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# How Producer Prices Affect the Consumer Inflation in Kazakhstan

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Effect on the Consumer Inflation in Kazakhstan by Producer Prices.
**NBRK – WP – 2022 –5**

# How Producer Prices Affect the Consumer Inflation in Kazakhstan.

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## Abstract

Pursuing the inflation targeting policy involves the introduction and ongoing improvement of the system for forecasting and analyzing macroeconomic variables, inflation in particular. Permanent progress is aimed at improving the quality of the analysis performed and increasing the accuracy of forecasts for the economic development through fine-tuning projection models as well as broadening the understanding of the causes and structure of inflationary processes.

In this paper, the authors used various statistical methods (causality test: the Toda-Yamamoto approach, as well as Wavelet analysis) to assess the impact of various producer price indices on the consumer inflation in Kazakhstan.

*Key Words: inflation, producer price index, consumer price index, wavelet analysis, causal relationship.*

*JEL-Classification: E31, E19, E39*

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## 1. Preamble

Inflation is an indicator that measures the price growth over a definite period of time (Mankiw and Taylor, 2020). In Kazakhstan, inflation is measured by using the consumer price index – CPI, which includes more than 500 products. Inflation is one of the most important macroeconomic indicators that reflects the state and quality of the economy. High inflation rates can lead to significant imbalances in the economy and can negatively affect the wealth and income of the population. Stable and low inflation rates, on the contrary, contribute to the economic growth and wealth accumulation, forming appropriate expectations among economic agents.

In order to keep inflation at steadily low levels for a consistent and prospective development of the economy, many central banks of both developed and developing countries adhere to the inflation targeting regime. The implementation of this regime requires a public definition of the inflation goal and the use of tools available to the central bank to achieve it (Jahan, 2017).

Since 2015, the National Bank of the Republic of Kazakhstan has been adhering to the principles of inflation targeting. The implementation of the inflation targeting policy involves the introduction and ongoing improvement of the system for forecasting and analyzing macroeconomic variables, inflation in particular. In this regard, an ongoing improvement of this system and professional development of analysts involved in these processes is critical for the National Bank. Permanent progress is aimed at improving the quality of the analysis performed and increasing the accuracy of forecasts for economic development through fine-tuning projection models as well as broadening the understanding of the causes and structure of inflationary processes.

There is a large number of factors that affect the very nature of inflation processes. The main inflation drivers can be supply-side and demand-pull inflation, imported inflation.

This paper discusses the influence from supply-side inflation, which is determined and calculated via the producer price index – PPI.

The PPI reflects an average change in prices for final products and production services of industrial enterprises in Kazakhstan. The index tracks changes in producer prices, excluding value-added and excise taxes, trade mark-up, and transport and promotion costs. According to the Methodology[3], producer prices include all market prices related to production and manufacturing irrespective of whether goods (services) are delivered to the domestic or foreign markets. The index covers the price changes broken down by types of products and services produced at different stages.

Figure 1 shows the dynamics of various producer indices for the last ten years.

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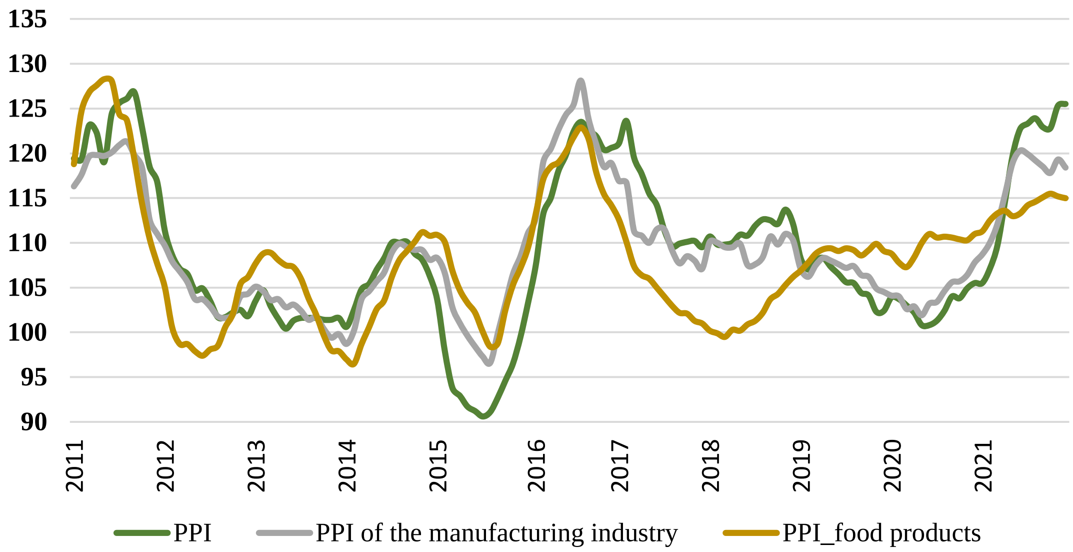
[3] On approval of the Methodology for construction of producer price indices in the industry. Order of the Chairperson of the Committee on Statistics of the Ministry of National Economy of the RK as dated May 31, 2016 No. 98

**Figure 1. The PPI dynamics for 2011-2021, YoY**




*Source: BNS ASPR RK*

The effect of the producer price index on consumer prices is related to the fact that the change in prices for raw materials extends to the interim price of goods, as well as to final products. The rise in prices for raw materials affects the prices of interim products, producer prices of final products and, ultimately, consumer goods. Therefore, the growth in producer prices in the end causes the rise in consumer prices (Rogers, 1998).

At the same time, albeit not explicitly, there is an inverse relationship between these variables, whereby changes in prices for final consumer goods affect the cost of raw materials, and hence the cost of production. This is because the producer's final price usually includes a mark-up on production costs such as payroll costs, as well as raw materials, which can rise during periods of general price increases – inflation. In this regard, rising consumer prices are forcing producers to raise wages, thereby creating additional upward pressure on producer prices (Colclough and Lange, 1982).

Meantime, the relationship between producer prices and consumer prices can be not only one-way (PPI $\rightarrow$ CPI or CPI $\rightarrow$ PPI) but also two-way (PPI $\leftrightarrow$ CPI), or can be no relationship whatsoever (Akcay, 2011).

In this paper, the authors used various statistical methods (Granger causality test, including the Toda and Yamamoto approach, as well as wavelet analysis) to assess the impact of various producer price indices on the consumer inflation in Kazakhstan.

The study consists of several parts. The second section is presented by a literature review, which discusses similar studies by other authors with a description of the results obtained. The third section describes the methodology. It is followed by the section with a discussion of outcomes, where the authors describe the assessment results. The final section of the paper represents findings from this study and further recommendations.

## 2. Literature Review

The relationship between producer and consumer price indices has long been one of the important topics to study in the area of economics. The results of research can be useful both for the economic science and for the decision-making process in the field of monetary policy. Empirical studies on this topic are carried out based on the example of various countries and at different time intervals.

The generally accepted and more intuitive view is that there is a one-way relationship between producer prices and consumer prices. At the same time, in some studies, both a one-way causal relationship (PPI $\rightarrow$ CPI or CPI $\rightarrow$ PPI) was revealed and the presence of mutual effect of indices on each other (PPI $\leftrightarrow$ CPI). However, the outcomes of studies may differ depending on the methods and data used.

In most works, vector autoregression models (VAR) or error correction models (VECM) were used for such analysis.

Debby and Anggraeni (2018) investigated the relationship of indicators in Indonesia based on a vector autoregression model with the Granger causality test. Unlike other studies, the study examined not only the general PPI and CPI, but also the relationship of the corresponding sub-indices of prices for food, drinks, tobacco products, and clothing. The authors concluded that general producer prices could be a leading indicator for the consumer inflation, the impact of the shock fades within 6-7 months. At the same time, the food consumer price index has a two-way relationship with the food producer price index, i.e. they both can be leading indicators for each other. Finally, consumer prices of clothing are a leading indicator for producer prices of clothes. In a similar work, using common indicators in the UK and Turkey, the authors obtained a result on the mutual causal relationship of the CPI and PPI. As in the previous work, the authors used an estimate based on vector autoregression with obtaining impulse responses, the Granger test (Topuz, 2017)

In his study, Akcay (2011) examined the causal relationship between PPI and CPI using the data from five European countries. Cointegration and Granger causality tests using the Toda and Yamamoto approach for the period from 1995 to 2007 showed the effect of producer prices on consumer prices in France and Finland, the presence of a two-way relationship in Germany, and no significant relationship in Sweden and the Netherlands.

The results of one-way relationship between the PPI and CPI in Malaysia was also reported by Ghazali (2008). As in the previous study, both the standard Granger causality test and the modified Wald test proposed by Toda and Yamamoto are used in the work.

In some cases, the authors divided the time series into separate periods. Thus, in the work of Ceylan (2020), the relationship between indicators in the United States was studied based on two periods: 1947-1982 and 1983-2019. The presence of cointegration between variables allowed the author to build a vector error correction model. As a result, a long-term one-way causal relationship between the CPI and PPI was found, especially in the second period. The effect of demand-pull inflation is explained by the fact that firms are adapting prices based on expected consumer inflation by adjusting wages and setting mark-ups. The same results (demand-pull inflation) are obtained by Ülke (2013), who studied the relationship between the PPI and CPI in Turkey based on a vector error correction model and a Granger causality test. The outcomes of the study showed that the CPI is the cause for changes in producer prices in the long run. In the short term, the relationship between the indices was not revealed.

Economists Sidaoui, Capistrán, Chiquiar, Ramos-Francia (2009) from the Bank of Mexico investigated the relationship between the PPI and CPI in Mexico based on a sample and out-of-sample Granger causality test using a vector error correction model. In contrast to previous work, they concluded that a one-way Granger causal relationship from industrial to consumer prices exists in the long run, but there is no relationship between them in the short run.

Yin, Jia (2013) in their study used the Granger causality test in the Momentum threshold vector error correction model (M-TV ECM) between the PPI and CPI in seven countries (Canada, Denmark, Indonesia, Japan, Pakistan, Spain, and Uruguay). A two-way relationship was found in all countries except Spain, where one-way effect of the CPI on PPI was observed.

However, traditional full-sample methods ignore sub-sample causation. Besides, such methods cannot detect changes over time when assessing the relationship between variables. The traditional Granger causality test faces the problem of model specification, number of lags, and spurious regression.

Another method aimed at identifying and analyzing the relationship of variables is wavelet analysis. The idea of using this method as a separate mathematical construction appeared back in the mid-1980s. The essence of wavelet analysis is to evaluate the spectral characteristics of a time series as a function of time, showing how the various periodic components of the time series change over time. The wave conversion splits the time series into biased and scaled versions of the function – a mother wave with limited spectral range and limited duration over time (Conraria, Azevedo, Soares, 2008).

Contrary to classical econometric methods for assessment of causal relationships, wavelet analysis has such advantage as:

– data visualization both in terms of time and frequency representation;

– study of the concurrent dynamics of indicators and changes in causal relationships over time;

– no restrictions on the cointegration test and determination of the number of lags. Relationships between variables may be unstable due to structural changes and full sample results may be undesirable (Khalid Khan, 2018).

In addition, this tool does not require stationarity of the input data (Roueff and Sachs, 2009).

At present, wavelet analysis is widely used in physics, geophysics, astronomy, epidemiology, signal processing, and oceanography. Unfortunately, despite all its opportunities, this method is rarely used in economics. Many economists give preference to traditional econometric methods, overlooking the possibility of using wave analysis to study economic data and their relationships. At the same time, wavelet analysis has been widely used in the field of finance (Conraria, Azevedo, Soares, 2008).

The work of Tiwari, Mutascu, Andries (2013) on the example of Romania can be considered as the first study where wavelet analysis is used to determine the relationship between producer prices and consumer prices. Based on the results of the study, it is noted that both variables are in the same phase for most of the time (coincidence of the movement path, as well as local maxima and minima). In some periods, there is a dependence of the CPI on PPI, and in other periods, producer prices depend on consumer prices (demand-pull inflation). Meanwhile, in certain periods, the synchronous movement of two variables under the influence of common factors indicates the absence of dependence of one variable on the other. In addition, the authors point out that the relationship between the consumer price index and producer price index, in addition to internal factors, depends on external conditions as well.

The study of Khan, Su, Tao and Chu (2018) is another work where researchers determine the relationship between producer prices and consumer price index in the Czech Republic through wavelet analysis. As in the case of Romania, the results of the study indicate that the relationship between the PPI and CPI is multidirectional and also show the absence of causal relationships in certain periods. In this case, the dependence of two variables is short-term.

In addition, the authors consider the role of the exchange rate in the causal relationship between inflation and producer prices. The inclusion of the exchange rate enhances the mutual influence of the two variables on each other and expands the time horizon of this influence. Comparison of estimated results indicates that the causal relationship between consumer prices and producer prices is more sensitive to external factors.

A two-way relationship between producer and consumer prices is also observed in Mexico (Tiwari, Suresh, Arouri, Teulon, 2014). Unlike Romania and the Czech Republic, where the leading effect of one of the two variables depends on the observed period, in Mexico this dependence depends on the time horizon. So, in the short term (months 1-7), there is a dependence of producer prices on consumer prices, and in the medium term (months 8-32), on the contrary, consumer inflation depends on producer inflation. The study also reports that such causal relationship of two variables provides great opportunities for the Mexico's central bank to implement the inflation targeting policy.

In Kazakhstan, no similar studies of relationship between producer prices and consumer prices were found; therefore, this paper addresses various approaches.

## 3. Data and Methodology

### *Data*

The study used monthly data on producer price indices and consumer price indices during the period from 2011 to 2021, as well as their components that were published on the Taldau information-analytical system's platform of the BNS ASPR[4].

The data on components include food producer price indices and, accordingly, indicators of food consumer inflation, and, as an alternative to the general producer price index – the producer price index in the manufacturing industry, producer price index of consumer goods. The latter includes mainly such goods as food products, fuel and lubricants, i.e. does not include export-oriented commodities.

The data for classical econometric methods are presented as base indices (2010 = 100), seasonally adjusted (Census-12) and taken logarithmically. When using wavelet analysis, the original data without pre-processing was taken.

### *VAR/Causality Tests*

This study uses vector autoregressive (VAR) models as the first method to investigate the relationship between producer and consumer prices. The Granger causality test was used for the data analysis.

Vector autoregressive models are widely used in the analysis of relationship between current and past values of variables. In such models, changes in a variable are explained by a system of simultaneous equations of lagged values of the variable itself and other variables used in the analysis. For a set of $n$ time series, the underlying model can be shown as:

$$X_t = C + A_1 X_{t-1} + A_2 X_{t-2} + \cdots A_p X_{t-p} + \varepsilon_t \qquad (1)$$

where $X_t = (X_{1t}, X_{2t} \dots X_{nt})$ time series vector, $C = (C_1, C_2 \dots C_n)$ – a vector of constant terms, $A_i = (A_1, A_2 \dots A_n)$ – a coefficient matrix, p – the order of lag in the model and $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t} \dots \varepsilon_{nt})$ – a random error vector (white noise).

Testing for data stationarity is one of the first steps in the time series analysis based on VAR models. Time series data may or may not include a unit root. If the mean and variance of a variable change over time, we can say that this variable is nonstationary, i.e. it includes a unit root. In this paper, the stationarity test is carried out using the augmented Dickey Fuller test (ADF).

Causality test can be done depending on the order in which the variables are integrated. If the variables are integrated at the first-order difference I(1) and are cointegrated, then the equation is built on the first-order difference variables and the error correction mechanism is activated. To determine cointegration, the Engle-Granger test based on the cointegration equation estimated using the least squares method is used.

According to the Granger causality test developed by Granger (1969) and based on a regression process, $X_t$ causes the Granger causality $Y_t$, if the values of the variable $Y_t$ can be explained by the values of the variable $X_t$. Granger had defined simple causality as the following model:

$$X_t = \sum_{j=1}^{m} a_j X_{t-i} + \sum_{j=1}^{n} b_j Y_{t-i} + \varepsilon_t \qquad (2)$$

[4] The Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan

$$Y_t = \sum_{j=1}^{p} c_j X_{t-i} + \sum_{j=1}^{q} d_j Y_{t-i} + \eta_t \tag{3}$$

*m, n, p* and *q* parameters denote the optimal lag length, which is determined according to one or more of the following criteria: Akaike, Schwarz or Hanna-Queen criteria (AIC, SC and HQ). If values of *bj* differ from zero significantly, $Y_t$ is the Granger cause for $X_t$. Therefore, if values of *cj* differ from zero significantly, then $X_t$ is Granger cause for $Y_t$. If both cases exist, then there is a bidirectional relationship.

In addition to the Granger approach, a modified version of the Granger causality test is used to assess reliability of the results.

A modified Wald test was proposed by Toda and Yamamoto (1995) to investigate causality. This procedure was proposed in order to overcome the problem of out-of-range asymptotic critical values when performing causality tests in non-stationary time series.

Unlike the traditional Granger causality test, the Toda-Yamamoto approach is applied in vector autoregression in levels rather than first difference of variables.

The advantage of using the Toda-Yamamoto approach is that in order to test the Granger causal relationship in the framework of a vector autoregression model, it is not necessary to pre-test the variables for stationarity and cointegration, provided that the maximum order of integration does not exceed the optimal lag in the model.

However, the Toda-Yamamoto procedure does not replace the traditional pre-testing of unit roots and cointegration in the time series analysis. They are considered complementary.

The Toda-Yamamoto approach includes the assessment of an extended vector autoregression model (k + dmax), where k – is an optimal lag value in the original model and dmax – is a maximum order of variable integration.

$$X_t = \alpha_0 + \sum_{i=1}^{k+d} \alpha_{1i} X_t + \sum_{j=1}^{k+d} \alpha_{2j} Y_{t-j} + u_t \tag{4}$$

$$Y_t = \beta_0 + \sum_{i=1}^{k+d} \beta_{1i} Y_t + \sum_{j=1}^{k+d} \beta_{2j} X_{t-j} + v_t \tag{5}$$

The Toda-Yamamoto approach uses a modified Wald (MWald) test to determine zero constraints on the parameters of the original model. The coefficients of the lagged dmax vectors are ignored in the model. If the input data is stationary, then the Toda-Yamamoto approach becomes equivalent to the standard Granger test.

### *Wavelet Analysis*

A wavelet is a zero-mean function localized both in frequency and time. A wavelet can be characterized by how localized it is in time (Δt) and frequency (Δω – flow capacity). The classical version of the Heisenberg's uncertainty principle is based on the fact that there is always a trade-off between localization in time and frequency. In this context, Δt and Δω should be properly defined. The Morlet wavelet provides a balance between time and frequency localization and therefore allows good identification and separation of periodic signals.

Being complex, the Morlet wavelet provides a complex transformation of both amplitude and phase information, which is important for studying synchronism between different time series. In its simplified version, the Morlet wavelet is defined as:

$$\psi_0(\eta) = \pi^{-1/4}\, e^{i\omega_0\eta}\, e^{-1/2\eta^2} \tag{6}$$

where $\omega_0$ – non-dimensional frequency, and η – non-dimensional time.

The idea behind the continuous wavelet transform (CWT) is to apply the wavelet as a band-pass filter to the time series. The wavelet is time-expanded and changes its scale (s) so that $\eta = s \cdot t$ and normalizes it. For the Morlet wavelet, the Fourier series ($\lambda_{wt}$) is nearly equal to the scale.

The continuous wavelet transform of a ($x_n, n = 1, \dots, N$) time series with uniform time step δt, is determined as a convolution $x_n$ with scaled and normalized wave.

$$W_n^X(s) = \sqrt{\frac{\delta t}{s}} \sum_{n'=1}^{N} x_{n'} \psi_0\left[(n' - n)\frac{\delta t}{s}\right] \tag{7}$$

The wavelet power is defined as $|W_n^X(s)|^2$. Complex argument $W_n^X(s)$ can be interpreted as a local phase.

The continuous wavelet transform has edge artifacts because the wavelet is not fully localized in time. Therefore, it is useful to introduce a cone of influence (COI) in which edge effects are not ignored. The COI is taken as the area where the wavelet power caused by the discontinuity at the boundary dropped to the value $\mathrm{e}^{-2}$at the boundary.

The statistical significance of the wavelet power can be estimated with respect to the null hypothesis that the signal is generated by a stationary process with a given background power spectrum $P_k$.

The wavelet transform can be viewed as a sequence of a series of band-pass filters applied to the time series, where the wavelet scale is linearly related to the significant period of the filter ($\lambda_{wt}$). Therefore, for a stationary process with a power spectrum $P_k$, the variance at a given wavelet scale under the convolution theorem for Fourier transforms is the variance in the corresponding range $P_k$. If $P_k$ is sufficiently smooth, then we can approximate the variance at a given scale with $P_k$ using the $k^{-1} = \lambda_{wt}$ transform. In their work, Gilbert and Compo (1998) used Monte Carlo methods to show that this approximation performs well for the AR1 spectrum. They then calculated that the probability that the wave power for a process with a given power spectrum ($P_k$) is greater than $p$

$$D\left(\frac{|W_n^X(s)|^2}{\sigma_x^2} < p\right) = \frac{1}{2} P_k \chi_v^2(p) \tag{8}$$

where $v$ equals 1 for real wavelets and 2 for complex wavelets.

Cross wavelet transform (XWT) of two time series $x_n$ and $y_n$ is defined as $W^{XY} = W^X W^{Y*}$, where * denotes a complex conjugation. Next, the power of the cross wavelet is determined as $|W^{XY}|$. The complex argument $\arg(W^{xy})$ is interpreted as the local relative phase between $x_n$ and $y_n$ in the time-frequency space. The theoretical power distribution of the cross wavelet of two time series with background power spectra $P_k^X$ and $P_k^Y$ is presented as Torrence and Compo (1998).

$$D\left(\frac{|W_n^X(s)W_n^{Y*}(s)|}{\sigma_X\sigma_Y} < p\right) = \frac{Z_v(p)}{v}\sqrt{P_k^X P_k^Y} \tag{9}$$

where $Z_v$(p) – confidence level related to probability $p$.

The cross wavelet power reveals areas with high total power. Another useful measure is how coherent the cross wavelet transform is in the time-frequency space. According to Torrence and Webster (1999), the wavelet coherence of two time series is defined as:

$$R_n^2(s) = \frac{|S\left(s^{-1}W_n^{XY}(s)\right)|^2}{S(s^{-1}|W_n^X(s)|^2) * S(s^{-1}|W_n^Y(s)|^2)} \tag{10}$$

where S – is a smoothing operator. This expression is similar to the definition of the traditional correlation coefficient and one can argue about the wavelet coherence as a localized correlation coefficient in the time-frequency space. The smoothing operator $S$ is defined by the following expression.

$$S(W) = S_{scale}(S_{time}(W_n(S))) \tag{11}$$

where $S_{scale}$ denotes smoothing along the wavelet scale axis, and $S_{time}$ – smoothing over time. The smoothing operator needs to be constructed in such a way that it has the same pattern as the wavelet used. A suitable smoothing operator for the Morlet wavelet is defined in the work by Torrence and Webster (1999):

$$S_{time}(W)|_s = \left(W_n(s) * c_1^{\frac{-t^2}{2s^2}}\right)|_s,$$

$$S_{time}(W)|_s = (W_n(s) * c_2\Pi(0.6s))|_n \tag{12}$$

where $c_1$ and $c_2$ are normalization constants, and $\Pi$ is the rectangle function. The factor 0.6 is the empirically determined decorrelation scale length for the Morlet wavelet (Torrens and Compo, 1999). In practice, both convolutions are performed discretely, so the normalization coefficients are determined numerically.

The level of statistical significance of wavelet coherence is estimated by Monte Carlo methods. A large ensemble of pairs of surrogate datasets is generated with the same AR1 coefficients as the input dataset. For each pair, the wavelet coherence is calculated. The level of significance for each scale is then evaluated using only values outside the cone of influence. Empirical testing shows that the AR1 coefficients have little effect on the level of significance. In this case, the specificity of the smoothing operator is of great importance. To estimate the significance level by the Monte Carlo method, about 1000 pairs of surrogate data sets are required. The number of scales per octave should be large enough to fix the rectangular shape of the scale smoothing operator, minimizing computation time (Grinsted, Moore, Jevrejeva, 2014).

## 4. Discussion of Outcomes

All used data demonstrate that the null hypothesis of a unit root in levels cannot be rejected. According to Table 1, all series are stationary at the first-order difference.

**Table 1. Results of the Augmented Dickey-Fuller Test***

*for the basic series (2010=100)*

| Variable | ADF test: level | | ADF test: 1-st diff | |
|---|---|---|---|---|
| | t-stat | prob. | t-stat | prob. |
| **lcpi** | -2.513063 | 0.3215 | -4.544349 | 0.0019*** |
| **lfood_cpi** | -2.865119 | 0.1776 | -3.774644 | 0.0213** |
| **lppi** | -1.987939 | 0.6021 | -6.603878 | 0.0000*** |
| **lppi_man** | -2.576622 | 0.2917 | -5.116436 | 0.0002*** |
| **lppi_consumer** | -2.357645 | 0.3999 | -5.391952 | 0.0001*** |
| **lfood_ppi** | -1.585569 | 0.7933 | -5.685921 | 0.0000*** |

*Note: H0 - data is not stationary or contains a unit root, is based on the Akaike information criterion, ***, **, ** – 1%, 5%, 10% confidence level, respectively*

*Source: the authors' computations*

Given that the variables are integrated at the first-order difference and are I(1), the hypothesis of cointegration between the variables is tested using the Engle-Granger test to determine the long-term relationship between the variables. Cointegration test statistics are presented in Table 2. The null hypothesis of no cointegration cannot be rejected, indicating that there is no long-term relationship.

**Table 2. The Engle-Granger Cointegration Test**

| Variable (lag) | tau-stat | Prob. |
|---|---|---|
| **lcpi** | -1.925752 | 0.5682 |
| **lppi** | -2.038884 | 0.5099 |
| **lcpi** | -1.748755 | 0.6559 |
| **lppi_man** | -1.386185 | 0.8043 |
| **lcpi** | -1.125790 | 0.8764 |
| **lppi_consumer** | -1.002424 | 0.9014 |
| **lfood_cpi** | -2.350242 | 0.3529 |
| **lfood_ppi** | -2.068188 | 0.4947 |

*Note: $H_0$ – the data is not cointegrated, the model contains a constant*

*Source: the authors' computations, initial data from the BNS ASPR RK*

Thus, the Granger causality test will be defined in terms of vector autoregression models on data with the first-order difference.

Determining the lag in vector autoregression models is an important step, since a larger or smaller lag leads to incorrect specification of the model. Most VAR models are estimated using symmetrical lags, i.e. the same lag length is used for all variables in all equations of the model. The lag length is often chosen using an explicit statistical criterion such as AIC or SIC. Table 3 shows the results using the

Akaike and Schwartz information criterion. The optimal lag for the models with the use of general CPI and PPI is 1, the maximum lag is 8 for a model using industrial and consumer food prices according to the Akaike criterion.

**Table 3. Optimal lag**

based on the Akaike (AIC) and Schwartz (SC) information criterion

| Lag | dlcpi dlppi | | dlcpi dlppi_manuf | | dlcpi dlppi_consumer | | dlfood_cpi dlfood_ppi | |
|---|---|---|---|---|---|---|---|---|
| | AIC | SC | AIC | SC | AIC | SC | AIC | SC |
| 0 | -11.99402 | -11.94829 | -13.98438 | -13.93865 | -15.23388 | -15.18815 | -11.16386 | -11.11765 |
| 1 | **-12.56274*** | **-12.42556*** | -14.52029 | **-14.38311*** | -15.68648 | **-15.54930*** | -11.98175 | **-11.84311*** |
| 2 | -12.54283 | -12.31420 | **-14.58340*** | -14.35477 | -15.71392 | -15.48529 | -11.92446 | -11.69341 |
| 3 | -12.52538 | -12.20529 | -14.57609 | -14.25601 | **-15.78097*** | -15.46088 | -11.88455 | -11.56107 |
| 4 | -12.49223 | -12.08069 | -14.58143 | -14.16989 | -15.74973 | -15.33819 | -11.87489 | -11.45899 |
| 5 | -12.47808 | -11.97509 | -14.53261 | -14.02962 | -15.72106 | -15.21806 | -11.91211 | -11.40378 |
| 6 | -12.42611 | -11.83166 | -14.50955 | -13.91511 | -15.67465 | -15.08021 | -11.91640 | -11.31565 |
| 7 | -12.36479 | -11.67890 | -14.47956 | -13.79367 | -15.65638 | -14.97048 | -11.88368 | -11.19050 |
| 8 | -12.41358 | -11.63622 | -14.42919 | -13.65183 | -15.61031 | -14.83296 | **-12.00595*** | -11.22036 |

*Source: the authors' computations*

According to Table 4, where the results of the Granger causality test are given, there is no relationship between the general PPI and CPI, i.e. these indicators cannot be used to forecast each other. There is a one-way relationship from producer prices in the manufacturing industry to consumer prices, with the narrower producer price index of consumer products being inversely affected by and dependent on consumer prices. Moreover, food producer prices are a leading indicator for the dynamics of food prices in Kazakhstan (at the 5% significance level). Two-way relationships were not found in any group of indicators.

**Table 4. Results of the Granger causality test**

| Dependent variable | Independent variable | Lag | Chi-sq | Prob. | Direction of causality |
|---|---|---|---|---|---|
| dlcpi | dlppi | **1** | 0.401479 | 0.5263 | ----- |
| dlppi | dlcpi | | 0.185002 | 0.6671 | |
| dlcpi | dlppi_manuf | **2** | 28.52456 | 0.0000 | ppi_manuf→ cpi |
| dlppi_manuf | dlcpi | | 2.602610 | 0.2722 | |
| dlcpi | dlppi_consumer | **3** | 1.589098 | 0.6619 | cpi → ppi_consumer |
| dlppi_consumer | dlcpi | | 19.01502 | 0.0003 | |
| dlfood_cpi | dlfood_ppi | **8** | 14.28621 | 0.0746 | food_ppi → food_cpi |
| dlfood_ppi | dlfood_cpi | | 6.453678 | 0.5966 | |

*Source: the authors' computations*

The lack of relationship between the general producer index and consumer prices may be determined by the fact that a significant part of products of Kazakhstani producers belongs to the mining industry and does not reflect goods included in the consumer basket.

The influence of food producers on the food inflation stems from the fact that most food products are produced in Kazakhstan, and the domestic self-sufficiency is about 80% on average.

At the same time, the impact of consumer inflation on producer prices of consumer goods (which also include food) may indicate that other goods included in the index may be affected by demand. However, the remaining goods mainly belong to the category of energy carriers (fuel and lubricants, coal, gas), whose prices were regulated for most of the analyzed period and also weakly depended on the pricing in world markets. In this regard, such impact can be explained by a general increase in the demand for all goods and services, which is accompanied by the rise in prices of end sellers. In turn, this causes a further increase in prices of domestic producers of consumer goods.

Meantime, the Toda-Yamamoto approach performed on the original time series found a one-way relationship only between producer prices in the manufacturing industry and consumer prices (Table 5).

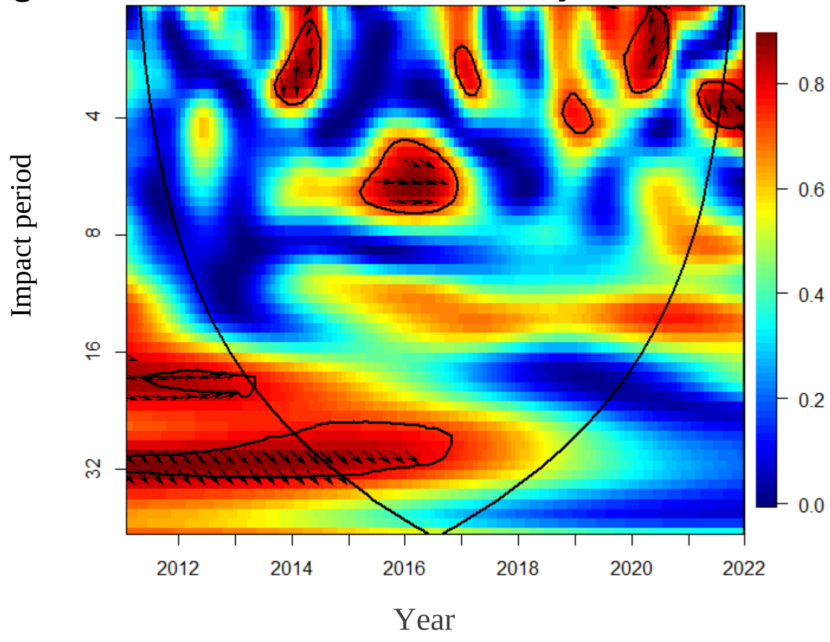
**Table 5. Results of the Granger (Toda-Yamamoto) causality test**

| Dependent variable | Independent variable | Lag | VAR Level (k+dmax) | Chi-sq | Prob. | Direction of causality |
|---|---|---|---|---|---|---|
| lcpi | lppi | 1 | 2 | 0.337240 | 0.9309 | ----- |
| lppi | lcpi | | | 0.007516 | 0.6671 | |
| lcpi | lppi_manuf | 2 | 3 | 28.52456 | 0.0000 | ppi_manuf→ cpi |
| lppi_manuf | lcpi | | | 2.357928 | 0.3076 | |
| lcpi | lppi_consumer | 3 | 4 | 3.023450 | 0.3880 | -------- |
| lppi_consumer | lcpi | | | 4.903698 | 0.1790 | |
| lfood_cpi | lfood_ppi | 8 | 9 | 12.94110 | 0.1139 | --------- |
| lfood_ppi | lfood_cpi | | | 6.842318 | 0.5537 | |

*Note: d (max) =1, since the order of integration is equal to 1. The choice of lag is based on the Akaike criterion. Source: initial data from the BNS ASPR RK, the authors' computations*

The results of wavelet analysis between producer prices and consumer prices shown in Figure 2, as in the case of results of the Granger causality test, did not demonstrate a significant relationship between variables over the analyzed period.

**Figure 2. The results of wavelet analysis between PPI and CPI.**

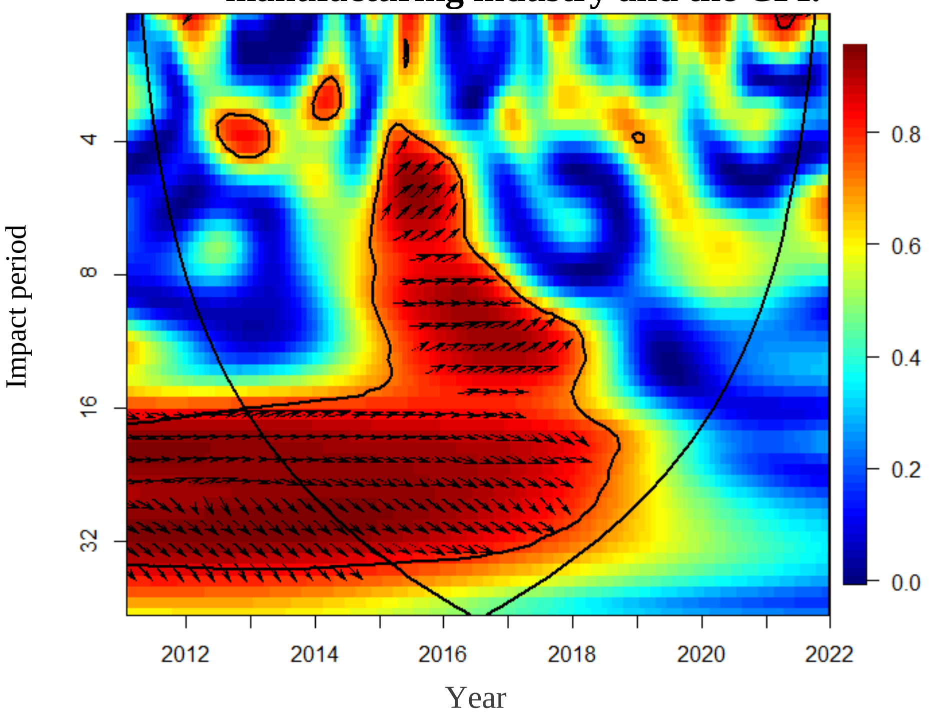


*Note: The black outline indicates a 5% significance level with respect to red noise, which is estimated based on Monte Carlo simulations using a phase-randomized surrogate series. Blue color indicates low coherence, while red indicates high coherence. The direction of arrows shows the phase difference, the procyclical direction is the arrow to the right; the acyclical direction is the arrow to the left. In the procyclical direction, the PPI is leading (lagging) relative to the CPI if the arrow points up (down) and to the right. With an acyclical direction, the PPI is leading (lagging) relative to the CPI if the arrow is pointing down (up) and to the left.*

*Source: the authors' computations.*

This is due to the fact that in addition to the manufacturing industry, the producer price index also includes the mining and quarrying sector, which has a weak dependence on end consumer prices and is more correlated with oil prices. At the same time, according to the ASPR BNS, in 2021, the share of the mining industry and quarrying accounts for about 54% of the overall producer price index. To even out this issue, we will further consider the relationship between producer prices in the manufacturing industry and consumer prices (Figure 3).

**Figure 3. The results of wavelet analysis between the PPI in the manufacturing industry and the CPI.**




Note: The black outline indicates a 5% significance level with respect to red noise, which is estimated based on the Monte Carlo simulations using a phase-randomized surrogate series. Blue color indicates low coherence, while red indicates high coherence. The direction of the arrows shows the phase difference, the procyclical direction is the arrow to the right; the acyclical direction is the arrow to the left. In the procyclical direction, the PPI in the manufacturing industry is leading (lagging) relative to the CPI if the arrow points up (down) and to the right. With an acyclical direction, the PPI in the manufacturing industry is leading (lagging) relative to the CPI if the arrow is pointing down (up) and to the left.

Source: the authors' computations.

In contrast to the results of the analysis of relationship between the PPI and the CPI, the results of wavelet analysis of the PPI in the manufacturing industry and the CPI show the presence of cross-impact. However, starting from October 2018, the dependence of the two variables actually stops. This is because in 2018, despite the national currency depreciation and steadily high values of producer prices, inflation slowed down and made up 5.3% at the end of the year. At the same time, the profitability of enterprises, both large and small ones, declined. Thus, the profitability of large and medium-sized enterprises in the first quarter of 2018 was 34.7%, and in the fourth quarter of 2018, it went down to 17.3%, and the profitability of small enterprises decreased from 19.5% to 10.4%.

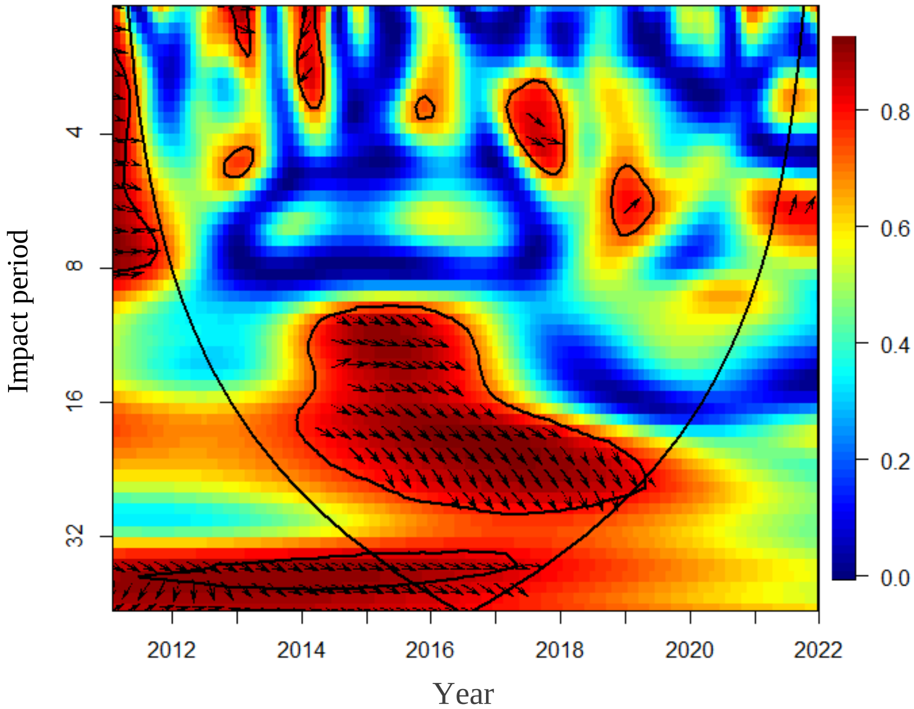
The slowdown in inflationary processes in this period was partly caused by reduced profits of enterprises. Manufacturers, suppliers and resellers at that time had the opportunity to “endure” the decline in profitability given its high values in previous periods. At times when the exchange rate appreciates, economic entities can increase profitability by retaining the level of prices for their goods and services. In turn, the depreciation of the exchange rate puts downward pressure on the level of profitability in certain sectors of the economy. In addition, in the third quarter of 2018, the inflationary pressure from the external sector weakened. Thus, the aggregate external inflation of the main trading partners (Russia, the EU, China), despite some acceleration of inflation in Russia, slowed down. Such slowdown was accompanied, first of all, by the annual appreciation of the tenge against the ruble.

At the same time, the lack of relationship in subsequent years is explained by the influence of various factors: 2019 – deceleration of inflation in response to a positive shock – lower tariffs for regulated services, 2020 – pent-up consumer demand in the environment of coronavirus pandemic, 2021 – growth in world prices and the impact of deferred consumer demand.

In the period from December 2015 to May 2016, the analyzed variables are procyclical, and the PPI in the manufacturing industry from months 4 to 8 is the leading indicator for the CPI. Later, as the period of impact increases, the leading properties of producer prices in the manufacturing industry over consumer inflation exhaust, and the two variables do not influence each other. Moreover, both variables are procyclical and their maximums and minimums coincide. It is noteworthy that already from months 16 to 32, consumer prices have a leading effect on the producer price index, which indicates the presence of an inflationary background in the economy associated with the influence of demand factors. Probably, during this period, producer prices are being restructured in response to consumer inflation (increasing wages, utility bills, etc.). In these periods (months 16-32), the impact of demand-pull inflation is observed almost over the entire analyzed period, and more precisely from the beginning of 2011 to October 2018.

Despite the existence of links between manufacturing producer prices and consumer prices, the authors of this study decided to delve into this issue and consider the impact of PPI of consumer goods. After all, the manufacturing industry, in addition to the usual goods, includes a wide range of products not included in the consumer inflation that can distort the relationship between producer prices and consumer prices. Figure 4 demonstrates the impact of producer prices of consumer goods and consumer inflation.

**Figure 4. The results of wavelet analysis between the PPI of consumer goods and the CPI**




Note: The black outline indicates a 5% significance level with respect to red noise, which is estimated based on Monte Carlo simulations using a phase-randomized surrogate series. Blue color indicates low coherence, while red indicates high coherence. The direction of the arrows shows the phase difference, the procyclical direction is the arrow to the right; the acyclical direction is the arrow to the left. In the procyclical direction, the PPI of consumer goods is leading (lagging) relative to the CPI if the arrow points up (down) and to the right. In the acyclical direction, the PPI of consumer goods is leading (lagging) in relation to the CPI if the arrow is pointing down (up) and to the left.

Source: the authors' computations.

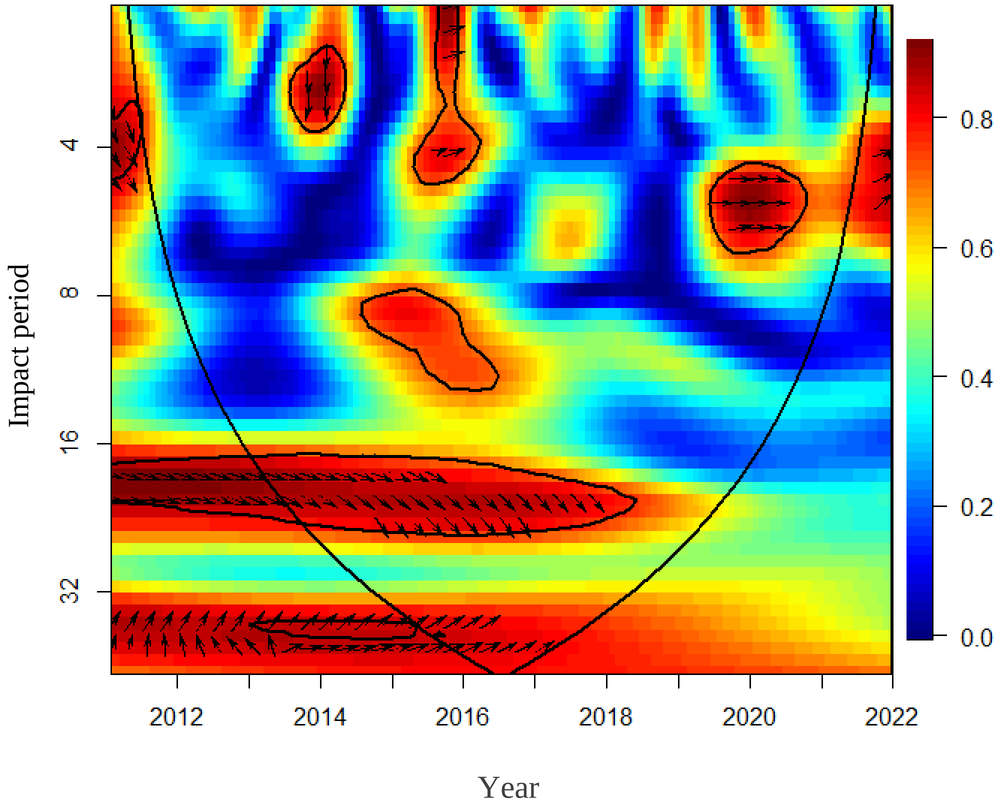
During the analyzed period, the dependence of the two variables is not homogenous. Thus, from November 2012 to February 2013, in the period of up to 2 months, there is a dependence of prices of consumer goods producers on the dynamics of consumer prices per se. However, already from the end of 2013 to March 2014, in the first four months of impact, producer prices are a leading indicator for consumer prices. In the period from March 2017 to February 2018, the dependence of producer prices on consumer prices is observed again, but already in a longer period (from 3 to 5 months). At the same time, as in the case of the manufacturing industry in general, the producer price index of consumer goods in the long term depends on the dynamics of consumer inflation, which can also be explained by the restructuring of producer prices in response to a new level of consumer prices.

Given a large share of imports in the non-food component of consumer inflation[5], one may suggest that the share of non-food products in the prices of consumer goods producers is not big, and the index itself is largely consisting of the

[5] According to preliminary data of the ASPR BNS, the share of imports in the non-food component made up 60.3% as of end-2020. In 2011-2019, the share of imports accounted for 60.4% on average.

food production. Perhaps, the food producer price index will demonstrate a higher coherence with the food component of consumer inflation.

**Figure 5. The results of wavelet analysis between the PPI of food products and the CPI of food products.**




Note: The black outline indicates a 5% significance level with respect to red noise, which is estimated based on Monte Carlo simulations using a phase-randomized surrogate series. Blue color indicates low coherence, while red indicates high coherence. The direction of the arrows shows the phase difference, the procyclical direction is the arrow to the right; the acyclical direction is the arrow to the left. In the pro-cyclical direction, PPI of consumer goods is leading (lagging) relative to the CPI if the arrow points up (down) and to the right. In the acyclical direction, the PPI of consumer goods is leading (lagging) in relation to the CPI if the arrow is pointing down (up) and to the left.

Source: the authors' computations.

The results of wavelet analysis of the cross-impact of food PPI and food CPI demonstrate the absence of strong correlations (Figure 5). At the same time, according to the Granger causality test, the PPI at the 5% significance level is the cause for the PPI. However, in some periods, the mutual dependence between the variables is still observed. From May 2015 to April 2016, the food PPI is the leading indicator for the food PPI with the impact period of 1 to 6 months. Already in the medium term (16-24 months), food producer prices depend on the consumer inflation until May 2018.

## 5. Findings and Recommendations for Future Research

In this paper, the relationship between the producer price index and the consumer price index has been empirically investigated. Various reasons can serve as the factors of inflationary processes, while producer prices are one of the important sources of information about the situation in the economy.

The application of traditional approaches and tests for causality has shown that producer price indices in the manufacturing industry as well as of food producers are the leading indicators for the consumer inflation. All relationships are one-way. At the same time, the use of wavelet analysis showed that the influence of two variables can be two-way and can change over time. In the short term, the producer price index is a leading indicator for the consumer inflation. Over time, in the medium term, the producer price index depends on the consumer prices. This effect is explained by the restructuring of producer prices in response to the acceleration of headline inflation, which forces producers to raise wages, and the general rise in prices causes the increase in the cost of production of goods.

There are many studies on this topic in the literature. The results may vary depending on the specific sample, methodology and approaches. Thus, classical econometric methods demonstrated a strong dependence of food consumer prices on food producer prices, while wavelet analysis did not reveal a strong dependence of final prices on food producer prices.

Further research in this area can be built by including the exchange rate and other variables to determine the degree of correlation of variables affected by various externalities.

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# 7. Attachments

Attachment A

## Summary of International Studies

| Authors | Paper Title | Year | Country | Data | Methodology | Outcome |
|---|---|---|---|---|---|---|
| Groups of Countries | | | | | | |
| Selçuk AKÇAY | The Causal Relationship between Producer Price Index and Consumer Price Index: Empirical Evidence from Selected European Countries | 2011 | Germany, France, Netherlands, Sweden, Finland | 1995-2007 MoM | VAR (Toda and Yamamoto no-causality test) | CPI ↔ PPI PPI → CPI (Finland, France) |
| Woo Kai Yin Jia Lin Xuan | Threshold Cointegration and Causality between CPI and PPI in Selected Countries– Some International Evidence | 2013 | Canada, Denmark, Indonesia, Japan, Pakistan, Spain, Uruguay | 1980-2012 MoM | Momentum threshold autoregressive (M-TAR) model, M-TVECM | CPI↔PPI CPI→PPI (Spain) |
| On a Country-by-Country Basis | | | | | | |
| Ülke, Volkan, Ergun, Ugur | The Relationship between Consumer Price and Producer Price Indices in Turkey | 2013 | Turkiye | 2003-2013 MoM | VECM, Granger causality test | CPI→PPI (long run) **X** (short run) |
| Debby Anggraen, Tony Irawan | Causality Analysis of Producer Price Index (PPI) and Consumer Price Index (CPI) in Indonesia | 2018 | Indonesia | 2010-2016 MoM | VAR model (Granger causality test) | PPI → CPI Food PPI↔ Food CPI Clothing CPI→PPI of clothing |
| Khalid Khan, Chi-Wei Su, Ran Tao & Chien-Chi Chu | Is there any relationship between producer price index and consumer price index in the Czech Republic? | 2018 | Czech Republic | 1999-2016 | Expenditure-switching model, Wavelet analysis | CPI ↔ PPI (depends on period) **X*** in certain periods |
| Jos´e Sidaoui Carlos Capistr´an Daniel Chiquiar Manuel Ramos-Francia | A Note on the Predictive Content of PPI over CPI Inflation: The Case of Mexico | 2009 | Mexico | 2001-2009 | ECM, Granger test | PPI → CPI (in the long run) |
| Ooi Ai Yee, Mohd Fahmi Ghazali | Do Producer Prices Cause Consumer Prices? Some Empirical Evidence | 2008 | Malaysia | 1986-2007 | ECM, Grange r causality tests and the Toda-Yamamoto causality approach | PPI → CPI |
| Aviral Kumar Tiwari, Mihai Mutascu, | Decomposing time-frequency relationship between producer price and consumer price indices in Romania through wavelet analysis | 2012 | Romania | 1981–2009 | Wavelet analysis | CPI ↔ PPI (depends on period) **X*** in certain periods |

| | | | | | | |
|---|---|---|---|---|---|---|
| Alin Marius Andries | | | | | | |
| Aviral Kumar Tiwari, Suresh K.G., Mohamed Arouri, Frédéric Teulon | Causality between consumer price and producer price: Evidence from Mexico | 2013 | Mexico | 1981–2009 | Wavelet analysis | CPI→PPI (1-7 months) PPI → CPI (8-32 months) |

X* - no relationship