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

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ABSTRACT

Phillips curves are often estimated without due attention being paid to the underlying time series properties of the data. In particular, the consequences of inflation having discrete breaks in mean 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 biased, and therefore spurious, estimates of Phillips curves. We suggest a method to account for the breaks in mean inflation and obtain meaningful and unbiased estimates of the short- and long-run Phillips curves in the United States.

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1. INTRODUCTION

'Modern' Phillips curves since Friedman (1968) and Phelps (1967) have been mostly estimated without due attention being paid to the statistical properties of inflation.[1] For example, a large majority of papers that estimate Phillips curves use a range of estimators that are appropriate only if the data have a constant mean and therefore proceed on the explicit or implicit assumption that inflation is stationary.[2] 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 that argue there can be multiple long-run rates of inflation are empirically irrelevant. 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. Therefore, 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 and at worst seriously misleading as an assumption.

In contrast with the literature that proposes inflation to be a stationary process, it has recently become popular to estimate Phillips curves under the maintained assumption that inflation is an integrated process of order one.[3] However, Graph 1 shows that United States quarterly inflation over the last fifty years appears to be bounded below at around zero and above by

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1 The 'modern' theories include the Friedman-Phelps expectations augmented Phillips curve, New Keynesian and hybrid theories.

2 A small selection of the substantial literature on the Phillips curve includes 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).

3 See King and Watson (1994), Stock and Watson (2007), Ireland (2007), Cogley and Sborbone (2005, 2006, 2008), Russell and Banerjee (2008) and Schreiber and Wolters (2007).

some moderate rate of inflation.[4] Strictly speaking, therefore, inflation can again only approximate an integrated process.[5]

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.

Shifts in the mean rate of inflation can be seen in Graph 1. These visual shifts can be identified more formally with the Bai and Perron (1998, 2003a, 2003b) technique to estimate multiple breaks in the mean of the 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 consequences of possible over- and under-identification of the number of shifts in mean inflation later on in the paper (see Sections 3 and 5).

If inflation is really a stationary process around shifting means, the popular assumptions employed in the empirical literature that inflation is either stationary or integrated will lead to

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[4] The bounded nature of United States inflation is apparent in developed economies in general although the upper boundary may differ. 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.

[5] Russell (2006) makes these arguments in greater detail.

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

biased estimates of Phillips curves. For example, if the data are assumed stationary and the 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, 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 assumed incorrectly to be I(1) and the data are differenced then the estimates will also be biased. The standard empirical Phillips curve literature provides no evidence that these two popular 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 popular assumptions in the empirical Phillip 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. We demonstrate that the bias due to the unaccounted shifts in mean in the estimation process is large and can explain nearly all the standard results in the empirical 'modern' Phillips curve literature.

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. Our preferred approach is a panel methodology provided by Russell (2011) who models inflation as containing a time varying mean where the changes in mean are discrete and inflation is 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

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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.

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 as commonly incorporated 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 long-run relationship between inflation and the markup. The inability to find any significant role for expected inflation in the NK and hybrid Phillips curves may be because the standard approach in the empirical literature is a poor proxy for the formation of price expectations. Alternatively, it may be that price-setting agents are not as forward looking as modelled in the NK and hybrid theories. In contrast, the insignificant lags in inflation in the Phillips curve appear to be due to the inclusion of the markup which acts as an error correction mechanism. If the markup is excluded from the Phillips curve then the lag in inflation is significant and considerably less than one as demonstrated in Section 4 although the lead in inflation remains insignificantly different from zero.

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 calculating 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.

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]

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

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, Galí 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 Galí and Gertler (1999) and Galí,

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

Gertler and Lopez-Salido (2001) incorporate agents that are both backward and forward looking and $\delta_f + \delta_b = 1 - d$.[9]

While the magnitude of the discount rate, d, is not identified explicitly in the theories without supplementary assumptions most of the empirical work on the NK and hybrid models proceed on the assumption that $d = 0$. 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'.

The empirical Phillips curve literature over the past thirty five years produces remarkably similar results. In the F-P and NK 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. This is interpreted as evidence that forward looking agents dominate backward looking agents in the price setting process. The 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.

2.2 Generating inflation as a stationary process

To examine the biases due to assuming inflation is stationary or integrated 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 based on those 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:

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9 Equation (1) is this paper's point of departure from the standard Phillips curve literature. Due to space constraints we have not set out the micro-foundations of equation (1) and instead refer the reader to the Phillips curve references cited above and the clear exposition provided by Woodford (2003) and Galí (2008).

$$x_t = 0.937967 x_{t-1} + \omega_t \quad (2)$$

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.[10] 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

$$y_t = -0.205406 x_t + \upsilon_t \quad (3)$$

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 estimating equation (1) using United States inflation and markup data with the dynamic inflation terms restricted to zero. 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 are estimated 10,000 times using Monte Carlo techniques to obtain the average values of the statistics and estimated coefficients from the models.[11]

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10 See Appendix A for further details concerning the generated data.

11 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.

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:

$$y_t^{MS} = y_t + \mu_t^i \qquad (4)$$

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 inflation data, y_t^{MS}, and the forcing variable, x_t. In the NK and hybrid models the lead in inflation is significantly greater than zero and insignificantly different from 1. In the F-P 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). The Monte Carlo analysis demonstrates that the shifts in the mean rates of inflation alone can generate the NK and hybrid Phillips curve result that the sum of the coefficients on the dynamic inflation terms is insignificantly different from 1. For the F-P 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 Galí and Gertler (1999) to use labour's income share which they find significant in their estimated Phillips curve model.[12]

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.[13]

A popular approach in the literature is to then proceed to difference the data so as to remove the unit root.[14] Equation (1) is therefore re-parameterised as:

$$\Delta^2 p_t = \psi_f \, E_t\left(\Delta^2 p_{t+1}\right) + \psi_b \, \Delta^2 p_{t-1} + \psi_z \, \Delta z_t + \omega_t \qquad (5)$$

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 (5) are estimated with the GMM

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12 Galí 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.

13 In contrast the mean ADF test statistic of – 3.778 for the generated stationary data, y_t, strongly suggests the data is stationary (critical values of -3.467, -2.877 and -2.575 at the 1, 5 and 10 per cent levels respectively).

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

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 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.

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 (4)? The solution suggested in Russell (2011) is to 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:

$$\Delta p_t^n = \phi^n + \phi_f \, E_t^n \left(\Delta p_{t+1}^n\right) + \phi_b \, \Delta p_{t-1}^n + \phi_z \, z_t^n + \eta_t^n \qquad (6)$$

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 3 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 estimated structural breaks model 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 3 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 4. 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 4. 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 4. 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 final column headed ND excludes the insignificant dynamic inflation terms from the estimated model and shows that the estimate of the coefficient of the forcing variable is insignificantly different from its ‘true’ value.

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 4). 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.

A result of some interest reported here and in Table 1 is that 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.

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 than 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 and insignificant may simply be due to the unaccounted shifts in the mean rate of inflation.

These Monte Carlo results also lead us to the stark conclusion that the standard estimation of Phillips curves, based either on the assumption that inflation is stationary or that it is necessary to difference the data prior to estimation, provide unreliable results and cannot therefore be used to validate any of the competing 'modern' Phillip curve theories.

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.[15] Two panel estimators present themselves. The random effects estimator 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 models are reported below. 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.

Using this approach to estimating Phillips curves has a number of advantages. The Monte Carlo analysis above demonstrates that even when the Bai-Perron technique fails to identify

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15 For a very clear exposition of estimating dynamic time series models using panel techniques see Bond (2002) and Hsiao (2003).

the inflation regimes exactly the biases due to any remaining non-stationarity in the data are insignificantly small. Consequently, the panel approach provides unbiased estimates of the coefficients on expected inflation, ϕ_f , and lagged inflation, ϕ_b, in equation (6) allowing us to enquire into the veracity of the three competing ‘modern’ Phillips curve theories. It is also the case that 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 as the instruments at the start of a regime would be drawn from the end of the preceding regime. And finally, based on the estimates we can examine the proposition that the long-run Phillips curve is vertical with some confidence.

3.1 Estimates of the United States Phillips Curves

Table 5 reports 2SLS estimates of the F-P, NK and hybrid Phillips curves from equation (6) using two lags of inflation and the forcing variable as instruments.. Columns 1 to 3 of Table 5 report the panel estimates with the restriction that the estimated constant from each regimes is the same such that, $\phi^1 = \phi^2 = . . . = \phi^9$. 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 5 are the fixed effects estimates of the Phillips curves.[16] 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. 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 only the regimes that we are confident are 'stationary' (regime numbers 1, 2, 3, 6, 7, 8, and 9) using the panel technique. The results are reported in columns 9 to 12 of Table 5. 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. These results 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. 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.

4. 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.

16 The test that the coefficients ϕ_f, ϕ_b and ϕ_z are the same across inflation regimes cannot be rejected at the 5 per cent level of significance. See 'parameter constancy' in Table 5.

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.[17] If we estimate a panel AR(1) model of inflation using only the 'stationary' inflation regimes (i.e. regimes 1, 2, 3, 6, 7, 8 and 9) then the estimated autoregressive coefficient is 0.1596 with a standard error of 0.0662 and a *t*-statistic of 2.4.[18] This implies a median adjustment lag back to the mean rate of inflation of around 0.38 of one quarter. 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 with a standard error of 0.0676 and a *t*-statistic of -13.0 implying a similar median adjustment lag of 0.33 of one quarter.[19] 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.[20] This implies an infinite median adjustment lag. However, this estimation of persistence proceeds under the erroneous assumption that inflation has a constant mean.[21]

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

18 Further lags in the AR model of inflation are insignificant.

19 This is a re-parameterisation of the markup only model in column 12 of Table 5 so as to estimate the adjustment coefficient in the error correction model.

20 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.

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

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 '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 '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 remains. 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. This 'successful central bank policy' example is irrelevant only if the set of all possible inflation outcomes does not include a stationary process.

Finally, the question is not why is inflation so very persistent? Since Perron (1989) we know the answer to that. It is because of the shifts in mean inflation. The question is why is the persistence in inflation around its shifting mean so very low? The answer is that inflation depends very strongly on the mean rate of inflation and not on past or future rates of inflation.

5. An Alternative Hypothesis: 'Over-breaking' of the Data

Some observers might argue that some or all of the eight breaks in mean inflation that we identify are invalid and represent 'over-breaking' the data relative to the 'true' number of breaks. If correct this over-breaking of the data would introduce a downward bias in both our estimates of persistence and the dynamic inflation terms in our estimated Phillips curves. These observers would further argue that an alternative hypothesis is that inflation is a highly persistent process with no breaks in mean and that our finding of low inflation persistence is simply due to the over-identification of eight invalid breaks in the mean rate of inflation.[22]

[22] The alternative hypothesis could instead characterise inflation as a highly persistent process with a small number of breaks in mean. However, allowing for a small number of breaks in the DGP makes it easier to

To examine this alternative hypothesis we conduct the following experiment. First we generate 190 observations of data, w_t:

$$w_t = \alpha w_{t-1} + \upsilon_t \qquad (7)$$

where $w_0 = 0$, α is the measure of persistence and υ_t is a random draw from a normal distribution with a mean of zero and a standard error of $\sigma = 0.003272$.[23] Second, the Bai-Perron technique is applied to the generated data (break in mean model: $w_t = \gamma_{k+1} + \tau_t$) to identify k breaks in mean before partitioning the data into unbalanced cross-section time series panels. Third, we use the cross-section panel methodology outlined above to estimate an AR(1) model of the generated data, w_t:

$$w_t^n = \upsilon_0^n + \upsilon_1 w_{t-1}^n + \varepsilon_t^n \qquad (8)$$

with the fixed effects ordinary least squares (OLS) estimator to retrieve the estimated coefficients and standard errors where υ_0^n and ε_t^n are the fixed effects and disturbance terms respectively and $n = k + 1$. The process is repeated 10,000 times applying breaks $k = 0$ to 15 to the generated data using Monte Carlo techniques and the mean values of the estimated coefficients and standard errors are retrieved.[24]

The top two panels of Graph 2 show the mean estimated AR(1) coefficients form the Monte Carlo simulations after imposing breaks $k = 0$ to 15 in highly persistent data assuming $\alpha = 1.0$ and $\alpha = 0.844559$ in the data generating process (DGP) described by equation (7). The former is a common assumption in the empirical Phillips curve literature that inflation is

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reject the alternative hypothesis outlined here. Consequently, we assume no breaks in mean in the DGP to make it more difficult to commit a type one error with the experiment.

23 The number of observations is equal to that used in the estimation of United States Phillips curves in Section 3 and the standard error is from an AR(1) model of United States inflation. The Monte Carlo analysis was estimated with Rats 7.2 with a seed value of 171193.

24 The distributions of the estimated coefficients in the Monte Carlo analysis are uni-modal and not heavily skewed. Inference is unaffected by focussing on the median value of the estimated parameters. Almost identical empirical results are obtained if we estimate an AR(1) time series model of the generated data using OLS and a series of shift dummies to account for the shifts in mean identified by the Bai-Perron technique.

a random walk and the later is the estimated AR(1) coefficient of United States inflation data used in Section 3. The thick line represents the relationship between the mean of the estimated coefficients and the number of invalid breaks. The thin lines delineate the 95 per cent confidence interval of the estimated AR(1) coefficients.

The top two panels demonstrate that 'over-breaking' highly persistent data does introduce a downward bias to the estimated AR(1) coefficient. However, what is striking is the change in the bias diminishes with the increasing number of breaks and the mean estimated coefficient converges on a lower boundary of around 0.57 and 0.46 when α equals 1.0 and 0.844559 respectively. The diminishing change in the bias with increasing breaks is not entirely surprising. The Bai-Perron technique ranks the breaks in mean from largest to smallest and therefore as we increase the number of breaks in the estimated model the size of the breaks diminishes along with any additional bias. However, note that this bias is due to identifying *invalid* and not valid breaks in the data.

What is remarkable about this experiment is that it gives an almost unequivocal rejection of the alternative hypothesis that our estimate of low United States inflation persistence is due to the 'over-breaking' of highly persistent data. Consider the top panel of Graph 2 when the generated data are a random walk with $\alpha = 1.0$. Shown as dashes on the graph are the minimum and maximum values of the estimated AR(1) coefficients when we impose eight breaks.[25] Also shown on the graph as a solid dot is our estimate of United States inflation persistence (0.1596) along with the associated 95 per cent confidence interval shown as triangles.[26] The upper 95 per cent confidence interval of United States inflation persistence is less than the minimum estimated AR(1) coefficient from the Monte Carlo simulations by a wide margin. Even when the data are generated assuming $\alpha = 0.844559$ the upper 95 per cent confidence interval of United States inflation only overlaps with 0.0338 of the first percentile of the distribution of estimated AR(1) coefficients from the Monte Carlo simulations (see the middle panel of Graph 2). We might conclude therefore that our estimate

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25 We incorporate eight breaks in the empirical model of United States inflation estimated in Section 3.

26 The upper 95 per cent confidence interval is equal to 0.1596 plus 1.96 times the standard error of the estimate, 0.0662 which equals 0.2920.

of United States inflation persistence of 0.1596 is extremely unlikely to be due to the over-breaking of highly persistent data.

One might also ask whether we can be confident that the eight breaks that we identify are valid. The lower panel of Graph 2 repeats the exercise assuming a DGP of low persistence where $\alpha = 0.2$. What we find is that if we impose two invalid breaks on the generated data the estimated coefficients are on average only very marginally significant. In a modelling sense we would not impose more that 2 breaks on the data. Consequently, given our low estimate of United States inflation persistence is significantly greater than zero after imposing eight identified breaks in mean we can be confident that the number of breaks we identify are valid in a statistical sense and that the estimated low inflation persistence reflects some underlying economic relationship rather than due to the over-breaking of highly persistent data.

6. ESTIMATES OF THE 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. This does not mean that the long-run Phillips curve is not vertical. Instead, to identify the long-run Phillips curve we need to first identify the 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 long-run value of the forcing variable, $\bar{z}^n$, in inflation regime, *n*, from equation (6) as:

$$\bar{z}^n = \frac{1}{\phi_z}\left[\overline{\Delta p}^n \left(1 - \phi_f - \phi_b\right) - \phi^n\right] \tag{9}$$

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 (6). However, in the fixed effects model $\phi^n = \overline{\Delta p}^n (1 - \phi_f - \phi_b) - \phi_z \bar{z}^n$ and the long-run value of the forcing variable is therefore its mean value.[27]

If we further assume that the n combinations of the long-run rates of inflation and the long-run values of the forcing variable lie loosely along the 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.

Table 6 provides two estimates of the long run Phillips curve using the markup only model estimated with the inflation regimes that we are confident are stationary (see column 12 of Table 5).[28] The first is an ordinary least squares estimate of the linear long-run Phillips curve. We see that there is a significant negative slope to the long-run Phillip curve of -0.2120. Given the long-run Phillips curve cannot be linear if it is not vertical a non-linear exponential model of the long-run Phillips curve is also estimated:[29]

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

The non-linear model is estimated in its linear form and also reported in Table 6. Both estimates of the long-run Phillips curve suggest that the curve has a small, significant negative slope where higher long-run rates of inflation are associated with a lower long-run markup. Given the long-run Phillips curve cannot be linear if it is not vertical then the non-linear long-run Phillips curve appears a better representation of the long-run inflation-markup relationship in the data.

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27 To be consistent with the short-run panel estimates the means of inflation and the markup are calculated over each regime less the first three observations to account for the instruments in the panel estimation.

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

29 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.

6.1 A graphical representation of the results

Graph 3 provides a graphical representation of the estimated 'markup only' model reported in column 12 of Table 5. 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. Finally, the thick line denoted LRPC is the non-linear long-run Phillips curve reported in Table 6.[30]

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.

7. 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 a stationary process around discrete shifts in mean. The Bai-Perron panel approach discussed above is within this framework.

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

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[30] 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.

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. 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.

The top panel of Graph 4 reproduces the Cogley and Sbordone inflation (solid line) and trend inflation (dashed line) data.[33] 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 4. The Cogley and Sbordone inflation gap is measured as the difference between actual and trend inflation and this is shown in the bottom 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 the top panel of Graph 4 are largely repeated in the inflation gap

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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 data are from Figure 1 of Cogley and Sbordone (2008). See the notes to Table 7 and Graph 3 for details of the data.

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.

To this end Table 7 reports single equation estimates of the hybrid Phillips curve using the Cogley and Sbordone measures of the inflation gap and markup gap.[34] 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 bottom panel of Graph 4 as thin horizontal lines. The data are then partitioned in line with the identified breaks in mean and the panel estimates are reported in Table 7. 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 in column 3 that allow for the changes in the mean inflation gap across episodes 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 12 in Table 5 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 4 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

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

found by Cogley and Sbordone in the hybrid Phillips curve to be due to insufficient de-meaning of the inflation data.

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.

8. 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 Sections 3 and 4 suggest the persistence of inflation around any particular mean rate of inflation is very low. This is in stark contrast with all 'modern' Phillips curve theories that conclude the sum of the dynamic inflation terms is equal, or very nearly equal, to one. 'Modern' Phillips curve theories very strongly predict that inflation is an integrated or near integrated process.

Second, we can find little or no evidence that the lead in inflation as argued and commonly 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. Fourth, given the New Keynesian model is not supported empirically the markup should be interpreted on an empirical level as an error correction mechanism.[35] On a behavioural level the markup may

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[35] 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.

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).

While our analysis above does not support the behaviour underpinning the Friedman-Phelps model it does reveal 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 mean rates of inflation and the long-run markup.

9. 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.

Finally, this paper demonstrates that assuming data are 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 are 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 magnitude 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.

10. References

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.

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.

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.

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., Galí, 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.

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.

Galí, J., (2008). *Monetary Policy, Inflation and the Business Cycle: An Introduction to the New Keynesian Framework:* Princeton University Press, Princeton.

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

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

Galí, 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.

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.

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.

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.

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. (2011). Non-stationary Inflation and Panel Estimates of United States Short and Long-run Phillips Curves, forthcoming in the *Journal of Macroeconomics*.

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 (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

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.

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.

Woodford, M. (2003). *Interest and Prices: Foundations of a Theory of Monetary Policy*, Princeton University Press, Princeton.

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

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 (NIPA Table 1.10, line 10) less taxes (NIPA Table 1.10, line 9). GDP implicit price deflator is nominal GDP at factor cost divided by constant price GDP at 2000 prices (NIPA 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 (NIPA 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.

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 Durbin-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^{MS}_{t+1}		- 0.3772 (- 0.5)	- 0.4464 (- 0.7)
Δy^{MS}_{t-1}	- 0.6013 (- 6.6)		- 0.6006 (- 4.6)
Δy^{MS}_{t-2}	- 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^{MS}_t. 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: 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 4: 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)
$\bar{R}^2$	0.415	0.231	0.216	0.599	0.477	0.433	0.598
LM(1) LM(2) LM(3) LM(4)	[0.007] [0.011] [0.009] [0.006]	[0.000] [0.000] [0.000] [0.000]	[0.000] [0.000] [0.000] [0.000]	[0.588] [0.540] [0.529] [0.521]	0.061 [0.076] [0.084] [0.085]	[0.025] [0.035] [0.038] [0.039]	[0.355] [0.394] [0.412] [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 5: Panel Estimates of United States Phillips Curve

	All Inflation Regimes								Stationary Inflation Regimes			
	Restricted Constant				Fixed Effects				Fixed Effects			
	F-P	NK	Hybrid	Markup Only	F-P	NK	Hybrid	Markup Only	F-P	NK	Hybrid	Markup Only
	1	2	3	4	5	6	7	8	9	10	11	12
Δp_{t+1}^{n}		0.9835 (14.4)	0.6888 (5.6)			0.0636 (0.2)	0.3819 (1.0)			0.2392 (0.5)	0.4186 (0.9)	
Δp_{t-1}^{n}	0.4642 (6.1)		0.2754 (2.7)		0.1263 (1.6)		0.1748 (1.8)		0.0573 (0.7)		0.0845 (0.8)	
Δp_{t-2}^{n}	0.1477 (1.8)											
Δp_{t-3}^{n}	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)	- 0.0441 (- 2.2)	- 0.0438 (- 1.8)	- 0.0365 (- 1.4)	- 0.0469 (- 2.3)
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)	0.0288 (2.9)	0.0272 (2.1)	0.0215 (1.4)	0.0306 (3.2)
$\overline{R}^2$	0.786	0.711	0.785	0.340	0.838	0.827	0.816	0.835	0.810	0.795	0.774	0.810
AR(1)	[0.031]	[0.000]	[0.000]	[0.000]	[0.844]	[0.575]	[0.000]	[0.195]	[0.429]	[0.012]	[0.000]	[0.708]
AR(2)	[0.144]	[0.020]	[0.455]	[0. 000]	[0.020]	[0.033]	[0.119]	[0.024]	[0.065]	[0.090]	[0.152]	[0.068]
AR(3)	[0.088]	[0.668]	[0.668]	[0. 000]	[0.760]	[0.821]	[0.728]	[0.626]	[0.546]	[0.227]	[0.245]	[0.555]
AR(4)	[0.068]	[0.197]	[0.151]	[0. 000]	[0.551]	[0.542]	[0.285]	[0.729]	[0.399]	[0.305]	[0.292]	[0.403]
DW	2.121	2.769	3.027	0.485	2.048	1.886	2.665	1.82	2.051	2.378	2.747	1.94
Wald Tests – probability values												
Parameter Constancy	[0.000]	[0.209]	[0.383]	[0.000]	[0.134]	[0.336]	[0.128]	[0.413]	[0.253]	[0.669]	[0.393]	[0.261]
$\phi_f + \phi_b = 0$	[0.000]	[0.000]	[0.000]		[0.101]	[0.8426]	[0.197]		[0.481]	[0.527]	[0.326]	
$\phi_f + \phi_b = 1$	[0.044]	[0.809]	[0.545]		[0.000]	[0.004]	[0.303]		[0.000]	[0.046]	[0.332]	
F Tests – probability values												
Significant Variables	[0.000]	[0.000]	[0.000]	[0.000]	[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]	[0.000]	[0.600]	[0.946]	[0.000]

Notes to Table 5

Reported as ( ) and [ ] are *t*-statistics and probability values respectively. The dependent variable is, Δp_t^n and the forcing variable is the markup, mu_t. The panels for 'all the inflation regimes' 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. The 'stationary inflation regimes' include regimes 1, 2, 3, 6, 7, 8 and 9 with 151 observations. 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 in all models. Inference is not affected by the inclusion of fewer or more lags of the instruments. In columns 1 to 4 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 5 to 12 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_t^n 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 6: Estimates of the Long-run Phillips Curve

Linear:

$$\overline{\Delta p} = \underset{(14.3)}{0.1109} - \underset{(-13.4)}{0.2120}\,\bar{z}, \quad \bar{R}^2 = 0.32$$

The estimated coefficient on $\bar{z}$ is zero is rejected, $\chi_1^2 = 179.1191$, prob-value = 0.0000. Standard error of the regression: 0.0049.

Non-linear Exponential Model

$$Ln\left(\overline{\Delta p}\right) = \underset{(2.8)}{5.8436} - \underset{(-5.1)}{22.2860}\,\bar{z}, \quad \bar{R}^2 = 0.34$$

The estimated coefficient on $\bar{z}$ is zero is rejected, $\chi_1^2 = 26.1511$, prob-value = 0.0000. Standard error of the regression: 0.4920.

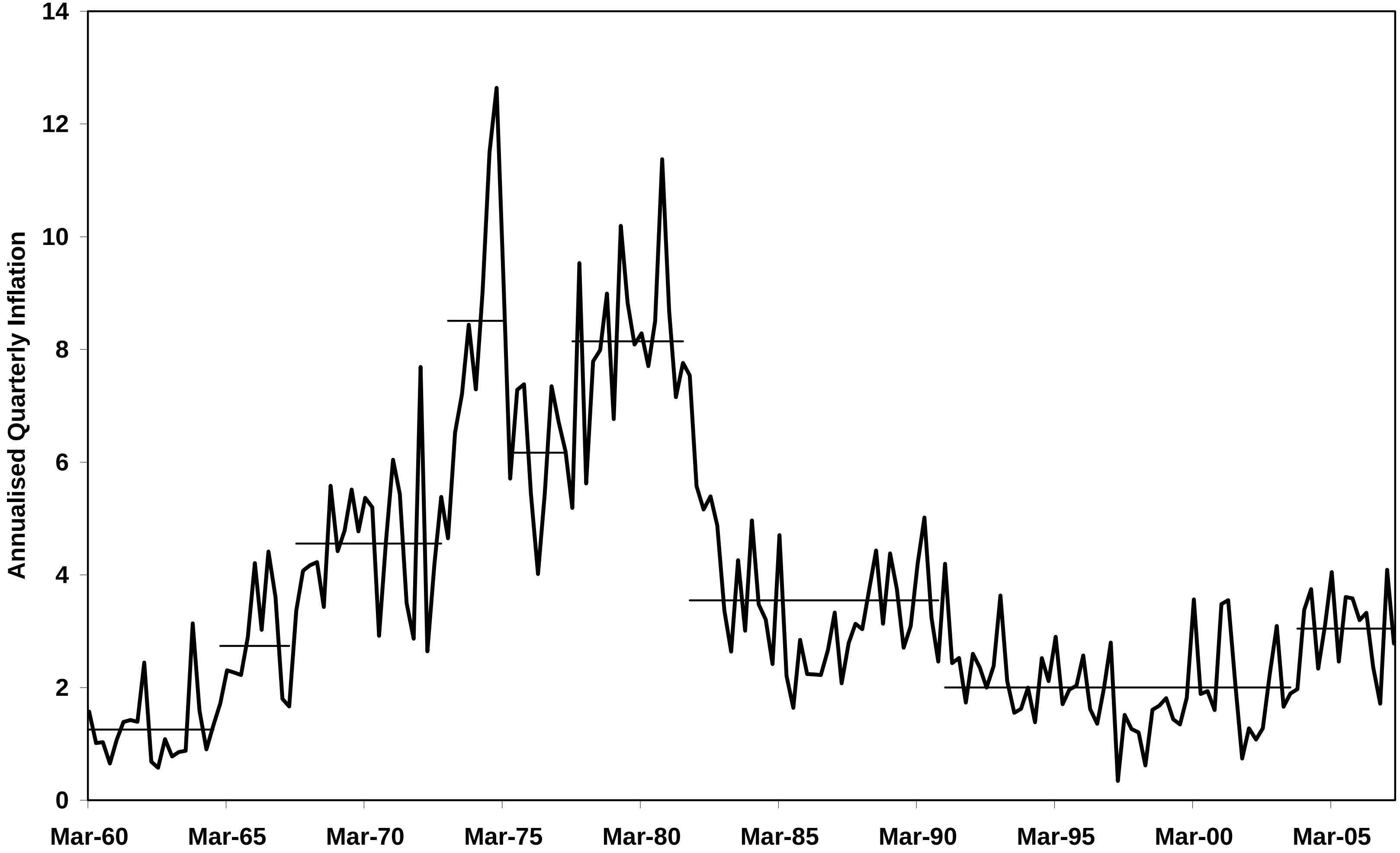
Notes: Numbers in ( ) are *t* statistics . The models are estimated using ordinary least squares in Eviews 7.1 with Newey-West HAC standard errors on 7 combinations of the long-run rate of inflation and long-run markup calculated from column 12 of Table 5.

Table 7: 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]

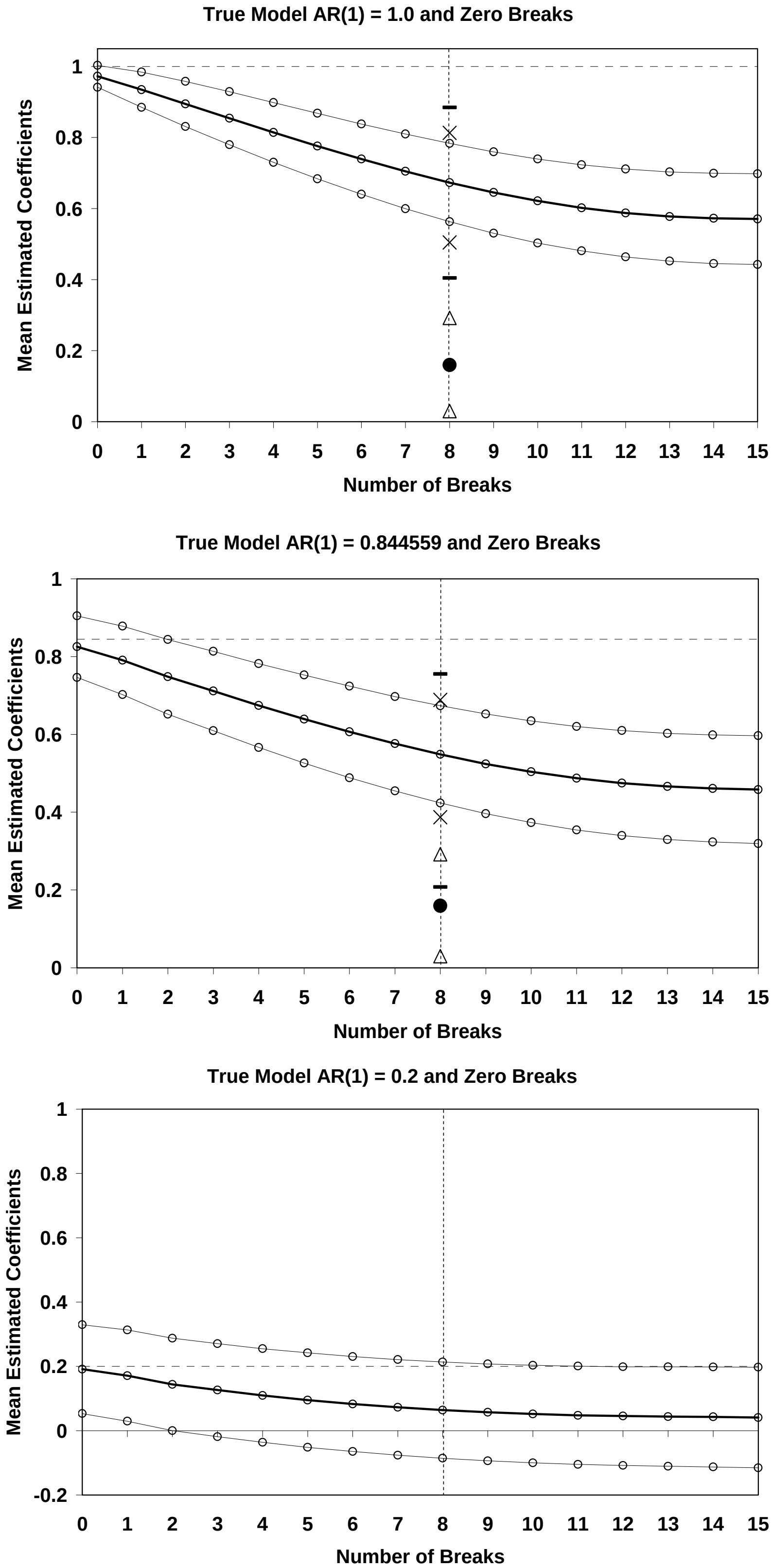
Reported as ( ) and [ ] are *t*-statistics and probability values respectively. Column 1 report time series estimates. Columns 2 and 3 report panel estimates where the data are partitioned in line with breaks identified with the Bai-Perron technique. The inflation, trend inflation and labour's income 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 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 gap. The time series 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-test instead of Wald test. See also notes to Graph 3.

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



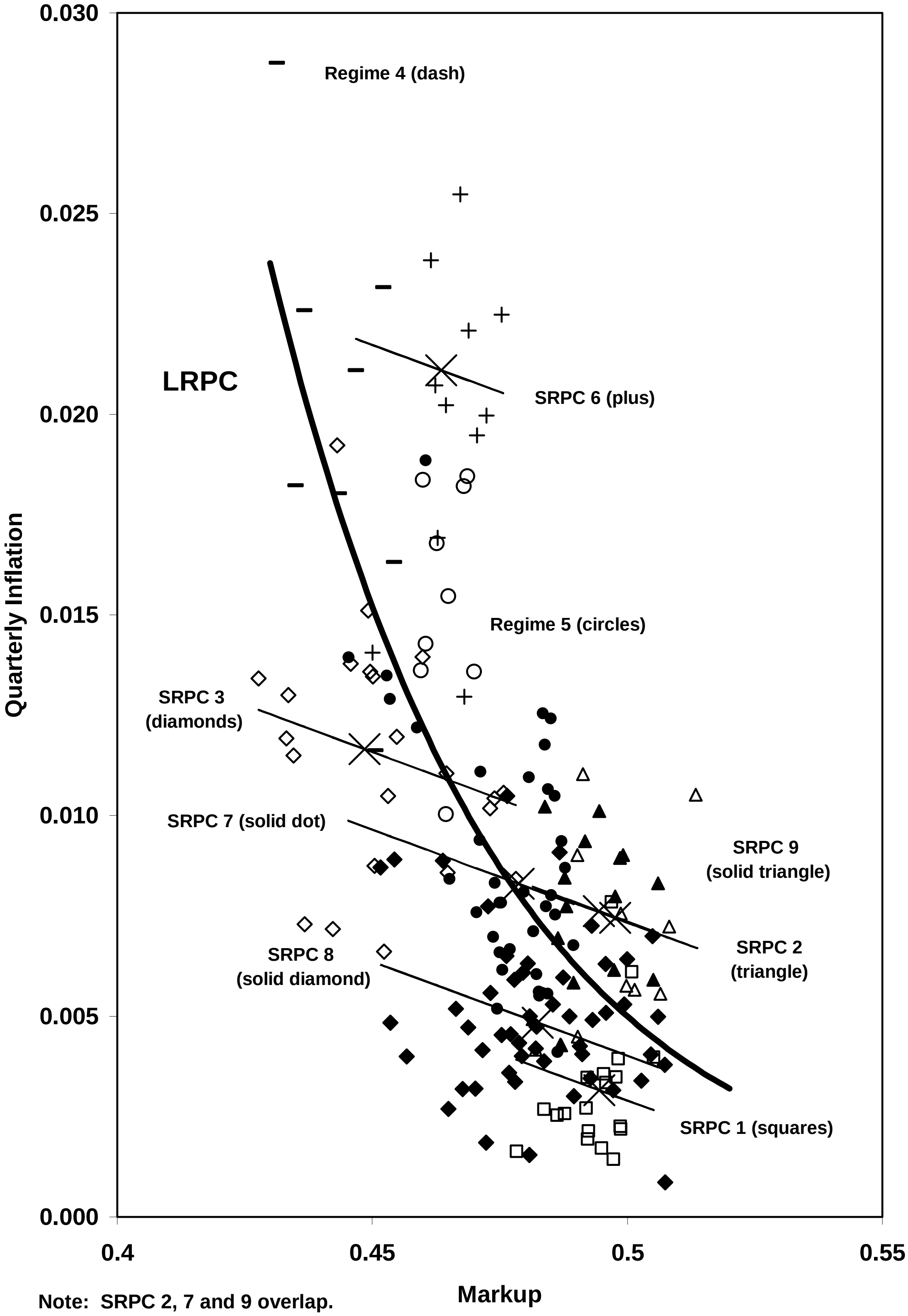
Notes: Horizontal dashed lines indicate the nine inflation regimes identified by the Bai-Perron technique (see Appendix 2 for details). Annualised quarterly inflation is measured as the change in the natural logarithm of the price index multiplying by 400.

Graph 2: The Impact of Over-breaking on Estimates of the AR(1) Coefficients



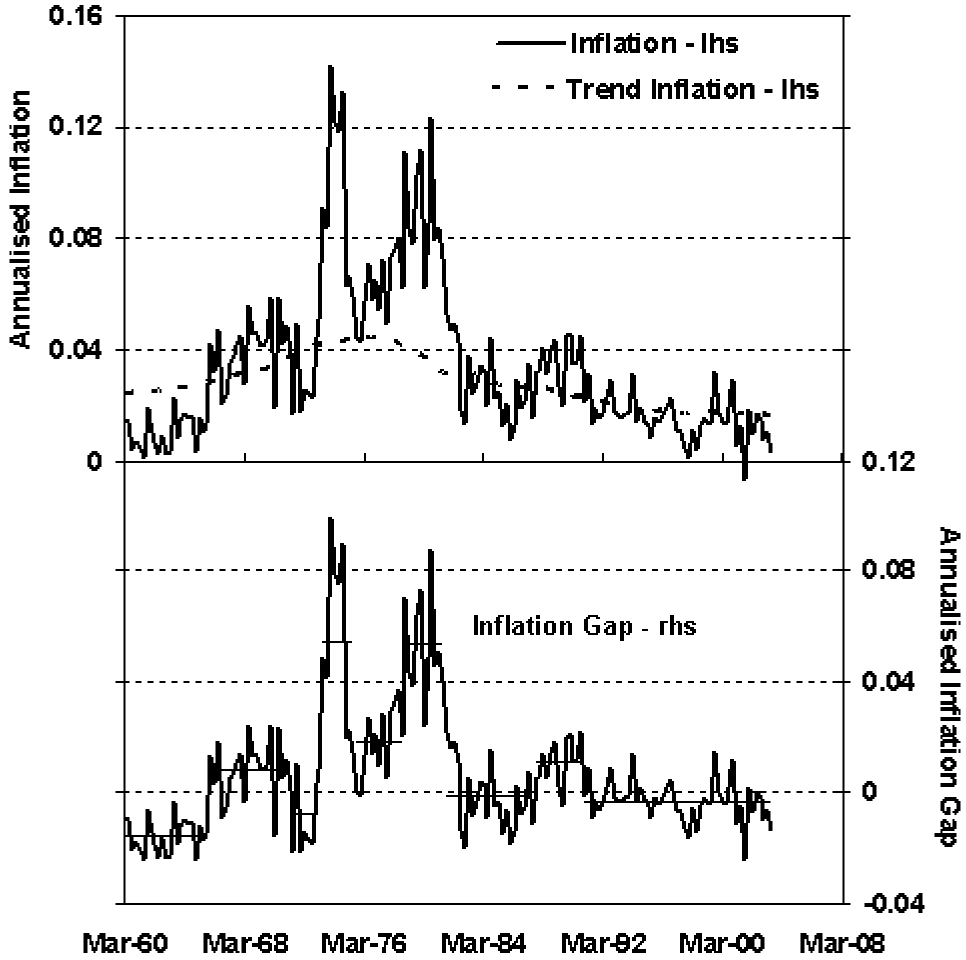
Notes: The dashes and crosses represent the maximum and minimum values and the first and 99th percentile estimates from the estimated AR(1) coefficients assuming eight breaks. The solid dot is the estimated United States inflation persistence of 0.1596 and the triangles delineate the 95 per cent confidence interval of the estimated persistence.

Graph 3: United States Inflation and the Markup



Note: SRPC 2, 7 and 9 overlap.

Graph 4: Cogley and Sbordone AER 2008 Inflation Data



Notes: In the top panel the data are the same as that reported in Figure 1 of Cogley and Sbordone (2008). Inflation is measured as the quarterly 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 and the markup 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 7 and Cogley and Sbordone (2008) for more detailed information concerning the data. In the bottom panel the inflation gap is calculated as inflation less trend inflation from the top panel and is the same as that used in the second stage of the Cogley and Sbordone (2008). The horizontal thin lines in the bottom panel represent the mean inflation gap for each episode as identified using the Bai-Perron technique.
