Tails of Inflation Forecasts and Tales of Monetary Policy*

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Abstract

We introduce a new measure called *Inflation-at-Risk* (I@R) associated with (left and right) inflation tail 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/deflation risks evolve over time. Moreover, changes in inflation risks matter for macroeconomic outcomes: they help predict future inflation realizations and have an impact on the interest rate the central bank targets.

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1 Introduction

Central banks devote a lot of resources to assess the risks to inflation. Most of the time, they monitor measures of inflation expectations, i.e. the first moment in the distribution of future inflation. However, central bankers often express additional concerns about both the extent and the balance of future inflation risks. They also regularly suggest that these higher-order moments affect their policy decisions.[1] The recent period of the Great Recession and its aftermath is an illustrative case. Standard measures of inflation expectations remained anchored throughout this episode. Nevertheless, issues such as whether price stability was at risk, whether the risks to inflation were equally balanced around its central tendency, or what the appropriate policy reaction to these risks was, were all hotly debated in policy circles. To date, however, these debates are largely conducted in qualitative terms and the literature offers little quantitative assessment of these inflation risks.

This paper makes two contributions to this issue. First, we propose a new approach to measuring inflation risk which allows us 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. Second, we show that changes in inflation risk matter for aggregate outcomes: they have predictive power for future inflation realizations beyond the usual measures of inflation expectations and they affect the interest rate the central bank targets.

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. The I@R measures correspond to extreme quantiles – typically the top and bottom 5% – in the subjective distribution of future inflation realizations. The measure can be estimated using the individual subjective probability distributions about future inflation provided by the Surveys of Professional Forecasters (SPF) and implementing the approach developed by Engelberg, Manski, and Williams (2009).

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 also on individual probabilistic assessments of inflation scenarios provided in surveys but characterize future

[1]Such so-called "risk management" approach to monetary policy has been advocated for instance by Greenspan (2004), Mishkin (2008) or Evans (2011).

inflation uncertainty via its conditional variance. In addition to *uncertainty*, I@R can also be used to characterize 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.[2]

Using quarterly US SPF data covering the 1969-2012 sample period, 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. One can distinguish three main regimes of inflation risk in the US over the 1969-2012 period. A period of high inflation uncertainty where the risks were clearly tilted toward high inflation outcomes from the 70s to the mid-80s. A period of high inflation uncertainty 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. Hence, 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.

We provide evidence that the dynamics of the subjective risk measures are not completely at odds with measures based on models or based on other sources of information. In particular, the large swings in uncertainty and asymmetry observed in survey risk measures correspond to changes in the dynamical properties of models of inflation featuring stochastic volatility (such as Stock and Watson (2007) or Levin and Piger (2008)). We also show that these measures are correlated with other recent measures of macroeconomic uncertainty that have been proposed in the literature. We document that our survey-based subjective of inflation uncertainty (IQR) potentially encompasses two different types of measure of uncertainty: the broad macroeconomic unpredictability measure of Jurado, Ludvigson, and Ng (2014) or the economic policy uncertainty index of Baker, Bloom, and Davis (2015). The two measures do indeed not necessarily evolve in unison. Indeed, an increase in macroeconomic unpredictability is not necessarily related to economic policy. Conversely, an increase in economic policy uncertainty does not necessarily lead immediately to greater forecast errors and unpredictability.[3] Interestingly, we uncover a correlation pattern of our measures of inflation uncertainty changes over time which suggests that the relative importance of the two types of uncertainty also evolved.

Quite strikingly, we show that the survey-based inflation risk measures contain information

[2]When normalized by the interquantile range, this asymmetry measure corresponds to Bowley's (1920) robust coefficient of skewness.

[3]see Bianchi and Melosi (2015) for a macroeconomic model featuring such type of *ex-ante* uncertainty.

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 two years ahead. The effects are economically significant: in our reference specification, a one standard deviation increase in the asymmetry of inflation risk predicts a 48 basis points increase in the GDP deflator inflation rate two years ahead. Depending on the horizon, the forecast Root-Mean-Square-Error (RMSE) is reduced by 15% to 35% compared to a model which does not include the asymmetry of the risk. This information also substantially improves the out-of-sample inflation forecasts in real-time: the uncertainty and asymmetry measures enable to out-perform the celebrated random walk model of inflation (see e.g. Atkeson and Ohanian (2001)). The same conclusions hold for predictions based on the consensus forecast of the SPF or inflation forecasting models which exploit the "gap" between current inflation and some slowly-varying local mean of inflation advocated by Stock and Watson (2007), Cogley, Primiceri, and Sargent (2010) and Clark (2011).

Finally, consistent with the risk management approach to monetary policy, we find that the federal fund rate reacts to measures of inflation risks other than first moments. Controlling for standard determinants of monetary policy, when inflation uncertainty increases, the target interest rates decreases. Moreover, when right tail inflation risk increases, the target interest rate increases. This can result holds even when one controls for the fact that risk measures can react to monetary policy decisions. Indeed, using the timing of the survey to deal with such endogeneity issue, we find that the effect of uncertainty becomes non-significant but the effect of asymmetry remains. This second effect is quantitatively important: for the US, a one standard deviation increase in the asymmetry of inflation risk increases the target interest rate by 25 basis points. Importantly, such positive impact of our asymmetry measure is also robust to controlling for the Fed's own macroeconomic forecasts. This implies that the reaction of the Fed to the asymmetry of inflation risks does not primarily result from the forecasting power of such variable for future inflation.

Our work contributes to the literature measuring macroeconomic risks. Engle (1982) examines conditional volatility of inflation. Stock and Watson (2002) consider models featuring stochastic volatility for various macroeconomic aggregates including inflation.[4] Jurado, Ludvigson, and Ng (2014) measure broad-based macroeconomic uncertainty from the conditional variance of the unforecastable component in a large number of economic

[4]More recently, Primiceri (2005) and Sims and Zha (2006) estimate a 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 featuring conditionally heteroscedastic shock processes.

variables. Gilchrist, Sim, and Zakrajsek (2014) rely on the unforecastable component in a large cross-section of stock prices. Baker, Bloom, and Davis (2015) develop measures of policy uncertainty based on newspaper coverage of the topics. We focus on the risks to inflation and use survey data. Zarnowitz and Lambros (1987) or more recently Rich and Tracy (2010) also provide survey-based measures of the conditional variance of US inflation relying on different non-parametric methods. Our analysis goes beyond volatility as it quantifies a (specific) tail macroeconomic risk and derives a measure of the asymmetry of such risks.[5] 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 therefore yields a (risk-neutral) measure of the risks of deflation or high inflation. Bloom (2009) also relies on option prices index to proxy macroeconomic uncertainty. By comparison, our survey-based measures of potential extreme events are model-free and are immune to changes in risk and liquidity premia.

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, defined as shocks to the conditional variance of productivity shocks, contribute non-trivially to investment hence macroeconomic fluctuations. Gilchrist, Sim, and Zakrajsek (2014) show that uncertainty affects credit spreads. Gourio (2012) develops a comparable approach based on changes in the probability of extreme events.[6] 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 show that they affect future inflation realizations and current monetary policy decisions.

Our results also emphasize that survey of inflation expectations contains useful information. Ang, Bekaert, and Wei (2007) and Faust and Wright (2013) show that surveys outperform a

[5]Curdia, 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. Rossi and Sekhposyan (2015) look at the probability associated to the realized forecast errors in the empirical distribution of errors. This allows them to distinguish between positive and negative errors.

[6]Schaal (2012) and Leduc and Liu (2015) investigate the macroeconomic impact of uncertainty through labor markets. See also Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011) for shocks on the volatility of a small open economy domestic interest rate.

large range of forecasting methods. Our paper builds further on the success of survey-based forecasts. Yet, our approach exploits hitherto untapped information obtained from survey data. D'Amico and Orphanides (2014) show that survey based inflation uncertainty is a determinant of the term premium in nominal bond returns while Kang and Pflueger (2015) provide evidence that such risk affect corporate bond yields. By comparison, we consider asymmetries in the distribution of future inflation and we investigate the impact of the risk measures on macroeconomic outcomes.

Finally, Ruge-Murcia (2003) and Kilian and Manganelli (2008) develop structural models in which monetary authorities can have non-quadratic valuation of inflation costs. Evans, Fisher, Gourio, and Krane (2015) show such asymmetry of the costs emerges when one considers the possibility of hitting the zero lower bound constraint on nominal interest rates. Similar to our findings, these papers show that monetary authorities should react more aggressively when right tail inflation risk increases. We do not attempt to estimate a structural model of policy maker preferences. Our results do not depend on specific structural assumptions about the central bank's loss function or 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 document several empirical regularities that we obtain looking at the behavior of these new indicators. 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 our new measures of survey-based inflation risk. While our focus is on inflation risk, the methods proposed here are, to the best of our knowledge, new to the literature on macroeconomic risk and are therefore of general interest. The first two subsections introduce the measures, a third subsection makes some comparison with more standard survey-based measures.

To compute our measures, we adopt the methodology of Engelberg, Manski, and Williams (2009) who consider matching generalized *beta* distributions to the individual discrete histograms. As the details of the estimation procedure are not of prime interest, we defer the analysis to Online Appendix section A where we also provide robustness checks involving a different 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:

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

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:

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

In addition, letting $\mathrm{E}_i(\cdot)$ 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:*

$$\mathrm{I@R}_t^h(p) = \mathrm{E}_i\left[q_{it}^h(p)\right]. \tag{2.1}$$

In the empirical application, we typically look at respectively the 5^{th} (p = .05) and 95^{th} (p = .95) percentiles but also consider the 25^{th} (p = .25) and 75^{th} (p = .75) percentiles. These measures amount to an average across individuals of their expected extreme low and high inflation outcomes – that is the average quantiles for left and right tail probabilities.[7]

The inspiration for these measures is the well known notion of Value-at-Risk which features prominently in bank capital requirements as stipulated in the Basel Committee accords. A motivation for looking at such extreme quantiles is that monetary policy statements by central bankers frequently allude to notions of risk management – in particular in terms of tail inflation risks – as an important factor in their decision making. In practice, central banks indeed frequently monitor macroeconomic risks.[8] Moreover, in theory, the preference of the central bank can lead to situation where perceived extreme events can affect optimal monetary policy decisions.[9]

Note that a difference with the standard risk management approach is that the focus is not only on the left tail – that is on potential losses. Indeed, in our case, and as noted earlier, we are interested in both tails of inflation risks: fear of price depression as well as high inflation.

[7] The fact we use the average across individuals to compute I@R is quite similar to the computation of the mean of central tendency forecasts across participants. Each individual participant has her/his private information to make tail risk assessments which we aggregate by computing averages.

[8] See e.g. Knuppel and Schultefrankenfeld (2011) for a description of central banks' practise in that regards.

[9] See e.g. Kilian and Manganelli (2008) or more recently Evans, Fisher, Gourio, and Krane (2015).

2.2 Survey-Based Measures of Uncertainty and Asymmetry

We can build further on the notion of the I@R survey-based quantiles to assess the overall extent of inflation risk and how balanced the risks of a high and a low inflation are.

A natural measure of inflation uncertainty is provided by the inter-quantile range of the conditional inflation distribution associated to a risk level p. The inter-quantile range pertains indeed 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 is defined as:

$$\mathrm{IQR}_t^h(p) = \mathrm{E}_i\left[q_{it}^h(1-p) - q_{it}^h(p)\right], \tag{2.2}$$

with p a chosen probability $< .50$ and E_i 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.

Second, and in addition to inflation uncertainty, the I@R measures can tell us whether the future inflation risks are symmetric, or instead tilted toward high or low inflation realizations. Indeed, one can simply calculate the following quantile-based measure of inflation distributional asymmetry:

$$\mathrm{ASY}_t^h(p) = \mathrm{E}_i\left[\left(q_{it}^h(1-p) - q_{it}^h(.50)\right) - \left(q_{it}^h(.50) - q_{it}^h(p)\right)\right], \tag{2.3}$$

with p a chosen probability $< .50$ and E_i 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. Symmetric distributions yield $\mathrm{ASY}_t^h = 0$, while negative (positive) values indicate that a probability mass associated to inflation lower (higher) than the median dominates and inflation is skewed to the left (right). In line with the previous section, in the empirical applications that follow, we focus on the two risk levels: $p = .05$ and $p = .25$.

Interestingly, the measure in (2.3) can be related to Bowley's (1920) robust coefficient of asymmetry:

$$\mathrm{RA}_{it}^h(p) = \frac{\left(q_{it}^h(1-p) - q_{it}^h(.50)\right) - \left(q_{it}^h(.50) - q_{it}^h(p)\right)}{q_{it}^h(1-p) - q_{it}^h(p)}. \tag{2.4}$$

The Bowley measure was primarily introduced as an estimate of skewness which is robust to outliers, since the quantiles in equation (2.4) are not affected by extreme tail observations.[10]

[10]The RA_{it}^h and related measures of asymmetry have received very limited attention in the empirical macro

Combining equations (2.3) and (2.4) makes apparent that the asymmetry measure we consider is 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 $\mathrm{IQR}_{it}^h(p) = q_{it}^h(1-p) - q_{it}^h(p)$ one can rewrite

$$\mathrm{ASY}_t^h(p) = \mathrm{E}_i\left[\mathrm{RA}_{it}^h(p) \times \mathrm{IQR}_{it}^h(p)\right].$$

To put it differently, our asymmetry measure can be viewed as a signed measure of uncertainty.

Another important characteristic of the IQR and ASY measures is worth emphasizing: 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 (2.3) can be respectively rewritten as:

$$\mathrm{IQR}_t^h(p) = \mathrm{E}_i\left[\mathrm{IQR}_{it}^h(p)\right], \quad \mathrm{ASY}_t^h(p) = \mathrm{E}_i\left[\mathrm{ASY}_{it}^h(p)\right].$$

Hence, both measures are similar to aggregating individual mean point forecasts obtained from computing the mean of central tendency forecasts across participants. The robust coefficient of skewness, RA, is more involved because of the intrinsic non-linearity. The average of individual $\mathrm{RA}_{it}^h(p)$ cannot be linked to the average of individual quantiles. We therefore prefer to work with ASY as an indicator of skewness.

Note also that the aggregation of each individual participant's view about quantiles may yield noisy, and perhaps biased, estimators of the underlying population counterparts. Hence, we view these average I@R, IQR and ASY measures only as providing some potentially useful information about the inflation risk perceived by forecasters. In the empirical application, we will show this is the case, namely that besides the average of mean point forecasts, the average IQR and ASY have predicting power for future inflation realizations.

2.3 Comparison with Alternative Measures of Uncertainty

Previous work developed alternative measures of macroeconomic risks including inflation risk. We provide a brief comparison with these measures, starting with the ones that are,

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.

like ours, based on survey of expectations.

2.3.1 Based on Surveys

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. More precisely, using our notation, the *consensus* forecast is defined as:

$$\mathrm{MPF}_t^h = \mathrm{E}_i(\mathrm{MPF}_{it}^h), \tag{2.5}$$

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

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

Data from the Surveys of Professional Forecasters is also often used (see e.g. Zarnowitz and Lambros (1987) and Wallis (2005)) to compute an alternative measure of forecast *uncertainty*, that is the average standard deviation (or variance) of the individual mean-point forecast defined as:

$$\mathrm{SDMPF}_t^h = \mathrm{E}_i\left(\mathrm{SDMPF}_{it}^h|i,t\right), \tag{2.7}$$

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

Our measures can be linked to several of the aforementioned indicators in some special cases. $\mathrm{I@R}_t^h(.50)$ 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 $\mathrm{IQR}_t^h(.05) = 2 \times 1.64 \times \mathrm{SDMPF}_t^h$. 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 extent of extreme low or high inflation fears.

2.3.2 Other Measures

Following Bloom (2009), the recent literature studying the impact of uncertainty on macroeconomic outcomes frequently relied on measures of stock market volatility – either ex-post, or measured in option prices such as the VIX – as proxies for uncertainty. Such measures are empirically positively correlated. However, as emphasized by Zarnowitz and Lambros (1987) or more recently Rich and Tracy (2010), there is no simple link between disagreement and such measures of uncertainty. Moreover, as Jurado, Ludvigson, and Ng (2014) also emphasize, uncertainty is a measure of the extent of the predictability of economic outcomes. It is therefore associated with the conditional variance of forecast errors.

We view our approach as complementary to that of Jurado, Ludvigson, and Ng (2014). As equation (2.7) indicates, our measure of uncertainty (IQR) is also linked to the conditional variance of the forecast errors. However, there are three main differences between the two approaches: *(i)* our measure is specific to inflation while their measures aggregate all types of risks; *(ii)* our measure is a subjective measure of *ex-ante* uncertainty while their measure relies on *ex-post* realized forecast errors; *(iii)* our approach allows for asymmetric risks while their uncertainty measure is symmetric.

Our measure is also linked to the economic policy uncertainty indexes of Baker, Bloom, and Davis (2015). Indeed, greater uncertainty about future fiscal and monetary policies entails greater uncertainty about future inflation, and hence an increase in its conditional variance. As Bianchi and Melosi (2015) emphasize, such uncertainty about future fiscal and monetary policies might not have been realized yet. So it can lead to greater uncertainty about future inflation today without necessarily implying that greater forecast errors have been realized yet. Like the index of Baker, Bloom, and Davis (2015) our measures are not tied to *ex-post* realized forecast errors. As we discuss in section 3.2.3 below, an appeal of the survey-based subjective measures is that they potentially encompass both forms of uncertainty (realized and non-realized ones) with their relative importance changing across time. Our approach also allows us to characterize whether inflation risk resulting from political uncertainty is more on the upside or on the downside.

3 Inflation Risks: Some Stylized Facts

Since our new measures capture hitherto undocumented features of SPF survey data, we start with reporting stylized facts about extreme events, the uncertainty and the asymmetry about future inflation outcomes that can be extracted from SPF data over the 1969-2012 sample. The survey provides individual mean point forecasts for the GDP/GNP deflator inflation rate one year ahead. It also gives individual forecast distributions about the deflator inflation rate of the current calendar year. Unfortunately, probability distributions for the CPI inflation rate started to be collected only in 2007Q1 - a sample too short to exploit for econometric analysis. Hence, our analysis focuses exclusively on the GDP deflator. A detailed description of the data appears in Online Appendix section B.

3.1 The Time Series Pattern of I@R, IQR and ASY

Figure 1 displays the time series of realized inflation, together with I@R(.05) and I@R(.95). The interval obtained will henceforth sometimes be referred to as the (*ex-ante* purely data driven) confidence interval. 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. 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 shock were better understood. This also includes a very low inflation realization in 1998, and a high outcome in 2005.

A closer investigation reveals that, on average, 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.[11] Agents appear to have a tendency to underestimate the range of inflation risks as their subjective distributions are too much concentrated around their point forecasts.

The I@R(.05) and I@R(.95) time series in Figure 1 appear at first sight to suggest that they evolved in parallel and followed the evolution of the average of mean point forecasts. It turns

[11]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 B.1 in Online Appendix section B for the details of how these extreme values changed over time.

out that this is not the case, as is revealed by examining the IQR and ASY measures.

The left panel of Figure 2 presents the time series of the IQR - .05/.95 measure over the 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%. 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.[12] Since the mid 90s, it exhibited a relatively mild upward trend, close to 2% after the recent crisis. 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. 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. 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 2 plots the time series of ASY - .05/.95 over the 1969-2012 sample. It shows that the asymmetry of inflation risks was also characterized by three main regimes. It increased to become more and more 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 where asymmetry decreased sharply to become negative, i.e. where risks of low inflation outcomes dominated. This peaked during the recession of 1990-91. Starting the early 90s, the asymmetry of inflation risk stabilized around more balanced levels. The ASY measure 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. The length of time 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.[13] This is another illustration of the fact that inflation expectations remained relatively anchored during the recent crisis period.

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

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

3.2 Comparison with Models and Other Measures of Uncertainty

In this subsection we make various comparisons between respectively IGR and ASY and other measures. In a first subsection, we address a data issue pertaining to the design of surveys used in our analysis.

3.2.1 Do Changes in IQR and ASY Result from Changes in the Design of the Survey?

There is a legitimate concern that some of the major changes to IQR and ASY are simply driven by the re-design in the number survey bins used for the SPF. This is particularly the case for 1991-1992, which overlaps with such a change in 1992Q1. It appears, however, that the substantial changes are due to more fundamental causes beyond the design of the survey. For instance, Levin and Piger (2008) implement Bayesian methods to identify, over a 1953Q1-2005Q2 sample, structural breaks in the parameter of the autoregressive process of GDP deflator inflation rate, including the variance of the innovation. They find evidence of three regime changes: one in the late sixties before the beginning of the SPF, one in the early eighties and one in the early nineties. As Figure 5 illustrates, the break date intervals they identify correspond to periods of structural changes in the IQR and ASY measures. These similarities between two very different approaches supports the view that changes in survey-based moments are not a purely an artefact of the survey design changes. We will further elaborate on this in the next subsection as well.

3.2.2 A Comparison with Parametric Density Forecasts

How do our survey-based measures of inflation risk compare with some of the parametric inflation density forecasting models? The answer is not straightforward as none of the commonly used models explicitly take into account separately the risks of a low versus a high inflation. We can nevertheless learn something from one of the most successful models, which is the so called UCSV model of Stock and Watson (2007). The model is among the best empirical specifications when compared to a large set of alternatives, see in particular the comprehensive survey by Faust and Wright (2013). Among the attractive features of the model is the fact that it not only provides a point forecast, like for instance the random walk model of Atkeson and Ohanian (2001), but also provides a density forecast. Let us first recall the model specification:

$$
\begin{aligned}
\pi_t = & \quad \tau_t + \eta_t^T & \eta_t^T \sim N(0, \sigma^2_{T,t}) \\
\tau_t = & \quad \tau_{t-1} + \eta_t^P & \eta_t^P \sim N(0, \sigma^2_{P,t}) \\
\log(\sigma^2_{T,t}) = & \quad \log(\sigma^2_{T,t-1}) + \psi_{1,t} & \\
\log(\sigma^2_{P,t}) = & \quad \log(\sigma^2_{P,t-1}) + \psi_{2,t} & (\psi_{1,t}\psi_{2,t})' \sim N(0, I_2)
\end{aligned}
\tag{3.1}
$$

The model is estimated via MCMC and yields, among other things, a posterior density of the permanent trend component τ_t. Based on this posterior density we can compute model implied probabilities of being below or above certain thresholds. Similar to Faust and Wright (2013, Figure 9) we focus on the probability of GDP deflator inflation rate being above 4 percent or below 0 percent. We look at the annualized inflation rate density forecasts for the next quarter.

Figure 3 shows the evolution of the UCSV model implied probability of the GDP deflator inflation being above 4 percent or below 0 percent over the 1985-2012 sample.[14] Complementary to Figure 3 are also the two panels in Figure 4. The left panel displays a scatter plot of the UCSV model implied probability of GDP deflator inflation being above 4 percent versus I@R(.75) and I@R(.95) respectively, the right panel displays a scatter plot of the probability of GDP deflator inflation being below zero percent versus I@R(.05) and I@R(.25) respectively.

The two plots are quite revealing. Arguably, the survey-based measures described in the previous section are possibly noisy. Yet, it is interesting how the I@R and UCSV are close in capturing uncertainty and asymmetry. This is not only intriguing, but also useful. Take for example the fact that in Q1 of 1992 the survey was re-designed, with an increase in the number of bins (see also our discussion at the end of the previous subsection 3.2.1). We note in Figure 3 the sharp drop in the right tail (inflation above 4 %) around the same time period as a major change in both uncertainty and asymmetry in Figure 2. Hence, despite the potential design flaws with surveys - such as changes in bins capturing the distributions and the difficulty measuring tail probabilities, the similarities from two very different approaches, is yet another piece of evidence that is comforting for the analysis appearing in the next section.

[14] Unlike the calculations reported in Faust and Wright (2013), we use *ex-post* inflation realizations and the probability to be above or below to be above 4% or below 0% (in annualized rate) over the next quarter. They use real-time data and the probability to be above 4% or below 0% on average over the next two years. However, despite some differences, our plot in Figure 3 looks broadly the same.

While there are similarities between our survey-based measures I@R and the calculations based on the posterior density of the UCSV permanent component, it should also be noted that the choice of inflation being above 4 percent or below 0 percent is based on threshold values which are somewhat ad hoc. In the 70s the 0 % and 4 % values appear less suitable. The advantage of our measures is that they are real-time survey-driven and do not require anchoring on some specific threshold values.

3.2.3 A Comparison with Recent Measures of Uncertainty

As discussed in Section 2.3, several recent papers proposed alternative measures of macroeconomic uncertainty. Table 1 displays the correlations of our risk measures with a set of such alternative measures. More specifically, we consider forecasters' disagreement and the VIX index as in Bloom (2009), the measure of broad macroeconomic unpredictability developed by Jurado, Ludvigson, and Ng (2014) and the policy uncertainty index build by Baker, Bloom, and Davis (2015). We also compare our measures with two more standard indicators: the conditional variance of inflation from a GARCH model and the realized volatility on stock markets. As the VIX measure is available only starting 1990, we consider two samples: one starting in 1990, and one in 1969.

The results show that our measure of subjective inflation conditional variance (IQR) is positively correlated with various alternative measures of uncertainty. The asymmetry measure (ASY) instead tends to be negatively correlated with measures of uncertainty: uncertainty is mostly associated with periods where downward inflation risks dominate upward ones. This is not very surprising as uncertainty measures are typically counter-cyclical and inflation declines in recessions. The episode of the 70s (where uncertainty was high and asymmetry positive) stands as an exception. Lastly, one should note that our survey measures of uncertainty have correlations with other measures which changes over time. In particular, it is striking to observe that the IQR is significantly positively correlated with the measure of unpredictability of macroeconomic variables over the 1969-2012 sample, but not with the measure of economic policy uncertainty, while the reverse holds over the 1990-2012 sample. As we mentioned in Section 2.3, an appeal of our indicators is that they potentially capture both types of uncertainty. This suggests the relative importance of these two forms of uncertainty can change over time and that these changes are reflected in the subjective measures of inflation risks.

All in all, we think the results illustrate that the proposed survey-based measures of inflation risks contain information that is a useful complement to existing measures.

4 The Impact of Inflation Risks on Future Inflation Realizations

In this section, we show that the new survey- and quantile-based measures contain valuable information about future realized inflation. We investigate predictive regressions in the context of an *in-sample/final releases* as well as an *out-of-sample/real-time data* exercise. We discuss the robustness of the baseline results to alternative modeling choices, and in particular to the estimation methods of the I@Rs.

4.1 In-Sample Analysis

We start with a discussion of how the survey-based risk measures improve the in-sample fit of future inflation realizations. Out-of-sample performances are more relevant for practical forecasting purposes. However, the in-sample regressions are also informative and have the advantage of exploiting the full sample.

4.1.1 Model Setup

To investigate whether I@R contains information about future inflation realizations, we rely on Mincer and Zarnowitz (1969) type regressions, namely regressions 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 $\pi^e_{t+h|t}$, and a vector of control variables Z_t :

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

with e_{t+h} 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 information, namely that $a_h = 0$, $b_h = 1$, and $C_h = 0$.

We consider the following variation of the regression appearing in (4.1):

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

with the horizon k potentially greater than the forecasting horizon h available in the surveys, and p the risk level to compute IQR and ASY.[15]

In all the following regressions, the inflation rate π_{t+k} is measured as the year-on-year change in the GDP deflator at date $t+k$. The macroeconomic controls Z_t are as follows: the latest observation available at time t of (a) the GDP deflator inflation rate, denoted π_t, (b) the output gap, denoted x_t, (c) the oil price quarterly inflation rate, π_t^{oil}, and finally (d) the percent quarterly change in the trade weighted USD exchange rate index, denoted by Δs_t. For the latter two variables, the changes are measured between two subsequent survey dates. The Online Appendix provides more details regarding the data.

4.1.2 Baseline Results

In the baseline specifications, expected inflation $\pi^e_{t+h|t}$ is the average of the individual mean point forecasts for the year-on-year GDP deflator inflation rate denoted MPF_t^h, with h being equal to 1 year. The IQR and ASY measures are computed for both $p = 5\%$ and $p = 25\%$. We consider two different horizons for the realizations: $k = 1$ and 2 years.

The empirical results are reported in Table 2, with the top panel pertaining to results obtained when the IQR and ASY measures based on the .05/.95 quantiles, and the lower panel covering the .25/.75 configuration. The results in both panels are qualitatively the same. As a reference point, Column (1) in Table 2 pertains to the regression (4.1) for the two forecasting horizons $k = 1$ and 2 years, when one regresses the realized inflation only on its expectation. Columns (2) and (3) add the IQR and ASY measures. The dispersion measure IQR has a negative and significant impact. For the forecasting horizons considered, the asymmetry measure, ASY, has, after taking into account expected inflation, a positive and significant impact on future inflation realizations.

In column (4), we add the IQR and ASY variables together. It is interesting to note that, at horizon $k = 1$ year both are significant, but IQR, is not significant beyond one year.[16] The

[15]Due to data limitations–fixed horizon inflation forecasts are only available up to 1-year–we consider cases where the horizon of the target variable, k, can be greater than h, the survey forecast horizon. Note also, one could consider the following regression:

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

The time series patterns displayed in Figure 1, 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 $\pi^e_{t+h|t} = \text{I@R}_t^h(.50)$.

[16]This confirms the results obtained with more traditional measures of inflation uncertainty. See e.g. Grier

table also reports the ratio of the root mean square error (RMSE) for each model compared with the one associated with a random walk (RW). We note that the lowest ratio is obtained for models involving the asymmetry measure.

Columns (5) and (6) report the results when one adds the macroeconomic controls Z_t to the two previous sets of regressors.[17] We note in column (6) that adding controls to the regression containing both IQR and ASY does not alter the previous results.

Overall, we find that the measure of inflation risk asymmetry contains information about future 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 $\hat{d}_{\text{2years}} \times \text{SD(ASY)} = 6.45 \times .074 \simeq 48$ basis points increase in the GDP deflator inflation rate two years ahead.

4.1.3 Robustness

We assess the robustness of the previous baseline results to various measures of expected inflation, to alternative measures of macroeconomic uncertainty, to changes in the specification of the inflation regression, and to alternative estimates of I@Rs. We keep the GDP deflator inflation rate as the dependent variable and focus exclusively on the 2-year horizon.[18]

In Columns (1) and (2) of Table 3, we consider two alternative measures for the expected inflation rate $\pi^e_{t+h|t}$. The results reported so far might be affected by the difference between the individual mean point forecasts and the central tendency in individual distribution of future inflation. We address this concern by using the average of medians of individual distributions, I@R(.50), denoted as MED, as the measure of inflation expectation, instead of the average MPF. The second one is related to the possibility that the previous results might only illustrate some form of imperfection in the information the forecasters have access to, and would disappear if an objective measure of inflation expectation, instead of a subjective one, were introduced in the test regression. We deal with this issue by using an expected inflation rate $\pi^e_{t+h|t}$ that is obtained from an AR(4) model for the inflation rate π_t.

and Perry (2000) or Fountas and Karanasos (2007).

[17] To 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 and 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.

[18] Similar results are obtained for the 1-year horizon.

In Columns (3) to (5), we verify that our results are not driven by a specific measure of inflation or macroeconomic risk. 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).[19] 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 purely stock market data-driven measure of the S&P 500 stock market index volatility, namely the quarterly cumulative sum of the squared first-difference of the series over the past 3 months.

Columns (6) to (8) check that the results are robust to different variations in the specification of the equation (4.2). The first two amount to modifying the dependent variable to either the first difference of inflation $\Delta\pi$ or a (pseudo) inflation forecast error $(\pi_{t+k} - \pi^e_{t+h|t})$ in order to take into account a potential non-stationarity of the inflation process. The last one deals with an alternative 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.[20]

Lastly, Columns (9) and (10) present the results obtained with two alternative measures of the I@R. The first method provides estimates of the I@R under the assumption of a uniform distribution over each bin of the survey.[21] The second methods still relies on the methodology of Engelberg, Manski, and Williams (2009) but double the length of the closing intervals.[22]

It is remarkable that one of the key results of the baseline analysis is preserved regardless of the different variations, namely: 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 when doubling the

[19] We also obtained the same results with the average dispersion associated with individual mean point forecasts of inflation (SDMPF).

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

[21] In that case, I@R estimates are obtained through linear interpolation of individual probability distribution for future inflation. Further evidence on the robustness to the estimation method of quantiles is also given in Table B.6. Table B.6 is similar to Table 2, but reports results where one uses a uniform probability distribution over each bin of the survey.

[22] See Table B.1 for the extreme values of inflation we consider.

length for the extreme intervals (entries ASY in column (9) of Table 3), or using a linear extrapolation method or (Table B.6). These results stem from the fact that these methods impact the standard deviation of the asymmetry. In particular, the linear 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 (about 25 basis points) for the full sample. Hence, according to this specification, a one standard deviation increase in the asymmetry leads to about $1.27 \times .26 = 33$ basis points increase in the GDP deflator inflation rate two years later, not too different from the 48 basis points found for the baseline estimates.

4.2 Out-of-Sample Analysis

4.2.1 Model Setup

The previous analysis involved final releases of macroeconomic data and analyzed the in-sample prediction performance. We complement this exercise with an evaluation of the out-of-sample performance of the I@R quantile-based measures in a real-time setting. More precisely, we use a set of reference models in which we incorporate various measures of inflation risk to construct pseudo out-of-sample forecasts. We compare their performance to the one of a simple Random Walk (RW) model of inflation. We also assess if the inflation risk measures improve the forecast performance compared to the original set of reference models.

Models which perform well out-of-sample are typically parsimonious as parameter proliferation tends to deteriorate out-of-sample forecast accuracy. Hence, we focus on simple models only. More precisely, we consider three specifications. The first two are the MPF and the UCSV model already discussed before. Note that unlike the MPF, our estimation of the UCSV model is not truly a real-time one as it uses final releases. A third specification is referred to as the AR-GAP model by Faust and Wright (2013). This postulates an autoregressive model of the "gap" between current inflation and some slowly-varying local mean of inflation, $g_t = \pi_t$ - $\overline{\pi}_t$.[23] Hence, we use three baseline forecasts: (1) the average of mean point forecast from surveys (MPF); (2) forecasts based on an AR(1) of inflation gap from its long-term component as measured in surveys (AR-GAP); and (3) the long-run trend

[23] As in Faust and Wright (2013), the long-run component of inflation is measured through the GDP deflator long-run forecasts provided in the Blue Chip survey. We are very grateful to Jonathan Wright for sharing this series with us. In practice, we estimate this model recursively using real-time data.

in the unobserved component stochastic volatility model of inflation (UCSV).

We start with computing forecast errors obtained with the three baseline models.[24] Next, using a recursive regressions, we project these forecast errors on the IQR and ASY variables. We use a recursive window scheme and an estimation sample which starts in 1974Q4 as, before, the average of the MPF is sometimes missing. For all three models, the forecasting sample is 1985Q1-2012Q2, as in the survey of Faust and Wright (2013). We consider 5 horizons: 1Q, 2Q, 3Q, 4Q and 8Q. Forecast comparisons are based on root-mean-square-error (RMSE) and a finite sample adjusted version of the Diebold and Mariano (1995) test statistic introduced in Clark and McCracken (2013). The target variable is the annualized quarterly GDP deflator inflation rate.

4.2.2 Results

Table 4 presents the RMSE ratio for the three sets of models relative to the RW. A value less than one means that the reference model outperforms the RW. As usual, stars indicate that the difference in performance is statistically significant according to the finite sample Diebold and Mariano's (1995) test statistic of Clark and McCracken (2013). In Panel A of Table 4, we consider the RW against the MPF. The first line, denoted REF which stands for reference model, shows that the MPF improves relative to the RW model with ratios around .9 which are significantly different from one for short horizons. This is reminiscent of several previous findings showing that surveys forecast inflation better than a RW model (see Ang, Bekaert, and Wei (2007) or Faust and Wright (2013)). When we add to the regression IQR, we see stronger improvements which are significant beyond the short horizons noted for the MPF. This also applies to ASY - .25/.75. In Panel B, we compare the RW with the AR-GAP model. Again, viewing AR-GAP as a reference model, we note that it outperforms the RW at 1 through 4 quarters and even at the 2 year horizon at 10 % level. Adding either IQR yields extremely poor results which are much worse - significantly so - than the RW model for short horizons, but a very good result for 8Q ahead. In contrast, adding our asymmetry measures yields the best improvements across almost all horizons.

Finally, we compare the UCSV to the RW in Panel C of Table 4. The results show that the UCSV performs much better than the RW, reflecting in part the fact that this version of the UCSV model uses final statistical releases while the RW uses real-time data. We also note that the survey-based risk measures do not improve the forecast performances compared to

[24] Forecast errors are calculated using final releases.

the basic version of the UCSV model. As the UCSV produces density forecasts, we can go further and investigate whether model-based (as opposed to survey-based) measures of uncertainty and asymmetry of inflation risks perform better than survey based measures. Strictly speaking, the UCSV does not feature time-varying asymmetry in its density forecast. Yet, we can exploit the model induced probabilities of a high and a low inflation realization presented in Section 3.2.2. More precisely, we construct two variables, PrUN and PrAS, which correspond to, respectively, the sum of the probabilities that inflation will be greater than 4% and will be lower than 0%, and the difference between the two probabilities. Interestingly, the latter asymmetry measure improves on the baseline UCSV performance for the 1Q and 8Q forecast horizons.

Table 4 shows that the uncertainty and asymmetry measures improve the forecasting performances of models which significantly do better than the RW. The next question is whether these improvements are statistically significant. We investigate this issue by comparing the forecast performance of each model to its own baseline specification. Table 5 show the results. Panel A shows that the ASY - .25/.75 and the IQR - .25/.75 and - .05/.95 reduce the forecast error by 5 to 10% compared to the MPF which already beats the RW by 9 to 14%. Several of these improvements are statistically significant. Likewise, Panel B shows that the ASY - .25/.75 and the IQR - .25/.75 improve the forecast performance by another 5 to 15% compared to the AR-GAP model which already beats the RW by 12 to 16%, with again, several of these differences being significant. Lastly, Panel C shows that the model-based asymmetry measure, PrAS, improves the forecast performance of a UCSV model by more than 5% 8Q ahead, which is again statistically significant.

4.2.3 Robustness

We focused on the 1985-2012 sample, similar to the recent survey of Faust and Wright (2013). However, as Figure 5 illustrates and as we already discussed in Section 3.2.1, the times series of realized inflation and the IQR and ASY measures are prone to regime changes over this period. Moreover, the improvement in forecast precision due to either the IQR or the ASY may change over time.[25] We therefore also implemented a test of forecast comparison under possible structural changes developed by Giacomini and Rossi (2010). Table 6 provides the results for the MPF and AR-GAP models. The results in the table show that IQR and ASY (for a risk of or $p = .25$) significantly improve the forecast performances compared to the

[25]See Figure **??** in the Online Appendix for an illustration.

baseline model of the SPF even if one allows for structural instability. The results are less convincing, however, for the AR-GAP model.

Lastly, Tables B.7, B.8 and B.9 in the Supplementary On-Line Appendix provide evidence that the results still hold when one relies on the alternative uniform smoothing estimation methods of quantiles.

4.3 Discussion: Why Would Relevant Information Not Be Included in Mean Point Forecasts?

The results imply that, the uncertainty and asymmetry in the distribution of inflation risks are informative for future inflation, but are not efficiently incorporated into the average of individuals' point forecasts. Put differently, the average of mean point forecasts differs from the conditional expectation: $\mathrm{MPF}_t^h \neq \mathrm{E}\{\pi_{t+h}|I_t\}$.

Diebold, Gunther, and Tay (1998) develop a probability integral test to assess whether the information contained in the subjective distribution is incorporated in the point forecasts. Diebold, Tay, and Kenneth (1999) implement this test on density forecasts for inflation. They reject the null that the mean point forecasts aggregate all the predictive information in the subjective distribution of future inflation. Our regression specification can be viewed as a particular specification of their general test. Our approach has the advantage of proposing practical measures that help improving inflation forecasts.

In this paper, we do not investigate the reason why forecasters imperfectly incorporate relevant information in their mean point forecast of future macroeconomic outcomes such as inflation rates. However, we think it can be linked to the recent literature showing that the empirical properties of surveys forecasts, including the predictability of the average forecast errors, are consistent with models of imperfect information where agents imperfectly observe the information that is relevant to forecasting in real-time (see e.g. Mankiw, Reis, and Wolfers (2003), Coibion and Gorodnichenko (2015), Coibion and Gorodnichenko (2012), Andrade and Le Bihan (2013) or Andrade, Crump, Eusepi, and Moench (2013)). As is well known from that literature, because they know that this information is noisy, agents incorporate imperfectly it into their own forecasts and the average of mean point forecasts is therefore a biased measure of the conditional expectation that can be calculated with ex-post data (that is with better information). We think that, in the spirit of this imperfect information approach, a model in which inflation is a non-linear process and forecasters do not observe the underlying conditional moments of future inflation but derives them from the idiosyncratic information that he/she observes would lead to the results that we obtain. We leave this analysis to further research.

5 Inflation Risks and Monetary Policy

We now investigate whether monetary authorities react to the inflation risk measures. We first estimate an extended Taylor rule to show that the federal fund rate react to the IQR_t^h and ASY_t^h measures. We then assess whether changes in regime affect such relationship. Lastly, we provide evidence that the reaction of the monetary authorities to the risk measures does not result from their information content for future inflation but from asymmetric preferences of the central banker.

5.1 The Reaction of Interest Rates to I@R

We investigate whether the interest rate targeted by the central bank, i_t, reacts to the inflation risk measures IQR_t^h and ASY_t^h. We control for a set of 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 Taylor-type monetary policy rule in difference:

$$\Delta i_t = \alpha + \beta \mathrm{IQR}_t^h + \gamma \mathrm{ASY}_t^h + \Gamma * X_t + u_t. \tag{5.1}$$

We use the US overnight money market rates (Fed fund rate) as the policy instrument i_t. In a first baseline specification, 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 last GDP deflator inflation rate available in real-time at date t, π_t^{rt}, the last real GDP growth rate observed in real-time, Δy_t^{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 oil price inflation rate at date t, π_t^{oil} 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 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 second result is 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 predicted otherwise.

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. Indeed, Romer and Romer (2000) showed that monetary policy decisions influenced the forecasts of professionals as they revealed information to the private sector. In other words the regression can be plagued by endogeneity. 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. These results are in line with the ones Bekaert, Horeova, and Lo Duca (2011) obtain. They 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.

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. An increase of one-standard deviation over a quarter in the asymmetry of the risk leads to a $\hat{\gamma} \times \mathrm{SD}(\mathrm{ASY}) = 1.936 \times .074 = 13.5$ 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 regimes and therefore differences in the policy rule of monetary authorities.

We estimate equation (5.1) for three different sub-samples. Before Volcker's tenure, 1970-1979; after Voclker'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. Two 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.[26] Second, and in contrast, the Great Inflation of the 70s is an completely different regime. Over that period, the uncertainty had almost a negative impact on the (second month) interest rate change whereas the asymmetry had no significant 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.

A related concern is that potential regime changes in policy may be responsible for the correlation between the variations in the ASY measures and the interest rate changes Δi_t. 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, risk to inflation should be less tilted to the upside. The regime change would therefore lead to a negative correlation between the change in the interest rate and the asymmetry of the risks. So, if anything, such an impact of regime changes on the asymmetry measure should lead to an underestimation of the interest rate reaction to the asymmetry of the risks.

[26] The reaction is slightly 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.This suggests that a greater stability of the perceived asymmetry of the inflation risk induced the Fed to be less sensitive to this risk.

5.3 Information of Preferences?

Why would the Fed pay attention to (factors affecting the) the asymmetry of inflation risk? There are two possible answers to this 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 therefore relies on an argument of informational superiority of the central bank over the private sector as suggested by evidence in Romer and Romer (2000). 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).[27] 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).[28] 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.[29] 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 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.[30] In essence, they are similar to the residuals of the linear interest rate

[27] Such asymmetry of the costs might be motivated by the possibility to hit the Zero Lower Bound as Evans, Fisher, Gourio, and Krane (2015) recently put forward.

[28] See, among many others, Orphanides and Williams (2007) or Woodford (2010) for applications to the design of monetary policy rules.

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

[30] See Christiano, Eichenbaum, and Evans (1999) for a survey.

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 brings to the fore several interesting issues for many strands of the macroeconomics literature. First, we extract from the subjective distributions measured by surveys, information so far very much neglected in the literature. These measures, pertaining to tail risks, uncertainty and asymmetry, are shown to be important and complementary to the usual average mean point forecast of inflation. Second, by the same token, we show that perceptions of extreme inflation risks by economic agents contain information that is valuable for policy makers so that they should not neglect them. Third, and consequently, we stress that higher moments in the subjective risk of future inflation matter for inflation realizations, that is variation in perceived macroeconomic risks matters not only to understand financial markets, but also contribute to macroeconomic outcomes. Fourth, we also show that central bankers react to the information contained in such inflation risks. We think the evidence underlines that these risk measures are a useful complement of the estimators of first moments of future inflation. The results also stress that risks matters for the dynamics of inflation and the determination of monetary policy.

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Figure 1: INF, I@R(.05) and I@R(.95)

The figure plots the time series of realized inflation in the US together with I@R(.05) and I@R(.95) from the US SPF over the 1968Q4-2012Q1 sample. The forecast horizon is the end of the current year. The computation of I@R(.05) and I@R(.95) is based on equation (2.1). The I@Rs series are averaged over the past 4 quarters and corrected for seasonal patterns in forecasts uncertainty associated with the shrinking forecasting horizon. More details appear in Appendix B.

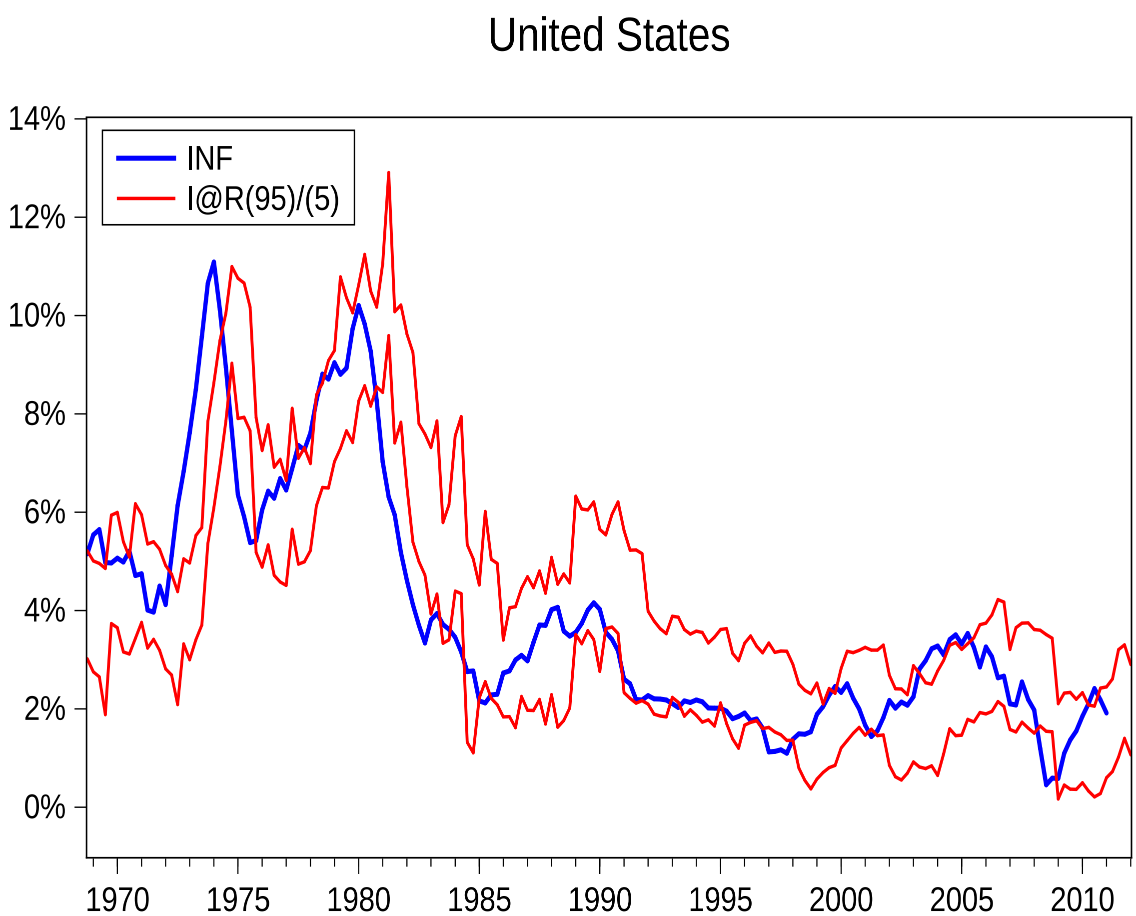
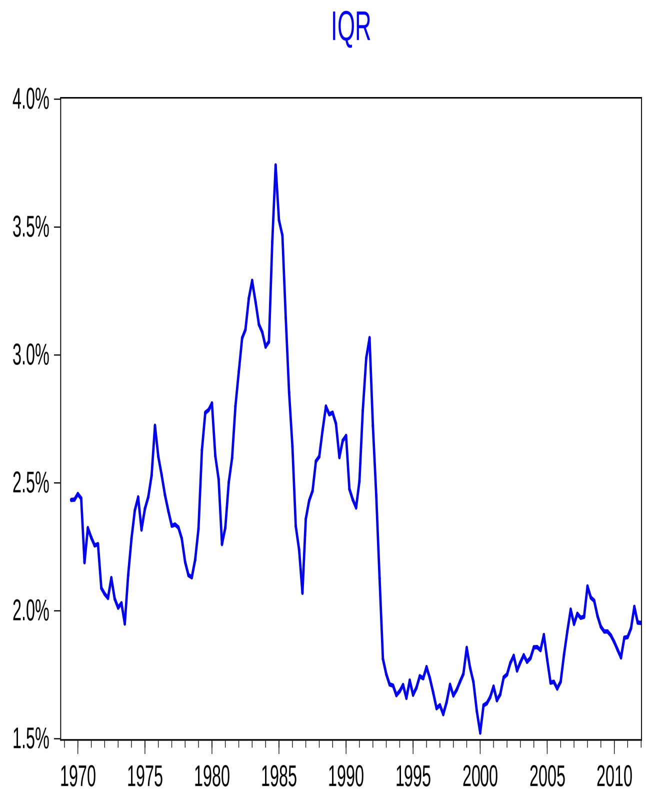


Figure 2: Inflation risk uncertainty (IQR) and asymmetry (ASY)

The left panel displays the time series of IQR over the whole 1968Q4-2012Q2 sample, the right panel displays ASY, where IQR is defined in equation (2.2) and ASY is defined in (2.3). Variables are averaged over the past 4 quarters. Data details appear in Appendix B.



(a) **Uncertainty** IQR **- .05/.95**

(b) **Asymmetry** ASY **- .05/.95**

Figure 3: Probabilities of high and low inflation from the UCSV Model

The Figure shows the probability of GDP deflator inflation being above 4 percent or below 0 percent on average over the subsequent quarter. Data cover the 1985Q1-2012Q2 sample. These are obtained from MCMC estimation of the unobserved components stochastic volatility model of Stock and Watson (2007) appearing in equation (3.1), applied to the GDP deflator inflation.

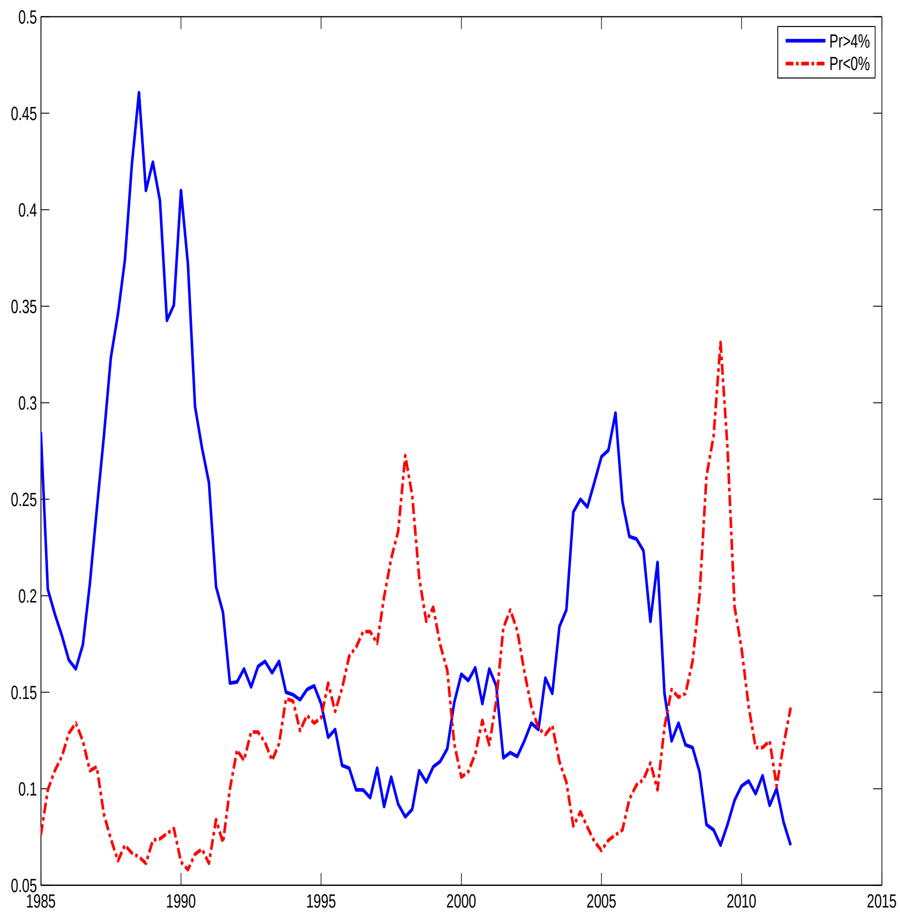
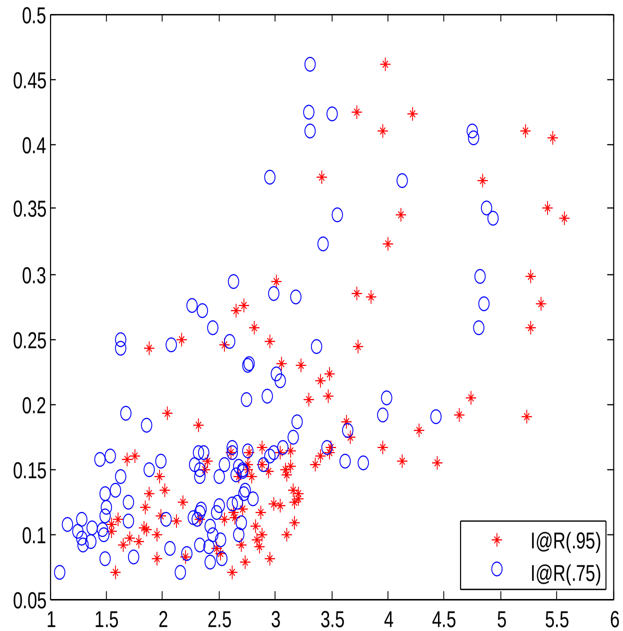
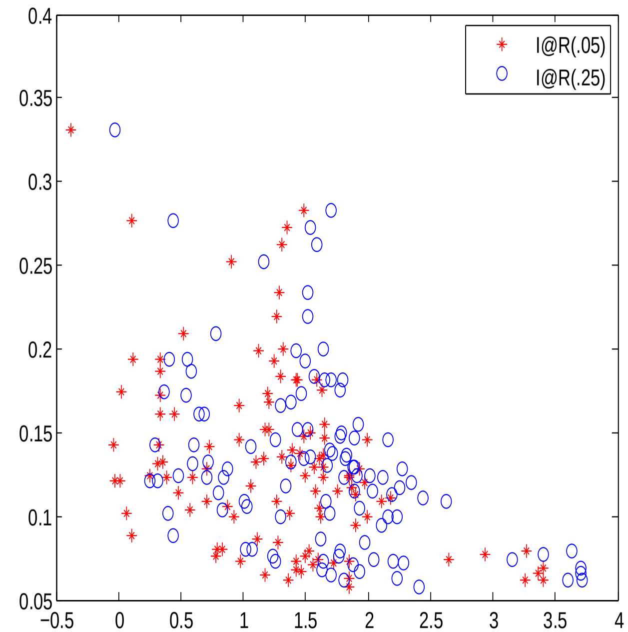


Figure 4: Probabilities of high and low inflation from the UCSV Model versus I@R.

The left panel displays a scatter plot of the probability of GDP deflator inflation being above 4 percent versus the survey-based I@R(.75) and I@R(.95) respectively. The right panel displays a scatter plot the probability of GDP deflator inflation being below zero percent versus the survey-based I@R(.05) and I@R(.25) respectively. The probabilities are depicted in Figure 3. Data cover the 1968Q4-2012Q2 sample.



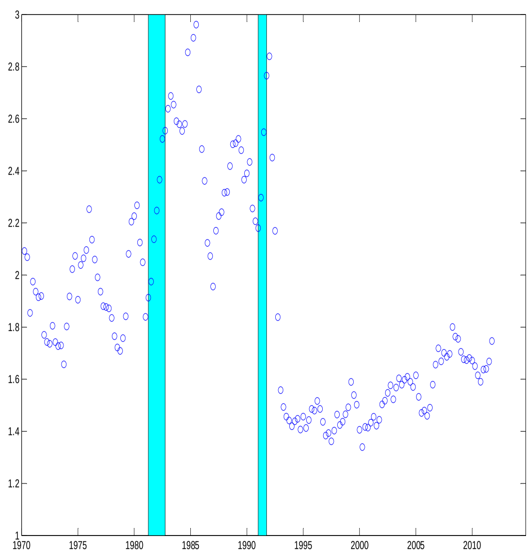
(a) $P(INF > 4)$ **versus** I@R(.75) **and** I@R(.95)



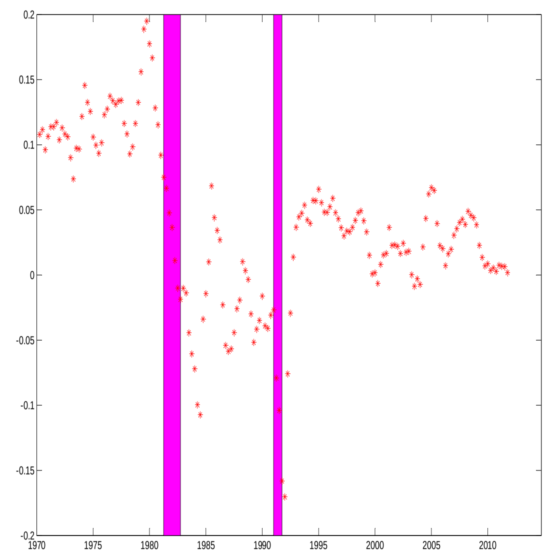
(b) $P(INF < 0)$ **versus** I@R(.05) **and** I@R(.25)

Figure 5: IQR, ASY and Structural Break Dates from Levin and Piger.

The left panel displays the time series of the IQR measure (obtained with a beta smoothing and for a risk of $p = .05$) as well as the dating of structural breaks in the DEF process obtained in Levin and Piger (2008). The right panel displays the time series of the ASY measure (obtained with a beta smoothing and for a risk of $p = .05$) as well as the dating of structural breaks in the DEF process obtained in Levin and Piger (2008). Data cover the 1970Q1-2012Q2 sample.



(a) **IQR**



(b) **ASY**

Table 1: The link between IQR and ASY with alternative measure of inflation risk

The Table reports the correlation of our proposed measures for inflation risk IQR and ASY with alternative ones used in the literature namely forecasters'disagreement (DIS), the Baker-Bloom-Davis index of policy uncertainty (BBD), the Jurado-Ludvingdson-Ng measure of broad macroeconomic uncertainty (JLN), the CBOE volatility index from option and future prices (VIX), a GARCH measure of inflation conditional variance (GARCH) and the stock market realized volatility observed over the past quarter (VOLSP5000). We consider two samples: 1969-2012, i.e. the longest sample for which the survey data measures are available and 1990-2012 i.e. the longest sample for which the VIX index is available. *, **, *** denotes significance at respectively the 5, 2.5 and 1 % levels.

Panel A: 1969-2012 sample

	IQR	ASY	DIS	BBD	JNL	GARCH	VOLSP500
IQR	1.00						
ASY	-0.16**	1.00					
DIS	0.32***	0.08	1.00				
BBD	-0.00	-0.24***	-0.06	1.00			
JNL	0.23***	-0.10	0.31***	0.21***	1.00		
GARCH	-0.01	0.08	0.13*	0.13*	0.53***	1.00	
VOLSP500	-0.04	-0.06	0.03	0.38***	0.30***	0.47***	1.00

Panel B: 1990-2012 sample

	IQR	ASY	DIS	BBD	JNL	VIX	GARCH	VOLSP500
IQR	1.00							
ASY	-0.63***	1.00						
DIS	0.25***	-0.19*	1.00					
BBD	0.23***	-0.30***	0.37***	1.00				
JNL	0.16	-0.15	0.46***	0.32***	1.00			
VIX	0.09	-0.24***	0.34***	0.41***	0.68***	1.00		
GARCH	0.04	-0.02	0.22**	0.24***	0.75***	0.54***	1.00	
VOLSP500	0.02	-0.05	0.23**	0.37***	0.65***	0.79***	0.78***	1.00

Table 2: The effect of inflation risk on inflation realizations

OLS estimation of equation (4.2) with risk measures based on *beta* smoothing. Controls include lagged inflation, the output gap (from CBO, in % of current RGDP), quarterly changes in trade-weighted USD and oil price (Brent) observed at the date of forecast. Estimation involves overlapping horizons, so standard errors are obtained 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. The sample covers 1974Q4-2012Q2.

	No Controls				Controls	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A: .05/.95 quantiles						
$h = 1$ year ahead						
MPF	1.009	1.148	0.983	1.086	0.616	0.691
	(11.231)	(11.914)	(13.122)	(12.787)	(3.954)	(4.706)
IQR		−0.855		−0.612		−0.37
		(−3.796)		(−2.314)		(−1.861)
ASY			6.958	6.041		4.337
			(4.483)	(3.835)		(3.662)
R^2	0.647	0.671	0.692	0.703	0.784	0.808
RMSE ratio	0.955	0.921	0.892	0.876	0.764	0.719
# obs	165	165	165	165	151	151
$h = 2$ years ahead						
MPF	0.818	0.956	0.785	0.872	0.588	0.631
	(4.4)	(4.188)	(4.943)	(4.218)	(2.328)	(2.405)
IQR		−0.845		−0.52		−0.226
		(−1.793)		(−1.02)		(−0.552)
ASY			8.834	8.055		6.451
			(3.126)	(2.855)		(2.476)
R^2	0.399	0.421	0.47	0.476	0.606	0.654
RMSE ratio	0.932	0.915	0.875	0.87	0.706	0.661
# obs	161	161	161	161	147	147
Panel B: .25/.75 quantiles						
$h = 1$ year ahead						
MPF	1.009	1.08	0.983	1.043	0.616	0.653
	(11.231)	(11.657)	(12.989)	(12.997)	(3.954)	(4.466)
IQR		−1.111		−0.914		−0.572
		(−2.27)		(−1.625)		(−1.342)
ASY			30.312	29.116		21.338
			(3.893)	(3.706)		(3.611)
R^2	0.647	0.655	0.686	0.692	0.784	0.806
RMSE ratio	0.955	0.943	0.9	0.892	0.764	0.724
# obs	165	165	165	165	151	151
$h = 2$ years ahead						
MPF	0.818	0.884	0.784	0.834	0.588	0.613
	(4.4)	(4.136)	(4.907)	(4.39)	(2.328)	(2.462)
IQR		−1.027		−0.769		−0.504
		(−1.179)		(−0.831)		(−0.698)
ASY			39.042	38.034		29.576
			(2.852)	(2.771)		(2.421)
R^2	0.399	0.405	0.464	0.465	0.606	0.651
RMSE ratio	0.932	0.927	0.88	0.879	0.706	0.664
# obs	161	161	161	161	147	147

Table 3: The effect of inflation risk on inflation realizations - Robustness

OLS estimation of equation (4.2) with alternative measures of expected inflation (EXP), alternative measures of inflation uncertainty (UNC), alternative formulation of the test regression (4.2), alternative measures of the I@R, alternative samples. See paragraph **Robustness** in subsection 4.1. All other aspects of the empirical implementation, including the specification of macroeconomic controls, are the same as in Tables 2.

	EXP Measure		**UNC Measure**			**Regression Specif.**			I@R **Measure**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	MED SPF	AR(4)	DIS SPF	GARCH INF	SP500 VOL	FIRST DIF.	FOR. ERRORS	SUR SYST	LIN PROBA	DOUBLE MIN/MAX
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)
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)
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)
RMSE ratio	0.632	0.646	0.575	0.581	0.582	0.572	0.651	-	0.591	0.594
# obs	145	145	144	144	144	144	144	176	144	144

Table 4: Out of sample forecast performances: Comparison with the Random Walk

The Table reports the out-of-sample RMSE ratios of $k-$quarter ahead forecasts of GDP deflator (quarter-over-quarter) inflation rate for different models against the benchmark of a pure Random Walk (RW). **,**,* indicate rejection at the 1%, 5% and 10% levels of the assumption of equal forecast accuracy based on the finite sample adjusted version of Diebold-Mariano statistic proposed by Clark and McCracken (2013).

Estimation Sample: 1974Q4-1984Q4					
Forecasting Sample: 1985Q1-2012Q2					
Horizon	1Q	2Q	3Q	4Q	8Q
Panel A: RW vs. MPF					
REF	0.8787**	0.8899**	0.9174	0.9209	
IQR - .25/.75	0.8339**	0.8307***	0.8481*	0.8420*	
IQR - .05/.95	0.8344**	0.8313***	0.8487*	0.8427*	
ASY - .25/.75	0.8196***	0.8134***	0.8340**	0.8236*	
ASY - .05/.95	0.8856*	0.9032*	0.9324	0.9358	
IQR+ASY	0.8450**	0.8641**	0.9154	0.8919	
Panel B: RW vs. AR-GAP					
REF	0.8889***	0.8674***	0.8651***	0.8747**	0.8567*
IQR - .25/.75	2.0441***	1.6116***	1.6513***	1.3150***	0.7213***
IQR - .05/.95	2.0463***	1.6142***	1.6536***	1.3173***	0.7206***
ASY - .25/.75	0.8416***	0.8011***	0.8030***	0.7771***	0.7380**
ASY - .05/.95	0.8969***	0.8878**	0.8756***	0.8920**	0.9134
IQR+ASY	0.8168***	0.8124***	0.7917***	0.7550***	0.7541**
Panel C: RW vs. UCSV					
REF	0.4802***	0.5089***	0.5354***	0.5856***	0.6990***
IQR - .25/.75	0.4845***	0.5130***	0.5536***	0.6261***	0.8404
ASY - .25/.75	0.4844***	0.5143***	0.5578***	0.6339***	0.8840
IQR+ASY	0.5025***	0.5245***	0.5425***	0.6129***	0.831
PrUN	0.4818***	0.5099***	0.5424***	0.6013***	0.7402***
PrAS	0.4776***	0.5092***	0.5357***	0.5815***	0.6639***

Table 5: Out of sample forecast performances: Role of inflation risk measures

The Table reports the out-of-sample RMSE ratios of $k-$quarter ahead forecasts of GDP deflator (quarter-over-quarter) inflation rate obtained when adding inflation risk measures to three simple baseline models for inflation: MPF, AR-GAP and UCSV. **,**,* indicate rejection at the 1%, 5% and 10% levels of the assumption of equal forecast accuracy based on the finite sample adjusted version of Diebold-Mariano statistic proposed by Clark and McCracken (2013).

Estimation Sample: 1974Q4-1984Q4					
Forecasting Sample: 1985Q1-2012Q2					
Horizon	1Q	2Q	3Q	4Q	8Q
Panel A: MPF					
RW	1.1381**	1.1237**	1.0901	1.0859	
MPF+IQR - .25/.75	0.9491**	0.9335*	0.9245	0.9144	
MPF+IQR - .05/.95	0.9496*	0.9341*	0.9252	0.9151	
MPF+ASY - .25/.75	0.9327**	0.9140*	0.9092	0.8944	
MPF+ASY - .05/.95	1.0078	1.0149	1.0164	1.0162	
MPF+IQR+ASY	0.9617	0.9709	0.9979	0.9685	
Panel B: AR-GAP					
multicolumn6l RW	1.1249***	1.1528***	1.1559***	1.1433**	1.1673*
AR-GAP+IQR - .25/.75	2.2995***	1.8578***	1.9088***	1.5034***	0.8420*
AR-GAP+IQR - .05/.95	2.3019***	1.8609***	1.9114**	1.5061***	0.8412*
AR-GAP+ASY - .25/.75	0.9467***	0.9235**	0.9282*	0.8884**	0.8614
AR-GAP+ASY - .05/.95	1.0089	1.0235	1.0122	1.0198	1.0662
AR-GAP+IQR+ASY - .25/.75	0.9188*	0.9366	0.9152*	0.8632*	0.8803
Panel C: UCSV					
RW	2.0826***	1.9650***	1.8679***	1.7076***	1.4305***
UCSV+IQR - .25/.75	1.0091*	1.0080	1.0340	1.0692	1.2022
UCSV+ASY - .25/.75	1.0087**	1.0107	1.0419	1.0825	1.2646
UCSV+IQR+ASY	1.0466*	1.0306	1.0134	1.0466	1.1874
UCSV+PrUN	1.0034	1.0020*	1.0132	1.0268	1.0589
UCSV+PrAS	0.9947	1.0006	1.0005	0.9931	0.9498**

Table 6: Out of sample forecast performances: Possible structural changes

The Table reports the Giacomini and Rossi (2010) test statistics for $k-$quarter ahead forecasts of GDP deflator (quarter-over-quarter) inflation rate obtained with the MPF and AR-GAP models for inflation. **,**,* indicate rejection at the 1%, 5% and 10% levels of the assumption of equal forecast accuracy. The test is based on recursive forecasting performances on the 1985Q1-2012Q2 forecasting sample. Each forecast exercise is implemented on a forecasting sample equal to a fraction $d = .5$ of the total forecasting sample size and a rolling estimation sample made of the latest 40 quarters.

Forecasting Sample: 1985Q1-2012Q2					
Horizon	1Q	2Q	3Q	4Q	8Q
MPF vs.					
RW	1.4070	1.7934	2.2950*	2.5700**	
MPF+IQR - .25/.75	3.5444***	4.0825***	3.4898***	4.0290***	
MPF+ASY - .25/.75	2.8184**	2.9894**	2.1937*	2.5419**	
AR-GAP vs.					
RW	0.9746	1.1470	1.1754	0.8883	1.4549
AR-GAP+IQR - .25/.75	1.1363	0.7307	1.2121	1.8425	2.3187*
AR-GAP+ASY - .25/.75	1.1986	0.6739	1.1524	1.7473	2.0353

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	−0.113	−0.664	−0.027	−0.029	−0.214	−0.254
	(−1.944)	(−1.23)	(−1.485)	(−0.261)	(−0.728)	(−1.308)	(−1.059)
ASY	1.936	1.158	0.439	1.202	0.743	2.272	1.830
	(1.737)	(2.139)	(0.23)	(1.791)	(1.63)	(2.028)	(1.875)
$\overline{R}^2$	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 last inflation rate available in real time π_t^{rt}, the last real GDP growth rate available in real time Δy_t^{rt}, and the energy inflation rate π_t^{com}. 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 isocele 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 isocele 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 isocele 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 isocele 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:

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

    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:

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

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 $\widehat{F}_{it}^h = F(x; \hat{a}_{it}^h, \hat{b}_{it}^h, L_{it}, U_{it})$ the corresponding *beta* distribution. The individual's $\hat{q}_{it}^h(p)$ is the quantile of the continuous distribution $\widehat{F}_{it}^h$ at the probability threshold p, namely:

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

Therefore $\widehat{\mathrm{I@R}}_t^h(p)$ is the cross-sectional average across survey respondents of $\hat{q}_{it}(p)$. Likewise, the empirical $\widehat{\mathrm{ASY}}_t^h(p)$ 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 (2.3). Note that in the remainder of the paper we will drop the hats and simply refer to $\mathrm{I@R}_t^h(p)$ and $\mathrm{ASY}_t^h(p)$ with the understanding that they are estimated quantities.

B SPF Data

The US survey of professional forecasters has been conducted every quarter since 1968Q4 and, although the number of respondent changed over time, it covers around 30 institutions. Since 1992Q1, each institution in the survey is asked to report, among others, GDP deflator forecasts. 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 information allowing to calculate both individual mean point forecasts for the quarterly inflation rates up to one year ahead, as well as individual mean point forecasts for the year-on-year inflation rate one year ahead. The US SPF also collects individual forecast distributions for the DEF inflation rate of the current calendar year. While individual mean point forecasts for the CPI inflation rate are available, probability distributions for CPI inflation rate have only be collected starting 2007Q1. We therefore deem the sample too short to exploit this information.

The design of the survey of individual probability distributions evolved over time. Before 1981Q3, future inflation scenarios were split into 15 different bins. The number of possible intervals dropped to 6 from 1981Q3 to 1991Q4. It finally increased to 10 from 1992Q1 onwards. Intermediate (hence closed) intervals had a length of 1% before 1981Q3, 2% up to 1991Q4, and they have been of 1% since then. In addition to the number of bins and the length of intermediate intervals, the closing values of these intervals were adjusted in 1973Q2, 1974Q4, 1981Q3, 1985Q2 and 1992Q1. Section 3.2 provides evidence that the changes, in particular the ones of 1981Q3 and 1992Q1, reflected changes in the underlying inflation process as estimated in Stock and Watson (2007), Levin and Piger (2008) or Faust and Wright (2013). Table B.1 details such changes in the design of the US SPF.

Individual probability forecasts are only available for so-called calendar forecast, i.e. forecasts for the end of current year GDP deflator, which implies a seasonal pattern in some risk measures we derive from these individual probability distribution. Indeed, the uncertainty associated to the inflation rate of a given year is mechanically reduced as one gets closer to the end of this specific year. We use seasonal dummies to account for this 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. For this seasonal adjustment, we considered the 1968Q4-1973Q1 and the 1973Q2-1974Q4 subperiods as a single one.

The survey started to be conducted in 1968Q4 and our latest observation is 2012Q2. Before 1974Q4, there are a few instances where 1-year ahead mean point forecasts are missing. The in-sample and out-of-sample analysis are therefore conducted on a 1974Q4-2012Q2 sample. Survey questionnaires are sent at the beginning of the 2nd month of each quarter and answers are collected within the first two-weeks of this month. Data realizations or real-time data are matched accordingly. To illustrate, in 2008Q1, the survey reports inflation mean point forecasts for 2008Q2, Q3, Q4 and 2009Q1 and probability forecast for the end of 2008. The latest GDP deflator observation available at the date of the forecast is the first release (advance estimate) of 2007Q4 GDP deflator. The same hold for real GDP and the output gap. For data like the (effective) exchange rate or the oil (brent) prices, that are available daily, we selected the value observed at the end of the second week of the months when survey are collected.

Table B.2 provides some descriptive statistics for the I@R, IQR and ASY measures when they are estimated using the Engelberg, Manski, and Williams (2009) methodology together with descriptive statistics for the inflation realizations and the MPF survey inflation forecasts. Table B.4 illustrates that the MPF, IQR and ASY are related to various macroeconomic determinants. Tables B.3 and B.5 report the same analysis when the individual quantiles are obtained from linear extrapolation of individual histograms.

Table B.1: Design of the US SPF survey

Information is provided by the Philadelphia Fed. Maximum and minimum values of inflation are needed in order to close open-ended extreme intervals. We postulate a length of extreme intervals that is twice the length of an intermediate interval.

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

Table B.2: Inflation risk measures: Descriptive Statistics

Descriptive statistics are reported for INF which refers to realized inflation final release data, MPF which is the mean point forecast of the SPF, I@R(.05) and I@R(.95) based on equation (2.1), IQR − .05/.95 defined in equation (2.2) and, ASY − .05/.95 defined in (2.3), and RA −.05/.95, the Bowley measure defined in (2.4). All the risk measures are based on the beta described in Section A using the methodology of Engelberg, Manski, and Williams (2009). 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. We also report the statistics for a .25/.75 level of risk. Data details appear in Appendix B.

	US, 1968Q4-2012Q2				**US, 1985Q1-2012Q2**			
	AVG	STD (TS)	STD (CS)	RHO	AVG	STD (TS)	STD (CS)	RHO
INF - Final	3.903	2.414		0.986 (39.365)	2.395	0.82		0.939 (25.578)
MPF	3.725	1.942	0.842	0.98 (50.386)	2.626	0.884	0.591	0.955 (35.587)
I@R(.95)	5.056	2.428	0.909	0.973 (42.27)	3.608	1.087	0.813	0.876 (21.971)
I@R(.75)	4.445	2.351	0.704	0.977 (38.884)	3.046	0.987	0.596	0.908 (25.711)
I@R(.25)	3.481	2.242	0.618	0.973 (36.53)	2.159	0.854	0.493	0.896 (20.614)
I@R(.05)	2.872	2.198	0.741	0.965 (34.501)	1.586	0.786	0.618	0.832 (13.842)
IQR - .05/.95	2.211	0.548		0.732 (12.015)	2.01	0.443		0.658 (6.733)
ASY - .05/.95	0.002	0.074		0.416 (4.195)	-0.013	0.073		0.301 (2.791)
RA - .05/.95	0.002	0.032		0.378 (4.201)	-0.005	0.034		0.252 (2.799)
IQR - .25/.75	0.964	0.254		0.517 (8.969)	0.886	0.239		0.456 (6.193)
ASY - .25/.75	0.000	0.016		0.36 (3.346)	-0.003	0.015		0.27 (2.495)
RA - .25/.75	0.000	0.014		0.367 (4.375)	-0.003	0.015		0.231 (2.581)

Table B.3: Inflation risk measures: Descriptive Statistics – Uniform smoothing

Descriptive statistics are reported for INF which refers to realized inflation final release data, MPF which is the mean point forecast of the SPF, I@R(.05) and I@R(.95) based on equation (2.1), IQR − .05/.95 defined in equation (2.2) and, ASY − .05/.95 defined in (2.3), and RA −.05/.95, the Bowley measure defined in (2.4). All the risk measures are based on the uniform smoothing of individual histograms. 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. We also report the statistics for a .25/.75 level of risk. Data details appear in Appendix B.

	US, 1968Q4-2012Q2				**US, 1985Q1-2012Q2**			
	AVG	STD		RHO	AVG	STD		RHO
		(TS)	(CS)			(TS)	(CS)	
I@R(.95) - Uniform	5.438	2.46	1.001	0.972 (45.885)	3.994	1.197	0.912	0.888 (25.263)
I@R(.75) - Uniform	4.553	2.346	0.682	0.978 (39.525)	3.166	1.027	0.57	0.921 (27.914)
I@R(.25) - Uniform	3.383	2.258	0.63	0.972 (35.561)	2.056	0.825	0.497	0.877 (17.805)
I@R(.05) - Uniform	2.503	2.221	0.848	0.956 (32.737)	1.231	0.743	0.739	0.733 (9.049)
IQR - .05/.95 - Uniform	2.934	0.885		0.669 (13.226)	2.763	0.858		0.622 (9.945)
ASY - .05/.95 - Uniform	0.018	0.258		0.665 (8.208)	0.014	0.215		0.489 (5.34)
RA - .05/.95 - Uniform	0.013	0.073		0.598 (8.206)	0.008	0.07		0.445 (4.637)
IQR - .25/.75 - Uniform	1.169	0.339		0.782 (15.362)	1.11	0.324		0.729 (16.459)
ASY - .25/.75 - Uniform	0.013	0.044		0.471 (5.046)	0.01	0.034		0.168 (1.879)
RA - .25/.75 - Uniform	0.013	0.033		0.436 (5.452)	0.009	0.029		0.207 (2.283)

Table B.4: Inflation risk measures: Correlation with other variables

Bivariate regression analysis. Entries are slope coefficient estimates, standard errors of regressions for MPF, IQR, ASY and RA involving a constant and a set of macroeconomic variables as single regressors: realized GDP deflation inflation rater (INF), the brent oil price quarterly change at the date of the survey (OIL), the output gap in percent of total output using the potential RGDP estimate from the CBO (OG), the NBER recession index (NBER), the USD trade weighted exchange rate quarterly change at the date of the survey (FOREX), the S&P 500 index (S&P 500) and the federal fund rate (FF) observed at the date of the survey. The sample is 1974Q4-2012Q2.

	Regressors						
	INF	OIL	OG	NBER	FOREX	S&P 500	FF
MPF	0.584 (16.005)	1.121 (2.006)	−3.273 (−0.273)	0.733 (1.711)	0.059 (3.745)	−0.456 (−0.255)	0.421 (10.97)
IQR - .05/.95	0.076 (4.593)	0.048 (0.174)	−4.298 (−1.049)	0.214 (1.366)	0.019 (3.743)	0.091 (0.133)	0.091 (5.573)
ASY - .05/.95	0.003 (1.319)	0.057 (1.703)	0.556 (2.638)	−0.017 (−0.906)	−0.001 (−1.63)	−0.13 (−1.829)	−0.003 (−0.977)
RA - .05/.95	0.001 (1.285)	0.018 (1.341)	0.213 (2.607)	−0.006 (−0.814)	−0.001 (−1.92)	−0.059 (−1.66)	−0.001 (−1.142)
IQR - .25/.75	0.03 (4.316)	−0.054 (−0.382)	−1.422 (−1.002)	0.076 (1.213)	0.007 (4.195)	0.22 (0.715)	0.036 (5.731)
ASY - .25/.75	0 (1.291)	0.011 (1.494)	0.107 (2.459)	−0.004 (−0.803)	−0.001 (−1.614)	−0.032 (−2.14)	−0.001 (−0.893)
RA - .25/.75	0 (1.426)	0.007 (1.135)	0.092 (2.31)	−0.002 (−0.574)	−0.001 (−1.869)	−0.028 (−1.881)	−0.001 (−0.945)

Table B.5: Inflation risk measures: Correlation with other variables – Uniform smoothing

Bivariate regression analysis. Entries are slope coefficient estimates, standard errors of regressions for MPF, IQR, ASY and RA 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, 1974Q4-2012Q2.

	Regressors						
	INF	OIL	OG	NBER	FOREX	S&P 500	FF
MPF	0.584	1.121	−3.273	0.733	0.059	−0.456	0.421
	(16.005)	(2.006)	(−0.273)	(1.711)	(3.745)	(−0.255)	(10.97)
IQR - .05/.95	0.059	−0.564	−6.781	0.136	0.03	1.471	0.119
	(2.228)	(−1.197)	(−1.129)	(0.613)	(3.571)	(1.207)	(3.783)
ASY - .05/.95	0.014	0.33	2.964	−0.084	−0.006	−0.328	−0.012
	(1.785)	(1.787)	(1.994)	(−1.935)	(−1.717)	(−0.856)	(−1.141)
RA - .05/.95	0.004	0.079	0.784	−0.033	−0.002	−0.013	−0.003
	(1.726)	(1.731)	(2.312)	(−2.412)	(−1.752)	(−0.12)	(−1.005)
IQR - .25/.75	0.021	−0.203	−2.291	0.063	0.013	0.467	0.047
	(1.834)	(−1.177)	(−1.011)	(0.723)	(3.2)	(1.188)	(3.174)
ASY - .25/.75	0.002	0.04	0.473	−0.014	−0.001	0.002	−0.002
	(1.727)	(1.627)	(2.55)	(−1.486)	(−1.846)	(0.042)	(−0.738)
RA - .25/.75	0.002	0.027	0.367	−0.014	−0.001	0.016	−0.001
	(1.679)	(1.613)	(2.887)	(−1.818)	(−1.739)	(0.346)	(−0.532)

Table B.6: The effect of inflation risk on inflation realizations – Uniform smoothing

OLS estimation of equation (4.2) with risk measures based on a uniform smoothing. Controls include lagged inflation, the output gap (CBO estimates, in % of current RGDP), quarterly changes in trade-weighted USD and oil price (Brent) observed at the date of forecast. Estimation involves overlapping horizons, so standard errors are obtained 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. The sample covers 1974Q4-2012Q2.

	No Controls				Controls	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A: .05/.95 quantiles						
$h = 1$ year ahead						
MPF	1.009	1.1	0.999	1.057	0.616	0.712
	(11.231)	(11.791)	(12.606)	(12.198)	(3.954)	(4.548)
IQR		−0.525		−0.32		−0.216
		(−4.12)		(−2.138)		(−1.879)
ASY			1.847	1.359		0.433
			(4.186)	(2.711)		(0.979)
R2	0.647	0.678	0.685	0.693	0.784	0.791
RMSE ratio	0.955	0.912	0.901	0.891	0.764	0.751
# obs	165	165	165	165	151	151
$h = 2$ years ahead						
MPF	0.818	0.912	0.802	0.842	0.588	0.683
	(4.4)	(4.396)	(4.789)	(4.344)	(2.328)	(2.507)
IQR		−0.542		−0.217		−0.15
		(−2.134)		(−0.928)		(−0.749)
ASY			2.473	2.142		1.269
			(2.948)	(2.461)		(1.781)
R2	0.399	0.43	0.467	0.468	0.606	0.63
RMSE ratio	0.932	0.907	0.877	0.877	0.706	0.684
# obs	161	161	161	161	147	147
Panel B: .25/.75 quantiles						
$h = 1$ year ahead						
MPF	1.009	1.108	0.981	1.057	0.616	0.719
	(11.231)	(11.95)	(13.485)	(13.112)	(3.954)	(4.668)
IQR		−1.558		−1.119		−0.712
		(−5.127)		(−3.535)		(−2.636)
ASY			12.388	9.787		5.103
			(5.022)	(3.817)		(2.349)
R2	0.647	0.688	0.698	0.716	0.784	0.803
RMSE ratio	0.955	0.897	0.883	0.856	0.764	0.729
# obs	165	165	165	165	151	151
$h = 2$ years ahead						
MPF	0.818	0.919	0.778	0.843	0.588	0.676
	(4.4)	(4.426)	(5.162)	(4.605)	(2.328)	(2.544)
IQR		−1.589		−0.93		−0.613
		(−2.518)		(−1.638)		(−1.147)
ASY			16.799	14.627		8.74
			(3.782)	(3.206)		(2.294)
R2	0.399	0.44	0.492	0.502	0.606	0.645
RMSE ratio	0.932	0.899	0.857	0.848	0.706	0.67
# obs	161	161	161	161	147	147

Table B.7: Out of sample forecast performances: Comparison with the Random Walk – Uniform smoothing

The Table reports the out-of-sample RMSE ratios of $k-$quarter ahead forecasts of GDP deflator (quarter-over-quarter) inflation rate for different models against the benchmark of a pure Random Walk (RW). **,**,* indicate rejection at the 1%, 5% and 10% levels of the assumption of equal forecast accuracy based on the finite sample adjusted version of Diebold-Mariano statistic proposed by Clark and McCracken (2013).

Estimation Sample: 1974Q4-1984Q4					
Forecasting Sample: 1985Q1-2012Q2					
Horizon	1Q	2Q	3Q	4Q	8Q
Panel A: RW vs. SPF					
REF	0.8787**	0.8899**	0.9174	0.9209	
IQR - .25/.75	0.8172***	0.8089***	0.8294**	0.8183**	
IQR - .05/.95	0.8207***	0.8139***	0.8350**	0.8240**	
ASY - .25/.75	0.8240**	0.8170***	0.8378**	0.8235**	
ASY - .05/.95	0.8673**	0.8802**	0.9187	0.8993	
RA - .25/.75	0.8437**	0.8446**	0.8686**	0.8601**	
RA - .05/.95	0.8939*	0.9181	0.9639	0.9498	
IQR+ASY	0.8406	0.8592**	0.9208	0.9554	
Panel B: RW vs. AR-GAP					
REF	0.8889***	0.8674***	0.8651***	0.8747**	0.8567*
IQR - .25/.75	1.9937***	1.5565***	1.6107***	1.2659**	0.7316**
IQR - .05/.95	2.0019***	1.5668***	1.6197***	1.2781	0.7320**
ASY - .25/.75	0.8518***	0.8144***	0.8118***	0.7880***	0.7168**
ASY - .05/.95	0.8644***	0.8394***	0.8375***	0.8186***	0.7687**
RA - .25/.75	0.8749***	0.8405***	0.8388***	0.8217***	0.7372**
RA - .05/.95	0.8798***	0.8597***	0.8619***	0.8476**	0.7873**
IQR+ASY	0.8696***	0.8327***	0.8217***	0.7978***	0.9998
Panel C: RW vs. UCSV					
REF	0.4802***	0.5089***	0.5354***	0.5856***	0.6990***
IQR - .25/.75	0.4824***	0.5175***	0.5538***	0.6168***	0.8055*
ASY - .25/.75	0.4821***	0.5150***	0.5498***	0.6089***	0.7844**
RA - .25/.75	0.4826***	0.5195***	0.5564***	0.6185***	0.7786**
IQR+ASY	0.4865***	0.5120***	0.5454***	0.6318***	0.8083*
PrUN	0.4811***	0.5132***	0.5432***	0.5966***	0.7208***
PrAS	0.4804***	0.5110***	0.5358***	0.5818***	0.6716***

Table B.8: Out of sample forecast performances: Role of inflation risk measures – Uniform smoothing

The Table reports the out-of-sample RMSE ratios of $k-$quarter ahead forecasts of GDP deflator (quarter-over-quarter) inflation rate obtained when adding inflation risk measures to three simple baseline models for inflation: SPF, AR-GAP and UCSV. **,**,* indicate rejection at the 1%, 5% and 10% levels of the assumption of equal forecast accuracy based on the finite sample adjusted version of Diebold-Mariano statistic proposed by Clark and McCracken (2013).

Estimation Sample: 1974Q4-1984Q4					
Forecasting Sample: 1985Q1-2012Q2					
Horizon	1Q	2Q	3Q	4Q	8Q
Panel A: SPF					
RW	1.1381**	1.1237**	1.0901	1.0859	
SPF+IQR - .25/.75	0.9376**	0.9185*	0.9107	0.8994	
SPF+IQR - .05/.95	0.9408**	0.9231*	0.9159	0.9045	
SPF+ASY - .25/.75	0.9403**	0.9206*	0.9139	0.8998	
SPF+ASY - .05/.95	0.9803	0.9796	0.9922	0.9710	
SPF+RA - .25/.75	0.9654*	0.9549	0.9497	0.9404	
SPF+RA - .05/.95	1.0005	1.0089	1.0299	1.0173	
SPF+IQR+ASY	1.0072	1.0437	1.0727	1.0981	
Panel B: AR-GAP					
RW	1.1249***	1.1528***	1.1559***	1.1433**	1.1673*
AR-GAP+IQR - .25/.75	2.2428***	1.7944***	1.8619***	1.4472***	0.8541
AR-GAP+IQR - .05/.95	2.2520***	1.8062***	1.8722***	1.4612***	0.8545
AR-GAP+ASY - .25/.75	0.9582***	0.9389**	0.9383*	0.9009*	0.8367*
AR-GAP+ASY - .05/.95	0.9724*	0.9676	0.9681	0.9359	0.8973
AR-GAP+RA - .25/.75	0.9842	0.9689	0.9696	0.9394	0.8605
AR-GAP+RA - .05/.95	0.9897	0.9910	0.9963	0.9691	0.9190
AR-GAP+IQR+ASY - .25/.75	0.9782	0.9600*	0.9498	0.9121*	1.1671
Panel C: UCSV					
RW	2.0826***	1.9650***	1.8679***	1.7076***	1.4305***
UCSV+IQR - .25/.75	1.0093**	1.0081	1.0339	1.0694	1.2314
UCSV+ASY - .25/.75	1.0071	1.0069	1.0270	1.0505	1.1868
UCSV+RA - .25/.75	1.0071	1.0083	1.0379	1.0741	1.1839
UCSV+IQR+ASY	1.0494*	1.0333	1.0133	1.0443	1.2120
UCSV+PrUN	1.0034	1.0020*	1.0132	1.0268	1.0589
UCSV+PrAS	0.9947	1.0006	1.0005	0.9931	0.9498*

Table B.9: Out of sample forecast performances: Possible structural changes – Uniform smoothing

The Table reports the Giacomini and Rossi (2010) test statistics for $k-$quarter ahead forecasts of GDP deflator (quarter-over-quarter) inflation rate obtained with the SPF and AR-GAP models for inflation. **,**,* indicate rejection at the 1%, 5% and 10% levels of the assumption of equal forecast accuracy. The test is based on recursive forecasting performances on the 1985Q1-2012Q2 forecasting sample. Each forecast exercise is implemented on a forecasting sample equal to a fraction $d = .5$ of the total forecasting sample size and a rolling estimation sample made of the latest 40 quarters.

Sample: 1985Q1-2012Q2					
Horizon	1Q	2Q	3Q	4Q	8Q
SPF vs.					
RW	1.4070	1.7934	2.2950*	2.5700**	
SPF+IQR - .25/.75	3.2985***	3.7006***	2.8565**	3.3603***	
SPF+ASY - .25/.75	2.8474**	3.3953***	2.3192*	2.7423**	
SPF+RA - .25/.75	3.3436***	4.1001***	3.1534***	3.6914***	
AR-GAP vs.					
RW	0.9746	1.1470	1.1754	0.8883	1.4549
AR-GAP+IQR - .25/.75	1.1158	0.7064	1.2160	1.8189	2.2909**
AR-GAP+ASY - .25/.75	0.7928	0.2558	0.7791	1.6015	3.2895***
AR-GAP+RA - .25/.75	0.8521	0.3975	0.6233	1.2147	2.7278**