Article

Use of the Discrete Fourier Transform and Fourier Series Analysis in Macroeconomic Modelling and Forecasting

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Abstract
The prices of goods often exhibit cyclical patterns, reflecting the business cycle of the economy. This paper develops a model to analyse and forecast these cyclical patterns, using data for the price of staple crops in Nigeria. The Baxter-King Filter is used to isolate the cyclical components and remove noise in the data, after which the Discrete Fourier Transform (DFT) is used to determine the frequencies of the key cycles. The Fourier series is used to reconstruct the price trends using periodic signals, eliminating short-term shocks and fluctuations. Results identify several cycles, with a strong annual pattern (13-14 months), a production-linked cycle (19 months) and longer-term cycles (47-53 months), along with harmonics, which are often missed by other methods. These findings demonstrate the value of combining the Baxter-King Filter and Discrete Fourier Transform as a powerful tool for uncovering price inflation dynamics and improving forecasting models for policy analysis.

Keywords: Fourier Transform, Economic Forecasting, Fourier Series, Discrete Fourier Transform

1. Introduction

Over time, inflation trends exhibit cyclical patterns, often influenced by the business cycle. These cycles repeat over multiple years and can be modelled using periodic functions. However, raw price data generally has significant noise and short-term shocks, which do not reflect the overall trend and cannot be easily modelled or approximated. This paper will use the Baxter-King filter and Fourier analysis to develop a model, aiming to isolate the long-term trend in food prices and forecast it using periodic functions. By providing a more accurate model of price cycles, this analysis can directly inform policy on food security and offer a clearer lens for understanding inflation dynamics beyond traditional metrics. This paper will demonstrate how Fourier analysis, a powerful non-parametric technique, can effectively isolate and model these cycles, offering a robust alternative to traditional time-series methods.

1.1. Literature Review

The technique of Fourier analysis has been previously explored as a tool to identify and isolate cycles in time series data. Omekara, Ekpenyong & Ekrete (2013) identified cycles in monthly inflation rates. To decompose and reveal cycles in the data, they applied a periodogram, after which they constructed a model using Fourier series analysis. Further, Fumi et al. (2013) conducted Fourier analysis and used the fast Fourier transform to deconstruct sales data from a fashion company, isolating the important frequencies and constructing a model using the inverse Fourier transform to improve inventory management.

Yukseltan et al. (2020) investigated how harmonic frequencies and Fourier series expansion can be used to model hourly electricity demand, demonstrating the accuracy of this method of analysis for short-term forecasting.

Thomson and van Vuuren (2016) explored the application of the Fourier series in macroeconomics by modelling and forecasting the South African business cycle, proving its accuracy in estimating the length of business cycles. They found the method effective in determining the current position of the economy in the business cycle, suggesting that the method offers a promising alternative to traditional time-series analysis methods such as time series ARIMA modelling and exponential smoothing. Additionally, they used the Hodrick-Prescott and Baxter-King filters to isolate the trend and cyclical components.

Across the literature, the effectiveness of using the Fourier transform to deconstruct and isolate cycles in long-term data and using the Fourier series to construct a forecasting model has been proven independently by many. However, combining these with other techniques such as periodograms or the inverse Fourier transform introduces the possibility of errors in the results.

This paper explores the use of the Baxter-King filter to smooth out price data for a staple crop in Nigeria across 64 months, from 2009 to 2014. It also investigates how the Discrete Fourier Transform can be used to determine important frequencies and harmonics to reflect long-term cycles. These frequencies are then used in conjunction with Fourier series analysis to construct a model to forecast future prices with relative accuracy.

2. Mathematical Background

2.1. Fourier Series Expansion

For a function $\mathrm{f}(x)$ which fulfils the Dirichlet conditions, there exists a Fourier series expansion (Bracewell, 2000). The conditions are as follows:

1. f is a periodic function on R. This means that there exists a period $\mathrm{T} \geq 0$ such that $\mathrm{f}(x) = \mathrm{f}(x+T)$ for all $\mathrm{x} \in R$.
2. f has only a finite number of maxima and minima in a period.
3. f has at most a finite number of discontinuous points inside a period.
4. f is integrable over the period of the function.

A function can be considered as a periodic function on R and thus have a Fourier series expansion by assuming the values of the function over the interval $[a, b]$ repeat and extend to $\mathrm{x} \in \mathfrak{R}$.

The Fourier series expansion of a function $f(x)$ is given by:

$$\mathrm{f}(x) = \frac{a_0}{2} + \sum_{n=1}^{\infty} a_n \cos(nx) + \sum_{n=1}^{\infty} b_n \sin(nx) \quad (1)$$

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2.2. Complex Form of the Fourier Series

Using Euler's Formula, $e^{i\theta} = \cos(\theta) + i\sin(\theta)$, the trigonometric series in (1) can be expressed in a more compact complex exponential form:

$$\mathrm{f}(x) = \sum_{n=-\infty}^{\infty} c_n \, e^{i\frac{n\pi x}{L}} \quad (2)$$

where L is half the period of the function and the complex Fourier coefficient, c_n, is calculated as:

$$c_n = \frac{1}{2L}\int_{-L}^{L} f(x)e^{-i\frac{n\pi x}{L}}\mathrm{dx} \quad (3)$$

2.3. Deriving the Fourier transform

For a non-periodic function, the Fourier series can be generalised to the Fourier Transform, which converts a function from the time domain, $\mathrm{f}(t)$, to the frequency domain, $\mathrm{F}(\omega)$.

The Fourier Transform of $\mathrm{f}(t)$ is given by:

$$\mathrm{F}(\omega) = \int_{-\infty}^{\infty} f(t)e^{-i\omega \mathrm{t}}\mathrm{dt} \quad (4)$$

The original function can be recovered from its transform using the Inverse Fourier Transform:

$$\mathrm{f}(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} F(\omega)e^{i\omega \mathrm{t}}\mathrm{d}\omega \quad (5)$$

2.4. The Discrete Fourier Transform

The Fourier Transform is designed to be used for continuous data in the form of a function $\mathrm{f}(x)$. Since economic data is collected at discrete time intervals, to process it we use the Discrete Fourier Transform (DFT). Converting (4) and (5) into discrete time, we get a sequence of N complex frequency components, $\mathrm{F}(n)$:

$$\mathrm{F}[n] = \sum_{k=0}^{N-1} f[k]e^{-i\frac{2\pi \mathrm{nk}}{N}} \quad (6)$$

2.5. Data Filtering

The Discrete Fourier Transform operates under the assumption that the signal it is deconstructing is periodic and stationary. In an economic context, we can assume the price data to be somewhat periodic, given the existence of the business cycle. However, as prices keep increasing, stationarity cannot be assumed.

Without stationary data, the DFT would give disproportionate weight to fluctuations in later years where the scale is larger, thus distorting the identification of cycles. To make the data stationary, it needs to be detrended, obtaining a cycle which oscillates around a constant mean. This prevents the overall upward trend from being misinterpreted by the DFT as a very powerful, low-frequency cycle, thereby allowing the true, more subtle cyclical patterns within the data to be identified clearly. Detrending can simply be done by finding a trend using linear regression, which in this case is $\mathrm{y} = 22.287\mathrm{x} + 10923$, with x representing the month (ranging from 1- 64).

Additionally, short-term fluctuations and outliers will need to be eliminated from the data. Since this investigation aims to model and forecast cyclical trends in food prices, it requires a filter that preserves these patterns. There are several filters that can be considered for this, such as using first differences, which extracts the cyclical component of a time series. However, it involves a reweighting of frequencies, making models prone to errors. Another option is the widely-used Hodrick-Prescott filter, which allows for cyclical trend extraction with a 0 phase shift in addition to its trend-elimination properties. However, computation using this filter generally results in an infinite-order moving average, making it unsuitable for direct processing of data. The Baxter-King filter, a variant of the Hodrick-Prescott filter, separates the cyclical component from a time series

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in finite samples, overcoming the limitations of other filters. The Baxter-King Filter decomposes the time series into three components: cycle (c_t), trend (τ_t), and the irregular component (ε_t), which is given by

$$y_t = \tau_t + c_t + \varepsilon_t \quad (7)$$

To obtain a new time series, y_t^*, a symmetric moving average can be applied such that

$$y_t^* = \sum_{k=-K}^{K} \beta_k y_{t-k} \quad (8)$$

Where β_k, defined as a fixed constant statistical weight which determines the importance of the term to the larger trend and K is the maximum shift in the time series, known as the lag length. Applying the inverse Fourier transform on the frequency response function, we get

$$b_k = \frac{1}{2\pi}\int_{-\pi}^{\pi} \beta(\omega) e^{i\omega k} \quad (9)$$

Using (9) as the weights, the cyclical components of this filter can be found as:

$$c_t = \sum_{k=-K}^{K} b_k y_{t-k} \quad (10)$$

To test the necessity of this filter, this analysis was conducted both with and without the use of the Baxter-King filter. When data was analysed after detrending but without filtering, the frequencies with the highest amplitudes obtained by the Fourier transform were found to correspond to cycles of 5.33, 12.8, 16, 32 and 64 months. Three of the 5 major trends obtained are harmonics of the same fundamental frequency, which is the overall trend of 64 months. Thus, the useful data obtained from a non-filtered analysis provided only insight into short-term fluctuations, proving the need for filtering of data for the creation of long-term forecasting models.

3. Method and Results

This analysis uses the 'Monthly food price estimates by product and market' data from the World Bank Microdata Library (given in the appendix), which provides monthly food price estimates by region for 35 markets ranging from 2007 to 2023. The food prices of cassava meal in the Bade region from 2009 to 2014, a period of 5 years with relatively low external conflict or events, were considered for a total of 64 data points.

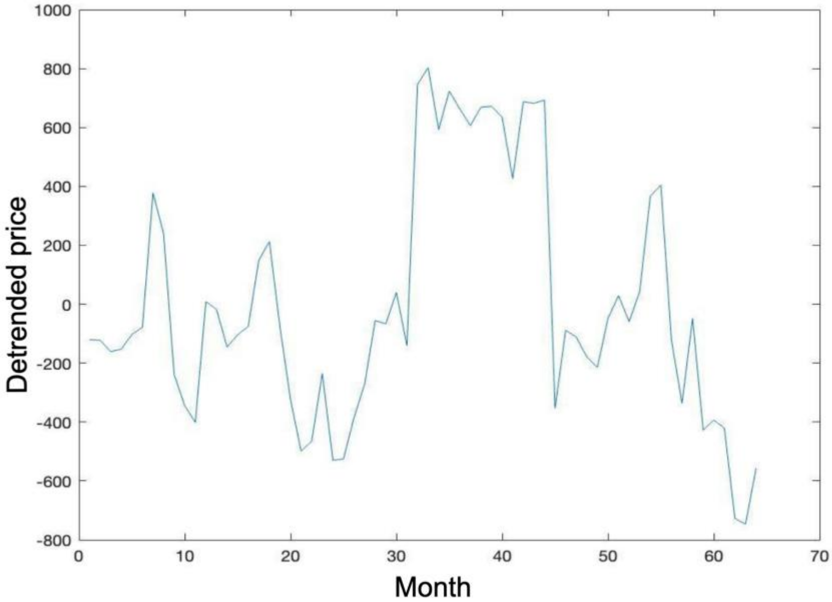
Filtering and visualisation of the data were done on MATLAB with the Econometrics Toolbox. Calculations were performed using Microsoft Excel and verified manually. Sample calculations for each step have been shown.

The trend line for this dataset was obtained as $\mathrm{y} = 22.287\mathrm{x} + 10923$ using simple regression. The detrended prices have been calculated in Table 1.

Datapoint	Price (NGN)	Trend	Calculation	Detrended price
1.	10823.9	10945.7163	$10823.9 - 10945.7163$	-120.83216
2.	10844.86	10968.4133	$10844.86 - 10968.4133$	-122.16458
3.	10828.15	10988.9138	$10828.15 - 10988.9138$	-161.167
4.	10859.08	11011.6108	$10859.08 - 11011.6108$	-152.52941

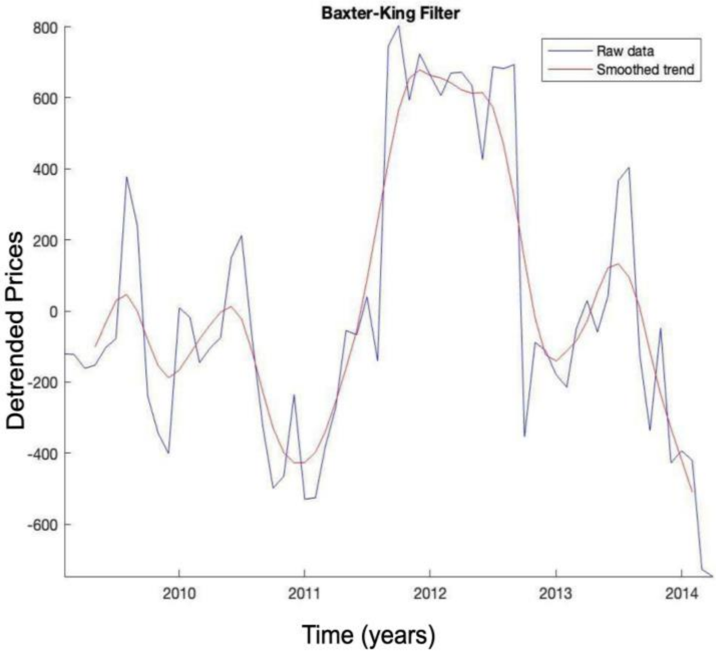
***Table 1:** Sample of original and detrended prices of Cassava Meal in months 1-4*

To take a domain for the periodic function, the time series data in months was converted into whole number values corresponding to the month number, with January 2009 being considered as month 1 and April 2014 being considered as month 64. Graph 1 displays the isolated trend for food prices, which is assumed to be periodic over the domain [0,64].



***Graph 1**: Detrended price data for cassava meal (January 2009-April 2014)*

Next, the data must be filtered to isolate medium and long-term cycles before it can be used for the Fourier Transform. Graph 2 visualises the effects of the Baxter-King filter as applied on MATLAB.



***Graph 2**: Smooth trend obtained using Baxter-King Filter on detrended price of cassava meal*

The cyclical components in the time-series, organised by month number, are given in Table 2.

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S. No.	Datapoint (Detrended Price)	Cyclical Component
1.	-120.832	0
2.	-122.165	0
3.	-161.167	-8.057077
4.	-152.529	-40.556275

***Table 2**: Sample calculation of cyclical components obtained by BK filter*

Note: The filter was applied with a Lag Length of 2, resulting in it disregarding the first and last two input values, assumed here to be 0.
These cyclical components can now be put through the Discrete Fourier Transform to obtain the most prevalent frequencies.

S. No.	Input	Cyclical Trend	Frequency $\left(\frac{1}{T}\right)$	Fourier transform value
1.	-120.832	0	1	15.956703
2.	-122.165	0	0.50	-16.929577+34.806294i
3.	-161.167	-8.0570768	0.33…	50.638695-59.669321i
4.	-152.529	-40.556275	0.25	208.537978

***Table 3**: Sample calculation of frequencies (by month) and Fourier-transformed cyclical trend values*

Next, the amplitude and phase for each value need to be calculated.

S. No.	Fourier Transform	Amplitude	Phase (ϕ)
1.	15.956703	15.956703	0
2.	-16.929577+34.806294i	38.705151	2.0235001
3.	50.638695-59.669321i	78.260496	-0.8670834
4.	-182.292262+101.279906i	208.537978	2.6344672

***Table 4:** Sample calculation of phase and amplitude values from Fourier transform*

The frequencies are plotted against the amplitudes obtained in Graph 3.

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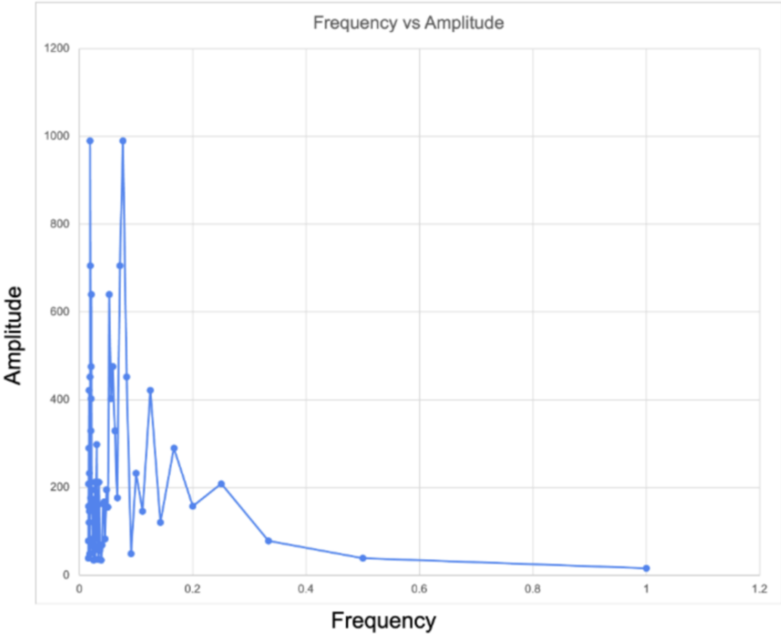

***Graph 3:** Frequency vs amplitude plot*

The frequency values with the highest amplitudes seen in Graph 3 can be taken as the values with the highest influence on the fluctuations observed in the price. The 6 frequencies with the largest amplitudes are summarised in Table 5.

S.No.	Amplitude	Frequency $\left(\frac{1}{T}\right)$	Time Period	Phase
1.	989.75582	0.07692308	13 months	0.7781936
2.	705.36873	0.07142857	14 months	-1.5975775
3.	639.68101	0.05263158	19 months	2.2625489
4.	639.68101	0.02127660	47 months	-2.2625488
5.	705.36873	0.01923077	52 months	1.5975775
6.	989.75582	0.01886792	53 months	-0.7781936

***Table 5**: Frequency, time period, and phase of 6 largest amplitudes*

From these calculations, it can be observed that time periods of 13, 14, 19, 47, 52, and 53 months contribute significantly to the periodic trends observed in the data. These time periods can be utilised to devise a Fourier series for this data.
The mean value of the amplitudes of all data points (a_n) was found to be 235.2717041, which was taken as the coefficient for the entire equation. For a frequency $f_n = \frac{2\pi}{T_n}$ and phase ϕ_n, the Fourier series from Equation (1) was found to be:

$$f(x) = a_n \sum_1^n \left[sin\left(\frac{2\pi}{T_n}(x+n) + \phi_n\right) + cos\left(\frac{2\pi}{T_n}(x+n) + \phi_n\right)\right]$$

In this equation, when ϕ_n is negative, $\frac{2\pi}{T_n}$ must also be taken as negative.
The time period and phase, obtained from the Fourier transformed values, are used to correct the phase shift of the various components, as the periodic cycle does not originally start from 0 in the data plot and experiences a phase shift due to lag in the Baxter-King filter.

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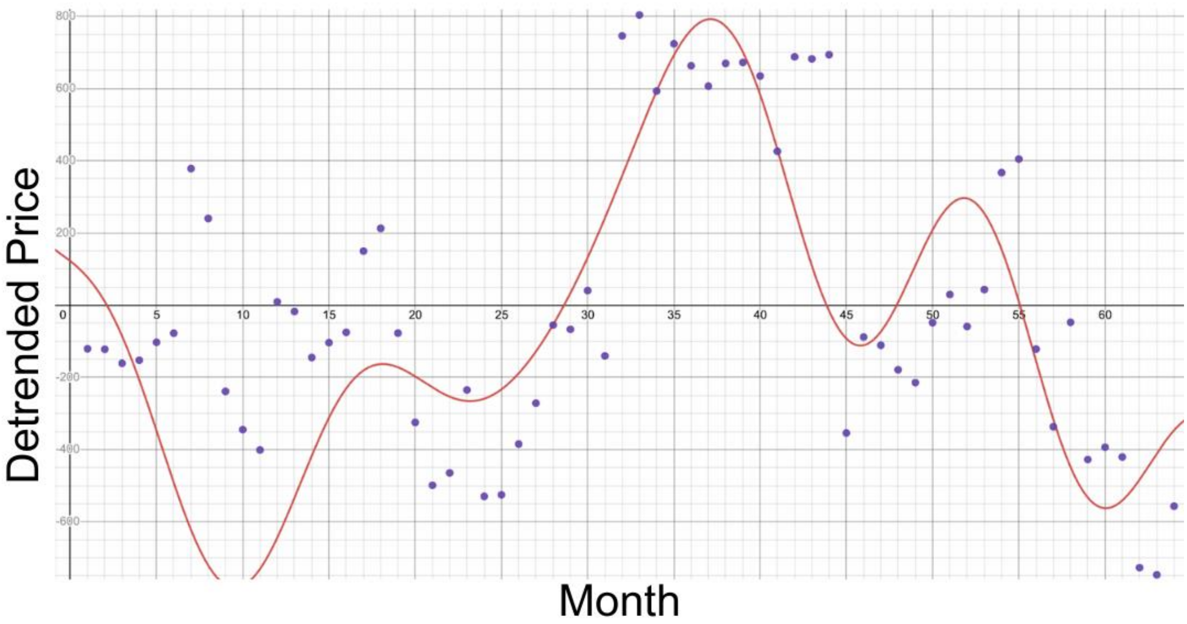
The full model was thus found to be:

$$
\begin{aligned}
f(x) = 235.271704\,[\, & sin\left(\tfrac{2\pi}{13}(x+13)+0.778194\right) + sin\left(\tfrac{-2\pi}{14}(x+14)-1.597579\right) \\
& + sin\left(\tfrac{2\pi}{19}(x+19)+2.262549\right) + sin\left(\tfrac{-2\pi}{47}(x+47)-2.262549\right) \\
& + sin\left(\tfrac{2\pi}{52}(x+52)+1.597577\right) + sin\left(\tfrac{-2\pi}{53}(x+53)-0.778194\right) \\
& + cos\left(\tfrac{2\pi}{13}(x+13)+0.778194\right) + cos\left(\tfrac{-2\pi}{14}(x+14)-1.597577\right) \\
& + cos\left(\tfrac{2\pi}{19}(x+19)+2.262549\right) + cos\left(\tfrac{-2\pi}{47}(x+47)-2.262549\right) \\
& + cos\left(\tfrac{2\pi}{52}(x+52)+1.597577\right) + cos\left(\tfrac{-2\pi}{53}(x+53)-0.778194\right)\,]
\end{aligned}
$$

This model can be confirmed to coincide with the detrended data values, plotted as purple points in Graph 4.



***Graph 4**: Model for cassava meal prices with data points*

Verification of this model can be done by plotting data for the next two years, from 2015 and 2016. This data has once again been detrended by plotting it and obtaining a new equation for the same. Out-of-sample verification data is represented in green.

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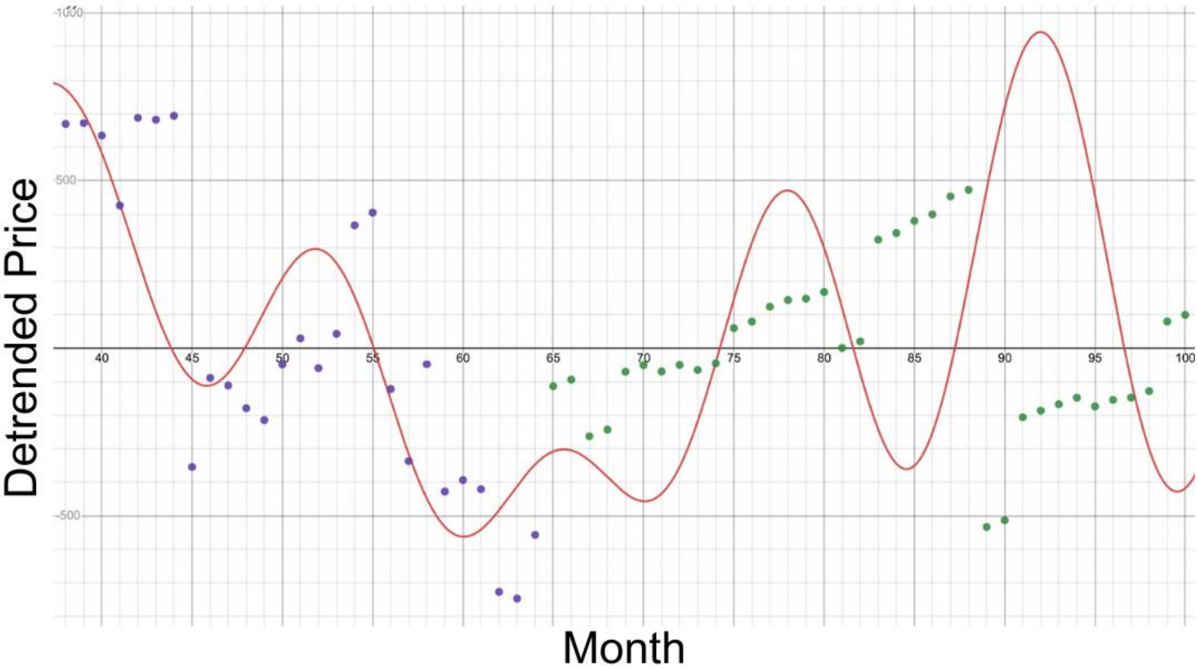
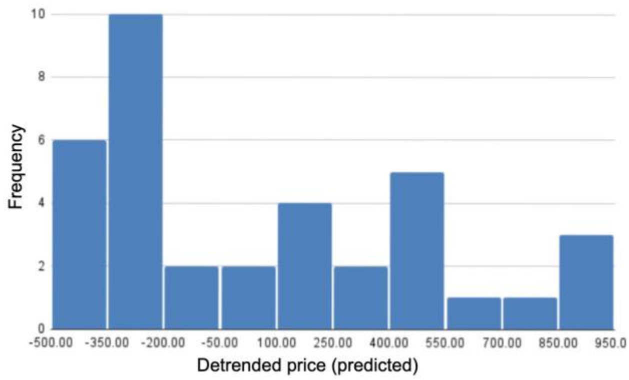


Graph 5*: Model for cassava meal prices with verification data (green)*

This graph shows that the model does forecast the general trend of the data, following an increase at month 75 and a decline at month 80, followed by an increase and then a decrease at months 87 and 95. On observation, the model looks to have a lag in its predictions. To assess the accuracy, a statistical test can be conducted.



Graph 6: *Histogram for forecasted data*

Since the forecasted data is not normally distributed in Graph 6, a non-parametric test such as the Mann-Whitney U test can be conducted.

$$H_0: x_1 = x_2$$
$$H_1: x_1 \neq x_2$$

Rejection of the null hypothesis suggests that the two sets of data belong to different populations, implying that the two samples are statistically significantly different from each other.

To conduct this test, the data must first be arranged in ascending order. The two datasets will then be combined, and each value will be assigned a 'rank', with the least value receiving a rank of 1.

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S. No.	Value	Rank
1.	-533.23	1
2.	-513.63	2
3.	-465.655	3
4.	-439	4

Table 6: *Sample of values and ranks for Mann-Whitney test*

Note: Orange denotes values belonging to the verification data while green denotes values from the forecasted data. Full table available in appendix.

From this:

$$R_I = \sum (ranks\ for\ verification\ data) = 1328$$
$$R_2 = \sum (ranks\ for\ forecasted\ data) = 1300$$

Next, to calculate the value of U and U',

$$\mathrm{U} = n_1 n_2 + \left(\frac{n_1(n_1+1)}{2}\right) - R_1 = 634$$
$$U' = n_1 n_2 + \left(\frac{n_2(n_2+1)}{2}\right) - R_2 = 662$$

Where n_1 and n_2 are the number of values in the given samples.

The larger of these values, U' in this case, can be compared against the critical U value,

$$U_{0.05(2),36,36} = \frac{n_1 \times n_2}{2} = 648$$

From the Mann-Whitney test tables, p = 0.8807 was obtained.

Keeping a 0.05 significance threshold, the null hypothesis fails to be rejected. This implies that there is no significant difference between the two samples. The p-value of 0.8807 indicates that there is an 88.07% probability of observing these results, or ones more similar, assuming both samples were drawn from the same population.

4. Discussion

The Mann-Whitney U test lends statistical support to the model's validity. The resulting p-value of 0.8807 indicates that there is no statistically significant difference between the distribution of the model's forecasted values and the actual verification data. This suggests that the model successfully reproduces the statistical characteristics of the real-world price cycles, providing a plausible forecast for the overall trend of price fluctuations. It can roughly forecast food prices despite external influences and is also able to forecast the larger trend of the rise and fall in food prices.

This method identified a few cycle pairs with very similar periods (13 and 14 months, and 52 and 53 months). Given the 64-month scope of the data, the model's ability to resolve such closely spaced frequencies is limited. These findings could be interpreted not as a set of fully distinct cycles, but as indicators of a few dominant cyclical phenomena. For instance, the 13 and 14-month results likely represent a single strong annual business cycle. Further strengthening this interpretation is the fact that the 13-month cycle is the fourth harmonic of the 52-month cycle, suggesting they are mathematically related components of the same underlying long-term trend. The appearance of both a fundamental period (around 52-53 months) and its harmonic reinforces the significance of this long-term cycle in the data.

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An interesting result was a 19-month cycle, which does not align with a simple business cycle based annual pattern. This period corresponds well with the duration of two consecutive production cycles for cassava. Cassava has a growth period of roughly 8-9 months (Nzola et al., 2021), after which farmers allow roots to dry before replanting approximately 10 days later (NAERLS, 2022). Combined with additional time for processing cassava plants into cassava meal, a single planting-to-market cycle takes approximately 9-9.5 months, with a short fallow period before the next batch is planted. The 19-month cycle observed could be caused by an alternating sequence of major and minor harvests, meaning the dominant price trough occurs only every second harvest, which serves as a production-based explanation for the observed phenomenon.

Another possibility is that the cycle is driven by the timeline of government agricultural policies. There can be a significant time lag between when a policy is announced, when it is implemented, and when its effects are felt in local market prices. This could create cycles longer than the typical seasonal or business cycles. While a fertiliser subsidy program might seem like a candidate for such a policy, existing research suggests that these specific subsidies have a relatively weak influence on local food prices in Nigeria (Takeshima and Liverpool-Tasie, 2015). Therefore, while this particular policy is an unlikely cause, the cyclical impact of other agricultural support programs remains a potential contributing factor.

The region for analysis lies in the Sahel region, which is prone to droughts and food scarcity (Adegun 10). It was found that "the 2006 – 2017 decades experienced very high incidences of droughts" (Eze 8). Scarcity due to regional drought could have influenced food prices, causing them to rise prematurely, explaining the peak seen in the verification data being early as compared to the model's forecasts.

The verification data was detrended separately from the data used to create the model, potentially leading to inconsistencies in the trend removed from both sets of data. The model requires the same trend to be removed from the overall data. However, doing this may be challenging for real-life application of the model as it requires recalculation for every new data point added.

5. Conclusion

This paper explored the use of the Baxter-King Filter and Discrete Fourier Transform, which combined have potential in the decomposition of different cycles and the creation of models to forecast food prices with high accuracy.

Despite the ability of the Fourier transform to isolate trends and cycles directly from a signal, the Baxter-King filter was proven to be necessary to remove noise and allow for the calculation of medium and long-term cycles rather than the short-term cycles uncovered with unfiltered data. The model successfully deconstructed the price movements into a long-term trend and several distinct cyclical components. The analysis identified significant business cycles, including a 19-month cycle which corresponds closely to the agricultural reality of a biennial "double-harvest" pattern in cassava production.

This research highlights the effectiveness of the Fourier Transform as a powerful, non-parametric tool for macroeconomic analysis, offering a robust alternative to traditional filtering methods. The ability to identify and quantify real-world, production-based cycles from price data alone illustrates the practical utility of this method for policy analysis and economic forecasting.

Future work could enhance the model by incorporating explicit variables or assigning different weights for time periods with external shocks, such as droughts or specific policy events. Furthermore, an in-depth investigation into the supply chain and inventory management practices of cassava distributors could provide a more detailed confirmation of the 19-month cycle's origins. Applying this methodology to other commodities or different economic regions could also further validate its effectiveness.

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Appendix

A. Food price data for cassava meal - January 2009 to April 2014

Month number	Month	Price of cassava meal (NGN)	Month number	Month	Price of cassava meal (NGN)
1	2009-01-01	10823.9	**17**	2010-05-01	11451.11
2	2009-02-01	10844.86	**18**	2010-06-01	11536.3
3	2009-03-01	10828.15	**19**	2010-07-01	11268.54
4	2009-04-01	10859.08	**20**	2010-08-01	11043.43
5	2009-05-01	10930.93	**21**	2010-09-01	10891.63
6	2009-06-01	10978.45	**22**	2010-10-01	10948.18
7	2009-07-01	11456.51	**23**	2010-11-01	11200.12
8	2009-08-01	11340.67	**24**	2010-12-01	10927.76
9	2009-09-01	10884.24	**25**	2011-01-01	10954.4
10	2009-10-01	10800.52	**26**	2011-02-01	11117.34
11	2009-11-01	10766.4	**27**	2011-03-01	11252.79
12	2009-12-01	11198.96	**28**	2011-04-01	11491.5
13	2010-01-01	11194.58	**29**	2011-05-01	11501.95
14	2010-02-01	11089.45	**30**	2011-06-01	11631.45
15	2010-03-01	11152.83	**31**	2011-07-01	11472.88
16	2010-04-01	11203.7	**32**	2011-08-01	12381.42

Month number	Month	Price of cassava meal (NGN)	Month number	Month	Price of cassava meal (NGN)
33	2011-09-01	12461.68	**49**	2013-01-01	11800.28
34	2011-10-01	12273.26	**50**	2013-02-01	11988.44
35	2011-11-01	12426.41	**51**	2013-03-01	12088.76
36	2011-12-01	12387.91	**52**	2013-04-01	12022.32
37	2012-01-01	12353.52	**53**	2013-05-01	12146.96
38	2012-02-01	12438.95	**54**	2013-06-01	12493.01
39	2012-03-01	12463.8	**55**	2013-07-01	12553.15
40	2012-04-01	12448.71	**56**	2013-08-01	12049.04
41	2012-05-01	12262.38	**57**	2013-09-01	11856.37
42	2012-06-01	12546.33	**58**	2013-10-01	12167.74
43	2012-07-01	12563.03	**59**	2013-11-01	11810.1
44	2012-08-01	12596.83	**60**	2013-12-01	11866.54
45	2012-09-01	11571.37	**61**	2014-01-01	11861.7
46	2012-10-01	11859.51	**62**	2014-02-01	11577.5
47	2012-11-01	11859.03	**63**	2014-03-01	11580
48	2012-12-01	11813.43	**64**	2014-04-01	11792.28

B. Mann-Whitney U test ranks

Rank	Value	Rank	Value	Rank	Value
1	-533.23	**25**	-153.97	**49**	143.6
2	-513.63	**26**	-147.57	**50**	148.11
3	-465.655	**27**	-147.52	**51**	149
4	-439	**28**	-127.92	**52**	154
5	-424	**29**	-113.32	**53**	167.71

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6	-411	**30**	-93.72	**54**	199
7	-404	**31**	-86	**55**	297
8	-385.131	**32**	-75	**56**	324.13
9	-347	**33**	-70.19	**57**	343.73
10	-343	**34**	-69.49	**58**	370
11	-335.079	**35**	-64.68	**59**	380.03
12	-311	**36**	-50.59	**60**	399.63
13	-307.941	**37**	-49.89	**61**	401
14	-305.07	**38**	-45.08	**62**	422
15	-300	**39**	-31	**63**	437
16	-262.54	**40**	-18	**64**	453.03
17	-242.94	**41**	0.98	**65**	469
18	-241	**42**	20.58	**66**	470
19	-221	**43**	59.95	**67**	472.63
20	-213	**44**	79.55	**68**	685
21	-205.89	**45**	79.84	**69**	752
22	-186.29	**46**	99.44	**70**	851
23	-173.57	**47**	114	**71**	894
24	-167.17	**48**	124	**72**	943

C. Steps taken in MATLAB to process data

Step 1: Import Data from Text file into MATLAB

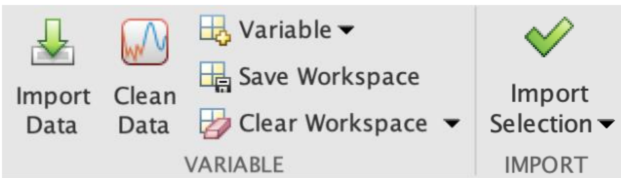

Figure 1a and 1b: *Import data into MATLAB*

Step 2: Create Timetable for Data

```
>> TT = readtimetable('cassavatime.mat');
```

Figure 2: *Command to create timetable*

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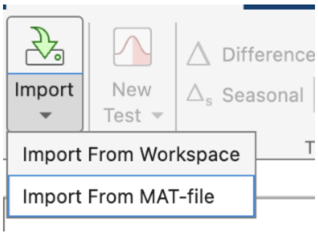
Step 3: Import data into Econometric Modeler and detrend



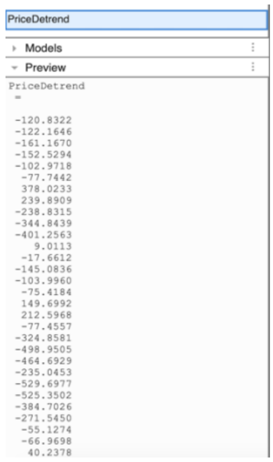


Figure 3a and 3b: *Importing and detrending data*

Step 4: Obtain the trend values

```
>> trend = TT.Price - TT.Price_detrended;
TT = addvars(TT,trend,NewVariableNames="Trend")
```

Figure 4: *Command to obtain trend values*

Step 5: Apply the Baxter-King Filter and plot

```
>> load('cassavatime.mat','TT')
bkfilter(TT,DataVariables=["DetrendedData"], ...
        LowerCutoff=2,UpperCutoff=8,LagLength=2);
```

Figure 5*: Command to apply and plot the Baxter-King Filter*

Step 6: Get cyclical component values

```
>> TTQ = rmmissing(TT);

[TQTT,CQTT] = bkfilter(TTQ, LagLength=2);
size(TQTT)
TQTTCut = rmmissing(TQTT);
CQTTCut = rmmissing(CQTT);


CQTTCut
```

Figure 6: *Command to get cyclical component values*

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