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Causality between consumer price and producer price : evidence from Mexico

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Abstract

We examine the relationship between two inflation indices, consumer price index (CPI) and producer price index (PPI) for Mexico, a case study country which has successfully implemented inflation targeting after the economic crisis and high inflationary situation in 1995. Since the causality running from PPI to CPI exemplifies the cost push nature of inflation and the opposite is the indicator of demand pull inflation, this analysis could provide significant policy implications. We contribute to the literature by decomposing the time-frequency relationship between CPI and PPI through continuous wavelet approach. Our results indicate a bidirectional relationship. In short periods (1 to 7 months scale) CPI is leading PPI, while for longer periods (8 to 32 months scale) PPI is the leading variable.

1. Introduction

The Mexican economic crisis of 1993–94 started mainly due to speculative capital flows and large current account deficit. Fixed exchange rate system, weak banking sector and the overspending of the economy were among the main factors that have caused the crisis. The Mexican government negotiated a 50 billion dollar financial package with international financial agencies to cope up with the situation. It implemented a flexible exchange rate system followed by a monetary policy strategy of inflation targeting. The Mexican central bank, Banco de México, started the disinflationary move just after the 1993–94 crisis. Inflation was brought down from 52% in 1995 to near 4% in recent years, barring the recent spurt due to drought situation. Thus, Mexico is a proven example of the capability of a central bank to target inflation of an economy after achieving the fiscal prudence (Ramos-Francia and Torres, 2005).

In this paper, we study the relationships between the consumer price index (hereafter CPI) and the producer price index (hereafter PPI) in Mexico using the Wavelet Transform Method (WTM). We chose Mexico because, as we explained above, this country constitutes an excellent case study as it successfully targeted inflation after the crisis in the mid-

1990s. Further, the relationship between CPI and PPI has not been discussed much in the Mexican context, with the exception of the study by Sidaoui et al. (2009) which has numerous methodological limitations. Investigating the causality between producer price and consumer price indices is an important issue since it helps to formulate concrete implications for central banks to target inflation. Theoretically, causality can run from PPI to CPI as well as from CPI to PPI. Causality running from PPI to CPI illustrates the cost push inflation. The cost push nature of inflation reflects the fact that changes in producers' price in the initial stage of the supply chain will be transmitted to the later stage and subsequently to the consumer price. Clark (1995) provides a theoretical point of view about price transmission mechanism running from PPI to CPI. The author points out that the price pass-through mechanism may be distorted by the possible offsetting of changes in PPI by opposite changes in the price of imported goods, which is a part of CPI. Further, Clark (1995) mentions firm pricing strategies and possible productivity gains as plausible distorting factors from PPI to CPI price pass-through mechanism. However, there is an alternative view of demand pull nature of inflation according to which the causality is rather running from CPI to PPI (Colclough and Lange, 1982). This is based on the argument that change in consumer price leads to spurts in input prices and that would affect the producer price as well. Jones (1986) argues that both demand pull and cost push natures are possible and expects bidirectional causality between PPI and CPI.

Even though the theoretical literature points out both the causal links running from PPI to CPI and from CPI to PPI, many central banks

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still use exclusively CPI for inflation targeting. Sidaoui et al. (2009) note that only 6 out of 24 central banks studied mentioned PPI as an indicator of inflation during the period 2007–2009. However, if causality is running from PPI to CPI, central banks need to target the PPI to control the CPI. The empirical literature in this area is still inconclusive about the nature of the link between PPI and CPI for developed and developing countries.

Methodologically, we contribute to this debate by using the continuous wavelet approach which is superior in several aspects to conventional causality tests used in most previous studies. First, conventional Granger-causality tests are just one shot measure i.e., these tests do not indicate if any causal relationships exist between frequency components of variables unlike the wavelet approach. In other words, the conventional Granger-causality tests ignore the possibility that the direction of the Granger-causality – if any – could vary over different frequencies, whereas the wavelet based approach does. Second, conventional Granger-causality tests ignore the possibility that the strength of the Granger-causality – if any – could vary over different frequencies, whereas the wavelet based approach does. Third, the conventional approach does not indicate the cyclical and anti-cyclical relation that may be present, but wavelet transformation can clearly show that. And last but not least, the wavelet approach we use helps in detecting the structural breaks and jumps, steps and volatility clusters.¹ Therefore, the wavelet approach we develop in this paper has advantages over the conventional causality analysis in the aforementioned areas.

Caporale et al. (2002) analyze the CPI–PPI link in the context of G7 countries using the causality approach of Toda and Yamamoto (1995) and show unidirectional causality running from PPI to CPI. Akdi et al. (2006a) examine the relationship between CPI and PPI in three inflation targeting economies: Sweden, UK and Canada. The authors have not found evidence of causality in the long run, while in the short run causality is running from CPI to PPI. Akdi et al. (2006b) show that there is a short-run causal relationship running from CPI to PPI for Turkey. Ghazali et al. (2008) examine the same issue for Malaysia and show a unidirectional causality running from PPI to CPI. Fan et al. (2009) found that CPI is Granger causing PPI for China illustrating the demand side factors' role in inflation. Shahbaz et al. (2009) found bidirectional causality between CPI and PPI for Pakistan using ARDL approach. Shahbaz et al. (2010) employ ARDL bound test and Johanson's cointegration approach as well as Toda and Yamamoto (1995) causality approach for examining the link between CPI and PPI in Pakistan. This study found bidirectional causality between CPI and PPI, while the causality from PPI to CPI is stronger. More recently, Fan et al. (2009) found unidirectional causality running from CPI to PPI in China and the later reacts to changes in CPI with a lag of 1–3 months. Finally, Akcay (2011) examines the link between PPI and CPI in the context of European countries and shows unidirectional causality from PPI to CPI for Finland and France and bidirectional causality between the two indices in Germany.

As for Mexico, Sidaoui et al. (2009) addressed this issue and observed that causality is running from PPI to CPI; PPI is useful to improve the predictability of CPI for Mexico. These authors have used Vector Error Correction Model (VECM) to examine the causal links. The VECM overcomes the first or the second differenced Vector Autoregressive (VAR) model by including the error correction term in the specification and thus minimizing the omitted variable bias. However, VECM framework used by Sidaoui et al. (2009) is based on linear specification. Further, it is unable to provide the direction of causality, if any, which can vary over frequencies. Moreover, the VECM approach does not allow

to assess the strength² of causality between the studied variables (Tiwari, 2012a,b). To overcome these limitations, Tiwari (2012a) examined the causality between CPI and PPI for Australia using frequency domain approach and observed that the consumer price Granger causes the producer price at the intermediate level, providing evidence of medium-run cycles. In another study, using the same frequency domain approach, Tiwari (2012b) found that CPI Granger causes WPI (wholesale price index representing producers' price index) for India at lower, intermediate and higher levels; WPI Granger causes CPI only at the intermediate level. Following the works by Tiwari (2012a,b), Shahbaz et al. (2012) applied frequency domain approach and showed unidirectional causal relationships from CPI to WPI at lower, intermediate and higher levels for Pakistan. In a recent work, Tiwari et al. (2013) extended the works by Tiwari (2012a,b) and Shahbaz et al. (2012) by integrating time concept with the frequency domain approach and studied the Granger-causality between variations in CPI and PPI for Romania. The authors decomposed the time–frequency relationship between CPI- and PPI-based inflation rates through a continuous wavelet approach. Their study provided strong evidence of cyclical effects in variables, while anti-cyclical effects are not observed.

Our study extends the existing literature by utilizing the continuous wavelet approach for Mexico to analyze the causal relationship between CPI and PPI. Previous studies such as Tiwari (2012a,b) and Shahbaz et al. (2012) utilize the frequency domain approach in which time concept was missing. Further, previous studies (Shahbaz et al., 2012; Tiwari, 2012a) have shown the existence of cyclical effects between variables but our study provides evidence of both cyclical and anti-cyclical effects. Our results show the evidence of volatility clustering and jumps in 1987 and thus the possibility of existence of structural breaks, corresponding to the high inflation era in Mexican economic history. Among the previous studies using frequency domain approach Shahbaz et al. (2012), and Tiwari (2012a) find unidirectional causality between CPI and PPI, whereas Tiwari (2012b) finds bidirectional causality between CPI and PPI. Using Wavelet transformation approach, Tiwari et al. (2013) provide evidence of bidirectional causal relationship between CPI and PPI. Our study also provides evidence of bidirectional causal relationship between CPI and PPI. The present study also extends Tiwari et al. (2013) by incorporating the rectified bias in the wavelet transform following Ng and Chan (2012).

The remainder of this paper is organized as follows. Section 2 introduces the methodology. Section 3 presents the data and empirical findings. Section 4 concludes with policy implications.

2. Methodology

2.1. The continuous wavelet transform (CWT)³

A wavelet is a function with zero mean and that is localized in both frequency and time. We can characterize a wavelet by how it is localized in time (Δt) and in frequency ($\Delta \omega$ or the bandwidth). The classical version of the Heisenberg uncertainty principle explains that there is always a trade-off between localizations in time and frequency. Without properly defining Δt and $\Delta \omega$, we will note that there is a limit on how small the uncertainty product $\Delta t \Delta \omega$ can be. One particular wavelet, the Morlet, is defined as

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0 \eta} e^{-\frac{1}{2}\eta^2}. \quad (1)$$

² That is VECM or VAR models are unable to detect that either one variable positively Granger-causes or negatively Granger-causes the other variables unless lag one is used in the specification.

³ The description of CWT, XWT and WTC is extracted from Grinsted et al. (2004). We are grateful to Grinsted and co-authors for making codes available, which were utilized in the present study.

¹ Note that the present wavelet approach does not identify date of structural breaks as a test based on time series does, however, one can assess the information through the wavelet power spectrum plots by looking the volatility clusters and jumps.

where ω_0 is a dimensionless frequency and η is a dimensionless time. When using wavelets for feature extraction purposes, the Morlet wavelet (with $\omega_0 = 6$) is a good choice since it provides a good balance between time and frequency localizations. We therefore restrict our further treatment to this wavelet. The idea behind the CWT is to apply the wavelet as a band pass filter to the time series. The wavelet is stretched in time by varying its scale (s), so that $\eta = s \cdot t$ and normalizing it to have unit energy. For the Morlet wavelet (with $\omega_0 = 6$), the Fourier period (λ_{wt}) is almost equal to the scale ($\lambda_{wt} = 1.03s$). The CWT of a time series ($x_n, n = 1, \dots, N$) with uniform time steps δt , is defined as the convolution of x_n with the scaled and normalized wavelet. We write

$$W_n^X(s) = \sqrt{\frac{\delta t}{s}} \sum_{n'=1}^N x_{n'} \psi_0 \left[(n' - n) \frac{\delta t}{s} \right]. \quad (2)$$

We define the wavelet power as $|W_n^X(s)|^2$. The complex argument of $W_n^X(s)$ can be interpreted as the local phase. The CWT has edge artifacts because the wavelet is not completely localized in time. It is therefore useful to introduce a Cone of Influence (COI) in which edge effects cannot be ignored. We take the COI as the area in which the wavelet power caused by a discontinuity at the edge has dropped to e^{-2} of the value at the edge. The statistical significance of wavelet power can be assessed relative to the null hypotheses that the signal is generated by a stationary process with a given background power spectrum (P_k).

Although Torrence and Compo (1998) have shown how the statistical significance of wavelet power can be assessed against the null hypothesis that the data generating process is given by an AR (0) or AR (1) stationary process with a certain background power spectrum (P_k), for more general processes one has to rely on Monte Carlo simulations. Torrence and Compo (1998) computed the white noise and red noise wavelet power spectra, from which they derived, under the null, the corresponding distribution for the local wavelet power spectrum at each time n and scale s as follows:

$$D \left(\frac{|W_n^X(s)|^2}{\sigma_X^2} < p \right) = \frac{1}{2} P_k \chi_v^2(p), \quad (3)$$

where v is equal to 1 for real and 2 for complex wavelets.

2.2. The cross wavelet transform

The cross wavelet transform (XWT) of two time series x_n and y_n is defined as $W^{xy} = W^X W^{Y*}$, where W^X and W^Y are the wavelet transforms of x and y , respectively, $*$ denotes complex conjugation. We further define the cross wavelet power as $|W^{xy}|$. The complex argument $\arg(W^{xy})$ can be interpreted as the local relative phase between x_n and y_n in time frequency space. The theoretical distribution of the cross wavelet power of two time series with background power spectra P_k^X and P_k^Y is given in Torrence and Compo (1998) as

$$D \left(\frac{|W_n^X(s) W_n^{Y*}(s)|}{\sigma_X \sigma_Y} < p \right) = \frac{Z_v(p)}{v} \sqrt{P_k^X P_k^Y}, \quad (4)$$

where $Z_v(p)$ is the confidence level associated with the probability p for a pdf defined by the square root of the product of two χ^2 distributions.

2.3. Wavelet coherence (WTC)

As in the Fourier spectral approaches, wavelet coherence (WTC) can be defined as the ratio of the cross-spectrum to the product of the

spectrum of each series, and can be thought of as the local correlation, both in time and frequency, between two time series. Thus, wavelet coherence near one shows a high similarity between the time series, while coherence near zero show no relationship. While the Wavelet power spectrum depicts the variance of a time series, with times of large variance showing large power, the Cross Wavelet power of two time series depicts the covariance between these time series at each scale or frequency. Aguiar-Conraria et al. (2008, p. 2872) defines wavelet coherence as "the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local (both in time and frequency) correlation between two time-series".

Following Torrence and Webster (1999), we define the Wavelet Coherence of two time series as

$$R_n^2(s) = \frac{|S(s^{-1} W_n^{XY}(s))|^2}{S(s^{-1} |W_n^X(s)|^2) \cdot S(s^{-1} |W_n^Y(s)|^2)}, \quad (5)$$

Where S is a smoothing operator. Notice that this definition closely resembles that of a traditional correlation coefficient, and it is useful to think of the wavelet coherence as a localized correlation coefficient in time frequency space. Without smoothing coherence is identically 1 at all scales and times. We may further write the smoothing operator S as a convolution in time and scale:

$$S(W) = S_{scale}(S_{time}(W_n(s))) \quad (6)$$

where S_{scale} denotes smoothing along the wavelet scale axis and S_{time} denotes smoothing in time. The time convolution is done with a Gaussian and the scale convolution is performed with a rectangular window (see Torrence and Compo, 1998 for more details). For the Morlet wavelet a suitable smoothing operator is given by

$$S_{time}(W)|_s = \left(W_n(s) * c_1^{-t^2/2s^2} \right)|_s \quad (7)$$

$$S_{scale}(W)|_n = (W_n(s) * c_2 \Pi(0, 6s))|_n \quad (8)$$

where c_1 and c_2 are normalization constants and Π is the rectangle function. The factor of 0.6 is the empirically determined scale decorrelation length for the Morlet wavelet (Torrence and Compo, 1998). In practice both convolutions are done discretely and therefore the normalization coefficients are determined numerically. Since theoretical distributions for wavelet coherence have not been derived yet, to assess the statistical significance of the estimated wavelet coherence, one has to rely on Monte Carlo simulation methods.

However, following Aguiar-Conraria and Soares (2011) we will focus on the Wavelet Coherence, instead of the Wavelet Cross Spectrum. Aguiar-Conraria and Soares (2011, p. 649) give two arguments for this: "(1) the wavelet coherence has the advantage of being normalized by the power spectrum of the two time series, and (2) the wavelets cross spectrum can show strong peaks even for the realization of independent processes suggesting the possibility of spurious significance tests".

2.4. Cross wavelet phase angle

Since we are interested in the phase difference between the components of the two time series, we need to estimate the mean and confidence interval of the phase difference. The circular mean of the phase over regions that are outside the COI with higher than 5% statistical significance is used to quantify the phase relationship. This is a useful

Table 1

ADF and PP test results for CPI and PPI series.

	Augmented Dickey Fuller(ADF) test			Phillips-Perron(PP) test		
	Intercept only	Intercept and trend	None	Intercept only	Intercept and trend	None
Ln(CPI)	-5.70*	-2.12	-0.08	-5.28*	-1.62	1.13
D(Ln(CPI))	-2.36	-9.21	-1.78	-8.33*	-10.60*	-5.50*
Ln(PPI)	-6.08	-2.13	-0.22	-595*	-1.56	-0.98
D(Ln(PPI))	-2.08	-3.71**	-1.59	-7.46*	-10.18*	-4.71*

Notes: * and ** indicate significance at 1% and 5% respectively.

and general method for calculating the mean phase. The circular mean of a set of angles $(a_1, a_2, \dots, a_n)$ is defined as

$$a_m = \arg(X, Y) \text{ with } X = \sum_{i=1}^n \cos(a_i) \text{ and } Y = \sum_{i=1}^n \sin(a_i) \quad (9)$$

It is difficult to calculate the confidence interval of the mean angle reliably since the phase angles are not independent. The number of angles used in the calculation can be set arbitrarily high simply by increasing the scale resolution. However, it is interesting to know the scatter of angles around the mean. For this we define the circular standard deviation as

$$s = \sqrt{-2 \ln(R/n)}, \quad (10)$$

where $R = \sqrt{X^2 + Y^2}$. The circular standard deviation is analogous to the linear standard deviation in that it varies from zero to infinity. It gives similar results to the linear standard deviation when the angles are distributed closely around the mean angle.

The statistical significance level of the wavelet coherence is estimated using Monte Carlo methods. We generate a large ensemble of surrogate data set pair with the same AR(1) coefficients as the input datasets. For each pair, we calculate the Wavelet Coherence. We then estimate the significance level for each scale using only values outside the COI.

3. Data and empirical results

We make use of monthly data on PPI and WPI for the period January, 1981–March, 2009 taken from IMF International Financial Statistics (IFS) CD-ROM (2010). First of all, descriptive statistics of variables⁴ have been analyzed. Further, we have examined the stationarity properties of the logarithmic data by using Augmented Dickey Fuller (ADF), Phillips-Perron (PP) and KPSS unit root tests.⁵ Results summarized in Table 1 show that both CPI and PPI are non-stationary in levels but stationary in first-differences.

Fig. 1 shows nature-seasonal pattern and seasonality adjusted series (data is adjusted for seasonality using Census-12) as well as QQ plots to get a first idea on the distribution of data.

Fig. 1 suggests that data exhibit seasonality and it has become somewhat smooth after treating it. QQ plots show that both series of data are non-normally distributed. Fig. 2 presents results of continuous wavelet

power spectrum of both CPI (in the top) and PPI (in the bottom) for seasonally adjusted and non-seasonally adjusted data. However, it should be noted that some of the recent works have shown evidence of bias toward low-frequency oscillations in the wavelet power spectra (WPS) or in the CWT (Liu et al., 2007; Velede et al., 2012). A bias problem towards low-frequency oscillations is found to have existed in the estimate of WPS. For example, a time series that comprises sine waves with different periods but the same amplitudes does not produce identical peaks (Liu et al., 2007). Similar problems exist in XWT (Velede et al., 2012). To address this point, we propose to make use of new wavelet tools recently introduced by Ng and Chan (2012) that allow to correct for bias in the WPS, CWT and XWT.⁶

It is evident from Fig. 2 that seasonal transformation of the data has improved the wavelet power (i.e., red color, within the thick black contour, is almost the same in the seasonally adjusted data vis-à-vis non-seasonally adjusted data). However, we focus on seasonally adjusted data only. The common features of the wavelet power of these two time series (CPI and PPI) show that there are some common islands. In particular, the common features in the wavelet power of the two time series are evident in 2–4 month scale that belongs to 1981–82, 4–8-month scale that belongs to 1983–84, and 60–64-month scale that belongs to 1985–88. In these different year scales, both series have the power above the 5% significance level as marked by thick black contour. Further, there is high power common area between these two series particularly during 1986–1998. However, the similarity between the portrayed patterns in these periods is not very clear and it is therefore hard to tell if it is merely a coincidence. The cross wavelet transform helps in this regard.

We further, analyzed the nature of data through cross wavelet and presented results in Fig. 3 for both seasonally adjusted and non-seasonally adjusted data for comparison purposes. As we indicated above, our focus is only on the seasonally adjusted data.

It is very interesting to see that in Fig. 3, the direction of arrows at different periods (i.e., frequency bands) over the time period studied is almost the same. Throughout the study period and in the areas of significant regions, the direction of arrows shows a phase relationship. However, in the high power regions we have some evidence, during the period 1985–1990 with 16–32-month scale as arrows are right-up, suggesting that PPI is the leading variable. We also have some significant areas in the higher scales, but they are affected by edge effects, therefore we ignored those areas in the discussion. Further, outside the areas with significant power, the phase relationship is also not very clear. The results would have been different if time series or frequency analysis methods are employed. We, therefore, speculate that there is a stronger link between CPI and PPI than that is implied by the cross wavelet power.

⁴ Time series plot and descriptive statistics of the variables are presented in Fig. A1 and Table A1 respectively, in the appendix. Noteworthy to mention that testing the stationarity is not the pre-requisite for wavelet analysis.

⁵ The KPSS test rejects the null hypothesis of stationarity for CPI with test value = 0.502 and PPI with test value = 0.489 which is greater than the critical value of 0.216 at 1% level of significance for constant and trend model.

⁶ In Figs. 2–4, on the x-axis observation values 50, 100, 150, 200, 250 and 300, respectively, correspond to 1985m3, 1989m5, 1993m7, 1997m9, 2001m11 and 2006m1. We are thankful to Ng and Chan for making codes available which were used in this research.

Fig. 1. Nature-seasonal pattern and seasonality adjusted data.

Finally, we relied on cross-wavelet coherency for reasons stated in Section 2. We present results of cross-wavelet coherency in Fig. 4.

The squared WTC of CPI and PPI is shown in Fig. 4. If we compare results of WTC and XWT (Fig. 3 versus Fig. 4), we find three main

differences. First, power of the wavelet has increased in Fig. 4 as indicated by dark red color within the thick black contours. Second, in comparison with the XWT a larger section stands out as being significant and all these areas show a clear picture of

Fig. 2. The continuous wavelet power spectrum of both CPI (in the top) and PPI (in the bottom) series.

phase relationship between CPI and PPI. It is worthy to note that the area of a time frequency plot above the 5% significance level (i.e., the area which is outside the thick black contour) is not a reliable indication of causality. Therefore, we will focus on the arrows that appear within the thick black contour. During the study period, for the more than 32-month scale we find that arrows are right indicating that both variables are in phase. However, we are unable to indicate which variable is leading and which variable is lagging. In the 8–32-month scale, we find that variables are right-up indicating that PPI is leading in the significant region. But in the 1–7-month scale, in the significant region throughout the study period, we find that CPI is

leading arrows as right down. Further, we also observe that both variables affect each other through cyclical movement whereas no anti-cyclical relationship is observed between the variables. These results are important findings which definitely one would not have drawn through the application of time series or Fourier transformation analyses.

The varying nature of the causal relationship between CPI and PPI over the frequency bands in the Mexican case may be due to market imperfections and/or frictions in the economy. The imperfections in the markets, particularly labor market, arise due to strong labor union and trade union which gradually pass it on to

Fig. 3. Cross wavelet transform of the CPI and PPI time series.

Fig. 4. Cross-wavelet coherency or squared wavelet coherence.

the other markets within the economy. Further, the causal relationship between CPI and PPI may vary depending upon the time-lag taken by the supply-side turbulence to pass on primary goods market and PPI. For example, Cushing and McGarvey (1990) argue that primary goods are used as input with lag period in production process of consumption goods and hence wholesale prices lead consumer prices. However, in this case the lag period is not defined. Of course, this lag will not be the same in each production cycle and it will create a non-linear lead-lag relationship between WPI and CPI. Apart from that, as consumer prices are a weighted average of the prices of domestic and imported consumption goods, which of course will not be constant or growing with some constant rate and hence, create a time-varying feedback relationship.

4. Conclusions and policy implications

We have analyzed the causality between CPI and PPI for Mexico for the period January 1981–March 2009. We decomposed the time frequency relationship through continuous wavelength approach. We checked the stationary properties of the data by using ADF, PP and KPSS unit root tests. First, we used the continuous power spectrum to check the common movements of the data under study. The common features in the wavelet power of the two time series are evident in the 2–4-month scale that belongs to 1981–82, 4–8-month scale that belongs to 1983–84, and 60–64-month scale that belongs to 1985–88. In a second step, we used cross wavelength spectrum and observed that in high power regions we have some evidence that in the 16–32-month scale the PPI is leading CPI during the period 1985–1990. Finally, we used the cross-wavelet coherency or Squared Wavelet Coherence (WTC) approach which indicated a strong bidirectional relationship between the variables. For example, in the 32-month scale the direction of the relationship is unclear, while for the 8–32-month scale the PPI is leading the CPI. The opposite is the case in the 1–7-month scale. Another important finding is that each variable is affected by the other variable through cyclical movements, while anti-cyclical movements are not affecting the variables. Sidaoui et al. (2009) find that the PPI is leading the CPI in the long run and the CPI inflation responds significantly to the short-run disequilibrium even though short-run relationship between CPI and PPI does

not exist. In our study we also find that the PPI is leading the CPI in the long run (8–32-month period). But in contrast to the findings of Sidaoui et al. (2009), we found that the CPI is leading the PPI in the short run. Thus, the relationship is bidirectional and this has significant policy implications.

The bidirectional relationship between CPI and PPI provides more freedom to the Banco de México to target inflation. Further, the Banco de México needs to examine the internal and external macro-economic factors that affect these two indices. If the Mexican central bank, Banco de México, wants to control inflation during the period 1 to 7 months, it has to target CPI since during this period CPI is leading PPI. On the other hand, if the Banco de México wants to control inflation during 8–32-month period, it should target PPI as PPI is the leading variable during this period. Inflation rate for more than 32 months is in phase out and the direction of relationship is not clear indicating the cyclical nature of inflation. During this period, the inflation rate may be decided by the external factors such as exchange rates and government spending. Feedback relationship shows that influences from the wholesale price index (WPI) to the consumers' price index (CPI) are stronger or dominating as compared to feedback from CPI to WPI in the longer horizon, which supports the Cushing-McGarvey (1990) hypothesis.

Barro and Gordon (1983) pointed out whether an increase in consumer prices can feed through to producer prices will depend critically on the behavior of monetary authorities. If the monetary authority announces an inflation target, which is considered to be credible by wage setters, then an increase in consumer price inflation above the central banks' target rate is perceived as temporary and has no effect on wages and, hence, on producer prices. Mexico started its inflation targeting with medium-term inflation objective for CPI inflation in 1999. Our empirical finding is consistent with the reality on the ground. Since Mexico adopted CPI inflation target, we did not find any evidence of feedback from CPI to PPI in the long-run horizon. However, we found evidence that CPI can feed through PPI in the very short run (1–7 months), which is understandable as CPI inflation may increase above the target rate only on the short run due to stochastic shocks. However, if Banco de México would like to target inflation in longer horizon (i.e., for 8–32-month period), PPI inflation targeting would be a more realistic tool.

Appendix A

Fig. 1A. Time series plots of the variables analyzed.

Table 1A
Descriptive statistics.

	Ln(WPI)	Ln(CPI)	Ln(CPI_SA)	Ln(WPI_SA)
Mean	2.829216	2.784229	2.784134	2.829090
Median	3.329341	3.328933	3.324668	3.325131
Maximum	4.832545	4.778199	4.775463	4.828016
Minimum	-1.966113	-2.207275	-2.221269	-1.995109
Std. dev.	1.976753	2.052372	2.052519	1.977121
Skewness	-1.073467	-1.064972	-1.065405	-1.074102
Kurtosis	2.938822	2.894205	2.895591	2.941133
Jarque-Bera	65.35179	64.42797	64.47612	65.42519
Probability	0.000000	0.000000	0.000000	0.000000
Sum	961.9336	946.6377	946.6056	961.8907
Sum sq. dev.	1324.660	1427.946	1428.150	1325.154
Observations	340	340	340	340

Table 2A
Toda and Yamamoto (TY) (1995) Granger causality.

VAR Granger causality/block exogeneity Wald tests			
Sample: 1981 M01 2009 M04			
Included observations: 336			
Dependent variable: Ln(CPI_SA)			
Excluded	Chi-sq	Df	Prob.
Ln(WPI_SA)	29.87036	4	0.0000
Dependent variable: Ln(WPI_SA)			
Excluded	Chi-sq	Df	Prob.
Ln(CPI_SA)	19.44169	4	0.0006

Notes: SA denotes seasonally adjusted data.

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