A PANIC Analysis on Regional and Sectoral Inflation: The Spanish Case

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Abstract:

This article applies the Panel Analysis of Nonstationarity in Idiosyncratic and Common components (PANIC) approach (Bai and Ng) to three panels of inflation rates for Spain using the Consumer Price Index for the regions and 12 groups of goods and services, and the Producer Price Index for 26 industrial sectors. This methodology, which has been barely used so far in the analysis of disaggregated series along the regional or sectoral dimensions, enables us to decompose the observed series into a common and an idiosyncratic component, thus allowing us to identify the source of nonstationarity in Spanish inflation. A common stochastic trend drives the observed series in the panel of regional CPI-based inflation. In combination with a stationary idiosyncratic component, this implies pair-wise cointegration and convergence among individual series. This gives an indication of increased geographical homogeneity in the consumption patterns exhibited by consumers in the different regions of Spain, as corroborated with a weighted sigma-convergence analysis. This result contrasts with the existence of more heterogeneity in the patterns of production across regions. The other two panels of group CPI-based and PPI-based sectoral inflation exhibit four common stochastic trends and much weaker evidence of cross-cointegration and convergence among the series involved.

Key words: Inflation, PANIC Methodology, Consumer and Producer Prices, Sectoral and Regional Analysis, Common Stochastic Trends, Persistence, Convergence.

JEL Classification: C23, E31, E58, R10

1. Introduction

This article investigates the stochastic properties of several inflation rates for the Spanish economy using the Consumer Price Index (CPI) for the regions (*Comunidades Autónomas*) and 12 groups of goods and services, and the Producer Price Index (PPI) for 26 industrial sectors over the past decades. For that purpose, we employ the Panel Analysis of Nonstationarity in Idiosyncratic and Common components (PANIC) approach proposed by Bai and Ng (2004a, 2004b) and further extended by Bai and Ng (2010). The use of the PANIC methodology, which has not been used so far in the analysis of disaggregated series along the regional or sectoral dimensions, conveys several important advantages over previous studies in the field of inflation persistence using panel methods. First, it enables us to allow for strong forms of cross-sectional dependence in the data such as cross-cointegration. This is essential since failure to allow for cross-sectional correlation when it is present in the data, leads to severe size distortions (see O'Connell, 1998; Maddala and Wu, 1999; Banerjee *et al*., 2005). Second, the PANIC approach allows us to decompose the observed inflation rate series into a common and an idiosyncratic component, and as a by-product, to determine the source of nonstationarity in the observed series, that is, whether it stems from the common factor(s) and/or the idiosyncratic components. Third, unlike other panel unit root tests allowing for a factor structure in the data such as those of Moon and Perron (2004) and Pesaran (2007) that assume the same order of integration for both the common and idiosyncratic components, the PANIC approach is flexible enough as to allow for a different order of integration in both components.

Fourth, the PANIC framework allows us to provide confirmatory evidence on the stochastic properties of inflation, since it provides both unit root and stationarity statistics that shift their respective null hypotheses. Fifth, PANIC can be used as a cointegration analysis for the inflation rates across the different dimensions studied (geographical and groups of goods and services for the CPI-based inflation rate and sectoral for the PPI-based inflation rate). The system of the N series forming each panel can be decomposed into a nonstationary part explained by the common stochastic trends ($\hat{r}_1$) plus $N-\hat{r}_1$ cointegrating vectors involving stationary linear combinations of the individual series forming the panel. In short, if we find evidence of a common stochastic trend driving the observed inflation rate series, combined with the existence of jointly stationary idiosyncratic series, this would indicate the presence of pairwise cointegration among the inflation rate series involved, which would be driven by a nonstationary common factor linking all inflation rates over time. This would show up as convergence patterns exhibited by the inflation series over time.[1]

Overall, our confirmatory PANIC analysis provides overwhelming evidence of non-stationarity in the three panels of Spanish inflation rate series disaggregated along several dimensions, which appears to be accounted for by the presence of a common stochastic trend in the panel of CPI-based inflation rates for the 17 regions and four common stochastic trends in the other two panels. This, coupled with the existence of a jointly stationary idiosyncratic component, provides evidence of pairwise cointegration across the regional CPI-based inflation rate series since a common stochastic trend is linking the inflation rate series over time, thereby making them converge. This contrasts with the existence of more heterogeneity in the patterns of production across regions, as reflected in the fact that regions are not specialising in the same manufacturing and energy products. The analysis of the panels of CPI-based inflation rates of 12 groups of goods and services and PPI-based inflation rates of 26 sectors renders much less evidence of cross-cointegration and convergence due to the existence of a larger number of independent common stochastic trends driving the series forming these two panels.

The rest of the paper is organised as follows. Section 2 provides an overview on the issue of inflation persistence as well as briefly reviews the main studies on the topic. Section 3 describes the PANIC methodology employed in the paper. Section 4 presents the results from the decomposition of the observed inflation rate series (along the different dimensions investigated) into a common and an idiosyncratic component and their respective time series properties obtained via PANIC. Section 5 provides some policy implications of the results and concludes.

2. Overview of the Issue and Brief Literature Review

Spain has traditionally fared rather poorly as far as inflation is concerned in that it has permanently been above its trade partners' inflation rate and the ECB's target of 2%. Back in the 70s and 80s, it even experienced two-digit inflation rates, which peaked in 1977 and subsequently decreased in a gradual fashion to bottom out at the end of the 90s (excluding the Great Recession years).

The causes put forward in the literature for this mediocre performance are catching-up growth during the 60s and 70s, an insufficient degree of competition in products and services markets, a

[1] In the extreme case in which there are no cointegrating vectors, there would be N independent common stochastic trends, and no evidence of cross-cointegration and convergence. At the other end, if there are no common stochastic trends ($\hat{r}_1 = 0$), it implies that there are N cointegrating vectors, thus indicating that all common factors are I(0) and the individual series are stationary (Gengenbach et al. 2010, p. 128).

dysfunctional labour market, a relatively non-credible central bank (only until 1994, when the Law of Autonomy of the Bank of Spain was enacted), higher dependence on imported energy than other European members, loose credit conditions during the recent and prolonged economic boom, and a bourgeoning aggregate demand from the 1995 recovery until the arrival of the Great Recession.

Inflation is considered to be a key variable within a monetary union framework. This is so because moderate but protracted inflation differentials can be considered important warning signals for detecting noteworthy competitiveness losses and oversized external imbalances across countries that have their hands tied by a common monetary policy. It is widely acknowledged that EMU member states running big current account deficits risk having to struggle with a painful internal devaluation when the economic boom turns into a bust. This downward adjustment process involves shifting resources from non-tradable to tradable sectors, which requires a real exchange rate depreciation to occur. Significant non-tradable price and wage inflation rigidity is the mechanism whereby such a correction is made unpleasant.[2]

Even when the focus of the analysis is shifted to the Great Recession, most industrial countries' inflation rates have shown resistance to falling during this economically convoluted period (see Simon *et al*., 2013, and Matheson and Stavrev, 2013). The reasons for these modest decreases are thought to be a low output gap –the observed unemployment rate is mostly structural in nature–, a successful pre-crisis monetary policy in keeping inflation low and stable, a greater influence of globalisation on wage and price setting, the existence of counter-cyclical mark-ups and a lower frequency of price changes by firms as inflation decreases.

Some recent studies[3] stress that the Spanish inflation has not come down as much as unit labour costs have and point to counter-cyclical mark-ups as the main cause. The reasons alluded to for accounting for this phenomenon are an overall reduction in competition in many markets during the Great Recession and the existence of restrictive financial conditions that exert upward pressure over the mark-ups.[4] It is interesting to note that this rise seems to occur in the tradable sector as well, where firms are usually subject to more competition. That is why the second cause appears more plausible: big companies have resorted to raising their mark-ups as a way to self-finance investments or to further the process of deleveraging, when faced with the worsening of credit conditions following the Great Recession (see for example Gilchrist *et al*., 2013, and Garicano and Steinwender, 2013, for an application to Spain).

[2] Existing low labour mobility can also contribute to slowing down the transfer of resources between sectors (Jimeno and Bentolila, 1998).
[3] See for example Montero and Urtasun (2013).
[4] A composition effect stemming from the exit of the less productive firms, whose mark-ups are lower than the more productive ones', might have also contributed to bidding up average mark-ups.

Without prejudice to the effects of these above changes on prices' behaviour, in this paper we set out to study inflation persistence in Spain, an economy that has long suffered from this economic problem. Although we are aware that there exist already publications out there dealing with this relevant topic,[5] we believe none of them approaches this issue using the same methodology as ours, one which we view as very rich and suitable for the issue at hand and that contributes to this literature by providing very robust results.

If, say, an adverse shock hitting the economy drives the actual inflation rate ashtray, an economy showing high inflation persistence will risk enduring painful adjustments until it is brought back down into line with the target. This onerous adjustment could either take place under the form of a more contractive monetary policy, in the case the country concerned retained its own currency –think of, for example, Brazil, an economy that has lately begun experiencing inflationary pressures–,[6] or as a temporary disinflationary unemployment-increasing period that put downward pressure on labour costs and mark-ups in the case of a country that lacks control over monetary policy –Portugal, Greece or Spain come to mind.

The measure of persistence on which we will centre throughout this work is inflation inertia –the sluggishness of this variable in adjusting to its long-run equilibrium– which can arise, among other sources, from the existence of indexation clauses well spread over the economy. This is the so-called "implicit persistence" and it associates itself with the lagged inflation variable inserted for instance in theoretical formulations and empirical estimations of the "hybrid" New-Keynesian Phillips curve (NKPC) –see for example Galí and Gertler (1999).[7]

Anticipating the conclusions reached in this article, we find high inflation persistence over the last decades, especially with regard to the regional CPI disaggregation for which the observed series appear to be driven by a common stochastic trend. This outcome should not be deemed as puzzling as the three aforesaid measures of persistence hint at the same result: it is well-known that the Spanish economy has long been plagued with different types of rigidities, widespread indexation,

[5] For instance, the Inflation Persistence Network (IPN) is a team of ECB and other Euro-system's national central bank researchers conducting a coordinated project on the patterns, determinants and implications of inflation persistence in the Euro-area and in its member countries. It produces articles and reports on the aforementioned subject.
[6] The Brazilian central bank has recently initiated a cycle of monetary tightening that has bid up the overnight interest rate (the so-called Selic rate) at the level of 10.75% (as of March 2014). This administered monetary squeeze ensued from the ever-growing deviation of the actual inflation rate from the target.
[7] Two additional measures of inflation persistence also linked to the "hybrid" NKPC are the indicators related to the state of the cycle or "explicit persistence" –concept that includes determinants of current inflation such as labour costs or the firms' real marginal costs and the output gap, and also captures rigidities in the wage- and price-setting process–, and the inflation expectation component –which comprises the backward- and forward-looking approaches.

backward-looking expectations, etc.[8] In addition, the fact that countries like Spain are mainly service-based economies, in which this sector accounts for an important chunk of total GDP, means that final prices tend to rely more on wages than on other more flexible input prices, as the tertiary sector is known to be the most labour-intensive one. It then follows that services prices are more sluggish in the adjustment than other sectors' output prices. Furthermore, inflation persistence tends to be lower in competitive environments and greater in those markets in which competition among firms is more restricted. In Southern European countries, Spain included, many markets are relatively shielded from competition and therefore inflation in those countries should be found quite persistent.[9] Implicitly, this suggests that, also within a given country, consumer price inflation should be more persistent than producer price inflation, as the former is comprised of many services and the latter mainly consists of manufacturing.[10]

It is worth repeating that special heed will be paid in this article to the disaggregation of the Spanish national figures into inflation rates across three different dimensions (geographical and groups of goods and services for the CPI-based inflation rate and sectoral for the PPI-based inflation rate) sourced by the National Statistical Institute (*Instituto Nacional de Estadística,* INE). We handle inter-annual data and make use of the longest possible homogeneous series currently available. Unfortunately, no long PPI series from a geographical perspective is available. We think that this kind of analysis can help shed some further light on, and make an empirical contribution to, this relevant subject.[11] As already commented above, inflation persistence may have an adverse effect on the economic performance of a country from several perspectives. Moreover, we would like to remark that the main objective of our article is to attempt to come up with general patterns in the data rather than concentrating on the specific results for each particular geographical unit, group of goods and services or sectors.[12] A key advantage of the PANIC analysis is that it provides us

[8] Galí and López-Salido (2001) and Fabiani *et al.* (2006) stress the importance of the backward-looking component in Spain in accounting for inflation persistence relative to the Euro-zone average. The former also finds wage frictions to be a relevant explanation of this phenomenon. On the other hand, Restoy *et al.* (2005) highlight the prominent role of wage indexation clauses as well as the dual inflation problems. Caraballo and Usabiaga (2009a, b) and Caraballo and Dabús (2013) present robust evidence for the presence of nominal rigidities in the determination of Spanish consumer and producer prices. Finally, Caraballo and Usabiaga (2009b) also emphasises the vulnerability of Spanish inflation to oil shocks.

[9] It is customary to confront European (and Spanish) results with USA's, a country often taken as the benchmark as far as price flexibility is concerned.

[10] Álvarez and Hernando (2006), Álvarez *et al.* (2010) and Romero-Ávila and Usabiaga (2012), focusing on the Spanish case, arrive at this result.

[11] Romero-Ávila and Usabiaga (2009, 2012) tackle a similar topic, but the former uses the aggregate inflation figures of a set of OECD countries and employs panel data techniques –for comparison purposes, they also apply univariate tests of the KPSS type, obtaining evidence of a unit root for Spain, which coincides with the results in this paper and of Romero-Ávila and Usabiaga (2012) for aggregate CPI inflation. The latter also makes use of several univariate tests, reaching the same conclusion of high persistence for different Spanish inflation series.

[12] From a more microeconomic viewpoint, the IPN generates publications for the Euro-zone and member countries, but employing empirical methodologies different from ours.

with evidence of the extent of cointegration and in turn convergence among the inflation rate series forming each panel. This will enable us to shed more light on whether there is more evidence of convergence in inflation rates across regions vs. inflation rates across groups of goods and services or sectors of production.

3. PANIC Approach

Unlike most second-generation panel unit root tests that only allow for weak forms of cross-sectional dependence (contemporaneous short-run cross-correlation), some panel unit root tests based on linear factor models are able to allow for stronger forms of cross-dependence such as cross-sectional cointegration. Among the panel procedures employing a factor structure are Moon and Perron (2004), Pesaran (2007) and Bai and Ng (2004a, 2004b, 2010). Whereas Pesaran (2007) only allows for one common factor, Moon and Perron (2004) and Bai and Ng (2004a, 2004b, 2010) allow for multiple common factors. However, only the panel tests of Bai and Ng (2004a, 2004b, 2010) are general enough to allow for cointegration across units, which implies that the observed series can contain common stochastic trends. In fact, under this framework the observed series is decomposed into a common and an idiosyncratic component, and if the latter component is found to be I(0), the observed series and the common factor would be cointegrated. In that particular case of cross-cointegration, the tests of Pesaran (2007) and Moon and Perron (2004) are likely to exhibit size distortions, as the common trends may be confused with the common factors and thus removed from the data in the defactoring process. Therefore, the tests on the observed series appear to yield stationarity if the remaining idiosyncratic component is stationary, despite the presence of non-stationary common factors.

Let us model the observed data on inflation rates (denoted by π_{it}) as the sum of a deterministic part, a common component and an idiosyncratic error term:

$$\pi_{it} = D_{it} + \lambda'_i F_t + e_{it} \tag{1}$$

where λ_i is an $r \times 1$ vector of factor loadings, F_t is an $r \times 1$ vector of common factors, and e_{it} is the idiosyncratic component. D_{it} can contain a constant and a linear trend. Since λ_i and F_t can only be estimated consistently when $e_{it} \sim I(0)$, we estimate a model in first-differences like $\Delta\pi_{it} = \lambda'_i f_t + z_{it}$, where $z_{it} = \Delta e_{it}$ and $f_t = \Delta F_t$.[13] We next use principal components to estimate the common factors $\hat{f}_t$, the corresponding factor loadings $\hat{\lambda}_i$ and the residuals $\hat{z}_{it} = \Delta\pi_{it} - \hat{\lambda}'_i \hat{f}_t$, so

[13] This representation corresponds to the factor model with a constant. For the representation in the case of a specification with a trend, we refer to Bai and Ng (2004a, p. 1137).

that we preserve the order of integration of F_t and e_{it}. As in Bai and Ng (2002), we normalise π_{it} for each cross-section unit to have a unit variance. The common factors and the residuals are then recumulated as follows: $\hat{F}_t = \sum_{s=2}^{t} \hat{f}_s$ and $\hat{e}_{it} = \sum_{s=2}^{t} \hat{z}_{is}$, which can be used to test for a unit root in the common and idiosyncratic components, respectively.

Before we proceed to test for a unit root in the common and idiosyncratic components, we employ information criteria to establish the number of common factors present in the panels of inflation rate series. We do so with the BIC_3 information criterion:

$$BIC_3(k) = \hat{\sigma}_e^2(k) + k\hat{\sigma}_e^2(k_{\max})\left(\frac{(N+T-k)\ln(NT)}{NT}\right) \tag{2}$$

where k is the number of factors included in the model, $\hat{\sigma}_e^2(k)$ is the variance of the estimated idiosyncratic components, and $\hat{\sigma}_e^2(k_{\max})$ is the variance of the idiosyncratic components estimated with the maximum number of factors (k_{max}=5).[14] The optimal number of common factors $\hat{k}$ is selected by applying $\arg\min_{0\le k\le 5} BIC_3(k)$. The BIC_3 is chosen over other alternatives (like the IC_p information criteria) because for a sufficiently general framework in which the idiosyncratic errors can be serially correlated and cross-correlated, the BIC_3 criterion has very good properties (see Tables VII and VIII in Bai and Ng, 2002). Along similar lines, Moon and Perron (2007, p. 387) note that the BIC_3 criterion "performs better in selecting the number of factors when min(N,T) is small (≤ 20)".

3.1. Analysis of the idiosyncratic component

Before presenting the methodology behind the PANIC approach, we note that we combine the use of the unit root tests of Bai and Ng (2004a, 2010) with the use of the stationarity tests of Bai and Ng (2004b), always within the PANIC framework, as dictated in the original articles.[15] Bai and Ng (2004a) estimate standard ADF specifications for a unit root in the idiosyncratic components:

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[14] The second argument in the loss function stands for the penalty for overfitting, which is intended to correct for the fact that models with a larger number of factors can at least fit as good as models with fewer common factors, but efficiency is reduced with the estimation of more factor loading parameters (Bai and Ng, 2002).

[15] The use of unit root statistics (for the case of testing the unit root null hypothesis) in tandem with stationarity statistics (for the case of testing the stationarity null hypothesis) enable us to conduct a confirmatory analysis on the stochastic properties of the inflation rate series. Therefore, when the null hypothesis is rejected with the panel stationarity test but not with the panel unit root test, all cross-sectional units contain a unit root; and when there is rejection with the panel unit root test but not with the panel stationarity test, all cross-sectional units may be I(0). In addition, when the respective null hypotheses in both panel unit root and stationarity tests are rejected, this indicates the existence of a mixture of stationarity and non-stationarity in the panel, whereas if the respective null hypotheses in both tests are not rejected, the results would be inconclusive in all likelihood due to the poor information provided by the dataset. See more details in Shin and Snell (2006, p. 136).

$$\Delta\hat{e}_{it} = \delta_{i,0}\hat{e}_{i,t-1} + \sum_{j=1}^{p_i}\delta_{i,j}\Delta\hat{e}_{i,t-j} + u_{it} \tag{3}$$

The ADF t-statistic for testing $\delta_{i,0} = 0$ is denoted by $ADF^c_{\hat{e}}(i)$ or $ADF^\tau_{\hat{e}}(i)$ for the cases of only a constant and a constant and a linear trend in specification (1), respectively.[16] To raise statistical power, Bai and Ng (2004a) employ pooled statistics based on the Fisher-type inverse chi-square tests of Maddala and Wu (1999) and Choi (2001). Letting $\pi^c_{\hat{e}}(i)$ be the p-value associated with $ADF^c_{\hat{e}}(i)$, the pooled statistics are constructed as follows:[17]

$$P^c_{\hat{e}} = -2\sum_{i=1}^{N}\log\ \pi^c_{\hat{e}}(i) \xrightarrow{d} \chi^2_{(2N)} \text{ for } N \text{ fixed, } T \to \infty, \tag{4}$$

$$Z^c_{\hat{e}} = \frac{-\sum_{i=1}^{N}\log\ \pi^c_{\hat{e}}(i) - N}{\sqrt{N}} \xrightarrow{d} N(0,1) \text{ for } N, T \to \infty. \tag{5}$$

We also deploy the two Moon and Perron (2004) type pooled tests using the PANIC residuals to estimate a bias-corrected pooled PANIC autoregressive estimator and a panel version of the Sargan-Bhargava (1983) statistic that uses the sample moments of the residuals without the need to estimate the pooled autoregressive coefficients. A great advantage of the PANIC pooled statistics of Bai and Ng (2010) is that there is no need for least squares linear detrending that could lead to a fall in statistical power.

3.2. Analysis of the common component

We employ an ADF test for the case of a single common factor (*k=1*) or a rank test when *k>1* in order to test for non-stationarity in the common factors. When the panel only contains one common factor, we estimate an ADF specification for $\hat{F}_t$ with the same deterministic components as in model (1):

$$\Delta\hat{F}_t = D_t + \gamma_0\hat{F}_{t-1} + \sum_{j=1}^{p}\gamma_j\Delta\hat{F}_{t-j} + v_{it} \tag{14}$$

[16] The asymptotic distribution of $ADF^c_{\hat{e}}(i)$ is the same as the Dickey-Fuller distribution for the case of no constant, while that of $ADF^\tau_{\hat{e}}(i)$ is proportional to the reciprocal of a Brownian bridge.

[17] The same holds for the case of a trend, where $\pi^\tau_{\hat{e}}(i)$ is the p-value associated with $ADF^\tau_{\hat{e}}(i)$. The pooled statistics for the trend specification are denoted as $P^\tau_{\hat{e}}$ and $Z^\tau_{\hat{e}}$. Note that we do not pool individual unit root tests for the observed series, since under a factor structure the limiting distribution of the test would contain terms that are common across units. However, "pooling of tests for $\hat{e}_{it}$ is asymptotically valid under the more plausible assumption that $\hat{e}_{it}$ is independent across *i*" (Bai and Ng, 2004a, p. 1140).

The corresponding ADF t-statistics are denoted by $ADF_{\hat{F}}^{c}$ and $ADF_{\hat{F}}^{\tau}$ and follow the limiting distribution of the Dickey and Fuller (1979) test for the specifications with only a constant, and a constant and a trend, respectively. For the case of multiple common factors, the number of common stochastic trends ($\hat{r}_1$) in the common factors is determined using the modified rank tests labelled as the filter test MQ_f that assumes that the non-stationary components are represented by finite order vector autoregressive processes and the corrected test MQ_c that allows the unit root processes to exhibit more general dynamics.[18]

3.3. Using stationarity tests for the common and idiosyncratic components

As pointed out above, we employ the stationarity test of Kwiatkowski *et al.* (1992, KPSS) to be applied to both the common and idiosyncratic components following Bai and Ng (2004b). The univariate KPSS tests for the idiosyncratic components are denoted by $S_{\hat{e}_0}^{c}(i)$ and $S_{\hat{e}_0}^{\tau}(i)$ depending on whether trends appear or not in the specification, and the tests for the common factors are $S_{\hat{F}}^{c}$ and $S_{\hat{F}}^{\tau}$. The limiting distribution of $S_{\hat{F}}^{c}$ and $S_{\hat{F}}^{\tau}$ are those derived by KPSS for the cases of a constant, and a constant and a linear trend, respectively. However, the limiting distribution for testing $\hat{e}_{it}$ depends on whether $\hat{F}_t$ is I(0) or I(1). If all factors are I(0), $S_{\hat{e}_0}^{c}(i)$ and $S_{\hat{e}_0}^{\tau}(i)$ follow the distribution of the KPSS tests for the cases of a constant, and a constant and a trend, respectively. But if some factors are I(1), stationarity in the idiosyncratic component implies cointegration between the observed series and the I(1) common factors. In that case, we have to employ univariate cointegration tests denoted by $S_{\hat{e}_1}^{c}(i)$ and $S_{\hat{e}_1}^{\tau}(i)$ which have the limiting distribution of the cointegration test of Shin (1994).

Regarding the computation of pooled statistics, when the common factors are I(0) stationary, the p-values associated with the univariate KPSS tests for the idiosyncratic components can be used to compute the pooled tests of Maddala and Wu (1999) and Choi (2001). Otherwise, pooling is not valid since the non-stationarity of the common factors is transmitted to the residuals under the null hypothesis of stationarity because it does not vanish even asymptotically.

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[18] The determination of the number of stochastic trends in the system follows a sequential testing procedure, in which we first assume that the rank of the cointegrating space is zero, that is, the number of stochastic trends is equal to that of common factors (*m=k*). We then specify the null hypothesis that there are *m* stochastic trends against the alternative hypothesis of less than *m* common stochastic trends. If the null hypothesis is rejected, we then specify the null hypothesis of *m-1* stochastic trends and test it against the alternative of less than *m-1* common stochastic trends, and we continue this process until we fail to reject the null hypothesis or when *m=0* is achieved, in which case there are no common stochastic trends. The critical values of the MQ_f and MQ_c rank statistics are provided in Table I in Bai and Ng (2004a). See Carrion-i-Silvestre and Surdeanu (2011) for a similar procedure but under panel cointegration.

4. Results

4.1. Testing for cross-sectional dependence

Prior to conducting the PANIC analysis, we apply two cross-dependence tests to determine the possible existence of cross-correlation in inflation innovations for the three panels of inflation rate series under scrutiny (CPI-based inflation for the 17 Spanish regions, CPI-based inflation for 12 groups of goods and services and PPI-based inflation for 26 industrial sectors). These tests are those proposed by Breusch and Pagan (1980) and Pesaran (2004). Pesaran's test is based on the average of pair-wise correlation coefficients ($\hat{\rho}_{ij}$) of ordinary least squares residuals obtained from standard ADF regressions for each individual. The order of the autoregressive model is selected using the *t-sig* criterion in Ng and Perron (1995), with the maximum number of lags set at $p = 4(T/100)^{1/4}$. This test takes the form $CD = \sqrt{2T/(N(N-1))}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \xrightarrow{d} N(0,1)$. The CD statistic tests the null hypothesis of cross-sectional independence, is distributed as a two-tailed standard normal distribution and exhibits good finite-sample properties. In addition, Breusch and Pagan (1980) test the null hypothesis of cross-sectionally independent errors via the following Lagrange Multiplier (LM) statistic $CD_{lm} = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^{2} \xrightarrow{d} \chi^{2}_{N(N-1)/2}$. Even though throughout the analysis we compute all the results for the specification both with and without trends, since inflation is often characterised as a variable of the second type, we focus on the evidence obtained for the specification with no trends.[19] For the three panels we are able to reject the null hypothesis of cross-sectionally independent errors with the CD test at the 1% level of significance, whereas the null hypothesis of cross-independence is only rejected with the Breusch and Pagan LM test for the panel of CPI-based inflation rates for the Spanish regions. Given that Pesaran's statistic performs better than the LM statistic (see Pesaran, 2004), we draw on the results from the former, which strongly support the presence of cross-sectional correlation in the three panels. This in turn lends support to the use of PANIC that allows for cross-sectional dependence so that large size distortions in the tests are avoided (see O'Connell, 1998; Maddala and Wu, 1999; Banerjee *et al.*, 2005).

[Insert Table 1 about here]

4.2. Determining the optimal number of common factors

Before we proceed to test for a unit root in the idiosyncratic series and common factors in which the inflation rate series forming the three panels are decomposed, we estimate the common factors

[19] As will become apparent below, the main results are fairly robust to the inclusion of a linear trend in the specification.

through principal components and then select the number of factors present in the three panels investigated. Even though there are several information criteria to determine the optimal number of common factors in each panel, we base our conclusions on the BIC_3 procedure developed in Bai and Ng (2002), which outperforms alternative information criteria for short-N panels (see Bai and Ng, 2002, p. 205-207; Moon and Perron, 2007, p. 387; Gengenbach *et al.*, 2010, p. 134). Table 2 presents the results from the application of the BIC_3 criterion to the three panels of inflation series. This criterion selects one common factor for the panel containing CPI-based inflation for the 17 regions, whereas four common factors for the other two panels. For the reasons given above, we draw on the results obtained with the BIC_3 criterion that in all instances selects an optimal number of common factors below the maximum allowed.

[Insert Table 2 about here]

4.3. PANIC analysis of the panel of CPI-based inflation rates of 17 Spanish regions

Table 3 presents the results of the univariate ADF and KPSS tests applied to the idiosyncratic series, the respective univariate tests for the common factor as well as the pooled statistics of Bai and Ng (2004a, 2010) for the panel of CPI-based inflation rate series for the 17 Spanish regions over the period 1979(1)-2013(9).

The application of the univariate ADF and KPSS tests to the observed series of Spanish regional CPI-based inflation rates provides overwhelming evidence of nonstationarity in the series. Indeed, the ADF statistic fails to reject the unit root null hypothesis even at the 10% significance level for all the regions with the exception of Cantabria and Murcia. The KPSS test is able to strongly reject the stationarity null in inflation for all the regions at the 1% level of significance. Therefore, there is confirmatory evidence of nonstationary inflation rates in 15 regions, whereas the evidence is inconclusive for Cantabria and Murcia.

The next step is to establish the source of nonstationarity in Spanish regional inflation, i.e. whether the common and/or idiosyncratic series are nonstationary. Since in this case, the BIC_3 procedure selected only one common factor, we do not need to run the filtered test MQ_f and the corrected test MQ_c. Instead, we apply the ADF and KPSS statistics on the common factor and find clear-cut evidence of nonstationarity. This is because the null of a unit root cannot be rejected even at the 10% level with the ADF statistic, whereas the stationarity null can be strongly rejected with the KPSS statistic. This result holds irrespective of the inclusion of a linear trend in the specification (since the plot of the series indicates the possible existence of a downward trend). This indicates the existence of one common stochastic trend driving the 17 regional inflation rate series of Spain.

We now proceed to test for a unit root in the idiosyncratic series. The evidence appears to mostly favour the stationarity of the idiosyncratic series even at the univariate level since the unit root null is rejected with the ADF statistic for 15 regions at the 1% level, for Castilla-La Mancha at the 5% level and for the Basque Country at the 10% level. The application of the Shin statistic (as the presence of one nonstationary common factor prevented us from using the KPSS test) renders confirmatory evidence of stationarity for 9 regions (Aragon, Asturias, Balearic Islands, Canary Islands, Galicia, Madrid, Murcia, Rioja and Valencian Community). For the rest (Andalusia, Basque Country, Cantabria, Castilla Leon, Castilla-La Mancha, Catalonia, Extremadura and Navarra), the evidence appears inconclusive as the stationarity null is also rejected in this case (as occurred with the unit root null with the ADF statistic). To provide evidence of the stochastic properties of the idiosyncratic component for the panel as a whole, we apply the pooled Fisher-type inverse Chi-squared tests of Maddala and Wu (1999) and Choi (2001) in addition to the PANIC pooled Moon-Perron and Sargan-Bhargava type statistics. It is worth highlighting that we are able to reject the joint non-stationarity null hypothesis with the five pooled statistics at the 1% level of significance, irrespective of the inclusion of deterministic trends in the idiosyncratic series specifications. Hence, there is overwhelming evidence of the joint stationarity of the idiosyncratic component of the panel of CPI-based inflation rate series for the 17 Spanish regions.

Columns 12 and 13 of Table 3 present the ratio of the standard deviation of the idiosyncratic component to the standard deviation of the observed data (both expressed in first-differences) and the standard deviation of the common to the idiosyncratic component to have an idea of the relative importance of the common and idiosyncratic components. As pointed out by Bai and Ng (2004b), if all variations are idiosyncratic, the first ratio should take a value close to one, while the second should be small. In this case, with the exception of the Canary Islands that have a first ratio closer to one (0.738) and a second ratio close to one (1.245), the other regions display a very small first ratio along with a bigger second ratio, thus indicating that most regional inflation rate series are mostly affected by a strong common component that drives them over time.

In the case of the panel of CPI-based inflation rate series for the 17 Spanish regions the finding that the source of non-stationarity in the panel is a common stochastic trend driving the non-stationarity in the observed series appears clearly. This fact, combined with the presence of a jointly stationary idiosyncratic component, renders strong evidence of pairwise cointegration among the 17 regional inflation rate series, which appear closely tight together due to the presence of a strong common stochastic trend. In other words, CPI-based inflation exhibits convergence across the 17 Spanish regions due to cross-regional approximation over time of patterns involving the basket of goods and services consumed.

[Insert Table 3 about here]

4.4. PANIC analysis of the panel of CPI-based inflation rates of 12 groups of goods and services

In this section, instead of focusing on a geographical disaggregation, we will address the problem by disaggregating the CPI-based inflation rates into different groups of goods and services. Table 4 reports the results of the univariate ADF and KPSS tests for the idiosyncratic series, the rank tests for determining the number of common stochastic trends in the common factors as well as the pooled statistics of Bai and Ng (2004a, 2010) for the panel of CPI-based inflation rate series of 12 groups of goods and services over the period 1994(1)-2013(9).

Direct testing for a unit root in the observed data with the ADF and KPSS tests provide mixed findings. On the one hand, there are four groups of goods and services (1, 2, 4 and 7) for which the inflation rate is stationary, as given by the rejection of the unit root null with the ADF test coupled with the non-rejection of the stationarity null with the KPSS test. On the other, groups 3, 9, 11 and 12 appear to render nonstationary inflation rate series, as non-rejection of the unit root null with the ADF test is coupled with rejection of the stationarity null with the KPSS statistic. Finally, for groups 5, 6, 8 and 10, the evidence is inconclusive since the respective null hypotheses are rejected with both the ADF and KPSS statistics.

We proceed to determine the stationarity properties of the common and idiosyncratic series in which the observed inflation rate series are decomposed. As far as the analysis of the common factor is concerned, the filtered test MQ_f and the corrected test MQ_c (used to estimate the number of stochastic trends present in the four common factors that are found for this panel) select four stochastic trends. Next, we test for a unit root in the idiosyncratic series. For the no trend specification, the univariate ADF test rejects the unit root null hypothesis at the 10% significance level or better in eleven of the twelve series. The only exception is Group 11 (Restaurants, cafés and hotels).

We now present a confirmatory analysis by using the stationarity tests applied on the idiosyncratic series. However, since one of the common factors is nonstationary, we cannot use the KPSS stationarity tests. Instead, we need to employ the cointegration test of Shin (1994) applied directly to the idiosyncratic series. The Shin statistic tests for cointegration between the observed series and the common component, which is equivalent to testing for stationarity in the idiosyncratic series. The Shin test fails to reject the null hypothesis of cointegration between the observed series and the I(1) common component for only four groups (Groups 1, 6, 7 and 10: Food and non-alcoholic beverages, Health, Transport, Education), whereas the null hypothesis is rejected for the other eight series at conventional significance levels. Therefore, there is confirmatory evidence of stationary idiosyncratic series for the CPI-based inflation rate series associated with groups 1, 6, 7 and 10; nonstationary idiosyncratic series for group 11 and inconclusive evidence for the rest due to the rejection of the respective null hypotheses with both the ADF and Shin tests. The mixed results for these seven groups of goods and services may stem from the poor performance associated with univariate statistics, particularly the stationarity and cointegration tests of the KPSS type that are likely to exhibit substantial size distortions. To overcome this difficulty, we employ the pooled Fisher-type statistics proposed by Bai and Ng (2004a) in addition to the PANIC pooled Moon-Perron and Sargan-Bhargava type statistics developed by Bai and Ng (2010). By doing so, we are now able to strongly reject the joint non-stationarity null hypothesis with four of the five pooled tests (the exception being the pooled Sargan-Bhargava type statistic). Note we do not pool the univariate Shin statistics because the common factors were found non-stationary. From this analysis, we can thus infer the joint stationarity of the idiosyncratic component of the panel.

In regards to the two ratios reported in columns 12 and 13, we find that in groups 3, 5, 10, 11 and to a lower extent groups 1, 9 and 12 the first ratio takes a value close to one, while the second is small, which indicates that idiosyncratic variations prevail. In contrast, the inflation series associated with the other five groups are more largely affected by common factors.

Overall, the above decomposition of the original series into the idiosyncratic and common components indicates that the source of non-stationarity in the panel is primarily four independent common stochastic trends which drive the non-stationarity in the observed series, since the idiosyncratic series are found jointly stationary. Compared to the findings for the panel of regional CPI-based inflation, the panel of CPI-based inflation for 12 groups of goods and services provides less evidence of cross-cointegration, since the existence of pair-wise cointegration among individual inflation rate series can be completely ruled out due to the existence of more than a single common stochastic trend, as was the case of the former panel.

[Insert Table 4 about here]

4.5. PANIC analysis of the panel of PPI-based inflation rates of 26 sectors

In Table 5 we present the results from the PANIC procedures for the panel of PPI-based inflation rate series for 26 sectors over the period 1976(1)-2013(8). Direct application of the ADF and KPSS tests to the observed series indicates that apart from sector 12 that exhibits stationarity with both tests, sectors 2, 7, 15, 16, 19, 20, 21 and 22 display nonstationarity with both tests. The evidence appears inconclusive for the other seventeen sectors, as the respective null hypotheses are rejected with both the ADF and KPSS statistics.

Next, we try to establish the stationarity properties of the common factor(s) and idiosyncratic series in which the observed PPI-based inflation rate series are decomposed. Concerning the common factor, the filtered test MQ_f and the corrected test MQ_c point to four stochastic trends driving the inflation rate series. If, as with the previous panel of CPI-based inflation of 12 groups of goods and services, we are able to obtain evidence of a stationary idiosyncratic component, the finding of four independent common stochastic trends driving the observed series would give some evidence of cross-cointegration among the sectoral inflation rates forming the panel, though never the stronger result of pair-wise cointegration which would require the existence of only a common stochastic trend, as was the case for regional CPI-based inflation.

We now test for a unit root in the idiosyncratic series, focusing again on the no trend specification. It is remarkable that the univariate ADF test rejects the unit root null hypothesis at the 10% significance level or better for all the 26 sector-specific idiosyncratic series. This analysis is complemented with the application of the cointegration test of Shin (1994), which tests for cointegration between the observed series and the common factor, as an indirect way of testing for stationarity in the idiosyncratic series. The Shin test fails to reject the null hypothesis for eight sectors (sectors 3, 5, 10, 12, 13, 17, 25 and 26), whereas it strongly rejects the null of cointegration between the observed series and the I(1) common component for the rest. This implies that in eighteen sectors we find inconclusive evidence regarding the univariate stochastic properties of the idiosyncratic series, since the respective null hypotheses are rejected with both the ADF and Shin statistics. We hence use the panel statistics of Bai and Ng (2004a, 2010) which, by pooling information across the 26 sector-specific idiosyncratic series, are able to strongly reject the joint non-stationarity null hypothesis at the 1% significance level in all cases. This fact lends strong support to the joint stationarity of the idiosyncratic component of the panel of sectoral PPI-based inflation rates.

Finally, from the two relevant ratios shown in columns 12 and 13 of Table 5, we infer that most sectors have an important idiosyncratic component, the main exceptions being sectors 5, 12, 25 and to a lower extent sector 1 that exhibit a very small first ratio and a large second ratio. For these four sectors, the common component appears to prevail as the driving force behind the observed sectoral inflation rate versus idiosyncratic variations. Notwithstanding, for the panel as a whole the PANIC analysis provides evidence of jointly stationary idiosyncratic series coupled with the presence of four independent common stochastic trends driving the observed sectoral PPI-based inflation rate series.

[Insert Table 5 about here]

All in all, our confirmatory analysis (employing both unit root and stationarity tests that complement each other by taking alternative null hypotheses) of the stochastic properties of our three panels of inflation rate series, disaggregating along the geographical and sectoral dimensions as well as distinguishing between consumer and producer prices, has provided consistent evidence of the presence of a nonstationary common component that appears to explain the nonstationarity in the observed inflation rate series. In the case of the panel of CPI-based inflation we found evidence of a single common stochastic trend which, combined with the presence of a largely stationary idiosyncratic component, at least for the panel as a whole, provides evidence of pairwise cointegration among the Spanish regional inflation rate series. In other words, a common stochastic trend is keeping the regional CPI-based inflation rate series linked together over time, thereby fostering the convergence of CPI-based inflation rates across the Spanish regions. This contrasts with the evidence for the other two panels of group CPI-based inflation and sectoral PPI-based inflation for which the evidence of cross-cointegration is considerably lower, as given by the existence of four independent common stochastic trends behind the nonstationary behaviour of the observed series.

The three original series of our basic data are presented in an unpublished Appendix, which we do not show to save space. From a simple glance at them it can be safely asserted that there is a visible difference between the nature of the regional CPI inflation rate series and that of the other two series (CPI groups and PPI sectors). In addition, an unweighted standard deviation is displayed for each of these series as well in Figs 1-3. This statistic shows that regional CPI inflation rates clearly converge over time (sigma convergence), whereas the other two types of series seem not to do so, especially in the case of the CPI groups. To make our results more robust, we have also obtained weighted standard deviations in the three cases as follows (see Figs 1-3): by weighing the regional CPI by each region's population; the CPI groups by the corresponding weight in the shopping basket; and the PPI sectors by the corresponding weight relative to the overall data. Incidentally, the weights are observed to be quite different for each unit individually considered. We can conclude that, even if these weighted series are brought into the analysis, the aforesaid results are not found to change qualitatively.

With the aim of helping solve the puzzle that the results described in the preceding paragraph represent, Table 6 conveys information on the standard deviation of the weights given in the different regions to each CPI group considered. We compare the earliest year and the most recent one for which there is the necessary information available (1992 and 2011). In order to show that our results are robust, four distinct types of standard deviation are derived. Thus, both an unweighted and a weighted standard deviation (by regional GDP, regional employment and regional population) are calculated. It can be observed that in all the cases the standard deviation of the weights given in the different regions to each group decreases over time, except for housing (in the case of the weighted standard deviations) and for recreation and culture –it is worth recalling that both groups only account for roughly 18% of the representative consumer's shopping basket. Overall, this evidence shows that the composition of the Spanish CPI's shopping basket is unmistakably becoming more homogenous over time from a regional perspective. [20]

[Insert Figures 1 to 3 and Table 6 about here]

5. Conclusions

This article has applied the PANIC approach using both unit root and stationarity statistics that shift their respective null hypotheses to several inflation rates for the Spanish economy using the Consumer Price Index for the regions and 12 groups of goods and services, and the Producer Price Index for 26 industrial sectors over the last decades. Our confirmatory PANIC analysis has provided clear-cut evidence of non-stationarity driven by a common stochastic trend present in the panel of Spanish regional CPI-based inflation rate series. This, coupled with the finding of a jointly stationary idiosyncratic component, provides evidence of pairwise cointegration across regional CPI-based inflation rates. This is tantamount to saying that a common stochastic trend is linking these inflation rate series together over time, which may favour the occurrence of convergence of CPI-based inflation rates at the regional level, as observed in the actual data. In contrast, the evidence of cross-cointegration is considerably lower for the other two panels of CPI-based inflation of groups of goods and services and sectoral PPI-based inflation, since there are four independent common stochastic trends (instead of a single one) behind the nonstationary behaviour of the observed series.

Not surprisingly, these results overall confirm that Spanish CPI-based inflation rate series exhibit a very high degree of persistence, particularly from the geographical perspective, for which the observed series are driven by a single common stochastic trend that links all individual series

[20] In order to provide additional evidence in this respect, Caraballo and Usabiaga (2009c) analysed weights set in 1992 and 2009 concerning the three groups with the highest CPI weights in the consumption basket in 2009 –G1 (Food and non-alcoholic beverages), G7 (transport) and G11 (Restaurants, cafés and hotels), in this order–. They derived the standard deviation of the weights for these groups in each region in 1992 and 2009 relative to the national-wide weight. The standard deviation decreases over time for these groups, which points to greater homogeneity in the weights. This result can be thought of as an indication of increased geographical homogeneity in the consumption patterns exhibited by consumers in the different regions of Spain. In contrast to regional CPI inflation, we find no clear-cut regional convergence patterns as regards the PPI series (with such series being only available since 2003, which prevented us from applying PANIC to these series). This indicates that there is more heterogeneity in the patterns of production (than in those of consumption) across regions, as reflected in the fact that regions are not specialising in the same manufacturing and energy products, whose prices are covered in the PPI series.

together. A sigma-convergence analysis, or even a simple visual inspection of Spanish regional CPI-based inflation rate series, shows a tendency for the series to converge over time. A possible interpretation of this fact is that the typical CPI shopping basket has become more homogeneous across regions over time. Spaniards no longer consume different items depending upon the region in which they live, at least not to the same extent as in the past. The analysis of the evolution of the unweighted and weighted standard deviation of the weights assigned in the different regions to each CPI group appears to clearly back up that claim.

As far as CPI-based inflation disaggregated into distinct groups of goods and services is concerned, it exhibits a more heterogeneous behaviour, which is hard to capture and hence renders the existence of more than a single stochastic trend, as in the case of regional CPI-based inflation. In addition, CPI-based inflation rates of groups of goods and services are found to show a slightly lower-persistent behaviour than in previous works –Romero-Ávila and Usabiaga (2012)–, closely resembling here the relatively more flexible pattern followed by the sectoral PPI-based inflation series involved. It is worth mentioning that, differences in the methodologies applied in both works aside, both consumer price inflation series –ours and that analysed in the referred article– are not fully comparable since they differ in the range of groups of goods and services included, 8 groups (PROCOME) in the case of Romero-Ávila and Usabiaga (2012) and 12 groups (COICOP) in this work, as well as in the span of time available for the analysis, 1978(1)-2000(12) versus 1994(1)-2013(9), respectively.

Finally, as already indicated above, PPI-based inflation rates of 26 industrial sectors over the past decades also exhibit a less homogeneous behaviour than regional CPI-based inflation, which again explains why several common stochastic trends (and not just a single one) are needed to track the behaviour of sectoral inflation rates. Besides, they display a relatively flexible pattern, as the secondary sector tends to rely less intensively on labour, whose price (wages) is typically regarded as the most rigid, and more on other inputs, like energy, whose price fluctuates widely. Moreover, industry is usually subject to greater competition than, for example, services. Indeed, the former after all constitutes the tradable sector par excellence.

The overall result of our analyses, of high persistence, should come as no surprise whatsoever, given what the economic literature has come up with as regards the determinants of inflation persistence: lack of or insufficient competition in goods and services markets, a dysfunctional labour market (insider-outsider considerations, long-term unemployment problem, intermediate-level collective bargaining, etc.), the prevalence of backward-looking expectations, widespread indexation, the high proportion of services over total GDP, real wage rigidity, dual inflation problems, among others; all of them “diseases” the Spanish economy “contracted” long ago and is yet to get completely cured from them.

Against this background, sufficiently intense shocks to the economy (let us think of an oil supply shock) may either drive the inflation rate up or down, depending on its type. The aforementioned inflation persistence mechanisms coming into play ensure that it will take inflation a long time to go back to its original value, which we could assume, being optimistic, to be the inflation target. In other words, if not permanent, the shock can have long-lasting effects on the inflation rate. Countries deprived of control over monetary policy can commit to structural reforms so as to prevent or correct for the deviation of the actual inflation from the target and eliminate the differential between national inflation and its competitors’ inflation rate. These structural measures should attempt to give rise to more consumer price flexibility. Crucial reforms are those involving the strengthening of competition policy responsible for better regulating competitive conditions in product markets and a labour market reform that removes other roots of persistence in inflation. In the case of Spain, the goal of carrying out a profound labour reform has been attained in the 2010 and 2012 reforms (particularly in the last one). Its medium-run effects on unemployment and inflation, which are currently being debated, are yet to be seen, but this last reform can be considered an in-depth one, even though several national and international institutions call on the country to further deepen it –see for example IMF (2014). On the competition-enhancing reforms, nearly all the main necessary actions are yet to be completely implemented.

In summary, it is uncertain to what extent the prolonged and deep current crisis and the recent and announced reforms can succeed in helping decrease the high inflation persistence shown by the robust results of our work, which uses especially fitting econometric techniques according to the nature of the relevant problem analysed.

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TABLES AND FIGURES FOR MAIN TEXT

TABLES

Table 1: Cross-Sectional Dependence Analysis

	CPI 12 Groups	CPI 17 Regions	PPI 26 Sectors	CPI 12 Groups	CPI 17 Regions	PPI 26 Sectors
	No Trend Specification			Trend Specification		
LM test	9.816	1354.973*	39.669	9.718	1360.548*	41.569
CD test	5.002*	147.370*	17.301*	4.948*	147.674*	18.860*

Note: The CD-statistic and the LM-statistic test for the null of cross-sectional independence. The CD-statistic is distributed as a two-tailed standard normal distribution and the LM-statistic test as a $\chi^2_{N(N-1)/2}$ distribution. * implies rejection of the null hypothesis at the 1% significance level. The entries with no * imply failure to reject the null hypothesis.

Table 2: $BIC_3(k)$ Information Criterion

Number of factors (k)	CPI 12 Groups	CPI 17 Regions	PPI 26 Sectors
0	0.9096	0.3069	4.6233
1	0.6899	0.1358*	3.2502
2	0.5506	0.1466	3.0953
3	0.4814	0.1599	2.9605
4	0.4572*	0.1760	2.9343*
5	0.4817	0.1940	3.0498

Note: * represents the lowest value of the information criteria. See the text for the equation associated with the information criterion.

Table 3: Panel Analysis of Non-Stationarity in Idiosyncratic and Common Components of CPI Inflation, 17 Regions. 1979M1-2013M9

	No Trend Specification					Trend Specification						
	k	$ADF_y^c(i)$	$ADF_{\hat{e}}^c(i)$	$S_y^c(i)$	$S_{\hat{e}_1}^\tau(i)$	k	$ADF_y^\tau(i)$	$ADF_{\hat{e}}^\tau(i)$	$S_y^\tau(i)$	$S_{\hat{e}_1}^\tau(i)$	$\frac{\sigma(\Delta\hat{e}_{it})}{\sigma(\Delta\pi_{it})}$	$\frac{\sigma(\lambda'_i F_t)}{\sigma(\hat{e}_{it})}$
Andalusia	3	-1.713	-5.476***	3.465***	0.115	3	-2.485	-5.455***	0.810***	0.116*	0.209	9.387
Aragon	5	-1.721	-6.796***	3.529***	0.101	5	-2.581	-7.238***	0.811***	0.073	0.312	6.599
Asturias	0	-2.433	-4.379***	3.364***	0.100	0	-2.783	-4.689***	0.769***	0.083	0.379	3.716
Balearic	7	-1.982	-6.730***	3.481***	0.068	7	-2.555	-6.899***	0.821***	0.069	0.457	6.294
Basque Country	0	-1.661	-1.683*	3.668***	0.450**	0	-2.146	-3.274***	0.879***	0.147**	0.328	3.759
Canary Islands	1	-1.764	-2.734***	3.231***	0.057	1	-2.768	-4.210***	0.660***	0.058	0.738	1.245
Cantabria	7	-2.591*	-3.113***	3.287***	0.346**	7	-3.031	-4.952***	0.824***	0.158**	0.332	5.773
Cast. La Mancha	3	-2.128	-2.456**	3.266***	0.731***	3	-2.568	-5.354***	0.770***	0.171**	0.173	7.005
Castilla Leon	1	-1.862	-3.390***	3.398***	0.564***	0	-2.405	-4.446***	0.814***	0.182**	0.181	13.812
Catalonia	1	-2.212	-4.315***	3.613***	0.329**	1	-2.718	-4.319***	0.828***	0.143**	0.366	8.135
Extremadura	1	-1.629	-3.165***	3.396***	0.129	1	-2.303	-3.814***	0.796***	0.100*	0.306	6.236
Galicia	3	-2.062	-2.984***	3.505***	0.088	3	-2.773	-4.270***	0.785***	0.057	0.445	4.219
Madrid	4	-2.534	-6.909***	3.471***	0.069	4	-2.754	-6.805***	0.851***	0.067	0.363	5.191
Murcia	3	-2.675*	-3.603***	3.346***	0.071	3	-3.470**	-5.206***	0.708***	0.054	0.335	4.605
Navarra	0	-1.932	-4.625***	3.618***	0.523**	0	-2.839	-4.621***	0.747***	0.269***	0.263	7.636
Rioja	0	-1.775	-4.529***	3.487***	0.111	0	-2.888	-4.948***	0.678***	0.075	0.417	4.119
Valencian Com.	1	-2.508	-8.441***	3.485***	0.050	1	-3.203*	-8.349***	0.845***	0.047	0.222	7.265
Critical Values												
1%		-3.430	-2.580	0.743	0.536		-3.960	-3.167	0.215	0.185		
5%		-2.860	-1.950	0.463	0.324		-3.410	-2.577	0.149	0.122		
10%		-2.570	-1.620	0.343	0.235		-3.120	-2.314	0.120	0.098		
Bai and Ng (2004) Pooled Statistics												
		$P_{\hat{e}}^c$	252.855***		N.A.		$P_{\hat{e}}^\tau$	299.628***		N.A.		
		$Z_{\hat{e}}^c$	26.54****		N.A.		$Z_{\hat{e}}^\tau$	32.212***		N.A.		

Bai and Ng (2010) Pooled Statistics									
P_a^c	-16.773***				P_a^τ	-20.171***			
P_b^c	-6.438***				P_b^τ	-8.501***			
$PMSB^c$	-2.764***				$PMSB^\tau$	-3.444***			
Common Factor Analysis		**Critical Values**					**Critical Values**		
	Statistic	**1%**	**5%**	**10%**		**Statistic**	**1%**	**5%**	**10%**
$ADF_{\hat{F}}^c$	-2.091	-3.430	-2.860	-2.570	$ADF_{\hat{F}}^\tau$	-2.632	-3.960	-3.410	-3.120
$S_{\hat{F}}^c$	3.480***	0.743	0.463	0.343	$S_{\hat{F}}^\tau$	0.819***	0.215	0.149	0.120

Note: The augmented autoregressions employed in the ADF analysis select the optimal lag-order with the *t-sig* criterion of Ng and Perron (1995), setting a maximum lag-order equal to $p = 4(T/100)^{1/4}$. The stationarity tests are based on 12 lags of the Quadratic spectral kernel. The information criterion BIC_3 has chosen an optimal rank equal to 1. $P_{\hat{e}}$ is distributed as χ^2_{34}, with 1%, 5% and 10% critical values of 56.061, 48.602 and 44.903, respectively. $Z_{\hat{e}}$ is distributed as N(0,1) with 1%, 5% and 10% critical values of 2.326, 1.645 and 1.282. P_a^τ, P_b^τ and $PMSB^\tau$ are distributed as N(0,1) with 1%, 5% and 10% critical values of -2.326, -1.645 and -1.282.***, ** and * imply rejection of the null hypothesis at 1%, 5% and 10%, respectively.

Table 4: Panel Analysis of Non-Stationarity in Idiosyncratic and Common Components of CPI Inflation, 12 Groups of Goods and Services. 1994M1-2013M9

	No Trend Specification					Trend Specification						
	k	$ADF_y^c(i)$	$ADF_{\hat{e}}^c(i)$	$S_y^c(i)$	$S_{\hat{e}_1}^\tau(i)$	k	$ADF_y^\tau(i)$	$ADF_{\hat{e}}^\tau(i)$	$S_y^\tau(i)$	$S_{\hat{e}_1}^\tau(i)$	$\frac{\sigma(\Delta\hat{e}_{it})}{\sigma(\Delta\pi_{it})}$	$\frac{\sigma(\lambda'_i F_t)}{\sigma(\hat{e}_{it})}$
G1. Food and non-alcoholic beverages	4	-4.014***	-3.781***	0.209	0.119	4	-4.083***	-3.840***	0.141*	0.119*	0.958	0.149
G2. Alcoholic beverages and tobacco	5	-2.833*	-2.086**	0.319	1.382***	5	-2.838	-3.047**	0.319***	0.078	0.001	21.707
G3. Clothing and footwear	6	-1.719	-1.650*	1.540***	1.285***	6	-2.753	-2.568*	0.284***	0.241***	0.988	0.108
G4. Housing	3	-3.918***	-3.866***	0.167	0.356**	3	-3.877**	-3.890***	0.098	0.090	0.703	0.674
G5. Furnishings, household equipment and routine maintenance of the house	2	-2.617*	-2.536**	1.046***	0.747***	2	-4.366***	-4.279***	0.088	0.073	0.987	0.047
G6. Health	2	-4.395***	-3.905***	0.366*	0.199	2	-5.138***	-3.847***	0.165**	0.098	0.003	17.084
G7. Transport	1	-4.303***	-3.727***	0.049	0.134	1	-4.296***	-3.691***	0.049	0.097	0.012	8.459
G8. Communications	0	-4.721***	-2.348**	0.755***	1.033***	0	-5.042***	-3.096**	0.215**	0.106*	0.000	31.205
G9. Recreation and culture	7	-2.047	-1.982**	1.868***	1.434***	4	-2.644	-2.443*	0.201**	0.119*	0.950	0.183
G10. Education	0	-2.999***	-1.844*	0.606**	0.214	0	-2.209	-1.102	0.242***	0.153**	0.998	0.040

G11. Restaurants, cafés and hotels	0	-0.869	-0.848	1.111***	1.017***	0	-1.712	-1.634	0.449***	0.352***	0.972	0.082
G12. Miscellaneous goods and services	1	-2.366	-2.206**	0.782***	0.412**	1	-3.114	-2.853**	0.122*	0.122*	0.953	0.196
Critical Values												
1%		-3.430	-2.580	0.743	0.536		-3.960	-3.167	0.215	0.185		
5%		-2.860	-1.950	0.463	0.324		-3.410	-2.577	0.149	0.122		
10%		-2.570	-1.620	0.343	0.235		-3.120	-2.314	0.120	0.098		
Bai and Ng (2004) Pooled Statistics												
		$P_{\hat{e}}^{c}$	124.248***		N.A.		$P_{\hat{e}}^{\tau}$	115.283***		N.A.		
		$Z_{\hat{e}}^{c}$	14.470***		N.A.		$Z_{\hat{e}}^{\tau}$	13.176***		N.A.		
Bai and Ng (2010) Pooled Statistics												
		P_{a}^{c}	-3.624***				P_{a}^{τ}	-0.405				
		P_{b}^{c}	-2.153**				P_{b}^{τ}	-0.377				
		$PMSB^{c}$	-1.242				$PMSB^{\tau}$	-0.326				
Common Factor Analysis: Trends $\hat{r}_1$												
MQ_c	MQ_f											
4	4											

Note: The augmented autoregressions employed in the ADF analysis select the optimal lag-order with the *t-sig* criterion of Ng and Perron (1995), setting a maximum lag-order equal to $p = 4(T/100)^{1/4}$. The stationarity tests are based on 12 lags of the Quadratic spectral kernel. The information criterion BIC_3 has chosen an optimal rank equal to 1. $P_{\hat{e}}$ is distributed as χ^2_{34}, with 1%, 5% and 10% critical values of 56.061, 48.602 and 44.903, respectively. $Z_{\hat{e}}$ is distributed as N(0,1) with 1%, 5% and 10% critical values of 2.326, 1.645 and 1.282. P_a^{τ}, P_b^{τ} and $PMSB^{\tau}$ are distributed as N(0,1) with 1%, 5% and 10% critical values of -2.326, -1.645 and -1.282.***, ** and * imply rejection of the null hypothesis at 1%, 5% and 10%, respectively. Since $\hat{r}_1 > 1$, the estimated number of $\hat{r}_1$ stochastic trends in the common factors must be determined. We also employ the filtered test MQ_f and the corrected test MQ_c to estimate $\hat{r}_1$.

Table 5: Panel Analysis of Non-Stationarity in Idiosyncratic and Common Components of PPI Inflation, 26 Sectors. 1976M1-2013M8

	No Trend Specification					Trend Specification						
	k	$ADF_{y}^{c}(i)$	$ADF_{\hat{e}}^{c}(i)$	$S_{y}^{c}(i)$	$S_{\hat{e}_1}^{c}(i)$	k	$ADF_{y}^{\tau}(i)$	$ADF_{\hat{e}}^{\tau}(i)$	$S_{y}^{\tau}(i)$	$S_{\hat{e}_1}^{\tau}(i)$	$\frac{\sigma(\Delta\hat{e}_{it})}{\sigma(\Delta\pi_{it})}$	$\frac{\sigma(\lambda'_i F_t)}{\sigma(\hat{e}_{it})}$
S1	0	-4.373***	-4.407***	1.953***	0.379**	0	-4.954**	-5.358***	0.672***	0.112*	0.279	2.622
S2	2	-2.480	-2.802***	2.806***	0.800***	2	-3.898**	-4.453***	0.626***	0.116*	0.914	0.263
S3	2	-3.836***	-4.217***	1.880***	0.189	2	-4.844***	-5.226***	0.447***	0.043	0.955	0.150
S4	4	-2.608*	-2.794***	3.508***	1.584***	4	-5.134***	-4.598***	0.403***	0.101*	0.933	0.161
S5	1	-4.317***	-5.013***	0.570**	0.148	1	-4.678***	-5.142***	0.111	0.127**	0.001	23.944
S6	7	-3.719***	-4.082***	2.719***	0.743***	4	-4.248***	-4.544***	0.627***	0.057	0.985	0.068
S7	8	-2.070	-2.386**	4.053***	2.386***	2	-3.835**	-3.830***	0.943***	0.065	0.960	0.123
S8	6	-2.991**	-3.170***	2.807***	0.947***	6	-4.061***	-3.925***	0.595***	0.115*	0.960	0.088
S9	4	-3.005**	-3.371***	2.856***	0.819***	4	-4.436***	-4.629***	0.544***	0.068	0.929	0.184
S10	7	-5.112***	-5.760***	0.973***	0.106	7	-5.935***	-6.444***	0.156**	0.039	0.969	0.137
S11	8	-2.607*	-2.728***	3.647***	1.869***	1	-4.165***	-4.284***	0.624***	0.094	0.986	0.112
S12	1	-5.311***	-4.417***	0.204	0.186	1	-5.350***	-5.140***	0.166**	0.050	0.003	12.917
S13	1	-3.899***	-4.296***	1.275***	0.092	1	-4.462***	-4.907***	0.405***	0.038	0.811	0.371
S14	6	-2.920**	-2.878***	2.615***	1.050***	6	-4.744***	-4.643***	0.231***	0.115*	0.947	0.125
S15	8	-2.180	-2.171**	3.120***	1.266***	7	-2.905	-2.835**	0.817***	0.042	0.949	0.145
S16	8	-2.119	-2.350**	3.183***	1.374***	8	-3.128*	-3.571***	0.714***	0.125**	0.847	0.280
S17	3	-5.444***	-5.843***	0.678**	0.082	3	-5.760***	-6.102***	0.265***	0.062	0.883	0.313
S18	5	-2.944**	-3.072***	3.077***	1.138***	5	-3.842**	-3.705***	0.713***	0.085	0.978	0.075
S19	0	-1.871	-2.163**	3.753***	1.819***	0	-3.429**	-3.992***	0.828***	0.138**	0.927	0.189
S20	5	-2.355	-2.792***	2.959***	0.933***	3	-3.073	-3.353***	0.803***	0.063	0.947	0.127
S21	7	-1.698	-1.859*	3.748***	1.764***	7	-2.201	-2.192	0.975***	0.081	0.990	0.052
S22	7	-1.803	-1.878*	3.646***	1.611***	5	-3.250*	-3.518***	0.814***	0.060	0.969	0.117
S23	4	-2.982**	-2.219**	2.645***	1.002***	0	-4.056***	-2.862**	0.472***	0.142**	0.924	0.257
S24	8	-2.727*	-3.290***	3.370***	1.437***	8	-3.322*	-3.551***	0.658***	0.128**	0.991	0.068
S25	1	-4.968***	-5.289***	1.109***	0.166	1	-5.774***	-5.451***	0.269***	0.129**	0.004	17.826
S26	6	-3.809***	-4.683***	1.673***	0.227	6	-4.163***	-5.137***	0.555***	0.158**	0.474	1.889

Critical values								
1%	-3.430	-2.580	0.743	0.536	-3.960	-3.167	0.215	0.185
5%	-2.860	-1.950	0.463	0.324	-3.410	-2.577	0.149	0.122
10%	-2.570	-1.620	0.343	0.235	-3.120	-2.314	0.120	0.098
Bai and Ng (2004) Pooled Statistics								
	$P_{\hat{e}}^{c}$	338.448***		N.A.	$P_{\hat{e}}^{\tau}$	407.237***		N.A.
	$Z_{\hat{e}}^{c}$	28.089***		N.A.	$Z_{\hat{e}}^{\tau}$	34.834***		N.A.
Bai and Ng (2010) Pooled Statistics								
	P_a^c	-14.768***			P_a^{τ}	-11.898***		
	P_b^c	-5.264***			P_b^{τ}	-5.481***		
	$PMSB^c$	-2.133**			$PMSB^{\tau}$	-2.465***		
Common Factor Analysis: Trends $\hat{r}_1$								
MQ_c MQ_f								
4 4								

Note: The classification of PPI sectors appears in the Appendix. The augmented autoregressions employed in the ADF analysis select the optimal lag-order with the *t-sig* criterion of Ng and Perron (1995), setting a maximum lag-order equal to $p = 4(T/100)^{1/4}$. The stationarity tests are based on 12 lags of the Quadratic spectral kernel. The information criterion BIC_3 has chosen an optimal rank equal to 1. $P_{\hat{e}}$ is distributed as χ^2_{34}, with 1%, 5% and 10% critical values of 56.061, 48.602 and 44.903, respectively. $Z_{\hat{e}}$ is distributed as N(0,1) with 1%, 5% and 10% critical values of 2.326, 1.645 and 1.282. P_a^{τ}, P_b^{τ} and $PMSB^{\tau}$ are distributed as N(0,1) with 1%, 5% and 10% critical values of -2.326, -1.645 and -1.282.***, ** and * imply rejection of the null hypothesis at 1%, 5% and 10%, respectively. Since $\hat{r}_1 > 1$, the estimated number of $\hat{r}_1$ stochastic trends in the common factors must be determined. We also employ the filtered test MQ_f and the corrected test MQ_c to estimate $\hat{r}_1$.

Table 6: Standard Deviation of the Weights of the CPI-based Groups of Goods and Services in the Different Spanish Regions. Difference from 1992 to 2011 (%)

	Unweighted	Weighted by regional GDP	Weighted by regional employment	Weighted by regional population
G1. Food and non-alcoholic beverages	-7.73	-10.42	-11.29	-15.54
G2. Alcoholic beverages and tobacco	-7.51	-21.22	-19.25	-20.31
G3. Clothing and footwear	-21.35	-15.80	-13.89	-14.43
G4. Housing	-1.28	19.24	17.38	14.38
G5. Furnishings, household equipment and routine maintenance of the house	-25.13	-14.02	-11.26	-10.43
G6. Health	-24.54	-37.28	-37.09	-36.98
G7. Transport	-21.07	-12.16	-11.96	-9.50
G8. Communications	-7.64	-14.93	-17.97	-15.02
G9. Recreation and culture	28.76	13.02	15.94	15.15
G10. Education	-35.23	-36.08	-34.89	-36.42
G11. Restaurants, cafés and hotels	-6.74	-22.45	-20.90	-20.30
G12. Miscellaneous goods and services	-12.77	-22.64	-18.98	-17.03

FIGURES

Figure 1: Evolution of Standard Deviation. Regional CPI-based Inflation Rates

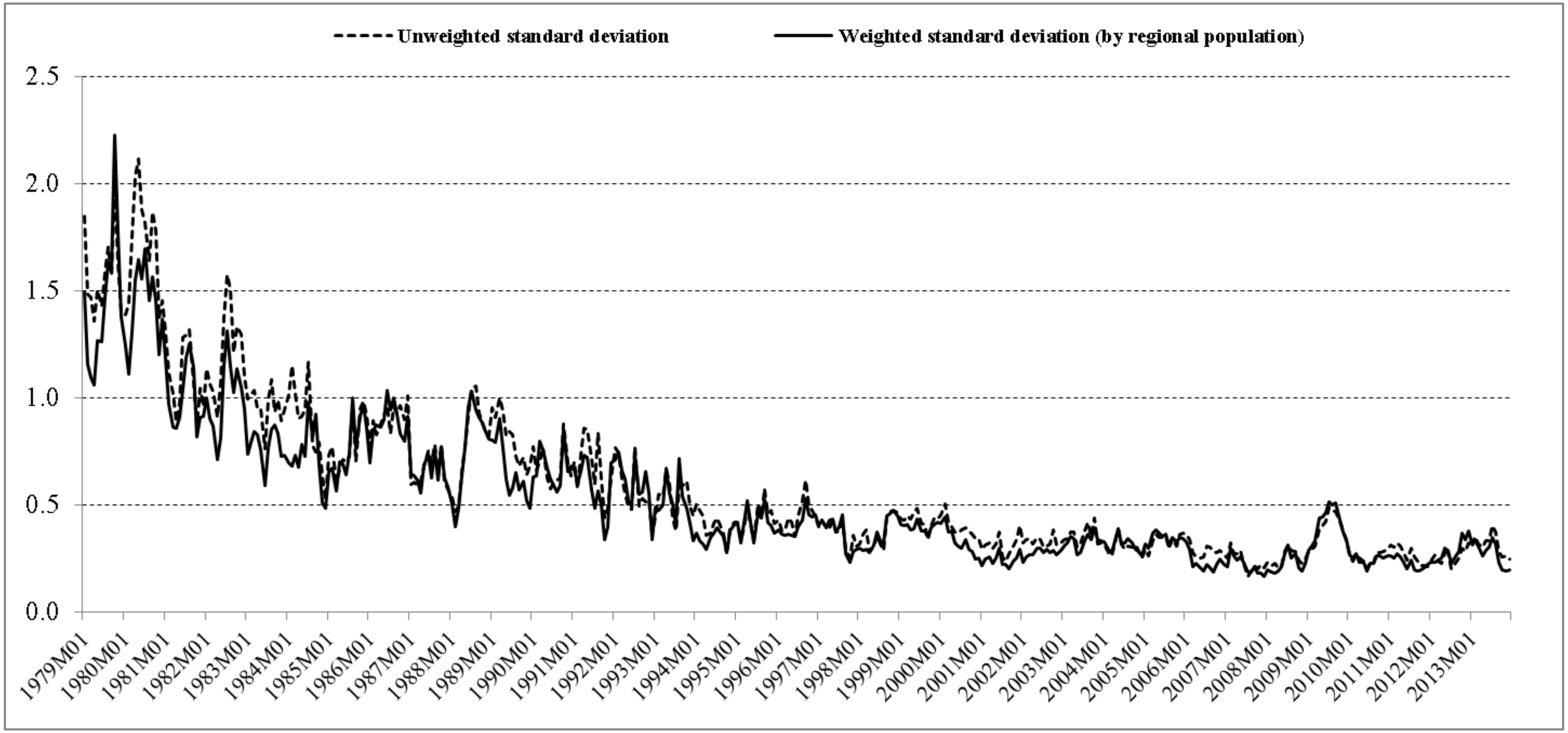


Figure 2: Evolution of Standard Deviation. CPI-based Inflation Rates of 12 Groups of Goods and Services

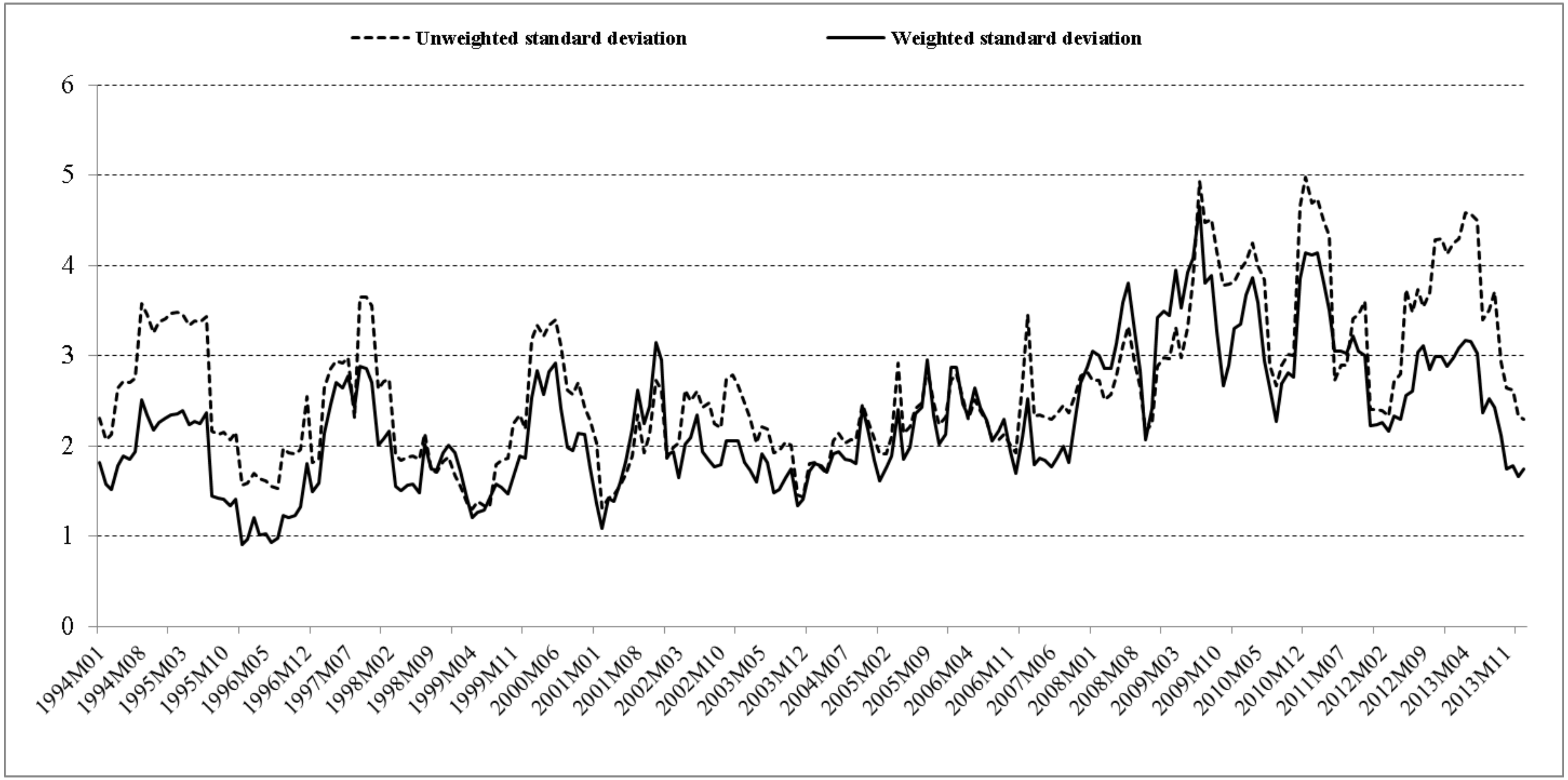
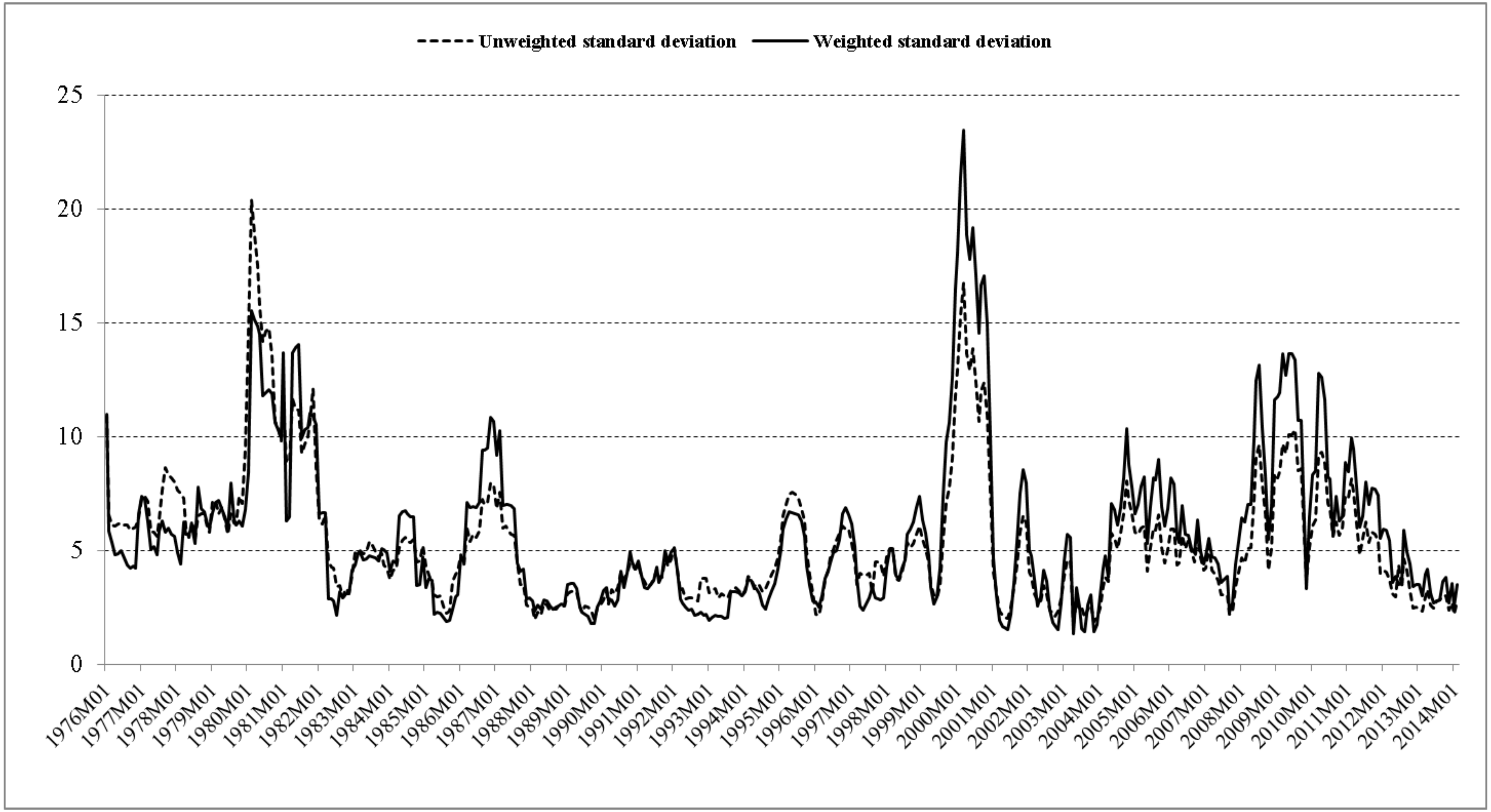


Figure 3: Evolution of Standard Deviation. PPI-based Inflation Rates of 26 Sectors



APPENDIX. Classification of PPI Sectors

S1	Mining of coal and lignite
S2	Other mining and quarrying
S3	Manufacturing of food products
S4	Manufacturing of beverages
S5	Manufacturing of tobacco products
S6	Manufacturing of textiles
S7	Manufacturing of wearing apparel
S8	Manufacturing of leather and related products
S9	Manufacturing of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
S10	Manufacturing of paper and paper products
S11	Printing and reproduction of recorded media
S12	Manufacturing of coke and refined petroleum products
S13	Manufacturing of chemicals and chemical products
S14	Manufacturing of basic pharmaceutical products and pharmaceutical preparations
S15	Manufacturing of rubber and plastic products
S16	Manufacturing of other non-metallic mineral products
S17	Manufacturing of basic metals
S18	Manufacturing of fabricated metal products, except machinery and equipment
S19	Manufacturing of computer, electronic and optical products
S20	Manufacturing of electrical equipment
S21	Manufacturing of machinery and equipment n.e.c.
S22	Manufacturing of motor vehicles, trailers and semi-trailers
S23	Manufacturing of other transport equipment
S24	Manufacturing of furniture
S25	Other manufacturing
S26	Electricity, gas, steam and air conditioning supply