Abstract

We introduce new measures called Inflation-at-Risk pertaining to unlikely low or high future inflation outcomes, i.e. (left and right) tail risk measures similar to Value-at-Risk. We estimate this measure for the US and Europe respectively, using US and Euro Area surveys of professional forecasters. We show that Inflation-at-Risk contains information that is not covered by the indicators of inflation risk typically used in the literature. More specifically, the new measure reveals that not only the extent but also the asymmetry of inflation risks evolve over time. These changes in the asymmetry have an impact on future inflation realizations as well as on the current interest rate central banks target. In our reference specification, a one standard deviation increase in the asymmetry of inflation risks signals a 45 basis points increase in future inflation realizations two years ahead and a 25 basis points increase in the current policy rate.

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1 Introduction

How do risks of potential future extreme inflation outcomes evolve through time? Do they impact future inflation outcomes? Do central banks react to such ex ante tail risks? Such questions are important to understand the sources and transmission mechanisms of business cycle fluctuations in monetary economies and therefore the design of optimal monetary policies. Indeed, the notion that central bankers go beyond conditional expectations of future inflation and react to inflation tail risk measures challenges the prevailing use of certainty equivalence arguments underlying a large set of models used for optimal monetary policy analysis. Moreover, the identification of monetary policy shocks in empirical models is potentially compromised if monetary policy authorities react to inflation risks in addition to conditional expectation. More generally, if changes in ex ante inflation tail risks have an impact on inflation realizations in addition to expected future inflation, this underlines that some form of non-linearities are important to characterize the dynamics of inflation.

In this paper, we introduce new measures of ex ante inflation tail risks. More specifically, we introduce the notion of Inflation-at-Risk, denoted I@R, inspired by the widely used Value-at-Risk concept in risk management. The measures pertain to perceived ex ante unlikely inflation outcomes and are characterized by extreme quantiles in the subjective distribution of future inflation realizations. We estimate these subjective perceptions of ex ante inflation risk, using the US and euro-area Surveys of Professional Forecasters (SPF) which report data on individual expectations as well as on the probability distributions of their inflation expectations. We recover individual quantiles from each forecaster’s answers to the surveys, implementing the methodology of Engelberg, Manski, and Williams (2009), and compute the average across SPF participants. We concentrate our analysis on the top and bottom 5% quantiles.

With I@R measures we can compute several objects of interest. First, I@R provides a natural characterization of inflation uncertainty via the inter-quantile range. Second, studying separately at fears of low inflation (left tail of the individual forecast distributions) and high inflation (right tail) leads to a natural characterization of the asymmetry of inflation risks. Indeed, survey data not only allow us to extract new measures of tail risk, they also yield the more traditional notions of risk. More specifically, we can compute the absolute distance between respectively the top 5% quantile vis-à-vis the median and, the bottom 5%
It is important to emphasize that asymmetry of subjective inflation risk beliefs cannot be uncovered by the usual inflation risk measures. By construction, neither the consensus forecast – namely the average of individual mean or median point forecasts, nor the disagreement in inflation forecasts – namely the cross-section dispersion of individual mean point forecasts, nor an alternative measure of inflation uncertainty – namely the average dispersion around each individuals’ mean point forecasts, can capture the asymmetry of subjective downside and upside inflation risks.

Using the new measures, we document some interesting features of inflation dynamics and monetary policy in the US and the Euro Area. First, using SPF data over the 1969-2012 sample for the US, and over the 1999-2012 sample for the Euro Area, we find that most of the time inflation realizations occur within a 90% ex-ante perceived inflation risk interval, i.e. the range obtained by the lower and upper I@R. There are important exceptions, however, notably during the 1970s and during the 2008-2009 financial crisis. Moreover, I@R reveals noticeable time series dynamics in the US and Euro Area, both in terms of the range between the right and the left tails as well as in the asymmetry of the upside and downside risks.

Second, we show that the ASY measures contain information about future inflation realizations. Controlling for a set of macroeconomic determinants, including expected inflation and the aforementioned traditional survey-based measures, perceived downside inflation risk predicts an increase in inflation outcomes 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 a 45 basis points increase in inflation 2 years ahead. Hence, time variations in higher moments (such as skewness, i.e. ASY) of the conditional inflation risk forecast distribution turn out to have an effect on inflation realizations.

Third, we also find that the US Fed fund rate, i.e. a monetary policy target rate, reacts to measures of inflation risks based on our I@R. More specifically, when ex ante asymmetry increases, i.e. upward inflation risk increases the target interest rate increases (again

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1As discussed later in the paper, the asymmetry measure is the cross-product of the interquantile range and the Bowley’s (1920) robust coefficient of skewness.

2Pesaran and Weale (2006) provide a survey of the existing literature on survey forecasts. See Mankiw, Reis, and Wolfers (2003), Andrade and Le Bihan (2010), Coibion and Gorodnichenko (2010), Patton and Timmermann (2010), Coibion and Gorodnichenko (2012) for recent references linking the properties of the consensus and the disagreement to various models of imperfect information. See also Boero, Smith, and Wallis (2008) and Rich and Tracy (2010) for recent work comparing the evolution of disagreement and uncertainty.
controlling for the usual macroeconomic information including the aforementioned traditional survey-based measures). The effects are quantitatively important: for the US, over the whole sample period, a one standard deviation increase in the asymmetry of inflation risk increases the target interest rate by 25 basis points.

Related literature


Our analysis also focuses on macroeconomic risks but goes beyond volatility. First of all, it quantifies a specific tail risk, as our I@R measure gives an estimate for perceived extreme inflation realizations. Subsequently it uses these tail risk measures to identify inflation risk asymmetries. 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. This allows them to get a measure of the risks of deflation or high inflation. Curdia, Del Negro, and Greenwald (2012) estimate a DSGE model with structural shocks featuring both time-varying volatility and fat-tailed distributions. These references do not look at the asymmetry of inflation or macroeconomic risks. By contrast, we emphasize its key role via the ASY measure we derived from I@R.

It is also important to note that, unlike the above references, our I@R and ASY measures are survey-based and therefore are (1) purely data-driven and (2) non-parametric, i.e. do not require to postulate a specific data generating process (DGP). We share this feature with papers by Zarnowitz and Lambros (1987), Giordani and Soderlind (2003), and Rich and Tracy (2010) who also rely on US survey data to characterize the uncertainty around individual mean point forecasts\footnote{See also the similar analysis by Boero, Smith, and Wallis (2008) on UK data, Rich, Song, and Tracy (2012) on Euro Area survey data, and Soderlind (2011) on both.}. However, these references do not investigate the asymmetry of inflation risks.
The empirical result that fluctuations in high-order moments of inflation contribute to
the dynamics of inflation realizations connects our work with the recent papers by Bloom
(2009), Gilchrist, Sim, and Zakrajsek (2010), Bloom, Floetotto, Jaimovich, Saporta-Eksen,
and Terry (2011), or Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe
(2011), which stress that uncertainty shocks, namely changes in the conditional second order
moments of some structural shocks, contribute to macroeconomic fluctuations. While the
former references study real economies, Basu and Bundick (2011), Fernández-Villaverde,
Guerrón-Quintana, Kuester, and Rubio-Ramírez (2011), and Vavra (2012) investigate the
effect of uncertainty shocks in sticky price models. We focus on the risks related to inflation
and we look at both a measure of the dispersion and a measure of the asymmetry of the
risks. We argue that one can relate our empirical findings to the aforementioned sticky price
models where the variance of the structural shocks underlying inflation is time varying.

As far as forecasting future inflation, it should be noted that another implication of our
empirical findings is that there is information in conditional higher moments that enable
us the out-perform the celebrated random walk model of inflation (see e.g. Atkeson and
Ohanian (2001) and Stock and Watson (2007)).

Finally, the study of the interaction between monetary policy and inflation risks links our
work to Hansen and Sargent (2008), Orphanides and Williams (2007), Woodford (2010),
and many others, who stress that, when decision makers face uncertainty about the state
of or the model for the economy and have a loss function that factors in an aversion to
this uncertainty, it can be optimal for a central bank to react to changes in the perception
of macroeconomic uncertainty. We show empirically that the actual reaction of central banks
is indeed affected by changes in the asymmetry of inflation risks, that is a signed
also provide evidence that US monetary authorities react asymmetrically to inflation risk
by estimating structural models in which monetary authorities are postulated to have
asymmetric preferences. Our paper does not attempt to estimate a structural model of
policy maker preferences. An advantage is that our results do not dependent on any specific
assumptions neither about the central bank’s loss function nor the economy’s DGP.

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. Appendix A details the data we use.

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 $\pi_t$ 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:

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

where $I_{it}^t$ 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):

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

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

$$I_{it}^h(p) = E_i \left[ q_{it}^h(p) \right]. \quad (2.1)$$

In the empirical application, we look at respectively the 5th ($p = .05$) and 95th ($p = .95$) percentiles.

Hence, 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 measure is the well known notion of Value-at-Risk that features prominently in bank capital requirements as stipulated in the Basel Committee accords.\footnote{See e.g. Jorion (2001), Gouriéroux and Jasiak (2009), among many others, for further details.}

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.

While public statements by central bankers frequently allude to notions of risk management – in terms of tail risks – into the conduct of monetary policy, and while a lot of central banks assess the balance of macroeconomic risks – again in terms of extreme event analysis such as stress tests – the idea of a link between monetary policy and extreme event analysis is empirically relatively unexplored.\footnote{See for instance speeches by Greenspan (2003) and Mishkin (2008) on the notion of monetary policy and risk management. See Knuppel and Schultefrankenfeld (2011) for a description of what central banks do in practice to assess macroeconomic risks.}

One exception is Kilian and Manganelli (2008) who introduce a model where under certain conditions the risk management approach practiced by central bankers is equivalent to expected utility maximization. They show that the type of risk-based decision rule implicit in 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. Kilian and Manganelli (2008) introduce tail-related measures of inflation risk that are comparable to our I@R measure\footnote{More specifically, their Definition 1a, page 1107, with $\alpha = \beta = 0$ corresponds to our left and right tail measures.} With tail-sensitivity potentially being asymmetric, they generalize monetary policy rules to the case of asymmetric and non-quadratic preferences on the part of central bankers. In their empirical implementation they estimate central banker preference and test the assumption of quadratic preferences underlying the Taylor rule. They find compelling evidence against symmetry during the Greenspan era.

### 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 interquantile 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:

\[
\text{IQR}^h_{it}(p) = \mathbb{E}_i \left[ q^h_{it}(1 - p) - q^h_{it}(p) \right],
\]

where \( \mathbb{E}_i \) 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 - 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:

\[
\text{RA}^h_{it}(p) = \frac{(q^h_{it}(1 - p) - q^h_{it}(50)) - (q^h_{it}(50) - q^h_{it}(p))}{q^h_{it}(1 - p) - q^h_{it}(p)}.
\]

with \( p \) a chosen probability < .50 and where \( \mathbb{E}_i \) denotes the expectation across individual forecasters \( i \). It is immediately clear that this measure captures asymmetries of the inter-quartile 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 \( \text{RA}^h_{it} = 0 \), while values diverging to \(-1\) (1) indicate skewness to the left (right). The \( \text{RA}^h_{it} \) 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 \( \text{RA}^h_{it} \). Hence, our measure is defined as:

\[
\text{ASY}^h_t(p) = \mathbb{E}_i \left[ (q^h_{it}(1 - p) - q^h_{it}(50)) - (q^h_{it}(50) - q^h_{it}(p)) \right].
\]

While in principle, we could consider different values of \( p \) – similarly to \( \text{IQR}^h_{it}(p) \) – 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

\[
\text{IQR}^h_t(p) = E_i \left[ \text{IQR}^h_t(p) \right], \quad \text{ASY}^h_t(p) = E_i \left[ \text{ASY}^h_t(p) \right].
\]

So, the measures catch the inter-quantile range and asymmetry of representative agent in 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 \(\text{IQR}^h_t(p) = q^h_t(1 - p) - q^h_t(p)\) one can rewrite

\[
\text{ASY}^h_t(p) = E_i \left[ \text{RA}^h_t(p) \times \text{IQR}^h_t(p) \right].
\]

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.\(^7\)

### 2.3 Comparison with existing survey-based risk measures

Most of the time, survey data is used to compute a so-called consensus forecast, i.e. the average of individual mean point forecasts, that is:

\[
\text{MPF}^h_t = E_i(\text{MPF}^h_{it}),
\]
where MPF$_{it}^h$ is the date $t$ mean point forecast of inflation at horizon $h$ quarters of an individual $i$, namely 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 $h$. SPF surveys are also commonly used to characterize the disagreement between forecasters which is defined as the standard deviation between individual point forecasts

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

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

\[
\text{SDMPF}_t^h = \mathbb{E}_i (\text{SDMPF}_{it}^h|i, t),
\] (2.7)

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

Our measures can be linked to the aforementioned indicators in some special cases. I@R$_{it}^h(.50)$ and MPF$_{it}^h$ 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 IQR$_{it}^h(.05) = 2 \times 1.64 \times \text{SDMPF}_t^h$. 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. These shortcomings of the standard measures are remedied by the analysis of I@R and the ASY measures we introduce.

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

\[
\widehat{\text{I@R}}_t^h(p) = \frac{1}{N_t} \sum_i \widehat{q}_{it}^h(p),
\]

\[
\widehat{\text{ASY}}_t^h(p) = \frac{1}{N_t} \sum_i \left[ \widehat{q}_{it}^h(1-p) + \widehat{q}_{it}^h(p) - 2 \times \widehat{q}_{it}^h(.50) \right].
\] (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 B.

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 overweight 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 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 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 $\hat{q}_{it}^h(p)$. On could potentially aggregate the individual distribution 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. Notably, 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\(^8\). As we discuss in the next section, we perform several robustness tests using either variations on the Engelberg, Manski, and Williams (2009) method, or alternative methods. The findings we report in the remainder of the paper are robust with respect to these variations.

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 A.

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 2 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%. It also shows that the consensus forecast (MPF) is less persistent than the inflation realizations.

\(^8\)The intervals of the histograms are determined by the survey design and vary through time. See Appendix A for details.
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 a well establish\(^9\) Our new I@R indicator allows us to answer a related question: to what extend were inflation outcomes *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* the I@R(.05) and I@R(.95) 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\(^10\) 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 \([5\%;95\%]\) 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 2 we note that I@R(.95) is on average 5.056%, 2.962% for the long and 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. Moreover, the time series standard deviation of the two extreme quantiles is roughly

\(^9\)Coibion and Gorodnichenko (2010) for the US and Andrade and Le Bihan (2010) for the Euro Area are two recent illustrations.

\(^{10}\)For 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 2 in Appendix A for more details.
the same, except for the Euro Area where the lower quantile appears more volatile. One may wonder whether this is due to the contribution of some forecasters who might often and radically change their opinion. We can therefore examine the cross-sectional dispersion of I@R. Namely, we compute for each survey the cross-sectional standard deviation 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.

In Figure 3 we superimpose evolution of the quantiles for the US and the Euro Area over the 1999-2012 overlapping sample. While the I@R(.05) evolution where comparable in the US and Euro Area, the I@R(.95) was lower and less volatile over time in the Euro Area compared to the US. 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. In contrast, the explicit growth objective in the mandate of the Fed may help better controlling the perceived downside risk of inflation compared to the Euro Area.

### 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.

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

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70s. The left panel of Figure 5 provide a snapshot over the 1999-2012 period for the US and a comparison with the Euro Area. In particular, IQR in the Euro Area went from 1.2% to 1.65% during 2008-09 and kept increasing since then to reach a 1.8% high. While inflation uncertainty did not return to its pre-crisis level, the perceived risk is still lower than for the US today and half of that in the US during the early 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 regimes. The asymmetry of inflation risk 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 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. This is another illustration of the fact that inflation expectations remained relatively anchored during the recent crisis period.

Table 2 provides some supplementary information from descriptive statistics on the IQR and ASY measures. Table 2 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 2 also illustrates how IQR dropped

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12This is related to the moderate impact on IQR as the ASY measure is the product of relative asymmetry and IQR.
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 3 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 3 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 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.

Interestingly, the information content in ASY is complementary to the one in IQR. 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. 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 HICP (DEFINE 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 $h$, $\pi_{t+h}$, on the the central tendency (i.e. mean or median) $h$-period ahead inflation forecast at date $t$, denoted $\pi^e_{t+h|t}$, and a vector of control variables $Z_t$:

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

with $e_{t+h}$ is the regression forecast error. These 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:

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

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. 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 include macroeconomic controls $Z_t$: the output gap $x_t$, commodity price inflation $\pi^c_t$, the change in the trade weighted USD exchange rate index $\Delta s_t$, and the lagged value of the realized CPI.

\footnote{One could also consider the following regression:

$$\pi_{t+k} = a_k + b_k \pi^e_{t+k|t} + c_k I@R^h_t(1-p) + d_k I@R^h_t(p) + C_k * Z_t + e_{t+k}.$$}

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 $\pi^e_{t+h|t} = I@R^h_t(0.50)$. 

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inflation rate $\pi_{t-1}^{\text{cpi}}$. Finally, we also consider various measures of expected inflation $\pi_{t+h|t}^{e}$.

In all baseline regressions, the inflation rate $\pi_{t+k}$ 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. We consider four different regressions. The first two do not have any control for expected inflation other than the MPF. The two last models include a vector $Z_{t}$ of other potential factors affecting future inflation realizations namely the output gap $x_{t}$, commodity price inflation $\pi_{t}^{\text{com}}$, the year-on-year change in a trade weighted USD exchange rate index $\Delta s_{t}$, and the lagged value of the realized inflation rate $\pi_{t-1}$.

4.2 Baseline estimation results

Table 4 displays the estimation results obtained for the full US sample using the baseline specifications of equation (4.2) and the GDP deflator series. As a reference point, Column (1) in Table 4 pertains to the regression (4.1) for the 3 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 a 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.\textsuperscript{14} It is surprising to note that the range of the risk IQR, has a negative impact, and it is not significant beyond one year. 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.\textsuperscript{15} Again the effect peaks at the 2 year

\textsuperscript{14}It 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 since we set $h = 1$.

\textsuperscript{15}To save space, we do not report the coefficient estimates for the control variables $Z_{t}$, but they are significant in line with the numerous evidence showing that the average of individual forecasters’ mean point
horizon. Likewise, the impact of IQR, stays negative and is not significant even at the one year horizon. The gains in terms of model fit are less striking, but still they represent up to nearly 10% of the initial adjusted $R^2$ for the 3-year forecast horizon and a gain of 3.9% 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. In particular, we construct out-of-sample forecasts using recursive estimations of two models: one with the MPF and real-time macroeconomic controls $Z_{rt}$ and one where we add the IQR and ASY measures. We compare these two models together and with a random walk model where the prediction is done using the real-time realization of inflation.

More precisely, we use the real time out-of-sample forecasts and the final releases of inflation to calculate the RMSE of each three models. The last two lines of each panels of Table 4 associated with the different forecasting horizons give two RMSE ratios. The first one compares the performance of the model with IQR and ASY with the model without any high order moments of inflation expectation. The second one compares that model with the RW. In addition to these ratios, we also implemented a test of forecast accuracy comparison developed by Clark and West (2007). Bold numbers indicate that the nesting model is significantly more precise. The results are striking: depending on the forecasting horizon, the IQR and ASY measures increase the precision of the out-of-sample forecast by 20 to 40%. The RMSE ratio of the RW model is lower than the one of this more general model. However, when one corrects for the supplementary estimation uncertainty associated to the more general model, using Clark and West (2007) test, one finds that it does better than the RW for the 1-year forecast horizon. This holds even though this statistical model is not optimized to produce precise forecasts.

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 forecasts (MPF) is not an efficient measure of expected inflation. We do not address such an issue in the present paper.

We replace the vector $Z_t$ of macroeconomic factors with $Z_{rt}$ based on real-time observations for the (year-on-year) real output growth rate $y_{rt}$, the quarterly oil price inflation rate $\Delta \text{oil}_t$, which is a proxy for the commodity price inflation, the year-on-year change in the trade weighted USD exchange rate index $\Delta s_t$, which we assume to be observed in real-time, and the lagged value of the real-time realized inflation rate $\pi_{t-1}^{rt}$.
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 $d_{2\text{years}} \times \text{SD}(\text{ASY}) = 6.063 \times 0.074 = 45$ bps 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 alternate estimations of the I@Rs, to variations of samples, and to changes in the specification of the inflation regression.

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. 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 3 to 6.5 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 $6.063 \times 0.074 = 45$ basis points increase in the CPI inflation rate two-years ahead. Similarly, a one standard deviation increase in the asymmetry measure signals a $6.063 \times 0.074 = 45$ basis points increase in the GDP deflator.

Finally, using IQR and ASY in real-time significantly improves the precision of CPI inflation out-of-sample forecasts by 30 to 40% compared to a model with just first-order moments of future inflation. The model with high order moments also significantly outperforms a random walk model for the 1-year and 2-year horizons.

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

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17 The 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.

18 The real time CPI inflation rate series starts in 1990Q1. Before this date, we use the real-time GDP deflator inflation as a substitute.
In Columns (1) and (2) of Table 6, we consider two alternative measures for the expected inflation rate $\pi_{t+k|t}$, namely $\text{I@R}(0.5)$ denoted as MED, and an AR(4) model of the inflation rate $\pi_t$. 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-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.

Columns (6) and (7) present the results obtained with two alternative measure of the I@R. The first also relies on the methodology of Engelberg, Manski, and Williams (2009) but doubles the length of the closing intervals. The second 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.

Finally columns (8) to (10) show the results for different variations in the specification of the equation (4.2). The two first variations amount to modifying the dependent variable to either the first difference of inflation $\Delta \pi$ or a (pseudo) inflation forecast error $(\pi_{t+k} - \pi_{t+h|t})$. This ensures stationarity of the dependent variable of the estimated model. 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. 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

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19 The results also apply to the 1-year and 3-year horizons but are not reported.
20 We 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).
21 See Table 1 for the extreme values of inflation we consider.
22 Rich and Tracy (2010) implement such a procedure in their study of the link between disagreement and uncertainty using the US SPF data.
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 IQRs are estimated using a linear extrapolation method (lines ASY in column (8)). This result is due to the fact that this 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 (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 45 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. It also holds in the Euro Area, where 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. Indeed, considering that MPF, IQR and ASY proxy respectively the first, second and third moments of future inflation, equation (4.2) can be reformulated as:

$$
\pi_{t+k} = a_k + b_k E_L\{\pi_{t+k}|I_t\} + c_k E_L\{(\pi_{t+k} - \mu_{t,k})^2|I_t\} + d_k E_L\{(\pi_{t+k} - \mu_{t,k})^3|I_t\} + \epsilon_{t+k},
$$

where $E_L\cdot|I_t\}$ the linear projection operator on an (unknown) information set $I_t$ (that includes the set of controls $Z_t$) and where $\mu_{t,k} = E_L\{\pi_{t+k}|I_t\}$. Therefore, our empirical findings show that the asymmetry of the probability distribution on future inflation has a positive impact on future realizations ($\hat{d}_k > 0$) and that the dispersion of this distribution has no direct impact ($\hat{c}_k$ insignificantly different from zero). The 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 $MPF^h_t \neq E\{\pi_{t+h}|I_t\}$ representing the conditional expectation (i.e. not the linear projection).

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23In this paper, we leave aside the study of the reasons why forecasters tend to ignore some relevant information to forecast the future inflation rates.
We now argue that state-dependent price-setting models with changes in the conditional variance of structural shocks underlying inflation can generate the type of non-linear effects that we find empirically. Assume that \( \text{MPF}^h_t = E_L \{ \pi_{t+h} | I_t \} \), that is that the MPF captures the expected dynamics of inflation in the absence of non-linear effects. Consider for instance an increase in the conditional variance of the structural shocks. It has two effects. The first one is to raise the size of a typical price adjustment hence the conditional variance of inflation. However, this mechanical increase in the conditional variance of inflation has no effect as such on the inflation realizations since it is associated with both larger positive and negative shocks to inflation. This is consistent with our finding that the IQR measure has no effect on future inflation realizations.\(^{24}\)

The second effect of an increase in the conditional variance of the structural shocks stems from the asymmetric price response to positive and negative shocks that characterizes state-dependent price setting models. As emphasized in Burstein (2006) and Devereux and Siu (2007), in these models, shocks that contribute positively to inflation generate greater price adjustments than negative shocks of equal magnitude. Indeed, 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, an increase in the standard deviation of the underlying structural shocks induces on average a larger reaction of positive price adjustments compared to negative ones. This will generate a rise in both the asymmetry of the inflation distribution and in the future realizations of inflation, which 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 brings information about future inflation. We analyze whether monetary authorities actually react to I@Rs in the next section.

\(^{24}\)In state-dependent pricing models, it also affects the frequency of price adjustment. Vavra (2012) underlines that changes in the conditional second moment of firms’ productivity increases the fraction of firms adjusting their prices but also the option of waiting and not changing its price. The first effect always dominates in his calibrations.
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 $\text{IQR}_t^h$ and $\text{ASY}_t^h$. 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:

$$\Delta i_t = \alpha + \beta \text{IQR}_t^h + \gamma \text{ASY}_t^h + \Gamma * X_t + u_t.$$  \hspace{1cm} (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, $\Delta i_t^Q$ 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, $\text{MPF}_t^h$, the past GDP deflator inflation rate observed in real-time, $\pi_{t-1}$ (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, $\pi_{t-1}^{oil}$, the past real GDP growth rate, $\Delta y_{t-1}$ observed in real-time and the past change in the interest rate $\Delta i_{t-1}$. 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$^t$ and ASY$^t$, observed at date $t$ can be influenced by the current monetary policy decisions, that is $\Delta i^Q_t$. In other words the regression can be plagued by endogeneity. However, the timing of the panel mitigates such endogeneity issue: while $\Delta i^Q_t$ 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, $\Delta i^M_t$ 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.$^{25}$

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 $\hat{\gamma} \times \text{SD}(\text{ASY}) = 1.936 \times .074 = 13.5$ bps increase in the policy rate when one does not control for feedback effect and to a $3 \times 1.158 \times .074 = 26$ bps when controlling and extrapolating the monthly reaction at the date of the survey to the whole quarter.

$^{25}$Bekaert, 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.
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 regimes and thus differences in the policy rule of monetary authorities.

One may first be concerned with the fact that the correlation between the variations in the ASY measures and the interest rate changes $\Delta i_t$ does not reflect a reaction of the US central bank to inflation risk but rather results from the impact of change in policy regime 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 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 where such that the asymmetry of inflation risk where 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 $2.272 \times 0.023 = 5.5$ basis points on the quarterly change of the policy rate in a wake of a one standard deviation shock in ASY.

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. The explanation thus relates to the more efficient use of information on the part of the central bank. 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 a high inflation is more costly than low inflation, as is the case in Ruge-Murcia (2003) or Kilian and Manganelli (2008). This optimal reaction to high order moments of future inflation could also be generated by setups in which central bankers are uncertain about the true state or model of the economy and have an aversion for this ambiguity as put forth in the robust control approach of Hansen and Sargent (2008).

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. If the Fed reacted to the asymmetry only to 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 7 shows

\footnote{The Greenbook forecasts are released with a lag. So this reduces our sample to 1970-2006.}
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 finally conclude this section by emphasizing that the effect of asymmetry on interest rate might bias the identification of monetary policy shocks. Indeed, most of the literature relies on linear structural VAR models to identify such shocks. In essence, these shocks are similar to the residual of the interest rate equation we estimate. Thus, if one fails to include the ASY measure in such models, one will bias the shocks. 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 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, even when one controls for the expectations of the Fed as in Romer and Romer (2004).

Since the asymmetry of the risks has at the same time a positive impact on the policy rate and a positive effect on inflation realizations, it is not clear whether the lack of control for non-linear effects in VAR would bias the estimation of a typical monetary policy shock upward or downward.\textsuperscript{27}

6 Conclusion

The paper puts to the fore several interesting issues for many strands of the macroeconomic literature. First, in the spirit of the finance literature, we stress that higher moments in the risk of future inflation matter. 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, which we call – by analogy to financial applications – Inflation-at-Risk, we show that the dispersion of inflation risk, and, more importantly, the asymmetry of inflation risk, matters and should not be neglected by policy makers. In particular, it turns out that the information

\textsuperscript{27}The fact that the asymmetry has in parallel still a positive effect on the inflation realizations suggests that the central bank wants or can only imperfectly counterbalance the effects of the asymmetry of the risk on inflation realizations.
contained in the risk of high inflation and/or low inflation gives valuable information on future realizations of inflation rates. Consequently, there is an interest for central banks to act as a Risk manager against inflation, since considering these extreme risks increases the accuracy of inflation forecast over the long-term.

Third and finally, we also show that the Fed interest rate instrument 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.
References


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Appendix

A Data Description

A.1 US and Euro Area SPF data

US survey of professional forecasters is conducted every quarter since 1969. Each institution is asked to report, among other things, forecasts about the GDP deflator. The survey provides mean point forecasts for the one year ahead GDP deflator inflation rate. In contrast, forecast distributions are only available for so-called calendar forecast, i.e. forecasts for the end of current year GDP deflator. As a consequence, the indicators features a strong seasonal patterns since, as time goes by, the event materializes, and uncertainty shrinks to zero. We thus use seasonally adjusted data to account for the intra-year declining uncertainty. 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.

Moreover, while the survey asks individuals about their mean point forecasts for a fixed horizon of 1 year, it collects information about the distribution of inflation for the end of the current year. This implies that the ASY and IQR measure are associated with a shrinking forecasting horizon over every given calendar year. This introduces a seasonal pattern in our IQR measure which we correct via seasonal dummies.

The ECB’s survey of professional forecasters is conducted every quarter since 1999. A detailed presentation and discussion of the data can be found in Bowles, Friz, Genre, Kenny, Meyler, and Rautanen (2007). 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 a forecasting fixed horizon of one year and two years. Respondents provide two important types of information. The usual mean point forecasts first but also forecast distributions over a set of (pre-specified) intervals. At the time of the writing this article, the last available survey round is 2012Q1, so that we have 50 time periods available.

The survey evolved through time due to changes in the perceived potential range of inflation: for the Euro Area, two new classes were introduced during 2008-09; for the US 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. In addition, the values of the bins in the questionnaire have been adjusted in 1975, 1981, 1985 and 1991.
Table 1 summarizes some key characteristics of the two surveys.

B 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 isocèle 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 isocèle 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 isocèle 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 isocèle 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:

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

where \( a \) and \( b \) are the two parameters defining the beta distribution, \( B(a,b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)} \), with \( \Gamma(b) = \int_{0}^{\infty} z^{(a-1)}e^{-z}dz \), 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:

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

with $J_t$ the number of class available in the survey at date $t$ and with $p_{ht}^h(k)$ 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 $\hat{a}_{ht}$ and $\hat{b}_{ht}$ the estimated parameters of the beta distribution for forecaster $i$ and date $t$ SPF and $\hat{F}_{ht}^h = F(x; \hat{a}_{ht}, \hat{b}_{ht}, L_{it}, U_{it})$ the corresponding beta distribution. The individual's $\hat{q}_{ht}^h(p)$ is the quantile of the continuous distribution $\hat{F}_{ht}^h$ at the probability threshold $p$, namely:

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

Therefore $\hat{I}_{ht}^h(p)$ is the cross-sectional average across survey respondents of $\hat{q}_{ht}(p)$. Likewise, the empirical $\hat{ASY}_{ht}^h(p)$ measure is the linear combination of the cross-sectional average across survey respondents of $\hat{q}_{ht}(p)$, $\hat{q}_{ht}(1-p)$ and $\hat{q}_{ht}(.50)$ as specified in equation (2.4). Note that in the remainder of the paper we will drop the hats and simply refer to $I_{ht}^h(p)$ and $ASY_{ht}^h(p)$ with the understanding that they are estimated quantities.
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 A.
Figure 2: Realized inflation, I@R(.05) and I@R(.95) (1-year horizon)

The figure plots the time series of realized inflation together with I@R(.05) and I@R(.95) for the US and Euro Area. The computation of I@R(.05) and I@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. Data details appear in Appendix A.
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) 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). Data details appear in Appendix A.
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 defined in equation (2.2) and ASY defined in (2.4). Data details appear in Appendix A.
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 defined in equation (2.2) and, ASY defined in (2.4). Data details appear in Appendix A.
Table 1: Design of surveys

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<td>1992Q1-present</td>
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<td>GDP deflator (yoy inflation)</td>
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<td>One year ahead</td>
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Table 2: Descriptive statistics

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<th>EA, 1999Q1-2012Q2</th>
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<td>AVG (TS) STD (CS)</td>
<td>AVG (TS) STD (CS)</td>
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<td>2.163 0.766</td>
<td>2.081 0.818</td>
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<td>(39.365)</td>
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<td>(9.392)</td>
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<td>2.962 0.599</td>
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<td>(42.27)</td>
<td>(9.642)</td>
<td>(8.774)</td>
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<td>I@R(.05)</td>
<td>2.872 2.198</td>
<td>1.128 0.582</td>
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<td>(34.501)</td>
<td>(8.211)</td>
<td>(15.345)</td>
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<td>IQR</td>
<td>2.211 0.548</td>
<td>1.84 0.181</td>
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<td>(12.015)</td>
<td>(2.876)</td>
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<td>ASY</td>
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<tr>
<td></td>
<td>(4.195)</td>
<td>(1.576)</td>
<td>(2.32)</td>
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</table>

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 A.
## Table 3: Bivariate regressions

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<tr>
<th></th>
<th>INF</th>
<th>OIL</th>
<th>OG</th>
<th>NBER</th>
<th>FOREX</th>
<th>S&amp;P 500</th>
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<td></td>
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</tr>
<tr>
<td></td>
<td>0.584</td>
<td>0.010</td>
<td>-3.273</td>
<td>0.733</td>
<td>0.060</td>
<td>-0.004</td>
<td>0.412</td>
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<tr>
<td></td>
<td>(16.005)</td>
<td>(1.702)</td>
<td>(-0.273)</td>
<td>(1.711)</td>
<td>(3.778)</td>
<td>(-4.634)</td>
<td>(11.539)</td>
</tr>
<tr>
<td><strong>IQR</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.076</td>
<td>-0.001</td>
<td>-4.298</td>
<td>0.214</td>
<td>0.019</td>
<td>-0.001</td>
<td>0.085</td>
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<tr>
<td></td>
<td>(4.593)</td>
<td>(-0.452)</td>
<td>(-1.049)</td>
<td>(1.366)</td>
<td>(3.797)</td>
<td>(-5.066)</td>
<td>(5.101)</td>
</tr>
<tr>
<td><strong>ASY</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td>0.003</td>
<td><strong>0.000</strong></td>
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<td>(1.319)</td>
<td>(1.899)</td>
<td>(2.638)</td>
<td>(-0.906)</td>
<td>(-1.662)</td>
<td>(0.051)</td>
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</table>

**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 4: The effect of inflation risk on inflation realizations (US GDP deflator)

<table>
<thead>
<tr>
<th>Controls</th>
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<th>k = 3 years</th>
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<td>MPF</td>
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<td>1.244</td>
<td>0.678</td>
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<td>IQR</td>
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<td>-0.292</td>
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<tr>
<td>ASY</td>
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<tr>
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<td>165</td>
<td>151</td>
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<tr>
<td>R^2</td>
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<td>0.757</td>
<td>0.823</td>
</tr>
<tr>
<td>RMSE ratio</td>
<td>0.999</td>
<td>0.923</td>
<td>0.807</td>
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</table>

Notes: OLS estimation of equation (4.4). MPF is the average of 1-year ahead individual mean point forecasts. IQR and ASY are based on the 95% – 5% I@R 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 Andrews’ automatic optimal bandwidth. 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 5: The effect of inflation risk on inflation realizations (US CPI)

<table>
<thead>
<tr>
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<td>RMSE ratio</td>
<td>0.801</td>
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Notes: OLS estimation of equation (4.4). MPF is the average of 1-year ahead individual mean point forecasts. IQR and ASY are based on the 95% – 5% I@R 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 Andrews’ automatic optimal bandwidth. 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

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<th>Regression Specif.</th>
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Notes: OLS estimation of equation (4.4) 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 4 and 5.
Table 7: Monetary policy reaction to IQR and ASY

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<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
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<td>∆FF</td>
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<td>2nd-Month</td>
<td>2nd-Month</td>
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<td>-0.113</td>
<td>-0.664</td>
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<td>(-1.23)</td>
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<td></td>
<td>(1.791)</td>
<td>(1.63)</td>
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<td>1.830</td>
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<td>(1.875)</td>
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| Notes: OLS estimation of equation (5.1). ∆it denotes the change in the fed-fund rate over a quarter. ∆im 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, the past inflation rate πt−1, the past energy inflation rate πt−1, and the past real GDP growth rate ∆yt−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.