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Mapping inflation dynamics

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MAPPING INFLATION DYNAMICS

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Abstract

CPI inflation is subject to structural changes and exogeneous shocks that can have a significant impact to its dynamic evolution. The observed interaction between the intrinsic side of inflation dynamics and the disturbances fuels a rich spectrum of behaviors. To accommodate the complex outcome of interactions, we propose a methodological strategy combining the non-parametric Recurrence Quantification Analysis (RQA), the GPH fractional integration coefficient d and the Phillips-curve based framework. The empirical findings demonstrate the nonlinear contribution of inflation inertia to the headline inflation dynamics, mainly over the last eight quarters of the sample alongside the occurrence of price shocks.

JEL-Classifications: C40, C50, E31, E52.

Keywords: Inflation dynamics, Inertia, RQA, GPH coefficient d, Entropy, Complexity, Phillips curve.

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1. Introduction

The objective of monetary policy is to maintain low and stable rate of inflation and mitigate the impact of severe macroeconomic fluctuations. In the aftermath of instability events, there has been a remarkable tendency to argue that aggregate behavior in real economic systems arises from no simple interconnectedness between their components producing destabilizing feedbacks. Evolution of such systems is intrinsically difficult to predict, and the inherent complexity allows multiple factors to affect policy variables. Under conditions of increasing uncertainty controlling or even influence economic outcomes emerges as a difficult endeavor. The multiplicity of determinants of inflation in the short-run and the evolution of inflation expectations over time revealed relative weaknesses of macroeconomics models. This paper aims at adding to the literature of inflation determinants and price stability by applying a mixed methodological approach for mapping inflation dynamics and exploring the heterogeneous dimensions of price instability.

Since 1960 the US CPI inflation was subject to multiple changes either structural or exogeneous affecting its dynamic evolution. The interaction between intrinsic structure and disturbances gave birth to a complex spectrum of dynamics. To accommodate the complex outcome of interactions, our approach combines the non-parametric Recurrence Quantification Analysis (RQA), the GPH fractional integration coefficient d and the Phillips-curve based framework. The RQA can provide an accurate description of the dynamic imprint of shocks into inflation. At the same time, inflation persistence is investigated through the fractional integration coefficient d. However, this quantification of dynamics cannot fully reveal the driving forces of inflation. To address this point, the most common structured approach for studying inflation is adopted. We augment the standard Phillips curve model, composed of lagged inflation and domestic output gap, with nonlinear lagged inflation, output growth, oil and food prices. The same model is also estimated using rolling regressions over a twenty-year window, to account for the varying role of explanatory variables over time.

The outline of the paper is as follows. Section 2 presents the RQA measures and application results, section 3 reports findings regarding the coefficient of fractional integration d, while in section 4 several Phillips curve specifications are analyzed and estimated. Section 5 concludes the paper.

2 Recurrence quantification analysis

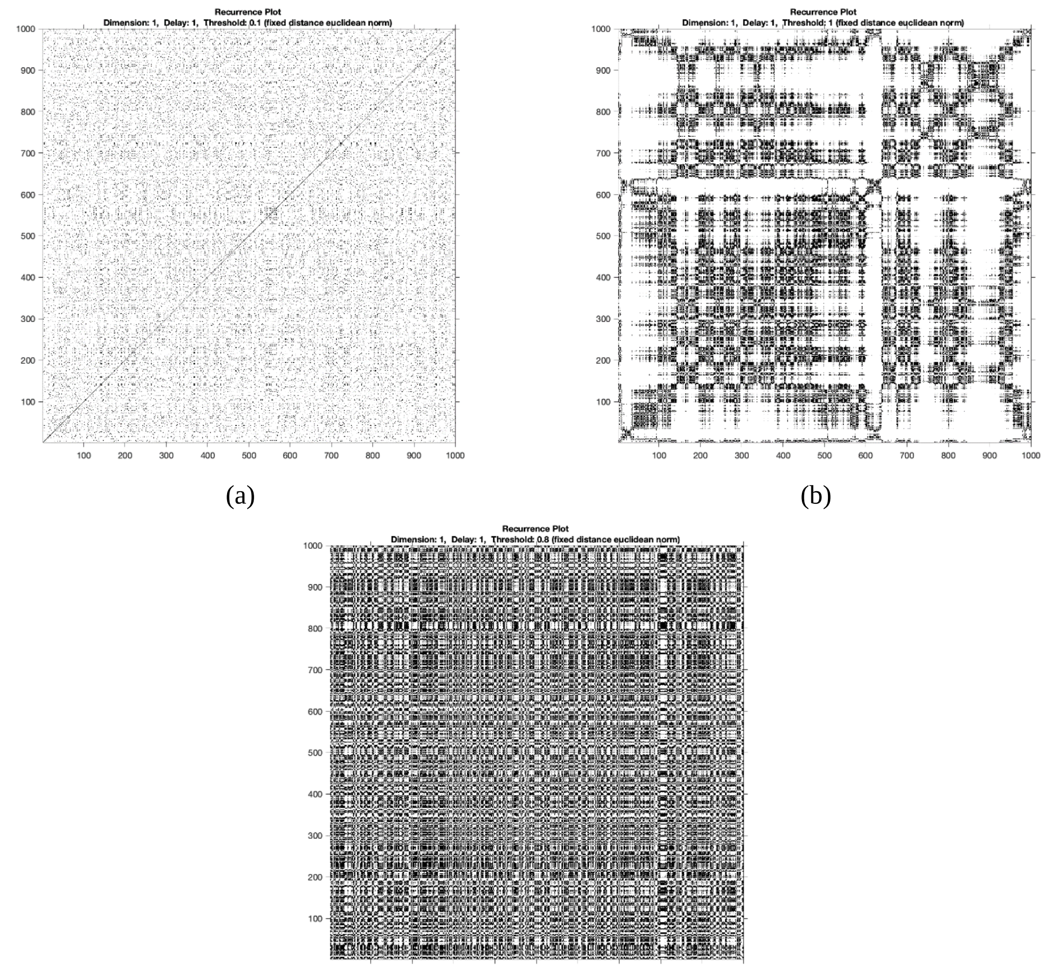
Real world processes are highly complex, noisy and non-stationary. Available data are, therefore, not normally distributed. Nevertheless, most linear and classical methods in statistics and time series analysis are built on normality and stationarity hypotheses. New concepts derived from nonlinear dynamics and complex systems try to overcome such limitations. Recurrence analysis is a powerful multipurpose approach for studying short and non-stationary variables, employing the fundamental property of recurrence in dynamical systems (Marwan et al., 2007; Kyrtsou and Vorlow, 2005; Karagianni and Kyrtsou and Karagianni, 2011). Recurrence plots (RPs) and recurrence quantification analysis (RQA) are tools which have been developed for the visualization and quantification of recurrences in dynamical systems by looking at their phase space representation (Webber and Zbilut, 1994; Marwan, 2008).

The RQA builds on the computation of the recurrence matrix, $\boldsymbol{R}$, providing a quantitative assessment for the presence of intermittent and regime-shifting behavior. First, the phase space trajectory for a time series x_t is reconstructed giving $\overrightarrow{x_t} = \left(x_t, x_{t+\tau}, \dots, x_{t+(m-1)\tau}\right)$, where τ is the time delay and *m* the embedding dimension. Then, recurrent points are identified, when the distance between the delayed vectors $\left\|\overrightarrow{x_i} - \overrightarrow{x_j}\right\|$ is less than the predefined threshold ε

$$\boldsymbol{R}_{i,j} = \Theta\left(\varepsilon - \left\|\overrightarrow{x_i} - \overrightarrow{x_j}\right\|\right)$$

$\|.\|$ is a norm. In our analysis, the Euclidean distance is used. If the states of the system at times i and j are similar, then $\boldsymbol{R}_{i,j} = 1$ and zero otherwise. An essential property of the RP is that for fully deterministic systems, the attractor will be revisited by the trajectory sometime in the future. Thereby, short line segments parallel to the main diagonal will be detected.

If the process is $i.i.d$ (Figure 1a), then the distribution of points in the RP looks erratic. Figure 1b displays the RP of a simulated AR(4) time series. Its autocorrelation structure leads to rectangular clusters of recurrent points in the RP. Horizontal lines denote intermittent states, i.e. states that do not change or change very slowly. In Figure 1c we can visualize the persistence of a noisy Mackey-Glass process, where the intensity of nonlinearity c is set to 10. Obviously, the series presents a rich structure with many laminar states distributed along the diagonal line.



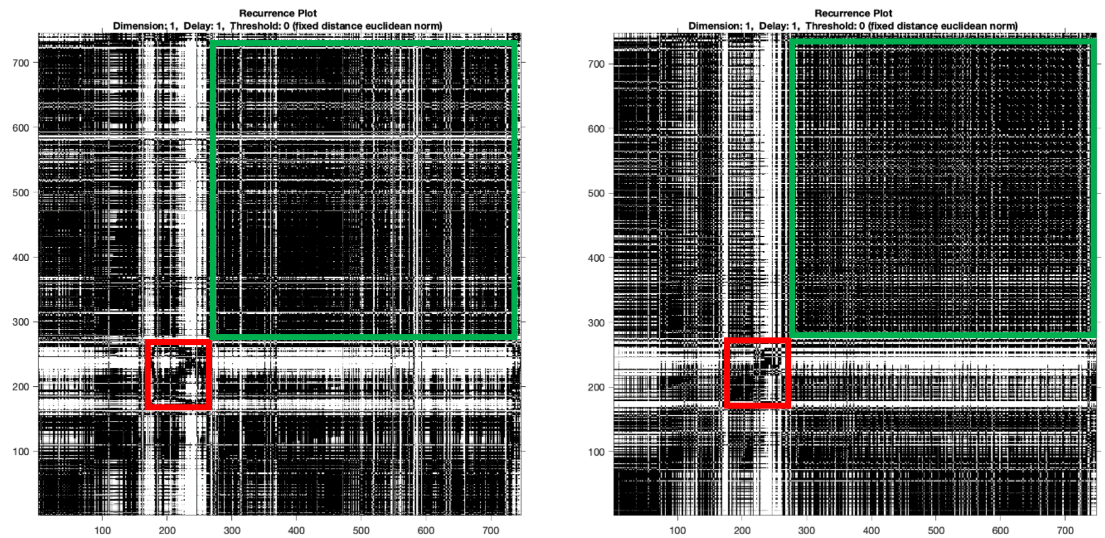
(a) (b) (c)

Figure 1: RPs of well-known systems (white noise (a), AR(p) (b), Noisy Mackey Glass (c))

The analysis in this section as well as in section 3 focuses on the dynamics of the US headline and core inflation (excluding food and energy prices) as a proxy of underlying inflation. The original price series in monthly frequency are available from January 1960 to March 2022. Inflation π_t corresponds to the monthly change of the CPI calculated as

$\pi_t = ln(\frac{CPI_t}{CPI_{t-1}})$. We use month-over-month changes to achieve a precise representation of dynamics and a more prescient inflation print.

The RPs of both inflation series are plotted in Figure 2. Their dense structure captures the strong autocorrelation pattern, subject to regime changes and rare events. The first significant transition occurs around the observation 240 (red frame) at the beginning of the Volcker era. In the next regime (green frame), headline inflation is more volatile than core inflation which exhibits dominant persistence with fewer and less intense changes (thin vertical and horizontal white bands).



(a) (b)

Figure 2: RPs of US headline (a) and core inflation (b)

Although the visual inspection leads to a useful taxonomy of dynamics, patterns in the data cannot be quantified with the single use of RPs. For this purpose, the RQA was developed to provide a rich set of dynamic measures. In the aim to capture and quantify irregularity within the RP of the inflation time series, we employ the invariant measure of entropy (ENT). ENT refers to the Shannon entropy of the distribution of the diagonal lines in the RP. More specifically,

$$\mathrm{ENT} = -\sum_{\mathrm{l}=\mathrm{l}_{\mathrm{min}}}^{\mathrm{N}} \mathrm{p(l)} \ln \mathrm{p(l)}$$

where $p(l) = P(l)/N_l$, $P(l)$ is the histogram of recurrences, while N_l is the sum of diagonal lines. ENT converges to zero within periodic windows, because of the occurrence of lines with identical length. For uncorrelated random sequences ENT is low, whereas nonlinear processes with large diversity in diagonal line lengths (irregular patterns) exhibit higher ENT values. In general, rising ENT is interpreted as high uncertainty that can be either stochastic or complex. In economics, high ENT signifies that agents need more information (set of variables) so as to be able to form accurately their expectations.

The ENT measure is calculated over a 20-year window with a 1-month time step. For the applications of RQA in macroeconomic variables Kyrtsou and Vorlow (2005) suggest the use of unreconstructed data. Thus, the time delay (τ) and embedding dimension (m) are set to one. Regarding the threshold ε selection, 10% of the standard deviation (ε=10%×σ) seems to be an appropriate choice. However, this percentage may vary according to the nature of time series and the research question.

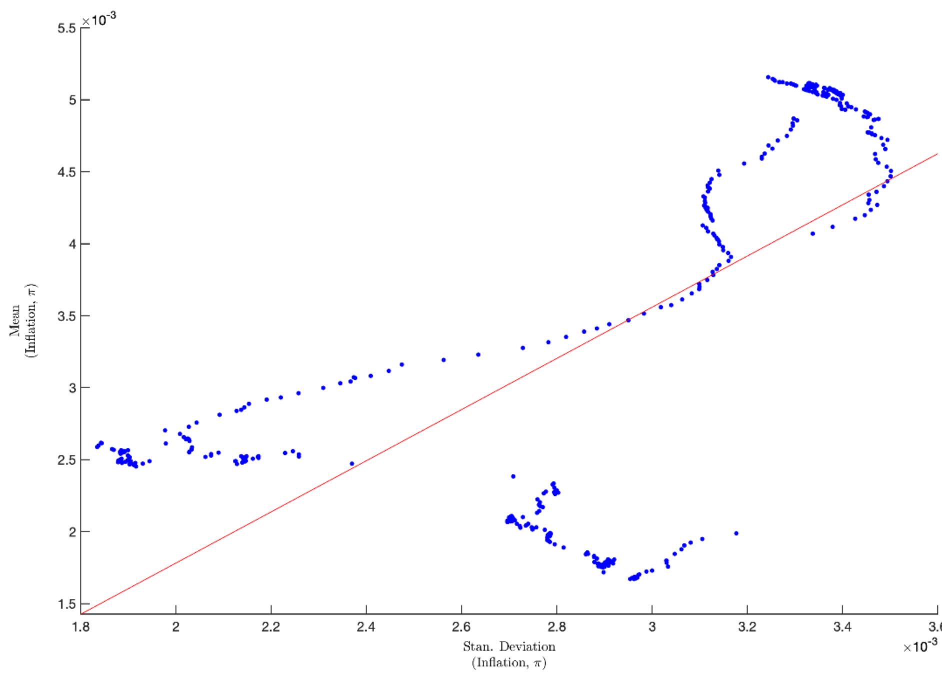


Figure 3: mean-std inflation plane. The scatterplot represents the relationship (depicted by the least-square line in red) between mean inflation (y axis) and its standard deviation (x axis).

In a next step, we explore inflation dynamics by visualizing different dimensions of inherent uncertainty quantified by ENT together with well-known statistical measures. Figure 3 reports the mean-standard deviation (std) plane for inflation. Both the 1st and the 2nd moment statistics are computed over a 20-year window sliding one time-step ahead. As we can see, a positive association arises. High mean inflation values tend to be more volatile. In the same vein, Figures 4-6 present in 2D-planes the dynamic relationship between the ENT values and the distributional characteristics of headline inflation.

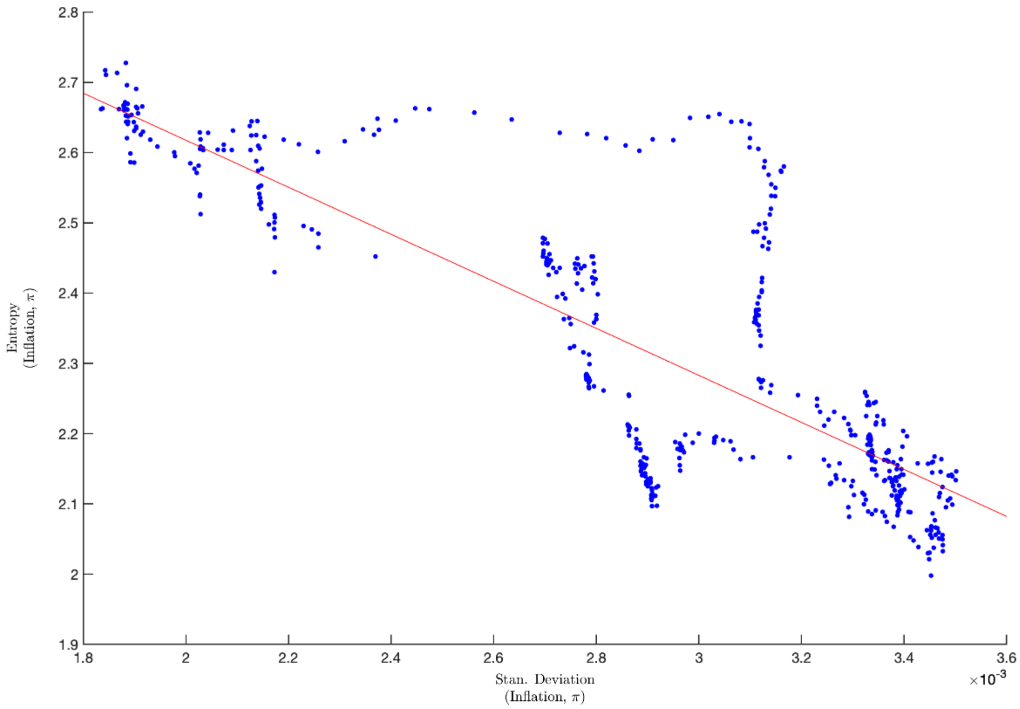


Figure 4: ENT-std inflation plane. The scatterplot represents the relationship (depicted by the least-square line in red) between ENT of inflation (y axis) and standard deviation of inflation (x axis).

From the visualized relationship in Figure 4, between ENT and the standard deviation of inflation, we can conclude that less (more) entropic behavior appears during windows of high (low) standard deviation. This interesting pattern highlights that the intensity of complexity is inversely associated with inflation gap (deviation from mean). In other words, factors affecting intrinsically inflation induce smoother gaps. The occurrence of exogenous shocks, leading to jumps in inflation, breaks the density of recurrences in the RP and lowers ENT. It turns out that different bands of inflation variability can tell a different story.

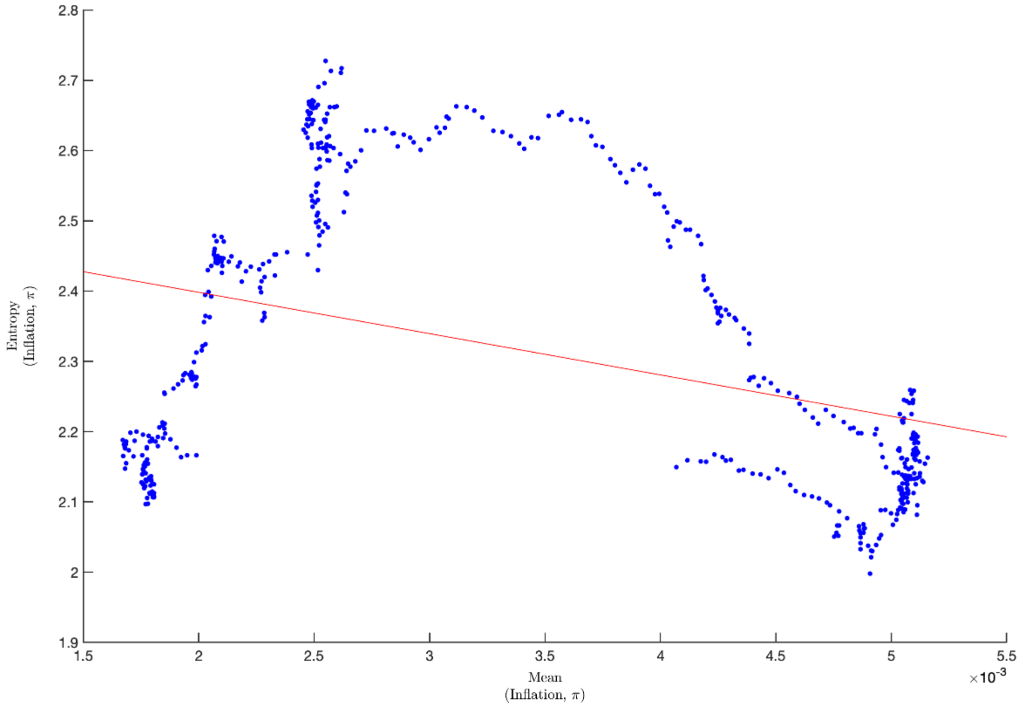


Figure 5: ENT-mean inflation plane. The scatterplot represents the relationship (depicted by the least-square line in red) between ENT of inflation (y axis) and mean inflation (x axis).

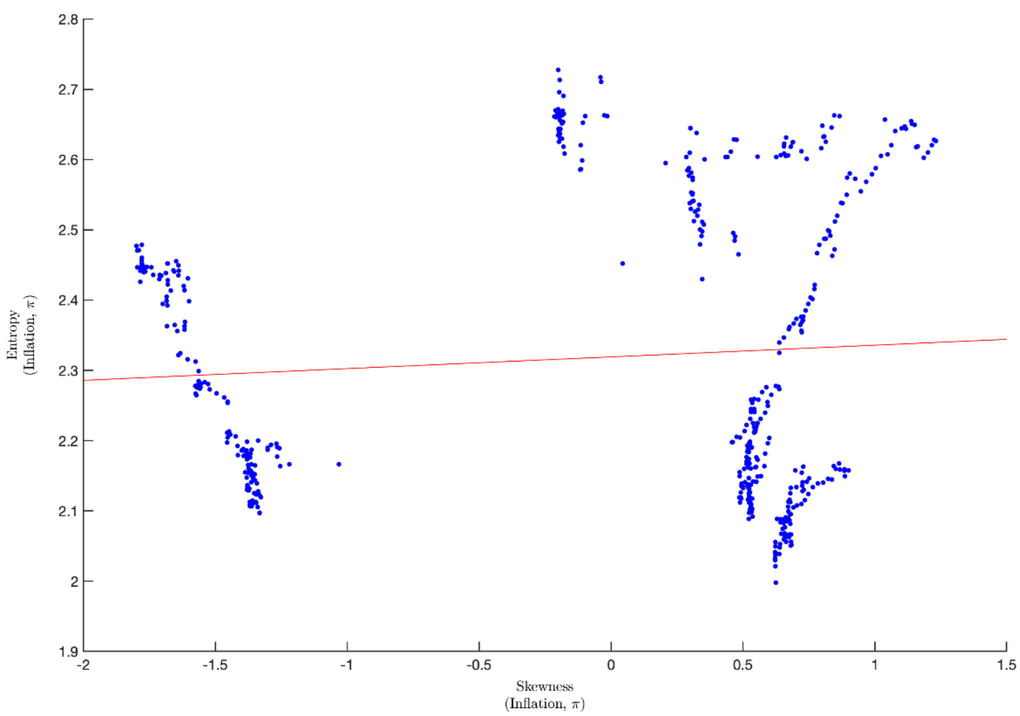


Figure 6: ENT-skewness inflation plane. The scatterplot represents the relationship (depicted by the least-square line in red) between ENT of inflation (y axis) and skewness of inflation (x axis).

The aforementioned trade-off between ENT and inflation gap is also confirmed, when we look at the level of inflation. In Figure 5, extreme low and high mean inflation rates are associated with lower entropy values. Nevertheless, when it comes to the distributional asymmetry of inflation, depicted in Figure 6, richer dynamics emerge at the right tail. ENT tends to increase more for positively skewed inflation values than for negative ones. The importance of endogenous dynamics, during regimes of rising inflation, was pointed out by Szybisz and Szybisz (2017).

In Figure 7, we plot the ENT of headline inflation for different values of ε (ε=wσ), by varying w from 0.10 to 1. Thereby, eleven ENT time series are produced. The incorporation of progressively increasing noise in the calculation of ENT induces an appealing clustering. For low levels of σ (<30%), ENT remains stable until 1990 and then it falls. For medium values of σ (<60%), a second band is formed. A steady rise of ENT is observed until the end of 1999, followed by a reversal which is interrupted by a pick around 2015 and a new entropic tendency after 2020. Allowing more σ in the computation of ENT just affects the sensitivity of estimates and underlines the apparent self-similar structure.

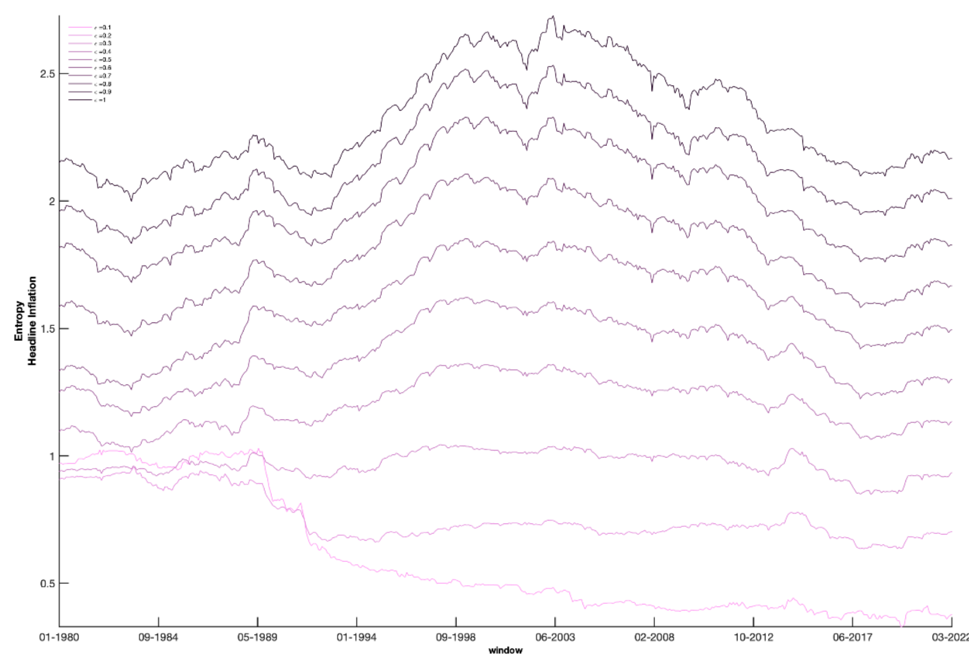


Figure 7: Dynamic ENT estimates (y axis) for headline inflation in a 20-year sliding window (x axis)

The revival of inflation dynamics in the last couple of years could be a cause of concern, if we take the significant heterogeneity in the CPI composition into account. Is a persistent volatile component able to drive the overall inflation dynamics and if yes, under which conditions and to what extent? Possible answers could be found in the evolution of structural dynamics of inflation. Plotting the ENT estimates of core inflation in Figure 8 reveals a more aggressive entropic behavior from 2008 onwards. The detected diversity of dynamics between headline and core inflation underpins the argument that price is a multilayer mechanism. As a result, exogenous shocks are transmitted heterogeneously into the various building blocks of inflation.

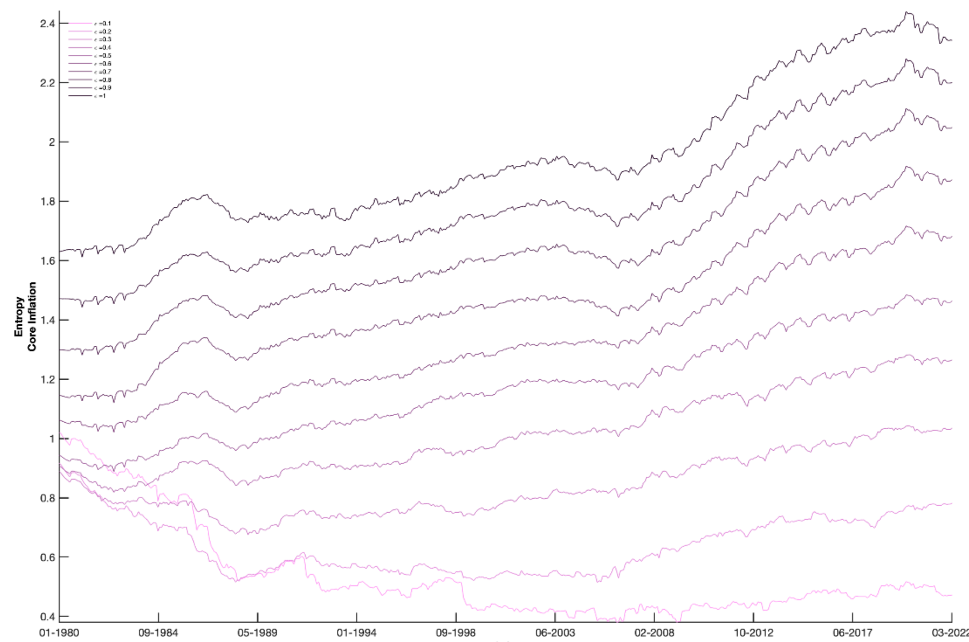


Figure 8: Dynamic ENT estimates (y axis) for core inflation in a 20-year sliding window (x axis)

3. Fractional integration coefficient d

In the presence of long-memory, a change of a variable is more likely to be followed by another change in the same direction. This momentum-type behavior defines persistence. Persistence in economics is the equivalent of inertia in physics (Fuhrer, 2010). When the sequence of changes is rather contrarian, so as a positive move tends to be followed by a negative one, then the process is characterized as anti-persistent.

Let's assume that a time series $x = \{x_1, \ldots\ldots, x_T\}$ with mean μ, follows an autoregressive fractionally integrated moving average process ARFIMA(p,d,q)

$$\Phi(B)(1-B)^d(x_t-\mu)=\Theta(B)\varepsilon_t$$

$$\text{with } \varepsilon_t \sim \text{i.i.d}(0,\sigma^2_\varepsilon)$$

B is the backward-shift operator, $\Phi(B)=1-\phi_1B-\ldots\ldots-\phi_pB^p$, $\Theta(B)=1-\theta_1B-\ldots\ldots-\theta_qB^q$, and $(1-B)^d$ is the fractional-differencing operator defined as

$$(1-B)d = \sum_{k=0}^{\infty}\frac{\Gamma(k-d)B^k}{\Gamma(-d)\Gamma(k+1)}$$

$\Gamma(.)$ is the gamma function. The parameter d is allowed to take any real value.

The stochastic process x is both stationary and invertible if all roots of $\Phi(B)$ and $\Theta(B)$ lie outside the unit circle and $|d|<0.5$ (Granger and Joyeux, 1980). Under the assumptions that $-1/2 < d < 1/2$ and $d \neq 0$, Hosking (1981) shows that the correlation function of an ARFIMA is proportional to j^{2d-1} as $j \rightarrow \infty$, delivering hyperbolically decaying autocorrelations. The process exhibits long memory if $0 < d < 1/2$, short memory for $d = 0$ and intermediate memory when $d < 0$. In the case that $0.5 \leq d < 1$ the process is non-stationary and possesses infinite variance but remains mean reverting. A widely-used method to estimate d and perform hypothesis testing, is suggested by Geweke and Porter-Hudak (1983) (GPH) built on the spectral regression

$$\log\{I(\lambda_{jT})\}=c - d\log\{4\sin^2(\lambda_{jT})\}+u_j, \quad j=1,\ldots\ldots\ldots,n$$

$I(\lambda jT)$ is the periodogram value at frequency λ_j depending on the sample size T. The slope coefficient of the OLS regression is a good estimate of d. $v = g(T) << T$ is the number of Fourier frequencies considered in the spectral regression. One of the main advantages of the GPH estimator is that it can detect effectively persistence without the need of making any assumption about the underlying process of inflation. Regarding the choice of bandwidth, we use the settings from the Kumar and Okimoto (2007) application in US inflation data who suggest adopting the bandwidth $T^{0.8}$. To shed light on the sensitivity of the persistence estimates to time, we calculate the d over a 20-year rolling window updated by 1-year increments.

The regime dependent behavior observed in Figures 7 and 8 is repeated in the evolution of US inflation persistence displayed in Figure 9. Starting by the headline inflation (solid blue line), the results indicate a persistent but still mean-reverting behavior of $d \in [0.5,1)$ until approximately 1999. In the post-1999 subperiod of the sample, lower d values [0,0.5) are detected implying the presence of long-memory except for some short-memory segments ($d = 0$). In general, the d coefficient values for core inflation (dashed red line) lag those for headline inflation. Since March 2021, the noticeable synchronization between the d estimates show that both inflation measures share similar levels of persistence.

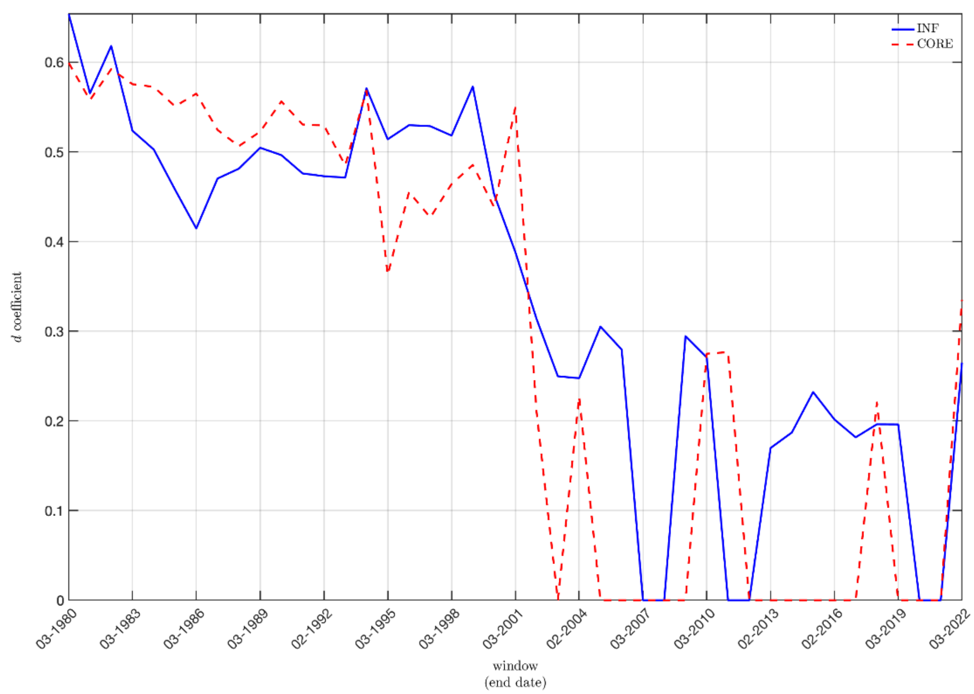


Figure 9: Dynamic d estimates (y axis) for headline and core inflation in a 20-year sliding window (x axis)

4. The nature of inertia in Phillips curve

To investigate the drivers of inflation dynamics, we first consider a variant of the Phillips curve that incorporates the domestic slack and backward-looking inflation expectations augmented with output growth and supply shocks. According to economic theory, when inflation is persistent a rather significant sacrifice ratio is required to reduce its level. This inertia can be modelled by included lagged inflation terms. An interesting alternative to account for inflation inertia together with exogeneous shocks is the triangle model of Gordon (1982) that we augment with demand dynamics proxied by the real GDP growth. As Gordon (2011) explains, the omission of supply variables makes the slack coefficient of the Phillips curve to be biased towards zero. Additionally, Tauber and Van Zandweghe (2020) support that the inclusion of output growth enriches the standard Phillips curve with dynamics caused by rising household consumption and habit formation. The effect of rigidities in consumer spending due to habit formation is also discussed in Fuhrer (2000). Milani (2009) reports that habit formation in consumption can help matching the observed inflation persistence. The significant role of consumption dynamics as the main driver of output dynamics in big-size economies has been recently pointed out by Kyrtsou & Mikropoulou (2022). All US variables used in this section are taken in quarterly basis and span from 1960.q1 to 2022.q1.

The first Philips curve specification is deployed as follows:

$$\pi_t=\delta_1\pi_{t-1}+\gamma_1 gap_t+\kappa_1 y_t+\lambda_1 oil_t+\varepsilon_t \qquad \text{model 1}$$

ε_t is an i.i.d stochastic disturbance with zero mean and finite absolute moments with variance σ_ε^2, π_t refers to the quarter-over-quarter CPI inflation calculated as the first logarithmic differences of prices. π_{t-1} is the lagged CPI inflation and captures the apparent inertia in inflation. gap_t is the output gap measured by the log deviation between real GDP and the Congressional Budget Office's estimate of potential GDP. y_t is the output growth, a measure of real activity dynamics. oil_t represents the supply shocks and it is proxied by the spot price of the West Texas Intermediate (WTI) blend of crude oil transformed in logarithmic returns.

The empirical results of the previous session demonstrated that the inherent structure of US inflation matters a lot, and any persistent evolution of prices is not alike. Dynamics may persist but it is the multiplicity of sources that determines the degree of inflation complexity and induces dissimilar inflationary regimes. Fuhrer (2010) highlights that inertial inflation has a twofold interpretation. It can be due to i) the persistence of real activity and supply shocks in the standard framework of a Phillips curve, and ii) the intrinsic persistence imprinted in lagged inflation terms. In the latter case, the price-setting mechanism causes inertia which is independent of the driving process. Mathematically speaking, inflation is governed by endogenous dynamics that are able to propagate initially temporary shocks and further fuel instability by introducing second-round effects. The amplifier is the lagged inflation in the Phillips curve equation.

To accommodate complex forms of inflation persistence, the backward-looking dynamics of model 1 are expressed in terms of nonlinear and linear components. We name this combination as inertia factor (IF).

$$\pi_t = \underbrace{\alpha_2 \frac{\pi_{t-i}}{1+\pi_{t-i}^{c}} + \delta_2 \pi_{t-1}}_{\mathrm{IF}} + \gamma_2 gap_t + \kappa_2 y_t + \lambda_2 oil_t + \varepsilon_t \qquad \text{model 2}$$

where i is the number of lags of the nonlinear inflation term. The optimal i is selected based on the best information criterion BIC. In real applications setting c=2 describes appropriately data dynamics, because of the high level of noise (Kyrtsou and Terraza, 2002). If δ is positive, then IF presents the properties of a nonlinear autoregressive process. In this case, the sum $\alpha+\delta$ designates the intensity of persistence. If δ is negative, then IF takes the form of a Mackey-Glass process able to generate feedback dynamics (Kyrtsou and Terraza, 2003). The sign of α-δ indicates the nature of feedback. Positive feedback dynamics dominate if $\alpha - \delta > 0$, inducing high irregularity in the data generating mechanism. When $\alpha - \delta > 0$, negative feedback dynamics determine the autocorrelation structure. Kyrtsou and Vorlow (2005) argue that a noisy Mackey Glass process, under specific parametrization, can present qualitative resemblance with the US CPI inflation. However, we have to keep in mind that data aggregation may significantly affect the identification of feedback structures.

According to Ball and Mazumder (2011) the most common supply shocks are changes in food and energy prices. Thereby, in the third and fourth Phillips curve specification we further augment models 1 and 2 with an additional supply component, i.e. food prices.

$$\pi_t=\delta_3\pi_{t-1}+\gamma_3 gap_t+\kappa_3 y_t+\lambda_3 oil_t+\varphi_3 food_t+\varepsilon_t \qquad \text{model 3}$$

$$\pi_t=\underbrace{\alpha_4\frac{\pi_{t-i}}{1+\pi^c_{t-i}}+\delta_4\pi_{t-1}}_{IF}+\gamma_4 gap_t+\kappa_4 y_t+\lambda_4 oil_t+\varphi_4 food_t+\varepsilon_t \qquad \text{model 4}$$

$food_t$ is a measure of food inflation calculated as the log difference of the food component of the Personal Consumption Expenditure.

Besides supply shocks, Cogley and Sbordone (2008) and Malikane and Mokoka (2012) suggest an alternative source of inflation inertia. It is shown that underlying inflation drives much of the headline inflation persistence. This effect is taken into account in a fifth model with the joint presence of underlying inflation ($\frac{\pi^*_{t-i}}{1+\pi^{*c}_{t-i}}$) and headline inflation (π_{t-1}) in the inertia factor.

$$\pi_t=\underbrace{\alpha_4\frac{\pi^*_{t-i}}{1+\pi^{*c}_{t-i}}+\delta_4\pi_{t-1}}_{IF}+\gamma_4 gap_t+\kappa_4 y_t+\lambda_4 oil_t+\varphi_4 food_t+\varepsilon_t \qquad \text{model 5}$$

Models 2, 4 and 5 recognize that inflation can exhibit significant and nonlinear persistence even in the absence of supply shocks. According to Gordon (2011), this condition constitutes an important challenge for policy makers to control inflation by altering public expectations directly.

To consider the effect of improved anchoring we split the data into two subsamples i.e. 1961q1-1998q4 and 1999q1-2022q1. The date 1999q1 seems to be a tipping point around which the anchoring process was completed (Mishkin, 2007; Jørgensen and Lansing, 2022). Besides introducing supply shocks proxies, we perform a Durbin–Wu–Hausman (Durbin, 1954; Hausman, 1978; Wu, 1973), test for endogeneity so as to ensure the consistency of the estimates. The set of instruments in the GMM estimation comprises a constant and four lags for inflation, output gap, output growth and supply shocks. To address possible serial correlation issues, we use Heteroskedasticity and Autocorrelation Consistent (HAC) estimates of the covariance matrix (Newey and West, 1987) with a Bartlett kernel and an automatic Newey-West bandwidth selection (Newey and West, 1994). The probability value of the respective J-statistics is also reported for each model together with the residual diagnostics. Regarding the nonlinear rule of thumb in IF, the selected optimal lag is i=3.

Table 1 reports the estimates of the five models, as well as the summary statistics of the inflation series. All J-statistics are not statistically significant at 5% level, implying rejection of endogeneity hypothesis. Additionally, the fact that the explanatory variables remain uncorrelated with the error term, in the various augmented Phillips curve specifications, mitigates the possibility of obtaining biased OLS estimates and spurious residual structure. As we can see, in the first column of Table 1 inflation exhibits strong linear and non-linear autocorrelation. It is moderately leptokurtic but highly right-skewed over the first subsample. Situation reverses in the second subsample. Kurtosis increases abruptly, while skewness reaches a large negative value. The time varying non-normal behavior of headline inflation can be visualized in Figure 10. After a pick around 2000, the kurtosis (red line) stabilizes until the beginning of the 2007-2009 financial crisis. Regarding core inflation, after the outburst in 2000, its kurtosis (green line) evolves almost steadily until 2020 where an abrupt jump takes place again.

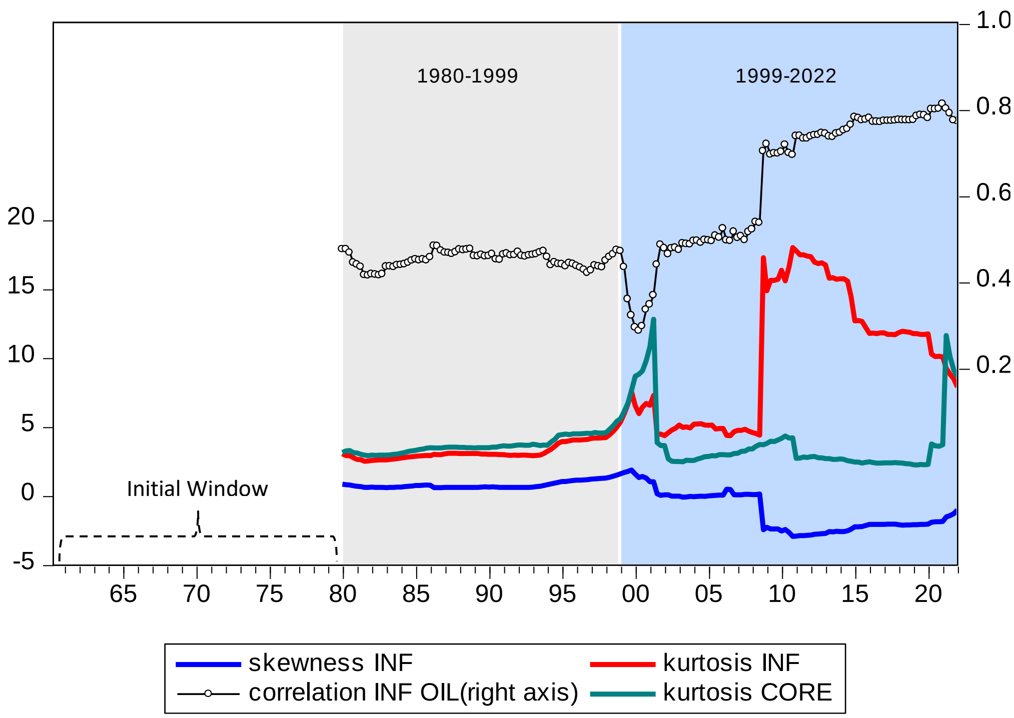


Figure 10: Rolling skewness and kurtosis of headline inflation. For comparison purposes, we jointly plot the skewness of core inflation and the correlation between headline inflation and oil. For all measures, the initial window 1960.q1-1979.q4 (20 years) is sliding by one observation ahead.

The divergence in terms of kurtosis between core (green line) and headline inflation (red line) comes to highlight the detected decoupling of the dynamic ENT estimates in section 2. In the aftermath of the 2007-2009 financial crisis, when headline inflation becomes highly leptokurtic, the correlation (black dotted line) between headline inflation and oil intensifies significantly. From 2020 to 2021, the tail-behavior of both inflation series desynchronizes and then reverses until the end of the sample.

The obtained Log-Likelihood estimates and residual diagnostics in Table 1 indicate that models 4 and 5 present the best fit. The δ coefficient is statistically significant and positive in all specifications implying that IF exhibits the properties of a nonlinear autoregressive process. Regarding the best 4th and 5th Phillips curve specifications, we also include the results of regressions on a third sample 2009.q4-2022.q1 covering the post-recession era.

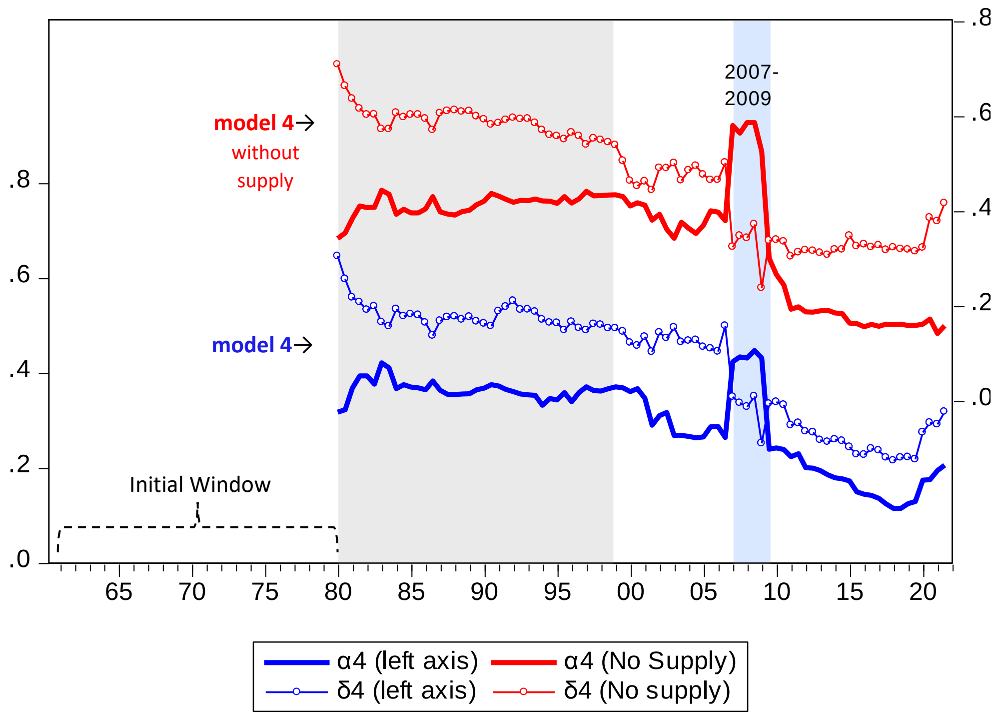


Figure 11: Rolling α and δ coefficients of the Mackey-Glass terms in the 4th backward-looking Phillips curve model, estimated by OLS. For comparison reasons, the same model is re-estimated without supply shocks. For both models, the initial window 1960.q1-1979.q4 (20 years) is rolled forward by two quarters at a time.

The role of different variables in the Phillips curve specifications augmented with supply shocks can also appear unstable through time (Mikolajun and Lodge, 2016).

Thereby, parameter instability constitutes an important feature of the Phillips curve. According to Forbes (2019), this may occur because of global economic events, changes in the labor market and the credibility of central banks. To account for the impact of structural instability on inflation persistence, we estimate time-varying coefficients for models 4 and 5 in rolling regression. As Albuquerque and Baumann (2017) point out this approach leads to lower Root Mean Square Error.

Figure 11 displays the statistically significant time-varying coefficients of the backward-looking component of the 4th Phillips curve equation. To investigate the degree of contribution of supply shocks, we re-estimate the model excluding oil and food variables and we plot the new α and δ coefficients (red lines). As we can see in Figure 11, during the 2007-2009 financial crisis the α coefficient (solid line, both colors) imposes on δ (dotted thin line, both colors). They keep on declining until 2020.q1, and then they go up suddenly. Interestingly, when the model 4 takes the effect of supply shocks into account, the distance between α and δ (blue lines) is smaller than the respective distance (red lines) in the version of model 4 without supply. The observed sensitivity of IF demonstrates the importance of the contribution of supply shocks to inflationary dynamics.

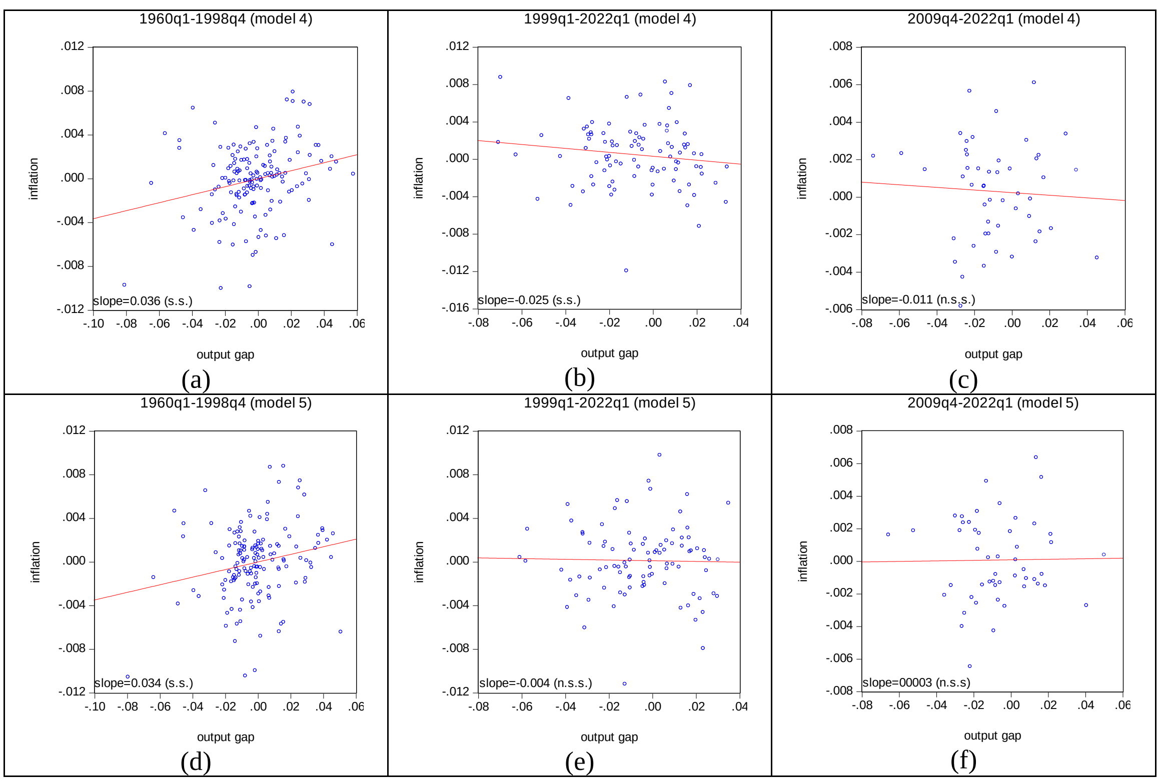


Figure 12: Sensitivity of inflation to output gap partialled on the regressors of models 4 and 5

Jørgensen and Lansing (2022) report three channels that justify diminishing inflation persistence over time. The improved anchoring can i) make inflation less sensitive to its lagged values, ii) reduce the sensitivity of inflation to reply to output gap movements and iii) make inflation more resilient to supply shocks. The aforementioned findings provide evidence about the first channel until 2020.q1. The second channel implies a flatter Phillips curve. This is what we observe in Figure 12. The curve is steeper with a positive and statistically significant slope over the first subperiod, followed by a clear downward trend. The flattening is more pronounced on the third subsample 2009.q4-2022.q1. This also comes in line with Costain et al., (2022) who show that in US data the slope of the Phillips curve is significantly higher between 1980-2000 than during the period of 2000-2019.

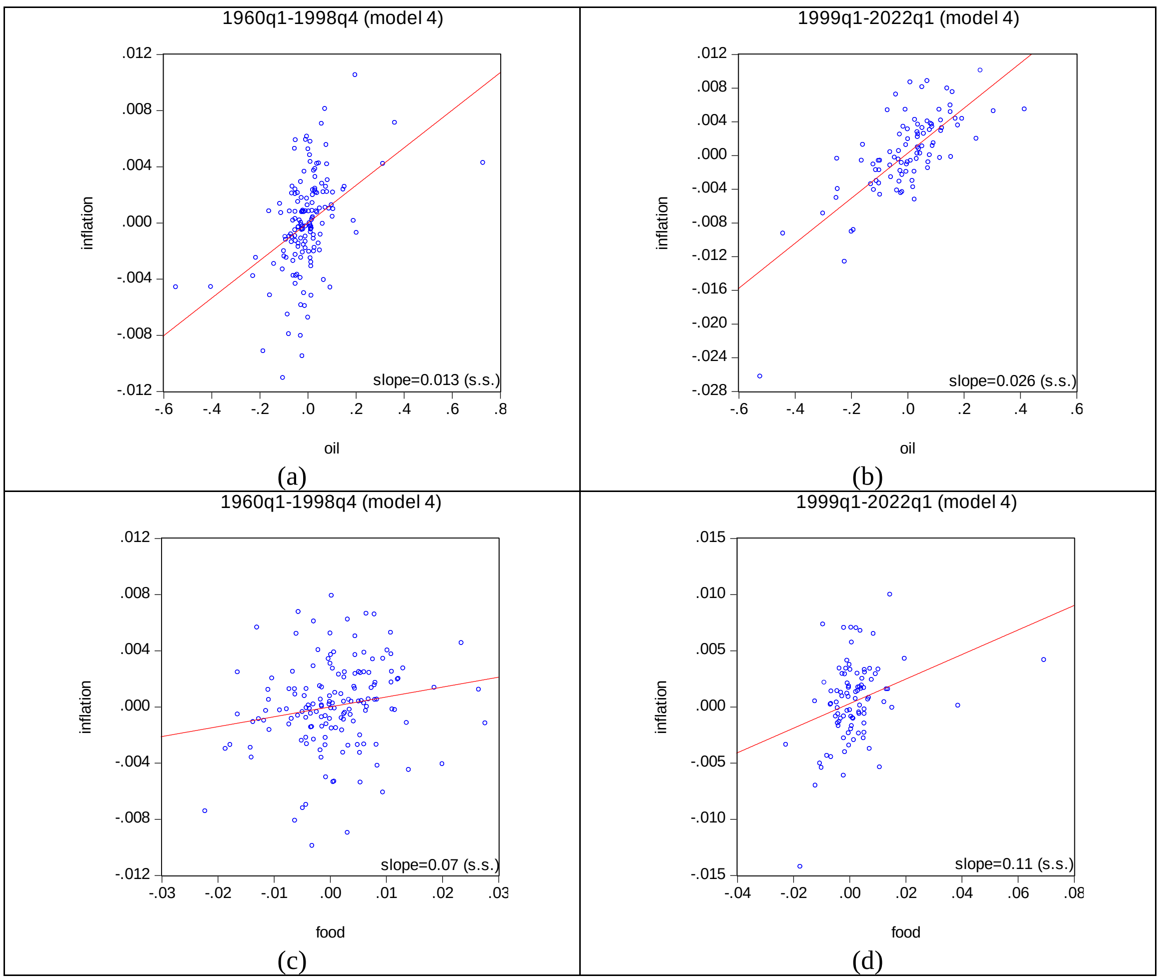


Figure 13: Sensitivity of inflation to oil (a,b) and food (c,d) partialled on the regressors of model 4

Regarding the effect of supply shocks, the rising sensitivity of inflation to oil and food factors over time (Figure 13) together with their impact on the intensity of inflation persistence (Figure 11) seem to contradict the third channel. Stock and Watson (2010) and Stock (2011) relate the detected decline in the slope coefficient in the backward-looking Phillips curve regressions to the improved anchoring of expected inflation. Occhino (2019) shows that a flatter Phillips curve can be caused either by a structural change unrelated to policy or by the conduct of monetary policy.

Figure 14 visualizes the evolution of the inertia factor in model 5 i.e. the statistically significant α and δ coefficents. The findings unveil three distinct behaviors: i) until 2004, δ is higher than α but both converge over time, ii) 2004-2007 is a period of stability, iii) since 2007 their relationship reverts, and they keep on deviating steadily after 2009. During the last eight quarters of the dataset α and δ exhibit a coupling behavior. The α coefficient (dotted blue line) increases abruptly from 2020 onwards, implying a meaningful evolution of the lagged core inflation.

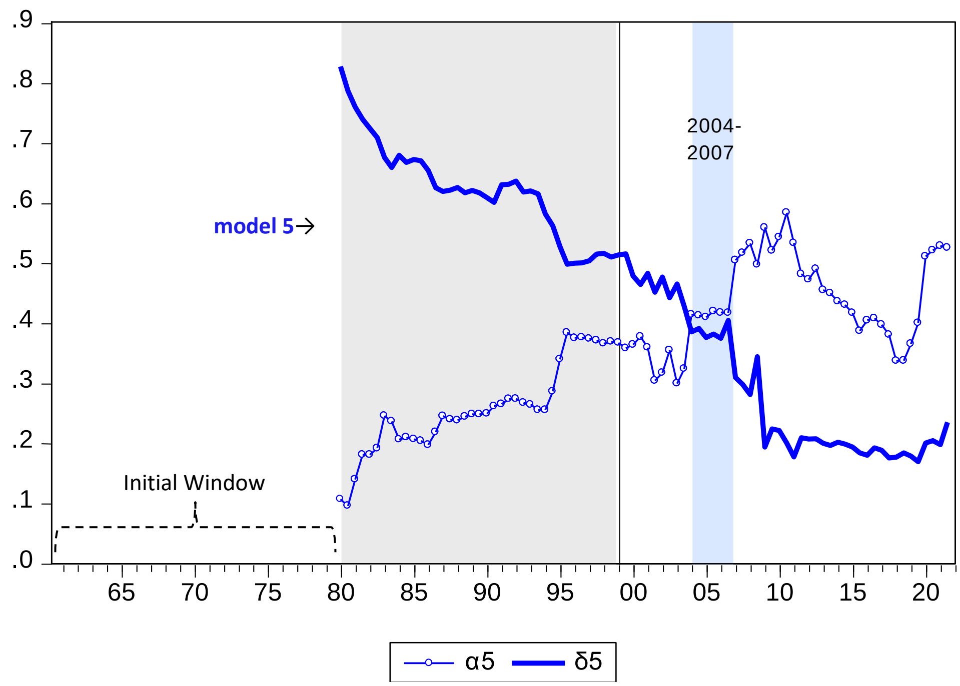


Figure 14: Rolling coefficients α and δ in the 5th backward-looking Phillips curve model, estimated by OLS. The initial window 1960.q1-1979.q4 (20 years) is rolled forward by two quarters at a time.

The estimates and results in Tables 1 & 2 show that from 2009.q4 to 2022.q1 the headline inflation remains highly leptokurtic, skewed and nonlinear. Accepting the null hypothesis of i.i.d for the residual term of model 5 (insignificant autocorrelation and normal moment statistics) in the 3rd subsample together with the rejection of nonlinearity in mean

(Tsay, 1986) and variance (McLeod–Li, 1983; Engle, 1982), demonstrate the effectiveness of the 5th Phillips curve specification to capture persistent inflation patterns.

5. Conclusion

The horizon that central banks generally choose to bring back inflation depends on the nature, the size and the persistence of shocks. Inflation persistence describes the time that it takes for a shock to dissipate, or it is just inherited from the driving process i.e. the output gap. It may be also attributed to high and nonlinear intrinsic inflation which is independent of the driving process, and it can propagate temporary shocks into the future. In the same vein, the response of economic policy to such shocks can boost inflation inertia. In any of the above scenarios the conclusion seems to be common. A good knowledge about the causes and characteristics of inflation inertia can provide the necessary information background for an effective and precise monetary policy.

In the presence of intrinsic structure, the complexity of the inflation process increases. The implementation of our methodological strategy revealed the progressive influence of underlying inflation on the overall inflation dynamics. Although idiosyncratic factors remain statistically significant, the noticeable contribution of the lagged underlying inflation after 2020 indicates the built-up of a systematic mechanism that nonlinearly affects headline inflation. The combination of empirical findings about rising complexity, persistence, and intrinsic inertia over this period, reflects the fact that exogeneous shocks, such as commodity price increases alongside supply disruptions, started having indirect effects on inflation. According to Almuzara and Sbordone (2022), sometime in 2021 the trend component dominated inflation dynamics. Indeed, inflation persistence tends to become an inherent characteristic of the economy feeding more inflationary pressures that can weaken the credibility of the central bank and cause the de-anchoring of the long-term inflation expectations. Under these circumstances, the vigorous policy actions adopted by the central bank and the strong commitment to reduce inflation are moves in the right direction.

Table 1: Phillips curve specifications and estimates

Coefficient	**Inflation**			**model 1**		**model 2**		**model 3**		**model 4**			**model 5**		
	1960q1-1998q4	**1999q1-2022q1**	**2009q4-2022q1**	**1960q1-1998q4**	**1999q1-2022q1**	**1960q1-1998q4**	**1999q1-2022q1**	**1960q1-1998q4**	**1999q1-2022q1**	**1960q1-1998q4**	**1999q1-2022q1**	**2009q4-2022q1**	**1960q1-1998q4**	**1999q1-2022q1**	**2009q4-2022q1**
α				-	-	0.385*	0.288*	-	-	0.356*	0.236*	0.232*	0.252*	0.482*	0.365*
δ				0.890*	0.556*	0.564*	0.439*	0.776*	0.419*	0.526*	0.355*	0.528*	0.627*	0.274*	0.472*
γ				0.012	-0.053*	0.045*	-0.037*	0.0008	-0.034*	0.036*	-0.025*	-0.011	0.035*	-0.004	0.0003
κ				0.103*	0.064*	0.071*	0.033	0.059**	0.053*	0.048**	0.031	0.052*	0.025	0.015	0.047*
λ				0.015*	0.025*	0.0139*	0.027*	0.0139*	0.025*	0.013*	0.026*	0.022*	0.014*	0.027*	0.022*
φ				-	-	-	-	0.129*	0.149*	0.071*	0.113*	0.079*	0.084*	0.102*	0.081*
α+δ				-	-	0.949*	0.727*	-	-	0.882*	0.591*	0.760*	0.879*	0.756*	0.837*
Log likelihood				644.03	381.1	660.36	391.85	651.23	389.63	663.01	397.58	226.91	654.53	400.46	227.83
prob J-statistics				0.644	0.542	0.775	0.424	0.940	0.530	0.864	0.603	0.877	0.959	0.872	0.843
				Residual Diagnostics											
Q(2)	0.758*	0.063*	0.012*	-0.249*	0.087	-0.041	0.137	-0.188*	0.121*	-0.045	0.132	-0.074	-0.120*	0.075	-0.098
Q(4)	0.659*	-0.082*	0.042*	-0.018*	-0.164	0.028	-0.110	-0.032*	-0.090	0.014	-0.051	-0.138	0.028*	-0.072	-0.108
Q(6)	0.576*	0.046	0.106	0.113*	0.037	0.024	0.103	0.134*	0.007	0.050	0.078	0.183	0.071*	-0.100	-0.018
Q(8)	0.456*	-0.015	0.190	-0.127*	0.114	-0.135	0.063	-0.160*	0.047	-0.161	0.038	-0.089	-0.158*	0.024	-0.022
$Q^2(2)$	0.745*	0.310*	0.000	0.202*	0.066*	0.080	0.128*	0.132*	0.088*	0.055	0.102*	-0.081	0.229*	0.070*	0.165
$Q^2(4)$	0.613*	0.112*	0.000	0.176*	-0.015*	0.096	-0.065*	0.144*	0.031*	0.160	-0.048*	-0.037	0.139*	-0.078*	-0.021
$Q^2(6)$	0.466*	0.064*	0.000	0.119*	0.158*	0.037	0.083	0.155*	0.201*	0.058*	0.101*	-0.003	0.199*	0.116*	-0.041
$Q^2(8)$	0.234*	-0.071*	0.000	0.065*	0.198*	0.071	0.031*	0.080*	0.158*	0.058	0.069*	0.119	0.004*	0.147*	0.068
skewness	1.14	-1.11	-1.09	0.03	-0.002	-0.35	-0.53	-0.072	0.024	-0.33	-0.26	-0.09	-0.28	-0.08	0.10
kurtosis	4.10	8.58	8.34	3.62	5.21	3.75	5.41	3.85	4.39	3.83	4.45	2.76	3.95	4.34	2.96
Jarque-Bera	41.97*	139.74*	125.07	2.53	19.02*	6.73*	26.75*	4.86	7.51*	7.30*	9.31*	0.19	7.88*	7.10*	0.09

* denotes statistical significance at the 5% level.

Table 2: Tests for nonlinearity in mean and variance over the subsample 2009q4-2022q1

Tests		**Inflation**	**Residuals of model 4**	**Residuals of model 5**
Engle (p=5)	Bootstrap	0.000*	0.860	0.130
	Asymptotic	0.019*	0.882	0.160
McLeod–Li (L=4)	Bootstrap	0.000*	0.750	0.130
	Asymptotic	0.021*	0.832	0.160
Tsay (k=5)	Bootstrap	0.040*	0.070**	0.120
	Asymptotic	0.060**	0.097**	0.133

Numbers refer to p-values based on bootstrapped (1000 replications) as well as asymptotic distributions.
*,** denote statistical significance at the 5% and 10% level respectively.
For comparison, results on headline inflation during the same period are reported.

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