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Abstract

This paper proposes a new approach to extract quantile-based inflation risk measures using Quantile Autoregressive Distributed Lag Mixed-Frequency Data Sampling (QADL-MIDAS) regression models. We compare our models to a standard Quantile Auto-Regression (QAR) model and show that it delivers better quantile forecasts at several forecasting horizons. We use the QADL-MIDAS model to construct inflation risk measures proxying for uncertainty, third-moment dynamics and the risk of extreme inflation realizations. We find that these risk measures are linked to the future evolution of inflation and changes in the effective federal funds rate.

Keywords: regression quantiles, inflation risk, quantile forecasting
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1 Introduction

One of the critical tasks of a central bank is to maintain price stability. In order to monitor the (expected) evolution of price dynamics, central banks rely not only on point forecasts but also on predictive densities. The latter can be used to study the uncertainty around the future path of inflation, as in, for example, the so-called fan charts' published by the Bank of England. Predictive densities can also help to assess the tail risks of inflation, see Kilian and Manganelli (2007) and Andrade, Ghysels, and Idier (2012) for examples of modeling such risk measures.

In our paper, we introduce the Quantile Autoregressive Distributed Lag Mixed-Frequency Data Sampling (QADL-MIDAS) regression model and use it in forecasting inflation quantiles. Furthermore, we use our approach to extract model-implied risk measures for inflation. Our paper contributes to the literature on modeling inflation risks in several ways.

First, we show that our model outperforms the standard Quantile Auto-Regression (QAR) model (i) in terms of out-of-sample forecasts of conditional quantiles, and (ii) by extracting persistent (conditional) high-order moments such as skewness of US year-on-year inflation. Second, we show that our model-based measures of inflation risk are linked to changes in the monetary policy rate and have predictive power for future inflation realizations.

Our paper relates to two strands of literature. From a methodological point of view, we extend the Q-MIDAS model to allow for an autoregressive term, which is essential when the response variable is highly persistent. Q-MIDAS and QADL-MIDAS models efficiently relate low-frequency data with high-frequency data by parameterizing regression using lag polynomial functions. Ghysels (2014) and Ghysels et al. (2016) introduced Q-MIDAS regressions to model equity returns and its higher-order moments, such as conditional skewness. Our model can also be viewed as an extension of the QADL model introduced by Galvao et al. (2013) that accounts for high-frequency information.

From an empirical perspective, our paper is linked to the literature on measuring inflation risks. Engle (1982) introduced an ARCH-type of models and applied it to analyze inflation uncertainty. Kilian and Manganelli (2007) quantified deflation and excessive inflation risks using a micro-founded model and estimated these risks using a GARCH model for US, German and Japanese inflation rates. Kilian and Manganelli (2008) proposed a generalization of the Taylor rule with asymmetric preferences in inflation. Andrade, Ghysels, and Idier (2012) analyzed inflation survey density forecasts and computed various risk (expected) inflation risk measures. We use our proposed quantile regression model to extract similar inflation risk measures and analyze the impact of these risks on monetary policy rates changes and future inflation realizations.

Results show that our proposed method outperforms a standard QAR benchmark model in fitting and forecasting conditional quantiles of inflation. First, by using a heteroskedasticity robust bootstrap method, we show that absolute inflation's changes are important in capturing the asymmetric behavior of the conditional distribution of inflation.

Next, we show that by using this model we perform much better in terms of out-of-sample forecasting. For headline inflation at long horizons, the forecasting gain can be as high as 34% relative to the benchmark model.

We also show that inflation risk measures extracted using our approach are significant predictors of future inflation and have a significant effect for monetary policy. The latter results are in line with Andrade, Ghysels, and Idier (2012), where, instead of using regression quantiles, inflation risk measures are computed from survey data of expected future inflation densities.

Our paper is organized as follows. First, in section 2, we introduce our methods and discuss in-sample results. Next, we show the out-of-sample results in section 3. Lastly, in section 4, we discuss the implications of several inflation risk measures for monetary policy and forecasting future inflation realizations. We conclude in section 5.

2 Modeling inflation quantiles

We base our analysis on a new conditional quantile regression model, which we call the Quantile Auto-Regressive Mixed-Frequency Data Sampling (QADL-MIDAS) regression model. While studies have already analyzed inflation series using conditional quantile methods, our approach stands out in two ways. We extract risk measures by using (i) realized inflation rather than survey-based data as in Andrade, Ghysels, and Idier (2012) and (ii) regression quantiles, as opposed to GARCH-type models (as in, for example, Kilian and Manganelli (2007)), which allow us to directly model h-step ahead inflation uncertainty while keeping the information set fixed. Unlike our model, conditional volatility models are problematic for forecasting multiple horizons due to temporal aggregation issues, as discussed in Ghysels (2014).

To fix notation, let $\pi_t = 1200\ \ln(P_t/P_{t-1})$ denote the (annualized) monthly inflation rate at time t, where P_t is the seasonally-adjusted monthly consumer price index (e.g. CPI), and let h-period realized inflation at time t be denoted by $\pi_t^{(h)} = h^{-1}\sum_{j=0}^{h-1}\pi_{t-j}$. Furthermore, let $\tilde{\pi}_t = 100\ \ln(P_t/P_{t-1})$ denote a (non-annualized) monthly inflation rate.

In order to extract inflation risk measures, we are interested in modeling the τ-th quantile of h-step ahead inflation series ($\pi_{t+h}^{(h)}$) using the information given at time t. Let $F_{t+h|t}(\pi^{(h)}) =$

$P(\pi_{t+h}^{(h)} < \pi|\mathcal{F}_t)$ be the (conditional) cumulative distribution function (CDF) of inflation, where $\mathcal{F}_t$ is the information set at time t. The conditional quantile τ of h-step ahead inflation $\pi_{t+h}^{(h)}$ is given by:

$$q_{\tau,t+h}(\pi_{t+h}^{(h)}) = F_{t+h|t}^{-1}(\pi^{(h)}). \tag{1}$$

Our starting point is the Quantile Auto-Regression (QAR) model introduced by Koenker and Xiao (2006). We extend this model to QADL-MIDAS, whereby the regression quantiles depend on past absolute values of inflation. Subsequently, we compare the two models in terms of in-sample and out-of-sample performance. In the following subsection, we describe the quantile regression models used in our paper.

2.1 Regression quantiles

Introduced by Koenker and Xiao (2006), the QAR model extends the classic Auto-Regression (AR) framework by allowing the regression coefficients to be quantile-level dependent. First, let us consider the AR(p) model for 1-step ahead prediction, which is given by:

$$\pi_{t+1} = \mu + \sum_{j=0}^{p-1} \alpha_j \pi_{t-j} + \epsilon_{t+1} \equiv \mu + \rho\pi_t + \sum_{j=0}^{q-1} \beta_j \Delta\pi_{t-j} + \epsilon_{t+1}, \tag{2}$$

where μ is the intercept and $\boldsymbol{\beta} = (\beta_0, \ldots, \beta_{p-1})$ is the vector of autoregressive coefficients. Following Manzan and Zerom (2015) notation, we express AR model such that ρ, which is $\rho = \sum_{j=0}^{p-1} \alpha_j$, represents the persistence of inflation and $q = p - 1$ are the number of lags.

To allow for AR coefficients to be quantile-level dependent, we consider a QAR model given by the following equation:

$$q_\tau(\pi_{t+1}|\mathcal{F}_t) = \mu_\tau + \rho_\tau \pi_t + \sum_{j=0}^{q-1} \beta_{\tau,j} \Delta\pi_{t-j}, \tag{3}$$

where $\tau \in (0, 1)$ is the quantile level and regression coefficients are quantile-specific. Clearly, when coefficients of (3) do not vary with τ, we are back to the classic AR model. Conversely, if they are not constant across quantiles, the impact of information contained in $\mathcal{F}_t$ on the distribution of π_{t+1} becomes quantile-specific.

We are interested in forecasting h-step ahead inflation quantiles,[1] hence we reformulate the QAR model as:

[1] In our empirical application, we forecast the US CPI year-on-year inflation 12 months ahead.

$$q_\tau(\pi_{t+h}^{(h)}|\mathcal{F}_t) = \mu_\tau + \rho_\tau \pi_t + \sum_{j=0}^{q-1} \beta_{\tau,j} \Delta\pi_{t-j}. \tag{4}$$

Note that such a formulation implies that our conditional forecasts are formed using a direct forecasting approach. That is, we regress the information available at time t on $t-h$ to forecast $t+h$ quantile. Quantiles cannot be easily temporally aggregated, therefore, iterative forecasts are not available (see Ghysels, 2014).[2]

In our proposed model, the h-step ahead conditional quantile of inflation depends on the current level and on an additional term. This is similar to the CAViaR model of Engle and Manganelli (2004) although different in subtle ways:

$$q_\tau(\pi_{t+h}^{(h)}|\mathcal{F}_t) = \mu\tau + \rho_\tau \pi_t + \beta_\tau Z_t(\theta), \tag{5}$$

with

$$Z_t(\theta_\tau) = \sum_{m=0}^{q-1} \omega_m(\theta_\tau) |\Delta\tilde{\pi}_{t-m}|.$$

While this is indeed similar to the CAViaR model - it involves mixed-frequency data: the horizon is h months, whereas the information set remains monthly. In a CAViaR model - like ARCH-type models - the quantiles and the information set pertain to the same frequency and therefore would involve past h period inflation. Note also that we use absolute values as this is often the variable chosen in CAViaR models. We opt for a specification that avoids parameter proliferation as is typical in MIDAS regressions, and, therefore, take a specific form for the polynomial ω_m using a normalized beta probability density function. Formally, the weights are defined as:

$$\omega_m = \frac{(1-x_m)^\theta}{\sum_{m=0}^{q-1}(1-x_m)^\theta}, \tag{6}$$

where $x_m = (m-1)/(h-1)$. Since ω_m depends on a single parameter θ, the model is parsimonious yet flexible enough to capture complicated dynamics of inflation.

Our model has several advantages over both QADL and QAR models. First, using a tightly parameterized polynomial, we avoid potential over-fitting problems even if we add a large number of lags for the DL term. Second, the parsimonious beta lag polynomial function ω_m allows us, as noted earlier, to specify the model at any sampling frequency (e.g. quarterly), while keeping the information set fixed at monthly frequency. Since real activity measures

[2]Direct versus iterative conditional mean forecasting of macroeconomic variables has been discussed by Marcellino, Stock, and Watson (2006) and Faust and Wright (2013) (the latter in the context of inflation forecasting). The direct approach tends to perform better in the case of a misspecified forecasting model, which is a reasonable assumption to make for any time series model a priori.

(such as real GDP) are measured quarterly, this is potentially an important feature that allows us to model the feedback effects of inflation risks towards real GDP while preserving the monthly information.

We estimate both QAR and QADL-MIDAS models by minimizing the usual check-loss function used in the quantile regression literature, see Koenker (2005) and Galvao, Antonio, Montes-Rojas, and Park (2013) among others for more detail.

2.2 Estimation results

We estimate the QAR and QADL-MIDAS models over the sample period starting 1960-01 to 2018-05 for CPI-based (headline) inflation.[3] For each model, we consider quantile levels (0.05, 0.25, 0.5, 0.75 and 0.95) for the 12-month ahead US headline inflation series.

We start our analysis with the QAR model, which is estimated using 12 lags for year-on-year inflation. The parameter estimates reported in Table 1 clearly indicate that the inflation persistence is heterogeneous across the quantiles. This result is in line with the recent literature on inflation quantiles, see Tsong and Lee (2011), Wolters and Tillmann (2015) and Manzan and Zerom (2015). For example, Tsong and Lee (2011) estimate an augmented Dickey-Fuller regression model for several countries and find that the parameter governing the persistence of inflation increases with τ. Our estimates also reveal that the persistence parameter ρ increases in quantiles, indicating that the lower-tail quantiles are less persistent than those of the upper tail. Besides, as in Manzan and Zerom (2015), our estimates also confirm that the upper tail is a unit-root or even an explosive process. We formally test the unit-root using ADF and KS tests and find that the upper-tail quantiles show unit-root-like behavior and that the lower-tail quantiles are mean-reverting (see Table A.3 in the Appendix). The results are similar to Manzan and Zerom (2015).

Next, we show our estimates of the QADL-MIDAS model for CPI headline year-on-year inflation, which are reported in Table 2. The model is estimated using one lag of past inflation and and 12 lags for absolute (past) inflation's changes.[4] The slope coefficient of the (weighted) absolute deviations' term, which is highly significant for most quantiles, shows large conditional asymmetry in the inflation rate. Interestingly, our estimates show that the sign of β coefficients is negative (positive) for lower (higher) quantiles. This latter result implies that periods of (absolute) large changes in inflation amplifies extreme realizations. Hence, in period of low (high) levels of inflation, an increase in inflation's variability triggers even lower (higher) inflation realization. Additionally, the persistence coefficient seems to be higher for the QADL-MIDAS specification relative to that of the QAR.

[3] Results for CORE inflation are given in the Appendix A.1.1

[4] Note that both QAR and QADL-MIDAS are estimated using the same information set.

TABLE 1: Parameter estimates of the QAR model

CPI (US)

Quantile	0.05	0.25	0.5	0.75	0.95
μ	**-0.454**	**0.569**	**0.952**	**1.471**	**2.597**
	(0.047)	(0.000)	(0.000)	(0.000)	(0.000)
ρ	**0.502**	**0.593**	**0.713**	**0.866**	**1.101**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
			Coverage		
Statistic	0.046	0.008	0.006	0.008	0.020
p-Value	(0.830)	(0.929)	(0.938)	(0.929)	(0.887)

Note: Parameter estimates of the QAR model for the year ahead CPI inflation rate. The standard errors are computed using a wild bootstrap tailored for quantile regression (see Feng, He, and Hu, 2011). We used 500 bootstrap replications.

TABLE 2: Parameter estimates of the QADL-MIDAS model

CPI (US)

Quantile	0.05	0.25	0.5	0.75	0.95
μ	0.062	**0.723**	**0.581**	**0.658**	**1.891**
	(0.371)	(0.000)	(0.000)	(0.002)	(0.000)
β	**-1.522**	-0.446	**2.738**	**3.507**	**2.335**
	(0.014)	(0.219)	(0.000)	(0.000)	(0.014)
θ	43.668	35.510	1.124	1.716	1.000
	(0.112)	(0.180)	(0.465)	(0.439)	(0.482)
ρ	**0.459**	**0.564**	**0.678**	**0.928**	**1.168**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
			Coverage		
Statistic	0.101	0.000	0.000	0.008	0.001
p-Value	(0.751)	(1.000)	(1.000)	(0.929)	(0.972)

Note: Parameter estimates of the QADL-MIDAS model for the year ahead CPI inflation rate. The standard errors are computed using wild bootstrap tailored for quantile regression (see Feng, He, and Hu, 2011). We used 500 bootstrap replications.

To visualize the comparison of 12-month ahead conditional quantiles implied by our two models, Figure 1 depicts the estimated 5%, 50% and 95% quantiles, together with realized inflation. During the late 1970s and 1980s, the difference between the upper-tail and lower-tail quantiles is notably large, it normalizes during the 1990s and 2000s, and recent financial crises squeeze the upper conditional quantile towards the median. The main difference between the two figures is in the variability of the estimated quantiles. The quantiles implied by the QAR are noisier than those of the QADL-MIDAS. As we will show in the rest of the paper, this feature makes the QADL-MIDAS more attractive as it delivers (i) more precise risk measures, and (ii) better forecasts.

Overall, the estimation results of (4) and (5) indicate that the dependence in the infla-

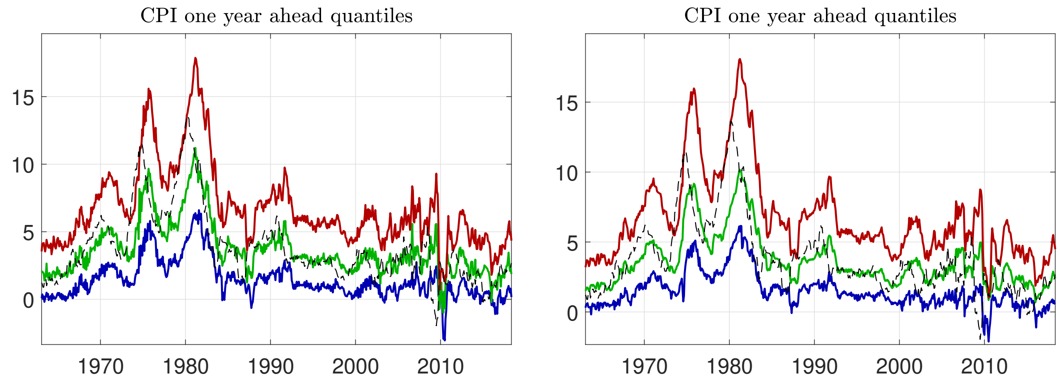

FIGURE 1: This Figure reports the Estimated 12-month ahead conditional quantiles of CPI inflation rate for the QAR model (left-panel) and the QADL-MIDAS (right-panel). Red line - 95% quantile, green line - median, blue line - 5% quantile and dashed line is the realize year-on-year inflation rate. (QAR model)

tion process is quantile-specific. The QADL-MIDAS add to the standard QADL model an important element, namely, a stress on the fact that the impact of absolute changes of past inflation on the inflation's distribution is quantile-dependent.

2.3 Parametric density estimates

Apart from estimating specific conditional quantiles, it is interesting to estimate the whole conditional density of the future inflation rate. There are several ways to do so. For example, for a given set of quantiles at each point in time, one can fit a non-parametric kernel (such as a Gaussian kernel) to get the interpolated density (see, for example, Korobilis (2017)). Alternatively, one may opt to fit a parametric density function by minimizing the ℓ_2 norm between the regression quantiles and the density implied quantiles. Such methods are employed and discussed by Ghysels and Wang (2014), Adrian, Boyarchenko, and Giannone (forthcoming) among others. The choice of density implies a very different feasible skewness/kurtosis combinations.

Similarly to Adrian, Boyarchenko, and Giannone (forthcoming), we opt for skew-t density, which is a flexible distribution function that has four parameters: location (μ), scale (σ), shape (α) and degrees of freedom (ν). The skew-t probability density function is:

$$f(y;\mu,\sigma,\alpha,\nu) = \frac{2}{\sigma} t\left(\frac{y-\mu}{\sigma};\nu\right) T\left(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{\nu+1}{\nu+\frac{y-\mu}{\sigma}}};\nu+1\right), \tag{7}$$

where t(.) and T(.) are the PDF and CDF of the Student-t distribution, respectively.

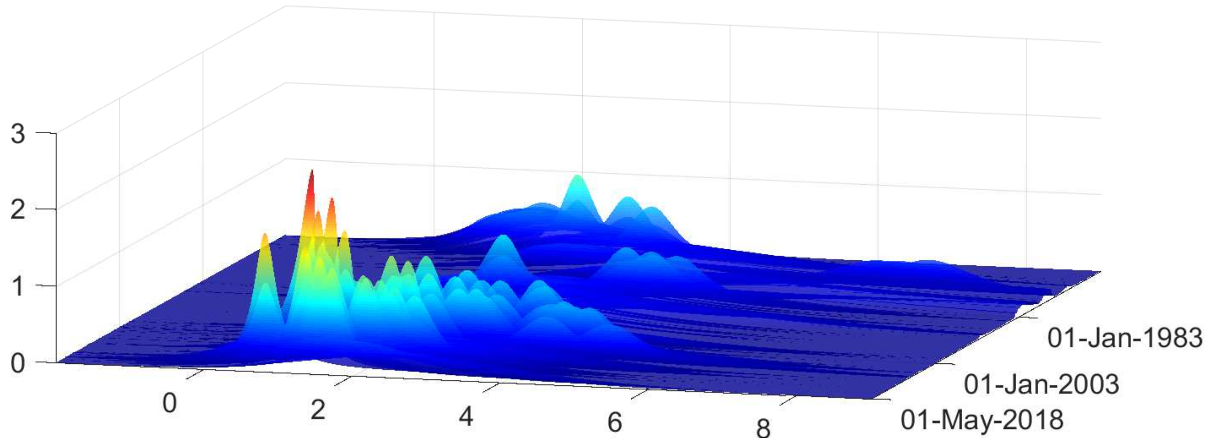

FIGURE 2: Conditional densities estimated by minimizing squared residuals between regression quantiles and skew-t distribution implied quantiles

We estimate the parameters by minimizing the following objective:

$$(\hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h}) = \underset{\mu,\sigma,\alpha,\nu}{\arg\min} \sum_{\tau} \left(\hat{q}_{\tau,t+h|t} - F^{-1}(\tau; \mu, \sigma, \alpha, \nu)\right)^2, \tag{8}$$

where $\hat{\mu}_{t+h} \in \mathbb{R}$, $\hat{\sigma}_{t+h} \in \mathbb{R}_+$, $\hat{\alpha}_{t+h} \in \mathbb{R}$, $\hat{\nu}_{t+h} \in \mathbb{Z}$. Since the degrees of freedom are natural numbers, we reduce the computational burden by profiling out ν parameter, which we grid search. To identify the parameters exactly, for a given ν parameter, we take three representative quantiles (0.05, 0.50 and 0.95) and minimize the distance between the skew-t and regression quantiles to estimate the remaining parameters. Then, we choose parameters that give the smallest ℓ_2 distance.

We plot skew-t implied densities for π^h_{t+h} inflation in Figure 2. The conditional density's location, scale, and shape is time-varying. In the early 1980s, the scale of the conditional densities is relatively high, which corresponds to the highly uncertain inflation period. Conversely, in the 2010s, we see that the conditional densities become spiky and negatively skewed.[5]

3 Forecast evaluation

In this section, we assess the out-of-sample forecasting performance of QADL-MIDAS against the benchmark QAR model at five quantile levels (0.05, 0.25, 0.5, 0.75, 0.95). Since we are interested in modeling inflation risk, our primary focus is to evaluate how models perform in

[5]In the Appendix add two additional plots: (i) the estimated parameters of the skew-t distribution (see Figure A.2) and (ii) the skew-t density implied quantiles together with the regression quantiles (see Figure A.3). The quantiles at different levels are very close to each other.

forecasting tails of inflation conditional distribution. For this reason, we evaluate our models at each quantile level rather than the whole conditional distribution.

3.1 The setup

We implement the direct forecasting approach using the QADL-MIDAS and QAR models described in the previous section. Using the QADL-MIDAS model, the h-step ahead quantile regression takes the following form:[6]

$$q_\tau(\pi_t^{(h)}) = \mu_\tau + \rho_\tau \pi_{t-h} + \beta_\tau Z_{t-h}(\theta), \tag{9}$$

with

$$Z_{t-h}(\theta_\tau) = \sum_{m=0}^{q-1} \omega_m(\theta_\tau) |\Delta\tilde{\pi}_{t-h-m}|,$$

where q is the number of lags of the absolute changes in inflation, $\tilde{\pi}$ and $\pi_t^{(h)}$ is the monthly and h-period ahead inflation rates, respectively, which are described in the previous section.[7] For both models, we use 12 lags for 12-step ahead and 3 lags for 3-step ahead forecasting, respectively; hence, the conditioning information set is the same for the QADL-MIDAS and the QAR.

To compute the h-step ahead forecast of conditional quantiles, we estimate the model parameters by off-setting the right-hand-side (RHS) variables h-steps back and use time t data to form the prediction. Formally, the forecast is computed as follows:

$$\hat{q}_\tau(\pi_{t+h|t}^{(h)}) = \hat{\mu}_\tau + \hat{\rho}_\tau \pi_t + \hat{\beta}_\tau Z_t(\hat{\theta}). \tag{10}$$

We employ an expanding window forecasting scheme using data covering the period for January 1960 to May 2018. Our initial in-sample period ranges from January 1960 to January 1995, and since we use direct forecasting approach, our first conditional quantile forecast is for January 1996, when we forecast 12 months ahead, and April 1995, in the case of 3-month ahead prediction.[8] The predictions for the following months are obtained as follow: (i) we add the February 1995 data point to our training sample; (ii) we estimate both models for both horizons; and (iii) we compute the forecasts based on these estimates. We repeat this procedure until the the end of the sample, i.e. May 2018 is our last out-of-sample forecast date.

[6] The framework is similar for the QAR benchmark model.

[7] To ease the notation, we do not indicate that regression parameters depend on the horizon of interest.

[8] The initial training sample includes 385 (412) observations to estimate the models with 12 months (3 months) of lagged data.

3.2 Evaluation criteria

We compare the forecasting results of QADL-MIDAS with the benchmark QAR model using Clark and West (2007) test for nested time series models adopted for quantile check-loss function, which was proposed by Yan and Tae-Hwy (2014). First, define $\hat{f}^{(m)}_{t+h|t} = \hat{q}_\tau(\pi^{(h)}_{t+h|t})$ as the conditional quantile forecast obtained from model $m \in \mathcal{M} = \{\text{QADL-MIDAS}, \text{QAR}\}$. The h-step ahead forecast errors from m-th model are defined as:

$$\hat{e}^{(m)}_{t+h|t} = \pi^{(h)}_{t+h} - \hat{f}^{(m)}_{t+h|t}. \tag{11}$$

Then, the quantile check-loss function $g(.)$ evaluated at the forecast error $\hat{e}^{(m)}_{t+h|t}$ is:

$$g\left(\hat{e}^{(m)}_{t+h|t}\right) = h\left(\hat{e}^{(m)}_{t+h|t}\right)\ \hat{e}^{(m)}_{t+h|t}, \tag{12}$$

where $h(\hat{e}^{(m)}_{t+h|t}) = (\tau - I(\hat{e}^{(m)}_{t+h|t} < 0))$ is the usual tick function. Following Yan and Tae-Hwy (2014), at each point in time we compute the (adjusted) sequence of check-loss-differential values

$$\hat{\text{cw}}_{t+h} = g\left(\hat{e}^{\text{QAR}}_{t+h|t}\right)\left(\hat{e}^{\text{QAR}}_{t+h|t} - \hat{e}^{\text{QADL-MIDAS}}_{t+h|t}\right), \tag{13}$$

and form the CW-statistic:

$$\text{CW} = \frac{\bar{cw}}{\sqrt{\text{Var}(\bar{cw})}}, \tag{14}$$

where $\bar{cw} = \frac{1}{T_{os}} \sum_{t=T_{is}+1}^{T} \hat{\text{cw}}_{t+h}$ and $\text{Var}(\bar{cw})$ is the HAC-adjusted sample variance, which we estimate using 13 lags (for both 3-month and 12-month forecasts).[9]

Using the CW statistic, we test the significance of better (worse) forecasting performance relative to the benchmark. Under the null hypothesis, the benchmark and the QADL-MIDAS model have the same mean-forecast error, against the one-sided alternative (larger benchmark's mean-forecast error compared to the QADL-MIDAS). Lastly, we compute the ratio of the average quantile check-loss evaluated at each quantile forecast. Specifically, for each model we compute

$$\hat{g}^{(m)} = \frac{1}{T_{os}} \sum_{t=T_{is}+1}^{T} g\left(\hat{e}^{(m)}_{t+h|t}\right), \tag{15}$$

for both models. We define the ratio of the average quantile check-losses as:

$$\text{ratio} = \frac{\hat{g}^{\text{QADL-MIDAS}}}{\hat{g}^{\text{QAR}}}. \tag{16}$$

[9]Here T_{is} denotes the initial sample size, T_{os} out-of-sample size and $T = T_{is} + T_{os}$.

Then, a ratio smaller than one means that our model performs better, and vice versa. We report and analyze results in the next section.

3.3 Results

In Table 3 we report out-of-sample results for yearly (left-panel) and quarterly (right-panel) inflation rates for 12-month and 3-month horizons, respectively. We show results for headline and core inflation on a monthly basis. In the case of 12-month ahead forecasts, we have 268 observations, while for 3 months ahead there are 277 out-of-sample predicted values.[10] In the first and fourth rows of Table 3, we report the average CW-statistic and note its significance in bold, in the second and fifth rows we report the p-value of the test, and in the third and sixth rows we report the ratio.

TABLE 3: Quantile out-of-sample forecast

	CPI									
	12-months					3-months				
	0.05	0.25	0.50	0.75	0.95	0.05	0.25	0.50	0.75	0.95
CW statistic	**2.289****	0.677	**2.304****	**3.127*****	**3.364*****	-2.681	1.288	-3.172	**3.507****	**3.550****
p-Value	(0.015)	(0.259)	(0.014)	(0.002)	(0.001)	(0.995)	(0.109)	(0.999)	(0.000)	(0.000)
ratio	0.796	0.951	0.959	0.886	0.657	1.122	0.958	1.034	0.903	0.829
	CPI CORE									
	0.05	0.25	0.50	0.75	0.95	0.05	0.25	0.50	0.75	0.95
CW statistic	-2.311	-1.930	0.346	**2.467*****	**2.779*****	-0.189	**3.240*****	**3.598*****	**3.597*****	**3.618*****
p-value	(0.986)	(0.967)	(0.370)	(0.009)	(0.004)	(0.572)	(0.001)	(0.000)	(0.000)	(0.000)
ratio	1.168	1.081	0.922	0.743	0.730	1.012	0.898	0.964	0.862	0.754

Note: These are the results for the out-of-sample forecasting for QAR (benchmark) and the baseline QADL-MIDAS CPI year-on-year data. The conditional quantile forecasts are evaluated using one-sided Clark and West adjustment for nested models for quantile regression models as proposed by Yan and Tae-Hwy (2014). CW statistics are adjusted using HAC Newey-West procedure. ** and * refer to 5 and 10 percent significance levels. We use a Bartlett kernel and a bandwidth of h-1.

Results for CPI headline inflation indicate that the QADL-MIDAS outperforms the QAR for longer horizons and mostly in the tails. The improvement in performance is as high as 35% (0.95 quantile, 12-month ahead). Interestingly, at the 0.25 quantile level 12-month ahead forecasts are better compared to the benchmark, but the improvement is not significant. The in-sample results also showed that, at this level, past absolute inflation's deviations are not significant. At the 3-month horizon, our model performs significantly better in forecasting upper-tail quantiles relative to the benchmark. For lower-tail quantiles, the results are mixed, with the QAR model outperforming the QADL-MIDAS model for extreme low quantiles realizations (0.05).

[10]Due to different number of lags and forecast horizons the number of out-of-sample forecasts is different for 12-months ahead and 3-months ahead cases.

Results for core inflation are different.Our model performs much better in forecasting at short horizons and the upper-tail quantiles At the 12-month horizon, our model produces forecasts that are more accurate at 0.75 and 0.95 levels (the gains are as high as 27%) but not for lower quantiles. At the 3-month horizon, our model outperforms the benchmark model four quantiles level out of five, the exception being the 0.05 quantile level.

Overall, the CW-statistic reveals that our model performed significantly better than the QAR for 12 out of 20 quantile levels for different horizons and inflation series.

4 The impact of inflation risk measures

In this section, we analyze inflation risk measures based on regression quantiles estimated using the QAR and QADL-MIDAS models. We begin by defining and comparing the time series of inflation risk measures. Subsequently, we assess the quality of in-sample and out-of-sample predictions.

4.1 Risk measures

First, we analyze inflation risk measures based on regression quantiles estimated using QAR and QADL-MIDAS models. Following Andrade, Ghysels, and Idier (2012), we compute three different (conditional) risk measures of inflation: (i) the inflation-at-risk (I@R), (ii) the inter-quantile range (IQR) and the robust asymmetry measure (ASY). We build inflation risk measures using conditional quantile estimates ($\hat{q}_{\tau,t|t-h}$) implied by our proposed QADL-MIDAS model, see (5) and the QAR model, see (4).

The I@R measure is given by the estimated (time t) conditional quantile at the τ level given information up to t-h:

$$\text{I@R}^{\tau}_{t|t-h} = \hat{q}_{\tau,t|t-h}. \tag{17}$$

The measure is inspired by the well-known financial risk measure called "Value-at-Risk". As noted by Andrade, Ghysels, and Idier (2012), the I@R measure allows looking at the probability of extreme inflation realizations. Hence, it can provide information on the risk of deflation or high inflation.

The IQR is computed by taking the difference between the upper- and lower-tail quantiles at the τ level:

$$\text{IQR}^{\tau}_{t|t-h} = \hat{q}_{1-\tau,t|t-h} - \hat{q}_{\tau,t|t-h}. \tag{18}$$

The IQR is a robust measure of uncertainty (volatility) risk based on conditional quantiles. The IQR pertains to the information about the possible future range of the realized inflation rate. All else being equal, as the IQR increases, extreme inflation realizations are more likely to occur.

The last measure of inflation risk measures the (a)symmetry of the distribution of future inflation's realizations. The robust asymmetry measure (ASY) is defined as the deviation of the upper- and lower-tail regression quantiles from the median, standardized by the IQR. At the τ level, it is defined as:

$$\text{ASY}^{\tau}_{t|t-h} = \frac{(\hat{q}_{1-\tau,t|t-h} - \hat{q}_{0.50,t|t-h}) - (\hat{q}_{0.50,t|t-h} - \hat{q}_{\tau,t|t-h})}{\hat{q}_{1-\tau,t|t-h} - \hat{q}_{\tau,t|t-h}}. \tag{19}$$

The intuition behind (19) is the following. For any τ, the numerator of (19) measures the degree to which the distance of the 1-τ quantile from the median differs from the distance between the median and the τ quantile. When the distribution is symmetric, the two distances are similar and $\text{ASY}^{\tau}_{t|t-h} = 0$, while when $(\hat{q}_{1-\tau,t|t-h} - \hat{q}_{0.50,t|t-h})$ is larger (smaller) than $(\hat{q}_{0.50,t|t-h} - \hat{q}_{\tau,t|t-h})$, the distribution is skewed to the right (left). The inter-quantile range (denominator) makes the measure unit-free and standardizes it to be between -1 and 1.

To gain some insight on model-implied measures of inflation risk, we plot in Figure 3 the time series pattern of the $\text{ASY}^{75}_{t|t-h}$ measure implied by the QAR model (left-panel) and by the QADL-MIDAS mode (right-panel). A striking result emerging from Figure 3 is that the $\text{ASY}^{75}_{t|t-h}$ measure based on the QAR model is very noisy and does not allow us to draw conclusions about the time series evolution of asymmetry.

Conversely, a casual inspection of the QADL-MIDAS measure of robust asymmetry allows us to infer that $\text{ASY}^{75}_{t|t-h}$ went through two main regimes. Before 2000, the distribution of inflation is mainly positively skewed, reflecting the fact that, from the beginning of the 70s until the early 2000s, the model-implied likelihood of an increase in inflation (above the median value) was larger than the risk of a decrease. As highlighted in Bernanke (2003), this was a *"long period in which the desired direction for inflation was always downward"*. After 2000, the $\text{ASY}^{75}_{t|t-h}$ becomes more volatile and it is, on average, negative. To better visualize this change, we plot on the right-panel of Figure 3 additional horizontal lines that reflect the unconditional mean of $\text{ASY}^{75}_{t|t-h}$ before (red lines) and after (green line) 2000-01 and the full-sample average (blue line). Before 2000-01, the average ASY is around 0.2; after this threshold, it is just below zero, while the full-sample mean is around 1.7. This period of change in regime in asymmetry coincides with the period when the FOMC (Federal Open Market Committee) started to raise concerns about asymmetry in inflation forecasts, see Bernanke (2003) and FOMC (2003). From that period on, policy-makers and scholars turned their attention to the risk of too-low inflation or deflation.

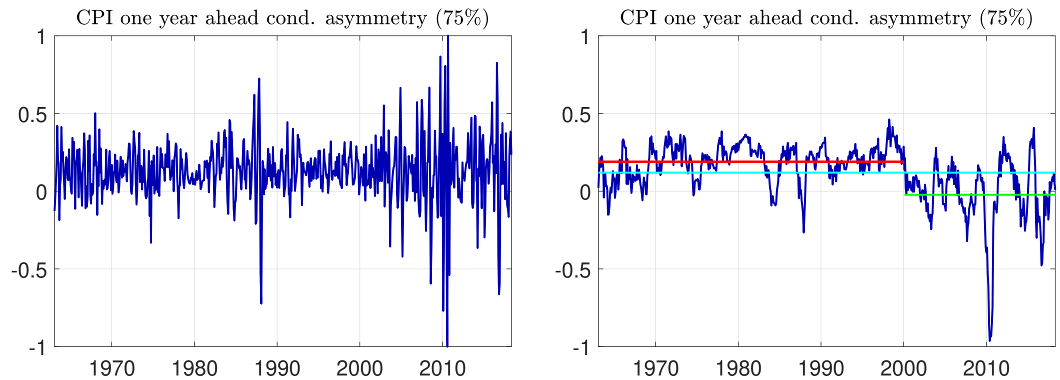

FIGURE 3: Estimated conditional asymmetry of year-on-year CPI inflation using QAR (left-panel) and using QADL-MIDAS (right-panel). Three horizontal lines show the unconditional mean of the asymmetry measure. Red - from 1960 to 200, blue - full sample, green - from 2000 to 2018.

In the remainder of the section, we run two robustness checks to assess the quality of the $\text{ASY}^{75}_{t|t-h}$ based on the QADL-MIDAS model.[11] The first robustness check assesses if our results are influenced by the conditional volatility dynamics of inflation or, rather, if we are truly estimating the conditional asymmetry. Intuitively, if we genuinely estimate the third conditional of inflation, by removing possibly asymmetric volatility dynamics, we still expect to estimate conditional asymmetry with similar dynamics. To disentangle the effects, we estimate the Tarch(1,1,1) model of Glosten, Jagannathan, and Runkle (1993) for monthly inflation series π_t and "de-Tarch" the data, as is done by Ghysels, Plazzi, and Valkanov (2016) for stock returns data. As opposed to standard the ARCH model, TARCH allows for asymmetric conditional volatility dynamics by dividing the innovation process into two disjointed elements, positive and negative. In consequence, by estimating the TARCH model, we are able to capture asymmetric volatility dynamics and clean the inflation data from these effects. Then, we estimate the same QADL-MIDAS model using de-Tarched inflation $\hat{\pi}^{dT}_t$ (see the Appendix for further details on the models employed).

We plot a conditional asymmetry measure estimated on actual and de-Tarched inflation data in the left-panel of Figure 4. We find that the simple correlation between the two estimates of conditional asymmetry is 0.69, indicating that the estimated conditional asymmetry of simple and deTarched inflation series seem to show similar time-variation.

As second robustness check, we also consider possible issues regarding the real-time estimation of inflation quantiles and corresponding risk measures. We estimate the baseline QADL-MIDAS model for the CPI US inflation using real-time vintages. We expand the

[11] Additional robustness checks are reported in the Appendix, section A.2.1

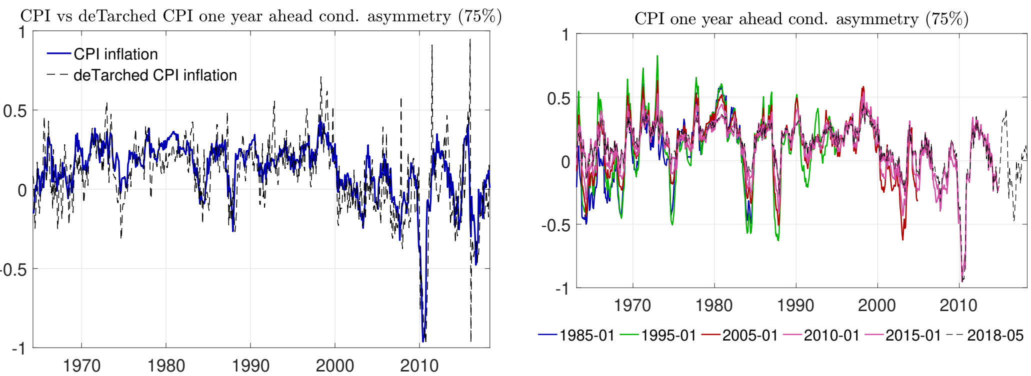

FIGURE 4: Estimated conditional asymmetry of year-on-year CPI inflation versus estimated conditional asymmetry based on deTarched CPI year-on-year inflation (left-panel) and real-time estimates of conditional asymmetry of year-on-year CPI inflation.

window starting 1985-01 by 10 years, additionally adding 2010-01 and 2018-05 to the analysis. We plot the estimates of real-time ASY measures in the right-panel of Figure 4. The dynamics of $\text{ASY}^{75}_{t|t-h}$ measures remain very close. Notably, measures are more volatile when estimated up to 1995-01. This, however, may be affected by shorter samples.

In our empirical application, we take 5^{th} ($\tau = 0.05$) and 95^{th} ($1 - \tau = 0.95$) and 25^{th} ($\tau = 0.25$) and 75^{th} ($1 - \tau = 0.75$) percentiles. The specific choice of the quantile levels is motivated by the available data sample of the CPI and questions we want to address: we seek to understand the evolution of extreme realizations of inflation yet keeping the estimation realistic, given that the observed data has only a few extreme realizations (hence 5^{th} and 95^{th} percentiles are appropriate choices to proxy for extreme quantiles).

4.2 In-sample analysis

In this subsection, we estimate predictive regressions and compare the performance of the QAR- and QADL-MIDAS-based inflation risk measures in explaining the future evolution of year-on-year inflation.

We consider two baseline regressions models linking the k-period ahead year-on-year inflation realizations, π^{12}_{t+k}, to a set of control variables and our model-implied measures of inflation risk. The first regression model is:

$$\pi^{12}_{t+k} = \beta_0 + \beta_1 \text{IQR}^{\tau}_{t|t-h} + \beta_2 \text{ASY}^{\tau}_{t|t-h} + \rho' C_t + \epsilon_{t+k}, \tag{20}$$

where (i) ϵ_{t+k} the regression forecast error, and (ii) C_t is a set of control variables containing: lagged realized inflation (π^h_{t-1}), commodity inflation ($\pi^h_{t,\text{com}}$), output gap computed using Industrial Production (u_t), and trade-weighted foreign exchange (twfx_t).

The second regression model is a variant of (20), with $\text{IQR}^{\tau}_{t|t-h}$ replaced by $\text{I@R}^{\tau}_{t|t-h}$:

$$\pi^{12}_{t+k} = \beta_0 + \beta_1 \text{I@R}^{\tau}_{t|t-h} + \beta_2 \text{ASY}^{\tau}_{t|t-h} + \rho' C_t + \epsilon_{t+k}. \tag{21}$$

We estimate (20) and (21) with and without control variables and for inflation risk measures computed at $\tau = \{0.05, 0.25\}$.

We report the empirical results based on (20) and (21) in two tables: (i) Table (4) for the QAR model and (ii) Table (5) for the QADL-MIDAS model. In each table, panels A and B report the results for (20) when τ equals 0.05 and 0.25, respectively. Panels C and D report the results for (21) and for the same quantiles. In each panel, we consider three forecasting horizons (k): 1, 1.5 and 2 years. For each forecasting horizon, we report in the first two rows (last two rows) the coefficients β_1 and β_2 and their p-values for the model with (without) control variables. For example, in Panel A of Table (4), the first two rows report the estimates of β_1 and β_2 and their p-values (in parentheses) for the regression based on (20) for k=1 and when the control variables are included in the analysis. In the same panel, the following two rows report the estimates and p-values for the same coefficients / regression equation / forecasting horizon when the control variables are excluded from the analysis.

TABLE 4: Parameter estimates (QAR model based)

	Panel A		**Panel B**		**Panel C**		**Panel D**	
	IQR 5%	**ASY 5%**	**IQR 25%**	**ASY 25%**	**I@R 5%**	**ASY 5%**	**I@R 25%**	**ASY 25%**
k = 1 year	-0.385	0.575	-0.104	0.510	**-0.246**	0.680	-0.167	0.354
	(0.056)	(0.296)	(0.184)	(0.217)	(0.017)	(0.232)	(0.058)	(0.387)
	-0.524	0.974	-0.147	0.694	**-0.313**	1.056	**-0.216**	0.478
	(0.008)	(0.069)	(0.066)	(0.107)	(0.002)	(0.063)	(0.014)	(0.265)
k = 1.5 years	**-0.480**	**1.183**	**-0.188**	0.700	**-0.278**	**1.242**	**-0.237**	0.426
	(0.021)	(0.047)	(0.023)	(0.067)	(0.008)	(0.034)	(0.009)	(0.253)
	-0.552	**1.560**	**-0.197**	**0.861**	**-0.314**	**1.606**	**-0.252**	0.572
	(0.006)	(0.009)	(0.015)	(0.027)	(0.002)	(0.007)	(0.005)	(0.133)
k = 2 years	0.012	1.049	0.012	0.223	-0.003	1.072	0.009	0.239
	(0.958)	(0.099)	(0.891)	(0.618)	(0.979)	(0.092)	(0.924)	(0.585)
	-0.111	**1.378**	-0.016	0.351	-0.060	**1.380**	-0.027	0.326
	(0.589)	(0.028)	(0.842)	(0.445)	(0.584)	(0.030)	(0.762)	(0.471)

Note: These are the parameter estimates for the regression models where we 1) include or exclude control variables (first and second rows respectively) 2) change the forecasting horizon (h = 1, 1.5 and 2 years) 3) risk measures and their quantile levels (IQR - inter-quantile range, ASY - conditional robust asymmetry, I@R - inflation-at-risk measure, i.e. respective conditional quantile, 5% and 25% refer to lower-tail quantile levels). Dependent variable is h-steps ahead CPI yoy inflation. The p-values in brackets correspond to double-sided t-test. T-statistics are adjusted using HAC Newey-West procedure. We use a Bartlett kernel and a bandwidth of $h - 1$.

We start by analyzing the performance of the QAR-based risk measures. The first result is that once we add control variables to the regression equation, none of the risk measures is linked to future two-year inflation realizations. For lower forecasting horizons, the measures of uncertainty (IQR) and of inflation-at-risk (I@R) are negatively related to future inflation realizations. The most informative variable seems to be the $\text{I@R}^{0.05}_{t|t-h}$, which is statistically significant for 1 and 1.5 years forecasting horizons. Turning to the robust asymmetry measure, when we include the control variables in the analysis the $\text{ASY}^{0.25}_{t|t-h}$ is clearly non-informative at any forecasting horizon. This result might be related to the high volatility of the variable documented in the previous section. Overall, we find that, except for some specific cases and forecasting horizons, the inflation risk measures based on the QAR contain limited information with respect to future inflation realizations.

TABLE 5: Parameter estimates (QADL-MIDAS model)

	Panel A		**Panel B**		**Panel C**		**Panel D**	
	IQR 5%	**ASY 5%**	**IQR 25%**	**ASY 25%**	**I@R 05%**	**ASY 5%**	**I@R 25%**	**ASY 25%**
k = 1 year	**-0.334**	0.380	**-0.185**	**1.188**	**-0.347**	**1.830**	**-0.304**	**1.710**
	(0.010)	(0.421)	(0.010)	(0.009)	(0.013)	(0.012)	(0.004)	(0.001)
	-0.348	0.276	**-0.197**	**1.180**	**-0.391**	**1.882**	**-0.333**	**1.752**
	(0.004)	(0.546)	(0.004)	(0.008)	(0.003)	(0.005)	(0.001)	(0.001)
k = 1.5 years	**-0.405**	0.724	**-0.246**	**1.780**	**-0.446**	**2.573**	**-0.400**	**2.470**
	(0.002)	(0.173)	(0.001)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)
	-0.355	0.604	**-0.217**	**1.708**	**-0.417**	**2.301**	**-0.371**	**2.351**
	(0.005)	(0.218)	(0.002)	(0.000)	(0.002)	(0.001)	(0.000)	(0.000)
k = 2 years	-0.155	**2.216**	-0.088	**2.598**	-0.211	**3.066**	-0.171	**2.921**
	(0.280)	(0.000)	(0.282)	(0.000)	(0.168)	(0.000)	(0.143)	(0.000)
	-0.136	**2.068**	-0.085	**2.515**	-0.207	**2.872**	-0.174	**2.841**
	(0.291)	(0.000)	(0.246)	(0.000)	(0.131)	(0.000)	(0.103)	(0.000)

Note: These are the parameter estimates for the regression models where we 1) include or exclude control variables (first and second rows respectively) 2) change the forecasting horizon (h = 1, 1.5 and 2 years) 3) risk measures and their quantile levels (IQR - inter-quantile range, ASY - conditional robust asymmetry, I@R - inflation-at-risk measure, i.e. respective conditional quantile, 5% and 25% refer to lower-tail quantile levels). Dependent variable is h-steps ahead CPI yoy inflation. The p-values in brackets correspond to double-sided t-test. T-statistics are adjusted using HAC Newey-West procedure. We use a Bartlett kernel and a bandwidth of h-1.

We now analyze the results based on the QADL-MIDAS risk measures. The most robust result emerging from Table (5) is that the $\text{ASY}^{0.25}_{t|t-h}$ is linked to future inflation realization at all forecasting horizons and independently of the model specification. The sign of the regression coefficient is always positive, and it increases with the forecasting horizon. This finding is in line with the results of Andrade, Ghysels, and Idier (2012), who obtain a similar sign and pattern for their survey-based measure of robust asymmetry. The inter-quantile range and the inflation-at-risk measures carry out a significant coefficient for forecasting horizons lower than two years. The sign of the coefficient is negative for both measures and increases (i) with the forecasting horizon, and (ii) as the quantiles become more extreme.

4.3 Out-of-sample analysis

We focus on the prediction of year-on-year inflation rates at three forecasting horizons (k = 1, 1.5 and 2 years). We denote by subscript T the out-of-sample forecasting period. Our forecasting exercise compares six different models:

1. **Random walk model (RW)**: where our forecasted value of inflation is its current value, i.e. $\pi^{12}_{T+k} = \pi^{12}_t$.

2. **Benchmark model**: where we estimate a restricted version of (20), i.e. we set to zero the parameters related to the inflation risk measures. In this case, the out-of-sample forecast is $\pi^{12}_{T+k} = \hat{\beta}_0 + \hat{\rho}' C_t$.

3. **ASY model**: where we use a restricted version of (20), i.e. we set β_1 to zero. Here, our out-of-sample forecast is $\pi^{12}_{T+k} = \hat{\beta}_0 + \hat{\beta}_2 \text{ASY}^{\tau}_{t|t-h} + \hat{\rho}' C_t$.

4. **IQR model**: where we forecast by means of a restricted version of (20), i.e. we set β_2 to zero. In this setting, our out-of-sample forecast is $\pi^{12}_{T+k} = \hat{\beta}_0 + \hat{\beta}_1 \text{IQR}^{\tau}_{t|t-h} + \hat{\rho}' C_t$.

5. **I@R model**: where adopt a restricted version of (21), i.e. we set β_2 to zero. Hence, our out-of-sample forecast is $\pi^{12}_{T+k} = \hat{\beta}_0 + \hat{\beta}_1 \text{I@R}^{\tau}_{t|t-h} + \hat{\rho}' C_t$.

6. **IQR + ASY model**: where we produce forecasts via an unrestricted version of (20). Therefore, our out-of-sample forecast is $\pi^{12}_{T+k} = \hat{\beta}_0 + \hat{\beta}_1 \text{IQR}^{\tau}_{t|t-h} + \hat{\beta}_2 \text{ASY}^{\tau}_{t|t-h} + \hat{\rho}' C_t$.

Models 3, 4 and 5 assess the forecasting power of each inflation risk measure separately, while the last model investigates the combining forecasting power of our proxies for the second- and third-conditional moment of inflation. We estimate the last four models by with QAR- and QADL-MIDAS-based inflation risk measures at 0.05 and 0.25 quantile levels. The out-of-sample period starts at 2008 May and risk measures are re-computed using real-time data.

Table (6) reports the result of the out-of-sample exercise for the risk measures based on QAR and QADL-MIDAS quantiles, respectively. Each table reports the ratios of out-of-sample mean squared forecasting errors (MSFE) of the risk-measures-based forecasting models over the MSFE the models with controls and the RW. The interesting result emerging from those tables is that the IQR^{τ} is the most informative variable in predicting inflation at all forecasting horizons. This result is robust to the model specification (QAR or QADL-MIDAS) and quantile choice (5% or 25%). The gain in forecasting precision can be substantial. For example, at a two-year forecasting horizon, if we benchmark the forecasting power of the QADL-MIDAS-based $\text{IQR}^{0.25}$ with the random walk model, the reduction in forecasting error can be as high as 42%. Another result emerging from this forecasting exercise is that the QADL-MIDAS-based measures outperform the QAR ones. The only exception to this general result is when we use forecasting models where we combine measures of uncertainty and asymmetry. In that case, QAR-based measures slightly outperform QADL-MIDAS ones.

TABLE 6: Out-of-sample conditional mean forecast evaluation

	QADL-MIDAS				QAR			
	Controls		RW		Controls		RW	
	0.05	**0.25**	**0.05**	**0.25**	**0.05**	**0.25**	**0.05**	**0.25**
	1 year horizon							
IQR+ASYM	1.013	1.032	0.942	0.959	0.945	1.011	0.879	0.941
IQR	0.880	0.891	0.818	0.829	0.880	0.885	0.819	0.824
ASYM	0.843	1.066	1.506	0.852	0.744	1.330	2.553	1.238
I@R	1.079	0.898	1.004	0.836	1.039	0.895	0.967	0.833
	1.5 years horizon							
IQR+ASYM	0.982	0.975	1.016	1.008	0.994	0.976	1.028	1.009
IQR	0.889	0.964	0.919	0.997	0.961	0.923	0.994	0.954
ASYM	1.347	1.477	1.494	1.561	1.237	1.383	1.347	1.430
I@R	1.329	0.986	1.374	1.019	1.137	1.013	1.1757	1.0474
	2 years horizon							
IQR+ASYM	0.939	0.982	0.807	0.845	0.894	0.869	0.769	0.748
IQR	0.705	0.675	0.607	0.581	0.782	0.837	0.673	0.720
ASYM	1.448	1.026	1.827	1.603	1.2147	1.431	1.766	1.2311
I@R	1.187	0.708	1.021	0.609	0.855	0.707	0.736	0.608

Note: These are the MSFE ratios of out-of-sample mean squared errors where the numerator is the model which includes risk measures and the denominator is either 1) the model only with controls, or 2) the random-walk. We use expanding window scheme, the out-of-sample period starts at 2008 May (which leaves ten years of out-of-sample forecasts to evaluate the performance), and risk measures are re-computed using real-time data. We forecast 1, 1.5 and 2 years ahead using 0.05 and 0.25 quantile levels for the risk measures.

4.4 Monetary policy implications

The last question we analyze is whether the Federal Reserve reacts to inflation risk measures. We investigate this issue by augmenting a Taylor rule with measures of inflation's distribution asymmetry (ASY^{τ}) and uncertainty (IQR^{τ}). The motivation for including information on higher-order moments in a central bank's reaction function comes from the risk management approach to monetary policy. In this setting, the central bank minimizes the risk that targeted variables exceeds upper or lower bound, see Kilian and Manganelli (2008) for model derivation and an application of the risk management approach to monetary policy. The FED staff and committees have implicitly recognized the importance of considering higher-order moments in monetary policy decisions. For example, in a recent speech, Yellen (2017) adopted inflation-risk-related terminology when stating that *"there is a 30 percent probability that inflation could be greater than 3 percent or less than 1 percent next year"*.

Based on Andrade, Ghysels, and Idier (2012), our augmented Taylor Rule-type regression equation is:

$$\Delta i_{t+1} = \beta_0 + \beta_1 \text{IQR}^{\tau}_{t|t-h} + \beta_2 \text{ASYM}^{\tau}_{t|t-h} + \rho' C_t + \epsilon_{t+1}, \tag{22}$$

where ϵ_{t+1} is the error term, Δi_{t+1} is the change in the effective federal funds rate (EFFR), and C_t contains (i) lagged value of the EFFR, Δi_t, (ii) headline inflation, π^h_t , (iii) commodity inflation, $\pi^h_{t,\text{com}}$, and (iv) a measure of output gap compute using industrial production, u_t. We estimate (22) for QAR- and QADL-MIDAS-based risk measures and for $\tau = \{0.05, 0.25\}$. We consider four different sample periods: (i) full sample period: 1963-2018, (ii) pre-Volcker period: 1963-1978, (iii) post-Volcker period: 1980-2018, and (iv) pre-crisis period: 1963-2008.[12]

TABLE 7: Parameter estimates (QADL-MIDAS model)

01-Mar-1963 to 01-Apr-2018

	IQR 5%	**ASY 5%**	**IQR 25%**	**ASY 25%**
coeff.	-0.014	**0.192****	-0.033	**0.120****
p-Value	(0.403)	(0.012)	(0.237)	(0.043)

01-Jan-1980 to 01-Apr-2018

	IQR 5%	**ASY 5%**	**IQR 25%**	**ASY 25%**
coeff.	0.004	**0.108***	0.001	0.072
p-value	(0.860)	(0.068)	(0.987)	(0.190)

01-Mar-1963 to 01-Dec-1978

	IQR 5%	**ASY 5%**	**IQR 25%**	**ASY 25%**
coeff.	**-0.054*****	**0.297****	**-0.101*****	**0.106****
p-value	(0.002)	(0.022)	(0.003)	(0.059)

01-Mar-1963 to 01-Nov-2008

	IQR 5%	**ASY 5%**	**IQR 25%**	**ASY 25%**
coeff.	-0.007	**0.279****	-0.035	0.136
p-value	(0.730)	(0.050)	(0.262)	(0.126)

Note: These are the parameter estimates for the regression models where we 1) include control variables 2) change the sample periods using real-time data and real-time conditional asymmetry measures. The dependent variable is the real-time change in effective federal funds rate. ***, ** and * refer to 1, 5 and 10 percent significance levels. We estimate the standard errors via a HAC Newey-West procedure. We use a Bartlett kernel and Andrews' automatic optimal bandwidth.

Table (7) reports the parameter estimates and p-values of β_1 and β_2 for the regression model (22). For the full sample, we find that the monetary policy rate reacts to inflation asymmetry (ASY^{τ}) independently of the quantile considered. Similarly, as in Andrade,

[12] The results QAR-based risk measures are available in the Appendix.

Ghysels, and Idier (2012), we find that there is a positive (and significant) relationship between policy rate changes and inflation asymmetry. This result indicates that when the conditional distribution of inflation is positively (negatively) skewed, and hence the risk of large high (low) inflation realization increases, the FED increases (decreases) the policy rate more than what is suggested by the Taylor Rule without inflation risk measures. This result is also confirmed over all the three sample splits for inflation asymmetry computed for a quantile level of 0.05.

Interestingly, we find that during the pre-Volcker period, all inflation risk measures had an impact on EFFR. For the asymmetry measure, the results resemble those in the full sample, where the policy rate reacts positively to ASY^{τ} changes. In the case of the uncertainty measure, we find that federal funds rates decrease as IQR^{τ} increases.

Overall, our results confirm the findings of Andrade, Ghysels, and Idier (2012) that conditional asymmetry is linked positively to policy rates changes.

5 Conclusion

Motivated by the growing interest of policy-makers in assessing and monitoring the of risk extreme inflation realization, we proposed a new approach to extract quantile-based inflation risk measures. Our framework accounts for absolute past inflation changes in quantile modeling and can handle mixed-frequency data sampling. We apply our model for headline and CORE inflation series and compared it to a standard QAR model.

We show that our model outperforms the QAR in terms of out-of-sample performance of predicting conditional quantiles. Depending on inflation series considered and on the forecasting horizon, the improvement in forecasting power can be substantial and generalized across quantiles.

We use our model-based quantiles to construct three inflation-risk measures related to the probability of extreme inflation realizations (I@R), the uncertainty or volatility risk (IQR), and the asymmetry of the distribution of future inflation's realizations (ASY).

Our paper show that these three risk measures, in various degrees, contain information about (i) the inflation dynamics (all of them), (ii) help in forecasting future realizations of inflation (IQR), and (iii) are important in explaining changes in policy rates (ASY), on top of standard Taylor Rule-type control variables.

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A Appendix

A.1 Section 2: additional results

A.1.1 Estimation results of section 2.2 based on CPI CORE

TABLE A.1: Parameter estimates of the QAR model

CPI CORE (US)

Quantile	0.05	0.25	0.5	0.75	0.95
α	**0.374**	**0.452**	**0.350**	**0.382**	**1.338**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ρ	**0.504**	**0.688**	**0.880**	**1.033**	**1.192**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
			Coverage		
Statistic	0.046	0.000	0.006	0.032	0.157
p-Value	(0.830)	(1.000)	(0.938)	(0.858)	(0.692)

Note: Parameter estimates of the QAR model for the year-ahead CPI CORE inflation rate. The standard errors are computed using wild bootstrap tailored for quantile regression (see Feng, He, and Hu, 2011). We used 500 bootstrap replications.

TABLE A.2: Parameter estimates of the QADL-MIDAS model

CPI CORE (US)

Quantile	0.05	0.25	0.5	0.75	0.95
α	**0.579**	**0.422**	**0.280**	**0.279**	-0.263
	(0.000)	(0.000)	(0.001)	(0.038)	(0.135)
β	**-2.710**	-0.220	**1.927**	**2.378**	**12.013**
	(0.026)	(0.333)	(0.024)	(0.024)	(0.000)
θ	1.429	1.000	1.018	1.254	1.000
	(0.479)	(0.488)	(0.481)	(0.482)	(0.451)
ρ	**0.521**	**0.699**	**0.817**	**0.969**	**1.171**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
			Coverage		
Statistic	0.020	0.000	0.006	0.000	0.001
p-Value	(0.887)	(1.000)	(0.938)	(1.000)	(0.972)

Note: Parameter estimates of the QADL-MIDAS model for the year-ahead CPI CORE inflation rate. The standard errors are computed using wild bootstrap tailored for quantile regression (see Feng et al., 2011). 500 bootstrap replications were used.

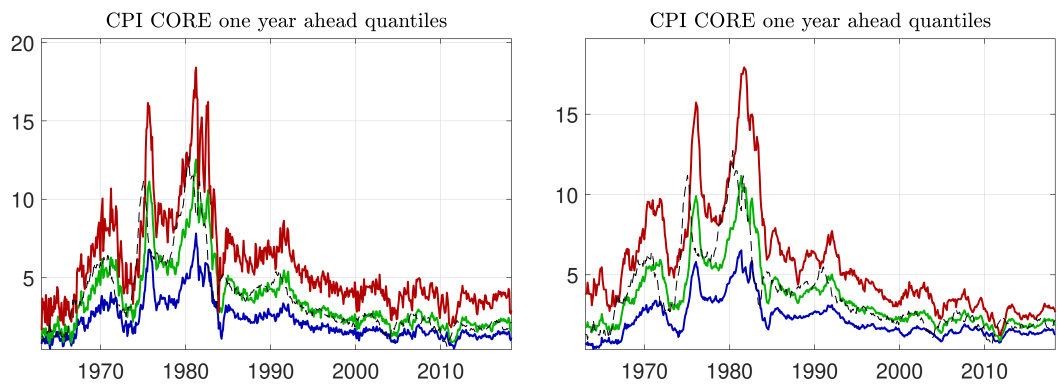

FIGURE A.1: This Figure reports the Estimated 12-month ahead conditional quantiles of CPI CORE inflation rate for the QAR model (left-panel) and the QADL-MIDAS (right-panel). Red line - 95% quantile, green line - median, blue line - 5% quantile and dashed line is the realize year-on-year inflation rate. (QAR model)

A.1.2 Unit-root test using QAR for CPI headline inflation

As in Manzan and Zerom (2015), we perform quantile specific and global unit-root tests for CPI headline inflation by running the following ADF regression:

$$y_t = \alpha_1 y_{t-1} + \sum_{i=1}^{q} \Delta y_{t-i} + u_t \tag{A.1}$$

where $y_t = \pi_t - \mu$ with π_t and μ denoting the inflation rate and its unconditional mean, respectively. The α coefficients, corresponding test statistics and critical values are reported in the table below.

TABLE A.3: Unit-root test results

τ	**0.05**	**0.25**	**0.5**	**0.75**	**0.95**	KS
α	0.657	0.777	0.908	0.972	0.979	
Test stat.	-2.626	-5.225	-2.365	-0.54	-0.174	5.225
critical value	-2.275	-2.509	-2.612	-2.489	-2.154	3.012

Note: Unit-root test estimates, test statistics and critical values to test quantile specific and global stationarity.

A.1.3 Skew-t density

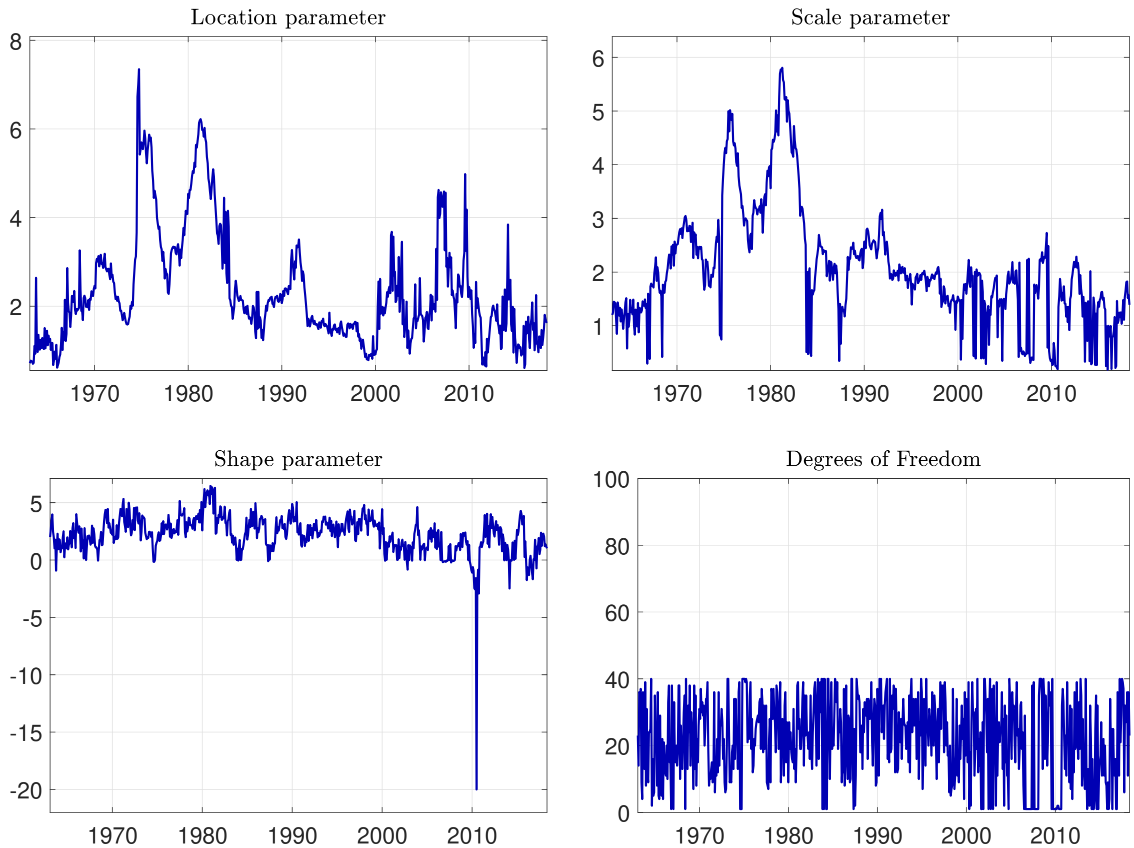

FIGURE A.2: Skew-t density parameters estimated using non-linear least squares estimator.

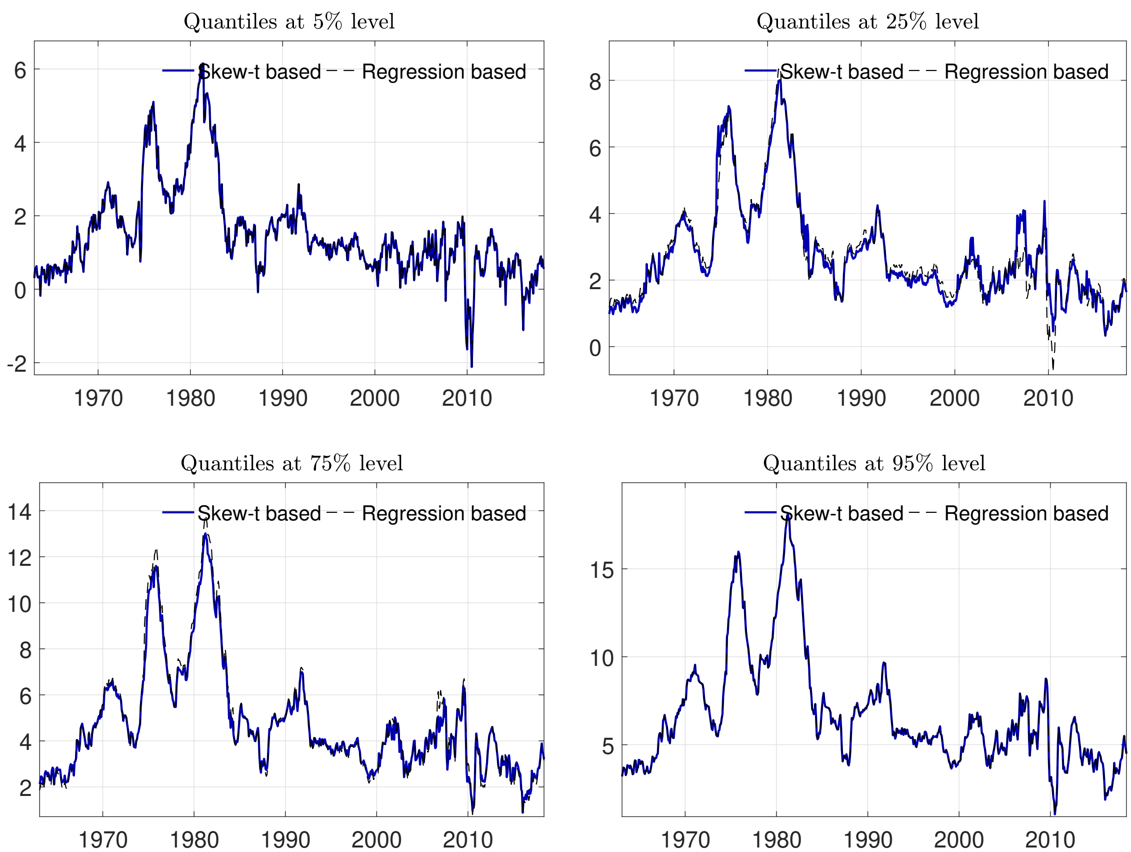

FIGURE A.3: Quantiles estimated by the regression model plotted together with Skew-t implied quantiles at the levels: 5 %, 25 %, 75 %, 95 %.

A.2 Section 4: additional results

A.2.1 Robust conditional asymmetry

Are our results influenced by the conditional volatility dynamics of inflation, or we are truly estimating the conditional asymmetry? To disentangle effects, we estimate the Tarch(1,1,1) model of Glosten, Jagannathan, and Runkle (1993) for monthly inflation series π_t and "de-Tarch" the data, as is done by Ghysels, Plazzi, and Valkanov (2016) for stock returns data. Then, we estimate the same QADL-MIDAS model using de-Tarched inflation $\hat{\pi}_t^{dT}$. Formally, we apply the following filter:[13]

$$\pi_t = \log(P_t/P_{t-1}) \tag{A.2}$$

$$\overset{AR(BIC)}{\rightarrow} \hat{\epsilon}_t = \pi_t - \hat{\pi}_t \tag{A.3}$$

$$\underset{\text{Gaussian}}{\overset{TARCH(1,1,1)}{\rightarrow}} \hat{\epsilon}_t^{dT} = \hat{\epsilon}_t / h_t \tag{A.4}$$

$$\rightarrow \hat{\pi}_t^{dT} = \hat{\pi}_t + \hat{\epsilon}_t^{dT} \tag{A.5}$$

We plot the conditional asymmetry measure estimated on actual and de-Tarched inflation data in Figure A.4, top-left panel. Interestingly, we find that the simple correlation between the two estimates of conditional asymmetry seems to be high (0.69). Specifically, estimated conditional asymmetry of simple and de-Tarched inflation series seems to show similar time-variation.

We also apply the unit-root model specification to extract the conditional asymmetry measure. The estimates of autoregressive term show that, indeed, the upper-tail quantiles are unit-root processes. Hence, we enforce the unit-root by subtracting autoregressive term from the left-hand-side variable and estimating the Q-MIDAS model. The model specification is:

$$\pi_{t+h}^{(h)} - \pi_t = \mu + \beta Z_t(\theta) \tag{A.6}$$

Conditional asymmetry dynamics remain similar, with a notable decrease in the volatility for the unit-root model implied asymmetry (see Figure A.4, top-right panel). The correlation remains high (0.58) even in this case.

Lastly, we add more linear dynamics to our model by adding more autoregressive lags. Such a specification should determine whether we ought to add more autoregressive dynamics to our model. Thus, we estimate the model with 3 months (1 quarter) of autoregressive lags:

$$\pi_{t+h}^{(h)} = \mu + \sum_{j=0}^{2} \rho_j \pi_{t-j} + \beta Z_t(\theta) \tag{A.7}$$

The estimated series are shown in the Figure A.4, bottom-panel. Adding more lags seems to increase the volatility of the asymmetry estimate.

[13] For the following three specifications, the term $\beta Z_t(\theta)$ remains the same as in the baseline specification.

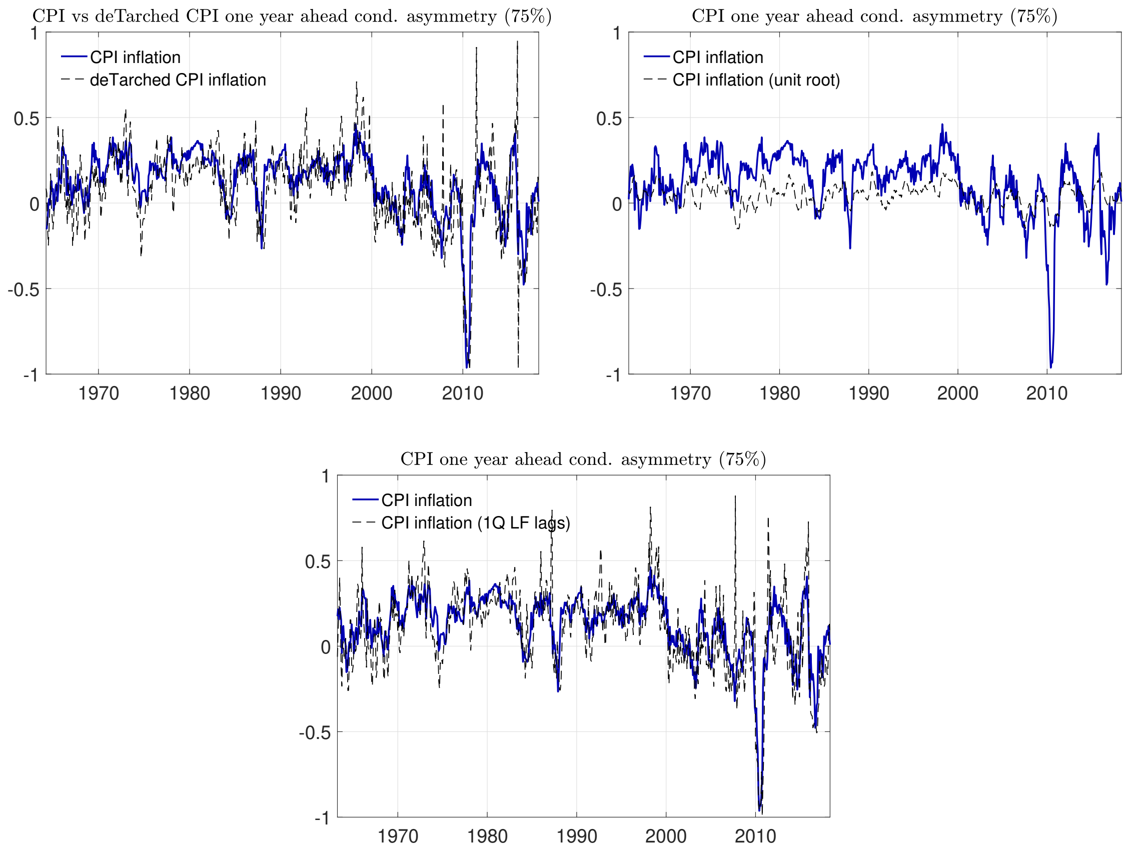

FIGURE A.4: Top-left panel: Estimated conditional asymmetry of year-on-year CPI inflation versus estimated conditional asymmetry based on deTarched CPI year-on-year inflation. **Top-right panel:** Estimated conditional asymmetry of CPI year-on-year inflation series vs the unit-root model model. **Bottom-panel:** Estimated conditional asymmetry of CPI year-on-year inflation series vs the model with 1-quarter of lagged inflation.

A.2.2 Regression results for CORE CPI

TABLE A.4: Parameter estimates (QAR) for (20) and (21)

	Panel A		**Panel B**		**Panel C**		**Panel D**	
	IQR 5%	**ASY 5%**	**IQR 25%**	**ASY 25%**	**I@R 05%**	**ASY 5%**	**I@R 25%**	**ASY 25%**
k = 1 year	-0.092	2.450	-0.137	**-4.378**	-0.140	1.935	-0.118	**-3.401**
	(0.655)	(0.092)	(0.077)	(0.000)	(0.359)	(0.174)	(0.234)	(0.000)
	-0.222	**3.095**	**-0.177**	**-4.924**	-0.251	2.102	-0.187	**-3.697**
	(0.261)	(0.045)	(0.016)	(0.000)	(0.092)	(0.149)	(0.052)	(0.000)
k = 1.5 years	-0.086	2.093	-0.153	**-4.517**	-0.026	1.973	-0.070	**-3.362**
	(0.695)	(0.134)	(0.066)	(0.000)	(0.845)	(0.178)	(0.450)	(0.000)
	-0.225	2.665	**-0.197**	**-5.139**	-0.156	2.038	-0.147	**-3.729**
	(0.266)	(0.079)	(0.010)	(0.000)	(0.232)	(0.182)	(0.095)	(0.000)
k = 2 years	0.120	1.621	-0.060	**-3.573**	0.139	2.149	0.040	**-3.058**
	(0.559)	(0.189)	(0.439)	(0.000)	(0.270)	(0.106)	(0.641)	(0.000)
	-0.025	2.023	-0.108	**-4.249**	-0.001	2.017	-0.042	**-3.448**
	(0.894)	(0.130)	(0.115)	(0.000)	(0.993)	(0.149)	(0.599)	(0.000)

Note: These are the parameter estimates for the regression models where we 1) include or exclude control variables (first and second rows respectively) 2) change the forecasting horizon (h = 1, 1.5 and 2 years) 3) risk measures and their quantile levels (IQR - inter-quantile range, ASY - conditional robust asymmetry, I@R - inflation-at-risk measure, i.e. respective conditional quantile, 5% and 25% refer to lower-tail quantile levels). Dependent variable is h-steps ahead CPI CORE yoy inflation. The p-values in brackets correspond to double-sided t-test. T-statistics are adjusted using HAC Newey-West procedure. We use a Bartlett kernel and a bandwidth of h-1.

TABLE A.5: Parameter estimates (QADL-MIDAS) for (20) and (21)

	Panel A		**Panel B**		**Panel C**		**Panel D**	
	IQR 5%	**ASY 5%**	**IQR 25%**	**ASY 25%**	**I@R 05%**	**ASY 5%**	**I@R 25%**	**ASY 25%**
k = 1 year	-0.192	**3.228**	-0.120	**-3.391**	-0.129	**2.839**	-0.174	**-2.949**
	(0.348)	(0.002)	(0.115)	(0.000)	(0.381)	(0.004)	(0.112)	(0.000)
	-0.319	**3.734**	**-0.160**	**-3.721**	-0.236	**3.059**	**-0.250**	**-3.179**
	(0.103)	(0.000)	(0.026)	(0.000)	(0.101)	(0.002)	(0.018)	(0.000)
k = 1.5 years	-0.185	**3.165**	-0.162	**-4.383**	-0.022	**2.895**	-0.140	**-3.539**
	(0.387)	(0.001)	(0.052)	(0.000)	(0.867)	(0.003)	(0.165)	(0.000)
	-0.322	**3.720**	**-0.206**	**-4.804**	-0.143	**3.158**	**-0.226**	**-3.861**
	(0.104)	(0.000)	(0.007)	(0.000)	(0.257)	(0.002)	(0.018)	(0.000)
k = 2 year	0.035	**2.519**	-0.089	**-4.191**	0.143	**2.720**	-0.032	**-3.615**
	(0.860)	(0.002)	(0.257)	(0.000)	(0.243)	(0.001)	(0.733)	(0.000)
	-0.109	**3.076**	-0.137	**-4.686**	0.013	**2.968**	-0.123	**-3.996**
	(0.543)	(0.000)	(0.050)	(0.000)	(0.908)	(0.001)	(0.150)	(0.000)

Note: These are the parameter estimates for the regression models where we 1) include or exclude control variables (first and second rows respectively) 2) change the forecasting horizon (h = 1, 1.5 and 2 years) 3) risk measures and their quantile levels (IQR - inter-quantile range, ASY - conditional robust asymmetry, I@R - inflation-at-risk measure, i.e. respective conditional quantile, 5% and 25% refer to lower-tail quantile levels). We use out-of-sample forecast for the last year where the parameter estimates are fixed and the forecast is updated when new observation becomes available. Dependent variable is h-steps ahead CPI CORE yoy inflation. The p-values in brackets correspond to double-sided t-test. T-statistics are adjusted using HAC Newey-West procedure. We use a Bartlett kernel and a bandwidth of h-1.

TABLE A.6: Parameter estimates (QAR model) for (22)

01-Mar-1963 to 01-Apr-2018

	IQR 5%	**ASY 5%**	**IQR 25%**	**ASY 25%**
coeff.	-0.001	0.037	-0.017	0.069
p-Value	(0.967)	(0.667)	(0.718)	(0.169)

01-Jan-1980 to 01-Apr-2018

	IQR 5%	**ASY 5%**	**IQR 25%**	**ASY 25%**
coeff.	0.019	-0.055	0.020	0.036
p-Value	(0.521)	(0.531)	(0.764)	(0.489)

01-Mar-1963 to 01-Dec-1978

	IQR 5%	**ASY 5%**	**IQR 25%**	**ASY 25%**
coeff.	0.018	**0.579*****	**-0.074*****	**0.160****
p-Value	(0.556)	(0.001)	(0.003)	(0.013)

01-Mar-1963 to 01-Nov-2008

	IQR 5%	**ASY 5%**	**IQR 25%**	**ASY 25%**
coeff.	-0.004	-0.069	-0.017	-0.006
p-Value	(0.878)	(0.481)	(0.747)	(0.942)

Note: These are the parameter estimates for the regression models where we 1) include control variables 2) change the sample periods using real time data and real time conditional asymmetry measures of respective risk measure. Dependent variable is real time change in effective federal funds rate. ***, ** and * refer to 1, 5 and 10 percent significance levels. We estimate the standard errors via a HAC Newey-West procedure. We use a Bartlett kernel and Andrews' automatic optimal bandwidth.

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