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REVIEW ARTICLE

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Exogenous shocks and time-varying price persistence in the EU27

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ABSTRACT

This paper analyses monthly price persistence in the EU27 countries over the period 2010–2022 using a fractional integration framework, where the measure of persistence is the fractional differencing parameter d. In addition to full sample estimates, subsample and recursive ones are obtained to examine time variation. On the whole, the results provide clear evidence that both the exogenous shocks considered (namely, the COVID-19 pandemic and the Russia-Ukraine war) have generally increased price persistence in the EU27 (despite their heterogeneity), although the recursive estimates suggest that their impact might have peaked and might now be decreasing. Therefore, any policies adopted to counteract those shocks should be gradually phased out. The exceptions are the Southern European countries, where price persistence appears to have decreased, though in Italy the recursive analysis indicates that it is now rising sharply.

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Price persistence; fractional integration; COVID-19 pandemic; Russia-Ukraine war

1. Introduction

The world economy has recently been hit by two exogenous shocks with global consequences, namely the COVID-19 pandemic and the energy crisis resulting from the Russian invasion of Ukraine. Both of them have had repercussions not only on the real economy, but also on prices, which have risen sharply in countries throughout the globe. An interesting issue is whether or not the effects of those shocks on prices will be long-lived in order to be able to adopt appropriate policy responses. This is the focus of the present study, which provides evidence on the degree of price persistence in each of the 27 European Union member states (EU27) over a sample period including both the COVID-19 pandemic and the Russia-Ukraine war. More specifically, the aim of the analysis is to establish whether there has been any time variation in the degree of persistence as a result of those two shocks. For this purpose, a fractional integration model for monthly log-prices is estimated first over a sample ending in December 2019

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(the period before the COVID-19 pandemic), then for one ending in January 2022 (the period before Russia-Ukraine war) and lastly for the full sample ending in December 2022; in addition, recursive analysis is carried out to shed further light on the possible presence of time variation.

The adopted framework is more general than the standard one based on the dichotomy between I(0) stationarity and the I(1) non-stationarity. Specifically, it allows for fractional as well as integer degrees of differentiation. Moreover, it produces a direct measure of persistence in the form of the estimated fractional differencing parameter d. Finally, it is informative on whether the effects of shocks are transitory or permanent and the nature of the dynamic adjustment process. This is essential information for policy makers to decide on appropriate actions. Note that our analysis is univariate and therefore cannot shed light on the specific channels through which shocks can affect prices. However, it is still useful to policy makers since knowledge of whether or not the effects of shocks will persist can help them decide on the appropriateness of policy intervention.

In the existing literature various papers have analysed inflation persistence using different methods. For instance, Franta et al. (2010) estimated ARFIMA models and found that among the new members of the European Union some (Bulgaria, Cyprus, the Czech Republic, Malta, Romania, and Slovakia) exhibit persistence levels similar to those of the euro area countries, whilst others (Estonia, Hungary, Latvia, Lithuania, Poland, and Slovenia) are characterised by much higher persistence. Caporale and Gil-Alana (2011) considered Gegenbauer processes for some European countries and found mean reversion in all cases, which implies that the effects of exogenous shocks on inflation are transitory and therefore there is no need for active policies to respond to them. Gil-Alana et al. (2016) analysed the inflation rate in the G7 countries allowing for nonlinearities; in particular, they applied fractional integration methods based on Chebyshev polynomials in time. They found evidence of unit roots in the UK, Canada, France, Japan and the USA, of mean reversion in Germany, and of explosive patterns in Italy. J. Cuestas et al. (2016) examined the inflation differentials between seven Central and Eastern European Countries (CEECs) and the Eurozone. They found evidence of nonlinearities in most cases, but of persistence only in a few ones. Note that a lot of the available empirical evidence can be rationalized in terms of the contracting model developed by Fuhrer and Moore (1995), in which agents are concerned with relative real wages.

Further evidence on inflation persistence was provided by Robalo Marques (2004) for both the US and the Euro Area; he pointed out that the results are sensitive to the function used to proxy the inflation mean, and found higher persistence in the 60s and 70s. Cogley et al. (2010) focused on the US inflation gap, measured as the difference between inflation and trend inflation, and reported that persistence increased during the 1980s and decreased after the Volcker disinflation, whilst Pivetti and Reis (2007) found that it was relatively stable. Mayoral (2007) modelled the inflation rates of 21 OECD countries using fractional integration methods and found generally high and relatively stable persistence. Caporale et al. (2020) applied long-memory techniques to long runs of data for the UK and the US by applying long-memory methods and also concluded that inflation persistence in these two countries was generally stable over the time period 1660–2016. However, Caporale and Gil-Alana (2020) found an increase in the degree of persistence in the 16th century and more recently after WWI and in the last quarter of the 20th century in the case of the UK when considering a longer sample from 1216 to 2010.

Caporale et al. (2022) again used long-range dependence methods and found high persistence in the G7 over the period January 1973 - March 2020. Finally, Caporale et al. (2023) evaluated the impact of the COVID-19 pandemic and of the Russia-Ukraine war on the degree of persistence of inflation in both the EU27 and the euro zone using a fractional integration framework. They found a significant increase in inflation persistence, but also that the full-sample results imply only temporary effects of the two shocks being considered.

In contrast to the studies discussed above, the present one focuses on log-prices rather than the inflation rate, and thus provides evidence on the degree of persistence of a possibly nonstationary series such as prices rather than taking first differences to make it stationary. It also makes an important contribution to the existing literature by examining in greater depth the case of Europe. More precisely, as in Caporale et al. (2023), it uses long-memory and fractional integration methods to analyse the impact of both the COVID-19 pandemic and the Russia-Ukraine. However, in contrast to that study, it focuses on the evolution of price themselves rather than the corresponding inflation rate. Moreover, it examines their stochastic behaviour in each of the 27 EU member states. In particular, it investigates time variation in price persistence in each of them, thus producing a novel set of empirical results not previously available in the literature.

The remainder of the paper is structured as follows: Section 2 outlines the methodology; Section 2 describes the data and discusses the empirical findings; Section 3 offers some concluding remarks.

2. Methodology

Different measures of persistence have been used in the literature. A simple one is given by the autoregressive coefficient in an AR(1) model (or the sum of the coefficients in an AR(p) one), with higher values corresponding to higher degrees of persistence. However, a serious limitation of this approach is that it imposes an exponential rate of decay on the autocorrelation values; moreover, it assumes stationarity I(0) of the series of interest. By contrast, in the present study we adopt a more general framework allowing for fractional orders of integration and a (much lower) hyperbolic rate of decay in the estimated differencing parameter d, which measures the degree of persistence. This type of model encompasses the standard AR(p) ones, which are a special case of the I(d) specification with d-differenced series.

More precisely, we estimate the following model:

$$y_t = \beta_0 + \beta_1 t + x_t, \quad (1 - L)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{1}$$

where y_t is the observed time series, in our case the (logged) Harmonized Index of Consumer Prices (HICP); β_0 and β_1 are respectively the intercept and the coefficient on a linear time trend; L is the lag operator, i.e., $L^k x_t = x_{t-k}$, and x_t is assumed to be I(d), where d is the degree of differentiation. As for the error term u_t, we assume (weak) autocorrelation[1]; however, instead of imposing a specific ARMA model, we use a non-

[1]Autocorrelation can be defined as weak or strong. Weak autocorrelation is usually associated to models with values of the autocorrelation function decaying at an exponential rate such as the AutoRegressive Moving Average (ARMA) models; strong autocorrelation is instead characterised by a much lower rate of decay, for instance a hyperbolic one as in the case of fractionally integrated models (with $d > 0$).

parametric method due to Bloomfield (1973) that approximates ARMA structures with very few parameters and is very suitable in the context of fractional integration, as shown by Gil-Alana (2004).

Note that the fractional differencing polynomial in L above can be expanded for any real d as

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots$$

and thus, x_t can be expressed as

$$x_t = d\, x_{t-1} - \frac{d\,(d-1)}{2} x_{t-2} + \ldots + u_t.$$

In this context, if the differencing parameter d is a non-integer value, x_t will be a function of all its past history, and the higher the value of d is, the higher is the degree of dependence between the observations. That is the reason why this parameter is used as a measure of persistence in the data. Moreover, if $d > 0$, the series exhibits long memory due to the fact that the spectral density function tends to infinity as the frequency approaches zero, and mean reversion takes place as long as d is smaller than 1 since the impulse response coefficients decay hyperbolically to zero. Covariance stationarity holds if $d < 0.5$, and the series becomes more nonstationary as d increases above 0.5, the reason being that the variance of the partial sums increase in magnitude with d (Franta et al., 2010). This type of processes was originally introduced by Granger (1980, 1981), Granger and Joyeux (1980) and Hosking (1981) and its justification was based on the concept of aggregation by authors such as Robinson (1978) and others. They are now commonly used in the analysis of time series data. Moreover, the fact that d can be any real number allows to consider a wide range of specifications, including: 1) short memory processes (if $d = 0$); 2) long-memory covariance stationary processes ($0 < d < 0.5$); 3) nonstationary processes with a mean reverting pattern ($0.5 \leq d < 1$); 4) unit roots or I(1) processes ($d = 1$), or even explosive patterns ($d \geq 1$).

It is also important to know that the estimation of the deterministic terms (β_0 and β_1) in Equation (1) are clearly affected by the assumptions made with respect to x_t. In particular, if x_t is assumed to be short memory or I(0), the results will be biased and inconsistent if it is in fact I(d) with non-zero d. Note that in our approach we jointly estimate all the parameters in the model, since the two equations in (1) can be jointly written as:

$$\tilde{y}_t = \beta_0 \tilde{1}_t + \beta_1 \tilde{t}_t + u_t, \quad t = 1.2, \ldots \tag{2}$$

where

$$\tilde{y}_t = (1-L)^d y_t; \quad \tilde{1}_t = (1-L)^d 1; \quad \tilde{t}_t = (1-L)^d t \,,$$

where 1 is a vector, whose elements are equal to 1 and t a time trend, and since u_t is I (0) by construction, we can use standard t-tests to determine the significance of the coefficients.

For the estimation we use a simple version of a testing procedure developed in Robinson (1994) that is based on the Lagrange Multiplier (LM) principle. It tests the null hypothesis H_o: $d = d_0$ for any real value d_0 in (1), and the chosen estimate of d is the value of d_0 producing the lowest statistic. This value is the same as the one obtained through the Whittle function in the frequency domain which is the objective function in Robinson's (1994) procedure. This method is very suitable for our purposes, since: (i) it allows us to estimate d, the degree of persistence, for any real value d_0, including possibly nonstationary processes ($d_0 \geq 0.5$) without needing to take first differences as instead required by standard procedures based on unit (or fractional) roots; (ii) it has an asymptotic normal distribution; (iii) it is the most efficient test in the Pitman sense (Pitman, 1948) against local departures, which is important since d_0 is a fractional value. A full description of this method can be found in Gil-Alana and Robinson (1997).

3. Empirical results

For the analysis we use the log transformation of seasonally unadjusted monthly data for the Harmonized Index of Consumer Prices (HICP) in each of the 27 European Union (EU) member states; these series have been obtained from Eurostat (the statistical office of the European Union) and are available on the Bloomberg platform, with the sample period going from January 2010 to December 2022. Figure 1 displays the HICP series for each of the EU27.[2] An upward trend in the most recent years is immediately noticeable.

It is noteworthy that a few series display some degree of seasonality, especially in the case of the Southern European countries. However, this does not seem to be an important issue, since when assuming a seasonal AR process for the error term, the corresponding coefficient is found to be very close to 0 in all cases, including Greece, Italy and Spain (these results are not reported to save space).

Table 1 displays the estimates of the differencing parameter d in Equation (1) and their associated 95% confidence intervals for each series and under three different specifications, namely: (i) setting $\beta_0 = \beta_1 = 0$, i.e., assuming that there are no deterministic terms in the model (column 2); (ii) setting $\beta_1 = 0$, i.e., including only an intercept in the model (column 3); (iii) allowing for both an intercept and a linear time trend (column 4). The coefficients in bold are those from the selected specification on the basis of the statistical significance of the estimated coefficients as indicated by the corresponding t-values. The sample period for these results ends in December 2019, i.e., before the onset of the COVID-19 pandemic.

Table 2 reports the estimated model coefficients for each series. It can be seen that the time trend is significant in all cases except that of Slovakia, indicating lack of statistical significance; more specifically, it is positive and ranges from 0.028 in Greece to 0.210 in Estonia.[3] Further, the estimated values of d are positive in all cases, which implies the presence of long memory ($d > 0$) in all countries except Malta, where the I(0) hypothesis cannot be rejected given the wide confidence interval. Evidence of mean reversion (d

[2]Note that we do not consider the aggregate series because, as already mentioned, Robinson (1978) and Granger (1980) both showed that fractional integration can result from the aggregation of heterogenous AR processes with time-varying coefficients. Similar arguments were later made by other authors such as Cioczek-George and Mandelbrot (1995), Taqqu et al. (1997), Chambers (1998), Parke (1999), Oppenheim and Viano (2004), Zaffaroni (2004), Beran et al. (2013), Vera-Valdés (2021) and others.

[3]Note that the significance of the time trend coefficient does not support the trend-stationarity representation since, as explained above, the two equations in (1) can be jointly estimated as in equation (2). A trend-stationary model would be supported by the data if $d = 0$, a hypothesis that is decisively rejected by the results reported in the tables.

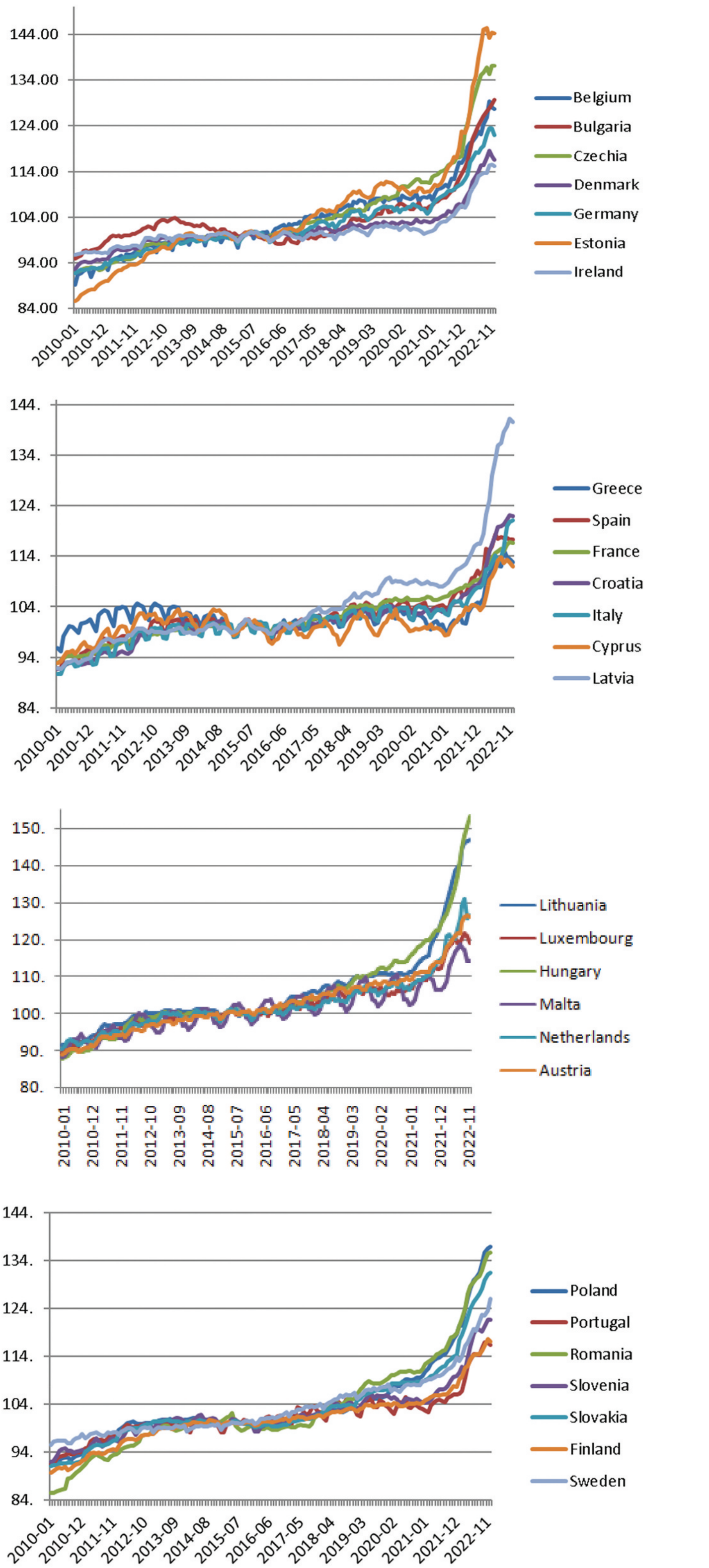

Figure 1. Monthly time series plots of the HICP series in the EU27 countries (2015 = 100).

Table 1. Estimates of the differencing parameter. Sample ending in December 2019.

Country	No terms	An intercept	An intercept and a linear time trend
AUSTRIA	0.93 (0.73, 1.21)	0.59 (0.53, 0.65)	**0.38 (0.23, 0.57)**
BELGIUM	0.92 (0.73, 1.19)	0.68 (0.61, 0.88)	**0.75 (0.59, 0.96)**
BULGARIA	0.94 (0.77, 1.22)	1.05 (0.91, 1.22)	**1.05 (0.92, 1.21)**
CROATIA	0.92 (0.74, 1.19)	0.82 (0.61, 1.23)	**0.87 (0.68, 1.20)**
CYPRUS	0.93 (0.76, 1.20)	0.75 (0.42, 1.26)	**0.80 (0.57, 1.27)**
CZECH REP.	0.92 (0.74, 1.21)	0.93 (0.74, 1.24)	**0.94 (0.77, 1.20)**
DENMARK	0.94 (0.74, 1.18)	0.62 (0.52, 0.95)	**0.79 (0.65, 0.97)**
ESTONIIA	0.94 (0.76, 1.19)	1.04 (0.73, 1.41)	**1.03 (0.84, 1.40)**
FINLAND	0.93 (0.75, 1.19)	1.01 (0.81, 1.25)	**1.00 (0.89, 1.16)**
FRANCE	0.91 (0.74, 1.20)	0.81 (0.61, 1.14)	**0.88 (0.72, 1.12)**
GERMANY	0.93 (0.72, 1.18)	0.79 (0.64, 1.42)	**0.80 (0.57, 1.36)**
GREECE	0.95 (0.78, 1.23)	0.28 (0.11, 0.55)	**0.43 (0.19, 0.70)**
HUNGARY	0.95 (0.76, 1.21)	1.02 (0.77, 1.31)	**1.02 (0.85, 1.28)**
IRELAND	0.92 (0.72, 1.19)	0.58 (0.46, 0.86)	**0.62 (0.45, 0.88)**
ITALY	0.93 (0.75, 1.21)	0.37 (0.28, 0.46)	**0.21 (0.07, 0.38)**
LITHUANIA	0.93 (0.75, 1.20)	0.70 (0.59, 0.86)	**0.72 (0.58, 0.88)**
LUXEMBOURG	0.92 (0.74, 1.20)	0.63 (0.53, 0.91)	**0.79 (0.65, 0.95)**
LATVIA	0.94 (0.74, 1.19)	0.81 (0.63, 1.07)	**0.83 (0.66, 1.09)**
MALTA	0.91 (0.72, 1.15)	0.68 (0.40, 1.47)	**0.68 (−0.08, 1.52)**
NETHERLANDS	0.92 (0.74, 1.19)	0.61 (0.51, 0.82)	**0.65 (0.49, 0.85)**
POLAND	0.93 (0.75, 1.20)	1.16 (0.99, 1.43)	**1.13 (0.99, 1.36)**
PORTUGAL	0.91 (0.74, 1.18)	0.46 (0.37, 0.55)	**0.35 (0.17, 0.58)**
ROMANIA	0.95 (0.77, 1.20)	1.11 (0.91, 1.36)	**1.10 (0.95, 1.32)**
SLOVAKIA	0.94 (0.74, 1.18)	**1.28 (1.10, 1.54)**	1.27 (1.09, 1.55)
SLOVENIA	0.94 (0.76, 1.24)	0.51 (0.43, 0.62)	**0.50 (0.37, 0.69)**
SPAIN	0.94 (0.76, 1.22)	0.36 (0.27, 0.46)	**0.24 (0.08, 0.44)**
SWEDEN	0.92 (0.73, 1.20)	0.89 (0.79, 1.04)	**0.88 (0.76, 1.04)**

The values in parenthesis are the 95% confidence bands of the estimates of d. In bold, the selected specification for each series on the basis of the statistical significance of the deterministic terms.

Table 2. Estimated coefficients in selected models. Sample ending in December 2019.

Country	D	Intercept (t-value)	Time trend (t-value)
AUSTRIA	0.38 (0.23, 0.57)*	89.85 (136.43)	0.151 (15.81)
BELGIUM	0.75 (0.59, 0.96)*	89.77 (123.12)	0.152 (6.33)
BULGARIA	1.05 (0.92, 1.21)	94.81 (220.44)	0.101 (2.07)
CROATIA	0.87 (0.68, 1.20)	91.59 (262.58)	0.097 (5.30)
CYPRUS	0.80 (0.57, 1.27)	93.23 (116.31)	0.058 (1.81)
CZECH REP.	0.94 (0.77, 1.20)	91.86 (277.10)	0.139 (5.99)
DENMARK	0.79 (0.65, 0.97)*	92.79 (272.63)	0.080 (6.16)
ESTONIA	1.03 (0.84, 1.40)	85.42 (197.49)	0.210 (4.66)
FINLAND	1.00 (0.89, 1.16)	89.59 (299.99)	0.121 (4.43)
FRANCE	0.88 (0.72, 1.12)	92.78 (245.10)	0.105 (5.08)
GERMANY	0.80 (0.57, 1.36)	91.69 (194.51)	0.118 (6.30)
GREECE	0.43 (0.19, 0.70)*	98.98 (141.25)	0.028 (2.61)
HUNGARY	1.02 (0.85, 1.28)	87.57 (231.25)	0.196 (5.19)
IRELAND	0.62 (0.45, 0.88)*	96.02 (285.13)	0.048 (6.56)
ITALY	0.21 (0.07, 0.38)*	93.67 (186.50)	0.088 (12.81)
LITHUANIA	0.72 (0.58, 0.88)*	91.54 (209.81)	0.152 (11.74)
LUXEMBOURG	0.79 (0.65, 0.95)*	89.58 (139.49)	0.139 (5.65)
LATVIA	0.83 (0.66, 1.09)	91.73 (209.53)	0.137 (7.04)
MALTA	0.68 (−0.08, 1.52)	88.99 (83.56)	0.135 (4.87)
NETHERLANDS	0.65 (0.49, 0.85)*	90.90 (161.44)	0.125 (9.35)
POLAND	1.13 (0.99, 1.36)	91.32 (342.21)	0.134 (3.17)
PORTUGAL	0.35 (0.17, 0.58)*	93.74 (179.17)	0.092 (12.30)
ROMANIA	1.10 (0.95, 1.32)	85.21 (185.44)	0.210 (3.20)
SLOVAKIA	1.28 (1.10, 1.54)	91.16 (306.88)	—–
SLOVENIA	0.50 (0.37, 0.69)*	93.15 (189.36)	0.101 (12.34)
SPAIN	0.24 (0.08, 0.44)*	94.87 (202.44)	0.082 (12.79)
SWEDEN	0.88 (0.76, 1.04)	95.47 (245.74)	0.102 (4.80)

In parenthesis in the third and fourth columns the associated t-values. * denotes evidence of mean reversion at the 95% level.

significantly below 1) is found for the following countries: Italy (d = 0.21); Spain (0.24); Portugal (0.35); Austria (0.38), Greece (0.43); Slovenia (0.50); Ireland (0.62); Lithuania (0.72); Belgium (0.75) and Denmark (0.79). In all these cases, the effects of shocks will be transitory and disappear in the long run. The unit root null hypothesis (i.e., d = 1) cannot be rejected for another group of 12 countries (Germany, Cyprus, Latvia, Croatia, France, Sweden, Check Republic, Finland, Hungary, Estonia, Bulgaria, Poland and Romania), while for Slovakia it is rejected in favor of values of d significantly higher than 1. Thus, there is a large degree of heterogeneity across the countries in the sample.

Next, we re-estimate the model by extending the sample to January 2022, thus incorporating the COVID-19 period but only before the Russian invasion to Ukraine. These results are reported in Table 3. It can be seen that the time trend coefficient is now statistically insignificant in the cases of Cyprus, Belgium and Slovenia while it is significant in Slovakia, and mean reversion is found only for a few countries, namely Italy (d = 0.18), Spain (0.23), Greece (0.38), Portugal (0.38), Austria (0.42) and Slovakia (0.59); in most cases the estimated value of d is now higher (see Table 5 for a direct comparison of the results for the different sample periods). The only exceptions are three Southern European countries: Italy (where d decreases from 0.21 for the sample ending in December 2019 to 0.18 for the extended one ending in January 2022); Spain (from 0.24 to 0.23) and Greece (from 0.43 to 0.38). Thus, the obtained evidence suggests that the COVID-19 pandemic increased the degree of persistence in the vast majority of EU countries.

In the following step, we obtain estimates based on the full sample ending in December 2022. These results are reported in Table 4. The time trend coefficient is

Table 3. Estimated coefficients in selected models. Sample ending in January 2022.

Country	D	Intercept (t-value)	Time trend (t-value)
AUSTRIA	0.42 (0.21, 0.65)*	89.63 (132.43)	0.156 (18.35)
BELGIUM	1.17 (0.62, 1.39)	88.82 (106.94)	—–
BULGARIA	1.16 (1.00, 1.34)	94.73 (207.85)	0.166 (2.10)
CROATIA	0.95 (0.75, 1.24)	91.51 (256.59)	0.115 (4.90)
CYPRUS	0.85 (0.37, 1.27)	93.25 (119.07)	—–
CZECH REP.	1.08 (0.86, 1.62)	91.79 (161.41)	0.228 (3.34)
DENMARK	1.05 (0.90, 1.26)	92.33 (236.28)	0.113 (2.77)
ESTONIIA	1.25 (1.03, 1.47)	85.30 (153.99)	0.304 (2.09)
FINLAND	1.14 (0.99, 1.36)	89.51 (283.12)	0.149 (2.98)
FRANCE	0.97 (0.79, 1.19)	92.69 (247.82)	0.114 (4.23)
GERMANY	1.06 (0.77, 1.54)	91.53 (181.47)	0.147 (2.67)
GREECE	0.38 (0.11, 0.73)*	99.48 (164.64)	0.020 (2.76)
HUNGARY	1.15 (0.98, 1.36)	87.49 (210.96)	0.274 (3.99)
IRELAND	0.87 (0.65, 1.16)	95.75 (241.35)	0.065 (3.55)
ITALY	0.18 (0.03, 0.34)*	93.79 (200.91)	0.082 (15.37)
LITHUANIA	1.03 (0.82, 1.24)	91.35 (185.86)	0.235 (5.02)
LUXEMBOURG	0.90 (0.76, 1.08)	89.31 (130.44)	0.152 (4.19)
LATVIA	0.97 (0.78, 1.21)	91.61 (205.66)	0.168 (5.23)
MALTA	0.91 (−0.07, 2.58)	88.10 (72.71)	0.126 (1.87)
NETHERLANDS	0.88 (0.67, 1.16)	90.28 (140.61)	0.157 (5.03)
POLAND	1.33 (1.17, 1.56)	91.23 (321.91)	0.258 (2.45)
PORTUGAL	0.38 (0.21, 0.62)*	93.83 (169.88)	0.083 (12.50)
ROMANIA	1.18 (1.03, 1.40)	85.17 (187.14)	0.271 (3.14)
SLOVAKIA	0.59 (0.41, 0.81)*	92.72 (180.54)	0.106 (12.10)
SLOVENIA	1.53 (1.23, 2.21)	91.18 (258.60)	—–
SPAIN	0.23 (0.03, 0.54)*	94.78 (195.97)	0.084 (15.34)
SWEDEN	0.97 (0.83, 1.15)	95.42 (222.67)	0.119 (3.86)

In parenthesis in the third and fourth columns the associated t-values. * Denotes evidence of mean reversion at the 95% level.

now insignificant in a higher number of cases, and the estimates of the degree of persistence are higher in all cases compared to those for the sample ending in January 2022 (see Table 5 for a direct comparison), with Italy (d = 0.63), Spain (0.69), Portugal (0.77) and Greece (0.82) now being the only countries displaying mean-reverting behaviour. Note that these four countries display a sharp increase in the degree of persistence after the second shock, as they move from stationary values to nonstationary ones. To make the results more clearly visible, we also include in Figure 3 a geographical map in which the degree of persistence of the EU27 is shown according to a colour scheme, the lowest values corresponding to red, the middle ones to yellow, and the highest ones to green and blue. It can be seen that there is a wide range of values, Italy exhibiting the lowest degree of persistence, with the EU peripheral countries (Greece and the Iberian peninsula) being characterised by slightly higher values, the core countries (France and Germany) being in the middle range, and more recent EU accessions (the Eastern European and Scandinavian countries) exhibiting the highest values.

Finally, we estimate the model recursively to analyse time variation in the degree of persistence as measured by d; specifically, we add one observation at a time to the sample ending in December 2019 (which includes 120 observations) to obtain the corresponding estimates up until December 2022, namely for a period which includes both the COVID-19 pandemic and the Russia-Ukraine war. Figure 2 displays both the recursive estimates and the 95% confidence intervals. It shows that, after an initial increase across the board, in the most recent period price persistence has subsided in the vast majority of the EU27,

Table 4. Estimated coefficients in selected models. Sample ending in December 2022.

Country	D	Intercept (t-value)	Time trend (t-value)
AUSTRIA	0.96 (0.82, 1.10)	88.74 (141.98)	0.234 (5.62)
BELGIUM	1.21 (1.10, 1.34)	88.75 (99.47)	—
BULGARIA	1.35 (1.23, 1.49)	94.65 (210.26)	—
CROATIA	1.22 (1.07, 1.43)	91.39 (222.16)	0.221 (2.40)
CYPRUS	1.02 (0.83, 1.33)	92.71 (109.05)	0.125 (1.67)
CZECH REP.	1.42 (1.26, 1.74)	91.13 (165.31)	—
DENMARK	1.16 (1.03, 1.34)	92.21 (196.58)	0.172 (2.17)
ESTONIA	1.40 (1.23, 1.65)	85.46 (122.19)	—
FINLAND	1.30 (1.17, 1.46)	89.46 (254.88.)	0.209 (1.85)
FRANCE	1.21 (1.08, 1.40)	92.53 (226.13)	0.174 (1.99)
GERMANY	1.18 (1.04, 1.43)	91.59 (157.00)	—
GREECE	0.82 (0.67, 0.97)*	96.12 (85.27)	0.089 (2.31)
HUNGARY	1.63 (1.49, 1.82)	87.64 (209.62)	—
IRELAND	1.17 (1.03, 1.35)	95.66 (211.71)	0.137 (1.71)
ITALY	0.63 (0.46, 0.81)*	97.52 (102.01)	—
LITHUANIA	1.30 (1.17, 1.43)	91.33 (164.27)	0.379 (2.12)
LUXEMBOURG	1.00 (0.88, 1.15)	89.13 (112.84)	0.192 (3.03)
LATVIA	1.42 (1.27, 1.69)	91.56 (159.41)	—
MALTA	0.95 (0.28, 2.88)	87.96 (70.51)	0.165 (2.08)
NETHERLANDS	0.96 (0.84, 1.11)	90.09 (94.95)	0.229 (3.61)
POLAND	1.43 (1.33, 1.58)	94.36 (241.10)	—
PORTUGAL	0.77 (0.60, 0.95)*	91.59 (120.29)	0.139 (6.24)
ROMANIA	1.31 (1.18, 1.48)	85.14 (178.01)	0.366 (2.28)
SLOVAKIA	0.94 (0.80, 1.10)	91.78 (155.03)	0.183 (5.09)
SLOVENIA	1.57 (1.42, 1.79)	91.18 (260.62)	—
SPAIN	0.69 (0.55, 0.83)*	92.14 (109.06)	0.140 (7.62)
SWEDEN	1.43 (1.28, 1.61)	95.19 (190.68)	—

In parenthesis in the third and fourth columns the associated t-values. * Denotes evidence of mean reversion at the 95% level. — Indicates lack of statistical significance.

Table 5. Summary of the estimates of d.

Country	December 2019	January 2022	December 2022
AUSTRIA	0.38 (0.23, 0.57)	0.42 (0.21, 0.65)	0.96 (0.82, 1.10)
BELGIUM	0.75 (0.59, 0.96)	1.17 (0.62, 1.39)	1.21 (1.10, 1.34)
BULGARIA	1.05 (0.92, 1.21)	1.16 (1.00, 1.34)	1.35 (1.23, 1.49)
CROATIA	0.87 (0.68, 1.20)	0.95 (0.75, 1.24)	1.22 (1.07, 1.43)
CYPRUS	0.80 (0.57, 1.27)	0.85 (0.37, 1.27)	1.02 (0.83, 1.33)
CZECH REP.	0.94 (0.77, 1.20)	1.08 (0.86, 1.62)	1.42 (1.26, 1.74)
DENMARK	0.79 (0.65, 0.97)	1.05 (0.90, 1.26)	1.16 (1.03, 1.34)
ESTONIIA	1.03 (0.84, 1.40)	1.25 (1.03, 1.47)	1.40 (1.23, 1.65)
FINLAND	1.00 (0.89, 1.16)	1.14 (0.99, 1.36)	1.30 (1.17, 1.46)
FRANCE	0.88 (0.72, 1.12)	0.97 (0.79, 1.19)	1.21 (1.08, 1.40)
GERMANY	0.80 (0.57, 1.36)	1.06 (0.77, 1.54)	1.18 (1.04, 1.43)
GREECE	0.43 (0.19, 0.70)	0.38 (0.11, 0.73)	0.82 (0.67, 0.97)
HUNGARY	1.02 (0.85, 1.28)	1.15 (0.98, 1.36)	1.63 (1.49, 1.82)
IRELAND	0.62 (0.45, 0.88)	0.87 (0.65, 1.16)	1.17 (1.03, 1.35)
ITALY	0.21 (0.07, 0.38)	0.18 (0.03, 0.34)	0.63 (0.46, 0.81)
LITHUANIA	0.72 (0.58, 0.88)	1.03 (0.82, 1.24)	1.30 (1.17, 1.43)
LUXEMBOURG	0.79 (0.65, 0.95)	0.90 (0.76, 1.08)	1.00 (0.88, 1.15)
LATVIA	0.83 (0.66, 1.09)	0.97 (0.78, 1.21)	1.42 (1.27, 1.69)
MALTA	0.68 (−0.08, 1.52)	0.91 (−0.07, 2.58)	0.95 (0.28, 2.88)
NETHERLANDS	0.65 (0.49, 0.85)	0.88 (0.67, 1.16)	0.96 (0.84, 1.11)
POLAND	1.13 (0.99, 1.36)	1.33 (1.17, 1.56)	1.43 (1.33, 1.58)
PORTUGAL	0.35 (0.17, 0.58)	0.38 (0.21, 0.62)	0.77 (0.60, 0.95)
ROMANIA	1.10 (0.95, 1.32)	1.18 (1.03, 1.40)	1.31 (1.18, 1.48)
SLOVAKIA	0.50 (0.37, 0.69)	0.59 (0.41, 0.81)	0.94 (0.80, 1.10)
SLOVENIA	1.28 (1.10, 1.54)	1.53 (1.23, 2.21)	1.57 (1.42, 1.79)
SPAIN	0.24 (0.08, 0.44)	0.23 (0.03, 0.54)	0.69 (0.55, 0.83)
SWEDEN	0.88 (0.76, 1.04)	0.97 (0.83, 1.15)	1.43 (1.28, 1.61)

The reported values are the estimates of d. Those in parenthesis are the 95% confidence intervals of the non-rejection values of d using Robinson's (1994) method.

with the exception of the Czech Republic, Hungary, Latvia, Malta and Slovenia, where there has been a slight increase over time, and most notably Italy, the only case where it has risen sharply after a period of relative stability. More specifically, price persistence appears to have jumped upwards in most countries in periods 8 and 9, corresponding to September-December 2021, and stayed at the higher level until periods 10 or 11, corresponding to the time interval March-June 2022, namely from the peak of the pandemic to the early stages of the Russia-Ukraine war. Afterwards, in period 13, corresponding to October-December 2022, price persistence decreased slightly or remained relatively stable in the majority of the countries with the exception of Italy, as already mentioned.

4. Conclusions

This paper analyses monthly price persistence in the EU27 countries over the period 2010–2022 using a fractional integration framework which encompasses a wide range of stochastic processes, where the measure of persistence is the estimated value of the fractional differencing parameter d. A related study had previously been carried out by Caporale et al. (2023), but for inflation as opposed to price persistence, and at the aggregate level (for the EU27 and the euro zone countries respectively), while the present contribution focuses on the individual EU member states. The model is initially estimated over the period from January 2010 to December 2019, which produces evidence of heterogeneity across the EU27. The sample is then extended to January 2022, with the aim of examining the possible

Figure 2. Recursive estimates of d as a measure of price persistence. The first estimate is d is based on a sample ending in December 2019, then one observation at a time is added recursively to obtain the following estimates. Thus, observation 1 corresponds to the sample ending in January 2020, observation 2 to the one ending in March 2020, etc. The red line corresponds to the estimated values of d whilst the black ones show the 95% confidence intervals.

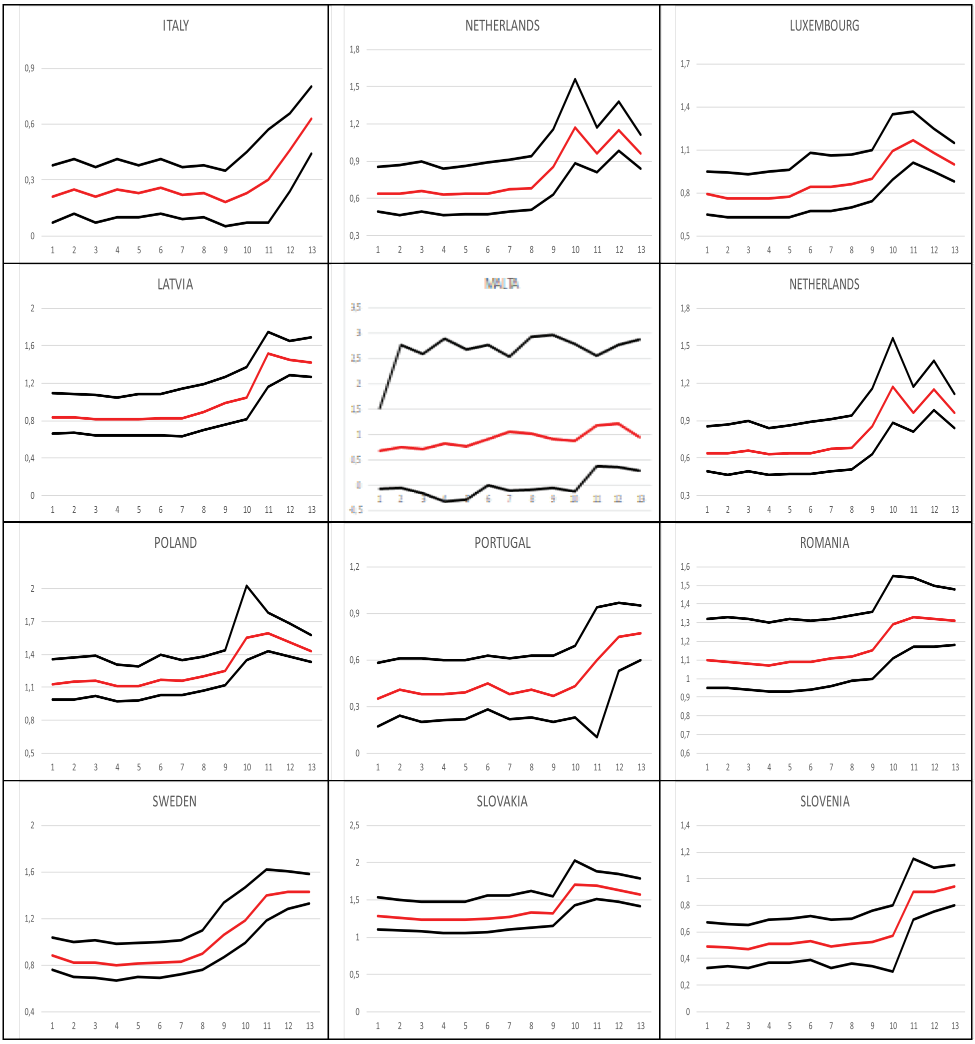

Figure 2. (Continued).

effects of the COVID-19 pandemic prior to the outbreak of the Russia-Ukraine war; this exogenous shock appears to have increased price persistence everywhere except in three countries from Southern Europe, namely Italy, Spain and Greece.

Extending the sample period further, i.e., to the end of December 2022 (to include the Russia-Ukraine conflict as well) results in higher estimates of d, with the same countries from Southern Europe as well as an additional one (i.e., Portugal) from the same region being the only ones to exhibit mean reversion. Finally, the recursive estimates suggest that price persistence has subsided in most cases (and increased very slightly in a few ones) in the most recent period, the only outlier being Italy, where a sharp increase appears to have occurred most recently.

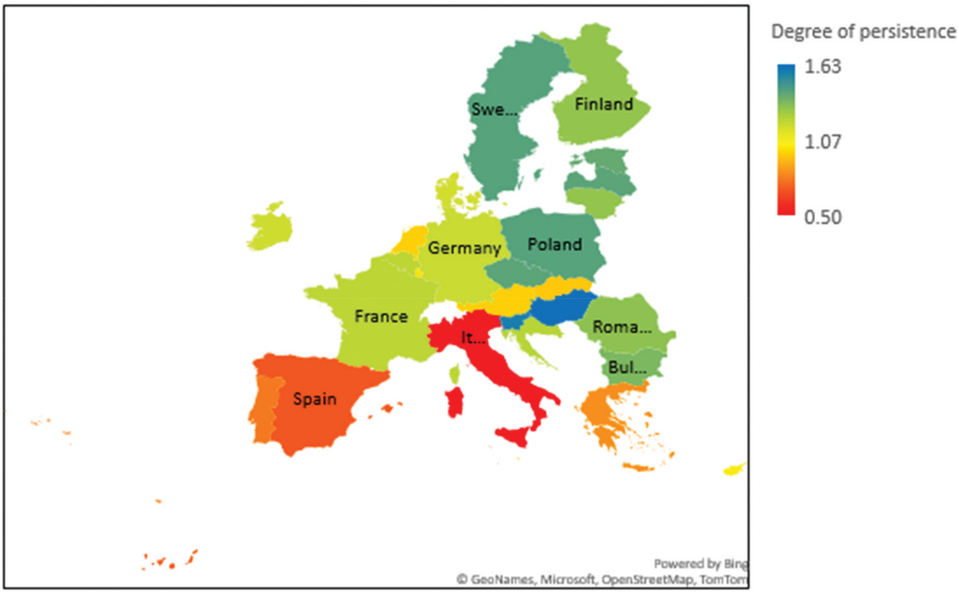

Figure 3. Coloured geographical map of the degree of persistence of the EU27 countries in the full sample.

On the whole, our analysis provides clear evidence that both the exogenous shocks considered have generally increased price persistence in the EU27 (despite their heterogeneity), although the recursive results suggest that their impact might have peaked and might now be decreasing, which is consistent with the aggregate findings of Caporale et al. (2023) for both the EU27 and the euro zone. The interesting exceptions are the Southern European countries, where if anything price persistence appears to have slightly decreased as a result of the COVID-19 pandemic, though it increased sharply after the onset of the Russia-Ukraine war.

It is interesting to consider the policy implications of these results for the European Central Bank (ECB). According to the EU Treaties, its main objective is to achieve an inflation rate of under 2% for the euro area, and to maintain price stability over the medium term. In response to the price increases caused by the two exogenous shocks examined in the present study the ECB has repeatedly increased interest rates. This has contained price increases, but also caused an economic slowdown in the euro area. It should be noted that the secondary mandate of the ECB is to contribute to the achievement of the objectives of the EU such as full employment. For this reason, and given the evidence that the effects of the shocks considered here will only be temporary, it would seem that policies adopted to counteract them should now be phased out. In particular, it might be appropriate for the ECB to hold interest rates steady and then gradually decrease them after the series of hikes which has occurred since July 2022.

A limitation of the present study is its univariate nature, which does not allow us to investigate the possible factors affecting the degree of persistence and thus to provide an explanation for the presence of outliers such Italy. Future work should adopt a multivariate framework to investigate these issues in the context of fractional cointegration, using frameworks such as the fractional CVAR (i.e., FCVAR) model proposed by Johansen and Nielsen (2010, 2012). Further possible extensions could consider non-linear structures in the deterministic part of the model, such Chebyshev polynomials in time (as in J. C. Cuestas & Gil-Alana, 2016), Fourier functions (Gil-Alana & Yaya, 2021) or neural networks (Yaya et al., 2021) within a fractional integration framework.

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