ASSESSING SHOCKS TO INFLATION EXPECTATIONS IN A DATA RICH ENVIRONMENT

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Abstract

We carry out a semi-structural analysis aiming at estimating the macroeconomic effects of shocks to inflation expectations. We estimate a Structural Factor Model for the euro area, which includes more than 200 quarterly variables. By using such a wide information set we are able to: 1) identify structural shocks which a small-scale VAR would not be able to retrieve; 2) avoid any variable selection bias; 3) exploit as many variables as we need to identify the shocks, and study their responses in a unified framework. We find that the euro area economy can be well described by four structural shocks, and assume that one of these shocks has an expectational nature. To achieve identification of this shock, we use a mix of zero and sign restrictions. Our results confirm an important role for inflation expectations in affecting the dynamics of real and nominal variables.

Keywords: Structural Factor Models, Inflation expectations.

JEL classification: C32, C53.

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The views expressed in this paper do not necessarily reflect those of the European Central Bank.
1 Introduction

The importance of inflation expectations in macroeconomics cannot be overstated. Economic theory has reached a consensus suggesting that economic expectations about inflation are a fundamental determinant of inflation and of macroeconomic outcomes in general. For example, consumer behavior is normally based on an Euler equation where the actual decisions are taken on the basis of expected inflation. Similarly, policymakers are often assumed, either directly or indirectly, to conduct their maker economic policies in a forward-looking manner.

Professional and consumer surveys of inflation expectations have been shown to provide valuable information about future developments of inflation. Central banks in particular closely monitor inflation expectations because these are an important information source to conduct monetary policy in a forward-looking manner and because inflation expectations anchor the Phillips curve, therefore determining the structure of the economy in which policies operate. Among the possible consequences of movements in expectations are changes in how the economy reacts to exogenous shocks to prices and the sacrifice ratio of monetary policy. Following these considerations, it is not surprising that expectations in surveys are widely used by policy makers in taking their decisions.

Information about expectations may be useful for the policymaker, but this does not necessarily mean that shocks to expectations have a strong impact on inflation itself. It may well be that the most of the variations observed in the service can be attributed to other variables, and that surveys are simply a good compendium of a very wide information set.

In contrast to the clear indications of economic theory and the practical importance of expectations, the empirical determination of the importance of expectations has encountered a number of difficulties. The first problem is related to the availability of data about expectations. Surveys about expectations are becoming widely available, but they normally refer to expectations of the year on year inflation. When mixed with quarterly data, which are the
empirical counterpart of current macroeconomic models including expectations, they produce impulse responses which are of difficult interpretation. Second, the effect of expectation and shocks has always been evaluated in the context of relatively small scale models, leaving open the question of whether the identified shocks are true macroeconomic disturbances or are produced as a result of a too small information set. Third, in the predominant structural VAR literature the identification of shocks often relies on very specific (and sometimes incredible) restrictions, sometimes imposed for the sake of simplicity and tractability of the model.

In this paper, we try to identify the role of expectations by dealing to some extent with the problems described above. We construct a series of expectations based on the Eurozone Barometer quarterly forecast for inflation in the euro area which we believe is a good indicator of quarter on quarter inflation expectations. We use a restricted version of the dynamic factor model introduced by Forni and Lippi (2001), which generalizes the model by Stock and Watson (2002). The factor model allows us to use a large number of macroeconomic variables, thus limiting the possibility that our shocks are influenced by omitted variables. Finally, our identification scheme is based on a mix of equality and inequality constraints which may make the behavior of variables compatible with a wide class of New Keynesian models. We are therefore able to achieve a robust identification of the effects of an expectation shock.

The paper is structured as follows. In Section 2 we review the literature on models using survey expectations. In Section 3 we describe the dataset. In Section 4 we present the model and its assumptions. In Section 5 we outline the estimation procedure. In Section 6 we discuss the determination of the number of common factors included in the model. In Section 7 we outline our identification strategy. In Section 8 we discuss the estimation results. In Section 9 we conclude and discuss policy implications.
2 Literature review

This short literature review focuses on models using survey expectations. The use of surveys has the advantage of not requiring the assumption of rational expectations, an assumption which has been central for example in many estimations of the Phillips curve. This assumption allows estimation with GMM, but the inflation parameter is not very precisely estimated and in our case it would amount to assuming away the central question of all paper, namely the relationship between expectations and inflation.

Structural VARs have been most often used to identify expectational shocks. For example, Leduc, Sill and Stark (2007) estimate a structural VAR including inflation surveys for the United States. Clark and Davig (2008) use at three-variate structural VAR including inflation, short-term and long-term inflation expectations. Paloviita and Viren (2005) analyze the interactions between inflation, inflation expectations and output gap in a trivariate structural VAR. Kelly (2008) discusses the direction of causality between inflation and inflation expectations in the UK on the basis of Granger causality tests. The advantage of these models is that they do not require the imposition of excessively stringent identifying restrictions and are able to take into account the complex interrelations among variables. However, in the case of expectations, such models have a drawback: it may be expected to the policymakers and agents decide on the base of a wide information set, which cannot be easily accommodated into a structural VAR. The identified shocks may therefore be a result of missing information. Trying to find a solution to this problem, Koop and Onorante (2011) address the curse of dimensionality and investigate the determinants of expectations by putting structural VAR models in the context of dynamic model averaging.

An alternative solution to the curse of dimensionality is the use of factor models. In particular dynamic factor models, as introduced by Forni and Lippi (2001), are particularly suited to provide estimations including a large number of macroeconomic variables, while keeping the
amount of restrictions which is necessary to identify a shock within acceptable limits. They have the further advantage of being able to identify a reduced number of macroeconomic shocks, despite the richness of the data environment in which they operate, therefore allowing an easier mapping of the few identified shocks with the small number of disturbances typical of theoretical models. These models have been successfully applied in different domains, but to our knowledge not to the identification of an expectational shock on inflation.

The choice between a structural factor model and a structural VAR has advantages and disadvantages, that we describe here. The advantages are those described in Forni and Gambetti (2010a) and Forni and Gambetti (2010b). First, in a factor model the number of shocks in the economy is endogenously determined, therefore providing useful guidelines for building macroeconomic models, while in a VAR there are as many shocks as variables. Second, compared to a structural VAR factor models make use of a very large amount of information; this may be important in our case because we know that the policymakers base their decisions and economic agents form their expectations on the basis of large amounts of information, and we want our expectational shocks to be real disturbances and not the result of omitted variables in the estimated model. There are, however, different ways of dealing with the curse of dimensionality within a VAR framework, for example by using model averaging. Third, the presence of a large macroeconomic set of variables allows for the computation of all relevant impulse responses. The main disadvantage of factor models, described in Stock and Watson (2005), is that they impose a relevant amount of restrictions on the data, while a structural VAR does not, and are therefore less general in describing the interaction among variables. On balance we think that both techniques are worth trying, and we concentrate here on the factor model.

The other problem in estimating models including inflation expectations is that, while the theoretical models generally make use of quarterly variables, there are no observable expectations at this frequency. Surveys are conducted at quarterly frequency but the forecasters are asked for their expected inflation rate on a year on year basis. This makes it difficult to iden-
tify an expectation shock in the quarterly model, because a change in expectations between surveys can be attributed to new expectations about any of the quarters included in the yearly horizon, or simply to base effects if recent data did not confirm the previous expectations for the past quarter.

In this paper, deal with both issues outlined above by proposing a way to derive quarterly expectations from an existing survey, and using these computed expectations with a large number of other macroeconomic variables to identify shocks to inflation expectations.

3 The dataset

We consider a panel of 235 quarterly time series with quarterly observations from 2002Q2 to 2010Q4 (36 obs.). The dataset contains inflation and activity measures, labour market indicators, and financial variables both at the country level (the 8 euro area countries included are DE, ES, FR, IT, NL, BE, FI and IE) and for the aggregate EA. Some financial indicators are included only at the aggregate level, however the financial sector is overall well represented in the panel. Key economic indicators for the US, UK and Japan are also included, together with oil and commodity prices. The data sources are the OECD (mainly the OECD Economic Outlook and the Main Economic Indicators databases), EUROSTAT, the IMF Financial Statistics, Datastream and Reuters.

Quarter-on-quarter inflation expectations are built on the basis of the Eurozone Barometer quarterly forecast for inflation in the euro area. This monthly survey, which takes place on the second Monday of each month, provides macroeconomic and financial forecasts for the current and several forthcoming quarters.

From this survey we construct our measure of quarter-on-quarter expectations. The survey

1 A detailed description of the dataset and data sources for each indicator is given in the Appendix.
conducted in the second month of each quarter is of particular interest: on the one hand, very little about the current quarter is known (only the flash estimate for inflation in the first month of the quarter has been released, a measure characterized by uncertainty and possible future revisions); on the other hand, macroeconomic data (including inflation and GDP) have just been published for the previous quarter, and therefore are known to the forecasters. We can then subtract the first three quarters of data from the year-on-year expectations ending in the current quarter and obtain the expectations of the inflation rate in the current quarter. The survey conducted in the second month has the additional advantage of being conducted approximately in the middle of the quarter, therefore it is a particularly good indicator of expectations for the period. This is important, since current expectations are those to determine the inflation outcomes in many versions of the Phillips curve. As a robustness check, we repeat our estimations using expectations for the following quarter, as implied by the forward-looking Phillips curve. However, these alternative measure does not have the same desirable properties, because only two quarters in the year-on-year horizon are actually data.

Nonstationary data have been seasonally adjusted when necessary and differentiated to obtain stationarity as required by the model. On the basis of test statistics indicating that inflation and interest rates are stationary, we did not differentiate these series. This differs from the standard data transformation in Stock and Watson (2005), who differentiate inflation and interest rate for the US.

4 The Structural Factor Model

We estimate the Structural Factor Model (SFM) by Forni et al. (2009), which in turn is a special case of the model in Forni and Lippi (2001) and Forni et al. (2005). We refer to these papers for a detailed description of the assumptions of the model, and limit ourselves to an outline of the main features.
Denote by \( x \) a panel of \( n \) stationary time series, where both the \( n \) and \( T \) dimensions are very large (virtually infinite). In a factor model, each variable \( x_{it} \) is assumed to be the sum of two unobservable components: the common component \( \chi_{it} \) and the idiosyncratic component \( \xi_{it} \). An important feature of this factor model and the closely related models by Stock and Watson (2002) and Bai (2003) is that the idiosyncratic components are allowed to be mildly cross-correlated (i.e. the factor model is *approximate*, as opposed to *exact*). The common component is assumed to be driven by \( q \) shocks \( u_t = (u_{1t} \ldots u_{qt})' \) which affect all variables in the panel, also referred to as *dynamic* common factors, with \( q \ll n \). Formally:

\[
x_t = \chi_t + \xi_t = B(L)u_t + \xi_t,
\]

where \( \chi_t = (\chi_{1t} \ldots \chi_{nt})' \), \( \xi_t = (\xi_{1t} \ldots \xi_{nt})' \), and \( B(L) \) is a one-sided \( n \times q \) filter. Eq. 1 is called *dynamic representation* of the factor model. An alternative representation, which is called *static representation*, is the following:

\[
x_t = \Lambda F_t + \xi_t.
\]

where the \( r > q \) entries of \( F_t \) are the *static* common factors, and \( \Lambda \) is the \( n \times r \) matrix of factor loadings.

The link between the two representations is given by defining the \( r \times 1 \) vector of the static common factors in terms of the shocks, as follows:

\[
F_t = N(L)H u_t
\]

where \( N(L) \) is an \( r \times r \) matrix polynomial and \( H \) is a maximum rank \( r \times q \) matrix.

Finally, it is assumed that \( N(L) \) results from inversion of the VAR\( (m) \) \( F_t = (I_r - A L - \ldots - A_m L^m)^{-1} \epsilon_t \). For simplicity, we assume \( m = 1 \), so that \( N(L) = (I_r - A L)^{-1} \), where \( I_r \) is the \( r \)-dimensional identity matrix, and \( A \) is an \( r \times r \) matrix. Notice that \( \epsilon_t = H u_t \), i.e. the residuals
of the VAR on the static factors have reduced rank \( q \). More precisely, \( \epsilon_t \in \text{span} \{ u_t \} \), i.e. the residuals belong to a \( q \)-dimensional linear space generated by the dynamic factors. Notice also that these latter, as well as the static common factors, are only identified up to a rotation.

5 Estimation

The estimation of the SFM is based on Giannone et al. (2004) and Forni et al. (2009). We make use of the static representation (2) together with the VAR(1) specification of the static factors:

\[
x_t = \Lambda F_t + \xi_t, \\
F_t = AF_{t-1} + \epsilon_t, \quad \text{with} \quad \epsilon_t = Hu_t.
\]

This state-space representation is equivalent to the dynamic representation (1), with filters defined as

\[
B(L) = \Lambda (I_r - AL)^{-1}H.
\]

Before estimating (4)-(5), the number of dynamic factors \( q \) and the number of static factors \( r \) have to be determined (see Section 6).

The estimation of the SFM is in four steps.

**STEP 1** Given a consistent estimator of the covariance matrix \( \hat{\Gamma}_x \), the static factors \( F_t \) are consistently estimated as the \( r \) largest principal components as in Stock and Watson (2002) and Bai (2003). We have also a consistent estimate of the loadings \( \Lambda \).\(^2\)

\(^2\)Alternatively, we can estimate the static factors as the \( r \) largest generalized principal components as in Forni et al. (2005). In this case we need consistent estimators of the variance-covariance matrices of the common and the idiosyncratic components, which can be obtained from the spectral decomposition of a consistent estimator of the spectral density matrix of the observables. The method by Bai (2003) does not require the spectral decomposition, used instead in Forni et al. (2005), and it is, in this sense, a static method. Although in theory we may miss some relevant information by computing only static principal components, in practice...
STEP 2 Given an estimate of the static factors $F_t$ and of the loadings $\Lambda$, we need to estimate equation (5) in order to have an estimate of the dynamic factors. This simply entails the estimation of a VAR on the estimated static factors.

STEP 3 Since the estimated residuals $\hat{\epsilon}_t$ have reduced rank, as they belong to the space spanned by the $q$ dynamic factors, principal components can be used to obtain a consistent estimate of the dynamic factors.

STEP 4 Since the static factors are unobserved and therefore estimated up to a unitary transformation $G$, then the reduced rank matrix $H$ is estimated up to the same transformation with the addition of a $q \times q$ unitary transformation $R$ that comes from principal component analysis. To interpret the dynamic factors as structural shocks, $R$ has to be identified by imposing economic meaningful restrictions. This is the procedure proposed in Forni et al. (2009), which we adopt in this paper. In order to give a structural interpretation to the dynamic factors, we restrict the entries of the rotation matrix $R$ by means of standard techniques used in the Structural VAR literature. In particular, we adopt an identification scheme which partially identifies only one shock by means of sign restrictions, short-run and long-run restrictions (see Section 8 for a detailed description of the identification assumptions in each of the exercises).

To account for estimation uncertainty, we adopt a two-step bootstrap procedure. We construct artificial data by extracting the shocks from a Normal distribution and construct the simulated common components by applying the filters given by the (non structural) impulse responses. In the second step, we adopt a standard non-overlapping block bootstrap technique for the idiosyncratic parts, which we add to the artificial common components. For each artificial sample we repeat the estimation and obtain non-structural impulse responses, which are then identified by imposing our identification assumptions. For each draw we retain the evidence is mixed and it has been shown that the two estimation methods deliver similar results in terms of forecasting performance (see e.g. Boivin and Ng, 2005; D'Agostino and Giannone, 2006).

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3We present results based on 1000 bootstrap replications.
4In the present paper we partition the idiosyncratic component into 5-year blocks.
first set of impulse responses which satisfies our restrictions. We compute point estimates by considering the rotation yielding the impulse response for the inflation expectations series, which is closest to the median response for this key variable obtained via bootstrap (see Fry and Pagan (2007)).

6 Determining the number of factors

Determining the number of factors is a crucial model selection step. In particular, the number of dynamic factors included in the model corresponds to the number of shocks which play a role in shaping the business cycle, and has therefore an important structural interpretation.

For determining the number $r$ of static common factors, we apply the widely used criterion proposed by Bai and Ng (2002), which yields $r = 4$. The same $IC$ criteria applied as suggested by Alessi et al. (2010) suggest $r = 10$. However, given that we only have 36 time observations, we cannot afford including 10 principal components, on which we estimate a VAR, therefore we stick to $r = 4$.

For determining the number $q$ of structural shocks, we apply several criteria, which have been recently proposed in the literature by Hallin and Liška (2007), Bai and Ng (2007), Amengual and Watson (2007), and Onatski (2009).

Table I reports the results of the Onatski test, i.e the p-values of the null hypothesis of $q = q_0$ shocks versus the alternative of $q_0 < q \leq q_1$ shocks. The test parameters have been set so to identify the number of shocks driving the dynamics at business cycle frequencies, i.e. between 6 and 32 quarters according to the definition given by Burns and Mitchell (1946). The null of zero common shocks is rejected against all alternatives at the 10% level, however whether the null can be rejected often depends on the alternative. In particular, the null of $q = 3$ cannot be

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5 We set an upper bound (10) to the number of rotation matrices extracted for each draw.

6 On our sample, this means $s_j = [4 \cdots 19]$. The outcome of the test is the same if frequencies between 2 and 12 years are included.
rejected against the alternative of $q = 4$, but if the alternative is either 4 or 5 shocks, then the
null of 3 shocks can be rejected. Indeed, when testing the null of $q = 5$ versus the alternatives
$q = 6$ and $5 < q \leq 7$, the null cannot be rejected against any alternative, with very high
p-values.
The criterion proposed by Hallin and Liška (2007) indicates the presence of 3 shocks for all
of the proposed penalty functions when only business cycle frequencies are included (and up
to 6 shocks when frequencies are not cut).
The criterion by Bai and Ng (2007) requires a prior consistent estimate of $r$. Referring to the
results of the criteria implemented for determining $r$, we set either $r = 5$ or $r = 10$. In the
first case, the test suggests $q = 3$, while in the second case it suggests $q = 4$.
Finally, the test proposed by Amengual and Watson (2007) extends the test by Bai and Ng
(2002) to estimate the number of dynamic factors $q$ by applying the information criterion to
the covariance matrix of residuals from a VAR for the static factors. This procedure yields
$q = 2$, $q = 3$ or $q = 7$ (7 being the maximum number of shocks allowed), depending on the
version of the criterion. Implementing the modification proposed in Alessi et al. (2010) within
the Amengual-Watson criterion yields always $q = 2$.
In summary, existing criteria for determining the number of shocks give different results.
Overall, there appear to be 2 or 3 main sources of business cycle fluctuations, which are al-
ways identified as common drivers, and at least 1-2 more shocks which are important enough
to be detected only by some of the criteria. Given the objective of this paper, i.e. investigating
the effects of shocks to inflation expectations, we conclude in favor of a four-shock specifi-
cation. Indeed, it is reasonable to assume that shocks to inflation expectations would not be
among the main sources of business cycle fluctuations, nevertheless we believe them to be
well represented in the dataset and want to be sure we include them in the model. As shown in
Table 2 which reports the percentage of variance explained by the first 10 dynamic common
factors, 4 common shocks explain 48% of the variance of the dataset. Finally, we estimate the
VAR on the static factors including only one lag, which is not over-demanding on a 4-variable
VAR given the short time dimension.

7 Identification of the shock on expectations

In this section we use a very simple neokeynesian DSGE model to illustrate the restrictions that we are going to implement to identify expectational shocks. As we are not aiming to fully identify an economic model, we are only interested in collecting stylized facts and behavioral restrictions that we can use for identification. In this sense, our identification strategy is similar to the one of a structural VAR, where restrictions are kept to a minimum.

For illustration purposes, take a standard three equations macroeconomic model as in Woodford, augmented with an expectational shock:

\[
\begin{align*}
y_t &= \delta y_{t-1} + (1 - \delta) y_{t+1} + \sigma (r - \pi^e) + \epsilon_y \\
\pi_t &= \alpha \pi_{t-1} + (1 - \alpha) \pi^e + ky_t + \epsilon_t \\
r &= \gamma_1 \pi_t + \gamma_2 y_t \\
\epsilon_t &= \rho \epsilon_{t-1} + \epsilon_e
\end{align*}
\]

A positive shock to inflation expectations shifts upwards the Phillips curve, increasing inflation and reducing output. For normal parameterizations monetary policy responds by increasing the interest rate to counteract the additional inflation. In order to distinguish the expectational shock from other supply-side, cost-push shocks stemming from the labor market or from external sources we impose that there is no contemporaneous increase in oil price, row materials or in wages. The exact dynamic of these variables may change in more sophisticated models due to the presence of nominal rigidities or habit persistence. As we want to have gen-
eral restrictions, we consider the impulse responses produced by three different neokeynesian models: the standard three-equation Woodford model outlined above, the model of Rabanal and Rubio-Ramirez (2003) featuring sticky prices but still without capital and the model by Smets and Wouters including capital, habits persistence and several different sources of rigidities, a model specifically designed to explain and forecast observed data series. Since we want to use survey expectations, which are not necessarily rational expectations, we have slightly changed the models and models inflation expectations as an exogenous shock with autocorrelation of 0.9 as estimated on the basis of univariate regressions of the surveys on their own past. Figures 1 to 3 report the impulse response functions resulting from each of the three models considered.

Looking at the common features of these impulse responses, our chosen behavioral restrictions are as follows: at impact and for one lag, a positive shock in inflation expectations increases inflation and increases the interest-rate. We also take into account the fact that real economies are driven by a multiplicity of shocks which goes beyond the single shock driving simple real business cycles and is even more complex than the reality depicted in more sophisticated models like Smets and Wouters (2007). In particular, the inflation expectation shock should not be confused with another supply shock. We impose therefore the additional restriction that the shock has no effect at impact on oil prices and raw materials. The table below summarizes the set of zero and sign restrictions we impose.

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<td>+</td>
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<tr>
<td>oil price</td>
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<tr>
<td>raw materials</td>
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8 Results

The impulse response functions are reported in Figures 4 and 5, along with one standard deviation confidence bands computed with bootstrap. Standard results emerge for the main macroeconomic aggregates. First, an increase in quarter on quarter inflation expectations has a cumulative permanent effect on US inflation expectations themselves, which therefore show as expected a relevant degree of persistence even when measured at the quarterly level. Second, the expectation factor acts in a similar way to a supply-side shock, reducing output and increasing the price level in the short run. The cumulative response of monetary policy is as high as a 5% increase in the interest rate over the first three years, an increase which is not surprising if one considers that our shock is of one percent within a quarter.

The cumulated impulse response functions are also reported for two key components of output, namely consumption and investment, and four labor market variables.

Private consumption and investment show similar patterns to output, with a short-lived increase at impact followed by a cumulative decrease reaching as low as -2%. Turning to labor markets, we find that compensation per employee follows the shocks to inflation expectations with a relatively long lag, becoming significant after three quarters and remaining significantly above zero for about three years. The dynamics of employment are somehow a puzzle, with our impulse response showing that an increase in inflation expectations employment increases employment in the short run.

We now turn to the variance decomposition in order to assess the importance of the expectation shock on two main macroeconomic variables. The expectations factor has a relevant effect on prices, accounting for about 25% of the variance in the short run, an effect remaining fairly stable over time. The variance decomposition of output shows a smoother effect, starting at about 4% within the first quarter and progressively increasing to almost 20% after two years, remaining broadly stable afterwards.
9 Conclusions

In this paper we have assessed the effects of shocks to inflation expectations, on activity, prices and labor market variables in the euro area. Overall, our results confirm an important role for inflation expectations in affecting the dynamics of real and nominal variables. The particular measure of quarter on quarter expectations we used, which allows us to correctly represent expectational shocks, and the relatively loose restrictions corresponding to a wide class of existing models, along with a wide range of robustness checks we performed on both identification, choice of the number of factors and sign restrictions, suggests that these results are robust and that the emphasis of inflation expectations typical of current macroeconomic models is probably not exaggerated. These conclusions are of particular importance in the current juncture, as the close monitoring of inflation expectations can provide useful information for the conduction of monetary policy in the euro area in a period of swinging commodity prices.
References


## Data sources and definitions

<table>
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<th>Name</th>
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<th>Aggregate EA</th>
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<td>OEO</td>
<td>EUROSTAT</td>
<td>OEO</td>
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<tr>
<td>PCR</td>
<td>Private final consumption expenditure, vol.</td>
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<td>ECB</td>
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<td>Datastream</td>
<td>IMF</td>
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<td>ECB</td>
<td>ECB</td>
<td>OECD</td>
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<td>Crude oil price, Brent</td>
<td>OEO</td>
<td>Eurozone</td>
<td>Barometer</td>
</tr>
<tr>
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<td>Raw material price index (excl. energy)</td>
<td>OECD</td>
<td></td>
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<tr>
<td>EXPECT</td>
<td>Inflation expectations</td>
<td>Eurozone</td>
<td></td>
<td>Barometer</td>
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Table 1: Results of the Onatski test for the number of shocks (p-values of the null $q = q_0$ against the alternative $q_0 < q \leq q_1$).

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<th>$q_1$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_0$</td>
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<td>0</td>
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<td>0.022</td>
<td>0.03</td>
<td>0.038</td>
<td>0.045</td>
<td>0.053</td>
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<td>0.31</td>
<td>0.129</td>
<td>0.152</td>
<td>0.176</td>
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<tr>
<td>2</td>
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<td>0.232</td>
<td>0.102</td>
<td>0.129</td>
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<td>0.801</td>
<td>0.074</td>
<td>0.102</td>
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Table 2: Cumulated variance explained by the first 10 dynamic factors.

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<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
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<tbody>
<tr>
<td></td>
<td>22.9</td>
<td>36.9</td>
<td>44.1</td>
<td>47.0</td>
<td>48.0</td>
<td>48.8</td>
<td>49.2</td>
<td>49.3</td>
<td>49.6</td>
<td>49.8</td>
</tr>
</tbody>
</table>
Figure 1: Impulse responses in the Woodford model.
Figure 2: Impulse responses in the Rubio-Ramirez model.
Figure 3: Impulse responses in the Smets and Wouters model.
Figure 4: Impulse responses to a 1% shock to q-o-q inflation expectations and 1 standard deviation bootstrapped confidence bands.
Figure 5: Impulse responses to a 1% shock to q-o-q inflation expectations and 1 standard deviation bootstrapped confidence bands.