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A MULTIPLE BREAK PANEL APPROACH TO ESTIMATING UNITED STATES PHILLIPS CURVES*

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ABSTRACT

Phillips curves have often been estimated without due attention to the underlying time series properties of the data. In particular, the consequences of inflation having discrete breaks in mean, for example caused by supply shocks and the corresponding responses of policymakers, have not been studied adequately. We show by means of simulations and a detailed empirical example based on United States data that not taking account of breaks may lead to spuriously upwardly biased estimates of the dynamic inflation terms of the Phillips curve. We suggest a method to account for the breaks in mean and obtain meaningful and unbiased estimates of the short- and long-run Phillips curves in the United States and contrast our results with those derived from more traditional approaches, most recently undertaken by Cogley and Sbordone (2008).

Keywords: Phillips curve, inflation, panel data, non-stationary data, breaks.

JEL Classification: C22, C23, E31

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1. INTRODUCTION

The large majority of papers that estimate Phillips curves over the past thirty five years proceed on the implicit or explicit assumption that inflation is a stationary process. For example, the work of Gordon (1970, 1975, 1977, and 1997), McCallum (1976), Sumner and Ward (1983), Alogoskoufis and Smith (1991), Roberts (1995), Galí and Gertler (1999), Batini, Jackson and Nickell (2000, 2005), Galí, Gertler and López-Salido (2001, 2005), Rudd and Whelan (2005, 2007), and Kiley (2007) use a range of estimators that are appropriate if the data have a constant mean which is implied by the assumption of stationarity.[1]

However, if inflation is stationary with a constant mean over the past fifty years in the developed world, this would imply only one long-run rate of inflation, one expected rate of inflation and one short-run Phillips curve. It means that all the 'modern' Phillips curve theories since Friedman (1968) and Phelps (1967) which argue there can be multiple long-run rates of inflation are empirically irrelevant.[2] Furthermore, it suggests that the original Phillips curve identified in Phillips (1958) did not 'breakdown' in the late 1960s and 1970s as there had been no change to the long-run rate of inflation. Unless we wish to reject our 'modern' understanding of the inflationary process we must conclude that assuming inflation has a constant mean is, at best, only an approximation.

There is growing recognition in the literature that assuming inflation is stationary is inconsistent with our theoretical and empirical understanding of the properties of the inflationary process over the past 50 years. For example, King and Watson (1994), Stock and Watson (2007) and Ireland (2007) difference the inflation data to overcome the apparent unit root in the inflation data. Similarly, Cogley and Sborbone (2005, 2006, 2008) also argue that inflation is an integrated process and model the gap between inflation and an estimated smooth time varying mean. We return to a detailed consideration of their approach in Section 3 of our paper. Russell and Banerjee (2008) and Schreiber and Wolters (2007) estimate long-run cointegrating relationships in the Engle and Granger (1987) sense between inflation and

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1 This is a small selection of the substantial literature on the Phillips curve over the past thirty five years.

2 The 'modern' theories include the Friedman-Phelps (F-P) expectations augmented Phillips curve, New Keynesian (NK) and hybrid theories. The term Friedman-Phelps Phillips curve acknowledges the intellectual shoulders that the 'modern' Phillips curve literature stands on rather than the somewhat pejorative term sometimes used in the literature of 'old' Phillips curve.

the rate of unemployment, which requires both these variables to be integrated processes. Strictly speaking, inflation can only approximate an integrated process since in the developed economies over the past fifty years inflation appears bounded below at around zero and above by some moderate rate of inflation.[3]

What then is the 'true' statistical process of inflation? To answer this question, begin by considering the inflation process as outlined in 'modern' Phillips curve theories. If shocks to an economy have zero mean and there is no change in monetary policy then we would expect inflation to vary around the long-run rate of inflation. In these theories, an increase in the long-run rate of inflation requires a loosening in monetary policy and the economy would converge on, and vary around, the new long-run rate of inflation. Consequently, 'modern' Phillips curve theories imply inflation is a stationary process around the long-run rate of inflation and that periodically, and possibly frequently, there are discrete changes in the long-run rate in response to discrete changes in monetary policy. Therefore, it seems reasonable to argue that the 'true' statistical process of inflation is a stationary process around shifting means.[4]

Graph 1 shows quarterly United States inflation over the past fifty years where the shifts in the mean rate of inflation are evident.[5] The low inflation of the 1950s and early 1960s is followed by a slight increase in inflation late in the 1960s. The high inflation of the 1970s and early 1980s following the two oil price increases initiated by the Organisation of Petroleum Exporting Countries (OPEC) is followed by two large reductions in inflation. The first is often referred to as the 'Volker' deflation and the second at the start of the 1990s coincides with a severe world-wide recession.

These visual shifts in mean inflation can be identified more formally with the Bai and Perron (1998, 2003a, 2003b) technique to estimate multiple breaks in the mean of the

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3 Russell (2006, 2007) makes these arguments in greater detail.

4 Two other non-stationary processes are possible for inflation but may be easily ignored. The first is inflation is trend stationary and the second is inflation is integrated of some order greater than 1. The former is unlikely unless the trend is a proxy for a unidirectional change in the monetary authorities' target rate of inflation. The later is also unlikely due to the bounded nature of inflation.

5 Inflation is measured as the quarterly change in the natural logarithm of the seasonally adjusted gross domestic product implicit price deflator at factor cost multiplied by 400. See Appendix 1 for details of the data used in this paper.

inflation data.[6] This technique identifies eight breaks in the mean rate of United States inflation and therefore nine ‘inflation regimes’ where the inflation data displays a constant mean. The regimes and their associated mean rates of inflation are shown on the graph as thin horizontal lines. From a purely visual perspective the Bai-Perron technique appears to have captured the major shifts in the mean rate of inflation in the United States although there are likely to have been some smaller shifts that have not been identified. We return to the issue of the possible under-identification of the number of shifts in mean inflation later in the paper.

If inflation is really a stationary process around shifting means then the common assumptions employed in the empirical literature that inflation is either stationary or integrated will lead to biased estimates of Phillips curves. For example, if the data are assumed stationary and shifts in mean are not accounted for then, as we show below, the estimated coefficients on the dynamic inflation terms (i.e. the leads and lags of the independent inflation variables) will be biased upwards.[7] Importantly, if the shifts in mean are frequent and / or large then the sum of the estimated coefficients on the dynamic inflation terms may equal 1 due to the shifts in mean inflation alone. Similarly, if inflation is incorrectly assumed to be an integrated process then the estimates will also be biased. For example, differencing the inflation data imposes the restriction that the coefficient on the first lag in inflation equals one. Standard tests may imply that this restriction is valid but if the estimated coefficients are biased towards one because of the breaks in the inflation series then the test of the restriction reaches an incorrect conclusion by construction. The standard empirical Phillips curve literature provides no evidence that these two common assumptions concerning the statistical process of inflation are valid in the sense that the biases introduced in the estimation of Phillips curves are numerically small and insignificant. This lack of evidence is all the more surprising given that ‘modern’ theories of the Phillips curve would lead us to expect that inflation does not have a constant mean and our empirical understanding suggests inflation is not an integrated process.

This paper sets out to measure the biases introduced into the estimation of ‘modern’ United States Phillips curves that stem from the two common assumptions in the empirical Phillip

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6 See Appendix 2 for details of the Bai-Perron estimates of the shifts in mean inflation.

7 This is a generalisation of the Perron (1989, 1990) argument that a trend stationary process with breaks is easily mistaken for an integrated process that contains a unit root.

curve literature. In the next section we use a Monte Carlo analysis to examine the biases due to the unaccounted shifts in the mean rate of inflation when estimating Friedman-Phelps (F-P), New Keynesian (NK) and hybrid Phillips curves. The analysis demonstrates that the size and significance of expected inflation (i.e. the lead in inflation) as commonly measured in the standard NK and hybrid literatures can be generated by the shifts in mean alone. Importantly, the shifts in mean also generate the result that the sum of the dynamic inflation terms equals one in the NK and hybrid models and for the F-P model the sum is large, positive, significant and only marginally less that one.

The Monte Carlo analysis then considers the methods employed in the literature to overcome the apparent non-stationarity in the inflation data. The literature provides several ways to proceed. For example, if we assume that inflation is an integrated process and difference the data to remove the unit root we demonstrate that this does not alleviate the biases in the estimation process. Instead, this re-parameterisation of the data only serves to maintain or increase the bias in the estimated Phillips curves.

Our preferred approach is provided by Russell (2007) who also models inflation as containing a time varying mean. However, in contrast with the approach discussed in the previous paragraph, the changes in the mean are discrete and inflation is thus modelled as a stationary process around shifting means. We begin by identifying the 'inflation regimes' via applying the Bai-Perron technique to the inflation data as described above. Each inflation regime can then be modelled as an individual time series of data. This allows us to reorganise the data into an unbalanced time series panel where each cross-section of data is an 'inflation regime'. We then estimate Phillips curve models using standard, and well understood, fixed effects time series panel techniques to account for the different mean rates of inflation across inflation regimes. The Monte Carlo analysis demonstrates that even though the Bai-Perron technique fails to identify exactly the inflation regimes in the data this methodology reduces the bias (due to the shifts in mean) to insignificant levels.

Section 3 estimates F-P, NK and hybrid Phillips curves with nearly fifty years of quarterly United States inflation data using the shifting means panel approach. In keeping with the recent NK and hybrid empirical literatures we estimate Phillips curves with the 'forcing' variable measured as the markup of price on unit labour costs.

Once the shifts in the mean rate of inflation have been accounted for in the estimation of the United States Phillips curves we find that; (i) there is no significant role for expected inflation in the NK and hybrid models of inflation; (ii) there is very weak evidence that any of the lags in inflation are significant in the inflation-markup Phillips curve; and (iii) there is a negative non-linear 'implicit' long-run relationship between inflation and the markup.

Our approach may be contrasted with the methods used recently by Cogley and Sbordone (2008) who suggest a 'third way' to deal with non-stationary inflation data. They begin by estimating a smooth time varying trend rate of inflation using a Bayesian VAR and then calculate the gap between inflation (which they describe as a random walk without drift) and the estimated trend rate of inflation. They then proceed to estimate the structural parameters of a hybrid New Keynesian Phillips curve conditioned on the inflation gap and labour's share of income. While the complexity of their two stage estimation procedure makes a full Monte Carlo analysis of the properties of the estimators derived from their Bayesian VAR approach infeasible the Cogley and Sbordone approach is considered later in the paper in terms of our Monte Carlo results and the estimates of the United States inflation-markup Phillips curve provided in Section 3.

To summarise, we argue that an understanding of the true statistical process of inflation is crucial in a range of theoretical, empirical and policy contexts. For example, if inflation is stationary around shifting means then all empirical work that does not adequately allow for the non-stationary properties of the data will lead to poorly estimated short and long-run Phillips curves, and further development of theories to explain the dynamics of inflation and policy will be badly misinformed by these biased estimates. We turn now to a detailed consideration of all these issues.

2. A MONTE CARLO ANALYSIS OF THE BIASES

2.1 'Modern' Phillips Curves

The 'modern' Phillips curve literature can be thought of in terms of restrictions to the reduced form of the hybrid Phillips curve:[8]

$$\Delta p_t = \delta_f \, E_t\left(\Delta p_{t+1}\right) + \delta_b \, \Delta p_{t-1} + \delta_z \, z_t + \varepsilon_t \tag{1}$$

where inflation, Δp_t, depends on expected inflation, $E_t\left(\Delta p_{t+1}\right)$, conditioned on information available at time t, lagged inflation, Δp_{t-1}, a 'forcing' variable, z_t, and an error term, ε_t, due to the random errors of agents and the shocks to inflation. Inflation is defined as the first difference of the logarithm of the price level such that: $\Delta p_t = p_t - p_{t-1}$ and lower case variables are in natural logarithms. There are numerous measures of the 'forcing' variable in the Phillips curve literature including the gap between the unemployment rate and its long-run level, the gap between real and potential output, real marginal costs, the markup of price on unit labour costs and labour's income share.

In the purely backward looking adaptive expectations Phillips curve model of Friedman (1968) and Phelps (1967) $\delta_f = 0$ and $\delta_b = 1$. In contrast, the New Keynesian (NK) Phillips Curve models of Clarida, Gali and Gertler (1999) and Svensson (2000) agents employ rational expectations and are purely forward-looking resulting in $\delta_f = 1-d$ and $\delta_b = 0$ where d is the rate of time discount. Finally, the hybrid models of Gali and Gertler (1999) and Gali, Gertler and Lopez-Salido (2001) incorporate agents that are both backward and forward looking and $\delta_f + \delta_b = 1-d$.

The magnitude of the discount rate, d, needs to be identified explicitly in the theory. There would appear to be several difficulties that follow from this observation. First, if the magnitude of d is not defined it can only be estimated *assuming* the underlying theory is true. Any estimated value of $1-d$ is therefore consistent with the theory and can be explained by

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8 For a general overview of Phillips curves see Henry and Pagan (2004).

risk averse agents and the rate of time discount. Consequently, empirical work cannot 'test' the NK theory and only estimates d assuming the NK theory is 'true'.

Second, and more seriously, even granting the NK theory is a true description of the underlying process generating the data, then $1-d<1$ introduces a conundrum for the NK and hybrid theories. This conundrum is described in the next paragraph.

The NK theory is derived by optimising around the steady state. If one interprets the 'steady state' as the long run in the NK and hybrid theories then the theoretical model is solved for a given long-run rate of inflation which may, or may not, vary. The model, therefore, identifies one short-run Phillips curve associated with each long-run rate of inflation. The conundrum is this. If we assume risk neutral agents and the real rate of interest is in the order of 0.04 then $1-d=0.96$. This implies that the NK and hybrid models describe the dynamics of a stationary inflation process as the absolute value of $1-d$ is less than 1. However, persistence in this short-run model (i.e. where the mean rate of inflation is constant in the steady state) is extremely high suggesting very persistent deviations in inflation from its long-run level in the short run. Reconciling this with the idea that, roughly speaking, agents act according to rationally formed expectations is difficult. Persistent deviations in the short run imply systematic expectation errors on the part of these agents and these errors take a long time to correct. In Section 3.3 we offer an alternative explanation based upon mean shifts in the inflation process.

Finally, it also means the NK and hybrid theories make no explicit predictions concerning the slope of the long-run Phillips curve as it only identifies the short-run Phillips curve for each long-run rate of inflation.[9] To identify the long-run NK and hybrid Phillips curves one needs to first estimate equation (1) for each long-run rate of inflation, i, and then calculate:

$$\bar{z}^i\Big|_{\overline{\Delta p}^i} = \frac{\hat{d}^i}{\hat{\delta}_z^i}\,\overline{\Delta p}^i \qquad (2)$$

9 The technique of optimising around the steady state changes the nature of the solution to one of deviations from particular steady state values. It cannot, therefore, identify the relationship between a range of steady state values.

where $\bar{z}^i\big|_{\overline{\Delta p}^i}$ is the long run value of the forcing variable in inflation regime i, the long-run rate of inflation in regime i is $\overline{\Delta p}^i$ and $\hat{d}^i$ and $\hat{\delta}_z^i$ are the estimated parameters from equation (1) for each of the inflation regimes. One can then examine combinations of $\bar{z}^i$ and $\overline{\Delta p}^i$ to observe the slope of the long-run Phillips curve. This issue is returned to following the estimation of the United States Phillips curves in Section 3.

However, most of the empirical work on the NK and hybrid models ignore this conundrum and proceed assuming $d = 0$ in both models. Consequently, on an empirical level all three models predict that $\delta_f + \delta_b = 1$ in equation (1) and the standard interpretation of this is that the long-run Phillips curve is 'vertical'.

This standard interpretation introduces its own difficulties in the estimation of Phillips curves in that if $\delta_f + \delta_b = 1$ then the inflation data are non-stationary. In this case, estimating equation (1) without accounting for the non-stationary data using techniques such as ordinary least squares, two stage least squares or generalised method of moments is invalid. If however the absolute values of the estimates of $\delta_f + \delta_b$ are less than one these estimation techniques are valid but the statistical process of the data is inconsistent with all three theories.[10]

The NK and hybrid models are often estimated using generalised method of moments (GMM) estimator with instrumental variables to overcome the problem of the correlation between expected inflation and the forcing variable with the error term. This estimation technique has received considerable attention in the econometrics literature in terms of the problems of weak instruments and whether or not the models are identified.[11] However, if inflation is

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10 In particular, if $\delta_f + \delta_b < 1$ then inflation is stationary with a constant mean and there is only one long-run rate of inflation, one expected rate of inflation and only one short-run Phillips curve. Furthermore, as there is only one long-run rate of inflation the data can only identify at most one combination of the long-run rate of inflation and long-run value of the forcing variable. Consequently, the data can not identify the slope of the long-run Phillips curve.

11 Pesaran (1981, 1987), Staiger and Stock (1997), Stock, Wright, and Yogo (2002), Mavroeidis (2004, 2005), Dufour (2003) and Dufour, Khalaf and Kichian (2006a, 2006b) focus on the poor performance of the estimator when the data are integrated or near integrated.

stationary around shifting means and these shifts are accounted for appropriately then the inflation data are far from integrated and so these criticisms of GMM estimation are less relevant.

The empirical Phillips curve literature over the past thirty five years produces remarkably similar results. In the Friedman-Phelps and the New Keynesian models the estimates of δ_b and δ_f are insignificantly different from the predicted values in their respective models. In the more general hybrid model that allows the inflation dynamics to include both leads and lags in inflation the sum of δ_b and δ_f is found to be insignificantly different from one with usually a larger coefficient on expected inflation which is interpreted as evidence that forward looking agents dominate backward looking agents in the price setting process. This repeated finding that $\delta_f + \delta_b = 1$ in all three models leads to one of the central 'tenets' of Phillips curve theories which is that the vertical long-run Phillips curve is empirically valid.

However, this consensus is built on empirical methods which do not adequately account for the non-stationary properties in the data. If inflation is stationary around shifting means as argued above then there will be an upward bias in the estimates of δ_b and δ_f. Furthermore, if the shifts are large and/or frequent then $\delta_f + \delta_b$ will be insignificantly different from 1 in all three estimated Phillips curve models. The following Monte Carlo analysis demonstrates the proposition that the estimates of δ_b and δ_f in equation (1) are severely biased due to the presence of unaccounted shifts in the mean rate of inflation in the data. The analysis considers in turn the biases associated with three assumptions employed in the empirical literature when estimating Phillips curves, namely, inflation is stationary, an integrated process of order one, and stationary around shifting means.

2.2 Generating inflation as a stationary process

We begin by generating 190 observations of a stationary forcing variable, x_t, and then use this variable to generate an 'inflation' series, y_t, that contains no dynamic inflation terms. The statistical characteristics of the generated variables are similar to that of the markup and inflation used in the next section to estimate Phillips curves for the United States. The forcing variable, x_t, is generated as:

$$x_t = 0.937967 x_{t-1} + \omega_t \tag{3}$$

where the first observation, x_0, is zero and ω_t is a random draw from a normal distribution with mean zero and a standard error of 0.006388.[12] The coefficient on the lagged forcing variable and the standard error are equivalent to those from an estimated AR(1) model of the markup.

The second generated series is the inflation series, y_t, such that

$$y_t = -0.205406 x_t + \upsilon_t \tag{4}$$

where υ_t is a random draw from a normal distribution with a mean of zero and a standard error of 0.004753. The coefficient on the forcing variable, x_t, is equivalent to the estimated coefficient from estimating equation (1) using United States inflation and markup data with the dynamic inflation terms restricted to zero.[13] By construction the forcing variable, x_t, and the inflation series, y_t, are stationary variables with constant means.

Using the generated inflation variable, y_t, and forcing variable, x_t, we estimate three versions of the Phillips curve as set out in equation (1) where we know by construction that $\delta_b = 0$, $\delta_f = 0$ and $\delta_z = -0.205406$ in the 'true' underlying Phillips curve model that generated the data. In keeping with the NK and hybrid Phillips curve literatures the models are estimated using GMM with three lags of both the generated inflation and forcing variables as instruments for the lead in inflation and the contemporaneous forcing variable. The models

[12] See Appendix A for further details concerning the generated data.

[13] The inflation and markup data are de-meaned in line the breaks in mean identified by the Bai-Perron technique and shown on Graph 1.

are estimated 10,000 times using Monte Carlo techniques to obtain the average values of the statistics and estimated coefficients from the models.[14]

Single equation estimates of the three models are reported in the first three columns of Table 1 under the headings F-P (Friedman-Phelps), NK (New Keynesian) and hybrid. In all three models the estimated coefficients on the dynamic inflation terms are very similar in magnitude to their 'true' values (i.e. zero) and insignificantly different from zero. The models also provide estimates of the forcing variable coefficient which are close numerically to its true value of -0.205406 and significantly different from zero. The fourth column headed 'ND' demonstrates that removing the inflation dynamics also leads to an estimated model that is very similar to the 'true' model. In all four models we can accept the restriction that the estimated coefficients equal their 'true' values in the data generating process (see F in Table 1). We can conclude, therefore, that we can retrieve fairly accurately the 'true' model that generated the inflation data by estimating any of the three modern Phillips curve models based on equation (1).

2.3 Generating inflation as a stationary process around shifting means

We now generate a 'mean-shift inflation' variable, y_t^{MS}, which adds to y_t the mean rate of inflation associated with each of the nine inflation regimes reported in Graph 1 and constructed as:

$$y_t^{MS} = y_t + \mu_t^i \tag{5}$$

where μ_t^i is the mean rate of inflation in regime *i* as reported in Table A2 of Appendix 2. Consequently, the only difference between y_t^{MS} and y_t is the mean rate of inflation associated with each of the inflation regimes.

The three right hand columns of Table 1 report the mean values of the Monte Carlo estimates from the three versions of the Phillips curve model but this time estimated with the mean-shift

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14 Inference is unaffected if the median instead of the mean values of the estimated parameters are considered. The distributions of the estimated coefficients and statistics are uni-modal and largely symmetrical with relatively low levels of skewness and kurtosis.

inflation data, y_t^{MS}, and the forcing variable, x_t. In the New Keynesian and hybrid models the lead in inflation is significantly greater than zero and insignificantly different from 1. In the Friedman-Phelps model the sum of the lags in inflation is 0.7108 which is significantly greater than zero and significantly less than 1 at the five percent level. In all three models we strongly reject the restriction that the estimates equal their true values (see F in Table 1). Finally, note that the Monte Carlo analysis demonstrates that the shifts in the mean rates of inflation alone can generate the New Keynesian and hybrid Phillips curve result that the sum of the coefficients on the dynamic inflation terms is insignificantly different from 1. For the Friedman-Phelps model the shifts in mean introduces a bias to the estimates which is only slightly less than 1.

Table 1 also demonstrates the bias is not confined to the estimates of the dynamic inflation terms but also affects the estimated coefficient on the forcing variable. In all three models estimated with the generated mean shift inflation variable the forcing variable is now insignificant at the 5 per cent level and numerically very small. As should be expected, the stationary forcing variable is unable to explain the generated mean-shift inflation variable which has a changing mean. The finding that the stationary forcing variable is insignificant is common in the empirical Phillips curve literature and motivates Gali and Gertler (1999) to use labour's income share which they find significant in their estimated Phillips curve model.[15]

An interesting result from the analysis is that it identifies the role that the lead in inflation plays in the estimation process. It appears that the interaction of the shifts in mean and the lead in inflation introduces severe serial correlation in the residuals. Furthermore, in the hybrid model that incorporates both a lead and lag in inflation it is the lead that is biased upwards and the lag in inflation remains numerically close and insignificantly different from its 'true' value of zero. This may well explain in part the standard finding in the hybrid Phillips curve literature that $\delta_f > \delta_b$ which is interpreted as forward looking agents dominating backward looking agents in the economy.

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[15] Gali and Gertler (1999) argue that potential output and long-run unemployment are difficult to measure and therefore deviations from these measures are poor predictors of inflation. The analysis here suggests insignificance of these variables in the inflation process may be less to do with measurement difficulties and more to do with misunderstanding the statistical process of inflation.

2.4 Assuming inflation is integrated

Testing the 10,000 generated mean-shift inflation series, y_t^{MS}, for the presence of a unit root using the augmented Dickey-Fuller test provides a mean value of the test statistics of – 2.615 which can be compared with the 5 per cent critical value of – 2.877 assuming a constant and no trend. Based on these results we might conclude erroneously that the generated mean shift inflation series is an integrated process of order one.

There are two streams in the literature that proceed assuming inflation is an integrated variable. The first argues explicitly that inflation is integrated and then proceeds to difference the inflation data so as to remove the unit root.[16] Equation (1) is therefore re-parameterised as:

$$\Delta^2 p_t = \psi_f \, E_t\left(\Delta^2 p_{t+1}\right) + \psi_b \, \Delta^2 p_{t-1} + \psi_z \, \Delta z_t + \omega_t \qquad (6)$$

where $\Delta^2 p_t = \Delta p_t - \Delta p_{t-1}$ is the second difference of the price level and the first difference in inflation. The F-P, NK and hybrid versions of equation (6) are estimated with the GMM estimator using the differenced generated mean shift inflation data, Δy_t^{MS} and the differenced forcing variable, Δx_t. The Monte Carlo results reported in Table 2 show that estimating the F-P, NK and hybrid forms of the Phillips curve using differenced data does not recover the 'true' underlying model that generates the inflation data.

For the F-P model we can reject the restriction that the estimated coefficients are equal to their 'true' values (see 'F' in Table 2). For the NK and hybrid models the imprecision of the estimates lead us to accept the restriction that the estimates are equal to their true values even though the lags in inflation are significant and the point estimate of the sum of the dynamic inflation terms are -0.3772 and -1.3475 for the NK and hybrid models respectively. The imprecision of the estimated models is further demonstrated by being able to accept the restriction that the sum of the dynamic inflation terms is equal to zero at the five per cent level of significance (reported as 'Σ' in Table 2) even though the lags in inflation are highly significant in the hybrid model. Consequently, if we incorrectly assume that the data are integrated and difference the data we will not retrieve the 'true' underlying model as we

16 For example see King and Watson (1994), Stock and Watson (2007) and Ireland (2007).

identify significant dynamic inflation terms in the F-P and hybrid models and the forcing variable is insignificant in all three models. Furthermore, a researcher who differences the inflation data in response to the unit root tests and the knowledge that these tests are in line with the predictions of the F-P, NK and hybrid models will be severely misled by the results even though their actions are supported by standard empirical tests.

If one unravels the estimates of the dynamic inflation terms from Table 2 then the sum of the dynamic inflation terms is one in all three models (F-P, NK and hybrid). Thus the differencing re-parameterisation does not overcome the problem of the shifting means in the inflation data and estimation and inference based on these models remains flawed.

The second stream that assumes inflation is an integrated process proceeds by estimating an integrated system to identify cointegrating relationships between inflation and the forcing variable.[17] To examine if the shifts in mean inflation lead to incorrect inference concerning the presence of a long-run cointegrating relationships in the data we estimate Johansen Trace tests between the generated variables. Table 3 reports the mean values of the eigenvalues, Trace test statistics, critical values and the proportion of the 10,000 generated models where the Trace Test indicates we should accept 1 cointegrating vector. In the top portion of Table 3 the test of cointegration is carried out on the two generated stationary variables, y_t, and, x_t. The mean Trace test statistics indicate that we would conclude no cointegration between these variables. Similarly, in the lower portion which reports the mean Trace test statistics between the generated 'mean-shift' inflation variable, y_t^{MS}, and the forcing variable, x_t, we again correctly conclude that the two generated variables are not cointegrated. Therefore, we may feel confident that the unidentified shifts in the mean rate of inflation alone do not lead us to erroneously accept there are long-run cointegrating relationships between inflation and the forcing variable.

[17] As well as the I(1) systems Phillips curve papers mentioned in the introduction one should include the work that estimates I(1) systems to identify a negative long-run cointegrating relationship between inflation and the markup of Banerjee, Cockerell and Russell (2001), and Banerjee and Russell (2001a, 2001b, 2004, 2005), Russell and Banerjee (2006, 2008), and Banerjee, Mizen and Russell (2007).

2.5 Assuming inflation is a stationary process around shifting means

How then can we retrieve the estimates of the 'true' model based on the generated data in equation (5)? The solution suggested in Russell (2007) is as follows. First, apply the Bai-Perron technique to identify the inflation regimes in the generated mean-shift inflation series, y_t^{MS}. Second, partition the generated mean shift inflation data into *n* cross sections of data where each cross section is an individual inflation regime identified in the first stage. Finally, estimate the Phillips curve models using a two stage least squares fixed effects panel estimator to account for different mean rates of inflation between the inflation regimes.

The panel fixed effects specification of the hybrid Phillips curve model of equation (1) is:

$$\Delta p_t^n = \phi^n + \phi_f \, E_t^n \left(\Delta p_{t+1}^n\right) + \phi_b \, \Delta p_{t-1}^n + \phi_z \, z_t^n + \eta_t^n \qquad (7)$$

where the '*n*' superscript indicates the inflation regime from which the data are drawn. The unobserved regime-specific time invariant fixed effects, ϕ^n, allow for shifts in the mean rate of inflation across regimes and η_t^n is a disturbance term which is independent across inflation regimes.

Table 4 reports the number of breaks in the mean rate of inflation identified using the Bai-Perron technique in the 10,000 generated mean-shift inflation series y_t^{MS}. The model with structural breaks estimated is the same as that used to estimate the breaks in mean United States inflation reported in Appendix 2. The mean and median numbers of regimes are 4.99 and 5 respectively. This can be compared with the 'true' number of 8 breaks in mean inflation in the generated data. We see in Table 4 that the Bai-Perron technique underestimates the number of breaks in ninety five per cent of the generated mean-shift inflation series (i.e. the technique finds less than eight breaks). Consequently, once the data are partitioned in line with the estimated breaks in mean inflation using the Bai-Perron technique we can expect some residual non-stationarity somewhere in the estimated inflation regimes.

Using the inflation regimes identified by the Bai-Perron technique in each of the 10,000 generated mean shift inflation series to partition the generated data, the mean values of the panel estimates of the Phillips curve models are reported in Table 5. Re-organising the data into an unbalanced time series panel format does not in itself affect the estimates. This is easily demonstrated by restricting the constant, ϕ^n, to be the same across all the inflation regimes when applying the fixed effects panel estimator to the generated data. This restriction is equivalent to assuming the mean rate of inflation is the same in each inflation regime. The mean results for the F-P, NK and hybrid models are reported in the first three columns of Table 5. Note the results are very similar to those reported in columns 4 to 6 in Table 1 in terms of the estimates of the dynamic inflation terms and the forcing variable.

Two stage least squares estimates of the fixed effects panel estimates of the three 'modern' Phillips curve models are reported in columns 4 to 6 of Table 5. We see that after allowing for the shifts in mean across regimes by using the fixed effects estimator all three estimated models are now insignificantly different from the 'true' underlying model that generates the data (see W in Table 5.). The dynamic inflation terms are all insignificant and the size of the forcing variable is around half its 'true' value of – 0.2054. The final column headed ND excludes the insignificant dynamic inflation terms from the estimated model and we find that the forcing variable is significant but remains half its 'true' size.

Having accounted for the shifts in mean in the estimation procedure we now conclude correctly that expected inflation and lagged inflation are insignificant in all three models. Furthermore, we can now easily accept the restriction that the estimated coefficients equal their 'true' values. However, note the imprecision in the NK and hybrid models is so large that we can simultaneously accept at the 5 per cent level that the sum of the dynamic terms equals zero and 1 (see Table 5). In contrast, the F-P model at the 5 per cent level accepts the restriction that the lag in inflation is zero and rejects the term is equal to 1. It appears that including the lead in inflation increases the imprecision of the estimates markedly both here and in the earlier analysis irrespective of whether it is significant.

Note also that the estimated value of the forcing variable is around half its 'true' value in all four models reported in columns 4 to 7 in Table 5. It appears that the residual non-stationarity in the data following the Bai-Perron stage of the analysis is not enough to bias the dynamic terms to significant levels. However, the non-stationarity biases the estimated coefficient on the forcing variable downwards in absolute terms. This is a consistent finding of the Monte Carlo analysis reported here that any non-stationarity in the inflation data also biases the stationary forcing variable.

The panel estimation procedure provides estimates that are insignificantly different from their 'true' values even though the Bai-Perron technique on average underestimates the 'true' number of the inflation regimes and by implication does not correctly identify the 'true' dates of the inflation regimes. However, even given the inaccuracies in the Bai-Perron technique we find that the Phillips curve models subsequently estimated using fixed effects panel techniques provide estimates that are insignificantly different from the 'true' model that generates the inflation data. At the very least this procedure leads to the correct inferences concerning the significance and size of ϕ_b and ϕ_f and a value for ϕ_z which is significantly different from zero, has the correct sign and marginally less from its 'true' value. Of course this analysis suggests that further gains can be made in reducing the bias of the estimated forcing variable by more accurately identifying the breaks in mean inflation.

In summary it appears that the standard results reported in the empirical literature based on the assumption that inflation is either a stationary process with a constant mean or an integrated process which is then differenced provide biased estimates of the underlying behaviour of agents. In particular, we might conclude that the standard findings in the empirical Phillips curve literature that (i) the dynamic inflation variables in the F-P, NK and hybrid Phillips curves sum to 1; (ii) expected inflation as measured in the NK and hybrid Phillips curve literature plays a significant and dominant role in the dynamics of inflation; and (iii) measures of the forcing variable that are stationary are insignificant may simply be due to the unaccounted shifts in the mean rate of inflation. These Monte Carlo results are another illustration of the difficulties in estimation and inference that arise when structural breaks in the series being modelled are not accounted for adequately. Furthermore, they also lead to the stark conclusion that standard estimation of Phillips curves that assumes that inflation is stationary, or integrated and differenced, provide unreliable results and cannot therefore be used to validate any of the competing 'modern' Phillips curve theories. In Section 3 below we present our preferred method of estimating the Phillips curve, having taken account of the discrete breaks in the inflation data. In Section 4 we also confront directly an alternative approach to allowing for non-stationarity in estimating NKPC models recently proposed by Cogley and Sbordone (2008) and discuss some difficulties associated with their approach.

3. PANEL ESTIMATES OF THE UNITED STATES PHILLIPS CURVES

We now turn to estimating Phillips curves with quarterly United States data for the period March 1960 to June 2007 using the shifting means panel methodology. In line with much of the recent empirical NK and hybrid Phillips curve literatures the models are estimated using the markup of price on unit labour costs as the forcing variable.

Before proceeding with the estimation of (7) there are a number of issues that need to be addressed.[18] First, the models are estimated using two stage least squares due to the lead in inflation, Δp_{t+1}^{n}, and contemporaneous forcing variable, z_t^n, being correlated with the error term. Two lags of inflation and the forcing variable are used as instruments. Second, the cross-section panels are unbalanced with a large variation in the number of observations between the smallest regime (9 observations) and the largest regime (51 observations). The problem is that when the individual cross sections are small it is well documented that the estimates are biased.[19] Therefore, a relevant question is, 'when are panels small?' One rule-of-thumb is that the cross section panels are considered 'small' if estimation is invalid due to too few degrees of freedom using an individual cross section of data. In our case the shorter inflation regimes are arguably invalid while the longer regimes are easily long enough to be valid. In any case, it is demonstrated below that the estimated Phillips curves are not affected in any meaningful way if we exclude the shortest inflation regimes.

Third, two panel estimators present themselves. The random effects model is strongly rejected by the data in favour of the fixed effects estimator. As the latter also has a ready interpretation as accounting for the different mean rates of inflation across inflation regimes, only the fixed effects set of models are reported below.

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[18] For a very clear and straightforward explanation of the problems surrounding the estimation of dynamic time series models using panel techniques see Bond (2002). For a more detailed treatment of these issues see Hsiao (2003).

[19] For example, see Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998) and Bond (2002) who overcomes the problem of 'dynamic panel bias' when *t* is very small by estimating the models with the Arellano-Bond estimator. Estimating the panel model via a forward orthogonal deviation Arellano-Bond estimator the results are not affected in an economic or quantitative sense.

Fourth, the panel fixed effects Phillips curve models of equation (7) restricts the coefficients on the dynamic inflation terms and the forcing variable to be the same across inflation regimes. This restriction is accepted by the data and reported in the relevant tables (see 'Parameter Constancy' in Tables 6 and 7).

Using this approach to estimating Phillips curves has a number of advantages. First, the Monte Carlo analysis above demonstrates that even when the Bai-Perron technique fails to identify the inflation regimes exactly the biases due to any remaining non-stationarity in the data are insignificantly small. Second, the estimated fixed effects have a ready interpretation as the mean rate of inflation in each inflation regime. Third, the panel approach provides unbiased estimates of the coefficients on expected inflation, ϕ_f, and lagged inflation, ϕ_b, in equation (7). This allows us to enquire into the veracity of the three competing 'modern' Phillips curve theories. Fourth, the estimates for any particular regime are conditioned only on data from the same regime. This is not the case if a single time series model was estimated that included shift dummies where the instruments at the start of a regime would be drawn from the end of the preceding regime. And finally, based on the results of our simulations we can examine the proposition with some confidence that the long-run Phillips curve is vertical.

The last advantage is particularly important on empirical and policy levels. The panel approach provides estimates of the individual short-run Phillips curves for each inflation regime. The panel estimates must be of the short-run Phillips curve as the mean rate of inflation, and therefore the long-run rate of inflation, is constant in each cross section inflation regime. As the data in each inflation regime is stationary by construction the estimated absolute value of $\phi_f + \phi_b$ must be less than 1. This does not mean that the long-run Phillips curve is not vertical. Instead, it means that the data in any one inflation regime cannot reveal the slope of the long-run Phillips curve as it only has one mean, or long-run, rate of inflation. One short-run Phillips curve can only identify one long-run combination of inflation and the forcing variable. However, we can calculate from the panel estimates the long-run value of the forcing variable associated with the mean rate of inflation in each inflation regime. This provides multiple combinations of the long-run inflation rate and forcing variable so that we can then examine if the combinations lie along a linear vertical line. This issue is returned to in Section 4 following the reporting of the estimates.

3.1 Estimates of the United States Phillips Curves

Table 6 reports 2SLS estimates of the F-P, NK and hybrid Phillips curves from equation (7) using the markup of price on unit labour costs as the measure of the forcing variable. Columns 1 to 3 of Table 6 report the panel estimates with the restriction that the estimated constant from each regimes is the same such that, $\phi^1 = \phi^2 = \ldots = \phi^9$. We see that many of the standard results in the literature discussed above are retrieved. In the NK and hybrid models the sum of the dynamic inflation terms sum to one and in the hybrid model forward looking behaviour dominates the backward looking behaviour of agents.

Reported in columns 5 to 8 in Table 6 are the fixed effects estimates of the Phillips curves. Having now accounted for the changing mean rates of inflation across inflation regimes we find that the sum of the estimated dynamic inflation terms in the F-P and NK models is significantly less than 1. In the hybrid model we can accept the sum of the dynamic inflation terms equals 1 but each dynamic term is individually insignificant at the 5 per cent level and the estimated coefficients sum to 0.5567. Importantly in the NK and hybrid models, expected inflation, Δp^n_{t+1}, as commonly measured in the literature plays no significant role in the dynamics of inflation. Of some interest is the finding that in all three models the dynamic inflation terms are jointly insignificant. In the F-P model the dynamic inflation term is insignificantly different from zero and significantly less than 1 and equal to 0.1263. Finally, except for the hybrid model where the variable is insignificant, the markup has a significant and negative impact on inflation.

3.2 The impact of the Bai-Perron estimates on the panel estimates

The Bai-Perron technique estimates nine inflation regimes. However, two inflation regimes (numbers 4 and 5 in Table A2 in Appendix 2) that coincide with the first OPEC oil price shock in the early to mid 1970s are identified having met the constraint in the Bai-Perron technique of the minimum number of quarters in an inflation regime. Consequently, these two regimes are likely not to have a constant mean rate of inflation and are non-stationary.

We therefore re-estimate the models using the panel technique after separating the data into ‘stationary’ inflation regimes (regime numbers 1, 2, 3, 6, 7, 8, and 9) and ‘non-stationary’ regimes (numbers 4 and 5). The results are reported in Table 7 and further demonstrate the need for the data to be stationary. With the stationary regimes, all three models demonstrate that the dynamic inflation terms are highly insignificant and that the 'best' model is simply inflation regressed on the markup. In the last four columns the panel technique is applied to the non-stationary inflation regimes where the dynamic inflation terms are individually significantly different from zero and jointly insignificantly less than one as in the standard Phillips curve literature.

Given that non-stationary regimes are small relative to the data in the stationary regimes the impact of the non-stationary regimes on the estimates reported in Table 6 is small. The results in the first four columns in Table 7 therefore reinforce the conclusion that the dynamic inflation terms in the F-P, NK and hybrid models have little significant role in determining the dynamics of the inflation-markup Phillips curve model once breaks are accounted for properly.

Note that the use of the Bai-Perron technique to identify the breaks in mean inflation is not driving the results. The Monte Carlo analysis in Section 2 demonstrates that even though the Bai-Perron technique does not identify the breaks exactly the fixed effects panel techniques used here provides estimates that are insignificantly different from the 'true' model. Furthermore, Perron (1989, 1990) and the analysis in Section 2 tells us the direction of the bias on the dynamic inflation terms due to incorrectly identifying the breaks and any residual non-stationarity in the data is upwards. Therefore, given the Bai-Perron technique has almost certainly not identified the breaks in mean inflation exactly this means that overturning the standard findings in the literature that the lead in inflation is significant and the dynamic inflation terms sum to 1 is made more difficult. This suggests these findings are robust to the choice of technique for identifying multiple structural breaks in the data.

3.3 Inflation Persistence

The lack of significant dynamic inflation terms in our estimated inflation-markup Phillips curves does not mean that inflation has low persistence. Persistence has two components. The first is persistence in the change in mean inflation following a shift in monetary policy. In our characterisation of the inflation data the shifts in mean are discrete and persistent. The second component is the persistence in inflation around any given constant mean rate of inflation. This may be characterised as the 'behavioural' element of persistence due to the interaction between agents, firms, and the structure of the economy. The second component is often measured by the sum of the j estimated autoregressive coefficients in an AR(j) model of inflation.[20] If we estimate a panel AR(1) model of inflation using only the inflation regimes that we are confident are stationary (i.e. regimes 1, 2, 3, 6, 7, 8 and 9) then the estimated autoregressive coefficient is 0.1596 which implies a median adjustment lag back to the mean rate of inflation of around 0.38 of one quarter.[21] Similarly, if we estimate a panel single equation unrestricted error correction model of inflation and the markup using the same data then the adjustment coefficient on the error correction term is – 0.8780 implying a similar median adjustment lag of 0.33 of one quarter.[22] We can therefore characterise deviations of inflation from its mean as having low persistence as shocks are extinguished very quickly while the shifts in the mean rate of inflation are very persistent.

The standard view that inflation is highly persistent comes from confusing these two components of persistence. Estimating an AR model of inflation persistence over the entire sample between March 1960 and June 2007 without accounting for the shifts in mean inflation leads us to conclude that inflation is highly persistent with the sum of the estimated autoregressive coefficients insignificantly different from one.[23] This implies an infinite median adjustment lag. However, this estimation of persistence proceeds under the erroneous assumption that inflation has a constant mean.[24]

Consequently, we argue that inflation appears to be highly persistent only because of the shifts in mean inflation that are due to changes in monetary policy. Once we account for the shifts in mean inflation the behavioural element of persistence is very low with shocks away from its mean level dissipating very quickly. It is the behavioural element of persistence that

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[20] For example see Altissimo, Bilke, Levin, Matha, and Mojon (2006), Cecchetti and Debelle (2006) and Benati (2008).

[21] Further lags in the AR model of inflation are insignificant.

[22] This is a reparameterisation of the markup only model in column 4 of Table 7 so as to estimate the adjustment coefficient in the error correction model.

[23] The sum of the estimated autoregressive coefficients is 0.9272 with a standard error of 0.0386. The F-test probability value that the sum of the coefficients is one is 0.0606. If we accept that the sum of the autoregressive coefficients is less than one then the median adjustment lag is around 9 quarters.

[24] The estimated coefficients in the AR model of inflation are unbiased only if inflation has a constant mean.

modern Phillips curve theories need to explain and not the persistence due to the changes in monetary policy. In particular, theories of the Phillips curve need to explain the low persistence in inflation around its mean level. This is in stark contrast with the almost obsessive desire of existing modern Phillips curve theories to conform to the incorrect belief that inflation is highly persistent. The fallacy of this desire is obvious if we consider a period when the central bank successfully delivers low stable inflation with a constant mean. In this case the persistence due to the shifts in mean disappears and only the behavioural element of very low persistence will remain. This is totally at odds with the prediction of modern theories of the Phillips curve that inflation is highly persistent and that inflation always contains, or very nearly contains, a unit root. The 'successful central bank policy' example is irrelevant only if the set of all possible inflation outcomes does not include a stationary process.

4. ESTIMATES OF THE IMPLICIT LONG-RUN INFLATION-MARKUP RELATIONSHIP

In our Phillips curve models estimated with panel techniques we are simultaneously estimating nine short-run Phillips curves associated with the nine mean, or long-run, rates of inflation identified earlier by the Bai-Perron technique. As the data are stationary by construction it should be of no surprise that the sum of the estimated coefficients on the dynamic inflation terms is significantly less than one.

To identify the long-run Phillips curve, therefore, we need to first identify the 'implicit' long-run value of the forcing variable associated with the long-run rate of inflation in each inflation regime. The latter is defined as the mean rate of inflation in each regime. The former is defined as the value of the forcing variable that will be attained when inflation is at its long-run rate and all inflation dynamics have been exhausted.

We can, therefore, write the implicit long-run value of the forcing variable, $\bar{z}^n$, in inflation regime, n, implied in equation (7) as:

$$\bar{z}^n = \frac{1}{\phi_z}\left[\overline{\Delta p}^n\left(1-\phi_f-\phi_b\right)-\phi^n\right] \tag{8}$$

where $\overline{\Delta p}^{n}$, is the mean rate of inflation in inflation regime, n. The parameters ϕ_f, ϕ_b, ϕ_z and ϕ^n are the estimated coefficients from the panel estimates of equation (7).

If we further assume that the n combinations of the long-run rates of inflation and the implicit long-run values of the forcing variable loosely lie along the implicit long-run Phillips curve then we can examine if the curve is vertical or has a significant positive or negative slope without the bias associated with the standard methods of estimating the Phillips curve.

The linear representation of the implicit long-run Phillips curve can therefore be represented as:

$$\overline{\Delta p}^{n} = \alpha_0 + \alpha_1 \bar{z}^{n} \tag{9}$$

and, one non-linear representation may be written as:

$$\overline{\Delta p}^{n} = \beta_0 \exp\left(\beta_1 \bar{z}^{n}\right) \tag{10}$$

Table 8 provides ordinary least squares estimates of the linear and non-linear implicit long-run Phillips curves. The implicit long-run values are calculated using the markup only model estimated with the inflation regimes that we are confident are stationary (see column 4 of Table 7).[25] We see that there is a significant negative slope to the implicit long-run Phillip curve of -0.1113. Given the long-run Phillips curve cannot be linear if it is not vertical then the non-linear long-run Phillips curve is a better representation of the long-run inflation-markup relationship in the data.[26]

For comparison, Table 8 also provides estimates of the long-run cointegrating relationship between inflation and the markup in the Engle and Granger (1987) sense assuming that inflation and the markup are integrated processes. Using all the data from March 1960 to

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[25] These estimates are chosen when calculating the implicit long-run Phillips curve as it avoids the biases introduced by the non-stationary data in regimes 4 and 5.

[26] If the long-run Phillips curve is not vertical then as inflation tends to an infinite rate the markup will exceed its defined boundaries of zero or a finite maximum. Therefore, if the long-run Phillips curve displays a negative slope then it must be non-linear and approach the vertical as the mean rate of inflation increases.

June 2007 we find that we can accept the hypothesis of one cointegrating vector. This approach to identifying the long-run inflation-markup relationship is that followed in a series of papers beginning with Banerjee, Cockerell and Russell (2001).[27] Their approach acknowledges that the 'true' statistical process of inflation is most likely stationary around frequent shifts in mean and that this process can be approximated as an integrated process for the purpose of estimating the long-run inflation-markup relationship. The estimated cointegrating long-run inflation-markup relationship of - 0.3503 reported in Table 8 is similar in size to the implicit long-run relationship of -0.1113 suggesting that approximating inflation as an integrated process and estimating cointegrating relationships between inflation and the markup is valid.[28]

The smaller negative slope of the implicit long-run inflation-markup relationship estimated using the panel approach compared with the slope of the cointegrating relationship from the VAR-ECM may be due to the exclusion of the relatively high inflation non-stationary inflation regimes numbered 4 and 5 from the panel analysis. If the long-run inflation-markup relationship is non-linear with a negative slope then the linear implicit long-run inflation-markup relationship coincides with the lower portion of the non-linear curve that has a smaller slope.

4.1 A graphical representation of the results

Graph 2 provides a graphical representation of the estimated 'markup only' model reported in the fourth column of Table 7. The graph shows quarterly combinations of the inflation rate and the markup between March 1960 and June 2007. The data from each inflation regime are represented by different symbols on the graphs. Shown as thin lines and denoted SRPC are the estimated short-run Phillips curves assuming the dynamics of inflation are exhausted. Shown as large crosses on the graph are the long-run combinations of inflation and the markup. As the two non-stationary regimes are excluded there are seven short run Phillips curves and seven long-run combinations of inflation and the markup shown on the graph.

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27 See also the references cited in footnote 18.

28 The estimated long-run cointegrating relationships reported in Banerjee and Russell (2001a, 2001b, 2005) for the United States are - 0.4065, - 0.5402 and - 0.3959 respectively. These estimates are remarkably similar given the different data samples, frequencies, and levels of aggregation employed in these papers.

Finally, the two thick lines denoted LRPC and LRPC (VAR) are respectively the non-linear estimate of the implicit long-run Phillips curve and the cointegrating long-run inflation-markup relationship reported in Table 8.[29]

The graph shows that the short-run Phillips curves for each inflation regime have a smaller negative slope than the long-run curve. While not explicitly modelled in the panel estimation process, the technique is able to identify the long-run markup associated with each mean rate of inflation. In the short run an increase in the rate of inflation is associated with a relatively large fall in the markup. However, if the increase in inflation persists in the long run then, when all adjustment has been completed, the markup recovers slightly to its new long-run level but still remains lower with a higher mean rate of inflation.

5. EMPIRICAL MODELLING OF TIME VARYING MEAN INFLATION

There are many ways to empirically model the time varying mean rate of inflation. We have demonstrated above that if we proceed under the assumption that inflation is integrated and difference the data then the bias in the estimates is either maintained or increased. Alternatively one might model inflation as we have as a stationary process around discrete shifts in mean. The Bai-Perron panel approach discussed above is within this framework.[30]

Some observers might be concerned with the idea that the mean or long-run rate of inflation changes in a discrete fashion. One response to this concern is that when we move between two consecutive inflation regimes the transition can be thought of as a series of empirically unidentifiable small discrete shifts in mean inflation. Alternatively, the transition could be thought of as a smooth transition. The New Keynesian literature on the time varying mean rate of inflation recently adumbrated in Cogley and Sbordone (2008) models the trend rate of inflation due to monetary policy as varying in a smooth fashion. In their paper they derive a model of the New Keynesian Phillips curve solved for a time varying trend rate of inflation.

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29 The short and long-run Phillips curves are drawn in Graph 2 over the range of the actual markup in each case. Note that the short-run Phillips curves for regimes 2, 7 and 9 overlap on the graph.

30 Within this framework we may also include Markov switching models of inflation such as Manopimoke (2009). Traditionally these models assume a very low number of breaks in inflation compared with the number of breaks that we think are necessary to demean the inflation data and be consistent with a believable number of short-run Phillips curves over the past fifty years. Consequently, the inflation data remains non-stationary and the estimates biased in these Markov models.

This approach contrasts with the conventional New Keynesian approach that solves the model assuming a constant mean rate of inflation.

Cogley and Sbordone undertake a two stage modelling exercise. First, they estimate a Bayesian VAR and compute the time varying trend rate of inflation assuming that the central bank's target rate of inflation is a random walk with reflecting boundaries.[31] They then calculate the difference, or gap, between inflation and the estimate of trend inflation. The second stage estimates the structural parameters of the United States hybrid Phillips curve conditioned on the inflation gap, labour's income share gap, the growth in output and the discount rate.[32] From their estimated structural parameters they conclude that the persistence in United States inflation can be explained by forward looking agents alone without the need for backward looking agents as long as the trend rate of inflation is allowed to vary over time in the postulated fashion.[33]

Graph 3 reproduces the Cogley and Sbordone inflation (solid line) and trend inflation (dashed line) data.[34] The data used in Cogley and Sbordone is essentially the same as ours and so it is not surprising that the shifts in the mean rate of inflation that are evident in our inflation data in Graph 1 are also evident in the Cogley and Sbordone inflation data in Graph 3. The Cogley and Sbordone inflation gap is measured as the difference between actual and trend inflation in Graph 3 and the inflation gap is shown in the top panel of Graph 4. Notice that because of the very smooth nature of the estimated time varying trend inflation the shifts in mean inflation that we see in Graph 3 are largely repeated in the inflation gap data. The Cogley and Sbordone technique should not be thought of as de-meaning the data and so we should expect estimation based on the inflation gap to be biased as the shifts in mean are not properly accounted for.

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[31] Note that in a finite sample a random walk with reflecting boundaries is observationally equivalent to a stationary process around very frequent shifts in mean.

[32] The first stage BVAR is also used to estimate the trend labour's share of income and this is used to calculate the gap between labour's income share and its trend level.

[33] The significant role for forward looking agents is derived from the median estimate of the degree of nominal rigidity of 0.588 per quarter.

[34] The data are from Figure 1 of Cogley and Sbordone (2008). See the notes to Table 9 and Graphs 3 and 4 for details of the data.

To this end Table 9 reports single equation estimates of the hybrid Phillips curve using the Cogley and Sbordone measures of the inflation gap and markup gap.[35] Column 1 provides the GMM time series estimates of the hybrid Phillips curve that do not account for the shifts in the mean inflation gap. We see δ_f and δ_b are insignificantly different from one and zero respectively implying no significant role for backward looking agents while forward looking agents are all that are necessary to explain the dynamics of inflation. These estimates of the hybrid model are entirely consistent with the Cogley and Sbordone conclusions.

The Bai-Perron technique identifies eight breaks in the mean of the inflation gap implying there are nine episodes where the mean inflation gap is constant. The means of each episode are shown in the top panel of Graph 4 as thin horizontal lines. The data are then partitioned in line with the breaks in mean identified in the first stage and the second stage 2SLS panel estimates are reported in columns 2 and 3.

Table 9 column 2 restricts the constant to be the same across the nine episodes which is equivalent to the assumption of a constant mean inflation gap across all episodes. Given the same assumption concerning the mean inflation gap the results in column 2 are very similar to those reported in column 1. In contrast, and in line with our analysis, the fixed effects panel estimates that allow for the changes in the mean inflation gap across episodes we find both the lead and lag in inflation to be insignificantly different from zero.

We can therefore interpret the Cogley and Sbordone results from the perspective of our analysis. Our estimates reported in columns 5 to 7 in Table 6 and columns 1 to 3 in Table 7 also find no significant role for backward looking agents. What is distinctive is that we also find no role for forward looking agents. Furthermore, our Monte Carlo analysis reported in column 7 of Table 1 and column 3 of Table 5 demonstrate that unaccounted shifts in the mean rate of inflation bias the coefficient for the lead in inflation leaving the lag in inflation to be insignificantly different from its true value. Consequently, we attribute the nominal rigidity of forward looking agents found by Cogley and Sbordone in the hybrid Phillips curve to be due to insufficient de-meaning of the inflation data.

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35 Cogley and Sbordone (2008) use labours income share instead of the markup where the former is the negative value of the later.

We acknowledge there are many possible approaches to deal with the time varying mean rate of inflation. However, all approaches are not alike. A valid approach must adequately de-mean the inflation data so that the estimates are unbiased. The Bai-Perron panel approach outlined above appears to be valid. In contrast, differencing the data on the assumption that inflation is integrated or estimating models of inflation gaps based on smooth estimates of trend inflation lead to very different conclusions that in our view are difficult to sustain based on a good understanding of the properties of the data.

6. Implications for the 'Modern' Theories of the Phillips Curve

What does this paper imply for the 'modern' theories of the Phillips curve? First, if one accepts that inflation may at times be a stationary process with a constant mean, then the absolute value of the sum of the dynamic inflation terms must by definition be less than one at those times. Furthermore, the estimates in Section 3 suggest the persistence of inflation around a constant mean rate of inflation is very low. This is in stark contrast with estimates of all 'modern' Phillips curve theories that show the sum of the dynamic inflation terms to be equal to one, with heavy weight on the forward looking dynamic inflation terms. Modern Phillips curve theories very strongly predict that inflation is an integrated process. In other words, the behaviour of the central bank has no influence on the statistical process of inflation.

This is counterintuitive at several levels. For example, the causation appears to run from how agents behave to how monetary policy is set. This is the reverse of the more reasonable standard view and Friedman's famous quote where monetary policy causes inflation. Moreover, given that central banks either explicitly or implicitly target a low rate of inflation, this implies that central banks attempt to set monetary policy so that inflation is a stationary process around a constant mean and that this mean may shift in response to shocks or a change in the target rate of inflation of the monetary authorities. Furthermore, when central banks adjust policy it is because they perceive the expected (or forecast) long-run rate of inflation has diverged from target. If monetary policy successfully offsets the divergence then we will eventually record no shift in the mean rate of inflation from target and so mean inflation remains unchanged. It is only when policy is unsuccessful that we will eventually record a divergence in the long-run rate of inflation from target and we will indentify a shift in the mean rate of inflation. This suggests the statistical process of inflation is determined by the process of monetary policy and its success and not by the behaviour of agents.

Second, consistent with the empirical findings in Russell (2007) there is no evidence that the lead in inflation as argued and measured in the New Keynesian and hybrid Phillips curve literatures is significant after allowing for the shifts in the mean rate of inflation. This term in the standard empirical analysis appears to only indicate there are unaccounted breaks in the mean rate of inflation and has no behavioural relevance.

Third, there is only marginal evidence that any lags in inflation are significant in the inflation-markup Phillips curve. Since unidentified breaks serve to increase the estimated coefficients on the dynamic inflation terms, the marginal significance may simply be due to residual non-stationarity in the inflation data due to unidentified or mis-identified shifts in means. Indeed, the panel models estimated with the data from the inflation regimes where we are more confident that the data are stationary suggest a clear acceptance of the hypothesis of insignificant dynamic terms.

Fourth, given the New Keynesian model is not supported empirically, the markup should be interpreted on an empirical level as an error correction mechanism.[36] On a behavioural level the markup may well proxy the average profit margin of firms as argued in the price-setting theories of Russell (1998), Russell, Evans and Preston (2002) and Chen and Russell (2002). Furthermore, in the developed world where agents sequentially experience extended periods of mean reverting inflation where each of these periods have different mean rates of inflation' it would be rational for agents (whether forward or backward looking) to recognise this statistical process. It is also rational, therefore, for agents to expect deviations in inflation and the markup from their long-run values to eventually be extinguished within a particular inflation regime and to expect these variables to return to their long-run levels over time. We should not be surprised therefore to find that the aggregate behaviour of agents in the inflation process can be approximated by an error correction mechanism such as that estimated in the

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[36] In natural logarithms, the markup, mu, of price, p, on unit labour costs, $w+l-y$, is: $mu = p - (w+l-y)$ which is the inverse of labour's share of income or the ratio of prices over unit labour costs.

panel models above and that leads and lags in inflation do not enter directly into the dynamics of inflation.

Fifth, if we model inflation as having a time varying mean then the subsequent empirical analysis must account for the non-stationarity in such a way that the estimates are not biased. For example, Cogley and Sbordone (2008) attribute the smooth time varying trend rate of inflation as due to monetary policy. This implies trend inflation is a proxy for the expected, or long-run, rate of inflation which in turn implies the inflation gap is a measure of the errors between actual and expected inflation made by agents and the monetary authorities in the inflation process. The top panel of Graph 4 shows these errors are large, persistent and unidirectional for long periods of time. For example, agents and the monetary authorities consistently underestimate inflation on average by around 3 ½ percentage points per annum for ten years between December 1972 and September 1982. These systematic errors are not inconsequential. If we assume that the actual and trend price levels are the same at the start of the 1960 March quarter then we can accumulate the errors to give a measure of the ratio of actual to trend prices which is shown in the bottom panel of Graph 4. [37] We find that in the first five years the price ratio falls systematically by around thirty per cent. In the ten years of positive errors following the first OPEC oil price shock we see the ratio increase by 300 per cent to a ratio of around 3. From that time on there is no systematic decline and the price ratio oscillates around 3. It seems difficult to envisage a situation where agents and the monetary authorities make the large and unidirectional errors between actual and expected prices that are implied by the inflation gap.

In contrast to a method that smoothes the expected rate of inflation our empirical modelling considers discrete shifts in the mean rate of inflation. This may be thought of as just one of many approaches to deal with the non-stationarity in the inflation data. However, for the estimates to be unbiased on an econometric level the approach must successfully demean the inflation data. This suggests that all approaches to dealing with the non-stationarity in the inflation data are not the same. We have shown that our approach is highly effective in reducing the bias in the estimates due to the shifts in mean inflation. By implication this also

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[37] The ratio of the price levels in the bottom panel is the antilog of the accumulated Cogley and Sbordone (2008) inflation gap assuming that the ratio is 1 at the start of the period. The minimum and maximum values of the price ratio are 0.7026 (September 1965) and 3.3144 (March 1991) respectively.

means that we remove the systematic errors between actual inflation and the time varying mean rate of inflation. Thus while the motivation for our framework comes from an empirical understanding of the data it can be thought of as just one approach to overcoming the time varying mean rate of inflation but in a way where the inflation data is appropriately demeaned.

Finally, in the 1960s macroeconomic policy was conceived on the implicit assumption that a permanent loosening in monetary policy would permanently increase output. The analysis above does not support the behaviour underpinning the Friedman-Phelps model but reveals the remarkable insight of Friedman and Phelps that 'real' economic variables are independent of the mean rate of inflation in the long run is empirically correct. But the insight is only true to a first approximation. The analysis in this paper demonstrates that at low to moderate mean rates of inflation it looks as though there is a significant negative long-run relationship between inflation and the markup.

7. CONCLUSION

Applied econometricians since Granger and Newbold (1974) have been careful to account for non-stationarity in the data. However, applied econometricians often think in terms of two 'popular' statistical processes; namely, stationary and integrated. In part this is because of the importance and the success of Granger and Newbold (1974) followed quickly by the widespread acceptance of the Dickey and Fuller (1979) univariate unit root test based on the null hypothesis of a unit root in the data. With the difficulties of estimating models with non-stationary data understood and the test for a unit root firmly established, the emergence of cointegration analysis with Engle and Granger (1987) provided a theoretically elegant solution to the difficulties of modelling integrated variables. These three important advances in econometrics are interlinked and may have led applied econometricians to overly focus on the two popular statistical processes. The strength of this focus is demonstrated by how the warnings of Perron (1989, 1990) concerning the biases due to breaks in series have been largely overlooked even after twenty years. These warnings are routinely ignored by applied econometricians in general and by nearly all applied Phillips curve researchers in particular.

In contrast, the addition of shifts in mean to a stationary process is often thought of as 'nuisance' shift parameters and not very interesting. This paper argues that in many cases the ‘true’ statistical process is stationary around shifting means and that the two ‘popular’ assumptions when analysing data can only be approximations of the ‘true’ process at best. As such, the approximations bring with them biases which are large and non-trivial in the case of inflation and the estimation of Phillips curves.

What then are the ‘stylised facts’ from these results that future Phillips curve theories need to explain? First, the long-run relationship between inflation and the markup may be non-linear and negative at low to moderate rates of inflation. Second, the lead in inflation as commonly estimated in the literature has no significant role in the dynamics of inflation. This does not mean that the dynamics of inflation are always insignificant. For example, in Phillips curve models defined on inflation and the unemployment rate there is no markup to act as an error correction mechanism. Consequently, in these models estimates of the inflation dynamics will most likely be significant but will not sum to one.[38] Third, given inflation is stationary within an inflation regime then the sum of the dynamic inflation terms must be less than one and may be close to or equal to zero in inflation-markup Phillips curve models. And fourth, the markup should be seen as an error correction term and possibly a proxy for the profitability of firms.

Finally, this paper argues that assuming data is stationary or integrated when the ‘true’ statistical process is stationary around shifting means leads to non-trivial large biases in the estimation of models. This argument is relevant to any empirical work where careful consideration of the data should alert the researcher that assuming the data is stationary or integrated is only an approximation of the ‘true’ statistical processes. Before proceeding with the estimation under these assumptions it would be prudent to examine the size of the biases due to the approximation using a Monte Carlo simulation. If the biases are large as argued by Perron (1989, 1990) and demonstrated here then the approximation is poor and should be avoided.

[38] For example, see the estimates reported in Russell (2007).

8. References

Akerlof, G.A., W.T. Dickens and G.L. Perry (1996). The Macroeconomics of Low Inflation, *Brookings Papers on Economic Activity*, vol. 1996, no. 1, pp. 1-76.

Akerlof, G.A., W.T. Dickens and G.L. Perry (2000). Near-Rational Wage and Price Setting and the Long-run Phillips Curve, *Brookings Papers on Economic Activity*, vol. 2000, no. 1, pp. 1-60.

Alogoskoufis, G. and R. Smith (1991). The Phillips Curve, The persistence of Inflation, and the Lucas Critique: Evidence from Exchange Rate Regimes, *American Economic Review*, vol. 81, no. 5, Dec., pp. 1254-1275.

Altissimo, F., Bilke, L., Levin, A., Matha, T. and B. Mojon (2006). Sectoral and Aggregate Inflation Dynamics in the Euro Area, *Journal of the European Economic Association*, April-May, vol. 4, no. 2-3, pp. 585-593.

Arellano, M. and S.R. Bond (1991). Some Tests of Specification for Panel Data: monte Carlo Evidence and an Application to Employment Equations, *Review of Economic Studies*, vol. 58, pp. 277-97.

Arellano, M. and O. Bover (1995). Another Look at Instrumental-Variable Estimation of Error-Components Models, *Journal of Econometrics*, vol. 68, pp. 29-52.

Bai J, Perron P. 1998. Estimating and testing linear models with multiple structural changes. *Econometrica* 66: 47-78.

Bai J, Perron P. 2003a. Critical values for multiple structural change tests, *Econometrics Journal,* vol. 6, 72-78.

Bai J, Perron P. 2003b. Computation and analysis of multiple structural change models, *Journal of Applied Econometrics*, vol. 18: 1-22.

Banerjee, A., Cockerell, L. and B. Russell (2001). An I(2) analysis of Inflation and the Markup, Journal of Applied Econometrics, Sargan Special Issue, vol. 16, pp. 221-240.

Banerjee, A., P Mizen and B. Russell (2007). Inflation, Relative Price Variability and the Markup: Evidence from the United States and the United Kingdom, *Economic Modelling*, vol. 24, pp. 82-100.

Banerjee, A. and B. Russell (2001a). The Relationship between the Markup and Inflation in the G7 Economies and Australia, Review of Economics and Statistics, vol. 83, No. 2, May, pp. 377-87.

Banerjee, A. and B. Russell. (2001b). Industry Structure and the Dynamics of Price Adjustment, Applied Economics, 33:17, pp. 1889-901.

Banerjee, A. and B. Russell (2004) A Reinvestigation of the Markup and the Business Cycle, Economic Modelling, vol. 21, pp. 267-84.

Banerjee, A. and B. Russell (2005). Inflation and Measures of the Markup, Journal of Macroeconomics, vol. 27, pp. 289-306.

Batini, N., B. Jackson, and S. Nickell. (2000). Inflation Dynamics and the Labour Share in the UK, Bank of England External MPC Unit Discussion Paper: No. 2 November.

Batini, N., B. Jackson, and S. Nickell. (2005). An Open-Economy New Keynesian Phillips Curve for the U.K., *Journal of Monetary Economics*, vol. 52, pp. 1061-71.

Benati, L.(2008); Investigating Inflation Persistence Across Monetary Regimes, *Quarterly Journal of Economics*, August, vol. 123, no. 3: pp. 1005–1060.

Blundell, R.W. and S.R. Bond (1998). Initial Condtions and Moment Restrictions in Dynamic Panel Data Models, *Journal of Econometrics*, vol. 87, pp. 115-43.

Bond, S. (2002). Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice, Centre for Microdata Methods and Practice Working Paper, CWP 09/02.

Cecchetti, S. and G. Debelle (2006). Has the inflation process changed?, *Economic Policy*, vol. 21, no. 46, April, pp. 311-352.

Chen, Y-F and B. Russell. (2002). An Optimising Model of Price Adjustment with Missing Information, European University Institute Working Paper, ECO No. 2002/3.

Clarida, R., Gali, J. and M. Gertler (1999). The Science of Monetary Policy: a New Keynesian Perspective, *Journal of Economic Literature*, vol. 37, pp. 1661-1707.

Cogley, T. and A.M. Sbordone (2005), A Search for a Structural Phillips Curve, Federal Reserve Bank of New York Staff Reports, no. 203.

Cogley, T. and A.M. Sbordone (2006), Trend Inflation and Inflation Persistence in the New Keynesian Phillips Curve, Federal Reserve Bank of New York Staff Reports, no. 270.

Cogley, T. and A.M. Sbordone (2008), Trend Inflation, Indexation, and Inflation Persistence in the New Keynesian Phillips Curve, *American Economic Review*, vol. 89, pp. 2101-26.

Dickey, D.A. and W.A. Fuller (1979), "Distribution of the Estimators for Autoregressive Time Series with a Unit Root," *Journal of the American Statistical Association*, 74, p. 427–431.

Dufour, J-M. (2003). Identification, Weak Instruments and Statistical Inference in Econometrics, Canadian Journal of Economics, vol. 36 (4), pp. 767-808.

Dufour, J-M., Khalaf, L. and M. Kichian (2006a). Inflation Dynamics and the New Keynesian Phillips Curve: An Identification Robust Econometric Analysis, *Journal of Economic Dynamics and Control*, vol. 30, pp. 1707-1727.

Dufour, J-M., Khalaf, L. and M. Kichian (2006b). Structural Estimation and Evaluation of Calvo-style Inflation models, Computing in Economics and Finance, Society for Computational Economics, no. 161.

Engle, R.F. and C.W.J. Granger, (1987). Co-integration and Error Correction: Representation, Estimation, and Testing, Econometrica, vol. 55, no. 2, May, pp. 251-76.

Friedman, M. (1968). The role of monetary policy, *American Economic Review*, 58, 1 (March), pp. 1-17.

Friedman, M. (1977). Nobel Lecture: Inflation and Unemployment, *The Journal of Political Economy*, vol. 85, no. 3, pp. 451-72.

Gali, J., and M. Gertler (1999). Inflation Dynamics: A Structural Econometric Analysis, *Journal of Monetary Economics*, vol. 44, pp. 195-222.

Gali, J., Gertler M., and J.D. Lopez-Salido (2001). European Inflation Dynamics, *European Economic Review*, vol. 45, pp. 1237-1270.

Gali, J., Gertler M., and J.D. Lopez-Salido (2005). Robustness of the Estimates of the Hybrid New Keynesian Phillips Curve, *Journal of Monetary Economics*, vol. 52, pp. 1107-18.

Gordon, R.J. (1970). The Recent Acceleration of Inflation and its Lessons for the Future, *Brookings Papers on Economic Activity*, 1:1, pp. 8-41.

Gordon, R.J. (1975). The Impact of Aggregate Demand on Prices, *Brookings Papers on Economic Activity*, 1:1, pp. 613-62.

Gordon, R.J. (1977). Can the Inflation of the 1970s be Explained? *Brookings Papers on Economic Activity*, vol. 6:3, pp. 613-62.

Gordon, R.J. (1997). Time-varying NAIRU and its implications for Economic Policy, *Journal of Economic Perspectives*, vol. 11, no. 1, pp. 11-32, Winter.

Granger, C.W.J. and P. Newbold (1974). Spurious Regressions in Econometrics, *Journal of Econometrics*, 2, pp. 111-120.

Granger, C.W.J. and P. Newbold (1977). *Forecasting economic time series,* Academic Press, New York.

Hansen, H. and K. Juselius (1995). *CATS in RATS, Cointegration Analysis of Time Series*, Evanston, Illinois, Estima.

Henry, S.G.B. and A.R. Pagan (2004). The Econometrics of the New Keynesian Policy Model: Introduction, *Oxford Bulletin of Economics and Statistics*, vol. 66, supplement, pp. 581-607.

Hsiao, C. (2003). *Analysis of Panel Data*, second edition, Cambridge University Press, New York.

Halunga, A.G., Osborn, D.R. and M. Sensier (2009), Changes in the order of integration of US and UK inflation, *Economic Letters*, vol. 102, pp. 30–32.

Ireland, P.N. (2007), Changes in the Federal Reserve's Inflation Target: Causes and Consequences, *Journal of Money, Credit and Banking*, vol. 39, no. 8, December, pp. 1851-82.

Kiley, M.T. (2007), A Quantitative Comparison of Sticky-Price and Sticky-Information Models of Price Setting, *Journal of Money, Credit and Banking*, supplement to vol. 39, no. 1, February, pp. 101-25.

King, R.G. and M.W. Watson (1994), The post-war U.S. Phillips curve: a revisionist econometric history, *Carnegie-Rochester Conference Series on Public Policy,* vol. 41, pp. 157-219.

Manopimoke, P. (2009). The New Keynesian Phillips Curve and Non-Stationary Inflation, mimeo, Department of Economics, University of Washington.

Mavroeidis, S. (2004). Weak Identification of Forward-looking Models in Monetary Economics, *Oxford Bulletin of Economics and Statistics*, vol. 66, supplement, pp. 609-35.

Mavroeidis, S. (2005). Identification Issues in Forward-looking Models Estimated by GMM, with an Application to the Phillips Curve, *Journal of Money, Credit and Banking*, vol. 37, pp. 421-48.

McCallum, B.T. (1976). Rational Expectations and the Natural Rate Hypothesis: Some Consistent Estimates, *Econometrica*, vol. 44, no. 1, January, pp. 43-52.

Perron, P., (1989). The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis, *Econometrica*, vol. 57, no. 6, November, pp. 1361-1401.

Perron, P., (1990). Testing for a Unit Root in a Time Series Regression with a Changing Mean, *Journal of Business and Economic Statistics*, no. 8, pp.153-162.

Perron, P., (1998). Further Evidence on Breaking Trend Functions in Macroeconomic Variables. *Journal of Econometrics*, 80 no. 2, 355-385.

Pesaran, M.H. (1981). Identification or Rational Expectations Models, Journal of *Econometrics*, vol. 16, no. 3, pp. 375-98.

Pesaran, M.H. (1987). *The Limits to Rational Expectations*, Blackwell, Oxford.

Phelps, E.S. (1967). Phillips curves, expectations of inflation, and optimal unemployment over time, *Economica*, 34, 3 (August), pp. 254-81.

Phillips, A. W. (1958). The Relation Between Unemployment and the Rate of Change of Money Wage Rates in the United Kingdom, 1861-1957, *Economica*, 25, pp 1-17.

Roberts, J.M. (1995). New Keynesian Economics and the Phillips Curve, *Journal of Money, Credit and Banking*, vol. 27, no. 4, part 1, November, pp. 975-84.

Rudd, J. and K. Whelan (2005). New Tests of the New-Keynesian Phillips Curve, *Journal of Monetary Economics*, vol. 52, pp. 1167-81.

Rudd, J. and K. Whelan (2007), Modeling Inflation Dynamics: A Critical Review of Recent Research, *Journal of Money, Credit and Banking*, supplement to vol. 39, no. s1, February, pp. 155-170.

Russell, B. (1998). A Rules Based Model of Disequilibrium Price Adjustment with Missing Information, Dundee Discussion Papers, Department of Economic Studies, University of Dundee, November, No. 91.

Russell, B. (2006). Non-Stationary Inflation and the Markup: an Overview of the Research and some Implications for Policy, Dundee Discussion Papers, Department of Economic Studies, University of Dundee, August, No. 191.

Russell, B. (2007). Non-stationary Inflation and Panel Estimates of United States Short and Long-run Phillips Curves, Dundee Discussion Papers, Department of Economic Studies, University of Dundee, August, No. 200.

Russell, B., J. Evans, and B. Preston. (2002). The Impact of Inflation and Uncertainty on the Optimum Markup set by Firms. European University Institute Working Paper, ECO No. 2002/2.

Russell, B. and A. Banerjee (2006). A Markup Model for Forecasting Inflation in the Euro Area, *Journal of Forecasting*, vol. 25, issue 7, November, pp. 495-511.

Russell, B. and A. Banerjee (2008). The Long-run Phillips Curve and Non-stationary Inflation, *Journal of Macroeconomics*, vol. 30, pp. 1792-1815.

Schreiber, S. and J. Wolters (2007). The long-run Phillips curve revisited: Is the NAIRU framework data-consistent?, *Journal of Macroeconomics*, vol. 29, no. 2, June, pp. 355-367

Staiger, D. and J.H. Stock (1997). Instrumental Variables Regression with Weak Instruments, Econometrica, vol. 65 (3), pp. 557-86.

Stock J.H. and M.W. Watson (2007), Why Has U.S. Inflation Become Harder to Forecast?, *Journal of Money, Credit and Banking*, supplement to vol. 39, no. 1, February, pp. 3-33.

Stock, J., J. Wright, and M. Yogo (2002). A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments, *Journal of Business and Economic Statistics*, vol. 20 (4), pp. 518-30.

Sumner, M.T. and R. Ward (1983). The Reappearing Phillips Curve, *Oxford Economic Papers* supplement on The Causes of Unemployment, new series, vol. 35, November, pp. 306-20.

Svennson, L.E.O. (2000). Open Economy Inflation Targeting, *Journal of International Economics*, vol. 50, pp. 155-83.

APPENDIX 1 DATA APPENDIX

The United States data are seasonally adjusted and quarterly for the period March 1960 to June 2007. The United States national accounts data are from the National Income and Product Account tables from the United States of America, Bureau of Economic Analysis. The data were downloaded via the internet on 9 October 2007.

United States Data

Variable	*Details*
GDP implicit price deflator at factor cost	Nominal GDP at factor cost is nominal GDP (Table 1.1.5, line 2) plus subsidies (Table 1.10, line 10) less taxes (Table 1.10, line 9). GDP implicit price deflator is nominal GDP at factor cost divided by constant price GDP at 2000 prices, Table 1.1.6, line 1. Inflation is the first difference of the natural logarithm of the GDP implicit price deflator at factor cost. Note that Graph 1 shows the estimated inflation regimes multiplied by 400 to be consistent with annualised inflation data.
The Markup	Calculated as the natural logarithm of nominal GDP at factor cost divided by wages, salaries and supplements, Table 1.10, line 2.

The Data Generated for the Monte Carlo Analysis

The data are generated using WinRATS pro 6.2 and 7.2. The forcing variable, x_t, is generated as: $x_t = 0.937967 x_{t-1} + \omega_t$ where the first observation, x_0, is zero and ω_t is a random draw from a normal distribution with mean zero and a standard error of 0.006388. The 'seed' value is: 250305.

The 'inflation' series, y_t, is generated as: $y_t = -0.205406 x_t + \upsilon_t$ where υ_t is a random draw from a normal distribution with a mean of zero and a standard error of 0.004753. The 'seed' value is: 171193.

The mean-shift 'inflation' variable, y_t^{MS}, is: $y_t^{MS} = y_t + \mu_t^i$ where μ_t^i is the mean rate of inflation in regime *i* as reported in Table A2 of Appendix 2.

The United States and the Monte Carlo data are available at www.BillRussell.info.

APPENDIX 2 IDENTIFYING THE INFLATION REGIMES

The Bai and Perron (1998, 2003a, 2003b) approach minimises the sum of the squared residuals to identify the dates of k breaks in the inflation series and, thereby, identify $k+1$ 'inflation regimes'. The estimated model is:

$$\Delta p_t = \gamma_{k+1} + \tau_t \tag{A2.1}$$

where Δp_t is inflation and γ_{k+1} is a series of $k+1$ constants that estimate the mean rate of inflation in each of $k+1$ inflation regimes and τ_t is a random error. The model is corrected for serial correlation with a minimum regime size (or 'trimming rate') of 5 per cent of the total sample (nine quarters). The final model is chosen using the Bayesian Information Criterion. If the model is not corrected for serial correlation the break dates are identical. The model is estimated using quarterly data for the period March 1960 to June 2007 for the United States. The results of the estimated model are reported in the table below. Note that Graph 1 shows the estimated inflation regimes multiplied by 400 to be consistent with annualised inflation data. The Bai-Perron technique was estimated using Gauss 5.0 and the programme was kindly made available by Pierre Perron on his personal internet site.

Table A2: Estimated Inflation 'Regimes' using the Bai-Perron Technique

Regime	*Dates of the 'Inflation Regimes'*	*Mean Rate of Inflation*
1	March 1960 to September 1964	0.003133
2	December 1964 to June 1967	0.006844
3	September 1967 to December 1972	0.011385
4	March 1973 to March 1975	0.021266
5	June 1975 to June 1977	0.015419
6	September 1977 to September 1981	0.020361
7	December 1981 to December 1990	0.008863
8	March 1991 to September 2003	0.005005
9	December 2003 to June 2007	0.007613

Table 1: Phillips Curve estimates from the generated data

	Constant Mean Rate of Inflation dependent variable y_t					Shifting Mean Rates of Inflation dependent variable y_t^{MS}		
	F-P	NK	Hybrid	ND		F-P	NK	Hybrid
y_{t+1}		0.0191 (0.0)	0.0186 (0.0)		y_{t+1}^{MS}		1.0315 (14.1)	0.9785 (5.2)
y_{t-1}	- 0.0104 (- 0.2)		- 0.0078 (- 0.1)		y_{t-1}^{MS}	0.2984 (4.4)		0.0377 (0.6)
					y_{t-2}^{MS}	0.2201 (3.1)		
					y_{t-3}^{MS}	0.1923 (3.1)		
x_t	- 0.2076 (- 8.1)	- 0.2017 (- 2.5)	- 0.2034 (- 2.1)	- 0.2052 (- 10.1)	x_t	- 0.0563 (- 1.8)	- 0.0146 (- 0.6)	- 0.0158 (- 0.6)
C	- 0.0000 (- 0.0)	- 0.0000 (- 0.0)	- 0.0000 (- 0.0)	- 0.0000 (- 0.0)	C	0.0027 (4.0)	- 0.0003 (- 0.4)	- 0.0002 (- 0.1)
R^2	0.76	0.77	0.83	0.70	$\bar{R}^2$	0.75	0.74	0.80
J test	0.4920	0.5185	0.5268	0.4964	J test	0.2911	0.4890	0.4835
LM(4)	0.4357	0.0746	0.0196	0.4478	LM(4)	0.1261	0.0000	0.0000
DW	1.99	2.02	2.01	2.00	DW	2.03	2.90	2.94
ADF_R	- 6.15	- 6.55	- 6.50	- 6.12	ADF_R	- 5.92	- 8.35	- 8.43
$\sum$	- 0.0104 [0.0656]	0.0191 [0.4795]	0.0108 [0.6472]		$\sum$	0.7108 [0.0699]	1.0315 [0.0769]	1.0161 [0.0947]
F	0.4230	0.4091	0.4392	0.4524	F	0.0000	0.0000	0.0000

Reported as ( ) and [ ] are *t*-statistics and standard errors respectively. The 'Constant Mean Rate of Inflation' models are estimated with the constructed inflation series, y_t, and the constructed forcing variable, x_t. The 'Shifting Mean Rate of Inflation' models are estimated with the constructed mean-shift inflation series, y_t^{MS}, and the forcing variable x_t. See Sections 2.2 and 2.3 for details of how the data are generated. The models are estimated with 190 observations using GMM with three lags of the dependent variable and the forcing variable as instruments. Further lags of the dependent variable and the forcing variable in the Friedman-Phelps and hybrid models are excluded on a 5% *t*-criterion. Reported as R^2 is the pseudo R^2. Reported as J Test is the significance of the Hansen test of instrument validity, LM(4) is the significance of the fourth order autocorrelation Lagrange multiplier test statistic, DW is the Durban-Watson test statistic, and ADF_R is the no intercept and no trend ADF test of the residuals where the 1%, 5% and 10% critical values are - 2.576, - 1.941 and - 1.616 respectively. $\sum$ is the sum of the generated 'dynamic inflation terms'. F is the F-test probability value that the estimated parameters are equal to their 'true' values of $\delta_f = 0$, $\delta_b = 0$, and $\delta_x = -0.205406$ in the data generating process. 10,000 Monte Carlo models estimated with WinRATS pro 6.2.

Table 2: Phillips Curve estimates from the differenced generated data

	F-P	NK	Hybrid
Δy_{t+1}^{MS}		- 0.3772 (- 0.5)	- 0.4464 (- 0.7)
Δy_{t-1}^{MS}	- 0.6013 (- 6.6)		- 0.6006 (- 4.6)
Δy_{t-2}^{MS}	- 0.2869 (- 3.3)		- 0.3005 (- 2.3)
Δx_t	0.0129 (- 0.8)	- 0.2089 (- 0.3)	0.0375 (- 0.1)
Constant	0.0000 (0.1)	0.0000 (0.5)	0.0001 (0.1)
$\overline{R}^2$	0.71	0.56	0.84
J test	0.2397	0.2298	0.3955
LM(4)	0.0405	0.0000	0.0029
DW	2.05	2.44	2.07
ADF_R	-7.13	- 7.54	- 7.23
$\sum$	- 0.8882 [0.1890]	- 0. 3772 [1.1864]	- 1.3475 [5.3564]
F	0.0052	0.1725	0.2447

The Δ symbol represents the lag difference such that $\Delta y_t = y_t - y_{t-1}$. The dependent variable is Δy_t^{MS}. Further lags of Δy^{MS} and Δx in the Friedman-Phelps and hybrid models are excluded on a 5% *t*-criterion. See the notes to Table 1 for further details concerning this table.

Table 3: Johansen Trace Tests on Monte Carlo Generated Data

Stationary Variables y_t & x_t					
Model	**Rank**	**Eigenvalue**	**Trace Test**	**95 % Critical Values**	**Cointegrating Vectors (%)**
(i) Constant	r = 0	0.124	32.604	15.340	8.44
	r = 1	0.039	7.550	3.841	
(ii) Constant and Trend	r = 0	0.134	35.966	18.149	3.48
	r = 1	0.046	8.907	3.841	
Mean Shift Variable y_t^{MS} and Stationary x_t					
Variables	**Rank**	**Eigenvalue**	**Trace Test**	**95 % Critical Value**	**Cointegrating Vectors (%)**
(i) Constant	r = 0	0.346	87.935	15.340	8.17
	r = 1	0.032	7.807	3.841	
(ii) Constant and Trend	r = 0	0.350	90.461	18.149	3.47
	r = 1	0.048	9.239	3.841	

Two VAR-ECM models are estimated with two lags of the variables; (i) unrestricted constant where the variables contain linear trends; and (ii) constant and trend where there are linear trends in both the variables and the cointegration relations. The 95 % critical values are from Tables B3 and B5 of Hansen and Juselius (1995). The data conforms to equations 3, 4 and 5 in the text and the models are estimated 10,000 times using Monte Carlo techniques. Mean values of the Eigenvalue and Trace test statistics are reported in the table. Inference is unaffected by including four lags of the variables or taking the median values of the statistics. The last column reports the percentage of times (out of 10,000) that we conclude one cointegrating vector from the Johansen trace test. The trace tests were calculated using johmle.src written by Tom Doan and graciously provided on the Estima web site. The models were estimated in Rats 7.2.

Table 4: Monte Carlo Bai-Perron Estimates of the Inflation Regimes

Estimated Number of Breaks k	Implied Number of Inflation Regimes	Frequency
1	2	3
2	3	365
3	4	1146
4	5	2286
5	6	2768
6	7	1893
7	8	1037
8	9	387
9	10	115

Statistical analysis of the number of breaks k.
Mean: 4.99, Median: 5, Standard Deviation: 1.469, Skewness: 0.225, Kurtosis: - 0.194.

The number of breaks k is estimated in the model: $y_t^{MS} = \gamma_{k+1} + \tau_t$ using the Bai-Perron technique where y_t^{MS} is the generated mean shift inflation variable, γ_{k+1} is a series of $k+1$ constants that estimate the mean rate of inflation in each of $k+1$ inflation regimes and τ_t is a random error. Frequency is the number of y_t^{MS} series that have the estimated number of breaks. The 'true' number of breaks in the series is 8 implying 9 inflation regimes. See Appendix 2 for further details concerning the Bai-Perron technique for estimating structural breaks. Bai-Perron technique estimated using Gauss 5.0 assuming a minimum regime size of 9 periods.

Table 5: Monte Carlo Panel Estimates of the Phillips Curve using the Generated Mean Shift Variable y_t^{MS} and the Forcing Variable x_t

	Restricted Constant			Fixed Effects			
	F-P	NK	Hybrid	F-P	NK	Hybrid	ND
y_{t+1}^{MS}		0.9683 (8.0)	0.9400 (4.4)		0.1567 (0.3)	0.1408 (0.3)	
y_{t-1}^{MS}	0.5198 (8.0)		0.0260 (0.4)	0.0211 (0.3)		0.0188 (0.2)	
x_t	-0.0920 (-2.5)	-0.0237 (-0.5)	-0.0230 (-0.5)	- 0.1095 (- 2.5)	- 0.1060 (- 1.6)	- 0.1100 (- 1.4)	-0.1113 (-2.7)
Constant	0.0044 (5.6)	0.0003 (0.2)	0.0003 (0.3)	0.0090 (24.1)	0.0077 (18.9)	0.0077 (18.4)	0.0092 (24.6)
$\overline{R}^2$	0.415	0.231	0.216	0.599	0.477	0.433	0.598
LM(1)	[0.007]	[0.000]	[0.000]	[0.588]	0.061	[0.025]	[0.355]
LM(2)	[0.011]	[0.000]	[0.000]	[0.540]	[0.076]	[0.035]	[0.394]
LM(3)	[0.009]	[0.000]	[0.000]	[0.529]	[0.084]	[0.038]	[0.412]
LM(4)	[0.006]	[0.000]	[0.000]	[0.521]	[0.085]	[0.039]	[0.420]
DW	2.339	2.928	2.954	2.004	2.169	2.171	1.960
Wald Tests – probability values							
$\phi_f + \phi_b = 0$	[0.000]	[0.000]	[0.000]	[0.662]	[0.724]	[0.845]	
$\phi_f + \phi_b = 1$	[0.000]	[0.880]	[0.934]	[0.000]	[0.343]	[0.528]	
W	[0.000]	[0.000]	[0.000]	[0.164]	[0.218]	[0.255]	[0.141]
F Tests – probability values							
Significant Variables	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Fixed Effects				[0.000]	[0.001]	[0.000]	[0.000]

Reported as ( ) and [ ] are *t*-statistics and probability values respectively. The forcing variable is, x_t, and the dependent variable is, y_t^{MS}. The data are partitioned into inflation regimes as estimated by the Bai-Perron technique. Details of the number of breaks found in the inflation series are reported in Table 4. The cross section models are then estimated using the 2SLS estimator with three lags of x, and, y^{MS} as instruments. The process is repeated 10,000 times using Monte Carlo techniques with GAUSS 5.0. The data used in the analysis is identical to that used in the estimation of the models reported in Tables 1 and 2. In the first three columns the constant (or fixed effect) in each panel is restricted to be the same such that $\phi^1 = \phi^2 = .. = \phi^n$. The fixed effects models in columns 4 to 6 the reported constant is the weighted average of the fixed effects. LM(1) to LM(4) are the Breusch-Pagan Lagrange multiplier tests of first to fourth order serial correlation in the residuals. W tests the estimates parameters are equal to their 'true' values of $\delta_f = 0$, $\delta_b = 0$, and $\delta_x = -0.205406$ in the data generating process. 'Significant Variables' tests $\phi_f = \phi_b = \phi_z = \phi^n = 0$. 'Fixed Effects' tests that the fixed effects are zero such that $\phi^n = 0$.

Table 6: Panel Estimates of United States Phillips Curve
All Inflation Regimes

	Restricted Constant				Fixed Effects			
	F-P	NK	Hybrid	Markup Only	F-P	NK	Hybrid	Markup Only
Δp^n_{t+1}		0.9835 (14.4)	0.6888 (5.6)			0.0636 (0.2)	0.3819 (1.0)	
Δp^n_{t-1}	0.4642 (6.1)		0.2754 (2.7)		0.1263 (1.6)		0.1748 (1.8)	
Δp^n_{t-2}	0.1477 (1.8)							
Δp^n_{t-3}	0.2805 (3.6)							
mu_t	- 0.0409 (- 2.6)	- 0.0064 (- 0.3)	- 0.0153 (- 0.9)	- 0.2106 (- 9.7)	- 0.0527 (- 2.5)	- 0.0571 (- 2.2)	- 0.0411 (- 1.5)	- 0.0581 (- 2.7)
Constant	0.0205 (2.6)	0.0032 (0.3)	0.0076 (0.9)	0.1094 (10.5)	0.0330 (3.3)	0.0356 (2.6)	0.0236 (1.5)	0.0367 (3.5)
$\overline{R}^2$	0.786	0.711	0.785	0.340	0.838	0.827	0.816	0.835
AR(1)	[0.031]	[0.000]	[0.000]	[0.000]	[0.844]	[0.575]	[0.000]	[0.195]
AR(2)	[0.144]	[0.020]	[0.455]	[0. 000]	[0.020]	[0.033]	[0.119]	[0.024]
AR(3)	[0.088]	[0.668]	[0.668]	[0. 000]	[0.760]	[0.821]	[0.728]	[0.626]
AR(4)	[0.068]	[0.197]	[0.151]	[0. 000]	[0.551]	[0.542]	[0.285]	[0.729]
DW	2.121	2.769	3.027	0.485	2.048	1.886	2.665	1.82
Wald Tests – probability values								
Parameter Constancy	[0.000]	[0.209]	[0.383]	[0.000]	[0.134]	[0.336]	[0.128]	[0.413]
$\phi_f + \phi_b = 0$	[0.000]	[0.000]	[0.000]		[0.101]	[0.8426]	[0.197]	
$\phi_f + \phi_b = 1$	[0.044]	[0.809]	[0.545]		[0.000]	[0.004]	[0.303]	
F Tests – probability values								
Significant Variables	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Fixed Effects					[0.000]	[0.376]	[0.977]	[0.000]

Reported as ( ) and [ ] are *t*-statistics and probability values respectively. The dependent variable is, Δp^n_t. The forcing variable is the markup, mu_t. The panels consist of 9 cross-sections with 190 observations in total and 160, 150 and 150 usable observations in the F-P, NK and hybrid models respectively. See appendices 1 and 2 for details concerning the data and the estimation of the inflation regimes. Lag length chosen by lag exclusion F-tests in all models except the restricted constant markup only model in column 4 where further dynamics do not improve the system diagnostics. Instruments are three lags of the independent variables all models. Inference is not affected by the inclusion of fewer or more lags of the instruments. In the first three columns the constant (or fixed effect) in each panel is restricted to be the same such that $\phi^1 = \phi^2 = .. = \phi^9$. In the fixed effects models in columns 4 to 6 the reported constant is the weighted average of the fixed effects. AR(1) to AR(4) are the Arellano-Bond tests of first to fourth order serial correlation in the residuals. 'Parameter Constancy' tests the estimated parameters for Δp^n_t and mu_t are the same across inflation regimes. 'Significant Variables' tests $\phi_f = \phi_b = \phi_z = \phi^n = 0$. 'Fixed Effects' tests the fixed effects are zero such that $\phi^n = 0$. Models estimated with 2SLS using Stata/SE 8.2 and Eviews 5.1.

Table 7: Panel Estimates of United States Phillips Curve

Stationary and Non-stationary Inflation Regimes

	Stationary Inflation Regimes				Non-stationary Inflation Regimes			
	F-P	NK	Hybrid	Markup Only	F-P	NK	Hybrid	Markup Only
Δp^n_{t+1}		0.2392 (0.5)	0.4186 (0.9)			1.3338 (2.2)	1.0890 (2.2)	
Δp^n_{t-1}	0.0573 (0.7)		0.0845 (0.8)		0.7218 (2.1)		0.6563 (2.3)	
Δp^n_{t-2}								
Δp^n_{t-3}								
mu_t	- 0.0441 (- 2.2)	- 0.0438 (- 1.8)	- 0.0365 (- 1.4)	- 0.0469 (- 2.3)	- 0.4409 (- 1.7)	0.8562 (1.7)	0.5250 (1.3)	- 0.1455 (- 0.6)
Constant	0.0288 (2.9)	0.0272 (2.1)	0.0215 (1.4)	0.0306 (3.2)	0.2050 (1.8)	0.2331 (- 1.7)	- 0.2510 (- 1.3)	0.0853 (0.7)
$\overline{R}^2$	0.810	0.795	0.774	0.810	0.645	0.672	0.806	0.534
AR(1)	[0.429]	[0.012]	[0.000]	[0.708]	[0.199]	[0.795]	[0.743]	[0.154]
AR(2)	[0.065]	[0.090]	[0.152]	[0.068]	[0.480]	[0.019]	[0.011]	[0.062]
AR(3)	[0.546]	[0.227]	[0.245]	[0.555]	[0.134]	[0.328]	[0.368]	[0.007]
AR(4)	[0.399]	[0.305]	[0.292]	[0.403]	[0.181]	[0.038]	[0.452]	[0.243]
DW	2.051	2.378	2.747	1.94	2.624	1.812	1.839	1.306
Wald Tests – probability values								
Parameter Constancy	[0.253]	[0.669]	[0.393]	[0.261]	[0.867]	[0.972]	[0.527]	[0.566]
$\phi_f + \phi_b = 0$	[0.481]	[0.527]	[0.326]		[0.064]	[0.075]	[0.019]	
$\phi_f + \phi_b = 1$	[0.000]	[0.046]	[0.332]		[0.432]	[0.610]	[0.203]	
F Tests – probability values								
Significant Variables	[0.000]	[0.000]	[0.000]	[0.000]	[0.006]	[0.023]	[0.015]	[0.010]
Fixed Effects	[0.000]	[0.600]	[0.946]	[0.000]	[0.064]	[0.152]	[0.464]	[0.007]

All modes estimated with 2SLS fixed effects estimator. Stationary inflation regimes include regimes 1, 2, 3, 6, 7, 8 and 9 with 151 observations. Non-stationary inflation regimes include regimes 4 and 5 with 18 observations. Inference is unaffected by estimating with only 1 or 2 lags of independent variables as instruments. See also notes to Table 6.

Table 8: Estimates of the Long-run Phillips Curve

Linear: $$\overline{\Delta p} = \underset{(2.7)}{0.0628} - \underset{(-2.4)}{0.1113}\,\bar{z}, \quad R^2 = 0.14$$

The estimated coefficient on $\bar{z}$ is zero is rejected, $\chi_1^2 = 5.8176$, prob-value = 0.0159.

Non-linear: $$\overline{\Delta p} = \underset{(0.4)}{2.1174}\exp(\underset{(-2.0)}{-11.3433}\,\bar{z}), \quad R^2 = 0.13$$

The estimated coefficient on $\bar{z}$ is zero is rejected, $\chi_1^2 = 4.1256$, prob-value = 0.0422.

VAR-ECM (linear): $$\Delta p = 0.1761 - \underset{(-4.5)}{0.3503}\,z$$

Unrestricted cointegration rank test (Trace test) for the null hypothesis H_0: r=0 is 15.85 {15.50} and H_0: r = 1 is 3.79 {3.84} indicating we can accept 1 cointegrating vector at the 5 per cent level. The VAR-ECM includes inflation and the markup as endogenous variables and estimated with four lags.

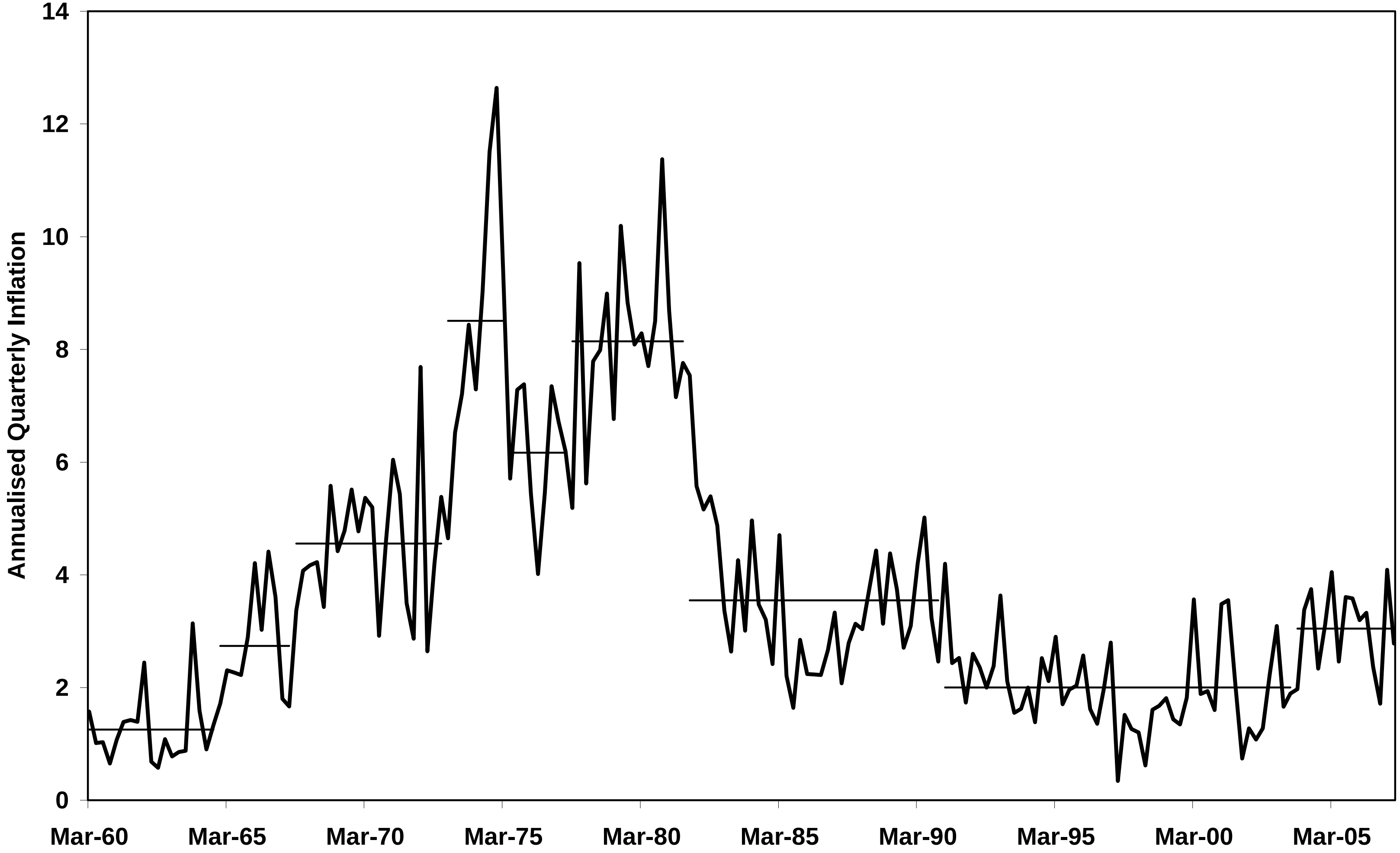
Notes: Numbers in ( ) and { } are *t* statistics and the 5 per cent Trace test critical values respectively.

Table 9: Estimates of the Hybrid United States Phillips Curves
Data from Cogley and Sbordone 2008

Time Series		Panel Estimation		
			Restricted Constant	Fixed Effects
$\Delta p\ gap_{t+1}$	0.9327 (4.0)	$\Delta p\ gap^{n}_{t+1}$	1.0839 (4.6)	0.0696 (0.1)
$\Delta p\ gap_{t-1}$	0.0224 (0.1)	$\Delta p\ gap^{n}_{t-1}$	0.0207 (0.1)	- 0.0073 (- 0.1)
$mu\ gap_{t}$	-0.0391 (- 0.6)	$mu\ gap^{n}_{t}$	0.0021 (0.1)	- 0.0347 (0.6)
Constant	- 0.0001 (- 0.1)	Constant	0.0000 (0.0)	0.0040 (1.7)
$\overline{R}^2$	0.503		0.4980	0.626
DW	2.895		3.051	2.124
Wald Tests – probability values				
$\phi_f + \phi_b = 0$	[0.000]*		[0.000]	[0.898]
$\phi_f + \phi_b = 1$	[0.537]*		[0.325]	[0.109]

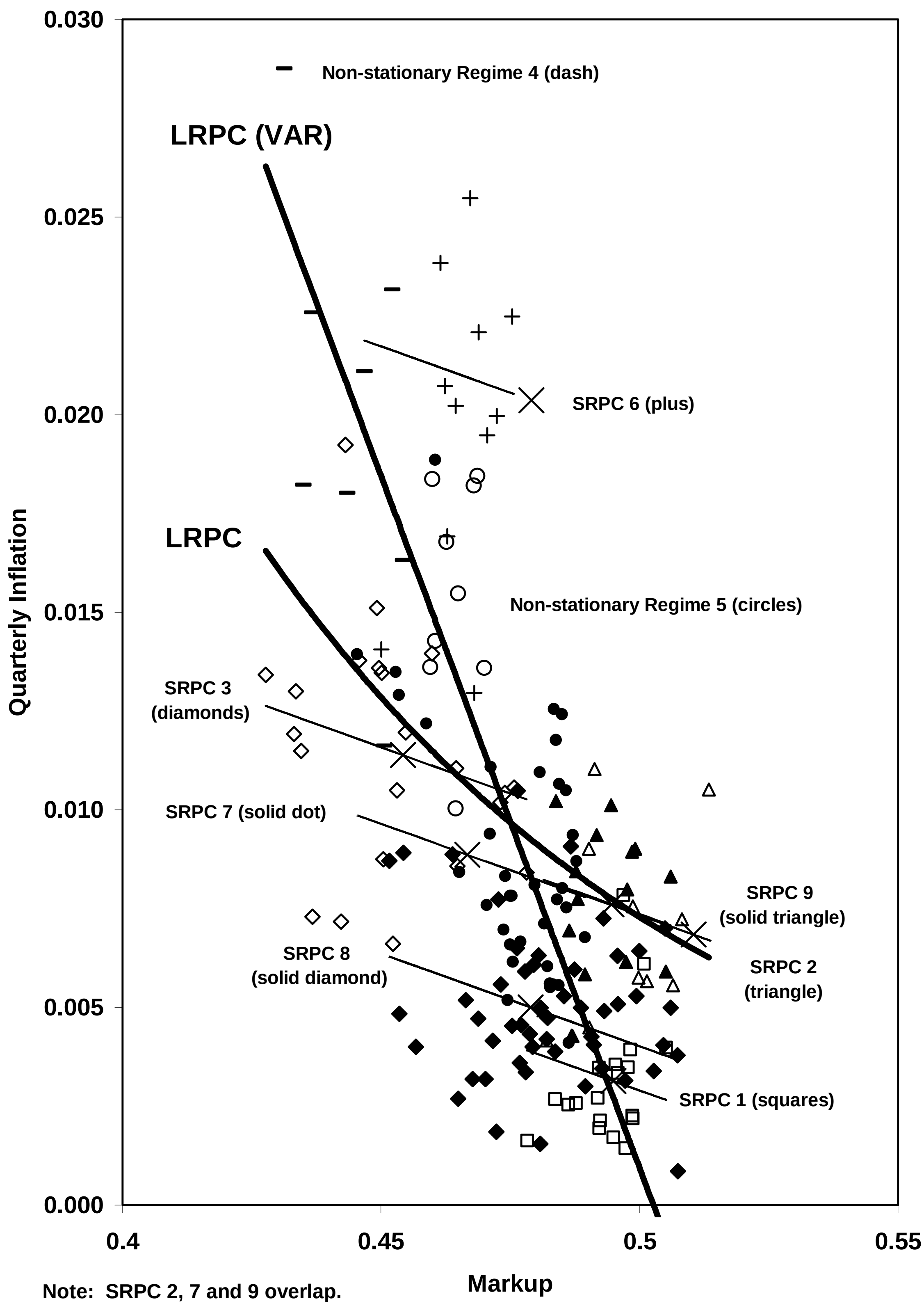
Reported as ( ) and [ ] are *t*-statistics and probability values respectively. Column 1 report time series estimates. Columns 2 and 3 report panel estimates where the data are partitioned in line with breaks identified with the Bai-Perron technique. The inflation, trend inflation, labour's income share and trend labour's income share data are from Cogley and Sbordone (2008) for the period March 1960 to June 2003. The inflation gap, $\Delta p\ gap$, is inflation less the BVAR estimate of trend inflation. The markup gap, $mu\ gap$, is the negative of labour's income share less the BVAR estimate of labour's income share. The dependent variable is the inflation gap and the forcing variable is the markup. The time series estimates are contain 170 observations. The panels consist of 9 cross-sections with 138 usable observations after allowing for instruments. Instruments are three lags of the independent variables for all models. Inference is not affected by the inclusion of fewer or more lags of the instruments. Models estimated with 2SLS using Eviews 5.1. * indicates F-tests. See also notes to Graph 3.

Graph 1: United States Quarterly Inflation, Seasonally Adjusted, March 1960 – June 2007



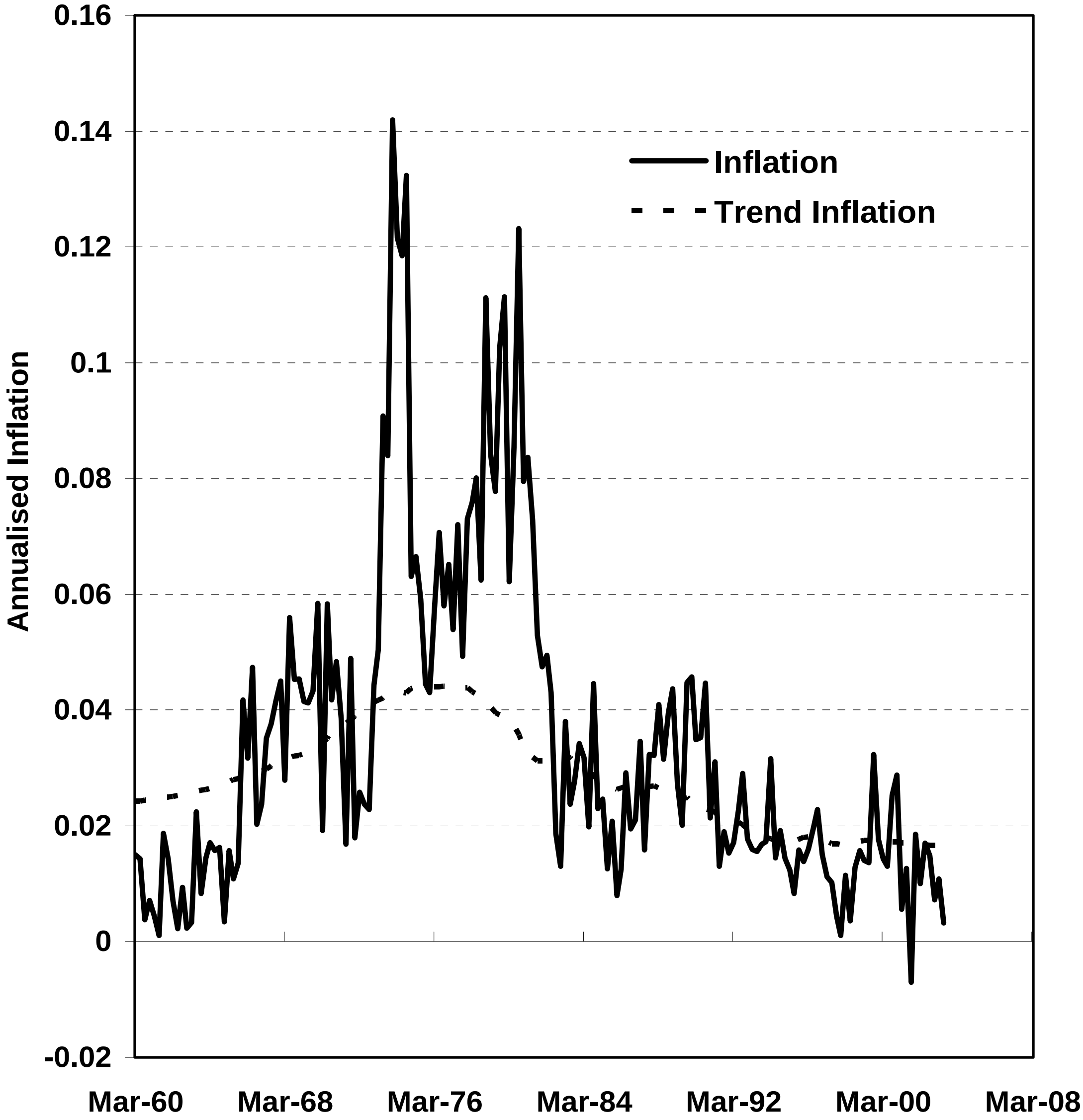
Notes: Horizontal dashed lines indicate the nine inflation regimes identified by the Bai-Perron technique (see Appendix 2 for details). Annualised quarterly inflation is measured as the change in the natural logarithm of the price index multiplying by 400.

Graph 2: United States Inflation and the Markup



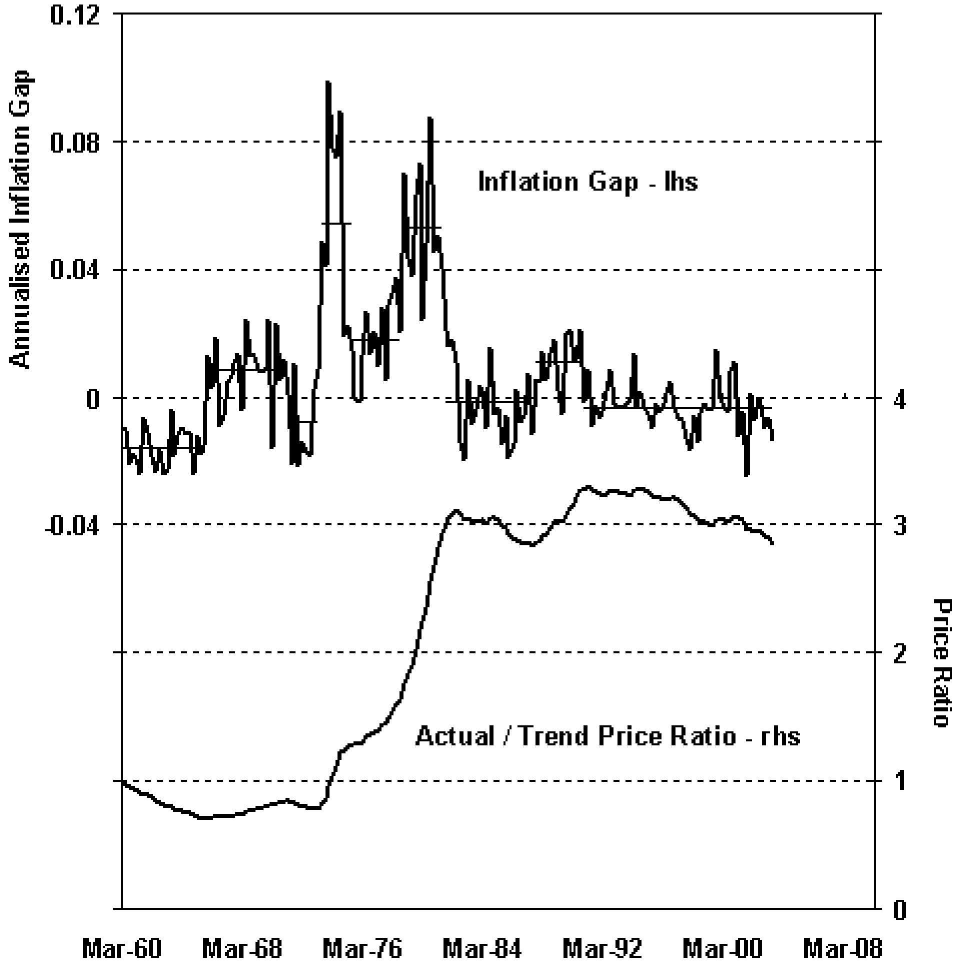
Note: SRPC 2, 7 and 9 overlap.

Graph 3: Cogley and Sbordone AER 2008 Inflation Data



Notes: The data is the same as that reported in Figure 1 of Cogley and Sbordone (2008). Inflation is measured as the change in the natural logarithm multiplied by four (to give the annualised rate) of the implicit gross domestic product deflator at market prices reported in Table 1.3.4 in the National Income and Product Account published by the United States Bureau of Economic Analysis. This is in contrast with our measure which is the same deflator but at factor cost to remove the direct effects on inflation of changes in indirect taxes and subsidies. While the later is theoretically appealing in practice the factor cost adjustment has little impact on the estimates. Trend inflation is the first stage BVAR estimate of inflation. See also the notes to Table 9 and Cogley and Sbordone (2008) for more detailed information concerning the data.

Graph 4: Cogley and Sbordone Inflation Gap and Implicit Ratio of Actual over Trend Price Levels



Notes: The inflation gap in the top panel is calculated as inflation less trend inflation from Graph 3 and is the same as that used in the second stage of the Cogley and Sbordone (2008). The horizontal thin lines in the top panel represent the mean inflation gap as identified using the Bai-Perron technique. See footnote 34 for details concerning the calculation of the Actual / Trend price ratio.