Momentum informed Inflation-at-Risk

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Growth-at-Risk

- [Adrian et al., 2019] pioneered Value-at-Risk approach applied to GDP growth (GaR) to capture vulnerability to the financial sector
  - Quantile regression to model parts of distribution directly
  - Lagged GDP is a location shifter
  - Financial sector induces skewness in the left tail of GDP growth
- Where does this nonlinear macro-financial linkage come from?
  - [Kohns and Szendrei, 2023] and [Mitchell et al., 2022b] find multimodality in forecasted GaR right before crises periods
  - **Potential explanation:** Economic agents' expectations diverge when uncertainty is high

Inflation-at-Risk (?)

- GaR has been researched extensively in the literature:
    - High dimensional GaR:
      [Mitchell et al., 2022a, Kohns and Szendrei, 2021]
    - Mixed frequency GaR:
      [Ferrara et al., 2022, Plagborg-Møller et al., 2020]
    - Non-US applications: [Figueres and Jarociński, 2020, Xu et al., 2023]
- Where is the IaR research?
- A distributional view of inflation seems natural
    - Inflation expectations matter
    - Both left and right tails of inflation distribution are important

Inflation-at-Risk (!)

- [Lopez-Salido and Loria, 2022, Banerjee et al., 2020] are IaR papers that attempt to estimate along the lines of [Adrian et al., 2019]
    - Inflation density papers like [Korobilis, 2017] exist but the focus is on density forecasting and not IaR
- But there is large time variation in coefficients for IaR IaR coefficients

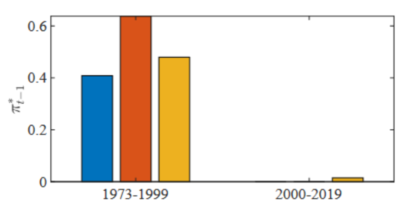

Figure 1: IaR inflation coefficient of [Lopez-Salido and Loria, 2022]

Table of contents

Tackling the time variation

Irrational economic agents

- Economic agents rarely form rational inflation expectations
  - Agents use **heuristics** [Kahneman and Thaler, 2006, Akerlof and Shiller, 2010, De Grauwe, 2011]
  - Waves of optimism/pessimism can have a critical role in shaping macroeconomic variables such as inflation [De Grauwe, 2011].
- Trusting the Central Bank communicated inflation projection is one (valid) strategy
  - The degree of trust in CB is crucial
  - CB will want to recover trust when it is under risk
  - Inflation dynamics will vary as CB will react differently

Momentum motivation

- Rapid changes in inflation can undermine the credibility of central bank targets and prompt agents to adjust their expectations more dynamically.
    - Rapid change in inflation can be measured by momentum of inflation $\Delta\pi_t = \pi_t - \pi_{t-1}$
- When inflation momentum is high:
    - Greater uncertainty in CB $\rightarrow$ variability in inflation expectations among agents
    - CB will act to recover trust
- Tale of two nonlinearities:
    - **Momentum conditioning**: capture trust in Central Bank guidance
    - **Quantile variation**: capture heterogeneity in (non-CB) heuristics

Methodology

Momentum informed IaR model

$$\pi_{t+h} = \beta_0(\tau|\Delta\pi_t) + \beta_1(\tau|\Delta\pi_t)\pi_t + \beta_2(\tau|\Delta\pi_t)\Delta y_t + \beta_3(\tau|\Delta\pi_t)\pi_t^{Exc} + \beta_4(\tau|\Delta\pi_t)Fin_t + \varepsilon_t \tag{1}$$

- $\beta_i(\tau|\Delta\pi)$ are the Momentum informed IaR coefficients
    - $\tau \in (0, 1)$ captures that the coefficient is allowed to vary by quantile
    - $\Delta\pi$ is some value of the momentum of inflation
- Variable choice follows [Lopez-Salido and Loria, 2022] and [Banerjee et al., 2020]
    - Δy_t real GDP growth [Banerjee et al., 2020]
    - π_t^{Exc} relative import prices [Lopez-Salido and Loria, 2022]
        - This measure was proposed by [Blanchard et al., 2015] to capture pass-through of nominal exchange rates and oil prices into inflation
    - Fin_t is financial conditions index [Adrian et al., 2019]

Estimation approaches

- $\beta_i(\tau|z)$ leads to two types of nonlinearity
  - $\beta(\tau|\cdot)$ is quantile regression
  - $\beta(\cdot|z)$ is conditioning on z
- Two approaches to estimate *given* a grid of z
  - Threshold QR [Galvao et al., 2011]
  - Conditionally Parametric QR [McMillen, 2015]
- Which way to go?
  - *TQR:* quantile specific thresholds? quantile specific number of regimes? **Difficult to know ex ante**
  - *CPQR:* only need a bandwidth (and a kernel)!
- We opt to go with CPQR

CPQR

$$
\begin{aligned}
\hat{\beta}_\tau &= \underset{\beta_\tau}{argmin} \sum_{t=1}^{T-h} w_t(z)\rho_\tau(y_{t+h} - x_t^T\beta_\tau) \\
w_t(z) &= K\left(\frac{z_t - z}{b_h}\right) \\
\rho_\tau(u) &= u(\tau - I(u < 0))
\end{aligned}
\tag{2}
$$

- The method is just a locally weighted quantile regression approach!
  - $K(z)$ is some kernel with b_h as bandwidth
    - Follow [McMillen, 2012, McMillen, 2015]: use tri-cube kernel
    - b_h selected using LFO CV.
  - $\rho_\tau(u)$ is tick-loss function from [Koenker and Bassett, 1978]

Extreme moment tails

- Extreme quantiles in extreme momentum is data sparse
  - Can lead to ‘jagged’ coefficient profiles
  - Is it true variation or only on account of data sparsity?
- Estimate quantiles jointly for each conditioning value
- Impose non-crossing constraints:
  - Non-crossing constraints ensure monotonically increasing in-sample quantiles
  - Special typed of fused shrinkage that shrinks away quantile variation if it leads to crossing
- How to impose non-crossing constraints in the CPQR setup?

Non-crossing CPQR

$$\hat{\beta}_\tau = \underset{\beta_\tau}{argmin} \sum_{q=1}^{Q} \sum_{t=1}^{T-h} w_t(z)\rho_{\tau_q}(y_{t+h} - x_t^T \beta_{\tau_q})$$
$$s.t.\ x_{WC}(i_t(z) > 0)^T \beta_{\tau_q} \geq x_{WC}(i_t(z) > 0)^T \beta_{\tau_{q-1}}. \tag{3}$$

- Follow [Bondell et al., 2010], and impose a single constraint across time which represents the worst case scenario possible in the data, denoted as x_{WC}
- $i_t(z)$ specifies observation used to ensure non-crossing: local non-crossing constraints
    - Constraints on the observations that would be used when calculating the fitted quantiles
    - Theorem 1 of [Bondell et al., 2010] applies only if we impose local non-crossing constraints!

Results

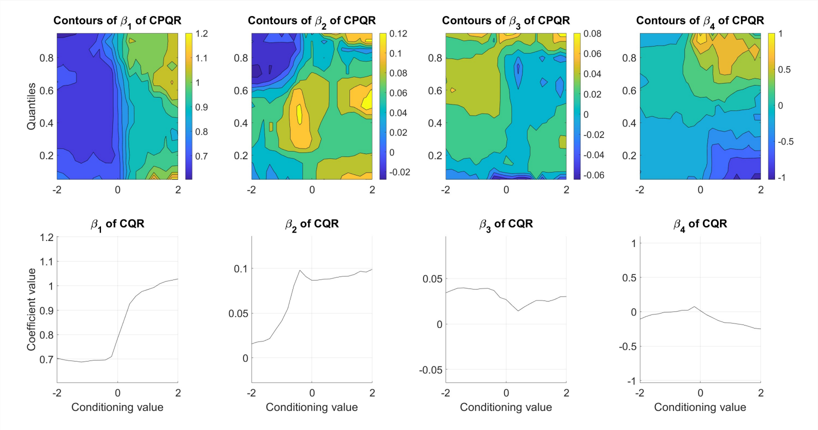

Figure 2: CPQR coefficients for h=4

Significance of nonlinearities here

OOS evaluation

- Use qwCRPS of [Gneiting and Ranjan, 2011]:

$$qwCRPS_{t+h} = \int_0^1 w_q QS_{t+h,q} dq, \tag{4}$$

- w_q places more weight at different parts of the density
  1. Equal weight
  2. Weight on central quantiles
  3. Weight on left tail
  4. Weight on right tail

OOS RESULTS

	$h=4$			
	CPQR	QAR(2)	NCQAR(2)	CQR
w_q^1	0.326*	0.363	0.362	0.330**
w_q^2	0.063*	0.069	0.069	0.064**
w_q^3	0.097*	0.105	0.104	0.098**
w_q^4	0.104	0.119	0.119	0.105**

Table 1: qwCRPS for the different weight profiles. Stars represent significance at the 10% (*), 5% (**), and 1% (***) level respectively.

In-sample results can be seen here!

Conclusion

Concluding thoughts

- Momentum conditioning is an important source of variation in inflation
- We find that different sectors impact inflation very differently:
    - Quantile variation is driven by the real sector in periods of falling inflation
    - Financial sector has more influence on the distribution during increasing inflation periods.
    - Global factors are less important in driving the shape of inflation: they act as location shifters
- Central Bank is not a silent observer: empirical strategy needs to account for dynamic nature of monetary policy

Thank you for your attention!

Paper available at: `https://arxiv.org/abs/2408.12286`

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VAR

VaR is a measure of how much value an asset can lose within a given time period, for a given probability level.

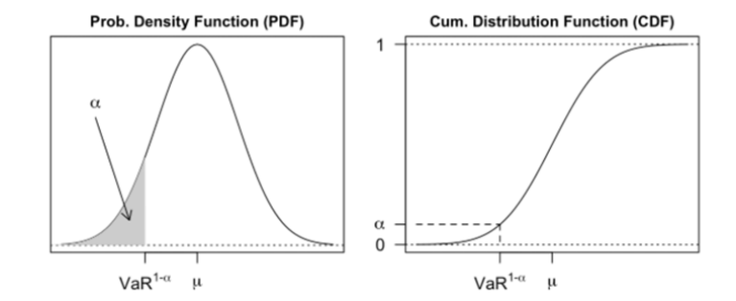


Figure 3: Value-at-Risk ($VaR^{1-\alpha}$) at $1-\alpha$ level represents the α quantile of the distribution

Back to Main Text

Large time variation in coefficients for IaR

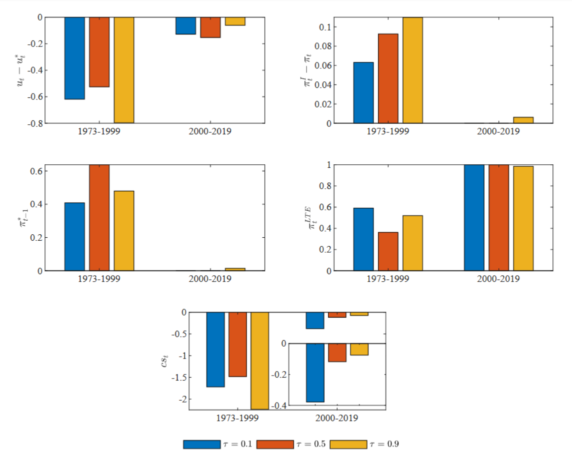


Figure 4: IaR coefficients of [Lopez-Salido and Loria, 2022]

Back to Main Text

Hausman test

- Notice that CQR (and QAR(2)) are efficient versions of CPQR.
- Can use the Hausman test to check which type of nonlinearity is important for the variables

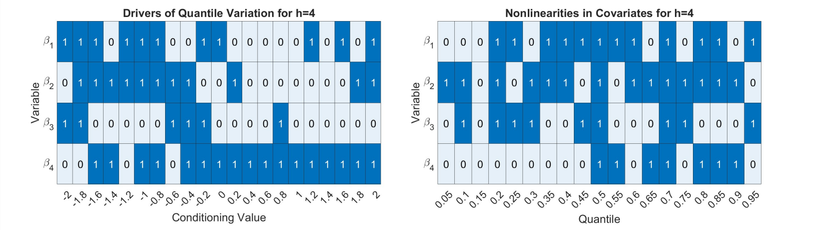
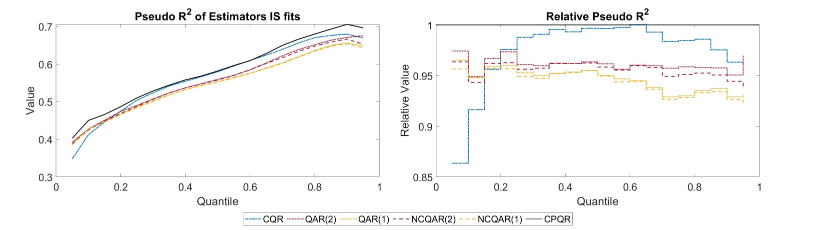


Figure 5: Hausman test results for h=4

Back to Main Text

IS evaluation



- Due to the conditionally parametric nature of the CPQR, calculating pseudo R^2 of [Koenker and Machado, 1999] directly is not possible
- Use the method proposed in [Kohns and Szendrei, 2023]:
  - (1) calculate the fitted quantiles; (2) use these as covariates in a separate quantile regression; (3) pseudo R^2 of this second regression to measure fit.
  - Related to VaR test of [Gaglianone et al., 2011].

Back to Main Text