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Forecasting inflation with consumer survey data – application of multi-group confirmatory factor analysis to elimination of the general sentiment factor

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Content

Abstract

This paper[1] examines the properties of survey based households' inflation expectations and investigates their forecasting performance. With application of the individual data from the State of the Households' Survey (50 quarters between 1997Q4 and 2010Q1) it was shown that inflation expectations were affected by the consumer sentiment. Multi-Group Confirmatory Factor Analysis (MGCFA) was employed to verify whether a set of proxies provides a reliable basis for measurement of two latent phenomena – consumer sentiment and inflation expectations. Following the steps proposed by Davidov (2008) and Steenkamp and Baumgartner (1998), it appeared that it was possible to specify and estimate a MGCFA model with partial measurement invariance. Thus it was possible to eliminate the influence of consumer sentiment on inflation expectations and at the same time to obtain individually corrected answers concerning the inflation expectations. Additionally, it was shown that the linear relation between consumer sentiment and inflation expectations was stable over time. As a by-product of analysis, it was possible to show that respondents during the financial crisis were much less consistent in their answers to the questions of the consumer questionnaire.

In the next step of the analysis, data on inflation expectations were applied to modelling and forecasting inflation. It was shown that with respect to standard ARIMA processes, inclusion of the information on the inflation expectations significantly improved the in-sample and out-of-sample forecasting performance of the time-series models. Especially out-of-sample performance was significantly better as the average absolute error in forecasts of headline and core inflation was reduced by half. It was also shown that models with inflation expectations based on the CFA method (after elimination of the consumer sentiment factor) provided better in-sample forecasts of inflation. Nevertheless, it was not confirmed for the out-of-sample forecasts.

Key Words: Inflation expectations, Inflation forecasts, Confirmatory Factor Analysis

JEL Classification: C32, E31, E37

[1] Project financed by the National Bank of Poland. Polish title of the project: „Prognozowanie inflacji na podstawie danych koniunktury gospodarstw domowych. Zastosowanie konfirmacyjnej analizy czynnikowej dla wielu grup do oczyszczenia prognoz inflacji z czynnika ogólnego nastroju gospodarczego."

1. Introduction

The development of business and consumer surveys was initiated in 1940s and stems from the assumption that survey data provide additional information on consumers' actions (Katona 1946, 1947). Survey data are usually used in the form of composite indices and mainly serve as explanatory variables for consumption or GDP changes (e.g. Curtin 1982, Carrol et al. 1994). However, according to the standardized European Commission questionnaire for the consumer survey data (see Appendix 1), there are two questions which refer to price changes in the past 12 months (Q5) and forecasted price changes in the forthcoming 12 months (Q6). Especially important for the monetary policy conduct are the inflation expectations of households. Although there are numerous studies on the performance of survey based inflationary expectations (e.g. Ang et al. 2007, Scheufele 2010), there is a constant debate on applicability of households' inflation expectations to forecast changes in the inflation dynamics. It was confirmed in various papers that the inflation forecasts provided by professionals is very useful in predicting changes in the price level (see Ang et al. 2007). However, the households' inflation expectations also provide better forecasts than time-series models or models based on the Phillips curve.

Although, the debate is still ongoing it seems that there are few questions that still need to be answered. They have not gained sufficient attention in the studies performed in the past but might be of key importance in assessing the performance of inflation expectations provided by households:

1. Do households, answering the question connected with inflation expectations, provide any additional information – concerning something else than inflation?
2. Is it possible to reliably account for the additional information included in inflation expectations and to reliably eliminate it from the data?
3. Are the inflation expectations, after accounting for the additional information, still forward looking and provide better forecasts of inflation?

First point that should be addressed is the information contained in the inflation expectations. Assuming their rationality, which was partially confirmed by the analysis of Ang et al. 2007, there should be no additional information included in or at least this additional information should have no impact on the unbiasedness of the inflation expectations. Nevertheless, the ubiasedness of responses in the consumer surveys can be merely confirmed for the long time horizons. Trehan (2010) points out that the forecasts made by households in the period of early 2010 are among the worst of all accessible alternatives, which is in contradiction with arguments presented for long time performance of this indicator (Ang et al. 2007). One of the hypothesis, that might be stated at this point, is that the weaker performance of the inflation expectations might have been a result of a larger bias associated with lower level of current economic sentiment, which was not investigated.

Second important point that should be addressed is the meaning of the concept of consumer sentiment in the consumer survey data. It is important to verify whether the understanding of questions and the mode of answering in different time periods remain constant. If it is not fulfilled it might lead to misinterpretations in comparisons of a consumer sentiment index values and then further lead to misinterpretation of the inflation expectations[2]. It should be verified, whether the index of consumer sentiment can be expressed on unidimensional scale and whether its values are coherent and can be compared between periods. When lack of coherence in respondents' answers occurs, it might indicate that the values of the consumer sentiment index reflect only unidimensional projections of a multidimensional phenomenon. In such situation the comparisons of values of the consumer sentiment index would be unjustified due to lack of constant meaning throughout the period of analysis.

Third important issue is connected with the forwardlookingness of inflationary expectations. Scheufele (2010) in his study examines different forecasting horizons for the inflationary forecasts from survey data. It might be the case that predictive ability of households is to a large extent limited and although the survey question refers to 12 months horizon, it should be examined whether responding pattern is associated with different lead (or lag).

All of these questions and potential doubts are addressed in this paper with application of data from the State of the Households Survey conducted at the Research Institute for Economic Development – Warsaw School of Economics. Since the Survey is conducted once a quarter, the analysis of the inflationary processes is carried out on a quarterly frequency. The analysis is conducted with multi-group confirmatory factor analysis. With this approach it is possible to check whether:

[2] Of course, under the assumption that inflation expectations are influenced by the level of consumer sentiment.

1. consumers provide some additional information answering the question on inflation expectations (namely: Do they include their perception of the consumer sentiment in their inflation forecasts?),
2. consumers are consistent in their answering pattern between periods (namely: Do they change their inflation expectations in reaction to changes in the consumer sentiment in the same way in all periods?).

Additionally, with multi-group confirmatory factor analysis one can not only check whether there is an influence of the consumer sentiment on the inflation expectations but also obtain inflation expectations individually corrected for the consumer sentiment level, which is essential in investigating the problem of forwardlookingness of inflation expectations.

The paper is organized as follows. In section 2 the historical data on inflation in Poland are presented. In section 3 the relation between inflation forecasts and the consumer sentiment is investigated. Then, it is checked, whether there is a difference in the relation between inflation expectations obtained from households opinions and those from the surveys conducted among professionals. Section 5 is devoted to the concept of measurement in business and consumer survey data. It is presented that multi-group confirmatory factor analysis enables to simultaneously account for changes in the consumer sentiment and the perception of inflation. Additionally, consumer sentiment is presented as a phenomenon measured with more than one indicator. Thus, it is possible to reliably account for the sentiment changes and to provide sufficient information for the extraction of inflation expectations from the data. Section 6 provides details on the specification and estimation of the measurement model for both inflation and consumer sentiment. Thus the problem of the implicit inclusion of consumer sentiment in inflationary forecasts is accounted for. In section 7 the time-series models of inflation are presented. At first, models for inflation in autoregressive and moving average specification are estimated in order to provide the most probable data generating process of inflation. Then, it is checked whether the inclusion of the inflation expectations in the model provide any additional information concerning the future inflation. It is also checked whether there is a lead of inflation expectations with respect to the headline and core inflation for the Polish economy. Finally, there are presented further areas of research and possible advantages of applying confirmatory factor analysis models to the forecasting of inflation (and also other crucial macroeconomic variables).

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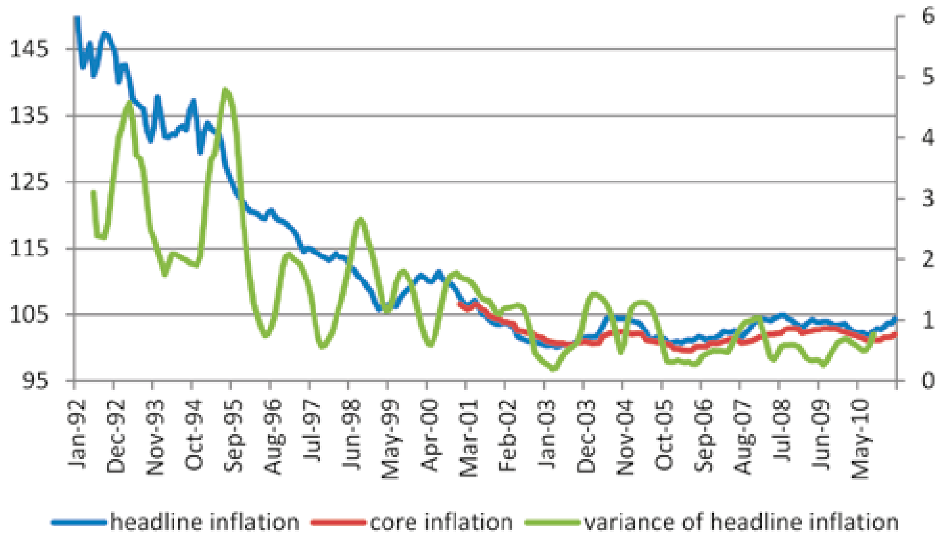
2. Inflation in Poland between 1996 and 2011

At the beginning of the transition period, inflation in Poland was highly unstable. Figure 1 depicts yearly growth rate of core inflation in Poland. On the basis of a graphical analysis it can be noticed that neither mean value of inflation nor its variance can be considered constant during that period.

Figure 1 Headline and core inflation in Poland between 1992 and 2011.



Source: National Bank of Poland, Central Statistical Office.

After 1989 one could observe in Poland a process of constant disinflation, i.e. a period of decreasing inflation rate[3]. Although, as pointed by Henry and Shields (2004), disinflation was also quite common in developed economies during the period, the transition process of Polish economy made it unique and difficult to analyse. Additionally, before 1999 variance of inflation was also much higher than afterwards. Figure 1 depicts the changes in moving inflation variance in the analyzed period[4]. Białowolski, Zwiernik and Żochowski (2011) show that results of the estimations – for the Future Inflation Indicator and inflation – of data generating processes lead to conclusion that both these processes are not stationary in the early stages of the market economy in Poland. Thus, the relations between the main macroeconomic variables and inflation were distorted in that period. It might also suggest that for the period before 1999, it might have been

[3] Figure 1 presents this process since 1992.

[4] The moving variance was calculated similarly to moving average – in period t, the variance from the subsample t – 6, . . . , t + 6 was calculated

very hard to obtain reliable inflationary forecasts and to model the inflation process with inflationary expectations. This is in line with suggestion of Golinelli and Orsi (2002) who notice that modelling of economies in transition is very complicated because:

a. The period in which prices are determined by the market is too short.
b. The structural changes associated with transition of these economies significantly distort relations between inflation, money supply, wages and exchange rates.

These observations and accessibility of data for the consumer sentiment indicated possible problems with modelling inflation in the transition period. Due to this, data sample was shortened and the analysis covered the period since 2001[5] in the case of headline inflation and core inflation rates.[6]

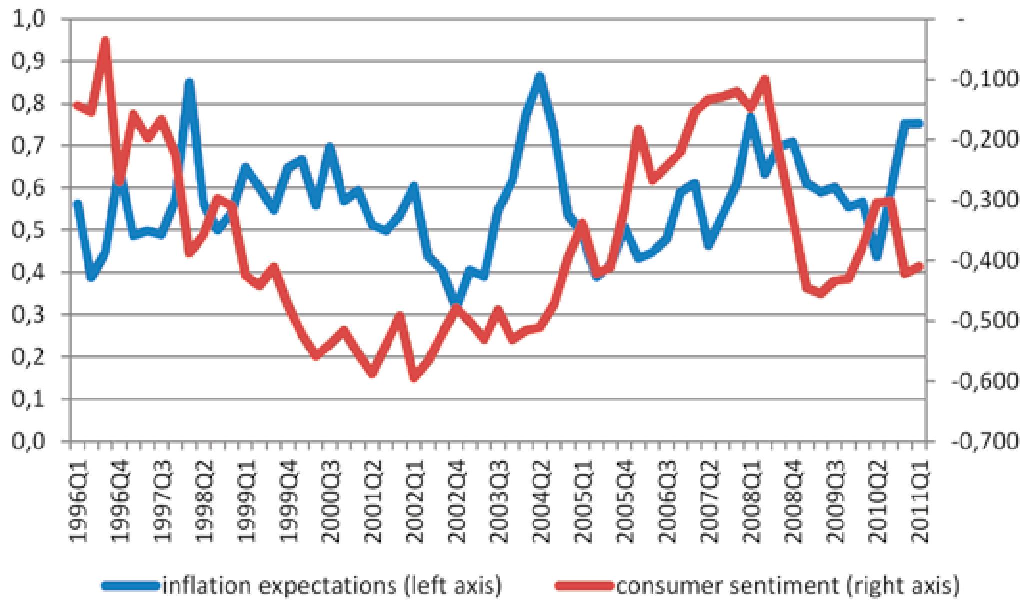
[5] The period of analysis for headline inflation rate was shortened in order to maintain the comparability of inflation generating processes in the section of time-series modelling.

[6] As an indicator of core inflation rate, time series of "inflation after exclusion of food and energy prices" is used.

3. Inflation expectations and consumer sentiment

Traditional measures of inflation expectations are calculated on the basis of aggregated answers to the question concerning price forecasts – "By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will…". Information on this topic is gathered in Poland by at least few research units[7], as it is based on standardized consumer questionnaire (European Economy 2006). In this paper data gathered by Research Institute for Economic Development are analyzed. The State of the Households survey, that serves as the base for the inflation expectations, has been conducted in line with the harmonized questionnaire since 1996. Figure 2 presents the information on balances concerning inflation expectations and consumer sentiment calculated in line with the methodology of the European Commission[8].

Figure 2 Inflation expectations and consumer sentiment calculated in line with the European Commission methodology.



Source: Research Institute for Economic Development – Warsaw School of Economics.

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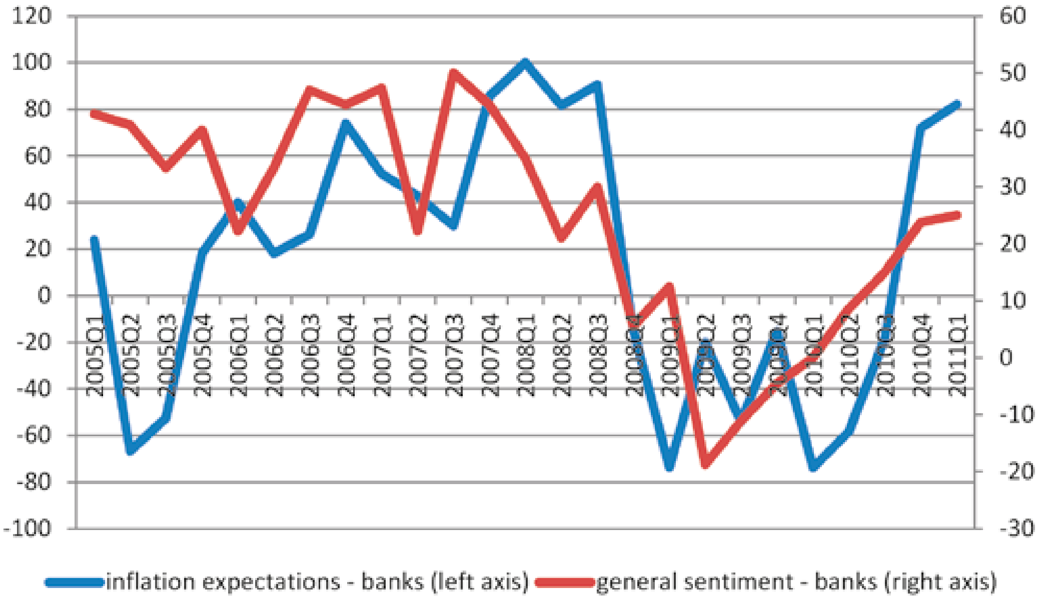
7 Among them there are: Research Institute for Economic Development – Warsaw School of Economics, Central Statistical Office, Ipsos.

8 The balances of the positive and negative answers of the question concerning inflation forecasts is calculated in line with the formula $BAL_{PRA.F} = f_1 + 0.5 f_2 - 0.5 f_4 - f_5$, where $\forall_{i \in \{1,2,3,4,5\}} f_i$ stands for the fraction of respondents that selected i–th option.
Standard calculation of consumer sentiment index (in line with the EC methodology) is performed with the following formula: $CSI = \dfrac{BAL_{FS.F} + BAL_{GES.F} + BAL_{SAV.F} - BAL_{UNEMP.F}}{4}$.

The data shows very weak interrelation between inflation expectations and the consumer sentiment. The correlation coefficient between the two series is at the level of -0.111. The correlation between the two series is not statistically significant[9]. It implies that there is no relation between the consumer sentiment and the inflation expectations. This opinion stays in contradiction with the opinions of the professional forecasters of the Polish economy – banks. According to the results of the business survey conducted in the banking sector "Business Situation in the Banking Sector in Poland" there is a highly positive relationship between expectations concerning the general situation in the economy and expected changes in the price level. This relation is presented on Figure 3.

Figure 3 Inflation expectations and forecasts of the general economic situation according to professional respondents from banking sector (12 months horizon).



Source: Research Institute for Economic Development – Warsaw School of Economics.

In the case of professional forecasters, the relationship between inflation expectations and the general sentiment is characterized by correlation 0.505, which indicates strong prevalence of demand components in the inflation process[10].

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[9] P-value for the correlation coefficient is 0.39.

[10] P-value for the correlation coefficient is 0.01. Additionally, correlation coefficient for the relation between the consumer sentiment and the consumer inflation expectations is different than the correlation coefficient for the relation between the general sentiment in the banking sector and the inflation expectations provided by bankers (p-value = 0.008)

Thus, taking into account the results of Scheufele (2010), one has to bear in mind that inflation expectations calculated with consumer survey data can be significantly biased, as the respondents seem to rarely take into account demand-pulled processes. They simply forget (or are unaware) that better business climate is likely to stimulate inflation in the economy.

In order to empirically show that there is a tendency to associate by respondents good consumer sentiment with lower expected inflation – by incorporating part of the consumer sentiment in the price expectations – multi-group confirmatory factor analysis (MGCFA) can be applied. Additionally, the results obtained with MGCFA can serve as an unbiased measure of inflation expectations.

4. Two factor multi-group confirmatory factor analysis measurement model applied to consumer surveys

Assuming that there is a negative relation between consumer sentiment and expected inflation one can conduct a correction of inflation expectations on the aggregate level. However firstly, one should check whether the influence of consumer sentiment on inflation expectations really exists – their co-movement might be associated with different economic processes. When this relation is confirmed, the elimination of the information associated with the consumer sentiment should be done on individual level (i.e. the answers obtained from respondents – household members – participated in the State of the Household Survey should be corrected using adequate statistical method). Additionally, referring to the individual data, it is necessary to verify, whether the concept of the consumer sentiment and its influence on inflation expectations are the same in all periods of analysis. Both these goals can be achieved with multi-group confirmatory factor analysis (MGCFA).

The purpose of using multi-group confirmatory factor analysis model is to verify the hypothesis that there is an underlying latent structure behind the observed data. In the case of inflationary expectations and consumer sentiment the applied measurement model should fit the data well in all periods of analysis and the measurement invariance (the same rules of measurement) should be applied to different time periods. It allows for comparison of means of latent variables, which can be conducted only when no changes in the perception of the consumer sentiment between periods occur. In the standard approach of calculating the consumer sentiment index (i.e. average of balances), the changes in the value of the consumer sentiment index might be a result of a movement in the natural level of optimism/pessimism concerning one particular area of the consumer sentiment. Such changes might be a consequence of numerous factors. They can result from a change in the level of natural sentiment in some area of consumer sentiment (e.g. people start to perceive future economic development more favourably than the climate to make major purchases). In such a case the answer to question concerning development of the general economy becomes "more easy" than answers to other questions. Additionally, the relation between variables might change. In reaction to change in moods people might become more willing to change their answers to some questions. Such situation might be often the case of unemployment forecasts, which might be significantly affected by media revelations or other factors (Białowolski 2010).

Elimination of the information of the consumer sentiment information from the inflation expectations implies that there exists some measure of the latent phenomenon (consumer sentiment). Consumer sentiment is a phenomenon that should be assumed complex and not directly observable so it is not possible to provide information about it with application of only one indicator (answer to a single question). Traditionally, the measures of consumer sentiment comprise an aggregated information from few selected questions from different fields of economic activity.

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Because different fields of economic activity are included in the measurement of consumer sentiment, it is crucial to establish the rules of measurement that would enable not only to account for different reactions and various natural levels of sentiment in different areas connected to the consumer sentiment but also to identify structural brakes in the time series that are caused by changes in the meaning of latent construct – consumer sentiment. The answer to each question reflecting the phenomenon is modeled at an individual level[11] as a linear function of the consumer sentiment[12]. Additionally, the model incorporates the inflationary forecasts, which are explained by two latent variables – consumer sentiment and "real" inflation expectations.

The model is estimated with maximum likelihood for all of the time periods simultaneously. In the adopted approach (MGCFA) the consumer sentiment is a latent phenomenon that is reflected by the proxies (questions). The formal structure of the estimated model in the case of *N* proxies (questions), one latent variable reflecting consumer sentiment, one latent variable reflecting inflationary forecasts and *T* time periods can be given by:

$$\forall_{t \in T} \mathbf{q}^t = \boldsymbol{\tau}^t + \boldsymbol{\gamma}_1^t CSI^t + \boldsymbol{\gamma}_2^t INF^t + \boldsymbol{\varepsilon}^t \text{, where} \tag{1.1}$$

in all time periods $\mathbf{q}^t$ is $N \times 1$ vector of question answers, $\boldsymbol{\tau}^t$ is $N \times 1$ vector of intercepts, $\boldsymbol{\gamma}_1^t$ is $N \times 1$ vector of factor loadings for the consumer sentiment, $\boldsymbol{\gamma}_2^t$ is $N \times 1$ vector of factor loadings for the inflationary expectations and $\boldsymbol{\varepsilon}^t$ is $N \times 1$ vector of measurement errors. In this specification, in order to ensure identifiability of the model one element of the $\boldsymbol{\gamma}^t$ vector (factor

[11] This "individual level" is based on the household members' answers to the questions designed to measure the consumer sentiment.

[12] It is possible to apply MGCFA approach both in linear and non-linear specifications (relation between the latent variable and its proxies). In the analyzed case – MGCFA model for inflation expectations and the consumer sentiment – a linear specification was adopted. It was assumed that if the fit statistics for the model with linear relations lie within the acceptable range the model can be accepted and there is no need to search for alternative specification – non-linear. Additionally, it is often the case for non-linear specifications in MGCFA that the estimation procedure does not converge and it is not possible to obtain results due to technical reasons.

loading) is set to 1[13] and one element (which must correspond to constrained to 1 factor loading) of $\boldsymbol{\tau}^t$ vector (intercepts) is set to zero. As it is assumed that inflation expectations are measured only by one proxy (one question) additionally for one element of $\mathbf{q}^t$ - inflationary expectations – corresponding error term in $\boldsymbol{\varepsilon}^t$ is set to 0 and corresponding element of $\boldsymbol{\gamma}_2^t$ is set to 1. All other elements of $\boldsymbol{\gamma}_2^t$ are equal to 0. Additionally, $E\left(\boldsymbol{\varepsilon}^t\right)=\mathbf{0}$ and $\forall_{t\in 1..T,p,q\in 1..N,p\neq q}\operatorname{cov}\left(\boldsymbol{\varepsilon}_p^t,\boldsymbol{\varepsilon}_q^t\right)=0$.

Unfortunately, the model estimated with these constraints only, neither allows for the time comparisons of the latent variable mean (CSI) nor inflation expectations (INF). To check for the possibility of time comparisons of the means of these two concepts (latent variables), the estimates of the measurement model have to fulfill the following three conditions (Steenkamp and Baumgartner 1998, Davidov 2008):

1. configural invariance,
2. metric invariance,
3. scalar invariance.

The lowest level of measurement invariance is the configural invariance. Sometimes, it is referred as "weak factorial invariance" (Davidov 2008). In our case, it requires that the same group of questions serve as proxies in order to measure the level of consumer sentiment and the same pattern of factor loadings is specified for each time period. In order to ensure configural invariance in the multi-group model, the model with such restriction should fit the data well with respect to commonly applied descriptive fit statistics (e.g. Hu and Bentler 1999).

Nevertheless, the configural invariance does not guarantee that the relationship between factors (CSI, INF) and their proxies (questions) is constant over time (Davidov 2008). It means that the meaning of question answers in time can be different. In order to check for the equal meaning of question answers in time, the metric invariance has to be established. It implies that the understanding of questions as well as the meaning of respondents' answers do not change over time. Only after the metric invariance is established can one assume that changes in the opinions, for instance, from "very positive" to "positive," have the same meaning in all periods of analysis.[14] It is established by fixing respective factor loadings to be equal over time and checking the model

[13] It is usually the first element of this vector. Instead constraining one factor loading to 1, the identification of the measurement model can be also ensured by setting the variance of latent variable to 1.

[14] In terms of the meaning of the latent phenomenon, the metric invariance implies that if latent variable (CSI) changes, then, on average, the same change in answer to a particular question in all time periods occurs.

fit. Assuming the same specification (eq. 1.1) of the measurement model, the vector of factor loadings ($\boldsymbol{\gamma}_1^t$) has to fulfill the condition $\forall_{t_1,t_2 \in 1..T; t_1 \neq t_2} \left(\boldsymbol{\gamma}^{t_1} = \boldsymbol{\gamma}^{t_2} \right)$.[15]

The final step in establishing the measurement invariance is connected with verification of scalar invariance. In order to check the existence of scalar invariance, apart from the equal factor loadings (metric invariance), one has to verify whether the model (eq. 1.1) fits the data well with additional constraint on the vector of intercepts ($\boldsymbol{\tau}^t$). Formally, the constraint can be presented as $\forall_{t_1,t_2 \in 1..T; t_1 \neq t_2} \left(\boldsymbol{\tau}^{t_1} = \boldsymbol{\tau}^{t_2} \right)$. In the case of consumer surveys, scalar invariance implies that the "natural zero level" of moods concerning different proxies (questions included in the measurement model) is checked to be constant throughout the period of analysis.

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If all these conditions are fulfilled, then full measurement invariance of the latent phenomenon can be established (Davidov 2008) and the CSI values can be directly compared.

It is due to the fact that the concept of consumer sentiment has constant meaning throughout the period of analysis. Additionally, only in such a situation (1) the changes in the level of consumer sentiment can be fully explained by the changes in the level of latent variable, (2) the influence of consumer sentiment on inflation expectations can be reliably eliminated from the data.

However, it might appear that the fit of the model (eq. 1.1) with constraints ensuring full measurement invariance is not satisfactory. Thus, full measurement invariance cannot be established. In such circumstances, in order to reliably conduct mean comparisons, it is sufficient to impose partial measurement invariance. In practice, it means that the equality of factor loadings and intercepts is ensured for two items only (see Steenkamp and Baumgartner 1998, Byrne et al. 1989). Formally, it can be presented as

$$\exists_{n_1,n_2 \in 1..N; n_1 \neq n_2} \forall_{t_1,t_2 \in 1..T; t_1 \neq t_2} \left(\boldsymbol{\tau}_{n_1}^{t_1} = \boldsymbol{\tau}_{n_1}^{t_2} \wedge \boldsymbol{\tau}_{n_2}^{t_1} = \boldsymbol{\tau}_{n_2}^{t_2} \wedge \boldsymbol{\gamma}_{n_1}^{t_1} = \boldsymbol{\gamma}_{n_1}^{t_2} \wedge \boldsymbol{\gamma}_{n_2}^{t_1} = \boldsymbol{\gamma}_{n_2}^{t_2} \right).$$

Model fit, that is necessary to assess model invariance at a given level, can be conducted in three ways assuming different levels of rigidity. The most basic and at the same time the most rigid approach is the value of χ^2 statistics. It provides the information on the deviations in reproducing by the model the sample variances and covariances, i.e it assesses the extent of the discrepancies in the error term matrix. Although it seems the most correct approach, it is rarely used in the applied research as a sole index of fit (Brown 2006). It is due to the fact that the value of χ^2 statistics is inflated by the sample size and the models are "routinely rejected even when

[15] In the case of $\boldsymbol{\gamma}_2^t$ it is not required as the vector has only one non-zero loading, which is fixed for all time periods.

differences between variance covariance matrix based on the sample and implied by the model are negligible" (Brown 2006, p. 81). The less stringent approach to evaluation of the model fit is based on the assessment of values of descriptive fit statistics. The most popular goodness-of-fit indices are: $\chi2$/df, Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) but also Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residuals (SMRM). There were developed certain rules for each of these descriptive fit statistics. These rules of thumb are mostly based on simulations (e.g. Chou and Bentler 1995 or Kaplan 1995). For the $\chi2$/df statistics it is usually assumed that it should be < 5 (or in more rigid approach <2) (Górniak 2000, p. 134). With respect to CFI and TLI indexes it is usually assumed that there value should be above 0.9 in order to judge the model as acceptable (Hox 2002, p. 239). With respect to RMSEA and SMRM, they should be below 0.08 (Browne and Cudeck 1993). For further discussion on the issues of model fit see Steenkamp and Baumgartner (1998), Hu and Bentler (1999), Marsh et al. (2004), and Davidov (2008). The least stringent approach is based on comparison of information criteria. In this approach, the best model is selected due to AIC or BIC statistics but the differences between model implied and empirical variance-covariance matrix are not checked. Additionally, no measure of whether the best model is a good one is presented.

In this paper an approach based on descriptive-fit statistics is adopted. The following descriptive goodness-of-fit statistics are applied: $\chi2$/df, CFI and RMSEA. As no comparisons between MGCFA models are made the information criteria are not applied. In order to accept the model and accept the values of latent variables (CSI and INF) generated by the model, it needs to have all the goodness-of-fit statistics within acceptable range. Acceptable fit needs to be obtained for the model with partial measurement invariance.

5. Specification and estimation of measurement model for the inflation expectations and the consumer sentiment

The steps presented in this section show that it is possible to obtain more coherent indicator of the consumer sentiment, when information on inflation expectations is included in the set of indicators. Additionally, it is shown that answers to the question concerning expected inflation contain both information on the consumer sentiment and "true" inflation expectations. At first, it is shown that if one searches for a good measure of the consumer sentiment the standard set of questions proposed by European Commission should be modified and should include inflation expectations. Later, it is shown how the information on inflation expectations can be derived from the data with MGCFA.

In order to measure the Consumer Sentiment with application of the standardized consumer questionnaire proposed by the European Commission one takes into account answers to four questions, i.e. Financial situation of a household (FS.F), General economic situation (GES.F), Unemployment in the economy (UNEMP.F), Savings of household (SAV.F). According to the standard procedure (European Economy 2006), in order to calculate the values of the CSI, a simple average of balances of the positive and negative answers to the four questions is calculated. However, this approach has significant drawbacks with respect to the issue of measurement. Firstly, these questions, despite being treated as consumer sentiment proxies, might react differently to changes in the sentiment of consumers, and these different reactions should be rather estimated than predetermined. Secondly, the answers to different questions might also be consistently and regularly biased in some direction. Thirdly, the magnitude of the bias might change between periods. To name an example of such a bias that is observable on the level of aggregates, one may indicate the phenomenon presented by Bovi (2006). In some countries it is the financial situation of a household that is perceived better than the general economic situation[16].

In order to overcome possible flaws of index calculated as the simple average, MGCFA can be employed and the measurement invariance between groups (quarters) can be checked. The verification of the model fit for the consumer sentiment index with application of the standard set of questions and, additionally, with one factor solution is performed on the dataset from the State of the Households' Survey conducted at the Research Institute for Economic Development at the Warsaw School of Economics. With the procedure presented in the previous point, a check of

[16] the opposite relationship was identified for the Polish economy (Białowolski and Dudek 2008).

measurement invariance for the model is performed. Sample ranging from 1997Q4 to 2010Q1 is used.

At first, the check of configural invariance is made. The results prove that the model with constrained error term correlations (equal to zero) has rather poor fit statistics (Chi-square/df=12.00, CFI=0.925, RMSEA=0.156). In particular, Chi-square/df and RMSEA are much above the commonly accepted level. Unfortunately, even for the model with partial measurement invariance it is not possible to reach the fit statistics within acceptable range. The results show that Chi-square/df=5.65, CFI=0.953, RMSEA=0.102, which implies Chi-square/df and RMSEA exceeding acceptable values (even for very liberal approach).

It stimulates search for alternative specifications of the model, which could provide a more coherent set of indicators for the consumer sentiment. The analysis of problems encountered during the estimation of model in standard specification show that a possible source of difficulties might be the choice of indicators. Their examination lead to the conclusion that they constitute a mixture of indicators connected on the one hand with household's situation (FS.F and SAV.F) and on the other hand with the general economic situation (GES.F and UNEMP.F). In order to unify the character of proxies an exploratory analysis is performed.

As a result it appeared that the following questions might be good indicators of the consumer sentiment: general economic situation forecasts (GES.F), current climate to make major purchases in the economy (MP.S), inflation expectations (PRA.F) and current climate to save (SAV.S). All of them refer to the general economic situation and do not directly correspond to the situation of a surveyed household.

Such a choice of proxies of CSI and relaxing the zero-constraint on correlation between the error terms of GES.F and PRA.F enables us to establish not only configural invariance but also partial metric and partial scalar invariance. The model for partial measurement invariance has the following fit statistics: Chi-square/df=3.58, CFI=0.923, RMSEA=0.085. The values are within acceptable range, which confirms partial measurement invariance for the model. The final structure of the measurement model for $CSI_{CFA,MODIFIED}$ can thus be presented by the following system:

$$\begin{cases} GES.F^t = 0 + 1 \cdot CSI^t + \varepsilon_1^t \\ MP.S^t = 0.661 + 0.395 \cdot CSI^t + \varepsilon_2^t \\ PRA.F^t = \tau_3^t + \gamma_3^t \cdot CSI^t + \varepsilon_3^t \\ SAV.S^t = \tau_4^t + \gamma_4^t \cdot CSI^t + \varepsilon_4^t \end{cases} \quad \boxed{\text{correlation}} \tag{1.2}$$

5

The results prove that this model can be estimated as one factor model. Nevertheless, the equality constraints for the measurement between quarters (groups) could not be set for the τ_3^t and γ_3^t. It means that, although the relation between consumer sentiment and answers to the question concerning inflation is stable for a given period of analysis, it is not stable for relations between periods. One of the solutions to this problem is to include additional latent variable in the model which is measured by a single indicator. This approach is in line with the objectives of the study. It is sufficient to assume that the second underlying factor in the measurement model is the individual forecast of inflation. Thus, on the individual data the following set of equations can be estimated simultaneously with maximum likelihood:

$$\begin{cases} GES.F^t = 0 + 1 \cdot CSI^t + \varepsilon_1^t \\ MP.S^t = \tau_2^t + \gamma_2^t \cdot CSI^t + \varepsilon_2^t \\ PRA.F^t = \tau_3^t + \gamma_3^t \cdot CSI^t + 1 \cdot INF^t \quad \boxed{\text{Correlation } \lambda_t} \\ SAV.S^t = \tau_4^t + \gamma_4^t \cdot CSI^t + \varepsilon_4^t \end{cases} \tag{1.3}$$

Estimation of the two factor model is also performed on the sample ranging from 1997Q4 to 2010Q1 with an additional assumption of zero correlation between the latent variables. Zero correlation between two latent variables (CSI and INF) is imposed on the individual level for the whole sample. This assumption implies that deviation from the average for a given consumer with respect to the sentiment indicator is not correlated with deviation from average of the same consumer with respect to his/her inflation expectations. Assumption of zero correlation does not imply that the correlation between two time series representing averages of the general sentiment and the averages of the inflation forecasts is zero.

Assumption of zero correlation at the respondent level seems justified for two reasons. First of all, in this specification we assume (and verify with MGCFA) that the set of four questions provides information only on the two latent phenomena – consumer sentiment and inflation expectations. We show that this solution – two factors with zero correlation – can be defended by the verification of partial measurement invariance in the multi-group confirmatory factor analysis model. Secondly, survey data are based on a common knowledge. Assumption of zero correlation implies that the deviations from the common knowledge (errors) in the area of inflation expectations are not correlated with deviations from the common knowledge (errors) in the area of consumer sentiment which seems reasonable.

In the estimation process a correlation between error terms of questions concerning general economic situation and savings climate is established. Estimated model proves to have good fit statistics and it is possible to ensure partial measurement invariance – the equality condition is imposed on τ_2^t, γ_2^t, τ_3^t, γ_3^t, which are assumed to be equal between periods and additionally $\forall_t \left(\tau_3^t = 0\right)$. The fit statistics of the model are as follows: Chi-square/df=3.73, CFI=0.908, RMSEA=0.081, which allows for establishing reasonable model fit and thus partial measurement invariance. The estimated model can be presented as follows:

$$\begin{cases} GES.F^t = 0 + 1 \cdot CSI^t + \varepsilon_1^t \\ MP.S^t = 1.193 + 0.247 \cdot CSI^t + \varepsilon_2^t \\ PRA.F^t = -0.408 \cdot CSI^t + 1 \cdot INF^t \quad \boxed{\text{Correlation } \lambda_t} \\ SAV.S^t = \tau_4^t + \gamma_4^t \cdot CSI^t + \varepsilon_4^t \end{cases} \qquad (1.4)$$

The results of estimation of the model's period specific parameters are presented in the table in Appendix 3. All the results prove to be as expected. There is a positive relationship between consumer sentiment index and the expected answers concerning the climate to major purchases. Better perception of consumer sentiment implies better climate to make major purchases – improvement by one point of the CSI improves the climate to make major purchases by 0.247 points. There is additionally positive relationship between the CSI and the expected answer to the question concerning savings forecasts. This relation proves not to be stable over time as τ_4^t and γ_4^t are different between periods. Nevertheless, the positive estimate of γ_4^t in all periods indicates positive relation between CSI and climate to save in all periods. In most of the periods there has been a negative estimate of the correlation between error term concerning expected answer to the question concerning the general economic situation expectations (GES.F) and the climate to save (SAV.S). According to Finkel (1995), error correlation might be caused by (1) memory effects, (2) similar wordings, or (3) meanings of items that induce similar responses over time, independently of the latent variable. In the consumer surveys, wording effect occurs very often. It might be hypothesised that the negative correlation between error terms in answers to these two questions might be caused by relatively stable character of answers to question concerning climate to save and more volatile answer patterns in the expected general economic situation[17].

[17] It implies that if respondents change their sentiment, their opinion in the area of general economic situation forecasts changes more than their opinion in the area of climate to save.

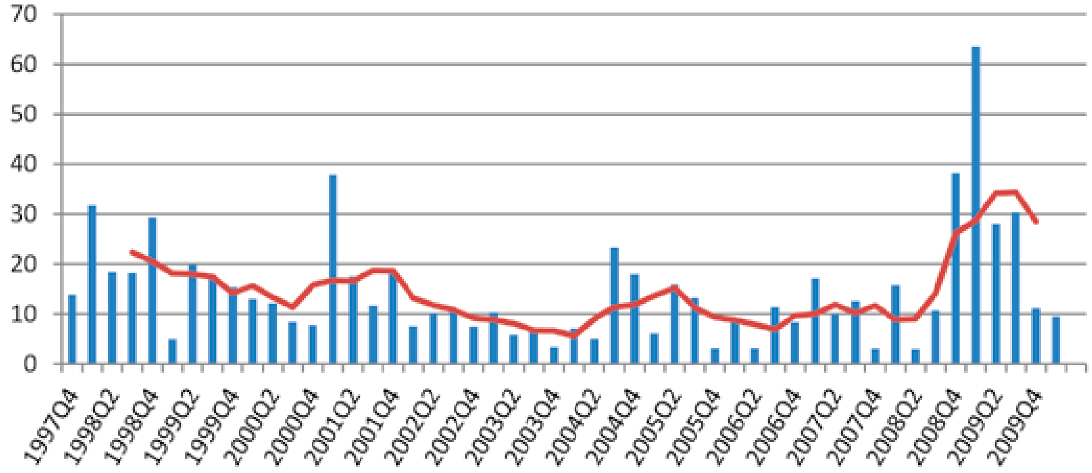
Finally, there is an influence of the consumer sentiment index on the expected value of the answer to the question concerning inflation expectations. If consumer sentiment improves by 1 point[18], consumers are expected to change their answer concerning the inflation expectations by 0.408 points in the direction of lower inflation[19]. Thus, the influence of the consumer sentiment on the inflation expectations is established. It should be underlined that this influence is partially a consequence of the assumed zero correlation between latent variables – consumer sentiment index (CSI) and inflation expectations (INF). The zero correlation assumption implies that for the whole sample (50 periods between 1997Q4 and 2010Q1) there is no correlation between individual level of assessment of the consumer sentiment and individual level assessment of inflation expectations.

The assessment of model fit with χ^2 statistics in the multi-group confirmatory factor framework allows for investigation of the model fit in different time periods. This provides additional information on the coherence of respondents answers in different time periods. Stable values of χ^2 contributions indicate that more-less in all periods the latent phenomena are understood in the same way. Outbursts of χ^2 contributions in certain periods indicate that in these periods respondents were confused answering the questionnaire and did not provide coherent information on the topics of interest – in this case latent constructs of CSI and INF. The information on χ^2 contributions for the analysis conducted above are presented on Figure 4.

[18] According to the scale in which consumer sentiment is measured, improvement by 1 point implies decrease in the value of the CSI. It is due to the fact that CSI is measured in metrics of the question concerning general economic situation. According to the scale of answers to this question – see the Appendix – the most optimistic option (it will get a lot better) is given the numeric value of one, the most pessimistic option (it will get a lot worse) is given the numeric value of five.

[19] Negative change in the value of CSI implies positive change in the $E(PRA.F)$ by 0.408 for each point change in the CSI. Positive change in the value of $E(PRA.F)$ implies lower inflation expectations.

Figure 4 Chi-square contribution in time periods of CFA model of inflationary expectations and its five period average



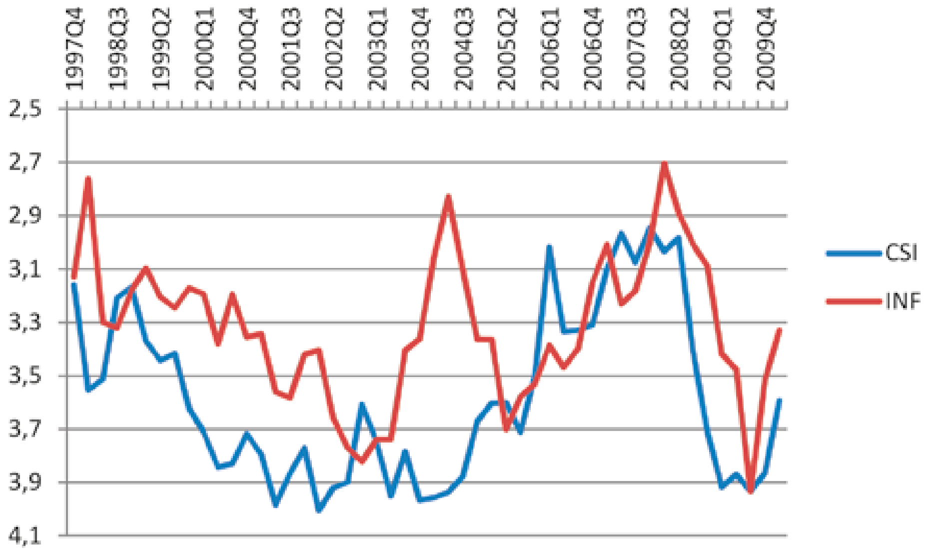
Source: Own calculations.

Chi-square contribution for the estimated model indicates that there were periods with significantly higher values of χ^2. It is connected with an increase in the level of uncertainty associated with lack of coherence in the respondents' answers to the set of four questions serving as proxies (GES.F, MP.S, PRA.F and SAV.S) to the two latent constructs (CSI, INF). The largest contribution to the χ^2 is observed for the first year of the financial crisis – between 2008Q4 and 2009Q3. Uncertainty observed during the first year of financial crisis is in terms of χ^2 statistics around four times higher than in the period of stability 2002 – 2007. The values observed during the period of crisis are comparable to the uncertainty observed at the verge of 2000 and 2001 when huge budget problems were announced.

With the proposed approach, averages of consumer sentiment (CSI) and inflation expectations (INF) can be computed in all periods of analysis.[20] On the following figure the values of a coherent indicator of consumer sentiment are compared with the average values of inflation expectations.

[20] The averages of consumer sentiment can be used in other research projects as a leading indicator of general performance of the Polish economy or as a leading indicator of the consumption expenditures. However, the analysis of leading properties of the consumer sentiment index is not the subject of this paper. It was essential to establish with the confirmatory factor analysis that the concept of the consumer sentiment is consistent in all periods of analysis and thus reliably eliminate it from the inflation expectations.

Figure 5 **Estimated average values of consumer sentiment index and inflation expectations obtained with multi-group CFA**



Source: Own calculations.

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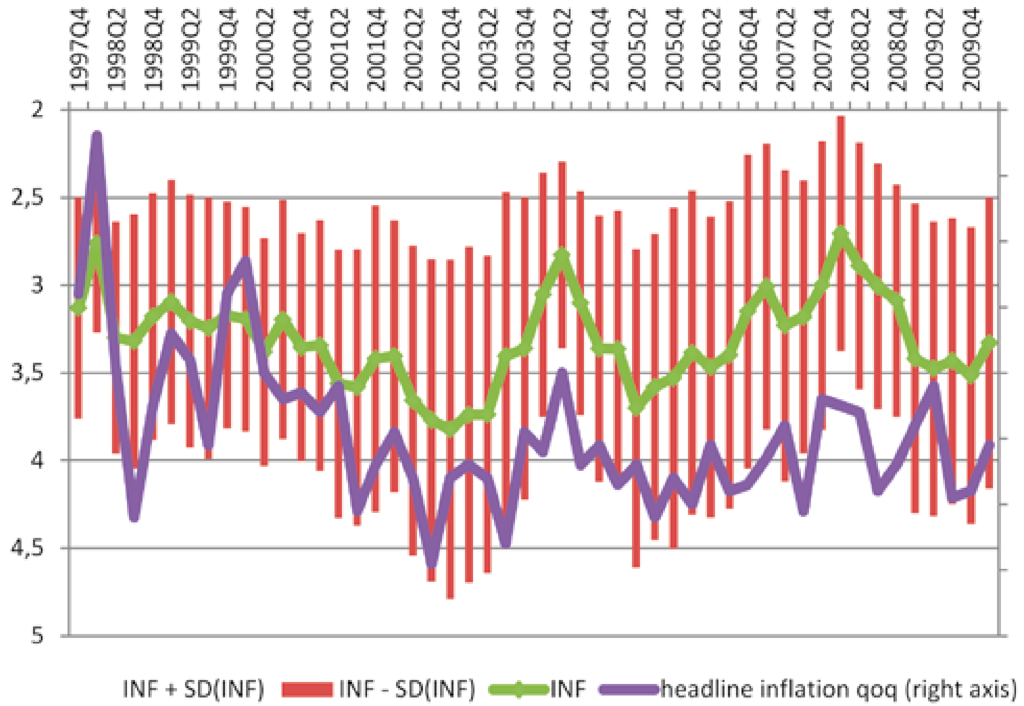
The relationship between average level of consumer sentiment (CSI) and inflation expectations (INF) is significantly altered after the influence of the individual sentiment is eliminated from the individual perception of inflation expectations. Compared to the relation between raw time-series presented on figure 2, the value of correlation coefficient between the two series changed from -0.111 to 0.475. After the sentiment component is eliminated from the data, households inflation expectations are positively related to the consumer sentiment, which means that better business climate more likely results in inflation outburst. Inflation expectations expressed by households are also much more in line with inflation expectations of professional forecasters (banks), which is confirmed by the correlation coefficient between the two inflation expectations time-series at the level of 0.77.

After the exclusion of the component associated with the consumer sentiment it was also possible to obtain information not only on the average value of inflation expectations but also its variance. It is depicted on Figure 6.

Figure 6 **Estimated average values of inflation expectations obtained with multi-group CFA (inflation expectations)**



Source: Own calculations.

Figure 6 depicts the relation between inflation expectations, variance of inflation expectations on individual level and the headline inflation in Poland. Co-movement of inflation expectations and headline inflation is noticeable. The cross-correlations between inflation expectations[21] and inflation measures are calculated. The results are presented in Table 1.

[21] Obtained both with standard "balance method" and with application of multi-group confirmatory factor analysis.

Table 1 Pearson correlation coefficients between inflation expectations and inflation rate[22]

Lead (-) / lag (+)	Headline inflation		Core inflation	
	$INF_{STANDARD}$	INF_{CFA}	$INF_{STANDARD}$	INF_{CFA}
-4 (yoy)	-0.29	-0.44	0.39	-0.37
-4 (qoq)	0.13	-0.30	0.11	-0.20
-3 (qoq)	0.20	-0.27	0.20	-0.23
-2 (qoq)	0.07	-0.19	0.34	-0.28
-1 (qoq)	0.37	-0.44	0.43	-0.36
0 (qoq)	0.54	-0.50	0.43	-0.28
+1 (qoq)	0.33	-0.29	0.20	-0.02

Source: Own calculations.

Although the estimation of the multi-group CFA model indicates that there is an influence of the perception of the general sentiment on inflation expectations, it seems that it has very limited impact on the accuracy of forecasts made by households with respect to the inflation level. Only inflation expectations leading inflation index by one quarter are in all cases significant at 95% level (for the confidence intervals see Appendix 2). Additionally, with analysis of Pearson's correlation coefficients it is not possible to check whether the inflation expectations obtained with application of the MGCFA perform better or worse with respect to any measure of inflation (comparing to the forecasts obtained with the standard "balance method").

Short time span of the series of inflation and inflation expectations in line with only minor differences between indexes obtained with application of the standard and MGCFA methods do not allow for assessing the forecasting performance of the inflation expectations. In order to provide additional arguments concerning the performance of the inflation expectations the time-series properties of headline and core inflation rates in Poland are investigated and then inflation expectations are included as an explanatory variable in the time-series models.

[22] INF_{CFA} stands for an index of inflation expectations calculated with application of the multi-group confirmatory factor analysis. $INF_{STANDARD}$ stands for an index calculated with standard method based on differences between shares of positive and negative answers. It is also referred to as "balance method".

6. Forecasting inflation with survey based inflation expectations

Before inflation expectations can be included in models designed to explain the inflation movements, one needs to investigate properties of the time-series of inflation. As mentioned by Clements and Hendry (1998, p. 14) “survey information can be a useful adjunct within formal models (...) rather than as a substitute for econometric systems”. Thus, the starting point of this section is to investigate the properties of the time series of inflation with integrated autoregressive moving-average models (ARIMA). It follows the standard Box-Jenkins approach to modelling stochastic processes (Greene 2003). It can be summarized in the following steps (Greene 2003, p.620): (1) transformation of the data to obtain stationary time series, (2) estimation of an ARIMA model, (3) verification of the properties of residuals, (4) application of the model for forecasting purposes. This procedure is implemented and after the properties of the inflation time series are evaluated, inflation expectations are included and their impact on the model fit is presented.

6.1. Time-series properties of the inflation series

Investigation of the time-series properties is based on the most popular set of scalar models (ARIMA). With prior ARIMA analysis the components resulting from seasonal, autoregressive or moving-average processes are eliminated from the series of inflation. According to Clements and Hendry (1998) these models present good enough historical performance comparing with other econometric specifications. Additionally, it is easy to include in an ARIMA specification as an exogenous variable an information obtained from the analysis of inflation expectations.

In the scope of an analysis, the general-to-specific approach is applied. As Welfe (2003, p. 210) indicates this approach guarantees finding of the proper structure of the model. In this paper, the final structure of the ARIMA model is derived in two steps. At first, with application of ADF, it is checked whether the series of inflation contain a unit root. Then, the best model among the competing ones is selected with application of BIC.[23]

For the purpose of analysis, data on headline and core inflation are taken into account. The data for both series are limited to the period 2001Q1 – 2010Q1. At first, the properties of year on year changes of inflation rate are examined.[24] It is investigated with Augmented Dickey-Fuller test whether the hypothesis of unit root can be rejected. Testing for H0 – there is an unit root, versus

[23] Similar model selection pattern is applied by Ang et al. (2007).

[24] Year on year changes are in line with the forecasting horizon of the inflation expectations in the consumer surveys.

H1 – there is an autocorrelation coefficient lower than one, lead to the conclusion that the H0 cannot be rejected at 5% significance level.[25] The results are presented in Table 1 and Table 2 in Appendix 4. Then, a set of competing models in ARIMA specification are estimated.[26] The selected models are presented in Table 2.

Table 2 The best ARIMA specification for time-series of inflation.

Inflation	Model	ARIMA(p,d,q)	BIC
Headline	$\Delta \inf_t^{headline} = \underset{(0.180)}{.520} \Delta \inf_{t-1}^{headline} + \underset{(0.155)}{.317} \Delta \inf_{t-3}^{headline} - \underset{(0.177)}{.437} \Delta \inf_{t-4}^{headline} + \varepsilon_t$	ARIMA(4,1,0)	79.09
Core	$\Delta \inf_t^{core} = \underset{(.181)}{.488} \Delta \inf_{t-2}^{core} - \underset{(.160)}{.339} \Delta \inf_{t-4}^{core} + \varepsilon_t$	ARIMA(4,1,0)	66.70
Source: Own calculations in Stata.			

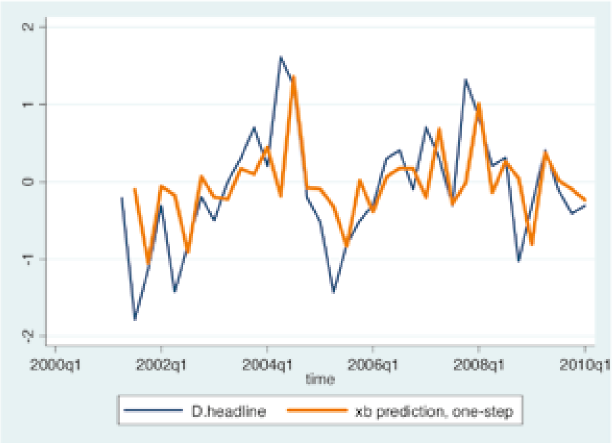
In specification associated with forecasting the headline inflation rate with ARIMA models with four lags proved to have significant coefficients associated with t-1, t-3 and t-4. It was also checked whether models with only two lags (namely t-1 and t-4) and one lag (t-1 or t-4) prove to be superior with respect to the BIC. As the value of BIC for those models was higher the final time-series model was the one with lags associated with t-1, t-3 and t-4. With respect to the core inflation, the best model contained four lags in autoregressive part and no moving-average term. In both specifications change in the inflation rate was positively affected by change in inflation rate. In case of both headline and core inflation the model predicts that positive shock to the growth of inflation increases the growth of inflation in the subsequent two quarters and decreases the inflation rate in four quarters. The results of model estimation – actual and fitted series of inflation – are presented on the figure below.

[25] The same conclusions are drawn from the Phillips-Perron test for unit Root. H0 cannot be rejected at 5% significance level.

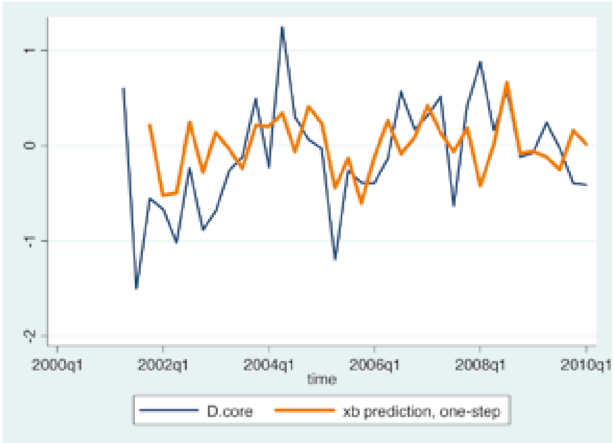
[26] Models are estimated with application of the general-to-specific approach – starting from the specification with four lags in autoregressive part and four lags in moving average part. Only models with zero constant term are specified and estimated – it is a consequence of elimination of the unit root and establishing that there is no unit root in the differenced series of inflation (headline and core).

Figure 7 Actual and fitted values for Δ headline inflation and Δ core inflation rates in Poland

Headline inflation



Core inflation



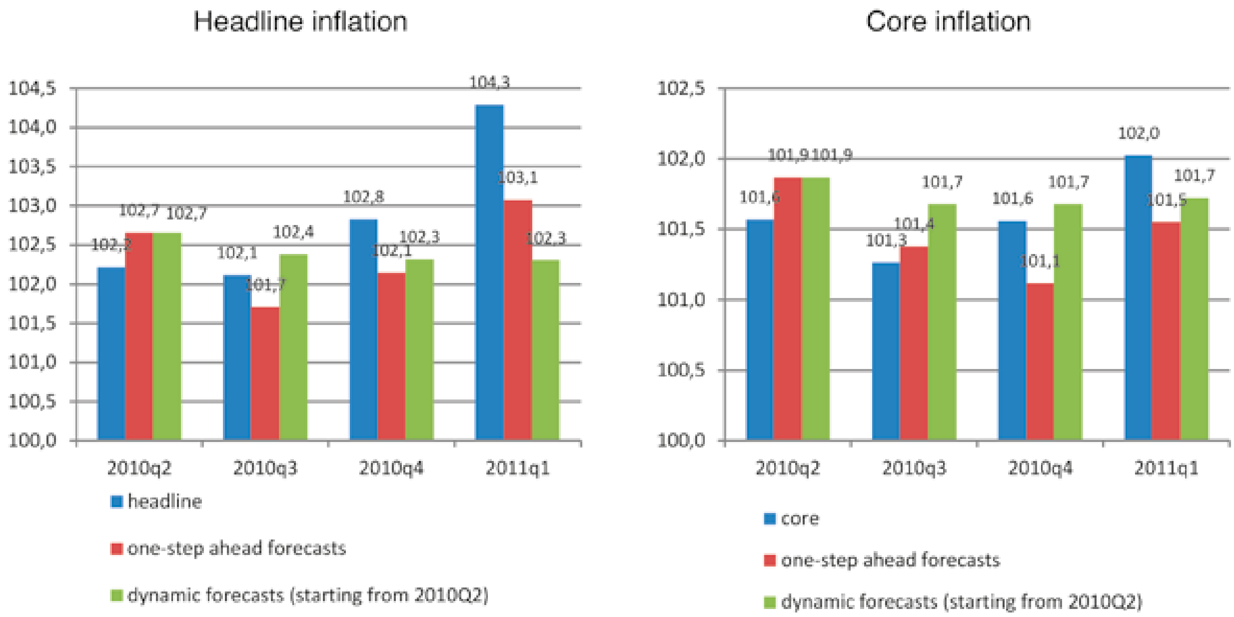
Source: Own calculations in Stata.

6.2. Forecasting inflation with ARIMA models

Estimates of the model parameters enable to evaluate out-of sample performance of the analyzed series. Period between 2010Q2 and 2011Q1 is not included in the analysis and due to this information on headline and core inflation can be used to present one period ahead forecasts but also dynamic forecasts obtained from time-series models in the specification presented in Table 2. The comparison of predicted and actual time series are presented on Figure below.

6

Figure 8 Predicted and actual values for headline inflation and core inflation rates in Poland between 2010Q2 and 2011Q1



Source: Own calculations in Stata.

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Predicted values diverge significantly from the actual results. Divergence, measured with mean absolute error (MAE), is presented in the table below.

Table 3 Mean absolute error of inflation forecasts with time-series models

Mean absolute error	Headline inflation	Core inflation
one step ahead forecasts	0.686	0.333
dynamic forecasts	0.801	0.283

Source: Own calculations.

Headline inflation for the period 2010Q2 – 2011Q1 is predicted with almost 0.7 pp. average error with respect to the actual value. Such a significant difference is obtained even though the forecasts are made only one quarter ahead. Divergence of predicted values from the actual ones increases to 0.8 pp. with dynamic forecasts made for four quarters – starting from 2010Q2. Significant differences are also visible when core inflation is taken into account. With application of time-series models the average absolute difference between actual and predicted values of core inflation is over 0.3 pp.. Surprisingly this number slightly decreases with dynamic forecasts but still remains close to 0.3 pp.

6.3. In-sample error of inflation predictions with consumer survey based inflation expectations

The next step of the analysis is oriented to incorporating the information from the inflation expectations into the time-series. After the optimal specification of ARIMA models for both headline and core inflation rate was established, it is possible to verify, whether there is any value added of the data on inflation expectations. Additionally, it is checked what is the relative performance for in-sample and then out-of-sample forecasts with survey based inflation expectations – both obtained from the conventional "balance method" but also for the data obtained with application of the multi-group confirmatory factor analysis.

The comparisons of estimation results of models specified in line with results from Table 2 but with additional information from inflation expectations are conducted for the following specifications:[27]

Headline inflation: $\Delta \inf_t^{headline} = \alpha \cdot INF_{t+q}^{CFA/BAL} + \varphi_1 \Delta \inf_{t-1}^{headline} + \varphi_2 \Delta \inf_{t-3}^{headline} + \varphi_3 \Delta \inf_{t-4}^{headline} + \varepsilon_t$

Core inflation: $\Delta \inf_t^{core} = \alpha \cdot INF_{t+q}^{CFA/BAL} + \varphi_1 \Delta \inf_{t-2}^{core} + \varphi_2 \Delta \inf_{t-4}^{core} + \varepsilon_t$.

The results for core inflation are presented in Table 4 and for headline inflation in Table 5.

6

[27] Models were estimated both with inflation expectations based on the results from the confirmatory factor analysis and standard balance method.

Table 4 Comparison of information criteria for ARIMA models with inflation expectations (ARIMAX) – core inflation rate

Lead (-)/lag(+) q	Inflation expectations obtained with CFA		Inflation expectations obtained with standard “balance method”	
	$\hat{\alpha}$	BIC[28]	$\hat{\alpha}$	BIC
-4	$\underset{(0.58)}{.11}$	72.98	$\underset{(1.03)}{-1.71}$	68.87
-3	$\underset{(0.60)}{-.29}$	72.66	$\underset{(1.12)}{-.46}$	72.91
-2	$\underset{(0.44)}{-.59}$	69.92	$\underset{(1.06)}{.48}$	71.55
-1	$\underset{(0.28)}{-1.20}$	59.58	$\underset{(0.80)}{2.20}$	63.56
0	$\underset{(0.30)}{-1.40}$	50.83 (*)	$\underset{(0.71)}{2.74}$	57.85
+1	$\underset{(0.28)}{-1.27}$	58.89	$\underset{(0.70)}{2.68}$	63.50
Source: Own calculations in Stata.				

Table 5 Comparison of information criteria for ARIMA models with inflation expectations (ARIMAX) – headline inflation rate

Lead (-)/lag(+) - q	Inflation expectations obtained with CFA		Inflation expectations obtained with standard “balance method”	
	$\hat{\alpha}$	BIC	$\hat{\alpha}$	BIC
-4	$\underset{(0.70)}{-.21}$	91.31	$\underset{(1.38)}{-1.60}$	89.93
-3	$\underset{(0.70)}{.38}$	87.25	$\underset{(1.48)}{-1.23}$	86.35
-2	$\underset{(0.90)}{-.32}$	85.20	$\underset{(1.36)}{-.58}$	85.20
-1	$\underset{(0.64)}{-1.10}$	79.63	$\underset{(1.02)}{2.39}$	78.68
0	$\underset{(0.54)}{-1.59}$	72.65 (*)	$\underset{(1.26)}{2.68}$	77.14
+1	$\underset{(0.63)}{-1.33}$	77.35	$\underset{(1.20)}{1.65}$	79.85
Source: Own calculations in Stata.				

Selection of the best model in the group of ARIMAX[29] models of inflation is done according to the BIC. With respect to both – headline and core inflation rates – better BIC values are obtained for the models in which inflation expectations obtained from the confirmatory factor analysis are applied. Additionally, in all situations (headline and core inflation but also CFA and “balance method”) the models proved to be the most successful with coincident indicator of

[28] BIC calculated in line with the formula BIC = -2*ln(likelihood) + ln(N)*k

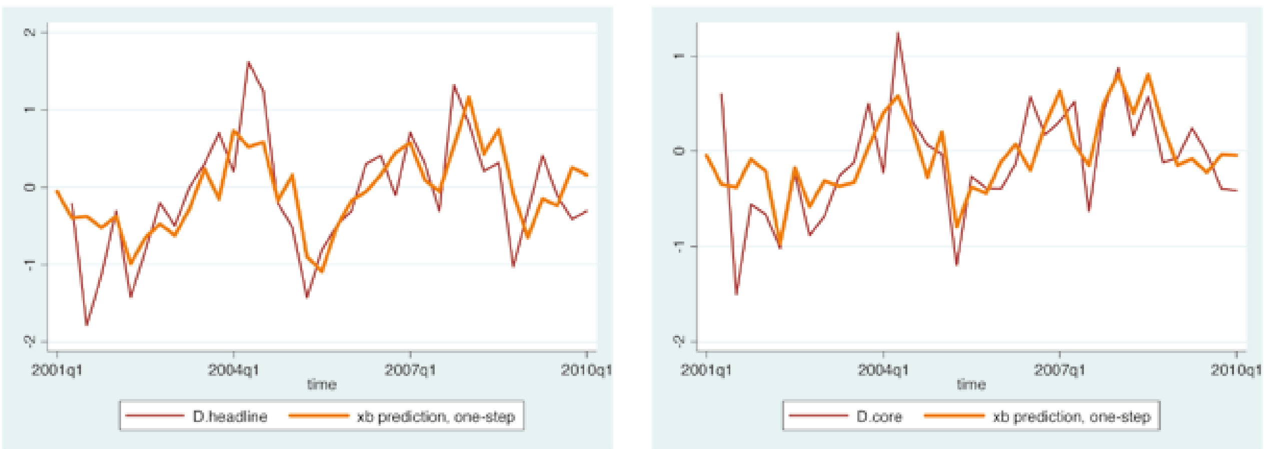
[29] ARIMA models with inflation expectations serving as an exogenous variable.

inflation expectations. It is a bit surprising as the horizon for inflation expectations is 12 months. For all models with four quarters lead coefficients standing in front of the inflation expectations term prove to be either not significant (models with CFA based index) or significant but with inverse sign (models with "balance method" based index).

Figure below presents graphically the fit of the best ARIMAX models for core and headline inflation selected according to the results presented in Table 4 and Table 5 respectively.

Figure 9 Actual and fitted values of ARIMAX models for Δ headline inflation and Δ core inflation rates in Poland (with inflation expectations)

Headline inflation　　　　Core inflation



Source: Own calculations in Stata.

Obtained in-sample forecasts are better for ARIMAX models of headline and core inflation – comparing to ARIMA specifications. Mean absolute error for both - ARIMA and ARIMAX specifications – for headline and core inflation is presented in Table below.

Table 6 Mean absolute error of in-sample inflation forecasts with time-series models (ARIMA) and time series models augmented with inflation expectations (ARIMAX)

Mean absolute error	Headline inflation	Core inflation
Naive	0.600	0.466
ARIMA	0.453	0.425
ARIMAX	0.418	0.333

Source: Own calculations.

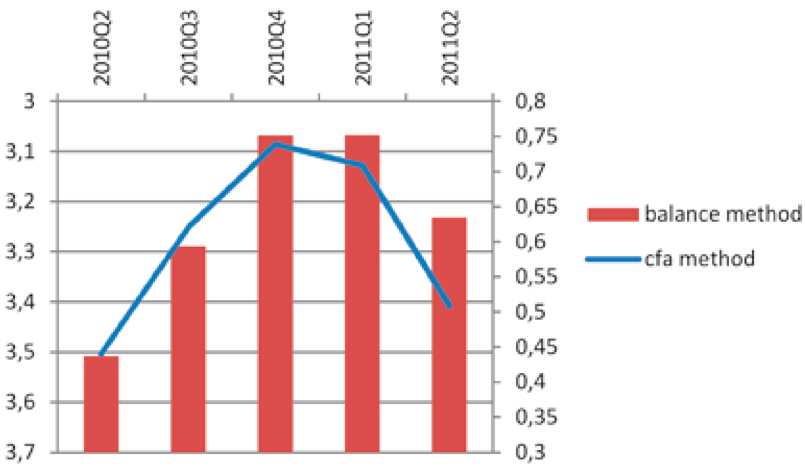
For both inflation measures improvement of the in-sample forecasts of the time-series models (ARIMA) with respect to naive predictions is visible. For headline inflation the mean absolute error is reduced by almost 0.15 pp. in each quarter. Further reduction is obtained by the inclusion of inflation expectations in the model – by almost 0.04 pp. With respect to core inflation prediction error is reduced moderately due to the time-series properties 0.04 pp., but additional 0.1 pp. of reduction in each quarter is obtained due to information provided by consumers' inflation expectations.

6.4. Out-of-sample forecasting of inflation with consumer survey based inflation expectations

In-sample properties of the inflation expectations are important but the real value added provided by inflation expectations can only be verified with out-of-sample forecasts. It is checked for the period 2010Q2 - 2011Q1 whether the one-period ahead forecasts obtained from ARIMAX models (with inflation expectations) outperform simple ARIMA specifications and forecasts obtained with naive forecasts. Additionally, the results for both models – with inflation expectations obtained after the elimination of consumer sentiment component (CFA based method) and raw series of inflation expectations (balance method) are presented.

In order to obtain the values for the mean of inflation expectations estimates of the CFA model (1.4) are applied to the data for the period 2010Q2 – 2011Q2. The results of the mean expectations for the period are presented on figure below. Additionally, the information on standard inflation forecasts obtained from the "balance method" are presented.

Figure 10 Inflation expectations calculated with application of MGCFA and with "balance method"

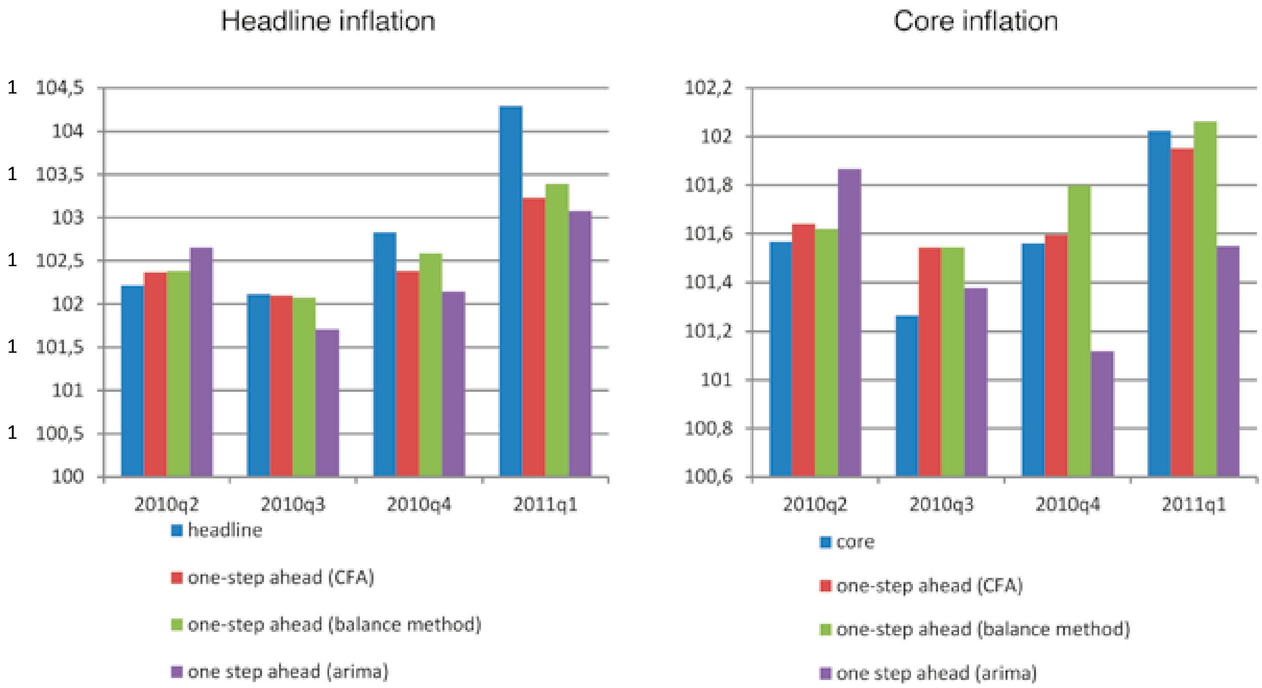


Source: Own calculations in MPlus based on data from RIED - WSE.

Although the two indexes of inflation expectations should not be directly compared, as they are measured on different scale, the index obtained with "balance method" seems to indicate higher inflation expectations from 2011Q1. With application of the CFA method inflation expectations seem to be more moderate. This difference can be explained by a significant decrease in the level of consumer's sentiment in that period. High inflation expectations ("balance method") in 2011Q1 and 2011Q2 result from a very negative perception of the consumer sentiment among respondents from the State of the Households Survey.

Inflation expectations from both specifications could be applied for an out-of-sample forecasts for the period 2010Q2 – 2011Q1. These out-of-sample forecasts can be compared with realization of the inflation during the period of analysis.

Figure 11 Predicted and actual values for headline inflation and core inflation rates in Poland between 2010Q2 and 2011Q1



Source: Own calculations.

It is clearly visible that inflation expectations improve the forecasting performance of time-series models oriented on explaining the behaviour of inflation. It is true both with headline and core inflation rates. The mean absolute error values for an out-of-sample forecasts are presented in Table 7.

Table 7 Mean absolute error of out-of-sample inflation forecasts with time-series models (ARIMA) and time series models augmented with inflation expectations (ARIMAX)

Mean absolute error	Headline inflation	Core inflation
Naive	0.773	0.411
ARIMA	0.686	0.333
ARIMAX (CFA)	0.420	0.116
ARIMAX (BAL)	0.335	0.152

Source: Own calculations.

Forecasts, based on Naive or even ARIMA predictions are in the case of headline inflation associated with almost 0.7 pp. average absolute error in the four quarters between 2010Q2 and

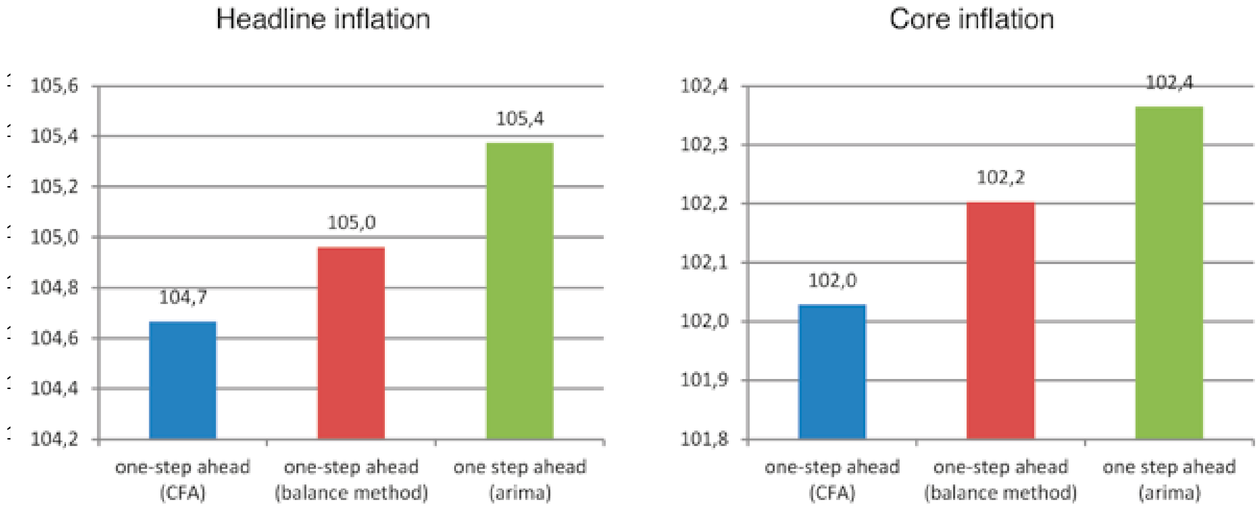
2011Q1. It is probably a consequence of explosion of inflation at the end of 2010 and in 2011Q1. In such a situation models based solely on time-series with no exogenous information perform poorly and their predictions can be improved by information from the business surveys (see Białowolski, Zwiernik, Żochowski 2011). It is also the case for the forecasts made for 2010Q2 – 2011Q1. Information provided by inflation expectations improves the forecasts significantly reducing the mean absolute error by half. Even larger improvement is associated with introduction of inflation expectations to the forecasts of core inflation rate. Forecasts based on Naive or ARIMA expectations make on average 0.411 and 0.333 pp. (respectively) error per quarter. Introducing the information from inflation expectations reduces this error by more than a half (0.116 – 0.152 pp.).

It is hard to establish whether the relative performance of inflation expectations obtained with application of the multi-group confirmatory factor analysis are superior to the inflation expectations obtained with standard balance method. For the time series of core inflation the inflation expectations obtained with MGCFA are slightly better. However, the conclusion is opposite with respect to the headline inflation.

6.5. Forecasts of inflation for 2011Q2

The conducted analysis shows that average of inflation expectations is the best indicator for the coincident inflation rate (both headline and core). Taking into regard that consumer survey data are available at the end of the first month of each quarter and statistics on inflation rate in a given quarter is available at the end of the first month in the following quarter, with coincident indicator of inflation expectations one obtains a forecast of the inflation rate with almost one quarter lead. Therefore forecasts for 2011Q2 are also calculated. Forecasts of core and headline inflation rates obtained both with CFA based index and with standard “balance method” are presented on Figure below.

Figure 12 Predicted values for headline inflation and core inflation rates in Poland between – 2011q2



Source: Own calculations.

Forecasts of inflation obtained based on ARIMA specifications show possible significant increase in the level of inflation in 2011Q2. With respect to headline inflation rate it is expected that it should increase between 2011Q1 and 2011Q2 by 1.1 pp. and with respect to core inflation magnitude of the increase should be 0.4 pp. Forecasts of headline and core inflation rate are reduced for models with exogenous information on inflation expectations. Additionally, forecasts are lower for models were inflation expectations are based on MGCFA. Expected rate of headline inflation should increase to 4.7% and for the core inflation rate it should remain at the level of 2.0%.

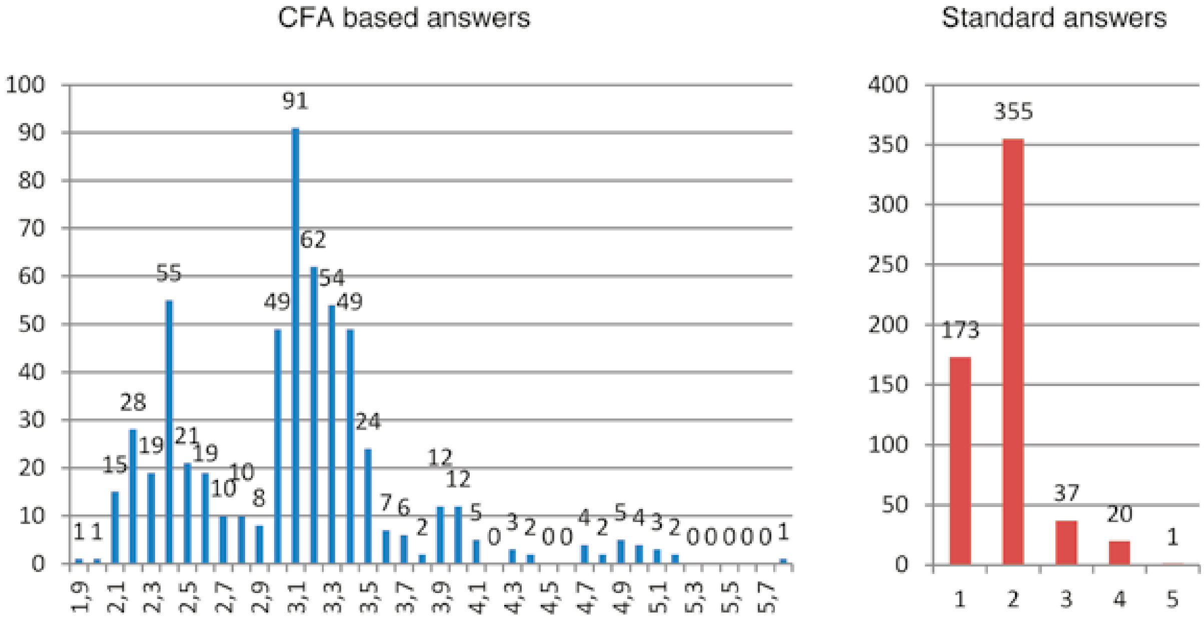
7. Further research

There are at least two areas that should be subject of further research – quantification of inflation expectations and information concerning the variance of inflation expectations. Both of them can be analyzed with standard approach (balance method) but it seems that an approach with multi-group confirmatory factor analysis provides additional information that can be subject to more detailed analysis.

7.1. Quantification of inflation expectations

One of the most important topics in the literature on consumer survey inflation expectations is connected with quantification of the inflation expectations. Usually, it is conducted with Carlson-Parkin method and there are numerous examples of application of this approach to survey data (for Poland see e.g. Łyziak 2004). However, an application of the index obtained with multi-group CFA provides more comprehensive information on consumer attitudes concerning inflation expectations. Standard data from the questionnaire provides normally only five categories of answers to the question concerning inflation expectations. With multi-group confirmatory factor analysis one obtains information on inflation expectations corrected for numerous possibilities of consumer sentiment level. The difference in answer pattern is clearly depicted on the graph below.

Figure 13 Histograms of inflation expectations in 1997q4 obtained with CFA and uncorrected



Source: Own calculations.

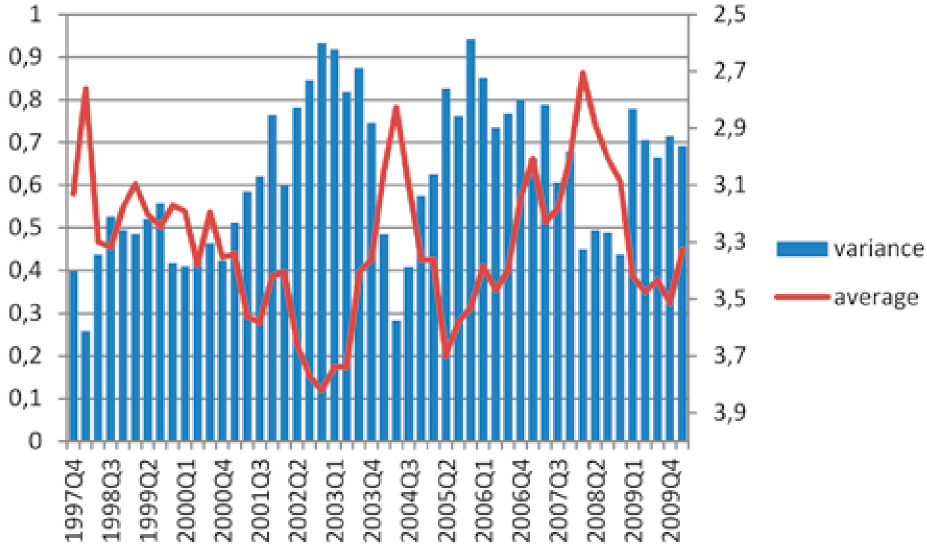
With MGCFA it is possible to check, whether the response pattern is constant over time and whether in each period respondents with a given level of consumer sentiment provide answers to the question on inflation expectations biased in a given direction. Thus, one may apply standard quantification techniques (e.g. Carlson-Parkin) and obtain more reliable assessment of inflation expectations among consumers.

7.2. Variance of inflation expectations

Although it seems to be important, the information on the variance of inflation expectations has not been taken into account. One may suspect, according to Friedman (1977) suggestion, that higher average inflation should result in more inflation uncertainty because it distorts relative prices and introduces additional risk to nominal contracts. This idea was formally proven by Ball (1992) and is currently referred as Ball-Friedman hypothesis. There are also formal proofs of an inverse hypothesis. Cukierman and Meltzer (1986) showed in a formal way that higher inflation should be accompanied by higher inflation uncertainty.

This pattern, although visible on the level of aggregates, is hardly visible on the individual level data. The relation between inflation expectations (average level) and variance of inflation expectations is depicted on figure below.

Figure 14 Inflation expectations (average) and variance of inflation expectations



Source: Own calculations in MPlus based on data from RIED - WSE.

Correlation between average inflation expectations and variance of inflation expectations is at the level of 0.72, which indicates that in the periods of high inflation expectations associated with low values of the indicator of inflation expectations, the variance of inflation expectations is very low. It implies that when there is a prevailing pessimism in the area of inflation almost all respondents forecast an increase in prices at an even faster pace. It should be subject to scrutiny, whether with the set of answers limited to only five cases, it is possible to catch the impact of Ball-Friedman hypothesis. Additionally, it should be verified whether there is a prevailing extreme response bias in the case of question concerning inflation level.

8. Conclusions

The proposed approach to the elimination of an influence of consumer sentiment on the inflation expectations should start a discussion about the methodology of the measurement of complex, latent phenomena in business and consumer surveys.

In this paper, it is shown that one of the areas in which Consumer Sentiment is clearly visible are inflation expectations. The results show that a standard set of questions – unemployment forecasts, general economic situation forecasts, household's savings forecasts, and household's financial situation forecasts – is not sufficiently coherent in time in order to generate reliable information on any unidimensional phenomenon measured in time. It is proposed that the proxies of consumer sentiment should refer only to the general economic situation. In consequence, questions concerning savings climate, general economic situation forecasts, climate for major purchases and price forecasts are included in the modified measurement model of CSI. The index created with the application of this set of questions fulfils the criterion of partial measurement invariance. It can be assumed that the values of such an index reflect unidimensional phenomenon, which can be called consumer sentiment.

However, the relation between consumer sentiment and answers to the question concerning inflation expectations is not stable between different periods of analysis, which indicates a possibility of other latent variable explaining the behaviour of price expectations. To account for this lack of measurement invariance additional latent variable is included in the model – inflation expectations. Thus it is possible to eliminate the influence of consumer sentiment on inflation expectations and at the same time to obtain individually corrected answers concerning the inflation expectations. Additionally, with MGCFA it is possible to check whether the linear relation between consumer sentiment and inflation expectations is stable over time. Although partial measurement invariance for this model is established and the stability of estimates is confirmed, it was noticed that during the financial crisis the interrelations between proxies of consumer sentiment and inflation expectations were disturbed.

In the following step of the analysis the data on inflation expectations is applied to modelling and forecasting of the time series of inflation. It is shown that with respect to standard ARIMA processes, inclusion of the information on the inflation expectations significantly improves the in-sample and out-of-sample forecasting performance of the time-series models. Especially out-of-sample performance is significantly better as the average absolute error in forecasts of headline and core inflation is reduced by half. It is also presented that models with inflation expectations based on the CFA method (after elimination of the consumer sentiment) provide better in-sample forecasts of inflation. Nevertheless, it is not confirmed for the out-of-sample forecasts.

In the further research we intend to apply the quantification techniques presented in this paper to the inflation expectations (cleared with MGCFA). As they comprise additional information concerning the level of consumer sentiment they provide larger base for quantifications and hopefully enable better forecasts of inflation.

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Appendix 1. Set of questions with answers in the standardized consumer questionnaire.

Question number and code	Question wording	Answer categories (representing also scale points)
Q1 (FS.S)	How has the financial situation of your household changed over the last 12 months? It has...	1.0 "got a lot better" 2.0 "got a little better" 3.0 "stayed the same" 4.0 "got a little worse" 5.0 "got a lot worse" -99 "don't know"
Q2 (FS.F)	How do you expect the financial position of your household to change over the next 12 months? It will...	1.0 "get a lot better" 2.0 "get a little better" 3.0 "stay the same" 4.0 "get a little worse" 5.0 "get a lot worse" -99 "don't know"
Q3 (GES.S)	How do you think the general economic situation in the country has changed over the past 12 months? It has...	1.0 "got a lot better" 2.0 "got a little better" 3.0 "stayed the same" 4.0 "got a little worse" 5.0 "got a lot worse" -99 "don't know"
Q4 (GES.F)	How do you expect the general economic situation in this country to develop over the next 12 months? It will...	1.0 "get a lot better" 2.0 "get a little better" 3.0 "stay the same" 4.0 "get a little worse" 5.0 "get a lot worse" -99 "don't know"
Q5 (PRA.S)	How do you think that consumer prices have developed over the last 12 months? They have…	1.0 "risen a lot" 2.0 "risen moderately" 3.0 "risen slightly" 4.0 "stayed about the same" 5.0 "fallen" -99 "don't know"
Q6 (PRA.F)	By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will…	1.0 "increase more rapidly" 2.0 "increase at the same rate" 3.0 "increase at a slower rate" 4.0 "stay about the same" 5.0 "fall" -99 "don't know"

Q7 (UNEMP.F)	How do you expect the number of people unemployed in this country to change over the next 12 months? The number will...	1.0 “increase sharply” 2.0 “increase slightly” 3.0 “remain the same” 4.0 “fall slightly” 5.0 “fall sharply” -99 “don't know”
Q8 (MP.S)	In view of the general economic situation, do you think that now it is the right moment for people to make major purchases such as furniture, electrical/electronic devices, etc.?	1.0 “yes, it is the right moment now” 2.0 “it is neither the right moment nor the wrong moment” 3.0 “no, it is not the right moment now” -99 “don't know”
Q9 (MP.F)	Compared to the past 12 months, do you expect to spend more or less money on major purchases (furniture, electrical/electronic devices, etc.) over the next 12 months? I will spend…	1.0 “much more” 2.0 “a little more” 3.0 “about the same” 4.0 “a little less” 5.0 “much less” -99 “don't know”
Q10 (SAV.S)	In view of the general economic situation, do you think that now is...?	1.0 “a very good moment to save” 2.0 “a fairly good moment to save” 3.0 “not a good moment to save” 4.0 “a very bad moment to save” -99 “don't know”
Q11 (SAV.F)	Over the next 12 months, how likely is it that you save any money?	1.0 “very likely” 2.0 “fairly likely” 3.0 “not likely” 4.0 “not at all likely” -99 “don't know”
Q12 (FIN.S)	Which of these statements best describes the current financial situation of your household?	1.0 “we are saving a lot” 2.0 “we are saving a little” 3.0 “we are just managing to make ends meet on our income” 4.0 “we are having to draw on our savings” 5.0 “we are running into debt” -99 “don't know”

Source: European Economy (2006), The State of the Households Survey – Research Institute for Economic Development.

Appendix 2. 95% confidence intervals for estimates of the Pearson's correlation coefficients presented in Table 1.

Lead (-) / lag (+)	Headline inflation		Core inflation	
	$INF_{STANDARD}$	INF_{CFA}	$INF_{STANDARD}$	INF_{CFA}
-4 (yoy)	(-0.53, -0.01)	(-0.64, -0.19)	(0.09, 0.62)	(-0.61, -0.07)
-4 (qoq)	(-0.15, 0.39)	(-0.53, -0.02)	(-0.21, 0.40)	(-0.48, 0.11)
-3 (qoq)	(-0.08, 0.45)	(-0.51, -0.01)	(-0.11, 0.48)	(-0.50, 0.09)
-2 (qoq)	(-0.21, 0.35)	(-0.44, -0.10)	(0.03, 0.59)	(-0.55, 0.03)
-1 (qoq)	(0.10, 0.59)	(-0.64, -0.19)	(0.13, 0.66)	(-0.61, -0.04)
0 (qoq)	(0.30, 0.71)	(-0.68, -0.26)	(0.12, 0.66)	(-0.55, 0.05)
+1 (qoq)	(0.06, 0.56)	(-0.52, -0.01)	(-0.13, 0.50)	(-0.35, 0.31)

Source: Own calculations.

Appendix 3. Period specific estimates for the model with partial measurement invariance.

Period of analysis	CSI_t (mean, variance)	INF_t (mean, variance)	(τ_4^t, γ_4^t)	λ_t
1997Q4	3.160, 0.472	3.129, 0.398	1.467, 0.424	-0.026
1998Q1	3.553, 0.332	2.762, 0.258	0.299, 0.764	-0.011
1998Q2	3.512, 0.579	3.299, 0.438	0.802, 0.629	-0.106
1998Q3	3.208, 0.554	3.320, 0.526	0.289, 0.634	-0.100
1998Q4	3.167, 0.445	3.179, 0.495	0.092, 0.903	-0.197
1999Q1	3.370, 0.476	3.096, 0.485	0.665, 0.682	-0.112
1999Q2	3.442, 0.420	3.204, 0.520	0.624, 0.704	-0.112
1999Q3	3.416, 0.504	3.245, 0.557	0.882, 0.636	-0.101
1999Q4	3.623, 0.345	3.171, 0.415	-0.104, 0.896	-0.172
2000Q1	3.710, 0.656	3.193, 0.410	0.261, 0.759	-0.208
2000Q2	3.842, 0.539	3.380, 0.423	0.211, 0.750	-0.177
2000Q3	3.829, 0.588	3.195, 0.464	0.395, 0.703	-0.241
2000Q4	3.718, 0.575	3.354, 0.423	1.435, 0.444	-0.078
2001Q1	3.795, 0.535	3.343, 0.511	0.155, 0.766	-0.253
2001Q2	3.984, 0.503	3.561, 0.585	-0.787, 0.966	-0.293
2001Q3	3.867, 0.511	3.582, 0.620	0.633, 0.637	-0.194
2001Q4	3.771, 0.537	3.420, 0.764	0.704, 0.653	-0.244
2002Q1	4.005, 0.682	3.405, 0.600	1.282, 0.494	-0.169
2002Q2	3.921, 0.539	3.658, 0.781	1.278, 0.534	-0.132
2002Q3	3.899, 0.500	3.770, 0.845	0.686, 0.666	-0.219
2002Q4	3.607, 0.574	3.822, 0.934	1.776, 0.411	-0.066
2003Q1	3.747, 0.560	3.738, 0.919	1.285, 0.538	-0.195
2003Q2	3.951, 0.576	3.738, 0.818	1.520, 0.469	-0.146
2003Q3	3.785, 0.590	3.405, 0.874	1.769, 0.418	-0.109
2003Q4	3.966, 0.603	3.361, 0.746	1.763, 0.412	-0.062
2004Q1	3.956, 0.397	3.054, 0.484	1.551, 0.463	-0.033
2004Q2	3.936, 0.315	2.828, 0.283	1.416, 0.479	0.019
2004Q3	3.877, 0.578	3.103, 0.408	1.108, 0.575	-0.103
2004Q4	3.671, 0.826	3.362, 0.575	1.059, 0.594	-0.205
2005Q1	3.602, 0.626	3.364, 0.625	1.166, 0.565	-0.038
2005Q2	3.600, 0.749	3.701, 0.826	1.526, 0.479	-0.108
2005Q3	3.712, 0.489	3.579, 0.762	0.781, 0.667	-0.194
2005Q4	3.500, 0.636	3.530, 0.943	1.597, 0.465	-0.101
2006Q1	3.018, 0.677	3.385, 0.852	1.264, 0.549	-0.187
2006Q2	3.334, 0.510	3.468, 0.735	2.462, 0.169	0.077
2006Q3	3.329, 0.655	3.398, 0.768	1.433, 0.487	-0.068
2006Q4	3.308, 0.338	3.150, 0.802	0.638, 0.738	-0.086
2007Q1	3.100, 0.428	3.008, 0.663	1.162, 0.555	-0.018
2007Q2	2.966, 0.444	3.230, 0.788	1.054, 0.623	-0.096
2007Q3	3.074, 0.480	3.181, 0.606	1.140, 0.564	-0.016
2007Q4	2.947, 0.526	3.001, 0.678	1.058, 0.618	-0.036
2008Q1	3.034, 0.475	2.705, 0.449	1.096, 0.602	-0.088
2008Q2	2.985, 0.398	2.890, 0.494	1.146, 0.574	-0.073
2008Q3	3.406, 0.357	3.006, 0.489	1.105, 0.549	-0.023
2008Q4	3.709, 0.456	3.088, 0.438	1.014, 0.545	-0.090
2009Q1	3.917, 0.350	3.418, 0.779	-1.856, 1.214	-0.375
2009Q2	3.870, 0.442	3.476, 0.705	0.943, 0.515	-0.065
2009Q3	3.932, 0.510	3.932, 0.664	0.260, 0.679	-0.242
2009Q4	3.864, 0.493	3.516, 0.715	0.345, 0.665	-0.124
2010Q1	3.593, 0.583	3.329, 0.691	0.496, 0.659	-0.185

Source: Own calculations in MPlus based on data from RIED WSE .

Appendix 4. Time-series properties of inflation series.

Table 1

Dickey-Fuller test for unit root – headline inflation

Number of obs = 36

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.668	-3.675	-2.969	-2.617

MacKinnon approximate p-value for Z(t) = 0.0798

Table 2

Dickey-Fuller test for unit root – core inflation rate

Number of obs = 36

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.674	-3.675	-2.969	-2.617

MacKinnon approximate p-value for Z(t) = 0.0787

Appendixes – not to be released

```
. arima D.core, ar(2 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -28.424543
Iteration 1:   log likelihood = -27.998894
Iteration 2:   log likelihood = -27.976242
Iteration 3:   log likelihood = -27.974488
Iteration 4:   log likelihood = -27.974308
(switching optimization to BFGS)
Iteration 5:   log likelihood = -27.974283
Iteration 6:   log likelihood = -27.974279
Iteration 7:   log likelihood = -27.974279

ARIMA regression

Sample:  2001q2 - 2010q1                        Number of obs      =        36
                                                Wald chi2(2)       =     10.96
Log likelihood = -27.97428                      Prob > chi2        =    0.0042

------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |   .4880935   .1815299     2.69   0.007     .1323015    .8438855
         L4. |  -.3389137   .1608992    -2.11   0.035    -.6542702   -.0235571
-------------+----------------------------------------------------------------
      /sigma |   .5206821   .0592972     8.78   0.000     .4044617    .6369025
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     36           .   -27.97428      3     61.94856    66.69911
-----------------------------------------------------------------------------
          Note:  N=Obs used in calculating BIC; see [R] BIC note



. arima D.headline, ma(1) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -44.252482
Iteration 1:   log likelihood = -39.670888
Iteration 2:   log likelihood = -39.545858
Iteration 3:   log likelihood = -39.541826
Iteration 4:   log likelihood = -39.541757
(switching optimization to BFGS)
Iteration 5:   log likelihood = -39.541756

ARIMA regression

Sample:  2001q2 - 2011q1                        Number of obs      =        40
                                                Wald chi2(1)       =     29.07
Log likelihood = -39.54176                      Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |                 OPG
```

```
    D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ARMA         |
          ma |
         L1. |   .7511313   .1393105     5.39   0.000     .4780877    1.024175
-------------+----------------------------------------------------------------
      /sigma |    .643552   .0586533    10.97   0.000     .5285936    .7585104
------------------------------------------------------------------------------


arima D.core cfa_mean_mc, ar(2 4) noconstant


ARIMA regression

Sample:  2001q2 - 2010q1                        Number of obs      =        36
                                                Wald chi2(3)       =     26.40
Log likelihood = -18.24592                      Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
core         |
 cfa_mean_mc |   -1.39691   .3030306    -4.61   0.000    -1.990839   -.8029809
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |   .1066721   .2117157     0.50   0.614     -.308283    .5216273
         L4. |  -.4638082   .2008762    -2.31   0.021    -.8575183   -.0700981
-------------+----------------------------------------------------------------
      /sigma |   .3962496    .056444     7.02   0.000     .2856214    .5068779
------------------------------------------------------------------------------


. arima D.core L.cfa_mean_mc, ar(2 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -22.957863
Iteration 1:   log likelihood = -22.594224
Iteration 2:   log likelihood = -22.570307
Iteration 3:   log likelihood = -22.567331
Iteration 4:   log likelihood = -22.566653
(switching optimization to BFGS)
Iteration 5:   log likelihood = -22.566364
Iteration 6:   log likelihood = -22.566159
Iteration 7:   log likelihood = -22.566159

ARIMA regression

Sample:  2001q2 - 2010q2                        Number of obs      =        37
                                                Wald chi2(3)       =     29.60
Log likelihood = -22.56616                      Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
core         |
 cfa_mean_mc |
         L1. |  -1.195024   .2756279    -4.34   0.000    -1.735245   -.6548035
-------------+----------------------------------------------------------------
```

```
ARMA         |
          ar |
         L2. |   .1902829   .2002295     0.95   0.342    -.2021596    .5827255
         L4. |  -.4337557   .1513043    -2.87   0.004    -.7303067   -.1372047
-------------+----------------------------------------------------------------
      /sigma |   .4400815   .0573277     7.68   0.000     .3277212    .5524418
------------------------------------------------------------------------------

. arima D.core L2.cfa_mean_mc, ar(2 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -28.197467
Iteration 1:   log likelihood = -27.756553
Iteration 2:   log likelihood = -27.703509
Iteration 3:   log likelihood = -27.690783
Iteration 4:   log likelihood = -27.687819
(switching optimization to BFGS)
Iteration 5:   log likelihood = -27.686959
Iteration 6:   log likelihood = -27.686626
Iteration 7:   log likelihood = -27.686606
Iteration 8:   log likelihood = -27.686606

ARIMA regression

Sample:  2001q2 - 2010q3                        Number of obs      =        38
                                                Wald chi2(3)       =     14.92
Log likelihood = -27.68661                      Prob > chi2        =    0.0019

------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
core         |
 cfa_mean_mc |
         L2. |  -.5910082   .4420804    -1.34   0.181     -1.45747    .2754535
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |   .3482452   .1602466     2.17   0.030     .0341677    .6623226
         L4. |  -.3596992   .1509706    -2.38   0.017    -.6555962   -.0638022
-------------+----------------------------------------------------------------
      /sigma |   .4968741   .0530307     9.37   0.000     .3929358    .6008124
------------------------------------------------------------------------------

. arima D.core L3.cfa_mean_mc, ar(2 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -29.457412
Iteration 1:   log likelihood = -29.105588
Iteration 2:   log likelihood = -29.035488
Iteration 3:   log likelihood = -29.020879
Iteration 4:   log likelihood = -29.006931
(switching optimization to BFGS)
Iteration 5:   log likelihood = -29.004333
Iteration 6:   log likelihood = -29.003585
Iteration 7:   log likelihood = -29.003565
Iteration 8:   log likelihood = -29.003565

ARIMA regression

Sample:  2001q2 - 2010q4                        Number of obs      =        39
                                                Wald chi2(3)       =     13.34
Log likelihood = -29.00357                      Prob > chi2        =    0.0040
```

```
------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
core         |
 cfa_mean_mc |
         L3. |  -.2948075   .6025774    -0.49   0.625    -1.475837    .8862226
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |   .4359568   .1713027     2.54   0.011     .1002098    .7717038
         L4. |  -.3743935   .1522363    -2.46   0.014     -.672771   -.0760159
-------------+----------------------------------------------------------------
      /sigma |   .5037307   .0538286     9.36   0.000     .3982285    .6092328
------------------------------------------------------------------------------

. arima D.core L4.cfa_mean_mc, ar(2 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -30.016436
Iteration 1:   log likelihood = -29.454161
Iteration 2:   log likelihood = -29.198592
Iteration 3:   log likelihood =  -29.18548
Iteration 4:   log likelihood = -29.168177
(switching optimization to BFGS)
Iteration 5:   log likelihood = -29.165323
Iteration 6:   log likelihood = -29.164567
Iteration 7:   log likelihood = -29.164545
Iteration 8:   log likelihood = -29.164544

ARIMA regression

Sample:  2001q3 - 2011q1                        Number of obs      =        39
                                                Wald chi2(3)       =     12.54
Log likelihood = -29.16454                      Prob > chi2        =    0.0058

------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
core         |
 cfa_mean_mc |
         L4. |   .1116865   .5839079     0.19   0.848    -1.032752    1.256125
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |   .4991095   .2000792     2.49   0.013     .1069615    .8912575
         L4. |  -.3064003    .238079    -1.29   0.198    -.7730266    .1602259
-------------+----------------------------------------------------------------
      /sigma |   .5065039    .055131     9.19   0.000     .3984491    .6145586
------------------------------------------------------------------------------

. arima D.core F.cfa_mean_mc, ar(2 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -23.668573
Iteration 1:   log likelihood = -22.497577
Iteration 2:   log likelihood = -22.408911
Iteration 3:   log likelihood = -22.385798
Iteration 4:   log likelihood = -22.344059
(switching optimization to BFGS)
Iteration 5:   log likelihood = -22.334155
Iteration 6:   log likelihood = -22.333218
Iteration 7:   log likelihood = -22.333215
```

```
Iteration 8:   log likelihood = -22.333213

ARIMA regression

Sample:  2001q2 - 2009q4                        Number of obs      =        35
                                                Wald chi2(3)       =     23.66
Log likelihood = -22.33321                      Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
core         |
 cfa_mean_mc |
         F1. |  -1.274588   .2840103    -4.49   0.000    -1.831238   -.7179378
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |  -.0309663   .2620538    -0.12   0.906    -.5445824    .4826498
         L4. |  -.4382496   .2420956    -1.81   0.070    -.9127482    .0362489
-------------+----------------------------------------------------------------
      /sigma |   .4524489   .0636888     7.10   0.000     .3276212    .5772766
------------------------------------------------------------------------------

. arima D.core F.bal_mc, ar(2 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood =  -25.72849
Iteration 1:   log likelihood = -24.718003
Iteration 2:   log likelihood = -24.687772
Iteration 3:   log likelihood = -24.682228
Iteration 4:   log likelihood = -24.642422
(switching optimization to BFGS)
Iteration 5:   log likelihood = -24.641279
Iteration 6:   log likelihood =  -24.63851
Iteration 7:   log likelihood = -24.638151
Iteration 8:   log likelihood = -24.638142
Iteration 9:   log likelihood = -24.638142

ARIMA regression

Sample:  2001q2 - 2009q4                        Number of obs      =        35
                                                Wald chi2(3)       =     20.22
Log likelihood = -24.63814                      Prob > chi2        =    0.0002

------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
core         |
      bal_mc |
         F1. |   2.681578   .6960546     3.85   0.000     1.317336     4.04582
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |  -.0299268   .2066249    -0.14   0.885    -.4349042    .3750506
         L4. |  -.3302338   .2089844    -1.58   0.114    -.7398357    .0793681
-------------+----------------------------------------------------------------
      /sigma |   .4859701   .0548721     8.86   0.000     .3784229    .5935174
------------------------------------------------------------------------------

. arima D.core bal_mc, ar(2 4) noconstant

(setting optimization to BHHH)
```

```
Iteration 0:   log likelihood =  -23.33483
Iteration 1:   log likelihood = -21.872259
Iteration 2:   log likelihood = -21.775162
Iteration 3:   log likelihood = -21.772694
Iteration 4:   log likelihood = -21.759748
(switching optimization to BFGS)
Iteration 5:   log likelihood =  -21.75829
Iteration 6:   log likelihood = -21.758079
Iteration 7:   log likelihood = -21.758074
Iteration 8:   log likelihood = -21.758074

ARIMA regression

Sample:  2001q2 - 2010q1                        Number of obs      =        36
                                                Wald chi2(3)       =     21.10
Log likelihood = -21.75807                      Prob > chi2        =    0.0001

------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
core         |
      bal_mc |   2.737854   .7118402     3.85   0.000     1.342673    4.133035
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |   .3088575   .2570735     1.20   0.230    -.1949974    .8127123
         L4. |  -.2861659   .2324496    -1.23   0.218    -.7417588    .1694269
-------------+----------------------------------------------------------------
      /sigma |   .4400163   .0479585     9.17   0.000     .3460195    .5340132
------------------------------------------------------------------------------

. arima D.core L.bal_mc, ar(2 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood =  -25.01262
Iteration 1:   log likelihood = -24.582047
Iteration 2:   log likelihood = -24.573086
Iteration 3:   log likelihood = -24.556758
Iteration 4:   log likelihood = -24.556337
(switching optimization to BFGS)
Iteration 5:   log likelihood = -24.556332
Iteration 6:   log likelihood = -24.556305
Iteration 7:   log likelihood = -24.556304

ARIMA regression

Sample:  2001q2 - 2010q2                        Number of obs      =        37
                                                Wald chi2(3)       =     19.60
Log likelihood =  -24.5563                      Prob > chi2        =    0.0002

------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
core         |
      bal_mc |
         L1. |   2.203269   .7984097     2.76   0.006     .6384146    3.768123
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |   .3940394   .2248692     1.75   0.080    -.0466962     .834775
         L4. |   -.392257   .1971169    -1.99   0.047     -.778599    -.005915
-------------+----------------------------------------------------------------
```

```
      /sigma |   .4646147   .0528993     8.78   0.000     .3609341    .5682954
------------------------------------------------------------------------------

. arima D.core L2.bal_mc, ar(2 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -29.172142
Iteration 1:   log likelihood = -28.653181
Iteration 2:   log likelihood = -28.523797
Iteration 3:   log likelihood = -28.509965
Iteration 4:   log likelihood = -28.505622
(switching optimization to BFGS)
Iteration 5:   log likelihood = -28.504446
Iteration 6:   log likelihood = -28.500564
Iteration 7:   log likelihood = -28.500563

ARIMA regression

Sample:  2001q2 - 2010q3                        Number of obs      =        38
                                                Wald chi2(3)       =     15.45
Log likelihood = -28.50056                      Prob > chi2        =    0.0015

------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
core         |
      bal_mc |
         L2. |   .4828367   1.063933     0.45   0.650    -1.602433    2.568106
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |   .4824783    .192852     2.50   0.012     .1044955    .8604612
         L4. |  -.3413209   .1566195    -2.18   0.029    -.6482894   -.0343524
-------------+----------------------------------------------------------------
      /sigma |   .5070749   .0540749     9.38   0.000       .40109    .6130598
------------------------------------------------------------------------------

. arima D.core L3.bal_mc, ar(2 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -29.716556
Iteration 1:   log likelihood = -29.233498
Iteration 2:   log likelihood = -29.226312
Iteration 3:   log likelihood = -29.134673
Iteration 4:   log likelihood = -29.130308
(switching optimization to BFGS)
Iteration 5:   log likelihood = -29.129635
Iteration 6:   log likelihood = -29.129482
Iteration 7:   log likelihood = -29.129431
Iteration 8:   log likelihood = -29.129431

ARIMA regression

Sample:  2001q2 - 2010q4                        Number of obs      =        39
                                                Wald chi2(3)       =     11.83
Log likelihood = -29.12943                      Prob > chi2        =    0.0080

------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
core         |
      bal_mc |
```

```
         L3. |  -.4585571   1.122682    -0.41   0.683    -2.658973    1.741858
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |   .5125675   .2019435     2.54   0.011     .1167656    .9083695
         L4. |  -.3707524   .1496249    -2.48   0.013    -.6640118   -.0774929
-------------+----------------------------------------------------------------
      /sigma |   .5048617   .0592952     8.51   0.000     .3886452    .6210782
------------------------------------------------------------------------------

. arima D.core L4.bal_mc, ar(2 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood =  -27.94949
Iteration 1:   log likelihood = -27.209151
Iteration 2:   log likelihood = -27.165109
Iteration 3:   log likelihood = -27.149388
Iteration 4:   log likelihood = -27.109563
(switching optimization to BFGS)
Iteration 5:   log likelihood = -27.109215
Iteration 6:   log likelihood = -27.108725
Iteration 7:   log likelihood = -27.108719
Iteration 8:   log likelihood = -27.108718

ARIMA regression

Sample:  2001q3 - 2011q1                        Number of obs      =        39
                                                Wald chi2(3)       =     16.58
Log likelihood = -27.10872                      Prob > chi2        =    0.0009

------------------------------------------------------------------------------
             |                 OPG
      D.core |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
core         |
      bal_mc |
         L4. |  -1.710649    1.03624    -1.65   0.099    -3.741642    .3203429
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L2. |   .4827466   .1770876     2.73   0.006     .1356612    .8298319
         L4. |   -.174354   .2494339    -0.70   0.485    -.6632355    .3145274
-------------+----------------------------------------------------------------
      /sigma |   .4818201   .0525493     9.17   0.000     .3788253    .5848148
------------------------------------------------------------------------------

arima D.headline F.cfa_mean_mc, ar(1 3 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood =  -30.53672
Iteration 1:   log likelihood = -30.101851
Iteration 2:   log likelihood =  -30.03688
Iteration 3:   log likelihood = -29.858947
Iteration 4:   log likelihood = -29.805035
(switching optimization to BFGS)
Iteration 5:   log likelihood = -29.804372
Iteration 6:   log likelihood = -29.787919
Iteration 7:   log likelihood = -29.787781
Iteration 8:   log likelihood = -29.787683
Iteration 9:   log likelihood = -29.787677
Iteration 10:  log likelihood = -29.787677

ARIMA regression
```

```
Sample:  2001q2 - 2009q4                        Number of obs      =        35
                                                Wald chi2(4)       =      8.92
Log likelihood = -29.78768                      Prob > chi2        =    0.0630

------------------------------------------------------------------------------
             |                 OPG
  D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
headline     |
 cfa_mean_mc |
         F1. |  -1.330498   .6292207    -2.11   0.034    -2.563748   -.0972479
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   .2488617   .1642891     1.51   0.130    -.0731391    .5708624
         L3. |   .2598453   .2040544     1.27   0.203    -.1400939    .6597846
         L4. |  -.3332351   .2233947    -1.49   0.136    -.7710805    .1046104
-------------+----------------------------------------------------------------
      /sigma |   .5616233   .0684529     8.20   0.000      .427458    .6957885
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     35           .   -29.78768      5     69.57535    77.35209
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. arima D.headline cfa_mean_mc, ar(1 3 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -27.610141
Iteration 1:   log likelihood = -27.457648
Iteration 2:   log likelihood = -27.385287
Iteration 3:   log likelihood =   -27.3698
Iteration 4:   log likelihood = -27.368823
(switching optimization to BFGS)
Iteration 5:   log likelihood = -27.367788
Iteration 6:   log likelihood = -27.367685
Iteration 7:   log likelihood = -27.367681
Iteration 8:   log likelihood =  -27.36768

ARIMA regression

Sample:  2001q2 - 2010q1                        Number of obs      =        36
                                                Wald chi2(4)       =     19.52
Log likelihood = -27.36768                      Prob > chi2        =    0.0006

------------------------------------------------------------------------------
             |                 OPG
  D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
headline     |
 cfa_mean_mc |  -1.591049   .5387133    -2.95   0.003    -2.646908   -.5351904
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   .3105427   .1759442     1.77   0.078    -.0343016    .6553871
         L3. |   .2310116   .1953652     1.18   0.237    -.1518972    .6139204
         L4. |  -.4209912   .1414555    -2.98   0.003    -.6982389   -.1437436
-------------+----------------------------------------------------------------
      /sigma |   .5110626   .0741184     6.90   0.000     .3657933    .6563319
```

```
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     36           .   -27.36768      5     64.73536    72.65296
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. arima D.headline L.cfa_mean_mc, ar(1 3 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -30.859419
Iteration 1:   log likelihood = -30.810703
Iteration 2:   log likelihood =  -30.80345
Iteration 3:   log likelihood = -30.796131
Iteration 4:   log likelihood = -30.788692
(switching optimization to BFGS)
Iteration 5:   log likelihood = -30.788475
Iteration 6:   log likelihood = -30.788461
Iteration 7:   log likelihood = -30.788453
Iteration 8:   log likelihood = -30.788451

ARIMA regression

Sample:  2001q2 - 2010q2                        Number of obs      =        37
                                                Wald chi2(4)       =     26.12
Log likelihood = -30.78845                      Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |                 OPG
  D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
headline     |
 cfa_mean_mc |
         L1. |  -1.098588   .6379074    -1.72   0.085    -2.348863    .1516875
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   .4475949   .2026147     2.21   0.027     .0504774    .8447125
         L3. |   .2979831   .1768436     1.69   0.092     -.048624    .6445902
         L4. |  -.4637391    .161394    -2.87   0.004    -.7800656   -.1474126
-------------+----------------------------------------------------------------
      /sigma |    .547095   .0891405     6.14   0.000     .3723829    .7218071
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     37           .   -30.78845      5      71.5769    79.63149
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. arima D.headline L2.cfa_mean_mc, ar(1 3 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -34.363458
Iteration 1:   log likelihood = -34.003853
Iteration 2:   log likelihood = -33.525055
Iteration 3:   log likelihood = -33.507754
```

```
Iteration 4:   log likelihood = -33.505252
(switching optimization to BFGS)
Iteration 5:   log likelihood = -33.504845
Iteration 6:   log likelihood = -33.503801
Iteration 7:   log likelihood = -33.503788
Iteration 8:   log likelihood = -33.503784
Iteration 9:   log likelihood = -33.503784

ARIMA regression

Sample:  2001q2 - 2010q3                        Number of obs      =        38
                                                Wald chi2(4)       =     19.83
Log likelihood = -33.50378                      Prob > chi2        =    0.0005

------------------------------------------------------------------------------
             |                 OPG
  D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
headline     |
 cfa_mean_mc |
         L2. |   .3161972   .8984755     0.35   0.725    -1.444782    2.077177
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   .5396473   .1844078     2.93   0.003     .1782146      .90108
         L3. |   .3332354   .1541699     2.16   0.031     .0310679    .6354029
         L4. |  -.4596997   .1695928    -2.71   0.007    -.7920955   -.1273039
-------------+----------------------------------------------------------------
      /sigma |   .5743483   .0762273     7.53   0.000     .4249455    .7237511
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     38           .   -33.50378      5     77.00757     85.1955
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. arima D.headline L3.cfa_mean_mc, ar(1 3 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -34.670885
Iteration 1:   log likelihood =  -34.55567
Iteration 2:   log likelihood = -34.522748
Iteration 3:   log likelihood = -34.474183
Iteration 4:   log likelihood =  -34.47193
(switching optimization to BFGS)
Iteration 5:   log likelihood = -34.467354
Iteration 6:   log likelihood = -34.466125
Iteration 7:   log likelihood =  -34.46601
Iteration 8:   log likelihood = -34.466008

ARIMA regression

Sample:  2001q2 - 2010q4                        Number of obs      =        39
                                                Wald chi2(4)       =     16.34
Log likelihood = -34.46601                      Prob > chi2        =    0.0026

------------------------------------------------------------------------------
             |                 OPG
  D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
headline      |
 cfa_mean_mc  |
          L3. |   .3811555   .6973139     0.55   0.585    -.9855546    1.747866
--------------+----------------------------------------------------------------
ARMA          |
           ar |
          L1. |   .5173329   .1899083     2.72   0.006     .1451194    .8895464
          L3. |   .3453641   .1593146     2.17   0.030     .0331131     .657615
          L4. |   -.467963   .1710404    -2.74   0.006     -.803196   -.1327301
--------------+----------------------------------------------------------------
       /sigma |   .5757936   .0783958     7.34   0.000     .4221406    .7294465
-------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     39           .   -34.46601      5     78.93202    87.24982
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. arima D.headline L4.cfa_mean_mc, ar(1 3 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -38.363039
Iteration 1:   log likelihood = -36.937178
Iteration 2:   log likelihood = -36.628719
Iteration 3:   log likelihood = -36.553765
Iteration 4:   log likelihood = -36.532002
(switching optimization to BFGS)
Iteration 5:   log likelihood = -36.508082
Iteration 6:   log likelihood = -36.497021
Iteration 7:   log likelihood = -36.496129
Iteration 8:   log likelihood = -36.496113
Iteration 9:   log likelihood = -36.496108
Iteration 10:  log likelihood = -36.496108

ARIMA regression

Sample:  2001q3 - 2011q1                        Number of obs      =        39
                                                Wald chi2(4)       =     23.03
Log likelihood = -36.49611                      Prob > chi2        =    0.0001

-------------------------------------------------------------------------------
              |                 OPG
   D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
headline      |
 cfa_mean_mc  |
          L4. |  -.2076268   .6988858    -0.30   0.766    -1.577418    1.162164
--------------+----------------------------------------------------------------
ARMA          |
           ar |
          L1. |   .5897085   .1595985     3.69   0.000     .2769011    .9025158
          L3. |   .2390387   .1751218     1.36   0.172    -.1041937    .5822711
          L4. |  -.4523767   .1832835    -2.47   0.014    -.8116057   -.0931476
--------------+----------------------------------------------------------------
       /sigma |   .6062201   .0843856     7.18   0.000     .4408273    .7716128
-------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
```

```
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     39           .   -36.49611      5     82.99222    91.31002
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. arima D.headline F.bal_mc, ar(1 3 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -32.334451
Iteration 1:   log likelihood = -31.477203
Iteration 2:   log likelihood = -31.375579
Iteration 3:   log likelihood =  -31.15266
Iteration 4:   log likelihood = -31.095131
(switching optimization to BFGS)
Iteration 5:   log likelihood = -31.071602
Iteration 6:   log likelihood = -31.037519
Iteration 7:   log likelihood = -31.036138
Iteration 8:   log likelihood = -31.035488
Iteration 9:   log likelihood = -31.035483
Iteration 10:  log likelihood = -31.035483

ARIMA regression

Sample:  2001q2 - 2009q4                        Number of obs      =        35
                                                Wald chi2(4)       =      9.21
Log likelihood = -31.03548                      Prob > chi2        =    0.0560

------------------------------------------------------------------------------
             |                 OPG
  D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
headline     |
      bal_mc |
         F1. |   1.652173   1.203096     1.37   0.170    -.7058518    4.010198
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   .4033928   .1900473     2.12   0.034     .0309068    .7758787
         L3. |   .2968096   .1708794     1.74   0.082    -.0381079    .6317272
         L4. |  -.3787565   .2050458    -1.85   0.065     -.780639    .0231259
-------------+----------------------------------------------------------------
      /sigma |   .5801273   .0759591     7.64   0.000     .4312502    .7290044
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     35           .   -31.03548      5     72.07097    79.84771
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. arima D.headline bal_mc, ar(1 3 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -30.273744
Iteration 1:   log likelihood = -29.998169
Iteration 2:   log likelihood = -29.782888
Iteration 3:   log likelihood = -29.659852
Iteration 4:   log likelihood = -29.630605
(switching optimization to BFGS)
Iteration 5:   log likelihood = -29.618954
```

```
Iteration 6:   log likelihood = -29.614483
Iteration 7:   log likelihood = -29.614399
Iteration 8:   log likelihood = -29.614341
Iteration 9:   log likelihood = -29.614339

ARIMA regression

Sample:  2001q2 - 2010q1                        Number of obs      =        36
                                                Wald chi2(4)       =     14.46
Log likelihood = -29.61434                      Prob > chi2        =    0.0060

------------------------------------------------------------------------------
             |                 OPG
  D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
headline     |
      bal_mc |   2.678937   1.264761     2.12   0.034     .2000499    5.157823
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |    .387787   .2185716     1.77   0.076    -.0406055    .8161795
         L3. |   .2638187   .2001984     1.32   0.188     -.128563    .6562003
         L4. |  -.3555263   .1668669    -2.13   0.033    -.6825795   -.0284731
-------------+----------------------------------------------------------------
      /sigma |   .5451421   .0785824     6.94   0.000     .3911234    .6991608
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     36           .   -29.61434      5     69.22868    77.14627
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. arima D.headline L.bal_mc, ar(1 3 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -30.422633
Iteration 1:   log likelihood =  -30.37312
Iteration 2:   log likelihood = -30.342676
Iteration 3:   log likelihood = -30.320568
Iteration 4:   log likelihood = -30.316594
(switching optimization to BFGS)
Iteration 5:   log likelihood = -30.314952
Iteration 6:   log likelihood = -30.313851
Iteration 7:   log likelihood = -30.313838
Iteration 8:   log likelihood = -30.313838

ARIMA regression

Sample:  2001q2 - 2010q2                        Number of obs      =        37
                                                Wald chi2(4)       =     33.50
Log likelihood = -30.31384                      Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |                 OPG
  D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
headline     |
      bal_mc |
         L1. |   2.385347   1.024805     2.33   0.020     .3767659    4.393927
-------------+----------------------------------------------------------------
```

```
ARMA         |
          ar |
         L1. |   .4971583   .1899436     2.62   0.009     .1248757     .869441
         L3. |   .3942608   .1561075     2.53   0.012     .0882957    .7002258
         L4. |  -.5002303   .1512679    -3.31   0.001    -.7967099   -.2037507
-------------+----------------------------------------------------------------
      /sigma |   .5379349   .0781955     6.88   0.000     .3846745    .6911953
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     37           .   -30.31384      5     70.62768    78.68227
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. arima D.headline L2.bal_mc, ar(1 3 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -33.953309
Iteration 1:   log likelihood = -33.775296
Iteration 2:   log likelihood = -33.664219
Iteration 3:   log likelihood = -33.518166
Iteration 4:   log likelihood = -33.517121
(switching optimization to BFGS)
Iteration 5:   log likelihood =  -33.50668
Iteration 6:   log likelihood = -33.506223
Iteration 7:   log likelihood = -33.506215
Iteration 8:   log likelihood =  -33.50621
Iteration 9:   log likelihood =  -33.50621

ARIMA regression

Sample:  2001q2 - 2010q3                        Number of obs      =        38
                                                Wald chi2(4)       =     18.02
Log likelihood = -33.50621                      Prob > chi2        =    0.0012

------------------------------------------------------------------------------
             |                 OPG
  D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
headline     |
      bal_mc |
         L2. |  -.5813047   1.361897    -0.43   0.669    -3.250574    2.087965
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   .5231467   .1797686     2.91   0.004     .1708068    .8754865
         L3. |   .3205862   .1551726     2.07   0.039     .0164534     .624719
         L4. |   -.458145   .1722994    -2.66   0.008    -.7958456   -.1204444
-------------+----------------------------------------------------------------
      /sigma |   .5746655   .0771527     7.45   0.000      .423449     .725882
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     38           .   -33.50621      5     77.01242    85.20035
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note
```

```
. arima D.headline L3.bal_mc, ar(1 3 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -34.234914
Iteration 1:   log likelihood = -34.099162
Iteration 2:   log likelihood = -34.061929
Iteration 3:   log likelihood = -34.038921
Iteration 4:   log likelihood = -34.029864
(switching optimization to BFGS)
Iteration 5:   log likelihood = -34.023077
Iteration 6:   log likelihood = -34.015187
Iteration 7:   log likelihood = -34.014923
Iteration 8:   log likelihood =  -34.01492

ARIMA regression

Sample:  2001q2 - 2010q4                        Number of obs      =        39
                                                Wald chi2(4)       =     14.62
Log likelihood = -34.01492                      Prob > chi2        =    0.0056

------------------------------------------------------------------------------
             |                 OPG
  D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
headline     |
      bal_mc |
         L3. |   -1.23334   1.477745    -0.83   0.404    -4.129667    1.662988
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   .4885949   .2036507     2.40   0.016     .0894469    .8877429
         L3. |   .3508654   .1475674     2.38   0.017     .0616386    .6400922
         L4. |   -.479028   .1706367    -2.81   0.005    -.8134697   -.1445863
-------------+----------------------------------------------------------------
      /sigma |   .5688609     .07616     7.47   0.000       .41959    .7181318
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     39           .   -34.01492      5     78.02984    86.34765
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. arima D.headline L4.bal_mc, ar(1 3 4) noconstant

(setting optimization to BHHH)
Iteration 0:   log likelihood = -37.278971
Iteration 1:   log likelihood = -36.020865
Iteration 2:   log likelihood = -35.845964
Iteration 3:   log likelihood = -35.814448
Iteration 4:   log likelihood = -35.808401
(switching optimization to BFGS)
Iteration 5:   log likelihood = -35.807071
Iteration 6:   log likelihood = -35.806437
Iteration 7:   log likelihood =  -35.80635
Iteration 8:   log likelihood = -35.806336
Iteration 9:   log likelihood = -35.806336

ARIMA regression
```

```
Sample:  2001q3 - 2011q1                        Number of obs      =        39
                                                Wald chi2(4)       =     18.95
Log likelihood = -35.80634                      Prob > chi2        =    0.0008

------------------------------------------------------------------------------
             |                 OPG
  D.headline |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
headline     |
      bal_mc |
         L4. |  -1.596792   1.382465    -1.16   0.248    -4.306373     1.11279
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |   .5296405   .1788835     2.96   0.003     .1790353    .8802456
         L3. |   .2214304   .1860393     1.19   0.234    -.1431999    .5860607
         L4. |  -.3282773   .2410866    -1.36   0.173    -.8007984    .1442437
-------------+----------------------------------------------------------------
      /sigma |   .5998979   .0780078     7.69   0.000     .4470053    .7527904
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |     39           .   -35.80634      5     81.61267    89.93048
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note
```