Macroprudential policy stance assessment: the case of Croatia

Tihana Škrinjarić
Bank of England

Content

Content

1. INTRODUCTION

- ESRB (2011): "*ultimate objective of macroprudential policy is the stability of the financial system, by increasing its resilience, taming the build-up of vulnerabilities in the system and smoothing out the financial cycle, which should ultimately contribute to economic growth*"
- One of the goals of MP is to reduce the probability of a future financial crisis, and its spillover to the real sector, as financial crises are costly (see empirical findings of Jordá et al., 2013; Reinhart and Rogoff, 2009, Laeven and Valencia, 2012, 2013)

- To achieve FS: prevent and mitigate systemic risk & fin. crisis > tail risk
- GFC showed that we need to consider distributions [previous models]

- *At-risk* approach/measures
  - inflation-at-risk in López-Salido and Loria (2021); bank capital-at-risk in Lang and Forletta (2019, 2020); house-price-at-risk in Deghi et al. (2020); Škrinjarić and Sabol (2024); unemployment-at-risk in Adams et al. (2020); capital flows-at-risk in Eguren-Martin et al. (2021); labour-at-risk in Botelho et al. (2023) , ….

1. INTRODUCTION

- ESRB (2011): *"ultimate objective of macroprudential policy is the stability of the financial system, by increasing its resilience, taming the build-up of vulnerabilities in the system and smoothing out the financial cycle, which should ultimately contribute to economic growth"*
- One of the goals of MP is to reduce the probability of a future financial crisis, and its spillover to the real sector, as financial crises are costly (see empirical findings of Jordá et al., 2013; Reinhart and Rogoff, 2009, Laeven and Valencia, 2012, 2013)

- To achieve FS: prevent and mitigate systemic risk & fin. crisis > tail risk
- GFC showed that we need to consider distributions [previous models]

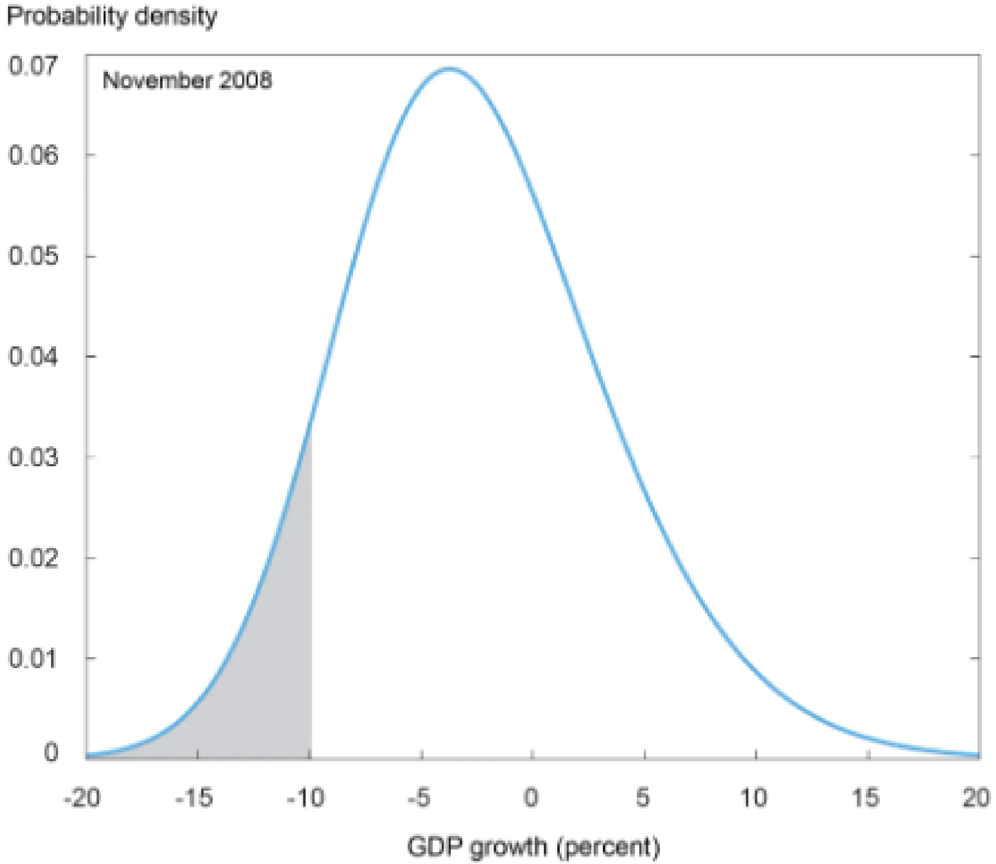
- *At-risk* approach/measures
  - inflation-at-risk in López-Salido and Loria (2021); bank capital-at-risk in Lang and Forletta (2019, 2020); house-price-at-risk in Deghi et al. (2020); Škrinjarić and Sabol (2024); unemployment-at-risk in Adams et al. (2020); capital flows-at-risk in Eguren-Martin et al. (2021); labour-at-risk in Botelho et al. (2023) , ….

1. INTRODUCTION

- *At-risk* is a concept from Finance (VaR)
- VaR is a measure of the risk of loss of investment. It estimates how much a set of investments might lose (with a given probability), given normal market conditions, in a set time period such as a day.

- For MP: measure and quantify the risks to economic outlook / other relevant variables
- To estimate *at-risk* values> Quantile regression

Large Downside Risks to Future Real GDP Growth When Financial Conditions Are Tight



Sources: Blue Chip Economic Indicators Survey; Federal Reserve Bank of Philadelphia; European Central Bank; authors' calculations.
Notes: The chart shows the distribution of average real GDP growth over the next four quarters, conditional on financial conditions as of the end of October 2008 and the November 2008 Blue Chip Economic Indicators Survey. The gray shaded area indicates the part of the distribution below the 10th percent quantile.

Source: NY FED (2023)

1. Introduction

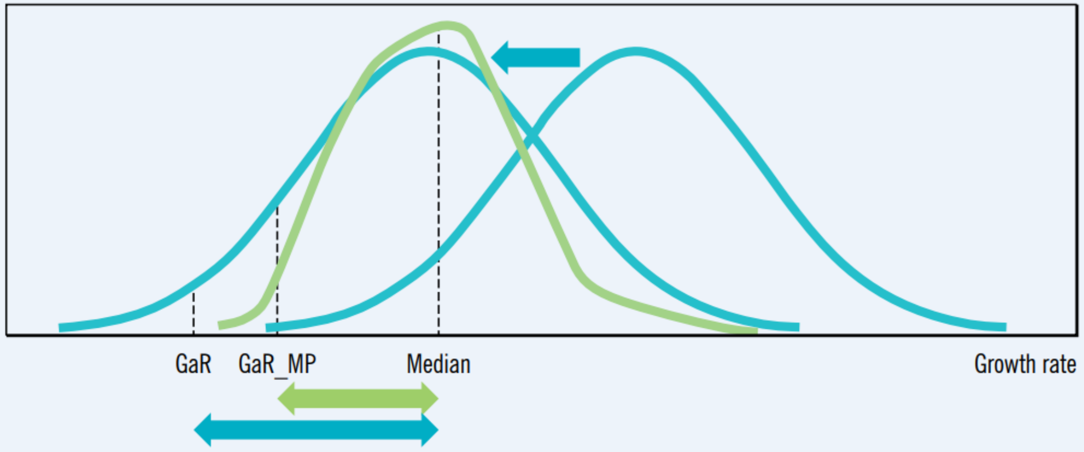
Assessment of MP stance/effectiveness

$$y^q_{t+h} = a^q + b^q_1 MPI_t + b^q_2 Stress_t + b^q_3 FinCycle_t + \boldsymbol{b}'\boldsymbol{X}_t + \varepsilon^q_t$$

- The growth-at-risk approach is one of the ways to assess the efficiency of macroprudential policy.
- The costs arising from the potential decrease in the average future growth and the benefits of macroprudential policy implementation in reducing the severity and probability of crises are observed through the projection of the full distribution of future economic growth.
- Initially: forecasting
- Now: macroprudential policy stance assessment

Sources: FSR (2023), Škrinjarić (2023)

Figure 1 Comparison of growth distributions before and after a negative shock, with and without macroprudential policy



Notes: The right distribution in blue denotes growth rate prior to shock. The left distribution in blue denotes future growth rate following a negative shock, without any macroprudential policy measures being implemented. The distribution in green denotes future growth rate following a negative shock, with the application of current macroprudential policy. DTT for the distribution marked in green is shorter than the one marked in blue. GaR and Gar_MP denote growth-at-risk in the economy with and without macroprudential policy.
Source: adjusted according to Duprey and Ueberfeldt (2020).

1. Introduction

- The purpose of this paper is to construct a GaR framework and empirically evaluate MP effects and stance for the case of an active country with respect to this policy: Croatia.

1. Introduction

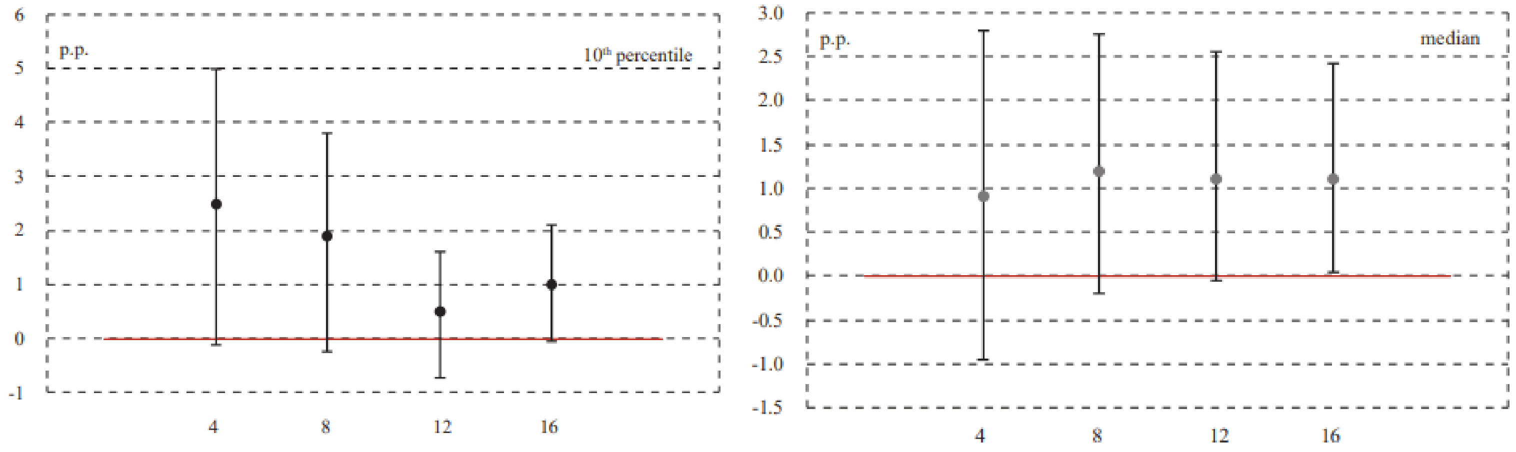
- The purpose of this paper is to construct a GaR framework and empirically evaluate MP effects and stance for the case of an active country with respect to this policy: Croatia.

- Findings:

Macroprudential policy effects on future growth

$$y_{t+h}^{q} = a^{q} + b_1^{q} MPI_t + b_2^{q} Stress_t + b_3^{q} FinCycle_t + \boldsymbol{b}'\boldsymbol{X}_t + \varepsilon_t^{q}$$

Panel (a) Model (1)



Content

1. Introduction
2. Literature review
3. Methodology
4. Results
5. Conclusions

2. Literature review

- Seminal papers: better short-term GDP-at-risk prediction (Adrian et al., 2016, 2019; Giglio et al., 2015, 2016)
- Extensions (1): medium-term prediction (Aikman et al., 2018, Plagborg-Møller et al., 2020, Adrian et al., 2019) …

Financial conditions or stress	Financial vulnerabilities	Structural and other factors
VIX	External debt	World growth
Bank lending standards	Credit to GDP gap	Growth of bigger economies
Term premiums	Credit growth	Energy prices
Interest rates	House price growth	Stock indexes
Financial conditions index	House prices relative to fundamentals	exchange rates,
Bond returns	Current account deficit	Supply Management indexes
Bond yield spreads	Corporate leverage	Employment
CDS spreads	Household debt to GDP	Unemployment
Equity returns	Solvency and leverage of credit institutions	Monetary aggregates
CLIFS	Composite indicators of variables above	Industrial production
HY bond spread	Debt service ratio	CPI
Bank bond spread		Producer price index
Loan growth		Housing permits
TED spread		Personal consumption
Term spread		Real personal income
Sovereign spread		Economic Sentiment Indicator
VSTOXX		Size of the economy
CISS		Degree of trade
Eonia		Financial openness
FED rate		FDI (foreign direct investment) flows
		Bank concentration
		Government revenues as a share of GDP
		Financial reform index
		Development in the security markets
		Privatisation of the banking sector
		Government effectiveness
		Control of corruption
		Rule of law
		Exports, imports

2. Literature review

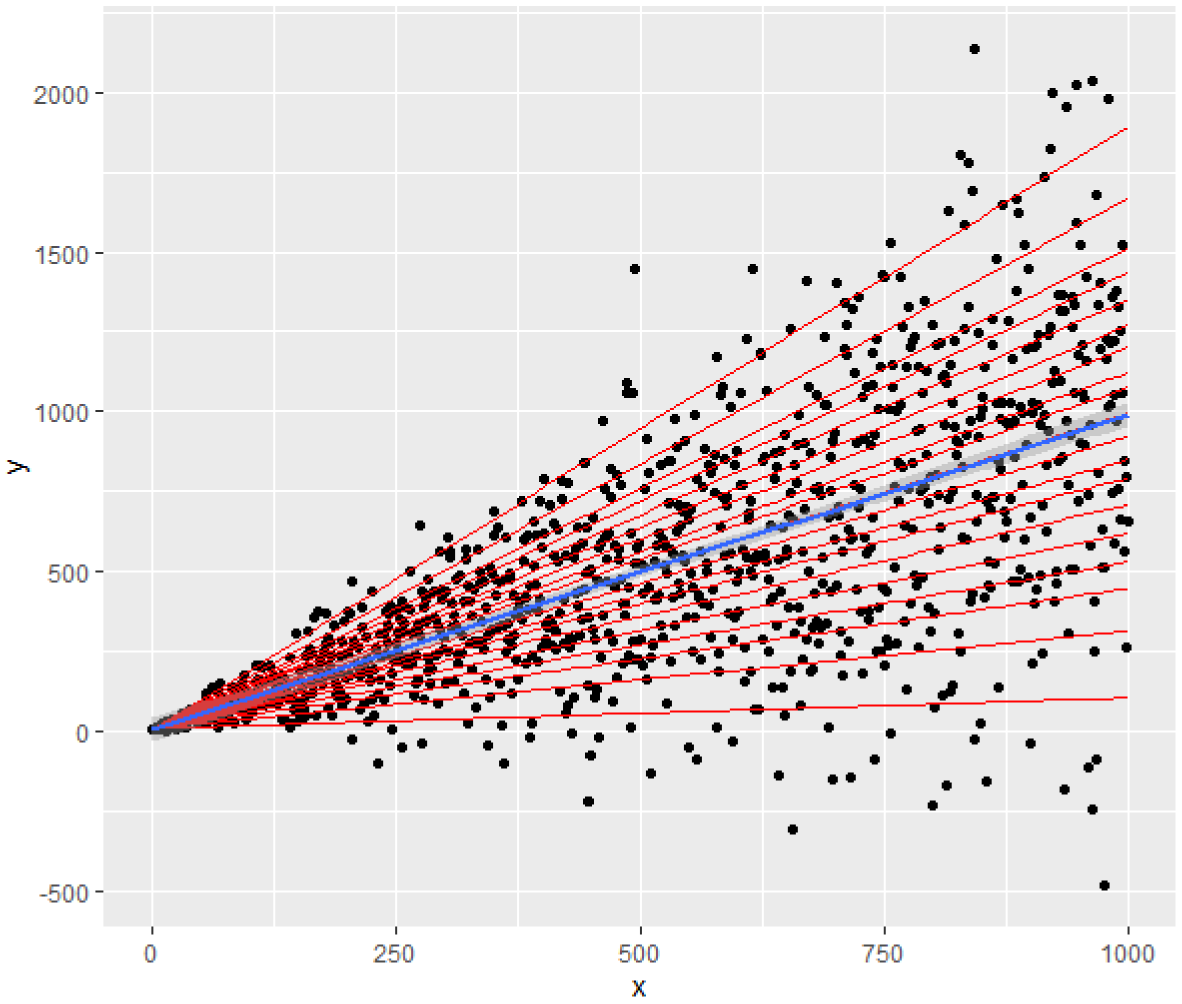
- Extensions (2): introducing macroprudential policy indicator to evaluate its efficiency

Sánchez and Röhn (2016), Duprey and Ueberfeldt (2018), Galán and Rodríguez-Moreno (2020), Galán (2020a, 2020b), Brandao-Marques et al. (2020), Cucic et al. (2022), Franta and Gambacorta (2020), Drenkovska and Volčjak (2022)

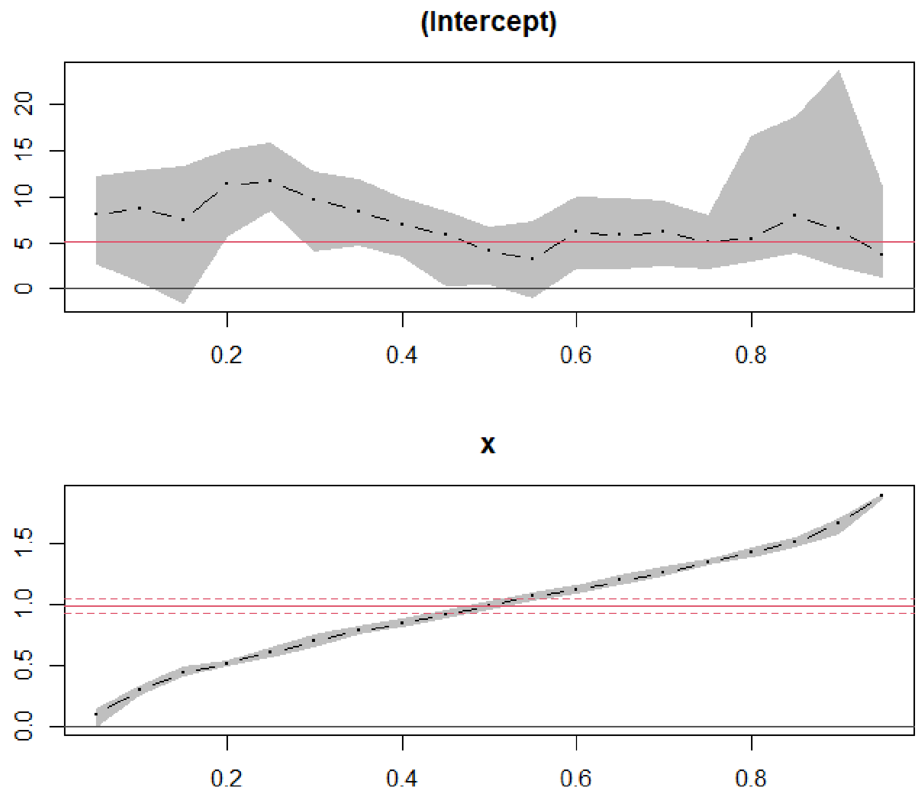
- Conclusions:
  - Single-country vs panel (comparability, diff indicators, lack of data)
  - Panel studies find results: costs in short term, benefits in longer term outweigh them
  - BBM measures > CBM

Content

3. Methodology – quantile regression



$$y(\theta) = \beta_0(\theta) + \sum_{k=1}^{K} x_i \, \beta_k(\theta) + \varepsilon_i(\theta)$$



3. Methodology

$$y_{t+h}(\theta) = \beta_0(\theta) + \beta_1(\theta) MPI_t + \beta_2(\theta) y_t + \beta_3(\theta) Stress_t + \beta_4(\theta) FV_t + \varepsilon_t(\theta),$$
$$\theta = 0.05, \ldots, 0.95$$

$$y_{t+h} = 100\% \times \left(\frac{r\_GDP_{t+h}}{r\_GDP_t} - 1 \right) / \frac{h}{4}$$

- Signs of coefs

3. Methodology

Data:
Quarterly, 1994 to 2022

GDP, inflation (for real GDP growth)
Financial stress: CLIFS and HIFS

Usual tests, pseudo R-squared to find best variable combo

Financial vulnerabilities variables

Abbreviation	**Description**	**Transformation**
C2GDP gap	Credit to GDP gap	Hodrick-Prescott filter gap, smoothing parameter for (narrow) credit series is 125K, for GDP is 1.600
Diff C2GDP ratio	Differenced credit to GDP ratio	One year difference of the (narrow) credit to GDP ratio
Diff Narrow credit	Differenced values of narrow credit	One year difference
d-SRI (ECB)	Domestic systemic risk indicator	See Lang et al. (2019)
ICSR (HR)	Indicator of Cyclical Systemic Risks	See Škrinjarić (2022, 2023a)
2y Diff Narrow credit	2-year differenced narrow credit	–
2y Diff C2GDP ratio	2-year differenced credit to GDP ratio	–
Diff ICSR (HR)	Differenced ICSR	–
Growth rate Narrow credit	One year growth rate of narrow credit	–

3. Methodology

MPI

- information about (de)activating MP tools over time
- counting the number of measures over time, by constructing indices based on a binary variable, or a variable that takes a couple of values
- Then sum tightening and reduce by loosening in given *t*

$$mpi_{i,t} = \begin{cases} 1, \text{if a measure } i \text{ is tightening} \\ 0, \text{absence of measure } i \\ -1, \text{if a measure } i \text{ is loosening} \end{cases}$$

- Values as is, cumulated, moving differences
- Issues: intensity, type of measures, sources

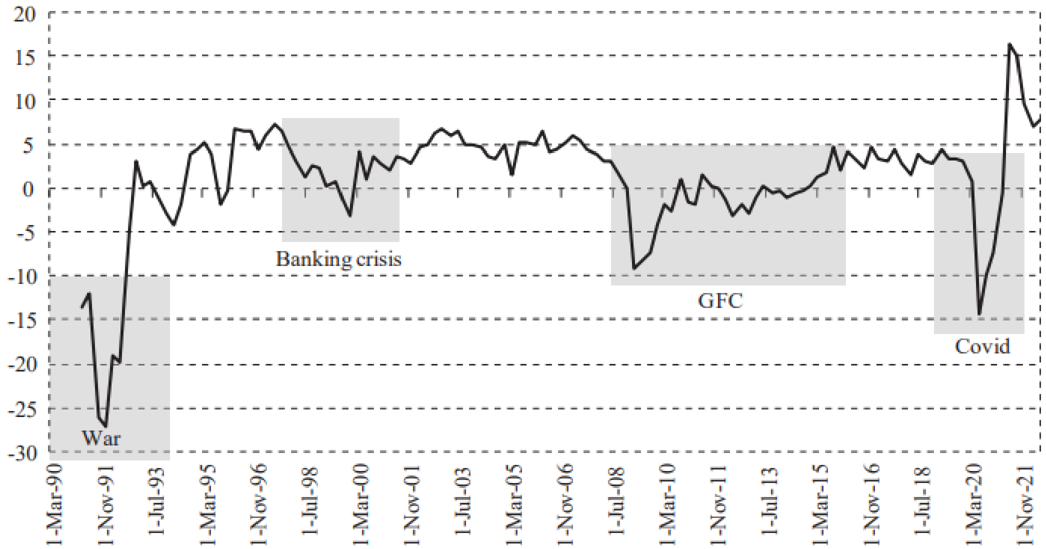
- Endogeneity > Ordered logistic regression on GaR RHS variables, several lags tested

Content

1. Introduction
2. Literature review
3. Methodology
4. Results
5. Conclusions

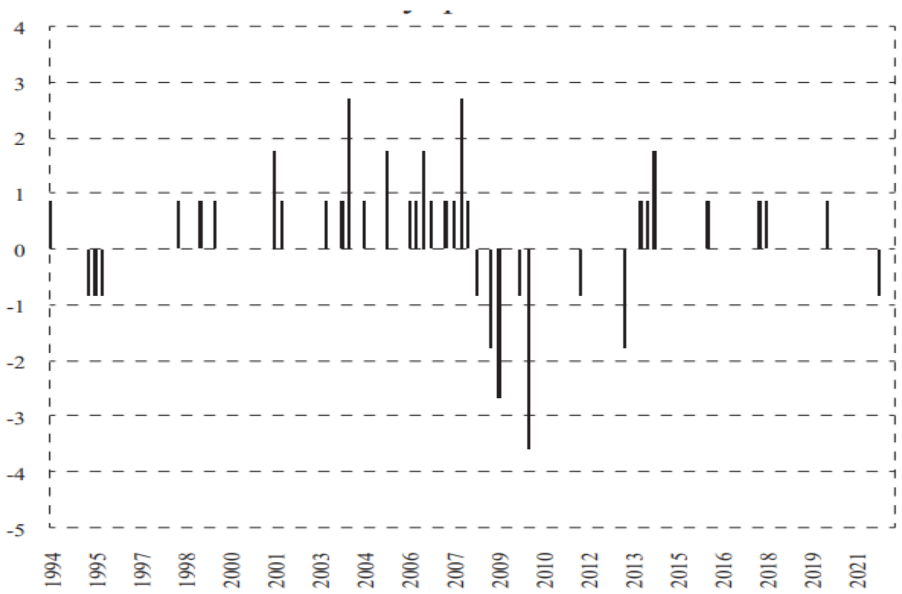
4. Results

Real GDP growth, year-on-year, in %



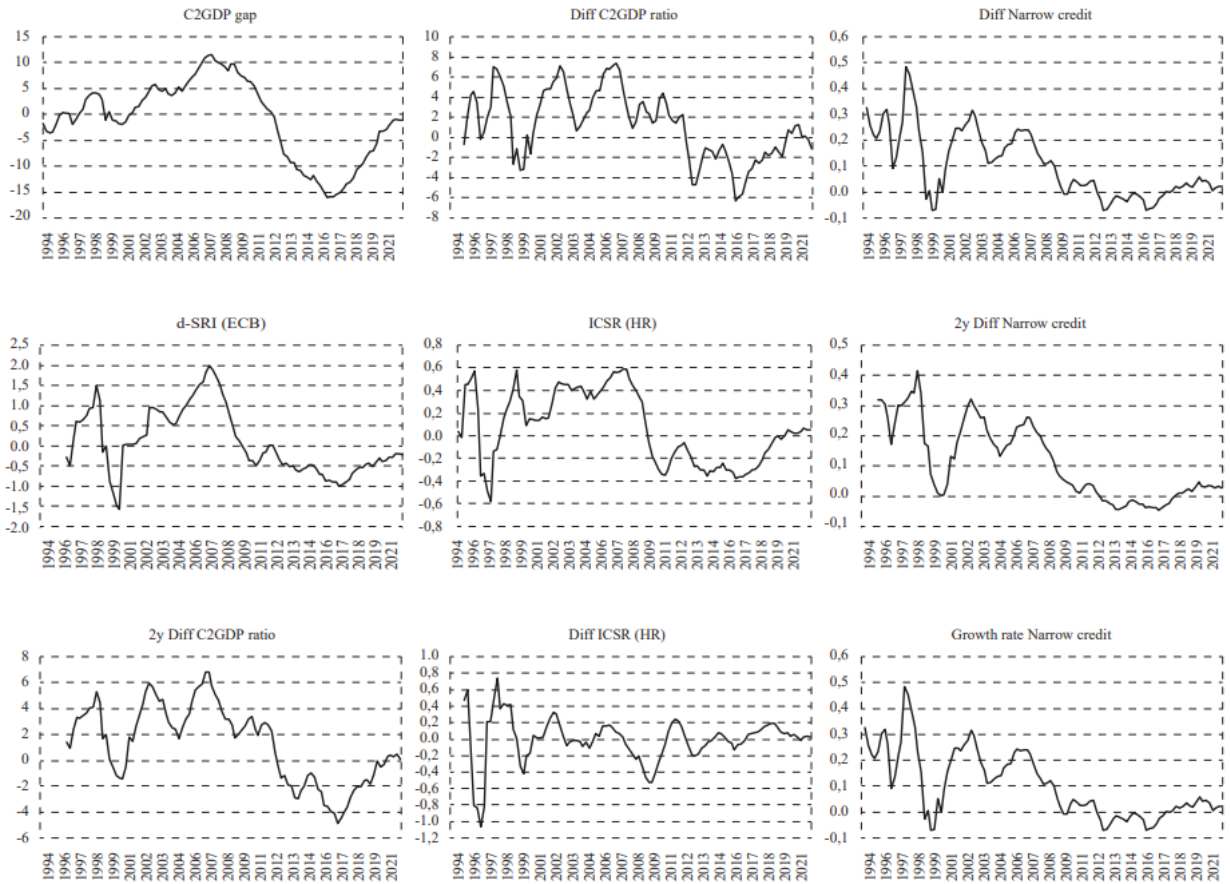
Source: CNB (2023), author's calculation.

Macroprudential policy index dynamics



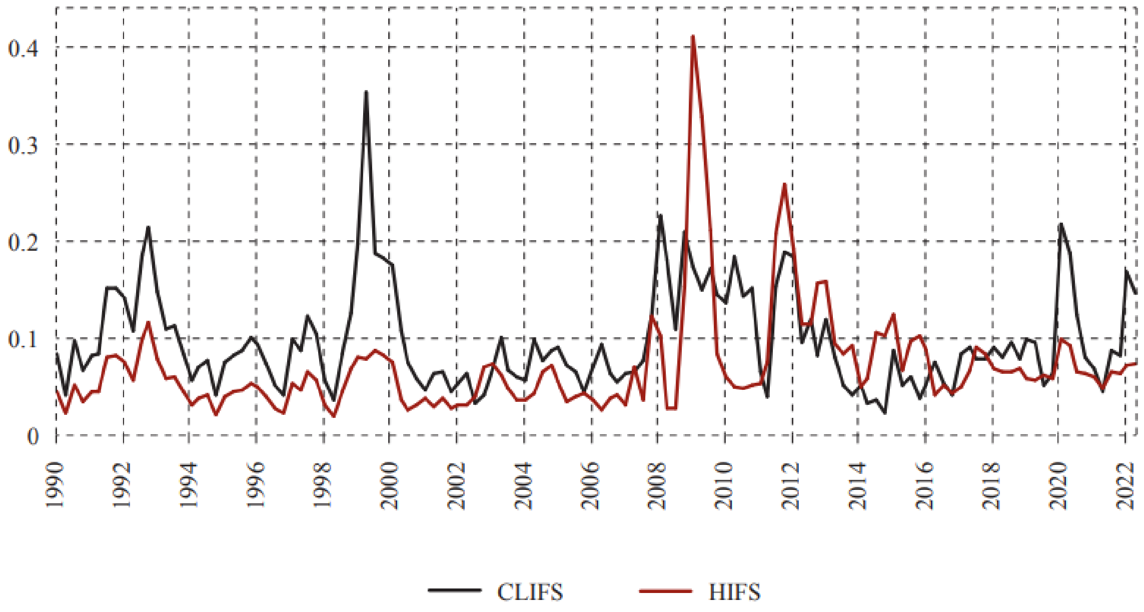
4. Results

Financial vulnerabilities in Croatia, different measures



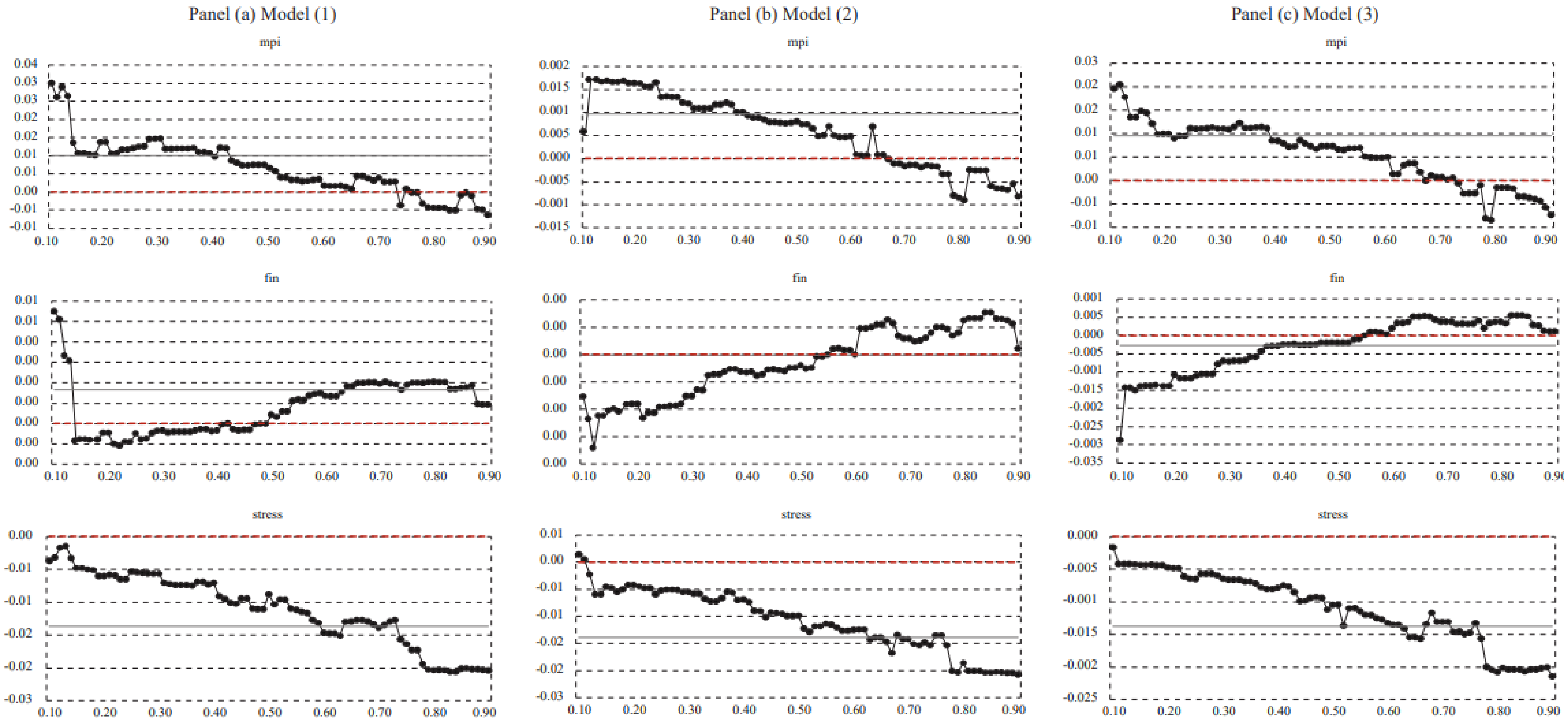
Note: C2GPD – credit to GDP, Diff – difference, i.e., year-on-year (y-o-y) difference, d-SRI – domestic systemic risk indicator, ICSR – indicator of cyclical systemic risk, 2y Diff – two-year difference. Growth rate of narrow credit is y-o-y.

Comparison of CLIFS (ECB version) to the HIFS (CNB version) of financial stress



4. Results

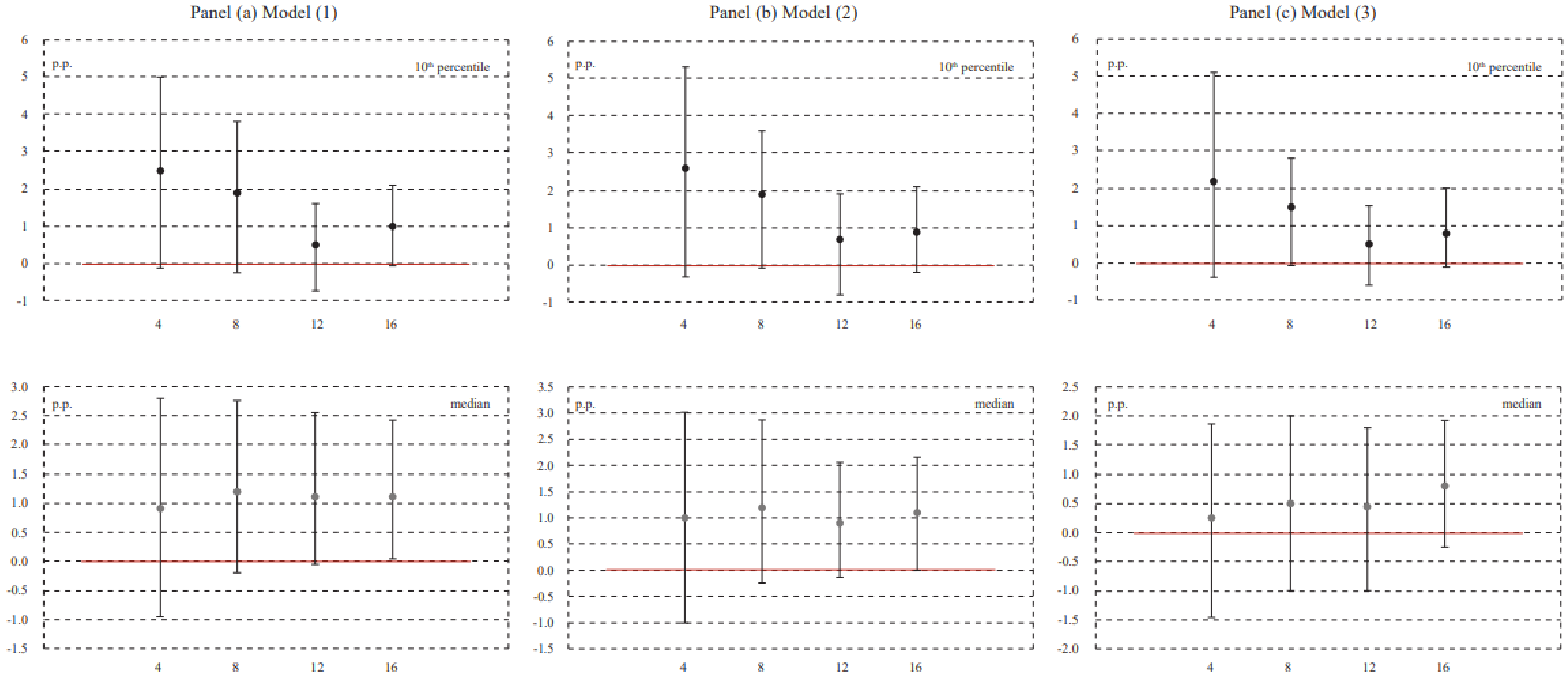
Estimated coefficients for models (1) – (3), h = 4 quarters ahead



Note: y-axes values should be multiplied by 100% to get p.p. growth interpretations. mpi – variant of macroprudential policy variable, fin – financial vulnerabilities variable as described in main text.

4. Results

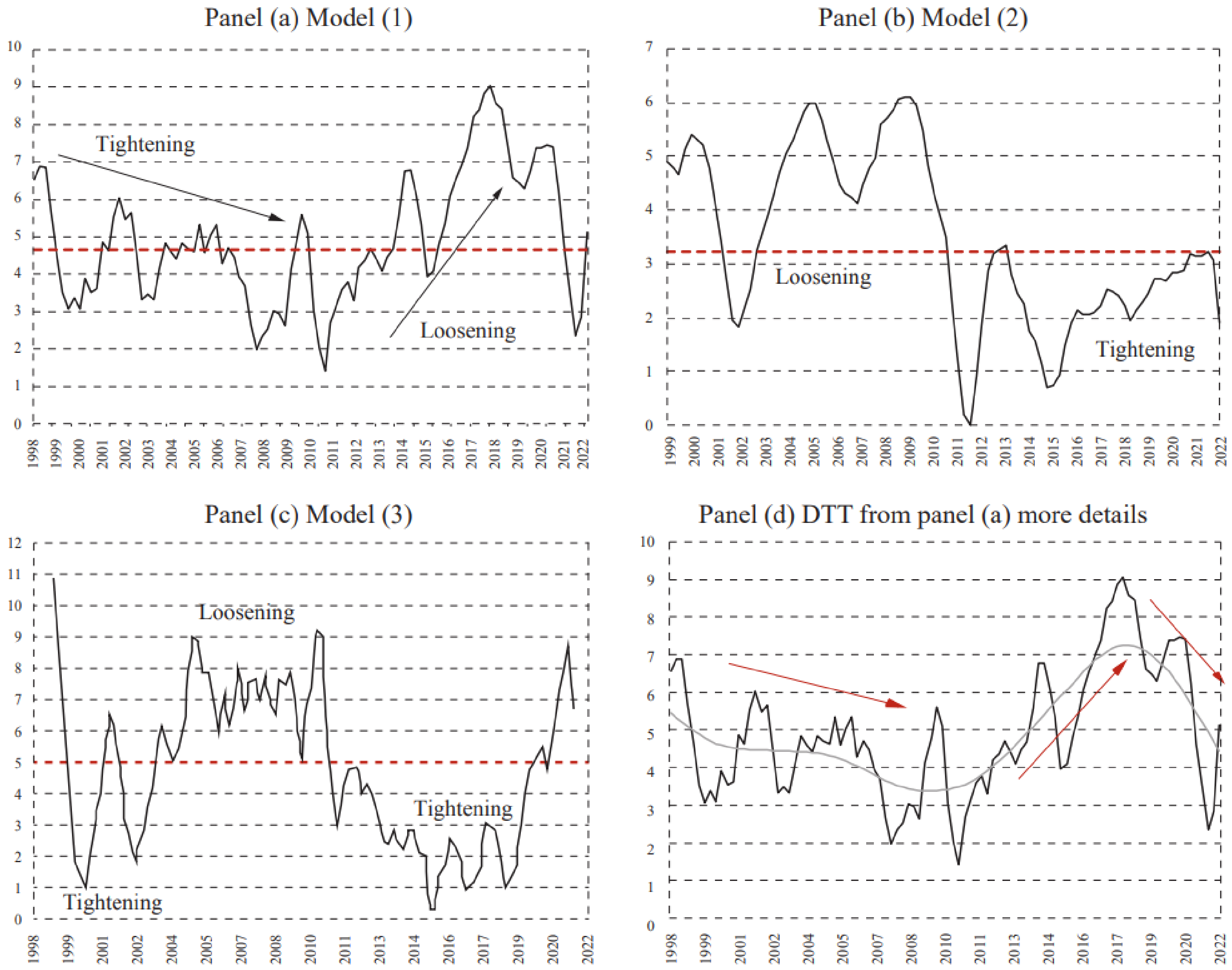
Macroprudential policy effects on future growth



4. Results

DTT = median – left tail

Distance to tail from models (1) to (3)



Note: Dashed lines indicate median values of distance-to-tails.

Content

1. Introduction
2. Literature review
3. Methodology
4. Results
5. Conclusions

5. Conclusion

- Methodology to evaluate effectiveness of MP
- Inconclusive; some positive results for lower tail
- Can be used for forecasting purposes and for what-if scenarios, ST

- Future work:
  - Longer time series, CEE panel, solve MPI indicator intensity issue
  - Combine with granular and micro models
  - Other applications (climate risks, high frequency models)

Thank you

APPENDIX

Appendix – Quantile Regression more formal (1/3)

With reference to a continuous and strictly monotonic cumulative distribution function $F_X\colon \mathbb{R} \to [0,1]$ of a random variable *X*, the quantile function $Q\colon [0,1] \to \mathbb{R}$ maps its input *p* to a threshold value *x* so that the probability of *X* being less or equal than *x* is *p*. In terms of the distribution function *F*, the quantile function *Q* returns the value *x* such that

$$F_X(x) := \Pr(X \le x) = p\,,$$

which can be written as inverse of the c.d.f.

$$Q(p) = F_X^{-1}(p)\,.$$

Let Y be a real-valued random variable with cumulative distribution function $F_Y(y) = P(Y \le y)$. The τth quantile of Y is given by

$$q_Y(\tau) = F_Y^{-1}(\tau) = \inf\{y : F_Y(y) \ge \tau\}$$

where $\tau \in (0,1)$.

Define the loss function as $\rho_\tau(m) = m(\tau - \mathbb{I}_{(m<0)})$, where $\mathbb{I}$ is an indicator function. A specific quantile can be found by minimizing the expected loss of $Y - u$ with respect to u:[1](pp. 5–6):

$$q_Y(\tau) = \arg\min_u E(\rho_\tau(Y-u)) = \arg\min_u \left\{(\tau - 1)\int_{-\infty}^{u}(y-u)dF_Y(y) + \tau\int_{u}^{\infty}(y-u)dF_Y(y)\right\}.$$

This can be shown by computing the derivative of the expected loss with respect to u via an application of the Leibniz integral rule, setting it to 0, and letting q_τ be the solution of

$$0 = (1-\tau)\int_{-\infty}^{q_\tau} dF_Y(y) - \tau\int_{q_\tau}^{\infty} dF_Y(y).$$

This equation reduces to

$$0 = F_Y(q_\tau) - \tau,$$

and then to

$$F_Y(q_\tau) = \tau.$$

If the solution q_τ is not unique, then we have to take the smallest such solution to obtain the τth quantile of the random variable *Y*.

Appendix – Quantile Regression more formal (2/3)

The τth conditional quantile of Y given X is the τth quantile of the Conditional probability distribution of Y given X,

$$Q_{Y|X}(\tau) = \inf\left\{y : F_{Y|X}(y) \geq \tau\right\}.$$

We use a capital Q to denote the conditional quantile to indicate that it is a random variable.

In quantile regression for the τth quantile we make the assumption that the τth conditional quantile is given as a linear function of the explanatory variables:

$$Q_{Y|X}(\tau) = X\beta_\tau.$$

Given the distribution function of Y, β_τ can be obtained by solving

$$\beta_\tau = \underset{\beta\in\mathbb{R}^k}{\arg\min} E(\rho_\tau(Y - X\beta)).$$

Solving the sample analog gives the estimator of β.

$$\hat{\beta}_\tau = \underset{\beta\in\mathbb{R}^k}{\arg\min} \sum_{i=1}^{n}(\rho_\tau(Y_i - X_i\beta)).$$

Note that when $\tau = 0.5$, the loss function ρ_τ is proportional to the absolute value function, and thus median regression is the same as linear regression by least absolute deviations.

Appendix – Quantile Regression more formal (3/3)

- The quantiles, or percentiles, or occasionally fractiles, refer to the general case of dividing a dataset into parts. Quantile regression seeks to extend these ideas to the estimation of conditional quantile functions — models in which quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates.
- In quantile regression, the median estimator minimizes the symmetrically weighted sum of absolute errors (where the weight is equal to 0.5) to estimate the conditional median function, other conditional quantile functions are estimated by minimizing an asymmetrically weighted sum of absolute errors, where the weights are functions of the quantile of interest. This makes quantile regression robust to the presence of outliers.

- Koenker and Basset (1978): Regression Quantiles
- Koenker and Hallock (2001): Quantile Regression
- Koenker (2017): Quantile regression 40 years on

Quantile regression - equation

- QR (Quantile Regression) is type of regression analysis that estimates the conditional median and other quantiles of the dependent variable
- Does not depend on the distributional properties of variables, error term does not have to be normally distributed, deals with heteroskedasticity, less sensitive to outliers

$$\beta_0(\theta) + \sum_{k=1}^{K} x_i\, \beta_k(\theta) + \varepsilon_i(\theta)$$

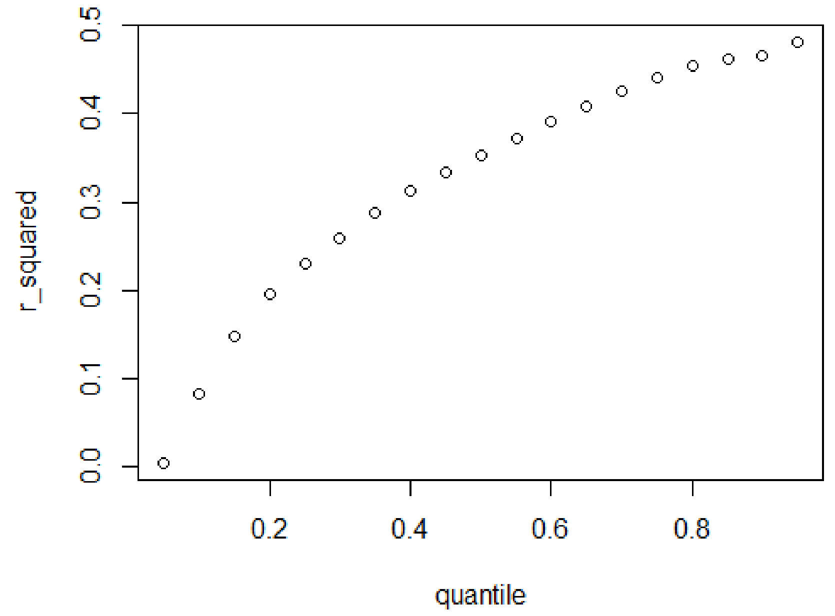
- θ is the quantile, ranging from e.g. 0.01, 0.05, to 0.95, 0.99, i.e. 0 < θ< 1
- Each parameter changes over the quantiles, and to estimate them:

$$\underset{\beta_k(\theta)}{\operatorname{argmin}} \sum_{i:y_i \geq \hat{y}_i} \theta \cdot I(\theta) \left| y_i - \beta_0(\theta) - \sum_{k=1}^{K} x_i\, \beta_k(\theta) \right| + \sum_{i:y_i < \hat{y}_i} I(\theta) \cdot (1-\theta) \left| y_i - \beta_0(\theta) - \sum_{k=1}^{K} x_i\, \beta_k(\theta) \right|$$

- Besides statistical properties, QR useful to test theory (e.g. post-modern portfolio theory and prospect theory), business/financial cycles, Lucas critique

Appendix – Goodness of fit, tests, inference (1/2)

- Pseudo R-squared: $R_\theta^2 = 1 - \frac{RASW_\theta}{TASW_\theta}$, *$RASW_\vartheta$* (*residual absolute sum of weighted deviations*), *$TASW_\vartheta$* (*total absolute sum of weighted deviations*)
- [compares at each quantile w.r.t. only having a constant]
- With real data, values can change in any direction from one quantile to other



Appendix – Goodness of fit, tests, inference (2/2)

- Asymmetry test and stability test: AT tests for asymmetric behaviour of coefficients from one tail of the distribution to the other; ST compares coefficients from one tail to the median value
- Inference can be conducted based on bootstrapping the estimated parameters
- Bootstrapping
    - Statistical procedure that resamples a single dataset to create many simulated samples
    - Allows to calculate standard errors, construct confidence intervals, and perform hypothesis testing
    - Alternative approach to traditional hypothesis testing
    - Very useful in circumstances where the asymptotic distributions of the test statistics of interest are unknown or statistically too complicated to derive, in cases where normality assumption have been violated thereby invalidate the use of conventional standard errors, confidence intervals as well as t-statistics

Appendix – Fitting t-distribution

The usual procedure after the QR estimation is to fit the skewed t-distribution of Azzalini and Capitanio (2003):

$$f(y;\mu,\sigma,\alpha,\upsilon) = \frac{2}{\sigma} t\left(\frac{y-\mu}{\sigma};\upsilon\right) T\left(\alpha \frac{y-\mu}{\sigma}\sqrt{\frac{\upsilon+1}{\upsilon\left(\frac{y-\mu}{\sigma}\right)^2}};\upsilon+1\right), \tag{15}$$

where $t(\cdot)$ and $T(\cdot)$ are the probability density function and cumulative density function respectively, μ is the location parameter, σ is scale, υ fatness, and α the shape parameter. Function (13) is used to smooth out the quantile function. In that way, the probability density function is obtained:

$$\underset{\mu,\sigma,\alpha,\upsilon}{\arg\min} \; \Sigma_\theta \left(\hat{Q}_{y_{t+h}} - F(\theta;\mu,\sigma,\alpha,\upsilon)\right)^2, \tag{16}$$

by matching the quantiles of the skewed t-distribution to the empirical quantiles obtained from the estimation. The empirical quantiles are usually the 5th, 25th, 75th and 95th. Some exceptions can be made to the 10th and 90th, when dealing with fewer data.