Time-Varying Persistence in US Inflation

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Abstract

The persistence property of inflation is an important issue for not only economists, but, especially for central banks, given that the degree of inflation persistence determines the extent to which central banks can control inflation. Further, not only is the level of inflation persistence that is important in economic analyses, but also the question of whether the persistence varies over time, for instance, across business cycle phases, is equally pertinent, since assuming constant persistence across states of the economy, is sure to lead to misguided policy decisions. Against this backdrop, we extend the literature on long-memory models of inflation persistence for the US economy over the monthly period of 1876:2-2014:5, by developing an autoregressive fractionally integrated moving average-generalized autoregressive conditional heteroskedastic (ARFIMA-GARCH) model, with a time-varying memory coefficient which varies across expansions and recessions. In sum, we find that, inflation persistence does vary across recessions and expansions, with it being significantly higher in the former than in the latter. As an aside, we also show that, persistence of inflation volatility however, is higher during expansions than in recessions. Understandably, our results have important policy implications.

Keywords: Persistence; US Inflation Rate; Time-Varying Long Memory.
J.E.L. codes: C12, C13, C22, C51, E31, E52.

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1 Introduction

The persistence property of inflation is an important issue for not only economists, but, especially for central banks, given that the degree of inflation persistence determines the extent to which central banks can control inflation. Understandably, the amount of research devoted (and still being carried out), given conflicting results[1] in analyzing the inflation persistence property for the US, as well as, other world economies is voluminous, to say the least.[2] Though various approaches[3] have been used to analyze the degree of inflation persistence, autoregressive fractionally integrated moving average (ARFIMA) models is, perhaps, the most popular approach. This is simply because of the fact that the model nests the unit root and stationarity properties of the data, given its generalized form.

Not only is the level of inflation persistence that is important in economic analyses, but also the question of whether the persistence varies over time, for instance being contingent on the state of the economy, is

[1]In analyzing the issue of the degree of persistence of the shocks, a related controversy exists concerning the possible existence of a unit root in inflation. On one hand, Nelson and Schwert (1977), Barsky (1987), Ball and Cecchetti (1990), and Brunner and Hess (1993) provide evidence that the U.S. inflation contains a unit root. On the other hand, Hassler and Wolters (1995), Baillie et al.,(1996), Baum et al., (1999), Bos et al., (1999), Baillie et al., (2002), Hsu (2005), Lee (2005), Ajmi et al., (2008) and Hassler and Meller (2014) among others have found evidence that inflation is fractionally integrated, suggesting that the differencing parameter is significantly different from zero and unity

[2]For a detailed survey in this regard, please refer to Balcilar et al., (2014) and Martins and Rodrigues (2014).

[3]The econometric methods have covered various unit root tests, state-spaced-based time-varying) autoregressive models, and more recently quantile regressions-based approaches. For a detailed literature review in this regard, refer to Tillmann and Wolters (2014) and Manzan and Zerom (forthcoming).

equally pertinent. This is because, assuming constant persistence across business cycle phases, is sure to lead to misguided policy decisions (as well as inaccurate forecasts). Against this backdrop, we extend the literature on long-memory models of inflation persistence for the US economy over the monthly period of 1876:2-2014:5, by developing an autoregressive fractionally integrated moving average-generalized autoregressive conditional heteroskedastic (ARFIMA-GARCH) model, with a time-varying memory coefficient[4] which varies across expansions and recessions.[5] In sum, we find that, inflation persistence does vary across recessions and expansions, with it being significantly higher in the former than in the latter. As an aside, we also show that, persistence of inflation volatility however, is higher during expansions than in recessions. The rest of the paper is organized as follows: Section 2 discusses the data and the model, with Section 3 devoted to the results. Finally, Section 4 concludes with some policy recommendations.

[4]For a detailed survey on ARFIMA models with a time-varying long memory coefficient, the reader is referred to Boutahar et al., (2008) and Aloy et al., (2013).

[5]Note that, ever since the work of Granger and Hyung (2000), Diebold and Inoue (2001), and Mikosch and Starica (2004) it is well-known that spurious long memory behavior can be detected in time series known to be theoretically short memory due to structural breaks (for detailed literature review in this regard, refer to Tsay (2008), Tsay and H ä rdle (2008) and Hassler and Meller (2014). In our case, we deal with this issue by assuming that the break dates are known and that we have two regimes in expansions and recessions.

2 Model and data description

We compute US Inflation as month-on-month percentage change in the US consumer price index (CPI) covering the monthly period of 1876:1-2014:5. Understandably, the data on inflation rate starts from 1876:2. The data on the CPI is sourced from the Global Financial Database. Note that, the starting and end-points of the sample coincides with the availability of data at monthly frequency at the time of the paper being written. Given our purpose of associating change in persistence with business cycle phases, we also recover the timing of US recessions from the National Bureau of Economic Research (NBER). Table 1 reports the sequence of peaks and troughs on a quarterly basis. As our analyses consider a monthly inflation time series, we set the end of recessions (and similarly of expansions) to the last month of the quarters indicated in Table 1. Figure 1 in the Appendix of the paper plots the month-on-month inflation rate along with the recession dates (indicated by shaded areas).

To motive the need for considering changes in the inflation persistence across business cycle phases, we perform a preliminary analysis. Firstly, in Table 2, we report a descriptive evaluation of the monthly inflation by comparing few indicators over the entire sample, and conditioning on the cycle regime. We note that, over recessions, inflation has a lower mean, and a somewhat higher volatility as compared to expansion periods. However, we also find that the very long inflation time series contains

Peak	Through
	December 1854 (IV)
June 1857(II)	December 1858 (IV)
October 1860(III)	June 1861 (III)
April 1865(I)	December 1867 (I)
June 1869(II)	December 1870 (IV)
October 1873(III)	March 1879 (I)
March 1882(I)	May 1885 (II)
March 1887(II)	April 1888 (I)
July 1890(III)	May 1891 (II)
January 1893(I)	June 1894 (II)
December 1895(IV)	June 1897 (II)
June 1899(III)	December 1900 (IV)
September 1902(IV)	August 1904 (III)
May 1907(II)	June 1908 (II)
January 1910(I)	January 1912 (IV)
January 1913(I)	December 1914 (IV)
August 1918(III)	March 1919 (I)
January 1920(I)	July 1921 (III)
May 1923(II)	July 1924 (III)
October 1926(III)	November 1927 (IV)
August 1929(III)	March 1933 (I)
May 1937(II)	June 1938 (II)
February 1945(I)	October 1945 (IV)
November 1948(IV)	October 1949 (IV)
July 1953(II)	May 1954 (II)
August 1957(III)	April 1958 (II)
April 1960(II)	February 1961 (I)
December 1969(IV)	November 1970 (IV)
November 1973(IV)	March 1975 (I)
January 1980(I)	July 1980 (III)
July 1981(III)	November 1982 (IV)
July 1990(III)	March 1991(I)
March 2001(I)	November 2001 (IV)
December 2007 (IV)	June 2009 (II)

Table 1: Cycle phases (quarter within parenthesis): source NBER - www.nber.org/cycles.html.

	Full sample			From 1920		
	All	Exp	Rec	All	Exp	Rec
Mean	0.002	0.003	0.000	0.002	0.003	0.000
Median	0.000	0.002	0.000	0.002	0.003	0.000
St.dev	0.007	0.006	0.008	0.006	0.005	0.008
Min	-0.032	-0.023	-0.03	-0.032	-0.023	-0.032
Max	0.057	0.057	0.030	0.057	0.057	0.030
Q(1%)	-0.014	-0.013	-0.021	-0.015	-0.008	-0.022
Q(99%)	0.021	0.022	0.019	0.018	0.019	0.015
Skew	36.379	32.199	20.908	0.308	1.931	-0.604
Kurt	1427	1083	450	10.29	18.69	1.51
IQ-range	0.005	0.005	0.006	0.005	0.005	0.011
N. zeros	606	403	203	261	215	46
N. obs.	1660	1183	477	1133	244	891

Table 2: Descriptive analyses

a large amount of zeros, that is periods with a flat price index. Those are concentrated in the first 40 years. Therefore, beside the full sample analyses, we also provide evidences on a shorter sample, starting in January 1920.

We find a confirmation of the full sample results: the average inflation is lower during recessions, while the volatility is higher. Notably, the presence of a large number of zeros has a relevant impact on asymmetry and kurtosis: their level is far more reasonable when we focus on data from 1920. On those reduced sample, we note that inflation is skewed to the left during recessions, and to the right on expansions. This suggest that extreme values drive the mean and variance outcomes, given that during recessions we have instances of drops in inflation (monthly inflation) while during expansions we observe large inflation values. Notably, the inflation density is more leptokurtic during expansions, signaling a higher probability of observing extreme inflation movements.

The long inflation time series we consider has not been seasonally adjusted. To verify the need of such an adjustment, we checked by means of the TRAMO-SEATS package. We found no evidences of seasonal patterns on overlapping subsamples of 50 years. We thus proceed on the analyses using the raw data.

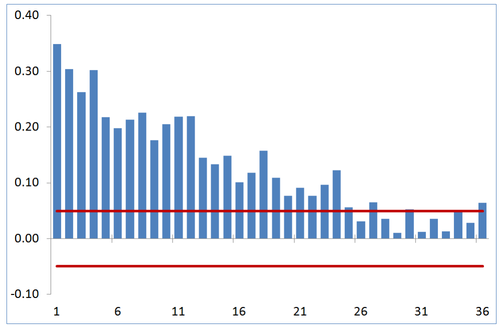
If changes in the persistence were present, one way of getting evidences is through the computation of the autocorrelation function conditional to the state of the economy. Mimicking Caporin and Pres (2013) we consider the following estimators of the autocorrelation at lag k

$$\rho_R\left(k\right) = \frac{\frac{1}{T_R - k}\sum_{j=k+1}^{T} x_t x_{t-1} S_t}{\frac{1}{T_R - k}\sum_{j=k+1}^{T} x_t^2 S_t} \tag{1}$$

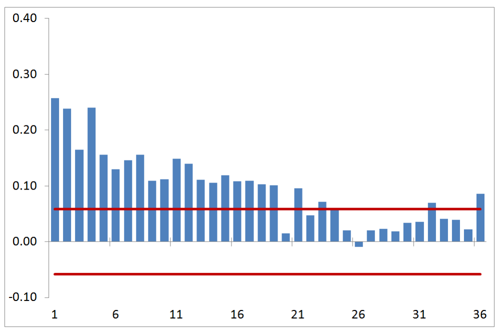
$$\rho_E\left(k\right) = \frac{\frac{1}{T_E - k}\sum_{j=k+1}^{T} x_t x_{t-1}\left(1 - S_t\right)}{\frac{1}{T_R - k}\sum_{j=k+1}^{T} x_t^2\left(1 - S_t\right)} \tag{2}$$

where x_t is the month t inflation rate in deviation from the sample mean, R stands for recession and E for expansion, S_t is an indicator function assuming value 1 during recessions, T is the total sample size, T_R is the number of months associated with a recession ($\sum_{j=1}^{T} S_t = T_R$), and T_E is the number of months where the economy is in expansion, $T_E = T - T_R$.

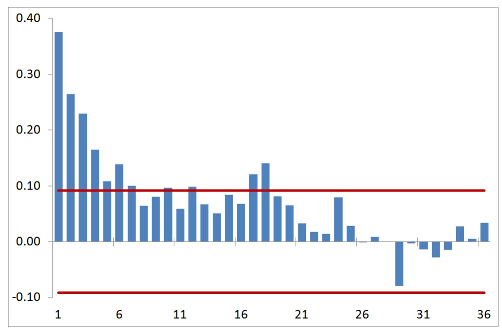
Figures 1 and 2 report the autocorrelations computed with the standard



(a) Full sample ACF



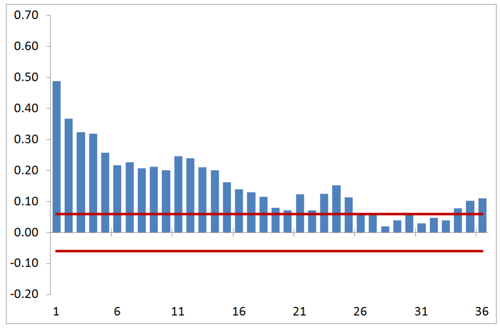
(b) Expansion ACF



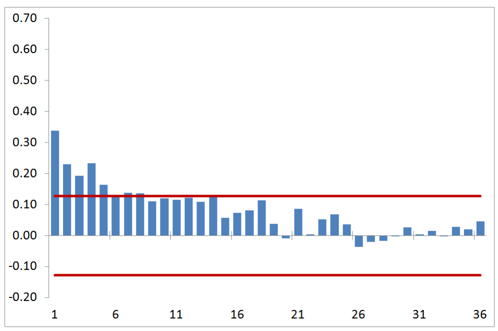
(c) Recession ACF

Figure 1: Autocorrelation functions (ACF) for the full sample (from 1876) computed with the classic estimator and by conditioning on the cycle phase.

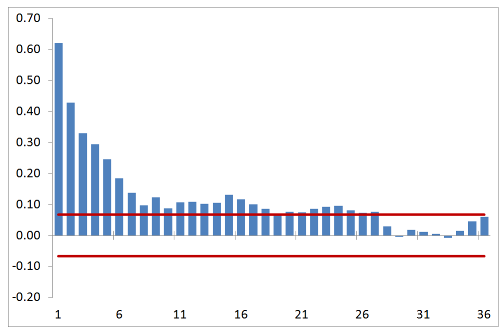
estimator, and by conditioning on the economy state, for both the full sample data (from 1876) as well as by restricting the sample from 1920. Notably, we have evidences of changes in the persistence over cycle phases, but also over time. In fact, while by looking at data from 1876 we note a decrease in the persistence during recessions, the opposite effect, an increase in persistence during recessions, is observed if we start the analysis in 1920. We relate such a change to the large amount of zeros included in



(a) Full sample ACF



(b) Expansion ACF



(c) Recession ACF

Figure 2: Autocorrelation functions (ACF) for the restricted sample (from 1920) computed with the classic estimator and by conditioning on the cycle phase.

the time series in the first 40 years. As a result, we believe that Figure 2 plots are closer to the true series behavior. The plots suggest that the inflation time series might be characterized by a mild long-memory behavior. In fact, the persistence is clear but not so strong as we might observe in the presence of long-memory. Nevertheless, the observed autocorrelation patterns could be associated with persistent short-memory processes.

To shed some light on the possible presence of long-memory and, at the same time, allow for a change in the persistence across economy states, we suggest to model the CPI growth rates as in Caporin and Pres (2013). Let y_t be the CPI growth, or inflation rate, we model it as follows

$$(1-L)^{d_t}\,\Phi\left(L\right)\left(y_t-\mu\right)=\Theta\left(L\right)\varepsilon_t \tag{3}$$

where d_t is a time varying memory coefficient, μ is the unconditional mean of the inflation, $\Phi\left(L\right)$ is an Auto Regressive polynomial, $\Theta\left(L\right)$ is a Moving Average polynomial, ε_t is the inflation shock which we assume to be identically and independently distributed with zero mean and variance σ_ε. The change in the memory coefficients has a step-wise evolution over time according to the change of the business cycle phase. As a consequence, there will be two different degrees of persistence over recession and expansion.

Given that the change in persistence varies according to an exogenous variable, and is thus not exactly a function of the time, the TVARFIMA model of Caporin and Pres (2013) becomes similar to the Threshold ARFIMA (TARFIMA) of Goldman et al. (2013); it differs from the TARFIMA model since the regime change is not associated with the level of the dependent variable (the CPI growth), as it happens in dynamic models with threshold-driven regimes; on the contrary, the change in the parameter structure depends on an exogenous variable, the dummy capturing recessions. The model might thus be compared to the approach of Haldrup and

Nielsen (2006a,b), and thus claimed to be equivalent to a Markov switching model where regimes are known.

In order to capture the possible presence of heteroskedasticity, the model is extended by allowing the error variance to change over time according to the TVFIGARCH model of Caporin and Pres (2009). Therefore, the inflation shocks variance will be denoted as σ_t and will evolve as

$$\sigma_t^2 = \omega + \beta(L)\,\sigma_{t-1}^2 + \left[1 - \beta(L) - \Psi(L)(1-L)^{\lambda_t}\right]\varepsilon_t^2 \tag{4}$$

where $\beta(L)$ and $\Psi(L)$ are short-memory polynomials and λ_t is the variance memory parameter that changes over time according to the business cycle phases.

Model estimation is performed by maximum likelihood methods, which are shown in Caporin and Pres (2013) to have appropriate asymptotic densities by means of Monte Carlo methods.

3 Persistence in US inflation

We fit the TVARFIMA-TVFIGARCH on the inflation time series both on the full sample as well as by restricting the analysis from 1920. Table 3 reports the estimated coefficients and we stress that the memory parameters are always statistically significant. Our empirical results suggests that the inflation persistence is changing across business cycle phases, and is higher during recessions. In fact, and focusing on the full sample results,

		Full sample			From 1920		
		Coeff.	Std.err.	T-stat	Coeff.	Std.Err.	T-stat
TVARFIMA	d_R	0.462	0.079	5.841	0.304	0.041	7.427
	d_E	0.274	0.038	7.242	0.241	0.027	8.863
TVFIGARCH	ω	0.008	0.008	0.943	0.000	0.008	0.050
	λ_R	0.269	0.025	10.854	0.241	0.018	13.117
	λ_E	0.400	0.083	4.815	0.326	0.043	7.501

Table 3: Estimation output for the full sample and restricted sample (from 1920). R denotes recession coefficients and E expansion coefficients.

while the memory coefficient in the mean equal 0.462 for recessions, it decreases to 0.274 in periods of expansion. Differently, the variance persistence moves from 0.269 in recessions up to 0.4 during expansions. This result is confirmed if we restrict the sample and consider data from 1920: in the mean, the memory coefficient decreases from 0.304 in recessions to 0.241 during expansions, while in the variance, the memory increases from 0.241 up to 0.326. We believe this is a relevant finding, and is also supported by a Wald-type test for equality across memory coefficients. In that case the null hypothesis is $d_E = d_R$ and the test statistic equals 86.6 in the full sample and 133.7 from 1920. Note that the test statistic is assumed to be asymptotically distributed as a Chi-square with 1 degree of freedom, thus strongly rejecting the null.

The fact the persistence is higher in recession than expansions might be motivated by the fact that recessions are shorter and more clearly identifiable than expansion phases. A supporting evidence is given by the average duration of the business cycle phases: while for recessions we have an average duration of 16.5 months, for expansions the value increases up to 41.4 months. Further, during expansions, we might have oscillations in the growth cycle that could affect the persistence. In addition, another line of reasoning could be that, while in our model we have two states, in reality we might have also stagnation and this is, in our analyses, associated with expansion and hence, could affect the persistence during expansion. As an aside, we also show that persistence of inflation volatility is higher in expansions than recessions. This is somewhat expected, as it implies that volatility persists on a low regimes during expansions, while we have a larger uncertainty and a large reaction to shocks during recessions (less persistence induce a larger reaction of volatility to innovations). The findings are substantially confirmed on the shorter period.

We note that the estimated models have a very simple structure, combining state-dependent memory coefficients with intercepts. We verified by means of standard approaches the presence of residual serial correlation, both in the mean and in the variance. Despite some mild evidences of residual serial correlation in the mean, associated with lag 4 (which has no economic intuition), alternative model specifications with different orders of both short memory AR and MA polynomials always provided non significant coefficients and residuals with the same mild findings of serial correlation. Moreover, we also checked for residual heteroskedasticity, without any evidence. As a final check, we also consider alternative GARCH-type models with short-memory only. The results were, overall, inferior to those of the TVFIGARCH specification.

4 Concluding remarks

Given that the degree of inflation persistence determines the extent to which central banks can control inflation, the persistence property of inflation is an important issue. Also, not only is the level of inflation persistence that is important in economic analyses, but also the question of whether the persistence varies over time, for instance, across business cycle phases, is equally pertinent. This is understandable since, assuming constant persistence across expansionary and contractionary states of the economy, is sure to lead to misguided policy decisions. Against this backdrop, we extend the literature on long-memory models of inflation persistence for the US economy over the monthly period of 1876:2-2014:5, by developing an autoregressive fractionally integrated moving average-generalized autoregressive conditional heteroskedastic (ARFIMA-GARCH) model, with a time-varying memory coefficient which varies across expansions and recessions. In sum, we find that, inflation persistence does vary across recessions and expansions, with it being significantly higher in the former than in the latter. As an aside, we also show that, persistence of inflation volatility however, is higher during expansions than in recessions. Understandably, our results imply that the policy stance of the Federal Reserve should be asymmetric, depending on not only what is the main concern of the Federal Reserve, i.e., level or volatility of inflation, but also whether the economy is in recession or expansion. More importantly, our results also imply that Federal Reserve faces a trade-off, in terms of policy decision that it takes on the interest rate-setting, depending on its attempt to control the level or volatility of the inflation rate.

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A Additional figure

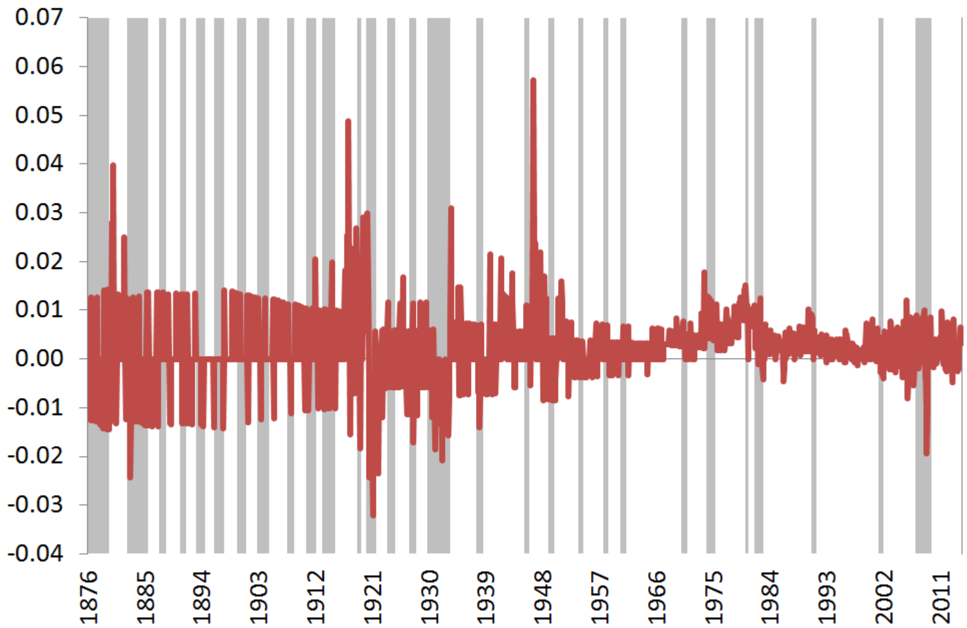

Figure A.1: Month-on-month US inflation from 1876:1 to 2014:5.