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 longer term 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. To achieve identification of the expectational shock, we use a mix of zero and sign restrictions derived from a small-scale New Keynesian general equilibrium model, which is able to accommodate two scenarios: in one case the shock influences only the public's perception of the central bank's inflation objective, while in the other case the actual objective changes as well. The results show that on average over the past decade the ECB has firmly reacted to signs of disanchoring of longer term inflation expectations, while its inflation objective has not changed.

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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. First, with very few exceptions, the focus has been on shorter-term inflation expectations, most probably because longer-term expectations are very stable. However, the central bank objective is in the medium to longer term, and its credibility is measured by longer-term expectations. 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 focus on the longer-term, by using 5-years-ahead inflation expectations provided by the ECB Survey of Professional Forecasters (SPF). We estimate 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.

3 The dataset

Our key measure of inflation expectations is the longer-term (5-years-ahead) expectations provided by the quarterly ECB Survey of Professional Forecasters (SPF). The ECB SPF has been collecting longer-term inflation expectations on a quarterly basis since the first quarter of 2001. The survey is carried out around the middle of the first month of each quarter, starting with the day of the euro area HICP release. Forecasters are asked to provide their expectation for euro area HICP inflation (annual percentage change, average over the year) in five years time.[1] On average, 45 respondents provide expectations for the longer-term horizon. This number is much higher than the number of respondents providing longer term forecasts to the other two main sources of survey-based inflation expectations for the euro area, namely Consensus Economics and the Eurozone Barometer, putting us on a safer footing with respect to the effects of outliers on the average expectation. Moreover, the analysis of the distribution of the individual point forecasts of the probability distributions provided by the forecasters allows for the assessment of the uncertainty surrounding the baseline outlook. Measures of uncertainty and disagreement among forecasters are indeed included in the panel.

The average SPF longer-term inflation expectation has been very stable since 2001, with some slight upward shift in 2003 - when the ECB announced its quantitative definition of price stability - and with the recent crisis (see Figure 1). Instead of using such measure of inflation expectations, we could have used measures of inflation expectations extracted from market data, in particular inflation-linked financial instruments, notably inflation-linked bonds but

[1] Notice that, in general, estimating a quarterly model including expectations for the year-on-year inflation rate makes it difficult to identify an expectation shock, because a change in expectations between two survey rounds 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 other words, one would be estimating only a moving-average of the shock. Another issue with these data is that the length of the forecast horizon varies, since in the first two quarters of each year the longer-term horizon corresponds to four calendar years ahead, while it corresponds to five calendar years ahead in the third and fourth quarter rounds. For example, the longer-term horizon was 2016 for surveys carried out in the first and second quarters of 2012, and 2017 for surveys carried out in the second half of the year. However, we believe that none of these issues is relevant when identifying shocks to longer-term expectations.

also derivatives like inflation-linked swaps. However, the use of financial instruments generally requires quite strong assumptions to extract inflation expectations. For example, in the case of break-even inflation rates calculated using inflation-linked bonds, it is necessary to estimate nominal and real term structures, which can be problematic if the number of available bonds is limited (in particular at short maturities). Market-based measures are anyway prone to liquidity distortions and require the estimation of an inflation risk premium component to compensate investors for the risks surrounding inflation expectations over the forecast horizon.[2]

We embed survey-based inflation expectations in a large 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.[3] Finally, 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.

[2]The calculation of inflation expectations embodied in financial asset prices is easier in the case of inflation-linked derivatives. However, markets for inflation-linked instruments in the euro area have been strongly developing only in recent years, and in the case of derivatives even at a later stage.

[3]A detailed description of the dataset and data sources for each indicator is given in the Appendix.

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 $\mathbf{x}$ 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 χ_{it} and the idiosyncratic component ξ_{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 $\mathbf{u}_t = (u_{1t} \dots u_{qt})'$ which affect all variables in the panel, also referred to as *dynamic* common factors, with $q << n$. Formally:

$$\mathbf{x}_t = \boldsymbol{\chi}_t + \boldsymbol{\xi}_t = \mathbf{B}(L)\mathbf{u}_t + \boldsymbol{\xi}_t, \tag{1}$$

where $\boldsymbol{\chi}_t = (\chi_{1t} \dots \chi_{nt})'$, $\boldsymbol{\xi}_t = (\xi_{1t} \dots \xi_{nt})'$, and $\mathbf{B}(L)$ 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:

$$\mathbf{x}_t = \boldsymbol{\Lambda}\mathbf{F}_t + \boldsymbol{\xi}_t. \tag{2}$$

where the $r > q$ entries of $\mathbf{F}_t$ are the *static* common factors, and $\boldsymbol{\Lambda}$ 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:

$$\mathbf{F}_t = \mathbf{N}(L)\mathbf{H}\mathbf{u}_t \tag{3}$$

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

Finally, it is assumed that $\mathbf{N}(L)$ results from inversion of the VAR(m) $\mathbf{F}_t = (\mathbf{I}_r - \mathbf{A}L - \ldots - \mathbf{A}_m L^m)^{-1}\boldsymbol{\epsilon}_t$. For simplicity, we assume $m = 1$, so that $\mathbf{N}(L) = (\mathbf{I}_r - \mathbf{A}L)^{-1}$, where $\mathbf{I}_r$ is the r-dimensional identity matrix, and $\mathbf{A}$ is an $r \times r$ matrix. Notice that $\boldsymbol{\epsilon}_t = \mathbf{H}\mathbf{u}_t$, i.e. the residuals of the VAR on the static factors have reduced rank q. More precisely, $\boldsymbol{\epsilon}_t \in \overline{\text{span}}\,\{\mathbf{u}_t\}$, 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:

$$\mathbf{x}_t = \boldsymbol{\Lambda}\mathbf{F}_t + \boldsymbol{\xi}_t, \tag{4}$$

$$\mathbf{F}_t = \mathbf{A}\mathbf{F}_{t-1} + \boldsymbol{\epsilon}_t, \quad \text{with} \quad \boldsymbol{\epsilon}_t = \mathbf{H}\mathbf{u}_t. \tag{5}$$

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

$$\mathbf{B}(L) = \boldsymbol{\Lambda}(\mathbf{I}_r - \mathbf{A}L)^{-1}\mathbf{H}. \tag{6}$$

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 $\widehat{\mathbf{\Gamma}}_0^x$, the static factors $\mathbf{F}_t$ 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 $\mathbf{\Lambda}$.[4]

STEP 2 Given an estimate of the static factors $\mathbf{F}_t$ and of the loadings $\mathbf{\Lambda}$, 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 $\widehat{\boldsymbol{\epsilon}}_t$ 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 $\mathbf{G}$, then the reduced rank matrix $\mathbf{H}$ is estimated up to the same transformation with the addition of a $q \times q$ unitary transformation $\mathbf{R}$ that comes from principal component analysis. To interpret the dynamic factors as structural shocks, $\mathbf{R}$ 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 $\mathbf{R}$ by means of standard techniques used in the Structural VAR literature. In particular, we identify all shocks by means of a combination of sign restrictions, short-run and long run restrictions (see Section 8 for a detailed description of the identification assumptions).

[4]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 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).

To account for estimation uncertainty, we adopt a two-step bootstrap procedure.[5] 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.[6] 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 first set of impulse responses which satisfies our restrictions.[7] 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 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 1 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).[8] The null of

[5] We present results based on 1000 bootstrap replications.

[6] In the present paper we partition the idiosyncratic component into 5-year blocks.

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

[8] On our sample, this means $s_j = [4 \cdots 19]$. The outcome of the test is the same if frequencies between 2 and

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 rejected against the alterative 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 always 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 specification. 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

12 years are included.

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.

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 $r = 4$.

7 Identification of the shock on expectations

For illustration purposes, consider a simple three-equations new Keynesian model. 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. We augment this model with the possibility of an expectational shock, allowing therefore expectations shocks to be estimated using survey data.

$$\hat{x}_t = \frac{h}{1+h}\hat{x}_{t-1} + \frac{h}{1+h}E_t\hat{x}_{t+1} - \sigma^{-1}(\hat{i}_t - E_t\hat{\pi}_{t+1}) + \eta_t \quad (7)$$

$$\hat{\pi}_t = \frac{\gamma_p}{1+\beta\gamma_p}\hat{\pi}_{t-1} + \frac{\gamma_p}{1+\beta\gamma_p}E_t\hat{\pi}_{t+1} + \kappa\hat{x}_t + \alpha\hat{Exp}_t + \varepsilon_t \quad (8)$$

$$\hat{i}_t = \delta_\pi\hat{\pi}_t + \delta_x\hat{x}_t + \delta_{Exp}\hat{Exp}_t + \nu_t \quad (9)$$

$$\hat{Exp}_t = \rho\hat{Exp}_{t-1} + \epsilon_t \quad (10)$$

Following this extension, and keeping in mind that the expectations we will use are long-term expectations, commonly assumed as indicating the public belief about the target of the central bank, our model is able to accommodate two very different scenarios. In the first scenario, both the perceived and the actual inflation objective change. This contemporaneous shift results in an observed behavior which is qualitatively similar to the one of a standard inflation shock in the model with rational expectations, with consequent response of the interest rate, inflation first increasing and then reverting to baseline, and a cost in terms of reduced output (see Figure 2). The second scenario is a disanchoring of the long-run inflation expectations that does not correspond to a shift in the inflation objective of the central bank. Following the shift in long term expectations, the central bank reacts more vigorously, accepting a higher price in terms of output loss in order to keep inflation closer to the target. As a consequence, the interest rate will be raised to such a level that inflation will only slightly increase before undershooting for a protracted period (see Figure 3). The euro area is a good natural experiment for distinguishing between the two scenarios. The European Central Bank explicitly announced an inflation objective, and maintained it in its communication strategy even through periods of higher inflation (up to 4% in 2008). Therefore, using European data we can test (in particular on the basis of the impulse response of prices to a disanchoring of inflation expectations) whether the second scenario has indeed been predominant.

Looking at the features of the impulse responses that are common among the two scenarios, we choose our identifying restrictions. A positive monetary policy shock is identified by imposing that the response of output and prices cannot be positive at impact, as well as the response of inflation expectations at impact. Demand and supply shocks are identified by standard sign restrictions, implying that while a demand shock moves prices and output in the same direction, a supply shock moves them in opposite directions. We also assume that inflation expectations cannot react within the same quarter to demand and supply shocks. This restriction is fully justified by the timing of the ECB SPF, which collects expectations in the middle of the first month of each quarter, when information on past quarter output growth and unemployment, for example, is not yet available and very little information is available for the current quarter. The first monetary policy decision of the quarter is available at the time of the survey, therefore in principle we cannot restrict the response of inflation expectations to a monetary policy shock to be zero at impact. However, in order to achieve identification of the expectational and monetary policy shocks, we need to impose this additional exact restriction. Given that the restriction is fully justified in two thirds of the cases, the imposed zero response at impact is only slightly different from the unrestricted one.[9] The table below summarizes the set of zero and sign restrictions we impose.

	MON POL	DEMAND	SUPPLY	EXPECT
Expectations	0	0	0	≥ 0
GDP	≤ 0	≥ 0	≤ 0	
Inflation	≤ 0	≥ 0	≥ 0	
Short rate	≥ 0			

8 Results

The impulse response functions to a positive shock to inflation expectations are reported in Figure 4, along with two standard deviation confidence bands computed with bootstrap. The size of the shock is normalized to 10 basis points, which correspond to two standard deviations. Standard results emerge for the main macroeconomic aggregates. Focusing first on the monetary policy reaction, the interest rate increases by 20 basis points at impact and up to 30 basis points in two quarters. This prompt monetary policy reaction comes at some cost in terms of output, which decreases at impact by 0.1 percentage points at impact and up to 0.5 percentage points in one year. Following an increase in long-term expectations, actual inflation, whose impulse response is the key discriminant between the two scenarios, does not respond at impact and then tends to decrease, by around 0.3 percentage points in slightly

[9] This has been tested by by imposing alternative identification schemes where inflation expectations are allowed to respond at impact to a monetary policy shock.

more than a year. The response of inflation is therefore consistent with the hypothesis that the central bank did not change its inflation objective and has therefore reacted more strongly to inflation expectations shocks in order to prevent a snowball effect via a self-reinforcing further disanchoring of expectations. This results seems natural in the case of the euro area, as the ECB has always and publicly maintained constant its inflation objective. Of course, the clear identification of this effect is due to the fact that the shocks of the recent years were mostly on the upper side, and more sophisticated identification techniques may be necessary to keep into account the asymmetry of the loss function of the central bank in case of possible recent deflationary shocks.

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 15% 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 15% after two years, remaining broadly stable afterwards.

9 Conclusions

In this paper we have assessed the effects of shocks to inflation expectations on activity and prices in the euro area, as well as the monetary policy reaction to such shocks. Overall, our results confirm an important role for inflation expectations in affecting the dynamics of real and nominal variables. Moreover, we show that the ECB has responded effectively to signs of disanchoring of longer-term inflation expectations. In an environment where the actual inflation objective does not change, monetary policy has more than an offsetting effect on output and inflation if expectations get deanchored.

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.

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Data sources and definitions

Name	Series	EA countries	Aggregate EA	US, UK, JP
GDP	Gross Domestic Product, vol.	OEO	EUROSTAT	OEO
PCR	Private final consumption expenditure, vol.	OEO	EUROSTAT	
GCR	Government final consumption expenditure, vol.	OEO	EUROSTAT	
INV	Gross fixed capital formation, vol.	OEO	EUROSTAT	OEO
HINV	Housing investment, vol.	OEO	EUROSTAT	OEO
IP	Industrial Production, Total, SA	EUROSTAT	MEI	
CPI	Consumer Price Index/All items	MEI	ECB	MEI
PPI	Producer Price Index, domestic	EUROSTAT	MEI	
EXP	Exports/goods and services, vol.	OEO	EUROSTAT	
IMP	Imports/goods and services, vol.	OEO	EUROSTAT	
LCOMP	Labour compensation	MEI	MEI	
ULC	Unit labour cost/Tot. economy or Manuf.	OEO	OEO	
EMPL	Total employment, persons	OEO	EUROSTAT	
UNEMPL	Unemployment rate	OEO	EUROSTAT	
EXR	Real effective exchange rate	MEI	MEI	
STN	Short term interest rate	OEO		OEO
LTN	Long term interest rate	OEO	MEI	OEO
HPRICES	House prices	OECD	OECD	OECD
HPERMIT	Housing permits		MEI	
DIVYIELD	Dividend yield		Datastream	
PER	Price/earnings ratio		Datastream	
EQUITY	Equity Index	IMF	Datastream	IMF
BANKS	Banks equity index	Datastream	Datastream	Datastream
SMVOL	Stock market volatility		Datastream	Reuters
CREDIT	Private credit	ECB	ECB	IMF
M3	M3	ECB	ECB	
M1	M1	ECB	ECB	
OIL	Crude oil price, Brent		OEO	
RAW	Raw material price index (excl. energy)		OECD	
EXPECT	Inflation expectations		ECB SPF	

q_1 / q_0	1	2	3	4	5	6	7
0	0.012	0.022	0.03	0.038	0.045	0.053	0.059
1		0.58	0.232	0.31	0.129	0.152	0.176
2			0.129	0.232	0.102	0.129	0.152
3				0.801	0.074	0.102	0.129
4					0.042	0.074	0.102
5						0.954	0.415
6							0.229

Table 1: Results of the Onatski test for the number of shocks (p-values of the null $q = q_0$ against the alternative $q_0 < q \leq q_1$).

	1	2	3	4	5	6	7	8	9	10
cum exp var	22.9	36.9	44.1	47.0	48.0	48.8	49.2	49.3	49.6	49.8

Table 2: Cumulated variance explained by the first 10 dynamic factors.

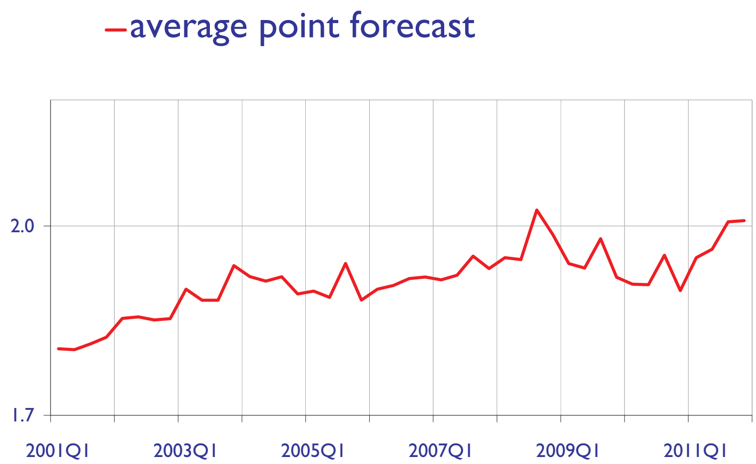

Figure 1: ECB SPF longer-term inflation expectations.

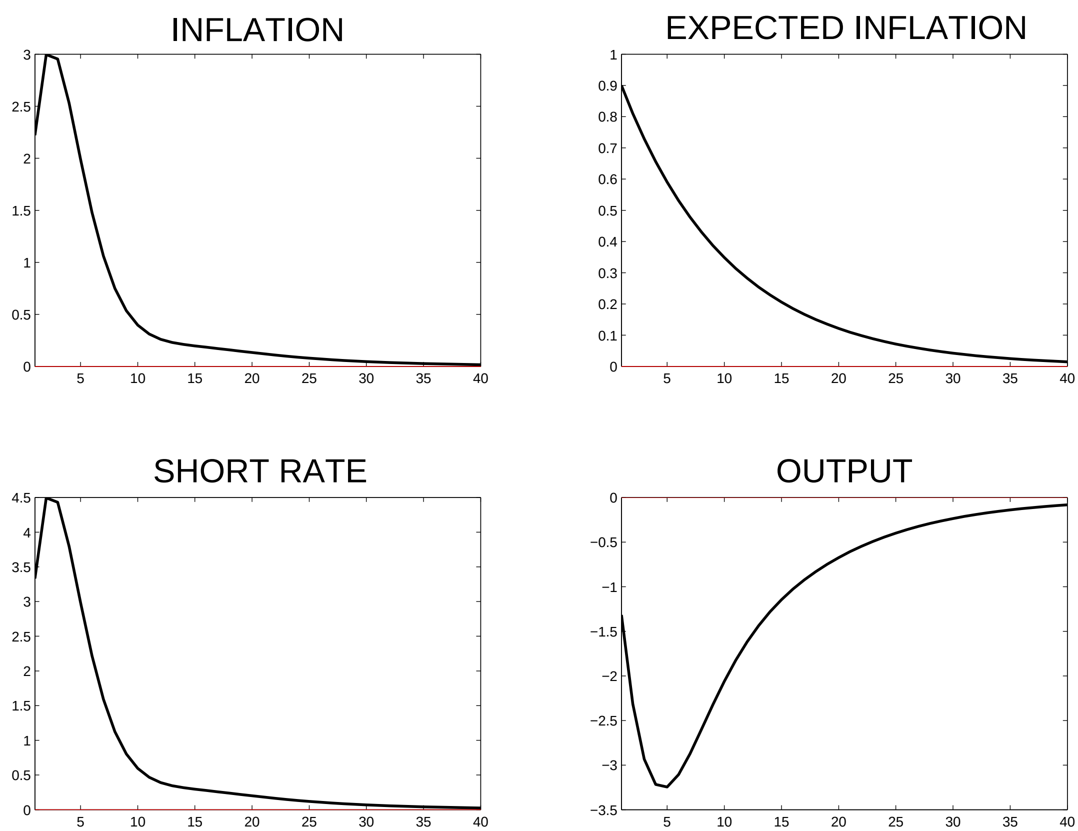

Figure 2: Impulse responses in the case of a shift in the actual inflation objective.

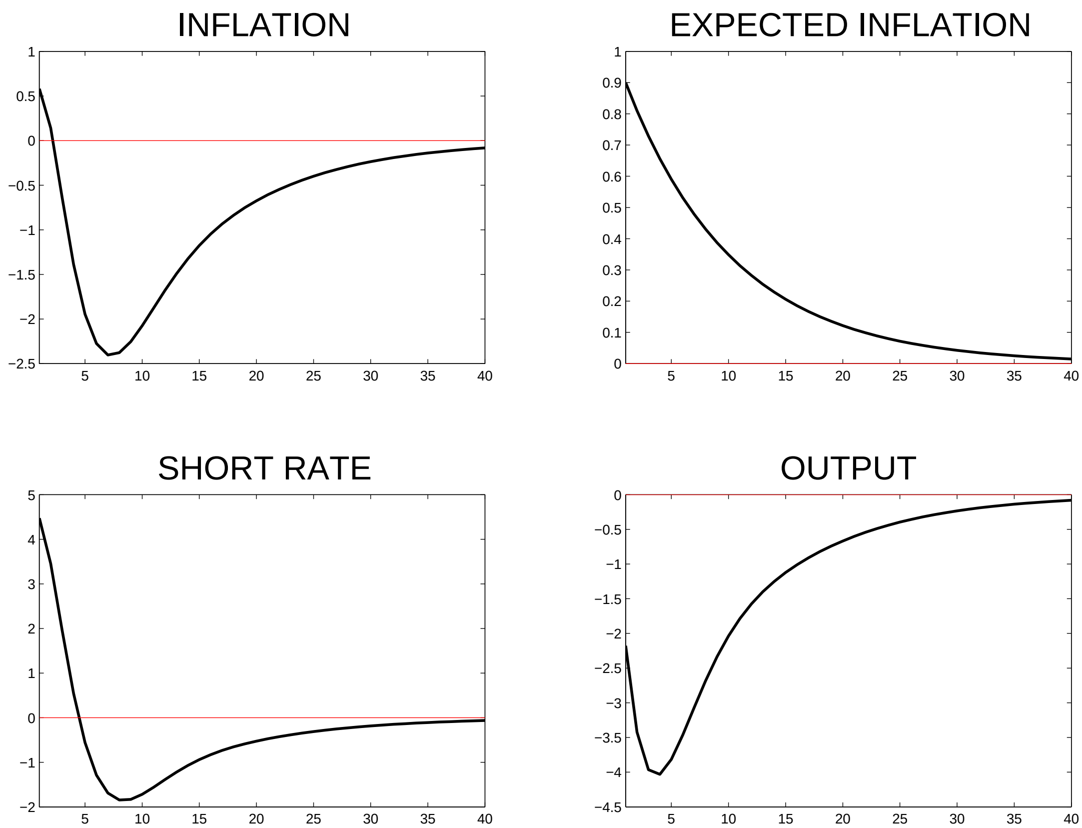

Figure 3: Impulse responses in the case of no shift in the actual inflation objective.

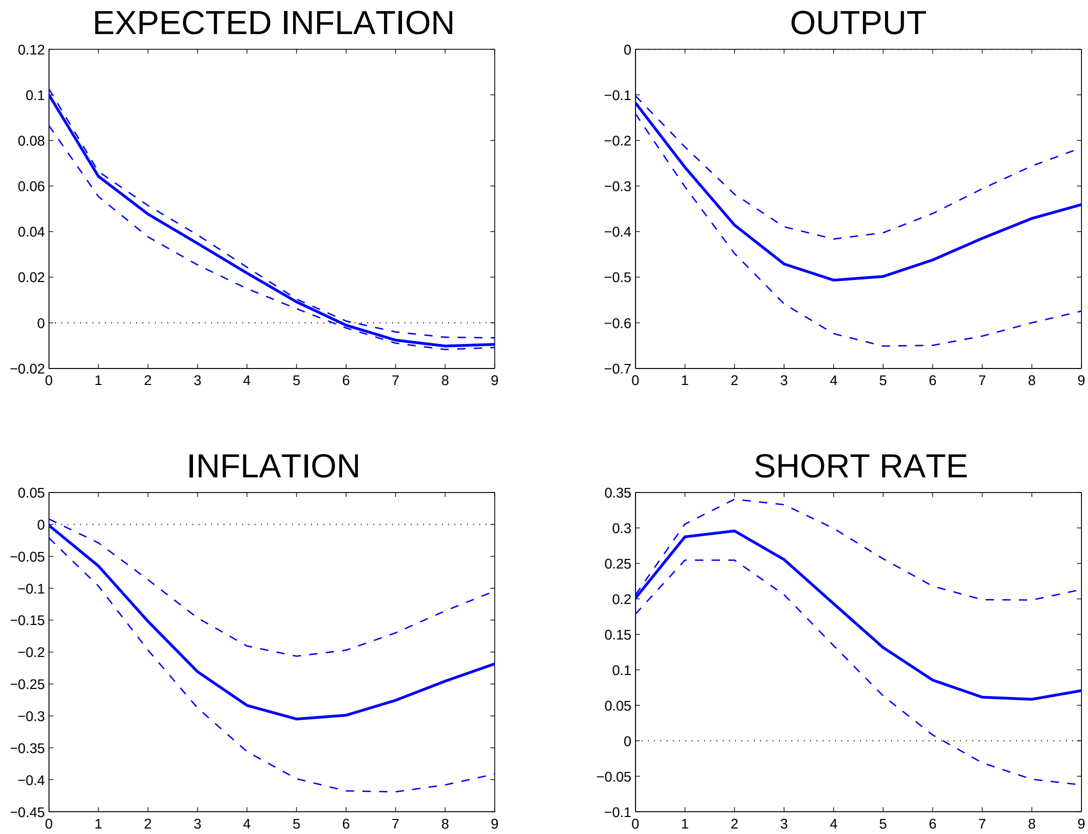

Figure 4: Impulse responses to a 0.1 percentage point (2 standard deviations) positive shock to longer-term inflation expectations and 95% bootstrapped confidence bands.