DOES THE PRICE OF OIL HELP PREDICT INFLATION IN SOUTH AFRICA? HISTORICAL EVIDENCE USING A FREQUENCY DOMAIN APPROACH

1. Introduction

Inflation targeting (henceforth, IT), as a framework to guide monetary policy, has brought to the fore the need to accurately forecast inflation. In fact, Leiderman and Svensson (1995) argue that IT requires good forecasting models of inflation as well as a clear understanding of the transmission mechanisms of monetary policy. Forecasting inflation, in turn, requires clarity on the key determinants of inflation. That said, the past episodes of oil price shocks have ignited keen interest among researchers, policy-makers as well as the media regarding the nature of the relationship between oil prices and inflation. To this effect, a number of studies highlight the fact that the nature of the association between oil prices and inflation is not conclusive (e.g. Hooker, 1996; Barsky and Kilian, 2001; Hooker, 2002; Cuñado and de Gracia, 2003; Leblanc and Chinn, 2004; Cuñado and de Gracia, 2005; de Gregorio *et al.*, 2007; Chen, 2009; Álvarez *et al.*, 2011). Barsky and Kilian (2001) argue that empirical evidence on the association between oil price shocks and consumer prices inflation is not clear-cut. Taking into account the presence of structural breaks in the data, studies by Hooker (1996, 2002) find evidence that inflation in the US has become less sensitive to oil prices shocks in the past decades. In the same vein, Chen (2009) also finds evidence of declining oil prices pass-through to inflation in nineteen industrialized countries. The author attributes this to a more responsive monetary policy to inflation. Also, Cuñado and de Gracia (2003, 2005) argue that oil prices have affected inflation only in the short-run in the case of some European and Asian countries. Leblanc and Chinn (2004) argue that in the case of the US, the UK, France, Germany and Japan, increases in oil prices will in all likelihood only have a modest effect on inflation. de Gregorio *et al.* (2007) also investigate the pass-through of oil prices changes to inflation for a set of 33 industrialized and emerging countries. The authors conclude that the pass-through of oil price fluctuations to inflation has considerably declined over the recent decades. In their study, Álvarez *et al.* (2011) found that the effect of oil prices fluctuations on inflation is limited in the Spanish and Euro area economies. Mishkin and Schmidt-Hebbel (2007) argue that countries using an IT framework tend to experience low long-run inflation as well as smaller inflation response to oil prices shocks.

In the case of South Africa, consumption of oil-derived products represents a key component in a number of economic activities, e.g. transportation. Given that South Africa heavily relies on imports to meet most of its oil requirements, the South African economy remains exposed to fluctuations in international oil prices. As such, a rise in international oil prices could potentially result in imported cost-push inflation in the South African economy. Given this backdrop, a number of studies (e.g. SARB, 1990; Aron and Muellbauer, 2005; Wakeford, 2006; Nkomo, 2006; Swanepoel, 2006; Niyimbanira, 2013; Gupta and Hartley, 2013; Chisadza *et al*., forthcoming) have investigated the association between oil prices and inflation in South Africa. Aron and Muellbauer (2005) conclude that given its small open economy status, South Africa is susceptible to external shocks which affect inflation e.g. an oil price shock. For instance, according to SARB (1990), oil price shocks directly caused the significant rise in consumer price inflation starting in 1974 *via* the rand price of petrol, other oil-based fuels as well as oil-based household products. Corroborating this finding, Wakeford (2006) argues that, generally, there is a direct association between oil prices and inflation in South Africa. The author also suggests that the impact of oil price shocks on the South African depends on the timing as well as the size of the shock. In the same perspective, in a study investigating the impact of crude oil prices on South Africa, Nkomo (2006) postulates that an increase in international crude oil prices partially explains the rise in South Africa's inflation. Also, Niyimbanira (2013) uses a cointegration approach and concludes that there is a significant long-run relationship between oil prices and inflation in South Africa. Based on standard Granger causality tests, the author also concludes that there exists unidirectional causality running from oil prices to inflation in South Africa. On the other hand, in a study using a sign restriction-based Vector Autoregressive (VAR) approach, Chisadza *et al*. (forthcoming) investigate the impact of oil shocks on the South African economy. The authors only find evidence that an oil supply shock translating in increased oil prices results in a short-run rise in inflation. Swanepoel (2006) also uses a variant of a VAR framework to show that the impact of an oil price shock on South Africa's consumer and producer prices is statistically insignificant. Finally, Gupta and Hartley (2013), use an autoregressive distributed lag

(ARDL) framework to analyze the role of nominal and real oil prices in forecasting inflation over an out-of-sample horizon encompassing the inflation targeting period. The study finds strong evidence in favor of the ability of both nominal and real oil price growth in predicting inflation over the short- (one-quarter-ahead) to medium-term (six-quarters-ahead).

Given this background, our paper adds to the existing literature on the relationship between oil prices and inflation in South Africa. Previous studies have relied on either a purely theoretical approach or a time-domain framework (using impulse response functions obtained from a VAR model) to investigate the relationship between oil prices and inflation in South Africa. However, our approach in analyzing the predictability of inflation in South Africa by means of movements in international oil prices is novel, since we use the frequency-domain framework following the work of Breitung and Candelon (2006). Essentially, the advantage of using the frequency-domain approach lies in the fact that it generates test statistics for any given frequency across spectra (see Adiguzel *et al*., 2013). As such, we are able to assess the predictability of inflation in South Africa using oil prices across different time horizons. Further, unlike the above studies on inflation and oil prices for South Africa, barring Chisadza *et al*. (forthcoming), which we follow, we do not convert the oil prices into the domestic currency by using the exchange rate. Hence, we filter out the possible effect of exchange rate on South African inflation, thus, identifying the oil price as exogenous. Also note that, before proceeding with analyzing predictability running from oil prices growth to inflation in South Africa, we test for the presence of structural breaks in the relationship between inflation and oil prices, given that we use a long historical data set covering 1922:M01-2013:M07. This allows us to investigate the predictive power of oil prices for inflation during different regimes. As such, the regime-specific frequency domain approach provides policy-makers with insights into the duration of cycles during which movements in oil prices can predict inflation in South Africa. Given the South African Reserve Bank's reliance on an IT framework to anchor monetary policy, our study helps to unpack the oil prices-inflation dynamics in South Africa. In turn, this will prove relevant in the formulation of monetary policy in South Africa. In fact, as noted by Wakeford (2006), the South African Reserve Bank's Monetary Policy Committee statements frequently identify the movement in oil prices as a key threat to the continued achievement of the inflation target.

In what follows, Section 2 presents the theoretical framework of the frequency-domain causality approach. Next, we discuss and present empirical results in Section 3. Finally, Section 4 concludes the paper.

2. Causality in the frequency-domain

Breitung and Candelon (2006) propose a framework to test for causality in the frequency-domain based on earlier work by Geweke (1982) and Hosoya (1991). Letting $Z_t = [x_t, y_t]'$ represent a two-dimensional vector of time series ($t = 1,\ldots,T$) and whose finite-order VAR representation is of the form

$$\Theta(L)z_t = \varepsilon_t, \tag{1}$$

where $\Theta(L) = I - \Theta_1 L - \cdots - \Theta_p L^p$ is a 2×2 lag polynomial with $L^k z_t = z_{t-k}$, Geweke (1982) and Hosoya (1991) define a measure of causality at a frequency ω as

$$M_{y\to x}(\omega) = log\left[\frac{2\pi f_x(\omega)}{|\Psi_{11}(e^{-i\omega})|^2}\right] = log\left[1 + \frac{|\Psi_{12}(e^{-i\omega})|^2}{|\Psi_{11}(e^{-i\omega})|^2}\right]. \tag{2}$$

According to Geweke (1982) and Hosoya (1991), y does not cause x at frequency ω if $|\Psi_{12}(e^{-i\omega})| = 0$. If the time series in the vector z_t are integrated of order 1 (that is, $I(1)$) and cointegrated, then $\theta(L)$ – the autoregressive polynomial – contains a unit root. The other roots fall outside the unit circle. Subtracting z_{t-1} from both sides of equation (1) yields

$$\Delta z_t = (\Theta_1 - I)z_{t-1} + \Theta_2 z_{t-2} + \cdots + \Theta_p z_{t-p} + \varepsilon_t = \widetilde{\Theta}(L)z_{t-1} + \varepsilon_t, \tag{3}$$

where $\widetilde{\Theta}(L) = \Theta_1 - I + \Theta_2 L + \cdots + \Theta_p L^p$.

If y does not Granger cause x then the (1,2) element of $\theta(L)$ is zero (Toda and Phillips, 1993). The measure of causality in the frequency domain is developed using the orthogonalized moving average (MA) representation

$$\Delta z_t = \widetilde{\Phi}(L)\varepsilon_t = \widetilde{\Psi}(L)\eta_t, \tag{4}$$

where $\widetilde{\Psi}(L) = \widetilde{\Phi}(L)G^{-1}$, $\eta_t = G\varepsilon_t$, and G represent a lower triangular matrix with $E(\eta_t, \eta'_t) = I$. In a bivariate cointegrated system we have $\beta'\widetilde{\Psi}(1) = 0$, where β represents a cointegration vector with $\beta' z_t$ being stationary (Engle and Granger, 1987). Similar to the stationary case, the measure of causality is given by

$$M_{y\to x}(\omega) = log\left[1 + \frac{|\widetilde{\Psi}_{12}(e^{-i\omega})|^2}{|\widetilde{\Psi}_{11}(e^{-i\omega})|^2}\right]. \quad (5)$$

Breitung and Candelon (2006) assume that ε_t in equation (1) is white noise with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t\varepsilon_t') = \Sigma$ (Σ is positive definite)[1]. Furthermore, Breitung and Candelon (2006) denote by G the lower triangular matrix of the Cholesky decomposition $GG' = \Sigma^{-1}$ such that $E(\eta_t,\eta_t') = I$ and $\eta_t = G\varepsilon_t$. Assuming that the system is stationary, its moving average (MA) representation is given by

$$\begin{aligned} z_t = \Phi(L)\varepsilon_t &= \begin{bmatrix}\Phi_{11}(L) & \Phi_{12}(L)\\ \Phi_{21}(L) & \Phi_{22}(L)\end{bmatrix}\begin{bmatrix}\varepsilon_{1t}\\ \varepsilon_{2t}\end{bmatrix} \\ = \Psi(L)\eta_t &= \begin{bmatrix}\Psi_{11}(L) & \Psi_{12}(L)\\ \Psi_{21}(L) & \Psi_{22}(L)\end{bmatrix}\begin{bmatrix}\eta_{1t}\\ \eta_{2t}\end{bmatrix}, \end{aligned} \quad (6)$$

where $\Phi(L) = \theta(L)^{-1}$ and $\Psi(L) = \Phi(L)G^{-1}$. Based on this representation, the spectral density of x_t is given by

$$f_x(\omega) = \frac{1}{2\pi}\{|\Psi_{11}(e^{-i\omega})|^2 + |\Psi_{12}(e^{-i\omega})|^2\}.$$

Using a bivariate framework, Breitung and Candelon (2006) develop a simpler approach to test the hypothesis that y does not cause x at frequency ω. The null hypothesis is thus

$$M_{y\to x}(\omega) = 0. \quad (7)$$

From equation (2), it follows that $M_{y\to x}(\omega) = 0$ if $|\Psi_{12}(e^{-i\omega})| = 0$. Given that $\Psi(L) = \Theta(L)^{-1}G^{-1}$ and

$$\Psi_{12}(L) = -\frac{g^{22}\Theta_{12}(L)}{|\Theta(L)|} \quad (8)$$

where g^{22} represent the lower diagonal element of G^{-1} and $|\Theta(L)|$ is the determinant of $\theta(L)$, it follows that y does not cause x at frequency ω if[2]

$$|\Theta_{12}(e^{-i\omega})| = \left|\sum_{k=1}^{p}\theta_{12,k}\cos(k\omega) - \sum_{k=1}^{p}\theta_{12,k}\sin(k\omega)i\right| = 0,$$

where $\theta_{12,k}$ is the (1,2)-element of θ_k. Therefore, the necessary and sufficient conditions for $|\Theta_{12}(e^{-i\omega})| = 0$ is

[1] Breitung and Candelon (2006) ignore any deterministic terms in equation (1) to keep the exposition simple. Nonetheless, the model generally includes a constant, trend or dummy variables in empirical applications.

[2] Assuming Σ is positive implies that g^{22} is also positive.

$$\sum_{k=1}^{p} \theta_{12,k}\cos(k\omega) = 0, \tag{9}$$

$$\sum_{k=1}^{p} \theta_{12,k}\sin(k\omega) = 0. \tag{10}$$

Because $\sin(k\omega) = 0$ for $\omega = 0$ and $\omega = \pi$, the condition (10) can be dropped in these particular instances.

Breitung and Candelon (2006) base their approach on the linear restrictions given by (9) and (10). Letting $\alpha_j = \theta_{11,j}$ and $\beta_j = \theta_{12,j}$, the VAR specification for x_t can be written as

$$x_t = \alpha_1 x_{t-1} + \cdots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \varepsilon_{1t}. \tag{11}$$

The null hypothesis $M_{y\rightarrow x}(\omega)=0$ translates into the linear restriction

$$H_0\colon\ R(\omega)\beta = 0 \tag{12}$$

where $\beta = [\beta_1, \dots, \beta_p]'$ and $R(\omega) = \begin{bmatrix} \cos(\omega) & \cos(2\omega) & \dots & \cos(p\omega) \\ \sin(\omega) & \sin(2\omega) & \dots & \sin(p\omega) \end{bmatrix}$.

The null hypothesis as defined in equation (12) can be tested using the F-statistic distributed as $F(2, T-2p)$ for $\omega \in (0, \pi)$.

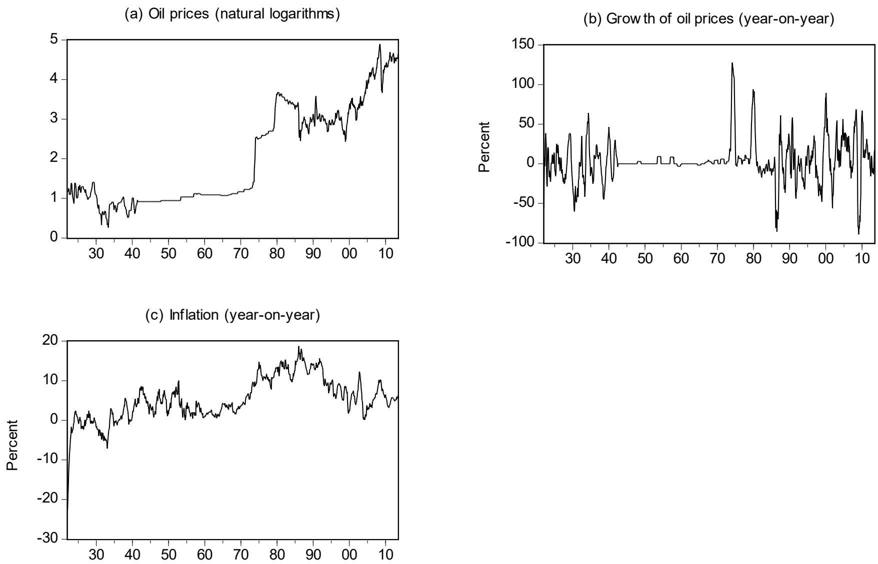
3. Empirical results

3.1 Data Description

We use monthly data of the Consumer Price Index (CPI) for South Africa spanning from 1921:M01 to 2013:M07, to compute the year-on-year growth rate of the CPI as a measure of inflation. Hence, the year-on-year growth transformation reduces our sample from 1922:M01 to 2013:M07, i.e., a total of 1099 observations, with the start and end date determined by data availability at the time of writing this paper. Furthermore, we use the West Texas Intermediate (WTI) – Cushing, Oklahoma spot prices quote for crude oil prices, as a measure of the exogenous world price oil. The choice of the WTI oil price is governed purely by the availability of data over the sample period for a measure of oil price. In fact, the WTI oil price data is available since 1859:M09. The data on both the variables of concern are obtained from the Global Financial Database (GFD). The Phillips-Perron (1988) unit root tests on the inflation and oil prices series reveal that the inflation variable is stationary, whereas the oil prices variable contains a unit root (see Table A.1 in the

Appendix)[3]. Since both time and frequency-domain tests of causality require us to ensure that the variables of concern are stationary, we address the non-stationarity issue in the oil prices variable by using year-on-year growth of oil prices, which, as shown in Table A.1, is stationary. Figures 2(a), (b) and (c) plot the natural logarithm of oil prices, year-on-year growth rate of oil prices in percentages and the inflation rate in percentages, respectively.

FIGURE 1 - *International Oil Prices and South African Inflation Rate*



Before conducting tests of causality, we need to determine the optimal lag-length by specifying a VAR model involving the two variables over the full-sample period. Based on the Akaike Information Criterion (AIC), we chose 4 lags as the optimal leg-length. Further, given that we use a long sample-period, over which the South African economy has undergone various structural changes, we performed the Bai and Perron (2003) sequential and repartition tests to check for any structural breaks in the relationship between inflation and the growth rate of oil prices. By performing the test on the inflation equation of the VAR, i.e., inflation being a function of

[3] Contrary to Nyimbanira (2013), we do not have to take into account the possibility of the two variables (that is, oil prices and inflation) being cointegrated as their order of integration differs.

a constant and four lags each of inflation and the growth rate of oil prices, we were able to detect three breaks (1936:M07, 1978:M09 and 1992:M05), translating into a total of four regime-specific samples that are subsets of the entire sample period, 1922:M01-2013:M07. The sub-samples are 1922:M01-1936:M06 (3), 1936:M07-1978:M08 (8), 1978:M09-1992:M04 (2) and 1992:M05-2013:M07 (4), with numbers in parentheses representing the optimal lag-lengths for the VAR specification.

3.2 Empirical Findings

For benchmarking purposes, we first perform the time-domain Granger causality test on the full sample as well as the identified sub-samples. As presented in Table 1, the null hypothesis that the growth rate of oil prices does not contain any predictive content for South African inflation is rejected at the level for the full sample, that is 1922:M01-2013:M07 as well as the periods 1936:M07-1978:M08 and 1992:M05-2013:M07. As such, the time-domain tests reveal that predictability of inflation in South Africa due to the growth rate of oil prices is regime-specific.

Table 1 - *Time-domain Granger Causality Test*

Sample	test statistic	*p*-value
1922:M01 - 2013:M07	13.94271 [4]	0.0075[a]
1922:M01 - 1936:M06	0.581256 [3]	0.9007
1936:M07 - 1978:M08	47.61165 [8]	0.0000[a]
1978:M09 - 1992:M04	0.374775 [2]	0.8291
1992:M05 - 2013:M07	20.12239 [4]	0.0005[a]

Notes: H_0: Oil prices growth does not have predictive content for inflation. [a], [b], and [c] indicate significance at the 1%, 5% and 10% level of significance, respectively. Numbers [ ] represent the Akaike Information Criterion (AIC)-based optimal lag length used in the VAR model.

Next, we turn our attention to the frequency-domain approach, and based on the entire sample, as well as, the identified inflation regime-specific sub-samples, we investigate both short- and long-run predictive ability of the growth rate of oil prices for inflation in South Africa. In the event predictability is established at any given frequency ω, we use the following relation to convert the frequency into the corresponding time period (cycle duration)

$$T = \frac{2\pi}{\omega},$$

where T is the time period, $\pi = 3.141592654$, and ω is the frequency such that $\omega \in (0,\pi)$[4].

Figure 3 presents the results of the causality tests in the frequency-domain. Specifically, the figure plots the test statistic (solid line) together with the 5% critical value (dashed line) for all $\omega \in (0,\pi)$[5]. The frequency-domain approach outcomes match those obtained using the time-domain approach. Essentially, we find that the growth rate of oil prices contains predictive power for South African inflation when considering the periods 1922:M01-2013:M07 (full sample) as well as 1936:M07-1978:M08 and 1992:M05-2013:M07. Nonetheless, as discussed earlier, the time-domain approach does not allow us to decompose predictability across different time horizons.

As shown in Figure 3(a), considering the period 1922:M01-2013:M13, we reject the null hypothesis that the growth rate of oil prices have no predictive ability for inflation in South Africa for frequencies ω such that $\omega \in (0,1.63)$. Translating these frequencies in time periods suggests that the growth rate of oil prices is a predictor of inflation in cycles of at least 3.9 months. Similarly, as shown in Figure 3(c), using the sample 1936:M07-1978:M08, we reject the null hypothesis of no predictability running from the growth rate of oil prices to inflation for $\omega \in (0,1.39)$ as well as $\omega \in (1.7,2.55)$. These frequency ranges correspond to cycles of at least 4.5 months and between 2.5 and 3.7 months, respectively. Based on the sample of observations 1992:M05-2013:M07, we reject the null hypothesis of no predictability running from the growth rate of oil prices to inflation at frequencies $\omega \in (0.24,\pi)$ [see Figure 3(e)]. This corresponds to a cycle of between 2 to 26.2 months. On the other hand, as depicted in Figures 3(b) and 3(d), we fail to reject the null hypothesis of no predictability running from the growth rate of oil prices to inflation based on the samples 1922:M01-1936:M06 and 1978:M09-1992:M04. As such, the growth rate of oil prices did not have any predictive content for inflation in South Africa during these periods.

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[4] This therefore implies that $T \in (2,+\infty)$.

[5] Following the usual practice, we reject the null hypothesis of no predictability in the cases where t-statistic > critical-value.

FIGURE 2 - *Frequency-domain Causality Test*

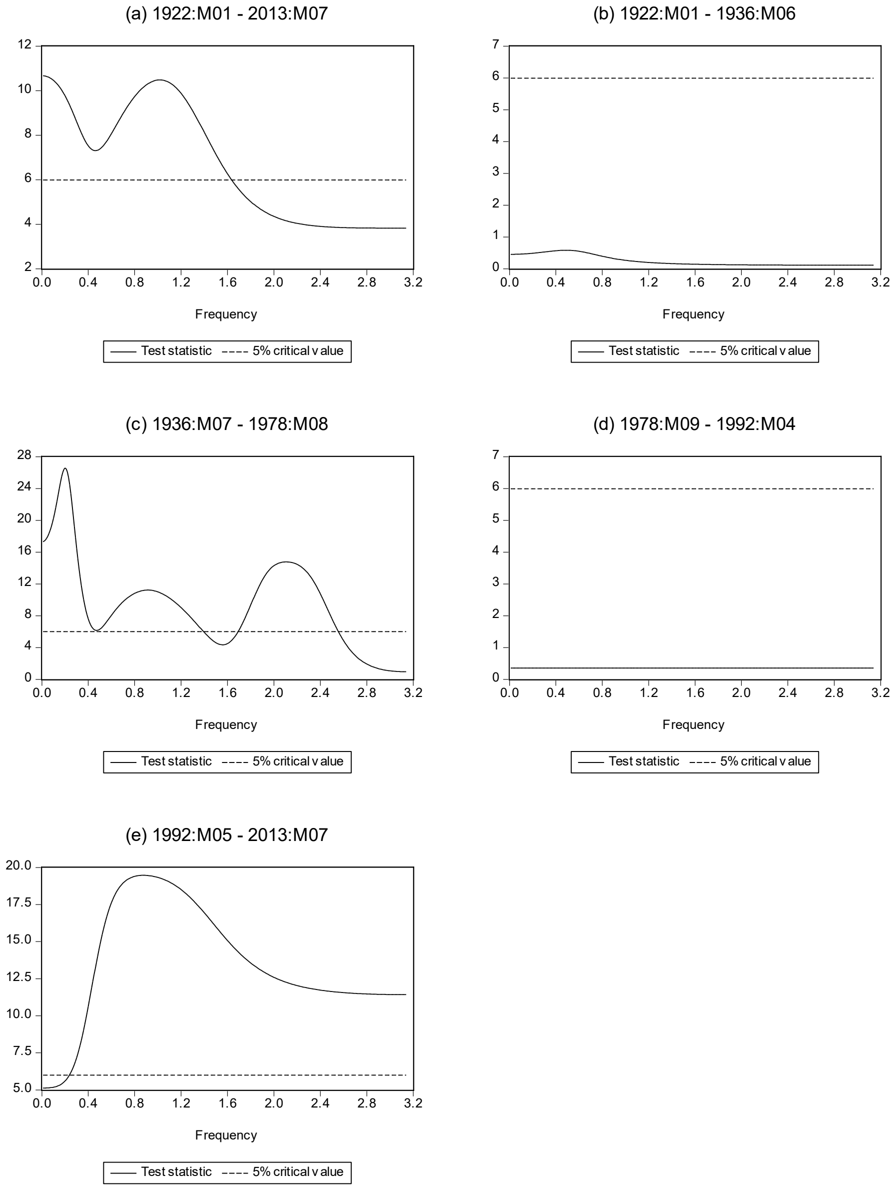

Table 2 presents a summary of the frequency-domain analysis of predictability running from the growth rate of oil prices to inflation in South Africa.

TABLE 2 - *Summary of the Frequency-domain Causality Test Results*

Sample	Duration of cycle (months)
1922:M01 - 2013:M07	3.9 and above
1922:M01 - 1936:M06	–
1936:M07 - 1978:M08	2.5 to 3.7, and 4.5 and above
1978:M09 - 1992:M04	–
1992:M05 - 2013:M07	2 to 26.2

Considering the entire sample (1922:M01-2013:M07), the frequency-domain test outcome shows that the growth rate of oil prices predicts inflation in South Africa during cycles lasting for at least about 4 months. On the other hand, the growth rate of oil prices is found to have no predictive content for inflation in South Africa during the period 1922:M01-1936:M06. Roussow (2007) states that, between 1921 and 1931, the South African Reserve Bank adopted credit and interest rate policies aimed at restoring prices to their level before the Great War. Consequently, South Africa experienced a deflationary episode.

Next, results show that the growth rate of oil prices had a predictive content for inflation in South Africa between 1936:M07 and 1978:M08. The growth rate of oil prices could help predict inflation over both short and long cycles. This period is characterized by the 1970s oil price shocks following the OPEC embargo.

During the period 1978:M09-1992:M04, we find that the growth rate of oil prices did not contain any predictive content for inflation in South Africa. According to Gidlow (1995), South Africa experienced many socio-political challenges during this period e.g. the intensification of international sanctions. Against this backdrop, foreign reserves dried up and domestic credit as well as money supply were allowed to significantly rise. In addition, the political priorities of the South African government at that time did not favour an increase in interest rates to keep inflation in check. As such, inflation pressures during this period were largely endogenous.

On the other hand, we find evidence that the growth rate of oil prices could help predict South African inflation in the period 1992:M05-2013:M07. However, it appears that the duration of the predictability cycles became strictly bounded. Results show that the growth rate of oil prices predicts inflation in South Africa in cycles lasting between 2 to about 26 months. As such, the growth rate of oil prices does not contain predictive power on South African inflation beyond approximately 2⅕ years. The adoption of an IT framework – which is forward-looking and dependent on inflation forecasts – to guide monetary policy in South Africa could explain this outcome. Also, Kahn (2008) postulates that monetary policy is required to address the possible impact of a supply shock (e.g. an oil price increase) on inflation expectations and the ensuing second-round effects. According to the author, this scenario panned out in June 2006 when a persistent rise in the price of oil, starting in 2004, led to the tightening of monetary policy. This mirrors our finding that while the growth rate of oil prices appeared to have predictive content for South African inflation over longer cycles, this has changed since the adoption of an IT framework in February 2000.

Against this backdrop, Kahn (2008) highlights a key challenge facing forward-looking monetary policy-makers in that it is difficult to establish *ex ante* the duration of a supply shock e.g. an increase in oil prices. Our findings, therefore, prove to be relevant for the conduct of monetary policy in South Africa in that (1) we establish that the association between the growth rate of oil prices and inflation is regime specific and (2) the adoption of IT has significantly restricted the duration of cycles during which the growth rate of oil prices contains predictive content for inflation. As such, depending on the prevailing regime, our findings show that monetary authorities can predict how long a change in oil prices will likely impact on inflation. Also, the results go in line with findings by Chisadza *et al*. (forthcoming) that the South African Reserve Bank does not explicitly target oil prices inflation. As such, the reduction in the duration of cycles of predictability running from the growth rate of oil prices to inflation can merely be construed as a consequence of the broader IT approach. Our findings also confirm the decline in the pass-through of oil prices changes to inflation as previously reported in other studies (see for example Hooker, 1996 and 2002; Chen, 2009; de Gregorio *et al*., 2007).

4. Conclusion

We investigate the ability of the growth rate of oil prices in predicting inflation in South Africa. To this effect, we perform Breitung and Candelon's (2006) frequency-domain causality test. We use data from a long historical sample spanning from 1922:M01 to 2013:M07 as well as four of its sub-periods identified by means of Bai and Perron's (2003) sequential and repartition tests of structural breaks performed on the relationship between inflation and the growth rate of oil prices. In the cases where predictability running from the growth rate of oil prices to inflation in South Africa can be established, the duration of cycles of predictability is found to be confined between 2 and about 26 months during the last regime-specific sample, which in turn, is the period encompassing the adoption of IT as a guiding framework for monetary policy in South Africa. Therefore, through our approach, monetary authorities in South Africa can not only predict the nature of the association between the growth rate of oil prices and inflation in South Africa during a given regime, but more importantly, assess the predictability cycle's likely duration. The current paper delves into the issue of short- and long-horizon in-sample predictability of the growth rate of nominal oil prices for the CPI-based South African inflation. Given this, future research will aim to analyze the role oil prices play in forecasting (both in- and out-of-sample) core inflation, i.e., a measure of inflation excluding energy and food from the basket of goods comprising the CPI.

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ABSTRACT

The association between oil prices and inflation has remained an intriguing issue for media, academic as well as policy enquiry. Against this backdrop, we perform the frequency-domain causality test to investigate whether the growth rate of oil prices has predictive content for inflation in South Africa. As a preliminary step in our analysis, given that we use a long historical data set spanning from 1922:M01 to 2013:M07, we investigate the possibility of structural breaks in the inflation equation. We detect three breaks which define four regimes. We then perform the frequency-domain test on the full-sample, as well as, the four identified regime-specific sub-samples. We find evidence of the growth rate of oil prices to have predictive content for South African inflation based on the full-sample, as well as, two of the four regime-specific sub-samples. Given that the frequency-domain test allows us to decompose the causality across different time horizons, results also suggest that cycles of predictability of South African inflation emanating from the the growth in international oil prices could last for much longer durations for periods preceding the adoption of an inflation-targeting framework for monetary policy in South Africa.

Keywords: Oil Prices, Inflation, Causality, Frequency-Domain

JEL Classification: C32, E31, E52

RIASSUNTO

Il prezzo del petrolio predice l'inflazione in Sud Africa? Evidenza storica attraverso l'utilizzo di un approccio basato sulla frequenza

La relazione tra prezzo del petrolio e inflazione è un problema di grande interesse sia per i media sia per la ricerca accademica e politica. Sulla base di questa considerazione abbiamo eseguito il test di causalità basato sulla frequenza per esaminare se l'aumento del prezzo del petrolio è predittivo dell'inflazione in Sud Africa. Come primo passo nell'analisi, premesso che utilizziamo un data set storico ampio – gennaio 1922-luglio 2013 – esaminiamo la possibilità di break strutturali nell'equazione di inflazione. Rileviamo tre break che definiscono quattro regimi. In seguito eseguiamo il test basato sulla frequenza sia sul campione completo che sui quattro sotto-campioni di specifici regimi. I risultati evidenziano che il tasso di aumento dei prezzi del petrolio è predittivo dell'inflazione in Sud Africa sulla base sia del campione completo che di due dei quattro sotto-campioni di specifici regimi. Considerato che il test basato sulla frequenza ci consente di scomporre la causalità per orizzonti temporali differenti, i risultati suggeriscono anche che i cicli di prevedibilità dell'inflazione in Sud Africa derivanti dalle variazioni dei prezzi internazionali del petrolio potrebbero essere molto più duraturi in periodi che precedono l'adozione di un obiettivo di politica monetaria inflation-targeting.

APPENDIX

Table A.1 - *Phillips-Perron (1988) Unit Root Tests*

		Oil prices	Growth rate of oil prices	Inflation
Trend and intercept	Level	–0.89	–8.05[a]	–5.61[a]
	First difference	–20.16[a]		
Intercept	Level	0.81	–8.01[a]	–5.38[a]
	First difference	–19.92[a]		
None	Level	–1.63	–7.90[a]	–3.12[a]
	First difference	–19.83[a]		
Conclusion		$I(1)$	$I(0)$	$I(0)$

Notes: [a], [b] and [c] indicate significance at the 1%, 5%, and 10% level of significance, respectively. PP statistics with trend and intercept (intercept only) [none] are –3.97, –3.41, and–3.13 (–3.44, –2.86 and –2.57) [–2.57, –1.94, –1.62] at 1%, 5% and 10% respectively.