Inflation Targeting: An Indirect Approach to Assess the Direct Impact

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Abstract

It is quite difficult to assess the benefits of inflation targeting (IT) since its immediate effect will be on inflation expectations, an unobserved variable. Due to lack of comprehensive data on inflation expectations, most studies so far concentrated on the impact of IT either on observable variables like output, unemployment, and inflation or compared post-IT surveys of IT countries with non-IT countries. In our study, we focus on a yet unanswered question, i.e., how the expectations *change* with the adoption of IT. We suggest that heterogeneous inflation expectations lead to long memory in actual inflation, and IT, if successful, should decrease this persistence by concentrating the public's expectations toward the announced target. Empirical results confirm our hypothesis with the disappearance of long memory process after the adoption of IT in all sample countries.

Keywords: Inflation Targeting, Long Memory Persistence, Heterogeneous Expectations, Aggregation

1. Introduction

Since its first adoption by the Central Bank of New Zealand, inflation targeting (hereafter IT) has proved to be a popular policy option among central banks. Along with the policy comparisons a plethora of theoretical and empirical literature[1] appeared on the relative performance of IT. Most of the issues revolved around its impact on observable policy variables like inflation (Siklos, 1999; Corbo et al., 2001; Petursson, 2004) and output (Bernanke et al., 1999; Corbo et al., 2001; Levin et al., 2004). However, an important measure of success for any monetary authority in reaching their ultimate goals depends on the extent to which the expectations of the public are reshaped by the announced or implemented policy (Woodford, 2004). The difficulty in observing the inflation expectations though, led some researchers to utilize consensus surveys for testing the effectiveness of IT (Johnson, 2001, 2003; Levin et al. 2004).

Surveys unfortunately provide very little information on the conditions prior to the adoption of IT. Therefore, the studies using them concentrate more on the comparison of inflation expectations of targeters versus the non-targeters in order to evaluate IT's effectiveness. However, the true assessment of how adoption of IT changes inflation expectations requires the comparison of expectations *before* and *after* the switch to IT. In this study, we offer an indirect methodology that enables one to make that very comparison by deriving inference on inflation expectations from long run dynamics of the inflation process. Two useful byproducts of our analysis are 1) offering an alternative explanation as to why long memory exists in inflation, and 2) providing an alternative theoretical explanation to the empirical evidence of the decline in inflation persistence for inflation targeting countries (Siklos, 1999; Corbo et al., 2001; Kuttner and Posen, 2001; Petursson, 2004; Levin et al., 2004).

The basis of our theory is to indirectly examine the distribution of inflation expectations through an analysis of the time series properties of inflation. As an initial step, we show how the heterogeneity in inflation expectations (in a discretionary policy environment) leads to increased persistence in actual inflation. If an IT monetary policy succeeds in decreasing this heterogeneity, inflation persistence will decline as well. Therefore, testing for and observing the reduction in persistence after the switch to IT will constitute the indirect evidence of IT's effectiveness in focusing the expectations toward the announced target. Our theoretical and empirical findings will also offer an explanation as to why there exists a long memory process[2] (fractional integration) in inflation. Observing the disappearance of inflation inertia after the switch to IT, we deduce that the aggregation of heterogeneous inflation expectations is the real culprit behind the long memory in inflation. In addition, our theory offers a possible theoretical justification to the empirical evidence of persistence declines in inflation after IT.

For any monetary policy to be effective, it is important that the public understands the central bank's actions and forms their expectations in accordance with these actions. The inflation targeting rule facilitates the public's understanding of the monetary policy and thus has an effect on the expectations of the public. According to Woodford (2004) and Faust and Henderson (2004), such a commitment to an announced target helps the public to form anchored expectations for the policy outcome. Siklos (1999), Corbo et al. (2001), and Petursson (2004) examine these effects of inflation targeting using multiple countries to find that the level and fluctuations of inflation along with its persistence have all decreased after the adoption of IT. While these authors concentrate on the "observable" effects of IT, others aimed to test its effectiveness on expectations directly. Johnson (2001, 2003) and Levin et al. (2004) utilize *Consensus Economic Forecasts* to measure the effectiveness of IT on inflation and output. While Johnson finds IT effectiveness on the mean, variability, and forecast errors of inflation, Levin et al.. shows that it holds for the sacrifice ratio as well. Our study forms a bridge between these two branches in the literature, deriving conclusions on unobservable changes such as the distribution of inflation expectations, using the analysis of observable ones, namely inflation persistence. In this regard, we make up for the lack of such analysis in the literature and explain how expectations *change* with the adoption of IT.

As a byproduct, our analysis contributes to the literature on long memory processes. Despite substantial evidence of its relevance in many macroeconomic series,[3] there have not been many papers establishing the economic origins of long memory processes in macroeconomic variables. Until recently, the most common[4] explanation for fractionally integrated processes in economics has been Granger's (1980) cross-sectional aggregation[5] of a large number of heterogeneous dynamic processes. Aggregation over individuals or firms has been advanced as the source of long memory in many empirical studies on aggregate economic series. Specifically regarding inflation, there have been only a few suggestions as to the *source* of long memory, namely aggregation in price indexes (Hassler and Wolters, 1995), aggregation of heterogeneous firm production (Abadir and Talmain, 2002), and persistence in money supply shocks (Scacciavillani, 1994). We propose instead the aggregation of heterogeneous inflation expectations as the reason behind inflation persistence. IT and its main goal, anchoring expectations (and therefore reducing their heterogeneity), provide us with a perfect lab experiment for the testing of our proposition.

Next section sets up the relation between the theoretical and the econometric framework. Section 3 describes the estimation technique and the results while the last section concludes.

2. Setup

In the subsections below, we formulate some conditions for inflation expectations heterogeneity to produce long memory process in inflation. One should keep in mind that the main purpose of the study is to propose a practical link between inflation persistence, inflation targeting and heterogeneous expectations. In this respect, we provide an economic theory to derive conclusions about the time series properties of inflation. It is quite possible that variations of the model below can be conceived to reach the same end goal.

Expectations

Earlier theoretical (Crettez and Michel, 1992; Naish, 1993) and empirical (Figlewski and Wachtel, 1981; Zarnowitz, 1985; Evans and Wachtel, 1993; Evans et al., 2001; Evans and Honkapohja, 2001) studies have shown that when information acquisition is costly, the use of adaptive expectations or adaptive learning models can be more fitting with the empirical observations.[6] The convergence of these models to rational expectations equilibrium (E-stability) only helped increase their appeal and use.

Utilizing a time varying gain representation (Figlewski and Wachtel, 1981; Evans and Honkapohja, 2001), the inflation expectation, π^{ie}, for agent i and period t+1 is

$$\pi_{t+1}^{ie} = \theta_{it}\pi_t + \left(1-\theta_{it}\right)\pi_t^* \tag{1}$$

where $i = 1,..,N$, π_t^* is the consensus inflation expectation or inflation target announcement (if there exists one) and θ_{it} is a (lack of) credibility weight according to how close consensus expectation or announcement is to actual inflation, i.e. $\theta_{it} = f_i\left[\left(\pi_t - \pi_t^*\right)^2\right]$ where $1 \geq \theta_{it} \geq 0$ and $\theta_{it}' > 0$.[7] In other words, as the central monetary authority fails to hit its target repeatedly, with a high mean or variance of $\left(\pi_t - \pi_t^*\right)^2$, then the public gives more weight to realized inflation than targets to form their expectations. Naturally, the opposite happens and θ_{it} decreases with more successful performance of the monetary authority. We assume an expectations augmented Phillips curve formulation for inflation[8]

$$\pi_t = K_t + \gamma\pi_{t+1}^e + z_t \tag{2}$$

where π_{t+1}^e is the aggregate expectation of inflation level π_t, K_t represents variables like money growth rate or output gap, and z_t is a white noise supply shock. Assuming the aggregate inflation expectation to be the mean of the individual forecasts (i.e., $\pi_{t+1}^e = \left(1/N\right)\sum \pi_{t+1}^{ie}$,[9] it can be shown that after linearization around the mean the reduced form for the individual inflation expectation follows an AR(1) process

$$\pi_{t+1}^{ie} = A_t + \theta_{it}^{\ *}\pi_t^{ie} + e_t \tag{3}$$

where the details of A_t, e_t, and on the linearization are provided in the Appendix. More importantly $\theta_{it}^* = \left(N\gamma\theta_{it}\right)/\left(N - \gamma\theta_{it}\right)$, which equals $\gamma\theta_{it}$ for large N and is less than or equal to 1. In other words, as the announcements become more credible and inflation expectations get aligned with the announced targets, the mean and the variance of the autoregressive parameter of individual expectations decline and the emphasis shifts toward the announcements in A_t.

Long Memory

Long memory models are generally used for series in which the order of integration is a fraction and the differencing operator, *d*, in the lag polynomial, $(1-L)^d$, is used to transform them into stationary series. After being introduced into the economics literature by Granger (1980), a large number of studies found evidence of its existence in many macroeconomic series. Granger showed that cross-sectional aggregation of a large number of heterogeneous dynamic processes could display time series properties that are neither unit root nor ARMA stationary. In these models the autocorrelation functions display hyperbolic decay as opposed to the geometric decline of the stationary ARMA series or the non-decreasing ACF of the unit root models. In his model, Granger emphasizes that there are two necessary conditions for cross-sectional aggregation of AR(1) parameters to produce long memory in the sum: 1) heterogeneity, and 2) some series having a unit root. It is trivial to show that the sum of *N* AR(1) series with identical parameters will still be an ARMA process, implying that the first condition about the heterogeneity of individual AR(1) coefficients is essential for obtaining long memory in the aggregate. For the second condition, Granger (1980) and a later study by Zaffaroni (2004) prove that unless enough of these individual AR(1) coefficients are allowed to approach to unity, the aggregate series will not be fractionally integrated. These necessary conditions form the second motivation behind our paper, namely, analyzing the role of the distribution of AR(1) coefficients of heterogeneous inflation expectations in the aggregation towards long memory in inflation.

We utilize two different distributions for the cross-sectional aggregation of AR(1) coefficients, the beta distribution used by Granger (1980) and a more general semi-parametric distribution by Zaffaroni (2004). Granger considers the cross-sectional aggregation of a large number of heterogeneous AR(1) processes

$$x_{it} = \alpha_i x_{it-1} + \varepsilon_{it} \tag{4}$$

where $i = 1,\ldots,N$, ε_{it} is white noise, $E(\varepsilon_{it}, \varepsilon_{jt}) = 0$, and $E(\alpha_i, \varepsilon_{jt}) = 0$ for all i, j, t. When (square root of) α_i has the beta distribution[10]

$$f(\alpha) = \frac{2}{B(p,q)} \alpha^{2p-1} \left(1-\alpha^2\right)^{q-1} \qquad \text{for } 0 \le \alpha \le 1 \tag{5}$$

where $B(p,q)$ is the beta function and N gets large, the aggregate series $x_t = \sum_{i=1}^{N} x_{it}$ will exhibit long memory and have a fractional order of integration,[11] $d = 1 - q/2$. Granger shows that decreasing the range of α from above (i.e., when α is not allowed to be close to unity) results in the disappearance of long memory; the conclusions do not change when α is restricted from below. This condition demonstrates that for fractional integration, $x_t \sim I(d)$, heterogeneity alone is not sufficient, but the coefficients α_i should also be allowed to approach to one, i.e., the mean should be high.

Our analysis extends Granger's by illustrating the analytical relation of the degree of fractional differencing to the first two moments[12] of the coefficient α, namely its mean (μ_α) and variance (σ_α^2). Mean and variance of the beta distribution are

$$\mu_\alpha = \frac{p}{p+q} \tag{6}$$

$$\sigma_\alpha^2 = \frac{pq}{(1+p+q)(p+q)^2} \tag{7}$$

Combining them with the previously mentioned fractional order of integration, $d = 1 - q/2$, helps us illustrate the relation between the order of integration and these moments. Substituting out p and q gives us

$$d = \frac{3\sigma_\alpha^2 - \mu_a \sigma_\alpha^2 - (1-\mu_a)^2 \mu_a}{2\sigma_\alpha^2} \tag{8}$$

The relations $\partial d / \partial \sigma_\alpha^2 > 0$ [13] and $\partial d / \partial \mu_\alpha > 0$ indicate that the degree of persistence crucially depends on the tail probability of the distribution of α close to one. A decrease in the variation or mean of α unambiguously lowers the degree of fractional differencing, and in extreme cases may eliminate it completely. A similar derivation for Zaffaroni (2004) is pushed in the Appendix for brevity.

Drawing a parallel between the two literatures, we assume that the x_{it} and α_i of Equations (4) and (A17) correspond to the individual inflation expectations, π_{it}^e, and the weights, θ_{it}^*, in Equation (3). Granger (1980) and Zaffaroni (2004) show that the aggregation of AR(1) models similar to Equation (3), results in fractionally integrated processes. Thus, the aggregation of the individual expectations, π_{t+1}^{ie} (to obtain the mean π_{t+1}^e), could induce a long memory process in the aggregate inflation expectation, which would in turn translate into long memory in inflation[14] via Equation (2).

$$\pi_{t+1}^{e} \sim I(d) \rightarrow \pi_t \sim I(d) \tag{9}$$

Such a derivation offers one possible reason for the evidence of long memory in the inflation process. Other potential reasons suggested to date are persistence in money supply (Scacciavillani, 1994), aggregation of heterogeneous firm production (Abadir and Talmain, 2002), and the aggregation of individual prices into a price index (Hassler and Wolters, 1995). We distinguish our model from the others by using the adoption of inflation targeting as an experiment since it is more likely to have an impact on inflation expectation heterogeneity than the other sources of long memory listed above.

It is widely accepted that an activist central bank can create an inflationary bias because of its opportunism in surprising the public to stimulate production. As a result, persistent inflation will become ingrained in the system via the public's expectations as in Equation (2). The adoption of inflation targeting is aimed at moderating inflation expectations by not only providing discipline in the setting of monetary policy, but also by improving the communication of policy goals and actions. Therefore, if inflation targeting is successful in decreasing the variability of inflation expectations, evidence of long memory processes present before the regime switch should disappear or be significantly reduced afterwards. In other words, in a successful IT regime, where the monetary authority will not deviate too much from its announced targets, the autoregressive parameter, $\theta_{it} = f_i\left[\left(\pi_t - \pi_t^*\right)^2\right]$, will decline and lose its heterogeneity, leading to the disappearance of long memory process. Empirical evidence of the decline in persistence would support our theory more than the other possible explanations of long memory in inflation since the adoption of inflation targeting should not have as sharp an impact on them.

3. Estimation

One of the main criteria of success of IT is the level of control it exerts on the public's inflation expectations. That is why the inflation targeting central banks communicate their targets clearly to the public. In return, they need to closely follow how the public responds to the target announcements in order to evaluate their effectiveness. Hence, it is quite common to observe detailed surveys of inflation expectations around the time of the switch to IT. The motivation of our study is the inadequacy of these measures of expectations prior to the adoption of IT and the resultant difficulty of measuring IT's true effect on expectations.

(Insert Table 1 here)

Table 1 displays survey information from Consensus Forecasts provided by *Consensus Economics*. Consensus Forecasts data consists of outlooks for over a 2 year forecast horizon by leading economists whose individual views are shown together with the average, or consensus, forecast. In other words, each month, every forecaster reports an expected rate of inflation for the end of current year and the next year. Among the countries in the dataset, only three, Australia, Canada and UK, have data both before and after the switch to IT. Examining the cross section of inflation forecasts for these countries, one can notice the short sample length before the new regime. UK leads the pack by three years of data before IT while Canada has only one. For comparison, we also include three non-targeting countries to control for the declining inflation rates across the globe. We pick the beginning of 1993 as the break point for the non-targeting countries (1994 for the US)[15] since most of the inflation targeting countries in our sample adopted the IT regime around that date. We should warn the reader at this point that we will use the non-targeting countries only in the descriptive parts of our research since any imposed break date and the choice of non-targeting countries will be open to rightful criticism. Inspection of the results reveals that *i*) the pre-targeting period data is quite short and insufficient to make any solid statements, and *ii*) likely due to the first point, the survey evidence fails to provide a clear picture about how the inflation expectations are affected with the adoption of the IT regime. All of the countries, inflation targeting or not, experience statistically significant declines in their mean inflation expectations. However, the heterogeneity, measured by the cross sectional variation of expectations among forecasters, changes significantly only in a small part of the countries, not forming a certain pattern one way or the other. Hence, survey comparisons of the pre- and post-targeting periods indicate that IT does not produce its desired impact on inflation expectations since targeting country surveys show similar patterns with those of the non-targeting countries.

The lack of clear evidence in survey data motivates our use of an indirect methodology to examine the actual inflation data in order to assess the direct impact of inflation targeting on expectations. The monthly CPI inflation data that ranges from 1961 until present is obtained from Global Financial Database.[16] Table 2 displays the descriptive statistics information for the inflation level in seven IT countries. The results also resemble the picture in survey statistics. Accordingly, we resort to our indirect route, which comprises of examining the persistence level (fractional root) in the inflation process to deduce information on the changes in the expectation level and heterogeneity.

(Insert Table 2 here)

We estimate the fractional differencing parameters in the inflation process for pre- and post-IT periods in our sample countries to observe whether the decreases in the mean and heterogeneity of inflation expectations induce a decline in the fractional root d, as suggested by our theory. Aside from numerous empirical studies that find evidence of long memory process in the inflation series of many countries, an additional advantage of the estimation of an ARFIMA(p,d,q) specification is to be able to represent the long run dynamics of the inflation series by a single parameter, d. The estimations are carried out using Non-Linear Least Squares (NLS).[17] The NLS applies a two-step approach of initially estimating d followed by the estimation of the short run ARMA parameters.[18] The function that is maximized is

$$-\frac{1}{2}\log\left(\frac{1}{T}\sum_{t=1}^{T}e_t^2\right)$$

where e_t is the residual of the two-step ARFIMA filter applied on the inflation series. Estimations are carried out using ARFIMA package in OX (Doornik, 1998). Since specifics of the method is beyond the scope of this paper we refer the reader to an excellent survey by Baillie (1996) and Ooms and Doornik (1999) for further details.

The estimation results for only $\hat{d}$ are displayed in Table 3 while the values or orders of the ARMA parameters are not reported to conserve space.[19] The values in parentheses below the estimates represent their corresponding standard errors. Examination of the results shows that the fractional root declines in every country with the adoption of inflation targeting. The pre- and post-targeting estimates of the fractional roots are statistically different from one another. We also run auxiliary Monte Carlo simulations (displayed in Appendix III) to confirm that the sample size differences between the pre- and post-IT are not the reason for the disappearance of long memory process. In addition to this simulation, we check the robustness of our results to 1-year movements of the regime change in both directions since it could be argued that the break dates could be misleading due to an initial transition (credibility) period. We find that these movements in the break date do not affect our fractional root estimates at all.[20] All of these findings are quite in line with the theory, showing that the long memory process that existed prior to the adoption of inflation targeting disappears for all sample countries except Israel, in which case the fractional root declines to a lower and stationary value. The results corroborate that once the heterogeneity and the level in individual inflation expectations is reduced, the persistence of the aggregate series will decrease.

(Insert Table 3 here)

One possible explanation to the results in Table 3 can be that the long memory in the pre-targeting period is the outcome of a long pre-targeting sample and possible structural breaks in it. When we equalize the pre and post-IT sample periods by shortening the former to equal the size of the latter, we find slightly lower fractional root estimates than the ones reported in Table 3, but still are significantly higher than zero. This indicates that the structural breaks are not the underlying reason for the longer memory length before inflation targeting.

Next, we aim to verify that the changes in inflation persistence are indeed caused by the changes in the distribution of expectations. For this purpose, we examine the persistence level in inflation expectations to see if they mimic that of the persistence in actual inflation process. Our theory shows that the persistence in actual inflation is the result of the persistence in inflation expectations, and hence, not finding similar dynamics in the expectations would weaken our hypothesis and favor other causes of persistence changes in inflation. We proxy for inflation expectations using the difference between the nominal and the inflation indexed bond rates from UK and Australia.[21] The fractional root estimates in Table 4 for the inflation expectations proxy illustrate that the long memory process, which existed before the regime switch, disappear once these countries adopt IT. The fractional root values of expectations' proxy are also statistically not different than the actual inflation parameters except for the pre-targeting period for Australia. These results validate our hypothesis that the distribution of expectations is the likely underlying reason for inflation persistence, and changes in this distribution that come with IT decrease inflation persistence. In this respect, our study offers an alternative explanation, heterogeneous inflation expectations, for the evidence of long memory process in inflation series.

(Insert Table 4 here)

4. Conclusion

The success of inflation targeting is very much dependent on how it reduces the heterogeneity in the public's inflation expectations and concentrates them around the target announcement. Due to insufficient data, the evaluation of this success has been empirically carried out using observable variables like output and various derivatives of inflation. Our study remedies this deficiency by showing a link between the distribution of inflation expectations and inflation persistence. The relation implies that as inflation expectations are moderated (declines in mean and heterogeneity), the (long memory) persistence of actual inflation process should diminish. In empirical tests utilizing seven countries, we show that the inflation persistence levels drop sharply with the adoption of IT.

We realize that the decline in expectations heterogeneity is a sufficient but not a necessary condition for the decline in persistence. However, unavailability of expectations data prohibits any irrefutable analysis of IT's effectiveness on inflation expectations. One can think of experimenting on ‘other’ reasons for the decline in inflation persistence to strengthen the empirical support for our theory; however, once one considers all the possible reasons of inflation, that option becomes questionable as well. Therefore, in the search for additional support of our theory, we use a proxy for inflation expectations (only for two countries, again due to insufficient data) to see if the dynamics of inflation expectations resemble that of inflation itself. This estimation shows that the time series properties of expectation proxy mimic the one in actual inflation, confirming IT’s effectiveness in reducing the inertia in inflation expectations via their level and heterogeneity.

As a byproduct of our study, we are also able to provide (and test) an alternative explanation as to why long memory exists in inflation. The current justifications are persistence in money supply, aggregation of heterogeneous firm production, and the aggregation of individual prices into a price index. The sharp decline in the memory length of inflation that closely follows the adoption of IT provides a stronger support to our theory on the impact of IT on expectations heterogeneity than the other explanations of long memory in inflation.

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Table 1: Descriptive Statistics from Consensus Forecasts

	Pre-targeting			Post-targeting		
	Mean	*Variance*	*Observations*	*Mean*	*Variance*	*Observations*
Australia	3.57	0.38	26	2.67	0.26*	153
Canada	4.84	0.18	15	2.14*	0.20	176
UK	4.88	0.48	39	1.98*	0.41	152
US	4.20	0.23	39	2.56*	0.17*	152
Germany	3.38	0.16	39	1.85*	0.14	152
France	3.18	0.16	39	1.65*	0.15	152

Notes: The switch date for France and Germany is artificially taken as 1993Q1 and for US it is taken as 1994Q1 to control for the overall decline of world inflation. Mean is the overall average of all inflation surveys before and after the regime adoption. The variance is defined as the average of cross sectional variation in the surveys. * indicates difference in mean and variance terms at 95% significance level.

Table 2: Descriptive statistics of annual inflation before and after adoption of inflation targeting

	Pre-Targeting			*Post-Targeting*		
	Mean	*Variance*	*Count*	*Mean*	*Variance*	*Count*
Australia	6.38	15.52	390	2.57	2.24	147
Canada	5.41	9.21	366	1.93	1.10	171
Finland	7.01	14.94	390	1.33	0.90	147
Israel	34.85	1608.70	363	6.53	27.61	174
Spain	9.16	24.55	408	3.02	0.75	129
Sweden	6.61	9.16	387	1.39	1.69	150
UK	7.56	23.83	381	2.52	0.57	156

Table 3: Estimates for long memory parameter (fractional root) in inflation before and after regime switch to inflation targeting

	Pre-targeting Coefficient (std.)	Post-targeting Coefficient (std.)	Switch Date
Australia	0.50^{**}	0.06	1993Q2
	(0.08)	(0.10)	
Canada	0.67^{**}	-0.13	1991Q2
	(0.11)	(0.07)	
Finland	0.78^{**}	0.02	1993Q2
	(0.21)	(0.06)	
Israel	0.85^{**}	0.26^{**}	1991Q1
	(0.16)	(0.07)	
Spain	0.81^{**}	-0.15	1994Q4
	(0.08)	(0.12)	
Sweden	0.41^{**}	0.08	1993Q1
	(0.14)	(0.10)	
UK	0.57^{**}	0.05	1992Q4
	(0.12)	(0.10)	

Notes: The regime switch dates used are by Cecchetti and Ehrmann (1999). ** represents 99% significance level. Model specifications are done using the AIC. Only the values for the long run parameters, *d*, are displayed in the table. The specific AR and MA orders and their values are available from the authors upon request.

Table 4: Estimates for long memory parameter in inflation expectations (from inflation indexed bonds) before and after regime switch to inflation targeting

	NLS		
	Pre-targeting Coefficient (std.)	Post-targeting Coefficient (std.)	Switch Date
Australia	0.97**	0.02	1993Q2
	(0.15)	(0.33)	
UK	0.95**	-0.06	1992Q4
	(0.24)	(0.11)	

Notes: ** represents 99% significance level. The proxy of inflation expectation used in the regression is the nominal bond rate minus the real rate of inflation indexed bonds. The sample is from 1985M1 for UK and 1985M7 for Australia.

Appendix I. Derivation of Individual Inflation Expectations

$$\pi_{t+1}^{ie} = \theta_{it}\pi_t + (1-\theta_{it})\pi_t^* \tag{A1}$$

$$\theta_{it} = f\left[\alpha_i\left(\pi_t - \pi_t^*\right)^2\right] \qquad \theta'_{it} > 0 \tag{A2}$$

$$\pi_t = K_t + \gamma\pi_{t|t-1}^e + z_t \tag{A3}$$

$$\pi_t^e = \frac{1}{N}\sum \pi_t^{ie} \tag{A4}$$

Linearizing (A1) around the mean (mean of expectations = mean of announcements)

$$\pi_{t+1}^{ie} = \theta^* + \left[\pi_t \frac{\partial\theta_{it}}{\partial\pi_t} - \pi_t^* \frac{\partial\theta_{it}}{\partial\pi_t} + \theta_{it}\right](\pi_t - \bar{\pi}) + \left[\pi_t \frac{\partial\theta_{it}}{\partial\pi_t^*} - \pi_t^* \frac{\partial\theta_{it}}{\partial\pi_t^*} + (1-\theta_{it})\right]\left(\pi_t^* - \bar{\pi}^*\right) \tag{A5}$$

Assuming the constant in the beginning is $\bar{\pi}$ and

$$\left.\frac{\partial\theta_{it}}{\partial\pi_t}\right|_{\bar{\pi},\bar{\pi}^*} = 2\left(\pi_t - \pi_t^*\right)f'\left[\left(\pi_t - \pi_t^*\right)^2\right] = 0 \text{ since } \bar{\pi}^* = \bar{\pi} \tag{A6}$$

$$\left.\frac{\partial\theta_{it}}{\partial\pi_t^*}\right|_{\bar{\pi},\bar{\pi}^*} = -2\left(\pi_t - \pi_t^*\right)f'\left[\left(\pi_t - \pi_t^*\right)^2\right] = 0 \text{ since } \bar{\pi}^* = \bar{\pi} \tag{A7}$$

Turning Equation (A5) into

$$\pi_{t+1}^{ie} = \bar{\pi} + \theta_{it}(\pi_t - \bar{\pi}) + (1-\theta_{it})\left(\pi_t^* - \bar{\pi}\right) + \eta_{t+1}^i \tag{A8}$$

$$\pi_{t+1}^{ie} = \theta_{it}\pi_t + (1-\theta_{it})\pi_t^* + \eta_{t+1}^i \tag{A9}$$

where the last term enters the equation for the truncated higher orders of approximation. Substituting equation (A3) into (A9)

$$\pi_{t+1}^{ie} = (1-\theta_{it})\pi_t^* + \theta_{it}\left(K_t + \gamma\pi_t^e + z_t\right) + \eta_{t+1}^i \tag{A10}$$

$$\pi_{t+1}^{ie} = (1-\theta_{it})\pi_t^* + \theta_{it}\left(K_t + \frac{\gamma}{N}\sum \pi_t^{ie} + z_t\right) + \eta_{t+1}^i \tag{A11}$$

Turning this into the AR(1) form in expectations

$$\left(\frac{N-\gamma\theta_{it}}{N}\right)\pi_{t+1}^{ie} = \left((1-\theta_{it})\pi_t^* + \theta_{it}K_t + \frac{\gamma\theta_{it}}{N}\sum\nolimits_{N\setminus\{i\}}\pi_t^{je}\right) + \gamma\theta_{it}\pi_t^{ie} + \left(\eta_{t+1}^i + \theta_{it}z_t\right) \tag{A12}$$

$$\pi_{t+1}^{ie} = A_t + \theta_{it}^{\ *}\pi_t^{ie} + e_t \tag{A13}$$

where

$$A_t = \left(\frac{N}{N-\gamma\theta_{it}}\right)\left((1-\theta_{it})\pi_t^* + \theta_{it}K_t + \frac{\gamma\theta_{it}}{N}\sum\nolimits_{N\setminus\{i\}}\pi_t^{je}\right) \tag{A14}$$

$$e_t = \left(\frac{N}{N-\gamma\theta_{it}}\right)\left(\eta_{t+1}^i + \theta_{it}z_t\right) \tag{A15}$$

$$0 \le \theta_{it}^* = \frac{N\gamma\theta_{it}}{N-\gamma\theta_{it}} \le 1 \tag{A16}$$

Appendix II. Derivation of the analytical relation between the mean and variance of α_i and the fractional root for Zaffaroni's (2004) semi-parametric distribution

Zaffaroni (2004) uses a more general semi-parametric distribution to illustrate how cross sectional aggregation can lead to long memory in the aggregate series. In a model similar to Granger's

$$x_{it} = \alpha_i x_{it-1} + u_t + \varepsilon_{it} \tag{A17}$$

he divides the disturbance term into common (u_t) and idiosyncratic (ε_{it}) shocks. Using a family of continuous distributions $\boldsymbol{\beta}$

$$\beta(\alpha, b) \sim C_b(1-\alpha)^b \tag{A18}$$

where $\alpha \in [0,1)$, $b \in (-1,\infty)$, and C_b is an appropriate positive constant, he displays that aggregation will lead to long memory models depending on the density of the distribution of α_i around unity. As b approaches –1, this density will become greater, resulting in stronger persistence. At negative values of b, the aggregation of the idiosyncratic or the common components will produce the degrees of differencing, $d=(1-b)/2$ or $d=-b$, respectively.

Deriving the mean of α for the distribution suggested by Zaffaroni (2004), we find that

$$\mu_\alpha = \frac{C}{(b+1)(b+2)} \tag{A19}$$

for $b \neq -1$. Since b is inversely related to d, persistence increases with higher means. As the non-central moments of their distribution are recurrent $\left(\mu_n = \left[nC/(1+b)(1+n+b)\right]\mu_{n-1}\right)$, the variance is $\sigma_\alpha^2 = \mu C/(b+2)(b+3)$, and d is also positively related to variance of α_i. Like Granger, not allowing α_i to vary *or* approach to 1 (by pushing b away from –1 toward positive values) will lead to an exponentially decaying autocovariance function, which is a property of short memory models.

Appendix III. Monte Carlo Simulations checking fractional root estimates with varying pre and post-regime sample size lengths

Table A1: Monte Carlo simulation for small sample properties of NLS

d	Mean (*full sample*)	Std. Dev. (*full sample*)	Mean (*pre-target*)	Std. Dev. (*pre-target*)	Mean (*post-target*)	Std. Dev. (*post-target*)
0	-0.01	0.04	-0.01	0.04	-0.02	0.10
0.1	0.09	0.04	0.09	0.04	0.09	0.10
0.2	0.19	0.04	0.19	0.04	0.19	0.11
0.3	0.29	0.04	0.29	0.04	0.30	0.10
0.4	0.40	0.04	0.39	0.04	0.41	0.11
0.5	0.50	0.04	0.50	0.04	0.53	0.10
0.6	0.60	0.04	0.60	0.04	0.64	0.11
0.7	0.71	0.04	0.70	0.04	0.76	0.11
0.8	0.81	0.04	0.81	0.04	0.88	0.11
0.9	0.91	0.04	0.91	0.04	0.97	0.09
1.0	1.00	0.03	0.99	0.03	1.03	0.07

Notes: Sample of 550 is split into 400 for the 1st part and 150 for the 2nd. Results are from 3000 iterations. ARFIMA model (0, *d*, 0) is chosen for ease of display.

Endnotes

[1] Leiderman and Svensson (1995), Bernanke and Mishkin (1997), Bernanke et al.. (1999), Siklos (1999) Mishkin and Schmidt-Hebbel (2001), Amato and Gerlach (2002), Johnson (2001, 2003).

[2] Long memory refers to when persistence of shocks is caused by either a unit or a fractional root. Unit root or $I(1)$ models have non-decreasing autocorrelation functions while fractionally integrated and stationary ARMA or $I(0)$ processes have hyperbolical and geometric declines, respectively. In other words, fractionally integrated models constitute a middle ground between the $I(1)$ and $I(0)$ worlds.

[3] Sowell (1992) and Abadir and Talmain (2002) show existence of long memory in aggregate economic activity, while Hassler and Wolters (1995), Baillie, et al. (1996) analyze fractional integration in aggregate prices. Andersen and Bollerslev (1997) and Liu (2000) provide evidence of long memory in asset price volatility.

[4] Recently Parke (1999) showed that a sequence of shocks with stochastic magnitude and duration can lead to long memory while Liu (2000) and Diebold and Inoue (2001) demonstrated that regime-switching processes can produce series that are observationally equivalent to fractional integration.

[5] Chambers (1998) extends this analysis by incorporating temporal aggregation to cross-sectional aggregation. Zaffaroni (2004) broadens Granger's results by using a milder semiparametric specification.

[6] These authors have found that forecast errors are not only serially correlated, but are also correlated with past information.

[7] Walsh (1999) provides a similar setup. Our θ_{it} also resembles Cukierman's (1992) definition of marginal credibility.

[8] Although we don't provide micro foundations for this formulation for brevity, the literature is rich with such examples.

[9] One can add an appropriate weight factor that discounts extreme inflation expectations into the formulation without any loss of generality.

[10] Granger chooses the beta distribution due to its mathematical convenience and adds that the choice of the distribution does not affect the results. Beta distribution is also flexible in terms of mimicking the normal and uniform distributions for particular values of p and q.

[11] Granger shows that for $0 \le q \le 1$, which corresponds to $d \ge 0.5$, the process will not have a finite variance. Values of $q \in (1,2)$ or $0 < d \le 0.5$ generate stationary long memory processes, and higher values will lead to intermediate memory or anti-persistence, $-1 < d < 0$. Further details can be found in Granger (1980).

[12] It is sufficient to concentrate on just the mean and variance of α since the beta distribution has the convenient property of having recurrent non-central moments. Higher non-central moments contain the same information as the variance, so finding the relation of the degree of fractional differencing to higher moments would not alter our conclusions.

[13] Note that the mean is between 0 and 1.

[14] This relation requires that the aggregate inflation expectations be cointegrated with the variable K_t, which is plausible since K_t represents variables like the output gap or money growth rate.

[15] Beginning in 1994, the FOMC began announcing changes in its policy stance, and in 1995 it began to explicitly state its target level for the federal funds rate.

[16] One can visit http://www.globalfinancialdata.com to obtain more information of the exact sources of each price series.

[17] We also run estimations with Exact Maximum Likelihood technique, but we prefer NLS due to EML's restriction of $d < 0.5$. The direction of the results is essentially identical and can be provided by the author upon request.

[18] The orders of ARMA are determined using the Akaike information criterion.

[19] Specific short run dynamics of each series and the information criteria are available from the author upon request.

[20] Since the fractional root represents the long run cycles in inflation, one would not expect the results to change in small break date adjustments.

[21] The series start in 1985 for both countries. We cannot use the same proxy for Canada since their inflation indexed bonds start in 1991, just around the time of their IT adoption.

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