Brunel University London

Department of
Economics and Finance

Working Paper No. 18-03

Economics and Finance Working Paper Series

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March 2018

http://www.brunel.ac.uk/economics

ON THE PERSISTENCE OF UK INFLATION: A LONG-RANGE DEPENDENCE APPROACH

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March 2018

Abstract

This paper examines the degree of persistence in UK inflation by applying long-memory methods to historical data that span the period from 1660 to 2016. Specifically, we use both parametric and non-parametric fractional integration techniques**,** that are more general than those based on the classical I(0) vs. I(1) dichotomy. Further, we carry out break tests to detect any shifts in the degree of persistence, and also run rolling-window and recursive regressions to investigate its evolution over time. On the whole, the evidence suggests that the degree of persistence of UK inflation has been relatively stable following the Bretton Woods period, despite the adoption of different monetary regimes. The estimation of an unobserved-components stochastic volatility model sheds further light on the issues of interest by showing that post-Bretton Woods changes in UK inflation are attributable to a fall in the volatility of permanent shocks.

JEL Classification: C14, C22, E31

Keywords: UK inflation; persistence; fractional integration

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The second- and third-named authors gratefully acknowledge the financial support received from the Ministerio de Economía y Competitividad: ECO2014-55236 (Luis A. Gil-Alana) and ECO2015-68815-P (Tommaso Trani).

1. Introduction

Inflation persistence has been extensively analysed in the literature because its properties have implications for both theoretical models and monetary policy. Central banks aim to anchor expectations in order to lower persistence and reduce the output costs of disinflation (Moreno and Villar, 2010), since high persistence is often due to backward-looking expectations in the presence of price and wage rigidities (Gali and Gertler, 1999). Alternatively, it might reflect the fact that private agents have limited information about the objectives of the central bank, which underlines the importance of transparency for monetary policy (Walsh, 2007).

After World War II (WWII), the degree of inflation persistence has been high in several countries (Miles et al., 2017), but there has been controversy over whether it has remained stable throughout the post-WWII period. Empirical tests based on autoregressive (AR) models, namely the approach most frequently used in the literature, suggest that it may have decreased when central banks started to follow inflation-targeting policies. However, studies based on such models usually find it difficult to reject the hypothesis that inflation has a unit root. Moreover, according to Pivetta and Reis (2007) and Stock and Watson (2007, 2010), no significant change in persistence can be detected over the post-WWII period if one accounts for uncertainty around point estimates or distinguishes between persistent and transitory changes in inflation.

The aim of the present paper is to provide further evidence on the stochastic behaviour of inflation by using long-memory (fractional integration) techniques to analyse the UK experience. The historical data for inflation in this country span a much longer time period than those for others, and therefore the UK experience is particularly suitable to examine persistence with long-memory methods. In particular, our sample includes more than 350 annual observations, from the Restoration of the English monarchy in the second half of the 17^{th} century until 2016. The advantage of using long-range dependence methods is that they do not require imposing the assumption of a unit root or a simple AR process, and therefore are much more general and flexible than the autoregressive-moving average (AR(I)MA) models most commonly used in the literature. In addition, in order to examine any possible changes in persistence**,** we also test for breaks and estimate persistence in the corresponding subsamples, and then we apply rolling-window or recursive methods to capture other forms of time variation. Finally, with the aim of shedding further light on our findings for the post-WWII period (during which inflation dynamics have been a source of controversy) we estimate the unobserved-components stochastic volatility outlier-adjusted (UCSVO) model of Stock and Watson (2016). The chosen fractional integration framework already represents an improvement relative to ARMA modelling, and the UCSVO model also enables us to interpret the evidence in terms of permanent or transitory changes in inflation.

The layout of the remainder of the paper is as follows. Section 2 reviews the literature, Section 3 outlines the methodology, Section 4 describes the data, and Section 5 discusses the results. Finally, Section 6 offers some concluding remarks.

2. Literature Review

The period following WWII has been characterised in many countries by high persistence (Miles et al., 2017). Theorists have followed two main approaches to explain this stylised fact (Meenagh et al., 2009). In New Keynesian DSGE models (e.g., Christiano et al., 2005) persistence is directly related to the specification of the Phillips curve and is not affected by changes in monetary regime. By contrast, on the basis of the Lucas (1976) critique one would expect economic agents to revise their decision rules in response to policy changes and therefore the reduced-form parameters of structural DSGE models, including inflation persistence, to change over time. Meenagh et al. (2009) report evidence confirming that persistence varies across regimes and conclude that models with little nominal rigidity are the most suitable to account for its behaviour. Dixon and Kara (2006) argue that the distribution of contract lengths explains inflation persistence better than indexation.

Numerous empirical studies have analysed inflation persistence using different approaches, but mainly estimating ARMA models. Papers on US inflation initially focused on point estimates, and found that inflation persistence had declined after the 1980s (Cogley and Sargent, 2002). However, subsequent studies allowing for uncertainty around point estimates concluded that it had remained stable (Pivetta and Reis, 2007). More recently, Stock and Watson (2007, 2010) have suggested a method to separate transitory and permanent components of inflation and reconcile the previous two findings. Stock and Watson (2016) refined this method further by including a model-based adjustment for large inflationary spikes (i.e., outliers).[1]

As for UK inflation in particular, some studies have focused on nonlinearities (Clements and Sensier, 2003; Arghyrou et al., 2005), whilst others have analysed its behaviour under different monetary regimes (e.g., Nelson, 2001, 2009; and Nelson and Nikolov, 2004). Benati (2008) examined inflation both in the UK (from 1718 to 2006) and in other countries in order to understand whether inflation persistence could be deemed structural in the sense of Lucas (1976). His results, based on both reduced-form and structural New-Keynesian models, do not support a structural interpretation of persistence, which is measured by estimating AR models as in much of the existing literature.[2]

The issue of seasonality is addressed by Osborn and Sensier (2009), who find that both seasonal patterns and persistence in (monthly) UK inflation have changed over time; specifically, both a univariate model and a Phillips curve representation of UK inflation

[1] Stock and Watson (2007) use a different method to adjust for possible outliers that requires knowing in advance whether large inflationary spikes are mean-reverting.

[2] Note, however, that Benati (2008) found reduced-form evidence that US inflation was highly persistent after the Volcker stabilisation period, a result that is consistent with those of both Cogley and Sargent (2002) and Pivetta and Reis (2007).

suggest the presence of a structural break that can be associated with the introduction of inflation targeting in October 1992; the reduction of inflation persistence after 1993 is seen as an indication of the success of the Bank of England's monetary policy.

As reported by Miles et al. (2017), UK inflation has behaved rather similarly to US inflation over the time period for which data are available for both countries, namely since the beginning of World War I (WWI). Specifically, both their level and volatility were initially rather high, but went down over time, especially during the Great Moderation (i.e., in the 1990s). Inflation volatility then increased again during the Great Recession brought about by the global financial crisis of 2007-8, when it reached values similar to those of the Great Depression of 1929. According to Miles et al. (2017), the only notable difference between the experience of these two countries is that, in the UK, the period of low volatility that characterised the 1990s had actually started with the end of the Bretton Woods monetary system, whilst this occurred much later in the case of US inflation.

3. Econometric Methodology

We estimate the following model:

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

where y_t stands for the rate of inflation, α and β are unknown coefficients corresponding respectively to the intercept and a linear time trend, the de-trended series x_t and the error u_t are assumed to be I(d) and I(0) respectively, and d is an unknown parameter, to be estimated together with α and β.

We examine the cases of both uncorrelated (white noise) and autocorrelated (Bloomfield, 1973) errors,[2] and estimate three different specifications of the model: i) without deterministic terms, setting $\alpha = \beta = 0$ a priori, in eq. (1); ii) with an intercept, with α being

[2]The model of Bloomfield (1973) is a simple (non-parametric) approach that approximates highly parameterised ARMA models and is highly suitable in the context of fractional integration (see, e.g., Gil-Alana, 2004).

unknown and $\beta = 0$ a priori; and iii) with a linear time trend, with α and β in eq. (1) both being unknown.

Regardless of the case considered, the model in eq. (1) implies that y_t is a stationary variable only if $d < 0.5$; otherwise, i.e., for $d \geq 0.5$, it is not covariance-stationary and is highly persistent.[3] In the latter case, y_t can either be mean-reverting (i.e., $d < 1$) or not. Therefore, since d is a real-value parameter, one can assess the degree of persistence of inflation with more accuracy than by using the competing AR(I)(MA) models, which have been frequently employed in the literature. In particular, the estimation of d enables one to distinguish between unit root and near-unit root processes. We use the parametric procedure of Robinson (1994) that yields Whittle estimates of d in the frequency domain (Dahlhaus, 1989), along with the non-parametric approach of Bloomfield (1973) when allowing for autocorrelation in the error term.[4]

After obtaining these two sets of results for the whole sample period, we estimate d using a rolling-window approach to detect any changes in the fractional degree of integration and, therefore, any possible time-variation in the persistence of inflation. In order to obtain reliable estimates, the window width is chosen to be 60 years. In addition we also estimate d with a recursive approach, starting with a sample of 60 observations, and adding recursively one more at a time. The possibility of structural breaks in the same fractional integration context is also investigated.

Finally, to gain additional insights into our results for the last part of the sample period (i.e., the post-WWI subsample), we estimate a UCSVO model. When trying to assess the (in)stability of inflation persistence, the literature has mostly focused on the post-WWI

[3] It is nonstationary in the sense that the variance of the partial sums increase in magnitude with d.

[4] Very similar results were obtained when using other more recent approaches (Sowell, 1992; Beran, 1995; Lobato and Velasco, 2007). The reason for choosing the method of Robinson (1994) is that it is the most efficient in the Pitman sense against local departures, and, unlike the other methods, it remains valid even in nonstationary contexts ($d \geq 0.5$).

period; the UCSVO framework enables one to analyse that issue in terms of permanent and transitory changes in inflation. In particular, the assumption behind the UCSVO model is that inflation can be decomposed into (i) a trend component following a martingale process and (ii) transitory shocks. Both the permanent shocks affecting the trend and the transitory ones are assumed to have a time-varying variance; a correction for outliers is also used in the case of the latter, which is useful to reduce the probability of a single large shock being taken as a signal of a more systematic increase in the volatility of transitory shocks.

The UCSVO model is estimated with Bayesian methods, with the posterior distribution of the variables of interest being obtained using a Markov chain Monte Carlo (MCMC) algorithm. In particular, we use the algorithm proposed by Stock and Watson (2016), which improves the accuracy of the estimates for two reasons. First, the posterior distributions of the stochastic volatilities are approximated with an accurate 10-component Gaussian mixture (Omori et al., 2007). Second, the algorithm is devised to avoid the general mistake found in the implementation of models with stochastic volatility by Del Negro and Primiceri (2015). Moreover, the framework of Stock and Watson (2016) is particularly suitable for our purposes, since it was developed to fit post-WWII US data, and, as already mentioned, Miles et al. (2017) documented that US inflation behaved very similarly to UK inflation during the last 100 years. See Appendix B for details about both the UCSVO model (Section B.1) and its estimation (Section B.2).

4. Data Description

The series examined is annual headline CPI inflation; the source is the Bank of England's historical macroeconomic dataset.[5] Following Miles et al. (2017), we start our analysis in 1660, which is the year of the Restoration of the British monarchy and precedes by a few

[5] "A millennium of macroeconomic data", version 3.1.

decades the *de facto* adoption of the Gold Standard monetary regime in 1717. Therefore, our sample period goes from 1660 to 2016.

Figure 1 displays the series under investigation. Visual inspection suggests that UK inflation was highly volatile around zero and not very persistent until approximately the start of the 20th century; both its level and degree of persistence have instead been higher since the official end of the Gold Standard (i.e., 1914).

[Insert Figure 1 and Table1 about here]

In order to obtain a clearer picture of how the level and volatility of inflation evolved over time, we report in Table 1 summary statistics for six subsamples. These are: the period preceding the *de jure* Gold Standard, the *de jure* Gold Standard, the Interwar period, the Bretton Woods regime, the interim regime between the Bretton Woods system and the adoption of inflation targeting by the Bank of England, and the inflation targeting regime. The table shows that inflation was generally low and volatile during the first three periods, with the interwar period being deflationary. Moreover, it declined over time until the Bretton Woods period, during which its volatility kept falling whilst inflation itself was generally higher than previously. After the end of the Bretton Woods system inflation volatility rose even further, until the adoption of inflation targeting by the Bank of England reduced both its level and volatility, with inflation stabilising around 2%.

[Insert Figure 2 about here]

Figure 2 reports some preliminary evidence on inflation persistence based on standard measures used in the existing literature, namely the Pearson statistic and the first-order autocorrelation coefficient in an OLS regression, applying both rolling and recursive window methods. Both suggest that inflation persistence was generally not significantly different from zero until approximately 1850. Subsequently, and most notably after WWI, persistence jumped and then reached a plateau. It is noteworthy that, while the rolling-window estimates suggest that it increased slightly also over the last part of our sample (i.e., during the Great Moderation and after 2000), the recursive window ones imply that the last upward correction in the post-WWI era occurred in the 1980s.

5. Empirical Results

5.1 Fractional Integration Analysis

Table 2 reports the estimates of *d* under the assumption of uncorrelated and autocorrelated errors, respectively, for the three models previously mentioned. The other estimated coefficients are shown in Table 3. The results indicate that a time trend is required regardless of the specification adopted for the error term. Under the assumption of white noise residuals**,** the estimated value of *d* is 0.22, which is significantly higher than 0 and implies long-memory behaviour. By contrast, when assuming that the error term u_t is autocorrelated as in the exponential spectral model of Bloomfield (1973), the estimated value of *d* is approximately equal to -0.08 and the I(0) null hypothesis (short memory) cannot be rejected, namely a lower degree of persistence is found in this case.[6]

[Insert Table 2 and Table 3 about here]

In the Appendix, Figure A.1 shows a slightly upward trend for both uncorrelated (in Figure A.1i) and autocorrelated errors (in Figure A.2ii); note, however, that the estimated coefficients (see Table 3) were obtained under the assumption of a constant differencing parameter over the whole sample period.

[Insert Table 4 about here]

Next we examine the possibility of structural breaks. For this purpose**,** we use first the Bai and Perron (2003) approach, and then the methods proposed by Gil-Alana (2008) and

[6] This is a common finding for macro series in the case of autocorrelated disturbances and is attributable to the competition between the fractional differencing parameter and that associated with the autocorrelation structure in accounting for the degree of dependence in the data (see, e.g., Gil-Alana and Robinson, 1997).

Hassler and Meller (2014), both specifically designed for the case of fractional integration. These methods are based on minimising the sum of squared residuals over different subsamples. The results indicate that there is a single break in the series around 1933. Therefore, we split the sample into the two corresponding subsamples, and estimate the differencing parameter for each of them. The results are displayed in Table 4. There appears to be a very significant increase in the degree of persistence after the break. In particular, under the white noise assumption for the error term, the estimated value of *d* increases from 0.12 in the first subsample to 0.73 in the second one. When allowing for autocorrelation in the disturbances, the estimates are much smaller, but there is once again a sharp increase from 0.29 in the first subsample to 0.34 in the second one. Note that these results provide evidence of long memory ($d > 0$) in the second subsample, regardless of the assumption made about the error term.

Even when allowing for breaks, the model still imposes a constant parameter for the degree of integration in each subsample with a sudden break around 1933. Next, we investigate if the differencing parameter has remained stable or not over the whole sample as well as the subsamples considered. In Figure 3, we display the 60-year rolling window estimates of *d*, once again for the two cases of uncorrelated and autocorrelated errors. The results are broadly consistent; the lower values in the latter case might be due to the competition between the differencing parameter and the Bloomfield one in describing the degree of dependence. As can be seen, inflation persistence was rather stable from 1660 till approximately 1776**.** Then, there was a slight increase till 1917-18, followed by a sharp jump to a stable higher level, and a further slight increase from 1981**.**

Given the results in Figure 3, we use once again Gil-Alana's (2008) approach to test for breaks in the series corresponding to the rolling-window estimates and obtain additional information on the evolution of persistence over time. The results are conclusively in favour of three breaks in these series, specifically, in 1776, 1917 and 1980. Table 5 reports the estimates of *d* (and their 95% confidence interval) for the corresponding subsamples.

[Insert Figure 3 and Table 5 about here]

Table 5i and Table 5ii show the results for uncorrelated and autocorrelated disturbances, respectively. The degree of persistence appears to have increased monotonically over time. In particular, in the case of uncorrelated errors, the estimated value of *d* increases from -0.25 in the first subsample to 0.13 in the second, 0.84 in the third and 0.99 in the fourth one, and the I(1) null hypothesis cannot be rejected in the last two subsamples. With autocorrelated disturbances, the estimate of *d* is initially equal to -0.89, and then moves over time to -0.48, -0.06 and finally 0.00; however, the corresponding confidence intervals are very wide and therefore the differences between the estimated parameters are not statistically significant.

To complete the fractional integration analysis, we re-estimate *d,* this time recursively, starting with a sample of 60 observations, (1660-1719) and adding one observation at a time. The estimated values of *d* (along with their 95% bands) for the case of uncorrelated errors are displayed in Figure 4(i). The time trend (not shown) becomes significant from the 98th subsample onwards, namely from the 1660-1816 subsample onwards. The estimate of *d* remains around -0.2 from the first subsample till the one incorporating the year 1822; then it jumps, and remains stable (slightly below 0) till the subsample ending in 1917. Subsequently it increases once more, and it remains significantly above 0 thereafter. It is noteworthy that the recursive estimates *d* are systematically lower than the first-order autocorrelation coefficients displayed in Figure 2, which suggests that standard AR(1) models might overestimate the degree of inflation persistence.

The recursive estimation under the alternative assumption of autocorrelated disturbances yields a similar picture, although the estimated values of *d* are about 0.20 smaller in all cases (see Figure 4ii).

[Insert Figure 4 and Table 6 about here]

Finally, the Gil-Alana (2008) tests on the recursive estimates of *d* imply that the break dates are 1822, 1917 and 1975. The estimated values of *d* for each subsample are reported in Table 6; it can be seen that *d* increases from the first to the second and then the third subsample, whilst it remains stable in the last one. In particular, with uncorrelated disturbances, the estimates of *d* for the four subsamples are -0.05, 0.51, 0.77 and 0.78, respectively; therefore there is evidence of long memory ($d > 0$) in the last three subsample. Under the assumption of autocorrelation, the corresponding values are -0.87, -0.25, -0.06 and -0.05, and the I(0) null hypothesis cannot be rejected for any of the last three subsamples.

To summarise, our results suggest that UK inflation has been highly persistent since the end of WWI. Moreover, the rolling- and recursive-window estimates of the fractional degree of integration *d* imply that the null hypothesis of a stable degree of persistence since WWI cannot be rejected. The slight increase in inflation persistence detected for the years after the 1980s by the rolling-window estimation is likely to reflect the fact that this method tends to overestimate the effects of the last regime change detected by the break tests.

5.2 UCSVO Analysis

Our findings for the latter part of the sample are consistent with those of Pivetta and Reis (2006) and Stock and Watson (2007, 2010) for the US, even though both these studies adopted econometric strategies that differ from ours. In particular, Stock and Watson (2007) proposed analysing trend inflation using an unobserved-components stochastic volatility model, which allows for an economically meaningful interpretation of the evolution of inflation in terms of permanent and transitory shocks. Next we describe the results obtained applying the most recent version of their model, namely the UCSVO model (Stock and Watson, 2016), which embeds a correction for outliers.

We estimate this model over two subsamples, namely: (a) 1918-2016 and (b) 1950-2016. The first is chosen on the basis of the previous empirical analysis: visual inspection of the data (Figure 1) suggests that the biggest change in the behaviour of UK inflation occurred at the end of WWI, and our tests have in fact detected a statistically significant break in 1917 in the context of both the rolling-window and recursive analysis. The choice of the second subsample follows the literature, with most studies examining the period starting around 1950 when the Bretton Woods system had just been put in place.

[Insert Figure 5 about here]

Figure 5 shows the results for both subsamples; specifically, it displays the variance of permanent and transitory shocks respectively and also the estimated outliers, which are allowed to occur every two years (see Section B.3 of the Appendix for the estimated trends and further results). It appears that the volatility of permanent shocks declined over time, whilst that of transitory shocks remained constant, regardless of whether the starting point of the estimation is the end of WWI or a few years after the beginning of Bretton Woods. The only slight differences between the results based on the first and second subsample are the narrower confidence bands and slightly smaller median estimate in the case of the latter. The difference in the level is not statistically significant, whilst the volatility of permanent changes in inflation was very high at the beginning of the 20th century, it remained so in the interwar period and during the 1970s, and then converged towards zero after the 1990s. Finally, in the most recent years (during the Great Recession and its aftermath) UK inflation appears to be driven mainly by outliers, the volatility of transitory shocks remaining essentially the same as in the past.

These findings suggest that inflation targeting has reduced the impact of permanent shocks on UK inflation, whilst transitory shocks have played a major role as a driving factor. The latter signal changes in relative prices, e.g. following commodity price shocks; they typically have negative but short-lived effects on consumption that are often difficult for monetary authorities to control. The main change appears to have been the decline in the volatility of permanent shocks rather than in their persistence, which is consistent with our previous finding that the degree of fractional integration remained more or less the same after 1917. Moreover, the break in UK inflation in the early 1980s detected by our tests is associated with a relatively high volatility of permanent shocks and some large outliers (see Figure 5).

6. Conclusions

This paper uses historical data spanning the period from 1660 to 2016 to examine the degree of persistence in UK inflation. We use long-range dependence (parametric and non-parametric) techniques, more specifically fractional integration models that are more general than those based on the classical I(0) v. I(1) dichotomy found in most studies and provide more accurate estimates of persistence. In addition we carry out break tests to detect any shifts in the degree of persistence and also run rolling-window and recursive regressions to examine its evolution over time. Finally, we estimate a UCSVO model to distinguish between permanent and transitory shocks to inflation.

On the whole, the evidence suggests that UK inflation can be characterised as a long-memory stationary process with a relatively stable degree of persistence in the period following the Bretton Woods period, despite the adoption of different monetary regimes. In particular, there is no clear evidence that inflation targeting has brought about a lower degree of inflation persistence, contrary to what claimed in other studies**,** such as Osborn and Sensier

(2009); the fact that these and related studies are based on relatively standard ARMA models and analyse a much shorter time series might account for the different findings. The UCSVO estimates suggest that inflation targeting might have reduced to some extent the impact of permanent shocks on inflation; however, it is their higher volatility as well as the presence of some sizeable outliers that appear to account for the break detected in the early 1980s.

Future work will aim to investigate possible nonlinearities, for instance applying the method of Cuestas and Gil-Alana (2016) based on Chebyshev polynomials in time.

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Figure 1: UK inflation rate (1660-2016)

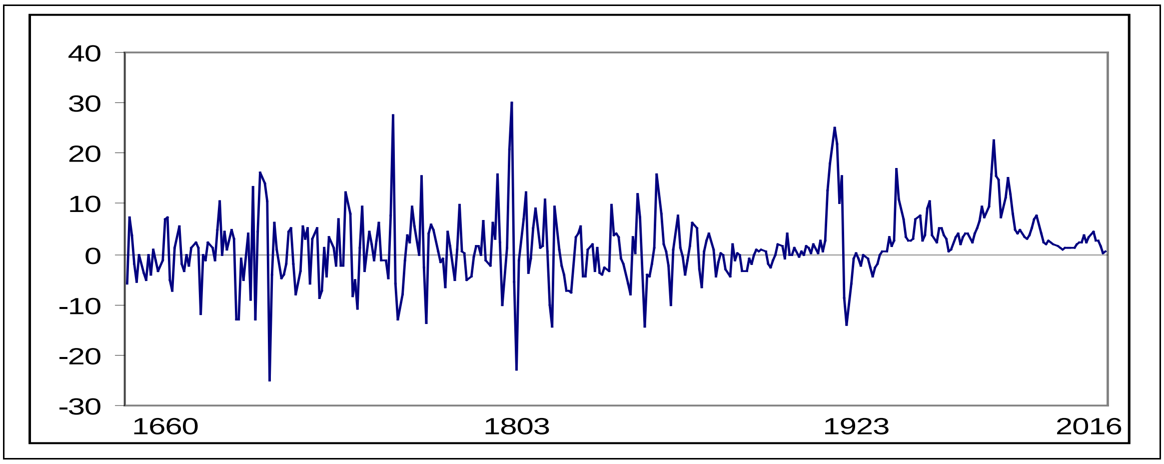


Figure 2: Rolling and recursive first-order autocorrelation coefficients

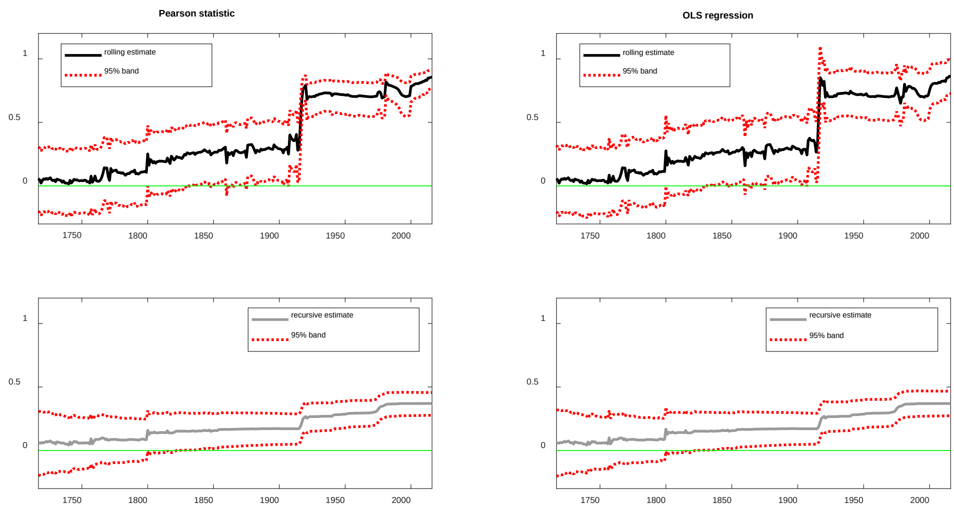


Table 1: Historical summary statistics

	Pre-"de jure" Gold Standard:	*"De jure" Gold Standard:*	*Interward period*	*Bretton Woods*	*Bretton Woods to inflation targeting*	*Inflation targeting*
Mean	0.55	0.03	-1.89	4.37	9.18	2.09
Median	0.39	0.20	-0.80	3.88	7.50	2.06
Min	-25.19	-14.40	-14.00	0.60	3.20	0.04
Max	30.02	15.66	3.40	10.65	22.70	4.46
Standard deviation	7.60	4.36	4.12	2.49	5.33	1.07

The entries are expressed as percentages. The historical breakdown is as follows: pre-“de jure” Gold Standard from 1660 to 1820, “de jure” Gold Standard from 1821 to 1914, Interwar period from 1921 to 1939, Bretton Woods from 1944 to 1971, Bretton Woods to inflation targeting from 1972 to 1991, inflation targeting from 1992 onwards.

Table 2: Estimates of *d* for the UK inflation rate

	No regressors	*An intercept*	*A linear time trend*
White noise	0.24 (0.16, 0.36)	0.25 (0.17, 0.35)	**0.22 (0.13, 0.35)**
Bloomfield	0.02 (-0.04, 0.09)	0.02 (-0.04, 0.10)	**-0.08 (-0.16, 0.02)**

In bold, the significant results according to the deterministic terms.

Table 3: Estimated coefficients for the UK inflation rate

	No regressors	*An intercept*	*A linear time trend*
White noise	0.22 (0.13, 0.35)	-0.96071 (-2.56)	0.01405 (1.77)
Bloomfield	-0.08 (-0.16, 0.02)	-1.10705 (-2.41)	0.01482 (6.49)

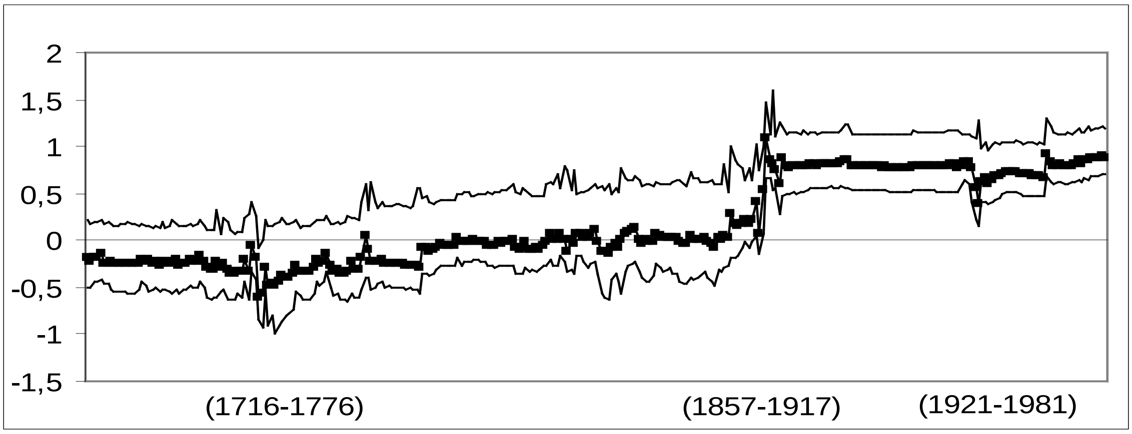
Table 4: Estimated coefficients for the UK inflation rate

i) White noise errors			
	No regressors	*An intercept*	*A linear time trend*
(1660 - 1933)	0.12 (0.00, 0.29)	**0.12 (0.00, 0.29)**	0.12 (-0.01, 0.29)
(1934 - 2016)	0.74 (0.57, 1.00)	**0.73 (0.57, 1.00)**	0.73 (0.56, 1.00)
ii) Autocorrelated errors			
	No regressors	*An intercept*	*A linear time trend*
(1660 - 1933)	-0.27 (-0.35, -0.16)	**-0.29 (-0.39, -0.15)**	-0.32 (-0.42, -0.18)
(1934 - 2016)	0.37 (0.13, 0.65)	**0.34 (0.13, 0.65)**	0.34 (0.11, 0.65)

In bold, the significant results on the basis of the deterministic terms.

Figure 3: Rolling-window estimates of *d* with 60 years of observations.

i) No autocorrelation (white noise)



ii) Autocorrelation (Bloomfield)

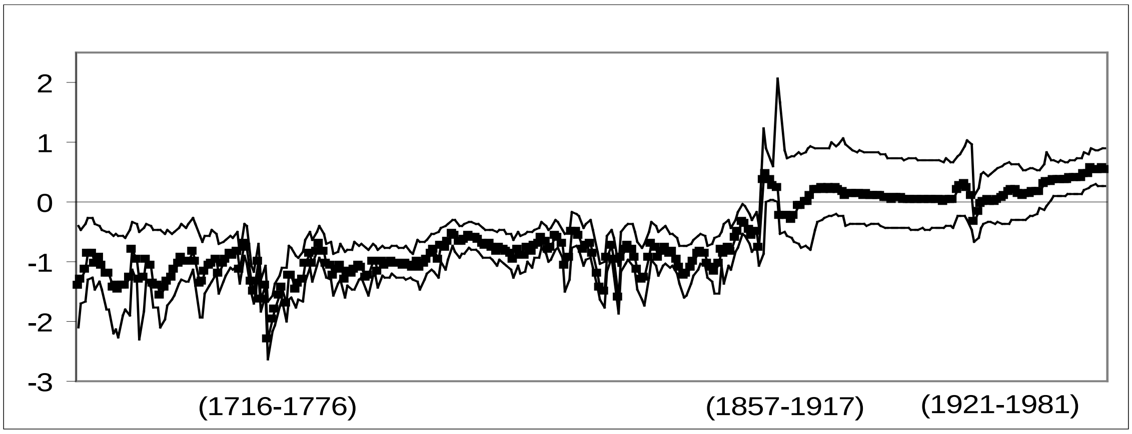


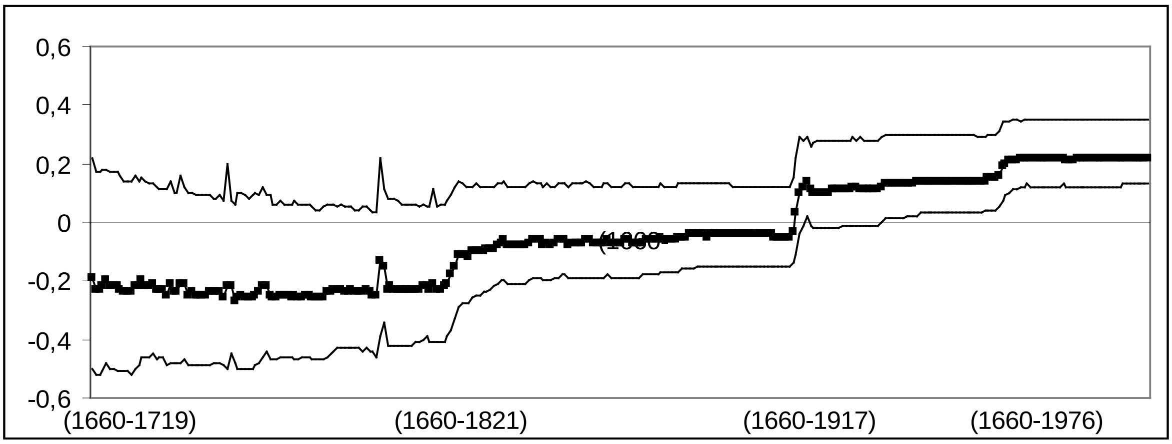
Table 5: Rolling window estimates of *d* for each subsample

i) White noise errors				
Period	*Dates*	*No regressors*	*An intercept*	*A linear trend*
1st subsample	1660 – 1776	-0.14 (-0.28, 0.10)	-0.13 (-0.30, 0.10)	**-0.25** **(-0.46, 0.07)**
2nd subsample	1777 – 1917	0.13 (-0.06, 0.47)	**0.13** **(-0.06, 0.45)**	0.13 (-0.07, 0.46)
3rd subsample	1918 – 1980	0.63 (0.42, 1.00)	**0.84** **(0.55, 1.11)**	0.85 (0.61, 1.11)
4th subsample	1981 – 2016	1.03 (0.57, 1.84)	**0.99** **(0.50, 1.63)**	0.99 (0.71, 1.84)
ii) Autocorrelated errors				
Period	*Dates*	*No regressors*	*An intercept*	*A linear trend*
2nd subsample	1777 – 1917	-0.47 (-0.64, 0.28)	-0.39 (-0.50, 0.23)	**-0.48** **(-0.62, 0.33)**
3rd subsample	1918 - 1980	0.13 (0.06, 0.44)	0.20 (-0.09, 1.08)	**-0.06** **(-0.39, 1.09)**
4th subsample	1981 - 2016	-0.47 (-0.97, 0.35)	-0.13 (-0.42, 0.21)	**0.00** **(-0.38, 0.95)**

In bold, the significant results on the basis of the deterministic terms.

Figure 4: Recursive estimates of *d* starting with 60 observations and adding one observation at a time

i) No autocorrelation (white noise)



ii) Autocorrelation (Bloomfield)

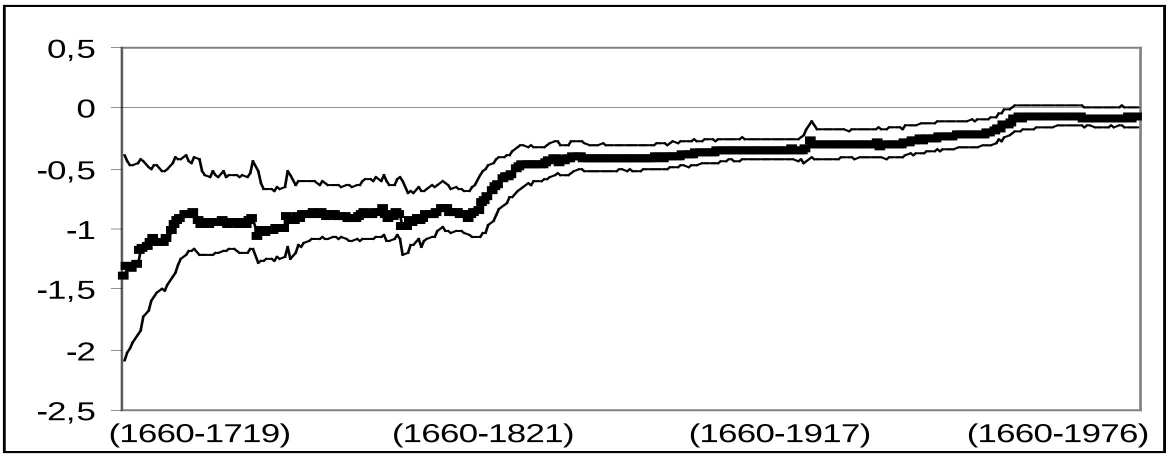
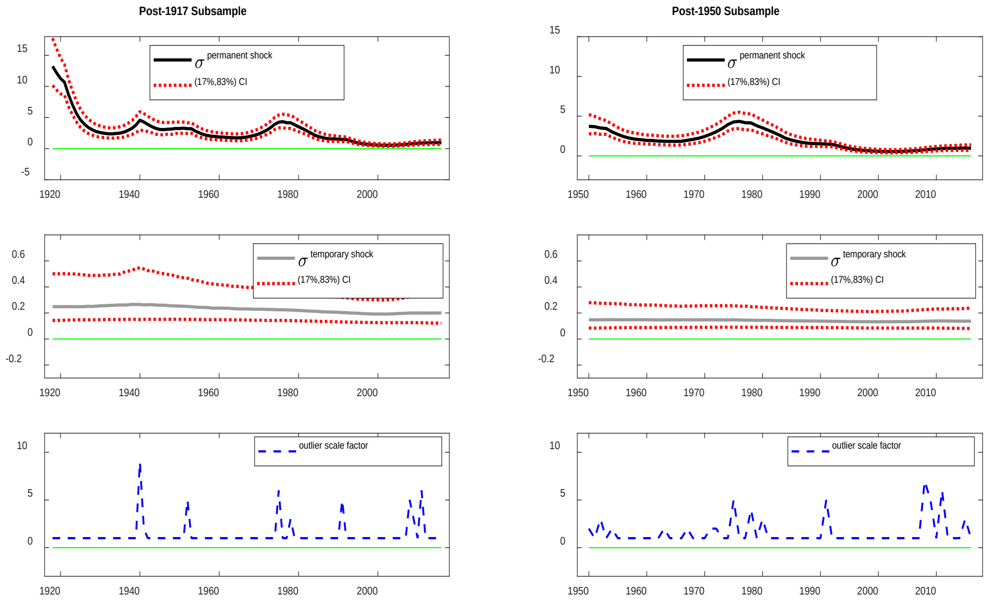


Table 6: Recursive estimates of *d* for each subsample

i) White noise errors				
Period	*Dates*	*No regressors*	*An intercept*	*A linear trend*
1st subsample	1660 – 1822	-0.05 (-0.16, 0.15)	**-0.05** **(-0.17, 0.16)**	-0.11 (-0.29, 0.14)
2nd subsample	1823 – 1917	0.54 (0.27, 0.85)	**0.51** **(0.26, 0.81)**	0.53 (0.30, 0.82)
3rd subsample	1918 – 1975	0.70 (0.45, 1.04)	**0.77** **(0.50, 1.07)**	0.77 (0.48, 1.07)
4th subsample	1976 – 2016	0.71 (0.49, 1.13)	0.60 (0.40, 1.18)	**0.78** **(0.54, 1.16)**
ii) Autocorrelated errors				
Period	*Dates*	*No regressors*	*An intercept*	*A linear trend*
1st subsample	1660 – 1822	-0.32 (-0.40, -0.22)	-0.37 (-0.45, -0.25)	**-0.87** **(-1.04, -0.57)**
2nd subsample	1823 – 1917	-0.40 (-0.93, 0.37)	-0.34 (-0.74, 0.33)	**-0.25** **(-0.69, 0.40)**
3rd subsample	1918 – 1975	0.12 (-0.28, 0.70)	0.13 (-0.32, 0.76)	**-0.06** **(-0.49, 0.75)**
4th subsample	1976 – 2016	-0.04 (-0.38, 0.49)	-0.02 (-0.31, 0.32)	**-0.05** **(-0.32, 0.59)**

In bold, the significant results on the basis of the deterministic terms.

Figure 5: Time-varying volatilities predicted by the UCSVO model

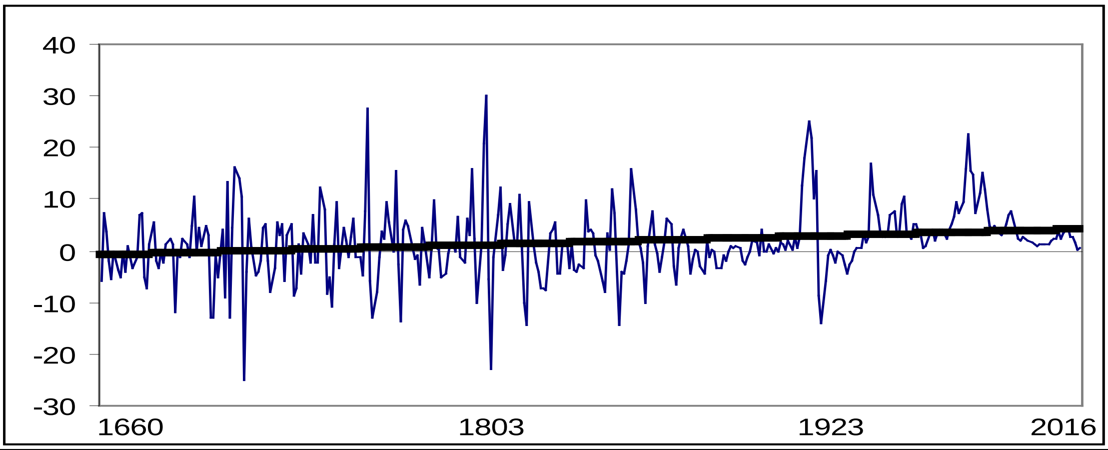


”σ permanent shock” is the volatility of changes in the permanent component of inflation, and “*σ transitory shock*” is the volatility of changes in the transitory component. After an initial burn-in phase of 10000 iterations, the results are based on 50000 replications, saving every 10 draws.

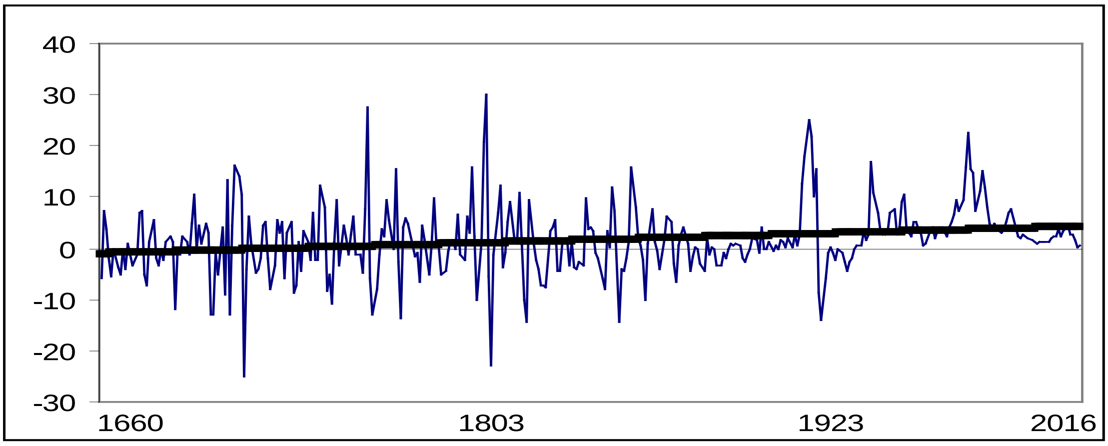
Appendix A

Figure A.1: UK inflation rate and estimated trends

i) White noise case



ii) Autocorrelation case



Appendix B

B.1 UCSVO Model

A UCSVO model (Stock and Watson, 2016) for trend inflation in the UK is as follows:

$$y_t = \tau_t + \varepsilon_{y,t} \tag{B.1}$$

$$\tau_t = \tau_{t-1} + \sigma_{\Delta\tau,t}\eta_t \tag{B.2}$$

$$\varepsilon_{y,t} = \sigma_{y,t}s_t\zeta_t \tag{B.3}$$

where y_t is the observed time series for inflation, τ_t is a martingale trend, $\varepsilon_{y,t}$ is a transitory shock and $\sigma_{y,t}$ is the corresponding volatility, $\sigma_{\Delta\tau,t}$ is the volatility of shocks to the trend, s_t is an *iid* random variable that generates outliers, and, finally, η_t, and ζ_t are idiosyncratic shocks. The two volatilities $\sigma_{y,t}$ and $\sigma_{\Delta\tau,t}$ follow a stochastic process as below:

$$\Delta\ln\sigma_{y,t} = \gamma_y u_{y,t} \tag{B.4}$$

$$\Delta\ln\sigma_{\Delta\tau,t} = \gamma_{\Delta\tau}u_{\Delta\tau,t}, \tag{B.5}$$

where $u_{y,t}$ and $u_{\Delta\tau,t}$ are random variables so that (ζ_t , η_t, $u_{y,t}$, $u_{\Delta\tau,t}$) is *iidN*(0, I_4).

The assumption embedded in eq. (B.3)-(B.4) is that transitory shocks are serially uncorrelated and their volatility evolves over time according to a logarithmic random-walk process. Conditional on such a process, transitory shocks are modelled as a mixture of normal distributions through the outlier scale factor s_t. The distribution generating this outlier scale factor is Bernoulli, so that s_t = 1 with probability 1 – p, and s_t = U[2,10] otherwise. The volatility of permanent shocks also follows a logarithmic random walk process.

B.2 Estimation

We estimate model (B.1)-(B.5) with Bayesian methods, which require priors for γ_y, $\gamma_{\Delta\tau}$, p, s and the initial values of τ_t, $\Delta\ln\sigma_{y,t}$ and $\Delta\ln\sigma_{\Delta\tau,t}$. We set these priors and calibrate the estimation following Stock and Watson (2016), who applied the UCSVO model to US data. Their setup is also suitable for the UK since, as recently documented by Miles et al. (2017), UK and US inflation have behaved very similarly during the last 100 years. However, we make a different assumption about the frequency of outliers compared to Stock and Watson (2016).[3]

The conjugate prior for p is $B(\alpha, \beta)$, and, by assumption, α and β reflect information from a subsample of 10 years, with outliers occurring every two years. The U[2,10] prior for the factor s is approximated with an equally-spaced grid of 9 points. The priors for γ_y and $\gamma_{\Delta\tau}$ are uninformative uniform priors, and their calibration allows to scale the standard deviation of annual changes in inflation. Given this scaling, $\ln\sigma_{y,t}$, $\ln\sigma_{\Delta\tau,t} \sim U[0,0.4]$, and we approximate this distribution using equally spaced grids of 5 points. Finally, the priors for τ_0, $\Delta\ln\sigma_{y,0}$ and $\Delta\ln\sigma_{\Delta\tau,0}$ are independent diffuse priors.

The mean and quantiles of the Bayesian posterior distributions are approximated using the Markov chain Monte Carlo (MCMC) algorithm, whereby $\ln\eta_t^2$, $\ln\zeta_t^2 \sim \ln\chi_t^2$. The approximation of the $\ln\chi_t^2$ is handled with a mixture of normal distributions, using the 10-component Gaussian mixture of Omori et al. (2007).[4] The analysis is based on 60000 iterations, the first 10000 of which constitute the burn-in phase. Of the remaining 50000 iterations, we save one every 10 draws.

[3] Note that nevertheless our assumption produces very similar results to those of Stock and Watson (2016 - see Section B.3 in this appendix).

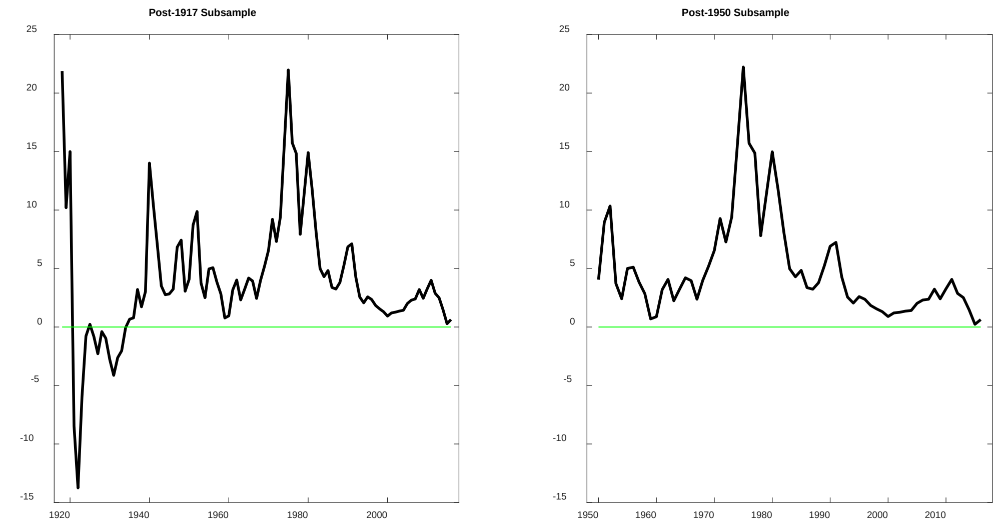
[4] See Stock and Watson (2016) for the specific sequence of steps. We partition the vector of variables for which we need to obtain posterior distributions in the same way as these authors.

B.3 Additional results

In the paper, we report the posterior distributions for $\sigma_{y,t}$, $\sigma_{\Delta\tau,t}$, and s_t for both the 1917-2016 subsample and the 1950-2016 subsample. In this appendix, we complete the set of results, reporting the posteriors for τ_t, γ_y, $\gamma_{\Delta\tau}$ and p. See Figure B.1, Table B.1 and Table B.2, respectively.

Furthermore, we repeated the estimation assuming that an outlier can occur every four years. This is the assumption of Stock and Watson (2016), who focus on quarterly data for the US over the period from 1960 to mid-2015. Our data for UK inflation are instead annual, and the reason for our baseline case of an outlier every two years is that when making this assumption the MCMC algorithm predicts large inflationary spikes in the 1940s and the 1980s, whilst this is not the case when the prior for p is associated with outliers occurring every four years. The estimated confidence bands around the median volatility of transitory shocks are slightly larger in the latter than in the former case, but all the other results are very similar.

Figure B.1: Trend inflation (τ_t) predicted by the UCSVO model



This graph displays the mean of the draws of the posterior distributions.

Table B.1: Selected values of the posterior distributions of γ_y and $\gamma_{\Delta\tau}$

Value (for variance)	*Prior (for volatility)*	*Posterior for γ_y*		*Posterior for $\gamma_{\Delta\tau}$*	
		Post-1917 Subsample	*Post-1950 Subsample*	*Post-1917 Subsample*	*Post-1950 Subsample*
0	0.2	0.24	0.24	0	0
0.1	0.2	0.24	0.23	0.1	0
0.2	0.2	0.21	0.21	0.01	0
0.3	0.2	0.18	0.17	0.18	0.05
0.4	0.2	0.13	0.15	0. 8	0.95

Table B.2: Posterior distributions of *p* for a selection of quantiles

Quantile	*Posterior for the Post-1917 Subsample*	*Posterior for the Post-1950 subsample*
0.17	0.1	0.12
0.5	0.15	0.19
0.83	0.22	0.28