

Price Stability, Inflation Convergence and Diversity in EMU: Does One Size Fit All?[†]

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Abstract

Using a unique data set of regional inflation rates we are examining the extent and dynamics of inflation dispersion in major EMU countries before and after the introduction of the euro. For both periods, we find strong evidence in favor of mean reversion (β -convergence) in inflation rates. However, half-lives to convergence are considerable and seem to have increased after 1999. The results indicate that the convergence process is nonlinear in the sense that its speed becomes smaller the further convergence has proceeded. An examination of the dynamics of overall inflation dispersion (σ -convergence) shows that there has been a decline in dispersion in the first half of the 1990s. For the second half of the 1990s, no further decline can be observed. At the end of the sample period, dispersion has even increased. The existence of large persistence in European inflation rates is confirmed when distribution dynamics methodology is applied. At the end of the paper we present evidence for the sustainability of the ECB's inflation target of an EMU-wide average inflation rate of less than but close to 2%.

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1 Introduction

In January 1999, eleven European countries adopted the euro as their new currency. One year later, another country, Greece, joined the currency union, other Central and East European countries are planning to do so in the next years. The establishment of the European Monetary Union (EMU) has been accompanied by heavy criticism from some economists and the success of the new currency has been doubted for a variety of reasons. Feldstein (1997) and Obstfeld (1997), e.g., argue that the EMU is not an optimum currency area in the sense of Mundell (1961). Referring to Friedman (1953), they think that - in the presence of market rigidities as in the case of European countries - nominal exchange rate adjustments across European countries would be required to achieve necessary changes in real exchange rates in response to asymmetric adverse shocks. Critics have considerable doubts that a single monetary policy can adequately meet the requirements of the various member countries ("Does one size fit all?"). One issue that was discussed in this context are the implications of the existing large heterogeneities in economic conditions across member countries on the adequacy of the ECB's inflation target of an EMU-wide average inflation rate of less than 2%. Sinn and Reutter (2001) argue that due to Balassa-Samuelson effects in less developed countries such as Ireland or Portugal, inflation rates in these countries will be relatively high. As a consequence, price dispersion across the member countries will be large and some more developed countries such as Germany might be threatened by deflation when the ECB strictly sticks to its target. Therefore, the two authors call for an increase in the ECB's upper inflation bound by at least 0.5%. Another issue of concern is that countries' efforts to follow a strict stability policy as prescribed by the Maastricht Treaty have been weakened after joining the EMU and - as a consequence - inflation rates will no longer converge but might even diverge in the near future.

In this paper, we want to contribute to the discussion on inflation dispersion across European countries and its implications for the ECB's monetary policy in several ways. First, we will shed some light on the dynamics of regional inflation rates by testing for the existence and degree of their mean-reverting behavior. This allows us to address the important issue of whether existing cross-regional differentials in inflation rates should be a major issue of concern for policy-makers. This would have to be the case if we found no or only very weak indications of mean-reverting behavior. Our second contribution is that we will provide evidence on the dynamics of the overall inflation dispersion across major EMU countries. We are particularly interested in the question of whether overall dispersion has decreased over time (σ -convergence). Additionally, using distribution dynamics methodology, we will analyze the within-distribution dynamics of European regional inflation rates. This will be done both for the case of a continuous and discrete distribution. In our last contribution, we will deal with the question of the adequacy of the ECB's inflation target. Using a statistically significant relationship between the cross-regional mean inflation rate and its dispersion we compute lower bounds for the average inflation

rate that ensure that only a negligibly small portion of regions faces deflation. We argue that this measure can - despite some shortcomings - serve as an indicator for the ECB to evaluate when the prevailing mean inflation rate has reached a critical value, in the sense that at a further decrease too many regions would face deflation. All the issues raised above will be examined using a unique set of regional aggregated and disaggregated regional European inflation data. The idea to use regional instead of national data is borrowed from the growth literature,¹ where it has been used to analyze convergence in per-capita incomes. While there already exists a comparable empirical literature on regional price dynamics for the U.S.A.,² analytical evidence for Europe is based on national data only.³ Evidence for U.S. cities indicates the existence of inflation convergence, but its speed is relatively slow.

The rest of the paper is organized as follows: In the next section, we present our data set and discuss some descriptive statistics. The results concerning mean-reverting behavior in inflation rates together with some sensitivity analysis are presented in sections 3 and 4. Section 5 examines the issue of σ -convergence in inflation rates and section 6 presents our results from applying distribution dynamics to our data. Section 7 takes a closer look at the relationship between the cross-sectional mean inflation rate and its dispersion and derives ‘critical’ mean inflation values. The last section summarizes our results and draws some policy conclusions.

2 Data and Descriptive Statistics

In the spirit of the empirical growth literature, we are using regionally disaggregated data to examine the question of inflation diversity and convergence in the EMU. There are several reasons that make such an approach desirable. The most obvious one is, that it enables us to increase the number of observations and thus to obtain more precise statistical results. For the case of the EMU, e.g., any cross-sectional examination with national data would be based on twelve observations only. However, when regional data are used, the number of available observations can be significantly increased. In our study, e.g., we are employing data from 77 regions. Another reason for employing intra-national data is that the extra (regional) dimension can help us understand aggregated inflation behavior as we will see below. Finally, as each country can be considered as a miniature monetary union, the use of regional data from well-established monetary unions can give us insights into future developments within the EMU. In this context, the study of U.S. cities is probably most helpful.

A shortcoming of this approach is that regional data are not readily available and thus have to be collected in a time-consuming process. Furthermore, even if one is willing to carry this burden, one may not be successful because some countries’ statistical offices do not compile data at a regional level. Unfortunately, this is also

¹See, e.g., Barro and Sala-i Martin (1992) Barro and Sala-i Martin (1995) and Sala-i Martin (1996a).

²See, e.g., Parsley and Wei (1996) and Cecchetti et al. (2002).

³See, e.g., Rogers (2001).

true for some EMU countries that are therefore missing in our sample. Nevertheless, we managed to compile a relatively broad data base of regional CPI data that includes most major EMU countries.⁴

To get an idea of the scope of our regional price data,⁵ we start by giving a short description of it. An overview of the included countries and regions is given in table 1. As one can see, we are using data from six EMU countries comprising a total of 77 regions. In our estimation analysis, we arrange these countries into two different groups, denoted as European ‘core sample’ and European ‘extended sample’ (see table 2 for a detailed description). These two groups differ with respect to the sample length and the coverage of included CPI subgroups. As table 2 shows, the European ‘core sample’ comprises data for German, Austrian, Finnish, Italian, Spanish and Portuguese regions and includes the total index and eleven subgroups.⁶ For all regions, the subgroups are constructed on the basis of an identical classification scheme, namely the COICOP (Classification of Individual Consumption by Purpose) scheme that was introduced in most EU countries in 1995.⁷ In our European ‘extended sample’, we extend the length of the sample period considerably (by five years). However, only total index data are available.

All data are annually and are available in index form. Inflation rates are computed as annual percentage changes in the price index in the following way:

$$\pi_t = 100 * (\ln P_t - \ln P_{t-1}) = 100 * (p_t - p_{t-1}), \quad (1)$$

where π_t denotes the inflation rate in period t , and P_t represents the respective price index in t . Small letters for P denote its natural logarithm.

To illustrate the importance and extent of regional inflation rate dispersion, figure 1 plots inflation rates for our European ‘core sample’.⁸ As one can see, regional dispersion is considerable, spanning a band of around 4% width. Interestingly, despite this relatively big dispersion, only very few regions have experienced deflation in the considered time period even when the aggregate EMU inflation rate was relatively low in 1998. As we will see, this - in addition to the fact that EMU-wide inflation rate has never fallen far below 2% - has to do with a statistically significant positive relationship between the mean inflation rate and its regional dispersion.

Another interesting issue concerns the ‘anatomy’ of the 4% band.⁹ As one might expect, regional inflation rates of individual countries are usually located in relatively close bands around a country’s mean rate (when compared to total EMU width). So, when several countries’ mean inflation rates are different (as is the case

⁴The biggest exception is France, for which no regional data are provided.

⁵In Weber and Beck (2001), we used an even broader sample of regional price data that additionally included North American, South American and Asian regions.

⁶For Austria, no data for subgroups are available.

⁷Italy provides regional data following the COICOP scheme from January 1996 on only and Austria stucked to its old scheme until the end of the 1990’s.

⁸Figure 1 plots the annual percentage change of inflation rates computed as $\pi_t = 100 * (\ln P_t - \ln P_{t-12})$ based on monthly data. In the following analysis only annual data are employed, however.

⁹In this context, it is noteworthy that the bandwidth varies considerably with the goods category under consideration. This will become clear in the discussion of the descriptive statistics presented in table 3.

for European countries), it is tempting to suppose that the observed 4% band can be considered to result from a ‘stacking’ of countries’ ‘bands’. However, this conclusion is not fully correct as figures 1 and 2 illustrate. Figure 1 highlights Italian inflation rates (total index). As becomes clear from this picture, Italian regional dispersion is almost as big as that for the total sample. The figure for food inflation rates (figure 2) illustrates another aspect that is not in line with the above idea and that will become important for the interpretation of some of our estimation results. In this figure, German data are highlighted. The picture shows that Germany changes its relative inflation ‘ranking’ throughout the sample period: Its inflation rates lie below the average rate at the beginning and end of the period but are above average within the sample period.¹⁰

Table 3 provides some descriptive statistics for our European ‘core sample’. Looking at the mean rates for the total index, we can see that the lowest average inflation rate prevailed in Germany, followed by Finland, Austria, Italy, Spain and Portugal. A look at the subcategories, however, provides a relatively differentiated picture concerning the ‘ranking’ of inflation rates across countries. Whereas Germany has the lowest inflation rates for most categories, this is not the case for the categories ‘alcoholic beverages and tobacco’, ‘clothing and footwear’ and ‘transportation’. Finland has one of the highest rates for ‘health’ but the lowest rates for ‘clothing and footwear’. Portugal on the other hand has one of the highest rates for ‘food and non-alcoholic beverages’ but one of the lowest rates for ‘clothing and footwear’. As we will see in the next section, these differences in the ‘ranking’ position will be quite important in understanding some of our analytical results.

Looking at the reported cross-sectional dispersion measures, we can see that dispersion at a national level is generally significantly lower than at the EMU level. Additionally, measured dispersions differ very significantly across goods categories and across countries. In the next section, we will turn to our analytical results concerning the extent of convergence in inflation rates (β -convergence) across European regions.

3 Cross-Sectional Evidence of Inflation Convergence

3.1 Methodology

To test for mean-reverting behavior (β -convergence) in inflation rates, we are using two different procedures. The most popular approach - particularly in the literature on relative prices - is to use Augmented Dickey-Fuller (ADF) tests. To increase precision, recent studies apply panel techniques developed by Levin and Lin (1992) and Levin and Lin (1993). We will turn to this methodology in section 4. Before, we will present results from an approach that has been intensively used in the empirical growth literature. We think that it can be very helpful for our purposes - particularly,

¹⁰Following Sala-i Martin (1996a), we speak of ‘leapfrogging’ or ‘convergence overshooting’ in this context. A more detailed discussion of this phenomenon and its implications for our results will be given in the interpretation of our analytical results.

since there are large similarities not only with respect to the nature of the data we use but also with respect to the question under consideration. Additionally, the methodology provides us with some measure of how fast convergence occurs.¹¹

In analogy to the growth literature, we test for inflation convergence by setting the average change in inflation rates over the considered sample period in relation to its initial value, i.e., by estimating regressions of the type:

$$\frac{1}{T}\Delta\pi_{i,t_0+T} = constant + b * \pi_{i,t_0} + \epsilon_{i,t_0,t_0+T}. \quad (2)$$

Here, T denotes the length of the sample period in years, π denotes the inflation rate computed as an average annual rate and t_0 denotes the initial period. $\frac{1}{T}\Delta\pi_{i,t_0+T} = \frac{1}{T}(\pi_{i,t_0+T} - \pi_{i,t_0})$ denotes the average change in the inflation rate over the sample period. ϵ_{i,t_0,t_0+T} represents an average of the error terms $\epsilon_{i,t}$ between t_0 and $t_0 + T$. The estimations are done using OLS.

If there is convergence in inflation rates, the estimated values for b will be negative. This would imply that prices of a country with an initially relatively high inflation rate would increase more slowly (or decrease faster) in the subsequent period than those of a country with an initially relatively low inflation rate. Thus, the existing inflation rate gap would diminish. As an extreme case, one could even imagine that ‘leapfrogging’ or ‘convergence overshooting’¹² occurs, i.e., that an existing inflationary gap not only diminishes but reverses in sign. As we will see, this actually happens in our sample and has important impacts for the short-run analysis. The estimated value for the slope coefficient b in equation (2) can be used to compute a rough measure of the convergence speed. Using an expression that is analytically derived in the growth literature, an estimate for the convergence rate can be obtained by solving the expression¹³

$$b = - \left(\frac{1 - e^{-\beta * T}}{T} \right) \quad (3)$$

for β using the estimated value for b from equation (2). The so derived value for β gives an estimate of the proportion by which an existing inflationary gap is reduced in each period. A problem that arises in the interpretation of this coefficient is that - unlike in the growth literature - the identity given in equation (3) cannot be derived in a stringent theoretical way. Nevertheless, as a comparison of the results in this and the next section shows, its use turns out to be very illustrative.

3.2 European ‘Core Sample’: Total Period

A graphical illustration of the estimation approach is delivered in figures 3 to 5 where we present selected graphs from our European ‘core sample’. Figure 3 plots total index data, whereas figures 4 and 5 plot data (total period) for the subcategories

¹¹It has to be noted, however, that - unlike in the growth literature - the reported measures for the adjustment speed lack a sound theoretical foundation. Still, they can give some idea on how fast convergence occurs. Additionally, the results are in line with some more accurate measures derived in the next section.

¹²See Sala-i Martin (1996b) for terminology.

¹³See, e.g., footnote seven of Sala-i Martin (1996b)

‘clothing and footwear’ and ‘food and non-alcoholic beverages’. In each figure, we plot changes in inflation rates over the respective sample period versus initial inflation rates. Included in each figure is a regression line that represents the fitted values from regression equation (2). As figures 3 to 5 indicate, inflation convergence does not seem to be very pronounced for the total index (when the total period is considered), but is very strong for the two subcategories ‘clothing and footwear’ and ‘food and non-alcoholic beverages’.

This impression is confirmed by our analytical results that are reported in table 4. As column two shows, all coefficients but the one for ‘health’ have the correct sign and all of the coefficients but the one for ‘health’ are significant. The values for the subcategories differ considerably and lie in the range between -0.06 (‘furnishings, household equipment and routine maintenance of the house’) and -0.333 (‘communications’) for the subcategories. The half-lives of inflation convergence derived for these b -values are reported in column five. For ‘food and non-alcoholic beverages’, ‘health’, ‘communications’, and ‘recreation and culture’, no half-lives could be computed as the solution of the nonlinear expression for β produces complex numbers. However, as the respective b -values show, convergence for these categories not only is present but occurs - given the absolute values - even at a higher rate than for the other categories. This is confirmed by inspection of figure 4 that demonstrates the strong negative relationship between changes in inflation rates and initial inflation rates for ‘food’-inflation rates. For the cases where half-lives could be computed, values vary between 1.4 years (‘alcoholic beverages and tobacco’) and 8.7 years (‘furnishings, household equipment and routine maintenance of the house’). For the total index, we obtain a value of 5.5 years. This result might appear somewhat puzzling: Whereas we obtain a b -value of -0.077 for the total index, all obtained values for the subcategories of the total index (with the exception of clothing and footwear) are larger in absolute value (with an average value of -0.18) and thus indicate higher convergence. To see, how such a result can arise, consider a case where we have only two regions (denoted as region 1 and 2) and two goods (denoted as subcategories A and B): Then, when there is a switch in the ‘ranking’ of good’s B inflation between region 1 and 2, i.e., at the beginning of the sample period, the inflation rate for good B is higher in region 1, and at the end of the period it is higher in region 2, we would get exactly the same results that we find in the data: While both goods exhibit strong convergence (highly negative slopes), the convergence for the total index is slow (slope is almost horizontal). The phenomenon that an existing differential not only vanishes but reverses has been called ‘leapfrogging’ or ‘convergence overshooting’ in the growth literature (see Sala-i Martin (1996b)). To illustrate that this ‘inflation switching’ actually happens in the data, we already discussed figure 2 that shows this pattern for the case of German ‘food’-inflation.

3.3 European ‘Core Sample’: Pre-EMU and EMU Subperiod

Table 5 reports estimation results for the pre-EMU and EMU subperiod of our European ‘core sample’. Looking at the figures for the first subperiod, we find strongly

significant and very fast convergence for both the total index and most subcategories (exceptions: clothing and footwear and health). The estimated b-values that are inversely related to the convergence speed now have an average value of -0.58 compared to -0.18 for the total period. Half-lives are much lower than observed for the total period and are usually far below one year.

For the EMU subperiod, we also find strongly significant convergence for both the total index and all subcategories (exception: clothing and footwear). However, convergence speeds have fallen considerably. The average b-value for the subcategories is -0.23, i.e., has fallen by around 60% in absolute value relative to the first subperiod. Half-lives have risen correspondingly and most of them are now longer than one year. The considerable differences in convergence speed between the two subperiods can be explained by the countries' enormous efforts in the pre-EMU subperiod to meet the Maastricht criteria that set strict limits on prevailing inflation rates. Thus, the extraordinarily high convergence rates in the pre-EMU period are probably due to such factors that could easily be affected by governments but had - as the results for the second subperiod show - only short-run impacts. Referring to possible explanations for these results, we think that fiscal policy and institutional factors such as changes in CPI composition/weights are responsible for the convergence dynamics in the years before 1998. Another factor that has probably played an important role is inflation expectations that were adjusted downward in the years immediately before the introduction of the euro.

Comparing the results for the subperiods to those of the total period, one observation is particularly noteworthy: The estimated b-values of most categories generally indicate smaller convergence in both subperiods than they do for the total period. Thus, convergence speeds for the total period cannot be derived as an average of the speeds prevailing in the two subperiods. This phenomenon can be explained as follows. When inflation rate adjustments are nonlinear in the sense that convergence is higher for higher inflation rate gaps and is slower when gaps become closer, we combine early periods with large convergence with later periods with smaller convergence when we consider long periods of time. Hence, the convergence rate derived for a longer time period (total sample period) is smaller than that for a shorter time period (pre-EMU and EMU subperiods) since the OLS estimate of b is negatively related to T.

3.4 European 'Extended Sample'

In table 6, we report convergence results for our European 'extended sample'. The results confirm major findings from the 'core sample'. All coefficients are significant and demonstrate convergence in inflation rates across European regions. The reported half-life for the total period is 4.2 years, for the first two subperiods we obtain lower rates ranging from 1.3 years for the pre-EMU period to about 1.4 years for the first subperiod. For the EMU subperiod, we obtain the highest half-life (15.2 years) that compares to the 19.6 years we obtained for the 'core' sample. A comparison among the three subperiods clearly shows us the efforts of EMU countries

to meet the Maastricht criteria. As table 6 shows, half-lives are low in the period before 1995 and fall somewhat more (1.3 years) in the pre-EMU period. However, as the increase in the EMU-period shows, these efforts have had only very short-run effects.

Summarizing the results of this section, we can conclude that there is evidence of significant inflation convergence across European regions. We have also seen that political impacts to speed up convergence are successful only in the short-run and that economic fundamentals seem to matter more in the long-run. Our estimates for the long-run convergence speed suggest a relatively low degree of inflation convergence with a considerable long-run half-life.

4 Panel-Unit-Root Evidence of Inflation Convergence

In the last section, we demonstrated that inflation convergence occurs across European regions. However, the speed at which it occurs is surprisingly low. In this section, we want to investigate this issue a little further by using an alternative methodology that makes more explicit use of the time series dimension of our data. Due to the shortness of our sample period, an analysis of individual inflation series does not seem to be reasonable. However, exploiting the large number of cross-sectional units, we can pool the data and use panel data econometric methods. In analogy to the PPP literature,¹⁴ we examine the mean-reverting behavior of inflation rates using the panel-unit root framework developed by Levin and Lin (1992) and Levin and Lin (1993).

Given our sample of inflation rates $\pi_{i,t}$ (with $i = 1, 2, \dots, N$ denoting the individual regions of our sample and $t = 1, 2, \dots, T$ representing the time index), the test for inflation convergence is based on the following equation

$$\Delta\pi_{i,t} = \rho\pi_{i,t-1} + \theta_t + \sum_{j=1}^{k_i} \phi_{i,j} \Delta\pi_{i,t-j} + \epsilon_{i,t}, \quad (4)$$

where Δ denotes the one-period (annual) change of a variable and θ_t represents a common time effect. $\epsilon_{i,t}$ is assumed to be a (possibly serially correlated) stationary idiosyncratic shock. The inclusion of lagged differences in the equation serves to control for serial correlation. As the subindex of k indicates, we allow the number of lagged differences to vary across individuals, whereby the respective number is determined using the top-down approach suggested by Campbell and Perron (1991). The inclusion of a common time effect is supposed to control for cross-sectional dependence caused, e.g., by common fiscal policy shocks. To take control of this effect, we transform the data by subtracting the cross-sectional mean leading to

$$\Delta\tilde{\pi}_{i,t} = \rho\tilde{\pi}_{i,t-1} + \sum_{j=1}^{k_i} \phi_{i,j} \Delta\tilde{\pi}_{i,t-j} + \epsilon_{i,t}, \quad (5)$$

¹⁴See, e.g., Wu (1996), Frankel and Rose (1996) or Goldberg and Verboven (1998) For overview articles, see Froot and Rogoff (1996) and Rogoff (1996).

where $\tilde{\pi}_{i,t}$ is computed as

$$\tilde{\pi}_{i,t} = \pi_{i,t} - \frac{1}{N} \sum_{j=1}^N \pi_{j,t}. \quad (6)$$

To see whether mean-reverting behavior in inflation rates is present, we test - following Levin and Lin (1993) - the null hypothesis that all ρ_i are equal to zero against the alternative hypothesis that they are all smaller than zero, i.e., we test the null hypothesis:

$$H_0 : \rho_1 = \rho_2 = \dots = \rho_N = \rho = 0,$$

against its alternative:

$$H_1 : \rho_1 = \rho_2 = \dots = \rho_N = \rho < 0.$$

If we can reject the null hypothesis of nonstationarity, inflation rates exhibit mean reverting behavior and thus any shock that causes deviations from equilibrium eventually dies out. The speed at which this occurs can be directly derived from the estimated value for ρ (denoted $\hat{\rho}$). Given $\hat{\rho}$, half-lives of convergence can be computed using the formula

$$t_{half} = \frac{\ln(0.5)}{\ln(\hat{\rho})}.$$

Unfortunately, as Nickell (1981) shows, for finite samples the estimates for ρ are biased downward. To correct for this downward bias, he suggests an adjustment factor that we also use for our results. Critical values for the test statistics are obtained using a parametric bootstrap based on 5,000 simulations of the data-generating process under the null hypothesis. Additionally, we restrict our discussion in this section on the European ‘extended sample’, since only for this group are reasonably long time series available.

Results are presented in table 7. As one can readily see, the null hypothesis of nonstationarity is clearly rejected. We obtain inflation half-lives of 2.3 years for the unadjusted coefficient and 17.0 years for the adjusted value. To examine whether the turbulences in 1992 and 1993 have had any significant influence on the convergence process, we also examined the case when the observations for this period were excluded. As we expected, the estimated ρ -coefficients drops somewhat in value with the unadjusted half-life now being 1.6 years and the adjusted half-life having a value of 5.4 years which is very close to the result we obtained in the last section. Thus, the results in this section confirm that convergence is present but occurs at a very modest speed with considerable half-lives. In the next section, we will examine how overall inflation dispersion has evolved across European regions.

5 σ -Convergence across European regions

In addition to the question of β -convergence in inflation rates, another important aspect of convergence concerns the evolution of the overall cross-regional dispersion of inflation rates. In this section, we will focus on the question of whether

cross-regional dispersion of European inflation rates has stayed constant over time, has diminished or has even increased in recent years. In analogy to the expression ‘ β -convergence’, the growth literature has used the term ‘ σ -convergence’ when decreasing overall cross-regional dispersion is observed.¹⁵

As we have indicated in the introduction, the question of σ -convergence in regional inflation rates is of greatest importance for European monetary policy-makers. To give an example, let us consider the following case: Imagine an economic area where initially 50% of the regions (in terms of GDP) have an inflation rate of 1% whereas the other half have an inflation rate of 3%. Then, overall inflation would be 2% and thus just in line with the ECB’s upper boundary. Imagine now that due to some asymmetric shocks (such as different spending policies or external shocks that have asymmetric effects) the inflation spread between the two regional clusters widens in the sense that now one half of the regions has an inflation rate of 4% and the other half 0%. Then, average inflation rate would still be 2%. The policy-maker, however, would face a very problematic situation. On the one hand, half of the regions would be threatened by deflation and thus would need an expansionary policy, whereas the other half would require a more contractionary policy. Thus, from the perspective of the ECB - and certainly also from the perspective of EMU citizens and firms - it would be desirable for overall inflation dispersion to have a relatively modest size (and would stay there, of course). More preferable would be the case of σ -convergence, i.e., a continuous decrease in overall dispersion over time. As Sala-i Martin (1996b) illustrates, in the presence of σ -convergence, some steady-state value for cross-sectional dispersion would finally be reached which would diminish the probability of contradictory claims on the central monetary authority. In the growth literature, some authors¹⁶ have gone so far in their emphasis of the importance of the concept of σ -convergence that they argue that it is *the* only important concept of convergence. We do not follow these arguments but rather consider the two concepts to be equally interesting and important for the following reason:¹⁷ Assume that dispersion across EMU regions has reached its steady state and is thus no longer diminishing. Additionally, imagine that β -convergence has also come to an end. This would mean that any existing inflation gap between two regions would remain constant forever with the consequence that the price levels of the two regions would diverge forever leading to an infinitely large (at least theoretically) difference in the price level between the two regions. Thus, even if overall dispersion has reached some acceptable steady state level, β -convergence still seems to be a desirable feature of cross-regional inflation dynamics.

A useful illustration of the relationship between the two concepts can be derived as follows, starting with the existence of β -convergence:¹⁸ In the presence of β -

¹⁵Both of these expressions (β - and σ -convergence) were actually introduced by Sala-i Martin (1990).

¹⁶See, e.g., Quah (1993b).

¹⁷Compare Sala-i Martin (1996b) and his reference to the U.S. NBA league and the Spanish soccer league for an analogous line of arguments.

¹⁸The following illustration closely follows Sala-i Martin (1996b).

convergence, there is a negative relationship between changes in inflation rates and its respective initial values. Based on this relationship, we tested for convergence using

$$\Delta\pi_{i,t} = \alpha + \rho\pi_{i,t-1} + u_{i,t}, \quad (7)$$

which can be rearranged to yield

$$\pi_{i,t} = \alpha + (1 - \beta)\pi_{i,t-1} + u_{i,t}, \quad (8)$$

where $1 - \beta = \rho - 1$ and $0 < \beta < 1$ for the case of convergence. The larger β , the faster is the convergence.

Defining cross-sectional dispersion as

$$\sigma_t^2 = \frac{1}{N} \sum_{i=1}^N (\pi_{i,t} - \bar{\pi}_t)^2 \quad (9)$$

(with $\bar{\pi}_t$ denoting the cross-sectional inflation mean in period t) and assuming that the sample variance is close to its theoretical equivalent for a sufficiently large value of N , an expression for the evolution of the cross-sectional dispersion can be derived as

$$\sigma_t^2 \approx (1 - \beta)^2 \sigma_{t-1}^2 + \sigma_u^2. \quad (10)$$

This equation shows that σ -convergence only occurs when $0 < \beta < 1$,¹⁹ i.e., when β -convergence is present. Thus, as Sala-i Martin (1996b) concludes, ‘ β -convergence is a necessary condition for σ -convergence’. There are two things to observe. First, even when the first-order difference equation for the evolution of σ is stable (i.e., σ -convergence occurs), dispersion can increase over time. This happens whenever the current dispersion is below its steady-state value implied by equation (10). Secondly, the presence of β -convergence does not necessarily imply σ -convergence, i.e., β -convergence is not a sufficient condition for σ -convergence. As Sala-i Martin (1996a) demonstrates, the case of β -convergence but missing σ -convergence will arise when ‘leap-frogging’ occurs to a large extent. As we have illustrated in figure 2, inflation rates for food indeed exhibit this pattern. In other words, the strong evidence of β -convergence found in the last two sections does not allow us to conclude that we will find σ -convergence across European regions.

Figure 6 plots the cross-sectional dispersion of annual inflation rates (total index) for the European ‘extended sample’. As the graph clearly shows dispersion has considerably decreased in the first half of the 1990s. After 1995, no further decline in overall dispersion can be observed. On the contrary, dispersion has increased in the last year of our sample.

To sum up results in this section, our evidence shows that σ -convergence for European regional inflation rates occurred at the first half of the 1990s and came to an end afterwards. Overall dispersion might already have reached some steady-state value such that further reductions in dispersion can probably not be expected (but are

¹⁹The case when β is negative is excluded.

not necessary either). β -convergence, i.e., movements within the given dispersion, however, will probably continue to occur. In the next section, we will study how the composition of European overall inflation distribution has evolved over time.

6 Distribution Dynamics

In the last section, we examined the evolution of the cross-regional inflation distribution by computing and analyzing standard deviations. Whilst this approach allowed us to draw interesting conclusions about the evolution of the size of overall inflation dispersion, it does not allow us to say anything about the evolution of the shape of the distribution and about the within-distribution dynamics. An interesting and important issue that could not be addressed using this ‘second-moment-approach’ is the dynamics of the composition of the left and right tails of the distribution: Does the composition remain relatively constant, i.e., do regions with relatively low/high inflation rates stay in this position for a prolonged period of time, or is the composition changing rapidly, i.e., do regions with relatively low/high inflation rates move away from the tail into the middle of the distribution relatively fast. As is clear, the second case is the preferred one from the perspective of any central banker as it avoids problems associated with diverging price levels across regions.

A first answer to this important question can be indirectly derived using our results on β -convergence. Given the evidence of strong β -convergence and relative constant overall dispersion, we can conclude that there is significant within-distribution dynamics. In this section, we want to take a closer look at this issue. To do so, we refer to an econometric methodology called distribution dynamics. Thus far, this methodology has been mostly applied in the economic growth literature,²⁰ where it has been used to study the dynamics of per capita income distribution. The idea behind distribution dynamics is to find a law of motion that describes the evolution of the entire considered distribution over time. Following the growth literature, we use a Markov processes to describe the dynamics of the cross-regional inflation distribution in period t , F_t . In analogy to the time-series literature, the dynamics of the cross-regional inflation distribution can be modelled as an AR(1) process in the following way:²¹

$$F_{t+1} = T^*(F_t), \quad (11)$$

where $T^*(.)$ denotes the operator mapping period’s t distribution into period’s $t + 1$ distribution. Depending on the nature of the underlying variable of interest X_t , this operator is either interpreted as the transition function/stochastic kernel of a continuous state-space Markov process or as the transition probability matrix of a

²⁰See Bianchi (1997), Hobijn and Franses (2001), Quah (1993a), Quah (1993b), Quah (1994), Quah (1996) or Quah (1997) amongst others. For a recent survey, see Durlauf and Quah (1999).

²¹The following exposition is a condensed representation of the methodology of distribution dynamics. A more technical exposition can be found in Quah (1997) or in the appendix of Durlauf and Quah (1999).

discrete state-space Markov process. In the former case, equation (11) translates to

$$F_{t+1} = \int_A P(x, A) F_t(dy). \quad (12)$$

Here, A is any subset of the underlying state space for X_t and $P(x, A)$ denotes the stochastic kernel that describes the probability that we will be in A in $t + 1$ given that we are currently in state x , i.e.,

$$P(x, A) = P(X_{t+1} \in A | X_t = x). \quad (13)$$

In the following analysis, we define the variable of interest X_t to be the deviation of a region's inflation rate from the cross-regional mean, the underlying state space is the real line R .

We also consider the discretized case. A discrete-case consideration has the advantage that it provides us with easily interpretable (discrete) probability distributions and transition probability matrices. The major drawback of this approach is, that any discretization will be more or less arbitrary. In light of the practical usefulness that concrete numbers for transition probabilities have for monetary policy-makers we think that the benefits of the discretization will outweigh its costs.²² For the discrete state-space case, equation (11) becomes

$$F_{t+1} = MF_t, \quad (14)$$

where M is an $n \times n$ transition probability matrix with n denoting the number of distinct states and row entries summing up to 1.

For the European 'extended sample', results for the continuous case are depicted in figures 7 and 8. Figure 7 represents the surface plot of the stochastic kernel for annual inflation rate transitions for the period of 1992 to 2004. On the x-axis (denoted by t), we plot the period's t inflation deviations from the cross-regional mean and on the y-axis (denoted by $t + 1$), we plot period's $t + 1$ inflation deviations from the cross-regional mean. On the z-axis, we plot the conditional transition density function $p(x, y)$ associated with the stochastic kernel $P(x, A)$ that has the property that

$$P(x, A) = \int_A p(x, y) dy, \quad (15)$$

²²Another problem of discretization is that it can remove the Markov property (see, e.g., Guihenneuc-Jouyaux and Robert (1998)). The results of Bulli (2000), who tries to evaluate the practical consequences of arbitrary discretizations, show that a regenerative discretization instead of our 'naive' discretization would probably not change our main results dramatically but would probably lead to even more pronounced results.

with y denoting elements in A .²³ If the probability mass was concentrated along the diagonal of the x-y plain, then any existing deviations from the cross-regional inflation mean in period t would be expected to remain basically unchanged over time. If on the other hand most of the probability mass in the graph was concentrated around the 0-value of the period- $t + 1$ -axis - extending parallel to the period- t -axis - then the period's t deviations would be basically expected to vanish until the next period. A look at figure 7 shows that the 'true' dynamic lies in between these two extremes. The probability mass is rotated clockwise by about 10° to 20° . This means, that regions with relatively low/high inflation rates in period t are expected to move back towards the mean at a one-year horizon. However, not all of the initial deviation is expected to vanish within this time horizon. This finding basically confirms our results from sections 3 and 4 where we found strong evidence in favor of β -convergence, though with considerable half-lives. An even clearer illustration of the outlined distribution dynamics is given in figure 8 where we present the contour plot of the transition density function (left panel) and show how the period's $t + 1$ conditional expected deviation of inflation rates behaves relatively to the period's t deviation (right panel). The plot for the conditional expected inflation deviation shows that deviations are expected to decrease. So, when the period's t deviation is -2% , then the period's $t + 1$ expected deviation is only around -0.9 and thus considerably lower (in absolute values). The contour plot shows that there is a considerable dispersion around this conditional expected value. Thus, whereas on average deviations are expected to decline, there is also a non-negligible probability that deviations will not change. On the other hand, it can happen that deviations will reduce drastically.

To get some numbers for transition probabilities across the inflation states at hand, we discretized the continuous state-space into five ranges with an approximately equal number of period t observations in each state. The results are presented in the upper panel of table 8. In the first column, the period's t states are reported. Columns two to six report conditional probabilities for the transition from the respective period's t state to period's $t + 1$ state. Row entries sum up - apart from deviations caused by rounding - to one. Comparing diagonal with off-diagonal elements, we see that for each state the conditional probability of staying in the current state is generally highest. However, unlike in the growth literature, off-diagonal entries are important, summing up to 0.4 or even more. In other words, the conditional probability of a change in period's t state is 40% or higher. Particularly interesting are the findings for the 'extreme' states, i.e., states that are defined by large negative or large positive period's t mean deviations. A region whose inflation rate is more than 0.7% below or above average in period t is expected to have a deviation of similar size with a probability of about 0.54, or, in other words, is expected to have

²³When A is identical to the underlying state space (R), the transition density function integrates to one, of course, i.e.,

$$P(x, A) = \int_R p(x, y) dy. \quad (16)$$

a lower deviation (in absolute terms) with a 54% probability. These numbers are noteworthy for a simple reason: If conditional probabilities of remaining into one of these extreme states were close to one, then any region that slipped into deflation when EMU average inflation rates approached very low values (and stayed there for some time) would have negative inflation rates for quite some time. If on the other hand, these probabilities were close to zero, then a low EMU average inflation rate would be of less concern for the ECB, as one could expect that any one particular region would not be affected by negative inflation rates for a long time. The reported figures in table 8 lie in between these two scenarios: They tell us that there is a significant dynamic back towards the mean when extreme deviations are reached, but the speed at which this occurs is modest.

The lower panel of table 8 reports some descriptive statistics on how the inflation ranking is changing over time within the given distribution. The table entries represent conditional probabilities for switching between quintiles of the overall distribution. The figures show that there are considerable dynamics within the distribution which is not surprising given our evidence in favor of β -convergence. From an economic point of view, this result is positive in the sense that any existing inflationary gap between regions can be expected to disappear in the long-run such that no dramatically diverging price level dynamics are to be feared. The question that we want to address in the next section is whether we can use the large cross-regional dimension of our data to create some device that the ECB can use when deciding on the appropriate monetary policy for the .

7 Mean Inflation and Cross-Regional Inflation Dispersion

As outlined in the introduction, the ECB has been criticized that its inflation target of an EMU-wide average inflation rate of less than (but close to) 2% is too low. Due to considerable regional inflation dispersion, it is argued, an inflation rate under 2% induces considerable deflationary risks for low-inflation countries such as Germany. As we already discussed and as figure 1 clearly shows, this argument is true at least insofar as there is considerable dispersion around the average inflation rate. The band that is generated by this dispersion has a width of around 4%. However, as we will show below, the band width is not constant over time and crucially depends on the size of the prevailing average inflation rate. Under these circumstances, critics of the ECB's inflation target are only right, when for EMU-wide inflation rates below 2% a significant proportion of regions face deflation at the then prevailing dispersion. In this section, we will show that our regional inflation data can be used to compute some form of 'critical' values for EMU-mean inflation that indicate when certain proportions of regions are facing negative inflation rates. The computation is done by approximating a theoretical distribution function to the observed empirical dispersion. As it turns out, a normal distribution fits the data sufficiently well such

that only the empirical mean and variance is needed to describe our data. However, to adequately represent actual inflation dispersion by its theoretical equivalent, the described link between mean inflation and inflation dispersion has to be taken into account. Otherwise, conclusions would be flawed as we will show below.

Similar to our finding of a significant positive relationship between a country's average inflation rate and regional inflation dispersion, a large branch of literature has empirically examined an analogous relationship between a country's inflation rate and its cross-sectional dispersion.²⁴ Theoretical models that try to explain this link can be mainly classified into two groups: menu-cost models (Sheshinski and Weiss (1977), Rotemberg (1983) and others) and signal extraction models (Lucas (1973), Barro (1976) and Hercowitz (1981)). Our results show that this relationship also has a regional dimension. It is easily conceivable that some of the mechanisms responsible for the link between the level of inflation and its variability across sectors generate a similar relationship between a country's average inflation rate and the cross-regional dispersion. Imagine, e.g., that price adjustments are costly. Then local suppliers will adjust their prices not continuously but in steps, with the step size positively depending on the level of average inflation. If price adjustment costs differ across regions or if there are region-specific shocks, staggered price setting across regions will occur and thus higher inflation will increase inflation dispersion across regions.

To determine 'critical' mean inflation values, we start by finding an appropriate theoretical approximation for the empirical inflation distribution. As already mentioned, a normal distribution seems to be a good candidate. The necessary first and second moments are computed by weighting each region's inflation rate by its respective share in total GDP.²⁵ In figure 10, we compare the kernel density estimate of the empirical inflation distribution (January 1992) with its theoretical normal approximation. As one can see, the fit is relatively good. Empirical statistics also indicate the appropriateness of our choice: The average skewness of all periods' inflation dispersions is -0.69 with a standard error of 0.72, i.e., it is not significantly different from zero. The average kurtosis is 3.3 (standard error: 2.0) and is thus only slightly different from 3.0. Thus, we conclude that a normal distribution fits our data sufficiently well and we can use the cumulative normal density function to examine more closely the link between average inflation and the proportion of regions facing deflation.

Before, however, we need to find a device to guarantee that the relationship between the mean inflation rate and its dispersion is observed. We do that by establishing a functional relationship between the two variables using estimation techniques (OLS). A graphical illustration of this relationship is given in figure 9. This graph clearly demonstrates the discussed positive link. Regressing the standard deviation of re-

²⁴See, e.g., Parks (1978), Fischer (1981) and Taylor (1981).

²⁵To compute weights, we are using national per capita GDP data from the OECD (2001 data). Weights are obtained by dividing the product of national per capita GDP data with a region's total population (obtained from <http://www.population.de>) by total GDP. Higher moments are computed using the same weights.

gional inflation rates in period t (denoted by σ_t) on the weighted average inflation rate (denoted by μ_t) delivers:²⁶

$$\sigma_t = \underset{(0.00001)}{-0.00002} + \underset{(0.0004)}{0.0044}\mu_t + \epsilon_t \quad (17)$$

$$R_{adj}^2 = 0.47$$

Not surprisingly, the result shows that there is a statistically significant positive relationship between inflation mean and dispersion. One important implication of this finding is that dispersion decreases considerably when average inflation decreases. Thus, it would be incorrect if one used the dispersion prevailing say at 2% to predict the proportion of regions in deflation for mean inflation rates below 2%. Such a conclusion would considerably overestimate this proportion. This will be illustrated in the following when we compute proportions of ‘deflationary’ regions in dependence of prevailing mean inflation rates for different ‘dispersion scenarios’. As a starting point we use the approximated distribution to compute ‘critical’ values for mean inflation rates. These ‘critical’ values are obtained by determining these mean inflation rates for which 1%, 2.5%, 5%, 10% and 25% of all regions face deflation. The computations are based on

$$\Phi\left(\frac{\pi - \mu_{crit}}{\sigma(\mu_{crit})}\right) = p_{crit}, \quad (18)$$

where $\Phi(\cdot)$ denotes the cumulative density function of the normal distribution, p_{crit} is the proportion of regions with deflation and μ_{crit} is the respective corresponding mean inflation rate. The expression $\sigma(\mu)$ indicates the dependence of the dispersion from the prevailing mean inflation rate. To determine the desired critical values for μ , we set π equal to zero and solve the above term for μ_{crit} using the result from equation (17). This results in:

$$\mu_{crit} = -\frac{-0.00002\Phi^{-1}(p_{crit})}{1 + 0.0044\Phi^{-1}(p_{crit})}. \quad (19)$$

To demonstrate the importance of taking into account the changes in dispersion in response to changes in the mean, we compute analogous critical values for the case when we take inflation dispersion computed at 2% (the ECB’s upper inflation bound) and 2.5% (the highest average annual rate since the introduction of the euro). The results are presented in the upper panel of table 9. Looking at the second column (where ‘dispersion-adjustment’ is taken into account), it becomes clear that only for relatively small mean inflation rates a considerable proportion of our sample regions face deflation. So, when average inflation is as low as 1.20%, only 5% of all regions have an inflation rate below zero. On the other hand, columns three and four (where critical values are computed based on the dispersion prevailing at an average inflation of 2% and 2.5%) clearly show that ‘critical’ values for the mean

²⁶Numbers in brackets denote standard errors.

inflation rate strongly increase when the adjustment in dispersion (corresponding to a decrease in the mean inflation rate) is not taken into account. The 5%-critical value, e.g., increases from 1.20% to 1.54%, i.e., almost a half percentage point, when it is computed on the basis of the dispersion that prevails at an average inflation rate of 2.5%.

To get a better idea of how fast the proportion of deflationary regions increases with decreasing mean inflation, the lower panel of table 9 reports the percentage of regions with deflation for mean inflation rate between 0.5% and 2.0%. As column two (adjusted case) shows, for mean inflation rates larger than 1% the proportion of deflationary regions is negligibly small. On the other hand, it increases dramatically with any further reduction below 1%. Columns three and four show that for dispersions prevailing at 2% and 2.5%, mean inflation rates of even 1.5% are already associated with a considerable proportion of deflationary regions. This shows that if dispersion stayed constant at the levels prevailing at higher mean inflation rates, the ECB's inflation target would probably be too low, as it would force the ECB to keep inflation rates in the narrow band between 1.5% and 2%. In face of an uncertain world where large and mostly unanticipated demand as well as supply shocks can occur, this would seem to be an almost impossible task. On the other hand, since mean and dispersion are moving together, the tolerable inflation range increases by about 0.5% reaching from 1% to 2% which is still fairly narrow but manageable. This view is enforced by the findings of the previous section where we showed that there are considerable within-distribution dynamics. Thus, when the average inflation rate reaches a certain 'critical' value and stays there for some time, it is very unlikely that the same regions that are initially affected by negative inflation rates will remain so throughout the time that the overall inflation rate stays low. As we described above, it is more likely that regions that are the first to be affected by negative inflation rates will 'revert' to the cross-regional mean after some time whilst other regions' inflation rates will fall below zero. Thus, the within-distribution dynamics will ease pressure on monetary authorities and increase their scope for conducting monetary policy.

8 Conclusions

The purpose of this paper was to study the nature of cross-regional inflation dispersion in EMU countries. We examined the dynamics of individual regions' inflation rates (β -convergence), the evolution of overall inflation dispersion (σ -convergence) and provided an approach that is useful for assessing which mean inflation rates are sustainable in face of the prevailing regional inflation dispersion. Using two different methodologies, we are able to confirm that inflation rates of individual regions exhibit significant mean reverting behavior. Or, in the NBA/soccer-league picture of Sala-i Martin (1996a): A region with a high inflation rank today will probably not have a high inflation rank in the future. Thus, monetary authorities do not have to

be too worried about individual regions with temporarily high inflation rates. The convergence process itself seems to be nonlinear in the sense that its speed seems to decrease the further it proceeds. As we also showed, ‘leapfrogging’ is present and has interesting implications for monetary authorities: First, it can lead to misleading conclusions with respect to the dynamics of the total-index-inflation rate when it happens in subcategories. Secondly, in its presence, σ -convergence does not necessarily happen even if strong β -convergence exists. This can particularly be seen for the second half of the 1990s where we find strong β -convergence for all groups of goods but no further reduction in overall dispersion. While exhibiting relative constancy after 1996, we show that overall dispersion has significantly reduced in the first half of the 1990s. The finding of a relatively stable cross-regional dispersion from 1996 on can be seen as some evidence that dispersion has reached a steady state. Moreover, a comparison of absolute figures between the three samples indicates the sustainability of this dispersion level.

Arguments for the feasibility of the ECB’s inflation target are delivered in our last section where we approximated the prevailing empirical inflation dispersion by a theoretical distribution to show that only at mean inflation rates below 1% a significant portion of regions face deflation. One shortcoming of this result is that the lack of high-inflation countries like Ireland or Greece might downward-bias our results. On the other hand, these countries only have a small weight in the computation of mean inflation rates. Additionally, their missing might well be compensated by the lack of other lower inflation countries like France, Luxembourg or Denmark.

Overall, the results of our analysis represent mostly good news for the ECB, but some caveats still apply. The good news is that

- regional inflation rates in Europe do not drift apart but tend to mean-revert,
- there are considerable within-distribution dynamics leading any region in the lower or upper tail of the cross-regional inflation distribution to move back towards the mean after some time,
- overall dispersion has reached a presumably sustainable level and
- the chosen inflation target does not excessively restrict the ECB’s policy scope and seems to be compatible with the prevailing cross-regional dispersion.

On the other hand, it is important to realize that convergence seems to occur only at a relatively modest rate. Additionally and more importantly, the ECB should definitely try hard not to let aggregate inflation fall below one percent as in this case the proportion of regions facing deflation will grow dramatically with any small further reduction. Therefore, following Bernanke (2002), we strongly recommend a buffer zone of at least 1% below which the ECB should not try to push inflation. Further research, both in empirical and particularly in theoretical respect, is needed to better understand the sources for regional inflation dispersion such that monetary authorities can better respond to it.

9 Tables

Table 1: Countries and Regions/Cities Included in Our Study

Germany (7 regions)
Berlin, Nordrhein-Westfalen, Niedersachsen, Bayern, Saarland, Baden-Wuerttemberg, Hessen
Austria (20 cities)
Amstetten, Baden, Bregenz, Dornbirn, Eisenstadt, Feldkirchen, Graz, Innsbruck, Kapfenberg, Klagenfurt, Krens, Linz, Salzburg, Steyr, St. Poelten, Villach, Wels, Wien, Wiener Neustadt, Wolfsberg
Finland (5 regions)
Uusimaa, Southern Finland, Eastern Finland, Mid-Finland, Northern Finland
Italy (20 cities)
Ancona, Aosta, Bari, Bologna, Cagliari, Campobas, Firenze, Genova, L'Aquila, Milano, Napoli, Palermo, Perugia, Potenza, Reggio Calabria, Roma, Torino, Trento, Trieste, Venezia
Spain (18 provinces)
Castilla la Mancha, Extremadura, Cataluna, Ceuta et Melilla, Galicia, Canarias, La Rioja, Madrid, Murcia, Asturias, Baleares, Navarra, Pais Vasco, Cantabria, Aragon, Andalucia, Valencia, Castilla Leon
Portugal (7 regions)
Centro, Alentejo, Algarve, Madeira, Lisboa e Vale Tejo (LVT), Acores, Norte

Table 2: Description of Samples

Countries	Range	Categories
European ‘Core Sample’		
Germany (germ), Austria (aust), Finland (finl), Italy (ital), Spain (spai), Portugal (port)	95.01-04.10: germ, aust (allit), finl, ital (allit), spai and port; 96.01-04.10: ital (subcategories)	All items + 11 COICOP subcategories
European ‘Extended Sample’		
Germany (germ), Austria (aust), Italy (ital), Spain (spai), Portugal (port)	91.01-04.10:	All items

Notes:

- 1) The COICOP subcategories are: food and non-alcoholic beverages (food); alcoholic beverages and tobacco (alco); clothing and footwear (clot); housing, water electricity, gas and other fuels (hous); furnishings, household equipment and routine maintenance of the house (furn); health (heal); transport (tran); communications (comm); recreation and culture (recr); education (educ); hotels, cafes and restaurants (hote).
- 2) For Germany, alco and educ are missing for Saarland; for Portugal, educ is excluded.
- 3) Terms in brackets denote the short names that are used for the respective country or subcategory.

Table 3: Some Descriptive Statistics for our European ‘Core Sample’

Category		germ	aust	finl	ital	spai	port	all
allit	mean	1.41	1.60	1.44	2.42	2.87	2.93	2.00
	std.dvt.	0.0012	0.0010	0.0009	0.0022	0.0020	0.0010	0.0071
food	mean	0.64	-	1.58	2.03	2.71	2.50	1.51
	std.dvt.	0.0027	-	0.0032	0.0045	0.0025	0.0022	0.0099
alco	mean	2.88	-	0.30	3.75	5.04	3.92	3.53
	std.dvt.	0.0007	-	0.0006	0.0010	0.0033	0.0045	0.0118
clot	mean	1.12	-	-0.16	2.55	2.63	0.58	1.58
	std.dvt.	0.0216	-	0.0056	0.0054	0.0063	0.0085	0.0183
hous	mean	1.85	-	2.04	2.90	2.85	3.11	2.31
	std.dvt.	0.0017	-	0.0023	0.0038	0.0029	0.0033	0.0057
furn	mean	0.48	-	0.90	1.63	2.06	2.36	1.16
	std.dvt.	0.0018	-	0.0019	0.0033	0.0042	0.0041	0.0082
heal	mean	3.09	-	3.02	2.16	2.18	3.49	2.78
	std.dvt.	0.0012	-	0.0025	0.0048	0.0043	0.0032	0.0056
tran	mean	2.40	-	1.44	2.27	2.45	3.68	2.45
	std.dvt.	0.0010	-	0.0016	0.0032	0.0017	0.0016	0.0041
comm	mean	-3.46	-	-1.16	-1.89	-1.13	-2.05	-2.47
	std.dvt.	0.0052	-	0.0111	0.0040	0.0015	0.0038	0.0117
recr	mean	0.40	-	1.68	1.70	1.99	1.37	1.08
	std.dvt.	0.0020	-	0.0013	0.0018	0.0048	0.0025	0.0079
educ	mean	2.52	-	4.12	2.64	4.34	7.62	3.46
	std.dvt.	0.0115	-	0.0005	0.0093	0.0045	0.0065	0.0165
hote	mean	1.56	-	2.51	3.04	4.08	3.98	2.60
	std.dvt.	0.0027	-	0.0009	0.0060	0.0026	0.0037	0.0120

Notes:

- 1) The short names used for the COICOP subcategories are explained in table 2.
- 2) The mean inflation rate (mean) is computed as the cross-sectional mean of all regional mean inflation rates (geometric mean) included in the respective sample. The computation of the standard deviation is likewise based on the cross-section of the geometric means of all regional mean inflation rates included in the respective sample.
- 3) Standard deviations are multiplied by 10,000.

Table 4: Cross-Sectional Evidence of Inflation Convergence (β -convergence): European ‘Core Sample’, Total Period

Category	\hat{b}	$t - stat$	R_{adj}^2	half-life
Baseline Regressions				
allit	-0.077	-8.40	0.61	5.5
food	-0.241	-8.05	0.56	-
alco	-0.138	-5.90	0.31	1.4
clot	-0.087	-3.69	0.25	4.9
hous	-0.124	-8.32	0.52	2.2
furn	-0.060	-3.13	0.18	8.7
heal	0.119	1.99	0.11	-
tran	-0.085	-3.67	0.23	5.1
comm	-0.333	-11.28	0.60	-
recr	-0.210	-16.40	0.75	-
educ	-0.100	-2.38	0.22	3.8
hote	-0.081	-3.92	0.20	5.5

Notes:

- 1) The short names used for the COICOP categories are explained in table 2.
- 2) Estimation results are based on the equation

$$\frac{1}{T} \Delta(\pi_{i,t_0+T}) = constant + \beta * \pi_{i,t_0} + \epsilon_{i,t_0,t_0+T}.$$

Here, T denotes the length of the sample period in years, π denotes the inflation rate computed as an average annual rate and t_0 denotes the initial period. Estimation results were obtained using OLS.

- 3) The figures for the half-lives are computed by solving the equation

$$\hat{b} = - \left(\frac{1 - e^{-\beta * T}}{T} \right)$$

for β , see Barro and Sala-i Martin (1992). Where the nonlinear solution algorithm produced complex numbers, results for half-lives are not reported.

- 4) T-Statistics are computed using White (1980) heteroscedasticity-consistent standard errors.

Table 5: Cross-Sectional Evidence of Inflation Convergence (β -convergence) across European Regions: ‘Core Sample’, Pre-EMU and EMU Subperiod

Category	\hat{b}	$t - stat$	R_{adj}^2	half-live
1996.01-1998.12				
allit	-0.365	-12.78	0.68	0.7
food	-0.968	-7.79	0.38	0.1
alco	-0.614	-6.66	0.46	0.2
clot	-0.009	-0.06	-0.02	75.1
hous	-0.444	-2.12	0.13	0.8
furn	-0.629	-4.41	0.29	0.1
heal	-0.280	-1.64	0.11	1.7
tran	-1.238	-7.67	0.55	0.0
comm	-0.519	-5.50	0.13	0.5
recr	-0.629	-3.43	0.31	0.1
educ	-0.508	-3.37	0.31	0.6
hote	-0.531	-4.03	0.29	0.5
1999.01-2004.10				
allit	-0.033	-1.50	0.01	19.6
food	-0.210	-3.70	0.27	1.8
alco	-0.158	-5.42	0.39	2.9
clot	-0.067	-0.68	0.00	9.0
hous	-0.316	-5.83	0.39	0.3
furn	-0.181	-4.28	0.20	2.3
heal	-0.258	-5.68	0.56	1.1
tran	-0.293	-2.07	0.18	0.6
comm	-0.386	-15.96	0.90	0.1
recr	-0.240	-7.03	0.37	1.3
educ	-0.295	-9.37	0.78	0.6
hote	-0.162	-3.94	0.19	2.8

Notes:

- 1) The short names used for the COICOP categories are explained in table 2.
- 2) Estimation results are based on the equation

$$\frac{1}{T}\Delta(\pi_{i,t_0+T}) = constant + \beta * \pi_{i,t_0} + \epsilon_{i,t_0,t_0+T}.$$

Here, T denotes the length of the sample period in years, π denotes the inflation rate computed as an average annual rate and t_0 denotes the initial period. Estimation results were obtained using OLS.

- 3) The figures for the half-lives are computed solving the equation

$$\hat{b} = - \left(\frac{1 - e^{-\beta * T}}{T} \right)$$

for β , see Barro and Sala-i Martin (1992). Where the nonlinear solution algorithm produced complex numbers, results for half-lives are not reported.

- 4) T-Statistics are computed using White (1980) heteroscedasticity-consistent standard errors.

Table 6: Cross-Sectional Evidence of Inflation Convergence (β -convergence) across European Regions: European ‘Extended Sample’

Category	\hat{b}	$t - stat$	R_{adj}^2	half-life
‘Extended Sample’				
1992.01-2002.12	-0.071	-23.94	0.88	4.2
1992.01-1994.12	-0.271	-10.77	0.62	1.4
1995.01-1998.12	-0.236	-20.93	0.81	1.3
1999.01-2002.12	-0.042	-1.99	0.02	15.2

Notes:

1) Estimation results are based on the equation

$$\frac{1}{T}\Delta(\pi_{i,t_0+T}) = constant + \beta * \pi_{i,t_0} + \epsilon_{i,t_0,t_0+T}.$$

Here, T denotes the length of the sample period in years, π denotes the inflation rate computed as an average annual rate and t_0 denotes the initial period. Estimation results were obtained using OLS.

2) The figures for the half-lives are computed solving the equation

$$\hat{b} = - \left(\frac{1 - e^{-\beta * T}}{T} \right)$$

for β , see Barro and Sala-i Martin (1992). Where the nonlinear solution algorithm produced complex numbers, results for half-lives are not reported.

3) The European ‘extended sample’ includes Germany, Austria, Italy, Spain, and Portugal (for more details, see table 2).

4) T-Statistics are computed using White (1980) heteroscedasticity-consistent standard errors.

Table 7: Panel Unit Root Tests (Levin and Lin (1993)) of Inflation Convergence: European ‘Extended Sample’

Sample	ρ	ρ_{adj}	$t - stat$	p-value	half-live	half-live (adj.)
Eur.Ext.Sample: 1992-2002	0.74	0.96	-9.61	0.012	2.3	17.0
Eur.Ext.Sample: 1994-2002	0.64	0.88	-14.63	0.001	1.6	5.4

Notes:

- 1) The European ‘extended sample’ includes German, Austrian, Italian, Spanish and Portuguese regions, see table 2 for details.
- 2) Results are based on the equation:

$$\Delta \tilde{\pi}_{i,t} = \rho \tilde{\pi}_{i,t-1} + \sum_{j=1}^{k_i} \phi_{i,j} \Delta \tilde{\pi}_{i,t-j} + \epsilon_{i,t},$$

where $\tilde{\pi}_{i,t}$ denotes the deviation of region’s i inflation rate from the cross-sectional mean. A detailed description of the estimation procedure is given in section A.

- 3) Bias adjustment is done using the formula given by Nickell (1981).

Table 8: Transition Probabilities (Annual Transitions) for the European ‘Extended Sample’, Deviations the from Cross-Regional Mean and Quantiles

Transition Probabilities for Deviations from Cross-Reg. Mean					
Dev. in t	Dev. in $t + 1$				
	< -0.70	-0.20	0.20	0.70	> 0.70
< -0.7	0.61	0.25	0.11	0.02	0.01
-0.2	0.34	0.35	0.17	0.06	0.09
0.2	0.05	0.3	0.23	0.25	0.17
0.7	0.03	0.1	0.19	0.34	0.34
> 0.7	0.01	0.04	0.11	0.3	0.54

Transition Probabilities for Quintiles					
Quint. in t	Quint. in $t + 1$				
	0.20	0.40	0.60	0.80	1.00
0.2	0.51	0.31	0.14	0.03	0.01
0.4	0.31	0.41	0.17	0.09	0.03
0.6	0.11	0.21	0.27	0.24	0.16
0.8	0.03	0.07	0.24	0.39	0.27
1.0	0.02	0.04	0.15	0.29	0.5

Notes:

1) Table entries report conditional probabilities for the event that an observation which is in period t in the state indicated in column one moves to one of the states indicated in columns two to six in period $t + 1$. The variable under consideration is the deviation of a certain region’s inflation rate from the cross-sectional mean of inflation rates. Each state includes all inflation rate deviations that lie within the indicated range. The state -0.20 , e.g., comprises all inflation rate deviations that lie in the range $[-0.70, -0.20[$. States were chosen such that each state has approximately the same number of observations.

2) Table entries in the lower panel report conditional probabilities for a region’s inflation rate to transit from the quintile of the sample distribution indicated in the first column to the quintile indicated in columns two to six. 0.2 , e.g., indicates the first quintile of the distribution.

Table 9: Relationship between the Average Inflation Rate and Proportion of Regions Facing Negative Inflation Rates, European ‘Extended Sample’

‘Critical’ Average Inflation Rates			
Prop. of ‘Defl.’ Regions	European Sample		
	‘disp.-adj.’	no ‘disp.-adj.’	
1%	1.99	1.99	2.18
2.5%	1.53	1.68	1.83
5%	1.2	1.41	1.54
10%	0.87	1.1	1.2
25%	0.41	0.58	0.63

Mean Inflation Rate and Percentage of Regions with Deflation			
Mean Infl. Rate	Prop. of ‘Deflationary’ Regions		
	‘disp.-adj.’	no ‘disp.-adj.’	
2	0.98	0.98	1.63
1.9	1.19	1.33	2.11
1.8	1.45	1.78	2.72
1.7	1.78	2.36	3.46
1.6	2.18	3.09	4.36
1.5	2.68	3.99	5.44
1.4	3.3	5.11	6.73
1.3	4.07	6.45	8.23
1.2	5.01	8.06	9.98
1.1	6.17	9.95	11.98
1	7.61	12.15	14.26
0.9	9.36	14.67	16.8
0.8	11.51	17.51	19.62
0.7	14.11	20.69	22.72
0.6	17.24	24.18	26.07
0.5	20.97	27.97	29.65
0.4	25.37	32.02	33.45
0.3	30.48	36.31	37.42
0.2	36.33	40.77	41.54
0.1	42.86	45.35	45.74
0	50	50	50

Notes:

- 1) The European ‘extended sample’ includes German, Austrian, Italian, Spanish and Portuguese regions, see table 2 for details.
- 2) Mean inflation rates (Mean Infl. Rate) are computed by weighting each regional inflation rate, $\pi_{i,t}$, with the respective region’s share in total GDP, i.e.,

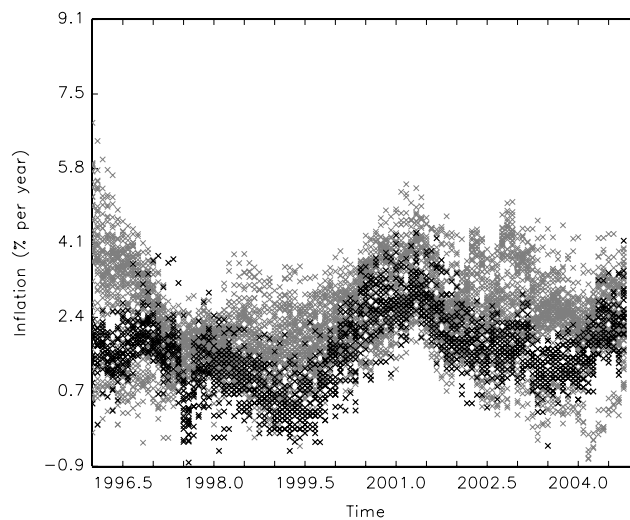
$$\hat{\pi}_t = \sum_{i=1}^N \gamma_i \pi_{i,t}.$$

γ_i represents the share of region’s i GDP (denoted as GDP_i) in total GDP (given by the sum over all GDP_i). γ_i is thus computed as $\gamma_i = \frac{GDP_i}{\sum_{i=1}^N GDP_i}$.

- 3) ‘Disp.-adj.’ (dispersion adjustment) refers to the case where the positive relationship between the prevailing mean inflation rate and its dispersion is being taken into account in the computations. ‘No disp.-adj.’ refers to the cases, when either inflation dispersion computed at an average rate of 2% (the ECB’s upper inflation bound) or 2.5% (the highest average annual inflation rate since introduction of the Euro) is taken for the computations.

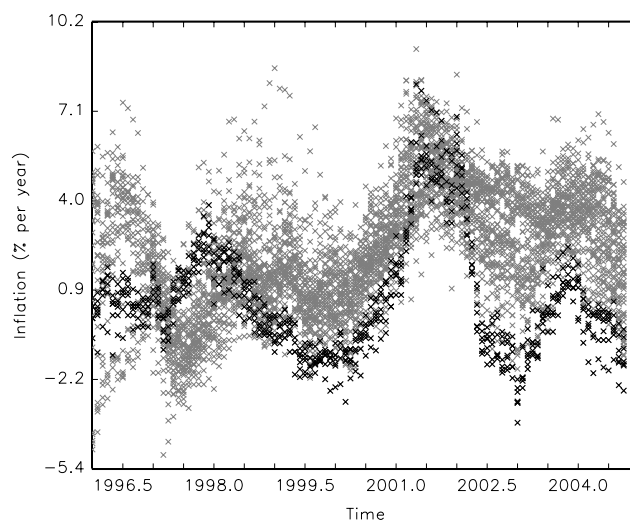
10 Figures

Figure 1: Regional European Inflation Rates: All Items, Emphasis on Italian Regions



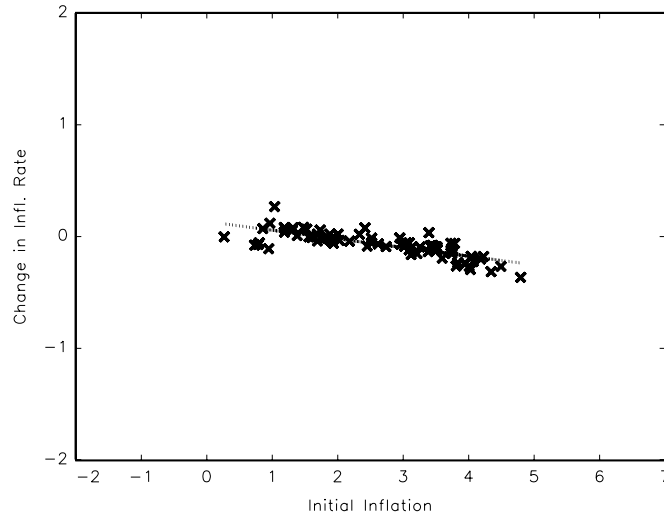
Note: Figure 1 plots cross-sectional inflation rates ('All Items') for Germany, Austria, Finland, Italy, Spain and Portugal. Inflation rates are computed as annual percentage changes in the underlying price index. Inflation rates of Italian regions are emphasized.

Figure 2: Regional European Inflation Rates: Food, Emphasis on German Regions



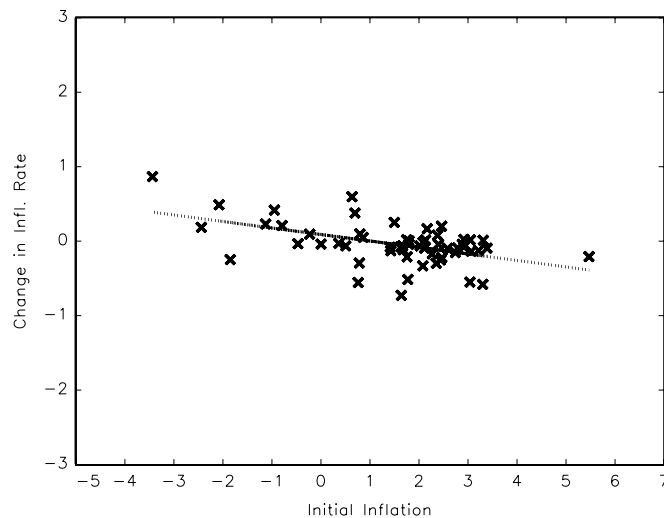
Note: Figure 2 plots cross-sectional inflation rates (COICOP subcategory 'Food and Non-Alcoholic Beverages') for Germany, Finland, Italy, Spain and Portugal. Inflation rates are computed as annual percentage changes in the underlying price index. Food-inflation rates of German regions are emphasized.

Figure 3: Change in Inflation vs. Initial Inflation: All Items, Total Period



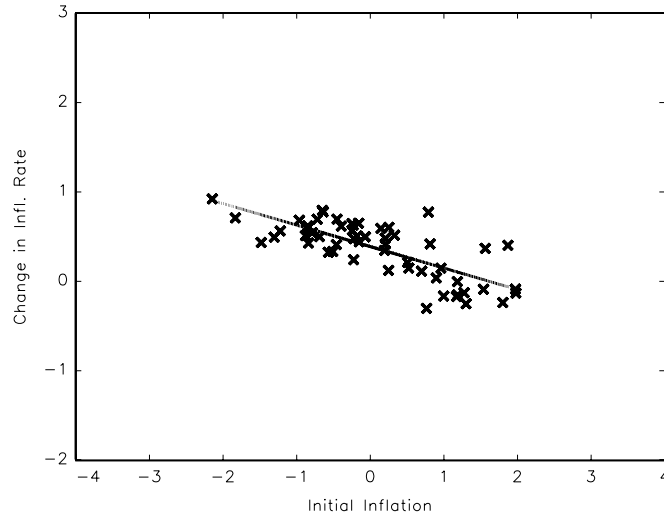
Note: Figure 3 plots average annual changes in inflation rates ('All Items') between 1996 and 2002 for Germany, Austria, Finland, Italy, Spain and Portugal versus their initial inflation rates in 1996. Inflation rates are computed as annual percentage changes in the underlying price index. The dotted line plots fitted values from a OLS regression.

Figure 4: Change in Inflation vs. Initial Inflation: Clothing and Footwear, Total Period



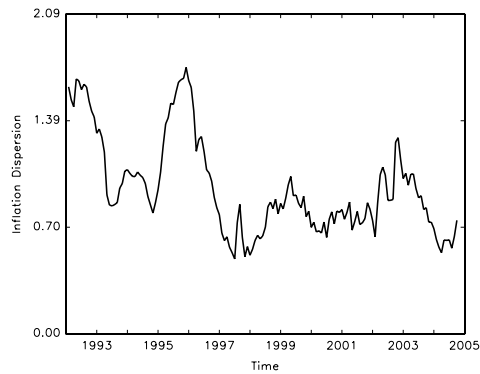
Note: Figure 4 plots average annual changes in inflation rates ('Clothing and Footwear') between 1997 and 2002 for Germany, Austria, Finland, Italy, Spain and Portugal versus their initial inflation rates in 1997. Inflation rates are computed as annual percentage changes in the underlying price index. The dotted line plots fitted values from a OLS regression.

Figure 5: Change in Inflation vs. Initial Inflation: Food, Total Period



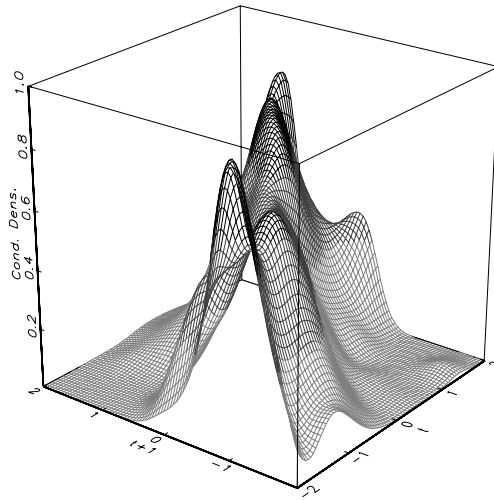
Note: Figure 5 plots average annual changes in inflation rates ('Food and Non-Alcoholic Beverages') between 1997 and 2002 for Germany, Austria, Finland, Italy, Spain and Portugal versus their initial inflation rates in 1997. Inflation rates are computed as annual percentage changes in the underlying price index. The dotted line plots fitted values from a OLS regression.

Figure 6: Cross-Regional Inflation Rate Dispersion: European 'Extended Sample'



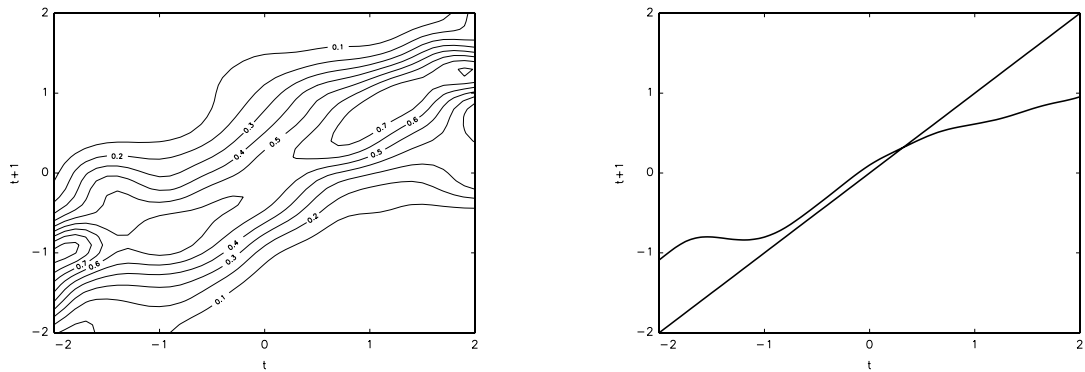
Note: Figure 6 plots the standard deviation of the regional inflation rates (total index) of our European 'extended sample' (Germany, Austria, Italy, Spain and Portugal) for the period from 1992 to 2002. Inflation rates are computed as annual percentage changes in the underlying price index. All figures are multiplied by 100.

Figure 7: Surface Plot of the Estimated Stochastic Kernel for Regional Mean-Inflation Rate Deviations, European ‘Extended Sample’, Annual Transitions



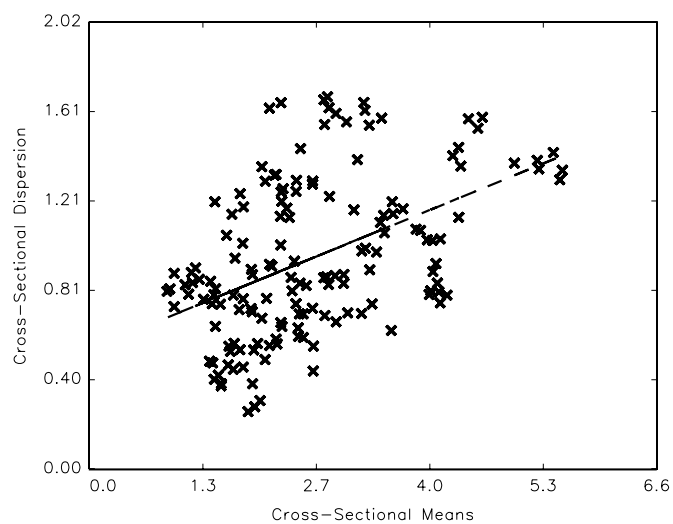
Note: Figure 7 represents the surface plot of the estimated stochastic kernel for cross-sectional mean inflation rate deviations of the regions included in the European ‘extended sample’ over the period 1983 to 2002. On the x-axis (denoted by t), period’s t inflation rate deviations from the cross-regional mean and on the y-axis (denoted by $t + 1$), period’s $t + 1$ inflation rate deviations from the cross-regional mean are plotted. On the z-axis, the transition density function $p(x, y)$ associated with the stochastic kernel $P(x, A)$ is plotted.

Figure 8: Contour Plot of the Estimated Stochastic Kernel and Conditional Expected Next Period’s Mean for Regional Mean-Inflation Rate Deviations, European ‘Extended Sample’



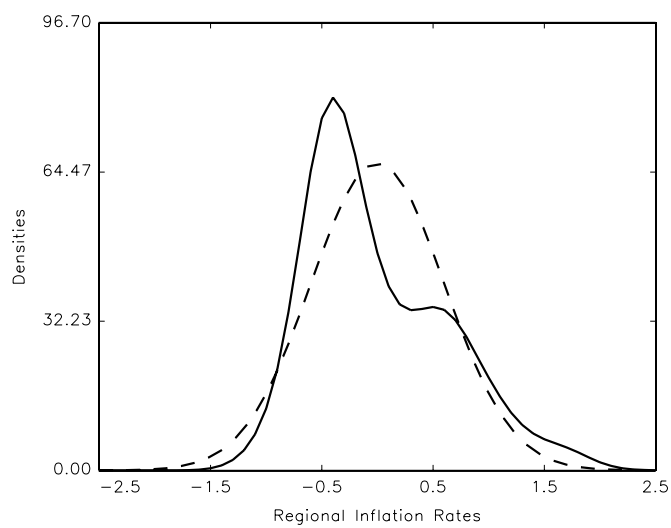
Note: The left panel of figure 8 represents the contour plot of the transition density function $p(x, y)$ associated with the stochastic kernel $P(x, A)$ that we computed for the European ‘extended sample’ (see figure 7). The right panel of figure 8 plots expected period’s $t + 1$ mean-inflation rate deviations conditional on period’s t mean-inflation rate deviations.

Figure 9: Cross-Regional Inflation Mean and Dispersion



Note: Figure 9 plots the standard deviations of regional inflation rates against their means for the period 1992.01 - 2004.10. Included countries are Germany, Austria, Italy, Spain and Portugal. Individual inflation rates are weighted by the respective region's weight in total GDP.

Figure 10: Regional Inflation Dispersion: Empirical Density Estimate and Theoretical Approximation



Note: Figure 10 plots the kernel density estimate of the empirical distribution of regional inflation rates of our European 'extended sample' versus the density from a normal distribution that is used as an approximation. The empirical distribution is that prevailing in January 2000.

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A Levin-Lin Panel Unit Root Test

A.1 The Test Procedure

To obtain the Levin-Lin panel-unit root results in section 4, we proceed as follows: Let $\pi_{i,t}$ (with $i = 1, 2, \dots, N$ and $t = 1, 2, \dots, T$) be a balanced panel of inflation rates consisting of N individual regions with T observations, respectively. The starting point of our analysis is the following test equation:

$$\Delta\pi_{i,t} = \rho_i\pi_{i,t-1} + u_{i,t}, \quad (\text{A.1})$$

where $-2 < \rho_i \leq 0$, and $u_{i,t}$ has the following error-components representation

$$u_{i,t} = \theta_t + \epsilon_{i,t}. \quad (\text{A.2})$$

In this specification, θ_t represents a common-time effect and $\epsilon_{i,t}$ is a (possibly serially correlated) stationary idiosyncratic shock.

The Levin-Lin test procedure imposes (both for the null hypothesis of non-stationarity and for the alternative hypothesis of stationarity) the homogeneity restriction that all ρ_i are equal across individual regions. Thus, the null hypothesis can be formulated as:

$$H_0 : \rho_1 = \rho_2 = \dots = \rho_N = \rho = 0,$$

and the alternative hypothesis (that all series are stationary) is given by:

$$H_1 : \rho_1 = \rho_2 = \dots = \rho_N = \rho < 0.$$

To test this null hypothesis we proceed as follows:

1. First, we control for the common-time effect by subtracting the cross-sectional means:

$$\tilde{\pi}_{i,t} = \pi_{i,t} - \frac{1}{N} \sum_{j=1}^N \pi_{j,t} \quad (\text{A.3})$$

Having transformed the dependent variable we proceed with the following test equation:

$$\Delta\tilde{\pi}_{i,t} = \rho\tilde{\pi}_{i,t-1} + \sum_{j=1}^{k_i} \phi_{i,j} \Delta\tilde{\pi}_{i,t-j} + \epsilon_{i,t}. \quad (\text{A.4})$$

The lagged differences of $\tilde{\pi}_{i,t}$ are included to control for potential serial correlations in the idiosyncratic shocks $\epsilon_{i,t}$. Whereas we equalize the ρ_i across individuals we allow for different degrees of serial correlation k_i (with $i = 1, \dots, N$) across them. The number of lagged differences for each region is determined by the general-to-specific method of Hall (1994) which is recommended by Campbell and Perron (1991).

2. The next step in our testing procedure is to run the following two auxiliary

regressions

$$\Delta \tilde{\pi}_{i,t} = \sum_{j=1}^{k_i} \phi_{1i,j} \Delta \tilde{\pi}_{i,t-j} + e_{i,t}. \quad (\text{A.5})$$

$$\tilde{\pi}_{i,t-1} = \sum_{j=1}^{k_i} \phi_{2i,j} \Delta \tilde{\pi}_{i,t-j} + \nu_{i,t-1}. \quad (\text{A.6})$$

and to retrieve the residuals $\hat{e}_{i,t}$ and $\hat{\nu}_{i,t-1}$ from these regressions.

3. These residuals are used to run the regression

$$\hat{e}_{i,t} = \rho_i \hat{\nu}_{i,t-1} + \eta_{i,t}. \quad (\text{A.7})$$

The residuals of (A.7) are used to compute an estimate of the variance of $\eta_{i,t}$:

$$\hat{\sigma}_{\eta_i}^2 = \frac{1}{T - k_i - 1} \sum_{t=k_i+2}^T \hat{\eta}_{i,t}^2 \quad (\text{A.8})$$

4. Normalizing the OLS residuals $\hat{e}_{i,t}$ and $\hat{\nu}_{i,t-1}$ by dividing them through $\hat{\sigma}_{\eta_i}$ yields:

$$\tilde{e}_{i,t} = \frac{\hat{e}_{i,t}}{\hat{\sigma}_{\eta_i}} \quad (\text{A.9})$$

$$\tilde{\nu}_{i,t-1} = \frac{\hat{\nu}_{i,t-1}}{\hat{\sigma}_{\eta_i}} \quad (\text{A.10})$$

5. The normalized residuals are used to run the following pooled cross-section time-series regression:

$$\tilde{e}_{i,t} = \rho \tilde{\nu}_{i,t-1} + \tilde{\epsilon}_{i,t}. \quad (\text{A.11})$$

Under the null hypothesis, $\tilde{e}_{i,t}$ is independent of $\tilde{\nu}_{i,t-1}$, i.e., we can test the null hypothesis by testing whether $\rho = 0$. Unfortunately, the studentized coefficient

$$\tau = \frac{\hat{\rho}}{\hat{\sigma}_{\tilde{\epsilon}} \sum_{i=1}^N \sum_{t=2+k_i}^T \tilde{\nu}_{i,t-1}^2}$$

with

$$\hat{\sigma}_{\tilde{\epsilon}} = \frac{1}{NT} \sum_{i=1}^N \sum_{t=2+k_i}^T \tilde{\epsilon}_{i,t}$$

is not asymptotically normally distributed. Levin and Lin (1993) compute an adjusted test statistic based on τ that it is asymptotically normally distributed. However, we do not make use of their adjustment procedure but use bootstrap methods to compute critical values for the null hypothesis. This procedure is described in section A.2.

A.2 Bootstrap Procedure

Since the finite-sample properties of the adjusted τ statistics are unknown and since idiosyncratic shocks may be correlated across individual regions we rely on bootstrap methods to infer critical values for the τ statistics. More precisely, we employ a nonparametric bootstrap where we resample the estimated residuals from our model. The starting point of our bootstrap approach is given by the hypothesized data generating process (DGP) under the null hypothesis

$$\Delta\pi_{i,t} = \sum_{j=1}^{k_i} \phi_{i,j} \Delta\pi_{i,t-j} + \epsilon_{i,t}. \quad (\text{A.12})$$

Our procedure is as follows:

1. We retrieve the OLS residuals from estimating the DGP under the null hypothesis. This yields the vectors $\hat{\epsilon}_1, \hat{\epsilon}_2, \dots, \hat{\epsilon}_T$, where $\hat{\epsilon}_t$ is the $1 \times N$ residual vector for period t .
2. Then, we resample these residual vectors by drawing one of the possible T residual vectors with probability $\frac{1}{T}$ for each $t = 1, \dots, T$.
3. These resampled residual vectors are used to recursively build up pseudo-observations $\Delta\hat{\pi}_{i,t}$ according to the DGP (using the estimated coefficients $\hat{\phi}_{i,j}$).
4. Next, we perform the Levin-Lin test (as described in subsection A.1) on these observations (without subtracting the cross-sectional mean). The resulting τ is saved.
5. Steps two to four are repeated 5,000 times. The collection of the τ statistics form the bootstrap distribution of these statistics under the null hypothesis.