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de Navarra

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# Working Paper nº 05/11

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Working Paper No.05/11  
January 2011

### ABSTRACT

This paper first shows that survey-based expectations (SBE) outperform standard time series models in U.S. quarterly inflation out-of-sample prediction and that the term structure of survey-based inflation forecasts has predictive power over the path of future inflation changes. It then proposes some empirical explanations for the forecasting success of survey-based inflation expectations. We show that SBE pool a large amount of heterogeneous information on inflation expectations and react more flexibly and accurately to macro conditions both contemporaneously and dynamically. We illustrate the flexibility of SBE forecasts in the context of the recent financial crisis.

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# Exploring Survey-Based Inflation Forecasts\*

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## Abstract

This paper first shows that survey-based expectations (SBE) outperform standard time series models in U.S. quarterly inflation out-of-sample prediction and that the term structure of survey-based inflation forecasts has predictive power over the path of future inflation changes. It then proposes some empirical explanations for the forecasting success of survey-based inflation expectations. We show that SBE pool a large amount of heterogeneous information on inflation expectations and react more flexibly and accurately to macro conditions both contemporaneously and dynamically. We illustrate the flexibility of SBE forecasts in the context of the recent financial crisis.

**JEL Classification:** E31, E37, E43, E44

**Keywords:** Inflation Forecasting, Disaggregation, Surveys, Time Series, ARIMA Models, Long Memory Time Series

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\*We thank Lorena Picapietra for great research assistance.

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# 1 Introduction

Inflation expectations are one of the most important variables in Macroeconomics and Finance. Popular macroeconomic theories, such as the trade-off between inflation and unemployment, as well as empirical explanations of macro dynamics hinge upon the behavior of inflation expectations. They are also crucial in financial markets, where both the government and the private sector closely monitor inflation expectations at different horizons for asset pricing purposes -especially for fixed income securities- and in commercial banking.

Survey-based inflation forecasts are increasingly being subject to both empirical and theoretical analysis (see, for instance, Forsells and Kenny (2004) and Mestre (2007)). The recent literature has highlighted the good forecast properties of Survey-Based Expectations (SBE). In particular, Ang, Bekaert, and Wei (2007) show that annual inflation SBE beat a wide variety of time series Rational Expectations (RE) models in terms of out-of-sample forecasting. In this paper we show that this is also the case for quarterly SBE. In this context, a natural question thus arises: Why is this the case?

This paper provides some empirical explanations for the success of inflation SBE forecasting. It first shows that SBE pool a large amount of heterogeneous dynamics across agents. It also shows that SBE react faster and more accurately to macro conditions both contemporaneously and dynamically. In particular, we show that SBE are correctly revised in the right direction after changes in the monetary policy stance. We illustrate the survey-based prediction flexibility in the context of the recent financial crisis. We also show that the SBE term structure is a good predictor of future inflation changes.

Plenty of studies on SBE have tried to determine whether SBE were consistent with RE (see Cukierman and Wachtel (1979), Evans and Wachtel (1993) and Thomas (1999),

among others). All of them concluded that SBE forecast errors were persistent and predictable thus rejecting the hypothesis of rationality of SBE in the macro-econometric sense (Muth (1961) and Lucas (1976)). As a result, the use of SBE in both theoretical and empirical analysis nearly vanished from the literature in the 1980s and 1990s. Nevertheless, several authors have recently explored some features of inflation SBE as key indicators of the way private sector expectations are formed. In particular, Mankiw, Reis, and Wolfers (2003) and Carroll (2003) report an increase in SBE heterogeneity across agents in times of higher inflation or economic turbulence. A related strand of the literature has tried to rationalize this and other stylized facts by means of theoretical models based on learning (Branch (2004) and Capistran and Timmermann (2009)). In light of the out-of-sample predictive success of SBE relative to standard RE models (Ang, Bekaert, and Wei (2007)), some authors have postulated and estimated Phillips curves with SBE, such as Adam and Padula (2003), whereas in the finance literature, inflation SBE are being used to analyze and predict yield curve dynamics (see Kozicki and Tinsley (2006), Piazzesi and Schneider (2008) and Chernov and Mueller (2008)). With respect to all these works, the present paper provides some reasons for the empirical advantages of SBE relative to RE: efficient aggregation of heterogeneous expectations across agents and flexible adaptation to the macro-finance environment.

This paper proceeds as follows. Section 2 performs forecasting analysis showing that inflation SBE typically beats out-of-sample RE forecasts at different forecast horizons with quarterly and annual data. Section 3 highlights some of the key differences between SBE and RE. In particular, it shows that SBE react faster and more flexibly to the arrival of new macro-finance information. For instance, SBE revisions are significantly more sensitive to monetary policy fluctuations than RE. Section 4 concludes.

## 2 SBE Prediction Power

In this section, we compare the out-of-sample forecasting performance of quarterly and annual SBE with respect to several popular empirical RE models at different horizons. We then show that the term structure of SBE has predictive power over future short and medium-run inflation changes.

### 2.1 Forecast Accuracy of SBE and RE Time Series Models

Throughout the paper, we work with CPI inflation mean survey data from the Survey of Professional Forecasters (SPF), provided by the Federal Reserve Bank of Philadelphia and available online.<sup>1</sup> CPI inflation data is retrieved from the Bureau of Labor Statistics. Quarterly inflation rates are computed as logarithmic differences of CPI levels and time series forecasts of inflation at horizons higher than one are iterated. We carry out predictive analysis with both quarterly and annual forecasts. CPI inflation rate forecasts are available from the third quarter of 1981 onwards. Our sample finishes on the first quarter of 2008. While the quarterly data includes forecasts from one to five quarters ahead, the CPI annual surveys forecast inflation just one year ahead, starting from the following quarter. Both sets of forecasts are available on a quarterly basis. The quarterly SBE is conducted in the middle of a given quarter. As a result, SBE participants possess information on the state of the economy during the first half of the quarter, which is absent in RE models. However, SPF participants do not possess additional information in terms of months of inflation, since the CPI announcement is released during the third week of the following month. Thus, the last month of inflation available for SPF forecasters is the last month of the previous quarter, exactly the same as in the alternative

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<sup>1</sup>See <http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/>

RE models estimated here. We will show throughout the article that the relative forecasting advantage of SBE is by no means restricted to the one-quarter ahead forecasts and extends to longer horizons.

[Insert Table 1 and Figure 1 About Here]

Table 1 lists the main descriptive statistics of quarterly and annual survey inflation expectations across forecasting horizons. The quarterly inflation expectations mean is slightly increasing in the forecasting horizon, whereas the standard deviation exhibits a U-shape, with the one and five-quarters ahead forecasts showing greater standard deviation. The three, four and five-quarter ahead inflation forecasts display a high degree of autocorrelation whereas the one-quarter ahead forecast autocorrelation decays relatively fast. Quarterly inflation forecasts are highly cross-correlated, especially at longer forecast horizons. As for the annual inflation SBE, the statistics are similar, but slightly higher overall. Figure 1 plots the five quarterly inflation forecasts. Inflation expectations at different forecast horizons exhibit a clear positive co-movement. They were quite high at the beginning of the 1980s, but have progressively gone down and stabilized after 1995. One-quarter ahead expectations exhibit a higher degree of short-term volatility, whereas the four and five-quarters ahead counterparts are smoother. Figure 2 plots the annual inflation forecasts. It shows a similar pattern to the quarterly counterparts, with a steady decline of inflation forecasts since the early 1980s and a stabilization period starting in 1995.

[Insert Figure 2 About Here]

In order to gauge the relative predictive accuracy of SBE inflation forecasts, we compare them with several popular time series RE models used in the literature, which we list below:

1. VAR(1):  $X_t = A + BX_{t-1} + \varepsilon_t$ ,  $X_t = [\pi_t \quad u_t \quad i_t]$ ,
2. AR(1):  $\pi_t = \mu + \rho\pi_{t-1} + \varepsilon_t$ ,
3. ARMA(1,1):  $\pi_t = \mu + \phi\pi_{t-1} + \theta\varepsilon_{t-1} + \varepsilon_t$ ,
4. Random Walk:  $\pi_t = \pi_{t-1} + \varepsilon_t$ ,
5. ARFIMA(0,d,0):  $(1 - L)^d(\pi_t - \mu) = \varepsilon_t$ .

The first four models are among the ones recently employed by Ang, Bekaert, and Wei (2007) in their study. We estimate the AR(1) and VAR(1) models by OLS, whereas the ARMA(1,1) is estimated via maximum likelihood. The VAR(1) is the only multivariate model we analyze here, as it includes the inflation rate ( $\pi_t$ ), the unemployment rate ( $u_t$ ) and the three-month T-Bill rate ( $i_t$ ) in the agents' information sets. These macro variables were retrieved from the FRED2 database made available online by the Federal Reserve of Saint Louis. The ARFIMA model, estimated through the testing procedure in Robinson (1994), allows for long-memory in the behavior of inflation, as estimated by many authors. Altissimo, Mojon, and Zaffaroni (2009) and Bils and Klenow (2004) provide motivation and evidence for long-memory in terms of the “slow” response of CPI inflation as the aggregation of the “fast moving” sectoral inflation processes. As is well-known, when  $d \in (0, 0.5)$ , the process is stationary (yet with a slower mean-reversion than pure short-memory models),  $d \in [0.5, 1)$  implies mean reversion but non-stationary variance, whereas  $d \geq 1$  implies non-stationarity and lack of mean reversion. Indeed, as Figure 3 shows, the recursive estimates of the ARFIMA model used in our forecasting exercise (estimating  $d$  in a moving window with an additional observation starting in the fourth quarter of 1982), show the existence of long-memory, as  $d$  hovers around 0.5 throughout the sample, moving from the non-stationary to the stationary region. We note that while the literature shows evidence of changes in the determinants and causes



of inflation dynamics (see Stock and Watson (2007)), our forecasting period focuses in the Great Moderation and thus we propose models with no regime switches or structural breaks.

[Insert Figure 3 About Here]

We use the standard Root Mean Squared Error (RMSE) statistic to assess the out-of-sample predictive power of each model. Figure 4 shows the RMSEs of the five time series models and of SBE for the alternative (one-to-five) forecast horizons and three different starting times as the out-of-sample forecasting periods: 1982:4Q, 1985:4Q and 1995:4Q. In the first two subsamples, SBE beat every other predictor across all forecast horizons. The two closest competitors are the ARMA(1,1) and ARFIMA models, whereas the worse model during these two forecasting periods is the random walk. Meanwhile, the VAR(1) and the AR(1) also display much higher forecasting errors than SBE. In the last subsample, SBE are beaten at the three shorter forecast horizons. At the one-quarter and two-quarter horizons, the random walk and the ARMA(1,1) have the two lowest RMSE, respectively, whereas the ARFIMA model dominates at the three-quarter horizon. As a result, SBE display the lowest RMSE in 12 out of 15 predictions, thus displaying a higher forecast accuracy than any of the time series models presented. In line with Ang, Bekaert, and Wei (2007) -who consider a much larger set of models- the ARMA(1,1) is the best time series model, beating the ARFIMA -the second best model- in 9 out of the 15 cases. Finally, the random walk model predicts well at the one-quarter horizon in the latter subsample.

[Insert Figure 4 About Here]

Figure 5 shows the RMSE of the annual inflation prediction at the one year forecast horizon. SBE again dominates every other model across subsamples. The best time

series model is now the long-memory ARFIMA(0, $d$ ,0), followed by the ARMA(1,1) and the AR(1). The VAR(1) and the random walk do worse than the other models across subsamples.

[Insert Figure 5 About Here]

## 2.2 The Predictive Content in the Term Structure of Inflation Forecasts

Quarterly surveys contain information on the expectations of inflation rates from one to five quarters ahead. In this section, we show that this term structure of inflation forecasts provides good predictions of the longer-term inflation rate across the future quarters (from two to five quarters for a given period) as well as of future changes with respect to the current inflation level. We also compare these forecasts with those implied by our identified best quarterly time series model, the ARMA(1,1).

We first run the following set of regressions:

$$\pi_{t,t+k} = \alpha + \theta \frac{1}{k} \sum_{i=1}^k E_t \pi_{t+i} + \varepsilon_{t,t+k}, \quad k = 2, \dots, 5, \quad (1)$$

where  $\pi_{t,t+k}$  is the longer-term annualized inflation rate from time  $t$  to time  $t+k$  and  $E_t \pi_{t+i}$  is the expected annualized inflation rate for the  $t+i$ -th quarter ahead. Thus, if the term structure of inflation expectations predicts well long-run inflation,  $\alpha$  should be close to zero and  $\theta$  should be close to one. Table 2 lists the Generalized Method of Moments (GMM) estimation for both SBE and ARMA(1,1) expectations. It shows the parameter estimates and the standard errors corrected with  $k-1$  lags corresponding to the extent of overlapping errors. In both instances and across forecast horizons,  $\alpha$  is

positive and significantly higher than one, and  $\theta$  is positive and significantly higher than zero (yet significantly lower than unity). Thus, changes in the term structure of inflation forecasts predict changes in the aggregate longer-run inflation rates in the right direction, but do not account for all the dynamics of long-run inflation rates. Notice that the  $\theta$  coefficient is uniformly higher and closer to unity under SBE. At the same time, since  $\alpha$  is positive, there is a negative predictive bias across horizons, so that both SBE and ARMA short-term inflation forecasts underpredict long-run inflation rates. This negative bias is however more evident with ARMA forecasts.

As a second exercise, we now test the power of the term structure of SBE inflation forecasts on predicting future inflation changes. To do so, we run these linear regressions with both SBE and ARMA(1,1) expectations:

$$(\pi_{t+k} - \pi_t) = \alpha + \beta(E_t\pi_{t+k} - \pi_t) + \epsilon_{t,t+k}, \quad k = 1, \dots, 5. \quad (2)$$

Table 3 shows the GMM parameter estimates together with the Newey-West corrected standard errors. Since we deal with changes in inflation expectations up to five quarters ahead ( $k$  goes from 1 to 5), we estimate these regressions via GMM and the standard errors are again computed adjusted with  $k - 1$  Newey West lags. We also compare the results obtained with expectations formed with the ARMA(1,1) model. The results with SBE are very encouraging. In all instances, we cannot reject that  $\alpha$  is different from zero, so that there is no bias at all. The  $\beta$  coefficient is always positive, significantly different from zero and not different from one, except at the one-quarter forecast horizon. The results with the ARMA(1,1) expectations are not so good, as  $\alpha$  is significantly negative across forecast horizons, implying a positive predictive bias and thus a systematic over-prediction of inflation. With regard to  $\beta$ , it is significantly higher than one across forecast horizons, except for the three-quarter ahead prediction. Thus, according to this

specification, changes in expected future inflation imply more than one-to-one changes in realized future inflation changes.

[Insert Tables 2-4 About Here]

We finally test the predictive power of the SBE and ARMA models over future inflation changes when the reference inflation rate is the unknown next quarter inflation rate:

$$(\pi_{t+k} - \pi_{t+1}) = \alpha + \beta(E_t\pi_{t+k} - E_t\pi_{t+1}) + \epsilon_{t,t+k}, \quad k = 2, \dots, 5. \quad (3)$$

Table 4 shows the results. Unlike the previous exercise, where the reference inflation rate is current inflation, this set of regressions involves prediction of changes of two unknown inflation rates -next period and the following ones-. Most of the parameters are now non-significantly different from zero across forecast horizons and models, thus implying that the term structure of (survey-based or ARMA) inflation expectations does not predict well future inflation changes involving two unknown inflation rates in the future.

### 3 Some Explanations

Why are out-of-sample inflation SBE forecasts more accurate than time series models? This is a crucial question, but no conclusive answer has been reported in the literature. The main motivation for this paper is to take a stab at this important question. We first document how SBE aggregate a large pool of heterogeneous information. We then study the conditional correlations between inflation SBE and RE in order to differentiate them both with contemporaneous regression and dynamic VAR analysis.

### 3.1 Aggregation of a Pool of Heterogeneous Forecasters

SBE pool data from a large amount of sources. Participants in the SPF are drawn from different business men and women who forecast inflation rates from 1 to 5 quarters ahead (only 1 year ahead with annual data). The SPF shows the time series predictions of each individual forecaster. Some of the forecasters' time series are discontinued or contain very few data observations. In order to work with reasonably large individual forecasts, we discard individuals with less than 20 observations. Additionally, if some of the observations are missing, we perform linear interpolation of up to two missing forecasts in a row. We ended up with 30 forecasters predicting quarterly inflation and 40 predicting annual inflation.

In order to have a quantitative measure of the heterogeneity in the expectations across agents, we perform the following experiment. We fit an AR(1) process for each forecaster series and plot the auto-regressive coefficient with the shock standard deviation across forecasters.<sup>2</sup> Figure 6 presents the results for quarterly data, where the term structure of inflation forecasts goes from 1 to 5-quarters ahead. It shows that there is a large amount of variability in both the auto-regressive coefficients –ranging essentially from 0 to 0.90– and shock standard deviation –from 0.1 to 2.4–. Two points are worth noting. First, the disagreement in persistence is higher in the two and four-quarter ahead forecasts, whereas there is a uniform decline in the shock standard deviation as the forecast horizon lengthens. Second, except in the first period, there is a negative relation between the auto-regressive coefficient and the shock standard deviation. Thus, there seems to be an economically significant trade-off between shock size and propagation in the way forecasters form their expectations. Figure 7 shows the analogous scatter plot with annual data, where we only have one-year ahead forecasts. The conclusions are very

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<sup>2</sup>Results are robust to alternative stationary ARMA models.

much analogous to those obtained with quarterly data.

[Insert Figure 6 and Figure 7 About Here]

Robinson (1978) showed that the aggregation of autoregressive processes with different propagation coefficients, such as the one described for the inflation SBE, can give rise to a fractionally integrated (long-memory) stochastic process. In order to verify this hypothesis, we estimate a univariate long-memory model for the full term structure of quarterly SBE and also for annual inflation SBE. The estimated model has the following form:

$$(1 - L)^d(\pi_{t,t+1}^e - \mu) = \epsilon_t, \quad (4)$$

where  $d \in R$  is the fractional integration parameter. We perform two sets of estimates. In the first one,  $\epsilon_t$  is assumed to be *i.i.d.*, whereas in the second we permit weak autocorrelation in  $\epsilon_t$  through the non-parametric model of Bloomfield (1973), where the short-term dynamics correspond to the Bloomfield order 1, similar to AR(1)/ARMA(1,1) dynamics. Table 5 shows the estimates of  $d$  across frequencies and forecast horizons.<sup>3</sup> The results clearly point to the existence of long-memory in inflation SBE. Except for one-quarter-ahead quarterly inflation SBE,  $d$  is always higher than 0.5, with values uniformly lower in the models with autocorrelated  $\epsilon_t$ . Regarding the term structure dimension, the longer horizon inflation forecasts tend to have higher integration orders, although this relation is non-monotonic. Thus, while the one-quarter ahead forecast has a very similar integration order than inflation (see Figure 3, where  $d$  is around 0.5), the remaining SBE have a higher integration order. Finally, annual SBE display a higher integration order than quarterly expectations. In the case of *i.i.d.* error terms,  $d$  is very close to 1, and is thus in the neighborhood of the unit root.

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<sup>3</sup>We alternatively estimated the model without an intercept and with a linear time trend and the results were similar to those reported.

[Insert Table 5 About Here]

To summarize, we have estimated very heterogeneous processes for the individual expectation series. Since SBE out-of-sample prediction performance is very good, we can conclude that SBE aggregate very diverse information quite efficiently. This expectational heterogeneity implies that SBE can be well described as a long-memory process with mean reversion, as confirmed by our ARFIMA estimations. In the next section we show that this long-memory dependence of SBE is consistent with a flexible adaptation to changes in the macroeconomic environment.

## 3.2 Different Adaptation to Macro Conditions

In this subsection, we show that SBE do indeed adapt and react differently to macro conditions than standard time series models. We show three pieces of evidence. In the first one, we perform linear regression analysis of the expected inflation rates with respect to the contemporaneous macro variables. Then we analyze how agents revise their expectations as they get new information across forecast horizons. Finally, we perform dynamic impulse response analysis of expectations with respect to a set of relevant macroeconomic variables. In all cases, we compare the results under SBE and the ARMA(1,1), the best inflation time series model with quarterly data.

### 3.2.1 Inflation Expectations and Macro Variables

We first study the effects of macroeconomic variables on the level of the inflation expectations in the context of a simple linear regression model:

$$E_t\pi_{t+k} = \alpha + \beta\pi_t + \gamma u_t + \delta i_t + \varepsilon_t, \quad k = 1, \dots, 5. \quad (5)$$

Table 6 shows the results of the GMM estimations for both survey-based and ARMA expectations with standard errors computed with 3 Newey-West lags in order to account for the autocorrelation in the error terms. There are similarities in results across expectations and forecast horizons. Across models, the constant is positive and the response to inflation is positive. These coefficients are always significant under ARMA expectations, whereas with SBE they are significant in the one-to-three quarters ahead regressions. The  $R^2$ 's are overall quite high, ranging from 45% to 78%, increasing in the forecast horizon and always higher for the SBE regressions, except in the one-quarter ahead forecast regressions.

[Insert Table 6 About Here]

There are however some relevant differences to be noted among the reactions of inflation expectations to macro variables. First, under SBE, there is a positive and significant reaction to the level of unemployment -except on the one-period ahead forecast- whereas the analogous reaction under ARMA expectations is negative but not statistically significant. Second, under SBE, as the forecasting horizon lengthens, the constant becomes smaller, while the reaction to unemployment and the interest rate becomes larger. In the ARMA prediction, the constant becomes larger and the response to the interest rate slightly smaller. This, in itself, implies that SBE place more weight on the variables as the forecast horizon increases, whereas the ARMA predictions put more weight on the constant. Indeed, when we run the regressions of the difference of survey-based and ARMA inflation expectations on the set of macro variables, we found the following: First, this difference is persistent with a significant first order autocorrelation ranging from 0.25 (one-quarter ahead forecast) to 0.71 (five-quarter ahead forecast). Second, we find that the ARMA expectations systematically place more weight on the constant and inflation



on the one-hand and less on unemployment and the interest rate on the other. Thus, SBE react more flexibly and rapidly to information not contained in the inflation series.<sup>4</sup>

### 3.2.2 Revisions of Inflation Expectations

The SBE dataset contains information regarding the revisions of inflation expectations. Thus for instance, we can gauge how agents changed their inflation expectations for a given quarter as this time period approached. This provides relevant information because it shows how agents utilize the new available information to correct and form their forthcoming inflation expectations. In the ARMA setting this information is also available, as agents change their inflation expectations for the next forecasting period as new inflation information arrives. We estimate the following regressions, where expectations revisions are a function of our set of macro variables:

$$E_t\pi_{t+1} - E_{t-i}\pi_{t+1} = \alpha + \beta\pi_t + \gamma u_t + \delta i_t + \varepsilon_t, \quad i = 1, \dots, 4. \quad (6)$$

Table 7 shows the results of the GMM estimations for both survey-based and ARMA expectation revisions with standard errors computed with 3 Newey-West lags. The regressions'  $R^2$ 's were lower than for the regressions in expectations levels, ranging from 4% to 39%, were increasing in the revision distance and were always higher for SBE than for the ARMA specifications. Across models, an increase in inflation implies an upwards revision of inflation expectations across all revision timings. There is also a negative response of inflation expectations to the unemployment rate across sets of expectations and forecast horizons. This coefficient is always significant in the case of SBE and in the three-to-five quarters ahead ARMA regressions. In both cases, the sensitivity of inflation

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<sup>4</sup>We also performed all the regressions in this subsection on the lagged values of the variables and found very similar results.

revisions increases with the lag of the expectations timing.

[Insert Table 7 About Here]

Regarding the differences across revisions, we first note that the difference between survey-based and ARMA expectation changes is correlated across different timings (going from -0.11 (when  $i = 1$ ) to 0.42 (when  $i = 4$ ), thus implying somewhat persistent differences across revisions in expectations. These systematic differences across expectations can be explained by two facts. First, SBE revisions react negatively and significantly to positive interest rate changes. Thus, in agreement with conventional economic reasoning, contractionary monetary policy is perceived by agents in the surveys as having a negative effect on inflation. Notice that this is true starting with the two-period difference in the expectations ( $E_t\pi_{t+i} - E_t\pi_{t+1}$ ,  $i = 2, \dots, 4$ ). So, it still takes two quarters for agents to revise their expectations. In the case of the ARMA expectations, the analogous reaction is much smaller and never statistically significant. Second, regarding the constant in the regression, this is higher under SBE than in the ARMA model. Additionally, in the SBE case, it is significant for all cases except for the one-period revision change, whereas under ARMA expectations it is never significant. This implies that participants in SBE shift their expectations upwards systematically across the sample period, independently of the relevant macro dynamics.

### 3.2.3 Dynamics

So far we have analyzed the contemporaneous reaction of survey-based and ARMA inflation expectations (and revisions of expectations) to macroeconomic variables. We now turn to a dynamic analysis of the reaction of inflation expectations to macroeconomic shocks. To this end, we construct a linear vector auto-regressive (VAR) model with a set

of macroeconomic variables and the difference between SBE and ARMA inflation expectations (henceforth expect-dif). In this way we can assess whether a specific shock triggers economic and/or significant differences in inflation expectations dynamic reactions. We estimate a VAR(1) model with the five variables in the following order: expect-dif, inflation, unemployment, interest rate and consumer confidence (retrieved from the FRED2 database). The lag order was the one preferred by the BIC criterion. We set inflation expectations as the first variable, implying that it reacts with a lag to all macro shocks. Consumer confidence, however, reacts contemporaneously to all macro variables. Alternative orderings, however, yielded very similar results. To facilitate the analysis, we standardize each of the variables before the estimation.

[Insert Figure 8 About Here]

Figure 8 shows the responses of the one-quarter inflation forecast expect-dif to the four structural shocks.<sup>5</sup> It shows that SBE react significantly more (positively) on impact to a positive consumer confidence shock than ARMA expectations. Thus, SBE seem to react strongly to consumer confidence dynamics. Also, SBE react significantly more positively to the unemployment shock than ARMA after one year. There seems to be no statistically significant differences in the reaction of SBE and ARMA expectations to the remaining shocks. In economic terms, SBE initially react more than ARMA to a positive inflation shock, but then the ARMA response becomes stronger after 3 quarters, reflecting the time dependence of ARMA expectations with respect to inflation. With respect to the unemployment shock SBE tend to react slightly more positively to the unemployment shock than ARMA. Finally, a contractionary monetary policy shock has a slightly more negative impact on SBE than on ARMA inflation expectations.

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<sup>5</sup>Results with two-to-five quarters ahead expect-dif were very similar and are available from the authors upon request.

Analogously to this previous exercise, we estimate a VAR(1) with the macro variables but now with difference in the one-period revision of inflation expectations instead of the difference in levels. The responses with two-to-four quarter expectations revisions were again very similar. All variables are again standardized before the estimation. Figure 9 shows the impulse response functions. It shows that following a positive inflation shock, SBE inflation expectations are revised upwards significantly more on impact than ARMA inflation expectations. Interestingly, following a contractionary monetary policy shock, SBE inflation expectations are revised downwards significantly more on impact than ARMA inflation expectations. The other two responses are not statistically significant throughout their dynamic path.

[Insert Figure 9 About Here]

To summarize, we have identified that SBE tend to react more flexibly than ARMA to consumer confidence shocks. Additionally, SBE are also revised more quickly and strongly following both inflation and monetary policy shocks.

### **3.3 The Crisis of 2008 and Inflation Expectations**

The recent crisis of 2008 provides an interesting episode to gauge the differences in the expectation formation between SBE and time series inflation expectations. The financial crisis starting in August 2007 has had negative real effects throughout the world and has implied a clear drop in the demand for U.S. goods, both internally and from abroad. Standard economic logic implies that this sharp drop in demand has consequences on the price setting, and indeed we have witnessed an important drop in prices, especially at the end of 2008.

Figure 10 shows the CPI quarterly inflation rate from the third quarter of 2007 -right after the onset of the financial crisis- to the second quarter of 2009 and the associated SBE and ARMA one-quarter-ahead inflation expectations. Therefore, it measures visually how accurate SBE and ARMA expectations have been during the recent crisis. It shows that CPI inflation experienced a sharp drop in the last quarter of 2008, coinciding with the worst quarter of the crisis in the U.S. SBE did predict a drop of inflation whereas the ARMA expectations did not decrease until the following quarter. It should be noted again that while ARMA expectations are formed with information up to September 30, SBE inflation expectations are set on November 15, in the middle of the quarter. Thus, the participants in the forecasts had more information on the state of the economy than the time series model. However, they did not know that prices had gone down in October, as the CPI announcement is released in the second half of the next month, right after SPF reporting.

[Insert Figure 10 and Figure 11 About Here]

Although SBE forecasters had some more information to predict CPI inflation for the fourth quarter of 2008, they, however, did not believe that the inflation drop was going to be permanent. As Figure 10 shows, inflation dropped in the fourth quarter of 2008, but then returned to positive values in the first and second quarters of 2009. Figure 11 compares the one-to-five quarter ahead survey-based and ARMA inflation forecasts. It shows that one-quarter ahead SBE behaved quite differently from two-to-five quarter ahead forecasts, whereas ARMA forecasts were very similar across forecast horizons. Interestingly, in November 15, SBE forecasters thought that CPI inflation was only going to be negative during the fourth quarter of 2008. At that time, they correctly predicted that the first and second quarter of 2009 inflation was going to be

at normal low positive values. Indeed, they predicted a -2.25% inflation rate for the 4th quarter of 2008 and a 0.5% inflation rate for the 1st quarter of 2009 -a large 3% inflation difference-. In contrast, the bottom panel of Figure 11 shows that this is not the case with the ARMA model. Due to its construction, once it predicted negative one-period-ahead inflation for the first quarter of 2009, it also predicted (incorrectly) two and three-period-ahead negative inflation. In particular, the ARMA model predicted a -2.5% inflation rate one-quarter ahead and a -2% two-quarters ahead -a small 0.5% inflation difference, consistent with a slow return to the mean for longer forecast horizons-. Therefore, this recent episode illustrates the high flexibility of SBE. Unlike ARMA expectations, they can *simultaneously* predict a relatively important drop in inflation one-quarter ahead and a return to normal inflation rates two-quarters ahead.

## 4 Conclusions

This paper first documents that SBE outperform standard time series models in predicting out-of-sample quarterly inflation in the U.S. across all forecast horizons. It also shows that the term structure of survey-based inflation forecasts provides valuable information on both future inflation changes as well as longer term inflation rates. We then provide some empirical explanations for the good results exhibited by SBE: aggregation of agents with heterogeneous inflation expectations dynamics, significantly faster and stronger revision of inflation SBE to inflation and monetary policy shocks, and more flexible adjustment mechanics.

Thus, an implication of our study is that SBE display a more flexible adjustment to macro conditions than standard time series models. SBE are not subject to the parametric constraints of ARMA and VARMA models and this may be an advantage

whenever there is a relevant shock hitting the economy and agents' information sets. We also showed that in the recent crisis, one-period ahead SBE have behaved qualitatively differently to two-to-five period expectations. This flexible behavior is hard to obtain with standard parametric time series models.

We also showed that SBE react to a larger pool of information than the best time series model, the ARMA(1,1). While this is partly due to the fact that the ARMA model is univariate and all its expectational adjustment comes through inflation, we also showed that the multivariate VAR was a much worse inflation predictor than the ARMA(1,1). It is thus clear that time series models tend to face a trade-off between out-of-sample predictability and information set size which SBE avoid by construction.

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Table 1: Survey Based Inflation Expectations: Descriptive Statistics

	$\pi^e(1)$	$\pi^e(2)$	$\pi^e(3)$	$\pi^e(4)$	$\pi^e(5)$	$\pi^e(1y)$
$\bar{\pi}^e$	3.16	3.16	3.25	3.32	3.38	3.43
$\sigma(\pi^e)$	1.13	0.95	0.96	0.98	1.01	1.22
$\rho(1)$	0.58	0.89	0.95	0.95	0.96	0.97
$\rho(2)$	0.43	0.84	0.90	0.92	0.93	0.95
$\rho(3)$	0.50	0.83	0.88	0.91	0.91	0.92
$\rho(\pi^e(1), \pi^e(i))$	1					
$\rho(\pi^e(2), \pi^e(i))$	0.82	1				
$\rho(\pi^e(3), \pi^e(i))$	0.74	0.97	1			
$\rho(\pi^e(4), \pi^e(i))$	0.71	0.95	0.99	1		
$\rho(\pi^e(5), \pi^e(i))$	0.71	0.94	0.98	0.99	1	

This table shows the descriptive statistics of quarterly survey-based inflation expectations across forecast horizons. It also shows in the last column the statistics of the annual 1-year ahead survey-based forecasts.

Table 2: **Prediction of Longer-Term Inflation through the Term Structure of Quarterly Forecasts**

	SBE		ARMA	
	$\alpha$	$\theta$	$\alpha$	$\theta$
$k=2$	1.52 (0.37)	0.48 (0.12)	1.99 (0.38)	0.32 (0.12)
$k=3$	1.39 (0.34)	0.51 (0.10)	1.86 (0.37)	0.35 (0.11)
$k=4$	1.43 (0.37)	0.50 (0.11)	1.94 (0.39)	0.33 (0.11)
$k=5$	1.63 (0.39)	0.43 (0.11)	2.09 (0.37)	0.28 (0.10)

This table shows the parameter estimates and standard errors (in parentheses) of this predictive equation:

$$\pi_{t,t+k} = \alpha + \theta \frac{1}{k} \sum_{i=1}^k E_t \pi_{t+i} + \varepsilon_{t,t+k}, \quad k = 2, \dots, 5.$$

The estimation is carried out through GMM as in Hansen (1982) with standard errors computed with  $k - 1$  Newey-West lags, in order to correct for the associated overlapping errors.

Table 3: **Prediction of Future Inflation Changes (I)**

	SBE		ARMA	
	$\alpha$	$\beta$	$\alpha$	$\beta$
$k=1$	-0.22 (0.18)	1.72 (0.16)	-0.45 (0.20)	1.50 (0.18)
$k=2$	-0.25 (0.20)	1.12 (0.13)	-0.63 (0.24)	1.54 (0.17)
$k=3$	-0.25 (0.19)	0.81 (0.14)	-0.58 (0.21)	1.10 (0.21)
$k=4$	-0.38 (0.23)	1.05 (0.12)	-0.81 (0.25)	1.51 (0.18)
$k=5$	-0.52 (0.27)	1.03 (0.12)	-0.97 (0.28)	1.47 (0.13)

This table shows the parameter estimates and standard errors (in parentheses) of this predictive equation:

$$(\pi_{t+k} - \pi_t) = \alpha + \beta(E_t \pi_{t+k} - \pi_t) + \epsilon_{t,t+k}, \quad k = 1, \dots, 5.$$

The estimation is carried out through GMM as in Hansen (1982) with standard errors computed with  $k - 1$  Newey-West lags, in order to correct for the associated overlapping errors.

Table 4: **Prediction of Future Inflation Changes (II)**

	SBE		ARMA	
	$\alpha$	$\beta$	$\alpha$	$\beta$
$k=2$	-0.05 (0.18)	0.21 (0.46)	-0.01 (0.47)	-0.35 (0.47)
$k=3$	-0.03 (0.19)	-0.24 (0.49)	0.10 (0.36)	-1.03 (1.92)
$k=4$	-0.05 (0.21)	0.15 (0.32)	-0.29 (0.36)	1.22 (0.92)
$k=5$	-0.22 (0.25)	0.48 (0.26)	-0.43 (0.54)	1.16 (1.39)

This table shows the parameter estimates and standard errors (in parentheses) of this predictive equation:

$$(\pi_{t+k} - \pi_{t+1}) = \alpha + \beta(E_t \pi_{t+k} - E_t \pi_{t+1}) + \epsilon_{t,t+k}, \quad k = 2, \dots, 5.$$

The estimation is carried out through GMM as in Hansen (1982) with standard errors computed with  $k - 1$  Newey-West lags, in order to correct for the associated overlapping errors.

Table 5: **Fractional Integration Estimates for Inflation SBE**

Quarterly	(1)		(2)	
1-quarter ahead	0.46	[0.39 0.58]	0.43	[0.35 0.63]
2-quarters ahead	0.65	[0.53 0.95]	0.54	[0.46 1.11]
3-quarters ahead	0.98	[0.66 1.16]	0.58	[0.50 1.15]
4-quarters ahead	0.85	[0.58 1.04]	0.63	[0.51 1.24]
5-quarters ahead	0.81	[0.59 1.02]	0.58	[0.50 1.17]
Annual	(1)		(2)	
1-year ahead	1.03	[0.88 1.19]	0.60	[0.51 1.19]

This table shows the estimated fractional orders of integration ( $d$ ) of inflation SBE across frequencies and horizons together with the 5% and 95% cumulative values of the distribution. We estimate the model  $(1 - L)^d(\pi_{t,t+1}^e - \mu) = \epsilon_t$  as in Robinson (1994). The columns in (1) are the estimates obtained with *i.i.d.*  $\epsilon_t$  whereas the columns in (2) are the estimates under the assumption that the error terms display short-term autocorrelation using the model of Bloomfield (1973) with order 1.

Table 6: Reaction of Inflation Expectations to Macro Variables

	SBE					ARMA				
	$\alpha$	$\beta$	$\gamma$	$\delta$	$R^2$	$\alpha$	$\beta$	$\gamma$	$\delta$	$R^2$
$k=1$	1.09 (0.36)	0.39 (0.08)	-0.01 (0.08)	0.21 (0.04)	0.45	1.54 (0.40)	0.49 (0.09)	-0.07 (0.08)	0.18 (0.04)	0.50
$k=2$	0.58 (0.29)	0.17 (0.07)	0.14 (0.06)	0.25 (0.03)	0.70	1.66 (0.39)	0.46 (0.08)	-0.06 (0.08)	0.18 (0.03)	0.50
$k=3$	0.42 (0.31)	0.14 (0.07)	0.19 (0.07)	0.26 (0.03)	0.75	1.76 (0.37)	0.43 (0.08)	-0.05 (0.07)	0.17 (0.03)	0.50
$k=4$	0.33 (0.34)	0.11 (0.08)	0.22 (0.07)	0.26 (0.02)	0.78	1.86 (0.35)	0.41 (0.08)	-0.04 (0.07)	0.17 (0.03)	0.51
$k=5$	0.25 (0.39)	0.12 (0.07)	0.24 (0.08)	0.27 (0.02)	0.78	1.95 (0.34)	0.38 (0.07)	-0.03 (0.07)	0.16 (0.03)	0.52

This table shows the parameter estimates and standard errors (in parentheses) of this predictive regressions:

$$E_t \pi_{t+k} = \alpha + \beta \pi_t + \gamma u_t + \delta i_t + \varepsilon_t, \quad k = 1, \dots, 5.$$

The table shows the GMM estimates with standard errors computed with 3 Newey-West lags and the regressions'  $R^2$ 's.



Table 7: **Revision of Inflation Expectations in Response to Macro Variables**

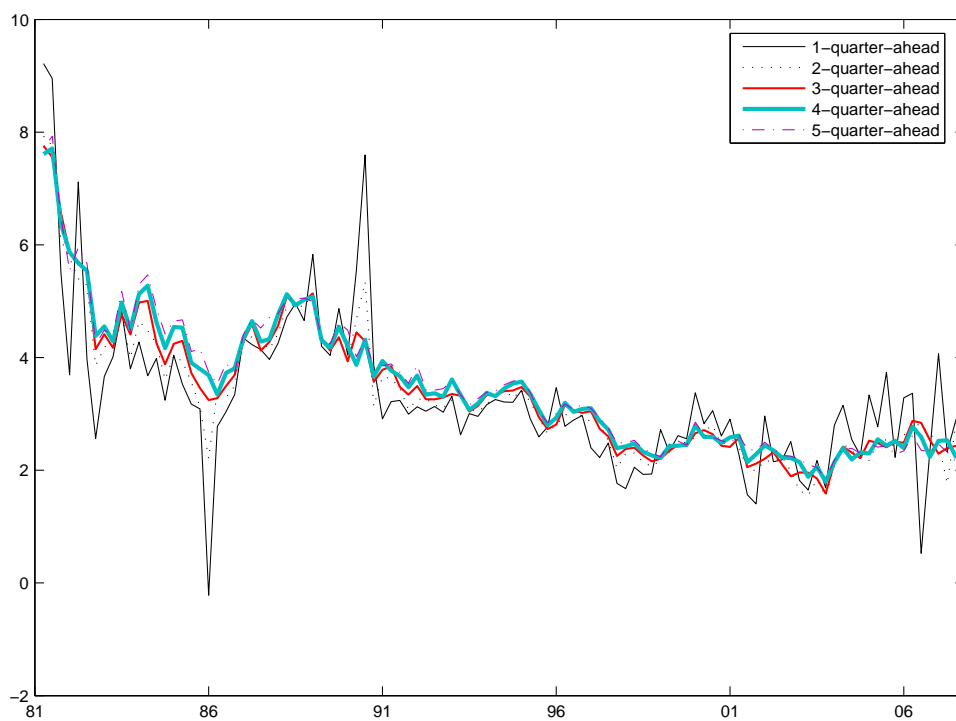
	SBE					ARMA				
	$\alpha$	$\beta$	$\gamma$	$\delta$	$R^2$	$\alpha$	$\beta$	$\gamma$	$\delta$	$R^2$
$i=1$	0.71 (0.29)	0.17 (0.07)	-0.16 (0.05)	0.05 (0.03)	0.11	-0.06 (0.37)	0.17 (0.07)	-0.08 (0.07)	-0.01 (0.03)	0.04
$i=2$	1.05 (0.36)	0.25 (0.07)	-0.25 (0.07)	-0.08 (0.04)	0.21	0.18 (0.51)	0.25 (0.09)	-0.17 (0.10)	-0.01 (0.03)	0.09
$i=3$	1.40 (0.38)	0.29 (0.08)	-0.34 (0.07)	-0.08 (0.04)	0.31	0.68 (0.61)	0.24 (0.09)	-0.26 (0.10)	-0.01 (0.04)	0.14
$i=4$	1.72 (0.45)	0.35 (0.08)	-0.43 (0.07)	-0.09 (0.04)	0.39	1.16 (0.77)	0.31 (0.10)	-0.39 (0.11)	-0.02 (0.05)	0.22

This table shows the parameter estimates and standard errors (in parentheses) of this predictive revision regressions:

$$E_t\pi_{t+1} - E_{t-i}\pi_{t+1} = \alpha + \beta\pi_t + \gamma u_t + \delta i_t + \varepsilon_t, \quad i = 1, \dots, 4.$$

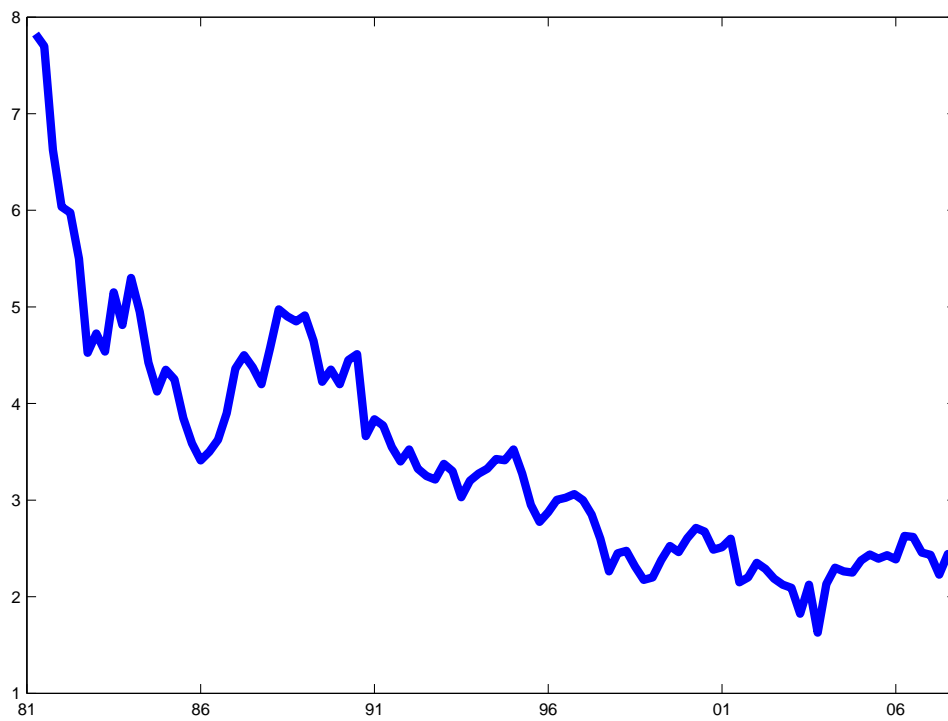
The table shows the GMM estimates with standard errors computed with 3 Newey-West lags and the regressions'  $R^2$ 's.

Figure 1: Quarterly Survey-Based Inflation Expectations



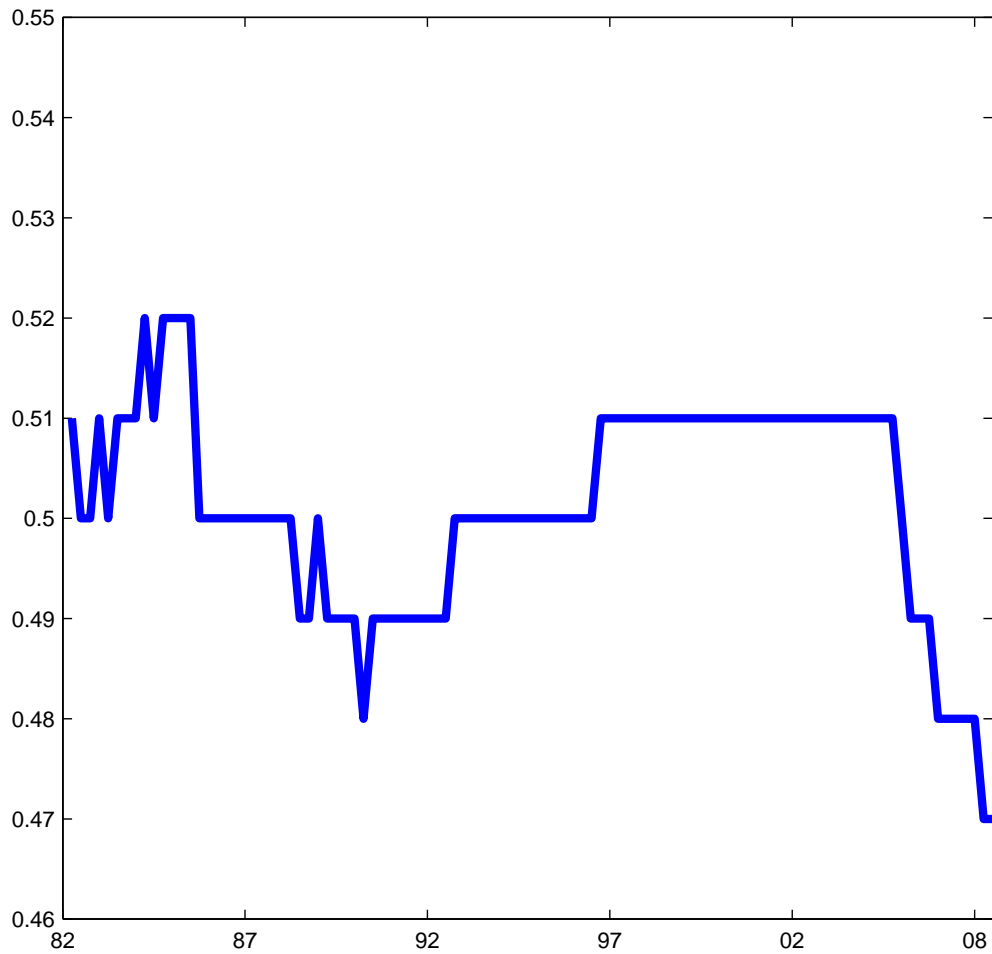
This graph plots the quarterly CPI inflation survey-based expectations at the alternative forecast horizons.

Figure 2: Annual Survey-Based Inflation Expectations



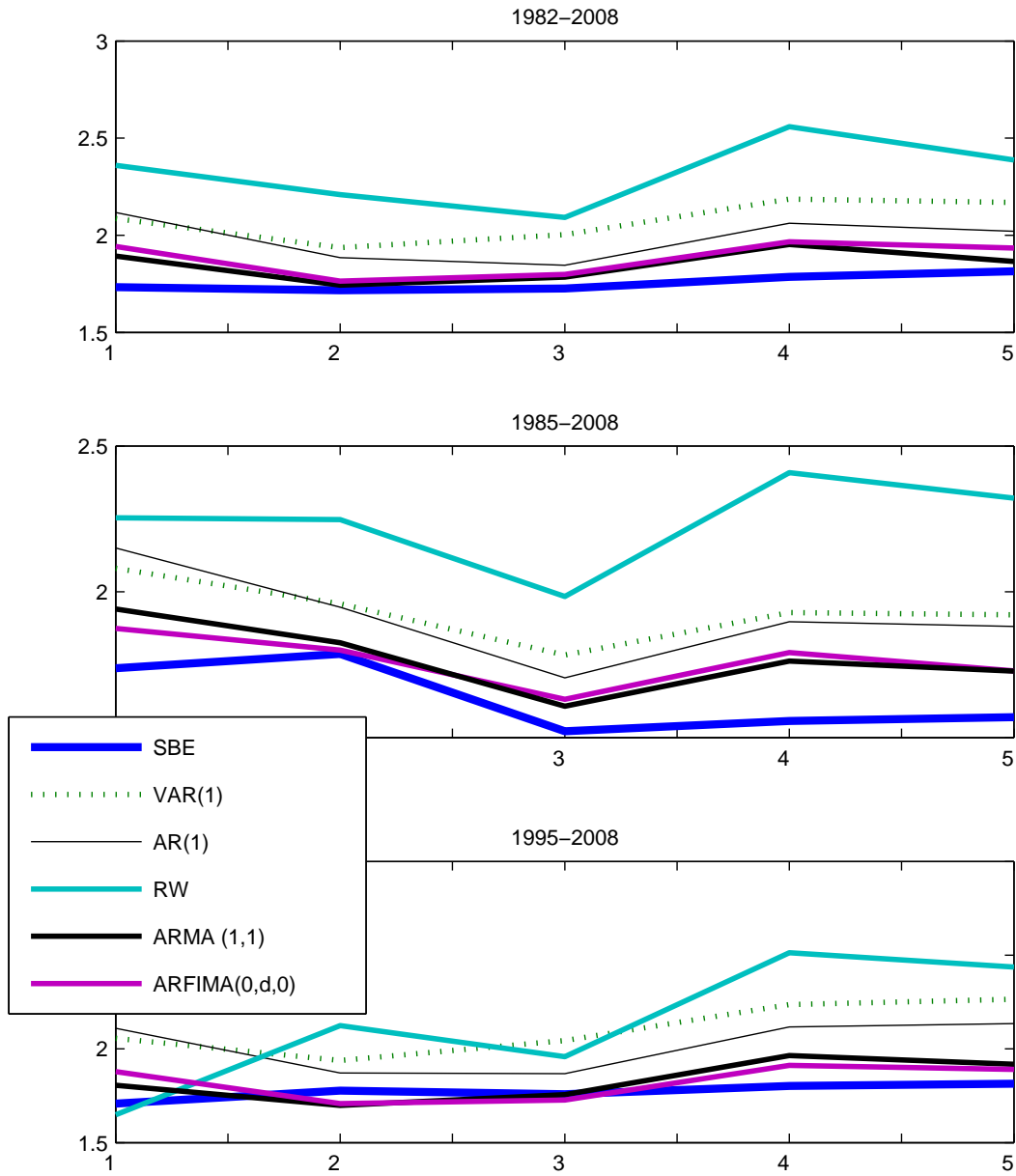
This graph plots the annual CPI inflation survey-based expectations.

Figure 3: Fractional Integration Parameter: Inflation



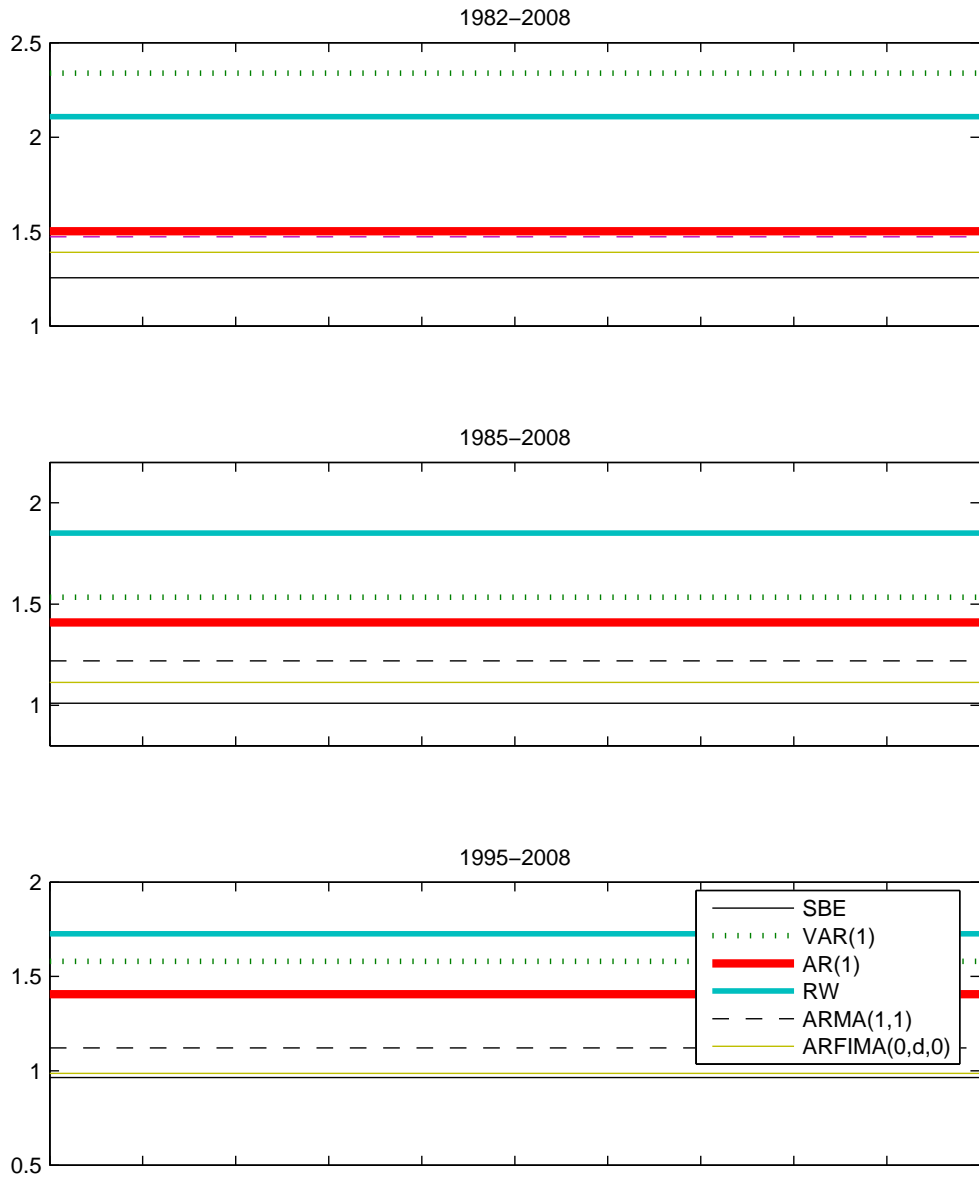
This graph plots the recursively estimated value of the fractional integration parameter  $d$  in an ARFIMA(0, $d$ ,0) model for the inflation rate with white noise standard errors. The first estimation starts with data up to the fourth quarter of 1982 and the recursive estimates are obtained including an additional observation up to the second quarter of 2008.

Figure 4: Quarterly Inflation Prediction: Root Mean Square Errors (RMSE)



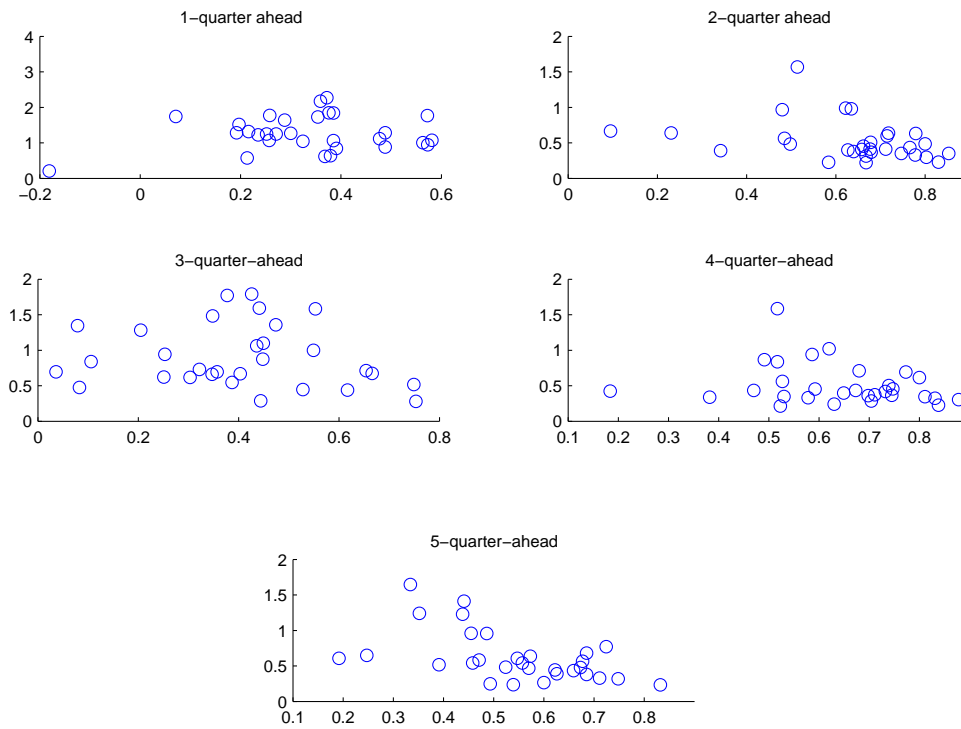
This figure compares the RMSE of the survey-based quarterly inflation prediction (from 1 to 5 quarters ahead) with those implied by the five alternative time series models considered in the paper.

Figure 5: Annual Inflation Prediction: Root Mean Square Errors (RMSE)



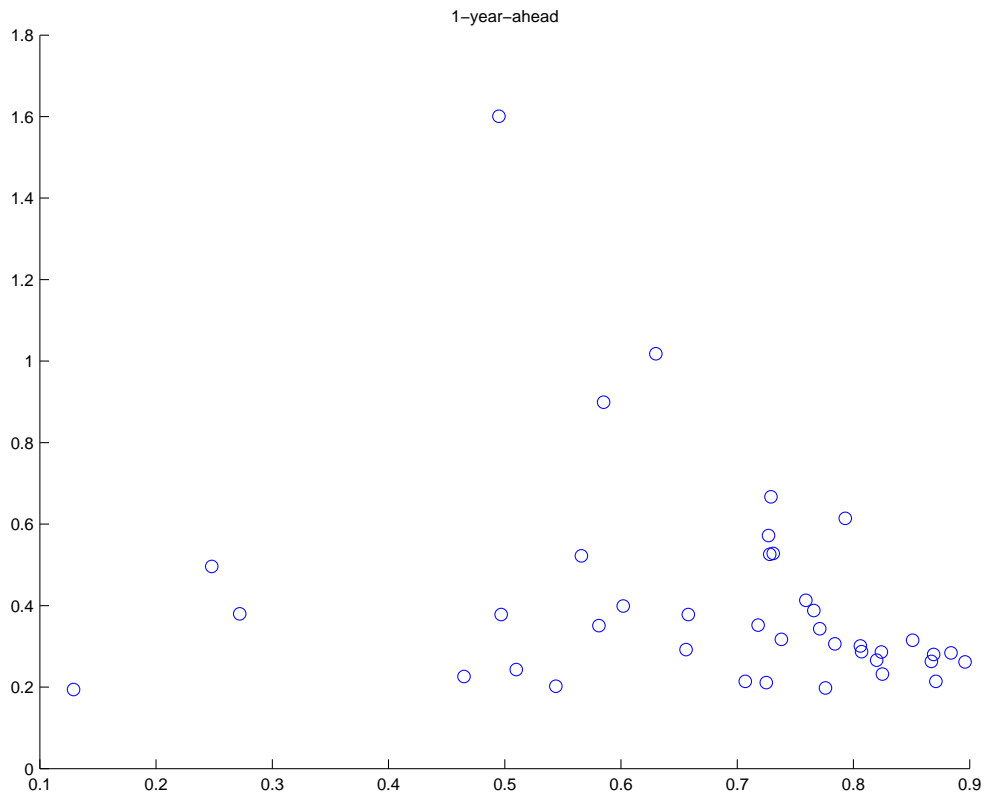
This figure compares the RMSE of the survey-based annual inflation prediction (one-year ahead) with those implied by the five alternative time series models considered in the paper.

Figure 6: Auto-Regressive Coefficient v/s Shock Standard Deviation: Quarterly Inflation



This set of scatter plots shows the values of the auto-regressive coefficients of the inflation SBE series (fit from an AR(1) process) with the associated shock standard deviation for each forecaster. The auto-regressive coefficients appear in the x-axis, whereas the shock sizes are in the y-axis. Each plot corresponds to one forecast horizons (from 1 to 5 quarters ahead).

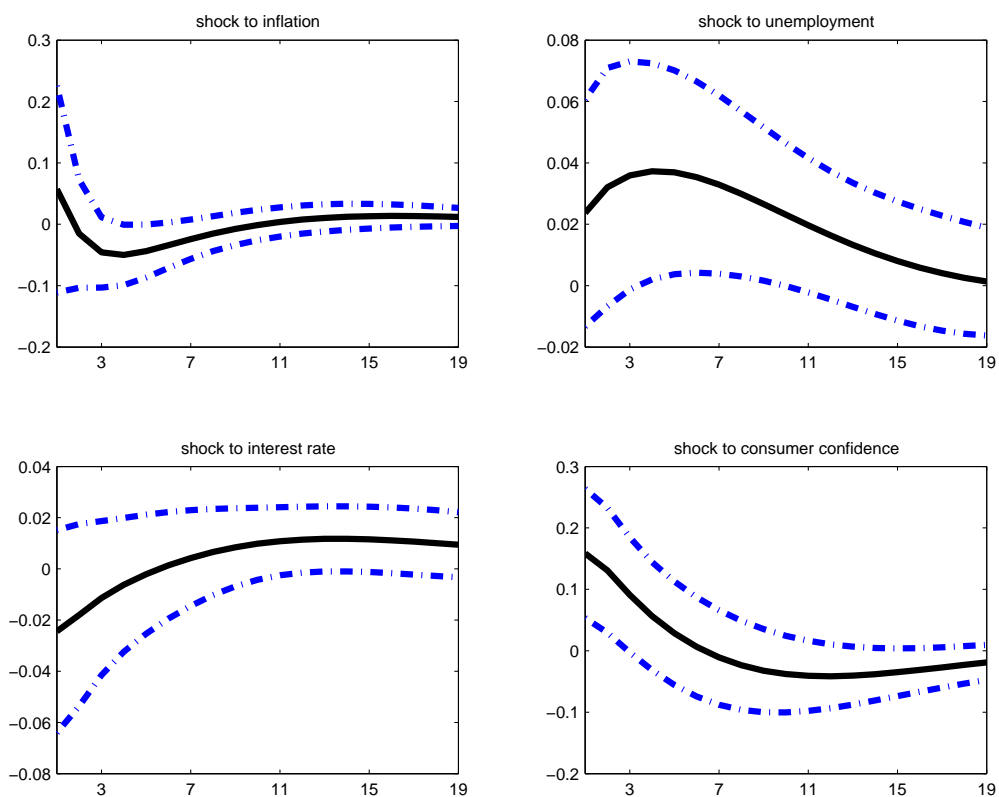
Figure 7: Auto-Regressive Coefficient v/s Shock Standard Deviation: Annual Inflation



This scatter plot shows the values of the auto-regressive coefficients of the inflation SBE series (fit from an AR(1) process) with the associated shock standard deviation for each forecaster. The auto-regressive coefficients appear in the x-axis, whereas the shock sizes are in the y-axis. The forecast-horizon is one-year-ahead.

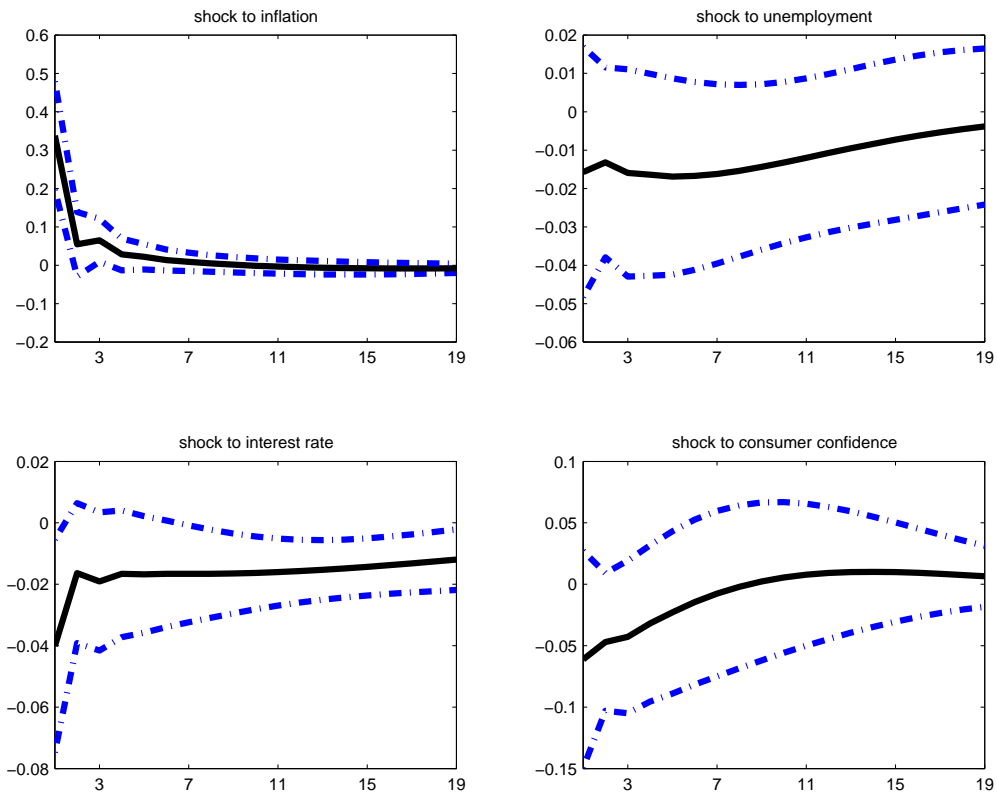


Figure 8: Impulse Response Functions of SBE - ARMA Inflation Expectations



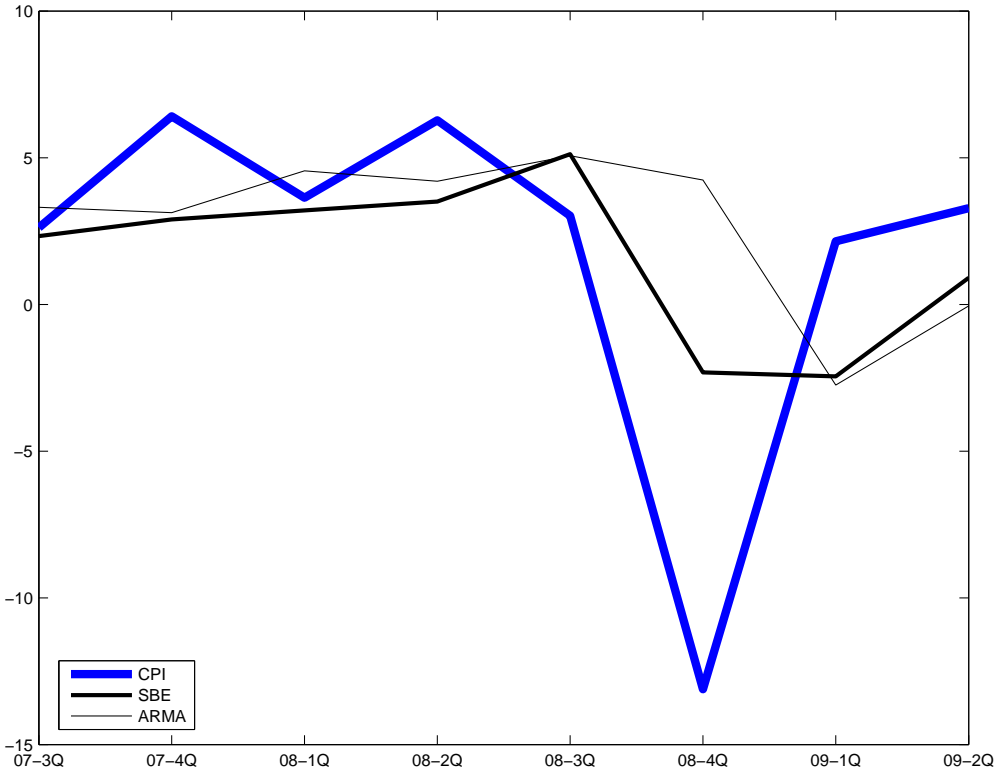
This figure plots the impulse response functions of the difference between one-period-ahead SBE and ARMA inflation expectations to the structural shocks identified in a recursive VAR(1).

Figure 9: Impulse Response Functions of SBE - ARMA Revisions of Inflation Expectations



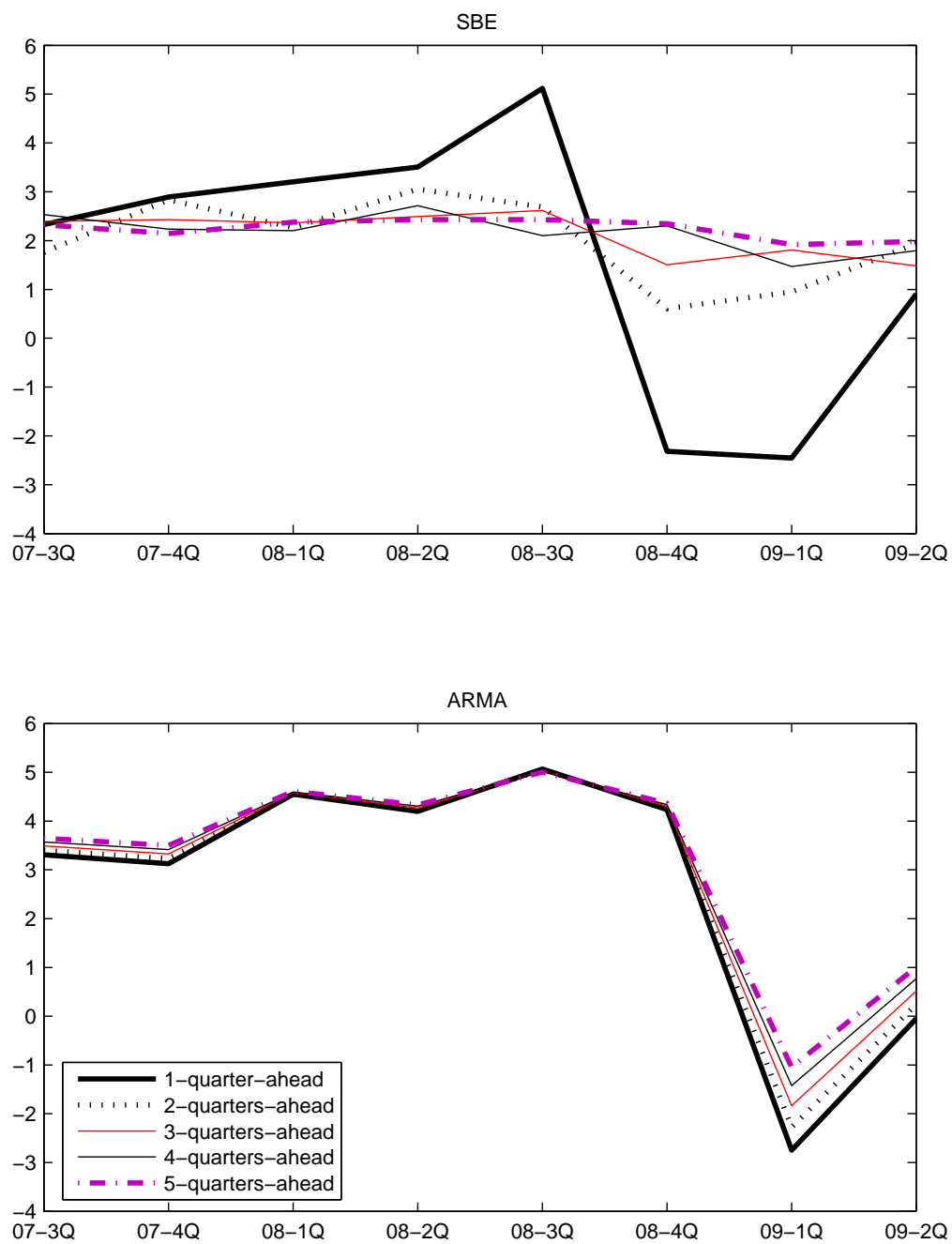
This figure plots the impulse response functions of the difference between one-period-ahead SBE and ARMA one-period revision of inflation expectations to the structural shocks identified in a recursive VAR(1).

Figure 10: Inflation and One-Period-Ahead Inflation Expectations in the 2008 Financial Crisis



This figure compares the one-period ahead SBE and ARMA inflation expectations with the quarterly CPI since the third quarter of 2007, at the beginning of the recent financial crisis.

Figure 11: SBE and ARMA Inflation Expectations in the 2008 Financial Crisis



This figure plots the set of SBE and ARMA inflation expectations from the third quarter of 2007 -at the beginning of the recent financial crisis- to the second quarter of 2009. Each expectation data point uses information from the previous quarter.