
Anchoring of Inflation Expectations: Do Inflation Target Formulations Matter?

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ABSTRACT

Inflation target formulations differ across countries and over time. Most widespread are point targets, target ranges, hybrid combinations of the two, or mere definitions of price stability. This paper proposes a novel empirical measure of expectations anchoring based on the cross-sectional distribution of private sector inflation point forecasts. Applying this to a panel of 29 countries, it finds three main results. First, a numerical target definition per se does not improve anchoring compared to a definition of price stability, while the formulation of a numerical reference point increases the degree of anchoring. Second, point targets and hybrid target formulations are associated with better anchoring than target ranges. Third, periods of persistent target deviations lead to an increase in tail risks to the inflation outlook. Conditional on such periods, point targets and hybrid targets attenuate tail risks to the inflation outlook, with a stronger quantitative effect for point targets. The results are consistent with models suggesting that target ranges are interpreted as zones where monetary policy is less active.

Keywords: Monetary Policy, Inflation Targeting, Expectations Anchoring, Survey Forecasts, Inflation Risk

JEL classification : E42, E52, D84

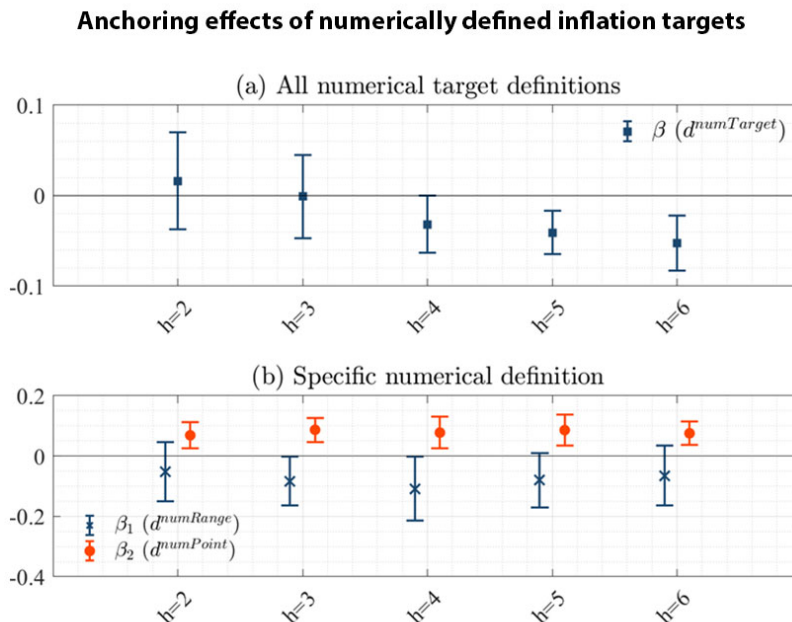
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NON-TECHNICAL SUMMARY

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 novel 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 find four main results. First, a numerical target definition *per se* does not improve anchoring, while the formulation of a numerical reference point increases unconditionally the degree of anchoring compared to a quantitative definition of price stability for forecast horizons of two to six years (see Figure). Second, point targets and hybrid target formulations are associated with better anchoring properties than target ranges. Third, periods of persistent inflation overshooting and undershooting lead to an increase in tail risks to the inflation outlook. Fourth, conditional on periods of persistent target deviations, a point target is associated with lower tail risks to the inflation outlook. Our results are consistent with models suggesting that targets ranges are interpreted as zones where monetary policy is less active.



Notes: Panel (a). Coefficient estimates for the effect of a numerically defined inflation target on the anchoring measure, in comparison to quantitative definitions of price stability without explicit numerical target. A positive coefficient means better anchoring. Panel (b). Coefficient estimates for the effect of the presence of a target range or tolerance band (range) and a focal point or point target (point) on the anchoring measure. A higher coefficient means better anchoring. All equations are estimated separately for each forecast horizon from h = 2 to h = 6 years.

Ancrage des anticipations d'inflation : les formulations des cibles d'inflation sont-elles importantes ?

RÉSUMÉ

Nous proposons une nouvelle mesure de l'ancrage des anticipations basée sur la distribution transversale des prévisions ponctuelles d'inflation du secteur privé. En appliquant cette mesure à un panel de 29 pays, nous trouvons quatre résultats principaux. Premièrement, la formulation d'un point de référence numérique augmente inconditionnellement le degré d'ancrage par rapport à une définition quantitative de la stabilité des prix pour des horizons de prévision de deux à six ans. Deuxièmement, les cibles ponctuelles et les formulations de cibles hybrides sont associées à de meilleures propriétés d'ancrage que les fourchettes de cibles. Troisièmement, les périodes de dépassement et de sous-dépassement persistants de l'inflation entraînent une augmentation des risques extrêmes pour les perspectives d'inflation. Quatrièmement, conditionnellement aux périodes de déviations persistantes de la cible, une cible ponctuelle est associée à des risques plus faibles pour les perspectives d'inflation. Nos résultats sont cohérents avec les modèles suggérant que les fourchettes de cibles sont interprétées comme des zones où la politique monétaire est moins active.

Mots-clés : politique budgétaire, régimes fiscaux, catastrophes naturelles, modèle de défaut souverain, données du panel

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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 Q2 2005 to Q2 2020. 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 real-time (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) downside risk to inflation and (ii) upside risk to 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 derive inflation anchoring measures within a framework proposed 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 explicit 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 baseline specification, we find that a numerical target *per se* is not necessarily superior to a quantitative definition of price stability. However, a target formulation that includes a numerical reference point, either as inflation point target or in a hybrid strategy, improves the anchoring of 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 risk to the inflation outlook, 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.

The findings are robust to a number of alternative specifications of the empirical model. In particular, we find similar results in a sample of only advanced economies, when we exclude countries with a bad inflation track record from the country sample, or if we take an anchoring measure from the unprocessed survey data.

Further, we test if target formulations can prevent unanchoring of expectations during periods of persistent deviations from target. 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 persistently low inflation impairs anchoring, consistent with results presented by Ehrmann (2015) for short-term expectations. Persistent overshooting, however, has no effect on the main measure of anchoring. Additionally, we find that persistent deviations from target have strong effects on the shape of the cross-sectional distribution of forecasts in the expected direction. Past undershooting raises downside risk to the inflation outlook and dampens the risk of above target inflation, while overshooting affects the distribution in the opposite way. This is in line with theories of information rigidities, which predict that gathering information has a higher return for forecasters who's current prediction is more distant to the signal, i.e. realized inflation. It is more likely that these agents revise their forecast and bring it closer to current inflation trends (Coibion and Gorodnichenko, 2015). 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 past inflation deviations. In economic terms, this implies that at times very high inflation rates or deflationary tendencies fall within the set of forecasters' beliefs, while the central tendency might not necessarily be affected.

In a final step, we ask whether one target formulation is more effective than another to curb the risk to the inflation outlook during periods of persistent deviations from target. To this end, the persistent inflation gap indicator is interacted with the classification of target types. We conclude that no target type fares significantly better in improving overall anchoring conditional on a persistent deviation. At the same time, we find differences to what extend the tails of the distribution are affected: inflation point targets fare best regarding shape-stability conditional on persistent target deviations. They attenuate the increase in the risk to below target inflation during periods of undershooting, while also significantly dampening the rise in the risk of above target inflation during periods of overshooting. Hybrid target formulations also attenuate the shift in the tails of cross-sectional distributions, but to a much lower extent 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 and Wieland, 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 and that announcing a target range or tolerance band 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 counterproductive for anchoring. In a related analysis, DAVIS and Kirpalani (forthcoming) find that central banks might want to preserve uncertainty about its inflation target to foster *ex post* commitment to the rule. For central banks with low reputation, this is a way to better anchor expectations over time. 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.

Further, our result of stronger anchoring properties for point targets or hybrid targets with explicit reference to a focal point are consistent with findings within a learning-to-forecast laboratory experiment conducted by [Cornand and M'baye \(2018\)](#). The announcement of a point target is associated with faster convergence of participants' expectations to target than under a range target in their setup.

This paper is primarily related to two empirical papers also differentiating between inflation target formulations. [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, including mere definitions of price stability. 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 \(2021\)](#), 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 of past inflation realizations is weaker for countries that have defined a target range or tolerance band for inflation. This implies weaker anchoring for pure point targets. The differences to our results can be explained by three factors. First, his work focuses on a shorter forecast horizon of one-and-a-half years. Second, the study covers a different subset of countries and a longer sample period starting in 1995. Third, the nature of the underlying test differs, as [Ehrmann \(2021\)](#) looks at the pass-through of realized inflation on inflation expectations. A lower pass-through coefficient for target ranges is not necessarily inconsistent with our finding of less probability of cross-sectional point forecasts around target. It is well possible that short-term inflation expectations respond less to inflation realizations, while being more distant to the announced inflation objective of the central

bank in levels. Since the notion of anchoring is not universally defined and merits to be analyzed from different angles, as discussed below, we consider his findings as complementary to ours.

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 criterion (v).¹ Less attention has been devoted on the level of long-term inflation expectations with respect to target, which is more closely related to the approach taken here. [Mehrotra and Yetman \(2018\)](#) use a three-dimensional panel data set, 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. They estimate parametric distribution functions to bins of inflation outcomes provided by each participant in these surveys. Their proposed anchoring measure is the probability density within a ± 0.5 percentage point interval around the central bank's inflation target. 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 density forecasts, it is not clear how these relate to the best projection ([Engelberg, Manski, and Williams, 2009](#); [Clements, 2014](#)).

¹This literature uses so-called pass-through regression models, usually measuring the effect of changes in short-term expectations on longer-term expectations ([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 break-even inflation rates respond to macroeconomic news ([Gürkaynak, Levin, and Swanson, 2010](#); [Beechey, Johannsen, and Levin, 2011](#); [Bauer, 2015](#); [Hachula and Nautz, 2018](#); [Speck, 2017](#)).

More broadly, this paper is also related to the empirical literature on the effects of the introduction of inflation targeting (IT) on inflation expectations. [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.

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:

$$\min_{\{i_t\}} E_t \sum_{\tau=0}^{\infty} \delta^{\tau} L_{t+\tau} \quad (2.1)$$

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 extent the central bank cares about the output objective. Substituting in a linear Phillips curve and taking the first order 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

$$L_t = \left[aI(\pi_t < \underline{\pi})(\underline{\pi} - \pi_t)^{\gamma_{(\cdot)}^L} + (1 - a)I(\pi_t > \bar{\pi})(\pi_t - \bar{\pi})^{\gamma_{(\cdot)}^H} \right],$$

$$+ \lambda \left[bI(y_t < \underline{y})(\underline{y} - y_t)^{\gamma_y^L} + (1 - b)I(y_t > \bar{y})(y_t - \bar{y})^{\gamma_y^H} \right]$$

with $0 \leq a, b \leq 1$ and $\lambda \geq 0$.

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 realizations 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

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

³This 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, $\underline{y} = \bar{y} = 0$.

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

$$E(L_{t+h}) = a \int_{-\infty}^{\bar{\pi}} (\bar{\pi} - \pi_t^e)^{\gamma_\pi^H} dF_{\pi_t^e}(\pi_t^e) + (1-a) \int_{\bar{\pi}}^{\infty} (\pi_t^e - \bar{\pi})^{\gamma_\pi^L} dF_{\pi_t^e}(\pi_t^e), \quad (2.2)$$

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

$$DAL_{\gamma_\pi^L}(F_{\pi^e}) = \int_{-\infty}^{\bar{\pi}} (\bar{\pi} - \pi^e)^{\gamma_\pi^L} dF_{\pi^e}(\pi^e) \quad (2.3)$$

$$DAH_{\gamma_\pi^H}(F_{\pi^e}) = \int_{\bar{\pi}}^{\infty} (\pi^e - \bar{\pi})^{\gamma_\pi^H} dF_{\pi^e}(\pi^e) \quad (2.4)$$

[Kilian and Manganeli \(2008\)](#) 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 $F_{\pi^e}^{(2)}$ if $|DAL_{\gamma_\pi^L}(F_{\pi^e}^{(1)})| \leq |DAL_{\gamma_\pi^L}(F_{\pi^e}^{(2)})|$ 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 existence 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 $U(DAL_{\gamma_\pi^L}(F_{\pi^e}^{(1)}), DAH_{\gamma_\pi^H}(F_{\pi^e}^{(1)})) > U(DAL_{\gamma_\pi^L}(F_{\pi^e}^{(2)}), DAH_{\gamma_\pi^H}(F_{\pi^e}^{(2)}))$.*

From substituting equations (2.2), (2.3) and model (2.4) into the central bank's optimization problem (2.1) and deriving the first order condition, [Kilian and Manganeli \(2008\)](#) obtain an implicit nonlinear, potentially asymmetric interest rate rule:

$$\frac{\partial E_t L_t(\pi_t)}{\partial i_t} = \frac{\partial E_t(\pi_t(i_t))}{\partial i_t} \left[-a\gamma_\pi^L \int_{-\infty}^{\bar{\pi}} (\bar{\pi} - \pi_t)^{\gamma_\pi^H - 1} dF_{\pi_t}(\pi_t) + (1-a)\gamma_\pi^H \int_{\bar{\pi}}^{\infty} (\pi_t - \bar{\pi})^{\gamma_\pi^H - 1} dF_{\pi_t}(\pi_t) \right] = 0 \quad (2.5)$$

The rule 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 (2.5), 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.

Before we derive the inflation risk measures, we briefly discuss pros and cons of five sets of data which provide densities over future inflation outcomes and are, therefore, candidates for the anchoring measures. First, density forecasts from macroeconomic 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 Schultefrankfeld, 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, as well as the historical availability of such forecasts. 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.

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.

For the empirical analysis, we propose three probability measures derived from the cross-section of inflation point forecasts closely related to (2.3) and (2.4). Since estimating the degree of risk aversion of each central bank is beyond the scope of this paper, we 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 downside risk to inflation (DAL) and upside risk to inflation (DAH) from the probability density across point forecasts as:

$$DAL_{it}^h = \int_{-\infty}^{\pi_i} dF_{\pi_{it}^h}(\pi_{it}^h) \quad (2.6)$$

$$DAH_{it}^h = \int_{\bar{\pi}_i}^{\infty} dF_{\pi_{it}^h}(\pi_{it}^h) \quad (2.7)$$

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

$$\begin{aligned} probT_{it}^h &= \int_{\underline{\pi}_i}^{\bar{\pi}_i} dF_{\pi_{it}^h}(\pi_{it}^h) \\ &= 1 - DAL_{it}^h - DAH_{it}^h. \end{aligned} \quad (2.8)$$

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 (AE) and 17 emerging market economies (EME).⁴ We follow [Castelnuovo, Nicoletti-Altimari, and Rodriguez-Palenzuela \(2003\)](#) and define dummy variables for five categories: (i) a mere quantitative definition of price stability, (ii) a range target for inflation, (iii) a range target with focal point, (iv) a point target with tolerance bands and (v) 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 always 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 categories (iii) and (iv) into *'hybrid targets'*. Third, we include also three central banks that never officially adopted inflation targeting as a framework for the conduct of monetary policy, namely the United States, the euro area and Switzerland. However, the inflation targets can be classified and the policy framework seems mature enough to include these countries in the empirical analysis.

Note that two sets of countries are excluded from the analysis. First, inflation targeting countries that have changed their target level between 2018 and 2020 are excluded, as long-term expectations might still be affected by target changes.⁵ Also, IT-countries with stable target values for which Consensus data is not available do not enter the empirical analysis.⁶

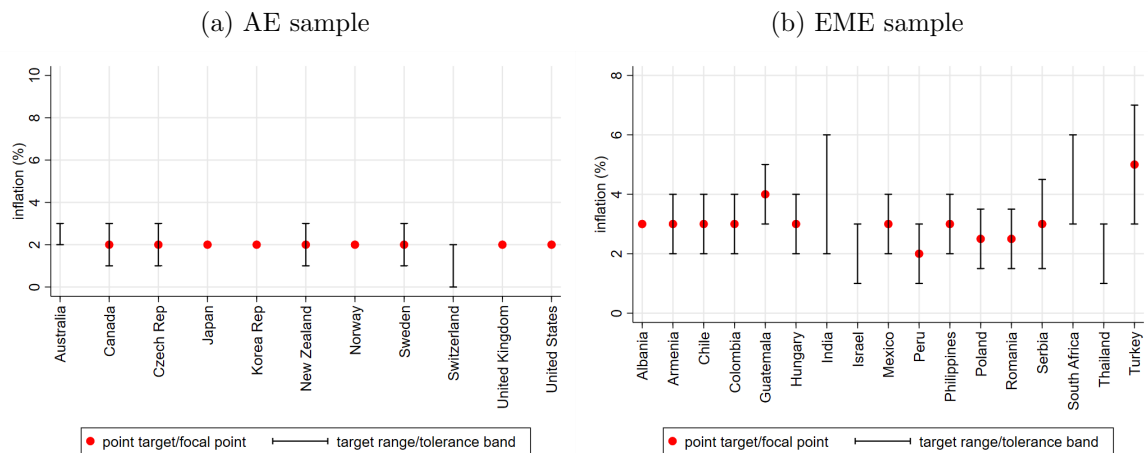
[Tab. A.2](#) in the [Appendix](#) provides all details regarding our classification choices. [Fig. 1](#) gives a snap shot of inflation objectives as of April 2020, while [Tab. A.1](#) in the [Appendix](#) shows summary statistics of inflation targets of the 29 countries covered in the analysis over time from Q2 2005 to Q1 2020. A couple of observations stand out. Despite some heterogeneity, there is convergence toward an inflation objective of two

⁴The sample of AE cover Australia, Canada, Czech Republic, euro area, Japan, New Zealand, Norway, South Korea, Sweden, Switzerland, United Kingdom and United States. The sample of EME contains Albania, Armenia, Chile, Colombia, Guatemala, Hungary, India, Israel, Mexico, Peru, Poland, Philippines, Romania, Serbia, South Africa, Thailand and Turkey.

⁵This applies to Brazil, Costa Rica, Dominican Republic, Georgia, Indonesia, Kazakhstan, Ukraine, and Uruguay.

⁶Consensus data is unavailable for Ghana, Iceland, Jamaica, and Uganda, which are all inflation targeting countries.

Figure 1: Quantitative inflation targets



Notes: Quantitative targets as of Q1 2020 of 11 AE countries (panel a) and 17 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.

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 Riksbank 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 onward, with explicit focus on the midpoint being introduced in September 2012 (Lewis and McDermott, 2016).

3.2 Estimating distribution functions for anchoring measures

For the computation of inflation risk measures as defined in equations (2.6) to (2.8), 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 on-

ward 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 (Q1), April (Q2), July (Q3) and October (Q4). 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

$$\hat{x}_{t+y \cdot 12|t} = \frac{k}{y \cdot 12} x_{t+k|t} + \frac{y \cdot 12 - k}{y \cdot 12} x_{t+y \cdot 12+k|t}$$

with $k \in \{(y - 1) \cdot 12 + 1, (y - 1) \cdot 12 + 2, \dots, (y - 1) \cdot 12 + 12\}$.

We cover fixed-horizon forecast from years $y = 2, 3, 4, 5$ 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 $MPF_{jit}^h(x)$ 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.⁷ However, as of Q2 2005 Consensus publishes the sample mean, the sample standard deviation, the lowest and the highest mean point forecast of the survey sample. To clarify the underlying data, we use the following notation:

$$\mu_{it}^h = E_t[MPF_{it}^h] = \frac{1}{N} \sum_{j=1}^N MPF_{jit}^h \quad (3.1)$$

$$\sigma_{it}^h = \sqrt{\frac{1}{N-1} \sum_{j=1}^N (MPF_{jit}^h - \mu_{it}^h)^2} \quad (3.2)$$

$$low_{it}^h = \min [MPF_{1it}^h, \dots, MPF_{Nit}^h] \quad (3.3)$$

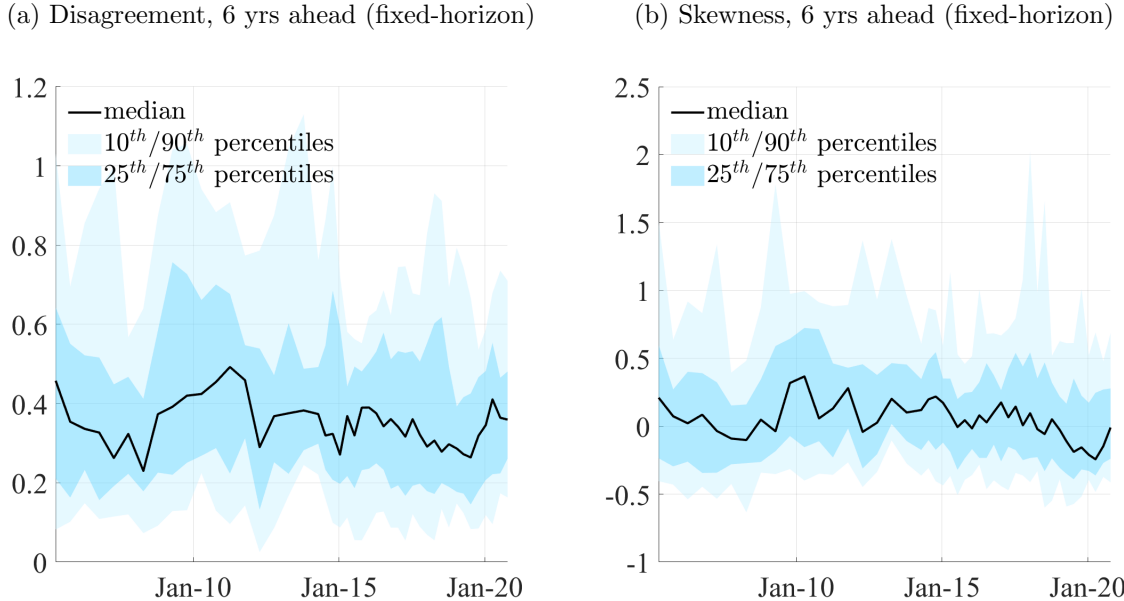
$$high_{it}^h = \max [MPF_{1it}^h, \dots, MPF_{Nit}^h] \quad (3.4)$$

[Fig. 2](#) 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

$$S_{it}^h = \frac{(high_{it}^h - \mu_{it}^h) - (\mu_{it}^h - low_{it}^h)}{high_{it}^h - low_{it}^h}. \quad (3.5)$$

⁷Consensus provides micro data for panelists participating in the monthly survey of projections for the current and next calendar year, which we use for bench-marking our results below.

Figure 2: Disagreement and skewness in long-term inflation point forecasts



Notes: 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. (3.5) in the main text.

The skewness 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 (3.5) is inspired by quantile-based measures of skewness, for example Bowley’s robust measure of skewness (Bowley, 1920). However, given that we do not know the median or percentiles, it is just an approximation to more conventional measures of skewness.⁸

Given the high amount of asymmetry reflected in Fig. 2(b), we consider two candidates for parametric continuous 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 the applied economics and finance literature.⁹ They differ to the extent that the generalized beta is defined over the closed support governed by two parameters $[l, r]$, while the

⁸Tab. B.1 in the Appendix shows the correlation of the skewness ratio (3.5) and conventional measures of skewness computed from available micro data at a shorter forecast horizons. All measures are highly correlated, fostering our confidence in the skewness ratio.

⁹Examples 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).

skew t -distribution is defined on \mathbb{R} .

To test which family of distribution functions fits the data best, 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 asterisk denotes a distribution estimated based on the full sample of survey responses. 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 fit a sequence of skew t -distributions to available limited data 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 (3.5), 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 a vector $P_i^{low}(\hat{F}_{JF}^*)$ and $P_i^{high}(\hat{F}_{JF}^*)$, respectively. [Fig. C.1](#) in the [Appendix](#) shows the histogram of these two vectors. The histograms feature a mode around the 3rd percentile in case of lowest survey responses, and around the 97th percentile in case of highest survey responses. Thus, ML-estimation attributes little probability density outside the min-max range of survey answers.¹⁰ We fit a 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. We do the same for the location of high observations, obtaining $\hat{f}_{high}^P(x)$.

We then exploit the kernel density in the SMM approach of step 2 as follows. First, we compute the percentile of data points low_{it}^h and $high_{it}^h$ from the candidate distribution $F_{JF}(\theta)$, obtaining simulated percentiles $\tilde{P}_i(low_{it}^h)$ and $\tilde{P}_i(high_{it}^h)$, respectively,

¹⁰The well-defined mode for the location constraint of high and low observations is another argument in favor of the skew t -distribution.

both conditional on $F_{JF}(\theta)$. Second, we compute the empirical pdf from the respective kernel density at point $\hat{f}_{(\cdot)}^P(\tilde{P}_i(\cdot))$, and subtract it from the highest density at the mode of the respective kernel density. For the case of lowest observations, we use the following notation

$$\Delta \hat{f}_{low}^P(\tilde{P}_i(low_{it}^h) | F_{JF}(\theta)) \equiv \hat{f}_{low}^P(mode) - \hat{f}_{low}^P(\tilde{P}_i(low_{it}^h) | F_{JF}(\theta)), \quad (3.6)$$

which is analogue for the highest observation. We refer to (3.6) as the *location constraint*. The value of the location constraint is smallest, the closest is the percentile of low_{it}^h in the candidate distribution to the mode of the kernel density. The intuition behind the inclusion of the location constraint 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

$$\hat{\theta}(W) = \arg \min_{\theta} \left[\hat{\psi}^{data} - \hat{\psi}^{sim}(\theta) \right]' W \left[\hat{\psi}^{data} - \hat{\psi}^{sim}(\theta) \right], \quad (3.7)$$

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

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

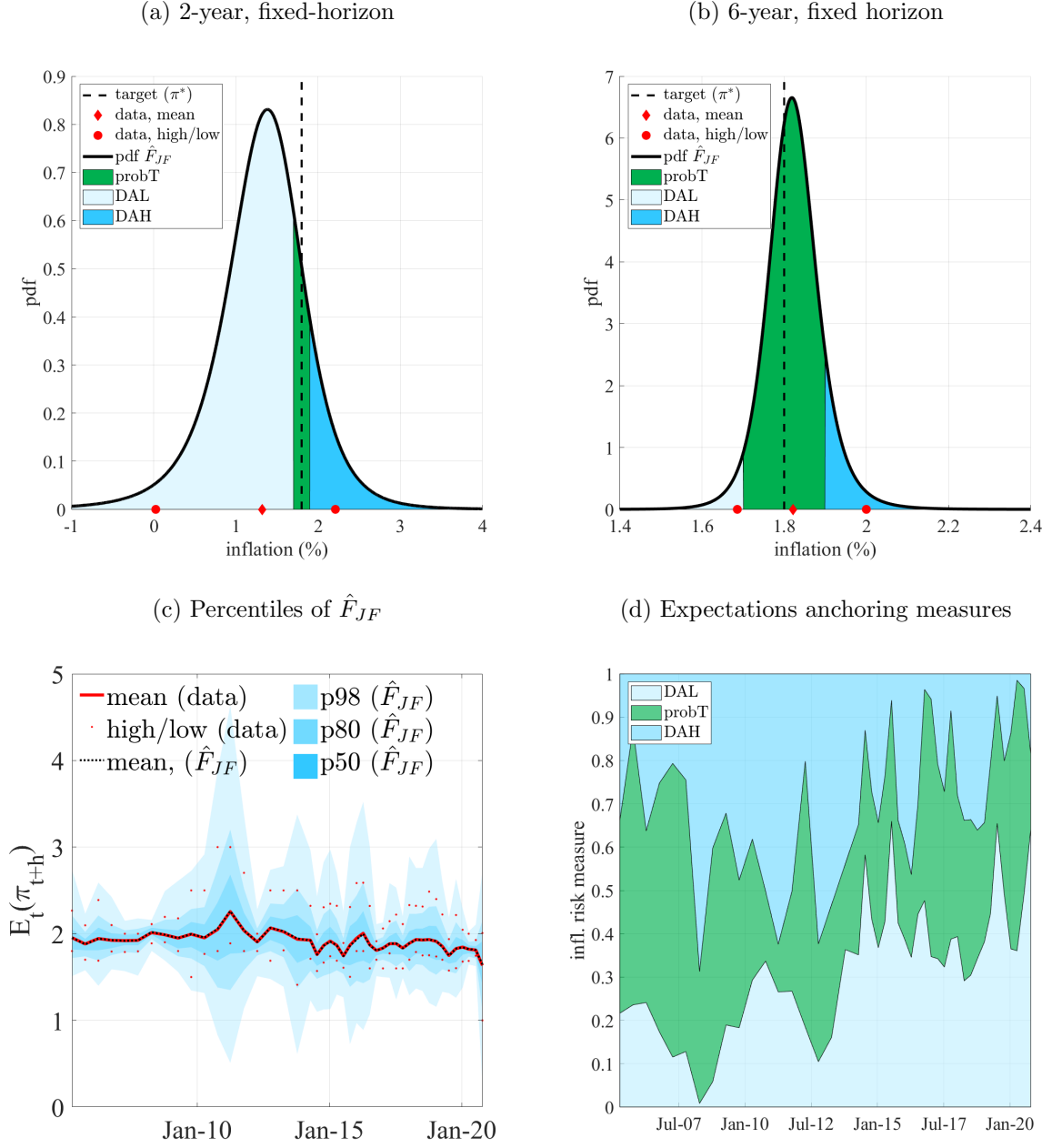
where a tilde denotes the simulated sample moment from the candidate distribution $F_{JF}(\theta)$. Let us further clarify how we compute the skewness ratio \tilde{S} in our simulations. In line with the modal value of the kernel densities of the location of highest and lowest observations using micro data (Fig. C.1), we take the 3rd and 97th percentiles of the density function $F_{JF}(\theta)$, respectively, and compute the skewness ratio as

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

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 (3.7) is minimized using a global search algorithm with

multiple starting points in order to insure that a global minimum is found.

Figure 3: Densities and anchoring measures, euro area



Notes: The skew t -distribution $F_{JF}(\mu, \sigma, a, b)$ is 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. Underlying raw data is from Consensus. Panel (a,b) Example estimated distribution $\hat{F}_{JF}(\mu, \sigma, a, b)$ for the euro area (Q1 2020).

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_{it}^h , DAH_{it}^h and $probT_{it}^h$ from equations (2.6), (2.7) and (2.8) 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. 3(a,b) 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 Q1 2020. The underlying survey data are plotted as red dots on the x-axis. The procedure successfully 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 skewness, 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. 3(c,d) 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. We refer to the *symmetry property* as the time-varying ratio of upside and downside risk to inflation, which we would like to emphasize and investigate more systematically in the next section.

Tab. 1 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. Over the two year horizon, forecasters never fully agree on inflation outcomes, while they occasionally do over a longer forecast horizon of 6 years. Skewness does seem to average out across the sample of countries.

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 downward risk to inflation (*DAL*) is negatively sloped, while upside risk to inflation (*DAH*) is stable over all forecast horizons in the full sample. While downside risk to inflation is more present in the AE sample, upside risk to inflation dominates in the EME sample.

Table 1: 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												
<i>distance, mean to target (midpoint)</i>												
fh2	0.52	0.82	0.00	13.89	0.36	0.34	0.00	1.99	0.72	1.14	0.00	13.89
fh4	0.35	0.47	0.00	5.09	0.24	0.23	0.00	1.18	0.48	0.63	0.00	5.09
fh6	0.30	0.37	0.00	3.53	0.22	0.24	0.00	1.31	0.41	0.46	0.00	3.53
<i>disagreement (sd)</i>												
fh2	0.37	0.24	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	0.35	0.20	0.04	1.24	0.45	0.32	0.00	2.42
fh6	0.37	0.29	0.00	2.45	0.32	0.23	0.00	1.79	0.44	0.34	0.00	2.45
<i>skewness ratio</i>												
fh2	0.023	0.21	-0.60	0.65	0.0035	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	0.071	0.30	-0.81	1.72
INFLATION RISK MEASURES												
<i>probT</i>												
fh2	0.15	0.15	0.00	0.83	0.18	0.15	0.00	0.68	0.12	0.14	0.00	0.83
fh4	0.22	0.21	0.00	1.00	0.25	0.19	0.00	0.97	0.19	0.23	0.00	1.00
fh6	0.27	0.25	0.00	1.00	0.32	0.25	0.00	1.00	0.20	0.24	0.00	1.00
<i>DAL</i>												
fh2	0.42	0.37	0.00	1.00	0.54	0.35	0.00	1.00	0.27	0.33	0.00	1.00
fh4	0.34	0.30	0.00	1.00	0.41	0.30	0.00	1.00	0.25	0.27	0.00	0.99
fh6	0.32	0.29	0.00	1.00	0.35	0.29	0.00	1.00	0.28	0.27	0.00	1.00
<i>DAH</i>												
fh2	0.43	0.37	0.00	1.00	0.29	0.29	0.00	1.00	0.61	0.37	0.00	1.00
fh4	0.44	0.32	0.00	1.00	0.34	0.27	0.00	0.99	0.55	0.35	0.00	1.00
fh6	0.41	0.31	0.00	1.00	0.33	0.26	0.00	0.98	0.52	0.34	0.00	1.00
<i>N</i>	924				510				414			

Notes: 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 (3.5) for details. Inflation risk measures computed from estimated density functions of a skewness extended t -distribution (Jones and Faddy, 2003) using data from panelists' cross-sectional point forecasts. AEs denote the subsample of 12 advanced economies, EMEs denote a subsample of 17 emerging market economies.

4 Empirical analysis

4.1 Determinants of expectation anchoring

We first examine the determinants of expectation anchoring based on a pooled regression of the following specification:

$$X_{it}^h = c + \beta_1 d_t^{fh3} + \beta_2 d_t^{fh4} + \beta_3 d_t^{fh5} + \beta_4 d_t^{fh6} + \delta_1 \sigma_{it}^{\pi 24m} + \delta_2 RQ_{it} + \nu_Y + \nu_i + \varepsilon_{it} \quad (4.1)$$

We regress dummy variables for forecast horizons of three to six years on a set of dependent variables X in country i at forecast horizon h . All regressions contain a measure for the regulatory quality (RQ) from the World Bank's Worldwide Governance Indicators (WGI) and a rolling window standard deviation of realized headline consumer price inflation with a backward looking horizon of 24 months ($\sigma^{\pi 24m}$). Further, the model includes a full set of year dummies (ν_Y) and country-specific fixed effects (ν_i).

The reference group, captured by the constant, is the cross-country average value of the variable of interest at the two year forecast horizon.

Tab. 2 shows the results. The term-structure of anchoring is upward sloping for both anchoring measures, namely the absolute distance of mean point forecasts with respect to the target midpoint (*distAbs*) in column (1), and the probability measure *probT* 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. In line with the findings of Capistran and Timmermann (2009), a one standard deviation increase in inflation volatility raises the dispersion of inflation forecasts, captured here by the standard deviation in column (2), by 0.180 which is a quantitatively significant amount. The term-structure of disagreement is slightly hump-shaped, which is consistent with previous findings (Andrade et al., 2016).

Regulatory quality has the expected positive effect on the level of anchoring.¹¹ It also lowers forecast dispersion. Regulatory quality is associated with a substantially lower skewness, higher risk of below target inflation and lower risk of above target inflation. This likely reflects that countries with better developed institutions had lower inflation outcomes over the sample under consideration.

Asymmetry, here captured by the skewness ratio from eq. (3.5), is negligible in the pooled model captured by the insignificant constant in column (3). As evident from Tab. 1, skewness is a feature in the cross-section of the data, but seems to average out in the aggregate. Inflation volatility does not affect skewness. Longer forecast horizons are associated with slightly more positive skewness, implying an upward sloping term structure of skewness. This is consistent with downside and upside risk to the inflation outlook. While downside risk to inflation in column (5) attenuates with higher inflation volatility, inflation volatility amplifies upside risk, see column (6). The term structure of the two disanchoring measures feature therefore 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 consider upside and downside deviations of realized inflation from the inflation target separately in order to analyze this question in more depth.

¹¹We use the measure proposed by Kaufmann, Kraay, and Mastruzzi (2010) who give the following definition: "Regulatory quality captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development."

Table 2: Determinants of inflation risk measures

	(1) distAbs	(2) stdev	(3) skewness ratio	(4) probT	(5) DAL	(6) DAH
sd infl. (24m)	0.374*** (0.0130)	0.180*** (0.00619)	0.00103 (0.00710)	-0.000374 (0.00536)	-0.0497*** (0.00821)	0.0501*** (0.00802)
Regulatory quality	-0.169*** (0.0125)	-0.0747*** (0.00598)	-0.0270*** (0.00688)	0.130*** (0.00518)	0.0888*** (0.00794)	-0.219*** (0.00776)
d^{fh3}	-0.127*** (0.0224)	0.0159 (0.0107)	0.0159 (0.0122)	0.0469*** (0.00925)	-0.0538*** (0.0142)	0.00693 (0.0138)
d^{fh4}	-0.170*** (0.0224)	0.0276*** (0.0107)	0.0318*** (0.0123)	0.0685*** (0.00925)	-0.0737*** (0.0142)	0.00517 (0.0138)
d^{fh5}	-0.198*** (0.0224)	0.0182* (0.0107)	0.0550*** (0.0123)	0.0964*** (0.00925)	-0.0887*** (0.0142)	-0.00775 (0.0138)
d^{fh6}	-0.215*** (0.0224)	0.00658 (0.0107)	0.0737*** (0.0123)	0.115*** (0.00926)	-0.0962*** (0.0142)	-0.0190 (0.0139)
Constant	0.427*** (0.0447)	0.290*** (0.0214)	0.0270 (0.0245)	0.00915 (0.0185)	0.302*** (0.0283)	0.689*** (0.0277)
adj. R-squared	0.28	0.27	0.04	0.18	0.09	0.23
N.Obs	4483	4483	4435	4483	4483	4483
year dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes. ***/**/* denote statistical significance at the 1%/5%/10% level. Robust standard errors reported in parentheses. Results for model (4.1) via pooled OLS, dependent variables are the absolute distance of realized inflation to target (*distAbs*), the cross-sectional standard deviation (*stdev*, as reported in the underlying Consensus data), the skewness ratio and the three probability-based measures of anchoring obtained from estimated distribution functions (*probT*, *DAL*, *DAH*).

4.2 Anchoring and inflation target formulations

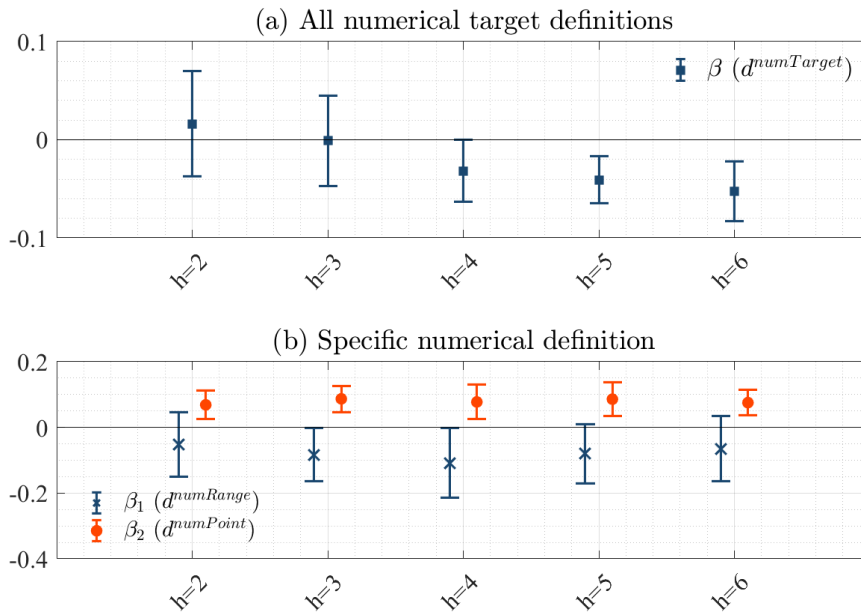
This section investigates the main question of the paper. First, we test whether the formulation of the inflation objective with a numerical definition changes anchoring. We estimate an econometric panel model of the form

$$probT_{it}^h = c + \beta d_{it}^{numTarget} + \delta_1 \sigma_{it}^{\pi^{24m}} + \delta_2 RQ_{it} + \nu_i + \nu_Y + \varepsilon_{it}. \quad (4.2)$$

The main variable of interest is a dummy $d^{numTarget}$ which takes the value of one if there is a numerically defined inflation target. We add two controls to this baseline specification. First, we include a rolling window standard deviation of realized headline consumer price inflation with a backward looking horizon of 24 months ($\sigma^{\pi^{24m}}$). This captures broadly the economic conditions and serves as a control for the business cycle. Second, we include regulatory quality (RQ) as a proxy variable for the conduct of policies in each country within the baseline specification. The main motivation for this is a concern about an omitted variable bias if the choice of the target formulation is correlated with the overall quality of macroeconomic stabilization policies. At the same time, we mitigate possible concerns about endogeneity by controlling for reg-

ulatory quality.¹² All remaining time-invariant country differences are accounted for by country-specific fixed effects ν_i . Finally, a full set of year dummies ν_Y account for common time trends, like shocks to global inflation and their implications for forecasts. Galati, Poolekka, and Zhou (2011) show evidence that the collapse of Lehman Brothers has led to changes in survey-based longer-term inflation expectations in the United States and the United Kingdom. Our sample includes an unbalanced panel of 29 countries for 15 years of quarterly data from Q2 2005 to Q1 2020.

Figure 4: Anchoring effects of numerically defined inflation targets (effects on $probT$)



Notes: Point estimates and 90% confidence intervals based on Driscoll and Kraay (1998) standard errors. Panel (a). Coefficient estimates for model (4.2) as of Tab. D.1.A in the Appendix for a numerically defined target ($d_{it}^{numTarget}$), with the anchoring measure $probT_{it}$ being the dependent variable. Panel (b). Coefficient estimates for model (4.3) as of Tab. D.1.B in the Appendix on presence of a target range or tolerance band ($d_{it}^{numRange}$) and a focal point or point target ($d_{it}^{numPoint}$). All equations are estimated separately for each forecast horizon from $h = 2$ to $h = 6$ years based on a fixed-horizon approximation.

Model (4.2) is estimated separately for each forecast horizon, the reference group is characterized by all target formulations without a precise numerical target definition, which feature a mere 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. Fig. 4(a) present the results for the main coefficient of interest β for dependent variable $X = probT$. Numerical target formulations do not have a significant effect on anchoring *per se*. Over horizons of

¹²We also tested a specification in which we replaced regulatory quality by government effectiveness, yielding similar results. Due to possible multicollinearity, we do not include both measures simultaneously.

5 and 6 years, there is even a significant negative effect, albeit this is quantitatively small. These findings are in line with [Bundick and Smith \(2018\)](#), who have found that anchoring improved in the US after the introduction of a numerical target, while there was no improvement in the cases of Japan. Sensitivity results show that the effect is more in favor of numerical target definition once countries with a poor inflation track record, specifically Japan and Turkey, are dropped from the sample.

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 $d_{it}^{numRange}$, while all target definitions with a reference to a point target or focal point are grouped into a variable $d_{it}^{numPoint}$. Note that the two categorical variables are not mutually exclusive in the case of hybrid target formulations. We estimate the following model:

$$probT_{it}^h = c + \beta_1 d_{it}^{numRange} + \beta_2 d_{it}^{numPoint} + \delta_1 \sigma_{it}^{\pi 24m} + \delta_2 RQ_{it} + \nu_i + \nu_Y + \varepsilon_{it} \quad (4.3)$$

Results in [Fig. 4\(b\)](#) show the estimated coefficients β_1 and β_2 for dependent variable $X = probT$. While the presence of an explicit range in the target formulation lowers the anchoring measure, a target definition which includes a reference to a numerical point increases the probability mass of point predictions around target. We provide the p-values of an F-test for equality in the two coefficients ($H_0 : \beta_1 = \beta_2$) in [Tab. D.1 B.](#) in the [Appendix](#). The test clearly rejects the null hypothesis of equal coefficients for horizons of three to six years. We thus conclude that there is a positive effect of an explicit reference to a point target on expectation anchoring. The effect is substantial, as it is associated with an anchoring measure 25 to 69 percent higher compared to the reference group.

We next explore the question of differential effects of numerical target formulations in more detail, exploiting more refined target formulations. To this end, only countries and episodes with a numerical target definition are compared.¹³ We estimate the following model

$$X_{it}^h = c + \beta_1 d_{it}^{hybrid} + \beta_2 d_{it}^{point} + \delta_1 \sigma_{it}^{\pi 24m} + \delta_2 RQ_{it} + \nu_i + \nu_Y + \varepsilon_{it}, \quad (4.4)$$

where d_{it}^{hybrid} 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. These classifications are mutually exclusive. Different dependent variables are considered for

¹³This 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.

X .

Fig. 5(a) shows the results for the main coefficients of interest (β_1, β_2) of model (4.4) for dependent variable $X = probT$.¹⁴ The result confirms that a reference to a focal point improves anchoring along all forecast horizons. The quantitative difference is sizable, in particular for medium-term horizons. 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. For the long-term horizon of 6 years, point targets are associated with a 90 percent higher probability of point predictions close to target compared to range targets, while hybrid targets feature a 60 percent higher probability. However, the coefficients of d^{hybrid} and d^{point} are never statistically different from each other according to the results from a corresponding F-test. Thus, we conclude that these two target types have a similar beneficial unconditional effect on anchoring.

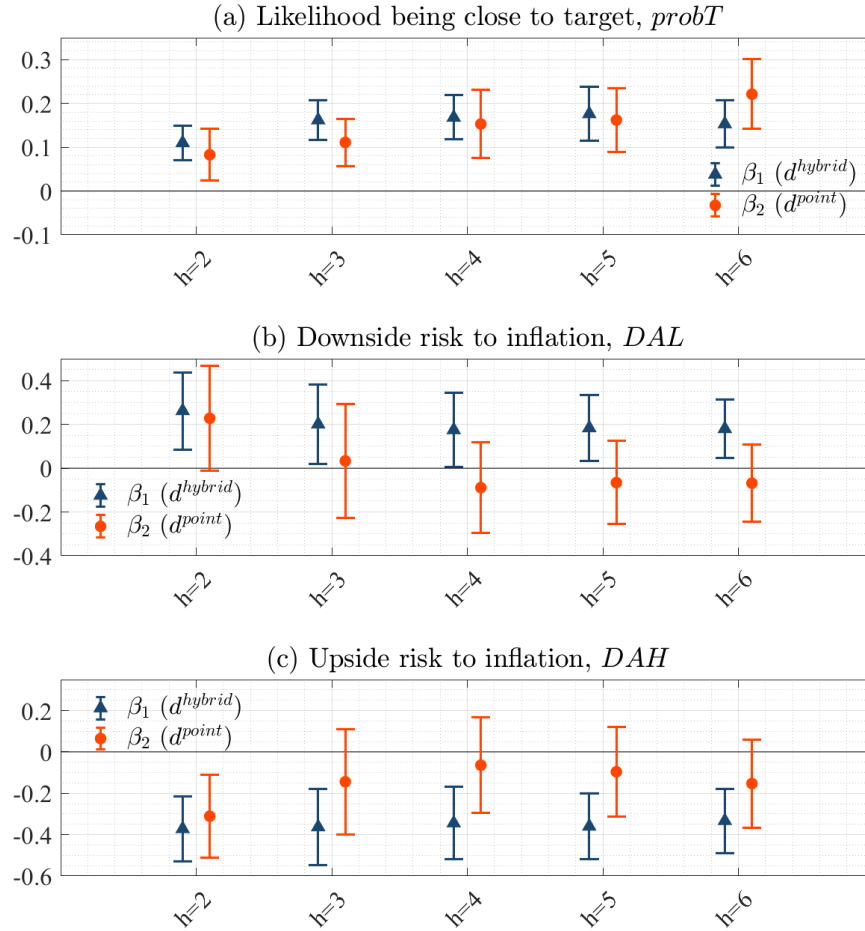
Next, we are interested in the differential effects of target formulations on the symmetry of the distribution of point forecasts around the inflation objective, a novel aspect in the empirical analysis of expectation anchoring. Fig. 5 (b) presents effects of the dummy variables on downside risk to inflation, while panel (c) contains effects on upside risk to inflation. Hybrid targets feature lower upside risk, while also exhibiting higher downside risk. We conclude that hybrid target formulations are associated with a downward shift in the entire cross-sectional distribution of point forecasts compared to target ranges. This effect is much less pronounced for point targets.

4.3 Inflation performance, anchoring and target formulations

Until now, we documented unconditional effects of inflation target formulations on the cross-sectional distribution of point forecasts. However, there might also be substantial differences over time associated with target formulations conditional on the economic context. A first indication is presented in Fig. 2 which shows that the shape, specifically skewness, is not stable over time, but features persistent fluctuations with periods of positive and negative skewness. Motivated by this observation, this section explores systematically the relation between target formulations, inflation performance and expectations anchoring. Following Neuenkirch and Tillmann (2014), we construct an indicator that captures the average deviation of realized inflation from target in

¹⁴See Tab. D.2 for the full regression table.

Figure 5: Disanchoring and numerically defined inflation targets



Notes: Point estimates and 90% confidence intervals based on Driscoll and Kraay (1998) standard errors. Coefficient estimates as of Tab. D.2 and Tab. D.3 in the Appendix for a hybrid target (d^{hybrid}) and a point target (d^{point}) on the anchoring measure $probT$ (Panel a), downside risk to inflation DAL (Panel b), and upside risk to inflation DAH (Panel c) in model (4.4). All equations are estimated separately for each forecast horizon from $h = 2$ to $h = 6$ years based on a fixed-horizon approximation.

country i in period t as

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

where the backward looking rolling window covers $T = 60$ months. CL denotes *credibility losses*. While we borrow the notation from Neuenkirch and Tillmann (2014), we interpret the indicator more broadly and do not limit it to credibility losses. Persistent deviations might also arise if economies get hit by very persistent shocks, a sequence of shocks with the same sign, or if a central bank pursues a secondary objective. 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

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

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

to capture persistent deviation due to periods of an inflation shortfall $CL_{it}^{(-)}$ and inflation overshooting $CL_{it}^{(+)}$ with respect to the midpoint of the inflation objective. [Tab. D.4](#) in the [Appendix](#) 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. In the empirical models below, we therefore use standardized series of $CL^{(+)}$ and $CL^{(-)}$ with mean zero and a standard deviation of one. To quantify the effects of persistent target misses on expectation anchoring, we specify the following empirical model:

$$X_{it}^h = c + \beta_1 CL_{it}^+ + \beta_2 CL_{it}^- + \gamma_1 \sigma_{it}^{\pi 24m} + \gamma_2 RQ_{it} + \nu_i + \nu_Y + \varepsilon_{it} \quad (4.5)$$

[Tab. 3](#) presents the results for forecast horizons of four and six years on various dependent variables. To get an idea of the relationship between the credibility loss indicator 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.

The two credibility loss indicators are associated with 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). The effect is generally larger for longer forecast horizons. Meanwhile, credibility losses do shift the tails of the cross-sectional distribution in the expected direction, cf. columns (4)-(7).

Our findings are consistent with forecasters' responses from a survey asking what

Table 3: Effect of persistent target deviations on expectation anchoring

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\pi - \pi^*$	probT(4)	probT(6)	DAL(4)	DAL(6)	DAH(4)	DAH(6)	Mean(4)	Mean(6)
$CL^{(-)}$	-0.103 (0.0831)	-0.0222** (0.0108)	-0.0301*** (0.0104)	0.0632*** (0.0146)	0.0850*** (0.0102)	-0.0410*** (0.0149)	-0.0549*** (0.00858)	-0.0407* (0.0232)	-0.0344*** (0.0125)
$CL^{(+)}$	0.722*** (0.201)	-0.00636 (0.00848)	-0.00169 (0.00735)	-0.00118 (0.0126)	-0.0373*** (0.00891)	0.00754 (0.0145)	0.0389*** (0.0110)	0.354*** (0.0561)	0.233*** (0.0275)
sd infl. (24m)	-0.151 (0.260)	-0.0106 (0.0226)	-0.0311 (0.0204)	-0.0303 (0.0258)	0.0182 (0.0209)	0.0409 (0.0247)	0.0129 (0.0179)	0.0933 (0.0681)	0.0236 (0.0344)
Regulatory quality	0.307 (0.505)	0.00819 (0.0698)	-0.117 (0.0842)	0.0930 (0.0586)	0.276*** (0.0930)	-0.101 (0.0749)	-0.160* (0.0847)	-0.919*** (0.165)	-0.761*** (0.100)
Constant	-0.0425 (0.542)	0.174** (0.0680)	0.353*** (0.0780)	0.235*** (0.0692)	0.0694 (0.0988)	0.592*** (0.0758)	0.578*** (0.0941)	3.582*** (0.153)	3.359*** (0.100)
country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N.Obs	3978	827	825	827	825	827	825	833	831
N.Countries	28	28	28	28	28	28	28	28	28
adj. R-squared	0.31	0.06	0.06	0.16	0.21	0.19	0.19	0.55	0.51

Notes. ***/**/* / denote statistical significance at the 1%/5%/10% level. Standard errors based on Driscoll and Kraay (1998) reported in parentheses. Results for model (4.5), dependent variables are the contemporaneous inflation gap ($\pi - \pi^*$), the expectations anchoring ($probT$), downside risk to inflation (DAL), upside risk to inflation (DAH) and the Consensus mean inflation expectation ($Mean$). All equations are estimated separately for each forecast horizon of 4 and 6 years based on a fixed-horizon approximation.

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).

Our finding that tails of the distribution (DAL , DAH) respond more strongly to the credibility loss terms than central tendency ($probT$) is consistent with models of information frictions in the process of expectation formation. In particular, models with noisy information as in Woodford (2002), Sims (2003) and Mackowiak et al. (2009) predict that gathering information has a higher return for agents who's current prediction is more distant to the signal, i.e. realized inflation. It is, thus, more likely that these agents revise their forecast and bring it closer to current inflation trends, as shown by the high coefficients on $CL^{(-)}$ for DAL , and on $CL^{(+)}$ for DAH . Coibion and Gorodnichenko (2015) have documented such information frictions in the mean forecasts of Consensus data, while the results shown here can be considered as complementary and extending their findings to tails in the cross-sectional distribution.

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.

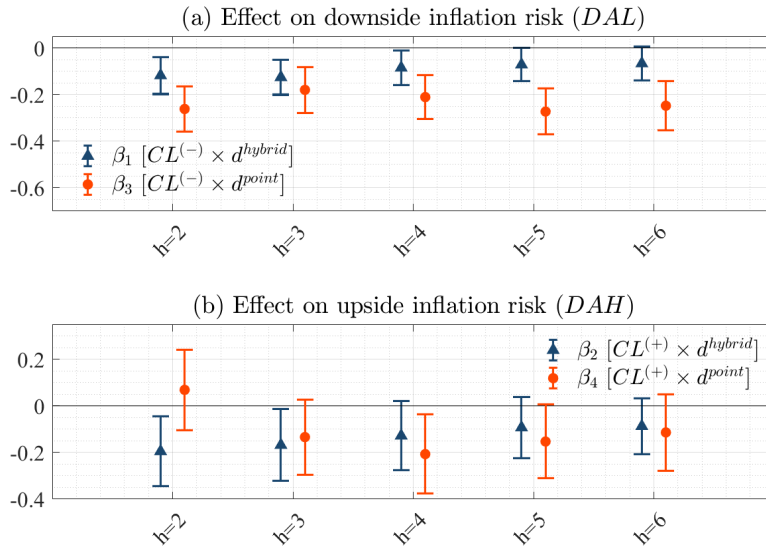
In a final step, we want to test whether the shift in the tails of the distribution conditional on persistent deviation from a central bank's inflation target depends on the target formulation. To this end, we interact the credibility loss terms with our dummy variables of hybrid inflation targets and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

$$\begin{aligned}
probT_{it}^h = & c + \beta_1 [CL_{it}^- \times d_{it}^{hybrid}] + \beta_2 [CL_{it}^+ \times d_{it}^{hybrid}] + \delta_1 d_{it}^{hybrid} \\
& + \beta_3 [CL_{it}^- \times d_{it}^{point}] + \beta_4 [CL_{it}^+ \times d_{it}^{point}] + \delta_2 d_{it}^{point} \\
& + \gamma_1 CL_{it}^+ + \gamma_2 CL_{it}^- + \gamma_3 \sigma_{it}^{\pi 24m} + \gamma_4 RG_{it} + \nu_i + \nu_Y + \varepsilon_{it} \quad (4.6)
\end{aligned}$$

Fig. 6 shows the results. Panel (a) presents the conditional effect on downside risk to inflation during periods of persistent inflation undershooting if the central bank operates with a hybrid or point target versus a range target. The negative coefficient shows that the adverse consequences of a rise in downside risk to inflation can be mitigated. While both target formulations with a reference to a focal point are beneficial, pure point targets have larger and more meaningful effect than hybrid targets, in particular over longer forecast horizons. We interpret those findings as consistent with theories showing that range targets and tolerance bands are perceived by professional forecasters as zones where monetary policy is less active (Orphanides and Wieland, 2000). The results are further inconsistent with the hypothesis that target ranges are fostering central bank credibility (Demertzis and Viegi, 2009).

Moving to Fig. 6(b), we find also beneficial effects on including a reference to a focal point in target formulations during periods of persistent overshooting. The negative coefficients again indicate that the tails of the cross-sectional distribution of forecasters are more stable, leading to a less strong increase in upside risk to the inflation outlook during periods of persistent inflation overshooting. Here, hybrid target formulations and point targets have quantitatively similar effects.

Figure 6: Risk of disanchoring conditional on target formulation and persistent target deviation



Notes: Point estimates and 90% confidence intervals based on Driscoll and Kraay (1998) standard errors. Coefficient estimates for model (4.6) as of Tab. D.5 in the Appendix for the interaction terms of the measure of persistent deviation CL^{\pm} and the hybrid target d^{hybrid} and a point target d^{point} , respectively. All equations are estimated separately for each forecast horizon from $h = 2$ to $h = 6$ years based on a fixed-horizon approximation.

5 Robustness

We consider a number of robustness checks for the main models of interest. Let us first reconsider the result on the presence of a numerically defined target from model (4.2). Tab. 4 shows the coefficient on the dummy $d^{numTarget}$ in alternative model specifications. The first row restates the baseline result for convenience. We consider the absolute distance of the mean point forecast to target as an alternative to our probability-based measure from estimated density functions. The results are confirmed, meaning that a numerical target is not beneficial for anchoring for forecast horizons of four to six years. Considering a specification with only advanced economies, the results are slightly weaker compared to the baseline, but do hold qualitatively. However, the results do change when we exclude Japan and Turkey from the sample, two countries which have the weakest inflation track record in the sample. In this case, the introduction of a numerical point target does improve anchoring for short forecast horizons of two years. However, the coefficient remain insignificant for longer forecast horizons. In our view, this does not dramatically change our conclusion that numerical target definitions do not *per se* improve anchoring. The baseline results are further robust to dropping inflation volatility and regulatory quality as controls, and dropping year dummies.

Table 4: Robustness: explicit numerical target ($d^{numTarget}$)

	(1) (h=2)	(2) (h=3)	(3) (h=4)	(4) (h=5)	(5) (h=6)
Baseline	0.0161 (0.0274)	-0.00110 (0.0235)	-0.0316* (0.0162)	-0.0408*** (0.0123)	-0.0527*** (0.0155)
Absolute distance, mean to target	-0.0483 (0.124)	0.0541 (0.106)	0.213** (0.0892)	0.311*** (0.0753)	0.231*** (0.0737)
AEs	0.0188 (0.0307)	0.0149 (0.0295)	0.00169 (0.0270)	-0.0142 (0.0171)	-0.0477** (0.0203)
w/o Japan, Turkey	0.0694** (0.0331)	0.0234 (0.0319)	0.00577 (0.0259)	-0.00740 (0.0249)	-0.0142 (0.0275)
No controls	0.0131 (0.0252)	-0.00395 (0.0208)	-0.0374** (0.0169)	-0.0473*** (0.0117)	-0.0560*** (0.0169)
No year dummies	0.0332 (0.0208)	0.00461 (0.0187)	-0.0269** (0.0121)	-0.0293*** (0.00964)	-0.0225 (0.0138)

Notes. ***/**/* denote statistical significance at the 1%/5%/10% level. Standard errors based on [Driscoll and Kraay \(1998\)](#) reported in parentheses. All equations are estimated separately for each forecast horizon of 4 and 6 years based on a fixed-horizon approximation.

Next, we reconsider the effect of a reference to a range and a focal point within the inflation target formulations as in model (4.3). [Tab. 5](#) shows the results, again with the baseline at the beginning. If we use the absolute distance of the cross-sectional mean to the inflation target as our dependent variable, the main message is preserved. A reference to a numerical focal point is associated with better expectation anchoring, thus lowering the absolute distance, while a reference to an explicit range is either neutral compared to a qualitative definition of price stability, or is associated with a larger absolute difference. If we consider a limited sample of only advanced economies, the baseline results gets stronger by an overall increase in the magnitude of estimated coefficients. The baseline results are also robust to the exclusion of Japan and Turkey from the country sample, excluding all control variables, and the exclusion of year dummies.

Finally, let us reconsider the effects of hybrid and point target formulations from model (4.4). [Tab. D.8](#) in the [Appendix](#) shows that hybrid point targets and point targets improve anchoring compared to target ranges in all considered robustness specifications by quantitatively similar amounts. Hybrid targets have larger coefficients at shorter forecast horizon of two years, while point targets have better anchoring properties at the longer horizon of six years.

Table 5: Robustness: range/hybrid/point ($d^{numRange}$, $d^{numPoint}$)

	(1) (h=2)	(2) (h=3)	(3) (h=4)	(4) (h=5)	(5) (h=6)
Baseline					
$d^{numRange}$	-0.0523 (0.0496)	-0.0830** (0.0413)	-0.108* (0.0540)	-0.0806* (0.0462)	-0.0653 (0.0506)
$d^{numPoint}$	0.0687*** (0.0223)	0.0869*** (0.0204)	0.0775*** (0.0266)	0.0859*** (0.0267)	0.0753*** (0.0201)
Absolute distance, mean to target					
$d^{numRange}$	0.126 (0.237)	0.152 (0.144)	0.113 (0.111)	0.139 (0.0921)	0.176* (0.0993)
$d^{numPoint}$	-0.315** (0.150)	-0.262** (0.129)	-0.227** (0.106)	-0.191** (0.0950)	-0.194** (0.0769)
AEs					
$d^{numRange}$	-0.00866 (0.0490)	-0.0324 (0.0378)	-0.0528 (0.0500)	-0.0223 (0.0484)	-0.0232 (0.0583)
$d^{numPoint}$	0.107*** (0.0276)	0.136*** (0.0276)	0.134*** (0.0339)	0.149*** (0.0342)	0.130*** (0.0326)
w/o Japan, Turkey					
$d^{numRange}$	-0.0219 (0.0539)	-0.0469 (0.0484)	-0.0671 (0.0577)	-0.0329 (0.0517)	-0.0156 (0.0543)
$d^{numPoint}$	0.0984*** (0.0247)	0.117*** (0.0264)	0.119*** (0.0310)	0.132*** (0.0314)	0.123*** (0.0282)
No controls					
$d^{numRange}$	-0.0503 (0.0471)	-0.0858** (0.0389)	-0.108** (0.0514)	-0.0824* (0.0441)	-0.0705 (0.0499)
$d^{numPoint}$	0.0669*** (0.0199)	0.0832*** (0.0194)	0.0743*** (0.0262)	0.0839*** (0.0267)	0.0695*** (0.0218)
No year dummies					
$d^{numRange}$	-0.0513 (0.0429)	-0.0872** (0.0346)	-0.121** (0.0514)	-0.101** (0.0422)	-0.0689* (0.0383)
$d^{numPoint}$	0.0736*** (0.0147)	0.0774*** (0.0134)	0.0594*** (0.0160)	0.0740*** (0.0171)	0.0887*** (0.0187)

Notes. ***/**/* denote statistical significance at the 1%/5%/10% level. Standard errors based on [Driscoll and Kraay \(1998\)](#) reported in parentheses. All equations are estimated separately for each forecast horizon of 4 and 6 years based on a fixed-horizon approximation.

6 Conclusion

The adoption of a quantitative target for inflation is common practice among central banks. At the same time, there remains remarkable heterogeneity with respect to the exact formulation of the inflation target. We classify these into four groups: mere definitions of price stability, target ranges, hybrid targets, and point targets. Do alternative inflation target formulations matter for expectations anchoring?

This paper provides evidence that a reference to a numerical target definition *per se* does not improve anchoring, while reference to a numerical focal point increase 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 numerical focal point steers inflation expectations closer to the inflation aim. The probability of inflation point forecasts within a close interval of ± 0.1 percentage points around target increases by 70 percent for forecast horizons of two years and 25 percent for forecast horizons of six years.

Focusing 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. During periods of persistent deviations of realized inflation from target, we find that tails in the cross-sectional distribution of point forecasts respond more than the central tendency, in line with models of information frictions (Coibion and Gorodnichenko, 2015). During such periods, inflation point targets are most successful in limiting the rise in upside and downside risks to the inflation outlook, while hybrid strategies have smaller beneficial effects. These results are consistent with the view that range targets are interpreted by professional forecasters as zones where monetary policy is less responsive.

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. We do not find substantial unconditional differences between point targets and hybrid target formulations. At the same time, there is no evidence for a credibility channel in the data, arising from explicit tolerance ranges. As a bottom line, 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 in periods of persistent deviation of inflation from target.

Some limitations apply to our results. The findings are based on a survey among professional forecasters who are 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 are 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 less attentive to central bank announcements.¹⁵ 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).

¹⁵See Afrouzi et al. (2015), Coibion, Gorodnichenko, and Weber (2019), and Lewis, Makridis, and Mertens (2020).

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ONLINE APPENDIX

Anchoring of Inflation Expectations: Do Inflation Target Formulations Matter?

by Christoph Grosse-Steffen¹

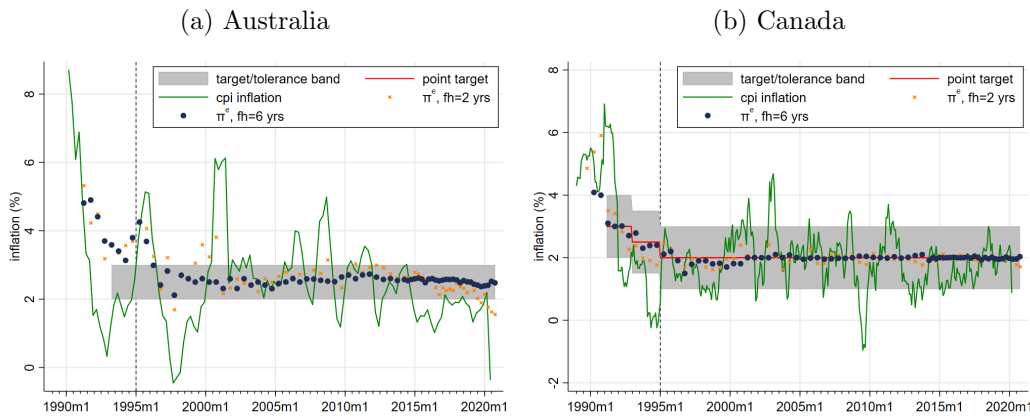
A Classification

Table A.1: Summary statistics of inflation targets

	mean	sd	min	max	groups	obs
no numerical target	1.74	.37	1	2	3	71
numerical target	2.5	.73	1	5	28	853
<i>within group of numerical inflation target (classifications)</i>						
Range target	2.34	.88	1.5	4.5	9	160
Range with focal point	2.2	.25	2	2.5	2	49
Point with tolerance band	2.74	.76	2	5	16	437
Point target	2.18	.36	1	3	8	207

Note. Summary statistics on the midpoint of the inflation objective for target classifications. [Tab. A.2](#) provides details on the classification for each country in the sample.

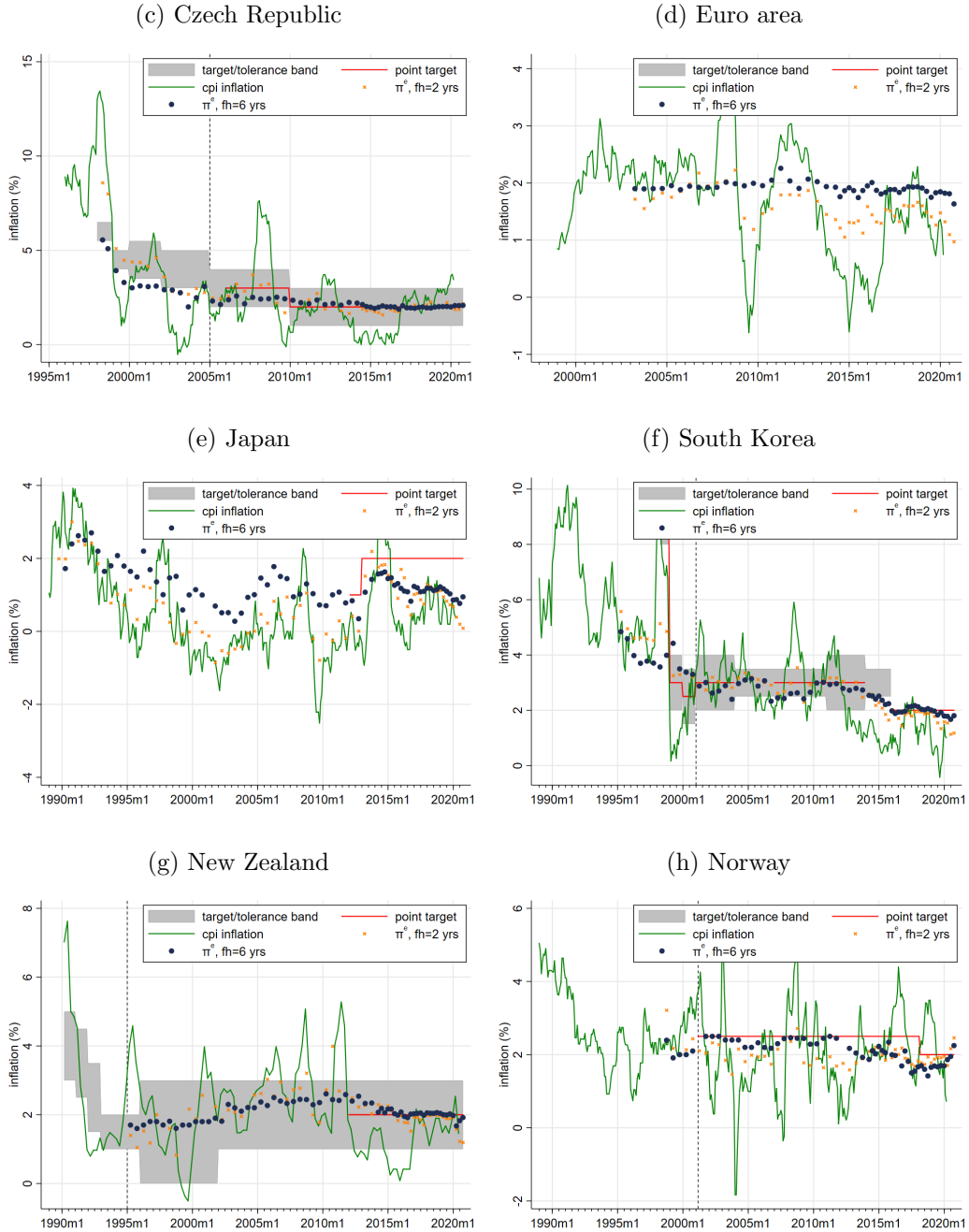
Figure A.1: Targets for monetary policy, AEs (1)



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, $fh = 6$ years. Yellow x=mean point forecast, $fh = 2$ years. Mean point forecasts are computed using a fixed-horizon approximation.

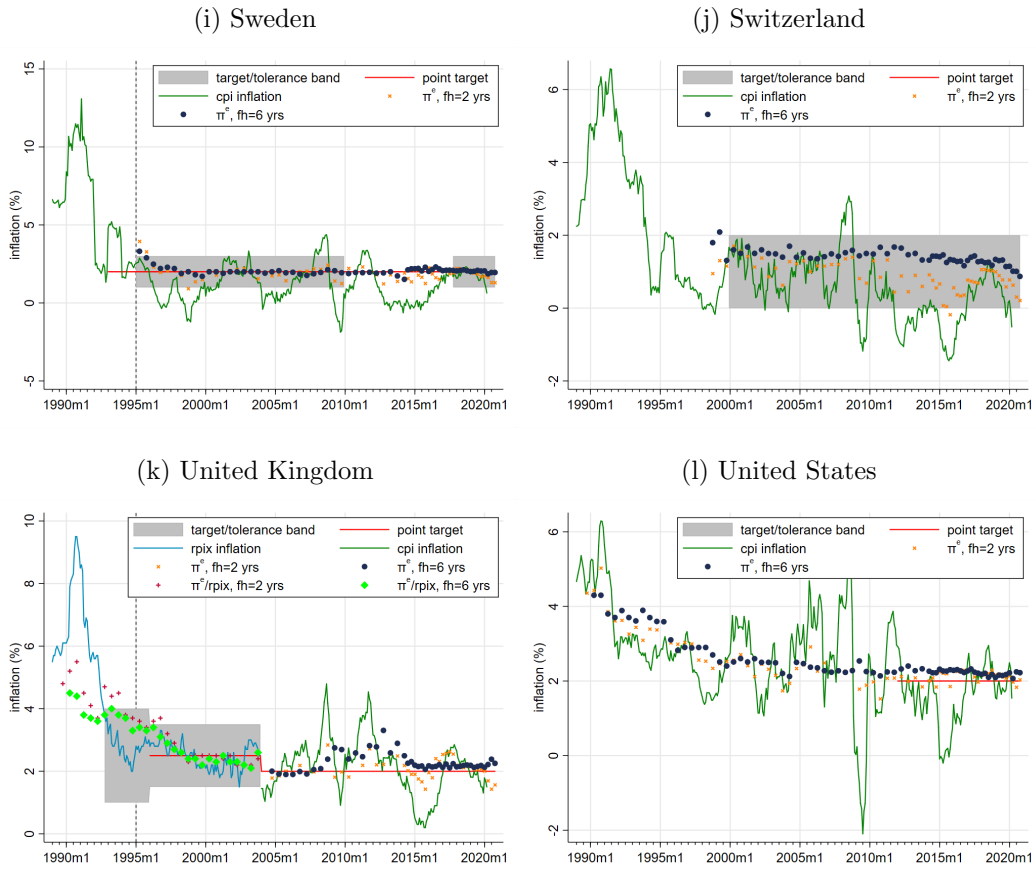
¹*Contact:* Banque de France, 31 rue des Petits-Champs, 75001 Paris, France. Email: christoph.grosse-steffen(at)banque-france.fr, tel.: +33 (0)1 42 92 49 42.

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



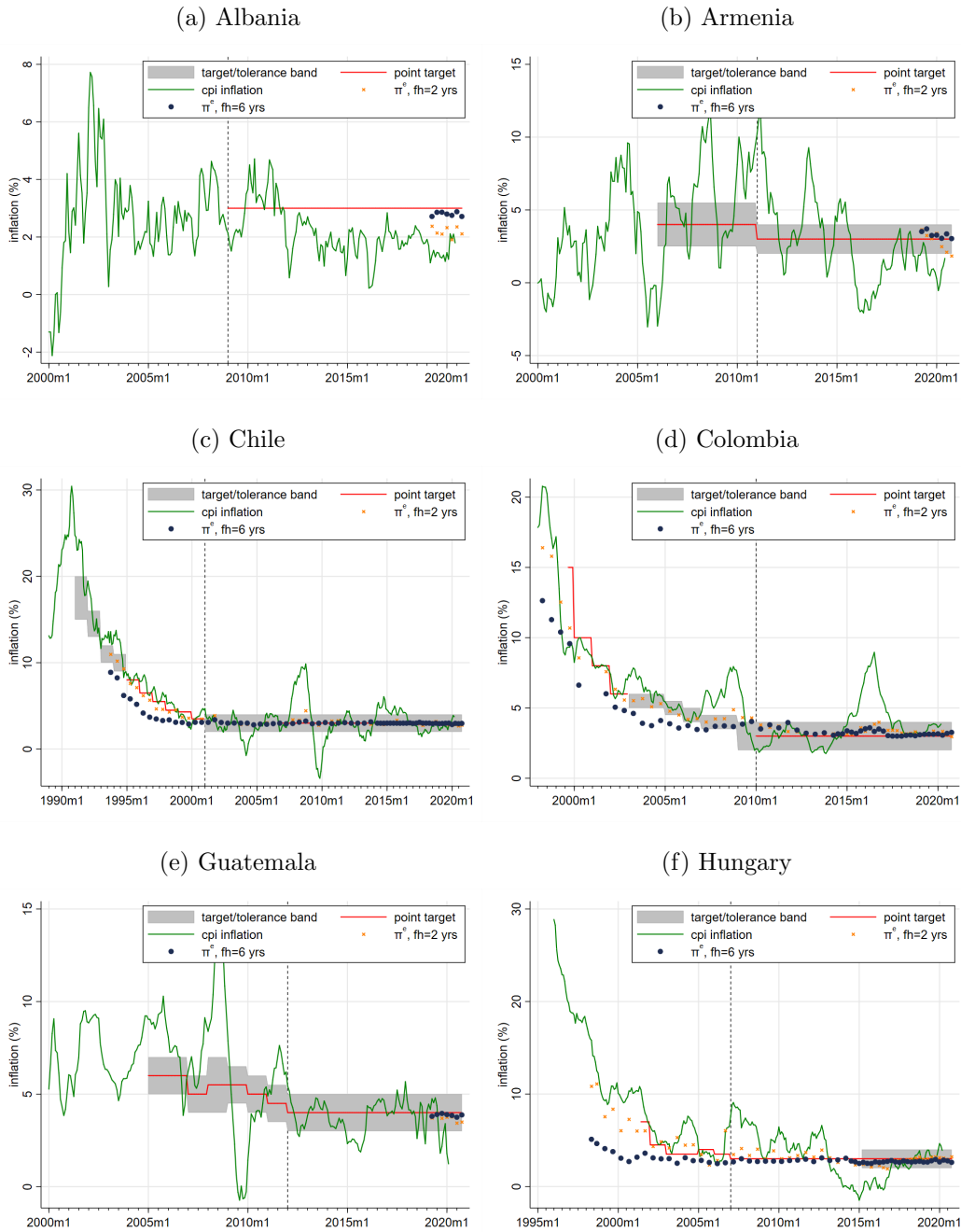
Notes: Green line=YoY CPI inflation. Vertical, dotted line=start date of a stable inflation target, following Roger (2009), with adjustments and extensions. Blue dots=mean point forecast, $fh = 6$ years. Yellow x=mean point forecast, $fh = 2$ years. Mean point forecasts are computed using a fixed-horizon approximation.

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



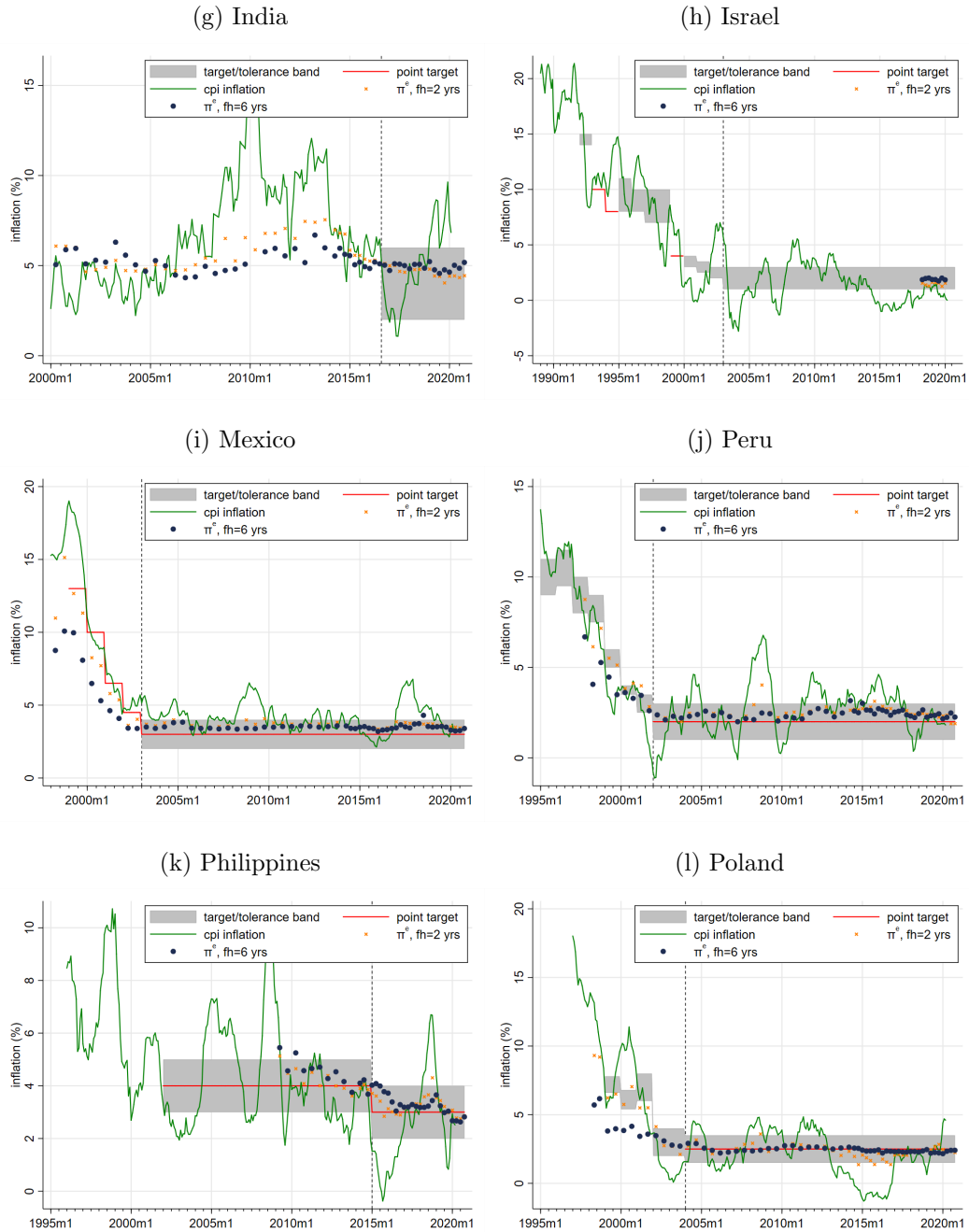
Notes: Green line=YoY CPI inflation. Vertical, dotted line=start date of a stable inflation target, following Roger (2009), with adjustments and extensions. Blue dots=mean point forecast, $fh = 6$ years. Yellow x=mean point forecast, $fh = 2$ years. Mean point forecasts are computed using a fixed-horizon approximation.

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



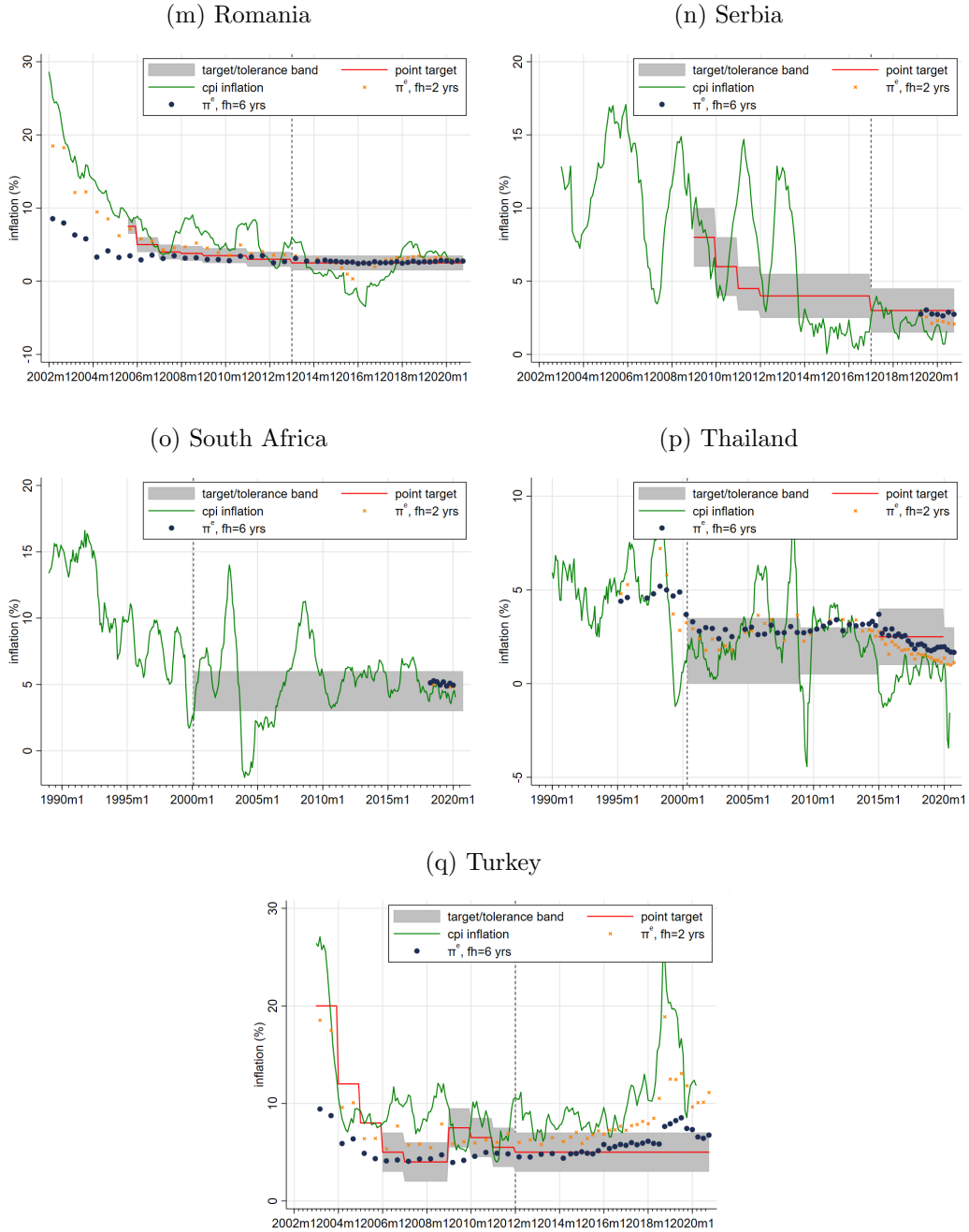
Notes: Green line=YoY CPI inflation. Vertical, dotted line=start date of a stable inflation target, following Roger (2009), with adjustments and extensions. Blue dots=mean point forecast, $fh = 6$ years. Yellow x=mean point forecast, $fh = 2$ years. Mean point forecasts are computed using a fixed-horizon approximation.

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



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, $fh = 6$ years. Yellow x=mean point forecast, $fh = 2$ years. Mean point forecasts are computed using a fixed-horizon approximation.

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



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, $fh = 6$ years. Yellow x=mean point forecast, $fh = 2$ years. Mean point forecasts are computed using a fixed-horizon approximation.

Table A.2: Target classification

	(1) NoExplAn	(2) QuantDef	(3) RangeTar	(4) Range-Point	(5) Point-ToI	(6) PointTar	IT introdate	stable
<i>Advanced Economies (AE)</i>								
Australia	-	-	1993m4	-	-	-	1993m4	1993m4
Canada	-	-	-	-	1991m3 -	-	1991m3	1995m1
Czech Republic	-	-	1998m1-2005m12	-	2006m1-	-	1998m1	2005m1
Euro area	-	1999m1 -	-	-	-	-	<i>no IT</i>	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 -	-	-	-	<i>no IT</i>	1990m1
United Kingdom	1990m1-1992m9	-	1992m10-1995m5	-	1995m6-2003m12	2004m1-	1992m10	1992m10
United States	1990m1-2012m2	-	-	-	-	2012m3 - 2020m7	<i>no IT</i>	1990m1
<i>Emerging Market Economies (EME)</i>								
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-Altamari, 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. Specifically, we use in this Appendix 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 panelists' point forecasts on consumer price inflation for 'next calendar year' at a monthly frequency. We fit the generalized beta distribution and a skew extended t -distribution, labeled here as *skew t*. Both distributions share a couple of similarities, namely being highly flexible and to allow for nonzero skewness. 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

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

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

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

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

$$F_{JF}(x; \mu, \sigma, a, b) = I(z; a, b),$$

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

The distribution's PDF is given by

$$f_{JF}(x; \mu, \sigma, a, b) = \frac{1}{\sigma} C_{a,b}^{-1} (1+\tau)^{a+1/2} (1-\tau)^{b+1/2},$$

$$\text{with } C_{a,b} = 2^{a+b-1} B(a, b) (a+b)^{\frac{1}{2}},$$

$$\text{and } \tau = \frac{x-\mu}{\sigma} \left(a+b + \left(\frac{x-\mu}{\sigma} \right)^2 \right)^{-\frac{1}{2}}.$$

B.1.3 Maximum likelihood estimation

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

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

$$\text{with } \hat{L} = f_{JF}(x_{jit}; \theta_{it}^{(JF)})$$

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

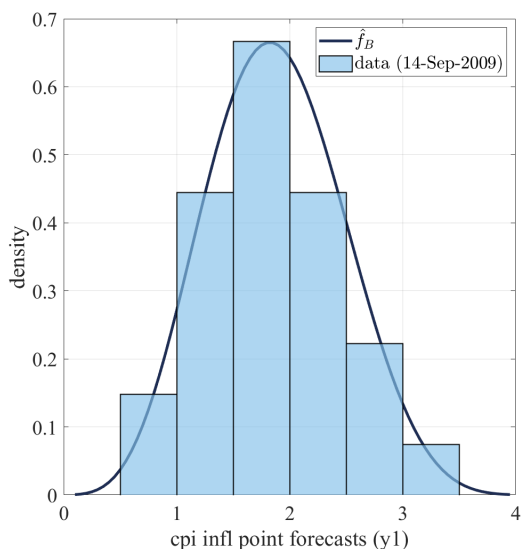
$$\hat{\theta}_{it}^{(B)} = \operatorname{argmax}_{\theta_{it}^{(B)} \in \Theta^{(B)}} \sum \ln \hat{L}_n(\theta_{it}^{(B)}, x_{jit})$$

with $\hat{L} = f_B(x_{jit}; \theta_{it}^{(B)})$

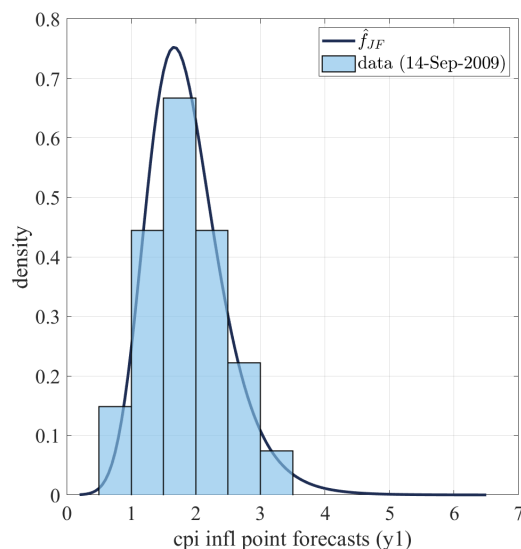
where $\theta_{it}^{(B)} = (a_{it}, b_{it}, l_{it}, r_{it})$.

Figure B.1: Histograms of survey data and parametric models

(a) pdf, generalized Beta



(b) pdf, skew t (JF)



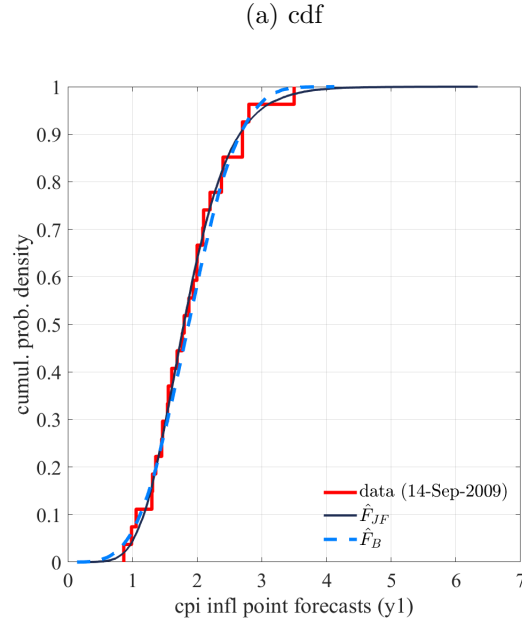
Note: Results of the estimated parametric density functions \hat{f}_B and \hat{f}_{JF} are shown for US consumer price inflation forecasts for the next calendar year of a Consensus survey published on 14 September 2009.

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.1 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.2 compares the empirical cdf, computed using the Kaplan-Meier nonparametric method, 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

Figure B.2: Empirical cdf compared with parametric models



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.

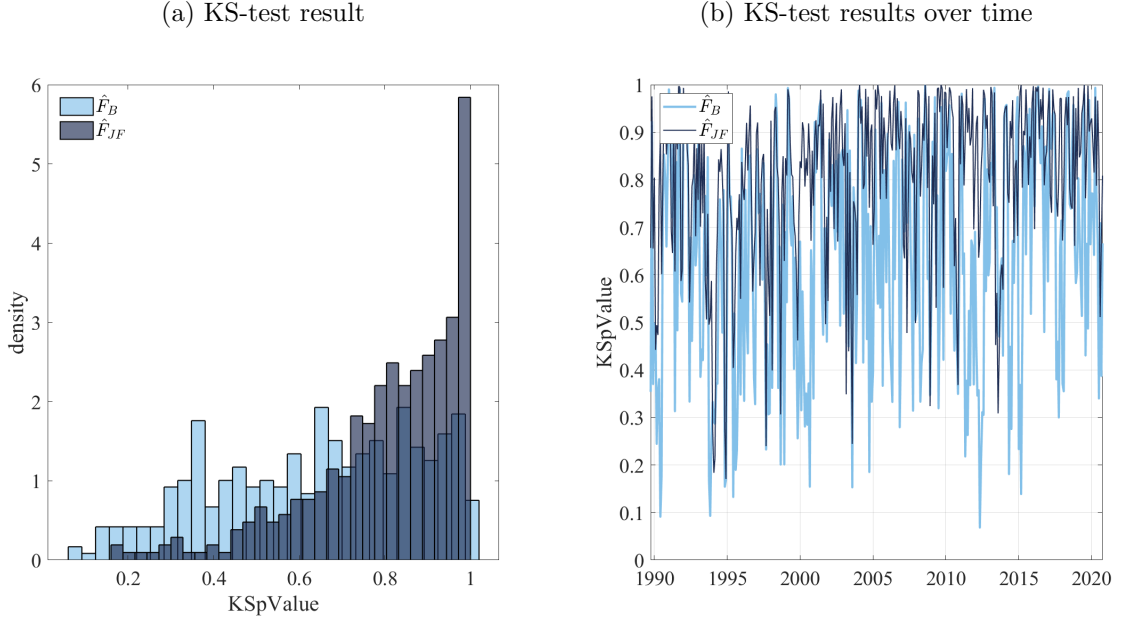
period t and country i in the sample. The KS-test uses the null hypothesis that the two underlying distribution functions are identical. Values of the KS-test above 0.05 indicate that the null cannot be rejected at the 5 percent confidence level.

Fig. B.3 shows the results of the KS-tests. Panel (a) presents test statistics across all countries and periods, while panel (b) shows the KS-test results for the United States as a time series. 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.3: Fit of the parametric models



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.

We further compute a percentile-based measure of skewness 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.1 shows summary statistics of the measures of sample skewness, specifically the minima and maxima of the skewness ratio and Kelly's skewness. Tab. B.1 also provides the correlation of the skewness ratio based on mean, lowest and highest sample observations with the alternative measures of skewness. 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.

Table B.1: Skewness in panelists' point forecasts

	median	[P(10)/P(90)]	N
<i>A. Levels, cross-country comparison</i>			
S_{it}	0.034	[-0.016/0.057]	24
$\min(S_{it})$	-0.460	[-0.565/-0.381]	24
$\max(S_{it})$	0.591	[0.482/0.682]	24
$\min(S_{it}^{Kelly's})$	-0.736	[-1.000/-0.594]	24
$\max(S_{it}^{Kelly's})$	0.714	[0.612/1.000]	24
<i>B. Correlations, cross-country comparison</i>			
$\text{corr}(S_{it}, S_{it}^{unbiased})$	0.951	[0.933/0.962]	23
$\text{corr}(S_{it}, S_{it}^{Kelly's})$	0.527	[0.345/0.745]	23
$\text{corr}(S_{it}, S_{it}^{Pearson2})$	0.531	[0.463/0.636]	23
$\text{corr}(S_{it}, S_{it}^{Pearson1})$	0.353	[0.204/0.441]	23

Notes: Skewness in panelists' point forecasts across countries compared to the skewness ratio $S_{it} = [(high_{it} - \mu_{it}) - (\mu_{it} - low_{it})] / (high_{it} - low_{it})$. Due to the lack of a standard measure of skewness, we compute a series of alternative measures and report the coefficient of contemporaneous correlation with the skewness ratio. Median and 10th and 90th percentiles computed from cross-section of countries.

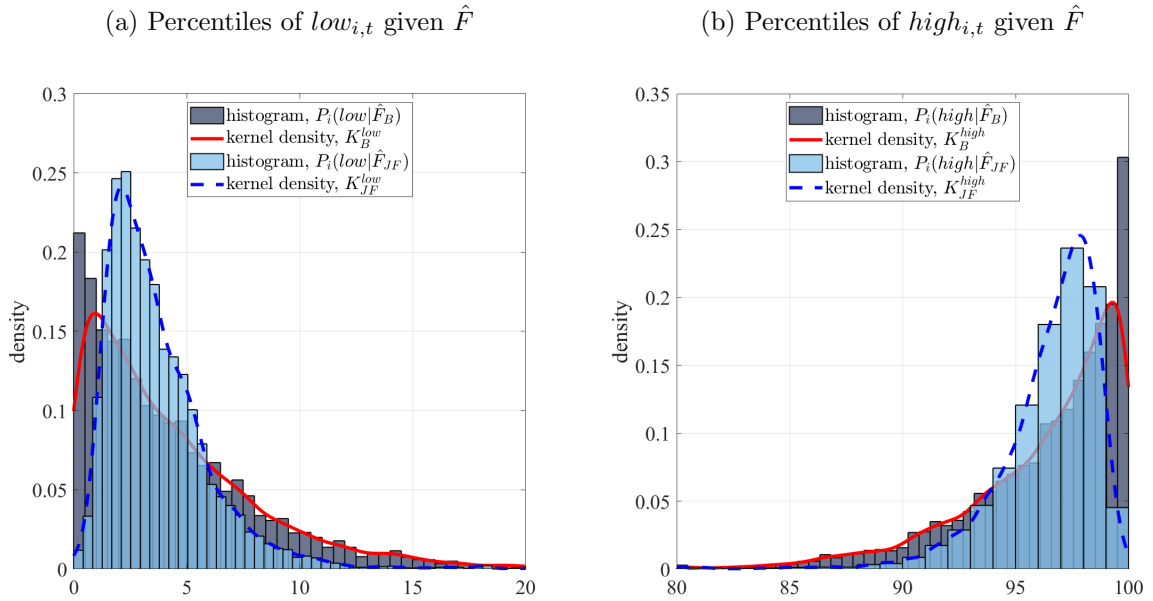
C Simulated method of moments

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. Further, we test how well the cross-sectional shape can be reproduced with only limited data.

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 asterisk denotes a distribution function estimated with the full cross-section as observations.

Figure C.1: 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 highest survey answers, respectively, across all countries i and periods t .

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.1 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.

Fig. C.1 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.1 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.1: Location of lowest/highest observation in estimated density functions

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.

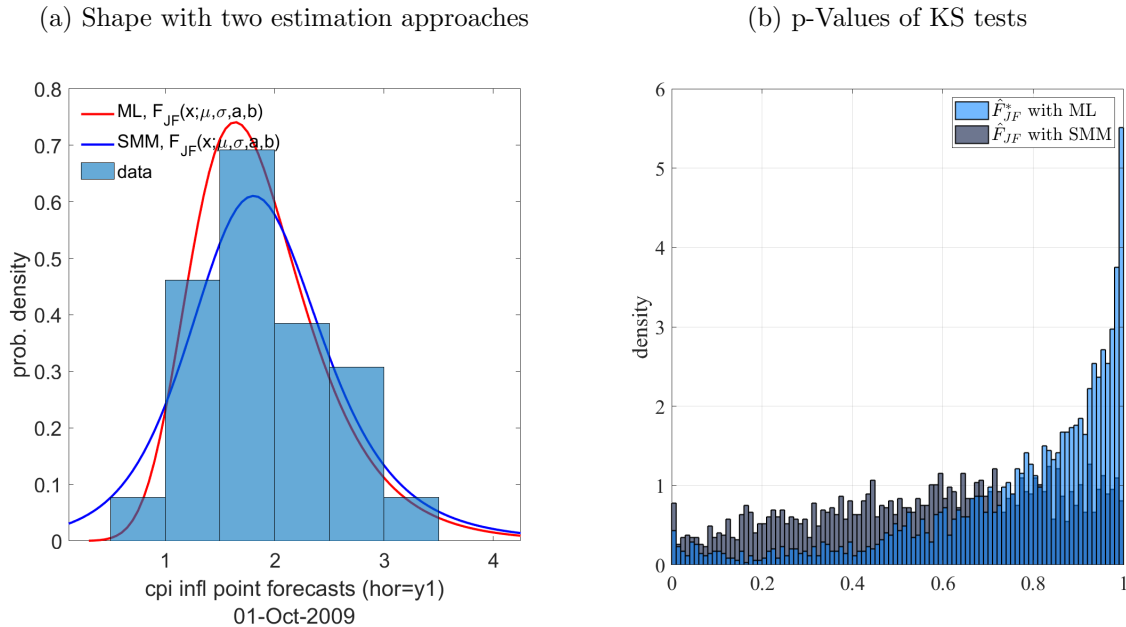
Tab. C.1 shows summary statistics of the location parameters $P_i^{low}(\hat{F}_{JF}^*)$, $P_i^{low}(\hat{F}_B^*)$, $P_i^{high}(\hat{F}_{JF}^*)$ and $P_i^{high}(\hat{F}_B^*)$. We find that the mode of the distribution of percentiles in case of the generalized beta is below the 5th percentile and above the 95th 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.

C.2 Shape reproduction with limited data on long-term forecasts

We estimate skew extended t distributions using limited information on the 'next calendar year' data in SMM estimation and compare it with the results obtained via ML estimation on the full micro data. Fig. C.2(a) shows the result US data on October 2009 as an example. It illustrates that the shape gets reasonably well reproduced when only the mean, standard deviation and the pair of lowest and highest observations are available. To gain a broader perspective, we perform the KS-test for estimated density function \hat{F}_{JF}^* under ML and using the full sample and for the case of SMM estimation with limited data \hat{F}_{JF} . Fig. C.2(b) shows that while density functions estimated via ML perform better, also KS-tests for density functions estimated with SMM and limited data most of the time cannot reject the hypothesis that the sample data is drawn from the corresponding estimated distribution function. In fact, while the ML estimation has 1.24 percent of p-values below 0.05, this is the case for 2.11 percent of estimated densities under SMM estimation.

Figure C.2: Comparing two estimation approaches

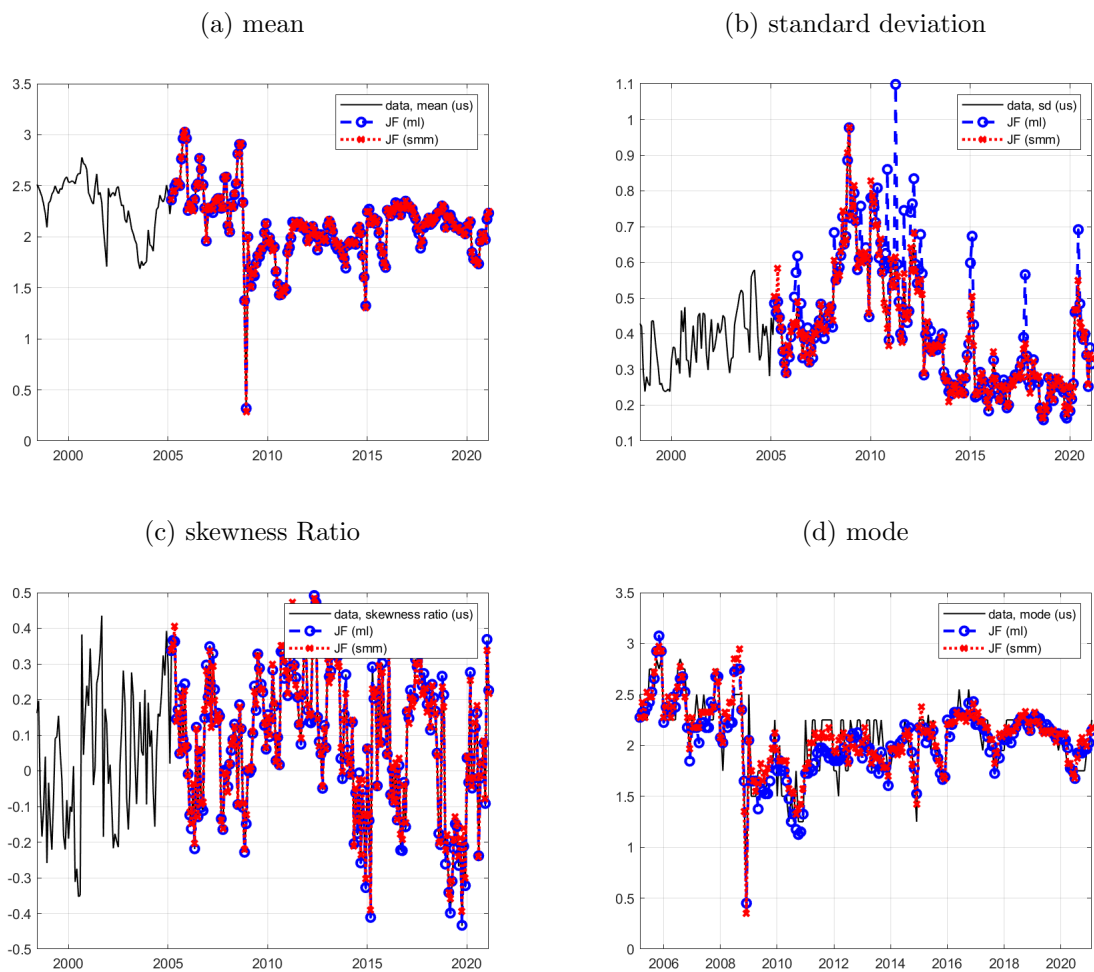


Note: Figure compares two estimation approaches. First, ML estimation with the full sample data. Second, SMM with limited data, i.e. the sample mean, standard deviation, the lowest and highest sample observation. Panel (a) shows one example, the fit for US data in October 2009. Panel (b) shows the p-Value of the KS-test evaluated for all estimated distributions in the sample of 24 countries.

Fig. C.3 shows four sample moments from US data and compares them with moments computed from the estimated parametric skew extended t distribution functions

under the two estimation approaches. The fit of parametric density functions regarding the mean is very good for both estimation methods (panel a). Regarding the cross-panelists' standard deviation, the SMM estimation has a better fit than ML estimation (panel b). The skewness ratio is also remarkably well matched (panel c). However, there are some deviations with respect to the mode of survey respondents, which is due to the fact that we fit continuous density functions, while survey responses can be grouped around some reference values due to rounding practices in the reporting of point forecasts (panel d).

Figure C.3: Moments of parametric distributions and US sample data on next-year inflation forecasts



Note: Figure compares moments computed from the survey data to moments from parametric density functions obtained via two estimation approaches. First, ML estimation with the full sample data of US next-year inflation forecasts. Second, SMM with limited data (i.e. the sample mean, standard deviation, the lowest and highest sample observation).

C.3 Nonparametric analysis of anchoring measures

We compute non parametric anchoring measures from the panel respondents of 'next calendar year' forecasts as a simple fraction of responses falling within a $+/- 0.1$ percentage point interval around the point target or midpoint of a target range. In analogy, we compute a non parametric measure of risk to the inflation outlook due to low inflation (*DAL*) and high inflation (*DAH*).

[Tab. C.2](#) shows the results of non parametric anchoring measures and compares them directly with anchoring measures for the 'next calendar year' fixed-event horizon from estimated continuous density functions under ML and SMM estimation, respectively. The non parametric anchoring measure is on average slightly higher than the anchoring measure derived from the continuous density functions. Due to a smoothing of the distribution in the continuous case, the tails are emphasized by construction. While the mean difference is slightly higher for functions estimated using SMM estimation compared to ML estimation, the mean difference is overall of very similar magnitude, thus not driven by the estimation approach. The level of correlation between the different anchoring measures ranges from 0.74 to 1.00 and is overall very high. We conclude from this comparison that SMM estimation is reproducing the shape of cross-sectional survey responses well.

Table C.2: Comparing anchoring measures from non parametric share and parametric distributions

cross-country...	average	p10	p90	N
<i>probT</i>				
average share (nonparametric)	17.07	3.02	28.17	24
mean diff (ML-share)	-3.57	-6.77	-0.91	24
mean diff (SMM-share)	-4.97	-11.01	-0.80	24
corr(share, ML)	0.90	0.83	0.96	24
corr(share, SMM)	0.86	0.74	0.92	24
<i>DAL</i>				
average share (nonparametric)	31.97	3.45	72.65	24
mean diff (ML-share)	1.60	-0.02	3.21	24
mean diff (SMM-share)	2.43	0.09	4.45	24
corr(share, ML)	0.97	0.95	1.00	24
corr(share, SMM)	0.96	0.85	0.99	24
<i>DAH</i>				
average share (nonparametric)	50.96	9.99	93.10	24
mean diff (ML-share)	1.97	0.03	4.32	24
mean diff (SMM-share)	2.54	-0.29	6.23	24
corr(share, ML)	0.98	0.94	1.00	24
corr(share, SMM)	0.97	0.92	0.99	24

Note: Table showing the mean of anchoring measure computed as a share of all responses in the survey panel ('average share', i.e. non-parametric). For a sample of 24 countries, the cross-country average, 10th and 90th percentiles are reported. 'mean diff' measures the average difference of the non-parametric share and the anchoring measure derived from the estimated parametric distribution \hat{F}_{jF}^* , with maximum-likelihood methods (ML) and using a simulated method of moments approach based on limited data, i.e. the mean, standard deviation, highest and lowest sample observation (SMM). 'corr' exhibits the contemporaneous correlation coefficient between anchoring measures.

D Additional results

Table D.1: Effect of numerically defined target on anchoring ($probT$)

A. Numerical target definition					
	(1) $probT$ (h=2)	(2) $probT$ (h=3)	(3) $probT$ (h=4)	(4) $probT$ (h=5)	(5) $probT$ (h=6)
$d^{numTarget}$	0.0161 (0.0274)	-0.00110 (0.0235)	-0.0316* (0.0162)	-0.0408*** (0.0123)	-0.0527*** (0.0155)
sd infl. (24m)	-0.0230*** (0.00849)	-0.0183 (0.0147)	-0.0344** (0.0138)	-0.0507*** (0.0122)	-0.0315** (0.0149)
Regulatory quality	0.0269 (0.0398)	0.0543 (0.0503)	-0.00413 (0.0588)	-0.0865 (0.0640)	-0.0646 (0.0709)
Constant	0.110** (0.0450)	0.153*** (0.0537)	0.304*** (0.0655)	0.391*** (0.0623)	0.375*** (0.0723)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	897	897	897	897	895
N.Countries	29	29	29	29	29
adj. R-squared	0.08	0.04	0.05	0.06	0.05
B. Role of inflation target types					
	$probT$ (h=2)	$probT$ (h=3)	$probT$ (h=4)	$probT$ (h=5)	$probT$ (h=6)
$d^{numRange}$	-0.0523 (0.0496)	-0.0830** (0.0413)	-0.108* (0.0540)	-0.0806* (0.0462)	-0.0653 (0.0506)
$d^{numPoint}$	0.0687*** (0.0223)	0.0869*** (0.0204)	0.0775*** (0.0266)	0.0859*** (0.0267)	0.0753*** (0.0201)
sd infl. (24m)	-0.0230*** (0.00850)	-0.0185 (0.0145)	-0.0351** (0.0134)	-0.0514*** (0.0116)	-0.0324** (0.0153)
Regulatory quality	0.0323 (0.0387)	0.0620 (0.0502)	0.00399 (0.0604)	-0.0782 (0.0658)	-0.0572 (0.0700)
Constant	0.0998** (0.0459)	0.127** (0.0549)	0.264*** (0.0654)	0.331*** (0.0654)	0.307*** (0.0688)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	897	897	897	897	895
N.Countries	29	29	29	29	29
adj. R-squared	0.10	0.07	0.07	0.08	0.06
p-val(F-test)	0.004	0.000	0.000	0.000	0.001

Notes. ***/**/*/ denote statistical significance at the 1%/5%/10% level. Standard errors based on Driscoll and Kraay (1998) in parentheses. F-test for $H_0 : d^{numRange} = d^{numPoint}$. All equations are estimated separately for each forecast horizon from $h = 2$ to $h = 6$ years based on a fixed-horizon approximation.

Table D.2: Effect of target types on anchoring ($probT$)

	(1) (h=2)	(2) (h=3)	(3) (h=4)	(4) (h=5)	(5) (h=6)
d^{hybrid}	0.110*** (0.0201)	0.162*** (0.0234)	0.168*** (0.0258)	0.176*** (0.0313)	0.153*** (0.0276)
d^{point}	0.0828*** (0.0300)	0.111*** (0.0274)	0.153*** (0.0400)	0.162*** (0.0372)	0.221*** (0.0406)
sd infl. (24m)	-0.0153* (0.00897)	-0.00993 (0.0158)	-0.0266* (0.0152)	-0.0438*** (0.0132)	-0.0294* (0.0158)
Regulatory quality	0.0534 (0.0572)	0.0824 (0.0622)	-0.0134 (0.0685)	-0.111 (0.0705)	-0.110 (0.0832)
Constant	0.0251 (0.0571)	0.0166 (0.0618)	0.162** (0.0693)	0.229*** (0.0703)	0.243*** (0.0811)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	827	827	827	827	825
N.Countries	28	28	28	28	28
adj. R-squared	0.12	0.08	0.08	0.10	0.08
p-val(F-test)	0.283	0.029	0.710	0.687	0.044

Notes. ***/**/* denote statistical significance at the 1%/5%/10% level. Standard errors based on Driscoll and Kraay (1998) in parentheses. F-test for $H_0 : d^{hybrid} = d^{point}$. Results for model (4.2) (A. Numerical target definition) and model (4.3) (B. Role of inflation target types). The dependent variable is the probabilistic measure of anchoring ($probT$). All equations are estimated separately for each forecast horizon from $h = 2$ to $h = 6$ years based on a fixed-horizon approximation.

Table D.3: Effect of target types on disanchoring measures (DAL , DAH)

A. Disanchoring from low inflation (DAL)					
	(1)	(2)	(3)	(4)	(5)
	DAL	DAL	DAL	DAL	DAL
	(h=2)	(h=3)	(h=4)	(h=5)	(h=6)
d^{hybrid}	0.262*** (0.0899)	0.201** (0.0923)	0.175** (0.0861)	0.184** (0.0768)	0.180** (0.0680)
d^{point}	0.228* (0.123)	0.0333 (0.133)	-0.0886 (0.106)	-0.0657 (0.0971)	-0.0684 (0.0897)
sd infl. (24m)	-0.0162 (0.0117)	-0.0320** (0.0138)	-0.0127 (0.0155)	-0.00606 (0.0171)	-0.0189 (0.0220)
Regulatory quality	-0.113 (0.0687)	0.134 (0.0869)	0.352*** (0.114)	0.425*** (0.105)	0.340*** (0.114)
Constant	0.293*** (0.0581)	0.0988 (0.0711)	-0.0737 (0.109)	-0.122 (0.103)	-0.0294 (0.108)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	827	827	827	827	825
N.Countries	28	28	28	28	28
adj. R-squared	0.22	0.16	0.18	0.17	0.14
p-val(F-test)	0.616	0.011	0.000	0.000	0.000
B. Disanchoring from high inflation (DAH)					
	(1)	(2)	(3)	(4)	(5)
	(h=2)	(h=3)	(h=4)	(h=5)	(h=6)
d^{hybrid}	-0.372*** (0.0806)	-0.363*** (0.0947)	-0.344*** (0.0899)	-0.360*** (0.0807)	-0.333*** (0.0791)
d^{point}	-0.311*** (0.103)	-0.144 (0.130)	-0.0641 (0.118)	-0.0959 (0.111)	-0.153 (0.109)
sd infl. (24m)	0.0316** (0.0145)	0.0419*** (0.0128)	0.0393** (0.0164)	0.0498** (0.0203)	0.0483** (0.0196)
Regulatory quality	0.0598 (0.0656)	-0.216** (0.0824)	-0.338*** (0.121)	-0.314*** (0.101)	-0.229** (0.0916)
Constant	0.682*** (0.0739)	0.885*** (0.0849)	0.912*** (0.114)	0.892*** (0.0996)	0.787*** (0.0902)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	827	827	827	827	825
N.Countries	28	28	28	28	28
adj. R-squared	0.30	0.27	0.26	0.25	0.23
p-val(F-test)	0.309	0.002	0.000	0.000	0.002

Notes. ***/**/* denote statistical significance at the 1%/5%/10% level. Standard errors based on Driscoll and Kraay (1998) in parentheses. Results for model (4.4), where the dependent variable is the probabilistic measure of anchoring ($probT$). All equations are estimated separately for each forecast horizon from $h = 2$ to $h = 6$ years based on a fixed-horizon approximation.

Table D.4: Summary statistics of credibility losses

	Full sample			AEs				EMEs				
	mean	sd	min	mean	sd	min	max	mean	sd	min	max	
$CL(-)$	0.92	1.39	0.00	6.11	0.89	1.05	0.00	5.11	0.94	1.64	0.00	6.11
$CL(+)$	1.62	4.73	0.00	69.61	0.27	0.51	0.00	2.54	2.94	6.34	0.00	69.61
N	4408			2172				2236				

Notes. Summary statistics of the credibility loss indicator computed from monthly data over the sample period 2005m4-2020m4 for 12 advanced economies (AEs) and 17 emerging market economies (EMEs).

Table D.5: Credibility loss and target types

	(1)	(2)	(3)	(4)	(5)	(6)
	probT(4)	probT(6)	DAL(4)	DAL(6)	DAH(4)	DAH(6)
d^{hybrid}	0.178*** (0.0266)	0.168*** (0.0336)	0.128** (0.0594)	0.130*** (0.0443)	-0.306*** (0.0740)	-0.298*** (0.0630)
d^{point}	0.167*** (0.0476)	0.220*** (0.0389)	-0.0241 (0.0885)	0.0239 (0.0772)	-0.143 (0.101)	-0.244** (0.0918)
$CL(+)$	0.0780* (0.0415)	0.0362 (0.0443)	-0.226*** (0.0793)	-0.158** (0.0774)	0.148* (0.0753)	0.121* (0.0635)
$CL(-)$	-0.0382* (0.0226)	-0.0670** (0.0273)	0.163*** (0.0334)	0.156*** (0.0345)	-0.125*** (0.0186)	-0.0886*** (0.0226)
$CL(+)$ \times d^{hybrid}	-0.0844** (0.0376)	-0.0382 (0.0410)	0.213** (0.0814)	0.125 (0.0776)	-0.128* (0.0759)	-0.0872 (0.0608)
$CL(-)$ \times d^{hybrid}	0.0106 (0.0245)	0.0407 (0.0298)	-0.0853** (0.0374)	-0.0666* (0.0369)	0.0747*** (0.0256)	0.0259 (0.0264)
$CL(+)$ \times d^{point}	-0.0851 (0.0710)	-0.00204 (0.0722)	0.292*** (0.0964)	0.116 (0.0890)	-0.207** (0.0866)	-0.114 (0.0835)
$CL(-)$ \times d^{point}	-0.00783 (0.0496)	0.0534 (0.0596)	-0.211*** (0.0478)	-0.248*** (0.0534)	0.219*** (0.0345)	0.195*** (0.0421)
sd infl. (24m)	-0.0281 (0.0236)	-0.0310 (0.0240)	0.0145 (0.0235)	0.0206 (0.0223)	0.0136 (0.0217)	0.0104 (0.0210)
Regulatory quality	-0.0533 (0.0814)	-0.130 (0.0971)	0.265*** (0.0986)	0.280** (0.124)	-0.211 (0.132)	-0.149 (0.102)
Constant	0.195** (0.0855)	0.252*** (0.0935)	0.000799 (0.0923)	0.00862 (0.108)	0.804*** (0.130)	0.739*** (0.0989)
country FE	Yes	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N.Obs	827	825	827	825	827	825
N.Countries	28	28	28	28	28	28
adj. R-squared	0.11	0.10	0.34	0.32	0.34	0.31

Notes. ***/**/* denote statistical significance at the 1%/5%/10% level. Standard errors based on Driscoll and Kraay (1998) in parentheses. Results for model (4.6), dependent variables are the probabilistic measure of anchoring ($probT$), downside risk to inflation (DAL), and upside risk to inflation (DAH). All equations are estimated separately for each forecast horizons. For brevity, results are only shown for horizons of 4 and 6 years.

Table D.6: Credibility loss and target types

	(1)	(2)	(3)	(4)	(5)
	DAL(2)	DAL(3)	DAL(4)	DAL(5)	DAL(6)
$CL(-)$ \times d^{hybrid}	-0.118*** (0.0396)	-0.126*** (0.0379)	-0.0853** (0.0374)	-0.0716* (0.0366)	-0.0666* (0.0369)
$CL(-)$ \times d^{point}	-0.262*** (0.0497)	-0.180*** (0.0504)	-0.211*** (0.0478)	-0.273*** (0.0504)	-0.248*** (0.0534)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	827	827	827	827	825
N.Countries	28	28	28	28	28
adj. R-squared	0.29	0.26	0.34	0.32	0.32

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

Table D.7: Credibility loss and target types

	(1)	(2)	(3)	(4)	(5)
	DAH(2)	DAH(3)	DAH(4)	DAH(5)	DAH(6)
$CL(+)$ \times d^{hybrid}	-0.195** (0.0769)	-0.168** (0.0789)	-0.128* (0.0759)	-0.0929 (0.0670)	-0.0872 (0.0608)
$CL(+)$ \times d^{point}	0.0686 (0.0880)	-0.134 (0.0821)	-0.207** (0.0866)	-0.153* (0.0806)	-0.114 (0.0835)
country FE	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes
N.Obs	827	827	827	827	825
N.Countries	28	28	28	28	28
adj. R-squared	0.35	0.32	0.34	0.34	0.31

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

Table D.8: Robustness (d^{hybrid} , d^{point})

	(1)	(2)	(3)	(4)	(5)
	(h=2)	(h=3)	(h=4)	(h=5)	(h=6)
Baseline					
d^{hybrid}	0.110*** (0.0201)	0.162*** (0.0234)	0.168*** (0.0258)	0.176*** (0.0313)	0.153*** (0.0276)
d^{point}	0.0828*** (0.0300)	0.111*** (0.0274)	0.153*** (0.0400)	0.162*** (0.0372)	0.221*** (0.0406)
Absolute distance, mean to target					
d^{hybrid}	-0.512*** (0.156)	-0.492*** (0.133)	-0.518*** (0.108)	-0.522*** (0.0975)	-0.479*** (0.0763)
d^{point}	-0.404** (0.175)	-0.421*** (0.131)	-0.459*** (0.0907)	-0.493*** (0.0872)	-0.541*** (0.0777)
AEs					
d^{hybrid}	0.171*** (0.0271)	0.254*** (0.0440)	0.269*** (0.0457)	0.289*** (0.0559)	0.282*** (0.0612)
d^{point}	0.142*** (0.0360)	0.162*** (0.0546)	0.221*** (0.0692)	0.228*** (0.0737)	0.305*** (0.0843)
w/o Japan, Turkey					
d^{hybrid}	0.108*** (0.0205)	0.157*** (0.0236)	0.165*** (0.0262)	0.173*** (0.0312)	0.148*** (0.0273)
d^{point}	0.0794** (0.0305)	0.109*** (0.0270)	0.156*** (0.0410)	0.163*** (0.0370)	0.222*** (0.0415)
No controls					
d^{hybrid}	0.106*** (0.0194)	0.154*** (0.0229)	0.168*** (0.0250)	0.182*** (0.0312)	0.153*** (0.0294)
d^{point}	0.0843*** (0.0265)	0.118*** (0.0270)	0.137*** (0.0417)	0.137*** (0.0382)	0.194*** (0.0392)
No year dummies					
d^{hybrid}	0.122*** (0.0199)	0.163*** (0.0218)	0.159*** (0.0193)	0.179*** (0.0215)	0.177*** (0.0282)
d^{point}	0.0945*** (0.0273)	0.114*** (0.0266)	0.150*** (0.0387)	0.169*** (0.0331)	0.236*** (0.0384)

Notes. ***/**/* denote statistical significance at the 1%/5%/10% level. Standard errors based on Driscoll and Kraay (1998) reported in parentheses. All equations are estimated separately for each forecast horizon of 4 and 6 years based on a fixed-horizon approximation.