Anchoring of Inflation Expectations: Do Inflation Target Formulations Matter?*

Christoph Grosse-Steffen‡

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Abstract

Does it matter whether the inflation objective is characterized as a mere definition for price stability or as a numerical target? Do point targets better anchor expectations than target ranges? In a panel of 29 countries, we find that the formulation of a numerical point target increases unconditionally the degree of anchoring compared to a quantitative definition of price stability. We use anchoring-measures that account for the entire cross-sectional distribution of private sector inflation point forecasts, making them consistent with risk-averse, potentially asymmetric central bank preferences. A point target is associated with lower downside risk to inflation during periods of persistent undershooting, and lower upside inflation risk during periods of overshooting compared to target ranges. Our results are consistent with models suggesting that targets ranges are interpreted as zones where monetary policy is less active.

Keywords: monetary policy, inflation targeting, expectations anchoring, survey forecasts, inflation risk

JEL Classifications: E42, E52, D84

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‡ *Contact:* Banque de France, 31 rue des Petits-Champs, 75001 Paris, France. Email: christoph.grossesteffen(at)banque-france.fr, tel.: +33 (0)1 42 92 49 42.

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1 Introduction

Inflation expectations are a pivotal intermediate target for central banks to achieve their inflation objective. While short-term inflation expectations are affected by economic conditions, longer-term inflation expectations reveal the credibility of central bank's inflation objective. Inflation targeting (IT) underscores this link by announcing an explicit numerical value for the inflation objective. Looking at real-world target formulations, the degree of heterogeneity of target formulations is striking. While some countries provide a point target, others define a range for inflation outcomes that the central bank intends to achieve. Hybrid solutions are also widespread, including a target range with emphasis on a focal point or point targets with a numerically defined tolerance band around it. Surprisingly little is known about the anchoring properties of alternative inflation target formulations.

This paper investigates empirically whether inflation target formulations matter for the anchoring of medium- to long-term inflation expectations. We use data from an unbalanced panel of 29 countries, covering the period from 2005m4 to 2020m4. To quantify the degree of anchoring, we propose a measure based on the cross-sectional distribution of private sector inflation point forecasts based on Consensus data for horizons of two to six years ahead. We summarize beliefs about inflation outcomes using a skew extended version of the *t*-distribution (Jones and Faddy, 2003), which we fit to the data using simulated method of moments estimation. The main measure of anchoring is given by the density of inflation forecasts falling within a tight symmetric interval around the midpoint of the inflation target. It is thus a (subjective) belief-based, probability measure of being on target. The density of forecasters' beliefs below and above the edges of the tight interval around target provide two further indices, (i) disanchoring due to low inflation and (ii) disanchoring due to high inflation, which capture the degree of asymmetry in the distribution across forecasters' "best predictions".

We document time-variation and cross-country variation in disagreement and asymmetry, implying significant variation in the tails of the cross-sectional distribution of long-term inflation forecasts. To motivate why asymmetry in the inflation outlook matters, we apply a framework developed by Kilian and Manganelli (2008) that generalizes monetary policy rules to the case of potentially asymmetric and non-quadratic central bank preferences. The resulting optimal forward looking policy rule contains a weighting of upside and downside risks to the inflation outlook, consistent with the proposed empirical anchoring measures. By emphasizing the balance of risks to inflation, the approach reconciles models based on expected utility with the risk management approach to central banking (Greenspan, 2004; Draghi, 2016; Powell, 2020).

We run a number of empirical tests to evaluate the performance of alternative target formulations. Quantitative targets for monetary policy are grouped in four categories: (i) no precise numerical target (but a quantitative definition of price stability), (ii) a target range, (iii) a hybrid target, i.e. a target range with a focal point or a point target with a tolerance band, and (iv) a point target. In our main specification, we find that a numerical target *per se* is not necessarily superior to a quantitative definition of price stability. However, a numerical target formulation with emphasis on a numerical point target, either as inflation point target or in a hybrid strategy, improves the anchoring of long-term inflation expectations. The probability-based measure is significantly more centered on target at all forecast horizons. Pure ranges, in contrast, feature weaker anchoring. When we compare only numerical target types, we find that hybrid target formulations are raising the probability measure of being on target by an economically significant amount and to a similar extent as inflation point targets. Are gains from better inflation anchoring symmetric around the inflation objective? Looking at the measures of disanchoring, we find that this is not the case. Forecasters' beliefs get not only compressed, but also shift: Lower risks of above target inflation are simultaneously associated with slightly more pronounced risk of below target inflation.

Further, we test the credibility of a target conditional on the inflation performance. Following Neuenkirch and Tillmann (2014), we use the gap of past inflation realizations from target over the past 60 months to differentiate periods of sustained undershooting from periods of sustained overshooting. We find that credibility losses due to low inflation impair anchoring, while above target inflation has no effect on the main measure of anchoring. These findings extend the results of Ehrmann (2015) to the longer-term horizon. Additionally, we find that credibility losses have strong effects on the shape of the cross-sectional distribution of forecasts in the expected direction. While past undershooting raises disanchoring due to low inflation and dampens disanchoring due to high inflation, overshooting affects the distribution in the opposite way. How is it possible to change shape while keeping the central tendency of the distribution across inflation point forecasts more or less stable? Intuitively, the results are generated by swings in the tails of the skew t-distribution, that are related in a systematic way to the credibility indicator. In economic terms, this implies that at times very high inflation rates or deflationary tendencies fall within the set of forecasters' beliefs, while the mean might not necessarily be affected.

In a final step, the credibility loss indicator is interacted with the classification of target types. This specification helps to answer the question whether one target formulation is more efficient than another to combat the risk of disanchoring due to either high or low inflation. We conclude that no target type fares significantly better in improving overall anchoring conditional on the credibility loss term. At the same time, we find differences to what extend the shape of the distribution is affected by undershooting: inflation point targets fare best regarding shape-stability conditional on persistent undershooting and overshooting. They dampen the increase in the measure for disanchoring due to low inflation during periods of undershooting, while also significantly dampening the rise in the measure of disanchoring due to high inflation during periods of overshooting. Hybrid target formulations also dampen the shift in the cross-sectional distribution of forecasts, but to a much lower extend compared to pure point targets.

From a theoretical standpoint, it is *a priori* not clear how target formulation affect the degree of anchoring, or the balance of risks to inflation. One strand of papers argues that a range target or tolerance band gives more flexibility to central bankers to pursue secondary objectives, putting the inflation objective at a lower priority (Svensson, 1997b; Orphanides et al., 2000). Such theories predict that lower probability mass is located in close proximity around target in the presence of a target range or tolerance band. Contesting this view, another strand of papers argues that inflation rates are practically never aligned with a point target, making such a target less credible for markets. Announcing a target range or tolerance band, thus, increases central bank credibility and promotes anchoring (Demertzis and Viegi, 2009; Andersson and Jonung, 2017). Stein (1989) takes this argument one step further, claiming that any clear announcement of policy objectives is interpreted as cheap talk due to an inherent time-inconsistency problem. His theory would favor vague quantitative definitions of price stability over an explicit numerical target. The model's prediction is that any numerical announcement is contraproductive for anchoring. Confronted with opposing theoretical predictions on the relationship between target formulations and anchoring, the question is empirical in nature.

Our empirical results have three important implications for this strand of literature. First, the weak anchoring of inflation expectations in the presence of pure target ranges is consistent with approaches suggesting that pure ranges are interpreted as zones where monetary policy is less active. Second, our findings are in line with predictions of the flexibility view, i.e. tolerance bands provide more room for interpretation of the inflation target during periods of sustained target deviations than point targets. Third, a vague target formulation which is based on a mere definition of price stability is dominated by a target type with reference to an explicit point target or focal point, indicating that central banks can reveal policy objectives credibly even in the presence of time-inconsistent objectives.

The paper is further related to a large empirical literature on the measurement of expectation anchoring. While there exists no widely-agreed definition of well-anchored inflation expectations, Afrouzi, Kumar, Coibion, and Gorodnichenko (2015) list five criteria that are recurrent in empirical tests of anchoring: (i) average beliefs being close to target, (ii) beliefs that are not too dispersed across agents, (iii) confidence in the belief, thus little (subjective) uncertainty about inflation projections, (iv) forecast revisions should be small, notably over longer horizons, (v) little co-movement between long-run and short-run inflation expectations. One contribution of this paper is to extend this list with a sixth criterion, emphasizing that more symmetric distributions are desirable from the perspective of a risk-averse central banker.

There is a large body of papers focusing on variants of criterium (v), also referred to as a pass-through regression (Jochmann, Koop, and Potter, 2010; Pooter et al., 2014; Lyziak and Paloviita, 2017; Buono and Formai, 2018). In a related approach, anchoring is measured by the extent to which long-term inflation expectations obtained from breakeven inflation rates respond to macroeconomic news (Gürkaynak, Levin, and Swanson, 2010; Beechey, Johannsen, and Levin, 2011; Bauer, 2015; Hachula and Nautz, 2018; Speck, 2017). It should be noted that it is well possible that long-term inflation expectations respond little to news, while being distant to the announced inflation objective of the central bank in levels, thus questioning the credibility of the target. This renders criterion (v) less suitable for the assessment of differential effects of target formulations.

Papers that focus on the level of long-term inflation expectations are more closely related to the approach taken here. Mehrotra and Yetman (2018) use a three-dimensional panel dataset, using the mean of long-run Consensus forecasts at all available forecast horizons, to estimate the perceived long-run anchor, which they then compare with alternative measures of long-term inflation projections. Moessner and Takats (2020) consider the distance of Consensus long-term inflation expectations from the inflation target as the anchoring property, without considering the differential effects of target types on anchoring. Anchoring as defined in Grishchenko, Mouabbi, and Renne (2019) comes closest to the here proposed anchoring measure. They construct conditional density inflation forecasts for the US and the Euro area from the survey of professional forecasters by fitting generalized beta distributions to bins of inflation outcomes provided in these surveys. While their measure is very similar to ours, an important difference is that our cross-sectional measure does not account for subjective forecast uncertainty, given that Consensus only collects point forecasts containing the best projection of each panelist. This has advantages and disadvantages at the same time. While it would be informative to consider all outcomes with positive probability mass from the sample of professional forecasters, it is not clear how density functions relate to the best projection, such that there is an interest in examining the cross-section of point forecasts only (Engelberg, Manski, and Williams, 2009; Clements, 2014).

This paper contributes primarily to the literature on the effects of target formulations on inflation outcomes and inflation expectations. Fatas, Mihov, and Rose (2007) document over a sample period of 1960 to 2000 and a large set of 42 countries that a quantitative definition of the inflation objective lowers inflation outcomes. Crowe (2010) finds in a sample of 11 countries that the introduction of IT reduces the forecast error of private sector forecasts. He concludes that this results from increased transparency about central bank objectives. Levin, Natalucci, and Piger (2004) look at pass-through of current inflation to long-term expectations in a set of 12 advanced economies, finding that the IT framework has helped to better anchor medium- to longer-run inflation expectation. Davis (2014) comes to the same conclusion in a larger set of 36 countries, considering the pass-through of shocks to inflation, inflation expectations and oil prices. Gürkaynak, Levin, and Swanson (2010) compare market-based inflation expectations of three IT countries (UK, Sweden, Canada) and the US, noting that far-ahead forward rates respond more to economic news and are more volatile in the US, suggesting higher anchoring in IT countries. Bundick and Smith (2018) conduct an event study around the introduction of numerical point targets in the US and Japan, finding that anchoring improved in the US but not in Japan.

There are two empirical papers differentiating between inflation target formulations, thus related to our main research question. Castelnuovo, Nicoletti-Altimari, and Rodriguez-Palenzuela (2003) document in a sample of 15 industrial countries that the adoption of a quantitative inflation aim improves anchoring. However, they do not find any significant difference between countries adopting a range target versus a point target. An important difference to our work is the sample period. While their data covers the period 1990-2002, our sample only starts in 2005 due to data availability on moments of the cross-sectional distribution, hence showing no overlap. Ehrmann (2020), work developed in parallel, distinguishes between range targets, point targets, and point targets with tolerance bands in a sample of 20 countries. He finds that pass-through is weaker for countries that have defined a target range or tolerance band for inflation, implying weaker anchoring for pure point targets. His work focusses on a shorter forecast horizon of one-and-a-half years. The differences to our findings might result from the nature of the underlying test. As argued before, a lower pass-through coefficient for target ranges is not necessarily inconsistent with less probability of cross-sectional point forecasts around target.[1] We therefore consider his findings as complementary to ours.

Finally, Cornand and M'baye (2018) run a learning-to-forecast laboratory experiment, comparing the macroeconomic outcomes within a New Keyensian model under two inflation target formulations, a point target and a target range. The announcement of a point target is associated with faster convergence of participants' expectations to target, broadly consistent with out empirical finding.

The paper is organized as follows. Section 2 presents a model of central bank inflation risk management to motivation the proposed anchoring measures. Section 3 presents the data and describes how we estimate continuous density functions of cross-sectional point forecasts. Section 4 contains the empirical analysis while Section 5 examines the robustness of the results. Section 6 concludes.

2 Measures of expectations anchoring accounting for asymmetry

This section derives measures of inflation expectations anchoring consistent with potentially asymmetric central bank preferences. We closely follow Kilian and Manganelli (2008) in the exposition. The optimal policy rule features a balancing of upside and downside risks to inflation. Based on Svensson's (1997a) idea of inflation forecast targeting, forward-looking risk measures are derived which serve as blue print for the empirical anchoring measures computed from continuous density functions estimated in Section 3 from a cross-sectional panel of professional forecasters.

2.1 Inflation risk management model

Let us first consider the seminal case of an expected utility maximizing central banker's problem of optimal monetary policy under discretion, where the central bank seeks to set a sequence of nominal interest rates $\{i_t\}_{t=0}^{\infty}$ that minimizes the objective function:

$$\min_{\{i_t\}} E_t \sum_{\tau=0}^{\infty} \delta^{\tau} L_{t+\tau} \tag{1}$$

Various proposals have been made for specifying the loss function L_t. The seminal linear-quadratic specification takes the form

$$L_t = \frac{1}{2}(\pi_t - \pi^*)^2 + \lambda \frac{1}{2}(y_t)^2,$$

where π_t denotes realized inflation, π^* is the inflation target and y_t an output gap measure. The parameter λ then captures to what extend the central bank cares about the output objective. Substituting in a linear Phillips curve and taking the first order

[1] Other differences between the two studies constitute a slightly different country coverage and sample period.

condition of the minimization problem gives rise to an implied interest rate rule under optimal policy that closely resembles the Taylor rule (Svensson, 1997b; Clarida, Galí, and Gertler, 1999).

Kilian and Manganelli (2008) propose a generalization to the problem of optimal policy toward asymmetric and risk-averse preferences.[2] They formalize 'upside risk' and 'downside risk' to price stability as situations in which a central banker is concerned about inflation realizations below a certain threshold, $\pi_t < \underline{\pi} < \pi^*$ or above a certain threshold $\pi_t > \bar{\pi} > \pi^*$. The resulting loss function takes the form

$$\begin{aligned} L_t = &\left[aI(\pi_t < \underline{\pi})(\underline{\pi} - \pi_t)^{\gamma_\pi^L} + (1-a)I(\pi_t > \bar{\pi})(\pi_t - \bar{\pi})^{\gamma_\pi^H} \right], \\ &+ \lambda \left[bI(y_t < \underline{y})(\underline{y} - y_t)^{\gamma_y^L} + (1-b)I(y_t > \bar{y})(y_t - \bar{y})^{\gamma_y^H} \right] \\ &\text{with } 0 \le a, b \le 1 \text{ and } \lambda \ge 0. \end{aligned}$$

The parameter λ captures, as before, the weight for the output objective. A set of indicator functions, denoted $I(\cdot)$, take the value of one if the condition inside the brace is fulfilled and zero otherwise. Parameters a and b then govern the degree of asymmetry, while $\gamma_{(\cdot)}^L$ and $\gamma_{(\cdot)}^H$ determine the risk aversion of the central banker to inflation and output gap realizations. This specification nests the possibility of a target zone of inflation, as losses occur only from inflation realisations outside the interval $[\underline{\pi}, \bar{\pi}]$. Note that this loss function also nests the standard quadratic and symmetric loss function with a point target for inflation stated above.[3]

To simplify the expression, let us ignore the output objective and set $\lambda = 0$. In expectation, the loss function can be rewritten as

$$E(L_{t+h}) = a \int_{-\infty}^{\underline{\pi}} (\underline{\pi} - \pi_t^e)^{\gamma_\pi^H} dF_{\pi_t^e}(\pi_t^e) + (1-a) \int_{\bar{\pi}}^{\infty} (\pi_t^e - \bar{\pi})^{\gamma_\pi^L} dF_{\pi^e}(\pi_t^e), \tag{2}$$

where Let F_{π^e} denote the probability density function over expected inflation realizations. For notational convenience, let us denote inflation risk measures under the distribtion of inflation expectations F_{π^e} as *disanchoring due to low inflation* (DAL) and *disanchoring due to high inflation* (DAH), respectively

$$DAL_{\gamma_\pi^L}(F_{\pi^e}) = \int_{-\infty}^{\underline{\pi}} (\underline{\pi} - \pi^e)^{\gamma_\pi^L} dF_{\pi^e}(\pi^e) \tag{3}$$

$$DAH_{\gamma_\pi^H}(F_{\pi^e}) = \int_{\bar{\pi}}^{\infty} (\pi^e - \bar{\pi})^{\gamma_\pi^H} dF_{\pi^e}(\pi^e) \tag{4}$$

Kilian and Manganelli (2008) define the general risk management problem as follows:

Definition 1. [Risk management problem] *Let $F_{\pi^e}^{(1)}$ and $F_{\pi^e}^{(2)}$ denote two alternative probability distributions for inflation expectations. Then $F_{\pi^e}^{(1)}$ is weakly preferred over*

[2] Ruge-Murcia (2003) and Cukierman and Muscatelli (2008) also analyse optimal policy under asymmetric preferences using a linex function to characterize central bank losses.

[3] This is the case under the parameterization $a = b = 1/2$ (symmetry), quadratic losses $\gamma_{(\cdot)}^L = \gamma_{(\cdot)}^H = 2$, a midpoint for inflation objective $\underline{\pi} = \bar{\pi} = \pi^*$, as well as deviations from output from the natural level standardized to zero, $\underline{y} = \bar{y} = 0$.

$F_{\pi^e}^{(2)}$ if $\mid DAL_{\gamma_\pi^L}(F_{\pi^e}^{(1)}) \mid \leq \mid DAL_{\gamma_\pi^L}(F_{\pi^e}^{(2)}) \mid$ and $DAH_{\gamma_\pi^H}(F_{\pi^e}^{(1)}) \leq DAH_{\gamma_\pi^H}(F_{\pi^e}^{(2)})$. If this condition does not hold, the central banker faces a risk management problem.

In words, the central banker needs to trade-off downside risk to inflation against upside risk to inflation. Without additional information about central bank preferences, it is impossible to characterize a solution to this problem. This requires the existance of a central bank utility function over alternative probability density functions, giving rise to a risk management model.

Definition 2. [Risk management model] *A central banker's preferences satisfy a risk management model if and only if there is a real valued function U in risks such that for all relevant distributions $F_{\pi^e}^{(1)}$ and $F_{\pi^e}^{(2)}$, $F_{\pi^e}^{(1)}$ is preferred over $F_{\pi^e}^{(2)}$ if and only if $U(DAL_{\gamma_\pi^L}(F_{\pi^e}^{(1)}), DAH_{\gamma_\pi^H}(F_{\pi^e}^{(1)})) > U\left(DAL_{\gamma_\pi^L}(F_{\pi^e}^{(2)}), DAH_{\gamma_\pi^H}(F_{\pi^e}^{(2)})\right)$.*

From substituting equations (2), (3) and (4) into the central bank's optimization problem (1) and deriving the first order condition, Kilian and Manganelli (2008) obtain an implicit nonlinear, potentially asymmetric interest rate rule:

$$\frac{\partial E_t L_t(\pi_t)}{\partial i_t} = \frac{\partial E_t(\pi_t(i_t))}{\partial i_t}\left[-a\gamma_\pi^L \int_{-\infty}^{\underline{\pi}} (\underline{\pi} - \pi_t)^{\gamma_\pi^H - 1} dF_{\pi_t}(\pi_t) \right.$$
$$\left. +(1-a)\gamma_\pi^H \int_{\bar{\pi}}^{\infty} (\pi_t - \bar{\pi})^{\gamma_\pi^H - 1} dF_{\pi_t}(\pi_t)\right] = 0 \qquad (5)$$

The rules is a weighted average of measures of downside risk and upside risk to inflation, where parameters a, γ_π^L and γ_π^H govern the response of the instrument to inflation risk. Thus, a risk-averse central banker takes into account the entire distribution of possible inflation outcomes and weights them according to her preferences.

2.2 Risk measures

Based on the optimal policy rule (5), we next derive measures of inflation risk, based on continuous probability density functions, which are consistent with preferences featuring risk aversion and potentially asymmetry. Further, we use the insights of Svensson (1997a), who shows that inflation targeting can best be operationalized via forecast targeting if the control lag of monetary policy is well understood. Then, the loss function of the central banker, based on realized inflation in the standard case, can be substituted by an intermediate loss function using inflation forecasts as inputs.

Five groups of candidate measures could in principle provide the basis for the anchoring measures that account for the entire shape of possible future inflation outcomes. First, density forecasts from macroeconometric models (Mitchell and Wallis, 2011). The disadvantage is that empirical model forecasts do not contain information about the credibility of central bank inflation objective as perceived by economic agents. Second, aggregated subjective probability forecasts as provided in the survey of professional forecasters (SPF). While the SPF provides a useful basis for the measurement of inflation risk (Grishchenko, Mouabbi, and Renne, 2019), this data is only available for the US and the Euro area. Third, central bank density forecasts for inflation (Knüppel and Schultefrankenfeld, 2012). While central bank inflation density forecasts become increasingly available for a larger set of countries, cross-country comparability of inflation risk assessments remains a constraint in empirical work. Fourth, option-implied inflation probability density functions that reflect the market assessment of inflation risk (Kitsul and Wright, 2013). While the financial market-based measures pose challenges with respect to the decomposition into inflation expectations, inflation risk premia and liquidity premia, they are also only available for a limited set of countries with sufficiently well-developed derivatives markets. We are going to focus, fifth, on the cross-sectional distribution of inflation point forecasts of the private sector. This data is available for a large set of countries through Consensus, directly comparable to each other, and measuring inflation expectations in real time.[4]

We do not interpret the density functions derived from the cross-section of point forecasts as density forecasts, but rather as a summary of beliefs across agents. Macroeconomic models that depart from the assumption of rational expectations have shown that dispersion in private sector inflation expectations provide relevant information for monetary policy (Orphanides and Williams, 2005). A related, but subordinated question is *why* professional forecasters disagree, hence giving rise to a cross-sectional distribution of forecasts. The literature based on models with Bayesian learning finds that the origin of disagreement can range from differences in private information sets and opinion, i.e. priors or models (Patton and Timmermann, 2010), inattentiveness of professional forecasters (Sims, 2003; Andrade and LeBihan, 2013), idiosyncratic uncertainty (Lahiri and Sheng, 2010), or dispersion in the interpretation of news (Manzan, 2011). For our analysis, the source for disagreement is of secondary importance. What matters is the relevance of dispersed beliefs for inflation outcomes and monetary policy decision.

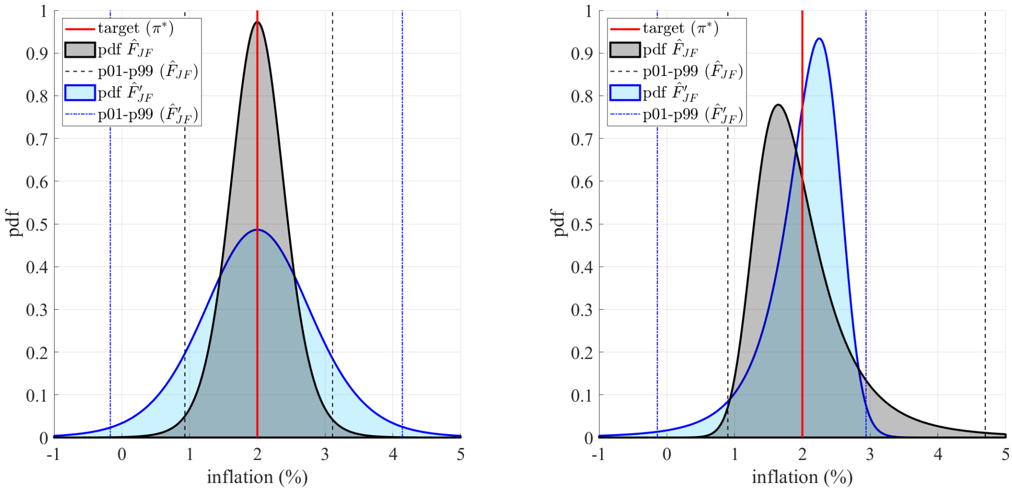
To gain further intuition, Fig. 1 illustrates possible cross-sectional distributions of point forecasts with *disagreement* and *skewness*. Panel (a) focusses on disagreement. While both distributions feature the same mean, the variance of cross-sectional point forecasts differs, leading to a significant amount of beliefs concentrated in the tails of the distribution. Panel (b) illustrates the symmetry of beliefs as captured by skewness of the underlying beliefs. While positive skewness implies a concentration of beliefs at high levels of inflation, negative skewness entails beliefs consistent with very low inflation rates. Notably, the central banker with a risk management model as characterized in definition (2) is unlikely to be indifferent between the four illustrative examples of cross-sectional inflation point forecasts.

For the empirical analysis, we therefore propose three probability measures derived from the cross-section of inflation point forecasts closely related to (3) and (4). Since estimating the degree of risk aversion of each central bank is beyond the scope of this paper, set $\gamma_\pi^L = \gamma_\pi^H = 0$. Further, let h denote the forecast horizon, and i the country. We then obtain empirical measures of disanchoring due to low inflation and

[4] To the extent that Consensus forecasts are a collection of point forecasts, they are parallels with projections of the members of the Federal Open Market Committe (FOMS) of the US Federal Reserve (Gavin and Mandal, 2003; Romer and Romer, 2008).

Figure 1: Illustrative distribution of inflation point forecasts

(a) Disagreement (b) Skewness



Note: Illustrative examples of parameterized skew $t-$distributions across inflation point forecasts, all featuring a mean of 2. Panel (a) shows two symmetric distributions around a hypothetical target of 2 percent. The disagreement measured as cross-sectional standard deviation of $F^{(1)}{}_{\pi^e}$ (light blue) is twice as large as the standard deviation of $F^{(2)}{}_{\pi^e}$ (dark grey). Panel (b) shows two distributions with non-zero skewness in the cross-section. $F^{(3)}{}_{\pi^e}$ (light blue) features negative skewness, whereas $F^{(4)}{}_{\pi^e}$ (dark grey) is positively skewed.

high inflation from the probability density across point forecasts as:

$$DAL_{it}^{h} = \int_{-\infty}^{\underline{\pi}_i} dF_{\pi_{it}^{h}}(\pi_{it}^{h}) \tag{6}$$

$$DAH_{it}^{h} = \int_{\bar{\pi}_i}^{\infty} dF_{\pi_{it}^{h}}(\pi_{it}^{h}) \tag{7}$$

Complementing these two measures of disanchoring, we define our main measure of anchoring as the cumulative density of point forecasts falling within a narrow interval around the inflation objective

$$\begin{aligned} probT_{it}^{h} &= \int_{\underline{\pi}_i}^{\bar{\pi}_i} dF_{\pi_{it}^{h}}(\pi_{it}^{h}) \\ &= 1 - DAL_{it}^{h} - DAH_{it}^{h}. \end{aligned} \tag{8}$$

3 Data

This section describes the classification of quantitative inflation targets and the approach of estimating continuous density functions to moments of the cross section of inflation point forecasts from private sector survey data.

3.1 Classification of quantitative inflation targets

We code the quantitative inflation targets of 29 countries. The sample of countries is composed out of 12 advanced economies (AEs) and 17 emerging market economies (EME).[5] We follow Castelnuovo, Nicoletti-Altimari, and Rodriguez-Palenzuela (2003) and define dummy variables for six categories: (i) no explicit announcement, (ii) a quantitative definition of price stability, (iii) a range target for inflation, (iv) a range target with focal point, (v) a point target with tolerance bands and (vi) an inflation point target.

Some remarks on the coding of inflation targets are in order. First, given the nuanced definition of inflation objectives in practice, the boundaries of central bank objectives defined as point targets versus range targets are not clear cut. We therefore acknowledge that there might be controversial views about the classification of some countries over time that we have chosen. Second, the objective is to collapse the variety of target specifications into the essential informational content that the public is able to understand in the context of noisy information and conflicting signals (Demertzis and Viegi, 2008, 2009). Therefore, in the empirical analysis, we merge classification categories (i) and (ii) into *'no numerical target'* and categories (iv) and (v) into *'hyprid targets'*. Third, we include also three central banks that never officially adopted inflation targeting as a a framework for the conduct of monetary policy, namely the United States, the Euro area and Switzerland. However, the inflation targets can be classified while the policy framework seems mature enough to be be integrated in the empirical analysis.

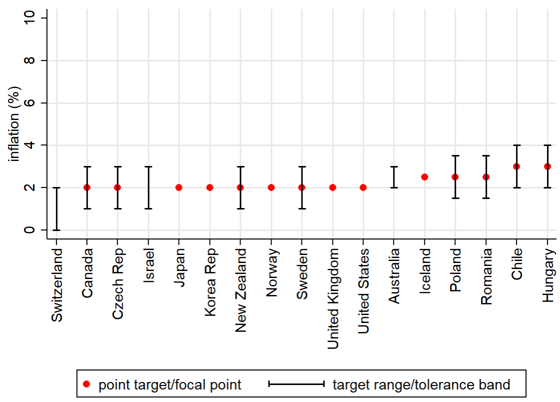
Tab. A.1 in the Appendix provides all details regarding our classification choices. Fig. 2 gives a snap shot of inflation objectives as of April 2020, while Tab. 1 lists summary statistics of the 29 countries covered in the analysis starting in April 2005. A couple of observations stand out. Despite some heterogeneity, there is convergence toward an inflation objective of two to three percent among central banks (Hammond, 2012). Second, there is significant cross-country variation with respect to the adoption of a point target versus a target range and hybrid versions. However, the majority of observations falls within the class of hybrid targets, which are dominated by point targets with a tolerance band. Fig. A.1 and Fig. A.2 in the Appendix document that there is also considerable intertemporal variation, as some central banks introduced or abandoned tolerance bands and point targets as part of the evolution of their monetary policy strategy. Examples include, but are not limited too, the cases of Sweden or New Zealand. Sweden started out in early 1993 by adopting a point target of 2 percent with a tolerance band of $+/-$ 1 percent. In May 2010, the executive board of the Rijksbank abandoned the tolerance band, only to reintroduce it under the name of a *variational band* in September 2017. New Zealand operated with a range target from 1990 onwards, with explicit focus on the midpoint since September 2012 (Lewis and McDermott, 2016).

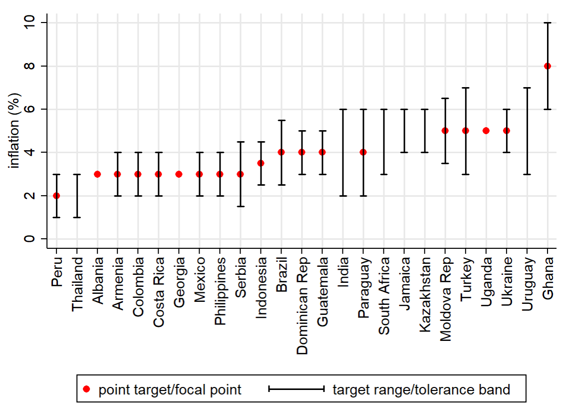
[5] The sample of AEs cover Australia, Canada, Czech Republic, Euro area, Japan, New Zealand, Norway, South Korea, Sweden, Switzerland, United Kingdom and United States. The sample of EMEs contains Albania, Armenia, Chile, Colombia, Guatemala, Hungary, India, Israel, Mexico, Peru, Poland, Philippines, Romania, Serbia, South Africa, Thailand and Turkey.

Figure 2: Quantitative inflation targets

(a) AE sample

(b) EME sample





Notes: Quantitative targets as of April 2020 of 17 AE countries (panel a) and 25 EME countries (panel b). Switzerland and the United States are the only countries not classified as official inflation targeters. Missing from the AE sample is the Euro area with an inflation objective of below, but close to, 2 percent, which cannot be translated into a specific number without controversy.

Table 1: Summary statistics of inflation targets

	mean	sd	min	max	groups	obs
no IT	1.74	.37	1	2	3	71
IT(all)	2.5	.73	1	5	28	855
Inflation target classifications						
Range target	2.35	.88	1.5	4.5	9	161
Range with focal point	2.2	.25	2	2.5	2	49
Point with tolerance band	2.74	.76	2	5	16	438
Point target	2.18	.36	1	3	8	207

Note. Summary statistics on the midpoint of the inflation objective for target classifications. Tab. A.1 in the Appendix provides details on the classification for each country in the sample.

3.2 Estimating distribution functions for anchoring measures

For the computation of inflation risk measures as defined in equations (6) to (8), we estimate parametric density functions using sample moments of the cross-sectional distribution of point forecasts from private sector forecasts collected by Consensus.

The survey is conducted across a wide range of countries. The survey covering long-term forecasts is available at biannual frequency from October 1989 onwards with surveys conducted typically in April and October over forecast horizons of $h = 0, 1, 2, 3, 4, 5, 6 - 10$ years. The survey frequency changed to quarterly in April 2014, the survey then being conducted in January, April, July and October. The underlying data characterizes fixed-event forecasts for specific calendar years. The forecast horizon thus changes in every survey round. We apply a fixed-horizon transformation to the data, extending the formula provided by Dovern, Fritsche, and Slacalek (2012) to a multi-year horizon

$$\hat{x}_{t+y\cdot 12|t} = \frac{k}{y\cdot 12}x_{t+k|t} + \frac{y\cdot 12 - k}{y\cdot 12}x_{t+y\cdot 12+k|t}$$
$$\text{with } k \in \{(y-1)\cdot 12+1, (y-1)\cdot 12+2, ..., (y-1)\cdot 12+12\}.$$

We cover fixed-horizon forecast from years $y = 1, 2, 3, 4, 5$ and 6, where the last series is a weighted average out of inflation forecasts over the five year horizon and the 6 to 10 years horizon.

Let $MPF^h_{jit}(x)$ denote the mean point forecast of panelist j in country i at time t of realizations of variable x over the forecast horizon h. Unfortunately, the micro data of all panelists mean point forecasts are not available from Consensus long-term forecasts.[6] However, Consensus publishes four moments of the cross-sectional distribution of long-term point forecasts as of April 2005, namely (i) the sample mean, (ii) the sample standard deviation, (iii) the lowest and (iv) the highest mean point forecast of the survey sample. To clarify the underlying data, let us denote the availabe data as follows:

$$\mu^h_{it} = E_t[MPF^h_{it}] = \frac{1}{N}\sum_{j=1}^{N} MPF^h_{jit} \tag{9}$$

$$\sigma^h_{it} = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(MPF^h_{jit} - \mu^h_{it})^2} \tag{10}$$

$$low^h_{it} = \min\left[MPF^h_{1it}, ..., MPF^h_{Nit}\right] \tag{11}$$

$$high^h_{it} = \max\left[MPF^h_{1it}, ..., MPF^h_{Nit}\right] \tag{12}$$

Fig. 3 documents substantial cross-sectional disagreement and skewness over the sample period. Plotted are the cross-country evolution of the median and percentiles of disagreement, measured as the standard deviation across panelists, and skewness. We measure skewness in country i in period t at horizon h by the following ratio

$$S^h_{it} = \frac{(high^h_{it} - \mu^h_{it}) - (\mu^h_{it} - low^h_{it})}{high^h_{it} - low^h_{it}}. \tag{13}$$

The ratio provides insights into the relative position of the mean with respect to the two most extreme survey responses. When the ratio is high, skewness tends to be positive, while skewness is low or negative if the ratio drops. Equation (13) is inspired by quantile-based measures of skewness, for example Bowley's robust measure of skewness. However, given that we do not know the median or percentiles, it is just an approximation to more conventional measures of skewness (Bowley, 1920). [7]

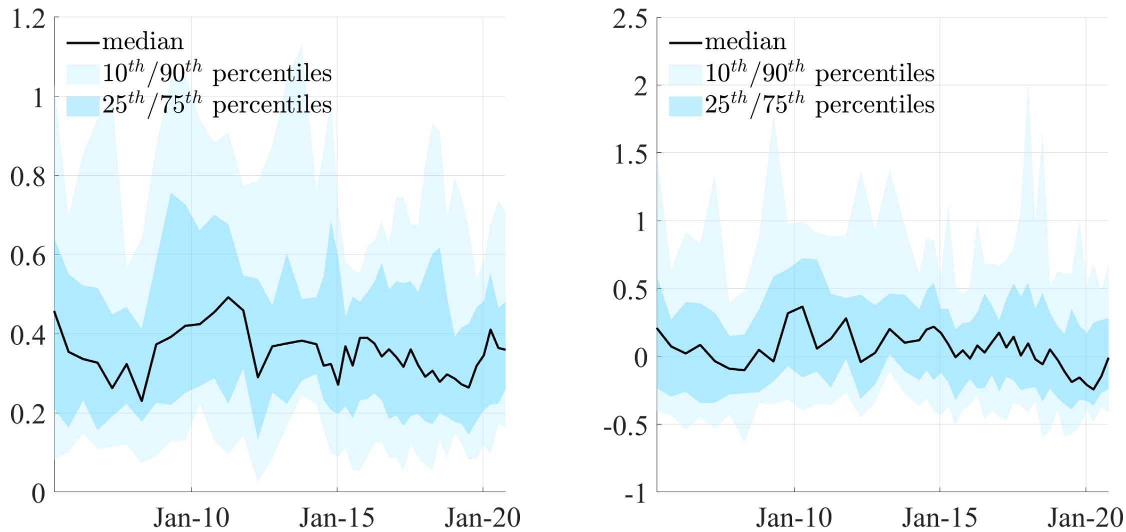
Given the high amount of asymmetry reflected in Panel (b) of Fig. 3, we consider

[6] Consensus provides micro data for panelists participating in the monthly survey of projections for the current and next calendar year, which we use for benchmarking our results below.

[7] Tab. B.2 in the Appendix shows the correlation of the skewness ratio (13) and conventional measures of skewness from available micro data at shorter forecast horizons. All measures are highly correlated, fostering our confidence in the skewness ratio.

Figure 3: Disagreement and skewness in long-term inflation point forecasts

(a) Disagreement, 6 yrs ahead (fixed-horizon) (b) Skewness, 6 yrs ahead (fixed-horizon)



Note: Reported is the evolution of disagreement and skewness across countries for long-term inflation point forecasts. Disagreement is measured as sample standard deviation, skewness is approximated by the relative position of the mean to lowest and highest sample observations, see eq. (13) in the main text.

two candidates for parametric continous density functions to be fitted to the available information on the cross-sectional distribution, namely the generalized beta distribution $F_B(a, b, l, r)$ and the skew $t-$distribution $F_{JF}(\mu, \sigma, a, b)$. Both density functions are based on four parameters, highly flexible, and provide numerous examples in applied economics and finance literature.[8] They differ to the extend that the generalized beta is defined over the closed support governed by two parameters $[l, r]$, while the skew $t-$distribution is defined on $\mathbb{R}$.

To test which family of distribution functions best fits the data, we take a two step approach. In a first step, we evaluate the goodness of fit using actual panelist responses over the next-year forecast horizon. We estimate density functions $\hat{F}^*_B(a, b, l, r)$ and $\hat{F}^*_{JF}(\mu, \sigma, a, b)$ using maximum-likelihood estimation. An asterisc denotes a distribution estimated based on the full sample. We compare the outcome with a Kolmogorov-Smirnoff (KS) test. Details and results are provided in Appendix B. Both families of continuous density functions fit the data well. However, we decide to proceed with the skew $t-$distribution based on the better performance in the KS-test. Furthermore, we prefer the property of the skew t-family not to require the restriction of the underlying support.

In a second step, we apply simulated method of moments (SMM) estimation to

[8] Examples for the generalized beta distribution can be found in the fitting of bins of inflation projections (Engelberg, Manski, and Williams, 2009; Boero, Smith, and Wallis, 2015; Grishchenko, Mouabbi, and Renne, 2019). The skew $t-$distribution was employed by Adrian, Boyarchenko, and Giannone (2019) and Ganics, Rossi, and Sekhposyan (2020).

fit a sequence of skew $t-$distributions to available statistics of cross-sectional point forecasts over horizons from two to six years ahead. We target five moments, the mean, the standard deviation, the skewness ratio (13), and the location of the lowest and highest reported inflation forecast in the estimated density function. While the first three moments are straightforward, the last two moments use an intermediate result from step 1. Specifically, for the estimated distribution functions where we have a full sample, $\hat{F}^*_{JF}(\mu, \sigma, a, b)$, we recover the percentile of the lowest and highest observation across panelists in vector $P_i^{low}(\hat{F}^*_{JF})$ and $P_i^{high}(\hat{F}^*_{JF})$, respectively. Fig. C.6 in the Appendix shows the histogram of these two vectors. The histograms feature a mode around the 3^{rd} percentile in case of lowest survey responses, and around the 97^{th} percentile in case of highest survey responses. Thus, ML-estimation attributes little probability density outside the min-max range of survey answers.[9] We fit a kernel density to the vector $P_i^{low}(\hat{F}^*_{JF})$,

$$\hat{f}^P_{low}(x) = \frac{1}{N\omega} \sum_{i=1}^{N} K\left(\frac{x - x_i}{\omega}\right),$$

where N is the number of observations, x_i are the percentiles in the vector $P_i^{low}(\hat{F}^*_{JF})$, ω the bandwidth and $K(\cdot)$ is the kernel smoothing function, which we choose to be a normal. We do the same for the location of high observations, $\hat{f}^P_{high}(x)$.

We then exploit the kernel density in the SMM approach of step 2 as follows. First, we compute the percentile of datapoints low^h_{it} and $high^h_{it}$ from the candidate distribution $F_{JF}(\theta)$, obtaining simulated percentiles $\tilde{P}_i(low^h_{it})$ and $\tilde{P}_i(high^h_{it})$, respectively, both conditional on $F_{JF}(\theta)$. Second, we compute the empirical pdf from the respective kernel density at point $\hat{f}^P_{(\cdot)}(\tilde{P}_i(\cdot))$, and substract it from the highest density at the mode of the respective kernel density. For the case of lowest observations, we use the following notation

$$\Delta \hat{f}^P_{low}(\tilde{P}_i(low^h_{it}) \mid F_{JF}(\theta)) \equiv \hat{f}^P_{low}(mode) - \hat{f}^P_{low}(\tilde{P}_i(low^h_{it}) \mid F_{JF}(\theta)), \tag{14}$$

which is analogue for the highest observation. We refer to (14) as the *location constraint*. The value of the location constraint is smallest, the closest the percentile of low^h_{it} in the candidate distribution is to the mode of the kernel density. The intuition behind the inclusion of the location contraint in the estimation procedure is to use the location of lowest and highest sample responses in estimated parametric density functions obtained from micro data as a penalty function to inform the estimation process for long-term forecasts, where this information is missing. The resulting SMM estimator takes the form

$$\hat{\theta}(W) = \arg\min_{\theta} \left[\hat{\psi}^{data} - \hat{\psi}^{sim}(\theta)\right]' W \left[\hat{\psi}^{data} - \hat{\psi}^{sim}(\theta)\right], \tag{15}$$

[9]The well-defined mode is another argument an favor of the skew $t-$distribution.

where $\theta = (\mu, \sigma, a, b)$, and

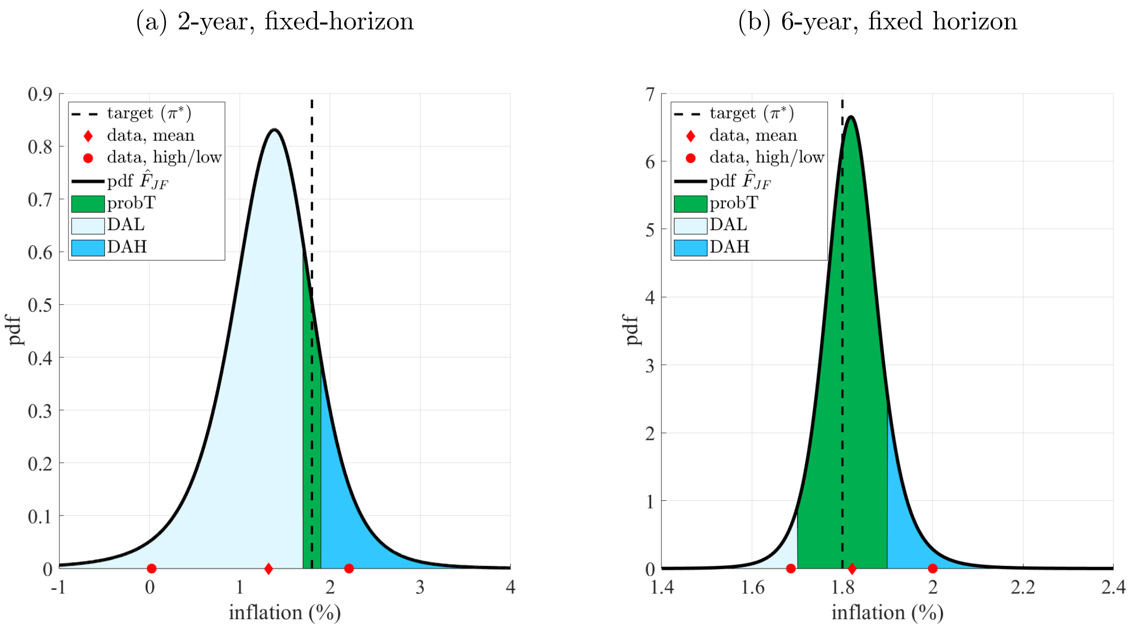
$$\hat{\psi}^{data} = \begin{bmatrix} \mu_{it}^h \\ \sigma_{it}^h \\ S_{it}^h \\ 0 \\ 0 \end{bmatrix}, \text{and } \hat{\psi}^{sim} = \begin{bmatrix} \tilde{\mu} \mid F_{JF}(\theta) \\ \tilde{\sigma} \mid F_{JF}(\theta) \\ \tilde{S} \mid F_{JF}(\theta) \\ \Delta \hat{f}_{low}^P(\tilde{P}_i(low_{it}^h) \mid F_{JF}(\theta)) \\ \Delta \hat{f}_{high}^P(\tilde{P}_i(high_{it}^h) \mid F_{JF}(\theta)) \end{bmatrix}$$

where a tilde denotes the simulated sample moment from the candidate distribution $F_{JF}(\theta)$. Let us further clarify how we compute the skewness ratio $\tilde{S}$ in our simulations. In line with the modal value of the kernel densities of the location of highest and lowest observations using micro data (Fig. C.6), we take the 3^{rd} and 97^{th} percentiles of the density function $F_{JF}(\theta)$, respectively, and compute the skewness ratio as

$$\tilde{S} \mid F_{JF}(\theta) = \frac{(P_{97} \mid F_{JF}(\theta) - \tilde{\mu} \mid F_{JF}(\theta)) - (\tilde{\mu} \mid F_{JF}(\theta) - P_3 \mid F_{JF}(\theta))}{P_{97} \mid F_{JF}(\theta) - P_3 \mid F_{JF}(\theta)}.$$

Given that we want to fit more moments than there are parameters to be estimated, the model is over-identified and we need to specify a weighting matrix W. We employ a matrix W that contains the inverse standard deviation of sample moments along the main diagonal. The estimator (15) is minimized using a global search algorithm with multiple starting points in order to insure that a global minimum is found.

Figure 4: Example estimated distribution $\hat{F}_{JF}(\mu, \sigma, a, b)$, Euro area (6 April 2020)



Note: The skew $t-$distribution $F_{JF}(\mu, \sigma, a, b)$ estimated via simulated method of moments using the cross-sectional mean, the standard deviation, and the highest and lowest reported values of inflation point forecasts at a given date t from a panel of professional forecasters. The example is based on Euro area data on inflation point forecasts over a 2-year and 6-year fixed-horizon approximation. Underlying raw data is from Consensus Economics.

As a result, we obtain a sequence of estimated continuous density functions $\hat{F}_{JF}(\mu, \sigma, a, b)$ for each country i, forecast horizon h and date t from which inflation risk measures DAL^h_{it}, DAH^h_{it} and $probT^h_{it}$ from equations (6), (7) and (8) can be computed. The thresholds are chosen as $\underline{\pi}_{i,t} = \pi^*_{i,t} - 0.1$ and $\bar{\pi}_{i,t} = \pi^*_{i,t} + 0.1$.

Fig. 4 illustrates the obtained continuous density functions across point forecasts using data from the Euro area for forecast horizons of two and six years from a survey published in April 2020. The underlying survey data are plotted as red dots on the x-axis. The procedure sucessfully constructs a probability density around the mean point forecast that is consistent with the moments provided in the survey data. In this example, medium-term forecasts feature negative skweness, while long-term forecasts exhibit positive skewness. Disagreement is significantly lower over the longer forecast horizon of six years. The example further illustrates why the underlying data does not allow to map the interval chosen for our anchoring measure into the official target corridors defined in central bank operational frameworks, usually defined as $+/-$ 1 percentage point around the inflation point target. The reason is that the underlying data are point forecasts that exhibit significantly lower dispersion than e.g. individual forecasters' uncertainty around the point forecast.

Fig. 5 summarizes some time-series properties of the estimated distribution functions, the underlying data and the anchoring measures. For the case of the Euro area, there is a trend since mid-2012 toward larger risk of disanchoring due to low inflation. At the same time, the main anchoring measure seems overall quite stable over the sample period. It is this feature of the data that we refer to as *symmetry property*, which we would like to emphasize and investigate more systematically in the next section.

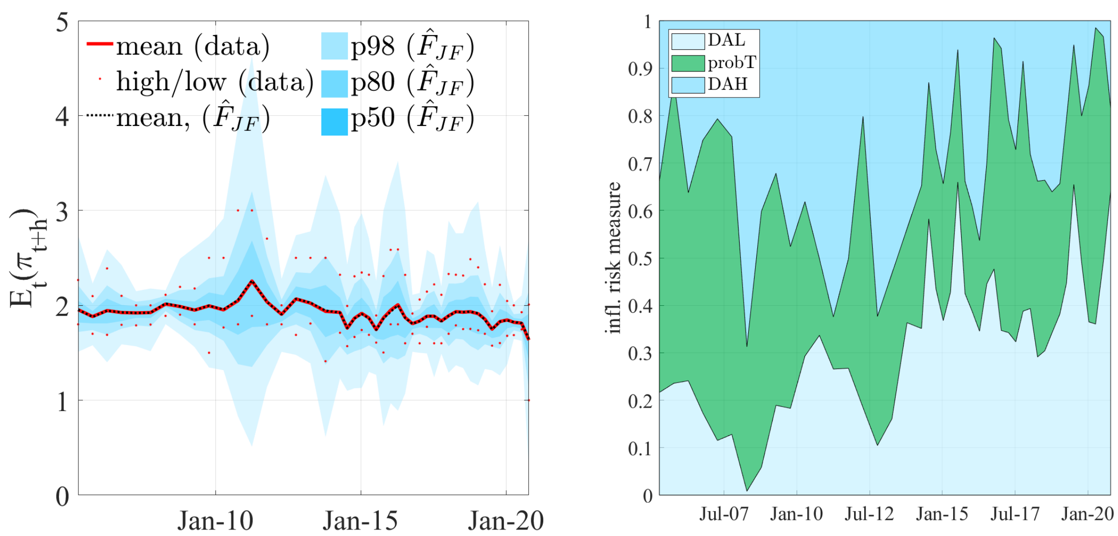
Tab. 3 provides summary statistics of the underlying survey data, converted to fixed-horizon forecasts, and inflation risk measures. To save space, just the forecast horizons of two, four and six years are reported. Some features of the data deserve to be mentioned. The consensus among point forecasts is on average more distant from target for shorter projection horizons and in EMEs. Disagreement is present in the full sample and in the two sub-samples. Interestingly, over the two year horizon, forecasters never fully agree on inflation outcomes. Skewness does seem to average out in the mean, while being slightly positive in the AEs and in the EMEs sample.

Turning to the inflation risk measures, we can refine some observations we made based on the raw survey data. The term structure of our probability measure of anchored inflation expectations has a positive slope. The term structure of disanchoring due to low inflation is negatively sloped, while disanchoring due to high inflation is stable over all forecast horizons in the full sample. While disanchoring due to low inflation is more present in the AEs sample, disanchoring due to high inflation dominates in the EMEs sample.

[Tab. 3 about here]

Figure 5: Time series properties of densities and anchoring measure, Euro area

(a) Percentiles of $\hat{F}_{JF}$ (b) Expectations anchoring measures



Notes: Skew $t-$distribution estimated via simulated method of moments to professional forecasters' cpi inflation projections over horizons of two to six years. Original data is from Consensus Forecast.

4 Empirical analysis

4.1 Determinants of expectation anchoring

In order to better understand the underlying data, we first examine the determinants of expectation anchoring based on a pooled regression of the following specification:

$$probT_{it}^{h} = c + \beta_1 d_t^{fh3} + \beta_2 d_t^{fh4} + \beta_3 d_t^{fh5} + \beta_4 d_t^{fh6} + \delta_1 d_t^{EME} + \gamma \sigma_{i,t}^{\pi 24m} + \nu_Y + \varepsilon_{it} \quad (16)$$

We regress the forecast horizon and a dummy variable capturing emerging market countries (EMEs) on different endogenous variables. All regressions contain a time-series of rolling window standard deviation of realized headline consumer price inflation with a backward looking horizon of 24 months. Further, the model includes a full set of year dummies. Hence, the reference group, captured by the constant, is the variable of interest at the two year horizon in an advanced economy.

Tab. 4 provides the corresponding results. The term-structure of anchoring is upward sloping, for the conventional measure of the distance of mean point forecasts with respect to the target midpoint in column (1), but also in the probability measure $probT_{it}^{h}$ in column (4). This is an important characteristic of well-anchored inflation expectations, which revert back to target over time in the sample of countries considered. Volatility of realized inflation has the expected effect on the distance to target and the probability to be on target. Periods of high volatility make it harder to be close to target. EMEs have on average less well-anchored inflation expectations. The distance to target is around one fifth larger, the probability around target roughly one fifth lower compared to AEs.

Inflation volatility increases disagreement among professional forecasters, as shown in column (2). The term-structure of disagreement is slightly hump-shaped, which is consistent with previous findings of relatively flat term structure of disagreement (Andrade et al., 2016). Disagreement is found to be only marginally higher in EMEs.

Asymmetry, here captured by the skewness ratio from eq. (13), is averaging out in the pooled model, as shown in column (3). Inflation volatility does not affect skewness. Longer forecast horizons have slightly more positive skewness, implying an upward sloping term structure of skewness.

Finally, disanchoring due to low inflation in column (5) rises with higher inflation volatility, while the latter dampens disanchoring due to low inflation, column (6). The term structure of the two disanchoring measures feature an interesting property: while DAH is stable over different forecast horizons, DAL is downward sloping, thus contributing to the increase in the probability measure around target. One might speculate whether this is due to predominantly disinflationary shocks over the sample period under consideration, leading to a 'targeting from below'. In Section 4.3 we are considering asymmetric credibility loss terms in order to analyse this question in more depth.

[Tab. 4 about here]

4.2 Anchoring and inflation target formulations

This section investigates the main question of the paper. First, we will test whether the formulation of the infation objective with a numerical definition changes anchoring. Bundick and Smith (2018) have found mixed effects for the cases of Japan and the United States. We revisit the question in an econometric panel model of the form

$$probT^{h}_{it} = c + \beta d^{numTarget}_{it} + \gamma \sigma^{\pi 24m}_{i,t} + \nu_i + \nu_Y + \varepsilon_{it} \tag{17}$$

The specification includes the same variable controlling for inflation volatility as model (16), namely a rolling window standard deviation of realized headline consumer price inflation with a backward looking horizon of 24 months. This captures broadly the economic conditions. Further, inflation forecasts are known to respond to inflation volatility (Capistran and Timmermann, 2009). A full set of year dummies ν_Y account for shocks to global inflation and their implications for forecasts. Galati, Poelekke, and Zhou (2011) show evidence that the collapse of Lehman Brothers has lead to changes in survey-based longer-term inflation expectations in the United States and United Kingdom. All remaining country differences are acounted for by country fixed effects ν_i. Our interest is in the effect of a dummy variable that takes the value of one if the inflation objective is described in a numerical precise way.

[Tab. 5 about here]

Tab. 5 A. present the results. Model (17) is estimated separately for each forecast horizon, the reference group are all target definitions without precise numerical target definition and that have, instead, a more vague definition of price stability. Standard errors are computed following the procedure proposed by Driscoll and Kraay (1998), which are robust to spatial dependence, heteroscedasticity and serial correlation. The coefficient of interest is insignificant for horizons of two to four years, implying that there is no significant effect on anchoring by the introduction of a numerical target formulation *per se*.

Next, we differentiate between range targets and point targets. We group all target definitions containing a numerical definition of a range or tolerance band into a variable $d_{i,t}^{numRange}$, while all target definitions with a reference to a point target are grouped into a variable $d_{i,t}^{numPoint}$. Note that the two categorical variables are not mutually exclusive. We estimate the following model

$$probT_{it}^{h} = c + \beta_1 d_{it}^{numRange} + \beta_2 d_{it}^{numPoint} + \gamma \sigma_{i,t}^{\pi 24m} + \nu_i + \nu_Y + \varepsilon_{it} \tag{18}$$

Results in Tab. 5 B. provide an interesting finding. While the presence of a numerical range lowers the anchoring measure, a target definition which includes a reference to a numerical point increases the probability mass of pointpredictions around target. We provide the p-values of an F-test for equality in the two coefficients ($H_0 : \beta_1 = \beta_2$). The test clearly rejects the null hypothesis of equal coefficients for horizons of three to six years.

Having documented a positive effect of a numerical reference to a point target on expectation anchoring, we next explore the question of differential effects of numerical target formulations in more detail. To this end, only countries and episodes with a numerical target definition are compared.[10] We estimate the following model

$$probT_{it}^{h} = c + \beta_1 d_{it}^{hybrid} + \beta_2 d_{it}^{point} + \gamma \sigma_{it}^{\pi 24m} + \nu_i + \nu_Y + \varepsilon_{it}, \tag{19}$$

where d_{it}^{hybird} contains all range targets with reference to a focal point, and point targets with a tolerance band. d_{it}^{point} is gauging the effect of pure point targets. The reference group is the group of numerical range targets without emphasis on a focal point.

[Tab. 6 about here]

Tab. 6 presents the results for model (19). As before, the reference to a focal point improves anchoring along all forecast horizons. The quantitative difference is sizeable, more than doubling the probability to be close to target. Pure point targets have a slightly higher coefficient than hybrid strategies at the longest forecast horizon of six years, while hybrid definitions have a larger coefficient at shorter horizons. However, the coefficients of d^{hybrid} and d^{point} are mostly not statistically different from each other according to the results from a corresponding F-test.

Tab. 7 contains the results of model (19) re-estimated with the two measures of dis-anchoring as endogenous variable. This specification allows to analyse the differential effects of target formulations on the symmetry of the distribution of point forecasts around the inflation objective. This aspect is novel in the empirical analysis of expectation anchoring. Panel A. presents effects on disanchoring due to low inflation,

[10] This excludes the Euro area from the sample, and observations of the United States before March 2012 and Japan before the introduction of numerical target in February 2012.

while panel B. contains effects on disanchoring due to high inflation. Hybrid target formulations are associated with a downward shift the distribution of point forecasts compared to target ranges. Specifically, hybrid targets feature lower upside risk, while also exhibiting higher downside risk.

[Tab. 7 about here]

To understand better the asymmetric effects of target types on the shape of the distribution of point forecasts, we explore the shift of selected moments in the cross-sectional distribution. Specifically, we define the difference between the mean, the 5^{th} percentile and the 95^{th} percentile of the cross-sectional distribution and the inflation target as

$$\begin{aligned} dist_{it}^{h} &= \pi_{it}^{*} - \mu_{it}^{h}, \\ G_{it}^{h}(05) &= \pi_{it}^{*} - P_{it}^{h}(05), \\ G_{it}^{h}(95) &= \pi_{it}^{*} - P_{it}^{h}(95), \end{aligned}$$

and analyse the quantitative differential effect of target types on these three distance-to-target measures according to model (19). To save space, Tab. 8 shows the results for forecast horizons of two and six years. The entire cross-sectional distribution of point forecasts gets compressed and shifts downward for countries operating with hybrid targets or point targets compared to range targets. This includes the distance of the cross-sectional mean to the inflation target for horizons of two and six years, as columns (1) and (2) show. The effects are not symmetric, however. Upside risk to inflation is curved in most effectively at a horizon of two years, as can be read from column (5). However, this beneficial effect comes also at a cost, as downside risk to inflation rises, as confirmed by lower tail observations reported in columns (3) and (4).

[Tab. 8 about here]

4.3 Credibility loss, anchoring and target formulations

While the previous section documents unconditional asymmetric effects of inflation target formulations on the cross-sectional distribution of point forecasts, Section 4.1 shows that the shape, specifically skewness, is not stable over time, but features persistent fluctuations with periods of positve and negative skewness. Motivated by this observation, this section explores systematically the relation between inflation performance and expectations anchoring. Following Neuenkirch and Tillmann (2014), we construct a credibility loss indicator and examine its conditional effects on expectations anchoring. We define credibility losses in country i in period t as

$$CL_{it} = \frac{1}{T-1} \sum_{s=t-T}^{t-1} (\pi_{is} - \pi_{is}^{*}) \mid \pi_{is} - \pi_{is}^{*} \mid$$

where the backward looking rolling window covers $T = 60$ months. The relatively long backward looking reference period is motivated with the intention to distinguish target misses due to interest rate smoothing from target misses due to possibly lower commitment for the inflation objective. While we are interested in the latter, also the former generates persistent target misses. Let us further define

$$CL_{it}^{(+)} = \begin{cases} CL_{it}, & \text{if} \quad CL_{it} \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

$$\text{and } CL_{it}^{(-)} = \begin{cases} \mid CL_{it} \mid, & \text{if} \quad CL_{it} \leq 0 \\ 0, & \text{otherwise} \end{cases}$$

to capture credibility losses due to periods of an inflation shortfall $CL_{it}^{(-)}$ and overshooting $CL_{it}^{(+)}$ with respect to the midpoint of the inflation objective. Tab. 2 presents summary statistics on the credibility loss indicators, revealing significant differences in the characteristics of $CL_{it}^{(-)}$ and $CL_{it}^{(+)}$. Credibility losses due to overshooting are almost twice as high on average and exhibit 3.5 times the standard deviation of inflation shortfalls. To quantify the effects of credibility losses on expectation anchoring, we specify the following empirical model

$$probT_{it}^{h} = c + \beta_1 CL_{it}^{+} + \beta_2 CL_{it}^{-} + \gamma\sigma_{it}^{\pi 24m} + \nu_i + \nu_Y + \varepsilon_{it}. \tag{20}$$

Besides our main measure of anchoring $probT_{it}^{h}$, we consider several outcome variables of interest on the left-hand side of model (20).

Tab. 9 presents the results for forecast horizons of four and six years. To get an idea of the relationship between credibility losses and contemporaneous inflation, column (1) shows that overshooting is related to contemporaneous inflation realizations above target, while shortfall has a negative sign but is not statistically significant.

Table 2: Summary statistics of credibility losses

Variable	Obs	Mean	Std. Dev.	Min	Max
$CL^{(-)}$	4,456	.92	1.39	0	6.2
$CL^{(+)}$	4,456	1.63	4.82	0	70.6

Notes. Data is pooled across all countries, sample period 2005m3-2020m4.

As suggested by the previous analysis, the two credibility loss indicators have asymmetric effects on anchoring properties. Credibility loss due to inflation shortfalls are associated with significantly lower probability of inflation being close to target, while credibility loss due to overshooting does not compromise expectations anchoring at conventional levels of statistical significance, cf. columns (2) and (3). Considering the distance of the mean prediction from target, both inflation shortfalls and overshooting have statistically significant effects, shifting the mean forecast in the expected direction, cf. column (8) and (9). Meanwhile, credibility losses do shift the tails of the cross-sectional distribution in the expected direction, cf. columns (4)-(7).

[Tab. 9 about here]

Our findings are consistent with forecasters' responses from a survey asking what influences their long-term inflation projections. Vincent-Humphreys, Dimitrova, and Falck (2019) present data showing that while 80 percent consider the central banks inflation target, 55 percent also use trends in actual inflation to form longer-term expectations. Our empirical results suggest that the cross-section of professional forecasters attaches different weights to the inflation target and the recent inflation track record, leading to changes in the tails of the cross-sectional distribution over time (Patton and Timmermann, 2010).

Ehrmann (2015) documents lower expectations anchoring during periods of inflation persistently undershooting the inflation target, while persistent target overshooting is not lowering anchoring. He considers short-term inflation expectations of up to one year ahead forecasts, measuring the effect of pass-through of current inflation on inflation expectations, forecasters' disagreement and forecast revisions. His sample covers ten industrialized economies from January 1990 to December 2014. Our results confirm his findings for long-term inflation expectations, a later sample period and a country sample that includes EMEs.

In a final step, we would like to know whether the shift in the tails of the distribution conditional on low credibility of the central bank's inflation target depends on the target formulation. To this end, we interact the credibility loss terms with our dummy variables of hybrid inflation targets and pure point targets, giving rise to the following model

$$\begin{aligned} probT^h_{it} =& c + \beta_1 d^{hybrid}_{it} \times CL^-_{it} + \beta_2 d^{hybrid}_{it} \times CL^+_{it} + \beta_3 d^{point}_{it} \times CL^-_{it} + \beta_4 d^{point}_{it} \times CL^+_{it} \\ & + \gamma_1 d^{hybrid}_{it} + \gamma_2 d^{point}_{it} + \gamma_3 CL^+_{it} + \gamma_4 CL^-_{it} + \gamma_5 \sigma^{\pi 24m}_{it} + \nu_i + \nu_Y + \varepsilon_{it}. \end{aligned} \tag{21}$$

Tab. 10 shows the results, as before in a sample that excludes all target definitions without an unambiguous numerical definition. We would like to highlight some results. First, the risk of disanchoring due to low inflation during periods of credibility loss from undershooting is significantly lower in the presence of a point target (col. 3-4). The interaction of pure point target strategies with $CL^{(-)}$ lower this risk by -0.154 and -0.170 percentage points for forecast horizons of four and six years, respectively. The risk from disanchoring due to low inflation is much less effectively contained in the presence of hybrid targets.

We arrive at a similar conclusion for periods of credibility loss due to overshooting. The respective interaction with pure point targets is significantly lowering the measure of disanchoring due to high inflation at both forecast horizons. Overall, these findings are consistent with the interpretation that range targets and tolerance bands are perceived by professional forecasters as zones where monetary policy is less active (Orphanides et al., 2000). The results are further inconsistent with the hypothesis that target ranges are fostering central bank credibility (Demertzis and Viegi, 2009).

[Tab. 10 about here]

5 Robustness

As robustness and extension to the previous analysis, this section considers disagreement as the outcome variable of interest in model (19). Disagreement is a different concept for expectation anchoring than the previously defined measures with reference to the central tendency of point forecasts. Lower disagreement is associated with better expectations anchoring. From a central bank perspective, disagreement is undesirable as models with imperfect information show that welfare costs of nominal rigidities are proportional to the amount of disagreement about price dynamics in the economy (Woodford, 2002; Mankiw, Reis, and Wolfers, 2004). Less dispersed beliefs about inflation might further enhance the expectation channel of monetary policy transmission (Capistran and Timmermann, 2009).

Tab. 11 presents the results on disagreement, measured by the cross-sectional interquartile range derived from the estimated continuous distribution function of cross-sectional inflation point forecasts. We find a strong and positive effect of inflation volatility on disagreement across all forecast horizon, in line with previous empirical findings (Ball, 1992; Dovern, Fritsche, and Slacalek, 2012). Further, point targets and hybrid targets are associated with lower levels of disagreement at medium-term forecast horizons of two to four years. We take this finding as further evidence for stronger anchoring in the presence of a numerical point target and emphasis on a numerical midpoint within a range or tolerance band.

Our findings sharpen previous empirical work on the effect of IT on forecast disagreement, while being broadly consistent with earlier results. Johnson (2002) finds in a sample of 11 advanced economies that the IT framework is not able to lower disagreement, a result later confirmed by Cecchetti and Hakkio (2010) and Siklos (2013). Confirming the non-result for advanced countries, Capistran and Ramos-Francia (2010) show that the adoption of IT lowers forecast disagreement in emerging market economies. Their work uses Consensus Economics forecast data for 25 countries, ending in November 2006 and limited to short-term forecast horizons of up to one calendar year.

[Tab. 11 about here]

6 Conclusion

The adoption of a quantitative target for inflation is commmon practice among central banks. While there is strong convergence toward a target between two to three percent, there remains remarkable heterogeneity with respect to the exact formulation of the inflation target. Do alternative inflation target formulations matter for expecations anchoring?

This paper provides evidence that a point target increases the degree of anchoring of inflation expectations over horizons of two to six years compared to central banks with a mere quantitative definition of price stability. Based on a panel of 29 countries, we show that a point target steers inflation expectations closer to the inflation aim.

Focussing only on the subset of countries operating with a numerical definition of the inflation objective, we find that the unconditional effects of point targets and hybrid targets are quantitative significant, increasing the probability of inflation falling within a narrow interval around the defined objective compared to target ranges. We find that inflation point targets are most successful in limiting upside and downside risks to the inflation outlook conditional on persistent deviations of inflation realizations from target, while hybrid strategies e.g. point targets with a tolerance band leave more room for interpretation of the inflation target during such episodes. The results are further consistent with the view that range targets are interpreted by professional forecasters as zones where monetary policy is less responsive.

The analysis is based on a measure of expectation anchoring derived from the cross-sectional distribution of private sector point forecasts. A contribution of the paper is to analyze the shape and asymmetry of cross-sectional beliefs about inflation for forecast horizons of two to six years in the context of expectation anchoring. The empirical measures are shown to be consistent with a risk management model with risk-averse and potentially asymmetric central bank preferences.

The results of this paper contribute to an unsettled debate about pros and cons of different types of inflation targets (Apel and Clausen, 2017; Chung et al., 2020). We document that it is common practice for central banks to change elements in the specification of their numerical inflation target. This paper suggests that point targets or focal points should be considered as an important device to improve expectations anchoring and the balance of risks to the inflation outlook.

Some limitations apply to our results. The findings are based on a survey among professional forecasters who are relatively well informed about central bank objectives and attentive to changes in the operational framework. While the views of professional forecasters are widely reported in the news and is likely to influence other agents in the economy (Carroll, 2003), recent research finds that households and firms have a poor understanding of inflation dynamics and are generally inattentive to central bank announcements.[11] If central bankers want to exploit the inflation target formulation as a policy tool to manage the inflation outlook, then these deficiencies might call for improved central bank communication (Coibion et al., 2020).

[11] See Afrouzi et al. (2015), Coibion, Gorodnichenko, and Weber (2019), and Lewis, Makridis, and Mertens (2020).

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Tables

Table 3: Summary statistics of survey data and inflation risk measures

	Full sample				AEs				EMEs			
	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
SURVEY DATA												
distance, mean to target (midpoint)												
fh2	0.53	0.82	0.00	13.89	0.39	0.39	0.00	1.99	0.70	1.11	0.00	13.89
fh4	0.36	0.48	0.00	5.09	0.26	0.28	0.00	1.60	0.48	0.62	0.00	5.09
fh6	0.32	0.38	0.00	3.53	0.23	0.27	0.00	1.76	0.41	0.45	0.00	3.53
disagreement (sd)												
fh2	0.38	0.25	0.06	3.45	0.32	0.12	0.11	1.10	0.43	0.32	0.06	3.45
fh4	0.39	0.27	0.00	2.42	0.33	0.19	0.04	1.24	0.45	0.32	0.00	2.42
fh6	0.37	0.28	0.00	2.45	0.29	0.18	0.00	0.88	0.44	0.34	0.00	2.45
skewness												
fh2	0.023	0.21	-0.60	0.65	0.0032	0.20	-0.55	0.63	0.047	0.21	-0.60	0.65
fh4	0.054	0.28	-0.77	0.87	0.028	0.27	-0.72	0.78	0.087	0.28	-0.77	0.87
fh6	0.092	0.30	-0.81	1.72	0.11	0.29	-0.78	1.18	0.072	0.30	-0.81	1.72
INFLATION RISK MEASURES												
probT												
fh2	0.15	0.14	0.00	0.82	0.18	0.14	0.00	0.58	0.12	0.13	0.00	0.82
fh4	0.21	0.21	0.00	1.00	0.24	0.19	0.00	0.97	0.19	0.22	0.00	1.00
fh6	0.25	0.24	0.00	1.00	0.31	0.24	0.00	1.00	0.20	0.23	0.00	1.00
DAL												
fh2	0.39	0.35	0.00	1.00	0.51	0.33	0.00	1.00	0.28	0.32	0.00	1.00
fh4	0.33	0.27	0.00	1.00	0.39	0.27	0.01	1.00	0.27	0.25	0.00	1.00
fh6	0.32	0.26	0.00	1.00	0.36	0.27	0.00	1.00	0.29	0.25	0.00	1.00
DAH												
fh2	0.46	0.35	0.00	1.00	0.31	0.28	0.00	1.00	0.60	0.35	0.00	1.00
fh4	0.46	0.30	0.00	1.00	0.37	0.25	0.00	0.96	0.54	0.32	0.00	1.00
fh6	0.43	0.29	0.00	1.00	0.34	0.24	0.00	1.00	0.51	0.31	0.00	1.00
N	969				525				444			

Summary statistics of survey data from Consensus, converted into fixed-horizon forecasts over horizons of two, four and six years. The measure of skewness is computed as a ratio of the mean relative to lowest and highest observations, see the main text for details. AEs denote advanced economies, EMEs denote emerging market economies.

Table 4: Determinants of inflation risk measures

	(1) distAbs	(2) stdev	(3) skewness Ratio	(4) probT	(5) DAL	(6) DAH
sd infl. (24m)	0.405***	0.177***	0.000906	-0.0357***	-0.0309***	0.0665***
	(0.0120)	(0.00372)	(0.00689)	(0.00521)	(0.00732)	(0.00743)
d^{fh3}	-0.124***	0.0419***	0.0187	0.0411***	-0.0487***	0.00755
	(0.0202)	(0.00706)	(0.0120)	(0.00906)	(0.0127)	(0.0129)
d^{fh4}	-0.170***	0.0509***	0.0317***	0.0644***	-0.0670***	0.00262
	(0.0202)	(0.00706)	(0.0120)	(0.00906)	(0.0127)	(0.0129)
d^{fh5}	-0.198***	0.0413***	0.0550***	0.0849***	-0.0763***	-0.00853
	(0.0202)	(0.00706)	(0.0120)	(0.00906)	(0.0127)	(0.0129)
d^{fh6}	-0.212***	0.0304***	0.0694***	0.104***	-0.0836***	-0.0207
	(0.0202)	(0.00706)	(0.0120)	(0.00907)	(0.0127)	(0.0129)
d^{EME}	0.0445***	0.0424***	0.0382***	-0.0425***	-0.158***	0.200***
	(0.0147)	(0.00455)	(0.00857)	(0.00645)	(0.00906)	(0.00920)
Constant	0.205***	0.191***	-0.0110	0.184***	0.464***	0.352***
	(0.0623)	(0.0222)	(0.0216)	(0.0164)	(0.0230)	(0.0233)
adj. R-squared	0.24	0.28	0.04	0.06	0.12	0.18
N.Obs	5368	9574	4580	4628	4628	4628
year control	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Pooled OLS, standard errors in parentheses. ***/**/*/ denote statistical significance at the 1%/5%/10% level.

Table 5: Effect of numerically defined target

A. Numerical targe definition

	(1) *probT* (h=2)	(2) *probT* (h=3)	(3) *probT* (h=4)	(4) *probT* (h=5)	(5) *probT* (h=6)
sd infl. (24m)	-0.0195***	-0.0184	-0.0313**	-0.0497***	-0.0308**
	(0.00732)	(0.0137)	(0.0134)	(0.0120)	(0.0152)
$d^{numTarget}$	0.0183	-0.00214	-0.0216	-0.0309**	-0.0386***
	(0.0231)	(0.0176)	(0.0134)	(0.0126)	(0.0141)
Constant	0.172***	0.216***	0.241***	0.264***	0.253***
	(0.0250)	(0.0225)	(0.0199)	(0.0226)	(0.0181)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	926	926	926	926	924
N.Countries	29	29	29	29	29
adj. R-squared	0.07	0.03	0.04	0.06	0.04

B. Role of inflation target types

	probT (h=2)	*probT* (h=3)	*probT* (h=4)	*probT* (h=5)	*probT* (h=6)
sd infl. (24m)	-0.0193**	-0.0184	-0.0316**	-0.0501***	-0.0313**
	(0.00732)	(0.0135)	(0.0131)	(0.0114)	(0.0154)
$d^{numRange}$	-0.0276	-0.0640*	-0.0855*	-0.102**	-0.0926**
	(0.0409)	(0.0349)	(0.0466)	(0.0445)	(0.0425)
$d^{numPoint}$	0.0733***	0.0760***	0.0670***	0.0725***	0.0585***
	(0.0186)	(0.0180)	(0.0233)	(0.0253)	(0.0183)
Constant	0.150***	0.185***	0.205***	0.221***	0.210***
	(0.0255)	(0.0226)	(0.0282)	(0.0287)	(0.0231)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	926	926	926	926	924
N.Countries	29	29	29	29	29
adj. R-squared	0.09	0.05	0.06	0.08	0.05
p-val(F-test)	0.003	0.000	0.000	0.000	0.000

Notes. Standard errors based on Driscoll and Kraay (1998) in parentheses. ***/**/*/ denote statistical significance at the 1%/5%/10% level. F-test for $H_0 : d^{numRange} = d^{numPoint}$.

Table 6: Effect of target types on *probT*

	(1) (h=2)	(2) (h=3)	(3) (h=4)	(4) (h=5)	(5) (h=6)
sd infl. (24m)	-0.0121	-0.0112	-0.0241*	-0.0441***	-0.0271*
	(0.00757)	(0.0145)	(0.0143)	(0.0127)	(0.0160)
d^{hybrid}	0.108***	0.138***	0.143***	0.157***	0.133***
	(0.0151)	(0.0225)	(0.0238)	(0.0274)	(0.0228)
d^{point}	0.0803***	0.0984***	0.117***	0.153***	0.163***
	(0.0246)	(0.0248)	(0.0363)	(0.0327)	(0.0325)
Constant	0.0494**	0.0703**	0.101***	0.139***	0.0916***
	(0.0190)	(0.0338)	(0.0344)	(0.0311)	(0.0224)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	855	855	855	855	853
N.Countries	28	28	28	28	28
adj. R-squared	0.11	0.06	0.07	0.09	0.07
p-val(F-test)	0.205	0.098	0.441	0.909	0.332

Notes. Standard errors based on Driscoll and Kraay (1998) in parentheses. ***/**/*/ denote statistical significance at the 1%/5%/10% level.

Table 7: Effect of target types on disanchoring measures (DAL, DAH)

A. Disanchoring from low inflation (DAL)

	(1) DAL (h=2)	(2) DAL (h=3)	(3) DAL (h=4)	(4) DAL (h=5)	(5) DAL (h=6)
sd infl. (24m)	-0.0139	-0.0312**	-0.0164	-0.0122	-0.0210
	(0.0114)	(0.0141)	(0.0159)	(0.0169)	(0.0225)
d^{hybrid}	0.234***	0.173*	0.139	0.132*	0.134*
	(0.0838)	(0.0925)	(0.0870)	(0.0771)	(0.0674)
d^{point}	0.196*	0.0650	-0.0250	-0.0323	-0.0288
	(0.105)	(0.118)	(0.101)	(0.0894)	(0.0757)
Constant	0.345***	0.358***	0.303***	0.314***	0.338***
	(0.0578)	(0.0777)	(0.0721)	(0.0655)	(0.0623)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	855	855	855	855	853
N.Countries	28	28	28	28	28
adj. R-squared	0.21	0.14	0.13	0.11	0.12
p-val(F-test)	0.530	0.039	0.001	0.000	0.000

B. Disanchoring from high inflation (DAH)

	(1) (h=2)	(2) (h=3)	(3) (h=4)	(4) (h=5)	(5) (h=6)
sd infl. (24m)	0.0260*	0.0424***	0.0405**	0.0564***	0.0481***
	(0.0137)	(0.0118)	(0.0163)	(0.0186)	(0.0181)
d^{hybrid}	-0.342***	-0.311***	-0.282***	-0.289***	-0.267***
	(0.0772)	(0.0930)	(0.0888)	(0.0781)	(0.0709)
d^{point}	-0.277***	-0.163	-0.0920	-0.121	-0.135
	(0.0933)	(0.120)	(0.110)	(0.0999)	(0.0936)
Constant	0.606***	0.571***	0.596***	0.547***	0.500***
	(0.0515)	(0.0691)	(0.0695)	(0.0597)	(0.0526)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	855	855	855	855	853
N.Countries	28	28	28	28	28
adj. R-squared	0.29	0.22	0.20	0.21	0.21
p-val(F-test)	0.217	0.013	0.000	0.001	0.007

Notes. Standard errors based on Driscoll and Kraay (1998) in parentheses. ***/**/*/ denote statistical significance at the 1%/5%/10% level.

Table 8: Asymetric effect of target types on disanchoring

	(1) *dist* (h=2)	(2) *dist* (h=6)	(3) $G05$ (h=2)	(4) $G05$ (h=6)	(5) $G95$ (h=2)	(6) $G95$ (h=6)
sd infl. (24m)	0.522***	0.230**	0.282**	-0.0125	0.880***	0.501***
	(0.186)	(0.0887)	(0.120)	(0.0513)	(0.273)	(0.153)
d^{hybrid}	-0.580***	-0.373***	-0.493***	-0.477***	-0.859***	-0.358**
	(0.140)	(0.0982)	(0.155)	(0.123)	(0.197)	(0.157)
d^{point}	-0.471**	-0.248*	-0.370*	-0.360**	-0.730**	-0.209
	(0.197)	(0.125)	(0.192)	(0.143)	(0.281)	(0.214)
Constant	-0.313	0.0832	-1.167***	-0.229*	0.104	0.417***
	(0.190)	(0.0949)	(0.222)	(0.118)	(0.421)	(0.139)
country FE	Yes	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N.Obs	964	961	855	853	855	853
N.Countries	28	28	28	28	28	28
adj. R-squared	0.28	0.22	0.21	0.07	0.33	0.22
p-val(F-test)	0.329	0.045	0.249	0.106	0.406	0.180

Notes. Standard errors based on Driscoll and Kraay (1998) in parentheses. ***/**/*/ denote statistical significance at the 1%/5%/10% level.

Table 9: Credibility loss indicator

	(1) $\pi - \pi^*$	(2) probT(4)	(3) probT(6)	(4) DAL(4)	(5) DAL(6)	(6) DAH(4)	(7) DAH(6)	(8) Mean(4)	(9) Mean(6)
$CL^{(-)}$	-0.101	-0.0145*	-0.0140*	0.0511***	0.0483***	-0.0366***	-0.0343***	-0.0218*	-0.0168*
	(-1.64)	(-1.87)	(-1.94)	(6.52)	(6.27)	(-4.57)	(-6.87)	(-1.80)	(-1.96)
$CL^{(+)}$	0.141***	-0.000651	0.000736	-0.00502**	-0.00957***	0.00567**	0.00884***	0.0565***	0.0444***
	(3.62)	(-0.40)	(0.57)	(-2.47)	(-5.62)	(2.10)	(4.36)	(5.08)	(5.62)
sd infl. (24m)	-0.156	-0.0312	-0.0375*	0.0281	0.0444**	0.00307	-0.00694	0.0723	0.0259
	(-0.62)	(-1.56)	(-1.89)	(1.43)	(2.05)	(0.13)	(-0.41)	(1.35)	(0.74)
Constant	-0.327	0.239***	0.240***	0.299***	0.314***	0.462***	0.446***	2.547***	2.465***
	(-1.21)	(10.33)	(14.41)	(17.83)	(14.57)	(23.66)	(32.64)	(61.17)	(38.88)
country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N.Obs	4409	926	924	926	924	926	924	932	930
N.Countries	29	29	29	29	29	29	29	29	29
adj. R-squared	0.31	0.05	0.05	0.16	0.17	0.15	0.18	0.47	0.42

Notes. t statistics in parentheses ***/**/*/ denote statistical significance at the 1%/5%/10% level.

Table 10: Credibility loss and target types

	(1) probT(4)	(2) probT(6)	(3) DAL(4)	(4) DAL(6)	(5) DAH(4)	(6) DAH(6)
d^{hybrid}	0.162***	0.121***	0.122*	0.130**	-0.284***	-0.252***
	(5.03)	(3.65)	(1.87)	(2.31)	(-4.10)	(-4.59)
d^{point}	0.143	0.128	0.0857	0.161*	-0.229**	-0.289***
	(1.61)	(1.63)	(0.95)	(1.95)	(-2.25)	(-3.06)
$CL^{(+)}$	0.0130	0.00654	-0.0412***	-0.0305**	0.0283**	0.0239**
	(1.65)	(0.77)	(-2.67)	(-2.19)	(2.08)	(2.20)
$CL^{(-)}$	-0.0183	-0.0374*	0.108***	0.104***	-0.0902***	-0.0669***
	(-1.29)	(-1.77)	(5.38)	(4.15)	(-9.09)	(-4.51)
$CL^{(+)} \times d^{hybrid}$	-0.0136*	-0.00585	0.0371**	0.0225	-0.0235*	-0.0167
	(-1.94)	(-0.76)	(2.32)	(1.59)	(-1.72)	(-1.58)
$CL^{(-)} \times d^{hybrid}$	0.00611	0.0272	-0.0581**	-0.0531*	0.0520***	0.0259
	(0.39)	(1.16)	(-2.42)	(-1.94)	(3.79)	(1.61)
$CL^{(+)} \times d^{point}$	-0.0142	-0.00392	0.0644***	0.0341**	-0.0502***	-0.0302**
	(-1.06)	(-0.30)	(3.99)	(2.42)	(-3.15)	(-2.25)
$CL^{(-)} \times d^{point}$	-0.00193	0.0356	-0.154***	-0.170***	0.156***	0.135***
	(-0.05)	(0.89)	(-5.06)	(-4.97)	(6.18)	(4.62)
sd infl. (24m)	-0.0258	-0.0325	0.0168	0.0262	0.00907	0.00622
	(-1.12)	(-1.30)	(0.74)	(1.14)	(0.45)	(0.33)
Constant	0.0854**	0.158***	0.249***	0.250***	0.665***	0.592***
	(2.13)	(4.01)	(3.51)	(3.80)	(11.73)	(12.18)
country FE	Yes	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N.Obs	855	853	855	853	855	853
N.Countries	28	28	28	28	28	28
adj. R-squared	0.08	0.08	0.31	0.30	0.32	0.31

Notes. t statistics in parentheses ***/**/*/ denote statistical significance at the 1%/5%/10% level.

Table 11: Effect of target types on disagreement (IQR)

	(1) IQR (h=2)	(2) IQR (h=3)	(3) IQR (h=4)	(4) IQR (h=5)	(5) IQR (h=6)
sd infl. (24m)	0.213***	0.189***	0.244***	0.195***	0.181***
	(0.0579)	(0.0568)	(0.0461)	(0.0484)	(0.0466)
d^{hybrid}	-0.129***	-0.0723*	-0.117**	-0.0306	0.0454
	(0.0435)	(0.0396)	(0.0503)	(0.0416)	(0.0478)
d^{point}	-0.128**	-0.00793	-0.0903	-0.0244	0.0548
	(0.0490)	(0.0654)	(0.0572)	(0.0653)	(0.0648)
Constant	0.455***	0.386***	0.346***	0.319***	0.225***
	(0.0964)	(0.0835)	(0.0896)	(0.0810)	(0.0468)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	855	855	855	855	853
N.Countries	28	28	28	28	28
adj. R-squared	0.26	0.18	0.22	0.14	0.13
p-val(F-test)	0.964	0.176	0.593	0.909	0.813

Notes. Standard errors based on Driscoll and Kraay (1998) in parentheses. ***/**/*/ denote statistical significance at the 1%/5%/10% level.

Online Appendix

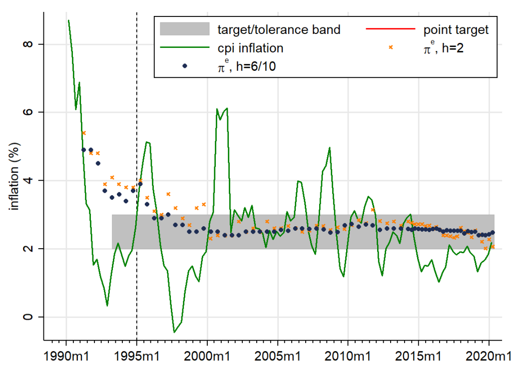
Anchoring of long-term inflation expectations: Do inflation target formulations matter?

by Christoph Grosse-Steffen[1]

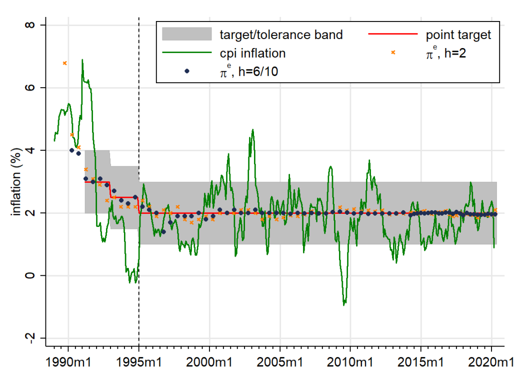
A Classification

Figure A.1: Targets for monetary policy, AEs (1)

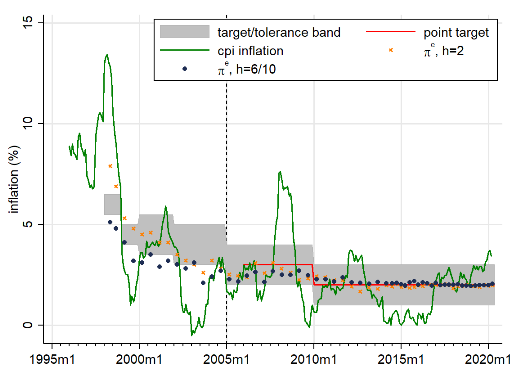
(a) Australia



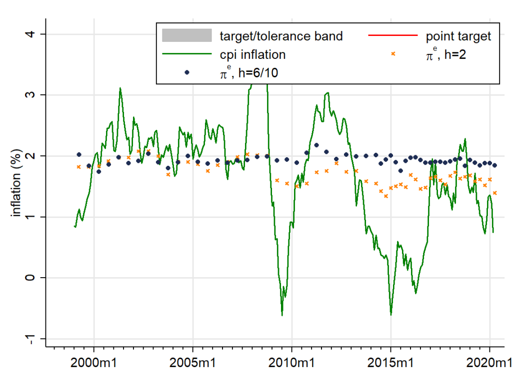
(b) Canada



(c) Czech Republic



(d) Euro area

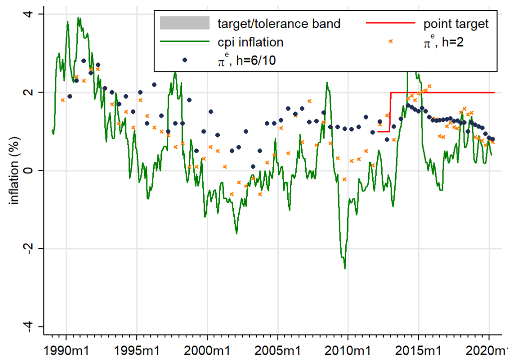


Notes: Green line=YoY CPI inflation. Vertical, dotted line=start date of a stable inflation target, following Roger (2009), with adjustments and extensions. No Consensus Forecast data available.

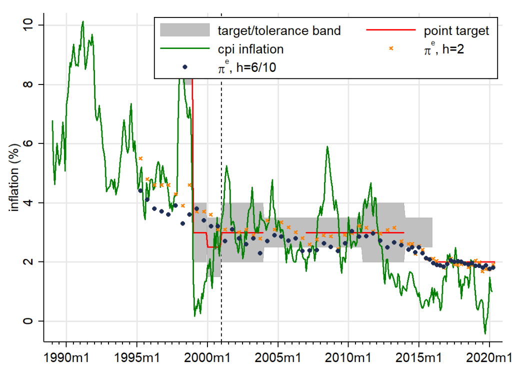
[1] *Contact:* Banque de France, 31 rue des Petits-Champs, 75001 Paris, France. Email: christoph.grossesteffen(at)banque-france.fr, tel.: +33 (0)1 42 92 49 42.

Figure A.1: Targets for monetary policy, AEs (2)

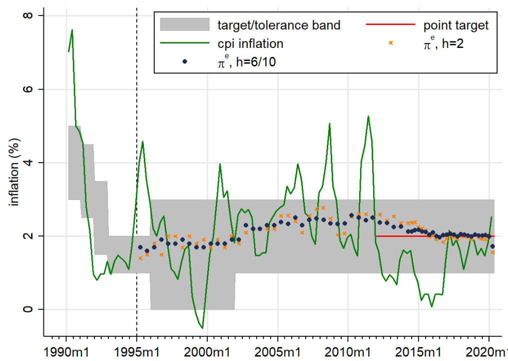
(e) Japan



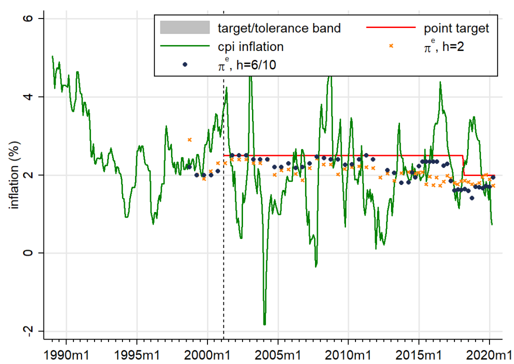
(f) South Korea



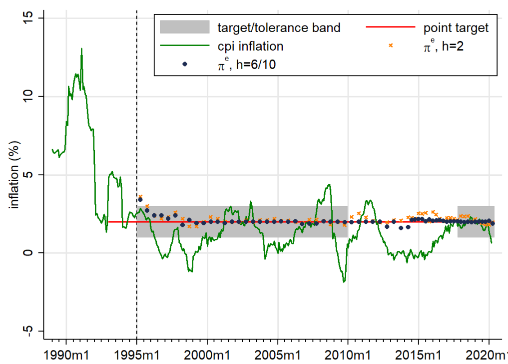
(g) New Zealand



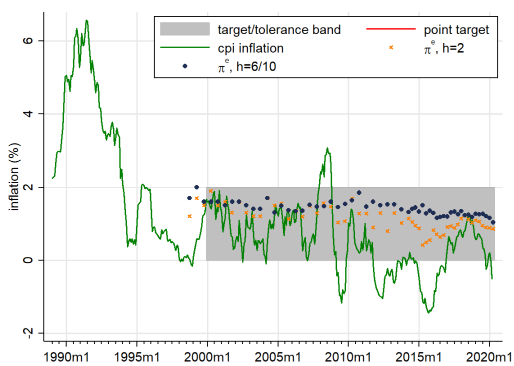
(h) Norway



(i) Sweden



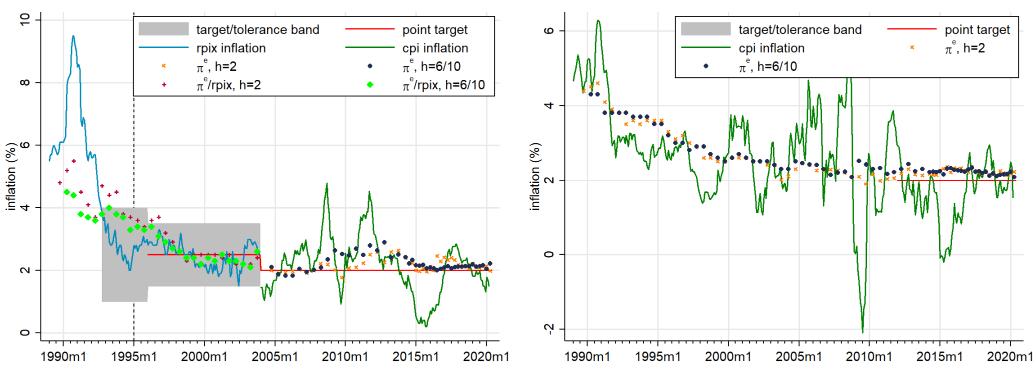
(j) Switzerland



Notes: Green line=YoY CPI inflation. Vertical, dotted line=start date of a stable inflation target, following Roger (2009), with adjustments and extensions. Blue dots=mean point forecast, $h = 6$ to 10 years. Yellow x=mean point forecast, $h = 2$ years.

Figure A.1: Targets for monetary policy, AEs (3)

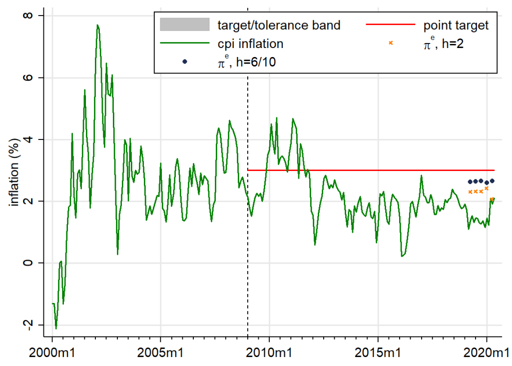
(k) United Kingdom (l) United States



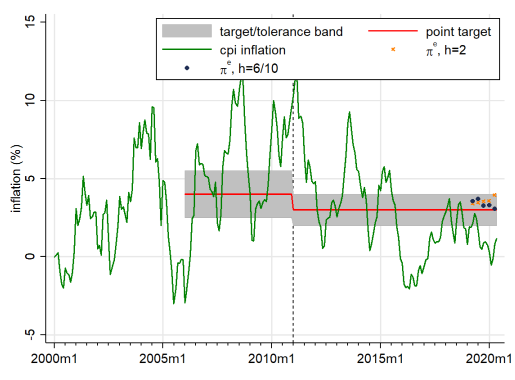
Notes: Green line=YoY CPI inflation. Vertical, dotted line=start date of a stable inflation target, following Roger (2009), with adjustments and extensions. Blue dots=mean point forecast, $h = 6$ to 10 years. Yellow x=mean point forecast, $h = 2$ years.

Figure A.2: Targets for monetary policy, EMEs (1)

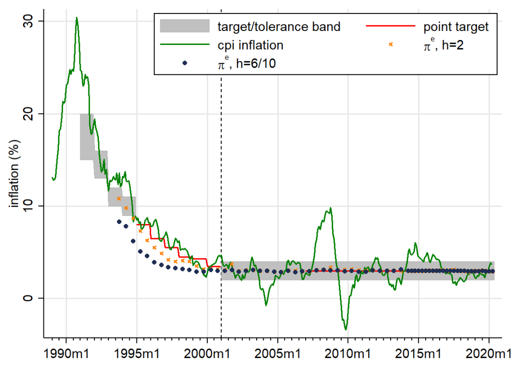
(a) Albania



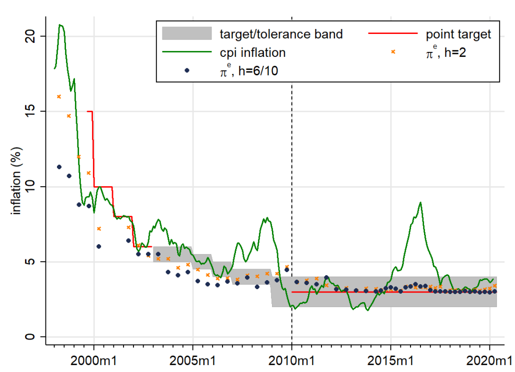
(b) Armenia



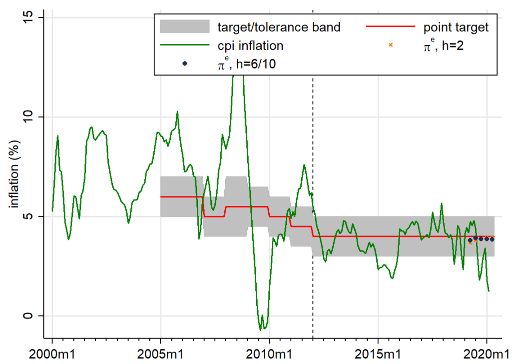
(c) Chile



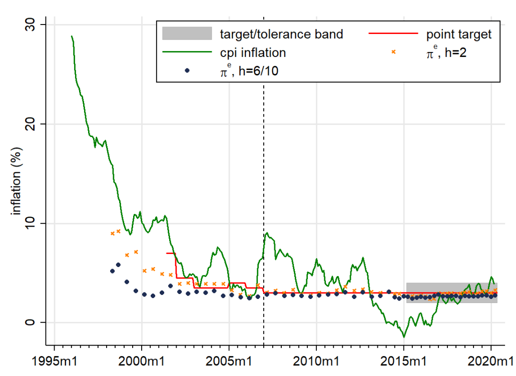
(d) Colombia



(e) Guatemala



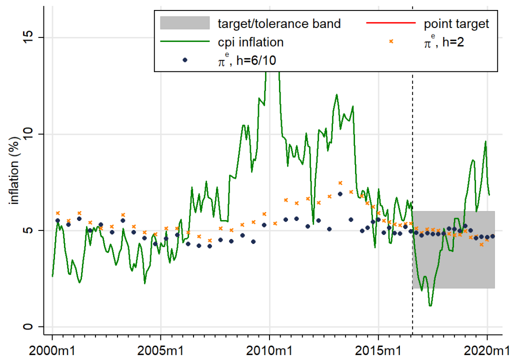
(f) Hungary



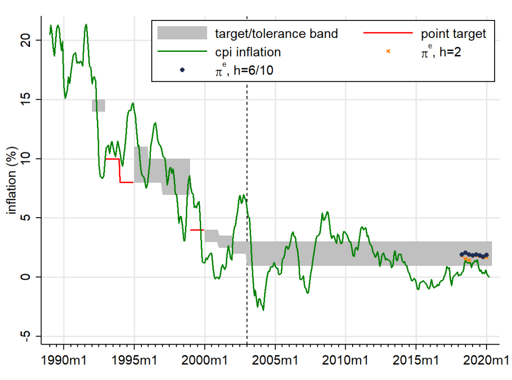
Notes: Green line=YoY CPI inflation. Vertical, dotted line=start date of a stable inflation target, following Roger (2009), with adjustments and extensions. Blue dots=mean point forecast, $h = 6$ to 10 years. Yellow x=mean point forecast, $h = 2$ years.

Figure A.2: Targets for monetary policy, IT countries (2)

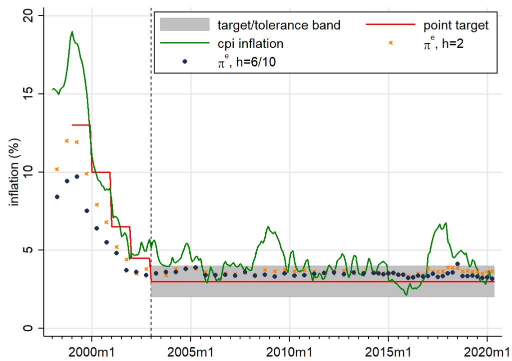
(g) India



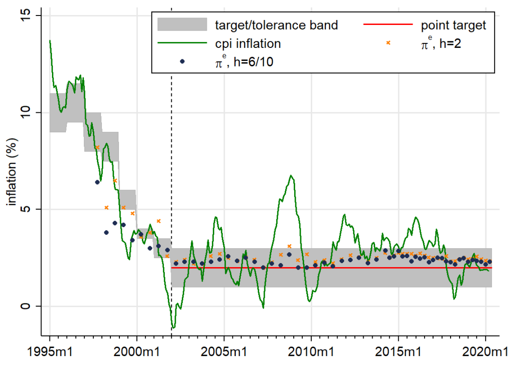
(h) Israel



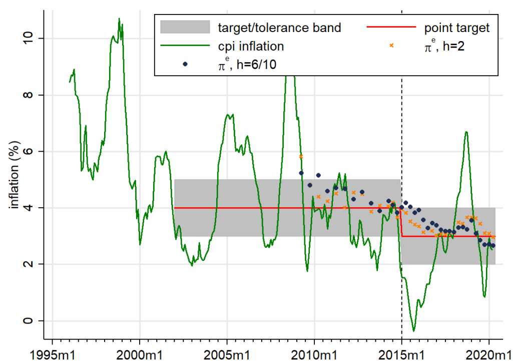
(i) Mexico



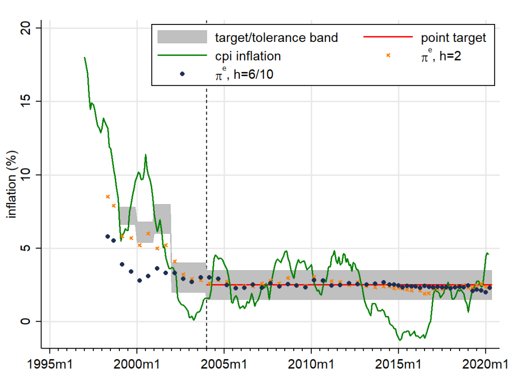
(j) Peru



(k) Philippines



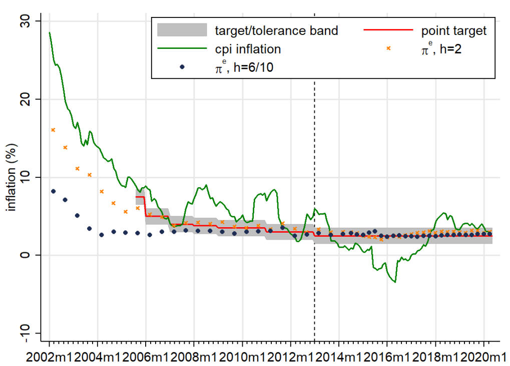
(l) Poland



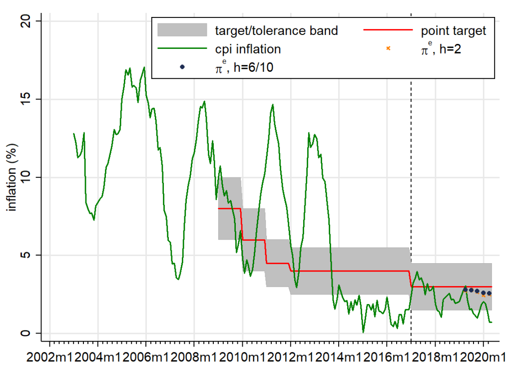
Notes: Green line=YoY CPI inflation. Vertical, dotted line=start date of a stable inflation target, following Roger (2009), with adjustments and extensions. Blue dots=mean point forecast, $h = 6$ to 10 years. Yellow x=mean point forecast, $h = 2$ years.

Figure A.2: Targets for monetary policy, EMEs (3)

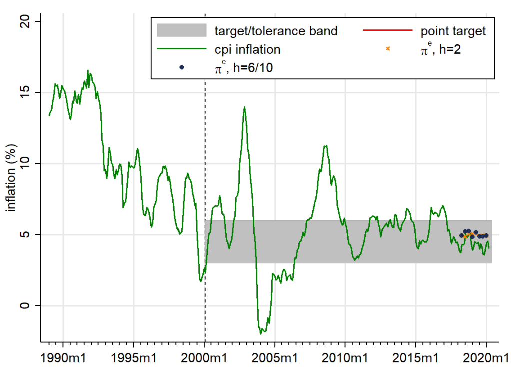
(m) Romania



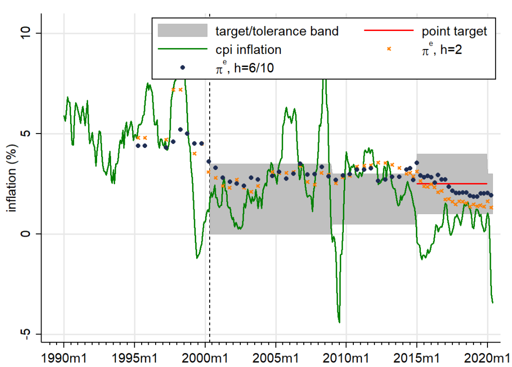
(n) Serbia



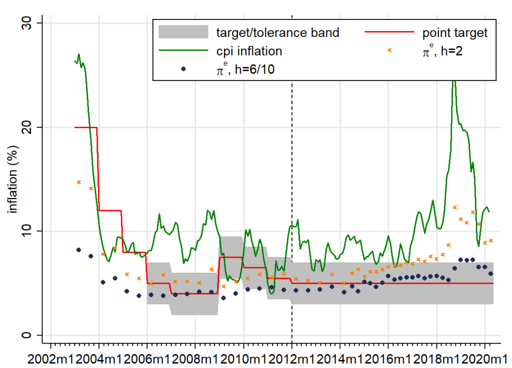
(o) South Africa



(p) Thailand



(q) Turkey



Notes: Green line=YoY CPI inflation. Vertical, dotted line=start date of a stable inflation target, following Roger (2009), with adjustments and extensions. Blue dots=mean point forecast, $h = 6$ to 10 years. Yellow x=mean point forecast, $h = 2$ years.

Table A.1: Target classification

	(1) `NoExplAn`	(2) `QuantDef`	(3) `RangeTar`	(4) `Range-Point`	(5) `Point-Tol`	(6) `PointTar`	IT introdate	stable
Advanced Economies (AE)								
Australia	–	–	1993m4	–	–	–	1993m4	1993m4
Canada	–	–	–	–	1991m3 -	–	1991m3	1995m1
Czech Republic	–	–	1998m1-2005m12	–	2006m1-	–	1998m1	2005m1
Euro area	–	1999m1 -	–	–	–	–	*no IT*	1999m1
Japan	1990m1-2006m2	2006m3-2012m1	–	–	–	2012m2 -	2012m2	1990m1
New Zealand	–	–	1990m1 - 2011m12	2012m1 -	–	–	1990m3	1993m1
Norway	–	–	–	–	–	2001m3 -	2001m3	2001m3
South Korea	–	–	2004m1-2006m12; 2014m1-2015m12;	–	1998m4-2003m12; 2007m1-2013m12;	2016m1-	1998m3	2001m1
Sweden	–	–	–	–	1995m1-2009m12; 2017m10-	2010m1-2017m9	1993m1	1993m1
Switzerland	–	1990m1-1999m11	1999m12 -	–	–	–	*no IT*	1990m1
United Kingdom	1990m1-1992m9	–	1992m10-1995m5	–	1995m6-2003m12	2004m1-	1992m10	1992m10
United States	1990m1-2012m2	–	–	–	–	2012m3 - 2020m7	*no IT*	1990m1
Emerging Market Economies (EME)								
Albania	–	–		–	–	2009m1-	2009m1	2009m1
Armenia	–	–	–	–	2006m1-	–	2006m1	2011m1
Chile	–	–	1991m1-1994m12	–	2001m1-	1995m1-2000m12	1991m1	2001m1
Colombia	–	–	2003m1-2009m12	–	2010m1-	1999m9-2002m12	1999m9	2010m1
Guatemala	–	–	–		2005m1-	–	2005m1	2012m1
Hungary	–	–	–	–	2015m3-	2001m6-2015m2	2001m6	2007m1
India	–	–	–	2016m8-	–	–	2016m8	2016m8
Israel	–	–	1992m1-1992m12; 1994m1-1998m12; 2000m1-	–	–	1993m1-1993m12; 1999m1-1999m12	1997m6	2003m1
Mexico	–	–	–	–	2003m1-	1999m1-2002m12	1999m1	2003m1
Peru	–	–	1994m1-2001m12	–	2002m1-	–	1994m1	2002m1
Poland	–	–	1999m1-2003m12	–	2004m1	–	1998m10	2004m1
Philippines	–	–	–	–	2002m1-	–	2002m1	2015m1
Romania	–	–	–	–	2005m8	–	2005m8	2013m1
Serbia	–	–	–	–	2009m1-	–	2009m1	2017m1
South Africa	–	–	2000m2-	–	–	–	2000m2	2000m2
Thailand	–	–	2000m5-2014m12; 2020m1-	2015m1-2019m12	–	–	2000m5	2000m5
Turkey	–	–	–	–	2006m1-	2003m12-2005m12	2006m1	2012m1

Notes: Targets for non-official inflation targeting (IT) countries are only considered for United States, United Kingdom, Euro area, Japan and Switzerland. Countries reporting the the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) to be an inflation targeter, but have changed the target between 2018 and 2020 are excluded from the analysis, as long-term expectations might still respond to changes in the target (*Brazil, Costa Rica, Dominican Republic, Georgia, Indonesia, Kazakhstan, Ukraine, Uruguay*). Also, IT-countries with stable target values for which Consensus data is not available are excluded (*Ghana, Iceland, Jamaica, Uganda*). Source: Related literature (Castelnuovo, Nicoletti-Altimari, and Rodriguez-Palenzuela, 2003; Mishkin and Schmidt-Hebbel, 2002; Roger, 2009; Hammond, 2012), , the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) and central bank websites.

B Goodness of fit with sample data

This section provides details on the first step of the derivation of the continuous density functions proposed in the paper. This step provides us with two important results. First, where are the observed highest and lowest observations across panelists located in an estimated, parameterized distribution function? This information will inform the *location constraint* in the simulated method of moments (SMM) estimation. Second, which family of distribution functions fits the survey data best? For the 'goodness of fit' analysis, we fit two parametric models to sample data from consumer price inflation point forecasts that are available at the shorter forecast horizons of 'current calendar year' and 'next calendar year' forecasts. We use raw survey data on the "next calendar year' projections.

B.1 Parametric analysis

For the 'goodness of fit' analysis, we fit two parametric models to sample data from point forecasts on consumer price inflation that are available from Consensus at the shorter forecast horizons of 'current calendar year' and 'next calendar year' forecasts at a monthly frequency. We use raw survey data on the 'next calendar year' projections and fit the generalized beta distribution and a skew extended $t-$distribution, labeled here as *skew t*. Both distributions share a couple of similarities, namely to feature skewness and being highly flexible to fit data. They differ mainly due to the bounded support of the generalized beta, while the skew t is defined on the whole real line $\mathbb{R}$.

B.1.1 The generalized beta distribution

Let the random variable x be distributed as a generalized beta distribution of parameters (a, b, l, r) if $(x-l)/(r-l)$ is distributed as $B(a, b)$. Let $F_B(x; a, b, l, r)$ denote the CDF of the generalized beta for a random variable $x \in [l, r]$, then we have

$$F_B(x; a, b, l, r) = \begin{cases} 0, & \text{if } x \leq l \\ \frac{Beta((x-l)/(r-l); a, b)}{B(a,b)}, & \text{if } l < x \leq r \\ 1, & \text{if } x > r \end{cases}$$

where $Beta(x; a, b)$ is the incomplete Beta function, given by

$$Beta(x; a, b) := \int_0^x t^{a-1}(1-t)^{b-1} dt.$$

The distribution's PDF is given by

$$f_B(x; a, b, l, r) := \frac{1}{(r-l)B(a,b)} \left(\frac{x-l}{r-l}\right)^{a-1} \left(\frac{r-x}{r-l}\right)^{b-1} \mathbb{I}_{[l,r]}(x; a, b),$$

where $I(x; \cdot, \cdot)$ denotes the incomplete beta function ratio.

B.1.2 The skew extended t-distribution

For the definition of the skew t, we refer to the distribution proposed by Jones and Faddy (2003) as in Ganics, Rossi, and Sekhposyan (2020). Let μ in $\mathbb{R}$, $\sigma, a, b > 0$ be parameters, then the distribution's CDF is defined as

$$F_{JF}(x; \mu, \sigma, a, b) = I(z; a, b),$$
$$\text{with} \quad z = \frac{1}{2}\left(1 + \frac{\left(\frac{x-\mu}{\sigma}\right)}{\sqrt{a + b + \left(\frac{x-\mu}{\sigma}\right)^2}}\right).$$

The distribution's PDF is given by

$$f_{JF}(x; \mu, \sigma, a, b) = \frac{1}{\sigma} C_{a,b}^{-1} (1+\tau)^{a+1/2} (1-\tau)^{b+1/2},$$
$$\text{with} \quad C_{a,b} = 2^{a+b-1} B(a, b)(a+b)^{\frac{1}{2}},$$
$$\text{and} \quad \tau = \frac{x-\mu}{\sigma}\left(a + b + \left(\frac{x-\mu}{\sigma}\right)^2\right)^{-\frac{1}{2}}$$

B.1.3 Maximum likelihood estimation

We are now ready to perform ML estimation using the next calendar year projections x_{jit} of panelist $j = 1, ..., n$ for country i in period t as our observed sample data, and maximizing

$$\hat{\theta}_{it}^{(JF)} = \text{argmax}_{\theta_{it}^{(JF)} \in \Theta^{(JF)}} \sum ln\hat{L}_n(\theta_{it}^{(JF)}, x_{jit})$$
$$\text{with} \quad \hat{L} = f_{JF}(x_{jit}; \theta_{it}^{(JF)})$$

where the parameter vector collects the four parameters $\theta_{it}^{(JF)} = (\mu_{it}, \sigma_{it}, a_{it}, b_{it})$. In analogy, we perform ML estimation of the parameter vector of the generalized beta distribution as

$$\hat{\theta}_{it}^{(B)} = \text{argmax}_{\theta_{it}^{(B)} \in \Theta^{(B)}} \sum ln\hat{L}_n(\theta_{it}^{(B)}, x_{jit})$$
$$\text{with} \quad \hat{L} = f_B(x_{jit}; \theta_{it}^{(B)})$$

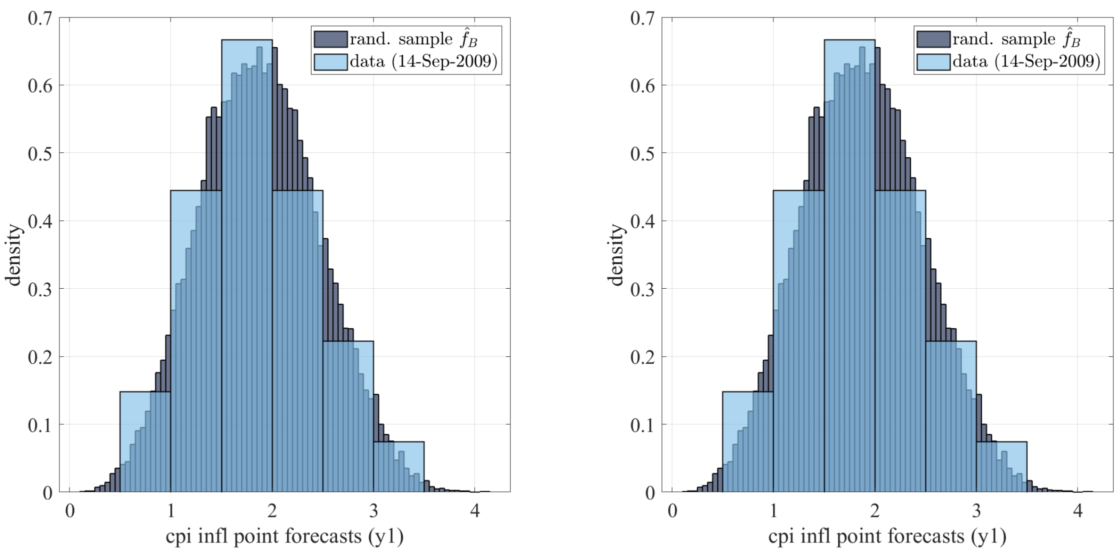
where $\theta_{it}^{(B)} = (a_{it}, b_{it}, l_{it}, r_{it})$.

B.2 Results

We estimate the vectors $\hat{\theta}_{it}^{(B)}$ and $\hat{\theta}_{it}^{(JF)}$ which we can then use for simulations in a 'goodness of fit' analysis. Fig. B.3 compares the histogram of the survey data from 14 September 2009 for US consumer price inflation forecasts with the estimated distribution functions. Both results look to be close approximations of the data. Fig. B.4 compares the empirical cdf, computed using the Kaplan-Meier nonparametric method,

Figure B.3: Histograms of survey data and parametric models

(a) pdf, generalized Beta (b) pdf, skew t (JF)



Note: Results are shown for US consumer price inflation inflation forecasts for the next calendar year of a survey published on 14 September 2009.

with the theoretical cdf of the estimated parametric density functions. Besides small differences, both models seem to represent the data reasonably well.

In order to come to a robust conclusion about model fit, we perform a Kolmogorov-Smirnoff test (KS-test) for the equality of the empirical cdf and the two candidate parametric density functions. We do this for each estimated model, thus for every period t and country i in the sample. The KS-test uses the null hypothesis that the two underlying distribution functions are identical. Values of the KS-test above 0.05 indicate that the null cannot be rejected at the 5 percent confidence level.

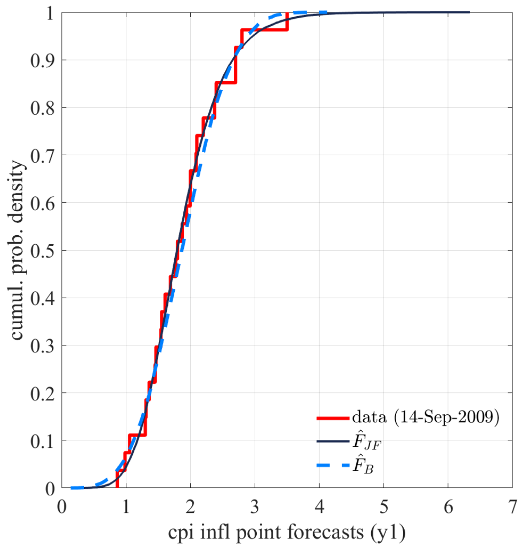
Fig. B.5 shows the results of the KS-tests. Panel (a) presents test statistics across all countries, while panel (b) shows the KS-test results over time. The KS-test of both parametric models is highly statistical significant most of the time, implying the the null of identity between the empirical cdf and the parameterized cdf cannot be rejected at conventional levels of statistical significance. However, the skew t distribution has on average higher p-values of the KS-test. Also, the minimum never falls below 0.1, which is the case for some results of the generalized beta distribution. Based on these results, we tentatively prefer the skew t over the generalized beta.

As a final step, we exploit the availability of micro data and compute various measures of skewness of the sample data. We then compare the skeweness ratio based on the relative position of the mean with respect to lowest and highest panel responses

$$S_{it} = \frac{(high_{it} - \mu_{it}) - (\mu_{it} - low_{it})}{high_{it} - low_{it}}.$$

Figure B.4: Empirical cdf compared with parametric models

(a) cdf



Note: Results are shown for US consumer price inflation forecasts for the next calendar year of a survey published on 14 September 2009. The empirical cdf is computed using the Kaplan-Meier nonparametric method.

We further compute a percentile-based measure of skweness known as Kelly's skewness

$$S_{it}^{Kelly's} = \frac{(P(90)_{it} - P(50)_{it}) - (P(50)_{it} - P(10)_{it})}{P(90)_{it} - P(10)_{it}},$$

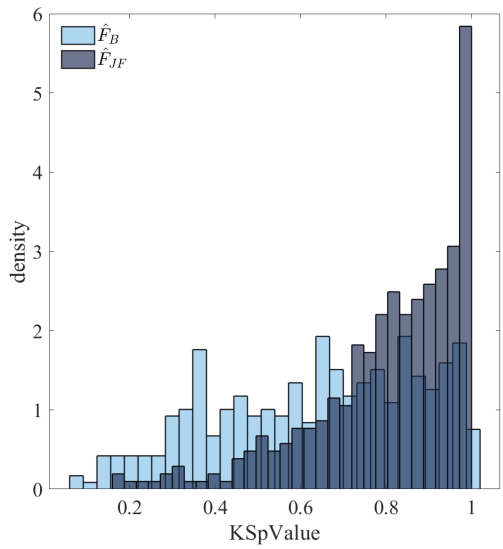
and Pearson's first and second skewness coefficient

$$S_{it}^{Pearson1} = \frac{\mu_{it} - mode_{it}}{\sigma_{it}},$$
$$S_{it}^{Pearson2} = \frac{3(\mu_{it} - median_{it})}{\sigma_{it}}.$$

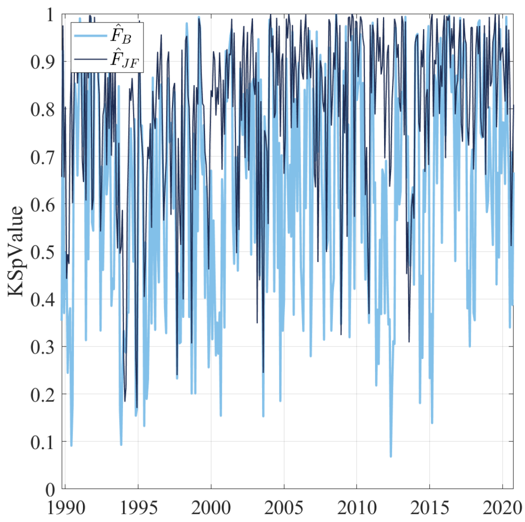
Tab. B.2 shows summary statistics of the measures of sample skewness, specifically the minima and maxima of the skewness ratio and Kelly's skewness. Tab. B.2 also provides the corrleation of the skewness ratio based on mean, lowest and highest sample observations with the alternative measures of skweness. We take this as encouraging piece of evidence that the distribution functions estimated via a simulated method of moments approach in step 2 can be well informed by the less conventional skewness ratio.

Figure B.5: Fit of the parametric models

(a) KS-test result



(b) KS-test results over time



Note: The Figure shows the p-value of the Kolmogorov-Smirnoff test (KS-test) for a sample of US point forecast data for inflation in the calendar year ahead, compared with the two parametric distributions estimated. The KS-test was evaluated under the null hypothesis that the two compared distributions are identical. Values above 0.05 indicate that the null cannot be rejected at the 5 percent confidence level. We do not report the KS-test statistic directly, since the critical values vary for different sample sizes.

Table B.2: Skewness in panelists' point forecasts

	median	[P(10)/P(90)]	N
A. Levels, cross-country comparison			
min(S_{it})	-0.460	[-0.603/-0.382]	25
max(S_{it})	0.586	[0.483/0.681]	25
min($S_{it}^{Kelly's}$)	-0.737	[-1.000/-0.599]	25
max($S_{it}^{Kelly's}$)	0.714	[0.620/1.000]	25
B. Correlations, cross-countries comparison			
corr(S_{it},$S_{it}^{unbiased}$)	0.951	[0.936/0.963]	25
corr(S_{it},$S_{it}^{Kelly's}$)	0.544	[0.362/0.749]	24
corr(S_{it},$S_{it}^{Pearson2}$)	0.545	[0.474/0.647]	25
corr(S_{it},$S_{it}^{Pearson1}$)	0.343	[0.183/0.436]	25

Note: Correlation coefficients computed from one-year ahead inflation point forecasts form Consensus. Median and percentiles report the results across N countries. The main text provides a description of the skewness measures.

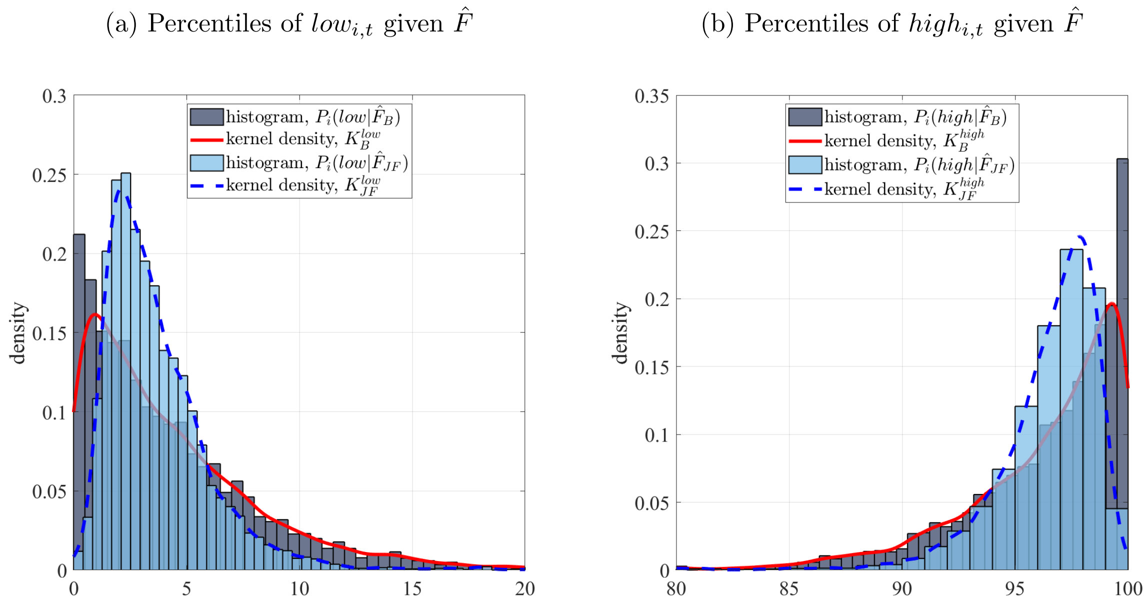
C Simulated method of moments

This section in the Appendix describes the simulated method of moments (SMM) approach in more detail. In particular, it describes the data used for the location constraint used in the SMM-estimator.

C.1 Location constraint

In order to inform the estimation procedure under SMM, we propose a *location constraint*. The location refers to the percentile of the respective lowest and highest panel response in the estimated skew t distribution function. Equipped with the results of the ML-estimation in step 1 in the form of a sequence of parameter vectors $\theta_{it}^{(JF)} = (\mu_{it}, \sigma_{it}, a_{it}, b_{it})$, we can compute the percentiles of the lowest and highest observation, which we denote by $P_i^{low}(\hat{F}_{JF}^{*})$ and $P_i^{high}(\hat{F}_{JF}^{*})$. To gain clarity, an asterisc denotes a distribution function estimated with the full cross-section as observations.

Figure C.6: Location of reported lowest/highest survey answer in estimated distributions



Note: Distributions of percentiles computed from survey data for estimated density functions $\hat{F}_B$ and $\hat{F}_{JF}$. Evaluated are the lowest survey answers ($low_{i,t}$) and higherst survey answers, respectively, across all countries i and periods t.

Fig. C.6 panel (a) shows the histograms of percentiles $P_i^{low}(\hat{F}_{JF}^{*})$ and $P_i^{low}(\hat{F}_B^{*})$, respectively. The mode of the distribution $P_i^{low}(\hat{F}_B^{*})$ is almost at zero, a result from the bounded support of the generalized beta distribution function. Thus, in many cases the ML-estimation assigns a parameterization $l = low_{it}$. The result contrasts a lot with the skew t distribution, defined on an unlimited support and exhibiting a well-defined mode. Fig. C.6 panel (b) shows the histograms of percentiles $P_i^{high}(\hat{F}_{JF}^{*})$ and $P_i^{high}(\hat{F}_B^{*})$. We make the same observation with respect to the location of the mode as for the location of the lowest sample responses in parametric distribution functions $F_B^*(\cdot)$ and $F_{JF}^*(\cdot)$.

Table C.3: Summary statistics of survey data and inflation risk measures

data	shape	mean	median	mode	sd	[P(5)/P(95)]	N
P_i^{low}							
	$\hat{F}_{JF}$	4.22	3.20	2.26	4.487	[1.17/8.97]	6402
	$\hat{F}_B$	4.34	3.21	0.21	4.074	[0.22/12.32]	6402
P_i^{high}							
	$\hat{F}_{JF}$	95.91	96.95	97.76	5.171	[91.50/98.97]	6402
	$\hat{F}_B$	96.29	97.38	99.99	3.665	[89.04/99.88]	6402

Note: Summary statistics P_i^{low} and P_i^{high} conditional on an estimated parametric distribution function $\hat{F}_{JF}^*$, $\hat{F}_B^*$. Data covering all countries i in the sample and all available periods t for monthly next-year forecasts of CPI inflation from Consensus.

Tab. C.3 shows summary statistics of the location parameters $P_i^{low}(\hat{F}_{JF}^*)$, $P_i^{low}(\hat{F}_B^*)$, $P_i^{high}(\hat{F}_{JF}^*)$ and $P_i^{high}(\hat{F}_B^*)$. We find that the mode of the distribution of percentiles in case of the generalized beta is below the 5^{th} percentile and above the 95^{th} percentile. In fact, this amounts to setting many times parameters that govern the support of the generalized beta distribution equal to the respective lowest and highest observation in the sample. This is not very desirable from the perspective that the sample data is considered as a realization from a random draw under an unknown distribution, since this gives zero probability mass to observations of inflation point forecasts below low_{it} or above $high_{it}$. We take this as a further argument to proceed with the skew t distribution.

We estimate kernel density to the vector $P_i^{low}(\hat{F}_{JF}^*)$,

$$\hat{f}_{low}^P(x) = \frac{1}{N\omega}\sum_{i=1}^{N} K\left(\frac{x - x_i}{\omega}\right),$$

where N is the number of observations, x_i are the percentiles in the vector $P_i^{low}(\hat{F}_{JF}^*)$, ω the bandwidth and $K(\cdot)$ is the kernel smoothing function, which we choose to be a normal. Fig. C.6 plots the resulting kernel density function on top of the histogram. This kernel density is used as location constraint in the SMM estimation as described in the main text.