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Relationship between CPI and PPI Inflation in Iran: Does Inflation Anchored by Liquidity Growth or Exchange Rate Growth?

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Abstract

This study examines how exchange rate growth and liquidity growth impact the relationship between consumer price index "CPI" inflation and producer price index "PPI" inflation in Iran from 2005 to 2023, using monthly data. We employ continuous wavelet transformation to capture the dynamic relationship between CPI and PPI across different frequency bands. Additionally, we use a vector auto-regressive with exogenous variables model to validate our findings and utilized the Granger causality test. In this study, CPI and PPI indices are divided into three categories: CPI and PPI of goods, CPI and PPI of services, and total CPI and PPI, which is the weighted mean of the two priors. Our models are applied separately to each category of CPI and PPI inflation. The results indicate that the relationship between CPI inflation and PPI inflation for goods is stronger and more reliable than for services. Also, we demonstrate how liquidity growth and exchange rate growth contribute to inflation through demand-pull and cost-push mechanisms, respectively. Finally, we highlighted that this relationship is more dependent on exchange rate growth than liquidity growth, particularly in recent years. This indicates that inflation in Iran during the studied period is predominantly driven by cost-push factors rather than demand-pull forces.

Highlights

- Demand-pull inflation can be identified when CPI inflation leads PPI inflation.
- Supply-push inflation can be identified when PPI inflation leads CPI inflation.
- Liquidity growth control is effective when demand-pull inflation is dominant.
- Exchange rate growth control is effective when Supply-pull inflation is dominant.

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1. Introduction

As far as we know, David Hume was the first to conceptualize the quantity theory of money and inflation. Since the late 20th century, many economists have explored various aspects of inflation. One of the most controversial issues in countries with high inflation regimes, like Iran, is understanding how the relationship between consumer price index "CPI" inflation and producer price index "PPI" inflation is influenced by exchange rate and liquidity growth.

The primary objective of this study is to thoroughly examine the relationship between Consumer Price Index (CPI) inflation and Producer Price Index (PPI) inflation over time, focusing on their dynamic interactions across various frequency domains. This analysis aims to capture how these interactions evolve in the short, medium, and long term. Additionally, the study seeks to investigate the extent to which exchange rate growth and liquidity growth influence this relationship. Despite numerous studies, the existing literature has not reached a consensus on whether CPI leads PPI or if PPI leads CPI. Moreover, it largely neglects the potential role of exchange rate growth and liquidity growth as contributing factors to this dynamic interaction. To address these gaps, we adopt the Continuous Wavelet Transform (CWT) approach, which allows us to analyze the direction and lead-lag relationships between CPI and PPI inflation over time and across different frequencies. By using CWT with phase diagrams, we can simultaneously observe the temporal and frequency-specific co-movement patterns of these two variables. This technique enables us to identify whether CPI or PPI takes the lead in influencing the other and whether this lead-lag relationship varies across different frequency domains. To further refine the analysis, we separately control for the effects of exchange rate growth and liquidity growth. This step helps to isolate the influence of these factors and quantify their role in explaining the observed co-movements between CPI and PPI inflation. The inclusion of these controls provides a clearer understanding of the mechanisms driving the dynamic interactions between CPI and PPI. In addition to the CWT analysis, we employ a Vector Autoregressive model with exogenous variables (VARX) to validate the findings derived from the wavelet approach. The VARX model enables us to statistically confirm the dynamic relationships between CPI and PPI inflation while incorporating exchange rate growth and liquidity growth as exogenous factors. However, as Granger & Lin (1995) pointed out, the direction and extent of causality between two variables can vary across different frequency bands. To complement our wavelet and VARX analyses, we also perform the Granger causality test (Granger, 1969). This test helps identify leading and lagging variables across time, irrespective of their frequency-specific dynamics, providing an additional layer of insight into the temporal interactions between CPI and PPI inflation. By integrating these methodologies, this study aims to contribute to the understanding of the dynamic relationship between CPI and PPI inflation. Specifically, it seeks to clarify the roles of exchange rate growth and liquidity growth in shaping these interactions.

A novel aspect of this study is the classification of CPI and PPI into three distinct categories: CPI and PPI of goods, CPI and PPI of services, and total CPI and PPI, which represents a weighted average of the first two categories. We then applied the CWT and VARX approaches to each category one by one, and then conducted the Granger causality test for all categories separately.

The structure of the research is such that after the introduction, in the second section the data and methodology has been studied, the third section shows the estimation and model results, and finally in the fourth section provided the conclusions and policy implications.

2. A Review of the Related Literature

In the following literature, we will focus on four main categories: the relationship between CPI and PPI, exchange rate growth with CPI and PPI inflation, liquidity growth with CPI and PPI inflation, and the effect of inflation expectation and inflation inertia on inflation. We will delve into each category in order.

The relationship between CPI and PPI can be understood in three ways. First, PPI can influence CPI, as the supply-side approach suggests that changes in the prices of crude materials and intermediate goods can impact the cost of final goods, thereby affecting consumer prices (Clark, 1995). Second, CPI can drive PPI; the demand-side approach posits that the demand for final goods and services dictates production input demand, impacting production costs and, consequently, producer prices (Caporale et al., 2002). Also, Cushing & McGarvey (1990) noted that primary goods demand is influenced by expected future consumer goods prices. Third, a bidirectional effect exists, indicating both mechanisms are at play.

According to the supply-side perspective, Caporale et al. (2002) identified unidirectional causality from PPI to CPI in France and Germany among the G7 countries. Ghazali et al. (2008) found a similar relationship in Malaysia. Akcay (2011) observed the same causality in Finland and France, while Alemu (2012) noted a unidirectional, nonlinear relationship from PPI to CPI. Which means that a rise in CPI due to an increasing PPI is faster than falling in CPI due to a decrease in PPI. Tiwari et al. (2013) used continuous wavelet transform analysis to show that PPI leads CPI in the 0.5-1.25-year frequency band. Filho (2019) pointed out that PPI captures domestic prices and intermediate imported goods, while CPI includes both domestic and final imported goods, demonstrating PPI's leading role in Brazil's CPI.

In line with the demand-side perspective, Colclough & Lange (1982) found that CPI leads PPI in the USA. Clark (1995) showed that PPI changes do not reliably predict CPI changes. Akdi et al. (2006a) found short-run causality from CPI to PPI in inflation-targeting economies like Sweden, the UK, and Canada. Akdi et al. (2006b) observed a similar short-run causal relationship from CPI to PPI in Turkey. Gang et al. (2009) reported that in China, CPI Granger-causes PPI, emphasizing the importance of demand-side factors. Tiwari (2012) used a continuous wavelet transform model and found that CPI leads PPI in Australia, but not the other way around.

From a bidirectional perspective, Caporale et al. (2002) found bidirectional causality in Italy, Japan, the UK, and the US, with no causality in Canada. Shabaz et al. (2009) identified a long-run bidirectional relationship between PPI and CPI in Pakistan, with a stronger effect from PPI to CPI. Akcay (2011) found bidirectional causality in Germany and no significant causality in the Netherlands and Sweden. Tiwari et al. (2014) revealed a bidirectional relationship in Mexico: PPI leads CPI in the long run (8-32 months), while CPI leads PPI in the short run (1-7 months). Sun et al. (2023) showed a bidirectional transmission mechanism between PPI and CPI in China, indicating both PPI's positive influence on CPI and the reverse.

About Exchange rate relationship with inflation, Dornbusch (1976) highlights that factors like import volume, import substitution possibilities, and the demand for intermediate goods in domestic production play a crucial role. Based on Svensson's (2000) work, the channels through which exchange rates can affect inflation can be explained as follows: 1) The exchange rate impacts the PPI of goods by increasing the prices of intermediate goods. 2) The exchange rate influences the CPI and PPI of services, potentially leading to higher wages or labor migration abroad. 3) The exchange rate affects the CPI of goods by raising the prices of imported final products.

In this matter, Ito & Sato (2007) studied the effect of currency depreciation on domestic prices in crisis-affected countries, including three Latin American nations, Turkey, and four East Asian countries. They found that exchange rate pass-through significantly increases both CPI and PPI. Bhattacharya & Yhomakos (2008) analyzed three major economies (Japan, the United Kingdom, and the United States) and finding that exchange rates are a unidirectional cause for domestic price variables. Ocran (2010) found that in South Africa, a 1% change in the exchange rate leads to a 0.125% increase in CPI and a 20% increase in PPI. According to Frankel et al. (2012), increased long-term inflation and fluctuations in exchange rates led to a stronger exchange rate pass-through effect on the CPI. An & Wang (2012) studying nine OECD countries and demonstrate exchange rate pass-through respectively and positively affects import prices, PPI, and CPI. Martinez et al. (2013) claim that the exchange rate impacts PPI more than CPI. Monfared & Akin (2017) analyzed Iran's quarterly data and showed that the exchange rate has a significant positive effect on CPI inflation. Khan et al. (2018) used a continuous wavelet transform approach for the Czech Republic and indicated CPI and PPI co-movement in the short run, significantly influenced by the exchange rate. Blagov (2019) identifies exchange rate nonlinearities as a significant factor influencing import price dynamics. From a policy standpoint, exchange rate volatility can still drive inflation, even in cases where exchange rate pass-through is minimal or absent. Nasir (2020) found that during periods of high economic uncertainty, central bank inflation forecasts are unreliable. Short-term predictions can be improved by giving more consideration to the impact of sharp internal currency depreciation. Citci & Kaya (2023) examined the impact of exchange rate uncertainty on inflation in 149 countries between 1980 and 2017 and found exchange rate uncertainty has a significant role on inflation.

On the other hand, many economists firmly adhere to the quantity theory of money, as famously articulated by Friedman (1970): "inflation is always and everywhere a monetary phenomenon." This idea has been supported by numerous studies examining the effect of money supply on inflation. Assenmacher-Wesche & Gerlach (2006) find that, for the euro area, Japan, the UK, and the US, money growth and inflation are closely linked at low frequencies, once interest rate effects on money demand are considered. Assenmacher-Wesche & Gerlach (2006) analyzed quarterly data for the euro area and found that money growth is a key factor in explaining low-frequency inflation variations. Su et al. (2016) reported mixed and varying results across different time periods. Meanwhile, Hung & Thompson (2016) analyzed data from OECD countries and concluded that inflation is not strongly influenced by changes in the money supply. Lu et al. (2017) found that inflation tends to increase with an expansion in the money supply. Monfared & Akin (2017) assert that money supply has a positive and significant effect on CPI inflation.

Economists commonly agree on the concept of inflation inertia, where past inflation influences current levels. Additionally, the self-fulfilling nature of inflation means that in certain situations, agents' expectations of inflation can materialize as actual inflation. In this matter, Gali & Gertler (1999) demonstrated inflation inertia, indicating that current inflation is significantly influenced by past inflation, by analyzing quarterly U.S. data. Gürkaynak et al. (2006) demonstrate that developed countries implementing inflation targeting policies have less sensitivity to economic news in inflation expectations compared to countries without such policies. Posen (2011) demonstrates how inflation expectations in Britain translate into actual inflation in the near future. Also, Wimanda et al. (2011) analyzed Indonesia's quarterly data and finding that inflation inertia significantly influences current inflation. An & Wang (2012) studied nine OECD countries and demonstrate a higher pass-through is linked to higher inflation rates in the past, which could lead to higher inflation of CPI and PPI.

3. The Study Model

3.1 Models, Variable, and Data Description

We have detailed CPI and PPI data from the central bank of Iran. We categorize items into goods and services and calculate CPI and PPI for each category. The data covers the period from 2005 to 2023, monthly.

Following this, we select the optimal lag for exchange rate growth and liquidity growth, which serve as exogenous variables, to control their impact on the CPI and PPI inflation of goods, services, and the total index. To this end, we calculate the p-value of the correlation between each exogenous variable and the CPI and PPI inflation for each category. Fig. 1 illustrates the p-value of each exogenous variable's lag with both CPI and PPI inflation of each category.

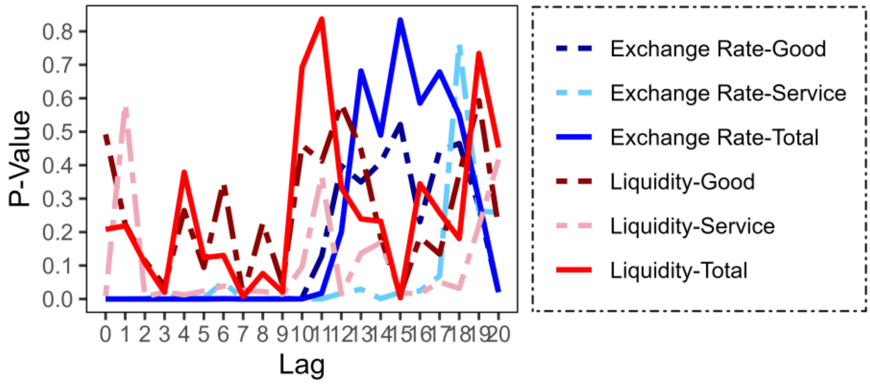


Fig 1. Correlation P-values of each CPI and PPI inflation with lags of exogenous variables

***Source**: Research Findings*

The best lag to use as an exogenous variable is the one with the minimum p-value across all lags. A lower p-value indicates a stronger correlation between the lag of the exogenous variable and CPI and PPI inflation, making it the most suitable for explaining changes in these inflation measures.

We consider only the p-value of the total CPI and PPI index to choose the optimal lag for exogenous variables. Based on Fig. 1, the best lag for the exchange rate is the zero lag (i.e., no lag), and the best lag for liquidity growth is the fifteenth lag.

Table 1 provides a detailed description of all the variables utilized in the models.

Table 1. Introduction of variables

Variable	Definition
CPIT.Inf	Monthly Consumer price inflation of total index (%)
PPIT.Inf	Monthly Producer price inflation of total index (%)
CPIG.Inf	Monthly Consumer price inflation of good index (%)
PPIG.Inf	Monthly Producer price inflation of good index (%)
CPIS.Inf	Monthly Consumer price inflation of service index (%)
PPIS.Inf	Monthly Producer price inflation of service index (%)
EXR.Grw	Monthly US Dollar growth of free market in lag zero (%)
LIQ.Grw15	Monthly Liquidity growth in lag fifteenth (%)

Notes: All the data are on a monthly frequency over the period 2005-2023.
(except LIQ.Grw15 that start from 2003)
***Source**: Research Findings*

Table 2 presents the summary of descriptive statistical indicators for the variables used in the model.

Table 2. The statistical summary of all the variables

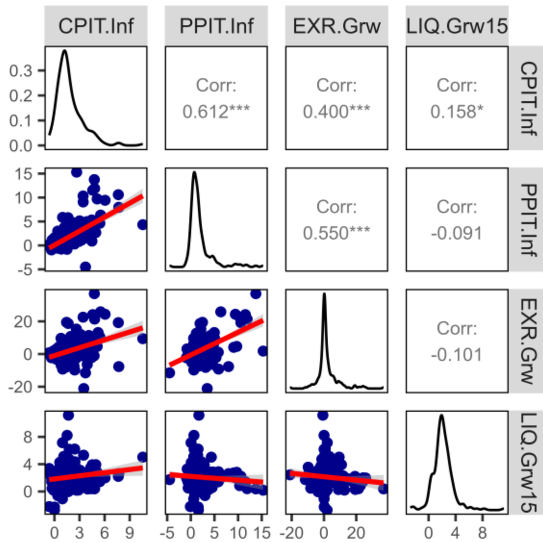
variables	Observation	Mean	Std.dev	Min	Max	Skew	Kurt	Shapiro test
CPIT.Inf	217	1.81	1.56	-0.63	10.57	1.73	5.11	0.87***
CPIG.Inf	217	1.97	2.28	-1.99	13.65	1.52	3.68	0.89***
CPIS.Inf	217	1.63	1.08	0.16	5.50	1.45	1.74	0.86***
PPIT.Inf	217	1.83	2.48	-4.51	15.31	2.66	8.99	0.71***
PPIG.Inf	217	1.86	2.92	-6.47	17.99	2.35	8.49	0.78***
PPIS.Inf	217	1.80	2.59	-2.75	15.00	2.57	7.79	0.72***
EXR.Grw	217	1.97	6.26	-21.11	36.95	1.81	7.30	0.80***
LIQ.Grw15	217	2.11	1.51	-2.72	11.17	1.28	7.19	0.89***

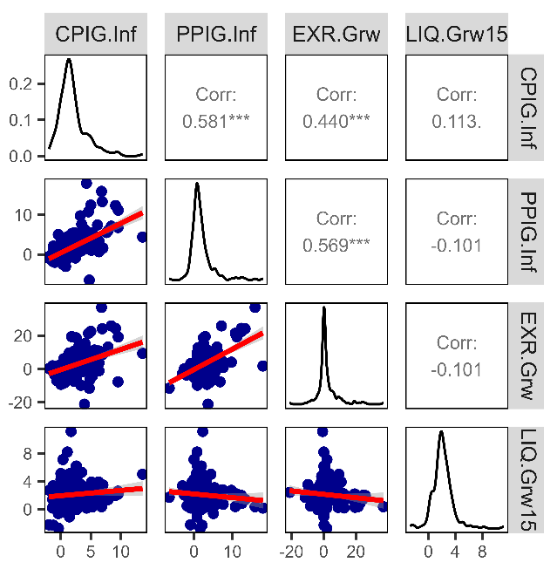
*Notes: ***Significance at the 1% level*

***Source**: Research Findings*

Based on the statistical description provided in Table 2, all variables exhibit a leptokurtic distribution, characterized by long and thick tails, along with a pronounced positive (right) skewness. This indicates a deviation from a normal distribution. The Shapiro-Wilk test further confirms this non-normality, as it rejects the null hypothesis of normal distribution for all variables at a 1% significance level.

To enhance the understanding of the statistical characteristics and interrelationships of the variables, we present Fig. 2. In the lower triangle of the matrix, scatter plots and linear regressions between the variables are shown. The upper triangle displays the estimated correlation coefficients between the variables, while the diagonal illustrates the distribution of each variable. From left to right, the first image represents CPI and PPI inflation for the total index, the second for goods, and the third for services.


CPIT.Inf
PPIT.Inf
EXR.Grw
LIQ.Grw15
Corr:
0.612***
Corr:
0.400***
Corr:
0.158*
Corr:
0.550***
Corr:
-0.091
Corr:
-0.101
CPIT.Inf
PPIT.Inf
EXR.Grw
LIQ.Grw15


CPIG.Inf
PPIG.Inf
EXR.Grw
LIQ.Grw15
Corr:
0.581***
Corr:
0.440***
Corr:
0.113.
Corr:
0.569***
Corr:
-0.101
Corr:
-0.101
CPIG.Inf
PPIG.Inf
EXR.Grw
LIQ.Grw15

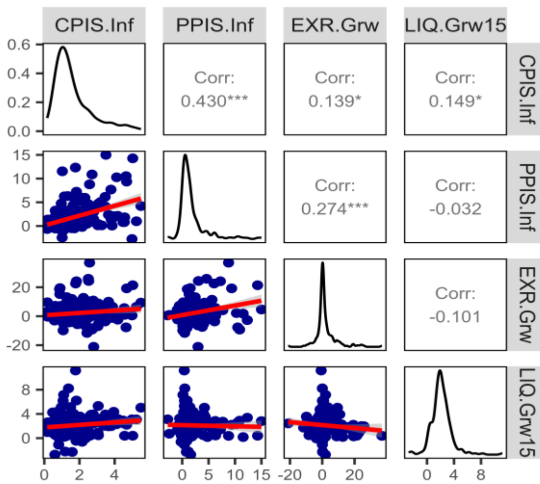
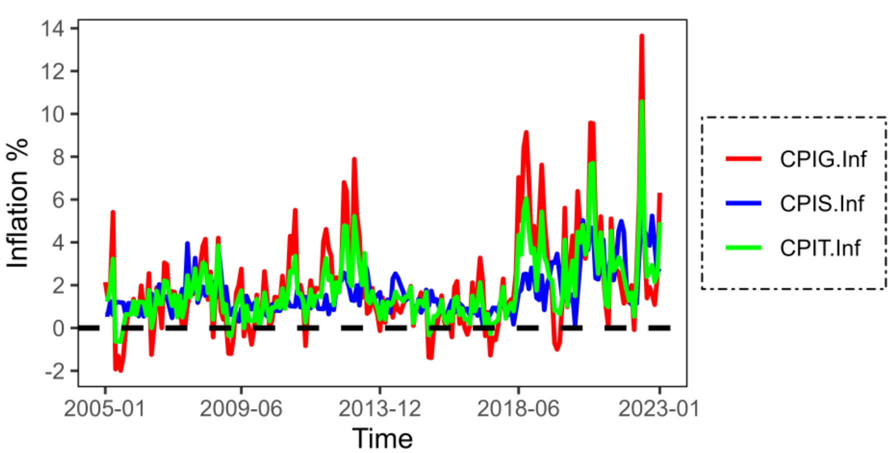


Fig 2. Correlation, scatter plots, linear regressions between variables, and the distribution of each variable

*(***Significance at the 1% level-- * Significance at the 5% level-- . Significance at the 10% level)*

***Source**: Research Findings*

In Fig. 3, the trends of consumer and producer price inflation for goods, services, and the total index are depicted. As expected, the total index reflects an average of the inflation rates for goods and services. Notably, there is an observable regime change in monthly CPI inflation following the intensified U.S. sanctions on Iran in the latter half of 2018. But there is no such regime change in PPI.



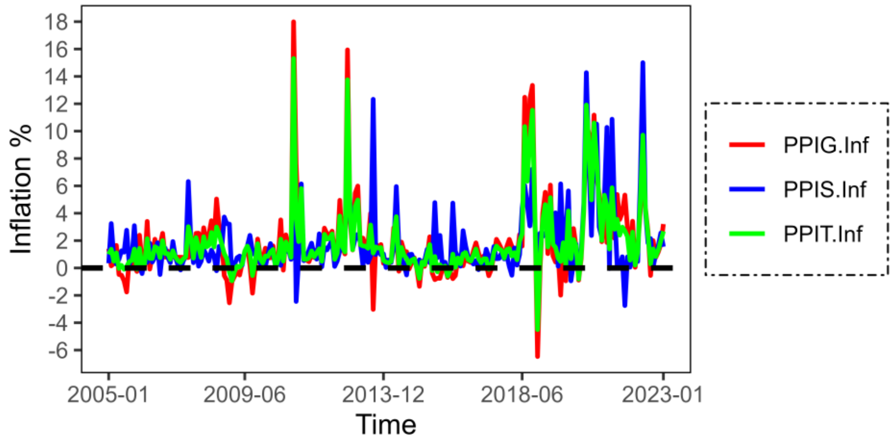


Fig 3. Time series of consumer and producer price inflation for goods, services, and the total index
***Source**: Research Findings*

In Fig. 4, the trends for exchange rate growth (zero lag) and liquidity growth (fifteenth lag) are illustrated.

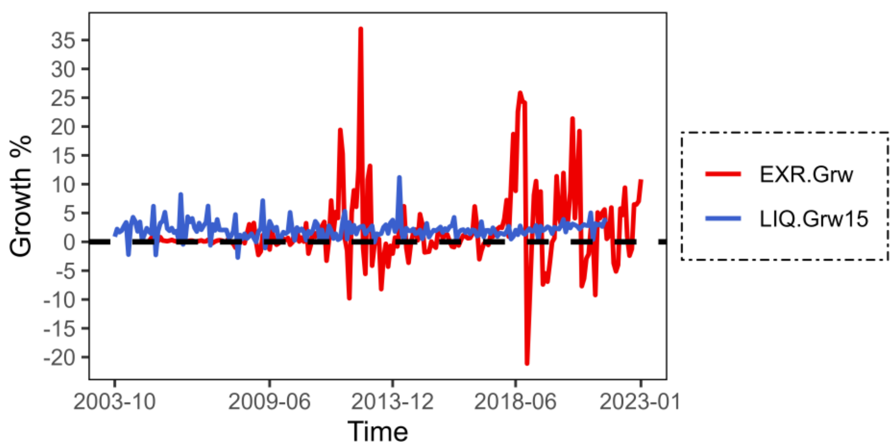


Fig 4. Time series of exchange rate growth zero-lag and liquidity growth fifteenth-lag
***Source**: Research Findings*

As anticipated, exchange rate growth shows greater volatility compared to liquidity growth. This difference arises because exchange rates are more susceptible to social and market sentiment, whereas liquidity growth reflects the fundamental of the government's fiscal and monetary systems.

3.2 Continuous Wavelet Transform

The Fourier and Laplace transforms convert time series into the frequency domain. The wavelet transform enhances this by enabling simultaneous analysis of time series in both time and frequency domains (Aguiar-Conraria et al., 2008). The Continuous Wavelet Transform (CWT) is applied to analyze the similarity between a time series and a chosen "mother wavelet" function (Loh, 2013). CWT is expressed as:

$$\mathrm{W}_{x,\psi}(\tau,s)=\int_{-\infty}^{+\infty}x(t).\psi^{*}_{(\tau,s)}(t)\,dt \tag{1}$$

In Eq. 1, $\mathrm{W}_{x,\psi}$ represent wavelet transform of time series $x(t)$, with mother wavelet function of $\psi^{*}_{(\tau,s)}$ that specified in Eq. 2.

$$\psi^{*}_{(\tau,s)}(t)=\frac{1}{\sqrt{|s|}}\psi_{(\tau,s)}\left(\frac{t-\tau}{s}\right),\quad s\ \&\ \tau\in\mathbb{R}, s\neq 0 \tag{2}$$

Where $\psi_{(\tau,s)}$ denote mother wavelet function which in this case we use the Morlet wavelet function that specified in Eq. 3. Also $'\tau'$ represent position parameter, that moving function across time series x(t). Besides, $'s'$ is scale factor that compressed mother wavelet (if$|s|<1$); and expand it (if$|s|>1$) (Aguiar-Conraria et al., 2008).

$$\psi_{\omega}(t)=\pi^{-\frac{1}{4}}\left(e^{i\omega t}-e^{-\frac{\omega^2}{2}}\right).e^{-\frac{t^2}{2}} \tag{3}$$

The Morlet wavelet function was initially proposed by Goupillaud et al. (1984). As Aguiar-Conraria et al. (2008) explained, the most appropriate value of $'\omega'$ to use from the Morlet wavelet function is $\omega=6$.

The power spectrum is used to measure the localized variance of a time series across all times and frequencies, defined as $|W_c(\tau,s)|^2$ (Hudgins et al., 1993). Additionally, assuming $|W_x(\tau,s)|^2$and $\left|W_y(\tau,s)\right|^2$are the wavelet transforms of x and y time series respectively, the reciprocal wavelet transform between the two time series x and y can be expressed as follows:

$$W_{xy}(\tau,s)=W_x(\tau,s).W_y^{*}(\tau,s) \tag{4}$$

The sign $'*'$ represents the complex conjugate. Using this relationship, the reciprocal wavelet power is defined as $\left|W_{xy}(\tau,s)\right|$, which illustrates the local covariance between two time series $x(t)$ and $y(t)$ for each ordered pair of time and frequency. Consequently, it serves as a quantitative measure of the similarity between the two time series.

Torrence & Compo (1998) utilized the cross-wavelet and auto-wavelet power spectrums to evaluate wavelet coherency. The wavelet coherency ratio is shown in Eq. 5.

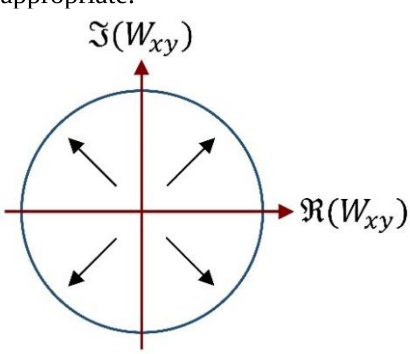
$$R_{xy}^2(\tau,s) = \frac{\left|S\left(s^{-1}.W_{xy}(\tau,s)\right)\right|^2}{S\left(s^{-1}.|W_x(\tau,s)|^2\right).S\left(s^{-1}.\left|W_y(\tau,s)\right|^2\right)} \quad (5)$$

In Eq. 5, $S(.)$ function is the smoothing operator in both scale and time. Similar to the Fourier transform, smoothing is necessary; otherwise, the correlation value would be one for all times and scales (Aguiar-Conraria et al., 2008). Wavelet coherency $R_{xy}^2(\tau,s) \in [0,1]$ is computed in a time-frequency space.

According to Bloomfield et al. (2004), since the Morelet wavelet is a complex function, it can be divided into real and imaginary parts. By dividing these parts, the phase difference between the time series $x(t)$ and $y(t)$ is defined as shown in Eq. 6.

$$\psi_{xy} = tan^{-1}\left(\frac{\Im\left\{S\left(s^{-1}.W_{xy}(\tau,s)\right)\right\}}{\mathcal{R}\left\{S\left(s^{-1}.W_{xy}(\tau,s)\right)\right\}}\right), \qquad \psi_{xy} \in [0,2\pi] \quad (6)$$

Where $\Im$ and $\mathcal{R}$ represent the imaginary and real components of the smoothed cross-wavelet transform, respectively. As Funashima (2017) demonstrated, there are at least three ways to interpret phase difference. However, he argued and demonstrated that the interpretation shown in Fig. 5 is the most appropriate.



If $(0 < \theta < \frac{\pi}{2})$ then $x(t)$ and $y(t)$ positively correlated and $x(t)$is lead variable.

If $(\frac{\pi}{2} < \theta < \pi)$ then $x(t)$ and $y(t)$ negatively correlated and $y(t)$ is lead variable.

If $(\pi < \theta < \frac{3\pi}{2})$ then $x(t)$ and $y(t)$ negatively correlated and $x(t)$ is lead variable.

If $(\frac{3\pi}{2} < \theta < 2\pi)$ then $x(t)$ and $y(t)$ positively correlated and $y(t)$is lead variable.

Fig 5. Phase diagram and interpretation for each quarter of the circle

Source*: Research Findings*

It is clear that, If $\theta = \frac{\pi}{2}$ or $\theta = \frac{3\pi}{2}$, there is no correlation between $x(t)$ and $y(t)$. Conversely, if $\theta = 0$ or $\theta = \pi$, $x(t)$ and $y(t)$ are perfectly correlated, positively and negatively, respectively.

3.3 Vector Auto-Regressive Model

The Vector Auto regression (VAR) model, introduced by Sims (1980), addresses the issue of simultaneity among variables by treating them equally. In this model, both endogenous and exogenous variables are included in the system, with each endogenous variable requiring its own corresponding equation.

A k-dimensional multivariate time series $\{y\}_{t=1}^{T}$ and an m-dimensional exogenous multivariate time series $\{x\}_{t=1}^{T}$ are governed by a vector autoregression with exogenous variables of order (p, s), referred to as $VAR_{k,m}(p, s)$, as formulated in Eq. 7.

$$Y_t = c + \sum_{i=1}^{p} A_i . Y_{t-i} + \sum_{j=1}^{S} B_j . X_{t-j} + u_t \tag{7}$$

where $'c'$ denotes a k-dimensional constant intercept vector, $'A_i'$ represents a , $k \times k$ endogenous coefficient matrix, $'B_j'$ represents a $k \times m$ exogenous coefficient matrix, and $'u_t'$ denotes a k-dimensional white noise vector that is independent and identically distributed with mean zero and nonsingular covariance matrix Σ_u (Nicholson et al., 2017).

To use the VARX model, all time-series, whether exogenous or endogenous, must be stationary. Therefore, we conduct the Phillips-Perron and Augmented Dickey-Fuller unit root tests to assess the stationarity of the variables. We also conducted the Zivot-Andrews test to examine whether the time series contains a unit root and to identify the presence of a structural break, potentially caused by sanctions. If any variable is found to be non-stationary, a cointegration test must be performed to avoid spurious regression.

We rely on information criteria like the Akaike, Schwarz, Hannan–Quinn, etc.; to determine the appropriate lags for endogenous variables. While we report the results from all recognized criteria, our primary measure for selecting lags is the Akaike information criteria (AIC).

3.4 Granger Causality Test

The Granger causality test operates on the principle that if x_t causes y_t, then past values of x_t should enhance the prediction of y_t in a regression model that includes both the past values of x_t and y_t. The test involves comparing a restricted model and an unrestricted model using the F-test statistic. Eq. 8, Eq. 9, and Eq. 10 represent the unrestricted model, restricted model, and the F-statistic, respectively.

$$Y_t = \alpha + \sum_{i=1}^{p} A_i . Y_{t-i} + \sum_{j=1}^{p} B_j . X_{t-j} + \varepsilon_t \tag{8}$$

$$Y_t = \alpha + \sum_{i=1}^{p} A_i . Y_{t-i} + \eta_t \tag{9}$$

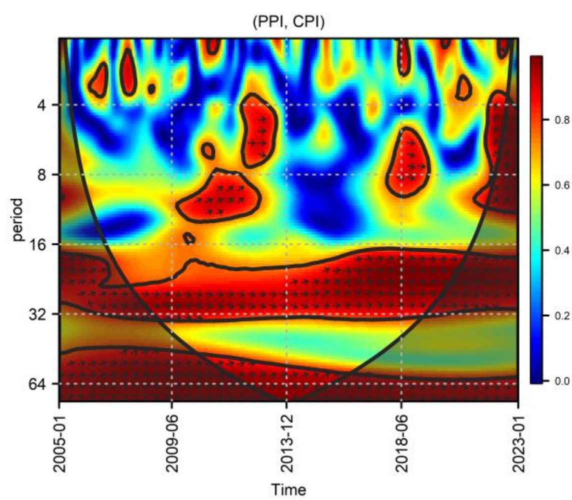
$$F = \frac{(RSS_{restricted} - RSS_{unrestricted})/m}{RSS_{unrestricted}/(n-k)} \quad (10)$$

In this context, $RSS_{restricted}$ and $RSS_{unrestricted}$ represent the residual sum of squares for the restricted and unrestricted models, respectively. The variable m indicates the number of restrictions, which corresponds to the number of lagged terms of x_t that are excluded in the restricted model. The variable n is the number of observations, while k denotes the number of parameters in the unrestricted model. The null hypothesis of the Granger test posits that x_t does not Granger-cause y_t, meaning x_t is not a leading factor for y_t (Granger, 1969).

4. Empirical Results

4.1 Continuous Wavelet Approach Result

In this section, we present the results of the CWT analysis. To begin, Fig. 6 illustrates the relationship between PPI inflation and CPI inflation for each category. Everywhere within the parabolic region, the results are both reliable and interpretable. Inside all contours, the statistical significance is at the 5% level, and where the arrows are depicted the significance is at the 9% level for the co-movement of the two selected variables.



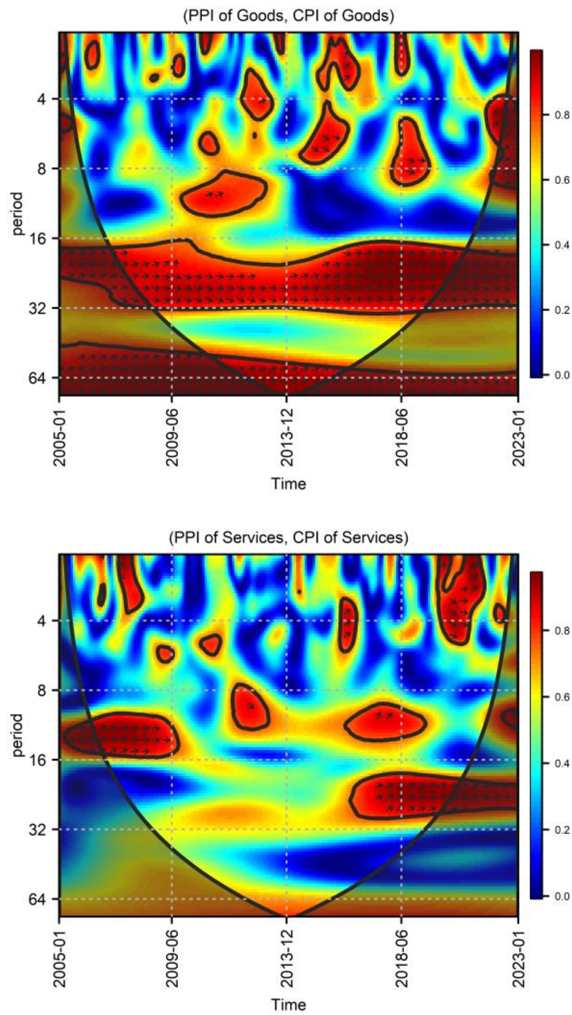


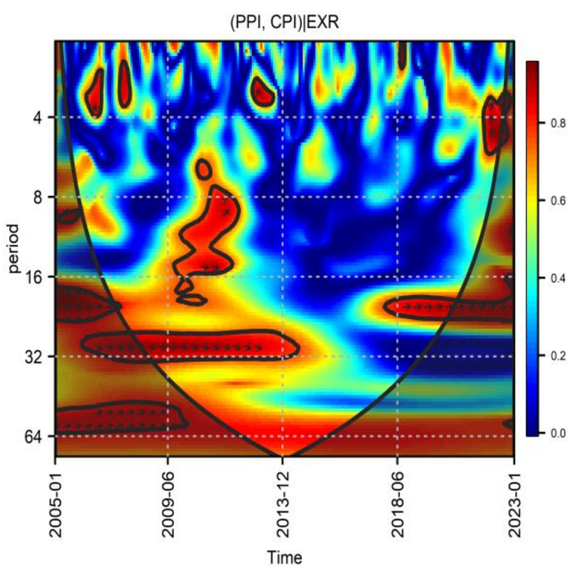
Fig 6. Continuous wavelet transform results for PPI and CPI inflation of goods, service, and total index

***Source**: Research Findings*

As depicted in Fig. 6, the co-movement between PPI inflation and CPI inflation is more pronounced for goods and the total index compared to services. This observation aligns with the dynamics of Iran's economy, where the government suppresses labor wages. Since government services and labor wages are significant components of the services index, the PPI reflects the actual economic conditions, whereas the CPI is suppressed by government intervention. Consequently, PPI inflation and CPI inflation in services show little to no co-movement across any frequency.

As shown in Fig. 6, the co-movement between PPI inflation and CPI inflation in the total index and goods is quite similar, which is likely due to the heavier weighting of goods in the total index compared to services. The strongest co-movement is observed in the 20-30 month frequency range. However, the phase difference, which indicates the lead-lag relationship, varies over time at a constant frequency. For instance, in the 30-month frequency band, CPI inflation leads PPI inflation from 2009 until late 2016. However, after Donald Trump assumed the U.S. presidency and intensified pressure on Iran, the phase shifted which indicates PPI inflation began to lead CPI inflation. This trend was further amplified by the U.S. withdrawal from the JCPOA deal in May 2018.

Following this, in Fig. 7, we examine the influence of exchange rate growth to grasp its impact on the PPI inflation and CPI inflation relationship.



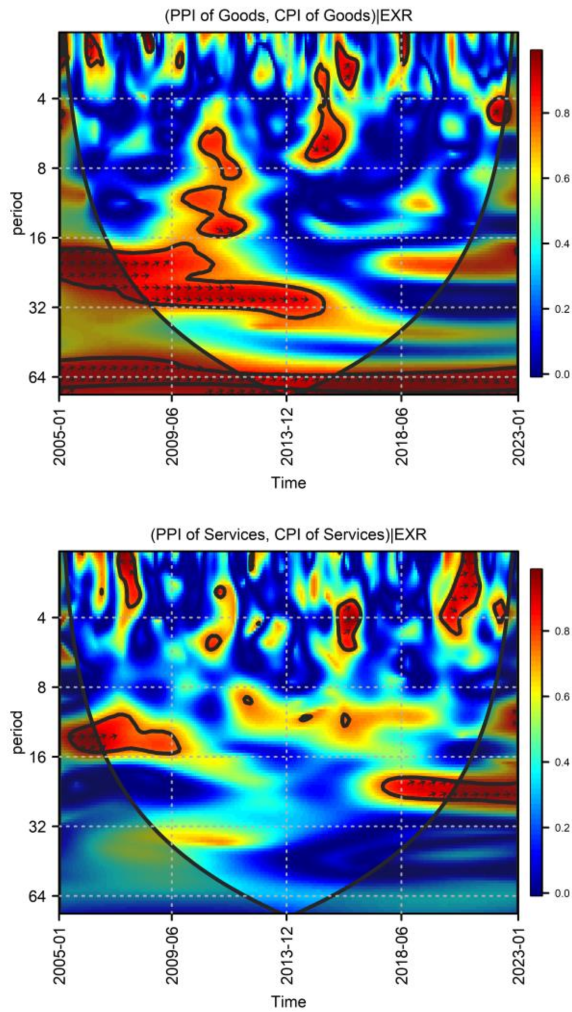
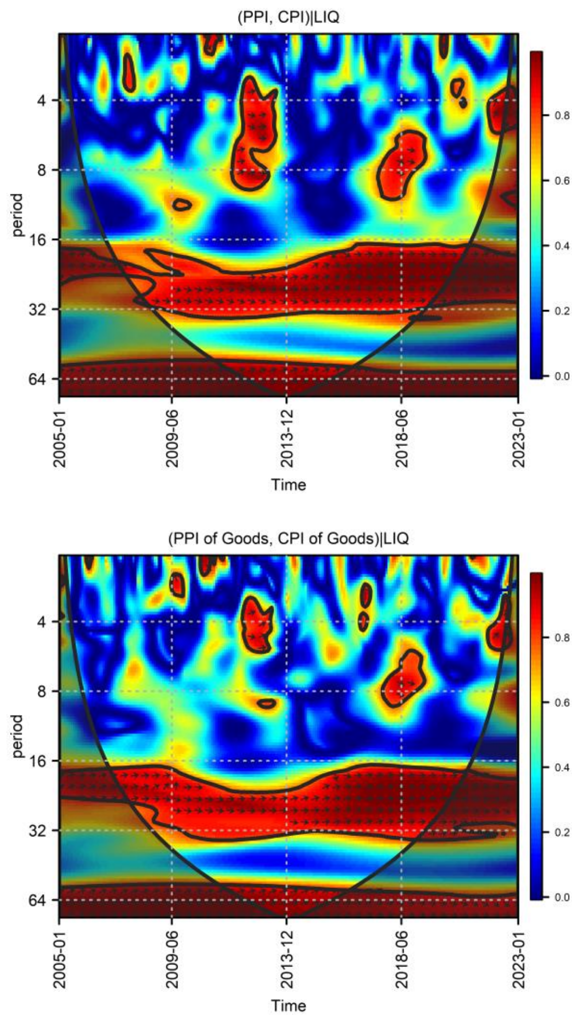


Fig 7. Exchange rate growth control in the CWT results for PPI and CPI inflation of goods, service, and total index
***Source**: Research Findings*

If the co-movement between PPI inflation and CPI inflation is absorbed by the exchange rate growth, it suggests that this variable shares a co-movement with both PPI inflation and CPI inflation, indicating it may be a driving factor behind their co-movement.

As seen in Fig. 7, exchange rate growth effectively absorbs nearly all co-movement in the 20-30 month frequency range over time. Upon closer inspection, it becomes evident that exchange rate growth primarily captures the co-movement when PPI inflation leads CPI inflation. This suggests that the exchange rate impacts the relationship between PPI and CPI inflation primarily through the cost-push mechanism, indicating that exchange rate fluctuations influence inflation by affecting production costs. Conversely, when CPI inflation is the leading factor, exchange rate growth fails to account for the inflation dynamics.

Next, in Fig. 8, we analyze the impact of liquidity growth to grasp its effect on the relationship between PPI inflation and CPI inflation.



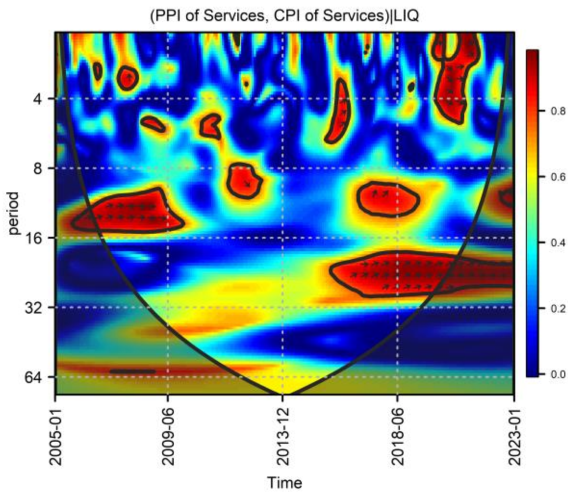


Fig 8. Liquidity growth control in the CWT results for PPI and CPI inflation of goods, service, and total index
***Source**: Research Findings*

As shown in Fig. 8, liquidity growth does not absorb any co-movement within the 20-30 month frequency range over time. However, a closer look reveals that, although liquidity growth appears to be less relevant to the PPI inflation and CPI inflation dynamics compared to exchange rate growth, it is more effective at absorbing co-movement when CPI inflation is the leading factor. This suggests that while liquidity growth may be generally less influential on inflation, it plays a role in explaining inflation dynamics from a demand-pull perspective, a factor that exchange rate growth does not address.

4.2 VARX Approach Result

In this section, we present the results of the VARX analysis. Before proceeding, it's essential to ensure the time-series variables included in the VARX model are stationary. To achieve this, we conduct the ADF, PP and ZA unit root tests. The outcomes of these tests are summarized in Table 3.

Table 3. The results of ADF, PP & ZA unit root tests

variables	ADF test	PP test	ZA test	SBP	results
CPIT.Inf	-6.57***	-7.97***	-5.90***	2018-04	stationary
PPIT.Inf	-7.53***	-9.84***	-6.79***	2020-05	stationary
CPIG.Inf	-6.75***	-7.98***	-6.09***	2018-04	stationary
PPIG.Inf	-7.33***	-9.71***	-6.43***	2020-05	stationary
CPIS.Inf	-5.50***	-7.32***	-7.25***	2015-10	stationary
PPIS.Inf	-8.94***	-11.97***	-10.38***	2020-05	stationary

EXR.Grw	-8.56***	-9.29***	-6.56***	2018-03	stationary
LIQ.Grw15	-11.50***	-16.12***	-6.61***	2007-08	stationary

*Notes: ***significance at the 1% level*
***Source**: Research Findings*

As indicated in Table 3, all variables reject the null hypothesis in both the ADF and PP unit root tests, confirming that they are stationary. The results of the Zivot-Andrews (ZA) unit root test with a structural break are presented. As evident, all variables are stationary when accounting for the structural break. Additionally, the estimated dates of the potential structural breaks are provided in Table 3.

To implement the VARX model for each category, we first need to determine the lag order for both endogenous and exogenous variables. The exogenous variables in the VARX model are exchange rate growth and liquidity growth. Since we previously determined their lag order, and each category includes only one of these variables, there's no need to apply information criteria for selecting the exogenous variables' lag. Thus, we only use the AIC to determine the lag order for the endogenous variables in our three VARX models for each category. The results of information criteria tests are provide in Table 4.

Table 4. The results of information criterion

variables	AIC	HQIC	SCIC
VARXG	4	1	1
VARXS	1	1	1
VARXT	4	1	1

***Source**: Research Findings*

Moreover, alternative methods exist for determining the lags of endogenous variables, one of which is the cross-validation approach. In this method, the optimal lag is determined by evaluating the residual sum of squared prediction errors during the test period. For each potential lag, a corresponding residual sum of squares is calculated. The lag that yields the minimum residual sum of squares is identified as the best lag.

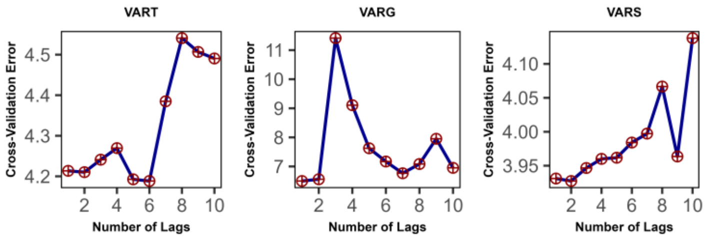


Fig 9. Cross-Validation Lag Selection for each VARX category
***Source**: Research Findings*

Based on Fig. 9, we can conclude that the optimal lag for the goods VARX model is the first lag, for the services VARX model is the second lag, and for the Total Index VARX model is the sixth lag.

Finally, since our primary purpose in using the VARX model is to validate the findings from the CWT model rather than predict the endogenous variable, we rely on the Akaike Information Criterion (AIC) to determine the optimal lags. This criterion selects lags that balance simplicity and explanatory power, aiming to provide the most parsimonious model with the highest explanatory capability, rather than solely minimizing prediction error.

We also use the variance inflation factor to check for multicollinearity in each VAR model we apply for each category. This test is conducted at the optimal lag selected based on the AIC. The Result are shown in Table 5.

Table 5. Variance Inflation Factor for each VARX category Variables

Variables	VIF	Result
	VARG	
$CPIG.Inf_{t-1}$	1.926	Negative (VIF<5)
$PPIG.Inf_{t-1}$	1.744	Negative (VIF<5)
$CPIG.Inf_{t-2}$	2.449	Negative (VIF<5)
$PPIG.Inf_{t-2}$	1.840	Negative (VIF<5)
$CPIG.Inf_{t-3}$	2.524	Negative (VIF<5)
$PPIG.Inf_{t-3}$	1.847	Negative (VIF<5)
$CPIG.Inf_{t-4}$	2.525	Negative (VIF<5)
$PPIG.Inf_{t-4}$	2.187	Negative (VIF<5)
$EXR.Grw_{t}$	1.822	Negative (VIF<5)
$LIQ.Grw_{t-15}$	1.116	Negative (VIF<5)
	VARS	
$CPIS.Inf_{t-1}$	1.267	Negative (VIF<5)
$PPIS.Inf_{t-1}$	1.308	Negative (VIF<5)
$EXR.Grw_{t}$	1.093	Negative (VIF<5)
$LIQ.Grw_{t-15}$	1.044	Negative (VIF<5)
	VART	
$CPIT.Inf_{t-1}$	3.132	Negative (VIF<5)
$PPIT.Inf_{t-1}$	2.209	Negative (VIF<5)
$CPIT.Inf_{t-2}$	2.961	Negative (VIF<5)
$PPIT.Inf_{t-2}$	1.998	Negative (VIF<5)
$CPIT.Inf_{t-3}$	2.917	Negative (VIF<5)
$PPIT.Inf_{t-3}$	1.945	Negative (VIF<5)
$CPIT.Inf_{t-4}$	2.148	Negative (VIF<5)

$PPIT.Inf_{t-4}$	1.946	Negative (VIF<5)
$EXR.Grw_t$	1.742	Negative (VIF<5)
$LIQ.Grw_{t-15}$	1.177	Negative (VIF<5)

***Source**: Research Findings*

As shown in Table 5, none of the variables included in the VARX models exhibit multicollinearity, as confirmed by the VIF test.

We set the maximum lag to 10 when evaluating the lag order using various information criteria. Based on the results shown in Table 4, we selected a lag order of 4 for CPI and PPI inflation in goods, a lag order of 1 for services, and a lag order of 4 for the total index. We also apply these optimal lags in the unit root tests and the Granger causality test. The VARX model for goods is outlined in Eq. 11 and Eq. 12, followed by the VARX model for services in Eq. 13 and Eq. 14. Lastly, the VARX model for the total index is presented in Eq. 15 and Eq. 16.

$$CPIG.Inf_t = Intercept + Trend + CPIG.Inf_{t-1} + CPIG.Inf_{t-2} + CPIG.Inf_{t-3} + CPIG.Inf_{t-4} + PPIG.Inf_{t-1} + PPIG.Inf_{t-2} + PPIG.Inf_{t-3} + PPIG.Inf_{t-4} + EXR.Grw_t + LIQ.Grw_{t-15} + \varepsilon_t \tag{11}$$

$$PPIG.Inf_t = Intercept + Trend + CPIG.Inf_{t-1} + CPIG.Inf_{t-2} + CPIG.Inf_{t-3} + CPIG.Inf_{t-4} + PPIG.Inf_{t-1} + PPIG.Inf_{t-2} + PPIG.Inf_{t-3} + PPIG.Inf_{t-4} + EXR.Grw_t + LIQ.Grw_{t-15} + \varepsilon_t \tag{12}$$

$$CPIS.Inf_t = Intercept + Trend + CPIG.Inf_{t-1} + PPIG.Inf_{t-1} + EXR.Grw_t + LIQ.Grw_{t-15} + \varepsilon_t \tag{13}$$

$$PPIS.Inf_t = Intercept + Trend + CPIG.Inf_{t-1} + PPIG.Inf_{t-1} + EXR.Grw_t + LIQ.Grw_{t-15} + \varepsilon_t \tag{14}$$

$$CPIT.Inf_t = Intercept + Trend + CPIGT.Inf_{t-1} + CPIT.Inf_{t-2} + CPIT.Inf_{t-3} + CPIT.Inf_{t-4} + PPIT.Inf_{t-1} + PPIT.Inf_{t-2} + PPIT.Inf_{t-3} + PPIT.Inf_{t-4} + EXR.Grw_t + LIQ.Grw_{t-15} + \varepsilon_t \tag{15}$$

$$CPIT.Inf_t = Intercept + Trend + CPIT.Inf_{t-1} + CPIT.Inf_{t-2} + CPIT.Inf_{t-3} + CPIT.Inf_{t-4} + PPIT.Inf_{t-1} + PPIT.Inf_{t-2} + PPIT.Inf_{t-3} + PPIT.Inf_{t-4} + EXR.Grw_t + LIQ.Grw_{t-15} + \varepsilon_t \tag{16}$$

The results of the VARX model for goods are detailed in Table 6.

Table 6. The results of VARX model for goods

	$CPIG.Inf_t$	$PPIG.Inf_t$
$Intercept$	-0.350 (0.248)	0.457 (0.355)
$Trend$	0.003 (0.002)	0.000 (0.003)
$CPIG.Inf_{t-1}$	0.387*** (0.064)	0.286*** (0.286)
$PPIG.Inf_{t-1}$	0.160*** (0.043)	0.259*** (0.062)
$CPIG.Inf_{t-2}$	-0.134** (0.068)	-0.158 (0.097)
$PPIG.Inf_{t-2}$	0.119*** (0.045)	0.016 (0.065)
$CPIG.Inf_{t-3}$	0.058 (0.068)	0.206** (0.097)
$PPIG.Inf_{t-3}$	-0.056 (0.061)	0.095 (0.065)
$CPIG.Inf_{t-4}$	-0.067 (0.061)	-0.116 (0.087)
$PPIG.Inf_{t-4}$	0.161*** (0.045)	0.005 (0.064)
$EXR.Grw_t$	0.141*** (0.017)	0.234*** (0.024)
$LIQ.Grw_{t-15}$	0.236*** (0.066)	-0.089 (0.095)
R^2	0.622	0.533
$Adjusted\ R^2$	0.601	0.508
Residual STDE	1.444	2.063
MSE	1.968	4.016
$F-Statistics$	30.076***	20.865***

*Notes: ***significance at the 1% level--** Significance at the 5% level*

***Source**: Research Findings*

The VARX model results for goods support our findings from the CWT analysis, showing that exchange rate growth has a more substantial impact on inflation compared to liquidity. Additionally, while the exchange rate significantly influences both CPI inflation and PPI inflation, liquidity growth only significantly affects CPI inflation.

The results of the VARX model for services are detailed in Table 7.

Table 7. The results of VARX model for services

	$CPIS.Inf_t$	$PPIS.Inf_t$
$Intercept$	0.128 (0.124)	0.474 (0.415)
$Trend$	0.002** (0.001)	0.005* (0.003)
$CPIS.Inf_{t-1}$	0.624*** (0.054)	0.205 (0.128)
$PPIS.Inf_{t-1}$	0.033 (0.021)	0.182** (0.070)
$EXR.Grw_t$	0.015* (0.008)	0.096*** (0.027)
$LIQ.Grw_{t-15}$	0.076** (0.033)	-0.050 (0.109)
R^2	0.570	0.166
$Adjusted\ R^2$	0.560	0.146
Residual STDE	0.717	2.398
MSE	0.500	5.591
$F-Statistics$	55.634***	8.362***

*Notes: ***significance at the 1% level--**significance at the 5% level--*significance at the 10% level*

***Source**: Research Findings*

The coefficient of determination for the VARX model in the services category is lower than that for goods, aligning with our CWT results that suggest a weaker relationship between PPI and CPI inflation in services compared to goods. Additionally, we conclude that the exchange rate does not significantly impact CPI inflation in services, likely due to government suppression of labor wages, which plays a dominant role in determining CPI for services. The VARX results for services support our hypothesis that the exchange rate significantly affects PPI inflation in the services sector. However, government measures to control labor wages and protect consumers in Iran disrupt the relationship between CPI and PPI inflation in this sector.

The results of the VARX model for total index are detailed in Table 8.

Table 8. The results of VARX model for the total index

	$CPIT.Inf_t$	$PPIT.Inf_t$
$Intercept$	-0.183 (0.160)	0.366 (0.312)
$Trend$	0.002* (0.001)	0.000 (0.002)
$CPIT.Inf_{t-1}$	0.361*** (0.066)	0.322** (0.128)
$PPIT.Inf_{t-1}$	0.166*** (0.033)	0.269*** (0.064)
$CPIT.Inf_{t-2}$	-0.175** (0.068)	-0.148 (0.133)
$PPIT.Inf_{t-2}$	0.068* (0.035)	-0.028 (0.068)
$CPIT.Inf_{t-3}$	0.121* (0.068)	0.186 (0.133)
$PPIT.Inf_{t-3}$	0.001 (0.035)	0.156** (0.068)
$CPIT.Inf_{t-4}$	0.001 (0.059)	-0.088 (0.115)
$PPIT.Inf_{t-4}$	0.091*** (0.035)	-0.003 (0.069)
$EXR.Grw_t$	0.087*** (0.011)	0.192*** (0.020)
$LIQ.Grw_{t-15}$	0.200*** (0.042)	-0.078 (0.082)
R^2	0.679	0.521
$Adjusted\ R^2$	0.661	0.494
Residual STDE	0.914	1.780
MSE	0.788	2.989
$F-Statistics$	38.643***	19.845***

*Notes: ***significance at the 1% level--**significance at the 5% level--*significance at the 10% level*
***Source**: Research Findings*

The VARX model results for the total index of CPI and PPI also reinforce our CWT findings, indicating that the exchange rate significantly impacts both

CPI inflation and PPI inflation through a cost-push mechanism. In contrast, liquidity growth affects only CPI inflation, suggesting that its influence operates through a demand-pull mechanism.

An important tool in the VAR model is the impulse-response function, which illustrates how a one-unit standard deviation shock to an endogenous variable (the impulse variable) influences other endogenous variables (the response variables). Fig. 10 shows the impact of a one-unit standard deviation shock to PPI inflation on CPI inflation for each category.

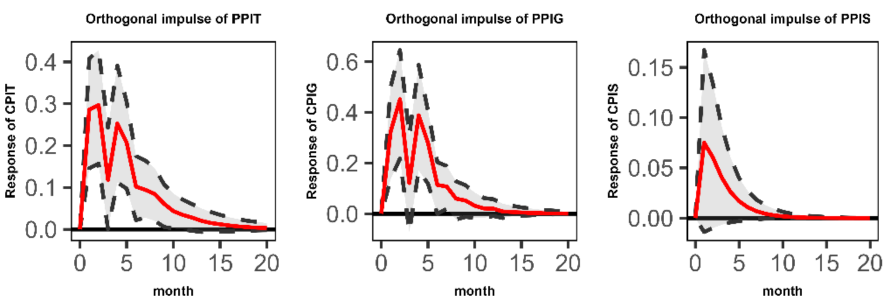


Fig 10. PPI impulse and CPI response for each VARX category
Source*: Research Findings*

Fig. 10 clearly illustrates that CPI inflation reacts with a delay to shocks from PPI inflation in each category. As anticipated, the impact of these shocks is absorbed in the goods sector more than the services sector. Additionally, these shocks tend to dissipate within approximately one and a half years.

Fig. 11 shows the impact of a one-unit standard deviation shock to CPI inflation on PPI inflation for each category.

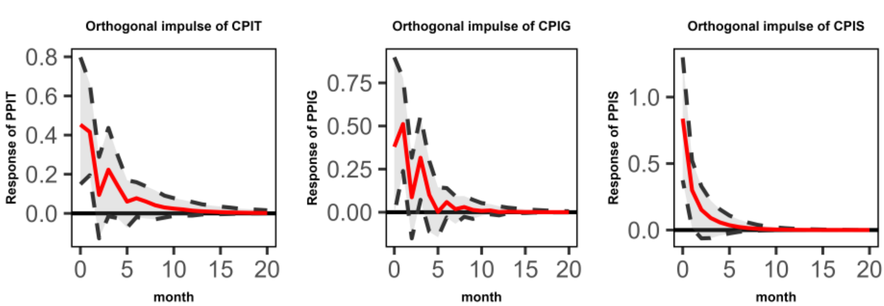


Fig 11. CPI Impulse and PPI response for each VARX category
Source*: Research Findings*

An intriguing finding is that PPI inflation responds to CPI shocks instantly, with no noticeable delay. This result aligns with expectations, given that inflation in Iran is largely driven by cost-push factors, so any shocks to CPI will respond by PPI immediately. Additionally, it is noteworthy that PPI in the services sector shows a greater absorption of CPI shocks compared to the goods sector.

4.3 Granger Causality test Result

The main idea behind the Granger causality test is to determine whether past values of one time series can help predict current changes in another. If past values are found to be useful, the series in question could be considered a leading or in some sense a causal variable. We applied this test to all variables included in our models, and the results are summarized in Fig. 12.

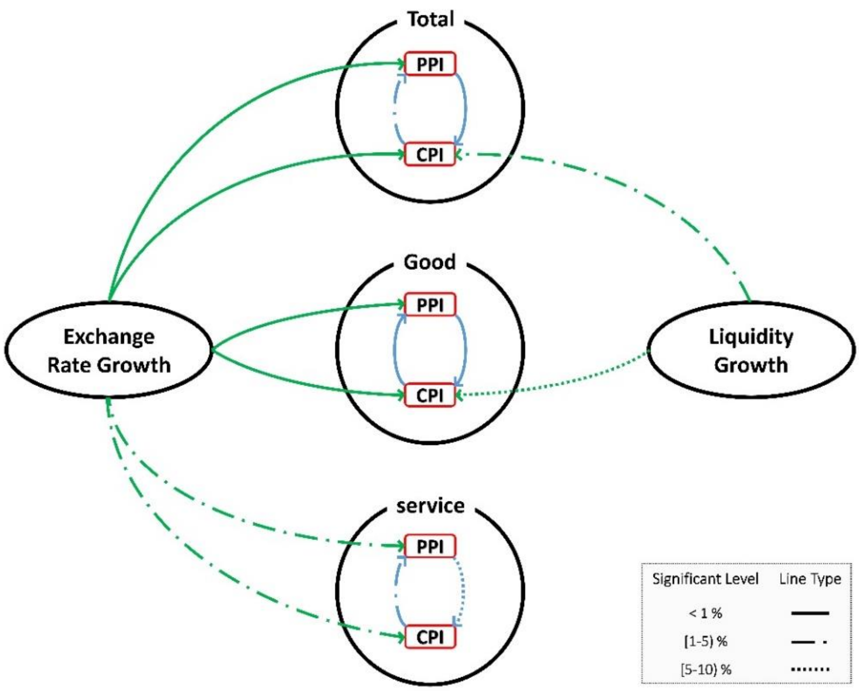


Fig 12. The Granger Causality test result for all variables

The Granger causality test further validate the findings from the CWT and VARX models, indicating that inflation in Iran is more closely related to exchange rate growth fluctuations than to liquidity growth.

Our findings align with those of Bhattacharya & Yhomakos (2008), Ocran (2010), Martinez et al. (2013), Monfared & Akin (2017), and Khan et al. (2018), who suggest that an increase in the exchange rate can drive inflation through the Producer Price Index (PPI) mechanism. These studies highlight that exchange rate fluctuations tend to have a stronger impact on PPI than on the Consumer Price Index (CPI), which is make sense given the cost-push nature of inflation transmission. Additionally, our results support the conclusions of Blagov (2019), Nasir (2020), and Citci & Kaya (2023), who emphasize that exchange rate uncertainty can significantly contribute to inflationary pressures. In the context of Iran's economy, particularly following the imposition of sanctions, both of these effects appear to hold true. The sharp rise in the exchange rate not only stimulated inflation but also created a more uncertain and unstable economic environment.

The relationship between liquidity growth and inflation has been a subject of extensive debate, yet many studies fail to fully capture the complexities of inflation dynamics. Hung & Thompson (2016) and Su et al. (2016) found no significant correlation between liquidity growth and inflation in OECD countries, while Assenmacher-Wesche & Gerlach (2006, 2008) argue that this relationship is only evident in the long run (low-frequency domain). This can be attributed to the fact that in developed economies, both domestic and external money demand generally grows in line with or even outpaces money supply expansion, making inflation less sensitive to liquidity fluctuations. Additionally, these economies effectively use interest rates as a tool to guide economic agents' expectations and control inflationary pressures. In contrast, developing economies with weaker institutional frameworks often experience liquidity growth that surpasses money demand, fueling inflation. For instance, Lu et al. (2017) demonstrate that money supply expansion drives inflation in China, while Monfared & Akin (2017) identify money growth as a key factor behind inflation in Iran. Our findings indicate that Iran’s inflation dynamics have shifted over time. Before the 2013 sanctions, inflation was primarily driven by liquidity growth, which stimulated consumer demand. However, after the sanctions were imposed, exchange rate growth emerged as the dominant driver of inflation, operating through a cost-push mechanism that raised production costs and overall price levels.

Concluding Remarks

From the three distinct models we applied—CWT, VARX, and Granger causality—on monthly inflation data, we observe the following: when supply-side inflation is dominant, driven by the cost-push mechanism, PPI inflation leads CPI inflation, making exchange rate growth a critical factor in determining inflation in Iran. On the other hand, when demand-side inflation prevails, driven by the demand-pull mechanism, CPI inflation leads PPI inflation, making liquidity growth a key determinant of inflation in Iran. Our findings suggest that inflation in Iran is primarily driven by supply-side factors rather than demand-side pressures. However, there are periods when demand-side influences take precedence. It is crucial to identify which mechanism is dominant at any given time to implement appropriate policy responses. In recent years, particularly following the intensification of sanctions on Iran, the supply-side factors have become more dominant. In this context, stabilizing exchange rate growth emerges as the most effective policy to control inflation. In this situation, controlling liquidity growth may not only fail to curb inflation but could also contribute to stagflation. It is also worth noting that controlling liquidity growth is an effective policy when inflation is driven by demand-side pull pressures.

This study acknowledges certain limitations that should be recognized. The first limitation concerns the availability of PPI data, which is only available from 2004, whereas CPI data extends back to 1982. Additionally, we faced constraints in accessing comprehensive data on liquidity growth and exchange rate growth over the longest possible time period. If more extensive historical data were available, we could better analyze periods when Iran was not under sanctions and gain a clearer understanding of inflation dynamics in that context.

Future research could explore alternative measures of inflation, such as point-to-point inflation, annual averages, or core inflation, to assess how these variables respond to liquidity growth and exchange rate fluctuations over time. Moreover, employing advanced econometric techniques, such as a Threshold Autoregressive model combined with wavelet transformation, could further enhance the analysis by capturing potential regime shifts and nonlinear dynamics in inflation behavior.

Author Contributions:

Conceptualization, all authors; methodology, Mohammad Amin Shojaeenia and Ahmad Barkish; validation, Abolmohsen Valizadeh; formal analysis, Mohammad Amin Shojaeenia and Ahmad Barkish; resources, Mohammad Amin Shojaeenia; writing—original draft preparation, Mohammad Amin Shojaeenia; writing—review and editing, Mohammad Amin Shojaeenia; supervision, Abolmohsen Valizadeh. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest:

The authors of this paper confirm that there are no conflicts of interest.

Data Availability Statement:

The data are available from [Central Bank of the Islamic Republic of Iran]. Restrictions apply to the availability of these data, which were used under license for this study. Data are available [https://www.cbi.ir/category/1904.aspx] with the permission of [Central Bank of the Islamic Republic of Iran].

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