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Regular Article

Food price resilience in Oman: A data-driven approach

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ABSTRACT

Oman relies heavily on food imports, making it particularly vulnerable to fluctuations in global markets and disruptions in supply chains. This study examines the resilience of food prices in Oman by analyzing the relationship between global and local food prices. Using monthly data from the FAO Food Price Index and Oman's consumer price index (CPI) for cereals, dairy, meat, sugar, and vegetable oils, we apply wavelet power analysis to explore both short-term and long-term connections between January 2013 and January 2024. The results show a strong positive relationship between global and Omani food prices, especially after 2020, with notable co-movement post-pandemic period. Among the food categories, cereals stand out with the strongest link, as local prices follow global trends. These findings highlight Oman's exposure to global price shocks and underline the need for policies that strengthen food security and build resilience against market volatility.

1. Introduction

The global food market has been marked by significant volatility over the past few decades. Climate shocks, geopolitical instabilities, and economic disruptions have posed persistent challenges for food security, particularly in countries that import food to meet domestic demand. Understanding the relationship between global and local food price dynamics has become increasingly critical for ensuring economic and social stability in such nations. Major events, such as the food crises of 2006–2008 and 2011–2012, have highlighted the fragility of global food supply chains and their susceptibility to shocks. These crises, fueled by rising demand, extreme weather events, and restrictive trade policies, led to sharp increases in the prices of staple foods such as wheat, rice, and maize. While some countries with robust domestic food production systems managed to buffer the impacts, nations reliant on imports faced severe consequences. The effects of these crises continue to shape the economic and food security landscapes of many countries, including Oman.

Oman is heavily dependent on imported food, with imports accounting for 14.8 % of the country's total imports in 2022 (NCSI). This reliance is driven by the country's limited capacity for domestic food production, constrained by arid land and scarce water resources (Al Abri et al., 2023). As a result, Oman's local food market remains highly sensitive to fluctuations in global food prices, which often translate directly into higher costs for consumers. The impact is especially pronounced for lower-income households, where food price spikes can significantly strain budgets and exacerbate socio-economic inequalities (Mohamed, 2014). Events in recent years further underscore the need for careful monitoring of food prices in Oman. The COVID-19 pandemic disrupted global supply chains through restrictions on movement, labor shortages, and logistical bottlenecks in shipping and storage. Also, the Russia-Ukraine conflict has driven up the prices of essential commodities like grains and vegetable oils, as these two countries are major exporters of these goods (Jagtap et al., 2022). These events have demonstrated how interconnected global food markets are, with local economies like Oman's bearing the brunt of such disruptions (Gulseven, Alhadi, & Salam, 2023), (Gulseven, Salam, & Alhadi, 2023).

The process through which global food price changes affect domestic markets is known as price transmission. This phenomenon varies across countries and commodities depending on factors such as government policies, supply chain efficiency, and market structures. Research indicates that price transmission is often asymmetric, with local prices responding more quickly to global price increases than decreases (Vavra & Goodwin, 2005). For Oman, where government intervention in domestic food production is limited, the direct impact of global price fluctuations on local markets is a critical issue that requires deeper investigation. While prior studies have explored price transmission and food price dynamics, limited attention has been given to Oman's unique challenges. Existing research has primarily focused on regions with more robust agricultural systems, leaving a gap in understanding for arid

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and import-dependent economies like Oman. Moreover, few studies have employed advanced analytical methods capable of capturing dynamic and multi-dimensional relationships between global and local food prices.

Recent literature emphasizes the importance of understanding how global agricultural market dynamics impact local food price stability, especially in food-importing countries vulnerable to international shocks. Study (Azam et al., 2020a) applied wavelet coherence methods to analyze vegetable oil markets, demonstrating significant price co-movement across global markets at multiple frequencies, highlighting how import-dependent nations could be impacted by these dynamics. Similarly (Jagtap et al., 2022), investigated the global food supply chain disruptions resulting from the Russia-Ukraine conflict, showing how geopolitical events quickly propagate through commodity markets, affecting food security globally. Also (Mastroeni et al., 2025), combined Rényi entropy with wavelet transforms to assess the influence of climate-related sentiment and equity markets on commodity prices, uncovering significant time-scale-dependent behavior in food price predictability. Another recent work by (Doroshenko et al., 2025) demonstrate the effectiveness of combining wavelet analysis with deep learning to predict commodity prices during periods of heightened economic and financial volatility. Their findings support the use of wavelet coherence in capturing complex, time-varying relationships in global food markets. Thus, wavelet analysis enables the simultaneous examination of short-term and long-term price dynamics, making it an ideal tool for this investigation (Crowley, 2005), (Ramsey & Zhang, 1997), (Almansour et al., 2024).

Despite this progress, evidence for arid and important dependent economies in the Gulf remains limited. While global–local food price transmission has been studied for major producers, limited research has examined arid, import-reliant economies such as Oman. This study applies wavelet coherence analysis to reveal time–frequency linkages that conventional econometric models overlook. Using wavelet analysis between global food prices and Omani food prices from January 2013 to January 2024, this research provides new insights into the resilience of Oman's food market to external shocks. Specifically, we analyze price transmission across cereals, dairy, oils, meat, and sugar prices. The findings from this study contributes to both academic literature and policy discussions by providing a detailed understanding of Oman's food price dynamics. By identifying the extent and nature of price transmission, this research offers actionable insights for policymakers to design strategies for specific timeframes to mitigate the impact of global food price volatility and strengthen food security in Oman.

2. Data and methods

In this research, we primarily use wavelet power analysis to determine the relationship between local food prices of the Sultanate of Oman and the global food price index. The data on world food prices is obtained from the FAO, which provides comprehensive data on global food prices for several food commodities and measures the monthly change in international prices of a basket of food commodities. This index is based on the average price of five commodity groups (meat, dairy, cereals, vegetable oils, and sugar) based on the average export shares of each group from 2014 to 2016. Data on local Omani food prices are obtained from the NCSI monthly reports based on the consumer price index of each food category. We use the wavelet package in R software to perform the quantitative analysis.

2.1. Data sources

The local food price data is collected from the NCSI. The data is then analyzed to determine trends in food prices over time. We used the food consumer price index (CPI) data from the NCSI as a proxy for the local Omani food prices, which calculates the average changes in the pricing of the products that producers make and sell. It is based on a basket of commodity products, the prices of which are gathered from different locations across the country. Based on data availability, we narrowed the scope of our analysis to essential food items aligned with the FAO index of food prices sub-indices. Cereals, dairy, edible oils, meat, and sugar were among the selected items. Using these specific items as a focus, the research attempts to analyze the trends and patterns in the prices of six staple food items between Oman and world food prices. Monthly data from January 2013 to January 2024 is collected to analyze time effect of global price changes on the local market. Table 1 shows the variables employed in the study along with brief descriptions and the sources.

Fig. 1 provides a combined boxplot for all FAO and Oman indices, which helps to identify the distribution, central tendency, and outliers for each category. The boxplot comparison shows that Oman's food price indices are more stable and less spread out than the FAO indices. Cereal and sugar price indices in Oman have narrow ranges and are close to their average values. Omani meat and dairy indices also show small changes over time. This means that food prices in Oman have been more consistent. The government may be using price controls or subsidies to keep prices steady. The FAO indices have larger spreads and more extreme values. Cereals and sugar, for example, show bigger changes and higher peaks. This reflects how global food prices react faster to events like droughts or wars. The smoother patterns in Oman suggest that the local prices are somewhat protected from outside shocks. This may be done through stable imports or food security policies. There are also possible delays in transmission mechanisms which we explore further using wavelet coherency analysis.

2.2. Wavelet coherency analysis

Wavelet analysis is an effective tool in various fields of study due to its ability to deal with the complexity of data that changes over time.

Table 1
Data variables.

	Variable	Description	source
1	Global food price index	A monthly indicator of the trend in global food commodity prices. Weights are based on the average export shares for each category. Data used from January 2013–January 2024	FAO
2	Global cereals price index	A combination of 10 quotations from the International Grains Council (IGC) that contains wheat, rice, and maze, weighted by export shares.	FAO
3	Global dairy price index	Includes butter, skimmed milk powder (SMP), whole milk powder (WMP), and cheese. Based on the world average export trade shares.	FAO
4	Global meat price index	Based on average export unit values and market prices for meat varieties, weighted by global average export trade shares.	FAO
5	Global sugar price index	Prices based on the international sugar agreement prices.	FAO
6	Global vegetable oil price index	It contains soybean, sunflower, rapeseed, groundnut, cottonseed, copra, palm kernel, palm, linseed, and castor oil prices. Based on the share of exports.	FAO
7	Oman food CPI	Calculates the average changes in the pricing of a basket of food commodities products. Data from January 2013–January 2024	NCSI
8	Oman cereal CPI	calculates the average changes in the pricing of bread and cereals.	NCSI
9	Oman dairy CPI	calculates the average changes in the pricing of dairy prices.	NCSI
10	Oman meat CPI	calculates the average changes in the pricing of meat.	NCSI
11	Oman sugar CPI	calculates the average changes in the pricing of sugar.	NCSI
12	Oman edible oil CPI	calculates the average changes in the pricing of edible oils.	NCSI

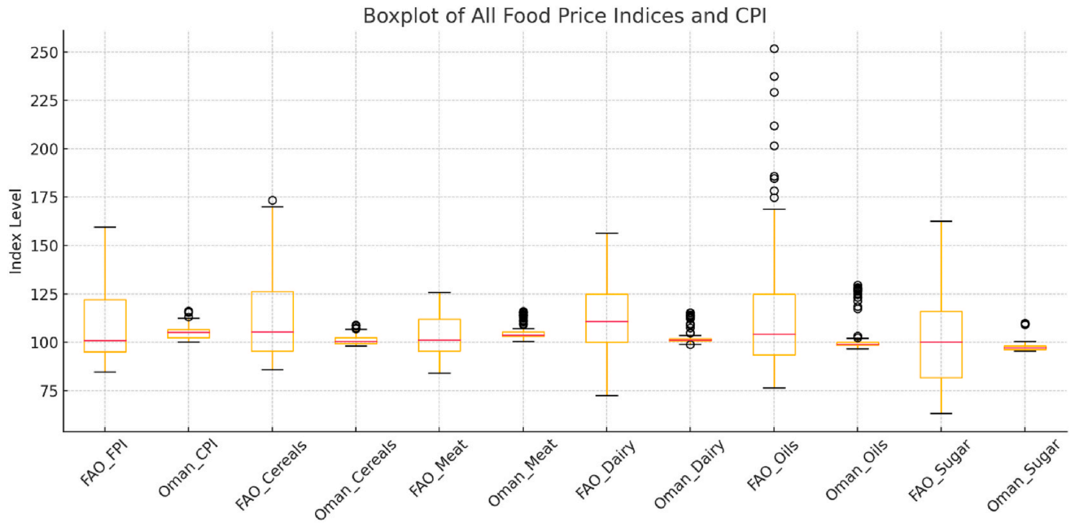

Fig. 1. Boxplot of all food price indices and CPI.

This technique can analyze both the time and frequency domain simultaneously (Fernández-Macho, 2012), (He & Nguyen, 2015), (Krüger, 2021). One of the most applied forms of wavelet-based analysis is wavelet coherence analysis (WCA) which is used for measuring the co-movement of two different variables in a time and frequency space. There are two types of wavelet analysis transforms, continuous wavelet transforms (CWT), and discrete wavelet transform (DWT). CWT is used to examine non-stationary signals, whose frequency and amplitude evolve over time. Meanwhile, DWT is a discrete version of CWT that is also used to determine the time-frequency signals. Compared with continuous wavelet transform (CWT), DWT provides superior computational efficiency due to the implementation methodology, since DWT relies on a filter bank approach whereas CWT requires numerical integration. Additionally, DWT exhibits a greater resilience to noise than CWT. Regarding accuracy, the CWT is preferred over other transforms when analyzing non-stationary signals because it can deliver enhanced precision when used with non-stationary signals. CWT does not require strict requirements regarding the sampling rate of the signal, providing greater accuracy for the analysis of non-stationary signals than the DWT. DWT analyzes time-series signals by decomposing them into discrete, non-overlapping frequency bands using orthogonal wavelet filters, providing compact representation and improved computational efficiency. DWT operates by decomposing signals into different frequency bands using orthogonal wavelet bases, which helps isolate and suppress noise components more effectively in lower frequency bands. In contrast, CWT produces a highly redundant and smoother representation, which, while better suited for analyzing non-stationary data, can be more sensitive to high-frequency noise. By simultaneously analyzing the time and frequency domains, wavelet theory overcomes time series and spectral analysis limitations. Wavelets can handle non-stationary data because of their scale and translation properties (Madaleno & Pinho, 2012).

The wavelet function is a square-integrable function with real values and zero average values. It exhibits an oscillatory motion as it traverses the t-axis, like that of a wave. This particular wavelet belongs to the Morlet wavelet family (Pal & Mitra, 2017), (Yi & Shu, 2012) which is as follows:

$$\varphi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-\frac{1}{2}t^2} \tag{1}$$

When wavelet analysis is applied to a constrained dataset over time, the Heisenberg uncertainty principle must be considered. According to this fundamental principle, it is not possible to identify both the temporal and spatial characteristics of patterns simultaneously and precisely in a dataset. As a result of Morlet wavelet's complexity, it can represent both time-dependent amplitudes and phases across a wide range of frequencies. The parameter governs the number of oscillations contained within the Gaussian envelope ω_0. The parameter ω_0 can be adjusted to achieve better or worse frequency resolution, allowing for flexibility in time-frequency analysis (Aguiar-Conraria et al., 2008), (Bouri et al., 2023), (Rua & Nunes, 2009). The $\pi^{-1/4}$ represents the wavelet's energy, also known as the central frequency and band. In addition, ω_0 is the parameter responsible for achieving an equilibrium between frequency and time localization. Morlet wavelet parameter ω_0, which represents the non-dimensional frequency and controls the trade-off between time and frequency resolution. Following standard practices in the literature we used the default value set in the wavelet comp package in R, which provides a good balance by ensuring the wavelet satisfies the admissibility condition while maintaining a compact time-frequency localization. The factor $e^{-\frac{1}{2}t^2}$ further defines the Gaussian envelope, which determines the characteristics of the wavelet and $e^{i\omega_0 t}$ represents the complexity of the wavelet analysis (Shaik et al., 2023).

The wavelet function consists of two parameters: (a), which denotes the time or location, and the scale (b), which is used as a control for the expansion of the wavelet. The higher the scale, the lower the wavelet, and this will result in lower frequencies and vice versa. The continuous wavelet transform (CWT) of a time series x(t) is defined as the convolution of x(t) with a scaled and translated version of a mother wavelet ψ:

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{|b|}} \varphi\left(\frac{t-a}{b}\right), a, b \epsilon R, b \neq 0. \tag{2}$$

(Torrence & Compo, 1998) suggested that CWT can be interpreted as a covariance for a specific scale and time. So, the squared wavelet coherence can be expressed as:

$$R^2(a,b) = \frac{\left\|S\left(b^{-1}W_{pq}(a,b)\right)\right\|^2}{S\left(b^{-1}W_p(a,b)^2 S\left(b^{-1}W_q(a,b)^2\right.\right.} \tag{3}$$

Where S is the smoothing operator for both the time and scale and the value of the wavelet coherence R^2 ranges from 0 to 1. The squared wavelet coherence R^2 takes values in the closed interval [0,1], where 0 indicates no local correlation and 1 indicates perfect local correlation between the two time series at scale s and time t. In equation (3), p and q represent the two time series under analysis, Specifically, p refers to the global food price index and q to the local (Omani) food price index. Also (Torrence & Compo, 1998) had introduced a function in order to differentiate the phase of the coherency of a two-time series, which is mathematically expressed as:

$$\theta_{x,y} = tan^{-1}\frac{I\{W_n^{xy}\}}{R\{W_n^{xy}\}}, \varphi_{x,y} \in (-\pi, \pi) \quad (4)$$

Where $\theta_{x,y}$ denotes the cross-wavelet transform between time series x and y. Thus, x and y as the two input time series (analogous to p and q in Equation (3), R and I are the real and imaginary parts of the smooth power spectrum. The wavelet phase differences are based on the values $\theta_{x,y}$ and it is between $(-\pi,\pi)$. So, the value of $\theta_{x,y}$ can determine whether the series is moving positively or negatively and which series is leading or lagging the other. The co-movement is represented in black arrows, with an arrow pointing rightward indicating positively correlated and in-phase movement. In contrast, the arrows pointed leftward mean the two-time series are negatively correlated and move in anti-phase. Moreover, the lead and lag relation between the two-time series can be indicated by the direction of the arrows as indicated by (Azam et al., 2020b), (Mastroeni et al., 2022). Here is the summary of the possible phase difference cases:

- If $\theta_{x,y} = 0$, the two series move together (in-phase/anti-phase), but there is no lead/lag relationship. Right/left-pointing arrow (⬅/➡).
- If $\theta_{x,y} \in \left(0, \frac{\pi}{2}\right]$, A positive co-movement is present between the two series (in-phase), with x leading y. So, the arrow will point up and to the right (↗).
- If $\theta_{x,y} \in \left(\frac{\pi}{2}, \pi\right]$, both series move in opposite directions (negative co-movement) with y leading x, and the arrow will point up and left (↖).
- If $\theta_{x,y} \in \left(-\frac{\pi}{2}, 0\right]$, There is a positive co-movement between the two series, with y leading x. In this case, the arrow will point down and right (↘).
- If $\theta_{x,y} \in \left(-\pi, -\frac{\pi}{2}\right]$, There is an out-of-phase (negative co-movement) between the two series, with x taking the lead over y. So, the arrow will point down and left (↙).

We implement the analysis in R using the *WaveletComp* package. Monthly data are indexed in equal time steps. For each pair we call *analyze.coherency()* and then plot the cross-wavelet power with *wc.image ()* and the time-averaged spectrum with *wc.avg()*. We use the Morlet mother wavelet with standard settings and apply Bartlett smoothing in the time and scale directions to stabilize the surfaces. Full R code is available on Appendix 1.

2.3. Study Framework

Fig. 2 below summarizes the steps involved in this study. We follow the methodology proposed by (Grinsted et al., 2004) in applying cross-wavelet transform and wavelet coherence, particularly in interpreting the phase relationships using directional arrows and identifying statistically significant zones through simulation. Their work forms the backbone of our time-frequency causality analysis.

Our approach is a systematic process, starting with data collection, preprocessing, and application of continuous wavelet transformation to both global and local price indices. Wavelet power analysis was then conducted to measure the strength and timing of relationships, identifying periods of significant alignment and lead-lag relationships. The results reveal which food categories exhibited the strongest co-movement and periods of heightened sensitivity to global price shocks. These findings provide a deeper understanding of how global price fluctuations affect local markets in Oman and serve as a foundation for policy recommendations aimed at enhancing food security and resilience to external shocks.

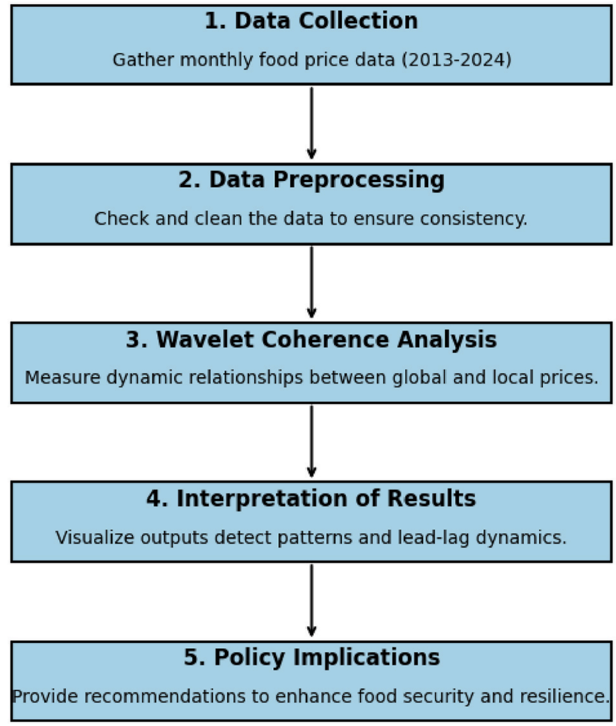

Fig. 2. Study framework.

3. Results and discussion

3.1. Visual analysis of trends

Fig. 3a, b, 3c, 3d, 3e, and 3f visualize the pairwise relationships between different essential food commodities over time. Both global and Oman prices show gradual trends with periods of noticeable fluctuations. Obviously, the FAO food prices exhibit higher variability compared to the more stable Oman CPI. In cereals, strong global fluctuations are observed with less pronounced local changes. For meat global and local indices appear more aligned with similar patterns albeit more stable Omani prices. For dairy FAO prices show larger variability, while local prices remain steady. Similarly, for cooking oils, we observe significant global variability with sharp peaks, but local prices show milder trends. Finally for sugar, both global and local prices display trends, but global prices show more fluctuations.

Global food prices exhibit sharp fluctuations driven by agricultural output, climate impacts, and export restrictions in major producing countries. Peaks in the global index often align with periods of drought or trade bans, causing significant variability. From 2013 to mid-2014, the FAO food price index experienced a decline due to higher production and harvest. FAO's food price index continued its downward trend, declining by 2015. This brought an end to the high cost of food worldwide, with the index reaching its lowest value in 2016 due to lower demand and excess global cereal output. When the COVID-19 pandemic emerged in early 2020, the FAO food price index initially experienced a sharp decline in prices due to COVID-19 containment measures. Following this decline, the FAO food price index rose sharply between mid-2020 and 2022, reaching its highest value since 2013. Several factors have contributed to this surge in food prices, such as the impact of the COVID-19 epidemic on supply chains, the Russia and Ukraine war and sanctions imposed on Russia, the recovery of world activities and demand after the COVID recession as well as the export bans and restriction measures (OECD, 2023).

Oman's food prices are relatively stable with smaller peaks and troughs, likely due to local price controls, government interventions, or reliance on long-term import agreements. This suggests that while

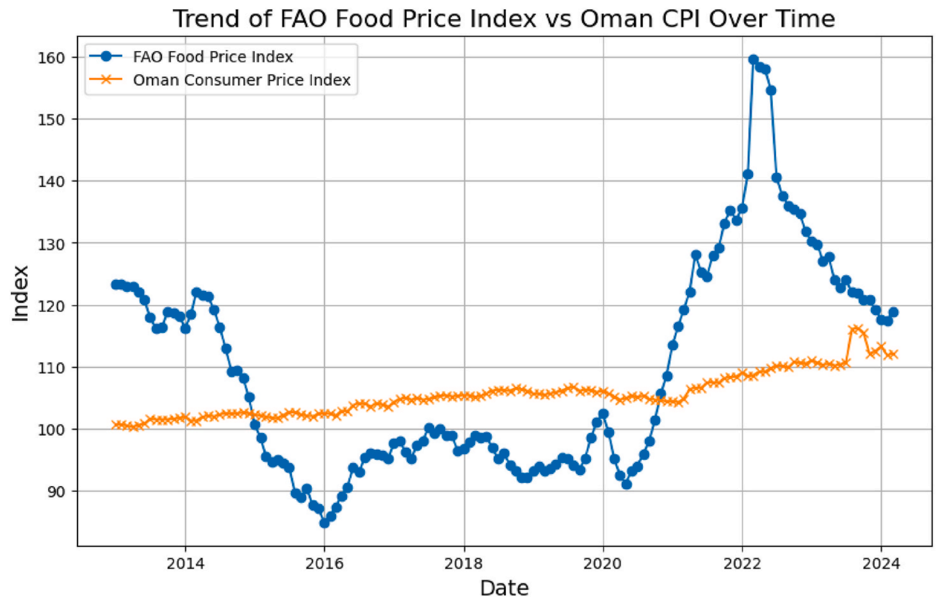

Fig. 3a. FAO vs Oman food price indices over time.

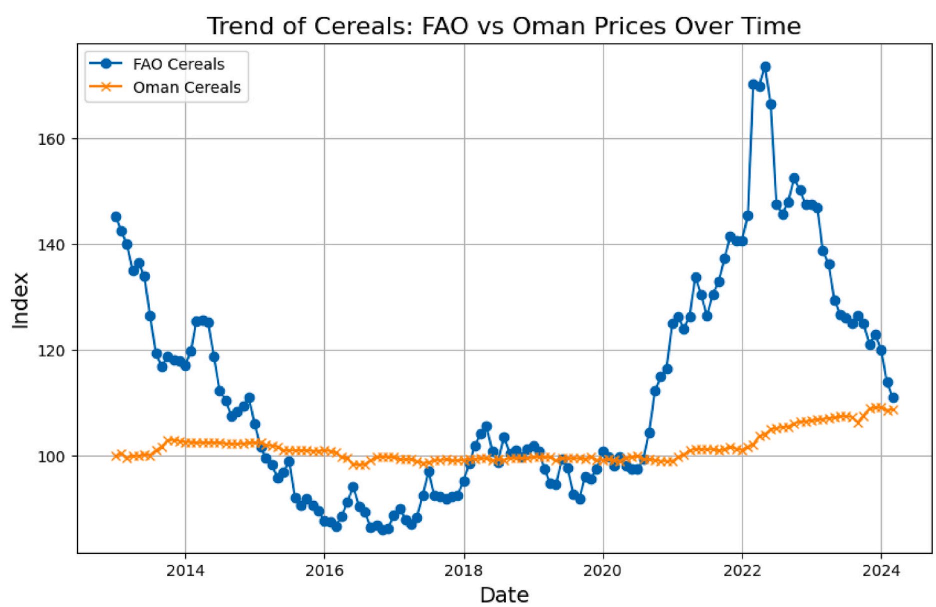

Fig. 3b. FAO vs Oman cereal price indices over time.

Oman's food prices are partially influenced by global trends, the responses are delayed or dampened, reflecting efforts to shield the local market from volatility. The most remarkable increase in the Omani food consumer price index was observed in 2021 and peaked in 2023. The increase in Omani food inflation prices could be explained by implementing Value Added Tax (VAT), reduction of water and electricity subsidies, and modest capital expenditure cuts (BTI, 2024 Oman Country Report, 2024).

Fig. 3b shows the contrasting trends in the CPI of Oman cereals and the FAO cereal price index evolution from 2013 to 2024. The FAO cereals price index has fluctuated widely and dropped dramatically from 2013 to 2016. Production volatility in major cereal-exporting countries, contributed significantly to stock replenishment. FAO cereals prices index started to increase and recovered gradually between 2017 and early 2019 due to higher energy costs. Particularly from mid-2020 to mid-2022, the global cereal price index increased sharply. The Russian-Ukraine conflict and its impact on the global market as these two countries are major wheat exporters and increasing demand worldwide boosted prices. Nevertheless, global cereal prices declined significantly from their peak after the Black Sea Grain Initiative and improved production.

On the other hand, Oman's CPI for cereals in Fig. 3 showed relatively stable changes from 2013 to 2021, compared to the sharp swings in the international cereals market. This is possible due to government interventions and mitigating solutions, such as strategic subsidies and caps on selected food items, particularly wheat, flour, and fuel. The exchange rate peg to the strong US dollar also helped shield Oman's domestic consumers from the unpredictable fluctuations in global prices. However, from 2021 onwards, Oman's cereal prices have increased gradually and peaked by the end of 2023. This can be explained by a variety of factors, including the implementation of the VAT taxes in April 2021, rising international food prices, and the fall in oil prices, and the disruptions of global supply chains.

The global meat index (FAO_Meat) shows a gradual upward trend

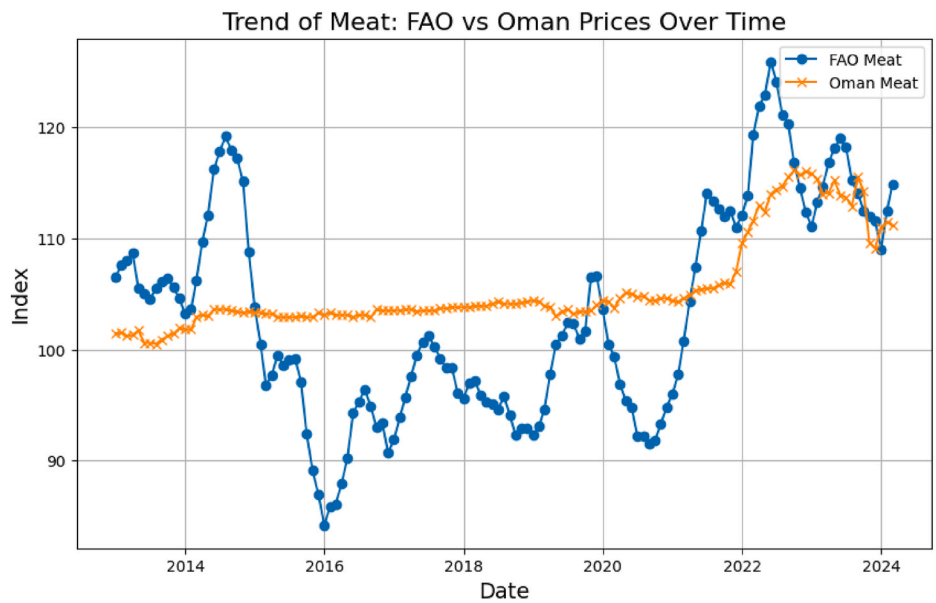

Fig. 3c. FAO vs Oman meat price indices over time.

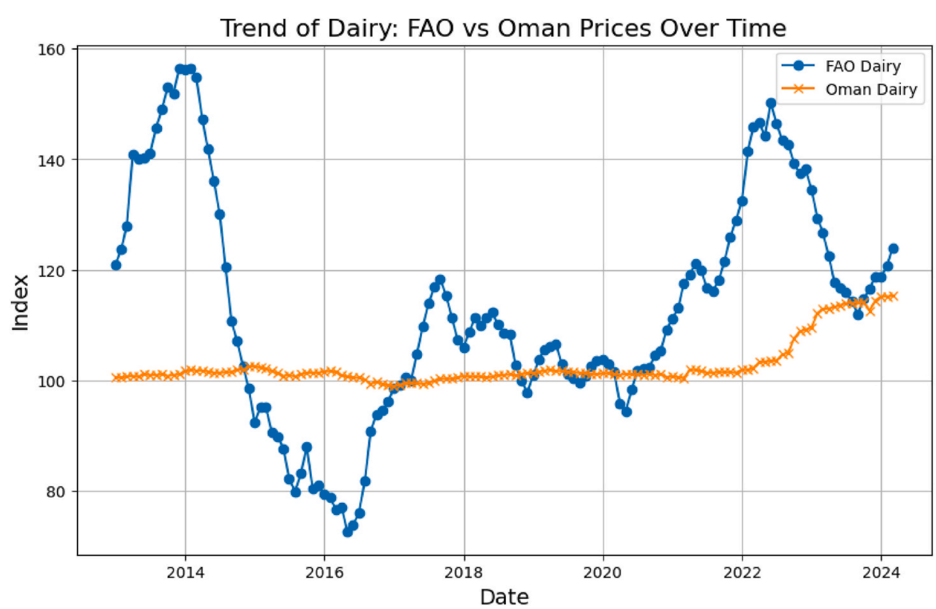

Fig. 3d. FAO vs Oman dairy price indices over time.

with occasional dips, reflecting rising global demand, supply chain constraints, and cost fluctuations. Events like disease outbreaks (e.g., African swine fever) create temporary global price spikes. Overall, the world meat price index (FAO) exhibits extreme volatility, with intense highs and lows, whereas the Omani meat price index shows moderate fluctuation with increases. FAO meat prices initially experienced a dramatic increase between 2013 and 2014 but then declined gradually in early 2015 and reached the lowest in 2016 as a reflection of lower demand from developing countries (FAO, 2024), (Mead et al., 2020). Since 2017, the world meat price index has fluctuated, reaching a high in 2017 and a low in mid-2020. However, a significant increase in world meat prices began in early 2021, followed by a surge to the peak in mid-2022. Several factors contributed to the sharp price increase, including limited export availability from major exporting nations due to challenging production environments such as higher input costs. Also, the war in Ukraine impacted meat exports and made the meat market even more volatile (FAO, 2022a). Despite this historical surge, meat prices have dropped due to decreased demand, improved supply chain stability, falling feed costs, and increased production (OECD, 2023).

Conversely, the meat CPI in Oman demonstrated minimal fluctuations, with a slight increase during the same period from 2013 to 2021 (see Fig. 6). From 2022 onwards, there was a noticeable sharp rise in Omani meat prices, which peaked in 2023, indicating overall price increases for meat. The introduction of VAT has contributed significantly to this price increase and economic recovery after the pandemic. Add to this the external factors such as supply chain disturbances caused by the Russian-Ukraine conflict and COVID-19 measures and the rise in global prices for food and energy (Alrahbi).

Fig. 3d shows Oman's dairy CPI and the World Dairy Price Index (FAO). Between 2013 and 2024, the FAO dairy price index and the Oman dairy price index differed markedly. Global dairy prices fluctuate frequently during the analysis period with considerable variation, while the consumer price index for Oman's dairy has remained relatively steady with slight increases. First, from 2013 to 2014, the world dairy

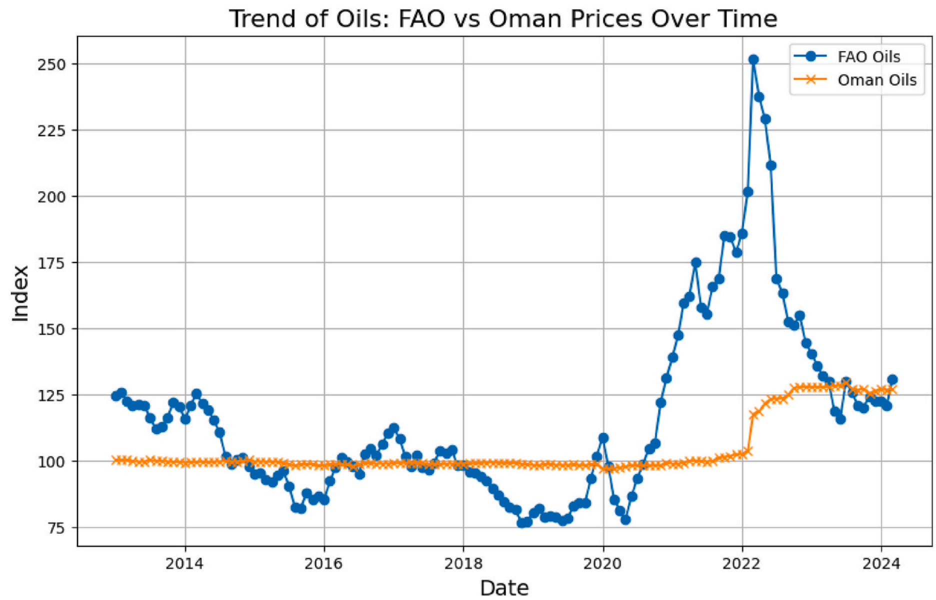

Fig. 3e. FAO vs Oman cooking oil price indices over time.

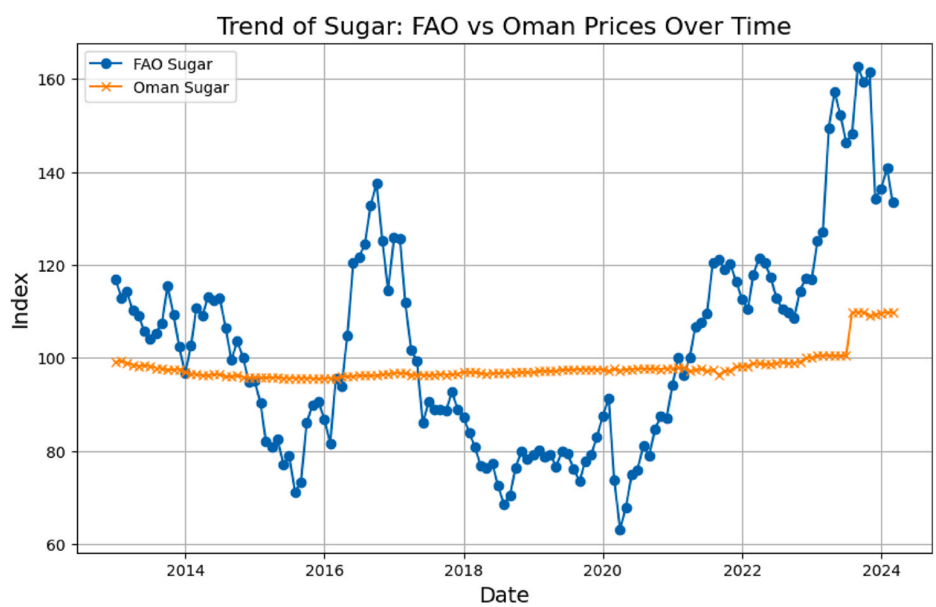

Fig. 3f. FAO vs Oman sugar price indices over time.

price index increased sharply, reaching its highest point in 2014. Despite this surge, the world dairy index declined at the end of 2014. It reached its lowest point around the beginning of 2016 owing to a decrease in Russian and Chinese imports, resulting in an export surplus and removing the milk quota scheme from the EU. Thereafter, global dairy prices increased again from 2016 and peaked in 2017 before declining and fluctuating from 2018 to early 2020. From mid-2020 to early 2023, the world dairy index increased significantly, reaching levels like early 2014.

In contrast, the CPI for dairy in Oman has shown a relatively stable pattern with steady increases from 2013 to 2021, implying that Omani dairy prices are less vulnerable to global market changes. This can be the outcome of specific regulatory actions and peculiarities by the government in the domestic market, such as maintaining powder milk stock, or it might also reflect consumers preferences for lower priced milk (Gulseven & Wohlgenant, 2017). After the pandemic price transmission from the international market to the Omani dairy market has become highly visible, as Oman is an importer of milk (Mbaga, 2013). On the other hand, at the domestic level, a major factor for the increase in Oman's consumer price index for dairy is the application of the value-added tax (Central Bank Of Omana).

Global vegetable oil prices are volatile, with extreme peaks driven by geopolitical conflicts and supply chain disruptions in major regions. Fig. 3e shows a highly dynamic pattern, with variations and upward trends throughout the period. The prices fluctuated moderately between 2013 and 2014, after which they declined and reached a low point in 2015, driven by higher production. Due to COVID-19 and its restrictive measures that impacted the supply chain, vegetable oil prices dropped dramatically in early 2020. A significant surge in global vegetable oil prices occurred in 2022, with prices hitting all-time highs due to the war between the Russian Federation and Ukraine, which are major exporters of sunflower oils (OECD, 2020).

However, the CPI for Oman oils display remarkable stability, with only slight variations across the period from 2013 to 2021. This stability suggests government measures such as subsidies, strategic reserves, or diversified import strategies to mitigate the effects of global price shocks, given the importance of edible oils in household consumption. Government interventions have stabilized local food prices during this period (Central Bank Of Omanb).

Global sugar prices exhibit moderate fluctuations due to factors such as crop yields in key regions. Prices dropped to their lowest point in 2015 due to a worldwide surplus in production combined with the depreciation of the Brazilian real. Nonetheless, the sugar price rose sharply towards the end of 2023, reaching a peak mainly due to lower production output from major exporting countries. This rise was also fueled by growing demand and restricted exports. Following a significant upsurge in 2023, prices began to decline by 2024 as the production of sugar increased in Brazil, but it remained relatively higher than the pre-pandemic level (OECD, 2023), (FAO, 2022b).

Oman's sugar prices on the other hand, display much smaller variations and steadier trends. This stability reflects strategic reserves or controlled import pricing mechanisms, which insulate the local market from global price shocks. While local sugar prices show some correlation with global trends, they remain relatively unaffected by extreme global market dynamics.

3.2. Correlation analysis

The heatmap provided in Fig. 4 visualizes the correlation between global and Omani food prices. The heatmap illustrates the correlation matrix between global (FAO) and local (Oman) price indices for food commodities, highlighting relationships that range from strong positive to weak correlations. A color gradient from blue (low correlation) to red (high correlation) visually represents these relationships.

The FAO Food Price Index shows strong correlations with global indices such as cereals (0.96), oils (0.91), and meat (0.86), indicating that these commodities significantly contribute to overall global food price trends. However, its correlation with Oman's Consumer Price Index is moderate (0.45), suggesting that global food price movements moderately influence the broader inflation trends in Oman.

The Oman Consumer Price Index on the other hand, is highly correlated with local indices for cereals (0.64), meat (0.87), dairy (0.77), oils (0.81), and sugar (0.74). Local prices are highly correlated with Oman's CPI, demonstrating their significant contribution to consumer price trends in Oman.

There is a moderate relationship between Oman's food prices and global food price indices. Cereals exhibit a moderate correlation between global and local indices (0.57), reflecting some influence of global prices on Oman's cereal prices. However, the relationship is likely stabilized by local interventions such as subsidies or controlled imports. Similarly, meat prices show a moderate correlation (0.62) between global and local indices, indicating Oman's reliance on meat imports. Dairy prices exhibit a weak correlation (0.41) between global and local indices, suggesting that Oman's dairy prices are less influenced by global trends, likely due to domestic production or import stabilization measures. Despite this, dairy prices moderately correlate with Oman's CPI (0.77), reflecting their importance in local household consumption. In contrast, vegetable oil prices show a moderate global-to-local correlation (0.62), indicating partial transmission of global edible oil price shocks to local markets. Finally, sugar displays the weakest global-to-local price correlation (0.36), indicating limited local impact from global sugar price fluctuations.

Overall, the correlation analysis reveals that while some commodities such as meat and oils show strong connections between global and local prices. Some other food commodities like dairy and sugar appear more insulated, likely due to local production or strategic interventions. These insights underscore the importance of commodity-specific policies in managing inflation and price stability in Oman. However, these correlations are averages over time. These are static numbers which might simply reflect the global food inflation trend. To have a better understanding of the time-varying dynamic relationships between global and local prices, further analysis is needed.

3.3. Wavelet analysis

This study examines the relationship between Omani CPI prices and

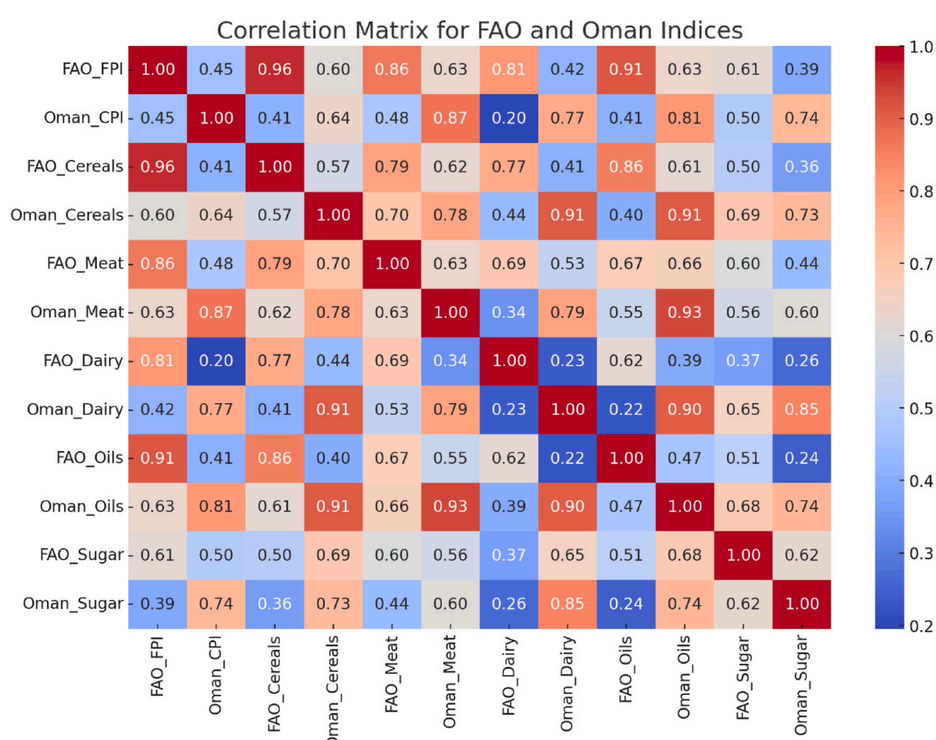

Fig. 4. Correlation between FAO vs Oman food price indices.

the world food price index with its subcategories, including cereals, vegetable oils, dairy products, sugar, and meat, to analyze how they move together. We also utilize wavelet power plots to measure the relationship between these variable pairs within the time and frequency sphere. The wavelet cross wavelet power plots in Figs. 5–10 show how each pair of the Omani consumer price index interacts with that of the world food price indices (FAO) for cereals, dairy products, vegetable oils, sugar, and meat. The color indicates the intensity of the relationship, with warmer (red) colors indicating a greater absolute relationship. A thick black line indicates the significance of this relationship at a level of 5 %, and the arrows in the figure indicate the direction of the phase relationship.

The vertical axis represents the frequency or period of the price relationship under consideration, while the horizontal axis represents the time dimension. A strong relationship is represented by warmer colors (red), while a weak relationship is represented by cooler colors (blue). Identified relationships that are significant at the 5 % level were determined using a Monte Carlo simulation and are marked by white contour lines. The lead or lags are indicated by arrows where arrows pointing right (left), and red colored (blue) indicate perfectly positive (negative) relationships without any evident lead or lag relationship. The "cone of influence" (COI) is shown in the figures as white regions, which are less reliable to interpret. COI marks the region where edge effects distort the reliability of the wavelet transforms. As a result, interpretations outside the COI are not statistically reliable and should be treated with caution. Consistent with (Grinsted et al., 2004), we disregard areas outside the cone of influence due to edge effects, ensuring robust interpretation of significant co-movement regions.

Inference in the wavelet framework is based on Monte Carlo simulation rather than on conventional regression p values. A scale representing the degree of relationship is represented by the asterisk where high relationship is denoted by red and a low relationship by blue. The wavelet power plots between every two variables are shown in the graph as (graph a) whereas (graph b) displays the average cross wavelet power plots between the two variables. The 0.05 and 0.1 thresholds were derived using Monte Carlo simulations built into the WaveletComp package, which evaluates the null hypothesis of no relationship. Thus, the 0.05 and 0.1 levels represent commonly used confidence intervals (95 % and 90 %) and help identify which power regions are statistically significant. Confidence intervals and effect sizes in the regression sense are not directly applicable to the time–frequency surface because dependence varies jointly over time and period. As a compact summary, we report time averaged spectra and highlight the frequency bands where joint variability is most pronounced.

The cross-wavelet power plots and the phase difference between the world food price index and the Omani food CPI are depicted in Fig. 5. As seen in the graph, the relationship between the two variables has changed in both frequency and time. From 2013 to 2020, the two indices had no significant short-term or medium-term relationship. However, the trend from 2020 to 2023 shows a higher relationship between Oman CPI and the world food price index as the wavelet coherence is high (red color) in two different frequencies. The first is in high frequencies during the 2–4 period cycle, indicating a short-run relationship. The second high long-term relationship is exhibited in the low frequencies (8–16 period).

The findings suggest a strong connectedness between global and Omani food prices at the end of the study period from mid-2020 to 2024. As the arrows are pointing to the left, this means that the Omani consumer price index is negatively related to world food prices. One possible explanation for these changes in the relationship is the recent government reforms which affected the domestic prices more than the global prices. The government has taken several measures to shield the local prices from the changes in global market prices.

However, this relationship has undergone some changes during and after the pandemic. Before 2020, these indices had no significant short-term or medium-term relationship. After the pandemic from 2020 onwards, the relationship between these two indices became highly visible even in the short term, starting within a few months. Therefore, the results imply that global food influences Omani food prices between 2020 and 2024. A key point of this analysis (2020–2024) is that it encompasses the COVID-19 pandemic and the Russian invasion of Ukraine, which led to increasing global oil and food prices, supply chain disruptions, and tighter labor markets, worsening the economic situation globally. So, Oman is heavily dependent on food imports from other regions of the world, putting it at risk in the event of a temporary disruption to global food exports. Also, at the domestic level, several factors have contributed to this relationship, such as the implementation of VAT, subsidies, and administrative fees, as well as the fiscal and strategic reforms taken by the country towards the 2040 vision. As shown in Fig. 5b, the average cross-wavelet power analysis also confirms our results, where the long-term relationship between the world food price index (FAO) and Oman CPI is more visible and significant.

The wavelet relationship between the world vegetable oil prices index and the Omani consumer price for edible oil is shown in Fig. 6 (a–b). Interestingly, the relationship between world vegetable oil prices and Omani CPI for oil is shown to be limited to specific times. It appears that these two variables are highly related at nearly all frequencies between 2020 and 2024, but there does not appear to be any reliance between 2013 and the latter years.

In the figure we observe a red island which reflects a high degree of relationship between the World Oil Prices Index (FAO) and the Omani CPI for oils during the period from 2020 to the end of 2022. The cross-wavelet power between the two indices is high to moderate across the low-frequency band for this period. A strong co-movement is exhibited almost in all periods, ranging from high frequencies at the 4–8 period scales and the 8–16 period scales to low-frequency bands 32–64, demonstrating that the world oil price index and Oman CPI for edible oils have a strong relationship over the short- and long-term horizons.

Furthermore, during the same period from 2021 onwards, a moderate cross wavelet power was identified in the 32–64 low-frequency band and long-run horizons. In this frequency band, a distinct trend in the relationship was noticed between the two variables as indicated by the arrow's direction, which shows that both variables are in anti-phase, with world vegetable oil price index is lagging, as evidenced by their arrows pointing left and up. Thus, as seen in the cross-wavelet power plot in Fig. 6a, the relationship between local and global vegetable oil prices has been very significant in recent years of the analysis at all frequency scales. The average cross-wavelet power graph in Fig. 6b is consistent with the results of wavelet analysis which shows that there is a strong short-to-long-term relationship between global and local Omani edible oil prices from 2020 to 2024.

Fig. 7a shows the cross wavelet power between the world dairy

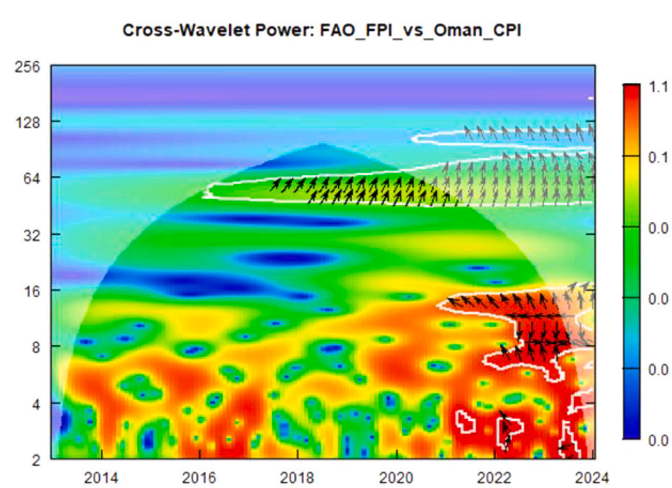

Fig. 5a. Cross-Wavelet Power between FAO and Oman food price indices.

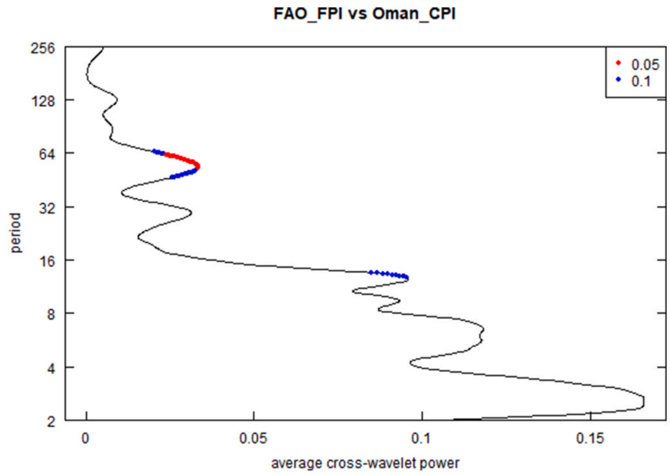

Fig. 5b. Average cross-wavelet power between FAO and Oman food price indices.

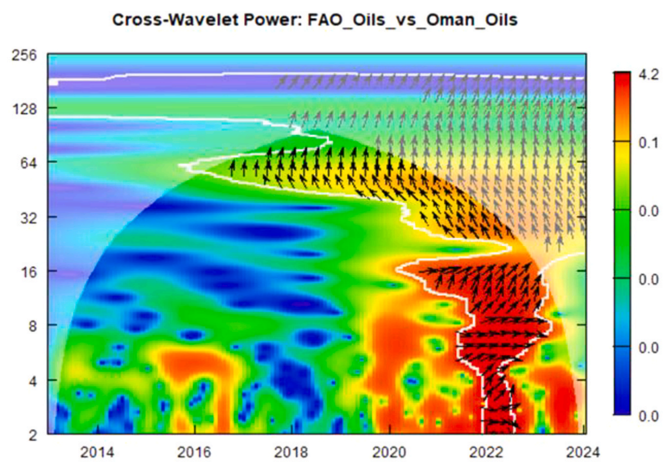

Fig. 6a. Cross-wavelet power between the FAO oil price index and Oman's oil CPI.

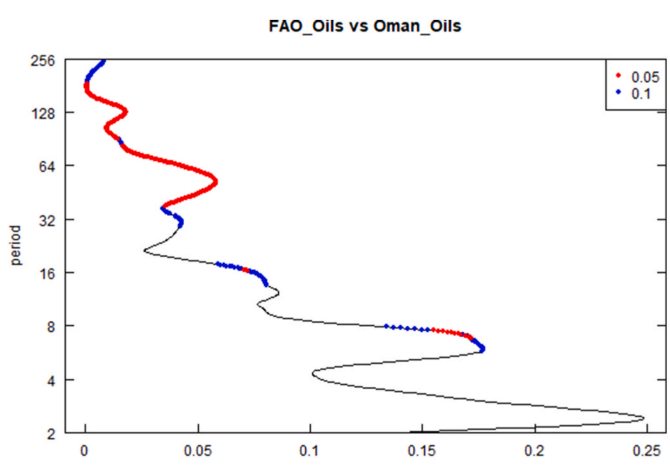

Fig. 6b. Average cross wavelet power between the FAO Oil Price Index and Oman's Oil CPI.

prices (FAO) and Oman's dairy consumer price index. A considerable relationship was identified between the global dairy price index and the Omani dairy products consumer price index between 2016 and 2024 in

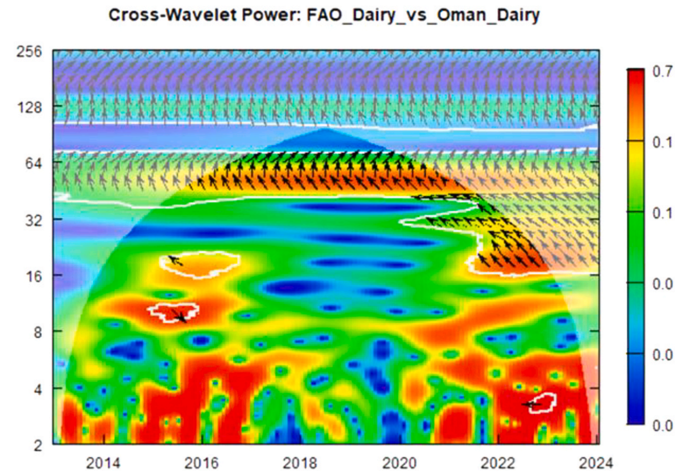

Fig. 7a. Cross-wavelet power between the FAO dairy price index and Oman's dairy CPI.

higher wavelet scales 32–64 and 16–32. The relationship between world dairy and Oman dairy prices has been mostly restricted to the long-term, where we do not observe any significant short-term relationship, and the nature of this connection is ambiguous, as reflected by the phase difference of the arrows throughout the period of the analysis. This is possible because of the large domestic dairy industry that could buffer the short-term effects of global price changes in Oman. Similarly, the average cross-wavelet power graph depicted in Fig. 7b confirms that there is no strong, continuous relationship throughout the entire period; nevertheless, there is an indication of a long-term relationship at the low frequencies in 32–64 periods of months, which is in the long-run horizons.

The wavelet power between global cereal prices and the CPI of cereals in Oman, as illustrated in Fig. 8a, was found to exhibit a significant and strong long-term association between the price of cereals in the world and Oman, specifically from 2014 to the middle of 2015, 2016 to the middle of 2018, and 2020 to 2024 at the 8–16 period, with subsequent alternating periods of lead-lag relationships.

The arrows corresponding to the period from 2014 to the middle of 2015 point down and to the left, indicating that the world cereal prices and the CPI for cereals in Oman are moving in opposite directions (out of phase) and negatively correlated with the world cereal prices as a lagged variable. However, the opposite form of the relationship was shown between the two variables during the period from 2016 to 2017 at the

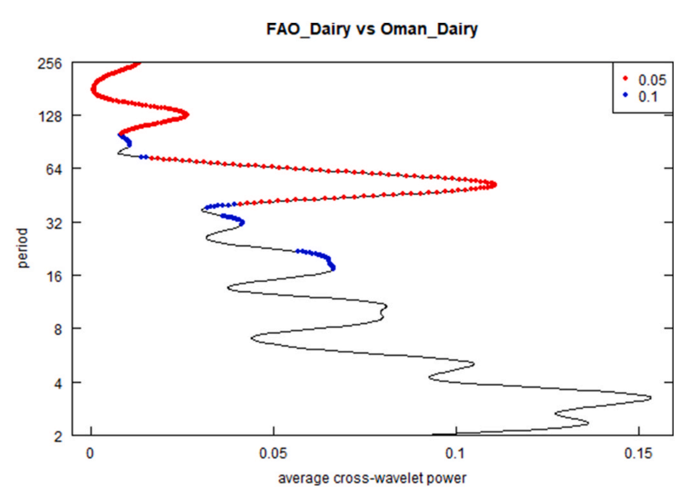

Fig. 7b. Average Cross wavelet power between the FAO Dairy Price Index and Oman's Dairy CPI.

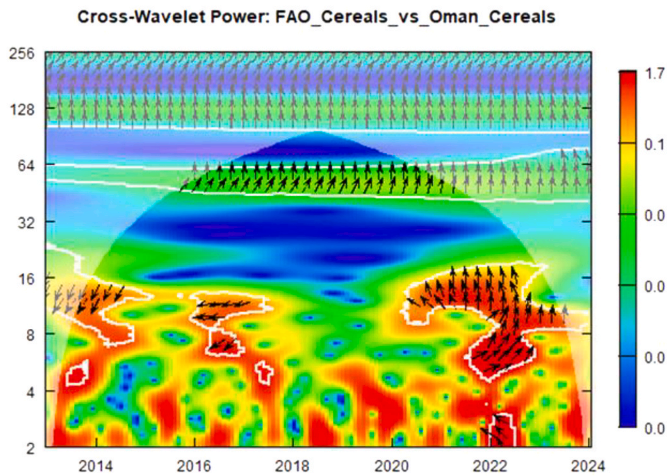

Fig. 8a. Cross-Wavelet Power between the FAO Cereals Price index and Oman's CPI for Cereals.

long-term frequencies cycle 8–16; the arrows are pointing to the left, which means that the two variables are out of phase and are negatively correlated with no evidence of led/lag relation. We observe that the price of Omani cereals and the world cereal price index have strong relationship between 2020 and 2024, particularly within the 2–4 and 8–16 period of frequency (months), respectively. Both two series are moving together in the same direction as the arrows are pointing up and to the right, .

The world cereals price index was statistically significant with the Omani consumer price index for cereals at the higher wavelet scale 8–16 as depicted in Fig. 8b. In addition, the plot gives more information on the strength of the relationship between the two variables, that are highly significant at higher frequency scales from 8 to 16, 32–64, and 64–128 respectively, indicating a long-term relationship between the indices. Overall, the findings suggest a strong long-term relationship between global and local prices, where Omani cereal prices follow global cereal prices. A noteworthy observation is that after the pandemic, this relationship has been even extended to shorter-term periods as low as 2–4 months, indicating that global cereal price changes are transmitted to Omani domestic cereal prices with a lag regardless of the different measures taken by the government to lower the volatility of prices.

Fig. 9a demonstrates the relationship between global meat prices and the Omani meat consumer price index. From 2016 to mid-2018, there was no relationship between global meat prices and Omani meat prices.

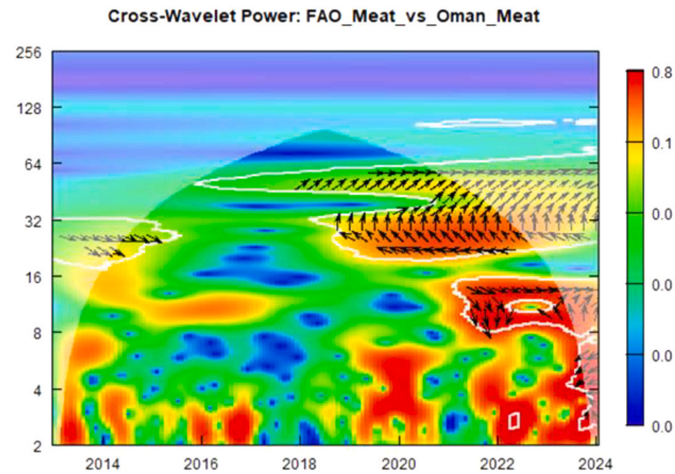

Fig. 9a. Cross-wavelet power between the FAO meat price index and Oman's CPI for meat.

However, from 2019 to 2024, the wavelet coherency between the two variables increased with a strong relationship at three different scales: 2–4, 8–16, and 16–64. During the period from 2019 to 2022, a long-term negative and strong relationship was found between global meat prices and the Omani meat consumer price index at the frequencies of scale between 16 and 32. Therefore, this implies that global meat prices co-move with Omani meat prices in the long run but with delays, mainly due to the government intervention in the food market in the country.

Considering the phase difference between the variables we found an unclear causality or led-lag relationship between the two indices throughout this period at long-term frequencies (16–32) based on the arrow orientation and whether world meat prices lead the Omani CPI for meat or vice versa. However, from mid-2021 to 2024, a statistically significant relationship and positive co-movement were observed between the two indices at the medium-term periods scale from 8 to 16. Before the pandemic, there was no relationship between the world meat price index and the Omani CPI for meat. However, a considerable rise in coherence was seen at timescales of 16–32 months in the relationship of global and local meat price movements in mid-2019 and has been extended to the short and long term after the pandemic 2020 onwards. Given the food price situation at the time, this finding raises the possibility of a contagion effect of the global shocks on food prices.

Along with the wavelet analysis, Fig. 9b shows the average cross-wavelet power graph that specifies how strong the relationship is.

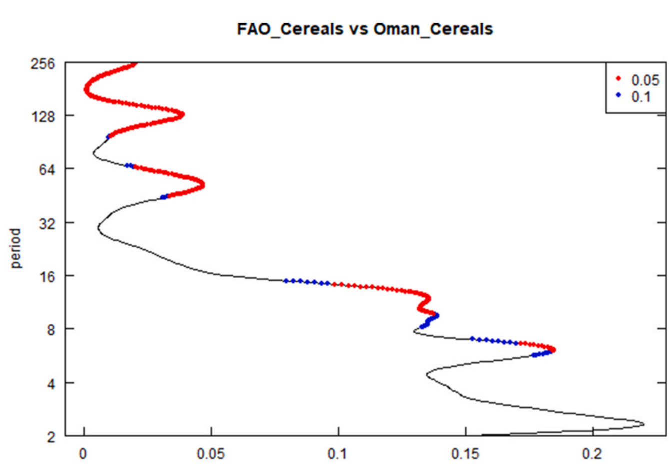

Fig. 8b. Average Cross wavelet power between the FAO Cereals Price index and Oman's CPI for Cereals.

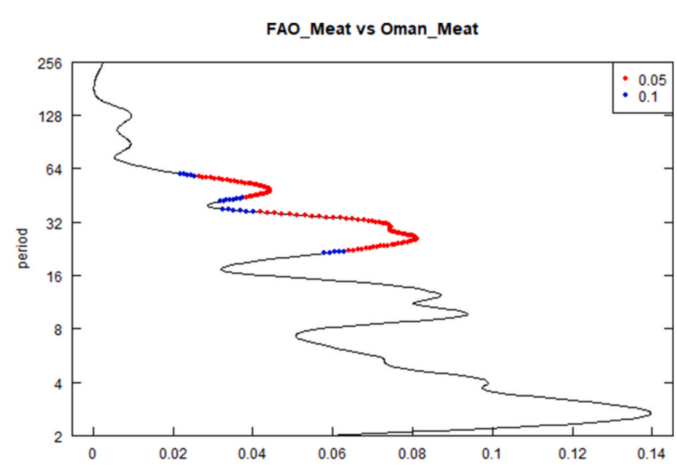

Fig. 9b. Average Cross wavelet power between the FAO Meat Price Index and Oman's CPI for Meat.

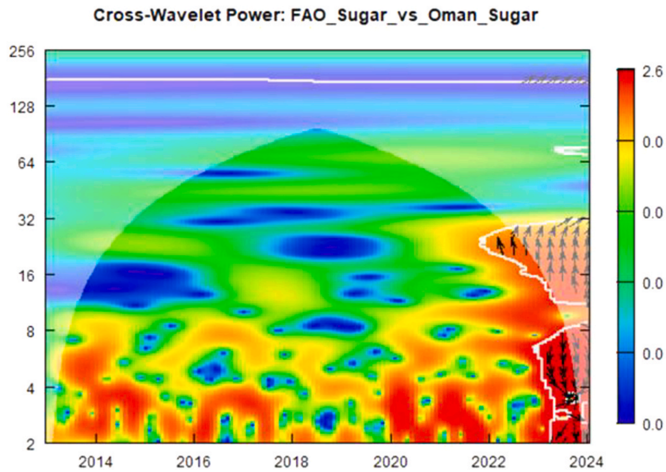

Fig. 10a. Cross-wavelet power between the FAO sugar price index and Oman's CPI for sugar.

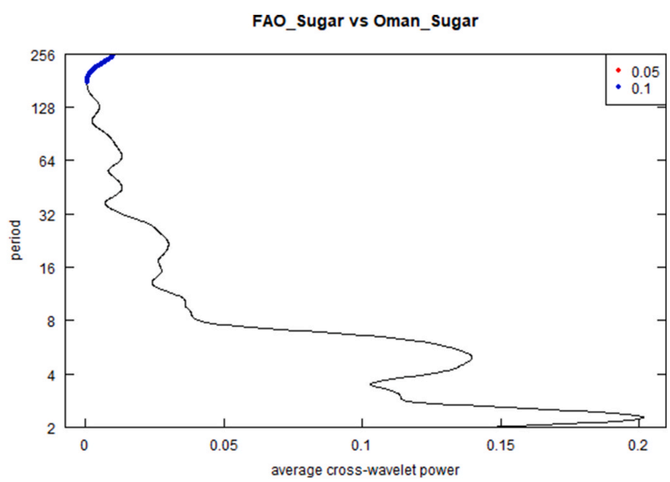

Fig. 10b. Average Cross wavelet power between the FAO Sugar Prices and Oman's CPI for Sugar.

There appears to be a similar pattern in both analyses in this case: a general lack of relationship over most time frames except in 2019–2024 at higher wavelet scales of 16–32 months. Therefore, there is a significant and inconsistent relationship between the world meat price index and the Oman CPI for meat, as confirmed by the findings in this study during the period from 2019 to 2024 at all frequencies from high to low scales.

Fig. 10a displays the relationship between sugar prices worldwide and the Omani consumer price index for sugar. Throughout the analysis period, the world sugar prices and Omani CPI for sugar are not much related. Nevertheless, a very strong relationship exists between the prices of sugar in the world and Oman in 2022 and 2024 at the short frequency band from 2 to 8 periods of scale. Another strong red island was exhibited between 2022 and 2024 at the long frequency bands from 8 to 16, indicating a long-term relationship between the two indices with no clear led and lag relationship between world sugar prices and Omani sugar prices, as seen by the mixed direction of the arrows. Based on the wavelet analysis, the findings reveal that local sugar prices have been disconnected from global prices until 2022. However, the relationship for both local and global sugar prices increased simultaneously and exhibited a strong co-movement in short and long-term frequencies from 2022 to 2024.

4. Conclusion and recommendations

4.1. Conclusion

This study examined the dynamic relationship between global and Omani food prices using wavelet analysis, focusing on the co-movement and lead-lag relationships across key food commodities such as cereals, vegetable oils, and dairy products. The results summarized in Table 2 reveal a strong relationship between global and local food prices, particularly for cereals and vegetable oils, with global price fluctuations leading local price changes over both short-term and long-term periods. The findings confirm that Oman's reliance on food imports makes it vulnerable to global price shocks, especially during periods of crisis like the COVID-19 pandemic and the Russia-Ukraine conflict.

The visual analysis of global and Omani food prices from January 2013 to January 2024, shown in Fig. 3a–f, highlights a noticeable upward trend in both global and local food prices, after the global food crises and the start of the COVID-19 pandemic. As expected, global prices became more volatile during certain periods, particularly after 2020, due to supply chain disruptions, geopolitical conflicts, and events like the Russia-Ukraine war. While Omani food prices were generally more stable, they also saw significant increases, especially in key items like cereals and vegetable oils, which heavily rely on imports. This co-movement points to a strong connection between global price patterns and local market conditions.

Figs. 5–10 shows that global and Omani food prices, especially for cereals, vegetable oils, and dairy, move similarly. The red spots highlight the times when these prices are closely connected. These connections occur during significant events such as the COVID-19 pandemic and the Russia-Ukraine war, which have led issues with food production and exports. Cereals stand out the most, where global prices clearly influence Omani prices. This means that when global prices fluctuate, Omani prices follow, especially when there's significant instability. In the short term (1–12 months), global prices tend to affect Omani prices after about three months.

For vegetable oils, the lead-lag relationship is more noticeable over the medium term (12–24 months), where changes in global prices tend to influence Omani prices with about a 6-month delay. This lag might be due to Oman's dependence on imports and potential delays in the supply chain. On the other hand, the price connection for dairy products seems weaker, with less impact from global prices. This could be due to local production efforts or strategies to import dairy from different sources,

Table 2
Summary of Wavelet Comovement by Commodity (Oman vs FAO, 2013–2024).

Commodity	Strongest window(s) (years)	Co-movement intensity	Notes
Food CPI (total)	mid-2020–2024	High post-2020	Short- and long-run coherence appears only post-2020.
Cereals	2014–mid-2015; 2016–mid-2018; 2020–2024	High	Long-run significance at 8–16 and higher scales; post-2020 extends to 2–4.
Vegetable oils	2020–2024	High in 2020–2024	Near-all-frequencies coherence post-2020.
Dairy	2016–2024 (long-run)	Medium	Long-run relationship; little, short-run significance; heterogeneous phase.
Meat	2019–2024	Medium–High, but inconsistent	Long-run relationship observed, particularly after 2019
Sugar	2022–2024	Low overall; strong spikes 2022–2024	Weak or absent earlier; marked co-movement only in 2022–2024 windows.

which help mitigate the effects of global price fluctuations.

The wavelet analysis also highlights clear differences in how price transmission works in the short and long term. In the short term (1–12 months), global price changes have a quicker impact on local prices, especially for cereals and vegetable oils. These short-term shifts are likely driven by immediate reactions to supply chain issues, export restrictions, and other external factors. On the other hand, the long-term dynamics (12–64 months) show that local prices adjust more slowly, with global trends influencing Omani prices over extended periods. Cereals exhibited significant and sustained relationship with global prices, particularly after 2020, with values approaching thresholds. In contrast, for items like meat and dairy, the long-term impact of global prices is weaker, suggesting that local factors—like domestic production and government policies—play a bigger role in keeping prices stable over time.

4.2. Policy recommendations

The findings of this study are consistent with previous research on how global and local food markets are connected. For example, Belke & Awad (Belke & Awad, 2015) also found that changes in global prices for cereals and vegetable oils are passed on to local markets with some delay, especially during crises. However, this study goes further by using wavelet analysis to offer a deeper look at how these relationships change over time and at different frequencies. A key contribution is the identification of both short-term and long-term price trends, providing valuable insights into when and how price transmission happens.

The findings on the delayed impact of global vegetable oil prices on Omani markets align with earlier research on the link between oil prices and food prices. The slow response of local prices to global changes in vegetable oils suggests that challenges in logistics and import dependency could play a big role in how prices are transmitted in Oman (Kotagama et al., 2014). These results have important implications for policymakers in Oman. The strong connection and lead-lag relationship between global and local prices highlight the need for strategies to reduce the effects of global price shocks on domestic markets. For instance, policymakers could look at boosting domestic production of key commodities like cereals and vegetable oils, which would lower reliance on imports. They could also work on diversifying import sources and improving the efficiency of supply chains to protect the local market from global price swings. Promoting diversification and sustainable trade aligns with broader GCC efforts toward ecological resilience (Alhattali et al., 2025).

The wavelet analysis also highlighted that global price shocks are transmitted to Omani markets with a time lag, providing a window of opportunity for policymakers to implement stabilization measures. The lead-lag dynamics are especially significant for cereals, where global prices lead Omani prices by approximately 3 months, and for vegetable oils, where the lag extends to around 6 months. Because Oman depends food imports, policymakers should look for ways to reduce the impact of global price changes on the local market. This could mean increasing domestic production of essential foods, finding new import sources, and making supply chains more efficient. The government could also use targeted subsidies or stockpiling during global crises to keep prices stable. However, it is important not to rely too much on subsidies, as they can cause market problems and put strain on the government's budget. The results also highlight the importance of improved infrastructure and logistics to mitigate the impact of global prices on local markets. By improving supply chain efficiency, Oman can better manage global price changes and protect its food security.

Our findings also point to the importance of targeted actions during global crises. For cereals and vegetable oils, where the 8–16 month band dominates, policies should focus on diversifying import origins and expanding grain storage. Storage should cover three to six months of consumption with regular rotation. Logistics and cold chain systems need upgrades to cut delivery times and reduce losses. Contracting should include more indexed or forward-priced imports to stabilize costs. Short-term signals in the 2–4 month band call for temporary support to low-income households when food prices rise sharply. For dairy, long-term patterns justify investment in cold chain capacity and medium-term supply contracts. An early warning dashboard can help trigger timely procurement, storage, and consumer support decisions based on FAO price movements. Since Omani food prices tend to respond to global shocks with a delay, this gives the government a window to apply price stabilization measures, like subsidies or stockpiling, to help prevent sudden increases in local prices. However, as Kotagama & Boughanmi (Kotagama & Boughanmi, 2019) caution, it's important not to rely too much on subsidies, as they can put pressure on government finances and cause distortions in the market.

In the future, studies could explore other factors, like exchange rates and oil prices, and how they affect food prices in Oman. Examining at other Gulf countries could also provide a helpful comparison of food price trends in the region. The study focuses on time–frequency comovement and does not implement alternative econometric models for robustness. Future work could compare the present findings with cointegration based specifications or VAR frameworks, and could report impulse responses or forecast error variance decompositions to test whether the same commodity level conclusions emerge in the time domain. Incorporating behavioral drivers such as public sentiment and market expectations along the lines of (Mastroeni et al., 2025) could further enrich future food price resilience models, especially in settings exposed to climate uncertainty. Future research could also extend our analysis by incorporating machine learning frameworks alongside wavelet analysis, as illustrated in (Doroshenko et al., 2025) to enhance predictive accuracy and detect nonlinear dependencies in food price behavior.

CRediT authorship contribution statement

Osman Gulseven: Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Formal analysis. **Amani Al Hadi:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Lokman Zaibet:** Validation, Funding acquisition, Conceptualization. **Behnaz Saboori:** Supervision, Methodology, Conceptualization. **Ibtisam Al Abri:** Writing – review & editing, Validation, Supervision, Conceptualization.

Data availability statement

The data used in this study are publicly available. Global food price indices were obtained from the FAO Food Price Index. National food price data were collected from the Consumer Price Index published by the National Centre for Statistics and Information (NCSI), Oman. Processed data and code used for analysis are available from the corresponding author upon reasonable request.

Ethical approval

Ethical approval is not applicable to this manuscript.

Declaration on the use of AI statement

Generative AI (ChatGPT) tools are used in assisting in copy-editing the final version of the manuscript. Original content is written by, and final content is verified by the authors.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Assoc. Prof. Dr. Osman Gulseven reports financial support was provided by Sultan Qaboos University. The project has been supported by Internal

Grant from Sultan Qaboos University. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1 –. R Code

```
# =====================================================
# Food Price Wavelet Analysis in Oman
# Version: 2025-10-05
# Description:
#   This script performs wavelet analysis between FAO global food price
#   indices and Oman's CPI indices. It automatically generates
#   line plots and cross-wavelet power spectra for each pair.
# =====================================================

# --- Setup environment ----------------------------------------
# ⚠ Update the working directory below before running using setwd("Working Directory") ⚠
rm(list = ls())                         # Clear all objects
pacman::p_unload()                      # Unload all packages
while (!is.null(dev.list())) dev.off()   # Close open graphics
cat("\014")                             # Clear console

# Load required packages
pacman::p_load(tidyverse, readxl, WaveletComp, lubridate)

options(scipen = 999)                   # Disable scientific notation
getwd()

# ================================
# Step 1: Load, Summarize, and Visualize Data
# ================================

# Read the CSV file into a data frame
food_prices <- read.csv("food_data_CPI_2.csv")

# Convert 'date' variable to Date type
food_prices$date <- ym(food_prices$date)

# Display structure and summary of dataset
str(food_prices)
summary(food_prices)

# --------------------------------------------------------------
# Plot global vs. local indices for each selected pair
# --------------------------------------------------------------

input_pairs <- list(
  c("FAO_FPI", "Oman_CPI"),
  c("FAO_Cereals", "Oman_Cereals"),
  c("FAO_Dairy", "Oman_Dairy"),
  c("FAO_Oils", "Oman_Oils"),
  c("FAO_Meat", "Oman_Meat"),
  c("FAO_Sugar", "Oman_Sugar")
)
```

```
for (pair in input_pairs) {
  v1 <- pair[1]
  v2 <- pair[2]

  # Plot time series for each FAO–Oman pair
  plot <- ggplot(food_prices, aes(x = date)) +
    geom_line(aes(y = .data[[v1]], color = v1)) +
    geom_line(aes(y = .data[[v2]], color = v2)) +
    labs(title = paste(v1, "vs", v2), x = "", y = "", color = "Variables") +
    theme_minimal() +
    theme(
      axis.text.x = element_text(size = 16),
      axis.text.y = element_text(size = 16),
      legend.text  = element_text(size = 14),
      legend.title = element_text(size = 16),
      plot.title   = element_text(size = 16)
    )

  print(plot)

  # Save plot
  filename <- paste0("plot_", v1, "_vs_", v2, ".png")
  ggsave(filename, plot, width = 9, height = 6)
}

# ========================================
# Step 2: Calculate Log-Differences (optional transformation)
# ========================================

log_vars <- c("FAO_FPI", "Oman_CPI", "FAO_Cereals", "Oman_Cereals",
              "FAO_Meat", "Oman_Meat", "FAO_Dairy", "Oman_Dairy",
              "FAO_Oils", "Oman_Oils", "FAO_Sugar", "Oman_Sugar")

for (var in log_vars) {
  # Compute first log-difference for each variable
  food_prices[[paste0(var)]] <- c(0, diff(log(food_prices[[var]])))
}

summary(food_prices)

# ========================================
# Step 3: Wavelet Power Analysis
# ========================================

# --- Step 3.1: Test one pair before batch processing -----------
v1 <- "FAO_FPI"
v2 <- "Oman_CPI"

# Perform wavelet coherence analysis (Morlet wavelet)
# Bartlett smoothing with window sizes t=5, s=1, 100 simulations
my.wc <- analyze.coherency(
```

. (*continued*).

```
  food_prices, my.pair = c(v1, v2),
  loess.span = 0, dt = 1, dj = 1/100,
  window.type.t = 1, window.type.s = 1,
  window.size.t = 5, window.size.s = 1,
  lowerPeriod = 2, upperPeriod = 256,
  make.pval = TRUE, n.sim = 100
)

# Save individual test plot
png(paste0("wavelet_", v1, "_vs_", v2, ".png"), width = 600, height = 450)
wc.image(
  my.wc,
  which.image = "wp", n.levels = 250,
  legend.params = list(lab = ""),
  timelab = "", periodlab = "",
  show.date = TRUE,
  main = paste0("Cross-Wavelet Power: ", v1, " vs ", v2),
  date.format = "%F"
)
dev.off()

# ========================================
# Step 3.2: Batch process all pairs and export figures
# =========================================

input_pairs <- list(
  c("FAO_FPI", "Oman_CPI"),
  c("FAO_Cereals", "Oman_Cereals"),
  c("FAO_Dairy", "Oman_Dairy"),
  c("FAO_Oils", "Oman_Oils"),
  c("FAO_Sugar", "Oman_Sugar"),
  c("FAO_Meat", "Oman_Meat")
)

for (pair in input_pairs) {
  v1 <- pair[1]
  v2 <- pair[2]

  # Perform wavelet analysis for each pair
  my.wc <- analyze.coherency(
    food_prices, my.pair = c(v1, v2),
    loess.span = 0, dt = 1, dj = 1/100,
    window.type.t = 1, window.type.s = 1,
    window.size.t = 5, window.size.s = 1,
    lowerPeriod = 2, upperPeriod = 256,
    make.pval = TRUE, n.sim = 100
  )

  # --- Plot 1: Cross-Wavelet Power Spectrum ---
  png(paste0("wavelet_", v1, "_vs_", v2, ".png"), width = 600, height = 450)
  wc.image(
```

. (*continued*).

```
        my.wc,
        which.image = "wp", n.levels = 250,
        legend.params = list(lab = ""),
        timelab = "", periodlab = "",
        show.date = TRUE,
        main = paste0("Cross-Wavelet Power: ", v1, " vs ", v2),
        date.format = "%F"
      )
      dev.off()

      # --- Plot 2: Average Cross-Wavelet Power ---
      png(paste0("wavelet_avg_", v1, "_vs_", v2, ".png"), width = 600, height = 450)
      wc.avg(my.wc, main = paste0(v1, " vs ", v2))
      dev.off()
    }

    # ====================================
    # End of Script
    # Notes:
    # - Outputs: time-series plots and wavelet power figures (.png)
    # - Morlet wavelet (ω0 = 6) used with Bartlett smoothing
    # - For replication, ensure the same dataset and parameters
    # ====================================
```

. (*continued*).

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