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Estimating pure inflation in the Polish economy

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Estimating pure inflation in the Polish economy

Michał Brzoza-Brzezina, Jacek Kotłowski^{*)}

Abstract

This paper uses a restricted factor model to estimate the HICP index excluding relative prices changes. The index thus obtained, hereinafter referred to as pure inflation, demonstrates stronger relationship to the central bank instrument (short-term interest rate) than the HICP index and selected measures of core inflation. Pure inflation has also a forecasting performance for future HICP comparable or better than that of competing models. The estimated variable indicates a much weaker role of changes in relative prices in the recent period of rising inflation (2006-2008) than during previous inflation increases (1999-2000 and 2004-05). This may show that inflation was mainly driven by demand pressures in the years 2006-2008.

JEL: C43, E31, E58

Key words: monetary policy, relative prices, factor model, core inflation

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1 Introduction

In this paper we estimate the common component of disaggregate inflation series measured with the Harmonised Index of Consumer Prices (HICP). In this specific case, the common component is defined as equiproportional changes in prices of individual groups of consumer goods and services. This means that the object of estimation is the HICP index excluding changes in relative prices which frequently influence standard inflation measures (HICP or CPI). Due to the above, the variable is called pure inflation (PI) throughout the paper.

The limited scale of impact of monetary policy instruments on relative prices is one of the significant determinants of central bank monetary policy. Central banks do not have any instruments which allow them to influence relative prices, e.g. the price of potatoes or beetroots. If a central bank wishes to influence the price of potatoes, it must remember that the price of beetroots will be independent of its policy. Central banks do not usually decide to influence the price of a selected good, deciding instead to determine a price index – normally the consumer price index. Such an index reflects the purchasing cost of a basket of consumer goods by a representative consumer and is calculated by a statistical office on the basis of individual prices and consumption structure.

In practice, such an index is influenced not only by equiproportional changes in all prices but also changes in relative prices. One of the reasons¹ is related to constant weights in the CPI. When the relative price of one good increases households must adjust their consumption structure because of the binding budget constraint. These adjustments leave the cost of the consumption basket unchanged – i.e. the “true” CPI does not change. However, since weights in the official CPI basket are adjusted only with a lag, “official” CPI will be temporarily affected by the change in relative prices (Bryan and Cecchetti 1993).

Despite the above drawback, the CPI index (as well as the HICP index) has significant advantages from the point of view of a central bank, particularly in the context of setting the objective of monetary policy. This concerns primarily its recognisability by the general public. Although central bank communication policy currently constitutes a very important tool of influencing agents’ expectations and thus future inflation, in the monetary policy process central banks also take into account medium- and long-term changes to price levels; the usefulness of the proposed measure is subject to interpretation in this context.

¹ See Ball and Mankiw (1995) for another explanation.

It is not, therefore, the authors' intention that the measure should become an index applied by a central bank in the context of setting and meeting the inflation objective. However, it may be assumed that pure inflation may become a useful tool for analyses conducted by the central bank owing to the fact that:

- it facilitates separating proportional changes in all prices from shifts in relative prices on which monetary policy has no influence;
- it may facilitate identifying sources of inflation pressure (excessively expansionary monetary policy or changes in relative prices);
- on the assumption that changes in relative prices affect the CPI/ HICP only in the short-term, it enables to separate the medium- and long-term inflation component, accordingly PI may also constitute a leading indicator of future inflation.

It is important to notice that due to the need to revise past pure inflation values after making a new model estimation, the index does not qualify as core inflation in its traditional meaning.²

The history of calculating alternative price indices whose task would be (*inter alia*) to support monetary policy is long and broad. Modern central banks use core inflation measures on a wide scale. Banks usually obtain the measures by excluding certain categories from the CPI (or the HICP) index. This may concern particularly the most volatile prices or those outside the direct influence of monetary policy (e.g. food or fuel prices). The tradition of separating relative prices is much less developed. Bryan and Cecchetti (1993) applied a factor model to that end so as to estimate the bias in the CPI being a result of fixed weights. The results obtained by the authors show that in the years 1967-1992, the average CPI bias amounted to 0.6 percentage points. Reis and Watson (2007a, 2007b) in turn estimated pure inflation in order to obtain answers to macroeconomic questions concerning, *inter alia*, the robustness of assumptions made by various economic schools on the influence of relative prices on the slope of the Philips curve. The authors stated, *inter alia*, that replacing traditional inflation measures with exogenous changes to pure inflation makes the correlation characteristic for the Philips curve disappear. In their opinion, this proves the significant role of relative prices in generating shocks that affect the real economy.

² More information on core inflation measures can be found in Rich and Steindel (2005) and in Woźniak (2002).

It is also worth invoking studies which applied a similar methodology to separate the common component in price series although they do not formally concern identifying pure inflation. Christadoro et al. (2001) used a factor model to identify the common inflation component (in a cross section of countries and price groups) in the euro area and to study its forecasting performance. They found that the common component has good forecasting ability towards the HICP index outperforming other indices applied as well as a random walk process. A similar method was applied by Amstad and Potter (2007) when calculating the core inflation measure on the basis of US data. Similarly to Christadoro et al. (2001), the authors came to a conclusion that the obtained measure has better forecasting ability towards the CPI than alternative indices.

As regards the tools applied, this study, similarly to the papers referred to above, is based on dynamic factor models. In the recent years, these models were applied, *inter alia*, for forecasting (Stock and Watson 2002a, 2002b; Forni, Hallin, Lippi, and Reichlin 2000; Kotłowski 2008) and to identify unobservable variables with an economic interpretation (Kose et al. 2003; Mumtaz and Surico 2008; Brzoza-Brzezina and Crespo Cuaresma 2008). In the first case, factor models are used to replace large datasets (which often contain a few hundred series) with a small number of common factors and then use the factors in the forecasting model. The procedure allows using an extensive information set without the need to limit the number of degrees of freedom when constructing a model. These models usually do not impose restrictions on factors or factor loadings. The second group uses factor models to identify factors which can be interpreted in economic terms, such as the global component of the business cycle, inflation, or real interest rates. In this case, restrictions which allow identifying the unobservable variable are imposed on the matrix of loadings.

Our study belongs to the second group. Imposing a unit restrictions on the vector loading the first common factor allows estimating the inflation rate which equiproportionally impacts prices of all goods and services. The factor identified in this way (*PI*) is responsible for ca. 63% of volatility of all 81 inflation series of individual groups of goods and services included in the model. Also, the index is less volatile than the remaining inflation measures under analysis (HICP, core inflation excluding the prices of energy and unprocessed food and core inflation excluding prices of energy, food, alcohol, and tobacco). Pure inflation also indicates a stronger relationship to short-term interest rates than other competing inflation indices. This concerns both the measures of spectral correlation and other measures which describe the influence of changes in interest rates on inflation. Finally, forecasting models based on PI perform comparably or better than competing models.

The further part of the article is structured in the following way: section two presents the factor model and the method of imposing restrictions, it also describes the data used in the study, section three describes the results and section four summarises the study.

2 Model and data

Let $\pi_{i,t}$ denote a change in the price of good i between periods $t-1$ and t , while π_t denotes an $N \times 1$ vector which includes price changes (inflation rates) of all N categories of goods and services. The linear factor model decomposes π_t as:³

$$(1) \quad \pi_t = \Lambda F_t + \varepsilon_t$$

where F stands for a vector of size $k \times 1$ of k unobservable factors, and Λ is an $N \times k$ matrix of factor loadings. With ε_t we denote an $N \times 1$ vector of idiosyncratic components for individual series. Factors contain information about common changes in all series, loadings allow presenting individual series as a linear combination of factors. Loadings also allow assessing the impact of a given factor on a given variable, which is important in case of factors having an economic interpretation. The number of factors may vary between 1 and N . The usefulness of factor models consists in the fact that usually a considerable part of the variance of analysed series may be expressed with the use of a few factors only. The issue of setting the number of factors will be discussed further in section three.

The idea to estimate pure inflation with the use of a factor model consists in imposing restrictions on the estimated model so that one of the factors corresponds to proportional changes in all prices and the remaining factors – to changes in relative prices. To that end, we distinguish one factor so that its changes have the same influence on all series of inflation $\pi_{i,t}$. The factor stands for pure inflation and is denoted by a_t . Separating factor a_t from the vector F allows writing the inflation vector as:

$$(2) \quad \pi_t = l a_t + \Gamma R_t + u_t$$

³ The modelling procedure follows Reis and Watson (2007b).

where l stands for a vector of ones of size $N \times 1$, Γ stands for an $N \times (k-1)$ matrix of loadings, R_t for a $(k-1) \times 1$ vector of factors responsible for changes in relative prices, while u_t for a vector of idiosyncratic price changes of individual categories of goods and services. The identification of vector a_t proposed in formula (2) is not unique. Thus, an additional assumption must be made that loadings connected with factors responsible for changes in relative prices sum up to zero for all goods, which meets the definition of pure inflation assumed in the study and can be presented as:

$$(3) \quad \sum_{i=1}^N \gamma_{ij} = 0 \quad \text{for } j=1,2,\dots,k-1,$$

where γ_{ij} denotes element (i,j) of matrix Γ .

There are many ways of estimating the factor model. In this study we estimate parameters and factors in formula (2) with restricted principal components. It is also possible to estimate factor models using maximum likelihood, or – in case of systems with a considerable number of parameters – also Bayesian methods (the review of estimation methods can be found in e.g. Eickmeier, Ziegler 2006). In our case finding estimates of parameters and factors results from minimising the sum of squared residuals in (2):

$$(4) \quad \min_{a,\Gamma,R} \sum_{i=1}^N \sum_{t=1}^T (\pi_{i,t} - a_t - \gamma_i R_t)^2$$

where γ_i denotes the i -th row of matrix Γ . This leads to consistent estimators (Bai i Ng 2002) for large T and N .

The data consisted of individual components of the Harmonised Index of Consumer Prices for Poland. The study used monthly data for the period from January 1996 to July 2008 (151 observations). Price indices of individual categories of goods and services included in the HICP inflation basket were derived from the Eurostat database. Series with missing observations and series for which at least 40 observations (in first differences) assumed zero values were removed from among the 94 available price indices. Thus, a total of 81 time series was obtained. The next step consisted in adjusting the data for seasonality and outliers. Due to lack of unambiguous indications of unit root tests the study arbitrarily assumes that all price indices are variables integrated of order one which means that the proposed decomposition will concern inflation, not its changes, similarly to studies by Reis and Watson

(2007a, 2007b). Inflation indices for individual categories of prices and services have been obtained according to the following formula:

$$(5) \quad \pi_{it} = \ln(P_{it} / P_{it-1}),$$

where P_{it} stands for the value of a price index (2005 = 100) for category i in period t .

Comparison of the features of pure inflation thus obtained with the features of selected core inflation measures constitutes an important element of the analysis. The core inflation indices used in the study also stem from the Eurostat database and are based on the Harmonised Index of Consumer Prices. Two core inflation indices were selected: inflation excluding the prices of energy and unprocessed food (the *COREFOOD* variable) and inflation excluding prices of energy, food, alcohol, and tobacco (the *COREALL* variable). The remaining variables used in the study originate from the database of the Central Statistical Office (GUS) (industrial production – the *PROD* variable) and ECOWIN (one-month money market rate – the *WIBORIM* variable).

3 Empirical results

3.1 Selection of the number of factors

Since in factor model estimation the results may depend significantly on the number of factors, before starting the estimation it was necessary to decide upon it.

The analysis of eigenvalues of correlation matrices is one of the standard methods of identifying the true number of factors. The sum of eigenvalues of the matrix equals the number of variables, i.e. $tr(R) = \sum_{i=1}^N \mu_i = N$, where μ_i stand for subsequent eigenvalues of matrix R arranged in a decreasing order. The ratio $\tau(k) = \sum_{i=1}^k \mu_i / N$ then shows the share of total variance explained by first k unobservable factors.

Bai and Ng (2002) propose a more formalised method of establishing the number of factors which is based on information criteria. Each criterion constitutes a sum of two values: the logarithm of the residual sum of squares from the factor model and a “penalty” for model overfitting. The residual sum of squares is a decreasing function of the number of factors in the model, while the value of the penalty function increases in k . The selection of the number

of factors in the model takes place by comparing values of the given criterion for different k . The number of factors r in the model is the value k for which the given criterion reaches its minimum value. Bai and Ng (2002) suggest the use of three different criteria which differ from one another in the form of the penalty function. At the same time, they show that all the three criteria are consistent, i.e. for $T, N \rightarrow \infty$ they indicate the true number of factors with probability of 1.

As a first step we specify the number of factors in the model. This was done for the unrestricted model (1).

Table 1. Selection of the number of factors in the model.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of factors	Eigenvalues	Difference of eigenvalues	Share in variance	Cumulative share in variance	IC1	IC2	IC3
1	51.269	47.106	0.633		-0.927	-0.919	-0.948
2	4.163	1.336	0.051	0.684	-1.002	-0.986	-1.045
3	2.828	0.689	0.035	0.719	-1.044	-1.020	-1.108
4	2.139	0.198	0.026	0.746	-1.068	-1.035	-1.152
5	1.940	0.217	0.024	0.770	-1.091	-1.050	-1.197
6	1.723	0.151	0.021	0.791	-1.113	-1.064	-1.239
7	1.572	0.317	0.019	0.810	-1.135	-1.077	-1.283
8	1.255	0.081	0.016	0.826	-1.145	-1.079	-1.313
9	1.174	0.146	0.015	0.840	-1.156	-1.082	-1.346
10	1.029	0.114	0.013	0.853	-1.164	-1.082	-1.375
11	0.915	0.084	0.011	0.864	-1.168	-1.078	-1.400
12	0.831	0.165	0.010	0.875	-1.172	-1.073	-1.425

Column (2) features the 12 largest eigenvalues of the correlation matrix arranged in a decreasing order. Column (3) features differences between them. Column (4) features shares of individual factors in variances of the correlation matrix, while column (5) presents cumulative shares. The last three columns of the table feature values of information criteria. Minimum values of criteria have been bolded.

Source: Own calculations.

Table 1 presents eigenvalues of the correlation matrix for relative changes in prices of all 81 categories of goods and services concerned. The obtained results show that the factor connected with the first eigenvalue is responsible for over 63% of volatility of individual inflation rates. Subsequent two factors explain almost 9% of volatility, while each of the remaining factors – not more than 3%. The difference between the first and the second eigenvalue is clearly higher than differences between subsequent values. Also, the differences between the second and the third value as well as between the third and the fourth one are marked. Subsequent differences are less marked, which indicates that the true number of factors in the model may equal 2 or 3.

The values of information criteria shown in the last three columns of Table 1 do not give unambiguous results. The first and the third criterion indicate that the number of factors in the model is 12, while the second criterion suggests that it is slightly lower and amounts to 9. Considering subsequent eigenvalues it may be expected that both numbers are overestimated in this case, particularly as differences between them are not monotonic starting from the fourth value. Due to this, relying to a greater extent on the analysis of eigenvalues of correlation matrices rather than on indications of information criteria it was assumed that the number of factors in the model is 3.

3.2 Estimation of pure inflation

Having established the number of factors, estimation of parameters of the restricted factor model (2) was conducted with principal components. The assumption of the unit value of the parameters loading the first factor means that the factor will be responsible for equiproportional changes in prices of all goods and services. Accordingly, we will call this factor pure inflation. The two remaining factors whose average influence on changes of all prices of goods and services should by definition be zero are responsible for changes in relative prices.

Subsequently, an evaluation of the unit restriction on the parameters loading the first factor was conducted. To that end, a regression of individual changes in prices of goods and services π_{it} against all three identified factors was conducted. Subsequently, with the use of the t-test, it was verified if the value of the parameters accompanying the first factor is equal to one.⁴ Chart 1a presents estimates of the parameter under analysis for all 81 regression equations arranged in an increasing order. Chart 1b presents values of t -statistics originating from testing the hypothesis that the parameters equal one. Chart 1c presents absolute values of the ratios of t -statistics to the critical value determined at the 5% significance level. Values higher than 1 indicate that the hypothesis of unit value of the parameter should be rejected.

Charts 1a-1c allows concluding that the restriction adopted in the model is confirmed by empirical data. Chart 1a shows that a marked majority of parameter estimates is around 1, while the majority of values in chart 1b oscillates around 0. From among 81 values in chart 1c, 4 are larger than 1, which approximately meets the adopted significance level.

⁴ Newey-West autocorrelation and heteroskedasticity consistent (HAC) covariance matrix estimator was used to estimate the standard error.

A positive evaluation of the unit restriction allows treating the related factor as pure inflation in further considerations. Its values have been presented in charts 2a-2c together with the HICP index and two measures of core inflation: *COREFOOD* and *COREALL*.⁵

Table 2 presents the basic descriptive statistics for each of the inflation indices and correlation coefficients between them. Charts 2a-2c and descriptive statistics in Table 2 show that the new inflation index *PI*, is less volatile and has a lower amplitude than the remaining three inflation measures. The standard deviation of *PI* amounts to 0.00346 and constitutes 80% of the HICP standard deviation. Also, the difference between the maximum and the minimum value of the index is visibly lower for pure inflation than for the remaining inflation indices and amounts to 0.012, i.e. 63% of the analogous value for the HICP index. The penultimate line of Table 2 features values of correlation coefficients between pure inflation and the remaining three inflation indicators and the last line presents the values of correlation coefficients between first differences of *PI* and other inflation indices. All three correlation coefficients assume quite high values exceeding 0.89. The correlation is stronger for core inflation measures than for the HICP index. For first difference of inflation, *PI* correlation with the remaining inflation measures is significantly lower, although for *HICP* and *COREFOOD* it is still statistically significant (amounting to 0.32 and 0.29, respectively).

Comparison of charts of year-on-year *PI* and HICP enables to conclude that the increases of HICP inflation observed in the years 1999-2000 and 2004-2005 were largely due to changes in relative prices of goods and services (Chart 2a). The significant decreases in HICP inflation in the years 1998-1999 and 2002-2003 were also mainly (but not solely) due to favourable changes in relative prices.

The situation was different in the period 2006-2008. Contrary to previous periods, the increase in HICP inflation observed since 2006 was also accompanied by a marked increase in the *PI* index which suggests that inflation acceleration in the years 2006-2008 does not only result from changes in relative price relations but mainly from the accelerated growth rate of the common price component, which may be attributed to a more expansionary monetary policy.

⁵ In order to enhance the clarity of charts, each of inflation indices was expressed as a annual change in the price level, i.e. the sum of twelve subsequent inflation indices expressed by formula (4). Also, the values of *PI* were adjusted in all charts so that the average value of the index equals the average value of the second inflation index shown in the chart.

Table 2. Descriptive statistics for selected inflation measures: *PIR* , *HICP*, *COREALL*, *COREFOOD*.

	<i>PIR</i>	<i>HICP</i>	<i>COREALL</i>	<i>COREFOOD</i>
Average	0.00000	0.00468	0.00461	0.00445
Median	-0.00117	0.00331	0.00249	0.00273
Maximum value	0.00816	0.01668	0.01593	0.01827
Minimum value	-0.00374	-0.00212	-0.00080	-0.00203
Maximum value – minimum value	0.01190	0.01880	0.01673	0.02030
Standard deviation	0.00346	0.00430	0.00451	0.00430
Asymmetry	0.81747	0.87717	0.77986	0.96776
Kurtosis	2.37756	3.13597	2.29874	3.09035
Jarque-Ber statistics	19.12795	19.35119	18.27823	23.46484
p-value	0.00007	0.00006	0.00011	0.00001
Cor. coeff. of PI with	-	0.894	0.959	0.967
		$\Delta HICP$	$\Delta COREALL$	$\Delta COREFOOD$
Cor. coeff. of ΔPIR with	-	0.323	0.114	0.293

Source: Own calculations.

When analysing the charts of *PI* and core inflation *COREALL* it is worth noting the significant similarity of both indices in the period under analysis (higher than in the case of *HICP*, as confirmed by the values of correlation coefficients for levels in Table 2). Clearer differences are visible only in the years 2004-2005, i.e. in the period directly following Poland's accession to the European Union, and in the first half of 2008. As in the years 2004-2005, changes in relative prices (including the increase in indirect taxes on certain goods) concerned largely the categories of goods and services which are included in the core inflation basket, the increase in core inflation was markedly higher than the increase in pure inflation. In the first half of 2008, the situation was the opposite. High increases in prices of energy and food triggered shifts in relative prices and pushed the core inflation index below the *PI* index. It is noteworthy that the discrepancy between the two inflation indices in the period is not wide. This is in line with the earlier observation that the increase in inflation in these years was also largely due to the accelerated growth rate of the common price component.

3.3 Pure inflation and monetary policy

In the subsequent stage we investigate the relationship between monetary policy and pure inflation. We check whether monetary policy influences changes in the general price level to a greater extent than it influences inflation indices which also include changes in relative prices. The analysis of the impact of monetary policy on individual inflation indices is based on the relationship between inflation and the short-term interest rate (1-month money market rate).

Four indicators were proposed to assess the strength of relationships between the variables under analysis. The first indicator is the spectral correlation coefficient which allows assessing the interdependence between variables separately for individual frequencies. The study analysed the average values of the spectral correlation coefficient for frequencies consistent with cycles of 1 to 4 years. This allows to omit frequencies connected with seasonal fluctuations and concentrate on medium-term dependencies. To supplement the analysis, average values of spectral correlation coefficients were also calculated for all frequencies.

The second indicator is the coefficient of determination (R-squared) from the regression of inflation on the current and lagged values of the interest rate. This shows which share of volatility of the given inflation index results from changes in the current and past values of the interest rate.

The third indicator used for this analysis is based on forecast error variance decomposition (FEVD) of the inflation index in a VAR model which includes a constant and three variables: inflation, the interest rate and the seasonally adjusted monthly growth rate of industrial production. In this case, the contribution of a shock to the interest rate to the forecast error variance of inflation was adopted as the measure of dependence between the variables. The analysis was supplemented with the results of the Granger causality test for the interest rate and inflation. Table 4 presents the results.

The values of spectral correlation coefficients presented in Table 4 show that both in the medium run and jointly for all frequencies under analysis PI is the index with the strongest link with the interest rate. As regards frequencies with longer cycles (1-4 years), a relatively strong connection with the interest rate was also observed in the case of the core inflation index excluding the prices of energy, food, alcohol, and tobacco. The connection was slightly weaker for core inflation excluding the prices of energy and unprocessed food. From among

the inflation indices under analysis, HICP inflation is the weakest correlated with the interest rate, both cyclical frequencies and for all frequencies. It is worth noting that spectral correlation coefficients do not provide information on the direction of dependence between variables; they only provide information on its strength.

Table 4. Dependence between the short-term interest rate (Wibor 1M) and selected inflation indices.

(1)	(2)		(3)	(4)	(5)	(6)
	Spectral correlation coefficient			Coefficient of determination	FEVD	Granger causality (p-value) H0: the interest rate does not Granger cause inflation
	Frequencies					
	<i>All</i>	<i>1-4 years</i>				
<i>HICP</i>	0.229	0.421		0.552	11.0	0.5478
<i>PI</i>	0.658	0.621		0.787	64.7	0.0140
<i>COREALL</i>	0.358	0.607		0.770	7.7	0.0009
<i>COREFOOD</i>	0.429	0.545		0.699	6.9	0.1236

Source: Own calculations. Columns (2)-(3) feature average values of spectral correlation coefficients between the interest rate (1-month Wibor rate) and inflation indices described in column (1). The average values of spectral correlation coefficients were also calculated for: all frequencies (column 2), and cyclical frequencies of 1 to 4 years (column 3).

Column (4) presents coefficients of determination from the regression of individual inflation indices on the current and the lagged (up to 12 periods) values of the interest rate.

Column (5) features the results of the forecast error variance decomposition (FEVD) for the variable which expresses the inflation index in the VAR model composed of three variables: monthly relative changes in industrial production, the given inflation index, and the interest rate (1M Wibor). The number of lags is the same in each of the models and amounts to 12. The contribution of a shock to the interest rate to the forecast error variance of inflation has been calculated on the basis of the Cholesky decomposition with the assumption of the following ordering of variables: production, inflation, interest rate. This particular order of variables stems from the assumption that changes in inflation and production trigger immediate changes in the interest rate (the monetary policy rule), while the interest rate impacts inflation and production with a lag. Also, the demand effect of production's impact on inflation is faster than the supply effect of inflation's impact on production.

Column (6) features the p-value of the Granger causality test which checks whether the interest rate Granger-causes inflation.

The second of the proposed measures is the coefficient of determination from the regression of a given inflation index on the current and lagged values of the interest rate. While the highest value of R-squared has been observed again in case of the *PI* index, the value is only slightly higher than the value of the subsequent inflation measure – *COREALL*. HICP inflation in turn has the weakest connection with the interest rate. It must be nevertheless stressed that in all cases the values of the R-squared coefficient are relatively high and *F* tests confirm their statistical significance.

Similar conclusions can be drawn on the basis of the third measure of dependence, namely the share of the interest rate shock in the forecast error variance of inflation. Column

(5) of Table 4 shows that the share is highest for the *PI* index (0.647) and markedly higher than for the remaining inflation measures. In addition, the results of the Granger causality test conducted under the same VAR model as FEVD confirm that the interest rate Granger-causes the *PI* index (at the 5% significance level).

The results indicate quite unanimously that monetary policy influences pure inflation to a greater extent than it does HICP inflation or core inflation indices. However, it must be stressed, that in case of some indicators (determination coefficient, spectral correlation coefficients) the differences between the results for *PI* and *COREALL* are slight.

3.4 Forecasting performance of the pure inflation index

The usefulness of pure inflation for monetary policy may also stem from its forecasting performance towards future values of the consumer price index. While changes in relative prices affect inflation mainly in the short-term, it may be expected that pure inflation will help forecast the HICP. Nevertheless, it must be stressed that the analysis of the forecasting ability of indices conceptually similar to the PI, such as core inflation, gives rise to controversies among certain authors (e.g. Cecchetti et al. 2000) although it is popular in the literature (e.g. Rich and Steindel 2005).

We considered forecast horizons of $h=4, 8, 12,$ and 16 months. The object of the forecast was:

$$(6) \quad y_{t+h}^h = \frac{\ln(HICP_{t+h}/HICP_t)}{h},$$

where $HICP_t$ stands for a seasonally adjusted index of consumer prices at constant base. Thus, the y_{t+h}^h variable expresses an average monthly change in prices over h months.

Forecasts have been obtained on the basis of the following model:

$$(7) \quad \hat{y}_{t+h}^h = \hat{\alpha}_h + \sum_{k=1}^K \hat{\beta}_{h,k} PI_{t-k+1} + \sum_{p=1}^P \hat{\gamma}_{h,p} y_{t-p+1}$$

where \hat{y}_{t+h}^h stands for the forecast of variable y_{t+h}^h , $y_t = \ln(HICP_t/HICP_{t-1})$ represents the monthly inflation rate and PI_t denotes pure inflation. Maximum lags K and P in the model have been chosen on the basis of the Bayesian Information Criterion (BIC). The forecast for

period $t+h$ is obtained directly from equation (7) on the basis of information available in period t .

Evaluation of the forecasting performance of a model based on PI has been carried out by comparing it to the accuracy of inflation forecasts prepared on the basis of other competing models. Four competing models were taken into account, namely the univariate autoregressive model, two autoregressive models with core inflation indices COREALL and COREFOOD, and a naive forecast. Each of the models will be briefly discussed below.

The autoregressive (AR) model

In the AR model, forecasts of variable y_{t+h}^h are calculated according to:

$$(8) \quad \hat{y}_{t+h}^h = \hat{\alpha}_h + \sum_{p=1}^P \hat{\gamma}_{h,p} y_{t-p+1},$$

where the value of the maximum lag P is established according to the BIC. Similarly to model (7), forecasts stemming from the autoregressive model are calculated directly for h periods ahead.

Autoregressive models with core inflation indices

Apart from current and lagged values of y_t , the set of explanatory variables also includes the COREALL or COREFOOD index. Forecasts from an autoregressive model with core inflation indices are calculated according to:

$$(9) \quad \hat{y}_{t+h}^h = \hat{\alpha}_h + \sum_{k=1}^K \delta_{h,k} CORE_{t-k+1} + \sum_{p=1}^P \hat{\gamma}_{h,p} y_{t-p+1},$$

where the variable $CORE = \{COREALL, COREFOOD\}$. In order to establish maximum lags K and P , again we apply the BIC criterion. As before, forecasts of variable y_{t+h}^h are calculated directly for h periods ahead.

Naive forecast

The naive forecast has been calculated according to:

$$(10) \quad \hat{y}_{t+h}^h = y_t$$

which means that the forecast of variable y_{t+h}^h equals its current value.

Forecasts of all five models were constructed to mirror the real time forecasting process to the greatest extent. The sample on the basis of which the study was carried out was divided into two subsamples. The *PI* was estimated according to the procedure described in Section 3.2 for data covering the period from January 1996 to January 2004. Subsequently, an initial specification of each of the forecasting models was carried out (the dynamic structure of models was determined with the use of the BIC), their parameters were estimated and the forecasts calculated. Observations from the second part of the sample were used to evaluate forecast accuracy. Forecasts were calculated for 4, 8, 12, and 16 periods ahead. After each forecast calculation the sample was extended by another observation, *PI* was estimated, the dynamic structure of models was established with the use of the BIC criterion, model parameters were reestimated, and subsequent forecasts were obtained. A total of 38 to 50 forecasts was generated, depending on the forecast horizon.

The criterion of the mean square error was applied for the evaluation of forecasting performance of the models. For each of the four competing models, the forecast error was calculated in relative form, i.e. as a ratio of the mean square error obtained on the basis of the given model and the mean square error for the factor model. Values higher than 1 indicate better forecasting performance of the model based on *PI*. The results of the West (2005) test are presented together with the values of relative mean square errors. The test verifies the hypothesis according to which the mean square error for the given competing model is the same as for the model based on the *PI*. Table 5 presents relative mean square errors and p-values from West tests (in parentheses):

Table 5: Comparison of forecasting performance of the model based on the *PI* index with competing models

Model	Forecast horizon			
	4	8	12	16
AR model	1.845 (0.027)	2.571 (0.078)	2.703 (0.126)	3.000 (0.081)
<i>COREALL</i>	1.510 (0.005)	1.781 (0.001)	1.441 (0.022)	1.530 (0.004)
<i>COREFOOD</i>	0.963 (0.621)	0.885 (0.430)	0.956 (0.845)	1.002 (0.990)
Naive forecast	1.943 (0.015)	2.532 (0.094)	2.778 (0.021)	2.841 (0.004)

In line with the presented results, the model based on the *PI* index produced much more accurate forecasts than the autoregressive model, the model based on the *COREALL* index and the naive forecasts. Differences in forecast accuracy with respect to the model based on the *COREFOOD* index turned out to be statistically insignificant.

4 Conclusions

We estimated the HICP inflation rate excluding the impact of changes in relative prices. These changes may significantly influence the traditional inflation measures thus making it more difficult for monetary authorities to discover the actual sources of inflation fluctuations. The calculations were based on a factor model with restrictions imposed on its parameters (Reis and Watson 2007a, 2007b).

The estimated measure called pure inflation (*PI*) is less volatile than HICP. Comparing the relationship between the short-term interest rate (directly influenced by the central bank) and selected inflation measures (HICP, core inflation and *PI*) shows that the *PI* index is relatively strongest influenced by monetary policy. Moreover, in when used to forecast future HICP it performs comparably or better than competing models based on core inflation measures or autoregressive processes.

The analysis of the *PI* index shows that periods of significant inflation increases in the years 1999-2000 and 2004-2005 were, to a great extent, connected with changes in relative prices. On the other hand, the acceleration of price increases observed in recent years (2006-2008) was identified primarily as an increase in pure inflation. This may prove that demand factors played a far more significant role in stimulating the current price increase.

Estimating the *PI* index for the Polish economy paves the way for further interesting studies. The use of a CPI database for a similar purpose or an attempt to construct an index conceptually similar to *PI* but meeting the axioms of core inflation could be interesting topics for further work.

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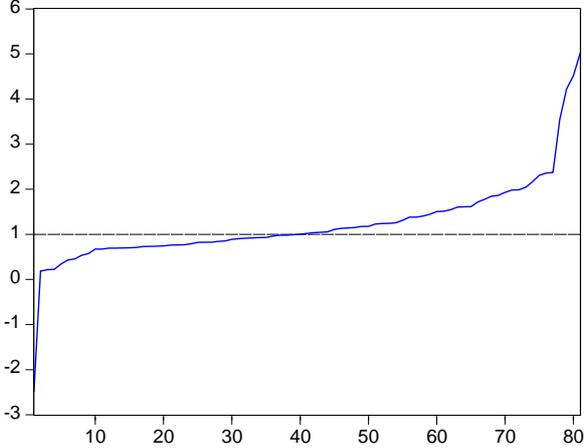
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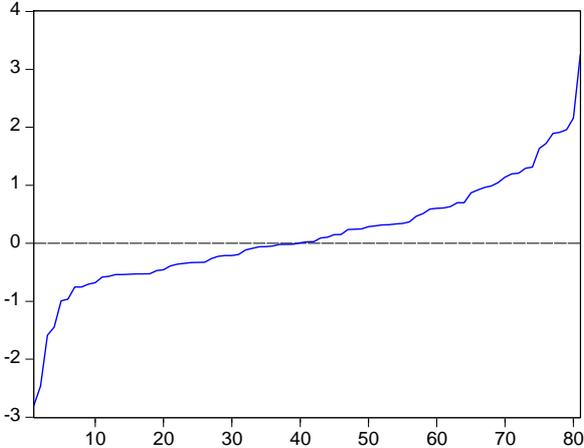
Annex

Chart 1a. Estimates of the parameters connected with the first factor in a regression of inflation indices of individual categories of goods and services on the first three factors (parameters arranged in increasing order).



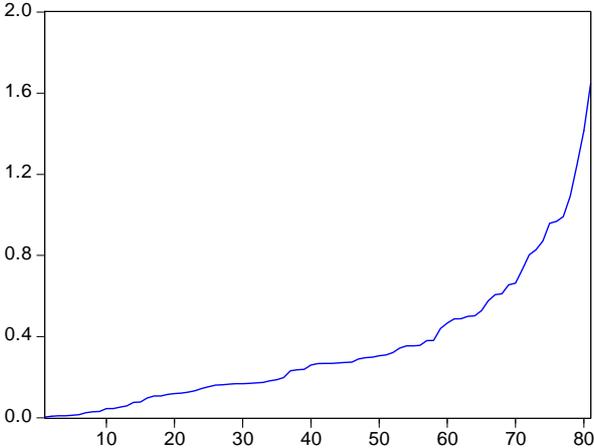
Source: Own calculations.

Chart 1b. Values of *t*-statistics from the test verifying the hypothesis of the unit value of the parameter connected with the first factor arranged in an increasing order.



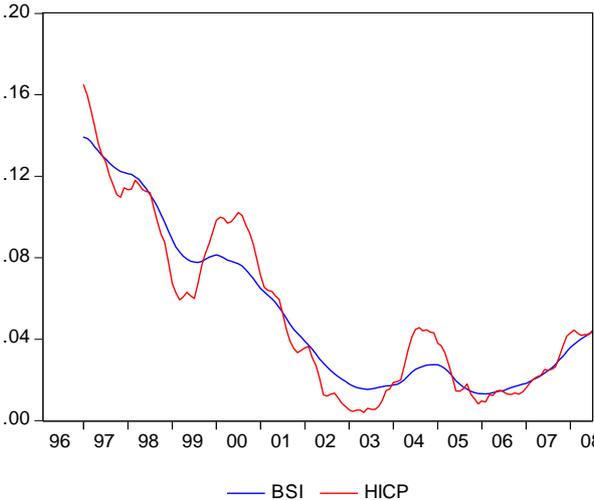
Source: Own calculations.

Chart 1c. Absolute values of t -statistics expressed as the ratios to the critical value (at the 5% significance level) arranged in an increasing order. Values higher than 1 call for rejecting the hypothesis of unit value of the parameter connected with the first factor.



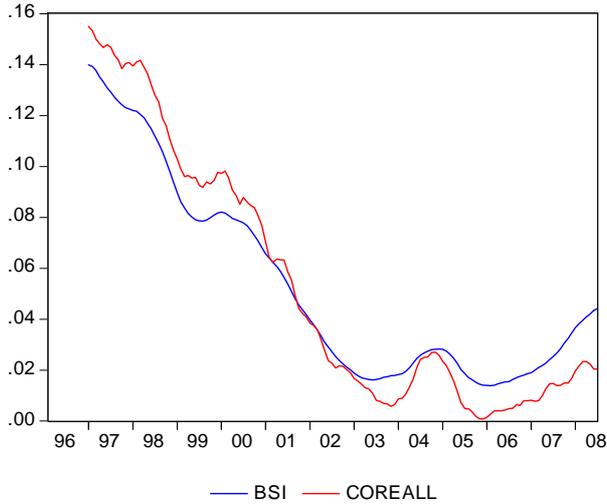
Source: Own calculations.

Chart 2a. Annual PI and $HICP$ inflation indices.



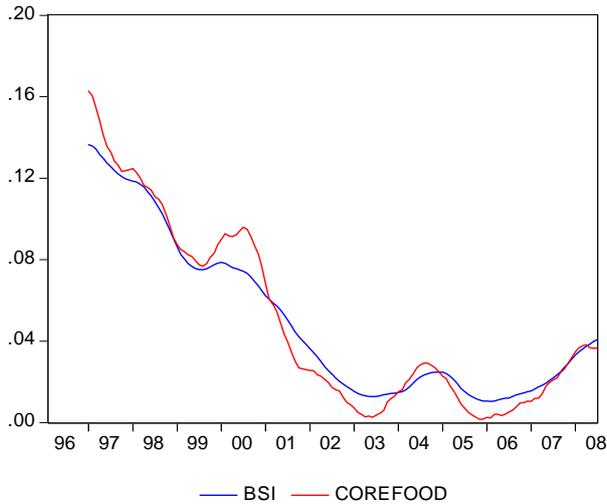
The values of the annual PI index were adjusted so that the average value of the index equals the average value of the second inflation measure featured in the chart.
 Source: Own calculations.

Chart 2b. Annual *PI* and *COREALL* inflation indices.



The values of the annual *PI* index were adjusted so that the average value of the index equals the average value of the second inflation measure featured in the chart.
Source: Own calculations.

Chart 2c. Annual *PI* and *COREFOOD* inflation indices.



The values of the annual *PI* index were adjusted so that the average value of the index equals the average value of the second inflation measure featured in the chart.
Source: Own calculations.