Spillover of Energy Commodities and Inflation in G7+Chinense Economies

Abstract:

We investigate the spillover trends of the Consumer Price Index (CPI) and energy commodities in the G-7 plus China by using the continuous wavelet transform (CWT) methodology. As there has been a major break in the data because of COVID-19 crisis, we split our analysis into pre and post-COVID-19 periods. Continuous Wavelet Transform (CWT) graphs show the distinct level of inflation in each of the countries. Variations in CPI and energy commodities in the pre and post-COVID-19 era has significant results for China, Canada and United States. Wavelet Transform Coherence (WTC) show significant relationship in all three energy commodities. For policy implications, our research reveals that variation in CPI and energy commodities in the pre and post COVID-19 era are crucial in policy discussions for macroeconomic aims of domestic policies, such as monetary or fiscal areas, with regard to the implications for policy. Our findings help policy makers to understand relationship between CPI and energy commodities i.e. depends on both internal and external macroeconomic conditions.

JEL codes: E31, E58, Q40, G15, C50

Keywords: inflation, price, oil shock, energy intensity, international financial markets, wavelet analysis

1. Introduction

With the onset of COVID-19 crisis, the monetary and fiscal authorities spent unprecedented amount of money to rescue businesses and to support workers that were furloughed. A comparison of the fiscal stimulus during COVID-19 with the global financial crisis of 2007-08 reveals that the stimulus package during COVID-19 was 4.4 times higher than during the global financial crisis of 2007-08.[1] Together with the supply chain disruptions and the economic stimulus, the global inflation has also sharply increased. The situation has been further aggravated with the Ukrainian War as the energy prices skyrocketed with the Russian invasion of Ukraine. The chart below shows the increase in the crude oil price in March 2022 after Russian invasion of Ukraine in February 2022. Against the backdrop of these developments, a natural question arises how inflation responds to the energy shocks. Therefore, in this paper we evaluate the behavior of energy commodities and analyze the association of energy commodities with inflation in G7 plus Chinese economies. In analyzing the relationship, we split the sample into pre and post-COVID-19 periods as COVID has been a major shock during the time periods of this study.

Further, earlier studies also illustrate that inflation can be a major reason for business cycle shocks. For instance, the Eurozone's inflation influences US expected inflation, making term structure models worthless for long-term inflation forecasting (Ciccareli and Garcia, 2015). Istiak et al. (2021) also examines inflation spillovers across the G7 nations, they discover that the USA and Japan are the main "exporters" of inflation. In addition, Balcilar and Bekun (2020) highlight the

[1] https://theconversation.com/coronavirus-comparing-todays-crisis-to-2008-reveals-some-interesting-things-about-china-132147

significance of inflation spillovers on commodity prices in Nigeria. Baurle et al. (2021) demonstrate how inflationary shocks produce heterogeneous inflation spillovers for Switzerland. Additionally, Halka and Szafranek (2016) demonstrate how Poland and other minor European economies are "net importers" of inflation from the Eurozone. Because of the risk of inflation spillovers, central banks should keep an eye on global inflation to guide local monetary policy.

Therefore, energy shocks have vital implications for the macroeconomy. They pose challenge for the monetary authorities and the Central Banks to achieve their objective of price stability. We have seen the inflation has been much above the targeted level of 2% in most of the economies and the monetary authorities have started increasing interest rates very sharply. This has raised questions on the global economic growth and a severe recession is expected in many economies.

As a result, our paper has novel contributions into three folds. First, we assess the consequences of shocks for estimated inflation and energy commodities on its major trading partners (G7 and China). Second, our results show that the relationship between CPI and energy commodities depends on both internal and external macroeconomic conditions, and that regulators should look into how prices react to monetary policy shocks at different stages of production in order to set an accurate and more reliable inflation target. Third, we examine the effects of continuous wavelet transform for CPI in China and G 7 countries, energy commodities, wavelet transform coherence for CPI and Crude oil and wavelet transform coherence for CPI and natural gas.

The remainder of the paper is organized as follows. Section 2 reviews the related literature on the energy and commodity markets, inflation and COVID-19 impact on energy markets. Section 3 provides the methodology on continuous wavelet transform and Section 4 describes the dataset.

Section 5 reports the empirical results and discusses the findings. Section 6 provides the main conclusion and policy implications.

2. Literature Review

2.1 Related Literature on Energy and Commodity Markets

Researchers and practitioners have begun to pay more attention to the carbon market as a crucial risk management tool since the creation of the European Union Emission Trading System (EU ETS) in 2005 (see, among others, Subramaniam et al., 2015). Parallel to this, the energy markets not only affect the sustainability of the global economy and financial markets, but they also have an impact on political stability, pose significant risks to the global economy, and are frequently affected by extreme occurrences related to terrorism, global economic inflation, and geopolitical conflicts (Sahir and Qureshi, 2007). Such extraordinary occurrences have significant, medium-term effects on the energy markets and may cause structural breakpoints, the effects of which could continue for years (Zhang et al., 2009). Furthermore, there are connections between the energy and financial markets (Sadorsky, 2012a; Tan et al., 2020), and earlier research indicates that these connections exist between carbon and energy assets as well (Medina and Pado, 2013).

In earlier research studies, cointegration or Granger causality tests were used to examine how energy commodity returns affected EUA returns. According to Mansanet-Bataller et al. (2007), there is proof that natural gas and crude oil have a beneficial effect. Alberola et al. (2008) show that coal returns have a negative influence on EUA returns and natural gas returns continue to have a positive impact. Furthermore, impact from EUA to different energy assets is taken into account by Fezzi and Bunn (2009) and Keppler and Mansanet-Bataller (2010). Chevallier (2011) draws attention to the carbon market's sensitivity to various macroeconomic, financial, and commodity shocks. More recent studies (Hammoudeh et al., 2014; Yu et al., 2015; Zhang and Sun, 2016; Dutta et al., 2018; Ji et al., 2018; Chevallier et al., 2019; Tan et al., 2021; Zhou et al., 2022) use more complex models and demonstrate evidence of a significant relationship between the returns and volatility of carbon and different energy assets, Although the significant relationship between these markets is widely understood theoretically and empirically, prior research indicates that the carbon and energy markets establish a complicated system (see Ji et al., 2018).

In order to examine asymmetric or fat-tail risk linked to critical upside (downside) risk in both bullish and bearish market scenarios, measuring higher moments could be very helpful (Amaya et al., 2015; Finta and Aboura, 2020; He and Hamori, 2021, Zhang et al., 2022). Additionally, Yu et al. (2015) demonstrate that non-Gaussian behaviour on the carbon and energy markets is gaining attention, indicating that return-/volatility-based analysis may not be sufficient to comprehend the underlying risk spillover between the carbon and energy markets.

2.2 Inflation and COVID-19 impact on Energy and Commodity Markets

Many studies are focus on what causes recessions (see Jagannathan et al, 2013; Stiglitz, 2010; Gaiotti, 2013; Bezemer, 2011; Mian and Sufi, 2010; Bentolila et al, 2018; Bagliano and Morana, 2012). However, the reason for the global recession in 2020 is unheard in modern times. A new kind of recession, distinct from previous recessions, was brought on by the coronavirus. Historically, recession has various factors; for instance, the collapse of the Thai baht in July 1997 resulted in panic, which sparked a regional financial crisis and an Asian economic recession that led to the Asian debt crisis of 1997 (Radelet and Sachs, 1998). Subprime mortgages, lax regulatory frameworks, and significant leverage in the banking sector all contributed to the 2008 global financial crisis, which resulted in a recession (Allen and Carletti, 2010). Nigeria had a recession in 2016 as a result of a decline in the price of crude oil, a balance of payments deficit, the implementation of a fixed-float exchange rate system, a rise in the price of gasoline at the pump, pipeline vandalism, and inadequate infrastructure. The aftermath of the global financial crisis, structural flaws in the Greek economy, and a lack of monetary policy flexibility as a member of the Eurozone all contributed to the recession that hit Greece in 2010 (Rady, 2012).

Recently, COVID-19 outbreak has changed how people live all around the world. The health, social, economic, and financial sectors are now faced with an unprecedented crisis (Baker et al., 2020). Markets for commodities are not exempt from the pandemic's negative effects. For instance, compared to prior crises, crude oil, which historically has played a significant role in transmitting volatility shocks, displayed an exceedingly unusual and completely distinct behaviour during April 2020 (negative prices were recorded for May 2020 futures). This critical commodity's peculiar performance has recently restored academic interest in the system of volatility transmission and connectivity in the commodity markets. During the GFC, the cyclical movement of energy, agriculture, and metal futures showed heightened volatility (Cheng and Xiong, 2014). The uncertainties connected to the unanticipated market moves in response to COVID-19 are to blame for these increases in volatility. While supply shocks coming from production and distribution concerns brought on by lockdowns, stockpiling of staple goods, and attempts to diversify investments using these assets can raise the price of commodity futures, a bad economic scenario and a worldwide recession can push prices down. During COVID-19, agricultural futures provided some protection from the asset values that were plummeting at an extreme left distribution. A recent analysis of 24 main commodities reveals evidence of the commodities' ability to act as safe havens against the widespread COVID-19 issue (Salisu et al., 2020).

2.3 An Overview of Chinese Markets and Commodities

Various academic research has been done on the Chinese market, mainly in connection to how it interacts with other stock markets and commodities (Yao et. al, 2018; Yu et. al; 2018). (Hammoudeh, Nguyen, Reboredo, and Wen, 2014). Although different equity sectors contribute differently to volatility, sectors do contribute to systemic risk (Eckernkemper, 2018). As a result, the volatility of one sector may spread to another, which in turn may have an impact on the whole system's volatility, the returns of market participants, and the choices made by policymakers. Therefore, identifying the cause and level of volatility is essential to identifying the sectors contributions to volatility and the network of sectoral interconnectedness in the Chinese stock market. Few studies examine the Chinese stock market at the sector level because the relationship between stock market and crude oil prices receives most of the attention (Huang et al. 2016; Yang, et al. 2016). Feng et al. (2018) examine risk spillover networks in several Chinese industries while taking different investment horizons into account. They demonstrate how the risk of one sector index affects another. According to Wu et al. (2019), the industrial sector is a key component of the network of return spillovers and that sectoral linkages in the Chinese stock markets vary over time.

2.4 Related Literature and Motivation on methodology

Various studies only analyze data in the time-domain, ignoring data in the frequency domain. The oil price may function like a supply shock at high and medium frequencies, affecting industrial output (see Naccache, 2011), whereas in the long term (i.e., at the lower frequencies), it is the industrial production that impacts the oil price through a demand effect.

It has long been standard practice to use Fourier analysis to reveal relationships between interest variables at various frequencies. The drawbacks of using the Fourier transform for analysis are complete loss of time information, which makes it difficult to distinguish between ephemeral relationships or recognize structural changes—both of which are crucial for time series macroeconomic variables used in policymaking. The results' dependability is a strong argument against using the Fourier transform. This technique is only appropriate when time series are stationary, which is not always the case, such as in the case of macroeconomic variables.

In order to remedy the dilemma and incorporate the time dimensions into the Fourier transform, Gabor (1946) devised a particular Fourier transform transformation. The short-time Fourier transformation is the name given to it. A time series is divided into smaller sub-samples for the short time Fourier transformation, and the Fourier transform is then applied to each sub-sample. However, because it needs identical frequency resolution over all different frequencies, the short time Fourier transformation approach was also challenged for its effectiveness (see, for details, Raihan et al., 2005).

In order to address the aforementioned issues, wavelet transform was created. By performing "natural local analysis of a time-series in the sense that the length of wavelets varies endogenously: it stretches into a long wavelet function to measure the low-frequency movements; and it compresses into a short wavelet function to measure the high-frequency movements," it has a significant advantage (Aguiar-Conraria and Soares, 2011). Wavelet has intriguing properties for conducting spectral analysis of a time series variable, but as a function of time. In other words, it demonstrates how the time series' change through time and at various periodic components, or frequency bands. It is important to note that the use of discrete wavelet transformations is the primary method of applying wavelet analysis in the fields of economics and finance. When using discrete wavelet analysis, there are several factors to take into account, such as the level at which we should decompose. It is also challenging to correctly comprehend the results of the discrete wavelet transformation. Continuous transformation makes it easier to obtain the variation in the time series data that may be achieved using any discrete wavelet transformation technique at any scale.

3. Methods

3.1. Data

3.2.Methodology

This study employs Wavelet as the analysis technique. The technique was introduced in 1980, but its usage has increased in the studies of economics and finance in the last decade (see e.g. Alam et al., 2019; Arif et al., 2021; Jammazi et al., 2015). Contrary to traditional regression analysis, wavelet analysis provides information about localized relationships. Wavelet analysis is widely used as an alternative to Fourier analysis as well. This technique has multiple advantages over the traditional Fourier analysis (Vacha and Barunik, 2012). It provides localized decomposition and evaluation of non-stationary functions, that are common in economics and finance, has become easier with this technique (Tabak and Feitosa, 2009). The accuracy level of the co-movement of different times series presented by wavelet is also higher than other tools available (see Xiang et al., 2021). First, we have observed the variation in CPI in China and G-7 countries along and movement of energy variables individually. This analysis is performed using Continuous Wavelet Transform (CWT). The energy variables include crude oil prices, average prices of coals and natural gas index. Instead of using absolute values of these variables, we have calculated the monthly changes in the values of these variables to accurately capture the variation in them. The signal is represented by Wavelet in terms of frequency and time concurrently. The small waves, called daughter wavelets, are combined together. These daughter wavelets are denoted by $\psi_{\tau,s}(t)$, growing and decaying in a limited time. The mother wavelet is denoted by Ψ_t. All the daughter wavelets result from this mother wavelet. The two control parameters of a wavelet are τ and s. τ is the location parameter determining the time position of the wavelet, whereas s is the dilation parameter (related to frequency) determining how the wavelet is stretched. Wavelets are defined as:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \ where\ s \neq 0\ ,\ \tau \in \Re \tag{1}$$

$1/\sqrt{s}$ in Equation (1) is the normalization factor. It ensures that wavelet transformations are comparable across time and scale.

There are three main conditions those must be satisfied by wavelet. These conditions are presented from equation (2) to equation (4) as follows:

$$0 < C_\psi = \int_0^\infty \frac{|\Psi(f)|^2}{f} df < \infty \tag{2}$$

$$\int_{-\infty}^{\infty} \psi(t) dt = 0 \tag{3}$$

$$\int_{-\infty}^{\infty} \psi^2(t) dt = 1 \tag{4}$$

Equation (2) is called the admissibility condition, where $\Psi(f)$ is the Fourier transform of the wavelet. As per this condition $s \neq 0$ and the condition given in Equation (3) is also met. According to the condition given in Equation (4), the wavelet has unit energy (see Vacha and Barunik, 2012).

The wavelet coefficient contains the information about wavelets-based decomposition of $\psi_{\tau,s}(t)$, and the function $x(t)$. It is defined as:

$$W_x(\tau, s) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t)\psi^*_{\tau,s}\left(\frac{t-\tau}{s}\right) \quad (5)$$

where ψ^* is the complex conjugate. In line with some of the previous studies (see e.g. Alam, et al., 2019; Arif et al., 2021; Firouzi and Wang, 2019; Jammazi et al., 2015), we have used the Morlet wavelet belonging to the family of analytic wavelets. An optimal resolution of τ and s is possible with Morlet Wavelet.

The co-movement of the change in CPI with change in energy variables is observed through Wavelet Transform Coherence (WTC). Following Torrence and Webster (1999), WTC is defined as:

$$\rho^2_{xy}(\tau, s) = \frac{|S(W_{xy}(\tau, s))|^2}{S(|W_x(\tau, s)|^2).S(|W_y(\tau, s)|^2)} \quad (6)$$

where S is a smoothing operator applied to time and frequency, given by:

$$S(W) = S_{scale}(S_{time}(W(s))) \quad (7)$$

S_{scale} and S_{time} in Equation (7) represent smoothing along the scale axis and time, respectively.

$\rho 2_{xy}(\tau, s)$ given in Equation (6) is used to measure the extent to which two time series move together over time and frequency (Akoum et al., 2012). It is akin to the square term of the correlation coefficient. The range of $\rho 2_{xy}(\tau, s)$ is from 0 to 1 where a value close to 1 shows a strong relationship and vice versa.

WTC analyzes the lags in two-time series *(x, y)*. The lag difference is represented by the angle ϕ_{xy} that helps evaluate the nature of the relationship between time series, whether it is positive or negative. The wavelet transform can be divided into real and imaginary parts because of its complexity based on the mother wavelet (see Jammazi, Lahiani, and Nguyen, 2015). The phase difference is defined as:

$$\phi_{xy}(\tau, s) = \tan^{-1}\left[\frac{\Im\{W_{x,y}(\tau, s)\}}{\Re\{W_{x,y}(\tau, s)\}}\right] \tag{8}$$

where $\Im$ and $\Re$ are imaginary and real parts, respectively. Keeping in view the above information, a graph of wavelet coherency shows the regions where two times series co-vary. The angle of arrows shall represent the nature of the relationship.

4. Results

4.1.Descriptive Analysis

Table 1 divides the descriptive statistics into two parts. In the first part, Panel A describes the descriptive statistics for the monthly changes in CPI across the G-7 countries plus China. Here we report the average monthly change in CPI during the period from February 2016 to October 2022. Among the countries under study, we analyze that the United Kingdom (0.29%), United States (0.28%), and Germany (0.26%) report the highest level of change in CPI on average. This is pertinent to the fact that the pandemic has decreased consumption and increased the real output in these countries (Apergis and Apergis, 2020). Also, we report the average change in CPI for Canada, Italy, and France as 0.24%, 0.21%, and 0.17%, respectively. These values are justified as Wren-Lewis (2020) notices reduced economic growth, high temporary inflation, and reduced social consumption during COVID-19. Moreover, the negligible change in the CPI of China point towards the effective government policies that have brought the prices under control (Hu et al., 2021).

In the second part, panel B presents the statistics for the monthly changes in the prices of energy commodities. Here we observe the volatility in the prices of crude oil, coal, and natural gas from February 2016 to October 2022. In this panel, we see that among all commodities under study the prices of coal (46.20%) and crude oil (44.37%) are the most volatile. Our findings are consistent with Mensi et al. (2021) who also found high volatility spillovers in the energy sector during COVID-19. While due to the decrease in the global demand for natural gas we report only a 37.42% maximum change in natural gas prices in comparison to coal and crude oil (Ghiani et al., 2020; Halbrügge et al., 2021).

4.2.Variations in CPI and energy commodities in the pre and post-COVID era

This section analyzes the pre and post-COVID trends in the consumer price index (CPI) and energy commodities of G-7 countries plus China. Figure 2 presents the Continuous Wavelet Transform (CWT) and shows the variance intensity of inflation in all the countries under study. In Figure 2 the horizontal axis presents the time dimensions and the vertical axis gives the period cycles. The power spectrum is color-coded, where the colors range from blue (low-power) to red (high-power), and the period frequency ranges from 2 months to 22 months. Here, black contours present the affected region at a 95% confidence level and the cone of influence, which displays the zone affected by edge effects is denoted by a solid curve line.

In Figure 1a we present the CPI trends of China, here we analyze high levels of consumer price index between the periods of January 2019 to February 2021 and March 2021 to October 2021.

The high levels of CPI are necessarily brought by the rise in demand for essential goods which ultimately increased the prices of necessities in China (Barua, 2020). While the gradual decrease in the levels of the CPI index reflects the strong confidence of the Chinese in their economy, built by the government's regulations on price and policies on the supply and allocation of material supply (Hu et al., 2021). In Figure 1b Canada presents similar patterns of CPI as China, where the major change occurred between the first nine months of COVID-19, i.e., March 2020 to November 2020. This is justified by the subsequent increase in per capita sales of alcohol and essential retail sales in Canada (Myran et al., 2021).

Moreover, the economic deterioration caused by the decrease in aggregate demand for face-to-face industries in Japan presents a considerably high inflation frequency during COVID-19 in Figure 2f (Watanabe, 2020). Also, following the findings of Leigh et al. (2022) the United States reports a high inflation index during the periods of October 2020 to February 2021 and January 2022 to October 2022 in Figure 2h. Whereas, Figures 2c, 2d, 2e, and 2g which present the following G-7 countries France, German, Italy, and the United Kingdom do not show any significant changes in the CPI index during the pre or post-COVID period.

Figure 3 presents the CWT for energy commodities, which are essentially crude oil, natural gas, and coal. Prior, analyzes by Wang et al. (2022) reveal unusual trends and characteristics in the entire energy market during the pandemic. Such unusual events received strong government attention and led to policies that then inflated the prices of crude oil. We receive similar, patterns of crude oil in Figure 3a which shows highly inflated prices during the period June 2019 to February 2021. Previously, Barua (2020) states that during COVID-19 the inflation in energy prices has been an important issue as it has strong spillovers to all other sectors and leads to an increase in overall headline inflation. These inflated prices of the energy commodities were found to be the by-products of the supply and demand oil-specific shocks which increased over time (Garzon and Hierro, 2021).

Likewise, Figures 3b and 3c report high volatility in coal and natural gas in the post-COVID-19 period (February 2021 to January 2022). Here we analyze coal and natural gas face less inflationary pressure as compared to crude oil, this is mainly due to the reason that crude oil was the major contributor of volatility spillovers to other markets (Mensi et al., 2021). Further, our findings are supported by Hordofa et al. (2022) who state that natural resources such as natural gas, oil, and coal have helped in improving the economic downtown caused during the COVID and post-COVID-19 period.

4.3. Consumer price index and energy commodities

In this section, we employ wavelet transform coherence (WTC) to analyze the relationship between CPI and all three energy commodities taken in this study. The association between two variables is significant if the arrows are located within the contour. Whereas the relationship between variables is defined by the direction of the arrows located inside the contour, here, the rightward (left) arrows present a positive (negative) relationship in the WTC. Moreover, the strong length of association is presented by the red area, as the warm colors (red) present high power and cold colors (blue) present low power in Figures 4, 5 and 6 (Aguiar-Conraria and Soares, 2014).

The association between CPI and crude oil is presented in Figure 4. Figure 4a presents islands of strong relationship between inflation and crude oil in China. However, during the period June 2019 to September 2022, we realize both leftward and rightward arrows in the contours. Previously, Narayan (2020) states that in the face of the pandemic the crude oil market has faced severe short-term shocks. In similar vein, Ma et al. (2021) found a bidirectional relationship between inflation and natural commodity prices in China at different frequencies and periods at the peak period of COVID-19. Whereas, when we talk about crude oil, China being its largest importer, has greatly affected the global markets during the Covid-19 (Niu et al., 2021). Figure 4b also presents islands of strong positive relationship between inflation and crude oil in Canada throughout our study. However, notably, a significant and very strong positive relationship has been found between CPI and crude oil in France and the United States in Figures 4c and 4h. These results are supported by Jawadi and Sellami (2022) and Mensi et al. (2020) who analyze the highly uncertain and leptokurtic behavior of oil prices during Covid-19. The uncertainty in oil prices leads to uncertainty in economic policy and ultimately increases the level of inflation. While, throughout our study, no significant relationship was detected between CPI and crude oil in Germany, Italy, Japan and the United Kingdom as depicted in Figures 4d, 4e, 4f, and 4g, respectively.

Further, the wavelet coherency between CPI and coal has been presented in Figure 5. Figure 5a shows the results for China and presents small islands of strong dependence between CPI and coal overall in our study. Small significant changes in coal prices point towards the richness of China in coal resources and its less dependence on external resources (Dai et al., 2022). Figure 5b shows a strong relationship between coal prices and inflation in Canada only in the pre-COVID-19 period. This is pertinent to the reason that the outbreak of COVID-19 has had a significant negative impact on the coal industry of Canada (Wang et al., 2022). Moving forward, among other countries (France, Germany, Italy, Japan, the United Kingdom and the United States) in the G-7 only Japan in Figure 5f shows positive and significant islands in the pre-COVID-19 period. While no relationship was detected during the COVID period in Japan. Our results are thus supported as Japan was the second largest investor in coal projects in the pre-COVID-19 period, but after the advent of COVID-19 Japan limited its spending on coal projects (Yanguas Parra et al., 2021).

Lastly, Figure 6 presents the wavelet transform coherence (WTC) for CPI and natural gas. Here in figure 6, we analyze the negative relationship between inflation and natural gas prices as depicted by the leftward arrows in the contours of various G-7 countries. The decrease in prices is due to the breakout of COVID-19, a significant decrease was realized in the global demand and extraction of natural gas (Ghiani et al., 2020; Halbrügge et al., 2021). In Figure 6d, Germany reports a significant negative relationship between inflation and natural gas overall in our study. Chen et al. (2022) justify our findings as he reports damaged market integration of the natural gas market in Europe during COVID-19. However, on similar patterns, Italy and the United Kingdom report a significant negative relationship in the post-COVID-19 and COVID periods respectively in Figures 6e and 6g. Whereas, the results in Figures 6a, 6b, 6c, and 6f depict no consistent relationship between the variables for China, Canada, France and Japan, respectively. The scattering of arrows in various directions shows the inconsistency in the relationships between variables. However, these findings so far demonstrate that the quarantine situation in COVID has decreased the demand for natural gas in various countries especially, Europe and China (Norouzi, 2021). Consequently, we find no significant results in Figure 6h for the United States. This is possible because the annual gas imports of the United States are only 3%, while among other countries it ranks first in producing natural gas (Worldometer, 2015).

5. Conclusion

We apply continuous wavelet transform (CWT) methodology to examine the trends of Consumer Price Index (CPI) and energy commodity in the G-7 plus China before and after the COVID-19. Continuous Wavelet Transform (CWT) illustrate the unique intensity of inflation in all the countries under our study. Our study reveals that the changes in the CPI for China and Canada is at high levels due to the increased demand for necessities, which caused an increase in the price of such necessities in both countries. During the COVID-19 economic downturn brought on by Japan's overall declining demand for face-to-face sectors, inflation frequency is disproportionately high. Also United States reports a high inflation index during the periods of October 2020 to February 2021 and January 2022 to October 2022. However, France, German, Italy, and the United Kingdom do not show any significant changes in the CPI index during the pre or post-COVID-19 period.

CWT for commodities used in the energy sector, primarily crude oil, natural gas, and coal reveal unusual trends and characteristics in the entire energy market during the pandemic. Our results for crude oil show highly inflated prices during the period June 2019 to February 2021. Energy price inflation has been a significant problem during COVID-19 since it has a significant impact on all other industries and raises headline inflation. It was discovered that the supply and demand shocks that caused these inflated energy commodity prices were specific to the oil sector and grew over time.

We also use wavelet transform coherence (WTC) to analyze the relationship between CPI and all three energy commodities taken in this study. We find China and Canada have strong positive relationship between inflation and crude oil. However, particularly, a significant and very strong positive relationship has been found between CPI and crude oil in France and the United States. While no significant relationship between CPI and crude oil was found throughout our analysis in Germany, Italy, Japan, and the United Kingdom. On the other hand, wavelet coherency between CPI and coal, results indicate strong relationship in China and observe pre-COVID strong relationship between coal prices and inflation in Canada. Considering wavelet transform coherence

(WTC) for CPI and natural gas, we find leftward arrows in the shapes of various G-7 nations, which demonstrate the inverse relationship between inflation and the cost of natural gas. Natural gas demand and extraction drastically decreased as a result of COVID-19 breakout, which is what ultimately led to the price decline.

For policy implications, our research reveals that variation in CPI and energy commodities in the pre and post-COVID-19 era are crucial in policy discussions for macroeconomic aims of domestic policies, such as monetary or fiscal areas, with regard to the implications for policy. Our findings indicate that the relationship between CPI and energy commodities depends on both internal and external macroeconomic conditions, and that the regulators should investigate how prices at various stages of production respond to monetary policy shocks in order to establish an accurate and more reliable inflation target.

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Table 1: Descriptive Analysis

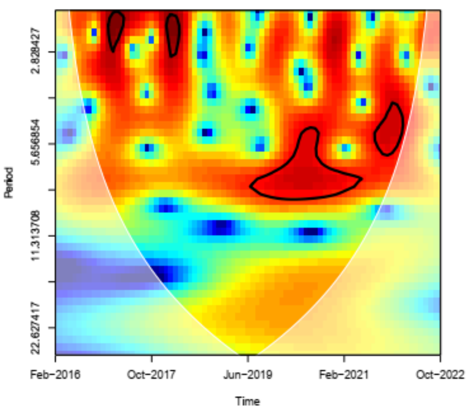
	Mean	S.D.	Min	Max
Panel A: Change in CPI				
Canada	0.24%	0.41%	-0.66%	1.43%
China	0.00%	0.51%	-1.66%	1.38%
France	0.17%	0.26%	-0.44%	1.04%
Germany	0.26%	0.53%	-0.85%	2.49%
Italy	0.21%	0.51%	-0.68%	3.42%
Japan	0.07%	0.23%	-0.90%	0.68%
United Kingdom	0.29%	0.46%	-0.77%	2.51%
United States	0.28%	0.31%	-0.80%	1.32%
Panel B: Energy Variables				
Crude Oil Average	2.05%	11.39%	-39.63%	44.37%
Coal Average	2.98%	10.26%	-32.70%	46.20%
Natural Gas Index	2.90%	13.75%	-32.68%	37.42%

Figure 1: Crude Oil Prices in 2022

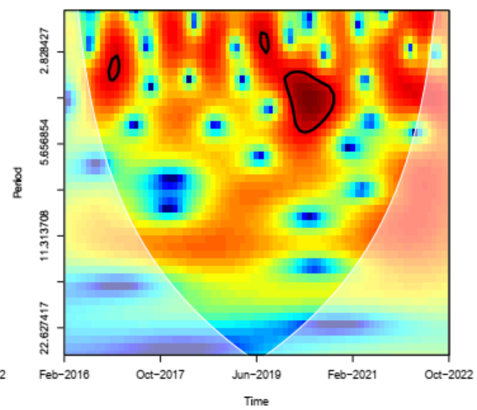
Figure 2: Continuous Wavelet Transform of CPI

This figure provides CWT for CPI in China and G-7 countries.

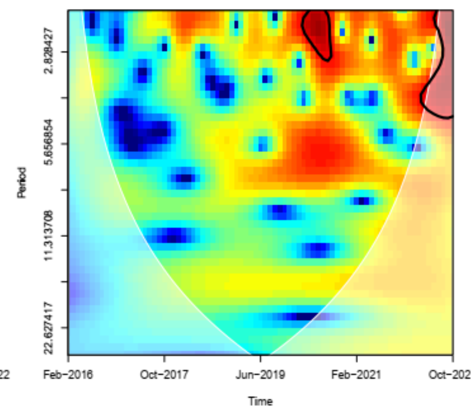
(a) China



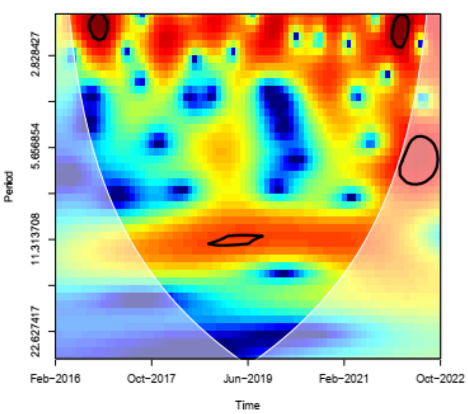
(b) Canada



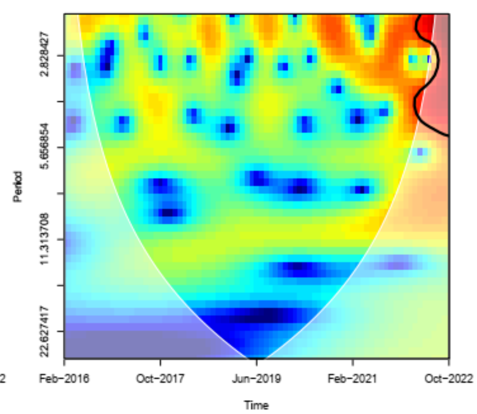
(c) France



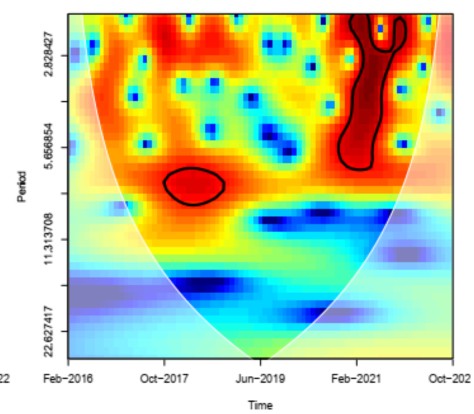
(d) Germany



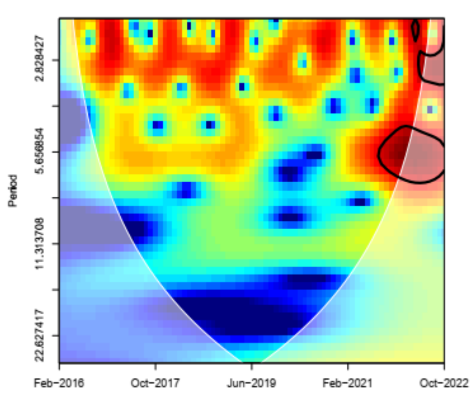
(e) Italy



(f) Japan



(g) United Kingdom



(h) United States of America

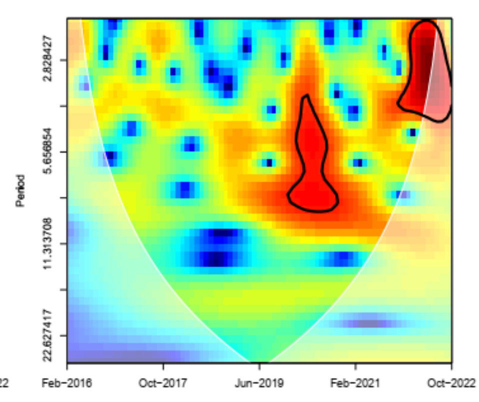


Figure 3: Continuous Wavelet Transform of Energy Commodities

This figure provides CWT for Energy Commodities

(a) Crude Oil (b) Coal (c) Natural Gas

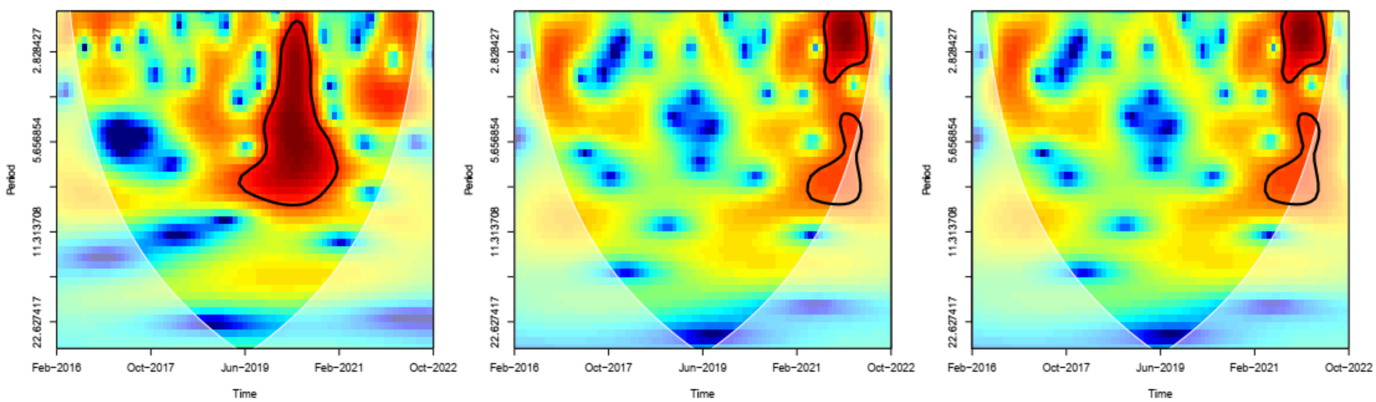


Figure 4: Wavelet Transform Coherence - Crude Oil

This figure provides WTC for CPI and Crude Oil

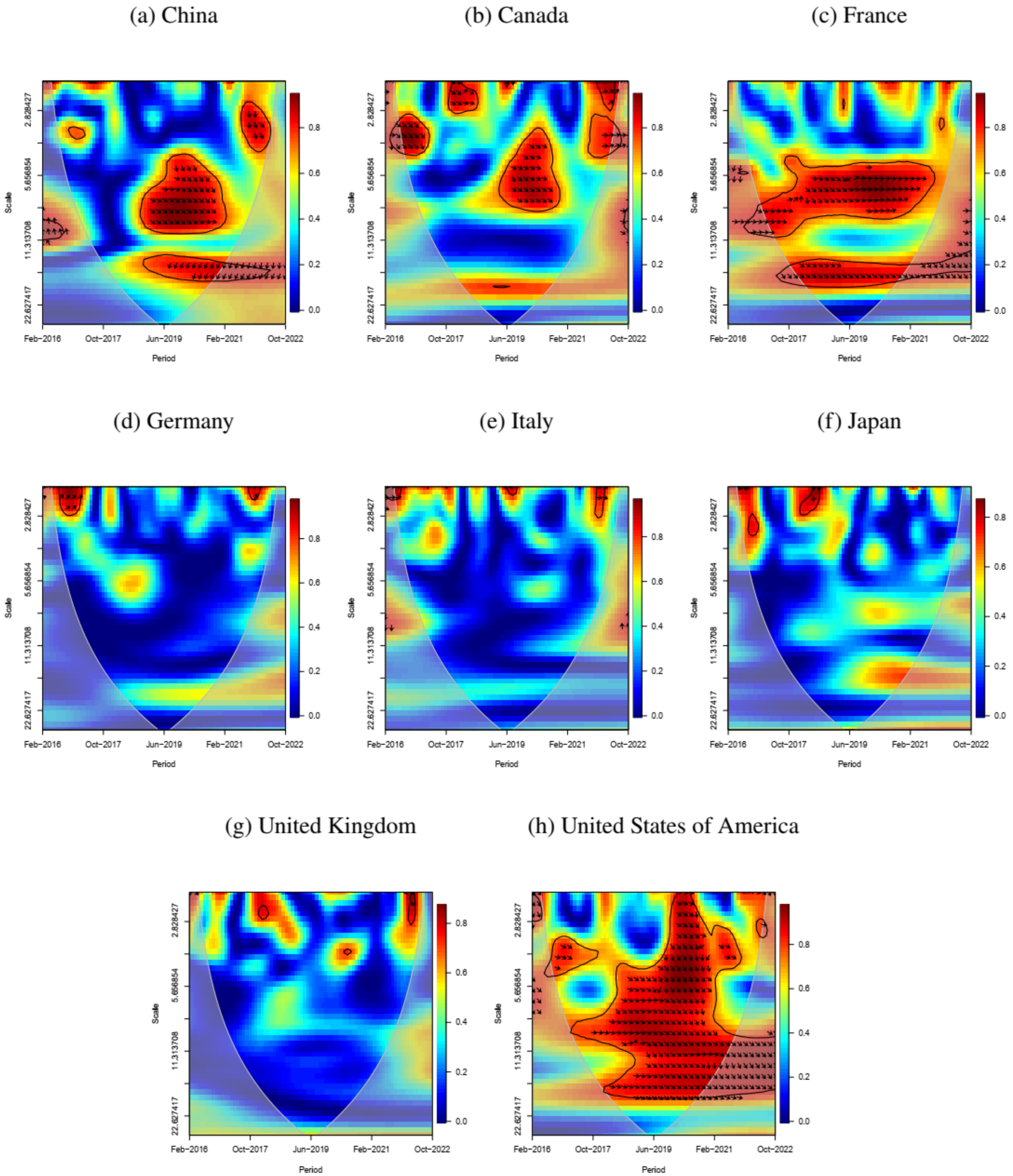
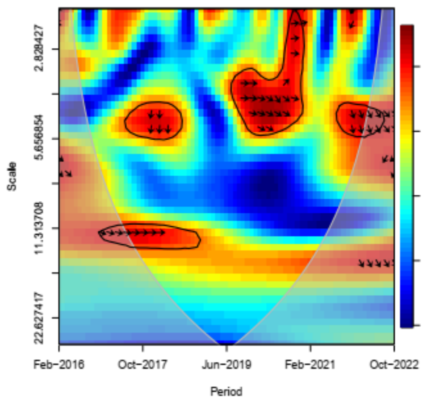


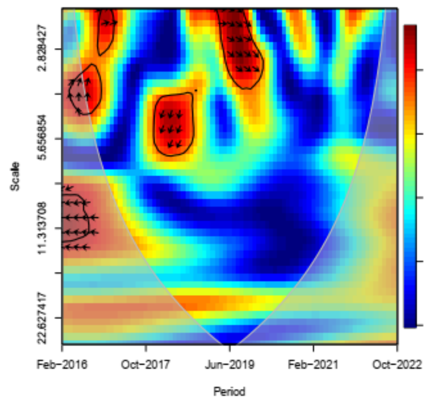
Figure 5: Wavelet Transform Coherence - Coal

This figure provides WTC for CPI and Coal

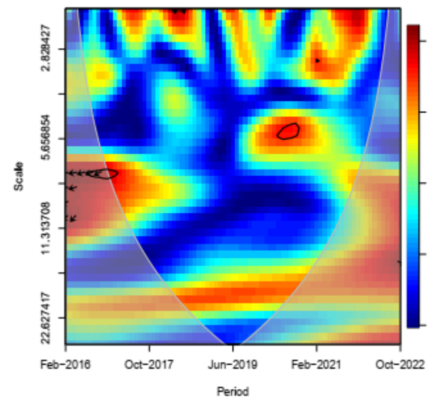
(a) China



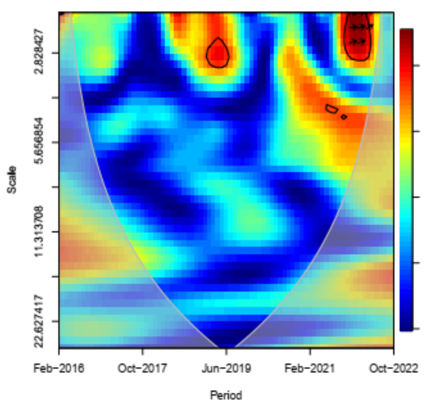
(b) Canada



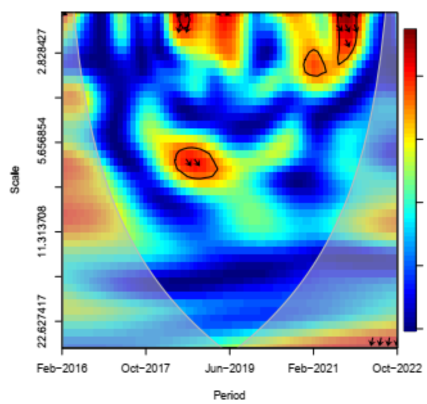
(c) France



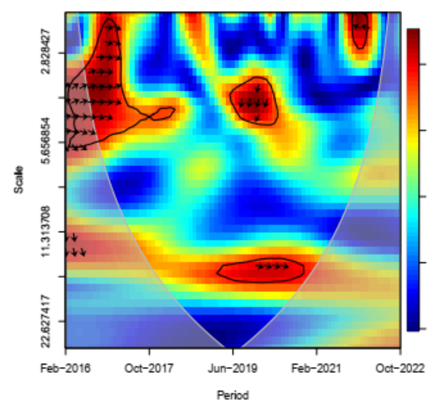
(d) Germany



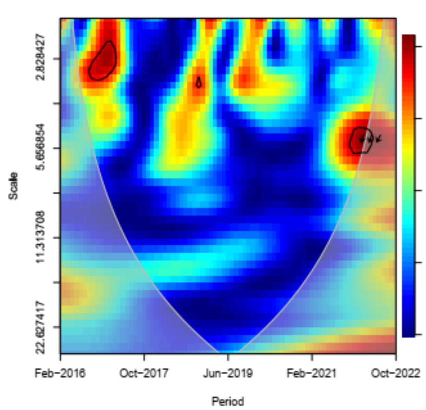
(e) Italy



(f) Japan



(g) United Kingdom



(h) United States of America

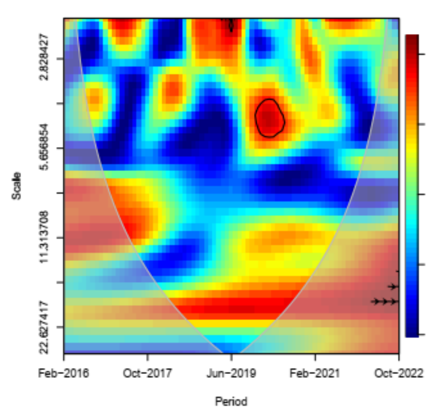
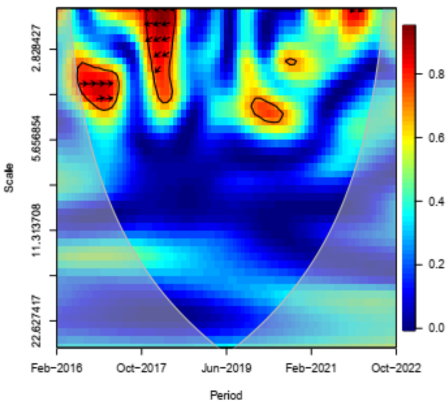


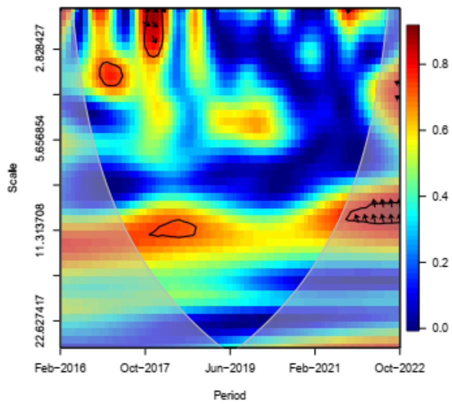
Figure 6: Wavelet Transform Coherence - Natural Gas

This figure provides WTC for CPI and Natural Gas

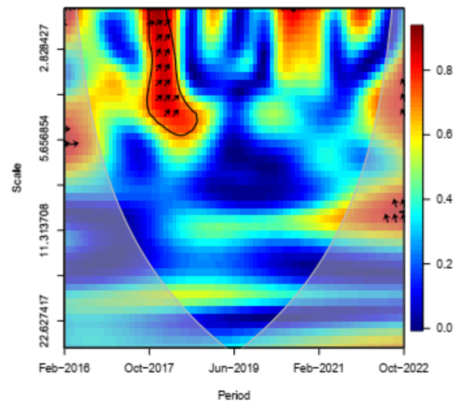
(a) China



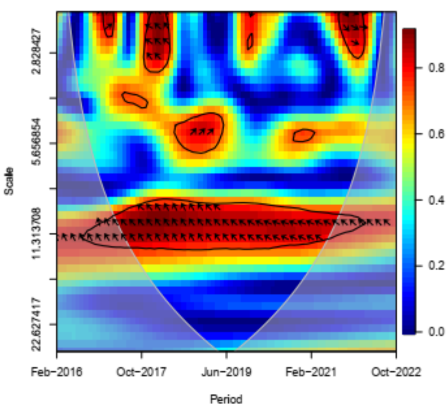
(b) Canada



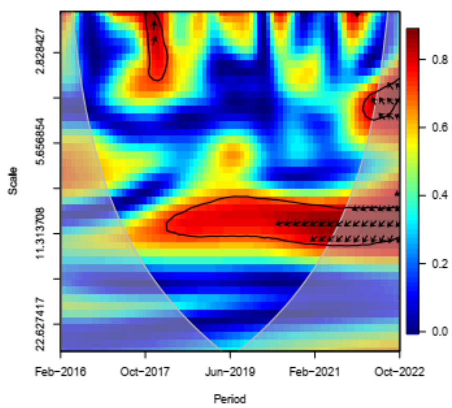
(c) France



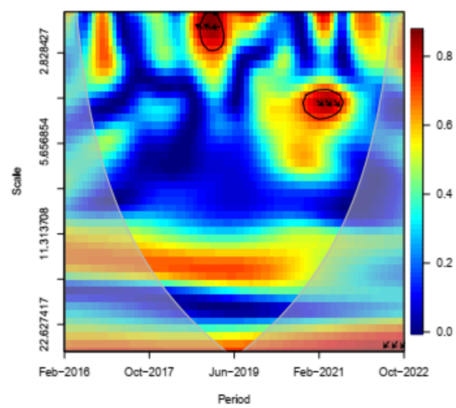
(d) Germany



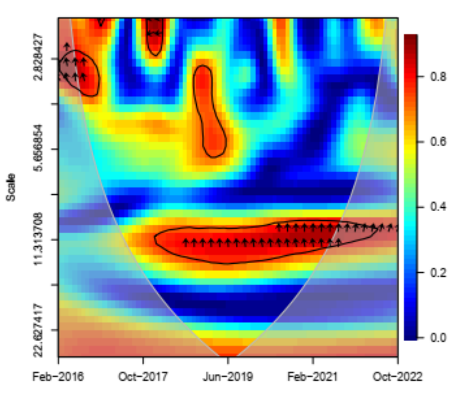
(e) Italy



(f) Japan



(g) United Kingdom



(h) United States of America