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On the Importance of Sectoral Shocks for Price-setting*

Guenter W. Beck[1], Kirstin Hubrich[2], and Massimiliano Marcellino[3]

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Abstract:
We use a novel disaggregate sectoral euro area dataset with a regional breakdown that allows explicit estimation of the sectoral component of price changes (rather than interpreting the idiosyncratic component as sectoral as done in other papers). Employing a new method to extract factors from over-lapping data blocks, we find for our euro area data set that the sectoral component explains much less of the variation in sectoral regional inflation rates and exhibits much less volatility than previous findings for the US indicate. Country- and region-specific factors play an important role in addition to the sector-specific factors. We conclude that sectoral price changes have a "geographical" dimension, as yet unexplored in the literature, that might lead to new insights regarding the properties of sectoral price changes.

JEL-Classifications: E31, E4, E5, C3

Keywords: Disaggregated Prices, Euro Area Regional and Sectoral Inflation, Common Factor Models.

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1 Introduction

A central element of a majority of contemporary macroeconomic models is the assumption of nominal rigidities in goods markets. The rationale for incorporating price stickiness into these models is provided by the fact that there exists strong empirical evidence in favor of stickiness in prices at an aggregate level. Moreover, the empirical fit of models usually improves considerably when nominal rigidities are allowed for. A standard assumption in DSGE models is Calvo pricing, where firms adjust prices according to staggered contracts (time-dependent pricing). Alternative assumptions include state-dependent pricing, information frictions or rational inattention. The relatively broad consensus about the importance of stickiness in nominal goods prices that emerged, has been challenged in recent years, however. Newer studies that analyze the behavior of micro price data have come to somewhat puzzling results: They find that these prices are not only very volatile, but also exhibit low persistence[1], in stark contrast to the findings concerning the behavior of aggregate data.

To reconcile the evidence on disaggregate and aggregate prices, several explanations have been put forward. One strand of the literature argues that the apparent persistence of aggregate inflation may be the result of an aggregation bias which arises as the consequence of aggregating heterogeneous sectoral price series.[2] Other authors such as Cogley and Sargent (2005) or Clark (2006) argue that the observed aggregate persistence of prices may reflect a structural break in the mean inflation during the sample. A third explanation presented in Boivin et al. (2008) states that the differences in inflation persistence at the aggregate and disaggregate level may be due to different responses of aggregate and sectoral prices to macroeconomic and sector-specific shocks. Decomposing a broad set of disaggregate sectoral price data into an aggregate and an idiosyncratic or sectoral component these authors find that the aggregate component exhibits considerable persistence but contributes only little to changes in sectoral prices. The sectoral component on the other hand shows no persistence but is very volatile and explains most of the movements in sectoral prices. Thus, the puzzling evidence on the different behavior of disaggregate and aggregate prices can be attributed to the fact that the former are mostly determined by very volatile sectoral shocks with low persistence whereas the latter are pre-dominantly influenced by highly persistent aggregate shocks with low volatility.

[1] See, e.g., the papers by Bils and Klenow (2004) or Alvarez et al. (2006).

[2] See, e.g., Granger (1980), Pesaran and Smith (1995) and Imbs et al. (2005).

The results by Boivin et al. (2008) are confirmed in a recent study by Mackowiak et al. (2009). Similar to Boivin et al. (2008) these authors decompose a large set of disaggregate monthly U.S. sectoral consumer price data into an aggregate and a sectoral component. They find that the sectoral component not only explains the bulk of variations in sectoral prices but that this component also shows no sign of persistence. In a second step, these authors relate their findings to three different models of price-setting and ask whether any of these models is capable to explain the observed patterns of sectoral price changes. The three models that the authors consider are multi-sector versions of the Calvo (1983) model, the sticky-information model a la Mankiw and Reis (2002) and the rational-inattention model by Mackowiak and Wiederholt (2009). They show that both the Calvo- and the sticky-information model are compatible with the observed pattern of sectoral price dynamics only for extreme parameter values and conclude that the rational-inattention model fits the observed behavior of sectoral prices best since it postulates that firms react more to sector-specific shocks than to aggregate macroeconomic shocks.

In this paper, we point to a potential problem of the two just mentioned papers which concerns the estimation strategy of the sectoral component. As discussed above, the two studies decompose sectoral price movements into an aggregate and an idiosyncratic component where the latter is interpreted as the sector-specific component. In other words, the sector-specific component is computed as a residual variable which, by construction, captures the effects of all factors that influence sectoral inflation rates but are not common to all of them. It might therefore represent a mixture of the actual sector-specific component and other non-sector-specific factors. As Boivin et al. (2008) point out one of these additional factors can be measurement errors. Below, we argue that other important, non-sector-specific elements in the residual variable are factors which result from aggregating geographic-specific factors across regions. If any or both of these aspects play an important quantitative role, the behavior of the sectoral component which Boivin et al. (2008) and Mackowiak et al. (2009) analyze might not correspond to the behavior of the actual sector-specific but might result from combining the effects of very different factors.

To examine the relative importance of the factors just discussed we use a novel and large disaggregate sectoral euro area dataset with a regional breakdown that allows for an explicit estimation of the sectoral component of price changes. This dataset enables us to decompose regional sectoral inflation rates into an aggregate, a sector-specific, a country-specific, a country-sector specific and an idiosyncratic component. Employing a new method to extract factors from over-lapping data blocks, we find that the sectoral component exhibits much less volatility than previous findings for the US indicate and explains much less of the variation in the data. Like previous US results, we find that the sector-specific component exhibits little persistence on average, although persistence varies substantially across sectors. Country- and region-specific factors play an important role in addition to the sector-specific factors. Our results also show that, if we proceed as in Boivin et al. (2008) or Mackowiak et al. (2009), we obtain "a sector-specific" component that behaves very similar to the ones obtained in these two papers.

The rest of the paper is organized as follows: In Section 2 we shortly describe our data and provide some stylized facts on the extent of differences in inflation rates across sectors and regions. In Section 3 we introduce the econometric framework used to analyze the determinants of changes in regional sectoral prices. In Section 4 we present and discuss the econometric results. In Section 5 we analyze additional features of the estimated econometric model and consider the transmission of aggregate, national and sectoral shocks. In Section 6 we extend the model to study the transmission of aggregate monetary policy shocks. Finally, in Section 7 we summarize the main findings and conclude.

2 Data and descriptive statistics

To determine and characterize the factors driving changes in sectoral prices we collected a large set of regional European sectoral price index data. More precisely, we compiled a data set which includes sectoral consumer price index (CPI) data from six EMU member countries (Austria (AU), Germany (DE), Finland (FI), Italy (IT), Portugal (PO) and Spain (ES)) and which comprises a total of 61 locations, covering about 60% of the euro area in terms of GDP. The regions are the same as in Beck et al. (2009), where we use an all items data set with a regional breakdown.[3] For each region, in addition to the all-items inflation considered in Beck et al. (2009), we have the following sectors: 1. food and non-alcoholic beverages (food); 2. alcoholic beverages, tobacco and narcotics (alco); 3. clothing and footwear (clot); 4. housing, water, electricity, gas and other fuels (hous); 5. furnishings, household equipment and routine household maintenance (furn); 6. health

[3] An overview of the regions included in our sample and the short names used in this paper is given in Tables A and B of Appendix A.

(heal); 7. transport (tran); 8. communication (comm); 9. recreation and culture (recr); 10. education (educ); 11. restaurants and hotels (hote). Overall, the data set includes 730 series, spanning the period 1995(1) to 2004(10) on a monthly frequency, non-seasonally adjusted and in index form.[4]

The inflation rate in a given country c, region r and sector s at time t (with $c = 1,...,C$, $r = 1,...,R_c$, $s = 1,...,S_r$, and $t = 1,...,T$), denoted by $\pi_{c,r,s,t}$, is computed as the month-on-month proportional change in the (log of the) respective sectoral price index, $p_{c,r,s,t}$, i.e.,

$$\pi_{c,r,s,t} = \ln(p_{c,r,s,t}) - \ln(p_{c,r,s,t-1}). \tag{1}$$

C denotes the number of countries in our dataset, R_c denotes the number of regions in country c and S_r denotes the number of sectoral series available for region r.

For our econometric analysis, the data are seasonally adjusted, standardized and series with clear signs of structural breaks or shifts in variance are dropped. Moreover, outliers larger than 4 standard deviations are replaced by averages of the adjacent observations. We have also dropped Austria, since sectoral data are only available at a regional level since 2001. The resulting "cleaned" data set contains 418 series.

Table 1 reports descriptive statistics for the (unstandardized) data series included in this cleaned data set. Results are reported for all data series (*Total sample*) and subsamples which include all series from a given country (*Data grouped by countries*) or a given sector (*Data grouped by sectors*). Several interesting features of the reported statistics are noteworthy. When looking at the total sample we can see that there exists considerable heterogeneity in mean inflation rates across series. Moreover, in line with findings of similar studies, we find that regional sectoral inflation rates are on average very volatile but exhibit little or no persistence.

The numbers in the second and third panel of Table 1 show that there are considerable differences in (long-run) average inflation rates both across countries (reaching from about 1.1% for German sectoral inflation rates to about 2.6% for both Spanish and Portuguese inflation rates) and sectors (reaching from about 1.3% for clothing to about 2.9% for hotel). Moreover, for all groups in these panels we can observe that - in line with the literature - the regional sectoral inflation rates are both very volatile and show little persistence. Interesting insights are provided by considering the deviation of the aver-

[4] For the remaining euro area countries comparable regional data are not available or at least not for a similar time span.

age correlation of the inflation rates within a group from the aggregate inflation rate of a group.[5] This statistic can be seen as a proxy measure for the degree of comovement in a given group. The results show that the extent of comovement is significantly higher when the series are grouped either by countries or sectors relative to the case when all series are taken into account. This indicates that regional sectoral inflation rates might not only be driven by sector-specific factors but that also country-specific factors might matter.

Table 2 reports descriptive statistics when the series of our sample are grouped by country-specific sectors. The reported numbers show that there is considerable dispersion in long-run average inflation rates across sectors even within countries. Volatility is large across national sectors and is comparable in size. Persistence on the other hand is always very low. The correlation is even higher than for the country-specific sectoral groupings.

Two final issues deserve a comment. First, to which extent has the cleaning process has changed the general pattern of our data? The results of Tables C and D of Appendix B report descriptive statistics for the raw data. They show that the pattern of the results for mean values, persistence and within-group correlations is similar to that of the cleaned dataset. As could be expected the numbers for volatility are smaller in the cleaned data set which is corrected for outlier values.

Second, are the sectoral regional inflation rates in the cleaned dataset stationary or integrated? Beck et al. (2009) run formal unit root tests on the all-items regional inflation series, but they also did not obtain a definitive answer, since the single equation tests did not reject non-stationarity in most cases while the panel tests systematically rejected non-stationarity. Hence, they performed the analysis for both the levels and the first differences of inflation, finding qualitatively similar conclusions. Therefore, we will focus on the levels of the inflation series.

In summary, the descriptive analysis of this section, based on a new dataset for the euro area with both a regional and a sectoral breakdown, confirms previous findings that sectoral price changes are not only very volatile but also exhibit litte persistence. Our results furthermore indicate that changes in sectoral price seem to have a “geographical“ dimension which has not been explored in the literature thus far.

[5]The aggregate inflation rate of a group is computed as a weighted average of the series included in the group, see footnotes to Table 1 for details.

3 Econometric model: A new approach

To analyze the determinants of changes in sectoral prices previous studies have proposed to decompose $\pi_{c,r,s,t}$ as follows:[6]

$$\pi_{c,r,s,t} = \alpha_{c,r,s} f_t^a + u_{c,r,s,t} \tag{2}$$

where $\alpha_{c,r,s} f_t^a$ represents the aggregate component and $u_{c,r,s,t}$ is interpreted as the sector-specific component. Based on this decomposition, the statistical properties of both the aggregate and sector-specific components are then examined, and the relative contribution of each component to the overall volatility of $\pi_{c,r,s,t}$ is determined. Previous studies found that the aggregate macroeconomic component exhibits relatively low volatility but high persistence, while the sector-specific component is found to display high volatility and no persistence. Moreover, the latter is found to explain about 85-90% or more of the movements in $\pi_{c,r,s,t}$, and therefore sectoral inflation rates essentially behave like the sector-specific component.

One problematic aspect of the methodological approach employed in previous studies, is that the sector-specific component $u_{c,r,s,t}$ is computed as a residual variable and therefore captures the effects of all factors which influence sectoral inflation rates but are not common to all of them. In other words, a (possibly large) part of $u_{c,r,s,t}$ could be unrelated to sectoral movements.

The use of regional sectoral inflation rates allows us to decompose the residual term $u_{c,r,s,t}$ further, and to explicitly extract a sectoral factor whose characteristics and relative importance in explaining variations in $\pi_{c,r,s,t}$ we can analyze. More specifically, we decompose $u_{c,r,s,t}$ as follows

$$u_{c,r,s,t} = \beta_{c,r,s} f_t^c + \gamma_{c,r,s} f_t^s + \delta_{c,r,s} f_t^{sc} + e_{c,r,s,t} \tag{3}$$

and therefore analyze the following model for $\pi_{c,r,s,t}$

$$\pi_{c,r,s,t} = \alpha_{c,r,s} f_t^a + \beta_{c,r,s} f_t^c + \gamma_{c,r,s} f_t^s + \delta_{c,r,s} f_t^{sc} + e_{c,r,s,t}. \tag{4}$$

In this equation, f_t^a are k_a aggregate factors common to all of the units (e.g., monetary

[6]See, e.g., equation (2) of Boivin et al. (2008) or equation (1) of Mackowiak et al. (2009). Inflation rates are demeaned and their variances are normalized to one before estimation.

policy, raw material prices, or external developments), f_t^c are k_c country-specific factors that only affect variables in country c (e.g. fiscal policy or nation-wide labour market legislation), f_t^s are k_s sector-specific factors that only affect variables in sector s (e.g. tariffs decided at the EU level on goods belonging to a specific sector or increases in the costs of inputs specific to a given sector), and f_t^{sc} are k_{sc} sector- and country-specific factors that only affect variables in sector s of country c (e.g. changes in value added taxes for goods in a specific sector or the implications of sectoral wage bargaining at the national level). $e_{c,r,s,t}$ denotes the remaining idiosyncratic component.

The factors within each group are assumed to be orthonormal, and the factors across groups are assumed to be uncorrelated with each other. The factors are also assumed to be uncorrelated with the idiosyncratic term $e_{c,r,s,t}$, which has limited correlation across units and over time in order to satisfy the conditions in Stock and Watson (2002a) and Stock and Watson (2002b). Under the assumptions we have made, the model is identified, which makes the loadings and the factors estimable.

3.1 A factor model for over-lapping data blocks

To estimate the different types of factors in (4), we extend previous literature on extracting factors from non-overlapping data-blocks[7] to over-lapping data blocks. We adopt a modified version of the non-parametric principal component based estimator of Stock and Watson (2002a) and Stock and Watson (2002b). With respect to the previous literature, we have the additional complication of several types of factors, which influence different over-lapping subgroups of variables. We estimate those imposing the assumption of no correlation among the factors.

Starting with the aggregate factors f_t^a, which influence all variables under analysis, Stock and Watson's method can be directly applied. Therefore, the k_a estimated factors $\widehat{f_t^a}$ coincide with the first k_a principal components of $\pi_{c,r,s,t}$.

Let us consider now the country-specific factors f_t^c. We might think of using as estimators the first k_c principal components of all variables for each country $c = 1,...C$. However, these principal components would depend on f^a and therefore the resulting estimators of f_t^c would be correlated with those of f_t^a. To tackle this problem we could take the principal components of $\pi_{c,r,s,t} - \widehat{\alpha}_{c,r,s}\widehat{f_t^a}$ for each country, where the loadings $\widehat{\alpha}_{c,r,s}$ are obtained by OLS regressions of $\pi_{c,r,s,t}$ on the estimated factors $\widehat{f_t^a}$. The use

[7] See e.g. Kose et al. (2003), Beck et al. (2009) and Moench et al. (2009)

of the estimated rather than true aggregate factors requires the total number of variables ($N = \sum_{c=1}^{C}\sum_{r=1}^{R_c}\sum_{c=1}^{S_r} 1$) to be large and to grow faster than the number of observations (T); in particular, it should be $\sqrt{T}/N \to 0$, see Bai and Ng (2002) for details. The use of the estimated rather than the true loadings is justified by the consistency of the OLS estimator when T diverges.

In order to estimate the sector-specific factors f_t^s, we could follow a similar procedure and use as estimators the first k_c principal components of $\pi_{c,r,s,t} - \widehat{\alpha}_{c,r,s}\widehat{f_t^a}$ for each sector. However, since some of the observations in $\pi_{c,r,s,t} - \widehat{\alpha}_{c,r,s}\widehat{f_t^a}$ are used to construct both the estimators of f_t^c and those of f_t^s, the resulting estimators would be correlated, in contrast with the assumption of no correlation between f_t^c and f_t^s. Therefore, we need an additional modification to estimate f_t^c and f_t^s.

Let us therefore consider the model

$$\begin{aligned} &\frac{1}{S_r}\sum_{s=1}^{S_r}\left(\pi_{c,r,s,t} - \widehat{\alpha}_{c,r,s}\widehat{f_t^a}\right) \overset{asympt}{=} \frac{1}{S_r}\sum_{s=1}^{S_r}\left(\pi_{c,r,s,t} - \alpha_{c,r,s}f_t^a\right) = \\ = &\left(\frac{1}{S_r}\sum_{s=1}^{S_r}\beta_{c,r,s}\right)f_t^c + \frac{1}{S_r}\sum_{s=1}^{S_r}\gamma_{c,r,s}f_t^s + \frac{1}{S_r}\sum_{s=1}^{S_r}\delta_{c,r,s}f_t^{sc} + \frac{1}{S_r}\sum_{s=1}^{S_r}e_{c,r,s,t}. \end{aligned}$$

If S_r is large, since the sector-specific factors f_t^s are orthogonal across sectors by assumption, the term $\frac{1}{S_r}\sum_{s=1}^{S_r}\gamma_{c,r,s}f_t^s$ vanishes. Hence, for each country, we suggest to estimate the country-specific factors as the first k_c principal components of the R_c ($c = 1,2,\ldots,C$) variables $\frac{1}{S_r}\sum_{s=1}^{S_r}\left(\pi_{c,r,s,t} - \widehat{\alpha}_{c,r,s}\widehat{f_t^a}\right)$, which are also no longer dependent on the sector specific factors when S_r is large. Then, for each sector, the sector specific factors can be estimated as the first k_s principal components of the $\sum_{c=1}^{C}\sum_{r=1}^{R_c} I(r_s)$ variables $\pi_{c,r,s,t} - \widehat{\alpha}_{c,r,s}\widehat{f_t^a} - \widehat{\beta}_{c,r,s}\widehat{f_t^c}$.[8]

This procedure requires the number of sectors S_r to be large. When this is not the case, an iterative method can produce better results. In the first step, f_t^c and f_t^s are estimated as indicated in the previous paragraph, which yields $\widehat{f_t^{c1}}$ and $\widehat{f_t^{s1}}$. In the second step, the residuals $\pi_{c,r,s,t} - \widehat{\alpha}_{c,r,s}\widehat{f_t^a} - \widehat{\gamma}_{c,r,s}\widehat{f_t^{s1}}$ are computed, and their first k_c principal components are used to construct $\widehat{f_t^{c2}}$. Notice that this is an alternative method to get rid of the correlation between $\widehat{f_t^c}$ and $\widehat{f_t^s}$. In the third step, the residuals $x_{c,r,s,t} - \widehat{\alpha}_{c,r,s}\widehat{f_t^a} - \widehat{\beta}_{c,r,s}\widehat{f_t^{c2}}$

[8] $I(r_s)$ represents a dummy variable equal to one if data for the considered sector s are available in region r and equal to zero if no data for sector s are available for region r.

are computed, and their first k_s principal components are used to construct $\widehat{f}_t^{s2}$. In the fourth step, the residuals $\pi_{c,r,s,t} - \widehat{\alpha}_{c,r,s}\widehat{f}_t^a - \widehat{\gamma}_{c,r,s}\widehat{f}_t^{s2}$ are computed, and their first k_c principal components are used to construct $\widehat{f}_t^{c3}$. The procedure continues like this until successive estimates of the factors are sufficiently close. In particular, we stop when $\max_c \left\{ \max_t |\widehat{f}_t^{c,i} - \widehat{f}_t^{c,i-1}| \right\} < 0.001$ and $\max_s \left\{ \max_t |\widehat{f}_t^{s,i} - \widehat{f}_t^{s,i-1}| \right\} < 0.001$

The final set of factors are the country- and sector-specific factors f_t^{sc}. For each sector in a given country, we use as estimators the first k_{sc} principal components of the $\sum_{r=1}^{R_c} I(r_s)$ variables $\pi_{c,r,s,t} - \widehat{\alpha}_{c,r,s}\widehat{f}_t^a - \widehat{\beta}_{c,r,s}\widehat{f}_t^c - \widehat{\gamma}_{c,r,s}\widehat{f}_t^s$ (i.e., for a given country, the dataset is composed of a given sector for each region).

In the presentation so far, we have considered the number of factors as known. To relax this assumption, the various $k_i s$ can be determined on the basis of a proper information criterion. We will follow the method proposed by (Bai and Ng (2002)) in our empirical analysis.

4 The determinants of changes in regional sectoral prices

In this section we present the results from decomposing changes in regional sectoral prices into their determinants, as discussed in the previous section. We start with reporting the results for the standard approach that decomposes sectoral regional inflation rates into an aggregate and an idiosyncratic component only. Afterwards, the results for the more disaggregate decomposition of sectoral price changes as shown in equation (4) are discussed. At the end of the section we illustrate the implications of our regional analysis for the findings of studies which use national or euro area wide data and discuss to which extent a weak factor structure might be an issue.

4.1 Results from previous decomposition approaches

The first two columns of Table 3 report results for the case where changes in sectoral regional prices are decomposed into an aggregate and an idiosyncratic component only. Thus, in this case we proceed analogously, e.g., to Boivin et al. (2008) and Mackowiak et al. (2009) and first extract the aggregate component from the inflation rates and then treat the residuals from regressing actual price changes on the estimated aggregate factor, denoted by $u_{c,r,s,t}$, as the sector-specific component. Since the Bai and Ng (2002) criterion indicates $k_a = 1$, the reported results are based on a model with one area-wide factor only. The characteristics of the so obtained aggregate and sector-specific components are very similar to those obtained by the above mentioned studies. We find, e.g., that the identified sector-specific component is on average more than four times more volatile than the aggregate component. For the median volatility the difference in volatility is even larger (by a factor of almost six). The persistence numbers show that the sector-specific component exhibits basically no persistence (the mean persistence parameter takes a value of -0.050, the median value is 0.071), whereas the aggregate component displays considerably more persistence (mean/median persistence value of about 0.3).[9]. Concerning the relative importance of the aggregate and the sector-specific component for explaining changes in sectoral prices our results also confirm previous findings. The numbers in the first two columns of the last panel of Table 3 show that the aggregate component explains only very little of observed changes (only about 8%) in sectoral prices whereas the idiosyncratic component $u_{c,r,s,t}$ explains the remaining 92% and therefore is the dominant determinant of sectoral regional inflation. Overall, the findings for the decomposition of sectoral regional inflation rates into an aggregate and an idiosyncratic component suggest that the extremely low persistence in sectoral regional inflation rates documented in Table 1 is due to the fact that sectoral regional inflation rates are almost exclusively driven by the nonpersistent idiosyncratic component, interpreted as sectoral component in previous studies.

4.2 Results from new approach: Detailed decomposition

As discussed in the previous section, the results we have achieved on the role of the sectoral component might no longer hold if the idiosyncratic component $u_{c,r,s,t}$ does not only represent the sector-specific factor but is a mixture of different factors. Since it is obtained by "cleaning" the sectoral regional inflation rates from the aggregate component it captures the effect of any factors that influence the respective sectoral prices and are not common to all sectoral prices. Potential determinants of changes in sectoral prices that are not common, but also not sector-specific, can be idiosyncratic measurement errors or

[9]Our numbers for the persistence of the aggregate component are substantially smaller than those reported, e.g., by Boivin et al. (2008). One major reason for this difference is that our data sample is different. If we restrict the data by Boivin et al. (2008) to a sample period comparable to ours, we obtain a significant drop in the persistence of the aggregate component. Evidence in favor of a substantial drop in the persistence of U.S. inflation in recent years is discussed in Mishkin (2007), for the euro area an analogous discussion is contained, e.g., in Altissimo et al. (2006)

what we call geography-related factors. The latter include country-specific factors such as national fiscal policy or nation-wide labour market legislation or country-sector-specific factors such as changes in value added taxes for goods in a specific sector in a given country. As a consequence, the properties of the true sector-specific component might considerably different from the characteristics obtained for $u_{c,r,s,t}$, which is commonly referred to as the sector-specific component.

To disentangle the impact of the various factors we decompose the residual variable $u_{c,r,s,t}$ into a country-specific, a sector-specific, a country-specific sectoral and an idiosyncratic component, as discussed in Section 3. The results for this decomposition are reported in columns three to six of Table 3. Since the Bai and Ng (2002) criteria systematically indicate $k_i = 1$, the reported results are based on a model with one area-wide, one country, one sector, and one country-sector factor. The obtained results show that our above drawn conclusions concerning the behavior and the relative importance of the sector-specific component for explaining changes in sectoral regional price changes, that are in line with previous results in the literature using the simple decomposition of sectoral price changes into a macroeconomic and a sector-specific component, need to be modified.

Whereas we confirm previous findings that the sectoral component is on average more volatile than the aggregate component, the difference in volatility is considerably smaller than in other papers (less than 50%). Moreover, even though our identified sectoral component still displays very low persistence on average, the difference in persistence relative to the aggregate component has become considerably smaller compared to previous findings. The median persistence of the sectoral component is now about 0.15 which compares to a median persistence of about 0.3 for the aggregate component.

It would be interesting to see whether we would observe a similar narrowing in the degree of persistence between the aggregate and the sectoral component if we considered a similar sample period as, e.g., Boivin et al. (2008) or Mackowiak et al. (2009). This would imply that sectoral factors are considerably more persistent than commonly thought. However, such a finding would not be too implausible from a theoretical perspective. Taking, e.g., the basic price-setting model used by Mackowiak et al. (2009) we can see that the sectoral component of the profit-maximizing price is a function of the relative price index for the sector and sector-specific productivity. Empirical studies which try to examine the dynamic behavior of sector- or industry-specific productivity find that, depending on the considered sector, it can exhibit a significant degree of persistence.[10]

The numbers for the sector-specific component in the last panel of Table 3 show that the sector-specific component explains on average only about 15% of the overall volatility in regional sectoral price changes. The number increases to about 35% when adding the contribution of the country-specific sectoral factor. However, even in this case it is still far below the 92% found above.

To sum up, our results for the sector-specific component differ significantly from previous findings in important dimensions. The relatively low volatility together with the small proportion of overall variance explained by the sector-specific component suggests that the sector-specific component is not the main driving force explaining movements and characteristics of sectoral regional price changes.

The question then arises which of the remaining elements in the idiosyncratic component $u_{c,r,s,t}$ is the major driving force behind changes in sectoral prices? The numbers in the third panel of Table 3 show that it is the region-specific idiosyncratic component $e_{c,r,s,t}$ which by far explains most of overall variation in sectoral prices (about 45% on average). Given its relatively high volatility and its low (on average negative) persistence we can conclude that $e_{c,r,s,t}$ is indeed the variable which predominantly determines the behavior of sectoral price changes. From an economic point of view, the idiosyncratic component can basically capture two effects: First, it can reflect measurement errors and secondly, it can reflect the reaction of price-setters to local conditions. Unfortunately, it is very difficult to obtain regional economic data at a monthly frequency which would allow us to examine this question.

Another noteworthy feature of our decomposition results concerns the behavior and the role of the country-specific factors. The third panel of Table 3 shows that the country-specific factors explain almost as much of overall volatility in sectoral prices as the pure sector-specific factors do. Moreover, on average they appear to be as volatile as the sector-specific components. However, they are considerably more persistent than either the sector-specific and even the aggregate components. To understand this result it is instructive to consider the potential factors underlying the country-specific components. As we argued in Section 3 we think that national fiscal policies and nation-wide labour market legislation are potential causes for the existence of country-specific factors.

Summarizing, the results of this subsection suggest that the sectoral component ex-

[10] See, e.g., the studies by Horvath (2000).

hibits much less volatility than previous findings for the US indicate, and explain much less of the variation in the data. Country- and region-specific factors play an important role in addition to the sector-specific factors.[11] The existence of a relevant country- and region-specific component can have important implications for previously obtained results in the literature. In the following, we will therefore shortly illustrate the relationship between our regional sectoral data and the aggregate sectoral data used by others. Furthermore, we will, based on this illustration, discuss potential implications of our results for previously obtained findings.

4.3 Relationship between previous and new detailed decomposition

Other studies of disaggregate sectoral data such as Boivin et al. (2008) or Mackowiak et al. (2009) use national (or in the case of the EMU euro-area wide) rather than regional data. To see the implications of our results for the other studies it is instructive to remember that national/euro-area wide data are obtained by aggregating regional price data. The weights which are used in this aggregation process normally correspond to the expenditure shares of the respective regions in total expenditure. The national/euro-area wide sectoral price index can therefore be thought of as computed as follows:

$$\pi_{s,t} = \sum_{c=1}^{C} \theta_c \sum_{r=1}^{R_c} \theta_{c,r} \pi_{c,r,s,t}, \tag{5}$$

where θ_c denotes the expenditure share of country c and $\theta_{c,r}$ denotes the expenditure share of region r of country c. As shown in Appendix A, this term can be written as:

$$\pi_{s,t} = \bar{\alpha}_s^{rc} f_t^a + \bar{\gamma}_s^{rc} f_t^s + \sum_{c=1}^{C} \theta_c \bar{\beta}_{c,s}^r f_t^c + \sum_{c=1}^{C} \theta_c \bar{\delta}_{c,s}^r f_t^{sc} + \bar{e}_s^{rc}, \tag{6}$$

where a bar above a variable/parameter denotes the weighted average of this variable and the upper indices r or c indicate whether the average is taken across regions of a country or countries.[12] Comparing this term with equation (2) we can see that the sector-specific component of Boivin et al. (2008) or Mackowiak et al. (2009), denoted by $u_{s,t}$ corresponds

[11]When examining the factors driving regional output fluctuations in the U.S. Clark (1998) also found that regional factors play a very important role in addition to industry composition.

[12]Weights used in computing averages correspond to the respective expenditure shares. The upper index *rc* indicates that averages are first taken across regions of a country and then across countries.

to the following expression:

$$u_{s,t} = \bar{\gamma}_s^{rc} f_t^s + \sum_{c=1}^{C} \theta_c \bar{\beta}_{c,s}^r f_t^c + \sum_{c=1}^{C} \theta_c \bar{\delta}_{c,s}^r f_t^{sc} + \bar{e}_s^{rc}. \tag{7}$$

This expression clearly illustrates two issues: First, while we can expect that the average effect of all terms apart from f_t^s is zero it is, secondly, clear that the time series properties of u_s crucially depend on the time series properties of the country-specific, the country-sector-specific and the region-specific components.

4.4 Month-on-month versus year-on-year changes

One potential problem of the results reported above concerns the very low proportion of variance explained by the aggregate factor. While this result is also found by other authors who analyze the behavior of sectoral prices[13] it casts some doubts on the appropriateness of the performed factor analysis. Indeed, Onatski (2006) and Kapetanios and Marcellino (2006) show that when the factor structure is weak (i.e., the fraction of variance explained by the first principal component is very small), the principal component based estimator of the factor is no longer consistent. Intuitively, there is too little commonality to separate what is common from what is idiosyncratic.

We therefore decided to redo our analysis using year-on-year changes in sectoral prices. This transformation averages out some of the idiosyncratic variation in the month-on-month series, thus strengthening the factor structure. The choice of this transformation has two additional positive side aspects. First, the year-on-year inflation rate is the key variable for monetary policy and, secondly, the twelve difference operator is also useful to remove seasonality from the price level series.[14]

The results are reported in Table 4. The Bai and Ng (2002) criteria still select one factor of each type, but the aggregate component now explains about 22% of the overall variation in sectoral price changes. Due to smoothing of the year-on-year transformation

[13]Mackowiak et al. (2009), e.g., report that the first common component explains about 7% of the overall variation in their data, Boivin et al. (2008) find that the first five principal components of their data sample explain only about 15% of overall variation.

[14]However, twelve differencing could introduce a moving average component into the error term of models where the year on year inflation rate is the dependent variable, when the true dependent variable is the month on month inflation rate. In our context we do not find this problem, since standard tests for no correlation of the residuals of the models that we will present do not reject the null hypothesis in most cases.

we get of course very different results in terms of volatility and, particularly, persistence of the components. All series are now substantially more persistent. However, the major result concerning the relative importance of the sectoral component for explaining changes in sectoral prices are mostly confirmed. The sectoral and country-specific sectoral component on average explain again only 35% of overall variation in price changes, as in the case for month-on-month inflation. Moreover, it is only slightly more volatile than the aggregate component, and its persistence is smaller that that of the aggregate component but only to a relatively small degree. Overall, our qualitative results for month-on-month inflation are confirmed.

5 Responses of sectoral regional inflation to aggregate and disaggregate shocks

In this section, we analyze the response of sectoral prices to aggregate and disaggregate shocks. In a first step, however, we examine the dynamic response of each factor to its own shock and illustrate the extent of heterogeneity across sectoral inflation rates in response to the different types of shocks.

Let us assume that each of the (orthogonal) aggregate, country, sector, and sector-specific factors is generated by a stationary AR(13) model, e.g.,

$$f_t^a = a_{1,a} f_{t-1}^a + \ldots + a_{13,a} f_{t-13}^a + \varepsilon_{t,a}$$

or in MA form

$$f_t^a = b_a(L)\varepsilon_{t,a}$$

where $\varepsilon_{t,a}$ is $i.i.d.$ $(0, \sigma_a^2)$ and the polynomial $b_a(L)$ is obtained by inverting the AR representation.[15] Substituting the AR model into the factor representation (4) in Section 3 yields

$$\pi_{c,r,s,t} = \alpha_{c,r,s} b_a(L) u \varepsilon_{t,a} + \beta_{c,r,s} b_c(L)\varepsilon_{t,c} + \gamma_{c,r,s} b_s(L)\varepsilon_{t,s} + \delta_{c,r,s} b_{sc}(L)\varepsilon_{t,sc} + e_{c,r,s,t}. \quad (8)$$

This model is an extension of the specification adopted by Mackowiak et al. (2009), whose

[15]The lag length is chosen to capture any potentially remaining seasonality in the monthly factors based on the month-on-month sectoral inflation rates, but the results are robust when using a lower order.

aggregate component would correspond to $\alpha_{c,r,s}b_a(L)\varepsilon_{t,a}$, while their sectoral component would coincide with $\beta_{c,r,s}b_c(L)\varepsilon_{t,c}+\gamma_{c,r,s}b_s(L)\varepsilon_{t,s}+\delta_{c,r,s}b_{sc}(L)\varepsilon_{t,sc}+e_{c,r,s,t}$. They analyze the transmission of aggregate and sectoral shocks to the disaggregate sectoral variables. Below, we perform a similar analysis, but before we separately consider the dynamic response of each factor to its own shock (e.g., the coefficients of $b_a(L)$), the transmission of the shocks to the sectoral series (e.g., through the coefficients of $\alpha_{c,r,s}$), and the decomposition of the non aggregate component into the country, sectoral, and country sectoral components. The additional information that we can recover is important to understand whether and how much heterogeneity there is in the dynamic response of each country or sectoral factor, whether and how much heterogeneity there is in the reaction of the disaggregate inflation series to the different shocks, and whether aggregating the reaction to country and sectoral shocks as in Mackowiak et al. (2009) can be expected to bias the results. For the sake of space, we will not consider explicitly the country-sectoral factors f_t^{sc}.

5.1 Dynamic response of factors to their own shock

Figures 1 and 2 report the response functions of each Aggr, C, and S factor to its own shock (namely, the first forty estimated coefficients of $b_a(L)$, $b_c(L)$ and $b_s(L)$). A few comments are in order. First, in almost all cases the response becomes insignificant after the second month. The only exception are Italy (4 months) and food and furniture(3 months). Thus, unlike Mackowiak et al. (2009) we find that the dynamic responses of sectors do not strongly differ relatively to those of the aggregate factor in terms of persistence (except for Italy). As discussed above the low degree of persistence in the aggregate shock might be due to our sample period. Second, the reaction of the country factors is fairly similar across countries, both in terms of initial value of the shock and of the shape of the response. Third, the reaction of the different sectoral factors is also fairly similar across most sectors with somewhat longer persistence in food and furniture.

5.2 Sectoral heterogeneity in response to aggregate and disaggregate shocks

The second issue we consider is the heterogeneity across sectoral inflation series in the response to the different types of shocks. Table 5 reports a set of summary statistics on the loadings of the different types of factors. Three main features emerge. First, the average size of the loadings of the aggregate factor, $\alpha_{c,r,s}$, is smaller than that of the country and sectoral loadings. In addition, the standard deviation is the second smallest, indicating that there is more homogeneity in the reaction to the aggregate factor than to almost all other types of factors. However, looking at Figure 3 that reports all the 418 aggregate factor loadings, it is clear that even in this relatively homogenous case there remains substantial heterogeneity, so that results based on average responses should be interpreted with care. Second, focusing on the largest countries, namely, Germany, Spain and Italy, the average size of the loadings of the country factor and the standard deviation are overall fairly similar. Hence, the reaction of the disaggregate inflation series in these countries to country-specific shocks should also be fairly similar. Third, there is substantial heterogeneity across sectors in the average sectoral loadings, with both positive and negative values. In addition, the standard deviations are also considerably larger than for country and aggregate factors. As a result, there should also be more heterogeneity in the responses to the sectoral shocks.

5.3 Response of sectoral prices to aggregate and disaggregate shocks

Finally, we obtain the estimated responses of the inflation series to aggregate, country or sectoral shocks by merging the response of the factors to their own shocks and the estimated loadings. In Figures 4 and 5 we plot the cumulated responses, that represent the shock responses of the price indices rather than inflation rates.

The two main results we obtain are the following. First, the responses to the country shocks are in all cases considerably larger than those to the aggregate shocks. This outcome is due to the size of the country loadings, which are much larger than the aggregate loadings, as we have seen. It is also worth mentioning that the responses of the aggregate and country factors are no longer statistically different from zero after two months (except for Italy after 4 months), so that from a statistical point of view, all the cumulated responses are not different from a flat line after that period of time. From an economic point of view, it is however noticeable that the country shock produce larger effects than the aggregate shock.

Second, there is substantial heterogeneity in the initial responses to the sectoral shocks, as expected given the documented heterogeneity in the sectoral loadings. The absolute size of the responses is somewhat lower than that of the responses to country shocks, but always larger than responses to the aggregate shock. The responses to sectoral shocks are also not statistically different from a flat line after about 2 months.

In summary, the analysis of this section has highlighted the presence of substantial heterogeneity in the responses to shocks to the national and sectoral factors, but also substantial homogeneity in the dynamics of factors belonging to the same group. The importance of non aggregate (country and sectoral) components for the development of disaggregate inflation series is confirmed, since country and sectoral shocks can have stronger effects on them than aggregate shocks.

6 Evaluating the effects of monetary shocks

To structurally identify one of the aggregate macroeconomic shocks and investigate whether we get economically plausible responses, we use the FAVAR framework to identify a monetary policy shock. Bernanke et al. (2005), Stock and Watson (2005) and Favero et al. (2005), among others, showed that factor augmented VARs (FAVARs) can provide a better econometric tool for the identification of monetary policy shocks and their effects than simple VARs. In particular, FAVARs permit to work with large information sets, avoiding the curse of dimensionality of standard VARs by assuming that all variables are driven by a small number of factors, which in turn evolve according to a VAR model. In this section, we assess whether the inclusion of factors in VARs improves our understanding of the effects of monetary policy in the euro area by changing the shape of the responses of main macroeconomic variables to monetary shocks or by decreasing the uncertainty about such responses. We also assess whether monetary shocks have a different impact on the aggregate, country and sectoral factors.

Following Favero et al. (2005), the baseline VAR model can be written as:

$$\begin{bmatrix} \mathbf{X}_t \\ i_t \end{bmatrix} = A(L) \begin{bmatrix} \mathbf{X}_{t-1} \\ i_{t-1} \end{bmatrix} + \varepsilon_t, \quad \varepsilon_t = \mathbf{B} \begin{bmatrix} \mathbf{u}_t \\ u_t^m \end{bmatrix}, \tag{9}$$

where the vector $\mathbf{X}_t$ contains the year on year growth in euro area industrial production (IP) and CPI, while i_t is a short term interest rate. We then include aggregate (Aggr-FAVAR), country-specific (CS-FAVAR) and sectoral (SE-FAVAR) factors in $\mathbf{X}_t$.

With respect to the Bernanke et al. (2005) model, the specification in (9) is slightly more general since it allows for IP growth and the interest to affect inflation in addition to the factors, and for the factors to react to developments in the three key macroeconomic variables. On the other hand, in (9) the policy shock is identified by conditioning not on the entire large information set but only on the factors, IP growth and inflation. However, the assumption of a factor model implies that the factors provide an exhaustive summary of the information in the large dataset.

The Aggr and CS FAVARs mimic the model of Boivin et al. (2008) in the sense that they only include aggregate (i.e. non sectoral and, in our case, non regional) information, while the SE-FAVAR permits to assess the role of the purely sectoral information. The lag length in the VAR and FAVARs is determined by the BIC criterion, which returns two for the VAR and one for the FAVARs. The sample period is fairly short, it covers 1997-2004, but the monthly frequency combined with the parsimonious specification of the models guarantees a sufficient number of degrees of freedom.

The monetary policy shock, u_t^m, the only one we are interested in, is identified with a Choleski decomposition. We assume that all variables and factors can affect the interest rate contemporaneously, namely, the monetary authority considers not only growth and inflation when taking its decisions but also a larger information set, summarized by the factors in our case. In addition, the factors are ordered before aggregate inflation, which is sensible from an economic point of view, but the results we obtain are robust to changing this order.

In Figure 6 we report the responses of the euro area IP growth and inflation to the monetary policy shock, and the response of the policy rate to an own shock, together with 95% analytical standard errors. In this baseline case, the price puzzle emerges in the short run, combined with an increase in IP growth notwithstanding the monetary restriction.

Figure 7 presents the responses computed in the CS FAVAR, which adds the country-specific factors to the baseline VAR. The reaction of inflation is now negative whereas the resonse of IP growth is still positive, however much smaller than in the baseline case. In addition, there is a differentiated reaction of the country-specific factors to the monetary policy shock, with negative values only for Italy.

As Figure 8 shows, adding the sectoral factors to the VAR generates a negative reaction of IP growth and inflation. In addition, there emerges some heterogeneity in the responses of the sectoral factors, with negative values only for the sectors food, health, housing, and transportation. Such heterogeneity emerges also in the responses of the sectoral prices in Boivin et al. (2008), and could be due to omitted sectoral characteristics, such as policy measures or different consumption habits.

It is not sensible to add all the three types of factors jointly to the baseline VAR due to collinearity problems. Actually, a regression of euro area inflation on the Agg, CS, and SE factors generates an adjusted R^2 of 0.96. Interestingly, the adjusted R^2 decreases to only about 0.27 when the CS and SE factors are dropped from the regression, confirming that national and sectoral movements are relevant to explain euro area inflation.

Finally, if the Agg factor is added to the CS-FAVAR or SE-FAVAR there are minor changes in the results, due to the orthogonality of the Agg factor with the CS and SE factors.

In summary, the results we have obtained in this section provide additional evidence in favour of the use of disaggregate price data, and of the inclusion of factors in monetary VARs. As we have seen, the larger number of regressors has no negative effects on the precision of the estimated responses, which actually improves, and, more importantly, the pattern of responses of output and inflation to the monetary shock becomes in general more in line with economic theory.

7 Conclusions

In this paper we use a novel and large set of euro area regional sectoral price data to analyze the importance and major characteristics of the determinants of sectoral price changes. We argue that previous studies by Boivin et al. (2008) and Mackowiak et al. (2009) might overestimate the importance of the sectoral component and might misinterpret its behavior since it is obtained as a residual variable which captures a mixture of the "true" sectoral component, measurement errors and geographical impacts.

Using a new method to extract factors from over-lapping data blocks, we find that the sectoral component explains on average only about 14% and the country-specific sectoral component only about 20% of the overall volatility in sectoral regional prices. This is substantially less than the 85-90% explained volatility by sector-specific shocks found in previous studies for sectoral prices. Moreover, our estimated sectoral component exhibits much less volatility than previous findings for the US indicate. Previous results on the low persistence of sector-specific shocks are confirmed in our analysis. On the other hand, country- and region-specific factors play an important role in addition to the sector-specific factors and explain about 60% of overall volatility in sectoral prices. Moreover, while the country-specific component exhibits a substantial degree of persistence, the region-specific component does not. We attribute this region-specific component mostly to idiosyncratic factors such as measurement errors and local influences, such as local input factors costs, e.g., rents of distribution facilities.

On the other hand, sectoral shocks, and country-specific shocks, can have a sizable impact on disaggregate inflation series, often larger than that from aggregate shocks, though less persistent. And when non-aggregate information in the form of country and sectoral factors is included in FAVAR models to identify monetary shocks and their transmission mechanism, the results are more in line with the theoretical expectations.

Overall, our results suggest that previous findings which showed that sectoral shocks to prices exhibit low persistence and are a dominant source of changes in sectoral prices need to be reconsidered. Disaggregate forces do play an important role in price determination, but sectoral shocks are complemented by regional (and for the euro area country-specific) shocks.

The results from our analysis suggests, that further research is needed on the importance of the ”geographical” or ”regional” dimension in other countries, including the US. Recent US studies investigating regional differences other than for CPI inflation include e.g. Clark (1998), Hamilton and Owyang (2009), Ng and Moench (2009). It is intuitive that consumers (and producers) are attentive to regional shocks, and that they are probably more attentive to regional than to aggregate shocks. Informational frictions might explain why consumers can obtain and process information on regional developments more easily. However, it is interesting and important to investigate the question whether consumers (or producers) are more attentive to regional shocks than to sector-specific shocks.

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8 Tables

Table 1: Descriptive statistics: Total sample, sectoral and country data

Sample	**Nobs**	**Level**		**Volatility**		**Persistence**		**Disp**	**Corr(x_i,x)**
		Mean	**Std**	**Mean**	**Std**	**Mean**	**Std**		
Total sample									
All	418	2.057	1.063	4.768	2.436	0.005	0.537	5.245	0.154
Data grouped by countries									
DE	77	1.090	1.056	5.222	2.637	-0.162	0.624	5.150	0.323
ES	120	2.630	0.818	4.538	1.840	0.136	0.337	4.511	0.501
FI	43	1.455	0.911	5.992	3.498	-0.326	0.965	6.223	0.503
IT	124	2.085	0.700	3.774	1.591	0.070	0.426	3.881	0.229
PO	54	2.577	1.148	5.941	2.865	0.067	0.338	6.367	0.212
Data grouped by sectors									
alco	30	1.835	1.130	4.246	2.146	0.066	0.387	4.042	0.400
clot	35	1.269	1.567	5.398	4.781	-0.329	1.120	6.580	0.241
food	60	1.909	0.829	4.945	1.369	0.309	0.309	4.362	0.518
furn	56	1.495	0.798	2.574	1.314	-0.011	0.376	2.811	0.286
heal	27	2.557	0.674	3.767	1.006	0.023	0.339	3.376	0.441
hote	53	2.938	1.081	4.548	1.641	-0.087	0.720	4.518	0.239
hous	58	2.539	0.612	4.803	1.556	0.114	0.239	4.101	0.512
recr	57	1.448	0.729	5.967	2.318	-0.078	0.472	5.311	0.338
tran	42	2.558	0.623	6.534	2.302	-0.106	0.248	5.145	0.578

Notes:
1) Table 1 reports descriptive statistics for the data series included in our cleaned data set. Results are reported for all data series (total sample) and subsamples which include all series from a given country (country data) or a given sector (sectoral data). Monthly inflation rates are multiplied by 1200.
2) The reported statistics include the mean and the standard deviation (std) of the time-series means of all inflation series included in a given group (level), the mean and the standard deviation (std) of the time-series standard deviation of all inflation series included in a given group (volatility), the mean and the standard deviation (std) of the persistence measures of all inflation series included in a given group, the time-series mean of the cross-sectional dispersion of all inflation series included in a given group and the mean correlation of all inflation series included in a given group with the group aggregate inflation rate.
3) The measure for persistence is based on the estimation of an AR processes with 13 lags.
4) The group aggregate inflation rate is computed as a weighted average of the series included in the group. Regions are weighted by their relativ economic size, sectors are weighted based on their euro area HICP weight in 2000.

Table 2: Descriptive statistics: Country-sector-specific data

Sample	Nobs	Level		Volatility		Persistence		Disp	Corr(x_i, x)
		Mean	Std	Mean	Std	Mean	Std		
Germany									
alco	6	0.702	0.352	2.891	1.266	-0.411	0.436	2.144	0.522
clot	7	0.205	2.382	3.470	1.200	0.121	0.432	3.849	0.460
food	12	0.672	0.381	5.362	0.712	0.236	0.067	2.641	0.873
furn	9	0.282	0.283	1.631	0.375	0.232	0.275	1.381	0.551
hote	10	1.415	0.278	6.505	1.698	-0.898	1.151	3.820	0.644
hous	11	1.617	0.350	2.886	0.598	0.199	0.501	1.867	0.726
recr	10	0.566	0.261	8.119	0.359	-0.621	0.500	3.395	0.744
tran	12	2.507	0.109	8.619	0.697	-0.230	0.203	3.470	0.909
Spain									
alco	15	2.170	0.809	4.634	1.397	0.191	0.272	3.192	0.693
food	17	2.729	0.235	4.217	0.417	0.592	0.073	2.366	0.811
furn	17	2.045	0.584	2.731	1.023	0.018	0.293	2.451	0.535
heal	18	2.262	0.528	3.567	0.922	-0.089	0.283	2.795	0.591
hote	17	4.011	0.318	3.912	1.102	0.144	0.365	3.235	0.565
hous	18	3.021	0.509	5.069	1.176	0.018	0.282	3.410	0.713
recr	18	2.146	0.574	7.497	1.795	0.104	0.265	3.193	0.921
Finland									
alco	4	0.546	0.212	1.406	0.181	0.229	0.247	0.483	0.873
clot	5	-0.171	0.597	12.783	1.882	-2.461	1.542	7.978	0.747
food	5	1.406	0.420	6.168	0.996	-0.091	0.347	3.124	0.865
furn	5	0.905	0.199	4.241	0.967	-0.438	0.465	3.452	0.581
heal	4	2.904	0.232	4.877	0.448	-0.092	0.176	2.695	0.758
hote	5	2.302	0.110	3.455	0.751	-0.013	0.126	2.165	0.762
hous	5	1.982	0.213	4.970	1.284	0.196	0.107	2.506	0.901
recr	5	1.694	0.135	4.726	1.299	0.084	0.288	2.742	0.752
tran	5	1.638	0.162	10.161	1.422	-0.188	0.179	4.206	0.910
Italy									
clot	18	2.248	0.645	2.149	0.588	0.082	0.527	2.018	0.344
food	19	1.832	0.367	4.069	0.664	0.396	0.196	3.081	0.660
furn	18	1.449	0.454	1.897	0.519	-0.104	0.414	1.638	0.385
hote	14	2.680	0.670	3.892	0.953	0.073	0.546	3.621	0.380
hous	19	2.675	0.368	5.831	1.273	0.107	0.214	3.888	0.696
recr	17	1.303	0.438	3.518	1.265	-0.052	0.567	2.771	0.550
tran	19	2.455	0.360	4.878	0.698	-0.031	0.502	2.898	0.763
Portugal									
alco	5	3.250	0.597	6.977	1.953	0.131	0.339	5.200	0.543
clot	5	0.676	0.955	12.407	1.876	-0.306	0.136	9.877	0.558
food	7	2.608	0.504	7.499	1.382	-0.203	0.147	5.710	0.655
furn	7	2.509	0.403	3.959	2.032	0.149	0.189	3.655	0.484
heal	5	3.340	0.668	3.598	1.168	0.518	0.095	2.857	0.566
hote	7	3.476	0.899	5.389	1.757	0.141	0.342	4.968	0.329
hous	5	2.872	0.379	3.986	1.572	0.224	0.110	2.580	0.723
recr	7	1.093	0.624	5.792	1.553	0.050	0.492	4.589	0.506
tran	6	3.755	0.228	4.587	0.675	-0.028	0.295	2.877	0.729

Notes:

1) Table 2 reports descriptive statistics for the data series included in our cleaned data set. Results are reported for sectoral data of each included country. See the notes of Table 1 for further details on the computation of the statistics.

Table 3: Volatility, persistence and relative importance of estimated factors: Month-on-month changes

	Aggr	**$\mathbf{u}_{c,r,s,t}$**	**C**	**S**	**CS**	**Idios.**
			Volatility			
Mean	0.216	0.959	0.280	0.294	0.377	0.643
Median	0.173	0.985	0.263	0.229	0.390	0.651
Min	0.000	0.769	0.001	0.001	0.001	0.244
Max	0.639	1.000	0.768	0.839	0.883	0.972
Std	0.174	0.057	0.160	0.232	0.224	0.176
			Persistence			
Mean	0.294	-0.050	0.570	0.084	-0.509	-0.359
Median	0.294	0.071	0.708	0.149	-0.181	-0.506
Min	0.294	-3.504	0.309	-0.565	-3.019	-3.158
Max	0.294	0.863	0.710	0.440	0.632	0.897
Std	0.000	0.486	0.167	0.260	0.620	0.585
			Variance explained			
Mean	0.077	0.923	0.104	0.140	0.206	0.474
Median	0.030	0.970	0.069	0.053	0.158	0.451
Min	0.000	0.591	0.000	0.000	0.000	0.065
Max	0.409	1.000	0.589	0.703	0.803	0.993
Std	0.104	0.104	0.106	0.179	0.184	0.238

Notes:
1) Table 3 reports summary statistics for the aggregate (Aggr), the residual component $u_{c,r,s,t}$, the country-specific (C), the sector-specific (S) country-sector-specific (CS) common components, the idiosyncratic component (Idios.). Inflation rates are computed as month-on-month proportional changes. Common components are computed as the product $\lambda_{c,r,s} f_t^x$ where $\lambda_{c,r,s}$ denotes the region-sector-specific loading of a series and f_t^x (with $x \in aw, c, s, cs$ denotes factor x. The decomposition of a time series is done according to equation (4). 2) Statistics are computed for the volatility and the persistence of the common components. The volatility of a time series is measured by the standard deviation of the series. The measure for persistence is based on the estimation of an AR processes with 13 lags.
3) The proportion of variance explained by a factor is computed as the product $\lambda_{c,r,s}^2 var(f_t^x)$ where $\lambda_{c,r,s}$ denotes the region-sector-specific loading of a series and f_t^x (with $x \in aw, c, s, cs$ denotes factor x. The decomposition of a time series is done according to equation (4). 4) The reported statistics include the mean value (mean), the median value (median), the minimum value (min), the maximum value (max) and the cross-sectional standard deviation (std) of the respective variables.

Table 4: Volatility, persistence and relative importance of estimated factors: Year-on-year changes

	Aggr	$u_{c,r,s,t}$	**C**	**S**	**CS**	**Idios.**
			Volatility			
Mean	0.402	0.871	0.384	0.311	0.295	0.359
Median	0.387	0.922	0.381	0.293	0.284	0.345
Min	0.000	0.373	0.003	0.002	0.001	0.009
Max	0.928	1.000	0.862	0.799	0.895	0.767
Std	0.244	0.140	0.232	0.193	0.179	0.148
			Persistence			
Mean	0.980	0.845	0.916	0.705	0.584	0.150
Median	0.980	0.860	0.933	0.675	0.701	0.213
Min	0.980	0.060	0.850	0.610	-1.395	-1.774
Max	0.980	1.614	0.949	0.862	0.894	0.824
Std	0.000	0.133	0.045	0.085	0.366	0.428
			Variance explained			
Mean	0.221	0.779	0.201	0.134	0.215	0.229
Median	0.150	0.850	0.145	0.086	0.157	0.184
Min	0.000	0.139	0.000	0.000	0.000	0.000
Max	0.861	1.000	0.743	0.638	0.767	0.914
Std	0.217	0.217	0.189	0.137	0.190	0.183

Notes:
1) Table 4 reports summary statistics for the aggregate (Aggr), the residual component $u_{c,r,s,t}$, the country-specific (C), the sector-specific (S) country-sector-specific (CS) common components, the idiosyncratic component (Idios.). Inflation rates are computed as year-on-year proportional changes. Common components are computed as the product $\lambda_{c,r,s} f_t^x$ where $\lambda_{c,r,s}$ denotes the region-sector-specific loading of a series and f_t^x (with $x \in aw, c, s, cs$ denotes factor x. The decomposition of a time series is done according to equation (4). 2) Statistics are computed for the volatility and the persistence of the common components. The volatility of a time series is measured by the standard deviation of the series. The measure for persistence is based on the estimation of an AR processes with 13 lags.
3) The proportion of variance explained by a factor is computed as the product $\lambda_{c,r,s}^2 var(f_t^x)$ where $\lambda_{c,r,s}$ denotes the region-sector-specific loading of a series and f_t^x (with $x \in aw, c, s, cs$ denotes factor x. The decomposition of a time series is done according to equation (4). 4) The reported statistics include the mean value (mean), the median value (median), the minimum value (min), the maximum value (max) and the cross-sectional standard deviation (std) of the respective variables.

Table 5: Loadings of aggregate, country- and sector-specific factors

Loadings for aggregate and country-specific factors						
Factor	**Aggr**	**DE**	**ES**	**FI**	**IT**	**PO**
Mean	0.00	0.10	0.08	0.12	0.08	0.09
Median	-0.01	0.11	0.09	0.10	0.07	0.10
Min	-0.08	-0.06	-0.01	-0.09	-0.06	-0.12
Max	0.11	0.22	0.15	xxx	0.20	0.27
Std	0.05	0.06	0.04	0.09	0.05	0.10

Loadings for sector-specific factors									
Factor	**alco**	**clot**	**food**	**furn**	**heal**	**hote**	**hous**	**recr**	**tran**
Mean	0.14	-0.08	0.10	-0.06	-0.16	-0.10	-0.05	0.07	0.13
Median	0.09	-0.04	0.07	-0.06	-0.20	-0.07	-0.05	0.01	0.12
Min	0.12	0.15	0.08	0.12	0.10	0.10	0.12	0.11	0.08
Max	-0.03	-0.43	-0.04	-0.28	-0.28	-0.33	-0.25	-0.11	0.00
Std	0.31	0.15	0.26	0.21	0.10	0.11	0.13	0.24	0.25

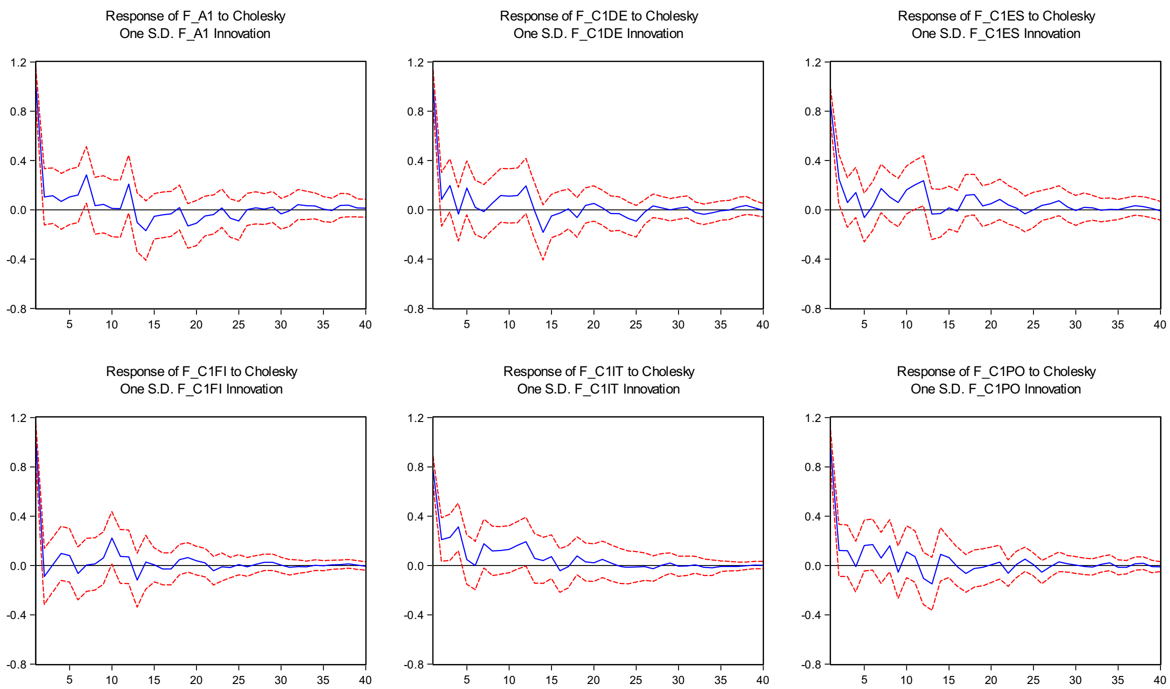
Notes:

1) Table 5 reports summary statistics on the loadings of the aggregate, country-specific and sector-specific factors.

2) The reported statistics include the cross-sectional mean value (mean), the median value (median), the minimum value (min), the maximum value (max) and the cross-sectional standard deviation (std) of the respective respective loadings.

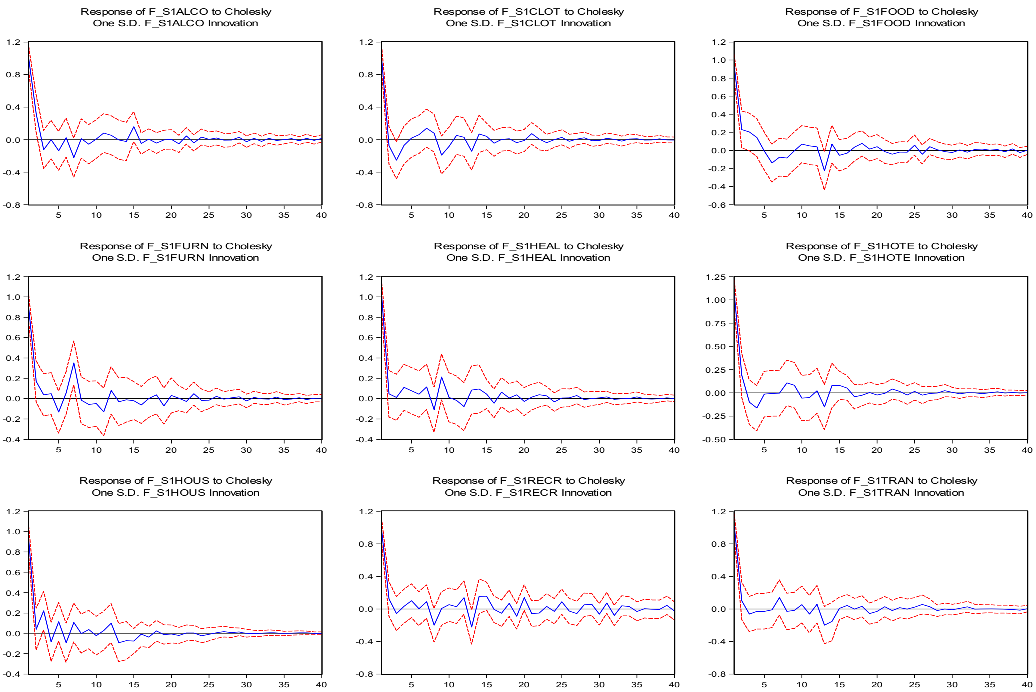
9 Figures

Figure 1: Response to one s.d. innovations ± 2 S.E.



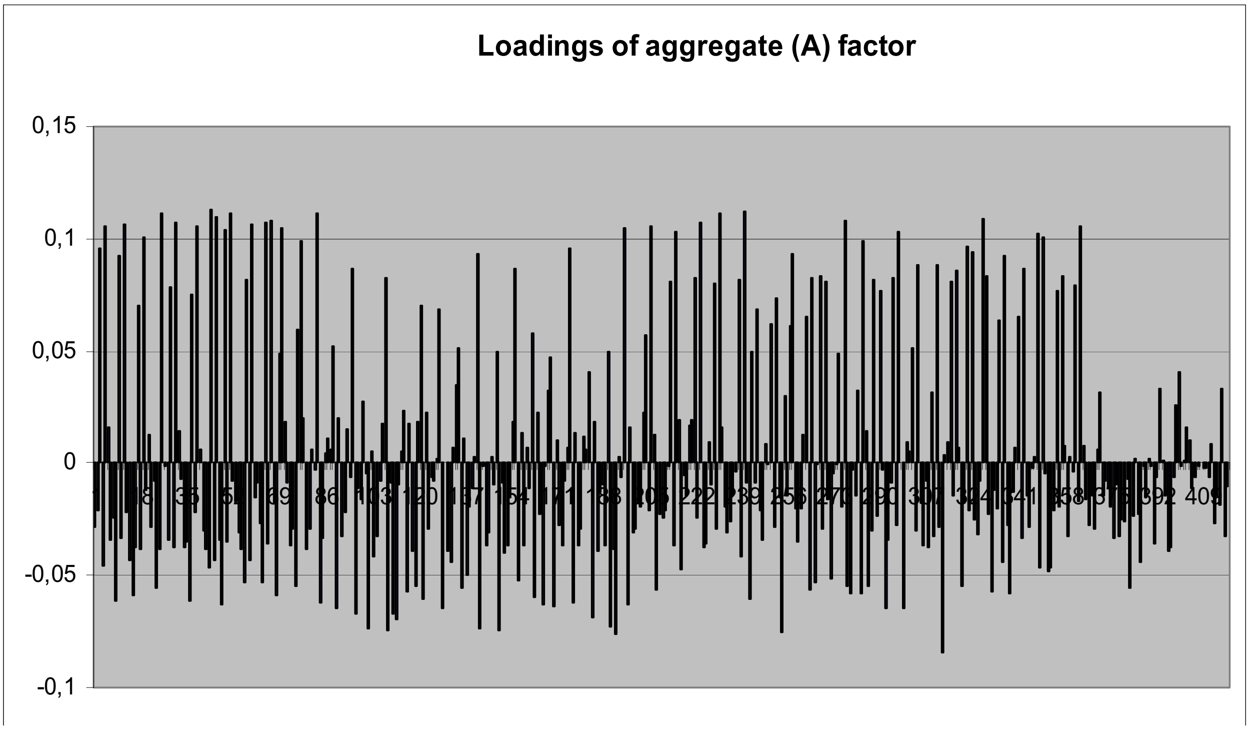
Note: *Figure 1 plots impulse response functions of the aggregate and the country-specific factors to its own shock (A=Aggregate, DE=Germany, ES=Spain, FI=Finland, IT=Italy, PO=Portugal).*

Figure 2: Response to one s.d. innovations ± 2 S.E.



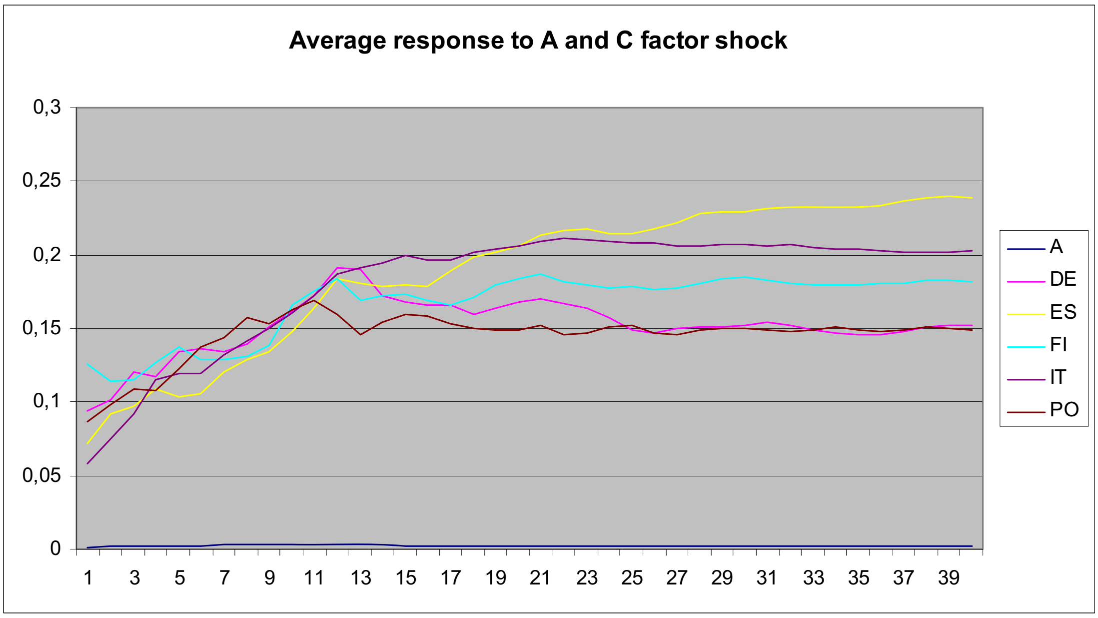
Note: *Figure 2 plots impulse response functions of the sector-specific factors to its own shock ((Food, Furniture, Healing, Hotel, Housing, Recreation, Transports, Alcohol, Clothing)).*

Figure 3: Loadings of the aggregate factor ($\alpha_{c,r,s}$) for the 418 inflation series



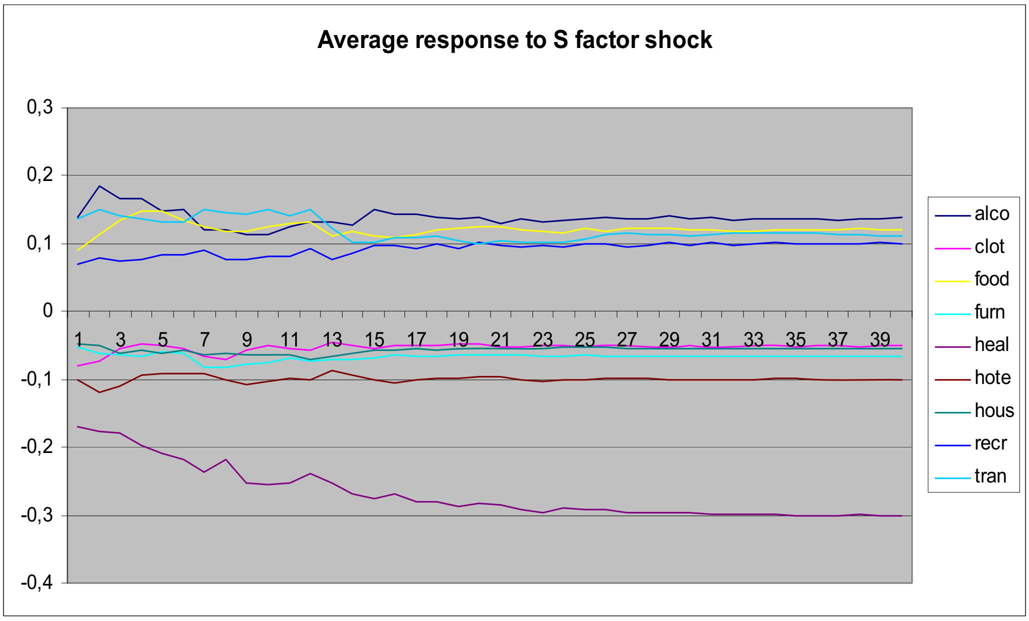
Note: *Figure 3 plots the loadings of the aggregate factor ($\alpha_{c,r,s}$) for the 418 inflation series.*

Figure 4: Average cumulated response of disaggregate inflation series to shock in aggregate (AW) and country (C) factors



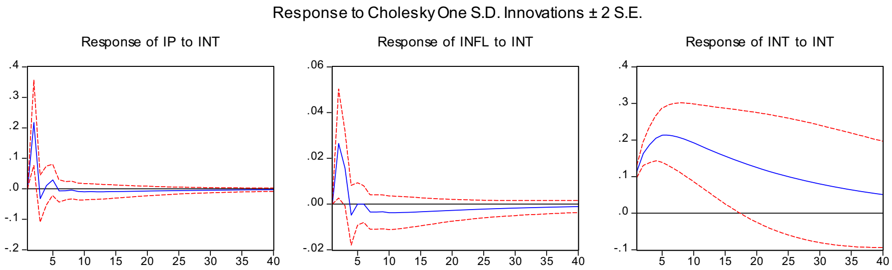
Note: *Figure 4 plots average cumulated responses of disaggregate inflation series to shock in aggregate (A) and country (C) factors (A=Aggregate, DE=Germany, ES=Spain, FI=Finland, IT=Italy, PO=Portugal).*

Figure 5: Average cumulated response of disaggregate inflation series to shock in sector (S) factors



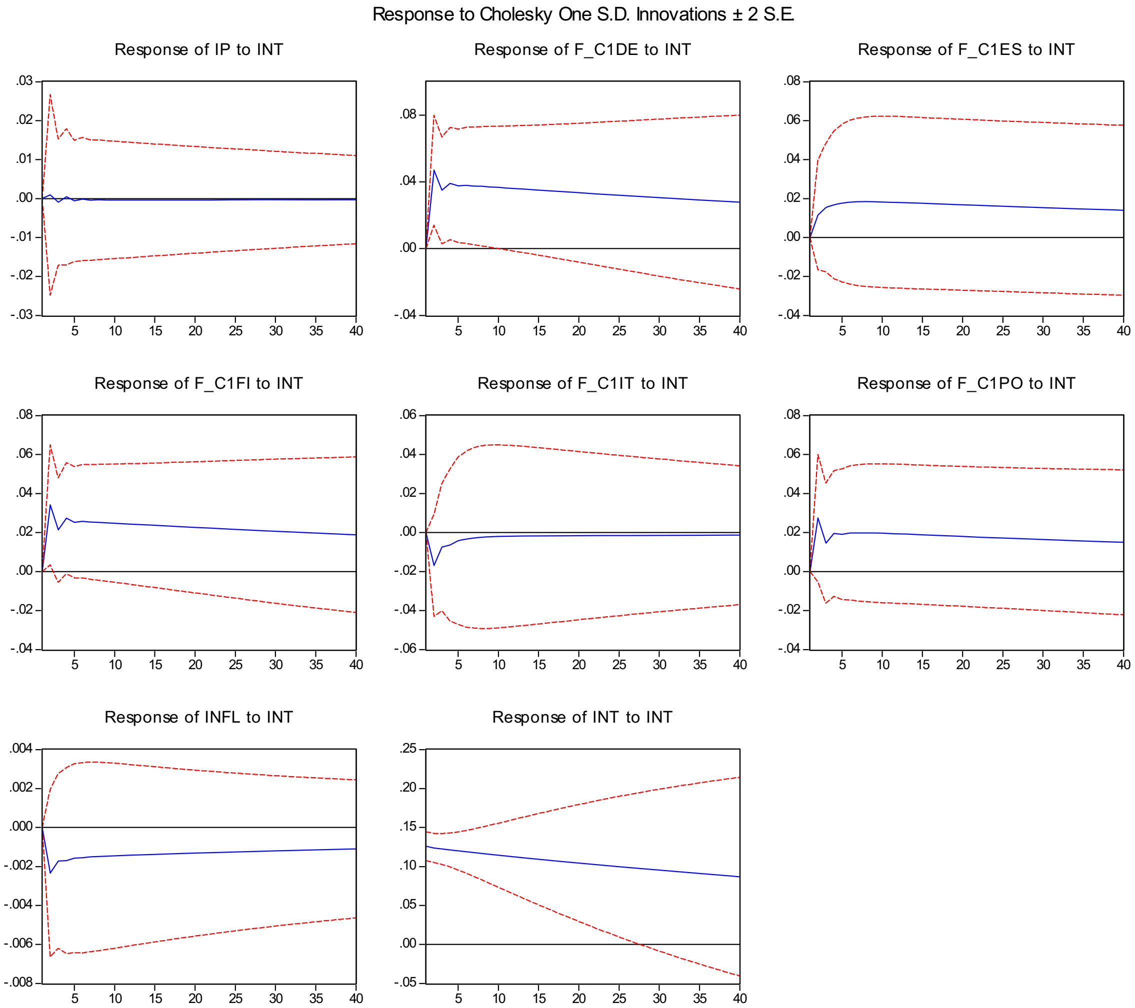
Note: *Figure 5 plots average cumulated responses of disaggregate inflation series to shock in sector (S) factors ((Food, Furniture, Health, Hotel, Housing, Recreation, Transports, Alcohol, Clothing)).*

Figure 6: Response to Cholesky-one s.d. innovations ± 2 S.E.



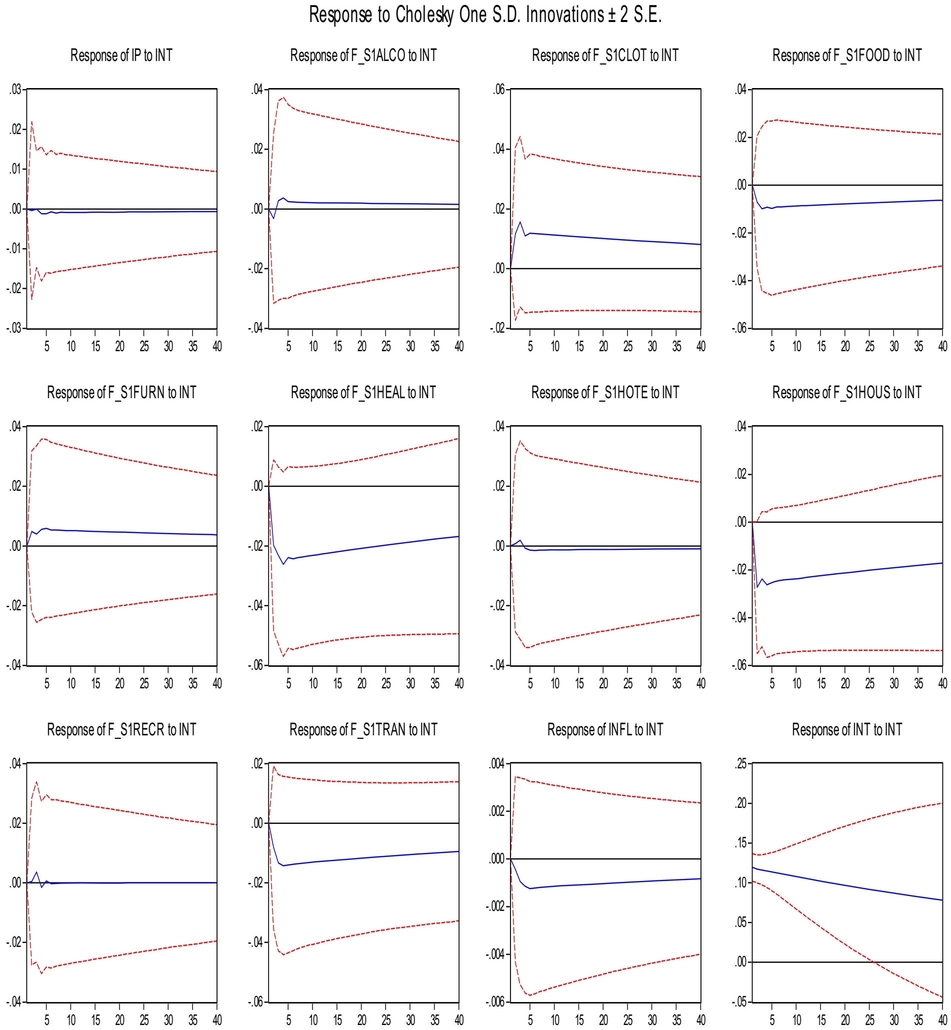
Note: *Figure 6 plots impulse response functions to a monetary shock in a standard VAR.*

Figure 7: Response to Cholesky-one s.d. innovations ± 2 S.E.



Note: *Figure 7 plots impulse response functions to a monetary shock in a FAVAR with country-specific factors (DE=Germany, ES=Spain, FI=Finland, IT=Italy, PO=Portugal).*

Figure 8: Response to Cholesky-one s.d. innovations ± 2 S.E.



Note: *Figure 8 plots impulse response functions to a monetary shock in a FAVAR with sector-specific factors (Food, Furniture, Healing, Hotel, Housing, Recreation, Transports, Alcool, Clothing).*

A Computation of the aggregate sectoral price index

In Section 4 we outline that the national/euro-area wide sectoral price index can be thought to be computed as:

$$\pi_{s,t} = \sum_{c=1}^{C} \theta_c \sum_{r=1}^{R_c} \theta_{c,r} \pi_{c,r,s,t}, \tag{10}$$

where θ_c denotes the expenditure share of state (U.S.) or country (euro area) c and $\theta_{c,r}$ denotes the expenditure share of region r of state/country c. Using equation (4), we obtain:

$$\pi_{s,t} = \sum_{c=1}^{C} \theta_c \sum_{r=1}^{R_c} \theta_{c,r} \left[\alpha_{c,r,s} f_t^a + \beta_{c,r,s} f_t^c + \gamma_{c,r,s} f_t^s + \delta_{c,r,s} f_t^{sc} + e_{c,r,s,t}\right]. \tag{11}$$

This term can be rearranged as follows:

$$\begin{aligned}
\pi_{s,t} &= \sum_{c=1}^{C} \theta_c \sum_{r=1}^{R_c} \theta_{c,r} \alpha_{c,r,s} f_t^a + \sum_{c=1}^{C} \theta_c \sum_{r=1}^{R_c} \theta_{c,r} \beta_{c,r,s} f_t^c + \sum_{c=1}^{C} \theta_c \sum_{r=1}^{R_c} \theta_{c,r} \gamma_{c,r,s} f_t^s \qquad (12) \\
&\quad + \sum_{c=1}^{C} \theta_c \sum_{r=1}^{R_c} \theta_{c,r} \delta_{c,r,s} f_t^{sc} + \sum_{c=1}^{C} \theta_c \sum_{r=1}^{R_c} \theta_{c,r} e_{c,r,s,t} = \\
&= f_t^a \sum_{c=1}^{C} \theta_c \sum_{r=1}^{R_c} \theta_{c,r} \alpha_{c,r,s} + \sum_{c=1}^{C} \theta_c f_t^c \sum_{r=1}^{R_c} \theta_{c,r} \beta_{c,r,s} + f_t^s \sum_{c=1}^{C} \theta_c \sum_{r=1}^{R_c} \theta_{c,r} \gamma_{c,r,s} \\
&\quad + \sum_{c=1}^{C} \theta_c f_t^{sc} \sum_{r=1}^{R_c} \theta_{c,r} \delta_{c,r,s} + \sum_{c=1}^{C} \theta_c \sum_{r=1}^{R_c} \theta_{c,r} e_{c,r,s,t}.
\end{aligned}$$

Since the parameters θ_c represent expenditure shares of a given state/country in total national/euro area wide expenditures we have $\sum_{c=1}^{C} \theta_c = 1$. Similarly, we obtain for the parameters $\theta_{c,r}$: $\sum_{r=1}^{R_c} \theta_{c,r} = 1$. Denoting the weighted average of a variable/parameter x across countries/regions as $\bar{x}^c/\bar{x}^r$ we can rewrite equation (13) as follows:[16]

$$\pi_{s,t} = \bar{\alpha}_s^{rc} f_t^a + \bar{\gamma}_s^{rc} f_t^s + \sum_{c=1}^{C} \theta_c \bar{\beta}_{c,s}^r f_t^c + \sum_{c=1}^{C} \theta_c \bar{\delta}_{c,s}^r f_t^{sc} + \bar{e}_s^{rc}. \tag{13}$$

Comparing this term with equation (2) we can see that the sector-specific component of

[16] Upper index rc indicates that averages are first taken across regions and then across countries.

Boivin et al. (2008) or Mackowiak et al. (2009) corresponds to the following expression:

$$u_{s,t} = +\bar{\gamma}_s^{rc} f_t^s + \sum_{c=1}^{C} \theta_c \bar{\beta}_{c,s}^r f_t^c + \sum_{c=1}^{C} \theta_c \bar{\delta}_{c,s}^r f_t^{sc} + \bar{e}_s^{rc}. \quad (14)$$

B Tables

Table A: Countries and Regions Included in our Study

Germany (12 NUTS-I Regions)
Regions: Baden-Württemberg, Bayern, Berlin, Brandenburg, Hessen, Mecklenburg-Vorpommern, Niedersachen, Nordrhein-Westfalen, Saarland, Sachsen, Sachsen-Anhalt, Thüringen **Data Source:** Statistical offices of the individual German states
Austria (9 NUTS II Regions)
Regions: Burgenland, Kärnten, Niederösterreich, Oberösterreich, Salzburg, Steiermark, Tirol, Vorarlberg, Wien **Data Source:** Statistics Austria
Finland (5 NUTS-II Regions)
Regions: Ita-Suomi, Etela-Suomi, Lansi-Suomi, Pohjois-Suomi, Aland **Data Source:** Statistics Finland
Italy (20 Major Cities of NUTS-II Regions)
Regions: Ancona, Aosta, Bari, Bologna, Cagliari, Campobasso, Firenze, Genova, L'Aquila, Milano, Napoli, Palermo, Perugia, Potenza, Reggio Calabria, Roma, Toino, Trento, Trieste, Venezia **Data Source:** Istituto Nazionale di Statistica (ISTAT)
Spain (18 NUTS-II Regions)
Regions: Andalucia, Aragon, Principado de Asturias, Baleares, Canarias, Caabria, Castilla y Leon, Castilla La Mancha, Cataluna, Ceuta y Melilla, Extremadura, Galicia, Communidad Madrid, Cummunidad Murcia, Navarra, Pais Vasco, La Rioja, Communidad Valenicana **Data Source:** Instituto Nacional de Estadistica (INE)
Portugal (7 NUTS-II Regions)
Regions: Acores, Algarve, Altenejo, Centro, Lisbon, Madeira, Norte **Data Source:** Instituto Nacional de Estatistica (INE)

Table B: Country/Region/Variable Short Names

Full	Short	Full	Short	Full	Short Name
		Countries			
Austria	AU	Germany	DE	Finland	FI
Italy	IT	Spain	ES	Portugal	PO
		Regions			
Cast. la Mancha	alba	Marche	anco		
Extremadura	bada	Baden-Württemb.	bade	Cataluna	barc
Puglia	bari	Bayern	baye	Berlin	berl
Emilia-Romagna	bolo	Brandenburg	bran	Burgenland	burg
Sardegna	cagl	Molise	camp	Ceuta e Melilla	ceut
Norte	coim	Algarve	evor	Centro	faro
Toscana	fire	Lisboa	func	Liguria	geno
Ita-Suomi	hels	Hessen	hess	Etela-Suomi	joen
Krnten	kaer	Lansi-Suomi	kokk	Galicia	laco
Canarias	lapa	Abruzzo	laqu	Alentejo	lisb
La Rioja	logr	Madrid	madr	Mecklenburg-Vorp.	meck
Milano	mila	Murcia	murc	Campania	napo
Niedersachsen	nied	Niedersterreich	nied	Nordrhein-Westf.	nord
Obersterreich	ober	Pohjois-Suomi	oulu	Asturias	ovie
Sicilia	pale	Baleares	palm	Navarra	pamp
Umbria	peru	Reg.Aut.d.Acores	pont	Reg.Aut.d.Madreira	port
Calabria	regg	Lazio	roma	Sachsen-Anhalt	saan
Saarland	saar	Sachsen	sach	Salzburg	salz
Pais Vasco	sans	Cantabria	sant	Aragon	sara
Andalucia	sevi	Steiermark	stei	Aland	tamp
Thringen	thue	Tirol	tiro	Piemonte	tori
Trento	tren	Friuli-Venezia	trie	Valencia	vale
Castilla Leon	vall	Veneto	vene	Vorarlberg	vora
Wien	wien				

Table C: Descriptive statistics: Total sample, sectoral and country data

Sample	**Nobs**	**Level**		**Volatility**		**Persistence**		**Disp**	**Corr**(x_i, x)
		Mean	**Std**	**Mean**	**Std**	**Mean**	**Std**		
				Total sample					
All	730	2.146	1.798	9.809	9.175	-0.142	0.826	11.989	0.117
				Data grouped by countries					
DE	142	1.291	1.952	11.315	7.885	-0.263	0.870	10.444	0.223
ES	216	2.788	1.494	10.619	9.850	-0.248	0.939	10.956	0.173
FI	60	1.491	1.395	12.550	12.081	-0.312	1.402	13.791	0.273
IT	228	2.016	1.483	6.379	3.151	0.083	0.412	6.227	0.200
PO	84	2.762	2.380	12.553	14.210	-0.151	0.593	15.571	0.160
				Data grouped by sectors					
alco	60	3.654	1.458	11.768	2.375	-0.019	0.567	7.194	0.410
clot	61	1.726	1.533	24.104	21.219	-1.166	1.867	21.511	0.600
food	61	1.890	0.839	7.081	2.441	0.342	0.504	6.276	0.496
furn	61	1.580	0.831	3.633	1.335	-0.060	0.442	3.533	0.357
heal	61	2.685	0.944	9.650	8.620	-0.059	0.359	6.427	0.247
hote	61	2.922	1.112	8.444	5.520	-0.393	1.112	8.104	0.276
hous	61	2.575	0.705	5.754	1.802	0.135	0.237	4.808	0.491
recr	61	1.574	0.735	12.443	6.497	-0.505	0.596	10.750	0.362
tran	61	2.721	0.646	7.732	1.934	0.003	0.292	5.523	0.658

Notes:

1) Table C reports descriptive statistics for the data series included in our raw data set. Results are reported for all data series (total sample) and subsamples which include all series from a given country (country data) or a given sector (sectoral data).

2) The reported statistics include the mean and the standard deviation (std) of the time-series means of all inflation series included in a given group (level), the mean and the standard deviation (std) of the time-series standard deviation of all inflation series included in a given group (volatility), the mean and the standard deviation (std) of the persistence measures of all inflation series included in a given group, the time-series mean of the cross-sectional dispersion of all inflation series included in a given group and the mean correlation of all inflation series included in a given group with the group aggregate inflation rate.

3) The measure for persistence is based on the estimation of an AR processes with 13 lags.

4) The group aggregate inflation rate is computed as a weighted average of the series included in the group. Regions are weighted by their relativ economic size, sectors are weighted based on their euro area HICP weight in 2000.

Table D: Descriptive statistics: Country-sector-specific data

Sample	Nobs	Level		Volatility		Persistence		Disp	Corr(x_i, x)
		Mean	Std	Mean	Std	Mean	Std		
Germany									
alco	11	2.835	0.103	10.705	0.309	-0.646	0.316	2.183	0.977
clot	12	0.351	1.766	7.704	4.372	0.076	0.750	5.645	0.750
food	12	0.603	0.391	8.846	0.979	0.323	0.054	3.384	0.923
furn	12	0.286	0.508	1.956	0.515	0.208	0.458	1.623	0.467
hote	12	1.371	0.508	18.505	4.090	-1.984	1.640	5.793	0.934
hous	12	1.616	0.319	3.756	0.685	0.178	0.207	2.110	0.742
recr	12	0.569	0.286	20.735	2.220	-1.070	0.468	4.219	0.937
tran	12	2.508	0.110	8.620	0.699	-0.231	0.203	3.470	0.910
Spain									
alco	18	4.981	0.714	13.112	2.290	-0.127	0.154	4.874	0.883
food	18	2.700	0.250	6.247	0.861	0.514	0.085	3.466	0.797
furn	18	2.093	0.594	3.872	0.911	-0.088	0.401	2.769	0.706
heal	18	2.232	0.590	4.337	0.837	-0.082	0.308	3.022	0.679
hote	18	4.042	0.368	5.947	1.543	-0.159	0.398	4.037	0.719
hous	18	3.150	0.454	5.401	1.695	0.072	0.176	3.726	0.715
recr	18	2.214	0.594	16.316	3.836	-0.617	0.510	4.876	0.972
Finland									
alco	5	-0.208	0.089	16.424	0.922	1.486	0.501	0.354	1.000
clot	5	0.700	0.591	49.104	4.782	-4.021	2.505	11.120	0.974
food	5	1.370	0.407	8.995	1.541	-0.014	0.503	3.698	0.917
furn	5	0.923	0.215	4.921	0.559	-0.551	0.441	3.786	0.638
heal	5	3.039	0.288	7.540	0.669	-0.432	0.353	3.462	0.837
hote	5	2.284	0.126	5.159	0.945	-0.014	0.209	2.739	0.816
hous	5	1.988	0.217	5.438	0.706	0.211	0.117	1.843	0.931
recr	5	1.764	0.135	7.475	0.793	-0.221	0.358	3.289	0.847
tran	5	1.635	0.153	10.466	0.789	-0.183	0.171	4.034	0.922
Italy									
clot	19	2.324	0.620	3.698	0.850	-0.034	0.664	2.541	0.642
food	19	1.826	0.368	4.927	0.834	0.439	0.168	3.572	0.681
furn	19	1.828	0.344	3.617	0.960	-0.123	0.429	2.341	0.596
hote	19	2.652	0.699	5.592	1.589	0.092	0.398	4.983	0.368
hous	19	2.718	0.420	7.509	0.955	0.182	0.203	4.268	0.714
recr	19	1.663	0.274	6.605	3.142	-0.140	0.428	4.412	0.568
tran	19	2.431	0.360	6.058	0.846	-0.021	0.260	3.365	0.779
Portugal									
alco	7	4.027	0.494	8.941	1.448	-0.169	0.379	5.791	0.641
clot	7	-0.011	1.034	50.375	19.804	-1.396	0.674	26.121	0.824
food	7	2.558	0.239	10.679	3.302	-0.075	0.248	8.406	0.667
furn	7	2.273	0.394	5.020	1.612	0.071	0.238	3.980	0.605
heal	7	3.532	0.522	5.580	2.706	0.480	0.245	3.998	0.559
hote	7	3.890	0.384	7.709	1.618	0.146	0.238	6.030	0.458
hous	7	2.839	0.677	6.227	2.130	0.041	0.475	3.792	0.709
recr	7	1.279	0.777	7.666	1.914	-0.439	0.782	5.973	0.467
tran	7	3.910	0.208	6.506	2.448	-0.133	0.381	4.146	0.719

Notes:

1) Table D reports descriptive statistics for the data series included in our raw data set. Results are reported for sectoral data of each included country. See the notes of Table 1 for further details on the computation of the statistics.

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