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Working Paper

The Relationship between Prices and Output in the UK and the US

CESifo Working Paper, No. 8970

Provided in Cooperation with:
Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Caporale, Guglielmo Maria; Claudio-Quiroga, Gloria; Gil-Alana, Luis A. (2021) : The Relationship between Prices and Output in the UK and the US, CESifo Working Paper, No. 8970, Center for Economic Studies and Ifo Institute (CESifo), Munich

This Version is available at:
https://hdl.handle.net/10419/235340

CESifo WORKING PAPERS

8970
2021

March 2021

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 8970*

The Relationship between Prices and Output in the UK and the US

Abstract

This paper analyses the relationship between CPI and real GDP in both the US and the UK using fractional integration and long-range dependence techniques. All series appear to be highly trended and to exhibit high degrees of integration and persistence, especially in the case of CPI. Since the two variables have different degrees of integration in each of the two countries, fractional cointegration tests cannot be carried out. We assume instead weak exogeneity of each of them in turn and test for causality by regressing the other variable against lagged values of the weakly exogenous one. We find that the only significant relationship implies the existence of a lagged effect of prices on output in the case of the US, which suggests a dominant role for demand shocks.

JEL-Codes: C220, C230, E320.

Keywords: real output, prices, persistence, fractional integration.

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March 21, 2021
Luis A. Gil-Alana gratefully acknowledges financial support from the Ministerio de Economía y Competitividad (ECO2017-85503-R).

1. Introduction

The relationship between prices and output is crucial to understanding the nature of economic fluctuations and to be able to discriminate between rival macroeconomic models. A lot of the literature in this area has focused on whether prices are procyclical or countercyclical, i.e. whether they move in the same or in the opposite direction to output. This depends on the nature of the underlying shocks: aggregate demand and/or monetary policy shocks should produce procyclical behaviour, whilst aggregate supply (technology) shocks should result in countercyclical behaviour. Friedman and Schwartz (1963, 1982) analysed US business cycles from the Civil War and concluded that monetary shocks were the main source of aggregate fluctuations and that prices were procyclical, a stylised fact that macro models had to be able to replicate to be data congruent (Bernanke, 1986; Mankiw, 1989). Such price behaviour is consistent with the Phillips Curve relationship and other models based on monetary surprises.

By contrast, in the Real Business Cycle (RBC) framework introduced by Kydland and Prescott (1990) business cycles are defined as deviations from trend (as in Lucas, 1977), technology shocks are the main driver of cycles and the correlation between the cyclical component of output and the price level was estimated to be negative. However, Cooley and Ohanian (1991) found a positive correlation between output and inflation (as opposed to prices) during the post-war period.

On the whole, the evidence concerning the US is mixed (see, e.g., Lee, 2006; Konstantakopoulou et al., 2009; Haslag and Hsu, 2012; Brock and Haslag, 2014; Keating and Valcarcel, 2015). Some studies argue that this might depend on the different sample periods used for the analysis, as the nature of the macro shocks driving cycles might have changed (see Backus and Kehoe, 1992, and Smith, 1992). Lee (2006) used the DCC-GARCH model to examine the dynamic correlation between US prices and output and

found that they tended to move in the same direction before World War II but in the opposite direction afterwards. Antonakakisa et al. (2017) analysed the time-varying correlation between US output and prices by incorporating short-term interest rates, output and inflation volatilities in the model in order to capture the role of monetary policy, output and inflation uncertainty; they found evidence of time variation and of a predominant role for technology shocks.

Concerning the international evidence, Backus and Kehoe (1992) considered ten countries with data spanning at least a century (Australia, Canada, Denmark, Germany, Italy, Japan, Norway, Sweden, UK and US) and found that prices were more persistent and generally procyclical before World War II (WWII) and countercyclical afterwards; however, in the case of the UK the correlation between the growth rates of output and growth, though positive, was relatively small in the earlier period and sensitive to the estimation method for output. Vázquez (2002) studied the co-movement between output and prices in the EU15 countries and found that the UK and others nine countries (Austria, Belgium, France, Germany, Greece, Italy, Luxembourg, Spain, Sweden and) exhibit a negative correlation between prices and output in the long run; in short-run the correlation becomes positive for France, Italy and Portugal; the remaining four countries, namely Denmark, Finland, Ireland and the Netherlands do not display any significant co-movement between prices and output. Smith (1992) found that prices behaved procyclically before World War I (WWI) and countercyclically after the Great Depression in the US, the UK, Canada, Australia, Sweden, Italy, Denmark, Norway, Japan and Germany.

Den Haan and Summer (2004) analysed the correlation coefficients in the G7 at different forecast horizons using a VAR methodology as in Den Haan (2000) and estimated positive short-term and negative long-term correlations in the post-WWII

period. Fiorito and Kolintzas (1994) also studied the G7 countries and concluded that the correlation between HP-filtered prices and output is negative during the post-WWII period. Finally, Pollin and Zhu (2007) analysed the relationship between inflation and economic growth in 80 countries over the 1961-2000 period; their results vary across countries but suggest a stronger positive correlation during periods characterised by more active demand management policies.

This paper aims to provide new evidence on the relationship between prices and output in both the US and the UK by focusing on the long-run rather than on cyclical fluctuations. For this purpose, it applies fractional integration and long-range dependence techniques; these are more general than the standard modelling approach based on the stationary I(0) versus nonstationary I(1) dichotomy which has been used in previous studies since they allow the differencing parameter to be a fractional value as well as an integer and therefore are more general and flexible. After analysing the stochastic behaviour of each individual series we examine their long-run linkages. Since the two variables have different degrees of integration in each of the two countries, fractional cointegration tests cannot be carried out for this purpose. We assume instead weak exogeneity of each of them in turn to carry out causality tests in a regression framework.

The rest of the paper is structured as follows: Section 2 outlines the methodology used for the analysis which is based on the concepts of fractional integration. Section 3 describes the dataset and presents the empirical results. Section 4 offers some concluding remarks.

2. Methodology

Stationarity is a crucial concept in time series econometrics. In particular, a series is said to be covariance (or second order) stationary if its first two moments are independent of

time. However, most macroeconomic series appear to be nonstationary. A standard approach to remove nonstationarity is to take first differences on the assumption that the differenced series will be stationary I(0). In such a case the original series is said to be integrated of order 1 or I(1). Following the seminal work of Nelson and Plosser (1982) many papers have therefore carried out standard unit root tests.[1] However, it is now well known that such tests have very low power under fractional alternatives,[2] as it is possible for a series to be neither I(0) nor I(1) but instead integrated of order d, where d can be any fractional value in the interval between 0 and 1, or even to be above 1. Gil-Alana and Robinson (1997) examined an updated version of Nelson and Plosser's (1982) dataset consisting of fourteen US macro variables and found that all except one were I(d) with $0 < d < 1$. Since then, fractional integration has been widely used for the analysis of macro series (see, e.g., Mayoral, 1996; Chambers, 1998; Michelacci and Zaffaroni, 2000; Caporale and Gil-Alana, 2013; Abritti et al., 2016).

Therefore, the model estimated in the empirical section is of the following form:

$$, \quad (1-L)^d x_t = u_t, \qquad t = 1, 2, ..., \tag{1}$$

where x_t stands for either the observed data or the errors in a regression model that may include deterministic terms such as a constant or a linear time trend or weakly exogenous variables, d is a parameter to be estimated from the data providing a measure of persistence, and u_t is an I(0) process that is assumed to be in turn a white noise or exhibiting (weak) autocorrelation.

Fractional cointegration is the extension of the concept of fractional integration to the multivariate case. A necessary condition to test for it in a bivariate context such as

[1] The most commonly used are the ADF test (Dickey and Fuller, 1979) and other tests developed by Phillips and Perron (1988), Kwiatkowski et al., (KPSS, 1992), Elliot et al. (ERS, 1996), Ng and Perron (NP, 2001), etc.

[2] See Diebold and Rudebusch (1991), Hassler and Wolters (1994), Lee and Schmidt (1996), etc.

ours is that the two individual series display the same degree of integration. Since this condition is not satisfied in our case (see below) cointegration tests cannot be performed; instead we analyse the relationship between the two variables by treating each of them in turn as weakly exogenous, i.e. the other variable is regressed against lagged values of the weakly exogenous one; we carry out the analysis by using a simple version of the tests of Robinson (1994) that allows the inclusion of deterministic or weakly exogenous regressors in a model where the errors are potentially I(d) and d may be any real value.

3. Data and Empirical Results

The quarterly series used are the consumer price index (CPI) and real gross domestic product (GDP) (index 2015=100) for both the UK and the US. The sample period goes from 1975Q1 to 2020Q2. The data sources are the OECD Statistics for the CPI series, Eurostat for UK real GDP and the US Bureau of Economic Analysis for US real GDP. Figure 1 plots both the UK and the US series. They all exhibit very similar behaviour, namely they are upward trending but experience a sharp fall coinciding with the Covid-19 pandemic.

[Insert Figure 1 about here]

As a first step we carry out univariate analysis, and estimate the following model:

$$y_t = \alpha + \beta t + x_t, \quad (1-L)^d x_t = u_t, \quad t = 1, 2, ..., \quad (2)$$

where y_t is the time series under examination and u_t is assumed to be I(0) and to follow alternatively a white noise or an autocorrelation process, in the latter case specifically the non-parametric model of Bloomfield (1973).[3]

[3] This is a non-parametric way of describing the I(0) error term that produces autocorrelations decaying at an exponential rate as in the AR case.

Table 1 reports the estimated values of d for the raw data and the three standard specifications considered in the unit root literature (Phillips and Schmidt, 1992), namely: i) no deterministic terms, ii) an intercept, and iii) and intercept and a linear time trend. The best model is selected on the basis of the statistical significance of the estimated regressors as indicated by their t-statistics. Table 2 shows the parameter estimates for all three specifications. Tables 3 and 4 provide the corresponding information for the logged series.

[Insert Tables 1 and 2 about here]

Concerning the original series, Table 1 shows that a time trend is required in all cases regardless of the assumption made about the process driving the errors; further, the estimates of d are higher for CPI than for real GDP in both cases. More specifically, the CPI series are characterised by orders of integration above 1 in both countries with white noise errors and in the case of the UK also with autocorrelated errors; however, the unit root null cannot be rejected for the US CPI series with autocorrelated errors. As for real GDP, the estimated value of d is below 1 and the series exhibits mean reversion with white noise errors in both countries; however, under the assumption of autocorrelated errors, the I(1) hypothesis cannot be rejected despite the fact that the estimated values of d are still below 1. Table 2 displays the estimated coefficients; as can be seen, there is a positive time trend in all cases.

[Insert Tables 3 and 4 about here]

As for the logged series (see Table 3 and 4) the orders of integration are significantly higher than 1 in the case of CPI, (with values between 1.35 and 1.46) whilst the unit root null cannot be rejected for real GDP, except for the UK series under the assumption of white noise errors, when mean reversion ($d < 1$) is found.

As explained before, the fact that the price and output series do not have the same order of integration in either country implies that cointegration analysis cannot be carried out. Therefore, we examine their linkages by estimating a model in which one of the two is treated as weakly exogenous as follows:

$$y_{1t} = \alpha + \beta y_{2t-k} + x_t, \quad (1-L)^d x_t = u_t, \quad t = 1, 2, ..., \qquad (3)$$

for k = 1, 2, and 3, where y_{1t} and y_{2t} stand for log CPI and log real GDP respectively in Tables 5 and 6 for both the UK and the US, whilst in Tables 7 and 8 the opposite holds, namely y_{1t} stands for log real GDP and y_{2t} for log CPI respectively for both countries.

[Insert Tables 5 and 6 about here]

Concerning the regression of log CPI on log real GDP, in the UK case (Table 5) the estimated values of d are much higher than 1 regardless of the lag length and range between 1.43 (k = 3 and 4 with white noise errors) and 1.73 (k = 1 with Bloomfield errors); however, the slope coefficient is not significantly different from zero in any single case. As for the US results (Table 6), the estimates of d are again much higher than 1 (between 1.53 and 1.59), but the slope coefficient is now significant for k = 4, which might reflect a seasonal effect given the quarterly frequency of the series examined.

[Insert Tables 7 and 8 about here]

When regressing instead log real GDP against log CPI, in the UK case (Table 7) the estimates of d are slightly above 1, the unit root null hypothesis cannot be rejected in any single case, and the slope coefficient is not significant in any case. By contrast, in the US case (Table 8) there is a positive relationship between previous values of CPI and real GDP, which suggests a lagged impact of demand shocks.

4. Conclusions

This paper applies a fractional integration approach to UK and US quarterly data on prices and output from 1975Q1 to 2020Q2 to analyse the stochastic behaviour of these two variables and their long-run relationship in both economies - unlike most of the existing literature that focuses instead on their correlation over the business cycle. The univariate analysis indicates that all series are highly trended and persistent, exhibiting high degrees of integration, especially in the case of CPI.

As for their linkages, since the two variables have different degrees of integration in each of the two countries, fractional cointegration tests cannot be carried out. We assume instead weak exogeneity of each of them in turn and examine causality by testing for the significance of the lagged values of the variable treated as exogenous. We find that the only significant relationship implies the existence of a lagged effect of prices on output in the case of the US, which suggests a dominant role for demand shocks. An alternative approach could be based on the AutoRegressive Distributed Lag (ARDL) model (see Pesaran and Shin, 1999), which does not require the assumption of equal orders of integration. However, this framework has yet to be extended to the case of fractional integration. Work in this direction is currently in progress.

References

Abbritti, M., Gil-Alana, L.A., Lovcha, Y. and Moreno, A. (2016). Term structure persistence, Journal of Financial Econometrics, 14(2), 331-352.

Antonakakisa, N., Gupta, R. and Tiwarie, A. K. (2017). The time-varying correlation between output and prices in the United States over 1800 to 2014, Economic Systems, 41(1), 98-108.Backus, D. K., and Kehoe, P.J. (1992). International Evidence of the Historical Properties of Business Cycles, American Economic Review 82 (4), 864–888.

Bernanke, Ben. S. (1986). "Alternative explanations of the money-income correlation," National Bureau of Economic Research Working Paper no.1842.

Bloomfield, P. (1973) An exponential model in the spectrum of a scalar time series, Biometrika 60, 217-226.

Brock, W. and J. Haslag (2014), "On Understanding the Cyclical Behavior of the Price Level and Inflation", Working Papers 1404, Department of Economics, University of Missouri.

Caporale, G. M., Gil-Alana, L. A., (2013). Long memory in US real output per capita. Empirical Economics 44, 591-611

Chambers, M.J., (1998). Long Memory and Aggregation in Macroeconomic Time Series, International Economic Review 39(4), 1053-1072.

Cooley, T. F. and Ohanian, L.E. (1991). The cyclical behavior of prices, Journal of Monetary Economics 28 (1),25–60.

Den Haan, W.J. and Summer, S.W. (2004), The Comovement between Real Activity and Prices in the G7. European Economic Review 48 (2004) 1333–1347.

Den Haan, W.J. (2000), The comovement between output and prices. Journal of Monetary Economics 46,3–30.

Dickey, D.A and Fuller, W. A. (1979) Distributions of the estimators for autoregressive time series with a unit root, Journal of American Statistical Association, 74 (366), 427-481.

Diebold, F. X. and Rudebush, G. D. (1991). On the power of Dickey- Fuller tests against fractional alternatives. Economics Letters, 35, 155-160.

Elliot, G., Rothenberg, T.J. and. Stock, J.H. (1996). Efficient tests for an autoregressive unit root, Econometrica 64, 813-836.

Fiorito, R., and Kolintzas, T. (1994), Stylized facts of business cycles in the G7 from a real business cycles perspective, European Economic Review 38, 253-269.

Friedman, M. and Schwartz, A.J. (1963). *A Monetary History of the United States, 1867-1960*, Princeton: Princeton University Press.

Friedman, M. and Schwartz, A.J. (1982). *Monetary Trends in the United States and United Kingdom: Their Relation to Income, Prices, and Interest Rates, 1867-1975*, NBER Books. National Bureau of Economic Research, Inc.

Gil-Alana, L.A. and. Robinson, P.M. (1997). Testing of unit roots and other nonstationary hypothesis in macroeconomic time series, Journal of Econometrics, 80, 2, 241-268.

Haslag, J. H. and Hsu, Y.-C. (2012). Cyclical Co-Movement Between Output, the Price-Level, and the Inflation Rate, in *Advances in Econometrics*. 30, 359–384.
Hassler, U., and Wolters, J. (1994). On the power of unit root tests against fractional alternatives. Economics Letters, 45(1), 1-5.

Keating, J. W. and V.J. Valcarcel (2015), "The Time-Varying Effects of Permanent and Transitory Shocks to Real Output", Macroeconomic Dynamics 19, 477–507.

Konstantakopoulou, I., Tsionas, E. and Kollintzas, T. (2009). Stylized Facts of Prices and Interest Rates over the Business Cycle, Economics Bulletin 29 (4), 2613–2627.

Kwiatkowski D, P.C.D Phillips, P. Schmidt and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?, Journal of Econometrics 54, 159–178.

Kydland, F. and Prescott, E.C. (1990). Business Cycles: Real Facts and a Monetary Myth, Federal Reserve Bank of Minneapolis Quarterly Review, 14(2).
Lee, J. (2006), "The Comovement between Output and Prices: Evidence from a Dynamic Conditional Correlation GARCH Model", Economics Letters 91 (1), 110–116.

Lee, D., and Schmidt, P. (1996). On the power of the KPSS test of stationarity against fractionally-integrated alternatives. Journal of Econometrics, 73(1), 285-302.

Lucas Jr., R.E. (1977), "Understanding Business Cycles," in *Stabilization of the Domestic and International Economy*, Karl Brunner and Allan H. Meltzer eds., Carnegie-Rochester Series on Public Policy, 5:7-29,Amsterdam: North Holland.

Mankiw, G.N. (1989), "Real business cycle: A new Keynesian Perspective," Journal of Economic Perspectives, Summer, 3(3), 79-90.

Mayoral, L., (2006), Further Evidence on the Statistical Properties of Real GNP, Oxford Bulletin of Economics and Statistics 68, 1, 901-920.

Michelacci C. and Zaffaroni, P. 2000, (Fractional) beta convergence, Journal of Monetary Economics 45(1): 129-153.

Nelson, C.R. and Plosser, C.I. (1982). Trends and random walks in macroeconomic time series: Some evidence and implications, Journal of Monetary Economics 10, 2 139-162.

Ng, S. and Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power, Econometrica 69, 519-1554.

Pesaran, M. H. and Shin, Y. (1999) An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis. In S. Strom, (ed) *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*, Cambridge University Press, Cambridge.

Schmidt, P. and P.C.B. Phillips, (1992), LM tests for a unit root in the presence of deterministic trends, Oxford Bulletin of Economic and Statistics, 54, 3, 257-287.

Phillips, P.C.B. and Perron, P. (1988). Testing for a unit root in time series regression, Biometrika 75, 335-346.

Pollin, R. and Zhu, A. (2006). Inflation and economic growth: a cross-country nonlinear. Journal of Post Keynesian Economics, 28(4), 593-614.

Robinson, P.M. (1994) Efficient tests of nonstationary hypotheses. Journal of the American Statistical Association 89, 1420-1437.

Smith, T. R. (1992), "The Cyclical Behavior of Prices", Journal of Money, Credit, and Banking 24 (4), 413–430.

Vázquez, J. (2002), The co-movement between output and prices in the EU15 countries: an empirical investigation. Applied Economics Letters, 9, 957-966.

Table 1: Estimates of d: raw data

i) White noise errors			
Series	No deterministic terms	An intercept	An intercept and a linear trend
CPI UK	1.05 (0.94, 1.17)	1.17 (1.09, 1.26)	**1.12 (1.06, 1.20)**
CPI USA	0.98 (0.87, 1.13)	1.21 (1.07, 1.36)	**1.16 (1.04, 1.30)**
REAL GDP UK	0.87 (0.73, 1.08)	0.80 (0.74, 0.87)	**0.74 (0.65, 0.85)**
REAL GDP USA	0.98 (0.85, 1.16)	0.86 (0.82, 0.93)	**0.81 (0.72, 0.92)**
ii) Autocorrelated errors			
CPI UK	1.04 (0.83, 1.26)	1.51 (1.36, 1.70)	**1.41 (1.25, 1.60)**
CPI USA	0.84 (0.57, 1.11)	1.01 (1.01, 1.29)	**0.97 (0.82, 1.17)**
REAL GDP UK	0.41 (0.36, 0.52)	0.94 (0.85, 1.10)	**0.89 (0.65, 1.11)**
REAL GDP USA	0.60 (0.52, 0.77)	0.97 (0.90, 1.10)	**0.92 (0.76, 1.10)**

In parentheses, the 95% confidence band for the non-rejection values of d at the 95% level. In bold, the selected model for each series on the basis of the statistical significance of the regressors.

Table 2: Estimated coefficients of the models from Table 1

i) White noise errors			
Series	d	Intercept (t-statistic)	Time trend (t-statistic)
CPI UK	1.12 (1.06, 1.20)	13.4034 (33.20)	0.5298 (9.93)
CPI USA	1.16 (1.04, 1.30)	21.7330 (58.79)	0.4792 (8.08)
REAL GDP UK	0.74 (0.65, 0.85)	39.9207 (23.73)	0.3385 (8.68)
REAL GDP USA	0.81 (0.72, 0.92)	31.3209 (32.41)	0.4176 (13.97)
ii) Autocorrelated errors			
CPI UK	1.41 (1.25, 1.60)	13.2100 (34.52)	0.6297 (3.31)
CPI USA	0.97 (0.82, 1.17)	21.7772 (59.53)	0.4650 (2.56)
REAL GDP UK	0.89 (0.65, 1.11)	40.2600 (22.66)	0.3207 (4.09)
REAL GDP USA	0.92 (0.76, 1.10)	31.4018 (31.65)	0.4143 (8.24)

In parentheses in column 2 the 95% confidence band for the non-rejection values of d, and in columns 3 and 4 the t-statistics.

Table 3: Estimates of d: Logged data

i) White noise errors			
Series	No deterministic terms	An intercept	An intercept and a linear trend
CPI UK	1.01 (0.92, 1.13)	1.45 (1.37, 1.55)	**1.35 (1.29, 1.41)**
CPI USA	0.98 (0.89, 1.10)	1.56 (1.48, 1.67)	**1.46 (1.39, 1.56)**
REAL GDP UK	0.98 (0.88, 1.11)	0.83 (0.77, 0.91)	**0.81 (0.74, 0.90)**
REAL GDP USA	0.98 (0.89, 1.11)	0.97 (0.87, 1.11)	**0.98 (0.91, 1.09)**
ii) Autocorrelated errors			
CPI UK	1.00 (0.84, 1.18)	1.55 (1.43, 1.70)	**1.40 (1.32, 1.54)**
CPI USA	0.95 (0.80, 1.15)	1.56 (1.43, 1.73)	**1.44 (1.33, 1.60)**
REAL GDP UK	0.89 (0.73, 1.09)	1.01 (0.87, 1.19)	**1.00 (0.83, 1.19)**
REAL GDP USA	0.93 (0.77, 1.13)	1.10 (0.92, 1.31)	**1.05 (0.90, 1.23)**

In parentheses, the 95% confidence band for the non-rejection values of d at the 95% level. In bold, the selected model for each series on the basis of the statistical significance of the regressors.

Table 4: Estimated coefficients of the models from Table 3

i) White noise errors			
Series	d	Intercept (t-statistic)	Time trend (t-statistic)
CPI UK	1.35 (1.29, 1.41)	2.6008 (276.26)	0.0197 (5.41)
CPI USA	1.46 (1.39, 1.56)	3.0861 (632.66)	0.0120 (4.13)
REAL GDP UK	0.81 (0.74, 0.90)	3.6998 (184.80)	0.0050 (8.15)
REAL GDP USA	0.98 (0.91, 1.09)	3.4544 (298.65)	0.0066 (8.55)
ii) Autocorrelated errors			
CPI UK	1.40 (1.32, 1.54)	2.5973 (262.91)	0.0232 (4.93)
CPI USA	1.44 (1.33, 1.60)	3.0862 (613.01)	0.0118 (4.22)
REAL GDP UK	1.00 (0.83, 1.19)	3.7020 (181.57)	0.0047 (3.13)
REAL GDP USA	1.05 (0.90, 1.23)	3.4534 (299.08)	0.0066 (6.12)

In parentheses in column 2 the 95% confidence band for the non-rejection values of d, and in columns 3 and 4 the t-statistics.

Table 5: Estimated coefficients from the regression of log CPI / log RGDP _ (UK case)

i) White noise errors			
Lag order	d (95% confidence band)	Intercept (t-statistic)	Slope coefficient (t-statistic)
k = 1	1.46 (1.39, 1.56)	2.5306 (17.65)	0.0491 (1.27)
k = 2	1.44 (1.37, 1.52)	3.0628 (9.78)	-0.0818 (-0.97)
k = 3	1.43 (1.37, 1.52)	2.8246 (8.65)	-0.0087 (-0.09)
k = 4	1.43 (1.36, 1.51)	2.7566 (28.45)	0.0192 (0.21)
ii) Autocorrelated errors			
k = 1	1.73 (1.53, 1.99)	2.4636 (17.23)	0.0667 (1.73)
k = 2	1.64 (1.52, 1.82)	2.9761 (9.42)	-0.0058 (-0.68)
k = 3	1.67 (1.51, 1.85)	2.8722 (9.75)	-0.0021 (-0.27)
k = 4	1.66 (1.50, 1.90)	2.8347 (9.60)	-0.0020 (-0.02)

In parentheses in column 2 the 95% confidence band for the non-rejection values of d, and in columns 3 and 4 the t-statistics.

Table 6: Estimated coefficients from the regression of log CPI / log RGDP _ (US case)

i) White noise errors			
Lag order	d (95% confidence band)	Intercept (t-statistic)	Slope coefficient (t-statistic)
k = 1	1.56 (1.48, 1.64)	3.1799 (22.58)	-0.0336 (-0.55)
k = 2	1.57 (1.38, 1.66)	3.3794 (17.68)	-0.0743 (-1.35)
k = 3	1.56 (1.48, 1.66)	3.09336 (16.04)	0.0144 (0.26)
k = 4	1.56 (1.48, 1.66)	2.7673 (14.48)	**0.1122 (2.03)**
ii) Autocorrelated errors			
k = 1	1.53 (1.42, 1.70)	2.9622 (21.03)	0.0406 (0.99)
k = 2	1.57 (1.45, 1.74)	3.3794 (17.91)	-0.0743 (-1.36)
k = 3	1.59 (1.43, 1.78)	3.1079 (16.28)	0.0102 (0.18)
k = 4	1.57 (1.41, 1.77)	2.7718 (14.59)	**0.1109 (2.02)**

In parentheses in column 2 the 95% confidence band for the non-rejection values of d, and in columns 3 and 4 the t-statistics. In bold, the significant slope coefficients at the 5% level

Table 7: Estimated coefficients from the regression of log RGDP / log CPI _ (UK case)

i) White noise errors			
Lag order	d (95% confidence band)	Intercept (t-statistic)	Time trend (t-statistic)
k = 1	1.03 (0.94, 1.17)	3.3462 (13.38)	0.1301 (1.37)
k = 2	1.02 (0.93, 1.16)	3.3309 (13.60)	0.1345 (1.45)
k = 3	1.02 (0.93, 1.15)	3.3397 (13.60)	0.1355 (1.46)
k = 4	1.02 (0.94, 1.16)	3.4060 (13.89)	0.1164 (1.25)
ii) Autocorrelated errors			
k = 1	1.03 (0.94, 1.16)	3.3249 (13.62)	0.1382 (1.50)
k = 2	1.02 (0.92, 1.15)	3.3309 (13.62)	0.1345 (1.45)
k = 3	1.02 (0.92, 1.16)	3.3397 (13.60)	0.1355 (1.46)
k = 4	1.02 (0.94, 1.16)	3.4060 (13.89)	0.1165 (1.25)

In parentheses in column 2 the 95% confidence band for the non-rejection values of d, and in columns 3 and 4 the t-statistics. In bold, the significant slope coefficients at the 5% level.

Table 8: Estimated coefficients from the regression of log RGDP / log CPI_(US case)

i) White noise errors			
Lag order	d (95% confidence band)	Intercept (t-statistic)	Time trend (t-statistic)
k = 1	1.08 (0.98, 1.36)	2.7601 (9.10)	**0.2275 (2.32)**
k = 2	1.08 (0.98, 1.35)	2.6888 (8.81)	**0.2561 (2.60)**
k = 3	1.08 (0.99, 1.35)	2.6097 (8.53)	**0.2859 (2.89)**
k = 4	1.09 (0.98, 1.35)	2.9327 (9.38)	**0.1890 (1.87)**
ii) Autocorrelated errors			
k = 1	1.08 (0.97, 1.37)	2.7601 (9.11)	**0.2275 (2.32)**
k = 2	1.08 (0.98, 1.38)	2.6888 (8.81)	**0.2561 (2.60)**
k = 3	1.08 (0.98, 1.37)	2.6097 (8.53)	**0.2859 (2.89)**
k = 4	1.09 (0.97, 1.38)	2.9327 (9.38)	**0.1890 (1.87)**

In parentheses in column 2 the 95% confidence band for the non-rejection values of d, and in columns 3 and 4 the t-statistics. In bold, the significant slope coefficients at the 5% level.

Figure 1: CPI and real GDP (2015=100)