

Inflation persistence in Hungary: A spatial analysis

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Abstract

On the basis of a disaggregated data set, we study inflation persistence in Hungary by focusing on regional cross-sectional variation. To this end, we use regional inflation series constructed from individual store-level price quotes. The price observations were collected for the CPI database at a monthly frequency and were provided by the Central Statistical Office of Hungary. In order to estimate inflation persistence, we assume time-varying-coefficient autoregressive models as described in Darvas and Varga (2007). The aim of the study is to describe the spatial patterns of Hungarian inflation persistence on the NUTS-3 level by using various exploratory spatial data analysis (ESDA) techniques. Furthermore, the structure of the database allows us to investigate the spatial differences at the sectoral level (in nine different product categories), as well. Previous researches found that while an apparent co-movement exists between the inflation rates in different regions, the decomposed inflation rates are quite disperse. We show that the overall level of inflation persistence decreased during the sample period, however, there are notable differences between the local patterns.

Keywords: inflation persistence, time-varying coefficient models, exploratory spatial data analysis

JEL: C22, E31

1. Introduction

Understanding the determinants and dynamic patterns of inflation is a crucial issue for modern economies since it can have implications for economic efficiency and wealth. Practically, many central banks follow an inflation targeting strategy in order to maintain price stability. There is a general consensus in the literature that inflation is a monetary phenomenon in the medium and the long run, and is determined by monetary policy. Nonetheless, over shorter horizons, various macroeconomic shocks temporarily move inflation away from its long-run trend. These shocks or their effects on inflation can be

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persistent and lead to persistent deviations of the level of inflation from its mean representing price stability. Inflation persistence is defined as the tendency of inflation to converge slowly towards the target level in response to shocks, therefore inflation persistence is a measure of the speed of adjustment (Dossche and Everaert 2005). It is the backward-looking component of inflation and it indicates that to what extent inflation is anchored to past rates. A higher degree of persistence means that the actual rate of inflation depends more on previous values. Low persistence indicates that the actual rate of inflation is independent of the previous periods' inflation dynamics, it is rather determined by actual shocks and the actual state of the economy. The degree of persistence can have a negative sign meaning that inflation is the opposite as in the previous period which refers to a correction process.

The most common measure of inflation persistence suggested in the literature is based on a univariate time-series model that assumes an autoregressive process, then, inflation persistence is measured as the sum of the autoregressive coefficients. Alternative measures are discussed in e.g. Pivetta and Reis (2007).

Altissimo et al. (2006) distinguishes three basic sources of inflation persistence: persistence that is inherited from persistent fluctuations in the determinants of inflation (extrinsic persistence); the dependence of inflation on its own past (intrinsic persistence); and persistence due to the formation of inflation expectations (expectations-based persistence).

A question often addressed in the inflation persistence literature is the time-variance of the persistence parameter, placing special emphasis on the structural breaks. O'Reilly and Whelan (2004) found that the parameters of the Euro-area inflation process are relatively stable, close to one, and there were no breakpoints in their sample. They tested their results with rolling regressions allowing for separate parameters for the inflation process over a sequence of moving windows. Gadzinski and Orlandi (2004) also compared inflation persistence across multiple countries, and suggested that there is a need to account for a structural break in the inflation series at the beginning of the 1990s. They emphasized the importance of using time-varying coefficient models.

Franta et al. (2007) conducted a comparative analysis of Central and Eastern European countries including Hungary, however, their estimates are constrained due to data limitations. Lendvai (2005) found evidence of a high inflation persistence in Hungary while the weights of the lagged and forward-looking components are roughly equal. Estimations for the degree of persistence in Hungary by the National Bank of Hungary (Magyar Nemzeti Bank 2008) suggested a high level of persistence, since agents assume permanent effects of monetary shocks.

Our work is linked to the literature of the microeconomic foundations of inflationary processes that have been investigated from the early 1980s, and a comprehensive survey of this literature appears in Taylor (1999). Empirical researches using disaggregated data sets started at the end of the 1980s (e.g. Cecchetti 1986, Lach-Tsiddon 1992) and new results have been continuously published since that time as researchers get access to micro data on prices in more details. These data sets include, among others, CPI/PPI price quotes, store-level scanner data and/or specific indicators derived from individual surveys on pricing policies followed by firms. According to a recent article dealing with the implications of micro data in macro models (Maćkowiak and Smets 2008), the degree of price stickiness appears to be conditional on the source of the shocks, i.e., price stickiness is different in response of macroeconomic, sectoral and idiosyncratic shocks.

A large-scale research project has been carried out by the Eurosystem central banks called the Inflation Persistence Network (IPN) which aimed to analyse micro price data in the euro area. The findings of the IPN were summarized by Dhyne et al. (2005), and a survey of the IPN evidence concerning price setting in the euro area were conducted by Altissimo et al. (2006). The latter found that inflation persistence had been moderate and had decreased in the respective period while the measured persistence had been different at the different levels of aggregation (euro area, national level, sectoral level, individual prices), namely, at higher levels of aggregation the adjustment of inflation had been slower. Further implications of aggregation were dealt with by Altissimo et al. (2007) in details.

Concerning spatial differences, the above mentioned studies focussed on cross-country comparisons, especially on comparative analyses of the eurozone countries or the US and the euro area. Our opinion is that investigating spatial differences in monetary (inflationary) processes is a relevant issue within a single country, as well. Such questions were discussed in the United Kingdom (Hayes 2005), in Italy (Fabiani et al 2004 and Veronese et al 2005), in Spain (Alberola-Marqués 2001) and in the United States (Schunk 2005) so far. Broda and Weinstein (2008) compared cross-border and within border price differences in the US and Canada, and found that the degree of market segmentation across the border is similar to that within borders.

Beck et al. (2006) took a novel approach to the analysis of inflation dynamics within and across euro area countries since their comparative researches were conducted at the regional level. They employed a model where regional inflation dynamics were explained by common euro area and country specific factors as well as an idiosyncratic regional component. They found that while the area wide factors are strongly significant and have a high explanatory

power, their loadings are different across different regions, which suggests that differences in regional inflation developments are partly due to area wide phenomena.

Micro-level analyses of inflation dynamics and price-setting behaviour have been conducted in Hungary, as well. The major studies in this field available in English language include Rátfai (2006, 2007), and Dusek (2008), however, these analyses cover only a fraction of the CPI basket. A detailed analysis of Hungarian data with a much higher coverage was conducted by Gábrriel and Reiff (2008).

The methodology of our research is based on the work of Darvas and Varga (2007) in which the authors conducted a comparative analysis of the dynamic patterns of inflation persistence in the United States, the eurozone and in four new EU members including Hungary. On the basis of previous empirical findings, they assumed that inflation persistence may change in time, and, for this reason, they used time-varying coefficient autoregressive models similar to that of Dossche and Everaert (2005) and Pivetta and Reis (2007).

The aim of our study is to analyse spatial differences in inflation persistence in Hungary with micro price data. We use the store-level individual price quotes of the Central Statistical Office of Hungary. A detailed description of the database can be found in Gábrriel and Reiff (2008) while the spatial differences were analysed by Reiff and Zsibók (2007). The rest of our paper is structured as follows: after introducing the database in section 2 and describing the methodology in section 3, section 4 presents the findings. Finally, section 5 concludes.

2. Data

We use a data set collected by the Central Statistical Office of Hungary (KSH), containing micro Consumer Price Index (CPI) data from December 2001 to June 2007 (altogether 67 consecutive months) where the observations were made at store-level.¹ The CPI coverage changes each year. For example, in 2006 we have data about 770 representative items of the 896 on the CPI item list, while in 2007, we have 747 out of 876. The total weight of these representative items in the consumer basket is 70.122% in 2006 and 69.272% in 2007, indicating a reasonable coverage.² The missing items have either regulated prices (e.g. kindergarten and school catering, electric energy, pipeline gas, highway toll stickers) or the

¹ For a detailed description of the data set see Gábrriel and Reiff (2008).

² The authors thank the Central Statistical Office for making it possible to use the data, and for Beáta Kollár and Borbála Mináry for discussions.

data collection methodology of KSH makes it impossible to investigate their pricing (e.g. new and used cars). The total number of observations is approximately 4.7 million.

Our original database contains 5 variables: product codes (5-digit representative item codes), prices, store codes, the dates of observations (year and month) and change codes. The “change code” indicates sales, normal price increases/decreases, price imputations³, forced store and/or product replacements, changes of suppliers, changes in product outfits, and mistakes in previous months' quotes. The store codes include a store identifier and a location identifier in terms of county which allows us to apply county-level investigations.

Monthly inflation rates were computed as the weighted averages of the item-specific monthly changes in the average price, based on the log differences of average prices. The CPI figures were computed, differently from KSH's method, with unchanged weights based on year 2006 which allows us to eliminate the methodological biases since changing weights themselves otherwise could lead to breaks in the time series. We selected 2006 as a basis of the weights because coverage was the largest in that year. A disadvantage of using 2006 weights instead of changing weights is that it decreases comparability with KSH data.

Regional disaggregation was made at two levels: at county-level, including 19 counties and the capital city, Budapest; and at regional level, including the seven NUTS-2 regions of Hungary.

3. Methodology

3.1. Time-varying coefficient methods

There are various methods to measure inflation persistence (see for example Dossche and Everaert 2005 and Altissimo et al. 2006), nevertheless, estimations suggest a certain degree of uncertainty since the use of different methods resulted different degrees of inflation persistence. Using univariate autoregressive time series models, authors found very high degree of persistence, while those who studied the estimated autoregressive models for sub-periods identified by the break points found significantly smaller persistence (see Darvas and Varga, 2007). There is a growing empirical literature in support of the notion that inflation persistence could be changing in time (see Gadzinski and Orlandi, 2004) which implies that it

³ Agents of the KSH can impute prices for at most two consecutive months, when for some reason they cannot observe temporarily the price of the required product in the required outlet. Imputed prices are not actually observed prices and therefore should be treated differently.

is reasonable to use time-varying coefficient methods to study the persistence of inflation. Darvas and Varga (2007) argue that the new member states of the EU (including Hungary) went through substantial structural changes during the transition period and are still changing in a faster pace than mature economies. For this reason, they stress that one cannot assume constant parameters concerning inflationary processes.

In this paper, we apply the methods of Darvas and Varga (2007) for the data set described in Section 2.⁴ The standard approaches in the literature measure inflation persistence in a single number which holds for the whole period and cannot say anything about the dynamics of the parameters. The authors compared the properties of two time-varying coefficient methods, (i) the maximum likelihood estimation of a state-space representation of the unobserved components models where the likelihood function was evaluated with the Kalman filter (Kalman 1960), and (ii) the distribution-free estimator of the same model via Flexible Least Squares (FLS) introduced by Kalaba and Tesfatsion (1988, 1989, 1990). An important difference between the two procedures is that while the FLS approach is distribution-free, Kalman filtering needs certain assumptions concerning the distribution of the innovations (e.g. normal distribution) and independence. A disadvantageous feature of the FLS estimator is, however, that it provides only point estimations while Kalman filter determines confidence intervals, as well.⁵

According to the widely-used procedures in the literature, we assume a first-order autoregressive process for inflation persistence:

$$\pi_{t,i} = \beta_{0,t,i} + \beta_{1,t,i} \cdot \pi_{t-1,i} + u_{t,i} \quad t = 1, \dots, T \text{ and } i=1, \dots, n, \quad (1)$$

where $\pi_{t,i}$ is the rate of inflation at time t and region (county) i , $\beta_{0,t,i}$ and $\beta_{1,t,i}$ are region (county) specific time-varying coefficients and $u_{t,i}$ denotes error terms. $T = 65$ and n can be 7 or 20 depending on the territorial units we choose to analyse (regions or counties). Our task is to give estimations for the sequences of the time-varying constant parameters and the time-varying first-order autoregressive parameters of the model. Traditional ordinary least squares (OLS) techniques are not suitable for estimating this model since we have to find time-varying coefficient sequences.

To apply the FLS algorithm, two main assumptions have to be made. The first one states that the residual errors of the estimation are small, that is,

⁴ Since the time series exhibit seasonality, first we carried out a seasonal adjustment procedure where seasonal effect is represented by the month averages (month-dummies) which were extracted from the individual observations and then the average of the 12 months' values were added.

⁵ For a more detailed comparison of the two approaches see Darvas and Varga (2007) and Montana et al. (2008).

$$\pi_{t,i} - (\beta_{0,t,i} + \beta_{1,t,i} \cdot \pi_{t-1,i}) \approx 0 \quad t = 1, \dots, T \text{ and } i = 1, \dots, n. \quad (2)$$

The second one states that the coefficients evolve slowly over time:

$$\beta_{o,t+1,i} - \beta_{o,t,i} \approx 0 \quad t = 1, \dots, T-1 \text{ and } i = 1, \dots, n, \text{ for both } o = 0 \text{ and } 1 \quad (3)$$

We have to find coefficient sequence estimates which satisfy both assumptions in an acceptable manner. The idea of the FLS method is to assign two types of residual error to each possible coefficient sequence estimate. One consists of the sum of squared residual measurement errors⁶, $r_M^2(\beta_i, T)$, regarding the first assumption, and the other is the sum of squared residual dynamic errors, $r_D^2(\beta_i, T)$, regarding the second, smoothness assumption, where β_i is the 2×1 vector of the region (county) specific coefficients to be estimated for each region i .

Our objective is to simultaneously minimize the two types of errors for each possible coefficient sequences. As described in Kalaba and Tesfatsion (1988), an incompatibility cost is specified for any β_i coefficient sequence, which is the weighted sum of the two kinds of errors:

$$C(\beta_i, \mu, T) = \mu \cdot r_D^2(\beta_i, T) + r_M^2(\beta_i, T) \quad (4)$$

By minimizing the incompatibility cost for β_i , given any weighting parameter $\mu > 0$, we will have the unique FLS estimate for β_i . Consequently, this procedure results a continuum number of solutions for a given set of observations, depending on the μ parameter. If μ approaches zero, the smoothness assumption will not be taken into consideration which results that while the sum of squared measurement errors will be brought down close to zero, the sequence of estimates will be volatile. If μ becomes arbitrarily large, we consider only the dynamic error. This is equivalent to the ordinary least squares solution, since r_M^2 is minimized subject to $r_D^2 = 0$, and the parameters will be constant. Consequently, the selection of the μ parameter is a rather important issue in this procedure. Kalaba and Tesfatsion have not suggested any way to set a given (optimal) value for the weighting parameter, instead they compared the properties of various estimations computed with different parameter values. To eliminate the problem of multiple solutions, Darvas and Varga (2007) suggested a procedure which leads to a unique, “optimal” estimate based on the selection of an “optimal” weighting parameter. For this purpose, they developed an iterative algorithm.

⁶ Similarly to the ordinary least squares (OLS) method.

In this study, we compute FLS smoothed estimations with two specific μ parameters: $\mu = 10^{1.5}$ and $\mu = 10^{2.5}$, as suggested by the simulation results of Darvas and Varga (2007). The problem is a conditional minimization problem which can be solved with a dynamic programming algorithm. Kalaba and Tesfatsion suggest an estimation mechanism which is based on a recursion to get the members of the unknown sequence of parameters.⁷

3.2. Exploratory spatial data analysis

For the analysis of spatial differences, we use exploratory spatial data analysis techniques.¹¹ ESDA comprises techniques for exploring spatial data: summarizing spatial properties of the data, detecting spatial patterns in data, formulating hypotheses which refer to the geography of the data, identifying cases or subsets of cases that are unusual (outliers) concerning their location (Haining, 2007). These methods provide measures of global and local spatial autocorrelation as well as spatial heterogeneity. The concept of spatial autocorrelation refers to the coincidence of value similarity with locational similarity (Anselin, 2001). There is positive spatial autocorrelation when high or low values of a random variable tend to cluster in space and there is negative spatial autocorrelation when geographical areas tend to be surrounded by areas with very dissimilar values (Le Gallo and Ertur, 2003). Spatial heterogeneity refers to the lack of structural stability of the various phenomena over space which may generate characteristic spatial patterns of economic development under the form of spatial regimes (core and periphery) (Anselin, 1988 and Le gallo and Ertur, 2003). We measure spatial autocorrelation with the Moran's I statistic (Cliff and Ord, 1973) which is formulated as follows:

$$I = \frac{n}{\sum_{i=1}^n \sum_{j=1}^n w_{ij}} \frac{\sum_{i=1}^n \sum_{j=1}^n (x_i - \bar{x})(x_j - \bar{x})w_{ij}}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (5)$$

where $(x_i - \bar{x})(x_j - \bar{x})$ is the product of the variables' deviation from the mean, w_{ij} is the general element of the spatial weight matrix and n is the number of spatial units. The expected

⁷ Practically, standard statistical software packages not allow us to perform this, therefore we use an own Gauss code.

¹¹ The software package used in the analysis is GeoDa 0.9.5-i.

value of I is $-1/(n-1)$, which is in our case $-0,0526$ since the number of spatial units is 19. Values of I larger than $E[I]$ indicate positive spatial autocorrelation and values smaller than $E[I]$ indicate negative spatial autocorrelation. The significance test of this statistic is carried out by a randomization procedure.

The spatial weight matrix is the means of expressing spatial dependence which is an $n \times n$ matrix where w_{ij} is higher than 0 when location i and j are considered to be neighbours and is 0 otherwise, and the diagonal elements are also 0. At this stage of the analysis, we assume two kinds of contiguity matrices. The first one is a binary contiguity matrix based on 1st order neighbourhood which means that if two spatial units share a common border they considered to be contiguous and a positive value is assigned in the matrix. The other one is a binary spatial weight matrix with a distance-based critical cut-off where the neighbourhood is defined on the basis of a fixed distance¹² (Euclidean distance) which is the same for all spatial units. Since the selection of the weight matrix is a central decision in the analysis, we present the results with both types of spatial weights in each case. The most important difference between the two weight matrices is that the capital city, Budapest has only one neighbour with the 1st order contiguity-based neighbourhood definition: Pest county, and it has 6 neighbours with the distance-based neighbourhood definition.

The Moran's I statistic is a global measure of spatial autocorrelation and does not inform about the spatial structure of the neighbourhood effects. For this reason, we use „local indicators of spatial autocorrelation” (Anselin, 1995) which help us identify spatial clusters with low or high values, as well as regions with low values surrounded by high values and regions with high values surrounded by low values (i.e. spatial instability). These spatial structures can be detected by the Moran scatterplot which plots the variable's values (x_i) against the spatially lagged values (Wx_i). Each point in the Moran scatterplot corresponds to a given region, and there are four quadrants of the Moran scatterplot. In the upper right quadrant we find locations with high values surrounded by neighbours with high values (“high-high”). In the lower left quadrant we find locations with low values surrounded by neighbours with low values (“low-low”). In these two quadrants spatial association is positive. In the upper left quadrant we find locations with low values surrounded by neighbours with high values (“low-high”), while in the lower right quadrants we find locations with high values surrounded by neighbours with low values (“high-low”). In these two quadrants spatial association is negative. The significance of the spatial clustering can be

¹² Distances are calculated between region centroids.

investigated by the local version of Moran's I statistic for each region i and year t ($I_{i,t}$). A positive value for $I_{i,t}$ indicates spatial clustering of similar values (high or low) whereas a negative value indicates spatial clustering of dissimilar values between a region and its neighbours (see Anselin, 1995 and Le Gallo and Ertur, 2003). Here, significance means that similar values are not randomly centered in certain locations, but there is a system behind the given spatial structure (Anselin, 1995).¹³

4. Results

In this section, we present the region-specific inflation persistence parameter series ($\beta_{1,i}$) and analyse their deviations from the county-level parameter series which is used as benchmark. To draw a more complete picture, we compare the dynamics of inflation persistence to the results presented by Reiff and Zsibók (2007) for the spatial differences of inflation and price levels. Additionally, we carry out a descriptive analysis of the local and global indicators of spatial autocorrelation.

4.1. Inflation rates

Monthly inflation rates were highly volatile in the sample period at the country-level. As depicted in Figure 1, it varied between -0.8 percent and 1.94 percent with a standard deviation of 0.48 percentage points. The data show seasonal fluctuations where local maximum points are in January each year, excepting 2006 (the highest monthly inflation rates were measured in May and June this year).

¹³ Alternatively, spatial clusters can be identified by the Ord and Getis (1995) statistic which, however, cannot study spatial instability (outliers).

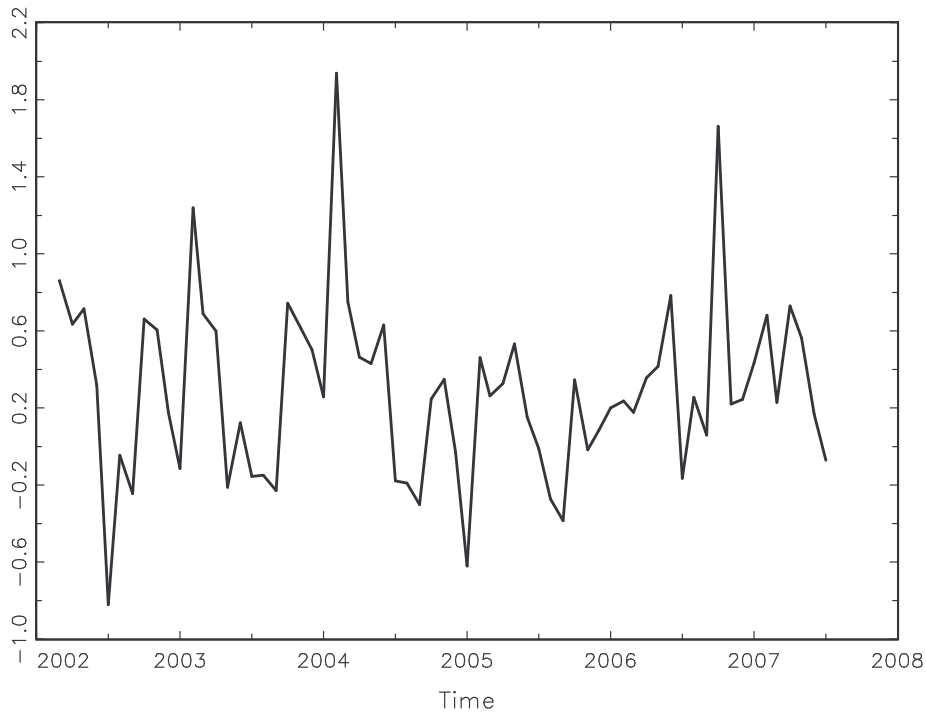


Figure 1. Country-level monthly inflation rates between January 2002 and June 2007 (percentages). Source: Authors' compilation from KSH data.

We can take a look at spatial differences by studying the cross-sectional standard deviation of regional-level monthly inflation rates (Figure 10 in the Appendix). The highest differences are measured in December and January each year, while the variation is relatively high in June and July each year, as well as in September 2006. The cross-sectional standard deviation varied between 0.05 and 0.46 percentage points in the sample period.

Average monthly inflation rates for the whole sample period on the NUTS-2 level are depicted on Figure 11 in the Appendix. Global spatial autocorrelation, measured by the Moran's I statistic, did not prove significant for the whole period, however, in 11 out of 66 months (16.67%) it was significant at the 5 percent pseudo-significance level with the distance-based weights (in 8 out of 66 months, 12.12%, with the 1st order contiguity-based weights). The values of Moran's I did not show a clear tendency and were highly volatile if we used monthly inflation rates. Nevertheless, they had similar values with the two kinds of weight matrices, excepting June 2003 where this statistic indicated a positive global spatial autocorrelation ($p = 0.09$) with the 1st order contiguity-based weight matrix, and a negative global spatial autocorrelation ($p = 0.06$) with the distance-based weight matrix. The highest negative spatial autocorrelation was measured in August 2004 (Moran's $I = -0.2986$ with the 1st order contiguity weight matrix, or -0.2917 with the Euclidean distance-based weight matrix) and the highest positive spatial autocorrelation was measured in May 2006 (Moran's I

= 0.2627 with the 1st order contiguity weight matrix, or 0.2785 with the Euclidean distance-based weight matrix). On Figure 12 and 13 in the Appendix, we compared the values of the Moran's *I* statistic to the original data set and to the cross-sectional standard deviation of monthly inflation rates, respectively.

Tests of the local spatial autocorrelation for the whole period were significant in two cases: in Szabolcs-Szatmár-Bereg county at 1 percent level (low-high quadrant), and in Bács-Kiskun County at 5 percent level (high-low quadrant). We found significant spatial clustering of low values in 41 cases and significant spatial clustering of high values in 31 cases with the distance-based weights (in 30 and 33 cases, respectively, with the 1st order contiguity-based weights). Spatial instability was more common, we found significant values in the low-high quadrant in 42 cases and significant values in the high-low quadrant in 28 cases with the distance-based weights (in 43 and 39 cases, respectively, with the 1st order contiguity-based weights). For monthly inflation rates, the indicators of local spatial autocorrelation did not show a clear picture, therefore it would be hard to interpret these results at this stage of the analysis.

Moran's *I* statistics are less volatile for yearly inflation rates (see Figure 14–15 in the Appendix) and the values are rather similar for the two different weight matrices. These statistics were significant at the 5 percent pseudo-significance level in only 5 and 4 out of 54 months (0.074% and 0.093%) with the distance-based and the 1st order contiguity-based weight matrices, respectively. The highest negative spatial autocorrelation was measured in February 2007 ($I = -0.2672$, with distance-based contiguity) and the highest positive spatial autocorrelation was measured in November 2005 ($I = 0.2360$, with distance-based contiguity). For yearly inflation rates, local spatial autocorrelation was significant for Szabolcs-Szatmár-Bereg county, however, with an opposite sign as in the case of monthly inflation rates (high-high quadrant), and also for Bács-Kiskun and Pest counties (high-low quadrant). The results are much clearer than in the case of monthly frequency data. We found significant spatial clustering of low values in 46 cases and significant spatial clustering of high values in 34 cases with the distance-based weights (in 31 and 37 cases, respectively, with the 1st order contiguity-based weights). We found values in the low-high quadrant in 13 cases, and in the high-low quadrant in 22 cases with the distance-based weights (in 20 and 21 cases, respectively, with the 1st order contiguity-based weights). In more details, Budapest and Pest County had similar results to each other: they were at the low-low quadrant at the first 6 months of the year 2003, after it, they moved to the high-low quadrant at the end of this year. Later, much less significant values were found for these two counties. For Baranya County we

found significant values in the first half of 2003 in the high-high quadrant. Significant clustering of low values were found for Bács-Kiskun County, Borsod-Abaúj-Zemplén County, Csongrád County and Nógrád County. Szabolcs-Szatmár-Bereg County was in the high-high quadrant until March 2005, after it, it moved to the low-high quadrant of the Moran scatterplot. See Figure 2 in support of these findings.

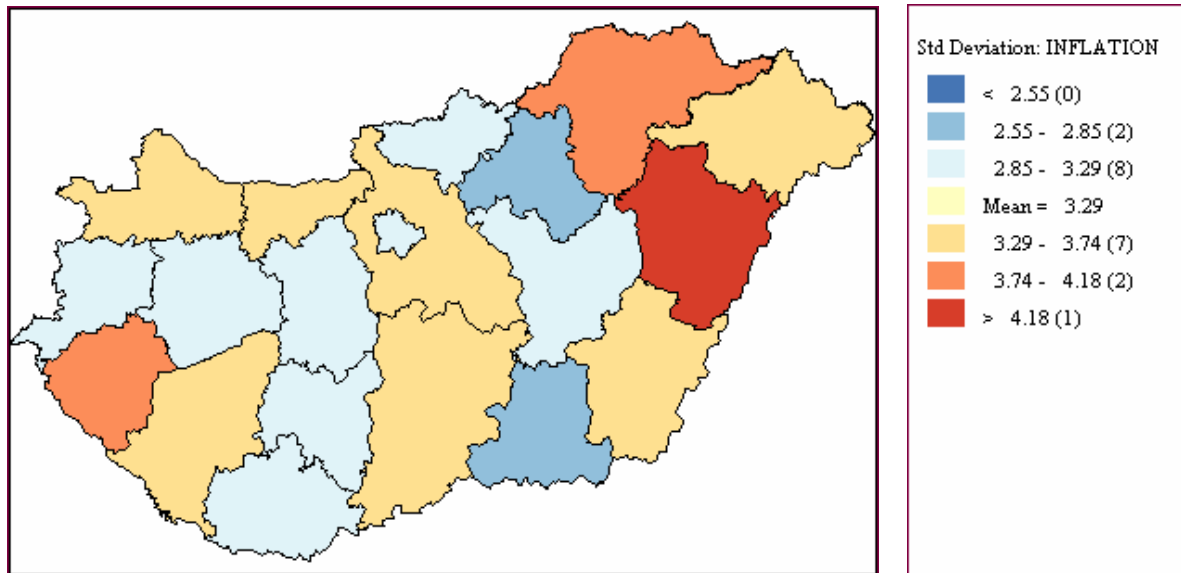


Figure 2. Average county-level yearly inflation rates between January 2003 and June 2007 (percentages). Source: Authors' compilation from KSH data.

4.2. Price levels

The presented findings raise the question of whether spatial differences in inflation rates can be explained by spatial price level convergence. If this were the case, inflation were higher in regions with relatively lower initial price levels than in regions with relatively higher initial price levels. This would cause price levels to approximate each other during the period. To investigate this question, we depict the deviation of regional-level prices from the country-level where country level is represented by 0 (Figure 3).

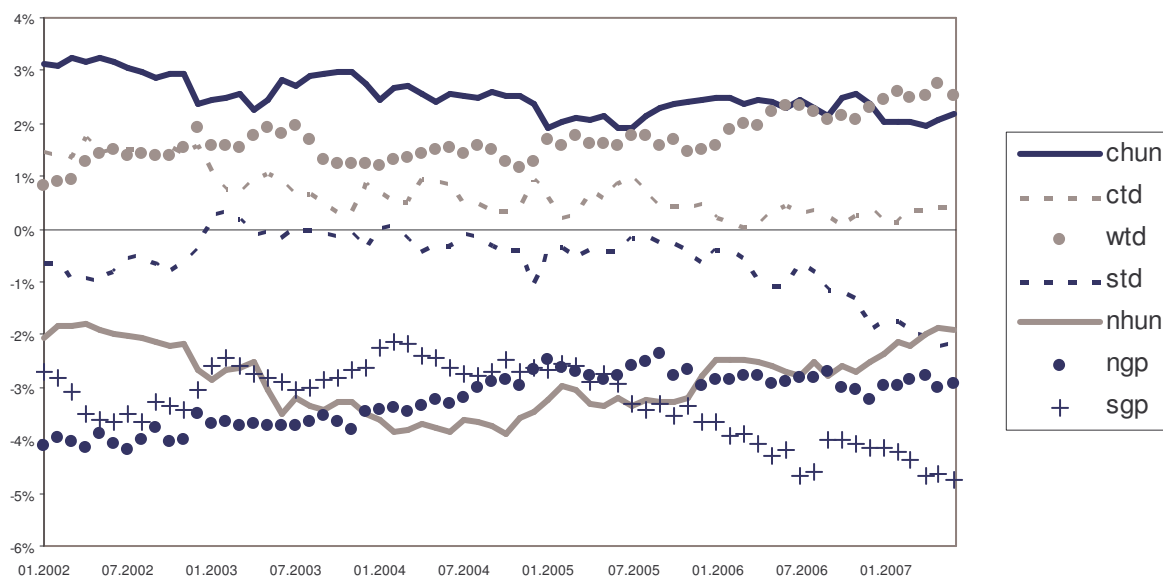


Figure 3. Regional-level relative prices (percentages). Source: Authors' compilation from KSH data.

Notes: chun: Central Hungary, ctd: Central Transdanubia, wtd: West Transdanubia, std: South Transdanubia, nhun: Northern Hungary, ngp: Northern Great Plain, sgp: Southern Great plain

It is clear from Figure 3 that the relative price levels and the spatial differences can be regarded more or less stable during the sample period. The cross-sectional standard deviation of the relative prices support this finding (see Figure 16 in Appendix), since it does not show a clear decreasing tendency which implies that the spatial differences have not decreased during the period.

The Moran's I statistic indicates positive spatial autocorrelation of the relative prices which was significant at the 5 percent pseudo-significance level in 49 out of 66 months (74.24%) with the 1st order contiguity-based weight matrix, however, in only 11 months (16.67%) with the distance-based weight matrix. Though Moran's I statistics are similar concerning the direction of their change, the values computed with the 1st order contiguity-based weight matrix exceed the values computed with the distance-based weights in each month. The differences were relatively high in 2003 and 2004 and decreased after that period. The highest level of global spatial autocorrelation was measured in July 2006 (Moran's $I = 0.2987$ with the 1st order contiguity-based weights) and in June 2007 (Moran's $I = 0.2641$ with the distance-based weights). The values were relatively high until August 2003, then stabilised at a relatively lower level until April 2005 while after that period they began to increase. (See Figure 16 in the Appendix.)

By investigating the local indicators of spatial autocorrelation we found significant clustering of high values in the case of Komárom which was significant in each month and in Győr-

Moson-Sopron, Vas and Veszprém. Significant clustering of low values was found in Békés, Csongrád and Hajdú-Bihar counties. In Budapest, we found significant values in the high-low quadrant in 22 months. These results indicate that high relative price levels are significantly clustered in the northwestern part of Hungary while low relative price levels are significantly clustered in the southeastern part of Hungary. Budapest with a high relative price level is surrounded by counties with generally low relative price levels (Figure 4).

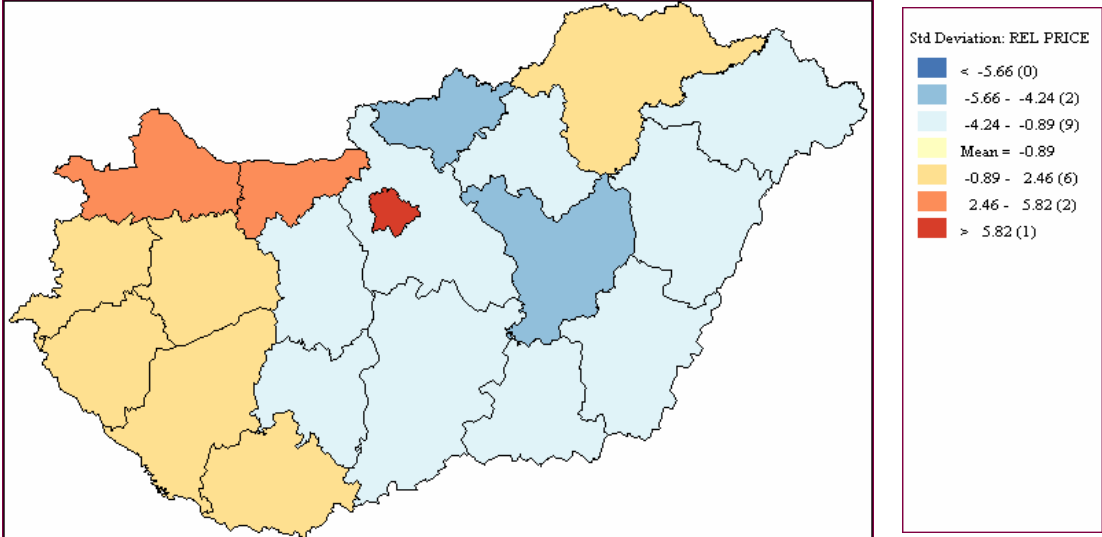


Figure 4. Average relative price levels between 2002-2007 (percentages). Source: Authors' compilation from KSH data.

4.3. Inflation persistence

Figure 5 shows the country-level inflation persistence computed from monthly data with different estimation methods. OLS estimates yielded a parameter value of 0.23. This method assigns a single parameter value to the whole sample period and cannot reflect the shifts in inflation persistence. The results of each time-varying coefficient estimation methods indicate that inflation persistence have decreased in the observation period.¹⁴ This means, that although inflation have generally risen, the influence of previous periods declined. This may refer to the phenomenon that agents are basically forward-looking, and generally anticipate future changes.

As described in Section 3, we compute FLS estimations with two different weighting parameters. With $\mu = 10^{1.5}$, the country-level estimated values declined from 0.33 to -0.06 , so this method, in contrast to other methods, yielded even negative AR(1) parameters in the

¹⁴ In this study, we focus on the results of the FLS estimation, while results yielded from Kalman filtering and Kalman smoothing are presented only for comparison.

period after January 2006. Setting $\mu = 10^{2.5}$ gives a much smoother, though continuously declining trend, where inflation persistence declined from 0.26 to 0.16.

The dynamic pattern of inflation persistence changed during the period, since it declined in a relatively fast pace before April 2003, then it declined much more slowly and it declined steeply until June 2006 which is followed by a more stable period.

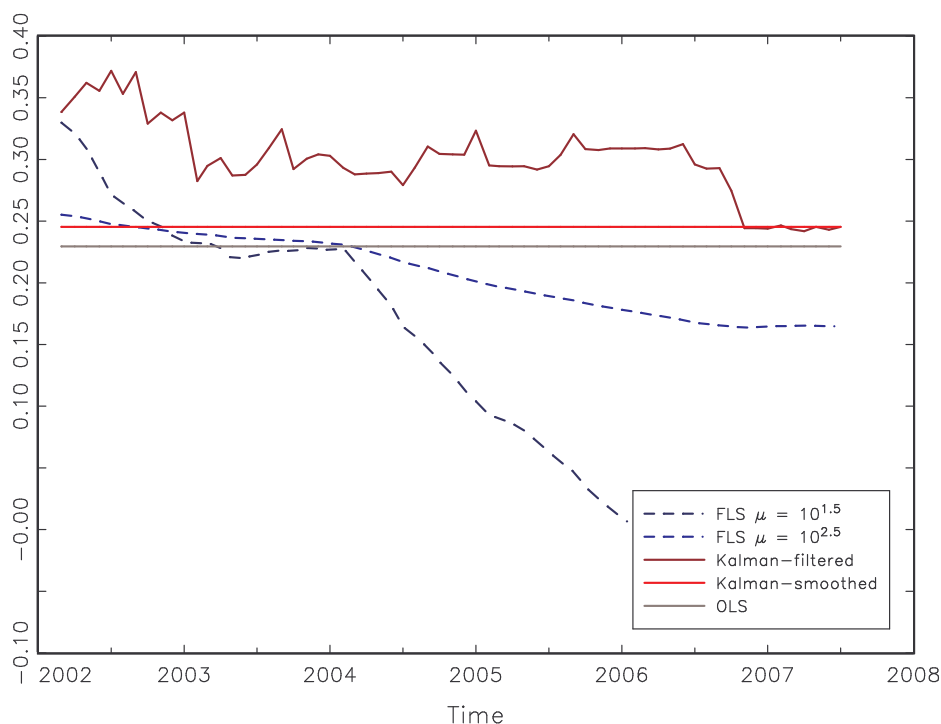


Figure 5. Estimated AR (1) parameters of the country-level monthly inflation series. Source: Authors' compilation from KSH data.

Note that with Kalman filtering, we can estimate confidence intervals around the parameter values. These confidence intervals are relatively wide which suggests that we cannot state that persistence declined significantly. (Details are presented in Figure 22 in the Appendix.)

In what follows, we investigate spatial differences in inflation persistence (Figures 6a and 6b). Similarly to the patterns of price levels, spatial differences are relatively large and stable in time in Hungary. This is even more characteristic of the FLS estimation with $\mu = 10^{2.5}$, since parameter estimations are less volatile in time. Our general findings are more or less reflected by the results obtained at the level of the individual regions, too, however, temporal differences are high. In Central Transdanubia, inflation persistence exceeds the country-level persistence during the whole period, and with $\mu = 10^{2.5}$, it is the highest between the regions. With $\mu = 10^{1.5}$, it is also the highest in the first 42 months of the period. Similar tendencies can be found in South Transdanubia, however, with an opposite sign, since persistence is

below the country level during the whole period. With $\mu = 10^{2.5}$, persistence is the lowest between the regions, and with $\mu = 10^{1.5}$, it is the lowest in the last 48 months of the period. South Transdanubia is the only region where we obtained negative AR (1) parameters with $\mu = 10^{2.5}$, and, with $\mu = 10^{1.5}$, persistence becomes negative in this region long before the other regions (in March 2004).

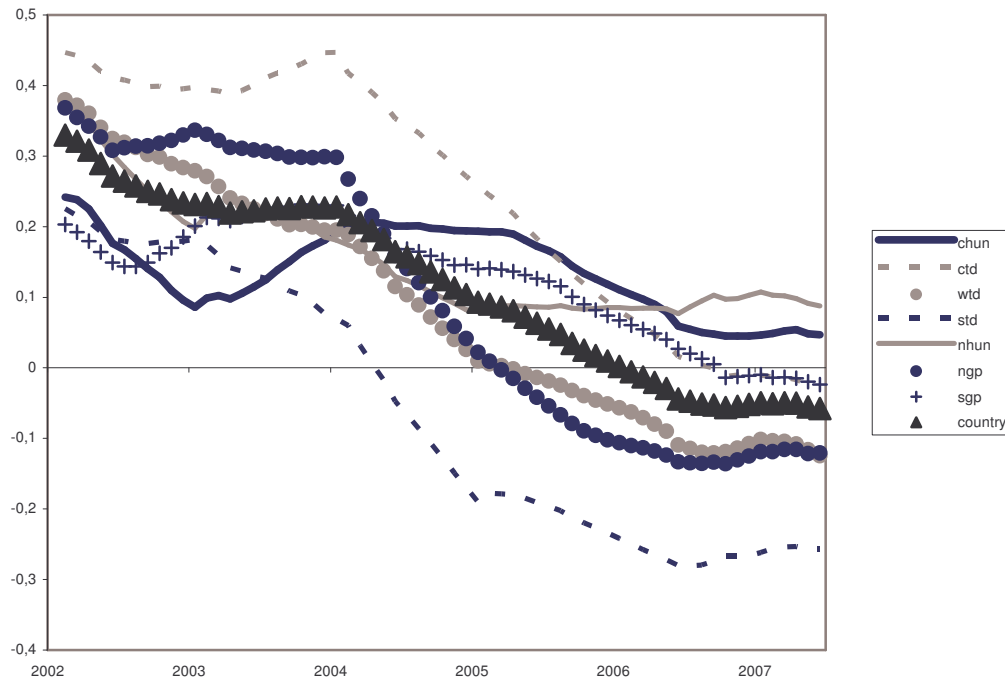


Figure 6a. Estimated AR (1) parameters of the regional-level monthly inflation series with FLS method ($\mu = 10^{1.5}$). Source: Authors' compilation from KSH data.

Notes: chun: Central Hungary, ctd: Central Transdanubia, wtd: West Transdanubia, std: South Transdanubia, nhun: Northern Hungary, ngp: Northern Great Plain, sgp: Southern Great plain

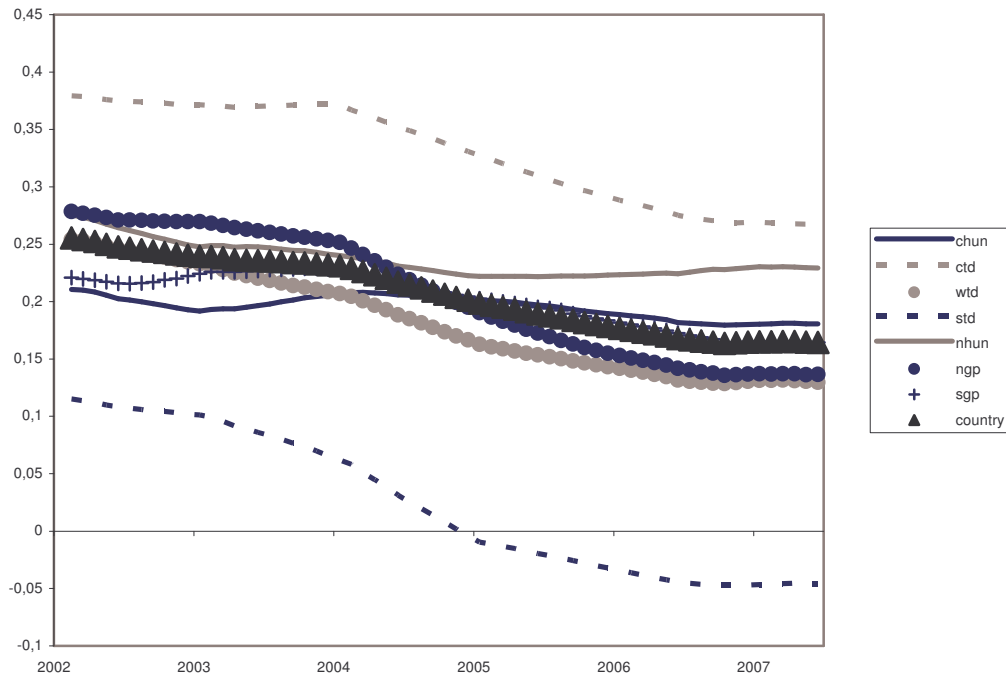


Figure 6b. Estimated AR (1) parameters of the regional-level monthly inflation series with FLS method ($\mu = 10^{2.5}$). Source: Authors' compilation from KSH data.

Notes: chun: Central Hungary, ctd: Central Transdanubia, wtd: West Transdanubia, std: South Transdanubia, nhun: Northern Hungary, ngp: Northern Great Plain, sgp: Southern Great plain

Figure 7 indicates the cross-sectional standard deviation of the estimated inflation persistence parameters. With higher μ , the variation has lower values and, similarly to the parameter values, it is less volatile in time. The lowest cross-sectional standard deviation values were measured at the beginning of the sample period: 0.088 (with $\mu = 10^{1.5}$) and 0.074 ($\mu = 10^{2.5}$). The highest values of the cross-sectional standard deviation were 0.136 (with $\mu = 10^{1.5}$), measured in January 2005, and 0.093 (with $\mu = 10^{2.5}$), measured in August 2006. Increased spatial differences can be assumed by the end of the sample period, even though a somewhat decreasing tendency can be seen after January 2005. We could not find such clear tendencies neither in the case of relative price levels, nor in the case of inflation concerning temporal changes of spatial differences. Relative prices, with some exceptions, seem to be relatively constant in time, as well as spatial differences. Concerning inflation, its rate and the spatial differences are not stable in time, however, we cannot discover any clear tendency, therefore we cannot claim anything about their long-run direction.

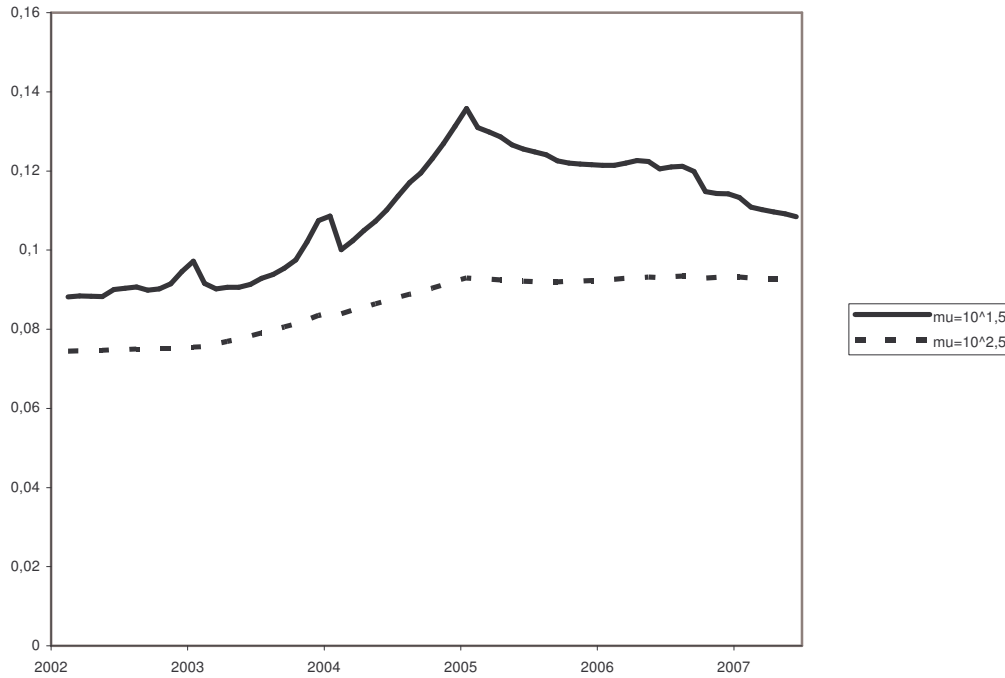


Figure 7. Cross-sectional standard deviation of the AR (1) parameter of the regional-level monthly inflation series estimated with FLS method. Source: Authors' compilation from KSH data.

Global spatial autocorrelation was significant at the 5% pseudo-significance level only in 6 out of 65 months (9.23%) with the distance-based weights, and was not significant in any cases with the 1st order contiguity-based weights concerning the AR(1) parameter of the inflation series with $\mu = 10^{1.5}$. The values of the Moran's *I* statistic computed with the distance-based weights were, in almost all cases, above the values computed with the 1st order contiguity-based weights. The highest values were measured in January 2003 ($I = 0.201$) and between August 2004 and December 2004 ($I = 0.2069$). It continuously increased after the beginning of the sample period until January 2003, as well as between January 2004 and December 2004, while it decreased between February 2003 and December 2003, and from January 2005.

For the AR(1) parameter of the inflation series computed with $\mu = 10^{2.5}$, the differences between the results with the two types of weight matrices were even more pronounced, and the deviations seem quite stable. The Moran's *I* statistic was not significant at the 5% and at the 10% pseudo-significance level, at all. With the distance-based weights, it was positive for the whole period and varied between 0.047 and 0.11. The dynamic patterns are similar in the case of the 1st order contiguity-based weights, however, at lower values: Moran's *I* statistic varied between -0.017 and 0.055. Global spatial autocorrelation tended to continuously

decline during the whole sample period, excepting the period between January 2004 and January 2005 in which it rose (see Figure 17–20 in the Appendix).

For the FLS estimation of the AR (1) parameters of the inflation series with $\mu = 10^{1.5}$, significant local spatial autocorrelation was measured for 9 out of the 20 counties. Until February 2003, significant spatial clustering of high persistence values was present in Vas, Veszprém and Zala counties (the western part of Hungary). In the second half of the year 2002, Jász-Nagykun-Szolnok County was in the high-low quadrant of the Moran scatterplot, then, in January and February 2003 it moved to the low-low quadrant. Significant clustering of high values were measured in Komárom-Esztergom County from November 2003 until October 2005, in Fejér County from April 2004 to July 2006, in Nógrád County from November 2005 till the end of the sample period and in Győr-Moson-Sopron County in the first 3 months of 2003 (these counties are quite near to the capital city and/or to the western border of Hungary). As inflation persistence started to sink, Komárom-Esztergom County moved to the low-high quadrant between November 2005 and March 2006. From June 2006 till the end of the sample period, Jász-Nagykun-Szolnok County was in the low-high quadrant.

If we used $\mu = 10^{2.5}$, local spatial autocorrelation was significant only in two counties. Significant local clustering of high inflation persistence was measured in Komárom-Esztergom County between the beginning of the sample period and July 2005, and in Fejér County between November 2003 and July 2005, and again from May 2006 till the end of the sample period. Komárom-Esztergom County moved to the low-high quadrant after May 2006. (See Figure 8a and 8b.)

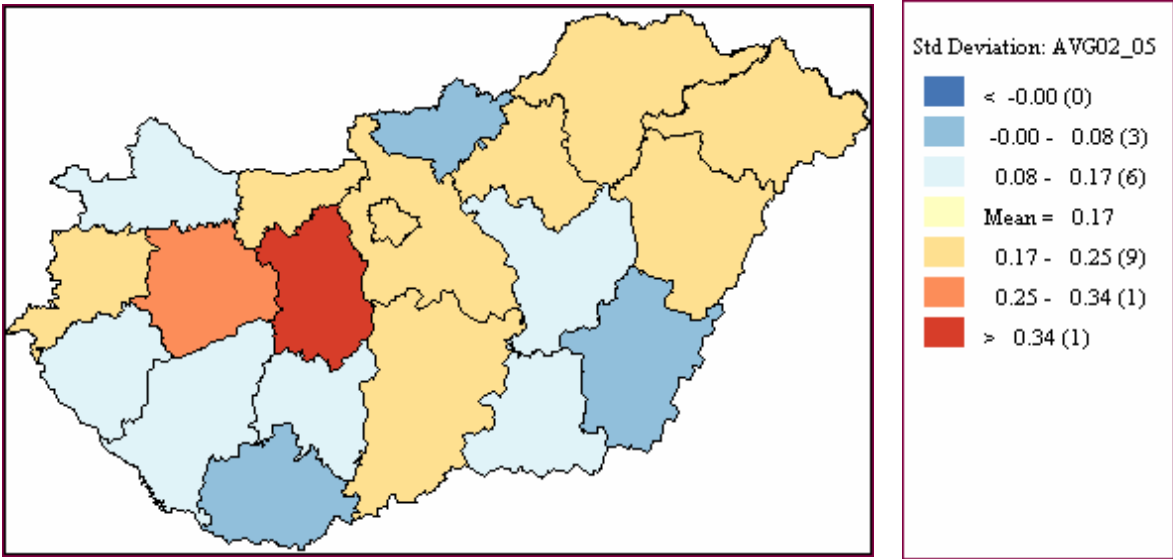


Figure 8a. Average values of the AR(1) parameter of the inflation series ($\mu = 10^{2.5}$) between February 2002 and July 2005. Source: Authors' compilation from KSH data.

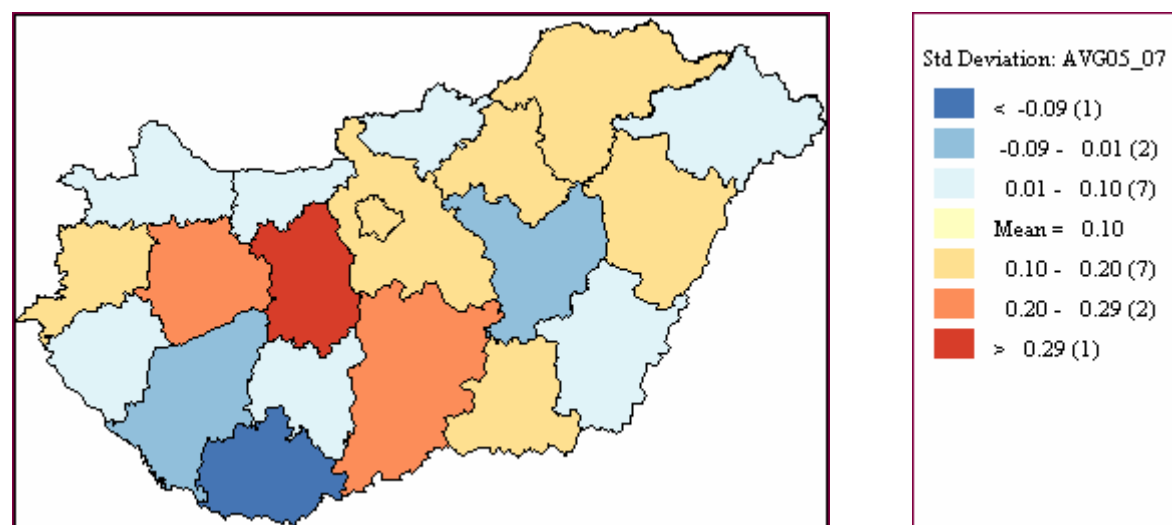


Figure 8b. Average values of the AR(1) parameter of the inflation series ($\mu = 10^{2.5}$) between August 2005 and June 2007. Source: Authors' compilation from KSH data.

We examined whether there is a co-movement between the regional-level series and the country-level series by using correlation coefficients. The results are presented in Table 1.

Region	Central Hungary	Central Transd.	West Transd.	South Transd.	North Hungary	North Great P.	South Great P.
$\mu = 10^{1.5}$	0.5285 (4.9415)	0.9233 (19.0818)	0.7720 (9.6408)	0.5449 (5.1574)	0.4892 (4.4525)	0.7223 (8.2901)	0.6747 (7.2562)
$\mu = 10^{2.5}$	0.4101 (3.5687)	0.9589 (26.8327)	0.8777 (14.5347)	0.7613 (9.3207)	0.4106 (3.5739)	0.9242 (19.2086)	0.8567 (13.1836)

Table 1. Correlation coefficients between the trend filtered regional-level series and the trend filtered country-level series of inflation persistence estimated with FLS method (t values are in parenthesis). Source: Authors' compilation from KSH data.

Correlation coefficients were computed for the trend filtered series where trend filtering was conducted with the Hodrick-Prescott filter (Hodrick and Prescott 1997). The coefficients proved to be significant at conventional significance levels. The data suggests that in Central Hungary and North Hungary, inflation persistence was relatively far from the overall trend, similarly, though to a smaller extent, to South Transdanubia. A very high correlation is reported in the case of Central Transdanubia.

4.4. Sectoral analysis

We divided the CPI-basket to the following 9 categories: processed food, unprocessed food, clothing and footwear, consumer durable goods, other non-industrial goods (e.g. household goods, pharmaceutical products), services, energy (electricity, gas and other fuels), alcoholic beverages and tobacco.

Previous analyses (Reiff and Zsibók 2007) found that in the unprocessed food category there was a very high level of co-movement, which is just the opposite to what had been observed in the clothing and footwear category, where there had been high variation between county-level inflation rates during the whole period, with the calculated inflation rate being negative in most of the counties. In the consumer durable goods category the co-movement was quite strong, possibly except for Baranya County, when one can see a gradual decrease in observed inflation rates. Somewhat similar tendencies can be found for Fejér County, however, in the opposite direction. The durable goods inflation rate was typically below zero. The services category showed a very high level of variance and a slightly decreasing but high level of inflation rate in comparison to other product categories. In the category of energy, the most dominant products are petrol and gasoline, and for this reason, the co-movement was very high while there was not any clear trend in the prices. In the categories of processed food and other non-industrial goods, the co-movement was moderately strong relative to other product categories. The price changes of tobacco and alcoholic beverages were largely determined by the changes in the excise duty. While tobacco showed a very high co-movement, the cross-county variation in the inflation rate of alcoholic beverages was perhaps surprisingly large, but also decreasing.

Figure 9a and 9b indicate that the persistence of inflation was relatively stable in the clothes, the other goods, the durable goods and the services categories, and it was much volatile in the unprocessed food, the tobacco and the energy categories. The decreasing tendency which is characteristic to the estimated persistence of the overall inflation series after 2004 can be detected in the categories of unprocessed food, alcoholic beverages, tobacco, services, durable goods. Reverse tendencies can be found in the clothes, other goods, and the processed food categories, while the persistence in the energy sector was highly volatile, even in the estimations when μ was set to $10^{2.5}$.

Negative inflation persistence was measured in the clothes sector and in the durable goods sector after the beginning of 2006, and in the other goods category until the second half of 2003 (only with $\mu = 10^{1.5}$). Persistence was around zero in the processed food category, especially between 2003 and 2006. It fluctuated at a higher level in the services, alcoholic

beverages and tobacco category, and similarly in the unprocessed food category, however, it dropped to near zero (or near 0.3, with $\mu = 10^{2.5}$) by the end of 2006.

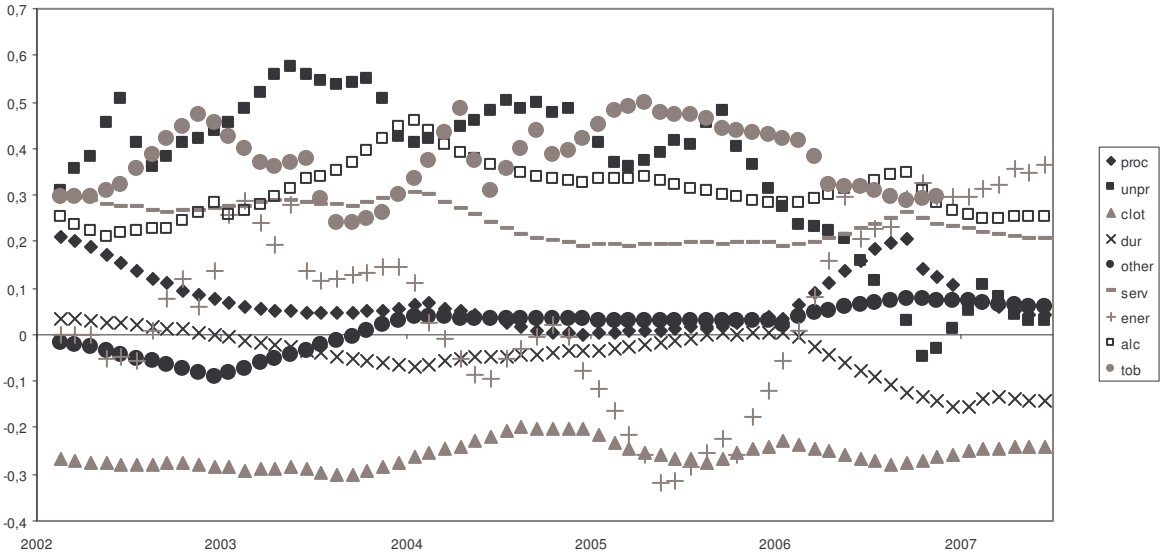


Figure 9a. FLS estimations of AR(1) parameter values by product categories ($\mu = 10^{1.5}$). Source: Authors' compilation from KSH data.

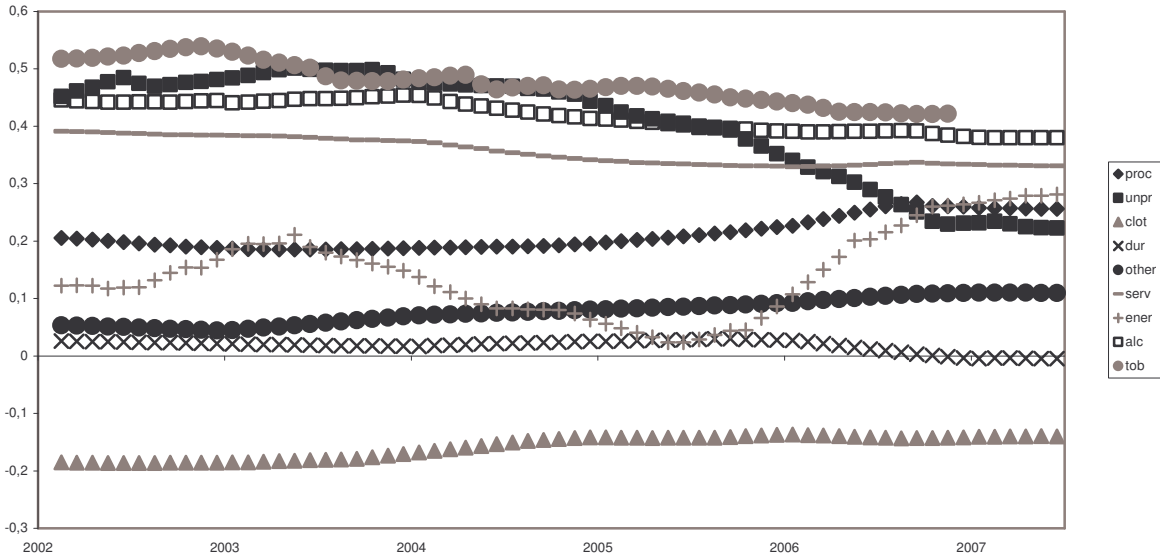


Figure 9b. FLS estimations of AR(1) parameter values by product categories ($\mu = 10^{2.5}$). Source: Authors' compilation from KSH data.

We analysed spatial differences by using the cross-sectional standard deviation (see Figure 21a and 21b in the Appendix) of the estimated AR(1) parameters. The lowest cross-sectional variation was measured in the energy sector, though it slowly increased during the sample period. Spatial differences were a bit higher, with also an increasing tendency in the unprocessed food sector. The tobacco, the services, the durable goods, the processed food and

the other goods sectors showed similar patterns to each other since spatial variation in persistence was relatively stable in time with a slightly increasing tendency at the end of the sample period. The highest spatial differences were measured in the clothes and the alcoholic beverages category, however, cross-sectional variation generally decreased.

5. Conclusion

In this study, we investigated the dynamics of inflation persistence between January 2002 and June 2007 in Hungary by using micro price data. We intended to analyse not only temporal changes but also spatial differences at the level of the 20 NUTS-3 regions of Hungary. We took a novel approach by using time-varying coefficient methods in order to investigate temporal changes. We found that inflation persistence decreased between 2002 and 2007 at the country-level and also at the regional-level. This means that inflation is less anchored in the past at the end of the sample period than before, therefore, inflation is determined by the actual innovations rather than past values. In contrast to other empirical investigations in the literature, our results indicate a quite moderate level of persistence (far below 1). These patterns could be detected in the different sectors, however, in not all of them. The spatial aspects of these phenomena were described by measures of global and local spatial autocorrelation which allowed us to investigate the neighbourhood effects. The interpretation of the results was highly dependent on the underlying series itself. For the highly erratic series of monthly inflation rates, we could not find a clear spatial structure, but for yearly inflation series, the indicator of global spatial autocorrelation evolved more smoothly. This is even more characteristic to the spatial autocorrelation indicators of the relative price levels and the inflation persistence coefficients, though the differences between the results obtained with the two kinds of weight matrices were higher.

A central element of these analyses is the selection of the spatial weight matrix. We aim to refine our research in the future by generating more sophisticated weight matrices and check the robustness of our results to the use of various different weight structures. So far, we used symmetric weight matrices, however, asymmetric spatial links can be assumed concerning the subject of our research. We think that a reasonable definition of neighbourhood connections would be determined by accessibility weights which incorporate the influence of communication between regions such as transportation links (see Anselin 1988).

The estimations of the model presented in Section 3 provided information about the constant parameters which were not analysed so far and worth future investigations.

Exploratory spatial data analysis techniques serve as a preliminary descriptive tool to look at the data prior to a more sophisticated spatial econometric formalization. This would be an obvious further direction of our research, nevertheless, a prerequisite for this is the extension of our data set with appropriate economic indicators.

Due to data limitations, the highest level of regional disaggregation is the NUTS-3 level, therefore we cannot improve the results in this respect.

Acknowledgements

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Appendix

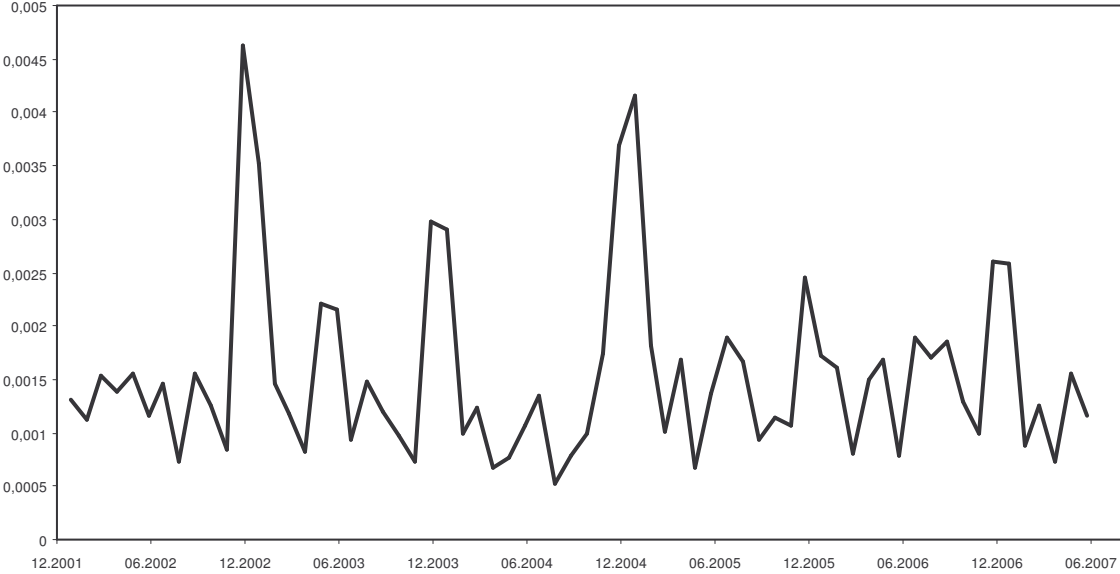


Figure 10. Cross-sectional standard deviation of regional-level monthly inflation rates (percentages). Source: Authors’ compilation from KSH data.

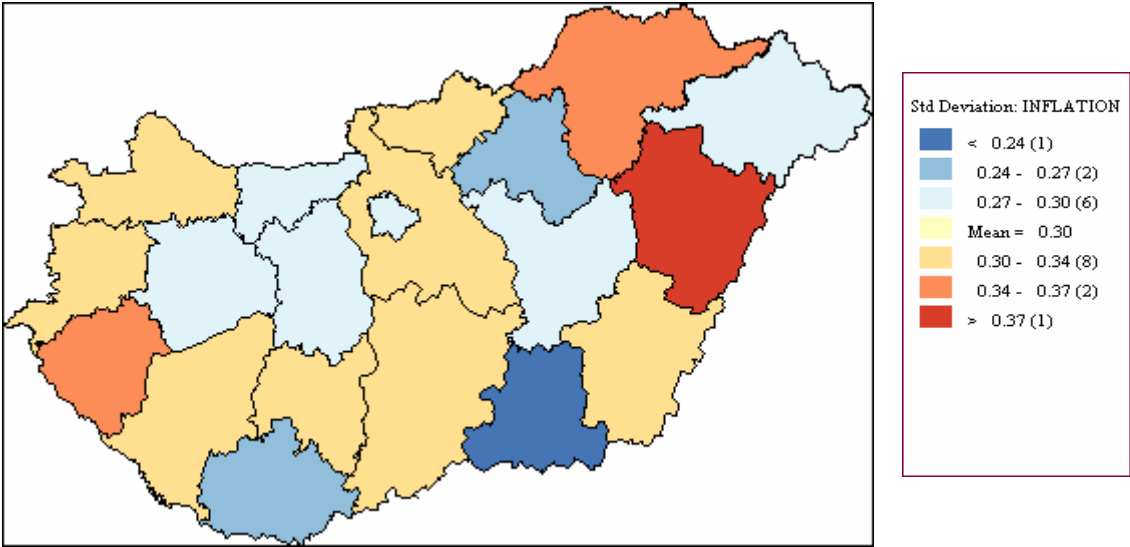


Figure 11. Average county-level monthly inflation rates between January 2002 and June 2007 (percentages). Source: Authors’ compilation from KSH data.

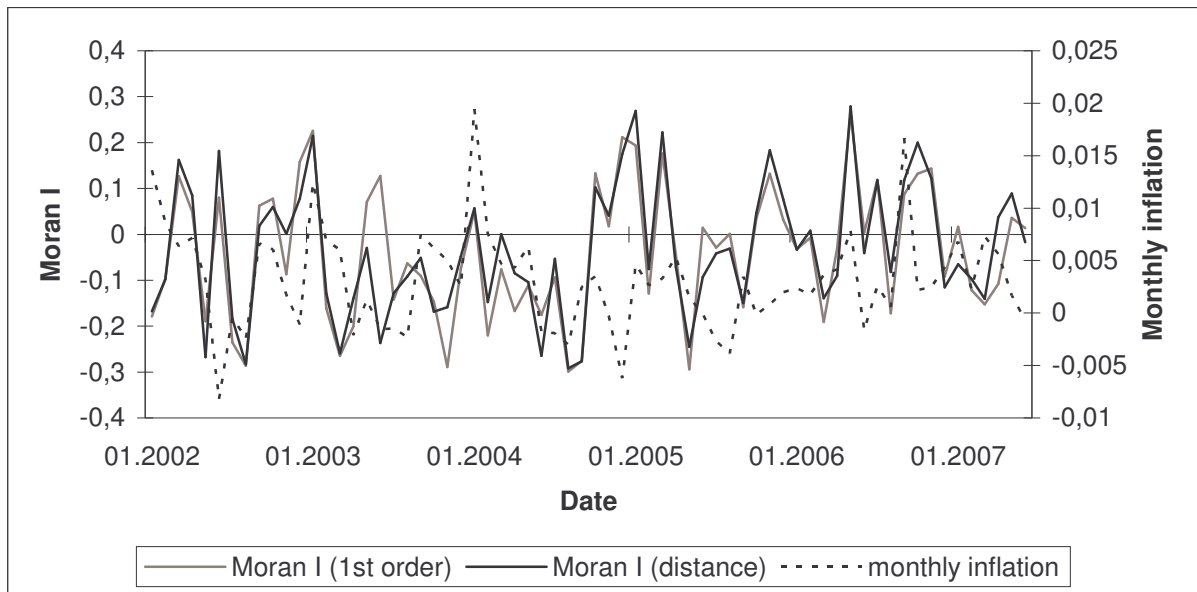


Figure 12. The co-movement of the Moran's I statistics and the monthly inflation rates. Source: Authors' compilation from KSH data.

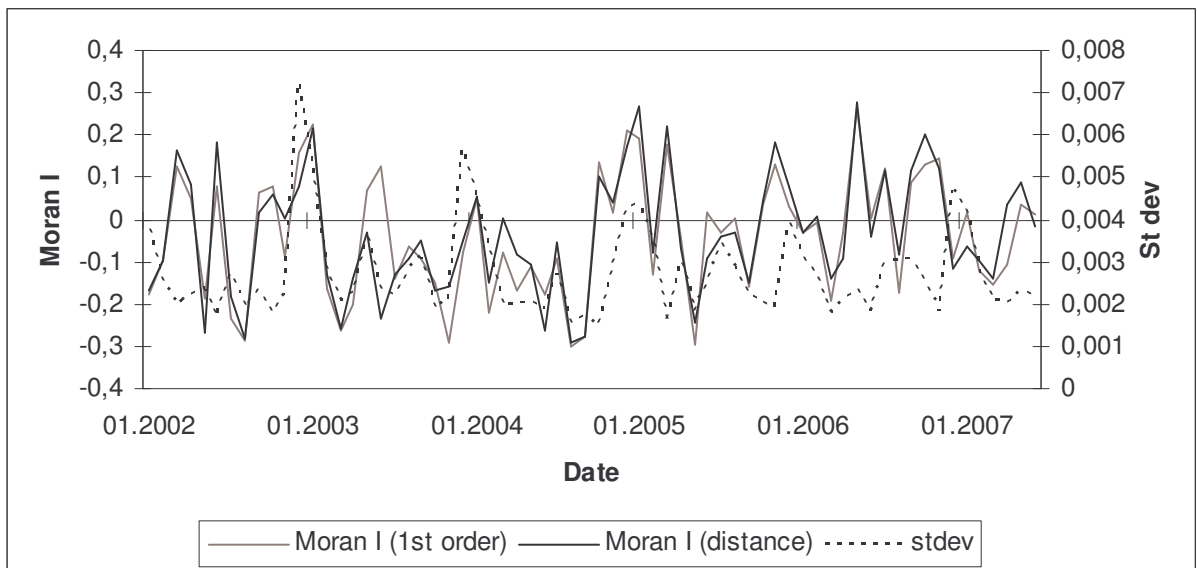


Figure 13. The co-movement of the Moran's I statistics and the standard deviation of monthly inflation rates. Source: Authors' compilation from KSH data.

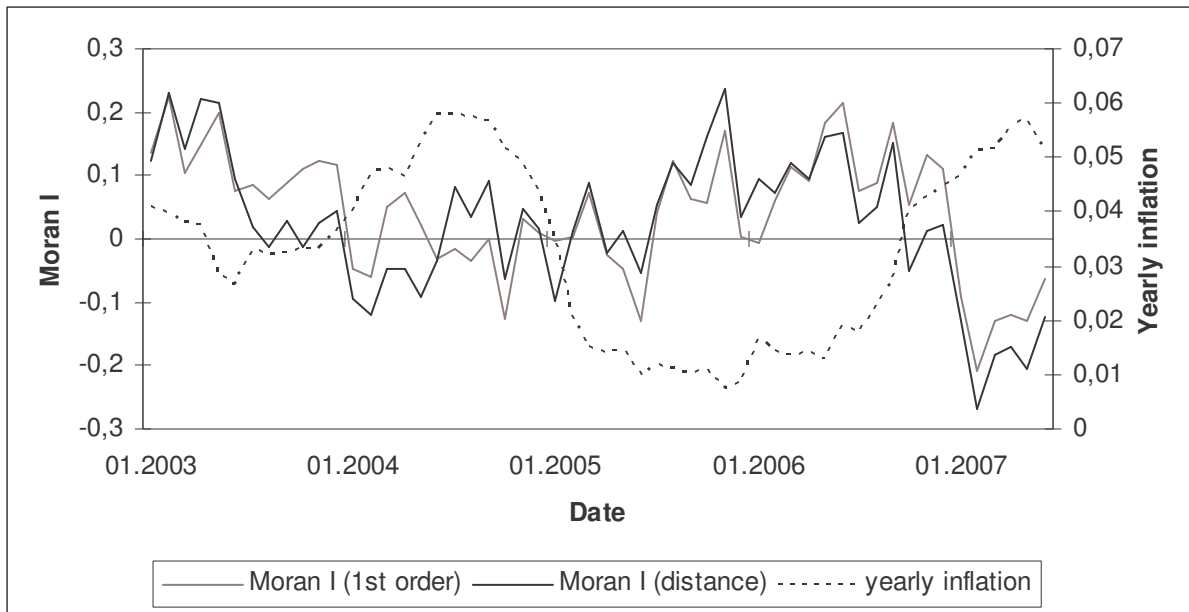


Figure 14. The co-movement of the Moran's I statistics and the yearly inflation rates. Source: Authors' compilation from KSH data.

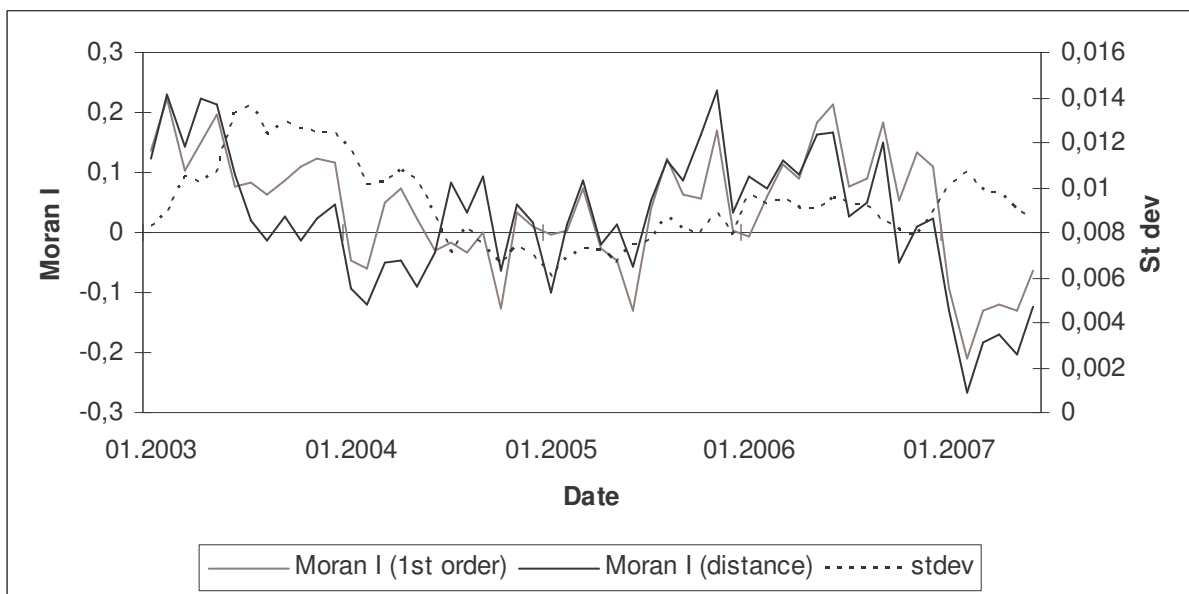


Figure 15. The co-movement of the Moran's I statistics and the standard deviation of yearly inflation rates

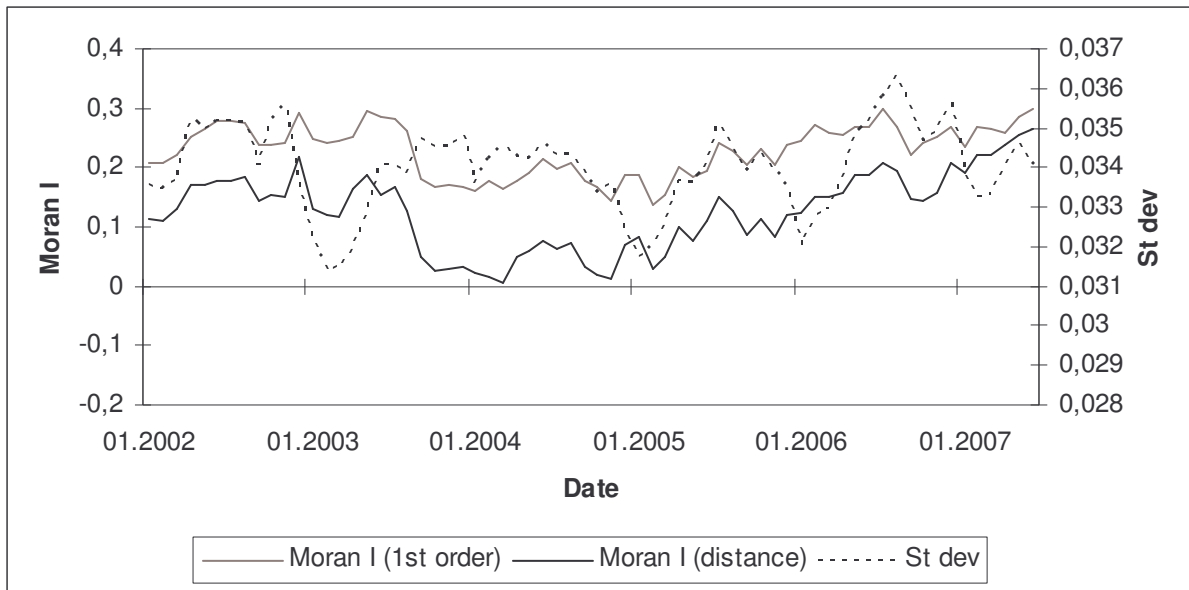


Figure 16. The co-movement of the Moran's I statistics and the standard deviation of relative price levels. Source: Authors' compilation from KSH data.

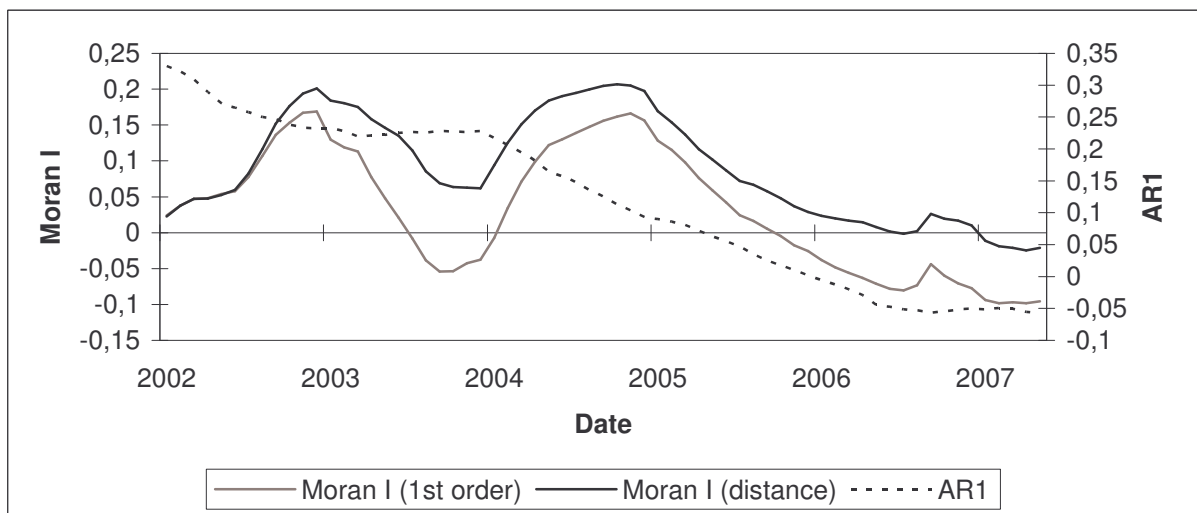


Figure 17. The co-movement of the Moran's I statistics and the AR(1) parameter of the monthly inflation series with $\mu = 10^{1.5}$. Source: Authors' compilation from KSH data.

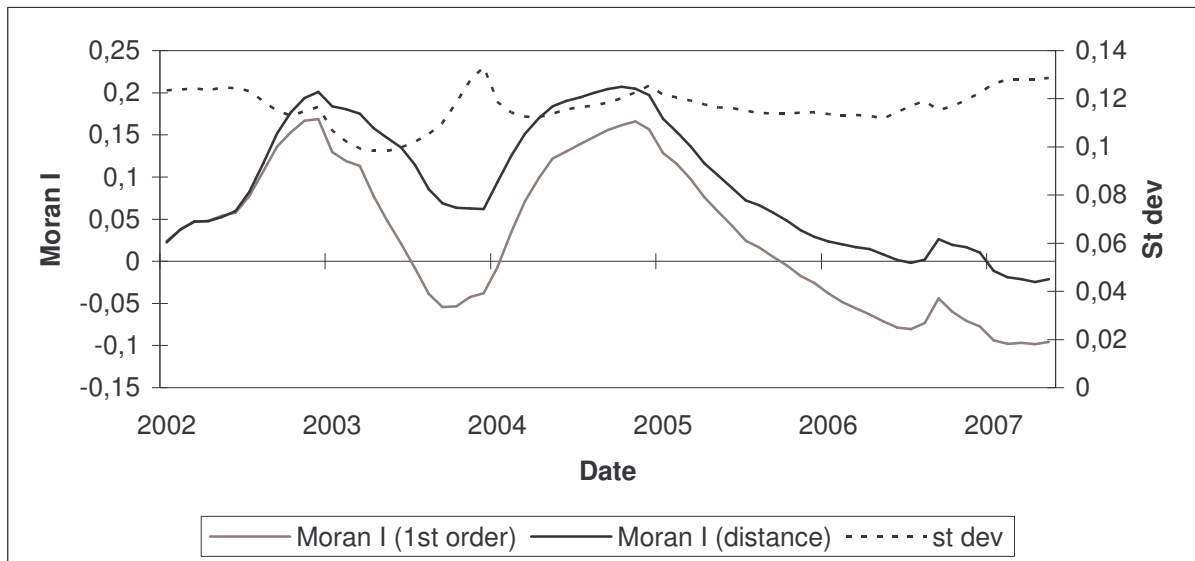


Figure 18. The co-movement of the Moran's I statistics and the standard deviation of the monthly inflation series' AR(1) parameter with $\mu = 10^{1.5}$. Source: Authors' compilation from KSH data.

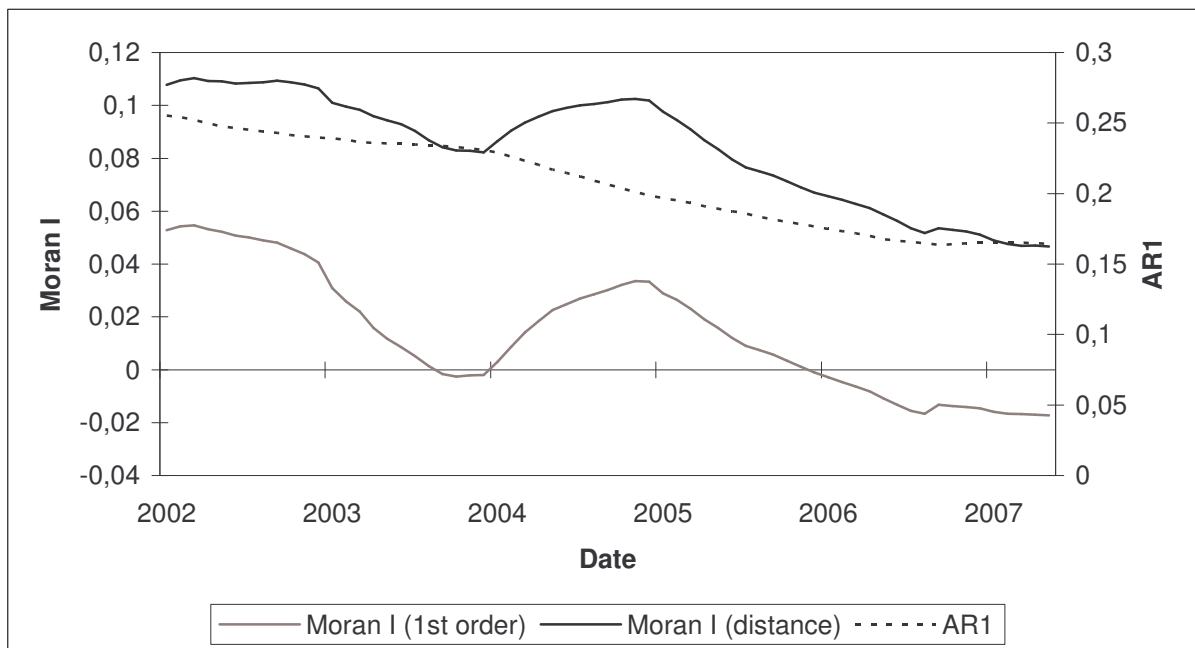


Figure 19. The co-movement of the Moran's I statistics and the AR(1) parameter of the monthly inflation series with $\mu = 10^{2.5}$. Source: Authors' compilation from KSH data.

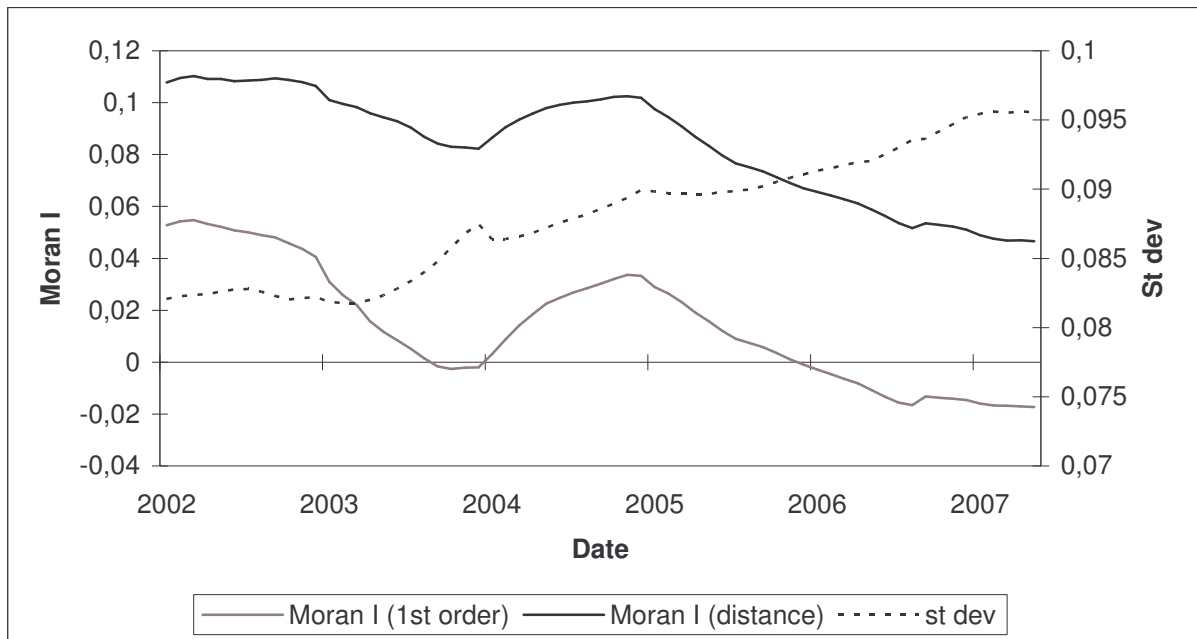


Figure 20. The co-movement of the Moran's I statistics and the standard deviation of the monthly inflation series' AR(1) parameter with $\mu = 10^{2.5}$. Source: Authors' compilation from KSH data.

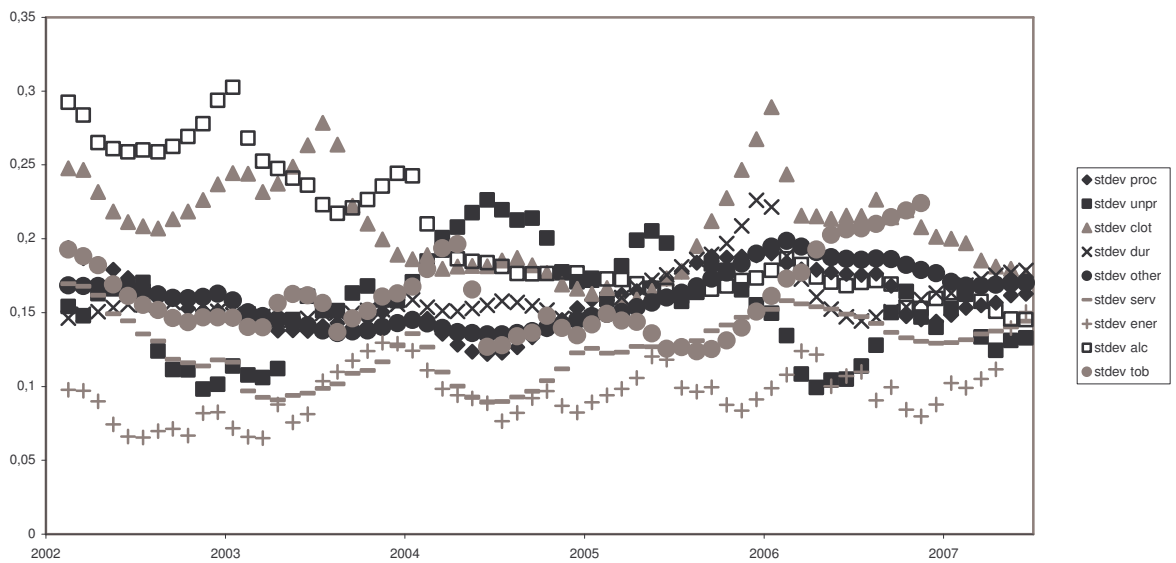


Figure 21a. Cross-sectional standard deviation of the estimated AR(1) parameters by product categories (FLS estimation, $\mu = 10^{1.5}$). Source: Authors' compilation from KSH data.

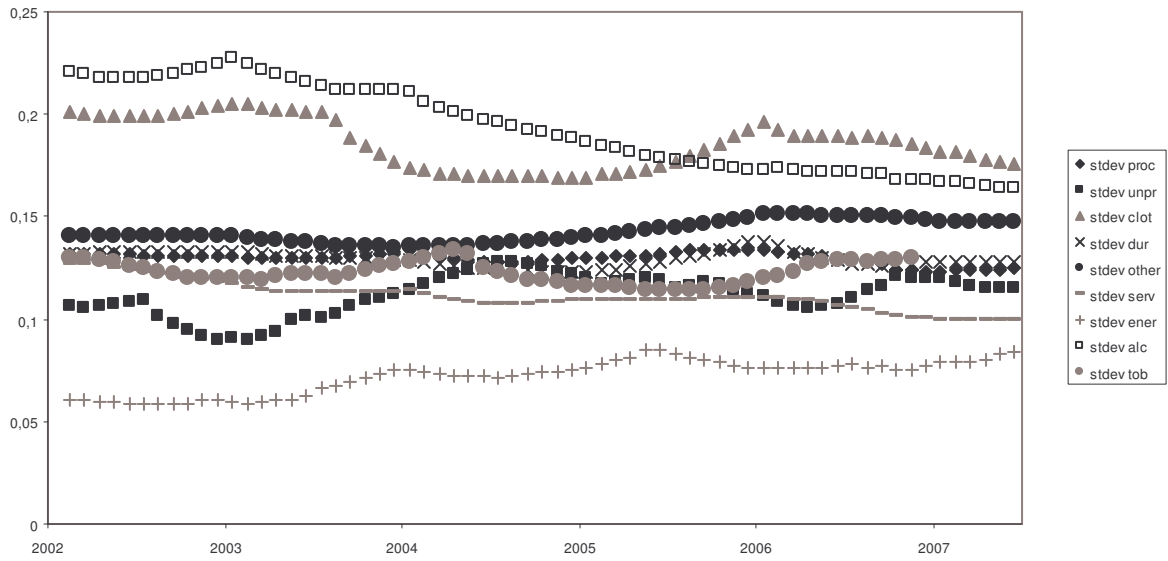


Figure 21b. Cross-sectional standard deviation of the estimated AR(1) parameters by product categories (FLS estimation, $\mu = 10^{2.5}$). Source: Authors' compilation from KSH data.

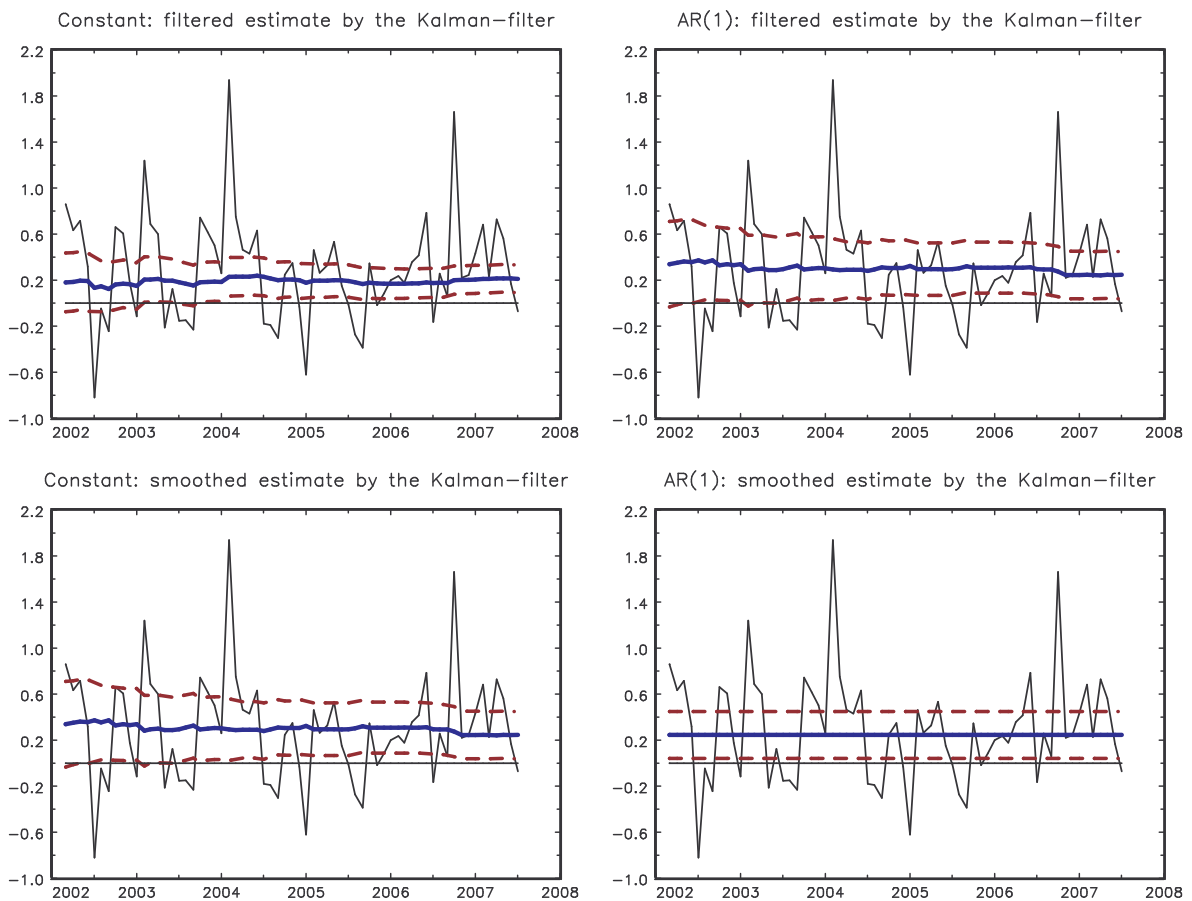


Figure 22. Time-varying intercept and autoregressive parameter estimates of the country-level monthly inflation series with Kalman filtering. Source: Authors' compilation from KSH data.