mean and unit standard deviation.
variance $P$. $\gamma$ captures the persistence of the observed data and $\beta$ represents the loadings of the relevant commodity price uncertainty measure on to the data. $Q$ is the variance-covariance matrix of measurement errors, $\eta_t$. The state innovation $\epsilon_t$ and the measurement error $\eta_t$ are assumed to be independently distributed. Since not all observations are available at time $t$, we replace the measurement equation (eq. 2) with:

$$Y_t^* = \gamma^* Y_{t-1}^* + \beta^* u_t + \eta_t^* \quad \eta_t^* \sim N(0, Q^*)$$

(3)

where $Y_t^* = S \times Y_t$ and $S$ is a selection matrix that contains the value 1 if there is valid data for the corresponding $Y_t$ and 0 if there is missing data. Since all our data are available at the same time, $S$ is an identity matrix when forecasts are made in the respective month and a null matrix for months when no forecasts are made. $Q^*$ is the variance-covariance matrix of the measurement errors $\eta_t^*$ for the selected data.

Denoting $u_{t|t-1}$ and $\Sigma_{t|t-1}$ as the model-predicted disagreement index and its associated
variance at time $t$ given time $t-1$ information, $u_{t|t}$ and $\Sigma_{t|t}$ as the updated values given time $t$ information, the Kalman filter recursion is given by:

$$u_{t|t} = u_{t|t-1} + K_t v_t$$

$$\Sigma_{t|t} = \Sigma_{t|t-1} - K_t \beta \Sigma_{t|t-1}$$

where $K_t = \Sigma_{t|t-1} \beta'(Q + \beta \Sigma_{t|t-1} \beta')^{-1}$ is referred to as the Kalman gain matrix and $v_t = (Y_t - \gamma Y_{t-1} - \beta u_{t|t-1})$ is the prediction error.

3. Estimates of metal and energy price uncertainty indices

Figure 2 shows the smoothed metal and energy uncertainty indices obtained by estimating our state-space model for 14 observed metal and 6 energy price forecast dispersions. The shaded areas indicate NBER-dated recessions in the US economy. The level of metal price uncertainty started to rise in 2004, temporarily peaked in late 2006 before significantly increasing during the 2008 financial crisis. However, despite this dramatic increase, the peak was short-lived, and the metal price uncertainty returned to its pre-crisis level in early 2010. There were also mild increases in 2012 and 2015, followed by downward trends between 2012-14 and 2016-19. The level of energy price uncertainty remained relatively stable and low before significantly increasing during the 2008 financial crisis. Like metal price uncertainty, energy price uncertainty temporarily lifted in early 2013 and 2016, subsequently correcting. In general, both metal and energy price uncertainties track each other closely with a correlation of 0.72.

4. The nexus between energy and metal price uncertainty and global uncertainties

We conduct bivariate Granger-causality tests between our measures of energy and metal price uncertainty and five existing measures of global economic/financial uncertainty: 1) a monthly global economic policy uncertainty index constructed from text scans for keywords (Baker et al. (2016)); 2) a monthly index of global economic uncertainty constructed from forecast variance (Bobasu et al., 2021); 3) a quarterly index of global output uncertainty constructed by applying stochastic volatility models to OECD output growth (Berger et al., 2017); 4) a similar quarterly index of global inflation uncertainty in OECD countries (Berger et al., 2017).
et al., 2017); and 5) a monthly global financial uncertainty index constructed by applying a dynamic factor model to volatility data from 42 countries (Caggiano and Castelnuovo, 2021).

<table>
<thead>
<tr>
<th>Measures of global uncertainty (GU)</th>
<th>Metal price uncertainty (MPU)</th>
<th>Energy price uncertainty (EPU)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GU to MPU</td>
<td>GU from MPU</td>
</tr>
<tr>
<td>1. Global economic policy uncertainty</td>
<td>0.04</td>
<td>0.75</td>
</tr>
<tr>
<td>2. Global economic uncertainty</td>
<td>0.00</td>
<td>0.70</td>
</tr>
<tr>
<td>3. Global output uncertainty</td>
<td>0.00</td>
<td>0.37</td>
</tr>
<tr>
<td>4. Global inflation uncertainty</td>
<td>0.43</td>
<td>0.38</td>
</tr>
<tr>
<td>5. Global financial uncertainty</td>
<td>0.09</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Numbers are p-values for the F-test statistics.
Note the sample size changes due to data availability of the 5 measures: from January 1995 to November 2019 for measure 1; from July 2000 to November 2019 for measure 2; from January 1995 to December 2012 for measures 3 and 4; and from January 1995 to November 2019 for measure 5.

Table 2: Bivariate Granger-causality tests between measures of global uncertainty and metal/energy price uncertainty
Table 2 shows the $p$–values of the bivariate Granger-causality tests. Focusing on metal price uncertainty, our results indicate that all measures of global uncertainty, except for the measure of global inflation uncertainty, cause our metal price uncertainty (at 10% or better). This is consistent with the findings in the literature that general economic uncertainty drives commodity market uncertainty (e.g. see Watugala (2020) and Van Robays (2016)). This may be because global uncertainty reflects demand/supply shocks to the real economy that in turn affect the demand for commodities (Leduc and Liu, 2016), and/or due to the fact that uncertainty changes the sensitivity of prices to demand and supply shocks (Van Robays, 2016). We find metal price uncertainty only causes global financial uncertainty.

Regarding energy price uncertainty, all measures of global uncertainty, except for the measures of global economic policy uncertainty and global inflation uncertainty, cause it. Our results also show that energy price uncertainty causes all measures of global uncertainty except for global economic policy uncertainty. Interestingly, we find that energy price uncertainty causes global inflation uncertainty, reflecting an important role energy prices play in product price-setting.

5. The impact of metal and energy price uncertainty on the global economy

What is the impact of metal and energy price uncertainty on the global economy? We answer this using a six-variable VAR model that includes the returns of the MSCI global stock market index (MSCIR), and a global financial market uncertainty (GFU) indicator (Caggiano and Castelnuovo, 2021), a measure of global economic activity (GEA) from Kilian (2009), a measure of global economic activity uncertainty (GEAU) from Bobasu et al. (2021), the returns of metal and energy price indices (MPR and EPR) from the IMF, and our measures of metal and energy price uncertainty (MPU and EPU). The global economic activity index is constructed as a percentage deviation from trend, and we standardize the rest of the data to have a zero mean and a unit standard deviation. All data are available monthly and our sample covers the period from July 2000 to November 2019.\(^5\)

The VAR model is identified using Cholesky decomposition with the following ordering: MSCI returns, global financial market uncertainty, Kilian’s measure of global economic activity, global economic uncertainty, the metal (energy) returns and our measure of metal (energy) price uncertainty. Figures 3 and 4 show the responses of the economy to a positive one standard deviation shock to metal and energy price uncertainty, respectively, with the grey band indicating the 68 percent confidence interval obtained using the bootstrap-after-bootstrap method proposed by Kilian (1998).

\(^5\)The starting point of our data is bounded by the availability of the global economic uncertainty data (Bobasu et al., 2021).
Following a positive one standard deviation metal price uncertainty shock, the returns in the global stock market fall and financial market volatility increases. Global economic activity does not significantly respond to the metal price uncertainty shock, although there is a significant increase in global economic uncertainty. The metal price uncertainty shock reduces the metal prices, with returns falling to as low as -0.3 percent after half a year and staying in the negative territory altogether for almost a year before beginning to recover. Note that these results remain robust when we use the global economic condition index constructed by Baumeister et al. (2020) as an alternative measure of global economic activity.

Similar to the metal price uncertainty shock, an energy price uncertainty shock reduces
global stock prices\textsuperscript{6} and increases global financial and economic uncertainties. Different to metals, global economic activity contracts significantly following a positive one standard deviation shock in energy price uncertainty, bottoming at around 8 percent below the long-run trend. Interestingly, an energy price uncertainty shock also leads to a larger (2-fold) decrease in energy prices compared to the effect of metal price uncertainty on metal prices, with energy returns falling to as low as -0.6 percent, remaining negative up to a year after the shock.

\textsuperscript{6}The effect of both metal uncertainty and energy uncertainty on the stock market is consistent with Bams et al. (2017) who proxied gold markets and oil markets uncertainty with the variance risk premia, extracted from futures and option contracts.
5.1. The response of global economic activity

The VAR results show that global economic activity responds to energy price uncertainty shocks, but not to metal price uncertainty. This makes us interested in the proportion of the global activity variance attributed to various shocks at different horizons. Table 5.1 shows the $k$-periods ahead forecast variance decomposition for global economic activity. Both metal and energy price uncertainty shocks account for a very small proportion of the forecast error variance of global economic activity in the short-run. However, energy price uncertainty is an important factor in explaining the fluctuations of global economic activity at horizons exceeding one year, contributing more than 10 percent of the fluctuations compared to metal price uncertainty that remains unimportant.

<table>
<thead>
<tr>
<th></th>
<th>MSCIR</th>
<th>GFU</th>
<th>GEA</th>
<th>GEAU</th>
<th>MPR</th>
<th>MPU</th>
<th>MSCIR</th>
<th>GFU</th>
<th>GEA</th>
<th>GEAU</th>
<th>EPR</th>
<th>EPU</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k = 1$</td>
<td>0.0</td>
<td>0.2</td>
<td>99.8</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.2</td>
<td>0.2</td>
<td>99.5</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>$k = 6$</td>
<td>4.5</td>
<td>8.0</td>
<td>75.5</td>
<td>4.9</td>
<td>7.0</td>
<td>0.1</td>
<td>4.6</td>
<td>5.6</td>
<td>79.8</td>
<td>4.2</td>
<td>2.9</td>
<td>2.8</td>
</tr>
<tr>
<td>$k = 12$</td>
<td>4.8</td>
<td>9.2</td>
<td>71.2</td>
<td>5.6</td>
<td>8.6</td>
<td>0.6</td>
<td>4.7</td>
<td>6.2</td>
<td>71.9</td>
<td>3.7</td>
<td>2.8</td>
<td>10.7</td>
</tr>
<tr>
<td>$k = 24$</td>
<td>4.2</td>
<td>8.0</td>
<td>73.5</td>
<td>5.1</td>
<td>8.6</td>
<td>0.6</td>
<td>4.1</td>
<td>5.4</td>
<td>68.0</td>
<td>5.3</td>
<td>3.4</td>
<td>13.9</td>
</tr>
<tr>
<td>$k = 36$</td>
<td>3.9</td>
<td>7.4</td>
<td>74.4</td>
<td>5.0</td>
<td>8.4</td>
<td>0.9</td>
<td>3.8</td>
<td>5.0</td>
<td>66.6</td>
<td>6.7</td>
<td>3.8</td>
<td>14.0</td>
</tr>
<tr>
<td>$k = 60$</td>
<td>3.7</td>
<td>6.8</td>
<td>75.3</td>
<td>4.7</td>
<td>8.3</td>
<td>1.2</td>
<td>3.6</td>
<td>4.7</td>
<td>65.4</td>
<td>7.8</td>
<td>4.1</td>
<td>14.4</td>
</tr>
<tr>
<td>$k = 120$</td>
<td>3.6</td>
<td>6.5</td>
<td>75.8</td>
<td>4.5</td>
<td>8.3</td>
<td>1.4</td>
<td>3.4</td>
<td>4.5</td>
<td>64.8</td>
<td>8.4</td>
<td>4.3</td>
<td>14.6</td>
</tr>
</tbody>
</table>

See definition note in Figure 3

Table 3: Forecast variance decomposition for global economic activity (GEA)

Another interesting question is whether the significant negative effect of an unexpected increase in energy price uncertainty on global activity is direct or indirect (i.e. coming via other variables)? To answer this question we employ counterfactual analysis as in Sims and Zha (2006). The counterfactual analysis is conducted by ‘muting’ the response of a particular variable to a shock and calculating the response of the variable of interest under this restriction. The original impulse responses are then compared with the counterfactual ones.

Figure 5 demonstrates the counterfactual impulse responses of global economic activity to an energy price uncertainty shock when the responses of the endogenous variables are muted one at a time. The original impulse responses (shown as blue solid lines) are compared to the counterfactual responses (shown as red dashed lines). The black dotted lines represent the 68 percent confidence bands for the counterfactual responses. In general, the response of global economic activity is moderated when the response of any other variable is muted. This muting effect is the strongest in the case of global financial uncertainty. However, in all cases the response of global economic activity to the energy price uncertainty shock remains significant, which supports a predominately direct effect of this shock on global economic activity.
activity.

![Graphs showing impulse responses of global economic activity and financial uncertainty to energy price uncertainty](image)

Figure 5: Benchmark and counterfactual impulse responses of global economic activity (GEA) to an energy price uncertainty (EPU) shock

5.2. *The link between the energy and metal price indices and their associated price uncertainty*

The negative impulse response of the energy and metal returns to their associated price uncertainty shocks are interesting. Apart from a direct link between commodity prices/returns and the associated uncertainty, there are three other potential channels through which commodity prices and commodity price uncertainty may be related. The first is that heightened energy/metal price uncertainty reduces global economic activity, thus reducing demand for commodities which in turn leads to a decrease in energy/metal prices. A second possible channel is that increased energy/metal price uncertainty causes a plunge in stock markets forcing portfolio investors to reduce their positions in energy/metal commodities resulting in lower energy/metal prices. A third possible channel is that increased price uncertainty creates uncertainty in financial markets (as measured by the global financial uncertainty...
index), leading to reduced demand for all risky assets, including commodities. It is therefore an empirical question which channel dominates in the link between energy/metal returns and the associated price uncertainty.

We investigate the relative importance of the three competing channels by again conducting counterfactual analysis. Figures 6 and 7 present the counterfactual responses of metal or energy returns to a metal or energy price uncertainty, respectively, when the responses of the following variables are muted one at a time: the MSCI returns, global financial uncertainty, global economic activity and global economic activity uncertainty. The counterfactual analysis shows that the impact of metal price uncertainty on metal returns is mediated through the response of global financial market, with an increase in metal price uncertainty stimulating global investors to sell metal commodities in their portfolio, causing metal prices to fall. Regarding the response of energy returns to its associated uncertainty shock, although all factors contribute some to the impact, we can conclude the direct effect of energy price uncertainty on energy returns is dominant.

Figure 6: Benchmark and counterfactual impulse responses of metal price returns (MPR) to a metal price uncertainty (MPU) shock
5.3. The driving force behind commodity price uncertainty fluctuations

Table 5.3 shows the $k$-periods ahead forecast variance decomposition for energy and metal price uncertainties. Both energy and metal price uncertainty fluctuations are predominantly self-driven in the short-run. In the long-run, at the 10-year horizon, their own shocks still explain a large proportion of variance (49.6% and 37.8% for energy and metal price uncertainties, respectively). However, global economic activity also plays a role for both commodity price uncertainties, explaining more than a quarter of the variance at horizons from two to ten years. Global financial uncertainty explains a significant proportion of metal price uncertainty at horizons from half a year to three years, but its importance for energy price uncertainty is limited.
### Table 4: Forecast variance decomposition for metal and energy uncertainties

<table>
<thead>
<tr>
<th></th>
<th>Metal</th>
<th></th>
<th>Energy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MSCIR</td>
<td>GFU</td>
<td>GEA</td>
</tr>
<tr>
<td>$k = 1$</td>
<td>2.4</td>
<td>4.2</td>
<td>0.1</td>
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<tr>
<td>$k = 6$</td>
<td>2.0</td>
<td>27.5</td>
<td>1.6</td>
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<td>3.3</td>
<td>18.0</td>
<td>11.8</td>
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<tr>
<td>$k = 24$</td>
<td>5.4</td>
<td>12.0</td>
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<tr>
<td>$k = 36$</td>
<td>5.4</td>
<td>10.5</td>
<td>31.2</td>
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<tr>
<td>$k = 60$</td>
<td>5.2</td>
<td>9.8</td>
<td>33.9</td>
</tr>
<tr>
<td>$k = 120$</td>
<td>5.2</td>
<td>9.6</td>
<td>34.4</td>
</tr>
</tbody>
</table>

See definition note in Figure 3

6. Conclusions

Our analysis of novel measures of energy and metal commodity price uncertainty based on commodity price forecasts from Consensus Economics enables us to better understand the differences and importance of these disagreements as uncertainty measures for the global economy. While these two commodity price uncertainty measures are highly correlated, the Granger-causality patterns between these measures and measures of global uncertainty are different. These results led us to making a comparison of the different implications of these two commodity classes in the global economy.

We estimated a simple VAR model involving the respective commodity price uncertainty indices and commodity returns, a global activity index, a measure of global economic uncertainty, financial conditions variables including MSCI returns and a measure of global financial uncertainty. We found that a positive shock to energy price uncertainty leads to a significant reduction in global economic activity while a metal price uncertainty shock does not. Our results showed that an increase in energy (metal) price uncertainty shock leads to a decrease in energy (metal) prices. Counterfactual analysis showed that the impact of an energy uncertainty shock on the global economy is mostly direct rather than transmitted via other variables. We also saw that in the case of energy prices the effect of the associated uncertainty is mostly direct while in the case of metal prices, financial markets play a significant role in the transmission of the associated uncertainty shock. This result underscores the hypothesis that markets for metals play an important role in hedging strategies in financial portfolios. Variance decomposition shows that global economic activity explains a significant proportion of both energy and metal uncertainty fluctuations, however global financial uncertainty only plays a significant role in metal price uncertainty.

Our results highlight the differences between energy and metal price uncertainty in regard to the global economy, and future research should investigate the impacts of these uncertainties.
on resource-rich economies compared to those that are resource importers. This will enable a deeper understanding of the drivers of foreign direct investment in resource sectors and the dynamics and patterns of real exchange rates and current accounts.
7. Reference


