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Abstract

This paper examines the impact of temporal aggregation on alternative definitions of inflation persistence. Using the CPI and the core PCE deflator of the US, our results show that temporal aggregation from the monthly to the quarterly to the annual frequency induces persistence in the inflation series.

Keywords: Aggregation, Inflation, Persistence.

JEL classification: C15, C22

Inflation persistence has become an important topic in both theoretical and applied economics. The term persistence is used to indicate the extent to which future values of a particular economic variable are related to past shocks of the same variable.[2] In other words, given a specific shock, inflation persistence can be interpreted as the tendency of the rate of inflation to converge slowly towards its long-run value. Thus, knowledge of the degree of inflation persistence is important. Uncertainties from price fluctuations are usually associated with the degree of inflation persistence, and this is valuable information for both monetary policy and macroeconomic modelling.

Different macroeconomic models are able to generate alternative explanations for the main sources of inflation persistence (see e.g., Taylor, 1980, Rotemberg, 1982, Calvo, 1983, Mankiw, and Reis, 2001, Minford, Nowell, Sofat, and Srinivasan, 2005). However, these models are generally silent with respect to what frequency the data should be sampled. Models at different levels of time aggregation are interpreted as being theoretically equivalent. In the light of this background, one relevant problem that deserves attention is the relationship between temporal aggregation and inflation persistence. By temporal aggregation we mean the process of moving from one unit of time measurement (e.g., monthly) to a larger unit (e.g., quarterly). In this paper, the question we want to explore is the following: does the unit of time adopted in empirical work on inflation persistence matter and, if so, by how much?

[2] From an econometric point of view, the concept of persistence is closely related to the order of integration of a variable.

The econometric literature has accumulated evidence showing that temporal aggregation may affect the properties and information content of the data generating process.[3] For instance, models estimated with high frequency data (e.g., monthly or quarterly) show fewer signs of persistence than models estimated with lower frequency data (e.g., annual data). One important implication of this is that results using temporally aggregated data can be unreliable, making it more difficult to distinguish empirically between alternative explanations of inflation persistence. For this reason, in this paper we depart from the approaches mentioned above and, specifically, concentrate on the impact of temporal aggregation on alternative definitions of inflation persistence.

In applied work the persistence of a stochastic process is determined by the Impulse Response Function (IRF), which is not invariant to time aggregation effects (see Rossana and Seater, 1995). These authors have also pointed out three main effects for a temporally aggregated ARIMA(p, d, q) process. The first effect, due to Brewer (1973), defines a limit for the MA structure of the aggregated series. The second effect, due to Tiao (1972), shows how all the AR coefficients and all but the first d MA coefficients go to zero as aggregation increases, that is, as we move from high to low frequency data. Consequently, the limiting aggregated model of an ARIMA

[3] After the pioneer work of Holbrook Working (1960), over the last ten years there has been a growing literature dealing with the problem of time aggegation in different fields of economics. Outstanding examples are Christiano, Eichenbaum, and Marshall, 1991, Rossana and Seater, 1992, Heaton, 1993.

process is an IMA(d, d). The third effect is due to small sample sizes. If the autocorrelations of the aggregated time series rise by proportionally less than $n^{\frac{1}{2}}$ they may become insignificant and suggest a model of order IMA(d, d^*), where $d^* < d$.

In addition to the above effects, there are three issues that need further consideration: (i) The statistical theory is not definitive because some of the results are asymptotic and leave open the question of what happens with actual data, for which the aggregation span is finite; (ii) Empirical research usually takes logs of the price level series to analyze inflation. However, the existing statistical theory of temporal aggregation applies only to unlogged data; and (iii) There is no unique definition of persistence, and alternative measures of persistence might be affected differently by time aggregation and small sample effects, specially when the AR structure of the series is higher than one.

Within this context, our aim in this paper is to shed some light on the effect of time aggregation on inflation persistence. In particular, we use data for the US, and to avoid the potential effects of the above mentioned issues on our empirical application, we also run Monte Carlo simulations with artificially created data.

The rest of the paper is organized as follows. Section one describes alternative measures of persistence commonly used in the literature. Section two presents the results and, finally, section three gives the conclusions.

1 Alternative Measures of Persistence

We assume that inflation (y) follows an autoregressive process of order p (AR(p)) which can be written as:

$$y_t = \alpha + \sum_{j=1}^{p} \beta_j y_{t-j} + \varepsilon_t \tag{1}$$

where ε_t is a serially uncorrelated random error. The above model can be reparameterized as:

$$\Delta y_t = \alpha + \sum_{j=1}^{p-1} \delta_j \Delta y_{t-j} + (\rho - 1) y_{t-1} + \varepsilon_t \tag{2}$$

where $\rho = \sum_{j=1}^{p} \beta_j$, and $\delta_j = -\sum_{i=1+j}^{p} \beta_i$. In the context of the above model inflation is said to be more or less persistent depending on how quickly it converges to its mean following a shock. In other words, how fast inflation absorbs the shock and reverts to its previous mean value. The path of shock absorption is defined by the Impulse Response Function (IRF). In a finite AR(p) model, the IRF is determined by the autocorrelation coefficients.

We follow Dias and Marques (2005) and present several scalar measures of persistence that have been proposed in the literature:

(a) Sum of autoregressive coefficients (ρ). A related measure is the cumulative impulse response (CIR) given by $CIR = \frac{1}{1-\rho}$. The larger is ρ, the larger is the impact of the shock in future values of inflation and the longer it will take to mean revert. Andrews and Chen (1994) point out a major disadvantage of this measure of persistence. In particular, the use of ρ could suggest two series as equally persistent even if they exhibit completely different patterns of mean reversion. Examples are a series that absorbs most of the shock in the initial periods while another series absorbs most of the shock in later periods; one series exhibits cyclical behavior while the other does not.

(b) Largest autoregressive root (lar). As the horizon following a shock increases, the impulse response of inflation to a shock becomes increasingly dominated by the largest root (see Stock, 1991 and 2002). In other words, the size of the impulse response, $\frac{\delta y_{t+j}}{\delta \varepsilon_t}$, is determined by lar as the horizon (j) grows large. A caveat of lar is that it ignores the effects of the other roots of the autoregressive process in the overall persistence of the series. Andrews and Chen (1994, p. 190 Table 1) point out this problem by detailing the impulse response function of two series with the same lar but with different magnitudes for the other roots. The IRFs differ significantly stressing the potential misleading properties of lar if used as the only measure of persistence.

(c) Half-life (h) is defined as the number of periods that it takes to reduce the initial size of the shock to at least half of it. In the case of an AR(1) process, $h = \frac{\ln 0.5}{\ln \rho}$; and for an AR(p) process there is no simple expression for h. This measure of persistence might not be appropriate in cases where the IRF is oscillating or the series is very persistent (see Murray and Papell, 2002, and Pivetta and Reis, 2006). Dias and Marques (2005) suggest computing the half-life directly from the IRF to avoid some of its drawbacks.

(d) The number of time periods (m) required for fifty percent of the total disequilibrium to accumulate. In order to compute this measure we first obtain the total disequilibrium over the whole horizon following the shock. Subsequently, we compute the number of time periods required for fifty percent of the total disequilibrium to accumulate. This measure solves one of the problems that arises when using ρ. Two series with equal ρ but different patterns of absorption have different m values.

(e) Absence of mean reversion (γ) as measured by Marques (2004). This measure is defined as the unconditional probability of a given process not crossing its mean in period t, or equivalently as 1 minus the probability of mean reversion of the process.[4] For a white noise process the expected value of γ, $E[\gamma] = 0.5$. Figures significantly above 0.5 indicate significant persistence. Under the null of a symmetric white noise process the following result holds,

$$\frac{\widehat{\gamma} - 0.5}{0.5/\sqrt{T}} \approx N(0,1)$$

Dias and Marques (2005) also show that

$$\sqrt{T}(\widehat{\gamma} - \gamma) \approx N(0, \sigma_\infty^2)$$

where $\sigma_\infty^2 = r_0 + 2\sum_1^\infty r_j$ with $r_j = cov(x_t, x_{-j})$. It is also possible to test the null of random walk using γ (see Burridge and Guerre, 1996) with the following statistic $K_T(0) = \frac{\sqrt{\frac{\sum(\Delta y_t)^2}{T}}}{\frac{\sum|\Delta y_t|}{T}} \frac{(T+1)}{\sqrt{T}}(1 - \widehat{\gamma})$.

[4] The estimator of γ is obtained as $\hat{\gamma} = 1 - \frac{n}{T}$ where n is the number of times the series crosses the mean during the whole sample with $T + 1$ observations.

In this section we have presented five alternative measures that represent different ways of measuring persistence. Measures (a) and (b) are simple numerical measures of persistence, while (c) and (d) reflect the speed of adjustment to the equilibrium measured in time periods, and (e) is the probability of the series reverting to the mean. The ADF statistic is also included as a standard test for a unit root.

2 Estimation results

2.1 Data and estimation

We consider two alternative measures of price level in the economy. Namely, the consumer price index (CPI), and the core Personal Consumption Expenditure deflator (PCE). The data consist of monthly observations of the CPI and the PCE for the US spanning from January 1947 to September 2005, and from January 1959 to September 2005, respectively. The source is the Federal Reserve Bank of St. Louis, FRED dataset. We create arithmetic temporal aggregates[5] from the actual highest frequency available data (monthly) as follows:

[5] If the data is in logarithmic form, then y_t^* is the geometric mean instead of the arithmetic mean of the inflation rates. We compared the correlation between the arithmetic and geometric means conditional on some price processes. The correlations were close to unity and the results qualitatively similar. Given this, for simplicity, we employ the arithmetic mean for the temporally aggregated data.

$$y_t^* = \frac{(y_t + y_{t-1} + y_{t-2} + ... + y_{t-(i-1)})}{i} \tag{3}$$

where y_t is the one month rate of inflation from the CPI or the PCE, and $i = 3, 12$. The temporally aggregated data will then follow the process:

$$y_t^* = \alpha + \sum_{j=1}^{p} \phi_j y_{t-j}^* + \varepsilon_t \tag{4}$$

The autocorrelation coefficients, ϕ_j, are affected by the level of temporal aggregation due to the factors mentioned above. The LS estimators typically exhibit an upward bias that could actually be quite large when estimating $AR(p)$ processes. The LS estimator could then be a misleading indicator of the true autoregressive parameter values providing biased persistence measures. We follow Andrews and Chen (1994) in order to obtain median unbiased estimates of ρ and lar, and we will keep the simple notation of ρ, lar, for the median unbiased estimates reported in the tables. Some selected measures of persistence such as CIR, h, and m will then be computed using the median unbiased estimators.

2.2 CPI Inflation

We first focus our attention on the US CPI from 1947 until 2005. Table 1 presents the persistence of the period-to-period CPI US inflation rates at different frequency levels. The overall conclusion is that time aggregation increases the persistence of the series, specially at the annual frequency, regardless of the measure of persistence. It is worth noting that the "expected" reduction in the sum of the autoregressive terms, ρ, due to the Tiao effect is not enough to offset the "time period" difference due to time aggregation.[6] In other words, the annual value of ρ implies a higher persistence than its monthly counterpart. The increase in the largest autoregressive root (lar) also gives a good measure of the significant increase in persistence. The half-life also displays dramatic increases in persistence. The proportion of the total disequilibrium to accumulate, m, gives a similar picture for monthly or quarterly data but almost doubles for annual data. The Marques measure of persistence (γ) also points to the same direction. The estimated γ increases and the hypothesis of equality of γ at different levels of aggregation can be rejected. Moreover, at the annual frequency, the unit root hypothesis, as tested by γ and the ADF statistic, cannot be rejected.

[6] Actually, the reduction of the ρ value from monthly ($\rho = 0.86$) to quarterly ($\rho^{i=3} = 0.85$), and annual ($\rho^{i=12} = 0.75$) is not enough to offset the level of aggregation. For instance, a value of $\rho^{i=3} = 0.85$, in quarterly terms implies a CIR $=(\frac{1}{1-\rho^i}) \simeq 7$ quarters; and in monthly terms would be 21 ($7i = 7 * 3 = 21$).Therefore the value of ρ in the aggregated series at level i, ρ^i, that would yield the same $CIR(\frac{1}{1-\rho^i})$ as the original series would be $\rho^i = -(i-1) + i\rho$. Below, we present a table with the corresponding values of ρ^i that would yield equal CIR if the original series had an autoregressive term of value ρ.

$i \backslash \rho$	0.85	0.90	0.95
3	0.55	0.70	0.85
12	-0.80	-0.20	0.40

2.3 Monte Carlo analysis

In order to formally assess the general impact of temporal aggregation on persistence measures we run a set of Monte Carlo experiments. As a first step we generate a series calibrated with the same autoregressive structure as the actual CPI monthly data estimated above plus a random error term with a distribution that matches the empirical one.[7] The second step was to aggregate the artificial series and compute all the alternative measures of persistence. We replicate this experiment 10,000 times and Table 2 presents the results. Overall, the alternative measures of persistence increase with the level of aggregation and the results are in line with those in Table 1. We find that the reason underlying those results might not be a straightforward one. To check whether those results are due to a small sample problem we generated sample sizes of 3,000 and 12,000 for the original series with same AR(p) structure as actual CPI inflation and analyze the results for aggregated series with 1,000 observations. The results for the mean values were very similar (except for the standard deviations that were much smaller, obviously) ruling out the small sample phenomenon as an explanation driving

[7] The residual analysis from actual data showed a non-normal distribution of the residuals with excess kurtosis and fatter tails. We decided to approximate that distribution with a $t-$distribution with eight degrees of freedom ($d.f.$) and a standard deviation of 0.02 that has all moments (hence $d.f. \geq 5$) but could display those features. In order to ensure that our assumption cannot be rejected we have applied two different tests following Stephens (1974). In particular, we applied the Kolmogorov statistic, and the Anderson-Darling statistic. They yielded values of 0.95 and 1.20, respectively. According to Stephens Table 1.0, the null of the a $t-$distribution with eight $d.f.$ could not be rejected.

those results. The second effect we check is the Tiao effect. In this case, the autoregressive roots seem to disappear with the level of aggregation. The quarterly series have lower p parameters than the monthly one, and the annual series lower than the quarterly one. However, they did not vanish completely. Aggregated series still keep some AR(p) structure, even for large samples. Recall that the Tiao effect is an asymptotic result and, in our particular case, we find that the Tiao effect holds but it does not completely eliminate the whole AR structure.[8]

The difference between the alternative measures of persistence is lowest for the quarterly frequency. For instance, there are only small differences between ρ and lar, and between h and m. In the light of our results the quarterly frequency provides a more 'homogenous' measure of persistence. This leads to the question of which frequency of data to use in empirical work. There is a trade-off between sample size (monthly data have more observations than quarterly), information content (monthly data have information about the monthly frequency while quarterly do not), measurement error (monthly data are likely to be more unreliable than quarterly or annual data – see Wilcox, 1992) and temporal aggregation effects (which increase in mov-

[8] To further examine this issue we have aggregated the monthly calibrated series at higher frequencies, $i = 24, 36$, and $1,000$; and computed the corresponding ρ values. They still were 0.46, 0.34, and 0.20 respectively. In other words, even with an original sample size of $1,000,000$, with a level of aggregation $i = 1,000$ the resulting aggregated series of size $1,000$ still displays an AR structure that does not vanish completely (an AR(1) with coefficient 0.20).

ing from monthly to quarterly, and specially, from monthly to annual data). Our conclusion is to agree with Rossana and Seater (1995) that quarterly data are the best compromise among frequency of observation, measurement error and temporal aggregation distortion.

2.4 Robustness checks

The high persistence of the series can also be an artifact of structural breaks (see Perron, 1989; and Stock, 1994). For this reason, we employ the sample period 1983-2005, that is believed to belong to the same regime in terms of inflation (see Levin and Piger, 2004) and the estimated $AR(p)$ model considered more robust. We apply the same experiment as above and the results are displayed in Tables 3 and 4 for the CPI series. The conclusions regarding both the estimations at different levels of aggregated data and the Monte Carlo experiments are qualitatively the same as in Tables 1 and 2. However, it is worth pointing three results. First, the persistence for this subsample is lower according to all measures of persistence. Second, the 'artificially' generated persistence is lower. In particular, in the case of the quarterly frequency, the difference in persistence with the monthly series is quite small. Third, the measure of persistence γ seems quite robust. According to Table 3, we cannot reject that the hypothesis that this measure of persistence is the same across different frequencies. This result is reinforced with the Monte Carlo that shows that most of the time γ would be considered to be equal and therefore robust to temporal aggregation.

This subsample might be considered a more "homogenous" one in terms of inflation periods, or let us say, possibly free from structural breaks. This fact strengthens the results of the previous section though to a lesser extent.

We have undertaken a second robustness check concerning the measure of the price index. The CPI series contains components, such as energy prices, that have very different persistence properties from other components that might distort the overall persistence of the price series. We then consider the core PCE deflator as an alternative measure of inflation for our persistence analysis. Tables 5 and 6 present the results for the sample 1983-2005.[9] Two conclusions can be drawn from that analysis. First, this series appears to be more persistent that the CPI series according to all the measures of persistence. Second, the overall trends previously found for the CPI series also hold for the core PCE.

3 Conclusions

The general conclusion of this paper is that the selection of the unit of time is important in empirical work on inflation persistence. In general, lower frequency implies higher persistence. In particular, temporal aggregation of inflation from the monthly to the quarterly to the annual frequency increases persistence. However, in some cases, aggregation from the monthly to the quarterly frequency has an almost negligible effect on persistence. Further-

[9] We have also undertaken the analysis for the sample 1959-2005. We do not report those results for space consideration but they are available from the authors upon request.

more, the Marques (2004) measure of persistence seems to be the one less affected by the temporal aggregation. These conclusions have been empirically documented using data for the US Consumer Price Index and the core Personal Consumption Expenditure deflator.

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Table 1. Estimates of persistence with actual CPI data for US 1947-2005.

	Monthly	Quarterly	Annual
ρ	0.860	0.850	0.750
lar	0.279	0.690	0.881
$\widehat{\gamma}$	0.668	0.822	0.807
$\gamma = 1$	11.21*	3.32*	1.82
$\gamma = 0.668$		4.81*	3.47*
ADF	-4.35*	-4.43*	-1.69
CIR	7	20	48
h	1	6	36
m	12	15	24

Notes: The order of the autoregressive process of the series chosen was such that leaves no remaining autocorrelation. We used 24, 8, and 2 lags for the monthly, quarterly, and annual, respectively. $\gamma = 1$ denotes the $K_T(0)$ statistic for the null of a unit root. $\gamma = 0.668$ denotes the Dias and Marques (2005) statistic for the null $\gamma = 0.668$. An asterisk denotes rejection of the null at five percent level. ρ and lar correspond to their median unbiased estimates. The figures for CIR, h, and m are expressed on a monthly basis and rounded to the nearest month.

Table 2. Monte Carlo simulations

calibrated for US CPI 1947-2005

	Quarterly		Annual	
ρ	0.823(0.04)		0.652(0.11)	
lar	0.665(0.06)		1.02(0.50)	
$\widehat{\gamma}$	0.792(0.03)		0.768(0.04)	
$\gamma = 1$	1.00		0.883	
$\gamma = 0.668$	0.964		0.594	
ADF	0.999		0.973	
	Quarters	ME	Years	ME
CIR	5.46	15	3.08	36
h	2.53(1.13)	9	2.86(0.58)	36
m	4.88(1.56)	15	1.75(2.26)	24

Notes: Figures in table are the mean values obtained from 10,000 replications. Numbers in parentheses are standard errors. The values for CIR correspond to the median. The values for $ADF, \gamma = 1$ and $\gamma = 0.668$ denote the proportion of times that the nulls of unit root and of $\gamma = 0.668$ are rejected, respectively. M.E. equivalent number of months for quarterly and annual aggregates (rounded)

Table 3. Estimates of persistence with actual CPI data for US 1983-2005.

	Monthly	Quarterly	Annual
ρ	0.520	0.540	0.567
lar	0.381	0.400	0.567
$\widehat{\gamma}$	0.630	0.629	0.770
$\gamma = 1$	7.01*	3.86*	1.20
$\gamma = 0.630$		-0.017	1.40
ADF	-11.63*	-6.00*	-3.22*
CIR	2	7	28
h	1	3	12
m	5	6	12

Notes: The order of the autoregressive process of the series chosen was such that leaves no remaining autocorrelation. In particular, we used 6, 2, and 1 lags for the monthly, quarterly, and annual, respectively. For the rest of statistics see notes to Table 1.

Table 4. Monte Carlo simulations

calibrated for US CPI 1983-2005

	Quarterly		Annual	
ρ	0.543(0.17)		0.497(0.18)	
lar	0.388(0.10)		0.640(0.19)	
$\widehat{\gamma}$	0.650(0.06)		0.705(0.11)	
$\gamma = 1$	0.998		0.369	
$\gamma = 0.630$	0.071		0.155	
ADF	0.894		0.453	
	Quarters	ME	Years	ME
CIR	2.26	7	2.07	25
h	1.11(0.32)	3	1.75(0.65)	21
m	4.10(4.70)	12	2.39(2.85)	29

Notes: See notes to Table 2.

Table 5. Estimates of persistence with actual core US PCE data 1983-2005.

	Monthly	Quarterly	Annual
ρ	0.833	0.934	0.926
lar	0.277	0.322	0.926
$\widehat{\gamma}$	0.705	0.923	0.954
$\gamma = 1$	5.73*	0.818	0.246
$\gamma = 0.705$		3.63*	-2.76*
ADF	-3.07*	-2.15	-2.13
CIR	6	45	162
h	1	3	60
m	17	42	60

Notes: The order of the autoregressive process of the series chosen was such that leaves no remaining autocorrelation. In particular,we used 9, 3, and 1 lag for the monthly, quarterly, and annual, respectively. For the rest of statistics see notes to Table 1.

Table 6. Monte Carlo simulations

calibrated for core US PCE 1983-2005

	Quarterly		Annual	
ρ	0.789(0.10)		0.540(0.39)	
lar	0.613(0.13)		0.791(0.24)	
$\widehat{\gamma}$	0.768(0.06)		0.723(0.09)	
$\gamma = 1$	0.861		0.280	
$\gamma = 0.705$	0.171		0.050	
ADF	0.625		0.358	
	Quarters	ME	Years	ME
CIR	4.97	15	2.56	31
h	2.65(1.36)	8	2.20(0.95)	26
m	4.14(2.19)	12	3.27(3.08)	39

Notes: See notes to Table 2.