Analyzing South Africa's inflation persistence using an ARFIMA model with Markov-switching fractional differencing parameter[1]

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ABSTRACT

The successful conduct of monetary policy relies on accurately characterising inflation's data generating properties. Monetary policy errors that allow inflation to transition to a high inflation regime that is very persistent might have costly economic implications as the central bank attempts to bring inflation to a lower regime, say at some target level. This paper studies the duration of inflation persistence over time and across various policy regimes. We test the inertial properties of South African inflation in a Markov-Switching autoregressive fractionally integrated moving average model. We isolate period of high inflation and low inflation and analyse how persistent it is. This is an unique application to South Africa. The use of a fractional differencing ARIMA model allows for the possibility that inflation is close to a unit root, however, still mean reverting. This implies that shocks to inflation is very persistent and take long to dissipate. The inflation persistence is measured using a test by Ng and Perron (2001). We show that inflation is more persistent during high inflation episodes relative to low inflation episodes and more volatile during low inflation periods compared to high inflation periods. We estimate that it takes approximately 70 months for 50 percent of the shocks to dissipate in a high inflation regime compared to 10 months in a low inflation regime. The model identifies three structural breaks - a low inflation regime from 1920 until 1960, a high inflation regime from 1961 until 2003, and another low inflation regime over part of the inflation targeting period, 2003-2014. We also show that inflation persistence in the high inflation regime transitioned to a low inflation regime only much later than the implementation of inflation targeting - hinting that agents take time to adjust expectations. This has an important consequence for monetary policy - monetary policy errors that allow inflation to transition to a high inflation regime may take many months for any corrective policy to become effective.

Keywords: Inflation persistence, MS-ARFIMA, inflation regimes
JEL classifications: E31, C20

Introduction

Monitoring inflation persistence is important for policy. Shocks that alter the path of inflation have consequences for the conduct of monetary policy and its ability to anchor inflation expectations. This paper forms part of a series of South African inflation persistence literature and differs from them in two respects- we explicitly model and test for long memory in inflation and analyze the persistence of inflation in two regimes; a high and low inflation regime.

We show that the response of inflation to economic shocks differ in various regimes. The successful conduct of monetary policy relies on accurately characterising inflation's data generating properties. Monetary policy errors that allow inflation to transition to a high inflation regime that is very persistent might have costly economic implications as the central bank attempts to bring inflation to a lower regime, say at some target level. Gil-Alana (2011) shows that South African inflation is stationary but has long range dependence - i.e. is very persistent. We build on this framework and estimate the long memory of inflation for two inflation regimes. Specifically, the results of this paper add to the suite of analysis that study inflation - in our case the persistence of inflation in different regimes. The comparative advantage of our approach over existing methodologies is two-fold: The persistence of inflation is dependent on the exact order of integration as opposed to models that explicitly estimate inflation as a stationary or non-stationary process. If inflation in reality is a near unit root, however, modelled as unit root using standard econometric tools then any shock to inflation is permanent. Conversely, shocks to inflation would be very short lived in a model where the order of integration equals 0. The fractional differencing framework allows for inflation to be persistent for a very long period, however, still mean reverting. The second comparative advantage, and the main contribution of this paper, is that we model this long memory over different regimes.

Persistence refers to an important statistical property of inflation - the current value of the inflation rate is strongly influenced by its history. I.e. do shocks to inflation give rise to long-term persistence? Changes to monetary policy, supply-push shocks such as changes in oil prices and wage spirals are able to influence inflation persistence (see Rangasamy 2009; Tsay 2008 and Balcilar 2004).

There are but a few papers in South Africa that focus on persistence specifically, however, many which focus on obtaining a measure of core inflation.

Rangasamy (2009) studies inflation persistence. He uses an ARMA type model that identifies persistence as the time it takes inflation to return to a time-varying inflation mean. To estimate persistence he uses inflation deviations from a time-varying inflation mean (calculated using an HP filter). This is to ensure that inflation is stationary and overcomes the possibility of estimating a unit root variable. Rangasamy (2009) shows that inflation has been persistent up until the implementation of inflation targeting in 2000. These results are also robust at a disaggregated level. He recommends that future research should take account of structural breaks that could bias persistence measures downward.

Other methods of core inflation also suggest that inflation is more persistent in a high inflation environment. Blignaut et al. (2009) calculates core inflation by using a trimmed mean measure of inflation. The trimmed-mean measure ignores short-run volatility aspects of inflation. This measure focuses on individual components that have a strong bearing on the current and future trend of inflation. The distribution of CPI components are positively skewed (trim 24% off the lower tail while only 17% from the upper tail).

It has been argued that inflation volatility has been higher since inflation targeting. Ruch and Bester (2013) identify core inflation by isolating its trend from various cyclical components using Singular Spectral Analysis. This removes most of the noise by eliminating the high frequency components from headline inflation such as exchange rate shocks or seasonal factors. They show that a model with trend coupled with inflation cycles at 65 months, 24 months and 42 months do well at explaining inflation. Overall, their findings are similar to Gupta and Uwilingiye (2012)[2] - the long-run cyclical components of inflation volatility have increased since inflation targeting. They, however, show that volatility has decreased since 2008.

The use of an autoregressive fractionally integrated moving average (ARFIMA) regression is based on the near unit root assumption of inflation.[3] ARFIMA models test for long-range dependencies when standard unit root tests have low-power in differentiating a series that is non-stationary I(1) from a stationary series I(0) with structural breaks. The difference parameter can take on fractional values for the order of integration. Moreover, the presence of level shifts tends to bias downwards the difference parameter (Tsay and Härdle 2009).

The idea that inflation has long memory, i.e. a near unit root, is well established. To name just a few, Backus and Zin (1993) found a fractional degree of integration in the US monthly inflation rate. Hassler (1993) and Delgado and Robinson (1994) provide strong evidence of long memory in the Swiss and Spanish inflation rates respectively. Baillie et al. (1996) examined monthly post-World War II CPI inflation in ten countries, and found evidence of long memory with mean reverting behaviour in all countries except Japan. Similar evidence was found in Hassler and Wolters (1995) and Baum et al. (1999).

In the context of structural breaks, evidence of long memory in inflation rates is found in numerous papers, including Bos, Franses and Ooms (1999, 2001), Baillie et al. (1996), Baillie et al. (2002), Gadea et al. (2004), Franses et al. (2006) and Gil-Alana (2008).

As an application to both long memory and different regimes, Tsay (2008) uses an ARFIMA model with a Markov-Switching fractional differencing parameter (MS-ARFIMA) to analyze US inflation. In essence the difference parameter is allowed to vary between multiple regimes. The timing and number of break points are endogenous. This addresses the possibility that fractional integration is likely to change under different regimes - in effect obtaining persistence measure for different regimes. Tsay (2008) shows that inflation volatility is higher in a high inflation regime compared to the low inflation regime - uncertainty is higher when inflation is already high.

Methodology

Our methodology is similar to Tsay and Härdle (2009).[4] The model of inflation can be specified as:

$$w_t = \mu_{s,t} I\{t \geq 1\} + (1-L)^{-d_{s,t}} \sigma_{s,t} z_t I\{t \geq 1\} = \mu_{s,t} I\{t \geq 1\} + y_t,\ \ \phi(L) z_t = \theta(L)\varepsilon_t \tag{1}$$

w_t is the observed year-on-year headline inflation rate at time t. $I\{.\}$ is an indicator function and z_t is a stationary ARMA process with zero mean and bounded positive spectral density $f_z(\lambda) \sim G_z$. The indicator truncates the effects of infinite past observations of z_t on w_t. $d_{s,t}$ is the fractional difference parameter that is allowed to be a Markov chain, which satisfies the assumption that s_t is independent of z_t. The roots of the polynomials $\phi(L)$ and $\theta(L)$ are outside the unit circle and share no common roots.

Furthermore, s_t takes on integer value of *1, 2,...,N*. Its transition probability matrix is:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1N} \\ p_{21} & p_{22} & \cdots & p_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{NN} \end{bmatrix} \quad (2)$$

where $p_{ij} = P(s_t = j | s_{t-1} = i)$ and $\sum_{j=1}^{N} p_{ij} = 1$ for all i. When $N = 1$ then (1) reduces to a standard ARFIMA(*p*,*d*,*q*) process:

$$\phi(L)(1-L)^d(w_t - \mu) = \theta(L)\varepsilon_t \quad (3)$$

p and *q* are the AR and MA orders, respectively. An $I(d)$ process is generally stationary when $d < 0.5$, nonstationary when $d = 1$ and has long-run dependence when $0 < d < 1$. For $d \in [0.5, 1]$ the process is mean reverting despite a non-stationary covariance function. ε_t is white noise.

We estimate a model with two regimes that characterize *p*+*q*+8 parameters in total using the procedures of Tsay and Härdle (2009):[5]

$$\omega = (\mu_1, \mu_2, p_{11}, p_{22}, \sigma_1, \sigma_2, d_1, d_2, \phi_1, \ldots, \phi_p, \theta_1, \ldots, \theta_q) \quad (4)$$

which represent the means, the transition probabilities, the standard deviation, difference parameters in the two regimes and the respective AR and MA coefficients.

We use Ng and Perron (2001) to get a measure of persistence. We are interested in analysing how long it takes for α percent of the effects to die out. This measure is defined as follows:

$$\tau_\alpha = \sup_k \left| \frac{\partial y_{t+k}}{\partial \varepsilon_t} \right| \leq 1 - \alpha, \quad 0 < \alpha < 1 \quad (5)$$

τ_α captures the time it takes for a fraction of α of the full effect of a unit shock to dissipate. As an example, for $\alpha = 0.5$, τ_α is the period beyond which $\left| \frac{\partial y_{t+k}}{\partial \varepsilon_t} \right|$ no longer exceeds 0.5.

Furthermore, we obtain impulse responses using Ehrmann et al. (2003) with an adaptation to the univariate case. We calculate the 95 percent confidence intervals using 2000 bootstrap samples. The impulse responses, a_k, that measures the response of w_{t+k}at time *t* of a unit shock are obtained as:

$$A(L) = (1-L)^{-d_{s,t}}\phi(L)^{-1}\theta(L) \quad (6)$$

Results

We estimate the MS-ARFIMA on year-on-year monthly CPI inflation from 1923:04 to 2014:04, with the start and end date being completely driven by availability of data, giving us a total of 1093 observations. The monthly CPI values were sourced from the Global Financial Database. As indicated in Table A1 in the Appendix, the mean inflation rate over the sample period is 5.49 percent with a standard deviation of about 5 percent. Inflation is skewed to the right and is non-normal with strong evidence of serial correlation and ARCH effects.

Table 1 contains the results of different MS-ARFIMA ($p,d_{s,t},q$) specifications. MS-ARFIMA ($1,d_{s,t},1$) has the lowest log-likelihood. Figure 2 plots actual vs. fitted inflation of the MS-ARFIMA ($1,d_{s,t},1$) model - the model fits the data well.

Long memory is established across the different specifications in both high and low inflation regimes. The minimum and maximum difference parameter for the high inflation regime is [0.41, 0.93] and for the low inflation regime [0.37,0.99]. The transition probabilities are high for both the regimes, indicating that inflation is persistent in both regimes. Interestingly, inflation volatility is lowest in the high inflation regime compared to the low inflation regime in the MS-ARFIMA ($1,d_{s,t},1$) model. The means in the two regimes are also significantly different - 11.22 percent vs. 1.12 percent.

The Ng and Perron (2000) test shows that inflation is considerably more persistent in the high inflation regime compared to the low inflation regime. It takes about 70 months for 50 percent of a unit shock to inflation to dissipate in the high inflation regime vs. 10 months in the low inflation regime. This corresponds to the regime impulse responses in Figure 3.

The MS-ARFIMA($1,d_{s,t},1$) model identifies three structural breaks - a low inflation regime from 1920 until 1960, a high inflation regime from 1961 until 2003, and another low inflation regime over part of the inflation targeting period, 2003-2014 (see Figure 3). Inflation persistence did not fall immediately since February 2000 (the official implementation of inflation targeting), but only much later in the second half of 2003. This implies that it took some time for agents' or the market's expectations to be anchored. Only when agents recognize the South African Reserve Bank's (SARB) commitment to inflation targeting do they adjust their behavior. Another indication is that agents perceive that the SARB is committed to a different inflation target other than the official target - implying that a higher inflation target would mean more inflation persistence in a high inflation regime. Using a small open economy DSGE model, Du Plessis et al. (2014) show that the SARB's inflation target is time varying and possibly outside the 3%-6% inflation band during the first couple of years of inflation targeting. This is supported by Naraidoo and Gupta (2010) suggesting that the inflation target has most likely been in the 4.5%-6.9% range.

The results would imply that the SARB would do well to keep inflation low. The economic costs could be high for an inflation targeting country if inflation was allowed to transition to a high inflation regime. It could take many periods for inflation to return to some desired lower inflation regime such as the mid-point of the inflation target. Merely stating an inflation target is not always sufficient to lower inflation to some desired path. Kabundi and Schaling (2013) show that inflation expectations for South Africa are not always well anchored - which is to some extent supported by timing of the low inflation threshold well after becoming an inflation targeter.

TABLE 1: PARAMETER ESTIMATES

	MS-ARFIMA(1,$d_{s,t}$,1)	MS-ARFIMA(1,$d_{s,t}$,0)	MS-ARFIMA(0,$d_{s,t}$,1)	MS-ARFIMA(0,$d_{s,t}$,0)
d_1	0.6714*** (0.0915)	0.4070*** (0.0574)	0.7237*** (0.0664)	0.9301*** (0.0342)
d_2	0.4508*** (0.0928)	0.3719*** (0.0587)	0.9838*** (0.0398)	0.9935*** (0.0266)
p_{11}	0.9973*** (0.0022)	0.9973*** (0.0022)	0.8881*** (0.0523)	0.9654*** (0.0191)
p_{22}	0.9989*** (0.0012)	0.9989*** (0.0012)	0.9962*** (0.0019)	0.9971*** (0.0017)
σ_1	0.5840*** (0.0189)	0.5954*** (0.0195)	1.1303*** (0.1389)	0.4894*** (0.0377)
σ_2	0.6906*** (0.0197)	0.6971*** (0.0200)	0.6297*** (0.0137)	0.6676*** (0.0149)
μ_1	11.218*** (1.0213)	12.2887*** (0.9636)	7.9422*** (0.3287)	11.543*** (0.7620)
μ_2	1.1157 (0.6980)	2.0096*** (0.7152)	0.9502 (0.6186)	0.9095 (0.6479)
ϕ	0.7422*** (0.0659)	0.9022*** (0.0362)	--	--
θ	-0.3113*** (0.0660)	--	0.0755 (0.0467)	--
log L	-1081.0251	-1105.1979	-1105.2744	-1115.1551

Notes: Standard errors of the estimates are given in brackets. *** *indicates significance at the 1% level. log L denotes the log likelihood.*

TABLE 2: PERSISTENCE ESTIMATE τ_α FOR MS-ARFIMA (1,$d_{s,t}$,1)

α	τ_α in High Inflation Regime	τ_α in Low Inflation Regime
0.30	28	6
0.35	34	7
0.40	42	8
0.45	53	9
0.50	70	10
0.55	95	12
0.60	135	14
0.65	200	17
0.70	318	20
0.75	551	26
0.80	1083	37
0.85	2595	59
0.90	8905	120
0.95	>12000	413
0.99	>12000	7672

Note: τ_α captures the time it takes for a fraction of α of the full effect of a unit shock to dissipate.

FIGURE 1: INFLATION VS. FITTED MS-ARFIMA (1,*ds*,*t*,1)

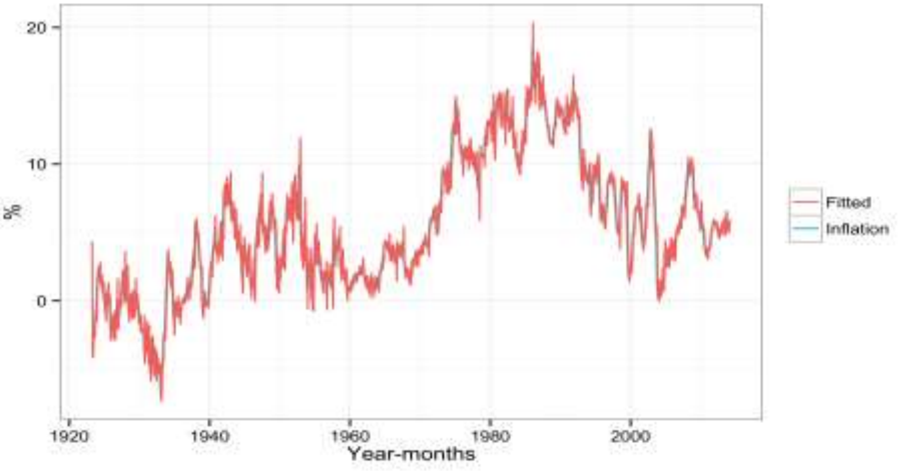


FIGURE 2: INFLATION VS. FITTED MEAN FROM MS-ARFIMA(1,*ds*,*t*,1)

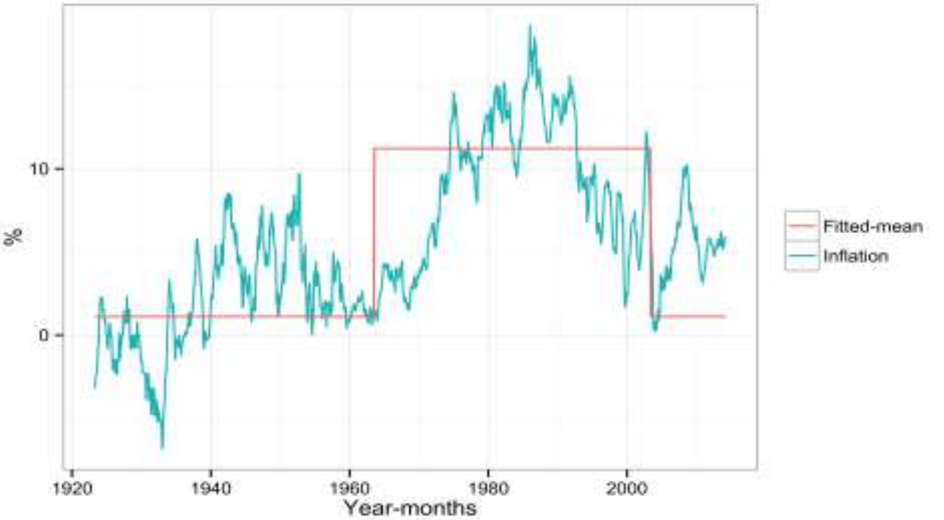
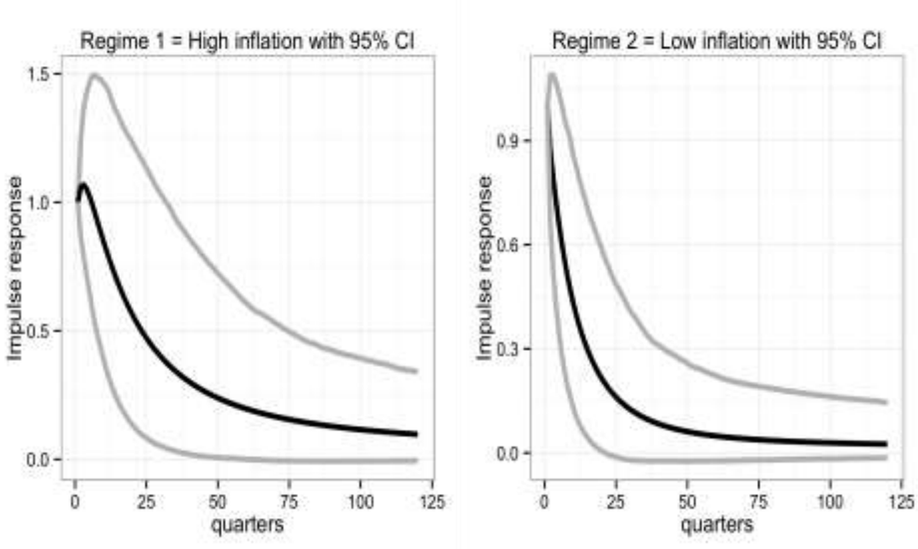


FIGURE 3: IMPULSE RESPONSES OF MS-ARFIMA(1,$d_{S,t}$,1) IN HIGH AND LOW INFLATION REGIMES



Conclusions

We analyse the persistence of inflation using a long time series of the South African Consumer Price Index. We use a novel econometric technique to model the data generating properties of inflation allowing for long range dependence during multiple regimes. We identify two inflation regimes: a low and a high inflation regime. We show that inflation is persistent in both a high and low inflation regime using a MS-ARFIMA model. Inflation, however, is considerably more persistent in a high inflation regime - it may take many months for shocks to inflation to dissipate. The persistence of inflation during a low inflation regime is considerably shorter - a motivation for keeping inflation low. The low inflation regime is more volatile compared to the high inflation regime, possibly due to shorter memory in a low inflation environment. It must be noted that the mean inflation rate during the low inflation regime is lower than the upper limit of the inflation target. We also show that inflation persistence in the high inflation regime transitioned to a low inflation regime only much later than the implementation of inflation targeting - hinting that agents take time to adjust expectations. This has an important consequence for monetary policy - monetary policy errors that allow inflation to transition to a high inflation regime may take many months for any corrective policy to become effective.

As part of future research, it would be interesting to extend this work to a FIGARCH model with Markov-switching fractional differencing parameter and analyze the evolution of the persistence of volatility across regimes.

Endnotes

[1]We would like to thank an anonymous referee for many helpful comments. However, any remaining errors are solely ours.
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[2]This is in contrast to Khan and De Jager (2011) who argue that inflation volatility has decreased since inflation targeting.
[3]The evidence for South Africa is mixed, based on standard unit root tests, results of which are available upon request from the authors.
[4]Alternative approaches to modelling the long-memory parameter as state-specific can be found in Haldrup and Nielsen (2006a,b), and more recently, Caporin and Prés (2013) where the states are observable.
[5]To estimate the parameters, Tsay and Härdle (2009) make us of the Viterbi (1967) algorithm. The reader is referred to their paper for the particulars of the estimation strategy.

Appendix

Table A1: Summary Statistics of year on year CPI inflation (1923:04-2014:04)

N	1093
Mean	5.4943
S.D.	4.9108
Min	-6.8397
Max	18.6188
Skewness	0.3239
Kurtosis	-0.5165
JB	31.1020***
Q(1)	1073.9741***
Q(4)	4138.6969***
ARCH(1)	1038.1345***
ARCH(4)	1035.1674***

Notes: N: Number of observations; S.D.: Standard deviation; Min: Minimum; Max: Maximum; JB: Jarque-Bera test statistic of normality; Q(k) is the Ljung-Box test for k-th order autocorrelation; ARCH(k) is the LM test of k-th order autoregressive conditional heteroscedasticity (ARCH) effect. *** *indicates rejection of the null at 1% level of significance.*

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