Extracting the Common Component of Biofuel Commodities and Assessing its Dynamic Relationship with Dubai Fatech Index and Philippines Consumer Price Indexes

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Abstract

This study calculates the common component of biofuel commodities from January 1994 to May 2022. It then uses the vector autoregression model to analyze the relationship between the common component, Dubai Fateh crude oil price, and Philippines food and transportation consumer price indexes. The impulse response function shows that a one-time shock on the LP common component creates a positive effect on crude oil prices, while a one–time shock in crude oil prices generates the same positive effect on the LP common component. From the decomposition of the LP common component, crude oil explains 0.066345 per cent of changes in the said variable, whereas food and transportation indexes describe 0.133670 per cent and 0.023652 per cent variability in the LP common component, respectively.

Keywords: prices of crude oil, biofuel commodity prices, LP common component, vector autoregression, variance decomposition, Philippines

1. Introduction

The Philippines, one of the pioneering countries to use renewable energy in Asia, enacted the Biofuel Act 2006/Republic Act 9367 to reduce the country's dependence on oil importation, increase employment, and improve the environment through better efficiency and air quality. These objectives paved the way for using biofuels (bioethanol and biodiesel) blended in all diesel and gasoline products (10% bio-ethanol and 2% biodiesel) distributed and sold in the Philippines.

Despite the apparent benefits of the Biofuel Act, it is still a significant concern due to the trade-off between food security and energy sufficiency. Less land will be intended for food, and

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more land will be allocated to produce commodities for energy needs. This is amid all ongoing land conversions from agricultural to industrial and residential uses due to the country's rapid development and continuous population growth. These concerns were highlighted in 2008 when the twin crises of high prices of crude oil and agricultural commodities caused a slowdown in world economies, including the Philippines. It was pointed out that biofuel production was one of the main culprits in the crisis [1]. However, it was argued that biofuel production does not significantly impact the world food market. Instead, the issue should be examined at a country level, where local policies and regulations determine biofuel's role in food prices [2].

Higher commodity and fuel prices in the world market resulted in skyrocketing inflation in the Philippines, adversely affecting the most vulnerable members of the society, the poorest of the poor. This situation puts more Filipinos under the poverty line as consumption of food commodities and services declines due to higher unemployment, lower export earnings, and household income [3].

This study aims to determine the common component of prices of commodities used in the production of biofuel. The common component will enable us to obtain a reference price among the biofuel commodities. Furthermore, this study will determine the co-movement of the common component, the Dubai Fatech index, and two major elements of the Philippines Consumer Price Index (CPI)—the food and non-alcoholic beverages index and the transportation index. Moreover, the study will assess the dynamic relationship among the common component, price of crude oil, food, non-alcoholic beverages index, and transportation index. The organization of this study is as follows. Section 2 presents a review of the literature. Section 3 describes the data and methodologies used in the study and explains the methodologies used. Section 4 presents the empirical results, and finally, Section 5 concludes.

2. Review of Related Literature

This section provides various papers that are related to our study and have significantly influenced this research. The utilization of complex network theory and Granger causality method to construct Granger Causality Network among price indices (PIGCN) presents a statistical method to analyze conduction fluctuations, particularly on crude oil price and China's domestic price index. Four price indices in China were chosen, including 36 sub-price indices as samples. Through the analysis of PIGCN structure, it was discovered that price transmission of oil price to price index could be divided into direct and indirect transmission. Direct transmission industries are mainly chemicals, natural gas fuels and materials that requiring refining and processing of crude oil. These industries used crude oil as a raw material for production and operations, so changes in oil prices have a more direct impact on these industries. The indirect transmission of crude oil to the price index owing to the rising cost of raw materials, which is passed on to the downstream of the industrial chain and control the price of final products. In a broad-spectrum, oil prices will be passed to the producer's price index (PPI) at first, then to the consumer's price index (CPI) [4].

The trends in bi-directional net return spillover index across crude oil and agriculture commodity markets were examined based on the findings. The directional association from the crude oil market to agriculture commodity returns was found lower than that on the contrary direction. Particularly, the crude oil market was a net receiver of return spillovers during the Covid-19 outbreak crisis, while it was a net transmitter of return spillovers in the pre-Covid-19 periods. Corn, soybean, and wheat markets were net transmitters of spill-over, while the copper, sugar, and oats were net recipients of return spillover over the period shown. The analysis includes the strong co-movement of crude oil prices and agriculture commodity markets during the Covid-19 outbreak compared to the pre-Covid-19 period [5].

A bottom-up model was created, and some sectors were evaluated, with a highlight on transportation. Rapeseed demand implied significant growth in energy consumption in 2030; the transport sector would be the main consumer, which would increase per capita from 105 to 132 vehicles per thousand persons for the same scenario. This growth is concentrated on individual transportation for passengers. The implementation of energy policies will reduce gasoline consumption per vehicle by 28% by 2030. It is important to use available resources mainly in sectors that generate added value, focus on the industrialization process, and not only allocate it to household consumption, which does not create added value in the domestic economy. In addition, the current policy of managing surplus electricity is focused on regional exports [6].

Furthermore, present economic conditions will not permit achieving a carbon neutral growth in the civil aviation sector with no alternative low-carbon fuels. While low-carbon fuels like liquid hydrogen may be sensible in the long term, only drop-in biofuels have been demonstrated for short-term applications. However, their present economic characteristics make necessary some incentive measures, at least during the introductory phase. As the drop-in biofuels for aviation have only been formed on an experimental scale, the possible cost of producing them in industrial conditions cannot be calculated with accuracy. However, most forecasts predict a higher cost than conventional fuel prices [7].

An investigation of the impact of global oil price shocks on six kinds of agricultural commodities produced was done in China. The global oil price variations are applied to one that is smooth fluctuation under the influence of daily information. The other one is the jump behavior caused by the emergency. Price volatility is observed as a combination of continuous process and jump process. The oil price is characterized by volatility clustering and jump behavior. As the oil price starts to fluctuate, people will enter into hedging transactions in the oil futures market to evade risks, leading to additional volatilities in the oil price. Oil price shocks have diverse effects on agricultural commodities. Cash crops are more susceptible to oil price shocks than food crops. Lastly, oil price shocks on most agricultural commodities are asymmetric. For wheat, corn, soybean, and bean pulp, adverse oil price shocks are more significant than positive [8].

The effect of crude oil and commodity prices on inflation has been the topic of substantial literature. One of the studies argued high commodity prices raise inflation, even at a slow pace of global economic growth. High commodity prices affect emerging markets' external and fiscal positions that rely on such exports. In addition, corn prices are related to oil prices in the long and short run. The U.S. Energy Policy Act of 2005 caused a significant increase in the share of the U.S. corn harvest used for ethanol production. Since that use ultimately depends on the price of oil relative to ethanol (and indirectly, corn), oil prices have become a relevant factor in global corn markets [9].

Studies have established a long-run equilibrium relationship between the prices of food and those of the main elements of the food price, namely agricultural commodities, energy, and labor. These three variables explain about half Finland's food price variability [10]. Government intervention in domestic oil prices is ineffective for price stability because the price indices are influenced by international oil prices [11]. Food and energy affect headline inflation in Chile, but only the former has significant second-round effects. In addition, the result does not imply that one should ignore the inflationary effects of oil prices since the conduct of monetary policy is one of the determinants of its limited effects on inflation [12].

The impact of crude oil prices on commodity prices received considerable attention. Studies have compared the pre and post-crisis periods' responses to world commodity prices from an oil price shock. The after-crisis responses of agricultural commodity prices to other oil-specific demand shocks driven by precautionary demand and speculative ones are highly significant, sharply contrasting with the pre-crisis period. Global economic and oil market activity can significantly affect agricultural commodity markets [13].

In the United States, linear Granger causality on individual commodities to price indices was used. Price indices are more prone to nonlinear causes of individual commodity prices. Furthermore, results show that one or more categories of the commodity classes of agricultural raw materials, Beverages, Food, Minerals, ores and metals, and vegetable oilseeds and oils exhibit bidirectional linear and nonlinear feedback effects concerning U.S. price indices [14].

No risks were transferred between any other markets before the commodity crisis, although, after the crisis, oil market risk was transmitted to corn, wheat, and soybean markets. It was discovered that volatility spillover from wheat to oil market for both periods. The sugar market seems to be neutral to oil market risks. The volatility responses of all agricultural markets to risk shocks in oil markets seem to be significant only for the post-crisis period [15].

Studies indicate that the underlying relationship between crude oil price and commodity prices lies in substitution-ability between crude oil and biofuels. One study showed a strong relationship between crude oil and corn markets with crude oil and ethanol in the U.S. The relationship between corn and ethanol drives by government policy than the marketplace. They claimed that a long-run cointegrating relationship does not strongly bind ethanol and corn market prices. Instead, it argued that price transmission between the two sectors is determined by the government mandate levels of ethanol use in gasoline production [16].

Studies have assessed whether food and oil markets were independent or dependent by studying the dependence structures and co-movement using different copula model specifications with time-invariant and time-varying dependence structures. The analysis supported the neutrality hypothesis for the overall sample that oil price fluctuations do not drive agricultural commodity price movements. This statement supports the observation that the increase in the relationship dependence in terms of sample among oil, corn, and soybean for the last three years is proven. This conforms to the soaring demand for corn and soybean commodities for bio-fuel production following increases in oil prices and policies of substantial subsidies for bio-fuels as an alternative energy resource. He added that his findings that the upper tail dependence was insignificant, meaning that extreme oil price movements did not affect food price spikes [17].

Several studies clarify that the crude oil market affects the core position in the commodity market. The volatility of spillover effects of the crude oil market on other commodity markets was comparatively more significant than that of other markets on the crude oil market. After the crisis, the degree of volatility spillover effects is weaker than before. This shows that the impact of the crude oil market on other commodity markets was more significant when crude oil prices were higher than when they were lower [18]. Another study using nonlinear causality analysis showed that the recent surge in the world agricultural commodity prices can be attributed to the changes in world oil prices and added that the findings could predict the prices of the agricultural commodities by following the fluctuations in the oil prices [19].

A study revealed that when food prices are low, these prices are very mildly connected to fuels and biofuels. Furthermore, it observed that ethanol connected to corn, wheat, and soybeans even in the short term and more intensely in the medium term. On the other hand, biodiesel has a very low correlation with the rest of the system in the short term. However, it becomes firmly and steadily connected to other fuel commodities in the medium term. In the pre-crisis period, the situation was corn, wheat, and soybeans were well connected with the whole network, but the sugars were less correlated [20]. A paper concludes that, among other factors, the increase in retail food prices was due to biofuels. It was estimated that biofuels caused an increase of about 23-35% above the normal increase in food prices over 2-3 years. It further argued that biofuels are a significant cause of higher food prices. In addition, corn demand for ethanol was influenced by government policy, and higher oil prices both stimulated food prices [21].

Commodity prices contain information about inflation in the U.S. He explained that one has to account for nonlinear linkages between the variables while interpreting the commodity price–inflation connection [22]. On the other hand, an increase in CPI will cause an increase in commodity prices and vice versa in the U.S. Since this type of feedback has nonlinear sources, a slight increase in commodity prices can lead to abnormal behavior of CPI [23]. It is suggested that the neutrality of agricultural prices in Turkey to world oil price changes may be due to the relatively low energy-intense production processes [24].

A multi-country study demonstrates that if crude oil prices remain high, the recent commodity price boom will last much longer than earlier booms, at least for food commodities, fertilizers, and precious metals. However, other items, especially metals and raw materials, will likely follow diverging paths [25]. Another paper used a multi-country, multi-sector, recursive dynamic, global computable general equilibrium model to simulate future oil price scenarios and assesses the corresponding impacts on bio-fuels production, agricultural outputs, land-use change, and global food supply. It revealed that a significant increase in oil price would drive the rapid and large-scale expansion of bio-fuels, with adverse effects on food supply as more and more land is allocated to bio-fuel production [26]. The substitutive economic effect of edible feedstock such as corn and soybean with fossil fuels is lower and higher crude oil price periods. The empirical results confirm their hypothesis that the price spillover effects from crude oil futures to corn and soybean futures are insignificant during the lower crude oil price period but are positively significant during the higher crude oil price period [27].

3. Data and methods

3.1. Data

This study used monthly time series data from January 1994 to May 2022. This comprises 341 observations per series of biofuel commodity prices such as coconut oil, maize, palm oil, rice, rapeseed oil, soybean oil, sugarcane, sunflower oil, and wheat. These commodities are the main components in producing biofuels [28]. This study uses data for the price of crude oil and the Philippines Consumer Price Index (CPI) and its components, particularly the food and non-alcoholic beverages index (food index, for brevity) and transportation index. All prices of biofuel commodities are in U.S. dollars per metric ton.

The data for crude oil is in Dubai Fateh price in U.S. dollar per barrel. The researchers gathered the source of biofuel commodity prices and crude oil prices from the World Bank. For the price of sugarcane, the researchers used the website of the U.S. Department of Agriculture, Economic Research Service. The data on food and transportation indexes were attained from the website of the Philippines Statistical Authority (PSA). A seasonal adjustment was employed, and data was changed to natural logarithms before using the U.S. Census Bureau X13 method.

Each series of the price of biofuels commodity, crude oil, Philippines food, and transportation indexes were examined for the presence of unit root tests [29] and [30]. The augmented Dickey-Fuller (ADF) and Phillips and Peron (P.P.) tests have null hypotheses of a unit root in the series. These tests were applied in level terms using the first difference of the variables in the study. The test equations included trend, intercept, and lag lengths [31]. To determine the statistical significance of the variables involved, such as the level and difference, those should be passed the distribution [32]. For the P.P. test the optimal bandwidth using Newey–West. Table 1 summarizes the results of these two methodologies, and based on the findings, the variables in consideration contain unit roots at levels. However, differencing once reveal that all the variables are stationary at a 1% level of significance (i.e., I(1)) [33]. Therefore, we used the stationary variables in differenced form.

Table 1: *Unit root test result*

Variables	ADF test		PP test	
	Level	First difference	Level	First difference
Price of coconut oil	-2.605 (0.2783)	-14.347 (0)	-2.857 (0.178)	-14.759 (0)
Price of maize	-2.501 (0.328)	-13.703 (0)	-2.377 (0.391)	-13.713 (0)
Price of palm oil	-2.498 (0.329)	-7.233 (0)	-2.120 (0.532)	-12.88 (0)
Price of rice	-2.766 (0.211)	-12.154 (0)	-2.425 (0.366)	-12.431 (0)
Price of rapeseed oil	-1.644 (0.773)	-16.20 (0)	-1.915 (0.645)	-16.472 (0)
Price of soybean oil	0.576 (-2.041)	-13.206 (0)	-1.992 (0.603)	-13.243 (0)
Price sugarcane	0.684 (-1.839)	-17.089 (0)	-2.084 (0.552)	-17.104 (0)
Price of sunflower Oil	-3.110 (0.105)	-13.084 (0)	-2.879 (0.171)	-13.084 (0)
Price of wheat	-2.126 (0.529)	-14.741 (0)	-2.035 (0.580)	-14.76 (0)
Price of Dubai crude Oil	-2.674 (0.248)	-13.342 (0)	-2.300 (0.432)	-12.815 (0)
Food index (PH)	-0.619 (0.977)	-18.361 (0)	-0.582 (0.979)	-18.369 (0)
Transportation index (PH)	-0.787 (0.964)	-17.553 (0)	-0.884 (0.955)	-17.584 (0)

Note: The values are t-statistics, with MacKinnon one-sided p-values in parentheses.

3.2. Methods

To extract the common component among the biofuel commodity prices, such as coconut oil, maize, palm oil, rice, rapeseed oil, soybean oil, sugarcane, sunflower oil, and wheat. This paper follows the methodology initiated by the study [34]. It measured the common component of international output growth fluctuations using time-varying weights. Their estimation involves the following steps. Step 1 starts with the measurement of conditional variance using univariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (1,1) models as follows:

$$y_{it} = c_i + \varepsilon_{it} \qquad \varepsilon_{it}|I_{t-1}\ N(0, h_{it}) \tag{1}$$

$$h_{it} = w_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1} \qquad w_i, \alpha_i, \beta_i > 0 \ and \ \alpha_i + \beta_i \geq 1 \tag{2}$$

Where y_{it} represents the bio-fuel commodity price i at time t whereas c_i denotes commodity-specific mean. ε_{it} is the error term, and it corresponds to information available at time t. Alternatively, Eq. (2) shows that the conditional variance is a function of the lag of the squared error of the mean equation, ε_{it-1}^2, or is called the Autoregressive Conditional Heteroskedasticity (ARCH) term. The forecast variance in the previous period, h_{it-1}, is called the GARCH term plus a constant, w_i.

From each univariate GARCH (1,1) model, $\hat{h}_{it}$ is estimated for each series $i = 1, 2, ..., 9$. The resulting conditional standard deviation, hit-1/2, can be interpreted as a time-varying measure of the contribution of the fluctuations in biofuel-commodity price i to fluctuations in the common component. Step 2 uses $h_{it}^{-1/2}$ in constructing the time-varying weights, W_{it}, as follows:

$$W_{it} = \frac{1}{\sqrt{h_{it+1}}} / \sum_{i=1}^{9} \frac{1}{\sqrt{h_{it+1}}}, \quad h_{it+1} \in I_t \tag{3}$$

And finally, step 3 calculates the common price of the different commodities, which is given by,

$$Z_t^G = \sum_{i=1}^{9} W_{it} \cdot y_{it} \tag{4}$$

The use of a time-varying weighting scheme suggests that when there is a shock in the biofuel-commodity price i and that shock is not transmitted to the prices of other commodities, the result of this shock to the common component would be minimized; and the shocks across biofuel-commodity prices can be shown to proliferate with no restrictions in the way shocks are transmitted [34].

The unrestricted Vector Autoregression (VAR) examines the dynamic impact of shocks on the system of variables of interest. The VAR model treats every endogenous variable as a function of the lagged values of all endogenous variables in the system [35]. The reduced form VAR model is given by the following equation:

$$\underline{x}_t = A_0 + A_1\underline{x}_{t-1} + A_2\underline{x}_{t-2} + \cdots + A_p\underline{x}_{t-p} + \underline{e}_t \tag{5}$$

where $\underline{x}_t\{lpcc_t, oil_t, food_t, trans_t\}$ is a (4x1) vector of $I(1)$ endogenous variables, cc_t the extracted common component, oil_t the price of Dubai fateh crude oil, $food_t$ the Philippines food index, and $trans_t$ the Philippines transportation index. A_0 is a (4x1) vector of constants, $A_1, \cdots, A_p$ are (4x4) matrices of coefficients, and $\underline{e}_t$ is a (4x1) vector of forecast error terms, which are white noise disturbance terms with zero means, constant variances, and serially uncorrelated. The forecast errors are composites of $\underline{\varepsilon}_t\{\underline{\varepsilon}_{lpcct}, \underline{\varepsilon}_{oilt}, \underline{\varepsilon}_{foodt}, \underline{\varepsilon}_{transt}\}$, a (4x1) vector of structural errors since, $\underline{e}_t = B^{-1}\underline{\varepsilon}_t$. The order of $VAR(p)$ is based on the Information Criterion [36].

Finally, through the dynamic lag structure of the VAR model, we traced the transmission mechanism of a one-time shock at time t to one of the innovations (error terms) on current and future values of the endogenous variables through impulse response functions (IRF) using generalized impulses responses [37]. The variance decomposition of oil_t, $food_t$, and $trans_t$ was analyzed using the following Cholesky decomposition of B^{-1} with a lower-triangular matrix as follows:

$$\underline{e}_t = \begin{bmatrix} e_{cct} \\ e_{oilt} \\ efoodt \\ etranst \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \beta 21 & 1 & 0 & 0 \\ \beta 31 & \beta[32] & 1 & 0 \\ \beta 41 & \beta 42 & \beta 43 & 1 \end{bmatrix} \begin{bmatrix} e_{cct} \\ e_{oilt} \\ efoodt \\ etranst \end{bmatrix} \tag{6}$$

4. Empirical Results

4.1. Trends of the data

Table 2 shows the bio-fuel commodity prices such as coconut oil, maize, palm oil, rice, rapeseed oil, soybean oil, sugarcane, sunflower oil, and wheat, as well as the price of Dubai Fateh crude oil, food index, and transportation index from January 1994 up to May 2022. The price of sunflower oil has the highest mean value from the given sample of 6.727318, while the price of sugarcane has the lowest mean value of 4.888807. For the price of Dubai Fateh crude oil, the mean value is 3.745701, while the indexes for food and transportation are 4.642980 and 4.431149, respectively.

In terms of the standard deviation, the price of coconut oil has the highest value of 0.457590. At the same time, the price of sugarcane has the lowest standard deviation, given by a value of 0.193443. The price of Dubai Fateh crude oil has a standard deviation of 3.745701, whereas the food and transportation indexes are 4.642980 and 4.431149 in that order.

Table 2: *Summary of descriptive statistics*

Variables	Mean	Median	Max.	Min.	Std. dev.	Observations
Price of coconut oil	6.721	6.644	7.721	5.652	0.458	341
Price of maize	5.007	5.051	5.852	4.321	0.382	341
Price of palm oil	6.466	6.485	7.483	5.455	0.392	341
Price of rice	5.857	5.908	6.810	5.098	0.363	341
Price of rapeseed oil	6.656	6.692	7.726	5.753	0.395	341
Price of soybean oil	6.589	6.611	7.582	5.659	0.393	341
Price sugarcane	4.889	4.855	5.316	4.493	0.193	341
Price of sunflower oil	6.727	6.654	7.767	5.807	0.417	341
Price of wheat	5.276	5.256	6.258	4.627	0.350	341
Price of Dubai crude oil	3.746	3.916	4.877	2.308	0.688	341
Food index (PH)	4.643	4.710	5.139	3.995	0.317	341
Transportation index (PH)	4.431	4.633	4.901	3.558	0.447	341

The graphs of the monthly prices of biofuel commodities, the price of crude oil, and food and transportation indexes are given in Fig. 1. The most prevalent characteristic in the figure is the sharp spikes in the prices of all biofuel commodities in the year 2008. These volatilities were attributed to increased production costs, energy prices, and demand [1]. Moreover, coconut oil, maize, palm oil, rice, rapeseed oil, soybean oil, sugarcane, sunflower oil, and wheat experienced another episode of increase from 2011 up to 2012 as these commodities were dependent on increased oil prices [38]. The price of rice slowly stabilized while the price of sugarcane started to intensify in 2011. This increase was directly due to European political risks and macroeconomic uncertainty [39]. All biofuel commodities prices went down after those two spikes occurred in 2008 and 2011 up to 2012. However, all prices of biofuel commodities except rice are increasing up to May 2022.

The price of crude oil declined for the same period of 2008. Its deterioration was triggered by the weakening global economic activities and the financial crisis in the U.S. [40]. Although after the decline, it went up and reached stability in 2011 – 2014 before constantly declining up to the year 2015. Notice the price volatility, which continues to rise, achieving the highest price up to May this year. The Food and transportation indexes are steadily increasing, although there is a decline for 2016 due to effective management of food and transportation prices. After those phases, food and transportation indexes steadily increased before decreasing in 2022. The graphical representations of the biofuel commodities are in Fig. 1.

4.2. Extraction of the common price method

The series representing the common component (LP common component) of commodity prices Z_t^G based on Eq. (4) and its cumulated component (LP cumulated common component) values are shown in Fig. 2.A. The LP common component manifests volatility in the year 2008, the year when most commodities have increased in the corresponding prices. On the other hand, the price of LP cumulated common component reflects the behavior of the bio-fuel commodity prices before and even after the 2008 crisis. The researchers found there is an increase in the trend of the series from 1994 up to around 1996. A continuous decline follows this in the cumulated common component of bio-fuel commodities, reaching its lowest level in 2000. It proceeded by a steep rise in the series peaking in 2008 when the crisis happened. After the crisis, volatilities remained in the series

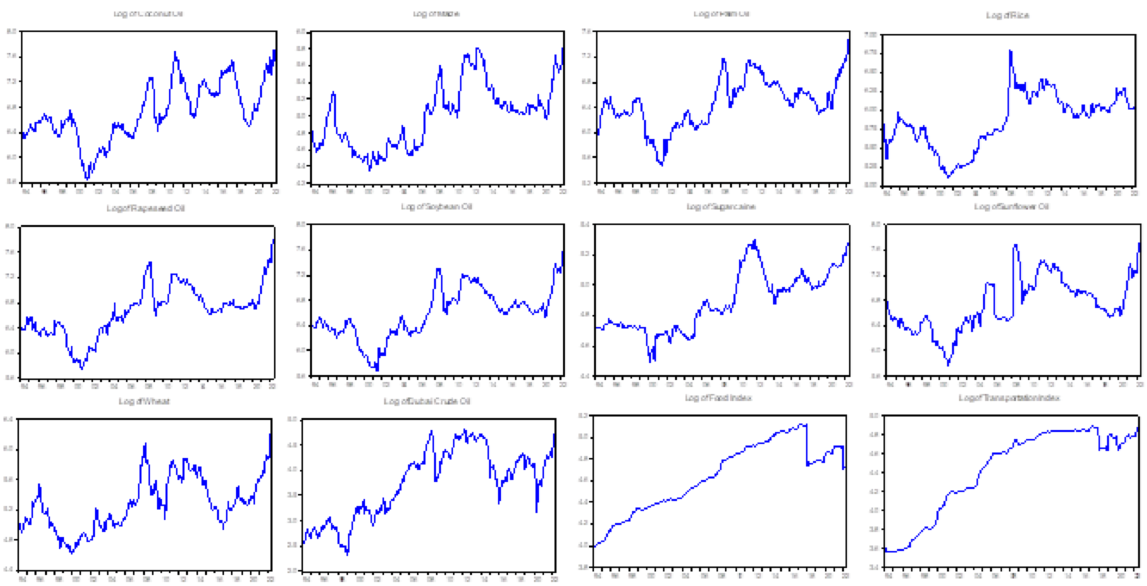

Figure 1: *Monthly prices of biofuel commodities, Dubai Fateh crude oil, food index and transportation index from January 1994 up to May 2022*

leading, rising in 2011 and declining in 2015 before going up to 2022.

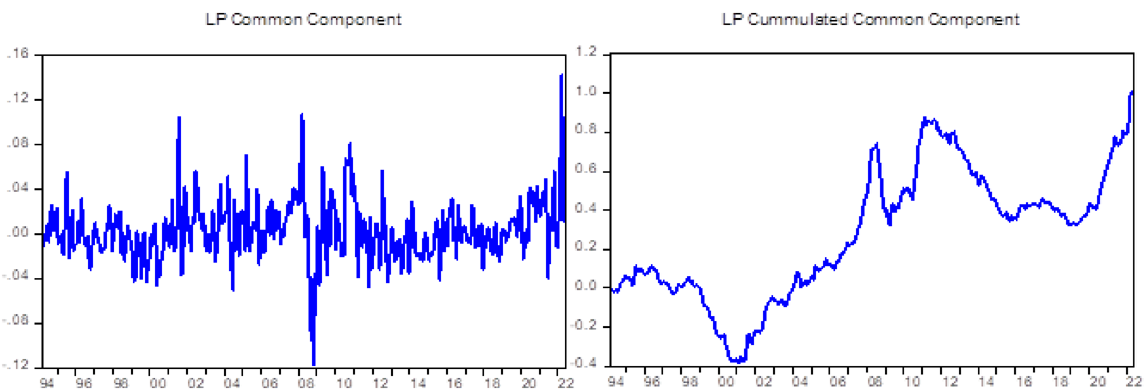

Figure 2: *Estimated LP common component and its LP cumulated common component*

In order to identify which biofuel-commodity price is the most responsive to the common component, individual regressions were calculated. Regressing two variables at level terms that are I(1) and are not cointegrated will give spurious results. However, if a linear combination of $Xt \sim I(1)$ and $Yt \sim I(1)$ is stationary, that is, $\varepsilon t \sim I(0)$, then the two series are cointegrated. It, therefore, follows that variables at level terms are used to examine the relationship [41]. Otherwise, different terms must be employed. Thus, we used residual-based cointegration tests such as [41] and [42], where both tests have null hypotheses of not cointegrated. The presentation of results of cointegration tests for individual regressions of biofuel commodity price i and cumulated common component in Table 3. These two tests gave consistent results where it was found that all biofuel commodities and LP common component are cointegrated, determined by both methods at the 1% level of significance. These results indicate that cointegrated series have a long-run equilibrium relationship. Thus, the first differences in the variables are included in the regression model to simplify the procedure, which will be presented later.

Table 3: *Engel-Granger and Phillips-Ouliaris tests*

Biofuel commodity price	Engel-Granger test	Phillips-Ouliaris test
Price of coconut oil	-13.596 (0)	-13.914 (0)
Price of maize	-14.327 (0)	-14.631 (0)
Price of palm oil	-13.304 (0)	-13.237 (0)
Price of rice	-13.304 (0)	-13.504 (0)
Price of rapeseed oil	-15.130 (0)	-15.216 (0)
Price of soybean oil	-15.420 (0)	-15.621 (0)
Price sugarcane	-12.398 (0)	-12.716 (0)
Price of sunflower oil	-13.310 (0)	-13.569 (0)
Price of wheat	-13.266 (0)	-13.546 (0)

Note: The probability values are given in parenthesis by MacKinnon.

4.3. Relationship of biofuel-commodity prices to LP common component

To verify the co-movement of biofuel commodity price *i* and the LP common component, the researchers plot these two on the same diagram to authenticate the path of both trends following one another. Fig. 3.A shows LP common component captures some of the main volatilities in the biofuel commodities with the exemption of rice and sugarcane prices specifically for the crisis period of 2008 and to the extent of unpredictability. As shown in the figure, the volatility in the price of rice is modest.

Compared to LP common component, it captures the instability of 2008. On the other hand, sugarcane prices are more volatile. However, the prominent segment can be found in 2013, although the volatility in LP common component is conspicuous in 2008. Other commodities and the LP common component follow each other's path, including during the crisis period.

Conversely, in Fig. 3.B, the LP cumulated common component is analyzed with the level terms of biofuel commodity price *i*. The prices of sugarcane and sunflower oil follow a separate path with the LP cumulated common component. The instabilities of these two biofuel commodities do not observe the direction of the LP cumulated common component since the price of sugarcane signifies volatility for the year 2011, while the price of sunflower oil suggests volatility for the years 2005 and 2008. A noteworthy of information that can be inferred from the graph is that all biofuel commodity prices follow the long-run path of the cumulated common component where it only captures the movement in the later periods.

To confirm statistically the linear relationship between bio-fuel commodity price i and LP cumulated common component, we refer to table 4.A and table 4.B. Differenced in the log of the price of soybean oil and differenced in the log of the price of palm oil have the highest correlation to LP common component of 81.5018% and 74.7124%, respectively. In comparison, the lowest value to the LP common component came from differenced in the log of the price of sugarcane and differenced in the log of the price of rice with estimated values of 29.0185% and 29.5604% in that order. It is presented in table 4.A.

Table 4.B demonstrates the correlation between biofuel commodity prices and the LP cumulated common component. The log of soybean oil, log of maize, and log of rapeseed oil have a very high correlation with 96.8331%, 94.5216%, and 94.0522% correspondingly to the LP cumulated

common component. At the same time, the log price of coconut oil, wheat, and rice prices have a moderate correlation with values estimated to be 86.6429%, 88.6438%, and 89.5086%, respectively. These correlation coefficients exhibit a strong to very strong linear positive relationship with the LP cumulated common component.

On the other hand, the researchers employed bivariate regressions to calculate and evaluate each biofuel commodity's responsiveness to the LP common component. Each biofuel commodity price is treated as a dependent variable, while the LP common component is regarded as the independent variable. The results of the individual regressions are presented in Table 5. Columns 2 and 3 display the constant and slope coefficients of the LP common component in that order, while columns 4 and 5 report the R^2 and adjusted R^2 correspondingly.

The slope coefficient from the regressions in Table 5 can be interpreted as biofuel commodity beta in that it measures the responsiveness of a biofuel commodity to movements in the common component. Notice that in column 3, the biofuel commodities have betas greater than one. It shows that the time-varying aggregated LP common component is less sensitive than the biofuel commodity. Differences in the price of sunflower oil, the price of palm oil, and the price of coconut oil are the most responsive to the LP common component having slope coefficients of 1.766976, 1.690979, and 1.617744, respectively. While the differences in the price of sugar, the price of rice, and the price of wheat are the least responsive, having smaller slope coefficients of 0.238204, 0.544101, and 1.199708 correspondingly.

Furthermore, the regression results show that the differences in the price of soybean oil, the price of palm oil, and the price of sunflower oil have the highest R^2. The values are 66.4255%, 55.8194%, and 40.9976% in that order. Furthermore, the difference in the price of rice has the lowest R2, which is 08.4207%. It only means that LP common component explains the differenced in the prices of soybean oil, palm oil, and sunflower oil better compared to what it can explain in other commodity prices, particularly the differenced in the price of rice.

Table 4A: *Correlation of differenced biofuel commodity price to LP cumulated common component*

Commodities	LP common component
Differenced log of price of coconut oil	63.321% (0)
Differenced log of price of maize	59.546% (0)
Differenced log of price of palm oil	74.712% (0)
Differenced log of price of rice	29.019% (0)
Differenced log of price of rapeseed oil	63.227% (0)
Differenced log of price of soybean oil	81.502% (0)
Differenced log of price of sugarcane	29.560% (0)
Differenced log of price of sunflower oil	64.029% (0)
Differenced log of price of wheat	53.259% (0)

Note: The coefficients are statistically significant at 1% level.

4.4. Impulse response functions (IRF)

The summary of the accumulated impulse response functions (IRFs) results is presented in Fig. 4. To set up the IRF, the difference in the price Dubai Fateh crude oil (dcrude oil) is treated as the impulse (source of shocks) whereas the LP common component, the difference in food index (dfood index), and the difference in transportation index (dtransportation index) are treated as the response. This is the setup of the first row in the figure. In the second row, the LP common

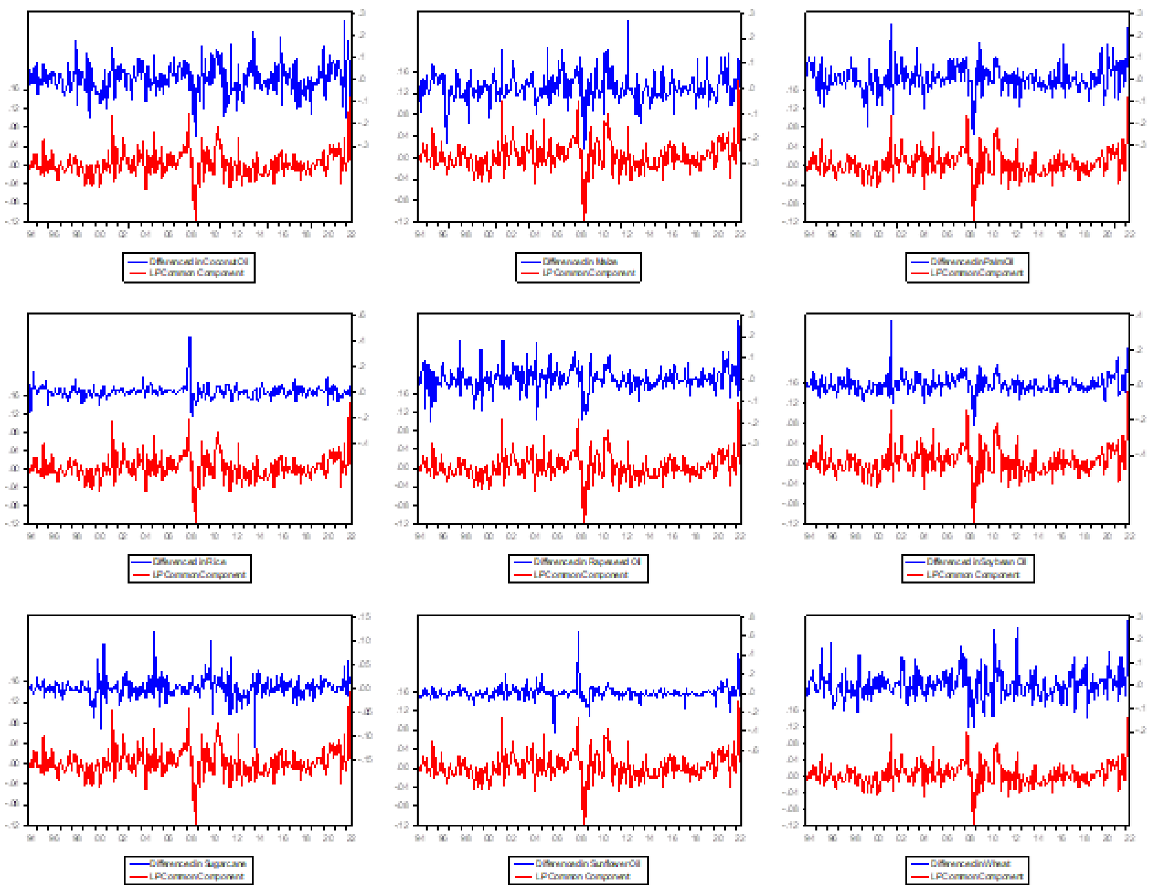

Figure 3A: *Biofuel commodity prices and LP common component*

Table 4B: *Correlation of biofuel commodity price to LP cumulated common component*

Commodities	LP common component
Log of price of coconut oil	86.643% (0)
Log of price of maize	94.052% (0)
Log of price of palm oil	93.406% (0)
Log of price of rice	89.509% (0)
Log of price of rapeseed oil	94.522% (0)
Log of price of soybean oil	96.833% (0)
Log of price of sugarcane	90.440% (0)
Log of price of sunflower oil	89.887% (0)
Log of price of wheat	88.643% (0)

Note: The coefficients are statistically significant at 1% level.

component is the impulse, whereas dcrude oil, dfood index, and dtransportation index are the responses. The Cholesky decomposition imposes a constraint that guarantees a limit to have structural ordering in the contemporaneous relationship among the endogenous variables [43] and [44].

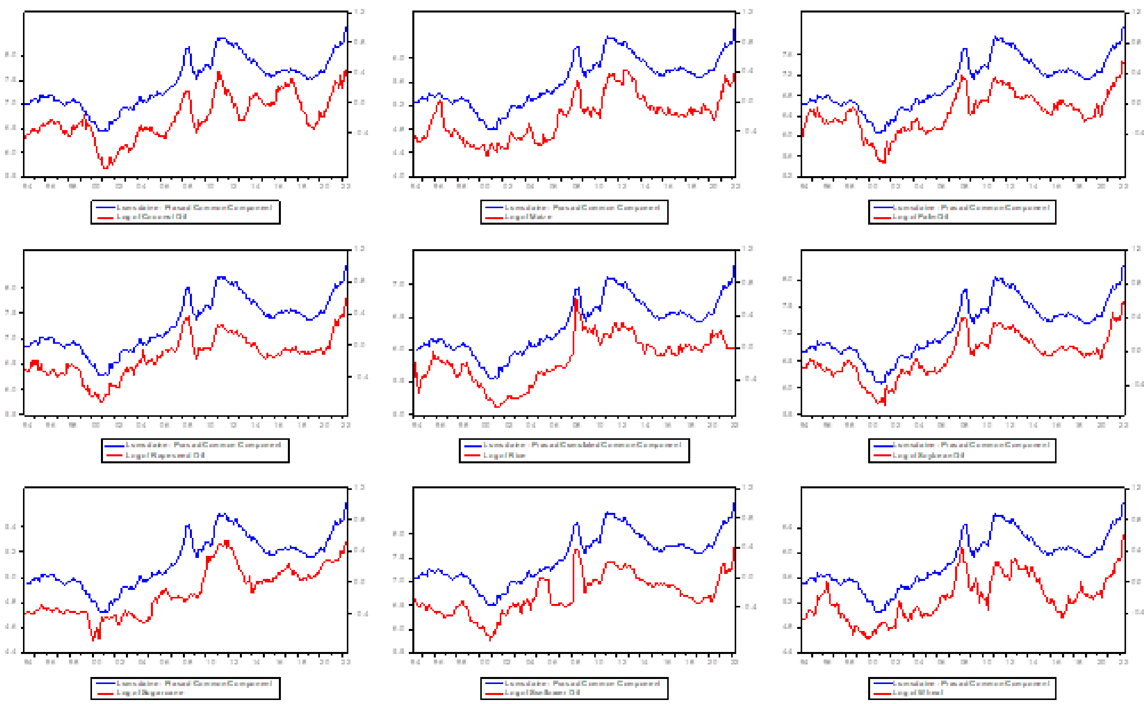

Figure 3B: *Biofuel commodity prices and LP common component*

Table 5: *regression results*

Dependent Variable	Constant	LP common component	R^2	Adjusted R^2
D(price of coconut oil)	-0.0013 (0.65)	1.618 (0)	40.10%	39.91%
D(price of maize)	-0.0008 (0.79)	1.244 (0)	35.46%	35.27%
D(price of palm oil)	-0.0006 (0.78)	1.691 (0)	55.82%	55.69%
D(price of rice)	-0.0008 (0.77)	0.544 (0)	8.42%	8.15%
D(price of rapeseed oil)	0.0002 (0.95)	1.294 (0)	39.98%	39.8%
D(price of soybean oil)	-0.001 (0.41)	1.535 (0)	66.43%	66.33%
D(price of sugarcane)	0.001 (0.42)	0.238 (0)	8.74%	8.47%
D(price of sunflower oil)	-0.002 (0.44)	1.767 (0)	41.0%	40.82%
D(price of wheat)	0.0002 (0.94)	1.20 (0)	28.36%	28.15%

Note: Probabilities are reported in parentheses.

The IRF revealed that a one-time shock on the LP common component positively affects the price of crude oil from the first month up to the third month. After this initial effect, it changes from the third month and declines, reaching the lowest point in the fourth month. Subsequently, it winds before attaining a steady – state in the tenth month. As the price of crude oil increases, there will be a persistent effort to develop a substitute for crude oil, specifically with biofuel commodities, until the price stabilizes. This finding confirms the result of [13–15, 18, 19, 25].

For dfood index, a one–time shock causes a downward response in the LP common component from the first month up to the third month, the lowest point of the LP common component. From that point, it slowly picks up, although it remains in negative territory. On the other hand, a one–time shock in the dtransportation index creates positive results from the first month up to the highest level in the third month, even though LP common component settles in a steady state position [45]. This only shows the subsidy provided by the Philippines government to the transportation sector to protect society.

A one–time shock to the LP common component generates a positive but declining outcome from the first month to the seventh month on the price of crude oil. Subsequently, in the eighth period, the behavior of the said variable changed, dropping to the negative from the seventh month up to the tenth month. At the same time, a one–time shock in the LP common component generates an upbeat effect on the food index, having the highest value in the second month, reaching a steady state up to the seventh month.

There are two reasons why the LP common component has a transitory effect on the food index: (1) the social subsidy provided by the national government to mitigate the effects of a rise in food index and; (2) the proactive monetary policy through the inflation targeting framework of the Bangko Sentral ng Pilipinas (Central Bank of the Philippines). The Philippines government is credited for insulating food prices from oil prices. These are consistent with the findings of [17,46,47].

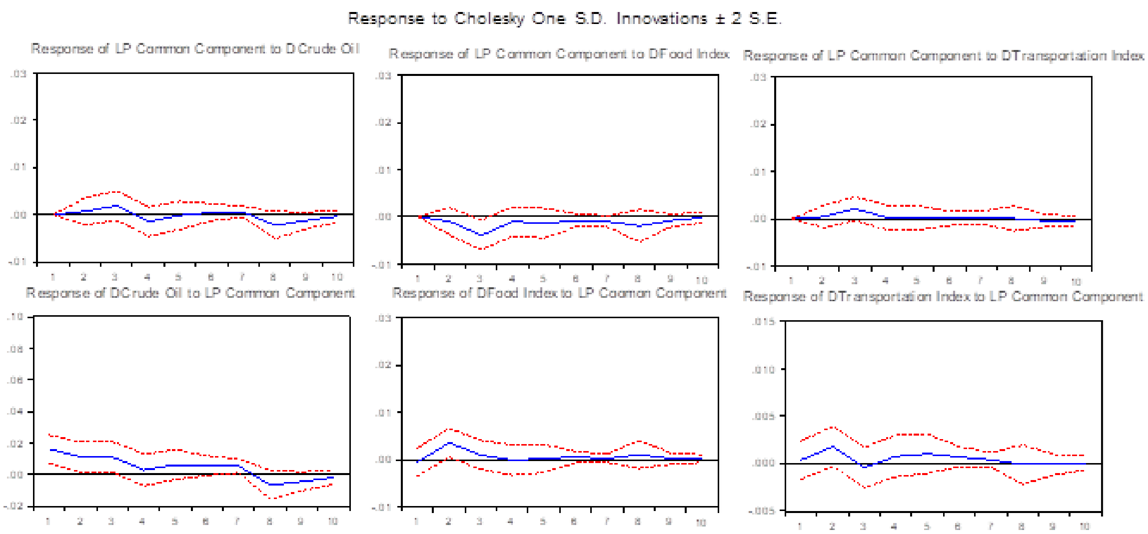

Figure 4: *Impulse response functions of common component, food index, and transportation index to crude oil price*

4.5. Variance decomposition (VD)

A variance decomposition (VD) is used to assist in the explanation of a vector autoregression (VAR) model. Once integrated, it specifies each variable's information to the other variables in the VAR model. It establishes that exogenous shocks can clarify each variable's forecast error variance to the other variables. The variance decomposition of the LP common component (Table 6A) and the variance decomposition of crude oil (Table 6B) show the price of crude oil, food index, and transportation indexes with a 10-month forecasting horizon. Where information on forecast horizon (period), standard error, and the percentage of future error variance due to shocks from crude oil prices, the LP common component, food index, and transportation index. In the decomposition of the LP common component, crude oil, food index, and transportation index, the citations are the second, fourth, seventh, and tenth months where the analysis concentrated on the second month.

From the decomposition of the LP common component, crude oil explains 0.066345% of changes in the said variable, while food index and transportation index describe 0.133670% and 0.023652% variability in the LP common component, respectively. Alternatively, the outcome of decomposition of crude oil described by the LP common component, food index, and transportation index are 5.149091%, 0.059282%, and 1.520127% in that order. These results show that the variation in LP common component is due to crude oil rather than the deviation in the food and transportation indexes. While for crude oil, the LP common component has the most significant effect, crude oil reacts less in the influence of food and transportation indexes [48].

Table 6A: *Variance decomposition of LP common component*

	Decomposition of LP common component		
	Crude oil	Food index	Transportation index
Second month	0.0663	0.1337	0.0237
Fourth month	0.8125	2.2509	0.5906
Seventh month	0.8404	2.557	0.5613
Tenth month	1.6853	3.0418	0.6291

Table 6B: *Variance decomposition of crude oil*

	Decomposition of crude oil		
	LP common component	Food index	Transportation index
Second month	5.1491	0.0593	1.5201
Fourth month	6.6274	1.3874	2.7832
Seventh month	7.6985	1.6110	3.7082
Tenth month	8.4864	1.7577	3.6728

5. Conclusion

This study measured the common component of monthly biofuel commodity prices such as coconut oil, maize, palm oil, rice, rapeseed oil, soybean oil, sugarcane, sunflower oil, and wheat using the LP common component for monthly data for periods of January 1994 up to May 2022. The relationship of the LP cumulated common component is also analyzed with the differenced price of Dubai Fateh crude oil in the world market and the Philippines CPI, particularly food and transportation. Furthermore, the impact of crude oil price on LP common component, food index, and transportation index was also established, which are of significant concern for policymakers.

In the regression analysis, the differences in the prices of sunflower, palm, and coconut oil are the most responsive to the LP common component having the highest slope coefficients. While the differences in the prices of sugar, rice, and wheat are the least responsive, having smaller slope coefficients. The outcome demonstrates that the LP common component justifies the difference in the prices of soybean oil, palm oil, and sunflower oil compared to the price of rice.

The derived LP common component has strong positive relationships to differenced biofuel commodities, while the LP cumulated common component has a very strong relationship. On the other hand, IRF revealed that a one-time shock on the LP common component positively affects the price of crude oil from the first month up to the third month.

From the decomposition of LP common component, crude oil explains 0.066345% of changes in the said variable, while food index and transportation index describe 0.133670% and 0.023652% variability in LP common component, respectively. Alternatively, the outcome of decomposition of crude oil described by the LP common component, food index, and transportation index are 5.149091%, 0.059282%, and 1.520127% in that order. The variation in the LP common component is directly to crude oil rather than the deviation in food and transportation indexes. For crude oil, the LP common component has the largest impact, whereas crude oil reacts less in food and transportation indexes.

Declaration of interest: None

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