

Tails of Inflation Forecasts and Tales of Monetary Policy*

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First Draft: January 15, 2011

This Version: November 1, 2012

*We would like to thank Marco Del Negro, Marty Eichenbaum, Rob Engle, Juan Angel Garcia, Malte Knoppel, Simone Manganelli, Massimiliano Marcellino, Julien Matheron, Cyril Monnet, Rob Rich, Barbara Rossi, Tom Sargent and Enrique Sentana for insightful comments on earlier drafts of the paper. Preliminary versions of this work benefited from comments of participants in seminars at the Banque de France, the ECB, the New York Fed, Vanderbilt University, the 26th Congress of the EEA, the 8th International Institute of Forecasters workshop, the *EC*² Conference on “The Econometrics of Policy Analysis: after the Crises and Beyond”, and the Bundesbank-Philadelphia Fed Spring conference on “Monetary Policy, Inflation and International Linkages”. Part of this research was conducted when the first author was visiting the NY Fed. The second author benefited from funding by the Banque de France, the European Central Bank and from a Marie Curie FP7-PEOPLE-2010-IIF grant. This paper does not reflect necessarily the views of the Banque de France nor of the European Central Bank.

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Abstract

We introduce a new measure called *Inflation-at-Risk* (I@R) associated with (left and right) tail inflation risk. We estimate I@R using survey-based density forecasts. We show that it contains information not covered by usual inflation risk indicators which focus on inflation uncertainty and do not distinguish between the risks of low or high future inflation outcomes. Not only the extent but also the asymmetry of inflation risks evolve over time. Moreover, changes in this asymmetry have an impact on future inflation realizations as well as on the current interest rate central banks target.

1 Introduction

The Great Inflation of the 1970s was a period where price stability was at risk. Engle’s (1982) ARCH paper and Stock and Watson’s (2002) Great Moderation paper, show that the conditional variance of future inflation was much higher during the 70s. As a consequence, the probability to reach inflation levels that are far from a given conditional mean increased. However, these inflation *uncertainty* measures treat the risk of inflation outcomes symmetrically. In this paper, we show that the distinction between inflation outcomes that are far below versus far above a given conditional mean actually matters.

We propose a new approach to measuring inflation risk that allows to investigate in a unified setup the evolution of (i) potential extreme high and low inflation realizations, and therefore (ii) inflation uncertainty, and (iii) the *asymmetry* of inflation risk. Our approach reveals that *both* the uncertainty and the asymmetry of inflation risks are time varying. Moreover we show that changes in the asymmetry of inflation risk have predictive power for future inflation realizations as well as for variations in the current interest rate monetary authorities target. Everything else being constant, when the distribution of future inflation is tilted to the right, future inflation realizations tend to be higher and monetary policy more restrictive.

To be more specific, we introduce the notion of *Inflation-at-Risk*, denoted I@R, inspired by the widely used Value-at-Risk concept in risk management. These I@R measures correspond to extreme quantiles – typically the top and bottom 5% – in the subjective distribution of future inflation realizations. They can be estimated using the individual subjective probability distributions about future inflation provided in the US and the euro-area Surveys of Professional Forecasters (SPF).¹

Beyond a quantification of tail risks, the survey-based I@R indicators provide a natural measure of perceived inflation *uncertainty* via the inter-quantile range. This measure is close to the one proposed by Zarnowitz and Lambros (1987) who rely like us on individual probabilistic assessments of inflation scenarios provided in (US) surveys but characterize future inflation uncertainty via its conditional variance.² However, and in addition to

¹More specifically, following the approach developed by Engelberg, Manski, and Williams (2009), we fit generalized *beta* distributions on each individual histogram. We then recover the population quantiles by averaging them across individuals.

²Giordani and Soderlind (2003) and Rich and Tracy (2010) also provide survey-based measures of the conditional variance of US inflation but relying on different non-parametric methods. See also Boero, Smith, and Wallis (2008) for the UK, Soderlind (2011) for the US and euro area, and Rich, Song, and Tracy (2012) for the euro area. In addition to estimating inflation uncertainty, this literature often compares it with the so-called disagreement among forecasters, i.e. the standard deviation of inflation mean point forecasts across

uncertainty, I@R also provides a measure for the *asymmetry* of inflation risks. We simply compute the absolute distance between respectively the top (5%) quantile vis-à-vis the median and the bottom (5%) quantile vis-à-vis the median inflation.³

We estimate these indicators of perceived inflation risk for two samples of quarterly SPF data: 1969-2012 for the US and 1999-2012 for the euro area. I@R reveals time series dynamics in both the range between the right and the left tails as well as the asymmetry of the upside and downside risks. For the US one can distinguish three main regimes of inflation risk over the 1969-2012 period. A period of high inflation uncertainty and where the risks were clearly tilted toward high inflation outcomes from the 70s to the mid-80s. A period of high inflation uncertainty and where the risks of relatively low inflation were dominant from the mid 80s to the early 90s. A period of low inflation uncertainty and more balanced inflation risks from the early 90s onward. So higher order moments in the conditional distribution of future inflation are time varying and periods where uncertainty is high can coincide with either right or left skewed distributions.

Moreover, we show that the asymmetry measure contains specific information about future inflation realizations. Controlling for a set of macroeconomic determinants including measures of expected inflation, perceived upside inflation risk predicts in-sample a higher inflation up to three years ahead. The effects are economically significant: in our reference specification, a one standard deviation increase in the asymmetry of inflation risk predicts, 2 years ahead, a 40 basis points increase in the GDP deflator inflation rate and a 50 basis point increase in the CPI inflation rate. This information also substantially improves the out-of-sample inflation forecasts in real-time. Depending on the horizon, the forecast RMSE is reduced by 20% to 40% compared to a model that does not include the asymmetry of the risk.⁴

Finally, we find that the interest rates the US and euro area monetary authorities target react to measures of inflation risks based on our I@R. More specifically, when right tail inflation risk increases, the target interest rate increases (again controlling for standard macroeconomic variables). The effect is quantitatively important: for the US, a one standard deviation

forecasters. Most of the references above exhibit a weak link between the two measures.

³As discussed later in the paper, this asymmetry measure is the cross-product of the interquartile range and the Bowley's (1920) robust coefficient of skewness.

⁴The asymmetry measure also enables to out-perform the celebrated random walk model of inflation (see e.g. Atkeson and Ohanian (2001) and Stock and Watson (2007)), according to the forecast accuracy comparison test of Clark and West (2007) which corrects for the absence of parameter estimation uncertainty of the random walk. None of the other more traditional survey-based measures makes such significant improvements according to the same test.

increase in the asymmetry of inflation risk increases the target interest rate by 25 basis points. The results holds when one controls for the Fed’s own inflation forecasts: the Fed reacts to the asymmetry of inflation risks beyond its own future inflation expectation. Ruge-Murcia (2003) and Kilian and Manganelli (2008) estimate structural models in which monetary authorities can have non-quadratic valuation of inflation costs. Similar to our findings, they show that monetary authorities react more aggressively when right tail inflation risk increases. We do not attempt to estimate a structural model of policy maker preferences. An advantage is that our results do not depend on specific structural assumptions about the central bank’s loss function or the economy’s DGP.

Our work contributes to the literature studying macroeconomic risks. Engle (1982) examines conditional volatility of inflation. Stock and Watson (2002) consider models featuring stochastic volatility for various macroeconomic aggregates including inflation.⁵ Our analysis goes beyond volatility as it quantifies a (specific) tail macroeconomic risk and derives a measure of the asymmetry of such risks.⁶ Christensen, Lopez, and Rudebusch (2011) rely on Treasury Inflation Protected Securities to measure deflation probabilities. Kitsul and Wright (2012) use options on inflation to estimate a risk-neutral probability distribution for future inflation which thus yields a (risk-neutral) measure of the risks of deflation or high inflation. By comparison, our survey-based measures of potential extreme events are model-free and (semi) non-parametric.

Our work is also related to the recent studies investigating the macroeconomic impact of changes in macroeconomic risks. Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksen, and Terry (2011) emphasize that uncertainty shocks, i.e. shocks to the conditional second order moments of productivity shocks, contribute non-trivially to macroeconomic fluctuations.⁷ These papers study real economies. Basu and Bundick (2011) and Vavra (2012) investigate the impact of uncertainty shocks in sticky price models. Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2011) focus on fiscal policy uncertainty shocks in such a setup. In comparison, we rely on non-structural characterizations of changes in the distribution of inflation as perceived by forecasters and

⁵More recently, Primiceri (2005) and Sims and Zha (2006) estimate structural VAR in which shocks have time-varying conditional variances, and Fernández-Villaverde and Rubio-Ramírez (2007) and Justiniano and Primiceri (2008) estimate structural DSGE models with such conditionally heteroscedastic shock processes.

⁶Curdia, Del Negro, and Greenwald (2012) point to the importance of rare events in their estimation of a DSGE model with structural shocks featuring both time-varying volatility and fat-tailed distributions. They do not consider asymmetric distributions.

⁷See also Gourio (2012) for an approach based on changes in the probability of extreme events. See Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011) for shocks on the volatility of a small open economy domestic interest rate.

show that they affect inflation and monetary policy outcomes.

The rest of the paper is organized as follows. In Section 2, we introduce our new indicators and describe how we estimate them. In Section 3, we underline several empirical regularities that we obtain looking at the behavior of these new indicators in US and European data. In Section 4, we document the impact of inflation risk on future inflation realizations and in Section 5 we investigate the interaction of perceived inflation risks and monetary policy. We conclude in Section 6.

2 New survey-based measures of inflation risk

We introduce two new measures of inflation risk and discuss how to estimate them using inflation survey data. While our focus is on inflation risk, the methods proposed here are to the best of our knowledge new to the literature on risk measures using survey data, and are therefore of general interest. The first two subsections introduce the respective measures, a third subsection compares them with the more usual survey-based measures, and a fourth subsection covers the estimation procedure.

2.1 Inflation-at-Risk (I@R)

We let π_t denote the date t inflation rate, and $F_{it}^h(x)$ individual i 's cumulative distribution function (CDF) conditional on date t information for the inflation rate at horizon $t + h$ namely:

$$F_{it}^h(x) = \Pr \{ \pi_{t+h} \leq x | I_t^i \},$$

where I_t^i is the information set of individual i at time t . Moreover, let $q_{it}^h(p)$ be individual i 's conditional quantile associated with probability level p (obtained from the above CDF assuming for simplicity it is strictly increasing):

$$p = \Pr \{ \pi_{t+h} \leq q_{it}^h(p) | I_t^i \} \quad \text{or} \quad q_{it}^h(p) = (F_{it}^h)^{-1}(p).$$

In addition, letting $E_i(\cdot)$ denotes the expectation across individuals, we can introduce the following new measure of inflation risk at date t , which we define as *Inflation-at-risk*:

$$\text{I@R}_t^h(p) = E_i [q_{it}^h(p)]. \tag{2.1}$$

In the empirical application, we look at respectively the 5th ($p = .05$) and 95th ($p = .95$) percentiles. Hence, we compute an average across individuals of their expected extreme low and high inflation outcomes – that is the average quantiles for left and right tail probabilities. The inspiration for these measures is the well known notion of Value-at-Risk that features prominently in bank capital requirements as stipulated in the Basel Committee accords.⁸ Obviously, in risk management the focus is only on the left tail – that is on potential losses. In our case, we are interested in both tails – as noted earlier – for potentially different asymmetric implications: fear of price depression versus inflation.

Monetary policy statements by central bankers frequently allude to notions of risk management – in particular in terms of tail risks.⁹ Moreover, central banks also assess the balance of macroeconomic risks (see e.g. Knuppel and SchulteFrankenfeld (2011) for a description of what central banks do in practice to assess macroeconomic risks). Nevertheless, the idea of a link between monetary policy and extreme event analysis is empirically relatively unexplored.¹⁰ Our model free measures facilitate such an empirical analysis.

2.2 The interquantile range (IQR) and asymmetry (ASY) of future inflation distribution

In this section we introduce two measures characterizing the distribution of future inflation that build further on the notion of the I@R survey-based quantiles. The first is the inter-quantile range of the conditional inflation distribution associated to a risk level p . It is a natural measure of inflation uncertainty, as it pertains to the range of possibly future inflation outcomes. More precisely, given the individual quantiles defined above, the average inter-quantile range of the future inflation distribution associated to a risk level p such that $p < .5$ is defined as:

$$\text{IQR}_t^h(p) = E_i [q_{it}^h(1 - p) - q_{it}^h(p)], \quad (2.2)$$

where E_i denotes the expectation across individual forecasters i . Since it is a measure related to second moments, it can potentially be compared with model-based conditional volatilities

⁸See e.g. Jorion (2001), Gouriéroux and Jasiak (2009), among many others, for further details.

⁹See for instance speeches by Greenspan (2003) and Mishkin (2008) on the notion of monetary policy and risk management.

¹⁰One noticeable exception is Kilian and Manganelli (2008) who introduce and estimate a risk management model of monetary policy. They show that the type of risk-based decision rule implicit in several FOMC statements can be derived from their framework and that this decision rule will coincide with the Taylor rule only under the restrictive assumption of quadratic (i.e. symmetric) preferences of the central banker. In their empirical implementation they find compelling evidence against symmetry during the Greenspan era.

– although it is of course survey- and quantile-based.

Another new measure is inspired by Bowley’s (1920) robust coefficient of asymmetry (skewness) which is defined as:

$$RA_{it}^h(p) = \frac{(q_{it}^h(1-p) - q_{it}^h(.50)) - (q_{it}^h(.50) - q_{it}^h(p))}{q_{it}^h(1-p) - q_{it}^h(p)}. \quad (2.3)$$

with p a chosen probability $< .50$ and where E_i denotes the expectation across individual forecasters i . It is immediately clear that this measure captures asymmetries of the inter-quantile range with respect to the median. It was primarily introduced as a measure of skewness that is robust to outliers, since the quantiles in equation (2.3) are not affected by them. The normalization in the denominator insures that the measure is unit independent with values between -1 and 1 . Symmetric distributions yield $RA_{it}^h = 0$, while values diverging to -1 (1) indicate skewness to the left (right). The RA_{it}^h and related measures of asymmetry have received very limited attention in the empirical macro and finance literatures, with a few exceptions including Kim and White (2004), White, Kim, and Manganelli (2008) and Ghysels, Plazzi, and Valkanov (2010) – who also provide further details and applications in equity market return asymmetries.

For our empirical work we will operate in a linear regression framework and in particular, for the purpose of hypothesis testing it will be more convenient *not* to normalize the RA_{it}^h . Hence, our measure is defined as:

$$ASY_t^h(p) = E_i [(q_{it}^h(1-p) - q_{it}^h(.50)) - (q_{it}^h(.50) - q_{it}^h(p))]. \quad (2.4)$$

While in principle, we could consider different values of p – similarly to $I@R_t^h(p)$ – we typically will consider the case of $p = .05$.

It is worth emphasizing several characteristics of the IQR and ASY measures. First, they are an average of individuals’ perception of the inter-quantile range and asymmetry in inflation risk. Indeed, the definitions given in equations (2.2) and (2.4) can be respectively rewritten as

$$IQR_t^h(p) = E_i [IQR_{it}^h(p)], \quad ASY_t^h(p) = E_i [ASY_{it}^h(p)].$$

So, the measures catch the inter-quantile range and asymmetry of an agent representative of the sample and they are consequently not a byproduct of aggregating the individual distributions into an aggregate one.

Second, combining equations (2.4) and (2.3) makes apparent that the asymmetry measure we use can be seen as the product of a measure of relative asymmetry in the distribution of inflation risks and a measure of the amount of uncertainty associated with future inflation as captured by the inter-quantile range of the future inflation distribution. Indeed, using the individual inter-quantile range expression $\text{IQR}_{it}^h(p) = q_{it}^h(1-p) - q_{it}^h(p)$ one can rewrite

$$\text{ASY}_t^h(p) = E_i [\text{RA}_{it}^h(p) \times \text{IQR}_{it}^h(p)].$$

So the asymmetry increases with the uncertainty associated to inflation expectations. Asymmetry can thus be viewed as a signed measure of uncertainty.

Third and finally, it should be pointed out that a finding of a negative ASY is not systematically related to a situation where deflation risks are important. The measure of asymmetry just informs on how risks are distributed around a given central tendency for future inflation. In case this central tendency is high, it can even be the case that ASY is negative while no respondent in the survey believes that there is a positive probability for a deflation to occur.

2.3 Comparison with existing survey-based risk measures

Most of the literature using survey data focuses on two other characteristics of the conditional distribution of future inflation: the “consensus” forecast, i.e. the average of individuals’ mean point forecasts, and the “disagreement” among forecasters, i.e. the cross-section dispersion of individual mean point forecasts.¹¹ More precisely, using our notation, the *consensus* forecast is defined as:

$$\text{MPF}_t^h = E_i(\text{MPF}_{it}^h), \quad (2.5)$$

where MPF_{it}^h is the date t mean point forecast of inflation at horizon h quarters of an individual i , namely $\text{MPF}_{it}^h = E(\pi_{t+h}|i, t) = \int \pi_{t+h} dF_{it}^h$, with F_{it}^h individual i ’s subjective CDF for inflation at horizon h . The *disagreement* between forecasters is defined as:

$$\text{DIS}_t^h = \left\{ E_i [\text{MPF}_{it}^h - E_i(\text{MPF}_{it}^h)]^2 \right\}^{1/2}. \quad (2.6)$$

¹¹Pesaran and Weale (2006) provide a survey of the existing literature on survey forecasts. See Mankiw, Reis, and Wolfers (2003), Lahiri and Sheng (2008), Andrade and Le Bihan (2010), Coibion and Gorodnichenko (2010), Patton and Timmermann (2010), and Coibion and Gorodnichenko (2012) for recent references linking the properties of the consensus and the disagreement to various models of imperfect information.

Data from the Surveys of Professional Forecasters is also used to compute an alternative measure of forecasts *uncertainty*, that is the average standard deviation (or variance) of the mean-point forecast defined as:

$$\text{SDMPF}_t^h = E_i (\text{SDMPF}_{it}^h | i, t), \quad (2.7)$$

where $\text{SDMPF}_{it}^h = \left\{ \int [\pi_{t+h} - E(\pi_{t+h} | i, t)]^2 dF_{it}^h \right\}^{1/2}$.

Our measures can be linked to several of the aforementioned indicators in some special cases. $\text{I@R}_t^h(.50)$ and MPF_t^h are equal under the assumption of symmetric individual's CDFs. Assuming furthermore that each individual's CDF follows a normal distribution (potentially heterogenous across agents), we have that $\text{IQR}_t^h(.05) = 2 \times 1.64 \times \text{SDMPF}_t^h$. More generally, the IQR and SDMPF measures convey the same type of information about the conditional dispersion of the conditional inflation distribution. The new survey-based I@R and ASY measures therefore complement the standard analysis of survey data since none of the standard measures MPF, DIS, and SDMPF, feature either asymmetries or reveal the extend of extreme low or high inflation fears. As noted by Zarnowitz and Lambros (1987), there is no simple link between disagreement and the measures of uncertainty.

2.4 Estimation method

The key to the estimation of the I@R and ASY measures is \widehat{F}_{it}^h (and hence \widehat{q}_{it}^h as well). Indeed, once we have those estimates we can compute empirical averages across the N_t number of individuals participating in the survey at date t , namely

$$\begin{aligned} \widehat{\text{I@R}}_t^h(p) &= \frac{1}{N_t} \sum_i \widehat{q}_{it}^h(p), \\ \widehat{\text{ASY}}_t^h(p) &= \frac{1}{N_t} \sum_i [\widehat{q}_{it}^h(1-p) + \widehat{q}_{it}^h(p) - 2 \times \widehat{q}_{it}^h(.50)]. \end{aligned} \quad (2.8)$$

The survey responses appear as discrete distribution histograms that are recorded for each respondent. To calculate the individual quantiles, we need to have continuous versions of these individual empirical distributions. Hence, we need to fit a continuous distribution matching the discrete histograms. We follow the methodology of Engelberg, Manski, and Williams (2009) who consider matching generalized *beta* distributions to the individual discrete histograms. The details of the procedure appear in Appendix A.

The basic idea is to fit a flexible class of distributions, using only a few parameters. Flexibility is important as we want to capture asymmetric distributions. An alternative and more classical method, implemented for instance in Zarnowitz and Lambros (1987), is to assume that the reported probabilities are spread uniformly across each bin (and in addition that the open ended intervals have finite width). An advantage is that one can also accommodate the potential asymmetry of the distribution. However, as Giordani and Soderlind (2003) argue, a lot of the individual distributions are unimodal, which suggests that more of the probability in each bin is closer to the center of the distribution. The uniform assumption has thus a tendency to overweigh the mass put on extreme values of the forecasts distribution and hence to inflate its dispersion.

Other studies, like for instance Giordani and Soderlind (2003), fit a normal distribution, which is constrained to be symmetric. This limit can be overcome by resorting to the skewed normal as is done in Garcia and Manzanares (2007). This latter method requires to estimate 3rd and 4th order moments of the individual forecast distributions, that is more parameters than for the generalized *beta*, and moreover high order moment-based estimators that are known to be very sensitive to outliers and tend to be noisy. Relying on normal distributions also have the drawback that incredibly high (technically infinite) future inflation events appear in the set of possible outcomes.

Finally, another important characteristic of our method is to rely on individual distributions to estimate the quantiles $\hat{q}_{it}^h(p)$. One could potentially aggregate the individual distributions cross-sectionally and then calculate quantiles. However, central limit arguments imply that this aggregated empirical distribution would tend to be Gaussian and thus potentially mask the asymmetries of the individual distributions.

It is fair to say, however, that the methodology of Engelberg, Manski, and Williams (2009) has some drawbacks too. It is not per se a good estimator of the tails. Notably, it depends on deciding where to close the endpoints of the extreme lower and upper survey response intervals.¹² As we discuss in the next section, we perform several robustness tests using either a variation on the Engelberg, Manski, and Williams (2009) method, or an alternative method. Our findings are robust with respect to these variations.

¹²The intervals of the histograms are determined by the survey design and vary through time. See Appendix B for details.

3 Inflation risk: some new US and European survey-based facts

Since our new measures capture hitherto undocumented features of SPF survey data, we start with reporting stylized facts about asymmetries and extreme outcomes extracted from SPF data over the 1969-2012 sample for the US and the 1999-2012 sample for the euro area. The data that we used are described in Appendix B.

3.1 Consensus inflation forecasts and I@Rs

As noted above, the most widely used measure extracted from surveys is the average of individual point forecasts, also often called the *consensus* forecasts. Figure 1 reports for the US and euro area both inflation realizations and mean point forecasts. The one-year ahead forecast is highly influenced by the previous observation of inflation and there are long periods of either systematically positive or negative forecast errors. In the US, inflation was systematically understated over the 70s, overstated over the 80s and 90s, and understated again in the 2000s. In the euro area, inflation was systematically understated according to the consensus forecast between 1999 and 2006, even as the consensus gradually trended upward from 1.2% to 2.2% over the period. It is also striking that inflation forecasts did not change much after the 2008 crisis.

Table 1 presents some descriptive statistics. Over the full sample inflation was on average 3.90% - and the MPF was 3.73% - for the full sample 1968Q4-2012Q2 in the US and 2.16% (MPF 1.93%) for the short sample 1999Q1-2012Q2. For the euro area, for the same short sample, inflation ran on average at 2.08% and MPF came in lower at 1.74%. Table 1 also shows that the consensus forecast (MPF) is less persistent than the inflation realizations. Particularly striking for both for the US and the euro area is that, over the 1999-2012 period, the time variance of inflation expectations was almost three times lower than the one of inflation realizations.

The fact that average forecast errors have *ex-post* predictable patterns and tend to adjust sluggishly to changes in the macroeconomic outlook is well established.¹³ Our new I@R indicator allows us to answer a related question: to what extent were inflation outcomes

¹³Coibion and Gorodnichenko (2012) for the US and Andrade and Le Bihan (2010) for the euro area are two recent illustrations.

ex-ante perceived by economic agents? Figure 2 displays the time series of realized inflation, together with $I@R(.05)$ and $I@R(.95)$ for the US and euro area. The interval thus obtained will henceforth sometimes be referred to as the (ex ante) confidence interval, which it is worth recalling is purely data driven. The results show that the frequency of realizations *outside* this 10% confidence interval is close to 30%. It is important to note that this result holds even though the range of inflation scenarios considered in the survey has always been larger than the range of inflation realizations.¹⁴ Agents have a clear tendency to underestimate the range of inflation risks due to subjective distributions that are too concentrated around their point forecasts. This result also holds for the more recent period both in the US and the euro area.

Some extreme events clearly fell outside the interval. This includes the beginning of the Great Inflation of the 70s and the Volcker contraction of the early 80s in the US. Forecasters were giving much less than a 5% probability for the peak in inflation of 1974, the fall in inflation of 1975, and the Volcker deflation of 1982-83. Surprisingly, the inflationary consequences of the 1979 oil shocks were better understood. This also includes a very low inflation realization in 1998, and a high outcome in 2005. Realizations hit more often the bounds of the confidence interval in the euro area, mostly the upper bound, in line with the fact that forecasters tended to understate inflation in the euro area over the 1999-2006 period.

Returning to the descriptive statistics in Table 1, we note that $I@R(.95)$ is on average 5.056% (2.962%) for the long (short) US samples, and 2.458% for the euro area. The corresponding lower quantile averages are respectively 2.87%, 1.13% and 1.13%. It is interesting to note that the time series standard deviations for $I@R$ are substantially larger than those of the MPF, despite their persistence is lower. On average, quantiles react more to economic developments than point forecasts. One may wonder whether this is due to the contribution of some forecasters who might often and radically change their opinion. We therefore examine the cross-sectional dispersion of $I@R$. Namely, we compute for each date in the survey the cross-sectional standard deviation of the $I@R$ s and then compute its sample average across time. For the US, the cross-sectional dispersion is greater for the $I@R(.95)$ but of comparable order to the MPF while it is lower for the $I@R(.05)$. Both are greater in the euro area, but still of an order comparable to the average disagreement associated with the differences in point forecasts among forecasters.

¹⁴For instance, according to the survey design and our choice on how to close extreme intervals, the potential inflation realizations could be in a range of 10% to -2% from 1992Q1 onward, and from 18% to 1% over the 1974Q4-1981Q2 period. See Table 8 in Appendix B for the details of how these extreme values changed over time.

In Figure 3 we superimpose the evolution of the quantiles for the US and the euro area over the 1999-2012 overlapping sample. While the levels of the $I@R(.05)$ evolution were comparable in the US and euro area, the $I@R(.95)$ was lower in the euro area compared to the US. The $I@R(.95)$ was also much less volatile in the euro area, with almost the same variance than the MPF, than in the US. The differences for the $I@R(.05)$ are less striking. These differences in the perception of inflation risk might partly reflect the “asymmetric” definition of price-stability “close to but below 2%” of the ECB.

3.2 The range and asymmetry of inflation risk

Looking at the $I@R(.05)$ and $I@R(.95)$ time series in Figure 2, it seems at first sight that they evolved in parallel with the average of point forecasts. It turns out that this is not the case. This is revealed by looking at the IQR and ASY measures.

The left panel of Figure 4 presents the time series of the IQR measure for the US over the whole 1969-2012 sample. Casual observation suggests that inflation uncertainty went through three main phases. It showed an upward trend from 2% to 3.75% during the 70s and the first half of the 80s. It sharply decreased after 1985 but stayed at a relatively elevated average of 2.75% up until the early 90s and then contracted significantly over the mid 90s to 1.6%. Since the mid 90s, it exhibited a relatively mild upward trend, close to 2% after the recent crisis. The evolution of inflation risks therefore followed the decrease in inflation realizations variance of the Great Moderation, but with a delay of about 5 to 6 years.¹⁵

The magnitude of the increase in inflation/deflation risk after the Great Recession was of a very small order compared to the levels reached in the wake of the Great Inflation of the 70s. The left panel of Figure 5 provides a snapshot over the 1999-2012 period for the US and a comparison with the euro area. In the US, while inflation uncertainty did not return to its pre-2007 level, the perceived risk is still almost half of that in the US during the early 80s. In the euro area, IQR went from 1.2% to 1.65% during 2008-09 and kept increasing since then to reach a 1.8% high, also way below the 3.75% reached in the US of the mid-80s. The anchoring of inflation expectations during the Great Recession is the positive mirror image of the time it took to significantly reduce the perceived inflation risk over the 80s.

The right panel of Figure 4 plots the time series of ASY for the US over the whole 1969-2012 sample. It shows that the asymmetry of inflation risks was also characterized by three main

¹⁵McConnell and Pérez-Quirós (2000) and Stock and Watson (2002) date the beginning of the Great Moderation in 1984.

regimes. It was clearly tilted towards high inflation fears during the 70s, in the wake of the oil price shocks and expansionary policies of the 70s. The Volcker contraction then resulted in a regime of negative asymmetry, i.e. where risks of low inflation values dominated, which peaked during the recession of 1990-91. Starting the early 90s, the asymmetry of inflation risk has been more balanced with a measure of asymmetry that fluctuated around zero.

The right panel of Figure 5 focuses on the 1999-2012 period and provides a comparison between the US and euro area. The asymmetry was most of the time positive for both economies with notable exceptions. In the US, ASY turned negative in late 1999 and beginning of 2000, in 2003, where deflation fears were repeatedly expressed during FOMC meetings, and since 2009, in the midst of the Great Recession. In the euro area the risks were always tilted to the right of the distribution, with the exception of the 2009-2011 years. For both economies, the length with which the asymmetry stayed in negative territories as a consequence of the Great Recession is unusual in light of what we observed in the prior three decades. Still the Great Recession had a relatively moderate impact on the value of the asymmetry.¹⁶ This is another illustration of the fact that inflation expectations remained relatively anchored during the recent crisis period.

Table 1 provides some supplementary information from descriptive statistics on the IQR and ASY measures. Table 1 shows that ASY is remarkably less persistent than any of the other inflation risk measures. In particular, the autocorrelation of IQR is about .73 in the US for the whole sample and about .99 in the euro area over 1999-2012. The autocorrelation for ASY in contrast is respectively of .42 and .48. Table 1 also illustrates how IQR dropped during the 90s in the US, with an average of 1.84% over the 1999-2012 period compared to 2.21% for the whole sample. The average level of ASY is close to zero in the US and slightly positive in the euro area. The time variance of ASY also declined over the 90s in the US, with a standard deviation of 3.1 basis points over the 1999-2012 sample compared to 7.4 basis points for the whole sample. As we will see below, although these values are quantitatively small, changes in the asymmetry of inflation risks can signal some economically significant changes on the future realizations of inflation.

Table 2 shows how the MPF, IQR and ASY characteristics of inflation expectations are correlated with a set of macroeconomic variables for the US (full sample). Table 2 underlines that the inflation MPF, IQR and ASY are related not only to nominal variables like CPI or oil price changes, but also to (1) real ones like the output gap or the NBER recession

¹⁶This is related to the moderate impact on IQR as the ASY measure is the product of relative asymmetry and IQR.

index, (2) financial ones like the S&P 500 index or the USD exchange rate, and (3) policy ones like the federal fund rate. Changes in inflation risks are thus not related only to pure nominal factors. In particular, and as the graphical analysis also revealed, the episodes of negative ASY values in the US are mostly related to economic slowdowns and recessions or to sharp declines in oil prices. This shows up in the positive correlation of the ASY with the output gap and the oil price. Interestingly, the information content in ASY seems complementary to the one in IQR, as the two measures do not correlate with the same macroeconomic variables. In the next two sections of the paper, we analyze further the link between macroeconomic variables and the measures characterizing inflation expectations by focusing on their impact on future inflation realizations and the interest rate targeted by monetary authorities.

4 The impact of inflation risk on inflation realizations

In this section, we show that the new survey- and quantile-based measures contain valuable information about future realized inflation even after one controls for the usual set of determinants for expected inflation. We investigate predictive regressions in the context of an in-sample/final statistical releases as well as an out-of-sample/real-time data exercise. We focus our analysis on the US GDP deflator measure of inflation for which we have a long time span and different policy regimes, but also provide results for the US CPI and the euro area harmonized index of consumer prices (HICP). We also implement a set of robustness checks, controlling for various measures of inflation expectations and dispersion of risks, different specifications of the test regression, alternative estimations of the I@Rs, and changes in the sample of data considered.

4.1 Assessing the information content of I@R

To investigate whether I@R brings information about future inflation realizations, we rely on Mincer and Zarnowitz (1969) type regressions to test whether variables have a forecast power beyond the information content of typical inflation forecasts. Namely, we consider the regression of future realized inflation at some horizon h , π_{t+h} , on the the central tendency (i.e. mean or median) h -period ahead inflation forecast at date t , denoted $\pi_{t+h|t}^e$, and a vector

of control variables Z_t :

$$\pi_{t+h} = a_h + b_h \pi_{t+h|t}^e + C_h * Z_t + e_{t+h}, \quad (4.1)$$

with e_{t+h} the regression forecast error. This type of regressions has been extensively used in the literature to test whether inflation expectations are unbiased and incorporate all relevant macroeconomic information, namely that $a_h = 0$, $C_h = 0$ and, $b_h = 1$.

We consider a number of variations of the above regression with the following benchmark specification:

$$\pi_{t+k} = a_k + b_k \pi_{t+h|t}^e + c_k \text{IQR}_t^h(p) + d_k \text{ASY}_t^h(p) + C_k * Z_t + e_{t+k}, \quad (4.2)$$

with the horizon k potentially greater than the forecasting horizon h available in the surveys, and p is the risk level to compute IQR and ASY.¹⁷ Note that the above regression has the flavor of Mincer and Zarnowitz (1969) type regressions with a measure of conditional variance (IQR) and conditional skewness (ASY). Besides those two risk measures we will also consider macroeconomic controls Z_t : the output gap x_t , commodity price inflation π_t^{com} , the change in the trade weighted USD exchange rate index Δs_t , and the lagged value of the realized CPI inflation rate π_{t-1}^{CPI} . Finally, we also consider various measures of expected inflation $\pi_{t+h|t}^e$.

In all baseline regressions, the inflation rate π_{t+k} is measured as the year-on-year change in the GDP deflator at date $t + k$. Expected inflation $\pi_{t+h|t}^e$ is the average of the individual mean point forecasts for the year-on-year GDP deflator inflation rate MPF_t^h , with h being equal to 1 year. The IQR and ASY measures are computed for $p = 5\%$. We consider three different horizons for the realizations: $k = 1, 2$ and 3 years.

4.2 Baseline estimation results

Table 3 displays the estimation results obtained for the full US sample and the GDP deflator series. As a reference point, Column (1) in Table 3 pertains to the regression (4.1) for the 3

¹⁷One could also consider the following regression:

$$\pi_{t+k} = a_k + b_k \pi_{t+h|t}^e + \tilde{c}_k \text{I@R}_t^h(1-p) + \tilde{d}_k \text{I@R}_t^h(p) + C_k * Z_t + e_{t+k}.$$

The time series patterns displayed in Figure 2, suggest that such a specification is more prone to co-linearity issues. This is not the case with equation (4.2) which turns out to be a constrained version of the above regression in the special case where $\pi_{t+h|t}^e = \text{I@R}_t^h(.50)$.

forecasting horizons $k = 1, 2$ and 3 years, when one regresses the realized inflation only on its expectation. Column (2) adds the IQR and ASY measures. For the forecasting horizons considered, the asymmetry measure, ASY, has a positive and significant impact on future inflation realizations, after taking into account expected inflation. This impact is persistent and reaches a maximum at the 2 year horizon.¹⁸ The range of the risk IQR, has a negative impact, and it is not significant beyond one year.¹⁹ In terms of model fit, adding these two regressors reduces the adjusted R^2 by 7.8 percentage points at the 2 year horizon, i.e. a reduction of more than 17% of the initial R^2 . It also reduces the ratio of the root mean square error (RMSE) of the model compared with the one associated with a random walk (RW) model by 6.9 percentage points.

Columns (3) and (4) report the results when one adds the macroeconomic controls Z_t to the two previous sets of regressors. Column (4) shows that the significance of the asymmetry ASY, is preserved when one adds standard controls.²⁰ Again the effect peaks at the 2 year horizon. Likewise, the impact of IQR, stays negative and is not significant beyond the one year horizon. The gains in terms of model fit are less striking, but still they represent up to a 4.4 percentage points increase of adjusted R^2 for the 2-year forecast horizon and a gain of 4.9 percentage points in the ratio of the model RMSE compared to the RW.

The previous analysis involves using final releases of macroeconomic data and comparing the in-sample predicted inflation rates of the different models with inflation realizations. We complement this first exercise with an evaluation of the forecasting power of our I@R quantile-based measures in a real-time setting. We construct out-of-sample forecasts using recursive estimations of two models: one with the MPF and real-time macroeconomic controls Z_t^{rt} and one where we add the IQR and ASY measures.²¹ We then compare these real time out-of-sample forecasts with the final releases of inflation and calculate the ratio of the RMSE of the each two models. In addition to these ratios, we also implemented a test

¹⁸It is interesting to note that the impact goes beyond the forecast horizon for which individuals' are actually surveyed, namely the end of the current year.

¹⁹This confirms the results obtained with more traditional measures of inflation uncertainty. See e.g. Grier and Perry (2000) or Fountas and Karanasos (2007).

²⁰To save space, we do not report the coefficient estimates for the control variables Z_t , but they are, at least for a subset of them, significant in line with the numerous evidence showing that the average of individual forecasters' mean point forecasts (MPF) is not an efficient measure of expected inflation. We do not address such an issue in the present paper.

²¹We replace the vector Z_t of macroeconomic factors with Z_t^{rt} based on real-time observations for the (year-on-year) real output growth rate y_t^{rt} , the quarterly oil price inflation rate Δoil_t , which is a proxy for the commodity price inflation, the year-on-year change in the trade weighted USD exchange rate index Δs_t , which we assume to be observed in real-time, and the lagged value of the real-time realized inflation rate π_{t-1}^{rt} .

of forecast accuracy comparison of nested models proposed by Clark and West (2007). This test accounts for the fact that, under the null of equal forecast accuracy, the nesting model would have a greater RMSE due to its greater number of parameters and thus its greater estimation noise.

Column (1) in the first panel of Table 4 presents the results associated with the different forecasting horizons k . The results are striking: depending on the forecasting horizon, the IQR and ASY measures increase the precision of the out-of-sample forecast by 21 to 41%. Bold numbers indicate that the null of equal accuracy between the two models is rejected at the 5%, that is in our case, that is that the ASY measure significantly improves the forecast accuracy.

We also gauge the forecast accuracy gain of the ASY measure by comparing it to another metric: the well known RW model. More precisely, we construct out-of-sample forecasts using recursive estimations of a simple regression of the change in inflation over the ASY measure. We compare the forecast of this simple model with the one of a random walk using the real-time data of GDP deflator. We also did the same exercise replacing the ASY with seven other indicators extracted from surveys, namely the MPF, I@R(95), I@R(50), I@R(5), IQR, UNC, and DIS. We look at RMSE ratios, for the 1-year forecast horizon. We also implement a Clark and West (2007) forecast accuracy comparison test.

The results are presented in the second panel of Table 4 (Column (1)). The RW is a more precise forecast than any of the simple model considered. However, among them, the ASY has the precision that is the closest to the random walk forecast. Moreover, when one corrects for the supplementary estimation uncertainty associated to the nesting model, using Clark and West (2007) test, one finds that the model with asymmetry does better than the RW for the 1-year forecast horizon. This is not the case for any of the 7 other survey based variables that we consider.

Overall, we find that the measure of inflation risk asymmetry contains information about realized inflation beyond the consensus forecasts and a set of standard inflation determinants at short and long horizons. The effects are economically significant. For instance, a one standard deviation increase in the asymmetry measure of inflation risks signals a $\hat{d}_{2\text{years}} \times \text{SD}(\text{ASY}) = 5.335 \times .074 = 39.5$ basis points increase in the GDP deflator inflation rate two years ahead.

4.3 Robustness checks

In this subsection we check the robustness of the previous baseline results to an alternative measure of inflation, to various measures of expected inflation or inflation uncertainty, to changes in the specification of the inflation regression, to alternate estimations of the I@Rs, and to variations of samples.

We start by examining whether the information content in the distribution of the future GDP deflator inflation realizations is informative about the future realizations of the CPI inflation rate.²² Table 5 presents the results obtained when conducting the same analysis as in the previous subsection, using CPI instead of the GDP deflator. Overall, the main results we obtained in the baseline case still apply here. In-sample and using final releases, the IQR and ASY measures improve the RMSE ratio with respect to the RW from 2.5 to 5.6 percentage points. The ASY measure has a positive and significant (in all but one regression) effect on future CPI inflation realizations, while the IQR measure has a negative and non-significant (in all but one regression) effect. The impacts are economically significant, with a one standard deviation increase in ASY signalling a $6.609 \times .074 = 49$ basis points increase in the CPI inflation rate two-years ahead. Moreover, looking at Column (2) in the first panel of Table 4, we see that using IQR and ASY in real-time significantly improves the precision of CPI inflation out-of-sample forecasts by 28 to 36% compared to a model with just first-order moments of future inflation. Looking at Column (2) in the second panel of Table 4, we see that a simple model with only the ASY measure also significantly outperforms a random walk model for the 1-year horizon.²³ According to Clark and West (2007) forecast accuracy comparison test, this improvement compared to the RW is not significant for the other survey based variables we consider.

We also considered various other modifications of the baseline specification, keeping the GDP deflator inflation rate as the dependent variable and focusing exclusively on the 2-year horizon.²⁴ In Columns (1) and (2) of Table 6, we consider two alternative measures for the expected inflation rate $\pi_{t+k|t}^e$, namely I@R(.5) denoted as MED, and an AR(4) model of the inflation rate π_t . In Columns (3) to (5), we consider three alternative measures of the dispersion in the distribution of inflation risks. The first is a widely used survey-

²²The US SPF does not provide probability distributions associated with individuals' CPI mean point forecasts before 2007Q1. Using this information to calculate ex ante quantiles for CPI inflation would therefore severely reduce our sample period.

²³The real time CPI inflation rate series starts in 1990Q1. Before this date, we use the real-time GDP deflator inflation as a substitute.

²⁴The results also apply to the 1-year and 3-year horizons but are not reported.

based measure, namely the cross-sectional dispersion of individual point forecasts (DIS). The second is a parametric estimate of inflation volatility based on a GARCH(1,1) model applied to monthly inflation rates. The third is a non-parametric measures of the S&P 500 stock market index volatility, built by taking, for each quarter, the cumulative sum of the squared first-difference of the series over the past 3 months.²⁵

Columns (6) to (8) show the results for different variations in the specification of the equation (4.2). The two firsts amount to modifying the dependent variable to either the first difference of inflation $\Delta\pi$ or a (pseudo) inflation forecast error ($\pi_{t+k} - \pi_{t+h|t}^e$) in order to take into account a potential non-stationarity of the inflation process. The last one deals with an alternate treatment of the seasonality that affects the uncertainty measure due to the construction of the US survey. Rather than using a seasonality adjusted measure of the IQR, as we do in the baseline model, we implement a Seemingly Unrelated Regression (SUR) estimation of a system of four different equations, one for each quarter in the year, allowing for the effects of the IQR variable to differ across quarters.²⁶

Columns (9) and (10) present the results obtained with two alternative measures of the I@R. The first uses the more traditional measure which postulates a uniform probability distribution over each bin of the survey so that I@R estimates are obtained through linear interpolation of individual probability distribution for future inflation. The second also relies on the methodology of Engelberg, Manski, and Williams (2009) but doubles the length of the closing intervals.²⁷ Finally, columns (11) and (12) give the estimates obtained for two alternate samples: the US over the 1981-2012 period and the euro area over the 1999-2012 period.

It is remarkable that one of the main results of the baseline analysis is preserved: the asymmetry of inflation risk has a significant and positive impact on the realization of inflation two years ahead. The size of the impact is of the same order across all specifications and robustness checks. A noticeable difference is that the coefficient of asymmetry is smaller when I@Rs are estimated using a linear extrapolation method or doubling the length for the extreme intervals (lines ASY in columns (9) and (10)). These results stem from the fact that these methods impact the standard deviation of the asymmetry. In particular, the linear

²⁵We also obtained the same results with two other measures of inflation conditional second moment: a non-parametric measures of inflation volatility, built by taking, for each quarter, the cumulative sum of the squared first-difference of the series over the past 3 months; and the average dispersion associated to individual mean point forecasts of inflation (SDMPF).

²⁶Rich and Tracy (2010) implement such a procedure in their study of the link between disagreement and uncertainty using the US SPF data.

²⁷See Table 8 for the extreme values of inflation we consider.

extrapolation method puts much more weight on the extreme values of inflation than the beta distribution smoothing does, so that the ASY has a much higher standard deviation of about 25 basis points for the full sample. Hence, according to this specification, a one standard deviation increase in the asymmetry leads to about $1.427 \times .25 = 36$ basis points increase in the GDP deflator inflation rate two years later, not far from the 40 basis points found for the baseline estimates. The result also holds for the US after the beginning of Volcker’s tenure, but is somehow more muted, with a one standard deviation increase in the asymmetry leading to a $3.703 \times .074 = 27.5$ basis points supplementary inflation two years later. Results are also comparable in the euro area, over the 1999-2012 period, a one standard deviation increase in the asymmetry signals a $15.164 \times .023 = 35$ basis points higher inflation two years later.

4.4 Discussion

The results of the two previous subsections imply that inflation is a non-linear process. Changes in the conditional higher moments of future inflation have an impact on future realizations, hence on the current conditional expectation of inflation. More precisely, if we consider that IQR and ASY proxy respectively the second and third conditional moments of future inflation, our results indicate that the asymmetry of the conditional distribution has a positive impact on future realizations while the dispersion of the distribution does not.²⁸

We deem the formal analysis of a model that could account for our empirical results to be beyond the scope of the present paper. However, we note that non-linear inflation processes naturally emerge in the context of price-setting models.²⁹ For instance, Burstein (2006) and Devereux and Siu (2007) emphasize the non-linear features of inflation in state-dependent price-setting models. They show that, in such a setup, prices adjust more to big shocks than to small ones and that prices adjust more to shocks that contribute positively to inflation than to ones that contribute negatively to it. We build on their analysis to conjecture that state-dependent price-setting models with changes in the conditional variance of macro

²⁸The results also imply that while informative, the asymmetry in the distribution of inflation risks is not efficiently incorporated into the average of individuals’ point forecasts, or put differently, that the average of mean point forecasts differs from the conditional expectation: $\text{MPF}_t^h \neq E\{\pi_{t+h}|I_t\}$. A possible explanation would be that $\text{MPF}_t^h = E_L\{\pi_{t+h}|I_t\}$, that is that the MPF captures the expected dynamics of inflation leaving aside the non-linear effects. In this paper, we do not investigate why forecasters tend to ignore some relevant information to forecast future inflation rates.

²⁹Although the practice of relying on first-order linearized approximated solutions leaves this non-linear character asides.

structural shocks underlying inflation can generate the type of non-linear effects that we find empirically.³⁰

Consider for instance a situation where the conditional variance of macro structural shocks increases.³¹ This has two effects. The first one is to raise the frequency and the size of a typical price adjustment, hence the conditional variance of inflation.³² However, this increase in conditional variance has no effect as such on the future realizations of inflation since it is associated with both larger positive and negative shocks which average effects cancel out. This is consistent with our finding that an increase in the IQR uncertainty measure has no effect on future inflation realizations.

The second effect of an increase in the conditional variance of macro shocks stems from the asymmetric price response to positive and negative shocks that Burstein (2006) and Devereux and Siu (2007) underline. Indeed, in their setups, it is relatively less costly for a firm to be above the price charged by its competitors (in the worse case, the firm makes a zero profit) than below it (in the worse case, the firm makes a loss). As a consequence, a structural shock contributing positively to inflation induces a larger adjustment of prices than a shock of equal magnitude that will contribute negatively to inflation. So an increase in the potential magnitude (i.e. the conditional variance) of the underlying shocks will generate a rise in both the asymmetry of the distribution of future inflation and the future realizations of inflation. This is consistent with our finding that the ASY measure has a positive effect on future inflation realizations.

If specific information about future inflation rates is conveyed by our indicators, then this gives a reason why our measures should be of interest for monetary policy: it provides information about future inflation. We analyze whether monetary authorities actually react to I@Rs in the next section.

³⁰These two references do not address this specific issue. A closely related reference is Vavra (2012) who investigates the response of inflation to common demand shocks when the cross-section variance of firm-level productivity varies over time. However, he does not consider the response of inflation when the variance of these common macro shocks changes over time.

³¹We consider mean-preserving transformations.

³²Vavra (2012) underlines that the (cross-section) uncertainty shock he considers increases the fraction of firms adjusting their prices but also the option of waiting and not changing a price. However, in his estimations the first effect always dominates.

5 Inflation risks and monetary policy

We now investigate whether our inflation risk measures affect the overnight interest rate targeted by monetary authorities. As in the previous section, we focus our analysis on the United States, where we have a long sample of data available, but we also present results for the euro area.

5.1 The reaction of interest rates to I@R

Since we showed that our inflation risk measures convey information about future inflation realizations, it is natural to wonder whether central bankers do rely on higher moments of inflation risk to determine their target interest rate.

We investigate this by focusing on the reaction of the interest rate targeted by the central bank, i_t , to IQR_t^h and ASY_t^h . We control for a set macroeconomic variables, X_t , that subsume the typical information monetary authorities use in order to attain their stabilization objectives of (future) inflation and output gap. We therefore estimate the following regression:

$$\Delta i_t = \alpha + \beta \text{IQR}_t^h + \gamma \text{ASY}_t^h + \Gamma * X_t + u_t. \quad (5.1)$$

In a first baseline specification, we use the US overnight money market rates (Fed fund rate) as the policy instrument i_t and we consider its quarterly change, Δi_t^Q as the dependent variable of the estimated regression. Our set of control variables X_t includes the average of individual one-year ahead mean point forecasts of inflation obtained from the SPF data, MPF_t^h , the past GDP deflator inflation rate observed in real-time, π_{t-1}^{rt} (since Orphanides (2001) made the case for using real-time data in order to achieve a fair empirical assessment of the Fed reaction to macroeconomic conditions), the past oil price inflation rate, π_{t-1}^{oil} , the past real GDP growth rate, $\Delta y_{t-1}^{\text{rt}}$ observed in real-time and the past change in the interest rate Δi_{t-1} . As in the previous section, we use a risk of $p = .05$ for the IQR_t^h and ASY_t^h measures.

Column (1) in Table 7 reports the OLS estimation results of equation (5.1) for the full sample of the US data 1969-2012. We find that the asymmetry (ASY) of the inflation risk has a significant and positive impact on the target interest rate changes. When inflation risks are skewed to upward values, the US target rate increases more than what economic conditions would have otherwise predicted. A second result is that inflation uncertainty (IQR) has a

significant negative impact on the US monetary target. A relatively higher uncertainty is associated with somehow lower change in the overnight interest rate.

A potential limit of this first-pass regression is that survey-based risk measures, IQR_t^h and ASY_t^h , observed at date t can be influenced by the current monetary policy decisions, that is Δi_t^Q . In other words the regression can be plagued by endogeneity. However, we can exploit the timing of the panel to mitigate such endogeneity issue: while Δi_t^Q is the end of quarter t interest rate change, survey data released over the same quarter t are in practice collected over the first two weeks of the second month of the quarter. We therefore checked that the estimation did not capture important feedback effects and used the interest rate changes observed every second month of a quarter, Δi_t^M as the dependent variable in the equation (5.1). The estimation results are presented in column (2) of Table 7. They show that the impact of the asymmetry is still significantly positive, with a coefficient lowered by a factor of less than 2, due to the fact that the regression now captures the impact over one month and not over a whole quarter. Note that the effect of IQR is divided by a factor of more than 3 and becomes non-significant. This suggests some important feedback loop effects from the interest rate changes to the perceived uncertainty with sequences of decreases in the interest rate leading to greater inflation uncertainty. This hints to less anchored expectations in times where activity slows down.³³

Overall, the results show that our asymmetry risk measure has some explanatory power for the evolution of the Fed target interest rate in addition to a set of standard macroeconomic determinants. Depending on the regression results one considers, an increase of one-standard deviation over a quarter in the asymmetry of the risk leads to a $\hat{\gamma} \times SD(ASY) = 1.936 \times .074 = 13.5$ basis points increase in the policy rate when one does not control for feedback effect and to a $3 \times 1.158 \times .074 = 26$ basis points when controlling and extrapolating the monthly reaction at the date of the survey to the whole quarter.

5.2 The impact of changes in monetary policy regime

We investigate whether the previous results hold over different subperiods. Indeed, as notably stressed by Clarida, Gali, and Gertler (2000), specific subsamples, especially before or after Volcker’s disinflation, might arguably be associated with different types of monetary policy

³³Bekaert, Horeova, and Lo Duca (2011) find evidence of a mild Fed’s loosening reaction in times of increasing stock market uncertainty, which they construct from the VIX option price index. They also document that monetary expansions entail increasing financial market uncertainty for horizons lower than a year.

regimes and thus differences in the policy rule of monetary authorities.

Potential changes in policy regime may also raise concerns that the correlation between the variations in the ASY measures and the interest rate changes Δi_t does not reflect a reaction of the US central bank to inflation risk but rather results from the impact of such regime changes on both variables. Typically, one could be concerned that the beginning of a more restrictive monetary policy regime triggers a sequence of positive interest rate changes and has an impact on the asymmetry of the risk. However, if this restrictive monetary regime is credible, it should have, if anything, a negative impact on the ASY, everything else being constant, being less tilted to the upside. The regime change would thus lead to a negative correlation between the change in the interest rate and the asymmetry of the risk. Regime changes could thus lead to an underestimation of the interest rate reaction to the asymmetry of the risks.

Consequently, we estimate equation (5.1) for different sub-samples. We look at three different period: before Volcker's tenure, 1970-1979; after Volcker's tenure, 1981-2012; and after the stabilization of inflation risk perception documented in Section 3, i.e. the 1990-2012 sample. The results appear in columns (3), (4) and (5) of Table 7. Three observations can be made. The first is that the policy rate reaction to the asymmetry (and the uncertainty) of inflation risks stays essentially the same when one considers the post-Volcker period. The second is that the reaction was more tamed since the 90s, with only a $3 \times .743 \times .074 = 15$ basis points impact of a one standard deviation shock in the asymmetry and of $3 \times .743 \times .031 = 7$ basis points if one takes into account the decline of the standard deviation in the asymmetry measure. This suggests that a greater stability of the perceived asymmetry of the inflation risk induced the Fed to be less sensitive to this risk. Third and last observation is that the Great Inflation of the 70s is an entirely different regime. Over that period, the uncertainty had almost a significant negative impact on the (second month) interest rate change whereas the asymmetry had a positive but insignificant impact. Since uncertainty sharply increased over that period, this suggests that it could be responsible for the lack of aggressiveness in the Fed reaction to rising inflation at that time. Still it holds that starting with Volcker's tenure, the Fed has been more aggressive when macroeconomic conditions were such that the asymmetry of inflation risk were on the upside.

5.3 Discussion

The previous results raise two questions. Are they specific to the US? And why would the Fed pay attention to (factors affecting the) the asymmetry of inflation risk? An answer to the first question is provided by looking at column (6) of Table 7. It gives the estimation results of equation (5.1) for the euro area over the 1999-2012 period. We find strikingly similar results. The uncertainty of inflation risk has a negative and insignificant impact on the overnight interbank market EONIA rate changes. And the asymmetry of the inflation risks has a positive and significant impact on the policy target interest rate. The effect is of comparable order over the same period with an impact of about $2.272 \times .023 = 5.5$ basis points on the quarterly change of the policy rate in a wake of a one standard deviation shock in ASY.³⁴

There are two possible answers to the second question. On the one hand, central banks may react to the asymmetry of inflation risk because they know that it conveys information about the future realization of inflation that other economic agents (and in particular the professional forecasters) do not observe or do not incorporate into their forecasts. This explanation thus relies on an argument of informational superiority of the central bank over the private sector. On the other hand, the preferences of central bankers could be such that it is optimal to react to asymmetry. This would be the case if the costs of inflation were non-quadratic as considered in Ruge-Murcia (2003) or Kilian and Manganelli (2008). This optimal reaction to higher order moments of future inflation could also be generated by setups in which central bankers are uncertain about the true state or the model of the economy and have an aversion to this ambiguity as put forth in the robust control approach of Hansen and Sargent (2008). In this approach, the decisions of monetary authorities are affected by the probabilities associated to worse case scenarios. Our ASY measure partially captures changes in the perceived probabilities of these extreme events.

To disentangle these two potential structural interpretations of our previous empirical findings we extend the set of controls X_t to introduce the inflation and RGDP growth rate Greenbook forecasts of the Fed's staff.³⁵ If the Fed reacted to the asymmetry only to the extent that it impacts its prediction of future inflation, then its effect on the target interest rate should disappear once one controls for the forecasts of the Fed. Column (7) of Table

³⁴The timing of the European survey mitigates the issue of the endogenous reaction of the survey based indicators to policy. Answers are collected over the first two weeks of a quarter, so they are almost predetermined compared with the target interest rate change over the whole quarter.

³⁵The Greenbook forecasts are released with a lag. So this reduces our sample to 1970-2006.

7 shows that this not the case. The Fed reacted to the asymmetry of the inflation risk beyond its own forecasts of future inflation. Actually, the coefficient is only slightly smaller, suggesting that most of the reaction to this variable comes from the preferences of the central bank.

We conclude this section by discussing the consequences of our results for the identification of monetary policy shocks. Most of the literature relies on linear structural VAR models to identify such shocks.³⁶ In essence, they are similar to the residuals of the linear interest rate equation that we estimate. Romer and Romer (2004) actually suggest that monetary policy shocks could, among other things, capture (unpredictable) non-linear reactions of monetary authorities to the economic outlook. We saw that, depending on the specification and period, the quantitative effects of a one standard deviation quarterly change in the asymmetry of the inflation risk on the interest rate range from 5.5 to 25 basis points. This is a sizable order of magnitude compared to the monetary policy shocks identified from quarterly data for instance in Romer and Romer (2004). Therefore, non-linearities could explain a significant share of the monetary policy shocks. Aside from potentially interpreting the nature of monetary policy shocks, our results also raise the issue of possible omitted variable biases in the estimates of the response to monetary policy shocks typically obtained with linear structural VAR models. This happens when the asymmetry of the risks correlates with other macroeconomic variables. Including the ASY measure in such linear models would help avoiding such potential biases.

6 Conclusion

The paper puts to the fore several interesting issues for many strands of the macroeconomic literature. First, we stress that higher moments in the risk of future inflation matter for inflation realizations, that is variation in macroeconomic risks matters not only to understand financial markets, but also contribute to macroeconomic outcomes. We extract from the subjective distributions measured by surveys, information so far very much neglected in the literature. These measures pertaining to tail risks and asymmetries are shown to be important and complementary to the usual average inflation expectations.

Second, by the same token we show that perceptions of extreme macro-risk by economic agents contain information that is valuable for policy makers. Using distribution quantiles,

³⁶See Christiano, Eichenbaum, and Evans (1999) for a survey.

which we call – by analogy to financial applications – Inflation-at-Risk, we show that the asymmetry of inflation risk gives valuable information on future realizations of inflation rates. So the information contained in the risk of high inflation and/or low inflation should not be neglected by policy makers.

Third and finally, we also show that the Fed and ECB interest rate instruments is affected by inflation risk asymmetry: for a given expected level of future inflation, the central bank is more restrictive when future inflation risk are more tilted to the upside. The effect of asymmetry on monetary policy interest rate is quantitatively big enough to potentially bias the identification of monetary policy shocks if such variables are omitted into typical linear SVAR analysis used to identify such structural shocks.

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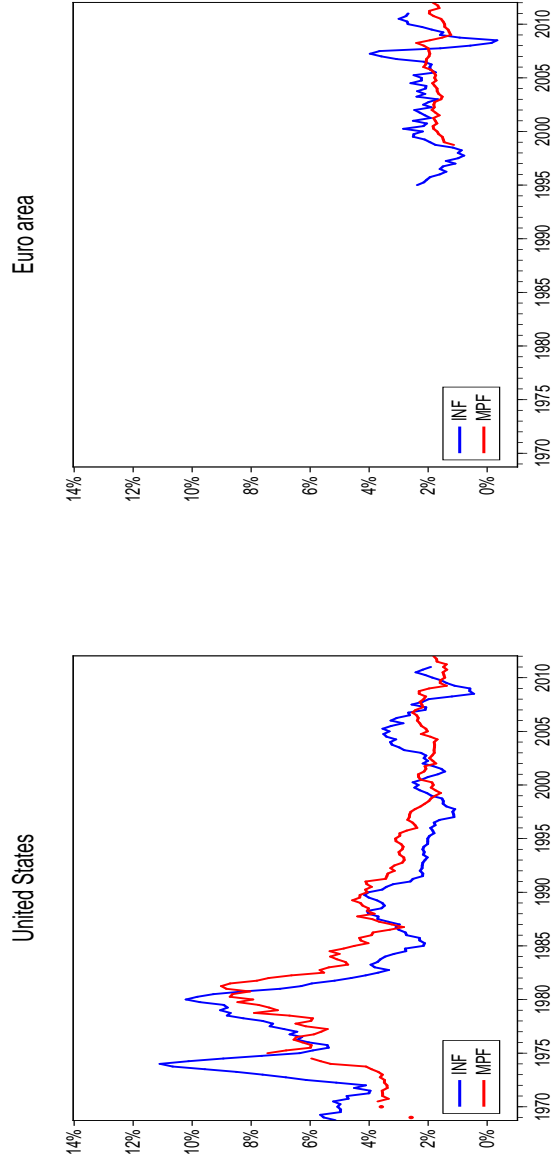
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Figure 1: Realized Inflation and Mean Point Forecasts

The plots report for the US and Euro Area both inflation realizations (INF) and one-year ahead mean point forecasts (MPF). The data covers the 1969-2012 sample for the US, and the 1999-2012 sample for the euro area. Data details appear in Appendix B.

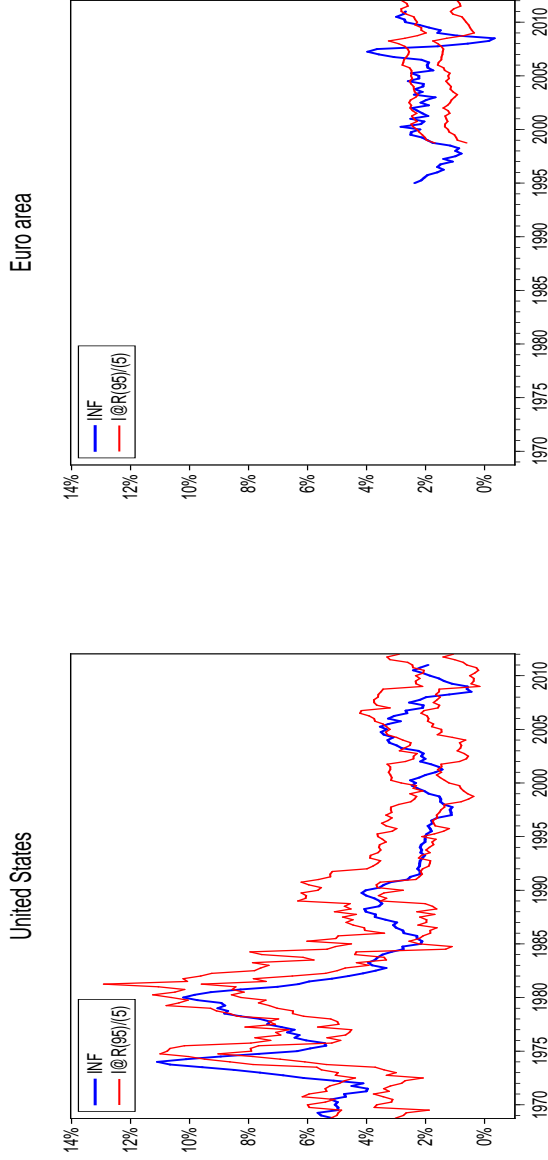


(a) INF and 1Y MPF, US

(b) INF and 1Y-MPF, euro area

Figure 2: INF , $I\textcircled{R}(.05)$ and $I\textcircled{R}(.95)$ (1-year horizon)

The figure plots the time series of realized inflation together with $I\textcircled{R}(.05)$ and $I\textcircled{R}(.95)$ (averaged over the past 4 quarters) for the US and euro area. The computation of $I\textcircled{R}(.05)$ and $I\textcircled{R}(.95)$ is based on equation (2.1). The data cover the 1969-2012 sample for the US, and over the 1999-2012 sample for the euro area. The US $I\textcircled{R}$ indicators are corrected for seasonal patterns associated with a shrinking forecasting horizon. Data details appear in Appendix B.



(a) INF , $I\textcircled{R}(5)$ and $I\textcircled{R}(95)$, US

(b) INF , $I\textcircled{R}(5)$ and $I\textcircled{R}(95)$, euro area

Figure 3: $I@R(.05)$ and $I@R(.95)$ in the US and the euro area (overlapping sample)

The plot reports the time series of $I@R(.05)$ and $I@R(.95)$ (averaged over the past 4 quarters) for the overlapping 1999-2012 sample for the US and Euro Area. The computation of $I@R(.05)$ and $I@R(.95)$ is based on equation (2.1). The US $I@R$ indicators are corrected for seasonal patterns associated with a shrinking forecasting horizon. Data details appear in Appendix B.

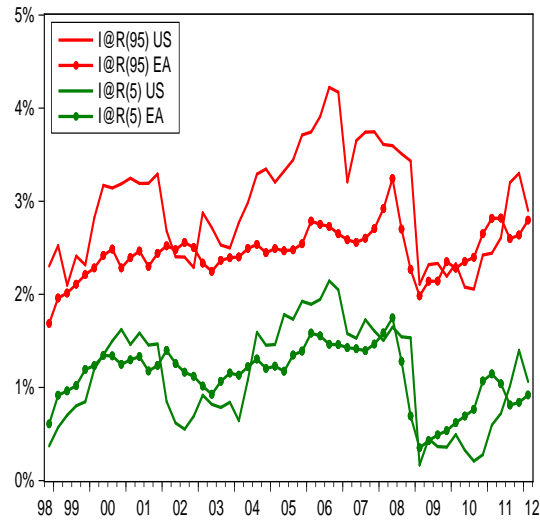
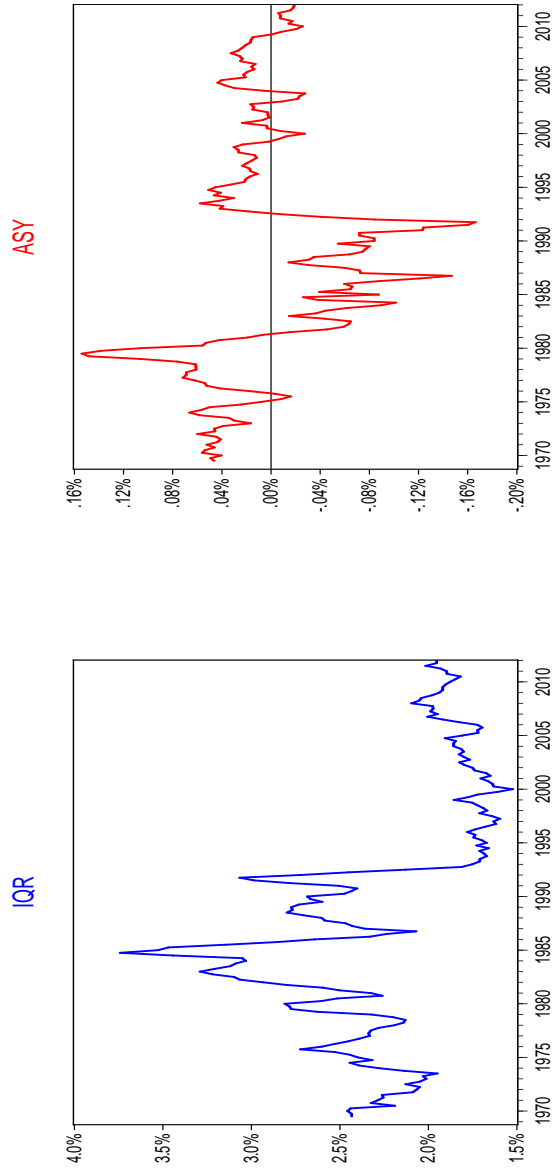


Figure 4: Inflation risk uncertainty (IQR) and asymmetry (ASY), US

The left panel displays the time series of IQR for the US over the whole 1969-2012 sample, the right panel displays ASY, where IQR is defined in equation (2.2) and ASY is defined in (2.4). Data are averaged over the past 4 quarters. Data details appear in Appendix B.



(a) Uncertainty, US

(b) Asymmetry, US

Figure 5: Inflation risk uncertainty (IQR) and asymmetry (ASY), US and EA

The left panel displays the time series of IQR for the US and the EA over the overlapping 1999-2012 sample, the right panel displays ASY, where IQR is defined in equation (2.2) and ASY is defined in (2.4). Data are averaged over the past 4 quarters. Data details appear in Appendix B.

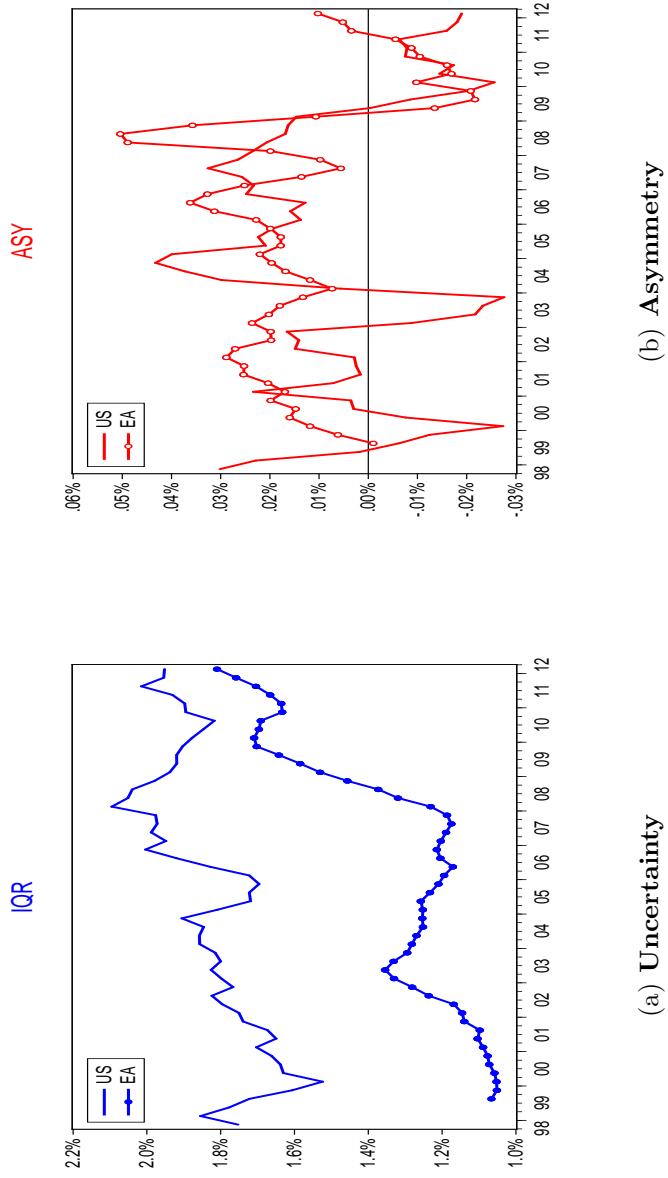


Table 1: Descriptive statistics

	US, 1968Q4-2012Q2		US, 1999Q1-2012Q2		EA, 1999Q1-2012Q2							
	AVG	STD (TS)	RHO	AVG	STD (TS)	RHO	AVG	STD (TS)	RHO			
INF	3.903	2.414	-	0.986 (39.365)	2.163	0.766	-	0.91 (18.897)	2.081	0.818	-	0.784 (7.446)
MPF	3.725	1.942	0.842	0.98 (50.386)	1.933	0.311	0.550	0.848 (14.05)	1.739	0.245	0.286	0.755 (9.392)
I@R(.95)	5.056	2.428	0.909	0.973 (42.27)	2.962	0.599	0.714	0.794 (9.642)	2.458	0.264	0.403	0.744 (8.774)
I@R(.05)	2.872	2.198	0.741	0.965 (34.501)	1.128	0.582	0.527	0.735 (8.211)	1.125	0.316	0.419	0.853 (15.345)
IQR	2.211	0.548	-	0.732 (12.015)	1.84	0.181	-	0.351 (2.876)	1.332	0.245	-	0.991 (26.615)
ASY	0.002	0.074	-	0.416 (4.195)	0.004	0.031	-	0.213 (1.576)	0.012	0.023	-	0.481 (2.32)

Notes: Descriptive statistics are reported for INF which refers to realized inflation, MPF which is the mean point forecast of the SPF, I@R(.05) and I@R(.95) based on equation (2.1), IQR defined in equation (2.2) and, ASY defined in (2.4). We report respectively AVG, STD, and RHO, the latter being the first order autocorrelation coefficient. Standard deviations are reported for the time series estimates (TS) and the cross-sectional variation (CS). The latter are computed as the sample average across surveys of the cross-sectional standard deviations. The data cover the 1969-2012 sample for the US, and cover the 1999-2012 sample for the euro area. Data details appear in Appendix B.

Table 2: Bivariate regressions (US, 1969-2012)

	Regressors						
	INF	OIL	OG	NBER	FOREX	S&P 500	FF
MPF	0.584 (16.005)	0.010 (1.702)	-3.273 (-0.273)	0.733 (1.711)	0.060 (3.778)	-0.004 (-4.634)	0.412 (11.539)
IQR	0.076 (4.593)	-0.001 (-0.452)	-4.298 (-1.049)	0.214 (1.366)	0.019 (3.797)	-0.001 (-5.066)	0.085 (5.101)
ASY	0.003 (1.319)	0.000 (1.899)	0.556 (2.638)	-0.017 (-0.906)	-0.001 (-1.662)	0.000 (0.051)	-0.002 (-0.777)

Notes: Entries are slope coefficient estimates of regressions for MPF, IQR and ASY involving a constant and a set of macroeconomic variables as single regressors: realized inflation (INF), oil price changes (OIL), output gap (OG), NBER recession index (NBER), USD (trade weighted) exchange rate (FOREX), S&P 500 index (S&P 500), and the federal fund rate (FF). The sample is US, 1968Q4-2012Q2. Boldfaced entries are statistically significant.

Table 3: The effect of inflation risk on inflation realizations (US GDP deflator)

	k = 1 year		k = 2 years		k = 3 years							
	No Controls (1)	Controls (2)	No Controls (3)	Controls (4)	No Controls (1)	Controls (2)	No Controls (3)	Controls (4)				
MPF	1.049 (13.935)	1.124 (16.285)	0.592 (4.391)	0.711 (6.013)	0.865 (5.075)	0.926 (5.148)	0.682 (3.193)	0.804 (4.306)	0.743 (2.631)	0.483 (1.733)	0.603 (1.837)	
IQR		-0.577 (-2.431)		-0.452 (-3.486)		-0.555 (-1.163)		-0.412 (-1.356)		-0.445 (-0.788)		-0.397 (-0.95)
ASY		4.996 (3.476)		2.75 (3.025)		7.945 (2.922)		5.335 (2.468)		7.75 (2.303)		4.827 (1.889)
# obs	165	165	151	151	161	161	147	147	157	157	143	143
\bar{R}^2	0.716	0.757	0.856	0.874	0.451	0.529	0.709	0.753	0.282	0.348	0.533	0.567
RMSE ratio	0.999	0.923	0.669	0.624	0.942	0.873	0.609	0.56	0.960	0.915	0.677	0.652

Notes: OLS estimation of equation (4.2). MPF is the average of 1-year ahead individual mean point forecasts. IQR and ASY are based on the 95% – 5% IQR measures. Regressions with controls include the output gap and energy price. Since the estimation involves overlapping horizons, we estimate the standard errors via a HAC Newey–West procedure. We use a Bartlett kernel and a bandwidth of $k - 1$, with k the forecasting horizon. The reported estimates involve final releases of macroeconomic data and comparing the in-sample predicted inflation rates. We complement this with an out-of-sample forecasts using recursive estimations of two models: one with the MPF and the macroeconomic controls Z . And one where we add the IQR and ASY measures. Moreover, rather than taking final data releases for the macroeconomic factors Z , we use data that are available in real-time. We use the real time out-of-sample forecasts and the final releases of inflation to calculate the RMSE of three models. The sample covers 1968Q4-2012Q2.

Table 4: Out of sample forecast performances

Forecasted variable:		DEF	CPI
		(1)	(2)
General Model with ASY vs. without			
Forecasting horizon:	1Y	0.594	0.642
	2Y	0.754	0.719
	3Y	0.791	0.685
Simple Univariate Model vs. Random Walk			
Forecasting horizon:	1Y		
Regressor:	ASY	1.028	0.931
	MPF	1.049	0.939
	I@R(95)	1.041	0.936
	I@R(50)	1.037	0.932
	I@R(5)	1.035	0.925
	IQR	1.059	1.027
	UNC	1.063	0.956
	DIS	1.039	0.931

Notes: Entries are RMSE ratios associated to out-of-sample inflation forecasts using recursive estimations and real-time data for different models. The first panel compares a forecasting model of inflation using the MPF and macroeconomic variables with one where the IQR and ASY measures are also added. The real-time macrovariables are the (year-on-year) real output growth rate y_t^{rt} , the quarterly oil price inflation rate Δoil_t , the year-on-year change in the trade weighted USD exchange rate index Δs_t , and the lagged value of the real-time realized inflation rate π_{t-1}^{rt} . The second panel compares a simple regression of the change in (real-time) inflation over the survey based measure of inflation expectations with a random walk. The survey measures considered are ASY, MPF, I@R(95), I@R(50), I@R(5), IQR, UNC, and DIS. Boldface numbers indicates that the null of equal forecast accuracy between the two models is rejected at the 5% level according to the test of Clark and West (2007).

Table 5: The effect of inflation risk on inflation realizations (US CPI)

	k = 1 year		k = 2 years		k = 3 years		k = 3 years					
	No Controls (1)	Controls (2)	No Controls (1)	Controls (2)	No Controls (1)	Controls (2)	No Controls (1)	Controls (2)				
MPF	1.245 (9.186)	1.342 (11.794)	1.169 (6.246)	1.109 (3.62)	0.993 (3.679)	1.109 (3.62)	1.485 (3.207)	1.693 (3.942)	0.769 (2.28)	0.827 (2.007)	1.382 (2.044)	1.527 (2.43)
IQR		-0.755 (-2.507)		-0.913 (-1.395)		-0.561 (-2.323)		-0.834 (-1.439)		-0.542 (-0.732)		-0.692 (-0.984)
ASY		6.646 (2.75)		8.719 (2.297)		4.778 (2.295)		6.609 (2.3)		9.053 (2.122)		6.544 (1.858)
# obs	165	165	151	161	161	151	147	147	157	157	143	143
\bar{R}^2	0.65	0.697	0.744	0.463	0.388	0.770	0.576	0.632	0.224	0.282	0.358	0.404
RMSE ratio	0.801	0.745	0.660	0.718	0.767	0.626	0.597	0.556	0.79	0.76	0.672	0.647

Notes: OLS estimation of equation (4.2). MPF is the average of 1-year ahead individual mean point forecasts. IQR and ASY are based on the 95% – 5% IQR measures. Regressions with controls include the output gap and energy price. Since the estimation involves overlapping horizons, we estimate the standard errors via a HAC Newey-West procedure. We use a Bartlett kernel and a bandwidth of $k - 1$, with k the forecasting horizon. The reported estimates involve final releases of macroeconomic data and comparing the in-sample predicted inflation rates. We complement this with an out-of-sample forecasts using recursive estimations of two models: one with the MPF and the macroeconomic controls Z . And one where we add the IQR and ASY measures. Moreover, rather than taking final data releases for the macroeconomic factors Z , we use data that are available in real-time. We use the real time out-of-sample forecasts and the final releases of inflation to calculate the RMSE of three models. The sample covers 1968Q4-2012Q2.

Table 6: The effect of inflation risk on inflation realizations - Robustness for two year horizon

	EXP Measure		UNC Measure		Regression Specif.		I@R Measure		Sample			
	(1) MED SPF	(2) AR(4)	(3) DIS SPF	(4) GARCH INF	(5) SP500 VOL	(6) FIRST DIF.	(7) FOR. ERRORS	(8) SUR SYST	(9) LIN PROBA	(10) DOUBLE MIN/MAX	(11) US 1981-2012	(12) EA 1999-2012
EXP	0.638 (3.234)	-	0.683 (3.087)	0.778 (4.025)	0.759 (3.968)	0.307 (1.269)	-0.152 (-0.736)	-0.760 (15.997)	0.863 (3.994)	0.867 (4.068)	0.678 (3.117)	-4.571 (-2.063)
UNC	-0.086 (-0.356)	0.024 (0.107)	0.365 (1.349)	0.815 (0.891)	0.028 (0.004)	-0.359 (-1.506)	-0.42 (-1.311)	-	-0.27 (-1.26)	-0.185 (-1.214)	-0.182 (-0.706)	-0.992 (-1.643)
ASY	6.01 (2.209)	6.213 (2.302)	6.133 (2.847)	6.079 (2.862)	6.126 (2.862)	5.483 (2.211)	5.555 (2.522)	2.196 (2.545)	1.427 (2.641)	3.035 (2.043)	3.703 (1.717)	15.164 (1.642)
RMSE ratio	0.632	0.646	0.575	0.581	0.582	0.572	0.651	-	0.591	0.594	0.653	0.489
# obs	145	145	144	144	144	144	144	176	144	144	125	46

Notes: OLS estimation of equation (??) for various measures of expected inflation (EXP) and inflation uncertainty (UNC). The various specifications are discussed in subsection 4.3. All other aspects of the empirical implementation are the same as in Tables 3 and 5.

Table 7: Monetary policy reaction to IQR and ASY

	Reference		Regime changes			Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. variable:	ΔFF	ΔFF	ΔFF	ΔFF	ΔFF	ΔEONIA	ΔFF
Change over:	Quarter	2nd-Month	2nd-Month	2nd-Month	2nd-Month	Quarter	Quarter
Sample:	US	US	US	US	US	EA	US
	1969-2012	1969-2012	1969-1979	1981-2012	1990-2012	1999-2012	1970-2006
IQR	-0.363 (-1.944)	-0.113 (-1.23)	-0.664 (-1.485)	-0.027 (-0.261)	-0.029 (-0.728)	-0.214 (-1.308)	-0.254 (-1.059)
ASY	1.936 (1.737)	1.158 (2.139)	0.439 (0.23)	1.202 (1.791)	0.743 (1.63)	2.272 (2.028)	1.830 (1.875)
\bar{R}^2	0.078	0.133	-0.007	0.249	0.280	.340	0.134
# obs	169	169	44	125	86	54	151
Controls	Real-time	Real-time	Real-time	Real-time	Real-time	Usual	Greenbook

Notes: OLS estimation of equation (5.1). Δi_t denotes the change in the fed-fund rate over a quarter. Δi_t^M denotes the change of the Fed fund rate over the second month of each quarter. IQR and ASY are based on the 95% – 5% quantiles. Regressions include a constant and a set of control of control variables X_t made of the individual one-year ahead mean point forecast observed in our survey data MPF_t^h , the past inflation rate π_{t-1} , the past energy inflation rate π_{t-1}^{com} , and the past real GDP growth rate Δy_{t-1} . Since the estimation involves overlapping horizons, we estimate the standard errors via a HAC Newey-West procedure. We use a Bartlett kernel and Andrews' automatic optimal bandwidth.

Appendix (For On-Line Publication)

A Survey-based density estimation

We follow the methodology of Engelberg, Manski, and Williams (2009) who consider matching generalized *beta* distributions to the individual discrete histograms. More precisely, one distinguishes three cases, depending on the number of classes (non-zero probability histogram bins) used by a respondent.

1. If a forecaster uses only one class by responding 100% probability for a given inflation interval from l to u , the probability distribution function is assumed to be an isosceles triangle with a peak of the distribution attained for $(l + u)/2$.
2. If a forecaster uses two adjacent intervals $(l_1; u_1]$ and $(l_2; u_2]$, with $u_1 = l_2$, one also postulates an isosceles triangle shaped distribution such that:
 - if $p_1 > p_2$, i.e. the probability assigned to the first interval is greater than the probability assigned to the second one, the isosceles triangle has a basis $[l_1; x]$ where $x \in (u_1; u_2]$. The use of Thales theorem (see Engelberg, Manski, and Williams (2009) for the details) allows to determine x .
 - if conversely, $p_1 < p_2$, the isosceles triangle has a basis $[x; u_2]$ where $x \in [l_1; u_1]$.
3. if a forecaster uses three or more intervals, each individual distribution is fitted with a generalized *beta* distribution whose cumulative distribution function F is:

$$F(x; a, b, L_{it}, U_{it}) = \begin{cases} 0 & \text{if } x \leq L_{it}, \\ \frac{1}{B(a,b)} \int_{L_{it}}^x \frac{(z-L_{it})^{a-1} (U_{it}-z)^{b-1}}{(U_{it}-L_{it})^{a+b-1}} dz & \text{if } L_{it} < x < U_{it}, \\ 1 & \text{if } x \geq U_{it}, \end{cases}$$

where a and b are the two parameters defining the *beta* distribution, $B(a, b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$, with $\Gamma(b) = \int_0^\infty z^{(b-1)} e^{-z} dz$, and where L_{it} and U_{it} are respectively the lower and upper bounds of the support used by the respondent i at date t .

To estimate the two parameters (a, b) characterizing the generalized *beta* distribution, one minimizes the squared distance between the discretized version of the empirical CDF and the continuous CDF

for each date t and forecasters i as follows:

$$\min_{a>1, b>1} \sum_{j=1}^{J_t} \left[F_{it}^h(u_j; a, b, L_{it}, U_{it}) - \sum_{k=1}^j p_{it}^h(k) \right]^2,$$

with J_t the number of class available in the survey at date t and with $p_{it}^h(k)$ the probability assigned by forecaster i to the interval $(l_k; u_k]$. Remark that the cumulative of the *beta* is evaluated at the upper bonds of the intervals. The restriction $a > 1$, $b > 1$ implies that the *beta* distribution is unimodal. The extreme upper and lower intervals in the SPF questionnaire are open-ended. An important step in the procedure is to close these open intervals with arbitrary chosen lower and upper values for inflation. We follow Engelberg, Manski, and Williams (2009) (and the common practice in this literature) by assuming that the two extreme intervals have a width of twice the size of the intermediate ones.

We denote \hat{a}_{it}^h and \hat{b}_{it}^h the estimated parameters of the *beta* distribution for forecaster i and date t SPF and $\hat{F}_{it}^h = F(x; \hat{a}_{it}^h, \hat{b}_{it}^h, L_{it}, U_{it})$ the corresponding *beta* distribution. The individual's $\hat{q}_{it}^h(p)$ is the quantile of the continuous distribution \hat{F}_{it}^h at the probability threshold p , namely:

$$\hat{q}_{it}^h(p) = (\hat{F}_{it}^h)^{-1}(p).$$

Therefore $\widehat{\text{I@R}}_t^h(p)$ is the cross-sectional average across survey respondents of $\hat{q}_{it}(p)$. Likewise, the empirical $\widehat{\text{ASY}}_t^h(p)$ measure is the linear combination of the cross-sectional average across survey respondents of $\hat{q}_{it}(p)$, $\hat{q}_{it}(1-p)$ and $\hat{q}_{it}(.50)$ as specified in equation (2.4). Note that in the remainder of the paper we will drop the hats and simply refer to $\text{I@R}_t^h(p)$ and $\text{ASY}_t^h(p)$ with the understanding that they are estimated quantities.

B SPF data

Table 8 summarizes some key characteristics of the US and EA surveys.

United States The US survey of professional forecasters has been conducted every quarter since 1968Q4 and, although its number changed over time, covers around 30 institutions. Each institution in the survey is asked to report, among others, forecasts about the GDP deflator since 1992Q1. Before that date, institutions reported GNP deflator forecasts, a difference that we do not take into account, considering these forecasts as GDP deflator forecasts for the whole sample. The survey provides individual mean point forecasts for the inflation rate one year ahead. It also gives individual forecast distributions about the deflator inflation rate of the current calendar

year. We also used individual mean point forecasts for the CPI inflation rate that are available. Unfortunately, probability distributions for CPI inflation rate started to be collected only in 2007Q1. We thus deem the sample too short to exploit this information.

The US SPF survey evolved through time. The number of available classes was 15 before 1981, then decreased to only 6 in the eighties, and finally increases again to 10 from 1992 onwards. The length of the an interval is 1%. It was 2% when the number of bins was only 6. In addition to their number, the values of the bins have been adjusted in 1973Q2, 1974Q4, 1981Q3, 1985Q2 and 1992Q1. We view these changes as resulting from changes in the perceived potential range of inflation of both the central bank and the public and do not deal with the issue of whether these changes induced changes in the inflation risk perceived by the public.

The fact that probability forecasts are only available for so-called calendar forecast, i.e. forecasts for the end of current year GDP deflator induce that they feature a seasonal pattern. Indeed, as time goes by over a year the uncertainty about the inflation rate for a given year is mechanically reduced. We thus use seasonally adjusted data to account for the intra-year declining uncertainty, correcting for seasonal dummies. More precisely, we withdraw quarter specific effects from the raw data, these effects being estimated over the different periods defined by the changes in the survey. For this seasonal adjustment, we considered the 1968Q4-1973Q1 and the 1973Q2-1974Q4 sub-periods as a single one.

Each round of the survey is coincident with FOMC meetings where Greenbook forecasts are discussed. Questionnaire are sent at the beginning of the 2nd month of the quarter and answers are collected within the first two-weeks of this month. This feature of the survey is used in order to gauge the response of monetary policy to its evolution, net of previous monetary policy decisions. Realizations of the data or real-time data are matched accordingly. More precisely, the Q1 survey is forecast prediction of the inflation rate over the beginning of Q1 to the end of Q4. The latest available information then is Q4. For CPI inflation, the latest information available in a Q1 survey round is January of a given year.

Euro area The ECB's survey of professional forecasters is conducted every quarter since 1999Q1. The survey covers around 90 institutions involved in forecasting and operating in the euro zone. Each institution is asked to report, among other things, forecasts for the (year-on-year) CPI inflation rate for fixed horizons of one year or two years. Respondents provide the usual mean point forecasts but also their forecast distributions over a set of intervals. The questionnaires consider 10 different classes with open intervals of 40 bps length (e.g. [1 to 1.4%[, [1.5 to 1.9%[]). We interpret them as 50bps intervals [1 to 1.5%[, [1.5 to 2%[]). Four new classes (associated to deflation probabilities) were added over 2009, two of which were removed since then. Unlike the US SPF, the individual subjective

probability distributions apply to the fixed horizon forecast and is thus not affected by seasonal patterns. Each round of the survey is conducted over the 1st month of a quarter. Questionnaires are sent at the beginning of this month and answers are collected within two-weeks. So the latest inflation rate available at the Q1 round is the inflation rate of December of the previous year and the Q1 forecast is for the inflation rate between Q4 and Q4.

Table 8: Design of surveys

Location	United-States								Euro area			
	1968Q4-1973Q1	1973Q2-1974Q3	1974Q4-1981Q2	1981Q3-1985Q1	1985Q2-1991Q4	1992Q1-present	1999Q1-present	2009Q1-2009Q3	2009Q4-present	HICP (yoy inflation)		
Target variable	GNP deflator (yoy inflation)								GDP deflator (yoy inflation)			
Target horizon	End of current year								1Y or 2Y ahead			
Nb of intervals	15			6		10	10	14	12			
Width of a bin	1%			2%		1%	.5%	.5%	.5%			
Maximum value	12%	14%	18%	16%	14%	10%	5%	5%	5%			
Minimum value	-5%	-3%	1%	0%	-2%	-2%	-1%	-3%	-2%			

Notes: These informations are provided by the Philadelphia Fed and the ECB. We postulate maximum and minimum values of inflation in order to close open-ended extreme intervals. We allow that their length be twice the length of an intermediate interval.