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INFLATION IN SOUTH AFRICA. A TIME SERIES VIEW ACROSS SECTORS USING LONG RANGE DEPENDENCE

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ABSTRACT

In this paper we examine the time series evolution of the log-CPI series in South Africa disaggregating the data by sectors. We examine the time period 1990m1 – 2008m12, that is, focussing on the post-apartheid period. The results indicate that the (total) inflation rate in South Africa is long memory, with an order of integration in the range (0, 0.5). The same happens with most of the data disaggregated by sectors with values of d above 1 in the log-prices. Evidence of I(0) inflation is obtained in some cases for "fruits and nuts", "vegetables" and "sugar", and evidence of mean reversion in the log-prices is only obtained in the case of "fish and other seafood". Policy implications are derived.

Keywords: Inflation; South Africa; long range dependence.
JEL Classification: C22; E31

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1. Introduction

Modelling the time series evolution of prices is a controversial issue that has not yet been resolved in the literature. Something that seems to be clear among researchers is that the log-prices series in all countries are nonstationary processes that require first differences to obtain more stable behaviours. Because of this many authors have decided to directly work on the first differenced series, which are the inflation series. However, also for the inflation rate, the controversy about its appropriate modelling still remains unresolved. Thus, for example, some authors argue that inflation is a stationary I(0) process. Examples in this context are the papers of Rose (1988) and Neusser (1991), and more recently, Culver and Papell (1997) and Cook (2009). On the other extreme, authors such as Johansen (1992), Ireland (1999), Henry and Shields (2003) and Bai and Ng (2004) assume that log prices are I(2) implying that inflation is I(1). The same happens with all those models that assume cointegration, using inflation as one of the variables in their models. Other more recent applications consider that inflation may be a fractionally integrated or I(d) process, where the number of differences required to render the series stationary I(0) is not an integer value but a fractional one. Applications in this mode are the papers of Backus and Zin (1993) for the US case, and Hassler (1993) and Delgado and Robinson (1994) for the Swiss and Spanish inflation rates respectively.

In this paper we focus on the case of South Africa for the post-apartheid period, and look at the statistical properties of the log-CPI series from a fractional viewpoint, including then as particular cases of interest those models based on stationarity I(0) and nonstationarity I(1) briefly mentioned above. Moreover, we also look at the data disaggregated by sectors to determine which are the sectors that display the highest degrees of dependence. This is an important issue given that the higher is the degree of dependence of a given series, more persistent is that series and stronger measures should be adopted to recover the series from a negative shock. On the contrary, if a series displays little persistence there is no need of strong policy measures since the series will recover itself from the shock relatively fast.

The outline of the paper is as follows: Section 2 presents a brief overview of the inflation in South Africa during the last twenty years. Section 3 deals with the statistical methods employed in the paper. Section 4 presents the data and the empirical results, while Section 5 refers to some concluding comments and extensions.

2. Inflation in South Africa. An overview

Inflation in South Africa averaged 4.5% in the 1940s, 3.8% in the 1950s and declined to 2.6% in the 1960s. However, during the last 40 years, inflation has remained at relatively high levels. Following the oil price crisis in the 1970s and 1980s and the isolation of the South African economy due to international sanctions to the country, inflation averaged 10% during the 1970s and reached 16.6% in the 1980s. This high level of inflation could be partly due to the high concentration in industry (Fedderke and Szalontai, 2005) coupled with economic policies that favoured import-substitution and non-competitive practices (Rangasamy, 2009). Moreover, the implementation of the pre-announced monetary target ranges in 1986 did not serve in light of the financial liberalization that began in 1980 (Aron and Muelbauer, 2007).

Inflation averaged 9.9% in the 1990s and 6.1% in the 2000s. During the 1990s, there was an eclectic approach to monetary policy formulation that gave prominence to intermediate objectives (Stals, 1997), and which Aron and Muelbauer (2007) describe as "opaque" and responsible for the costly impact on the economic growth during the decade.

The inflation targetting (IT) regime was adopted in February 2000 with the aim of contain inflation. The inflation target was defined in terms of headline inflation less mortgage interest costs, and the band was initially set as an annual increase of between 3% and 6% for the years 2002 and 2003, though it was revised upwards in the following years.[1] There have been two inflationary periods in the last ten years: the period spanning the second quarter of 2002 to the third quarter of 2003, and the period beginning in the fourth quarter of 2007. The first of these inflationary periods corresponds to a rapid depreciation of the rand, linked to a sudden increase in the outflow of short-term capital (Heintz and Ndikumana, 2010). In the second inflationary period, increases in global food and energy prices contributed to the highest rates of inflation in the IT period.

Focussing now on the empirical literature on South African inflation there are few articles dealing with this issue. Nell (2004) presents evidence suggesting that inflation dynamics in South Africa have been influenced by imported inflation, particularly after 1987. Hodge (2006) examined the relationship between inflation and growth in South Africa. He obtained evidence that, controlling for fixed investment, inflation has a negative impact on growth. Oosthuizen (2007) investigated the consumer price inflation across income distribution in South Africa, in line with the previous work of Kahn (1985), which calculated consumer price index for various groups defined by location, income and race. In another recent paper, Rangasamy (2009) examines the persistence of South African inflation. According to his results, persistence of inflation has declined in South Africa in recent years, especially during the inflation targetting (IT) regime, suggesting that IT provided a good anchor for inflationary expectations, despite the economy being subject to sizable external shocks during this period.

[1] See van der Merwe (2004) for a review of inflation targetting in South Africa.

Rossouw and Padayachee (2009) explored the factors that influence inflation credibility and expectations in South Africa, and the issue of inflation targetting in sub-Saharan countries has also been recently examined by Heintz and Ndikumana (2010).

3. The statistical model

Assuming that y_t is the time series of interest (in our case the log of South African CPI) we first consider the following model,

$$y_t \;=\; \alpha \;+\; \beta t \;+\; x_t\,, \qquad t \;=\; 1, 2, ..., \qquad (1)$$

$$(1 - L)^d\, x_t \;=\; u_t\,, \quad t \;=\; 1, 2, \ldots\,, \qquad (2)$$

where α and β are coefficients corresponding respectively to an intercept and a linear trend, and the regression errors x_t are supposed to be I(d), where d can be any real number. Therefore, u_t in (2) is I(0) and we do not specify any functional form for it yet. Firstly, note that this is a very general specification since it includes many cases of interest previously examined in the literature. If d = 0 in (2), y_t follows the "*trend stationary*" representation advocated by many authors for historical macroeconomic data. On the other hand, if d = 1 (with or without a linear trend) y_t follows an I(1) process, which is consistent with the "*stochastic difference*" representation in Nelson and Plosser (1982) and others. Here, if we permit short run dynamics in u_t of the ARMA(p, q)-type, y_t follows an ARIMA(p, 1, q) model. In the most general case, if d is fractional y_t displays long memory if d > 0, and y_t is an ARFIMA(p, d, q) process if u_t is ARMA(p, q).

Note that for -0.5 < d < 0.5, x_t in (2) can be represented in terms of an infinite autoregression of form:

$$\sum_{k=0}^{\infty} \pi_k\, x_{t-k} \;=\; u_t\;,$$

where

$$\pi_k = \frac{\Gamma(k-d)}{\Gamma(k+1)\Gamma(-d)},$$

and Γ representing the Gamma function. Alternatively, we can express the polynomial $(1 - L)^d$ above in terms of its binomial expansion, such that, for all real d,

$$(1 - L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - d L + \frac{d(d-1)}{2} L^2 - \ldots,$$

implying that (2) can be written as

$$x_t = d\, x_{t-1} - \frac{d(d-1)}{2} x_{t-2} + \ldots. + u_t.$$

Thus, if d is an integer value, x_t will be a function of a finite number of past observations, while if d is real, x_t depends upon values of the time series far away in the past, and the higher the value of d is, the higher the level of association between the observations will be. On the other hand, the above process also admits an infinite moving average representation such that

$$x_t = \sum_{k=0}^{\infty} a_k u_{t-k},$$

where

$$a_k = \frac{\Gamma(k+d)}{\Gamma(k+1)\Gamma(d)}.$$

Thus, the impulse responses are also clearly affected by the magnitude of d, and the higher the value of d is, the higher the responses will be.

The I(d) processes as presented by equation (2) are also characterized because the spectral density function is unbounded at the origin. This was first noticed by Adelman (1965) and Granger (1966). These authors pointed out that most aggregate economic time series have a typical shape where the spectral density increases dramatically as the frequency approaches zero. However, differencing the data frequently leads to overdifferencing at the zero frequency. Fifteen years later, Robinson (1978) and Granger (1980) showed that aggregation could be a source of fractional integration. Since then, fractional processes have been widely employed to describe the dynamics of many economic time series (Diebold and Rudebusch, 1989; Sowell, 1992; Gil-Alana and Robinson, 1997; etc.)[2].

The methodology employed to estimated the model given by (1) and (2) is based on the Whittle function in the frequency domain (Dahlhaus, 1989) along with a testing procedure developed by Robinson (1994). The latter is a very general method that allows us to test the null hypothesis of H_o: $d = d_o$ in (1) and (2) for any real value of d_o, including thus stationary ($d_o < 0.5$) and nonstationary ($d_o \geq 0.5$) hypotheses.[3]

4. Data and empirical results

The data examined in this section correspond initially to the log of the total CPI series in South Africa, for the time period 1990m1 – 2008m12. The data were obtained from the "Statistics South Africa" (http://www.statssa.gov.za).

[Insert Figures 1 and 2 about here]

Figure 1 displays the log-CPI data. We observe an increasing trend over time suggesting nonstationarity. Inflation is displayed in Figure 2, and the series has now an appeareance of stationarity.

[Insert Figure 3 and 4 about here]

Figure 3 displays the periodogram of the log-CPI data evaluated at the ordinate frequencies λ_j ($= 2\pi j/T$, $j = 1, 2, \ldots, T/2$). It is observed that the highest value corresponds to the smallest frequency, which is consistent with the long memory

[2] See Baillie (1996), Doukhan et al. (2003) and more recently Gil-Alana and Hualde (2009) for interesting reviews of I(d) models.
[3] The functional form of this method can be found in any of the numerous applications of his tests (Gil-Alana and Robinson, 1997; Gil-Alana, 2000; Gil-Alana and Henry, 2003; etc.)

property previously mentioned. Moreover, if we look at the periodogram of the first differenced data, displayed in Figure 4, it is still observed the highest value at the smallest frequency, suggesting that the log-CPI data may be I(d) with d > 1.

Figure 5 displays the log-prices for different sectors of the economy: "*commodities*"; "*services*"; "*food*"; "*grain products*"; "*meat*"; "*fish and other seafood*"; "*milk*", "*cheese and eggs*"; "*fats and oils*"; "*fruits and nuts*"; "*vegetables*"; "*sugar*"; and "*other*". We observe that the values increase along time in all series, with some possible seasonal components in the cases of "*vegetables*", "*sugar*" and "*fruits and nuts*". The sectorial inflation rate series are displayed in Figure 6 and their corresponding periodograms in Figure 7.

[Insert Figures 5, 6 and 7 about here]

If we focus on the values in the periodogram at the smallest frequency we observe differences across the series. Thus, for example, for "*commodities*", "*grain products*" and "*other*" the highest value takes place at the zero frequency; in other cases the value is finite and positive.

The first thing we do is to estimate the model given by equations (1) and (2) under the assumption that the error term (i.e., u_t in (2)) is a white noise process. Therefore, all the time dependence is then captured through the fractional differencing parameter d. The results of the Whittle estimates of d along with the 95% confidence interval using Robinson's (1994) parametric approach are displayed in Table 1. Starting with the total log CPI, we observe that if we do not include regressors, the estimate of d is slightly below 1; however, including an intercept, or an intercept with a linear time trend, the estimate is found to be much higher than 1. Moreover, the unit root null hypothesis (i.e., d = 1) cannot be rejected in the case of no regressors, but this hypothesis is decisively rejected in favour of H_a: d > 1 in the other two cases. This result is generally extensible to the dissaggregated data: thus, if we do not include regressors, the estimated value of d is found to be smaller than 1 in all except one series ("*fruits and nuts*") and the unit root null hypothesis cannot be rejected in any single case. On the other hand, including deterministic terms, the unit root is rejected in favour of higher orders of integration in all except two series: "*fish and other seafood*", and "*sugar*". In the latter, the unit root cannot be rejected, while in the former it is rejected in favour of mean reversion (i.e., $d < 1$).

[Insert Tables 1 and 2 about here]

In Table 2 we describe for each series the estimated values for the deterministic terms along with the fractional differencing parameter for the model which is the most adequate one according to the t-values reported in the same table. We observe three sectors ("*meat*", "*fruits and nuts*", and "*vegetables*") where only an intercept is required. In the remaining cases, the time trend must be included in the model. If we focus on the degree of time dependence we notice that the most persistent series is the one corresponding to "*food*" (with d = 1.471), followed by "*meat*" (d = 1.450), "*vegetables*" (d = 1.365), and "*grain products*" (d = 1.315). On the other hand, the less persistent ones are "*sugar*" (with d = 1.032) and "*fish and other seafood*", the latter with an estimated value of d strictly smaller than 1 (d = 0.911) and thus implying mean reverting behaviour.

Nevertheless, the results presented so far may be considered too simplistic in the sense that we do not allow for any type of weak dependence structure in the error term. Thus, in what follows, we assume that u_t is autocorrelated. First we consider an AR(1) process, and the results of the estimation of d again for the three cases of no regressors, an intercept, and an intercept with a linear trend are reported in Table 3. We observe here some cases where d is strictly below unity. Focussing now on the best specification for each series (in Table 4) we notice that for three series ("*meat*", "*fruits and nuts*" and "*vegetables*") the results indicate mean reversion; for another two series ("*food*" and "*sugar*") the unit root null cannot be rejected, and for the remaining eight series (including total CPI) the estimated value of d is found to be strictly above 1.

[Insert Tables 3 – 6 about here]

Higher AR orders produced essentially the same results. Nevertheless we also implemented another approach that is based on the exponential spectral model of Bloomfield (1973). This is a non-parametric method that produces autocorrelations decaying exponentially as in the AR(MA) case.[4] The results using this approach are presented in Tables 5 and 6. Unlike the AR(1) case, we observe now just a single case where mean reversion takes place, and corresponds to "*vegetables*". For "*meat*", "*fruits and nuts*", and "*sugar*", the I(0) case cannot be rejected and this hypothesis is decisively rejected in the remaining cases in favour of d > 1.[5]

[Insert Tables 7 and 8 about here]

Finally, noting that the series may also display some seasonal (monthly) features, we also consider for the error term a seasonal AR(1) process of form:

$$u_t = \phi u_{t-12} + \varepsilon_t, \quad t = 1, 2, \ldots,$$

with white noise ε_t. The results based on this model are reported in Tables 7 and 8. They are very similar to those based on white noise u_t. Thus, if we do not include regressors the unit root null cannot be rejected in any single case; including an intercept or an intercept with a linear time trend, the estimated value of d is found to be above 1 in all except two series: "*sugar*" (with d = 0.937 with an intercept, and d = 0.953 with a linear time trend), and "*fish and other seafood*", with d = 0.839 with an intercept, and d =

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[4] Applications of fractional integration using the exponential model of Bloomfield (1973) can be found in Velasco and Robinson (2000), Gil-Alana (2004), etc.

[5] Note that d > 1 in the log-CPI series implies that the inflation rates are long memory (d > 0).

0.878 with a linear trend. In the latter series, the I(1) hypothesis is rejected in favour of mean reversion.

Due to the disparity of the results depending on the specification of the error term we also conducted the analysis based on a semiparametric approach (Robinson, 1995), where we do not impose any particular specification for the error term. This method is based on the Whittle function in the frequency domain using a band of frequencies that degenerates to zero. The proper estimate of d is implicitly defined by:

$$\hat{d} = \arg\min_d \left(\log \overline{C(d)} - 2d \frac{1}{m} \sum_{s=1}^{m} \log \lambda_s \right), \qquad (5)$$

$$\overline{C(d)} = \frac{1}{m} \sum_{s=1}^{m} I(\lambda_s)\, \lambda_s^{2d}, \qquad \lambda_s = \frac{2\pi s}{T}, \qquad \frac{m}{T} \to 0,$$

where m is a bandwidth number, and $I(\lambda_s)$ is the periodogram of the raw time series, x_t,

$$I(\lambda_s) = \frac{1}{2\pi T} \left| \sum_{t=1}^{T} x_t\, e^{i \lambda_s t} \right|^2,$$

and $d \in (-0.5, 0.5)$.

Given the nonstationary nature of the log-CPI series the analysis is directly conducted on the inflation rate series. Figure 8 refers to total inflation, while Figure 9 reports the estimates for each sector. We display the estimates for a whole range of values of the bandwidth number m, i.e., with m = 1, 2, …, T/2. Along the estimates, we also report the 95% confidence band referring to the I(0) case. Starting with the total inflation series (in Figure 8) we observe that the estimates of d are above the I(0) interval in all cases, suggesting that inflation is long memory. This is consistent with the parametric results reported across Tables 1 – 6.

[Insert Figures 8 and 9 about here]

If we focus now on the individual sectors we observe that for "*commodities*", "*grain products*", "*milk, cheese and eggs*", and "*other*", the estimates are all above the I(0) inteval, strongly supporting the view that they are long memory. For another group of sectors ("*services*", "*food*", "*meat*", "*fruits and nuts*" and "*fats and oils*") there are some values within the I(0) interval for small bandwidth numbers, increasing then to values above 0 for the remaining bandwidth numbers. Finally, the only two series where we obtain evidence of I(0) or even values of d below 0 are those corresponding to "*vegetables*" and "*sugar*", which is once more consistent with the empirical evidence reported with the parametric approach.

In the final part of the article we examine the stability of the results across time. This is an important issue noting that fractional integration may be a consequence of the existence of breaks in the data (Diebold and Inoue, 2001; Granger and Hyung, 2004). Figures 10 – 13 display the estimates of d respectively for the cases of white noise, AR(1), Bloomfield, and seasonal AR(1) disturbances, starting with a sample of 120 observations (that is, 10 complete years of data) and then, adding succesively one observation each time. The results are fairly similar in the four cases.

[Insert Figures 10 – 13 about here]

We observe that the estimates are above 1 in all cases implying long memory inflation rates. In the four cases we observe an increase in the value of d around the observation 148, which corresponds to April 2002 and a second increase in the observation 169 (January, 2004). However the estimates are fairly stable across the sample. Performing other approaches of fractional integration with structural breaks (e.g. Bos et al., 1999; Gil-Alana, 2008) we do not obtain any evidence of breaks in the data.

5. Concluding comments and extensions

In this paper we have examined the time series properties of the inflation rates in South Africa for the time period 1990m1 – 2008m12, using both aggregated and disaggregated data by sectors. We focus on the persistence and the long memory characteristics of the data and use long memory models based on fractional integration. The results for the aggregate data indicate that the (total) log-CPI series may be well described in terms of an I(d) process with d significantly above 1, implying long memory for the total inflation rate.

Focussing on the disaggregated data, the results substantially vary depending on the specific sector examined. The highest degrees of dependence seem to take place in the cases of "*food*", "*meat*", "*grain products*" and "*fats and oils*", while the lowest degrees of persistence occur in the cases of "*vegetables*", "*sugar*" and "*fish and other seafood*".

The different degrees of dependence observed across sectors indicate that the duration of the shocks is different depending on the sector being examined and therefore, different policy measures must be implemented depending on the sector being affected. Thus, sectors which are highly persistent require stronger policy measures in case of a negative shock to recover their original levels than sectors which are less persistent since in the latter case the series will recover themselver faster.

This paper can be extended in several directions. First, the fact that total log-CPI in South Africa is found to be I(d) with d > 1 implies that models based on cointegration and that assume that inflation is I(1) or I(0) may produce missleading results due to the strong dependence observed in the data. In this context, alternative fractional cointegration methods as those proposed by Robinson and Hualde (2003) and Johansen (2008) should be implemented. On the other hand, multivariate models, including variables such as interest rates and/or unemployment may also be implemented from a fractional viewpoint.

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Figure 1: Log of the CPI in South Africa (Total)

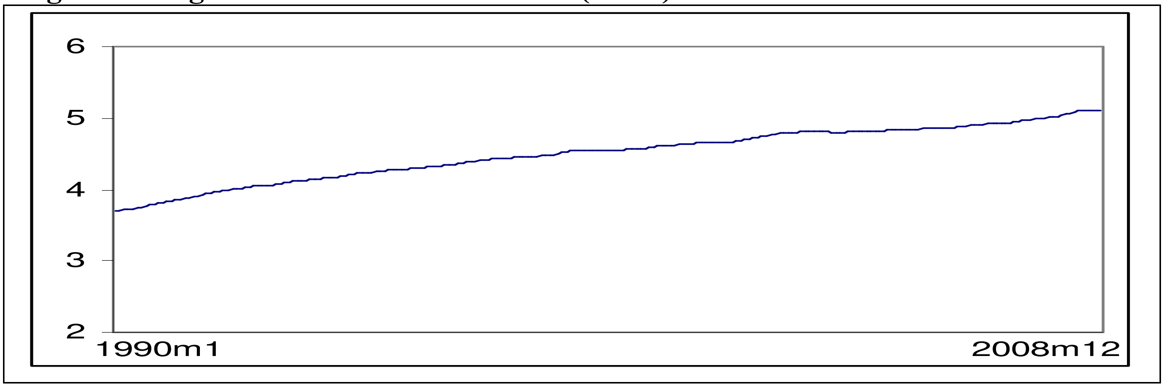


Figure 2: Inflation in South Africa (Total)

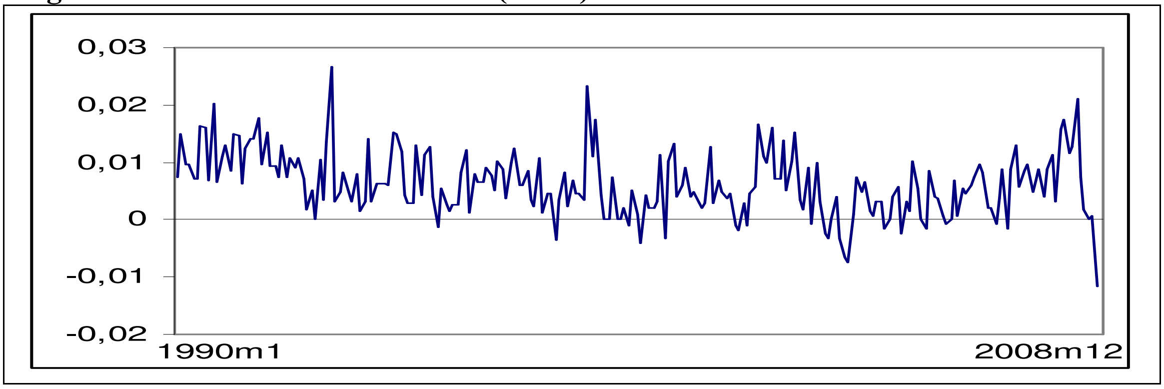


Figure 3: Periodogram of the log of the CPI in South Africa (Total)

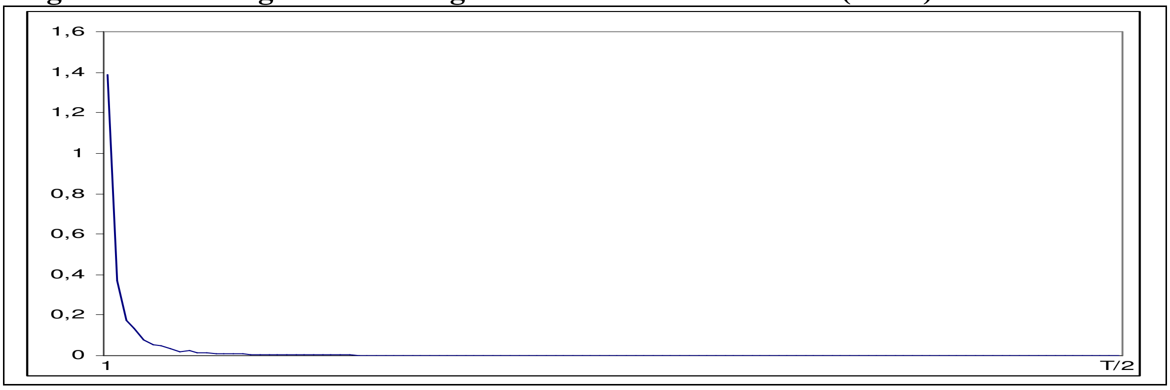


Figure 4: Periodogram of the inflation series (Total)

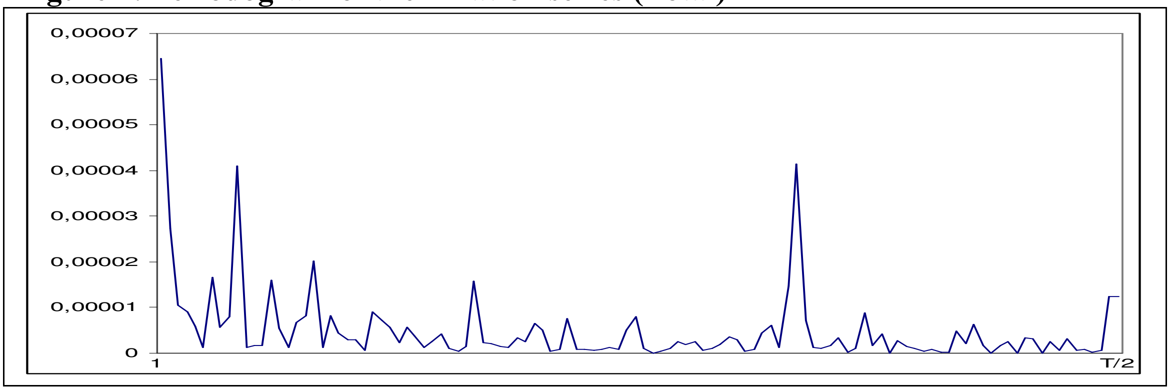


Figure 5: Log of CPI in South Africa

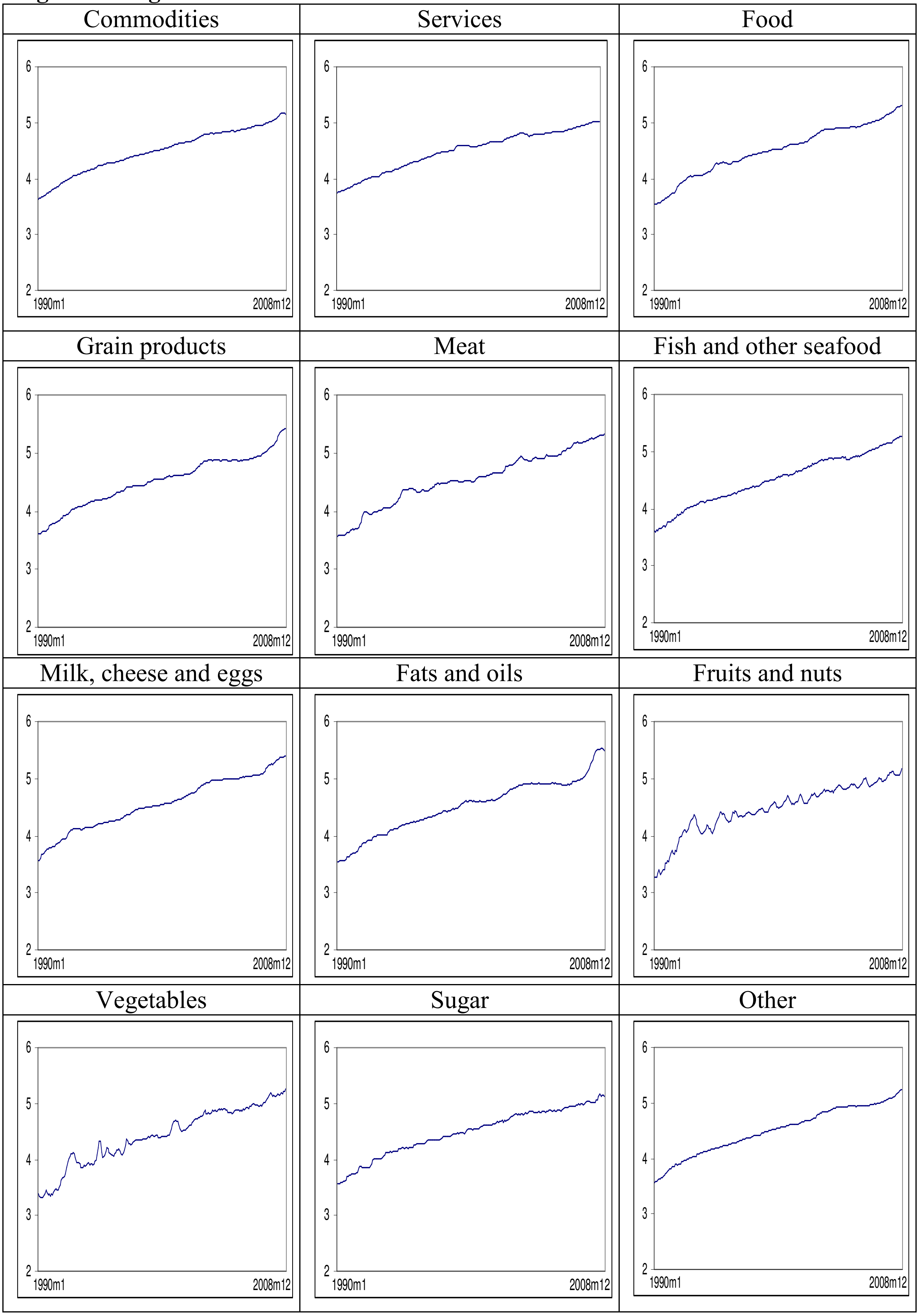


Figure 6: Inflation in South Africa

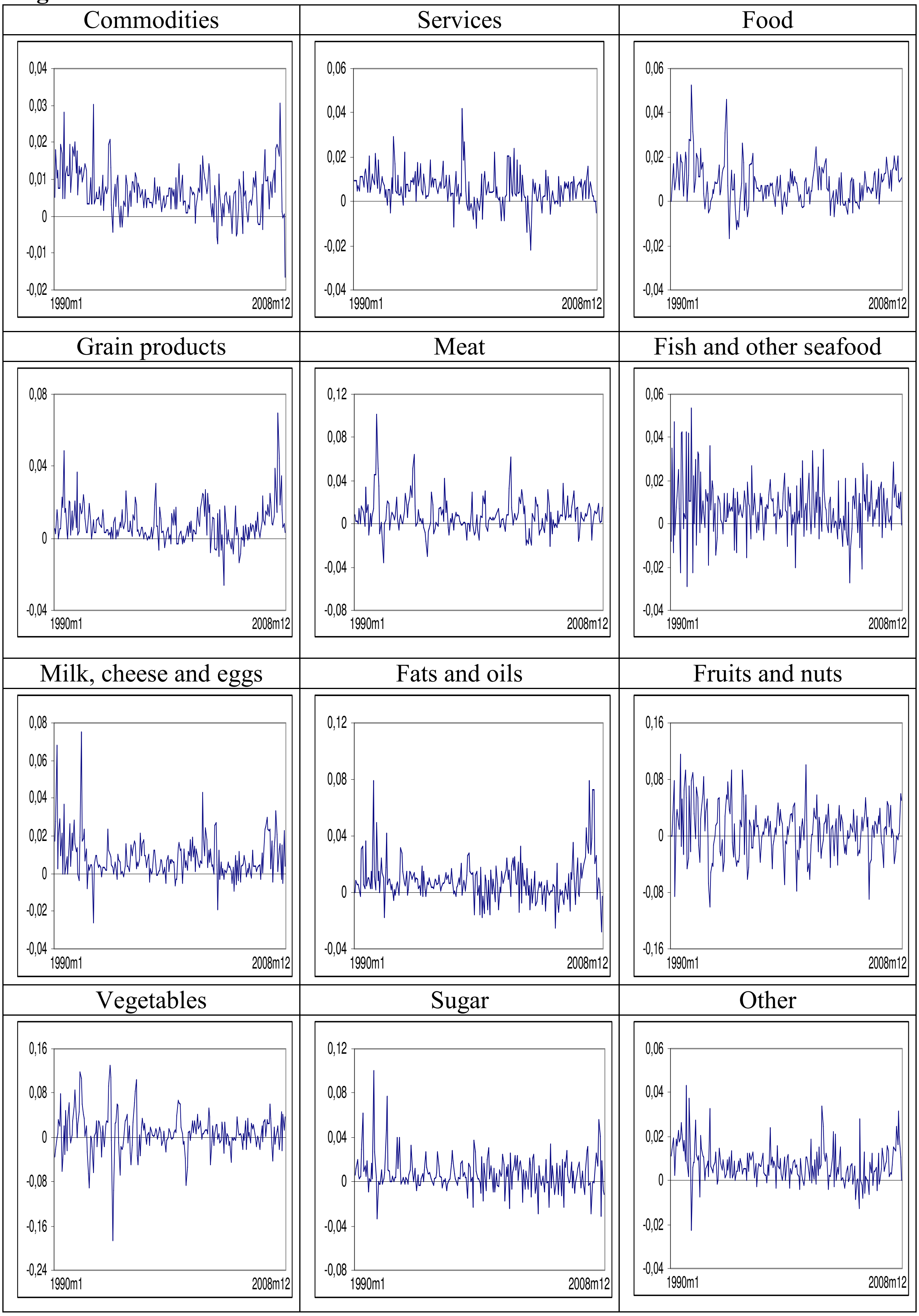


Figure 7: Periodograms of the inflation series

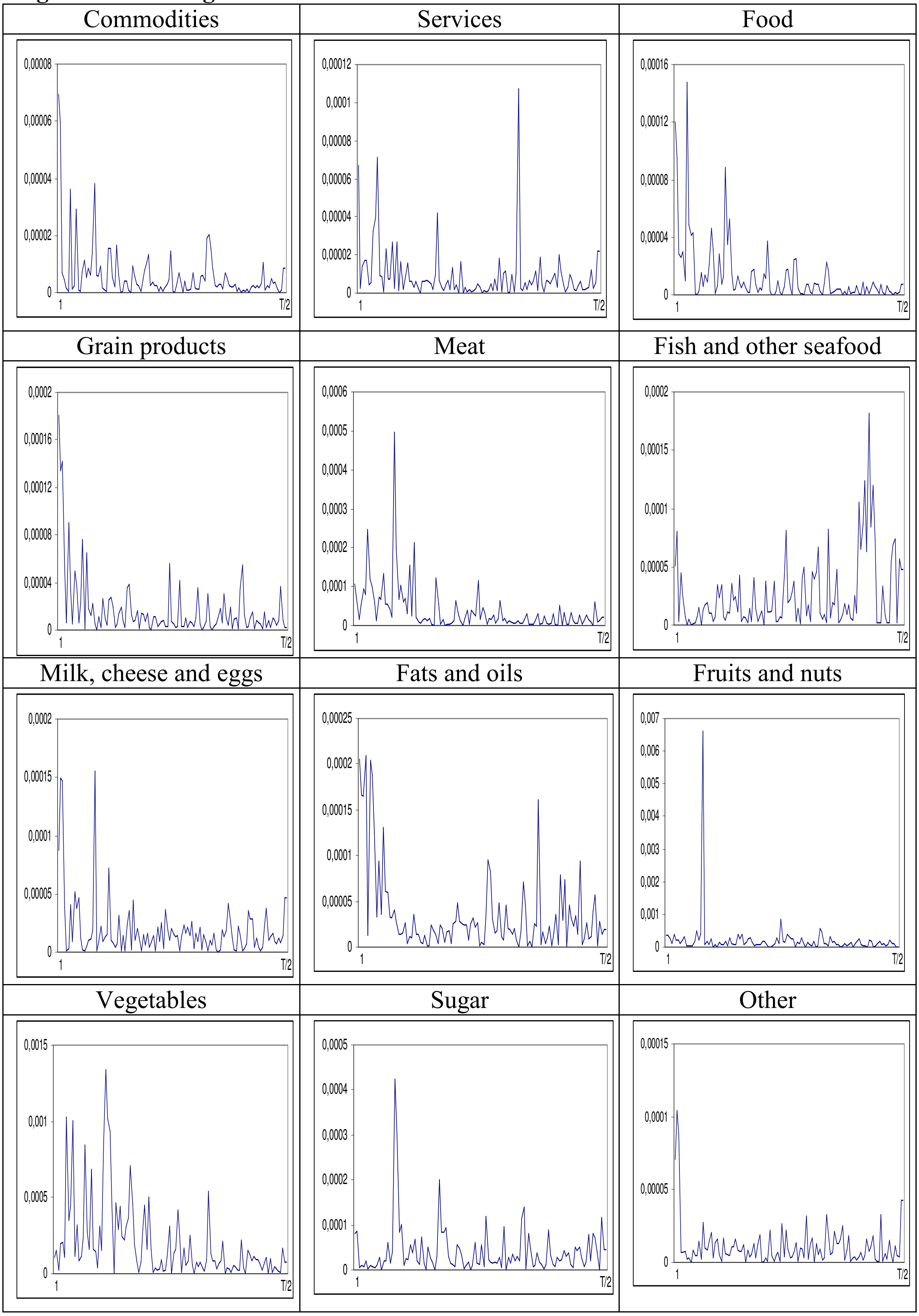


Table 1: Estimates of d (and 95% confidence band) for white noise errors

	No regressors	An intercept	A linear time trend
Total CPI	0.983 [0.907, 1.084]	1.332 [1.263, 1.421]	1.279 [1.210, 1.373]
Commodities	0.983 [0.907, 1.083]	1.337 [1.263, 1.434]	1.288 [1.214, 1.393]
Services	0.983 [0.906, 1.084]	1.222 [1.147, 1.313]	1.190 [1.121, 1.282]
Food	0.988 [0.911, 1.088]	1.500 [1.399, 1.636]	1.471 [1.363, 1.619]
Grain products	0.990 [0.915, 1.089]	1.330 [1.266, 1.414]	1.315 [1.250, 1.401]
Meat	0.987 [0.909, 1.089]	1.450 [1.323, 1.609]	1.439 [1.308, 1.602]
Fish and other seaf.	0.984 [0.908, 1.084]	**0.846 [0.776, 0.950]**	**0.911 [0.865, 0.968]**
Milk, cheese, eggs	0.995 [0.919, 1.094]	1.255 [1.183, 1.346]	1.222 [1.156, 1.307]
Fats and oils	0.984 [0.909, 1.083]	1.255 [1.192, 1.333]	1.249 [1.186, 1.328]
Fruits and nuts	1.006 [0.929, 1.108]	1.261 [1.133, 1.421]	1.247 [1.123 1.408]
Vegetables	0.987 [0.908, 1.091]	1.365 [1.201, 1.575]	1.361 [1.194, 1.577]
Sugar	0.984 [0.908, 1.083]	1.042 [0.920, 1.177]	1.032 [0.949, 1.152]
Other	0.990 [0.914, 1.090]	1.216 [1.153, 1.292]	1.172 [1.117, 1.243]

The values in brackets refer to the 95% confidence band of the non-rejection values. In bold, evidence of mean reversion at the 5% level.

Table 2: Estimated parameters in the selected models with white noise errors

	d-est. (95% band)	Intercept (t-value)	Linear trend (t-val.)
Total CPI	[1.210 (1.279) 1.373]	3.68076 (763.56)	0.00685 (5.300)
Commodities	[1.214 (1.288) 1.393]	3.63188 (676.51)	0.00741 (4.927)
Services	[1.121 (1.190) 1.282]	3.73769 (528.24)	0.00584 (4.769)
Food	[1.363 (1.471) 1.619]	3.53193 (497.89)	0.00857 (1.977)
Grain products	[1.250 (1.315) 1.401]	3.60278 (403.86)	0.00892 (3.140)
Meat	[1.323 (1.450) 1.609]	3.56582 (283.03)	-----
Fish and other seaf.	**[0.865 (0.911) 0.968]**	**3.59425 (285.22)**	**0.00726 (13.50)**
Milk, cheese, eggs	[1.156 (1.222) 1.307]	3.54378 (350.05)	0.00936 (4.552)
Fats and oils	[1.186 (1.249) 1.328]	3.53934 (261.99)	0.00902 (2.878)
Fruits and nuts	[1.133 (1.261) 1.421]	3.27561 (97.680)	-----
Vegetables	[1.201 (1.365) 1.575]	3.38667 (108.03)	-----
Sugar	[0.949 (1.032) 1.152]	3.54785 (221.46)	0.00698 (5.607)
Other	[1.117 (1.172) 1.243]	3.55966 (450.15)	0.00789 (6.314)

In bold, evidence of mean reversion at the 5% level.

Table 3: Estimates of d (and 95% confidence band) for AR(1) errors

	No regressors	An intercept	A linear time trend
Total CPI	1.379 [1.244, 1.564]	1.365 [1.241, 1.510]	1.291 [1.162, 1.477]
Commodities	1.377 [1.244, 1.562]	1.311 [1.181, 1.467]	1.243 [1.114, 1.436]
Services	1.380 [1.244, 1.566]	1.326 [1.176, 1.490]	1.268 [1.114, 1.457]
Food	1.382 [1.248, 1.565]	1.247 [1.062, 1.443]	1.158 [0.967, 1.364]
Grain products	1.378 [1.246, 1.560]	1.420 [1.312, 1.553]	1.397 [1.281, 1.543]
Meat	1.382 [1.245, 1.570]	**0.755 [0.513, 0.949]**	**0.763 [0.578, 0.935]**
Fish and other seaf.	1.385 [1.250, 1.570]	1.158 [1.055, 1.270]	1.113 [1.038, 1.212]
Milk, cheese, eggs	1.392 [1.259, 1.574]	1.332 [1.201, 1.488]	1.280 [1.161, 1.427]
Fats and oils	1.367 [1.235, 1.553]	1.423 [1.315, 1.549]	1.421 [1.307, 1.550]
Fruits and nuts	0.998 [0.849, 1.172]	0.859 [0.619, 1.119]	0.843 [0.611, 0.972]
Vegetables	1.370 [1.228, 1.559]	**0.741 [0.633, 0.844]**	**0.746 [0.642, 0.869]**
Sugar	1.373 [1.240, 1.558]	0.917 [0.771, 1.114]	0.896 [0.788, 1.062]
Other	1.383 [1.251, 1.564]	1.348 [1.262, 1.450]	1.277 [1.195, 1.380]

The values in brackets refer to the 95% confidence band of the non-rejection values. In bold, evidence of mean reversion at the 5% level.

Table 4: Estimated parameters in the selected models with AR(1) errors

	d-est. (95% band)	Intercept (t-value)	Linear trend (t-val.)
Total CPI	[1.162 (1.291) 1.477]	3.68074 (765.85)	0.00691 (5.062)
Commodities	[1.114 (1.243) 1.436]	3.63191 (669.66)	0.00722 (5.908)
Services	[1.114 (1.268) 1.457]	3.73740 (538.19)	0.00605 (3.424)
Food	[0.967 (1.158) 1.364]	3.53018 (484.62)	0.00820 (7.644)
Grain products	[1.281 (1.397) 1.543]	3.60296 (410.26)	0.00905 (2.250)
Meat	**[0.578 (0.763) 0.935]**	**3.57010 (281.71)**	**0.00764 (27.89)**
Fish and other seaf.	[1.038 (1.113) 1.212]	3.59245 (298.95)	0.00753 (5.344)
Milk, cheese, eggs	[1.161 (1.280) 1.427]	3.54299 (354.96)	0.01001 (3.736)
Fats and oils	[1.315 (1.423) 1.549]	3.54492 (283.54)	-----
Fruits and nuts	**[0.611 (0.843) 0.972]**	**3.28684 (98.862)**	**0.00796 (7.751)**
Vegetables	[0.642 (0.746) 0.869]	3.36548 (113.38)	0.00818 (13.70)
Sugar	[0.788 (0.896) 1.062]	3.55190 (224.75)	0.00687 (10.95)
Other	[1.195 (1.277) 1.380]	3.55905 (463.77)	0.00855 (4.191)

In bold, evidence of mean reversion at the 5% level.

Table 5: Estimates of d (and 95% confidence band) for Bloomfield errors

	No regressors	An intercept	A linear time trend
Total CPI	0.970 [0.844, 1.133]	1.390 [1.260, 1.557]	1.298 [1.185, 1.503]
Commodities	0.976 [0.850, 1.140]	1.337 [1.219, 1.484]	1.262 [1.151, 1.440]
Services	0.963 [0.837, 1.135]	1.336 [1.177, 1.551]	1.274 [1.117, 1.514]
Food	0.981 [0.848, 1.146]	1.269 [1.135, 1.441]	1.211 [1.095, 1.381]
Grain products	0.983 [0.858, 1.146]	1.433 [1.310, 1.585]	1.406 [1.281, 1.579]
Meat	0.960 [0.833, 1.140]	1.093 [0.868, 1.365]	1.078 [0.913, 1.334]
Fish and other seaf.	0.978 [0.851, 1.143]	1.263 [1.136, 1.401]	1.183 [1.086, 1.319]
Milk, cheese, eggs	0.988 [0.860, 1.168]	1.338 [1.205, 1.504]	1.279 [1.165, 1.441]
Fats and oils	0.971 [0.853, 1.139]	1.505 [1.339, 1.728]	1.504 [1.333, 1.729]
Fruits and nuts	0.993 [0.860, 1.168]	0.877 [0.579, 1.168]	0.928 [0.790, 1.141]
Vegetables	0.960 [0.832, 1.126]	**0.715 [0.622, 0.958]**	**0.754 [0.609, 0.960]**
Sugar	0.977 [0.850, 1.148]	0.953 [0.842, 1.117]	0.927 [0.836, 1.072]
Other	0.984 [0.857, 1.148]	1.407 [1.294, 1.534]	1.314 [1.214, 1.440]

The values in brackets refer to the 95% confidence band of the non-rejection values. In bold, evidence of mean reversion at the 5% level.

Table 6: Estimated parameters in the selected models with Bloomfield errors

	d-est. (95% band)	Intercept (t-value)	Linear trend (t-val.)
Total CPI	[1.185 (1.298) 1.503]	3.68072 (767.08)	0.00694 (4.926)
Commodities	[1.151 (1.262) 1.440]	3.63190 (672.68)	0.00729 (5.464)
Services	[1.117 (1.274) 1.514]	3.73738 (538.75)	0.00607 (3.342)
Food	[1.095 (1.211) 1.381]	3.53041 (490.23)	0.00836 (6.040)
Grain products	[1.281 (1.406) 1.579]	3.60298 (410.65)	0.00906 (2.171)
Meat	[0.913 (1.078) 1.334]	3.56149 (262.72)	0.00786 (5.906)
Fish and other seaf.	[1.086 (1.183) 1.319]	3.59276 (302.60)	0.00769 (3.880)
Milk, cheese, eggs	[1.165 (1.279) 1.441]	3.54301 (354.84)	0.01004 (3.746)
Fats and oils	[1.339 (1.505) 1.728]	3.54529 (292.57)	------
Fruits and nuts	[0.790 (0.928) 1.141]	3.27671 (96.403)	0.00810 (5.142)
Vegetables	**[0.609 (0.754) 0.960]**	**3.36512 (114.43)**	**0.00818 (13.37)**
Sugar	[0.836 (0.927) 1.072]	3.55051 (223.35)	0.00688 (9.390)
Other	[1.214 (1.314) 1.440]	3.55887 (467.75)	0.00810 (5.142)

In bold, evidence of mean reversion at the 5% level.

Table 7: Estimates of d (and 95% confidence band) for seasonal AR(1) errors

	No regressors	An intercept	A linear time trend
Total CPI	0.978 [0.882, 1.085]	1.355 [1.272, 1.461]	1.313 [1.229, 1.432]
Commodities	0.977 [0.882, 1.084]	1.335 [1.255, 1.438]	1.291 [1.212, 1.404]
Services	0.978 [0.883, 1.085]	1.248 [1.165, 1.349]	1.221 [1.141, 1.326]
Food	0.983 [0.890, 1.089]	1.500 [1.398, 1.642]	1.470 [1.360, 1.625]
Grain products	0.985 [0.890, 1.090]	1.323 [1.253, 1.412]	1.314 [1.243, 1.405]
Meat	0.985 [0.897, 1.090]	1.452 [1.326, 1.609]	1.443 [1.313, 1.603]
Fish and other seaf.	0.975 [0.882, 1.083]	**0.839 [0.779, 0.928]**	**0.878 [0.824, 0.944]**
Milk, cheese, eggs	0.995 [0.905, 1.096]	1.252 [1.177, 1.344]	1.220 [1.152, 1.306]
Fats and oils	0.983 [0.890, 1.087]	1.255 [1.193, 1.334]	1.249 [1.186, 1.329]
Fruits and nuts	0.999 [0.911, 1.106]	1.146 [1.036, 1.290]	1.139 [1.035, 1.278]
Vegetables	0.987 [0.904, 1.092]	1.353 [1.180, 1.575]	1.347 [1.171, 1.576]
Sugar	0.981 [0.893, 1.083]	0.937 [0.803, 1.094]	0.953 [0.860, 1.079]
Other	0.983 [0.887, 1.090]	1.197 [1.126, 1.279]	1.158 [1.098, 1.233]

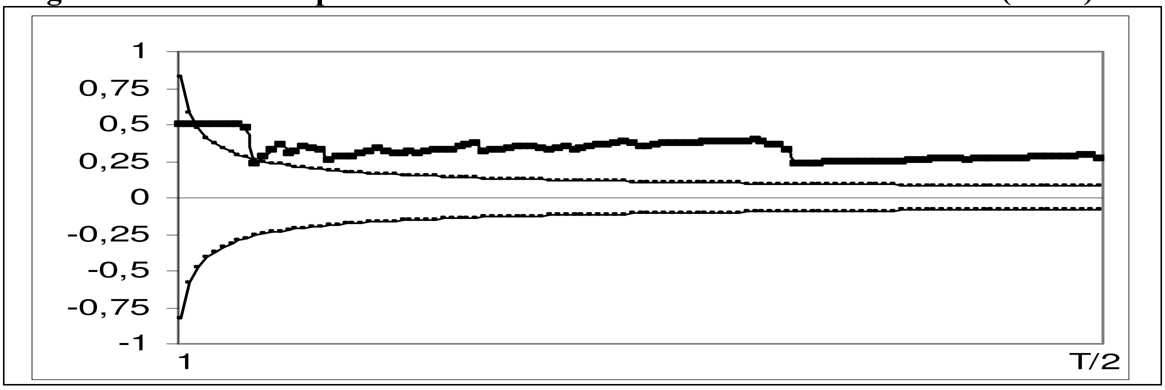
The values in brackets refer to the 95% confidence band of the non-rejection values. In bold, evidence of mean reversion at the 5% level.

Table 8: Estimated parameters in the selected models with seasonal AR(1) errors

	d-est. (95% band)	Intercept (t-value)	Linear trend (t-val.)
Total CPI	1.313 [1.229, 1.432]	3.68070 (767.82)	0.00702 (4.643)
Commodities	1.291 [1.212, 1.404]	3.63180 (676.21)	0.00743 (4.867)
Services	1.221 [1.141, 1.326]	3.73755 (531.02)	0.00591 (4.159)
Food	1.470 [1.360, 1.625]	3.53191 (497.89)	0.00857 (1.984)
Grain products	1.314 [1.243, 1.405]	3.60278 (403.79)	0.00891 (3.153)
Meat	1.452 [1.326, 1.609]	3.56588 (282.83)	-----
Fish and other seaf.	**0.878 [0.824, 0.944]**	**3.59535 (286.68)**	**0.00724 (15.84)**
Milk, cheese, eggs	1.220 [1.152, 1.306]	3.54380 (349.66)	0.00934 (4.583)
Fats and oils	1.249 [1.186, 1.329]	3.53934 (261.99)	0.00902 (2.877)
Fruits and nuts	1.139 [1.035, 1.278]	3.27016 (94.184)	0.00914 (1.968)
Vegetables	1.353 [1.180, 1.575]	3.38633 (107.49)	-----
Sugar	0.953 [0.860, 1.079]	3.54953 (220.59)	0.00690 (8.184)
Other	1.197 [1.126, 1.279]	3.55977 (448.83)	-----

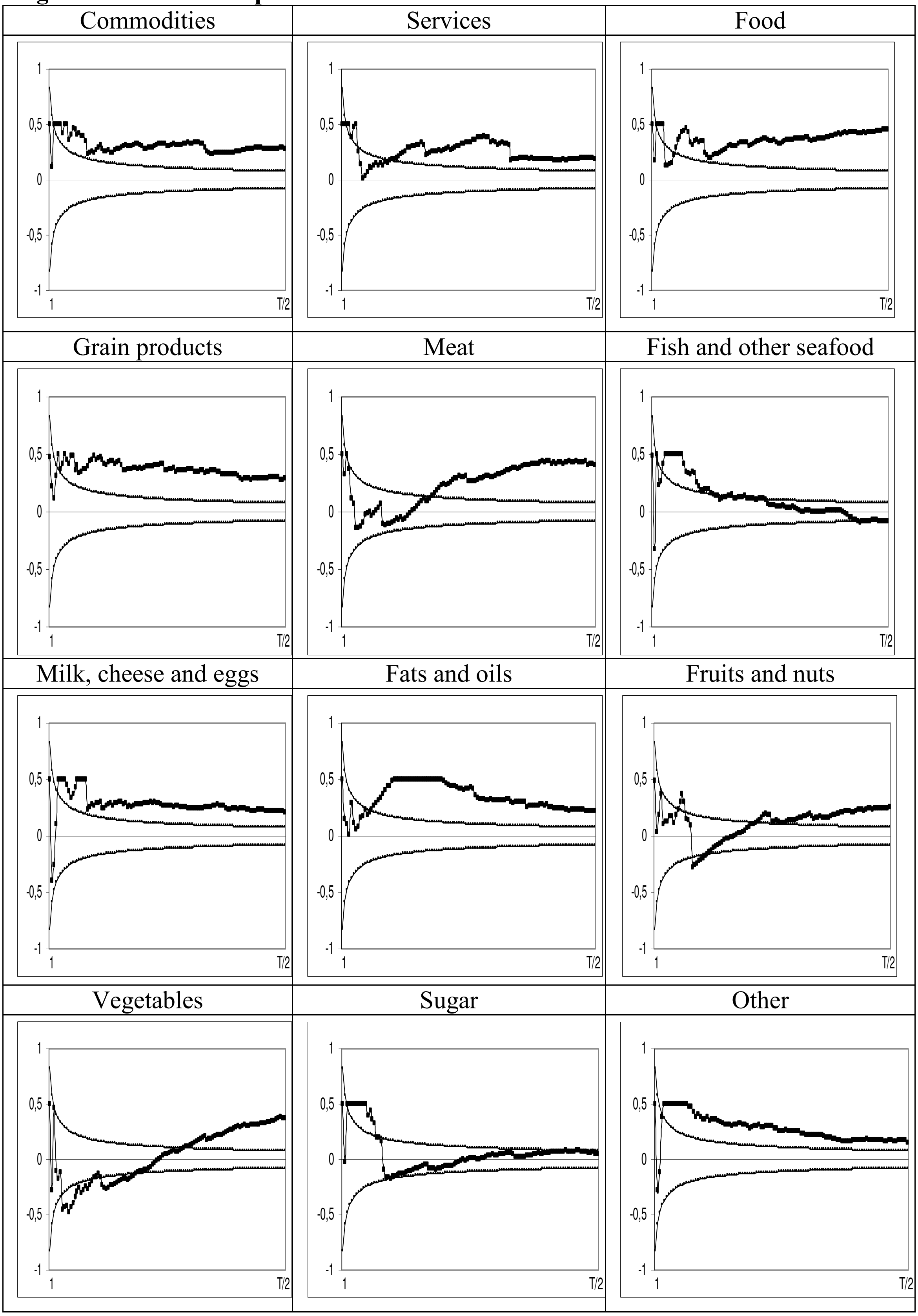
In bold, evidence of mean reversion at the 5% level.

Figure 8: Whitte semiparametric estimate of d in South Africa inflation (Total)



The horizontal axe refers to the bandwidth number m, while the vertical one displays the estimates of d.

Figure 9: Whittle semiparametric estimation of d in Inflation in South Africa



The horizontal axe refers to the bandwidth number m, while the vertical one displays the estimates of d.

Figure 10: Recursive estimates based on white noise disturbances

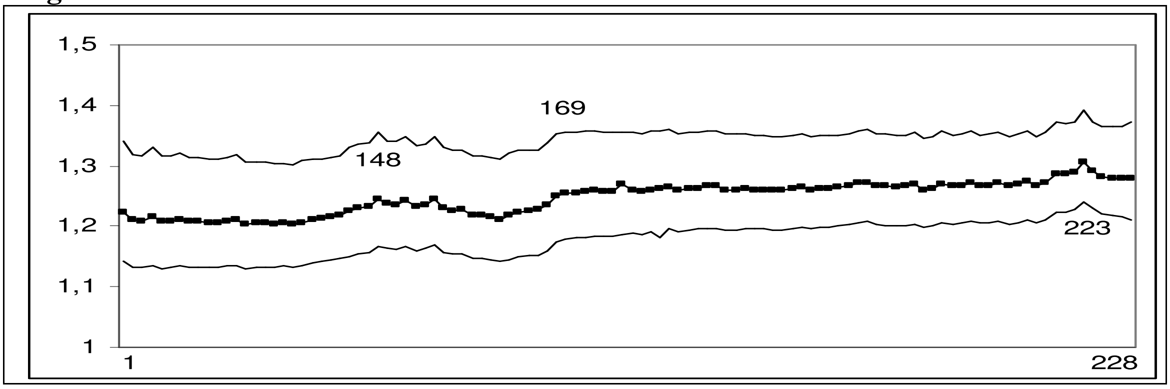


Figure 11: Recursive estimates based on AR(1) disturbances

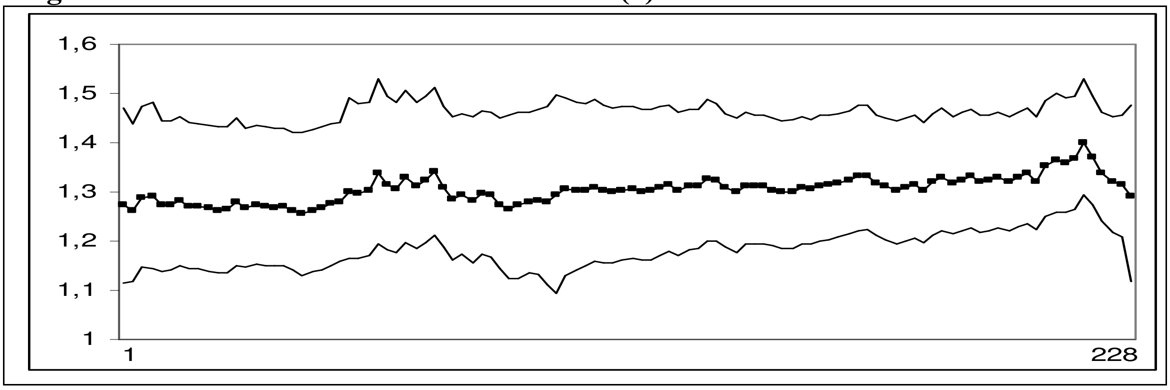


Figure 12: Recursive estimates based on Bloomfield disturbances

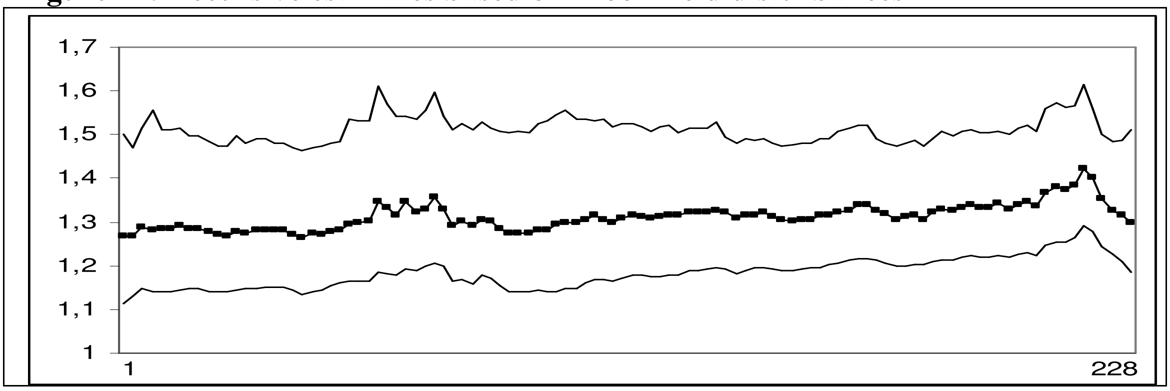


Figure 13: Recursive estimates based on seasonal AR(1) disturbances