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The Markup and the Business Cycle Reconsidered

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The Markup and the Business Cycle Reconsidered*

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Abstract

A fresh interpretation is provided of the influential finding that the markup of prices over marginal costs is counter-cyclical. Using Rotemberg and Woodford's (1991) data set we argue that the markup is best modelled as a variable that is integrated of order one. A consequence of this finding is that the markup cannot be related in the long run with business-cycle variables since these are traditionally thought of as being stationary. A distinction must therefore be made between the long- and the short-run in characterizing the behaviour of the markup. It is shown that the markup is negatively related to inflation in the *long-run*, while stationary transforms of the markup are counter-cyclically related to measures of the business cycle in the *short-run*.

Keywords: Inflation, Prices, Markup, Productivity, Business Cycles, Cointegration.

JEL Classification: C22, C32, C52, D40, E31, E32

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CONTENTS

1. INTRODUCTION

In their influential paper, Rotemberg and Woodford (1991) (henceforth called R-W) argue that the markup of prices on marginal costs is counter-cyclical.[1] Their argument is based on models of the pricing behaviour of firms operating in imperfectly competitive markets and is tested by estimating regressions of the markup on variables that proxy current and future demand.

The purpose of our analysis is to argue that there is a further level of complexity to the theoretical and empirical modelling above that is worthy of investigation. The argument has two elements. First that the markup and inflation are best modelled as integrated series. And second, that while business cycle variables certainly have an impact on the markup, inflation has an important influence on the markup in the long-run.[2] Another way of expressing this idea is to make a distinction between the short- and long-run effects on the markup as captured by the business cycle variables and inflation respectively. This observation is inspired by the empirical analysis in R-W and our own work (Banerjee, Cockerell and Russell (1998) and Banerjee and Russell (2000a, b)) that establishes a long-run relationship between the markup and inflation.

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1 A number of authors argue in favour of a counter-cyclical markup. For example, see the staggered pricing models of Calvo (1983) and Rotemberg (1982), elasticity-of-demand models of Gali (1994), customer market models of Phelps and Winter (1970), and the implicit collusion model of Rotemberg and Woodford (1992). Alternatively, see the macroeconomic models of Layard, Nickell and Jackman (1991), Lucas (1974), Kydland and Prescott (1988), and Blanchard and Kiyotaki (1987).

2 The long-run in the sense of Engle and Granger (1987).

In our papers we have made use of a variety of data-sets, ranging from Australian, G7 and gross product originating data on US industrial sub-sectors. These papers use as the measure of the markup the ratio of prices to unit costs in contrast with the constructed markup on marginal costs used by Rotemberg and Woodford *inter alia*. A direct link of our work with the existing literature has consequently been lacking because of the different measures of the markup and data sets used. Therefore, in order to provide a nested analysis of the issues, we make use of the same data set used by R-W to highlight the interrelationship between the short-run cyclical and long-run influences on the markup.

The existence of a long-run relationship between inflation and the markup implies that empirical investigations of short-run relationships between the markup, productivity, inflation and the business cycle may provide spurious results unless the long-run relationship between inflation and the markup is explicitly allowed for. Our paper allows for such a long-run relationship while empirically examining the cyclical behaviour of the markup and inflation.

The paper proceeds in the next section by briefly considering theories that link inflation and the markup. Theories of the cyclical behaviour of the markup are reviewed exhaustively in Rotemberg and Woodford (1999). In section 3 we begin the empirical analysis by estimating the R-W model of the markup. We show using a number of standard techniques that the specification of the empirical model in R-W is inadequate because of a missing integrated variable. In particular, this implies that the *t*-statistics cannot be interpreted using standard critical values and that the coefficient estimates may therefore demonstrate spurious significance.

We re-estimate the model to incorporate a long-run relationship between inflation and the markup while retaining all the variables in the original R-W specification. This specification of the model shows that the change in the markup is counter-cyclical and that there exists a negative long-run relationship between inflation and the markup.

In order to interpret the results of this re-estimation we show graphically that a subset of the variables in the long-run relationship when combined linearly with the estimated coefficients may act as a proxy for productivity. The markup on marginal costs derived in R-W adjusts the inverse of the real wage for cyclical variations in marginal productivity. Conceptually these cyclical variations are stationary and should not affect estimates of the long-run relationship between inflation and the markup. This implies that, in identifying the long-run relationship it does not matter if the markup on marginal costs or the markup on unit costs is used in the long-run specification.

To make this same point empirically we complete the empirical analysis by estimating a three variable system comprising the inverse of the real wage, productivity and inflation conditioned on the business cycle. We show that similar estimates of the long-run inflation coefficient can be obtained under this reduction. This shows that, as expected, the results are qualitatively insensitive to whether the analysis makes use of the markup on marginal costs or the markup on unit costs, conditional on allowing for integrated data and the presence of a long-run relationship between inflation and the markup. The counter-cyclicality perforce is between the business cycle and the *difference* of the markup, since the markup is an integrated variable.

2. INFLATION AND THE MARKUP

A short-run causal relationship between inflation and the markup is proposed by Benabou (1992), Athey, Bagwell and Sanichiro (1998) and Simon (1999) who argue that higher rates of inflation reduce the markup on marginal costs.[3] Benabou focuses on the behaviour of customers and argues that higher inflation leads to greater customer search that increases competition and leads to a lower markup. In contrast, Athey *et al.* and Simon focus on the behaviour of firms and argue that higher inflation increases the variance of cost increases making it more difficult for firms to collude when changing prices. The reduction in collusion increases competition and the markup falls with higher inflation.

While both Benabou and Simon implicitly argue that the relationship is of a short-run nature, both arguments can be extended to imply that inflation and the markup may also be negatively related in the long-run.[4] If competition remains higher with higher inflation in the long-run (due to permanently higher customer search or greater variance of cost changes) then the relationship between inflation and the markup will remain in the long-run. Russell, Evans and Preston (1997) and Chen and Russell (1998) explicitly argue that the markup and inflation are negatively related in the long-run. These papers focus on the difficulties that non-colluding imperfectly competitive firms face when

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3 The causal relationship is in contrast with a non-causal relationship that might be identified in the data if inflation is acyclical or pro-cyclical and the markup was counter-cyclical.

4 The empirical analysis of Benabou (1992) and Simon (1999) proceed assuming, either implicitly or explicitly, that inflation and the markup are stationary and consequently the possibility of a long-run relationship is not explored. Furthermore, the theoretical exposition makes no reference to any long-run effects on the markup of changes in the rate of inflation.

coordinating price changes with information is missing. These difficulties increase with higher inflation as prices need to be changed more frequently, by larger amounts in real terms, or some combination of the two. Given the basis of the difficulty in coordinating price changes the difficulties persist in the long-run and therefore the negative relationship between inflation and the markup persists in the long-run.

3. I(1) SYSTEM ESTIMATES OF THE MARKUP

3.1 Re-estimating the Rotemberg and Woodford Model

R-W model the relationship between the inverse of the real wage and the markup of price on marginal costs. They then proceed to derive estimates of the markup of price on marginal cost and show empirically that this derived markup is counter-cyclical.[5] In section 4.2 of their paper they present the following 'baseline' results using US quarterly data for the period June 1952 to December 1988:

$$m_t = \underset{(0.5)}{0.77} + \underset{(0.0007)}{1.4\times10^{-5}}\, t - \underset{(0.08)}{0.63}\, y_t + \underset{(0.015)}{0.058}\, q_t \qquad R^2 = 0.983 \quad DW = 0.16 \tag{1a}$$

$$m_t = -\underset{(0.6)}{0.72} - \underset{(0.0007)}{0.002}\, t - \underset{(0.09)}{0.42}\, y_t + \underset{(0.014)}{0.035}\, q_t \qquad r = 0.934 \quad R^2 = 0.997 \quad DW = 1.54 \tag{1b}$$

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5 The derived markup, m, adjusts the inverse of the real wage for the cycles in output, capital stock and hours of employment to obtain a measure of the markup on marginal costs. Conceptually the adjustment is a stationary process implying that the statistical properties of the derived markup should be the same as the inverse of the real wage.

where m is the derived markup of price on marginal costs assuming an average markup of 1.6 and an elasticity of capital labour substitution of 1.0, y_t is private sector output, q_t is Tobin's 'q' and t is a time trend.[6] Lower case variables are in logarithms. Results reported as (1b) are estimated allowing for first order serial correlation.

The R-W estimates implicitly assume (by including the deterministic trend variable in (1a) and (1b)) that the variables in their regressions are trend stationary. However, both univariate and multivariate tests for unit roots indicate that the markup, output and Tobin's 'q' variables are integrated processes.[7] It appears, therefore, that (1a) should be interpreted as a long-run or static cointegrating regression as long as the residuals are stationary. The autocorrelation coefficient estimate of 0.93 in the Cochrane-Orcutt transformed model (1b) however suggests that the residuals of (1a) contain a variable which is close to integrated.[8] The low value of the Durbin-Watson statistic in relation to the R^2 suggests the same phenomenon. It appears, therefore, that (1a) is a

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6 Private sector output is measured as constant price GNP less the value added of the Federal, State and local governments and the price index is the implicit price deflator of private sector output. See R-W for further details concerning the data.

7 This conclusion can be verified using PT and DF-GLS univariate unit root tests from Elliot, Rothenberg and Stock (1996) and by looking at the correlogram for each series that indicate high degrees of persistence of the correlations. Multivariate stationarity tests (*i.e.* generalisations of univariate Dickey-Fuller tests) confirm these results.

8 This is in addition to the problem that the common factor restrictions implied by the Cochrane-Orcutt transformation in (1.2) are strongly violated in this data set upon testing. Correcting for first-order autocorrelation is therefore not justified.

spurious regression.[9] Hence, including a deterministic trend is an inappropriate device for detrending the variables of the regression and the *t*-statistics cannot be interpreted conventionally. We corroborate this finding more formally in what follows in two ways. The first uses the slightly complicated device of simulating pseudo-data series for m_t in order to determine the sampling properties of the coefficient estimates in (1a) and (1b) by means of repeated estimation of these equations on pseudo data. The second approach is to determine the cointegrating rank of the variables in (1) by maximum likelihood methods.

3.1.1 Re-estimating the R-W Model – A Bootstrap Approach

Given the well known unreliability of tests for unit roots, a specification test may be undertaken that does not rely on such pre-testing. We construct 100,000 pseudo-series for m_t denoted $\tilde{m}_t$ by using the actual data series for y_t and q_t, the estimated coefficients (including that for the autocorrelation coefficient) reported by (1b) and re-sampling from the residuals e_t. The latter are taken to be white noise since the results are not sensitive to the value chosen for their variance. For each of these pseudo-series, regressions (1a) and (1b) are estimated for the given series y_t and q_t, and the empirical densities of the *t*-statistics for the coefficient estimates are tabulated.

For Data Generation Process 1 (DGP1), the $\tilde{m}_t$ series are generated simply as a constant and trend with an AR(1) error term (with r varying from 0 to 1), so

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9 Granger and Newbold (1974) gave $R^2 > DW$ as an informal criterion for judging a spurious regression.

that the null hypothesis of no influence from y_t and q_t onto m_t is true for this process.[10]

The models (1a) and (1b) are estimated with these generated $\tilde{m}_t$ and the actual y_t and q_t. Table A1 in the appendix provides the rejection frequencies (at 5 per cent significance level) of the *t*-statistics in models (1a) and (1b) if the critical values of a standard normal density are used. Thus, if the use of normal critical values were valid, one should expect a rejection frequency of the null hypothesis of insignificance of the coefficient estimates of y_t and q_t to be approximately 5 per cent. This indeed occurs when the value of r is 0. Significant size distortions are however evident even for values of r of 0.5 while if the value of the autocorrelation coefficient is 0.93 as in (1b), the rejection frequency is in fact close to 70 per cent.[11]

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[10] It may be seen from the specification of the data generation process given in the appendix, that the higher the value of r, the more dominant is the stochastic trend component in the $\tilde{m}_t$ process while for smaller values of r, the deterministic component predominates. This is seen most easily by re-writing the process for $\tilde{m}_t$ in slightly more expanded form as $\tilde{m}_t = [c(1-r)+gr]+g(1-r)t+r\tilde{m}_{t-1}+e_t$. We would therefore expect difficulties to arise with the use of standard critical values in cases where the error process is persistent, *i.e.* r is large. This observation is borne out fully in the results of the experiments described below.

[11] This finding replicates results reported in Banerjee, Dolardo, Galbraith and Hendry (1993) in their simulations on spurious regressions. Note that as expected the null hypothesis of $r = 0$ is rejected with frequency approximately equal to 5 per cent when r is zero in the data generation process and is rejected 100 per cent of the time for non-zero values of r in the data generation process. The rejection frequency of the constant is surprisingly low. This however, is a consequence of the asymptotic behaviour of the estimator of the constant

Two further points may be noted. Following on from above, the empirical quantiles of the *t*-densities (that may be computed as a by-product of this bootstrapping exercise) show that for the particular sample size the critical value that gives the correct size of 5 per cent is 6.0 for the coefficient of output, y_t, and 3.5 for the coefficient of Tobin's q. Therefore, both the coefficient estimates in (1b) reported above are in fact *insignificant* at 5 per cent if judged by the size adjusted critical values. This is not to suggest that y_t and q_t do not have an influence on the markup but simply to state that (1a) and (1b) are inadequate empirical descriptions of the data. Second, generating data with more stationary values of the autocorrelation coefficient lead to rejection frequencies closer to the nominal levels, so that the over-rejections can be attributed to the persistence in the residuals.

Table A2(i) and A2(ii) in the appendix report the results from repeating the above exercise where the data generation process and the model are given by (1b), labelled DGP2. The trend is omitted from the data generation process given that the actual variables in the data are already highly trending but is included in the model to mimic the effect of deterministically detrending variables that are trending stochastically. Rejection frequencies for test statistics computed as deviations from zero (Table A2(i)) and as deviations from their true values (Table A2(ii)) confirm the over-rejection phenomenon. The estimation of (1b) - which involves a Cochrane-Orcutt transform - is not justified, given the violation of the common factor restrictions on the data. Nevertheless, such a

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which is driven to zero at rate $1/T$ in a spurious regression (see Phillips (1996)). The rejection frequency for the trend coefficient is also small because of the low value for this parameter in the data generation process.

transform does ameliorate the over-rejection phenomenon to a certain extent (with the gain diminishing as the residuals become more integrated), although the sizes of the tests are still too large.

Thus based only on the data, and free from all pre-testing, we see that proper specification of the markup equation requires consideration of a missing integrated variable. The spurious-regression-like behaviour of the models above are generated entirely by the actual data, so that the markup inherits the integration properties of the right hand variables and must be related not only to y_t and q_t but also to a variable that, in accordance with theoretical models presented in Section 2, we shall take to be inflation. We show below that estimating a system with inflation incorporated leads to well-specified and interpretable results that encompass the R-W findings and lead to interesting observations on the behaviour of the markup in the short- and long-run.

3.1.2 Re-estimating the R-W Model by Maximum Likelihood

In the terminology developed by Engle and Granger (1987), the presence of a near-integrated variable in the residuals in equation (1b) may be taken to imply that the markup, output and Tobin's q are not cointegrated. That is, the cointegrating rank, r, of this trivariate system is zero. We therefore close this section by re-estimating equation (1b) using I(1) system techniques developed by Johansen (1988). In order to mimic (1) the system comprises the markup, output, Tobin's q and a trend in the cointegrating space. The constant is unrestricted. Table 1 indicates that the variables are not cointegrated since the trace statistic of $r = 0$ versus $r = 3$ lies well below the 90 per cent asymptotic critical value.[12] The result of no cointegration is entirely consistent with the findings reported above.

Table 1: Testing for the Number of Cointegrating Vectors
Estimated Values of Q(r)

$H_0 : r =$	Eigenvalues	$Q(r)$
0	0.0952	29.80 {39.08}
1	0.0770	15.20 {22.95}
2	0.0237	3.50 {10.56}

Notes: Statistics are computed with three lags of the core endogenous variables. The sample is from December 1952 to March 1989. $Q(r)$ is the likelihood ratio statistic for determining the rank, r, in the I(1) analysis. 90 percent critical values shown in curly brackets { } are from Table 15.4 of Johansen (1995).

3.2 Introducing Inflation into the Rotemberg and Woodford Model

It is argued above that there may exist a long-run relationship between the markup and inflation. In order to provide a unified framework, we proceed to estimate a four variable system comprising the markup, real output, Tobin's *q and* inflation. The estimated system is conditioned on the business cycle measured as linearly de-trended hours of private sector employment.[13] The results are reported in Table 2 and we can now conclude in favour of one cointegrating vector.

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[12] This result is supported by the eigenvalues of the companion matrix where we find two roots on the unit circle and the third close to unity with a value of 0.8801.

The results in Table 2 raise three interesting issues. First, the finding in R-W that the markup is related to output and Tobin's *q* is re-established. However, given that we argue that the data are difference stationary and not trend stationary, the level of output, y, and Tobin's *q* in the cointegrating vector can no longer be interpreted as business cycle measures of current and future demand. Moreover, as the markup is an integrated process it is now no longer appropriate to consider a relationship between the business cycle and the level of the markup unless the business cycle is also an integrated process. As the business cycle variable considered here is stationary, the only possible relationship is that between the change in the markup and the business cycle.

These observations are of course conditioned on the variables behaving like integrated processes for the time-period under consideration. In episodes where this is not the case, it may be possible to recover a R-W type specification in its entirety, that is, without the need to incorporate inflation and the markup would be influenced mainly by the business cycle. This is in contrast to the analysis above where the business cycle acts as a stationary perturbation around a long-run relationship between inflation and the markup.

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[13] Private sector employment data is from the R-W dataset. Hours of private employment is taken from the establishment survey and measured as total hours in non-agricultural payrolls less the hours employed in government services.

Table 2: I(1) System Estimates
Markup, Output, Tobin's *q* and Inflation

Cointegrating Vector: $m - 0.710\,y + 0.095\,q + 7.646\,\Delta p + 0.010\,t$
[0.207] [0.024] [1.341] [0.002]

Equation ⇒	Δm	Δy	Δq	$\Delta^2 p$
Error Correction Term	- 0.089 (- 3.5)	0.017 (0.6)	- 0.080 (- 2.3)	- 0.080 (-6.5)
Business Cycle	- 0.104 (- 2.6)	- 0.059 (- 1.4)	- 0.847 (- 2.9)	- 0.090 (- 4.7)
R^2	0.64	0.52	0.39	0.59

$$LM(1): c^2_{16} = 18.35,\ p-value = 0.30;\quad LM(4): c^2_{16} = 19.07,\ p-value = 0.26;$$
$$D-H: c^2_8 = 8.91,\ p-value = 0.35$$

Notes: Data sample is December 1952 to March 1989. Standard errors reported in [ ] brackets and *t* statistics are in ( ) brackets.

The system is estimated with three lags of the endogenous variables. Predetermined variables are linearly de-trended hours of private sector employment and a series of 'spike' dummies for December 1952, March and December 1953, September 1959, March 1971, September 1974, June 1978, June 1980, December 1982 and March 1989.

Trace statistics for 0, 1, 2 and 3 cointegrating vectors are 88.53 {58.96}, 35.85 {39.08}, 17.12 {22.95} and 3.66 {10.56} respectively where numbers in { } are the relevant 90% critical values. Inference concerning the number of cointegrating vectors is maintained if the system is estimated without pre-determined variables.

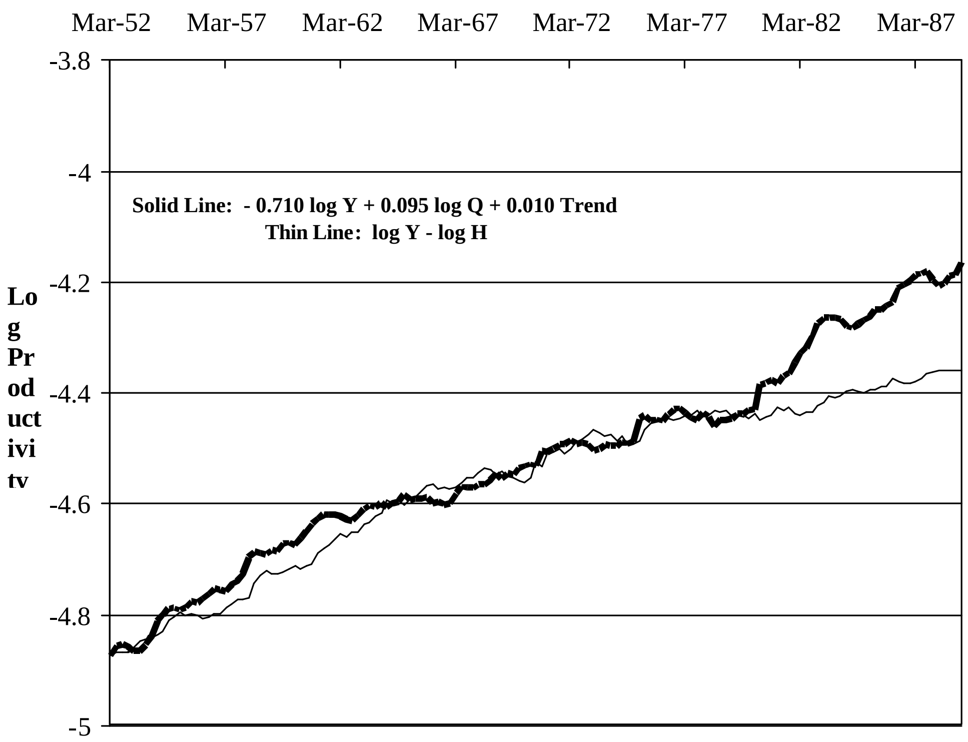
Moduli of the first five roots of the companion matrix are 1.0, 1.0, 1.0, 0.6461, 0.6461.

$LM(1)$ and $LM(4)$ are Lagrange multiplier tests for first and fourth order autocorrelation and D-H is Doornik-Hansen normality test.

Second, in order to interpret the estimated cointegrating vector, one may argue that y and q combine with the trend to proxy productivity in the model. The thick line in Graph 1 shows this estimated proxy as measured by output, Tobin's q and the trend variable weighted by the estimated coefficients from the cointegrating vector. The thin line shows average productivity measured as the logarithm of output divided by hours of private sector employment. We see that up until the last few years there is a high correspondence between these two measures of productivity.[14]

Graph 1

PRODUCTIVITY



[14] The divergence in the 1980s is due to the boom in the stock market that increases Tobin's q.

Finally, the cointegrating vector establishes a negative long-run relationship between the markup on marginal costs and inflation.

3.3 Estimating a Unit Cost Markup Model

The markup on marginal costs used above is an integrated process due to the integrated nature of the real wage series that it is derived from. Conceptually the adjustments made when deriving the markup on marginal costs from the real wage series reflect the impact of the business cycle on marginal productivity. Based on the arguments above, these short-run adjustments should be identified not in the long-run cointegrating relationship but by the short-run business cycle term. Therefore, these short-run adjustments should not affect the long-run estimates.

An alternative way to proceed, therefore, is to estimate a three variable system comprising the inverse of the real wage, $p-w$, productivity, $y-h$, and inflation, conditioned on the business cycle.[15]

The estimated long-run relationship is of the form:

$$mu = (p-w)+(y-h)-l\,\Delta p \tag{2}$$

where mu is the markup of price on unit labour costs net of the cost of inflation, Δp is price inflation, and l is a positive parameter and termed the inflation

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15 This specification substitutes the 'proxy' productivity terms of y_t, q_t and the time trend with actual productivity, $y-h$.

cost coefficient.[16] Short-run deviations from the long-run relationship are due to shocks and the business cycle. The symbol, Δ, represents the change in the variable. Estimating (2) allows us to identify separately the impact of the business cycle on the real wage, productivity and inflation. By imposing linear homogeneity on the model, this also allows us to estimate the long-run relationship between inflation and the markup on unit labour costs.[17]

In estimating the long-run relationship the usual tension between precision and stability is encountered. More observations lead to greater precision in estimating the long-run relationship but simultaneously increases the likelihood of breaks in the series due to non-modelled influences such as changes in competition and changes in data reporting regimes. The initial estimates indicate that there is a level shift in the relationship between inflation and the markup in June 1968.[18] The estimation proceeds with the inclusion of a shift dummy for the period December 1952 to March 1968. Four spike dummies are also included to capture the somewhat erratic short-run dynamics of the price, wage and productivity data.

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16 The long-run relationship is derived and considered in some detail in Banerjee *et al.* (1998) and Banerjee and Russell (2000a). The form of the long-run relationship is a generalisation of de Brouwer and Ericsson (1998).

17 The term $p-w+y-h$ is equivalent to the markup on unit labour costs and the inverse of labour's income share. Linear homogeneity implies a unit coefficient on productivity.

18 A similar break in the long-run relationship is evident in the United States estimates reported in Banerjee and Russell (2000a).

3.3.1 The System Results

Table 3 reports the trace statistics of the estimated system showing acceptance of the hypothesis of one cointegrating vector.[19] The normalised cointegrating vector is reported in Table 4 with linear homogeneity imposed. We see that the cost coefficient, l, is significant and positive indicating a negative long-run relationship between the markup on unit labour costs and inflation. Importantly, the real wage and productivity are found not to cointegrate if inflation is not included in the cointegrating space and this is shown in the lower panel of Table 3.

The dynamics of the estimated system are reported in Table 5. We see that productivity is counter-cyclical at the 5 per cent level of significance implying that marginal productivity is strongly counter-cyclical and outweighs any positive cyclical impact due to hoarded labour and capital. The real wage shows no significant cyclical behaviour. Given the acyclical nature of the real wage and the counter-cyclical nature of productivity this implies that the markup on unit costs is counter-cyclical. Consistent with the standard view that inflation is procyclical, the business cycle has a significant positive impact on the change in inflation.

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[19] Before estimating the I(1) system the series were tested for the presence of unit roots using PT and DF-GLS univariate tests from Elliot *et al.* (1996). It is found that the real wage, productivity and inflation are best characterised as I(1) processes and the business cycle is clearly I(0). The system analysis that follows supports the conclusions of the univariate tests.

Table 3: Testing for the Number of Cointegrating Vectors

Three Variable System: Inverse Real Wage, Productivity and Inflation

Null Hypothesis H_0: r =	Eigenvalues	Estimated Trace Statistic $Q(r)$
0	0.1633	30.58 {26.70}
1	0.0306	4.55 {13.31}
2	0.0001	0.01 {2.71}

Two Variable System: Inverse Real Wage and Productivity

Null Hypothesis H_0: r =	Eigenvalues	Estimated Trace Statistic $Q(r)$
0	0.0687	6.38 {13.31}
1	0.0051	0.34 {2.71}

Notes: Statistics are computed with 4 lags of the core variables. The sample is December 1952 to March 1989 with 146 observations and 127 degrees of freedom.

The shaded cell indicates acceptance at the 10 per cent level of significance. Critical values shown in curly brackets { } are from Table 15.3 of Johansen (1995).

Table 4: Normalised Cointegrating Vector

	$(p-w)_t$	$(y-h)_t$	Δp_t
Unrestricted	1	1.056	2.873 (0.655)
Linear Homogeneity Imposed	1	1	3.006 (0.653)

Notes: Likelihood ratio tests (a) linear homogeneity is accepted $c_1^2 = 2.02$, p-value = 0.15; (b) test of coefficient on inflation is zero is rejected, $c_1^2 = 19.25$, p-value = 0.00. Standard error reported in brackets.

Table 5: Dynamics of the I(1) System - Inverse Real Wage, Productivity and Inflation
December 1952 – March 1989

Dependent Variable Þ	Lag ⇓	*Inverse Real Wage* $\Delta(p-w)$	*Productivity* $\Delta(y-h)$	*Inflation* $\Delta^2 p$
Loading Matrix				
Error Correction Term	1	0.050	- 0.076	- 0.052
		(1.9)	(- 2.0)	(- 2.3)
Short-run Matrices				
Δ Log P/W	1	0.076	- 0.054	- 0.001
		(0.7)	(- 0.4)	(- 0.0)
Δ Log P/W	2	- 0.178	0.137	- 0.206
		(- 1.7)	(0.9)	(- 2.3)
Δ Log P/W	3	- 0.075	- 0.015	- 0.023
		(- 0.8)	(- 0.1)	(- 0.3)
Δ Log Productivity	1	0.154	- 0.135	0.045
		(2.5)	(- 1.6)	(0.9)
Δ Log Productivity	2	0.005	0.133	0.057
		(0.1)	(1.6)	(1.1)
Δ Log Productivity	3	0.118	- 0.256	0.125
		(2.0)	(- 3.2)	(2.5)
Δ Inflation	1	- 0.151	0.148	- 0.564
		(- 1.3)	(0.9)	(- 5.6)
Δ Inflation	2	- 0.055	0.157	- 0.208
		(- 0.5)	(1.0)	(- 2.1)
Δ Inflation	3	- 0.044	0.057	- 0.095
		(- 0.5)	(0.5)	(- 1.3)
Predetermined Variables				
Constant		- 0.026	0.037	0.022
		(- 2.1)	(2.2)	(2.1)
Step Dummy		- 0.007	0.005	0.002
		(- 4.3)	(2.4)	(1.3)
Business Cycle	1	0.012	- 0.064	0.045
		(0.8)	(3.2)	(3.6)

Notes: Reported in brackets are *t*-statistics. $ECM_t \equiv (p-w)_t + (y-h)_t + 3.006\Delta p_t$

Productivity is measured as log y – log hours of employment, p is the price level and w is the wage level. The business cycle is measured as linear de-trended log hours of employment.

Step dummy: December 1952 to March 1968. Spike dummies: December 1953, March 1965, September 1970, and September 1974.

System Diagnostics for the Restricted Model

Tests for Serial Correlation

Ljung-Box (36) $c^2(294) = 318.94$, p-value = 0.15

LM(1) $c^2(9) = 9.54$, p-value = 0.39

LM(4) $c^2(9) = 11.13$, p-value = 0.27

Test for Normality: Doornik-Hansen Test for normality: $c^2(6) = 4.94$, p-value = 0.55

4. INTERPRETING THE RESULTS AND CONCLUSION

The general theoretical arguments of R-W *inter alia* that the markup on marginal costs is counter-cyclical is supported but as a short-run relationship between changes in the markup and the business cycle as shown in Tables 2 and 5. The system results in Table 5 identify the source of the cyclical variation in the markup on unit costs as due to the counter-cyclical behaviour of productivity and not due to any cyclical behaviour of the real wage.

Furthermore, the finding of a long-run negative relationship between inflation and the markup in Banerjee *et al.* (1998) and Banerjee and Russell (2000a, 2000b) is re-established and it is shown that the real wage and productivity are not cointegrated unless inflation is included in the long-run relationship. The long-run relationship between inflation and the markup is likely to be important in an economic sense with a 1 percentage point increase in annual inflation leading to a 0.75 of a percentage point fall in the markup in the long-run. This estimate is numerically close to the value of 0.5 in Banerjee and Russell (2000a) using quarterly aggregate US national accounts data for the period December 1961 to June 1997 and 0.65 in Banerjee and Russell (2000b) using annual US industrial sector data for the period 1947 to 1997. This robustness of the estimate of the inflation cost coefficient to diverse data sources and time periods serves to link our analysis to existing traditional studies of markup behaviour.

Our results strongly contradict the argument that the negative relationship identified between inflation and the markup is due to a combination of the short-run behaviour of a counter-cyclical markup and procyclical inflation. A further implication is that the negative relationship identified by Benabou (1992) using

US retail sector data between inflation and the markup may be due to the long-run link between inflation and the markup.

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APPENDIX

$Data\,Generation\,\Pr ocess\,1$

$\tilde{m}_t = -0.72 - 0.002t + u_t$

$u_t = r\ u_{t-1} + e_t$

$e_t \sim N(0,1)$

$u_0 \sim N(0,(1-r^2)^{-1})$

$Model\ \ A\,(static\,regression))$

$\tilde{m}_t = c + gt + b_1 y_t + b_2 q_t + w_t$

$100{,}000\ simulated\ series\ \ for\ y_t\ \ from\ DGP\,1\ \ above$

$Actual\ \ y_t\ \ and\ q_t\ \ series\ used$

$T = 149$

$Model\ \ B\ (Dynamic\ OLS\ or\ Cochrane - Orcut\ (C-O))$

$\tilde{m}_t = c + gt + b_1 y_t + b_2 q_t + u_t$

$u_t = r\ u_{t-1} + e_t$

$100{,}000\ simulated\ series\ \ for\ y_t\ \ from\ DGP\,1\ \ above$

$Actual\ \ y_t\ \ and\ q_t\ \ series\ used$

$T = 149$

Table A1: Rejection Frequencies of t-statistics at Normal 5% critical value for 100,000 bootstrapped regressions

	$t_{c=0}$	$t_{g=0}$	$t_{b_1} = 0$	$t_{b_2} = 0$	$t_{r=0}$
r = 0					
Static	0.0549	0.0656	0.0523	0.0524	
C-O	0.0644	0.0765	0.0620	0.0612	0.0581
r = 0.50					
Static	0.2512	0.2611	0.2487	0.2597	
C-O	0.1205	0.1276	0.1181	0.1260	0.9997
r = 0.80					
Static	0.4841	0.4885	0.4839	0.5171	
C-O	0.3003	0.3058	0.2985	0.3408	1.0000
r = 0.934					
Static	0.6677	0.6640	0.6680	0.6925	
C-O	0.6051	0.6007	0.6050	0.6417	1.0000

$$Data\,Generation\ \mathrm{Pr}ocess\ 2$$
$$\tilde{m}_t = -0.72 - 0.42 y_t + 0.035 q_t + u_t$$
$$u_t = r\ u_{t-1} + e_t$$
$$e_t \sim N(0,1)$$
$$u_0 \sim N(0, (1 - r^2)^{-1})$$

$$Model\ \ A\ (static\ regression)$$
$$\tilde{m}_t = c + gt + b_1 y_t + b_2 q_t + w_t$$
$$100{,}000\ simulated\ series\ \ for\ y_t\ \ from\ DGP\ 2\ \ above$$
$$Actual\ \ y_t\ and\ q_t\ series\ used$$
$$T = 149$$

$$Model\ \ B\ (Dynamic\ OLS\ or\ Cochrane - Orcutt\ Estimation)$$
$$\tilde{m}_t = c + gt + b_1 y_t + b_2 q_t + u_t$$
$$u_t = r\ u_{t-1} + e_t$$
$$100{,}000\ simulated\ series\ \ for\ y_t\ \ from\ DGP\ 2\ \ above$$
$$Actual\ \ y_t\ and\ q_t\ series\ used$$
$$T = 149$$

Table A2(i): Rejection Frequencies of t-statistics (from zero) at Normal 5% critical value for 100,000 bootstrapped regressions

	$t_{c=0}$	$t_{g=0}$	$t_{b_1} = 0$	$t_{b_2} = 0$	$t_{r=0}$
ρ=0					
Static	0.0549	0.0523	0.0910	0.0667	
C-O	0.0644	0.0620	0.1029	0.0778	0.0581
ρ=0.50					
Static	0.2166	0.2201	0.2078	0.2722	
C-O	0.1206	0.1233	0.1205	0.1533	0.9996
ρ=0.80					
Static	0.4242	0.4532	0.4033	0.6330	
C-O	0.3148	0.3541	0.2982	0.5759	0.9999
ρ=0.934					
Static	0.6018	0.5979	0.6048	0.7467	
C-O	0.5424	0.5417	0.5449	0.7155	0.9999

Table A2(ii): Rejection Frequencies of *t*-statistics (from true values) at Normal 5% critical value for 10,000 bootstrapped regressions

	$t_{c=-0.72}$	$t_{g=0}$	$t_{b_1=-0.42}$ =	$t_{b_2=0.035}$	$t_{r=r_o}$
ρ=0					
Static	0.0524	0.0523	0.0523	0.0524	
C-O	0.0619	0.0620	0.0620	0.0612	0.0581
ρ=0.50					
Static	0.2103	0.2207	0.2106	0.3198	
C-O	0.1160	0.1223	0.1163	0.1881	0.0433
ρ=0.80					
Static	0.4193	0.4532	0.4210	0.6584	
C-O	0.3101	0.3542	0.3154	0.6061	0.2734
ρ=0.934					
Static	0.6029	0.5979	0.6012	0.7543	
C-O	0.5431	0.5417	0.5416	0.7253	0.0675