# Profit-to-Provisioning Approach for Setting the Countercyclical Capital Buffer: The Czech Example

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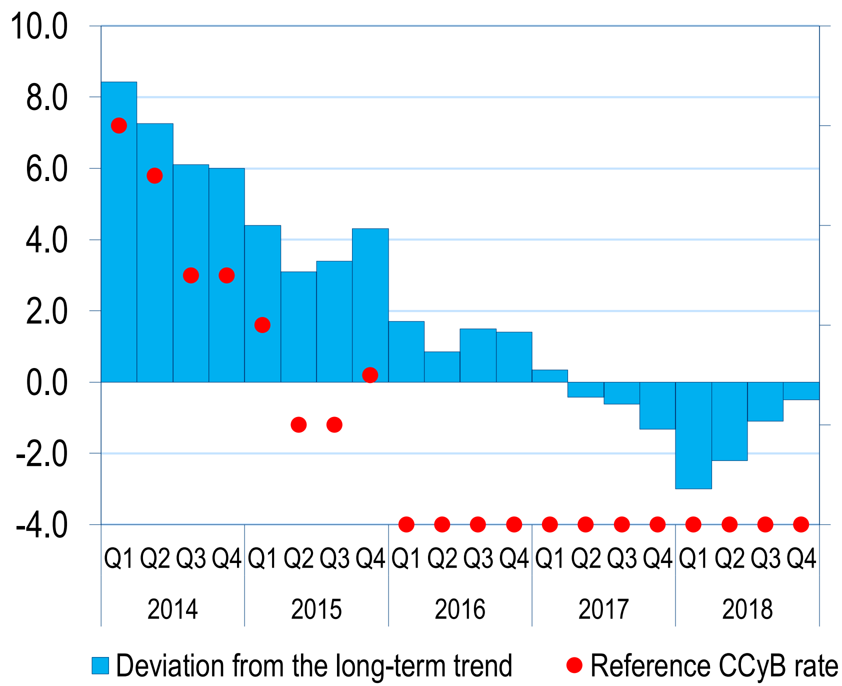
# Motivation: How to set the CCyB?

- BCBS (2010) and ESRB (2014) propose using the Hodrick-Prescott filter to estimate the deviation of the credit-to-GDP ratio from its long-term trend to determine the CCyB rate.
  - The indicator is not suitable for purely statistical reasons (Hamilton, 2017 RES).
  - The indicator is not suitable for converging economies (Geršl a Seidler, 2015 EEE).
  - Member States have room for another method of setting the CCyB rate.

**Credit-to-GDP gap**
(HP filter, lambda=400 000, 1995Q4 data)

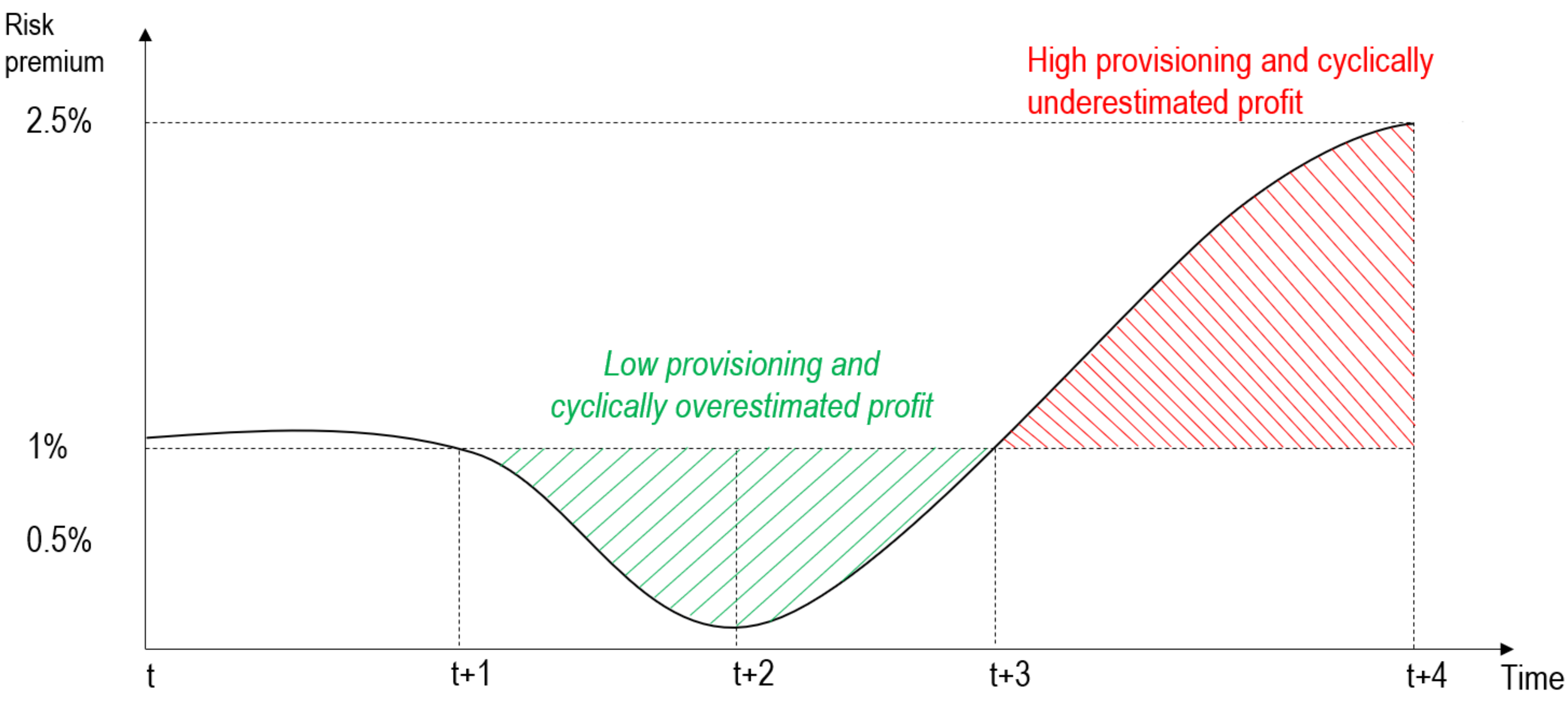



- Member States create their own CCyB setting methodology (Hájek a kol., 2017; Rychtárik, 2014; Bank of England, 2016; Banco de España, 2016…)
  - These are focused on determining the phase of the financial cycle (BIS, 2017)
  - Indicators measuring credit activity prevail. Indicators associated with credit standards, debt levels, or property price developments are also being used.
  - We develop indicators that capture cyclical developments **in the banking sector** (cyclical risks of underestimating the expected loss and overestimating profit).

## Our goal

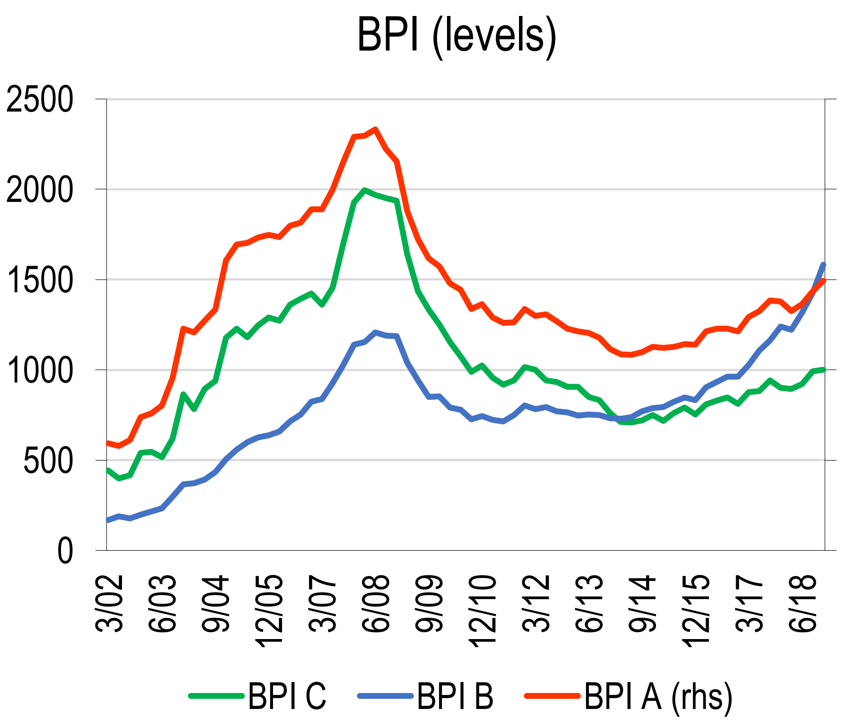


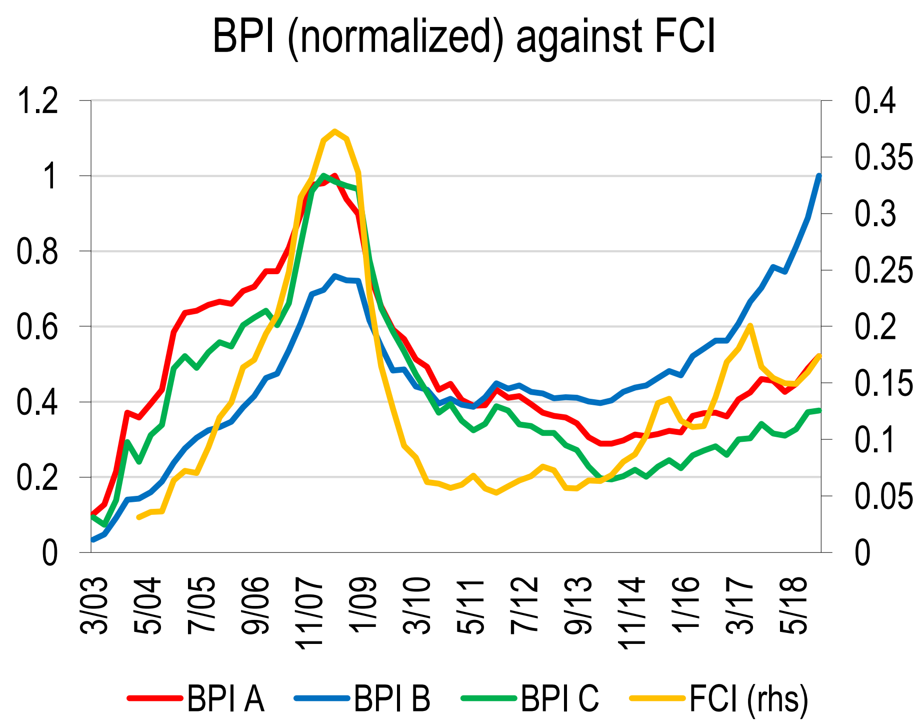
- Our goal is to design a simple approach that would mark the development of the financial cycle in the banking sector (the simpler, the better).
- The approach is mainly based on the development of banks‘ loan loss provisions and profit: profit-to-provisioning approach .
    - Loss provisions are procyclical (Beatty a Liao, 2014 JAE) and are related to the cyclical development of risk costs.



# Description of the proposed indicators

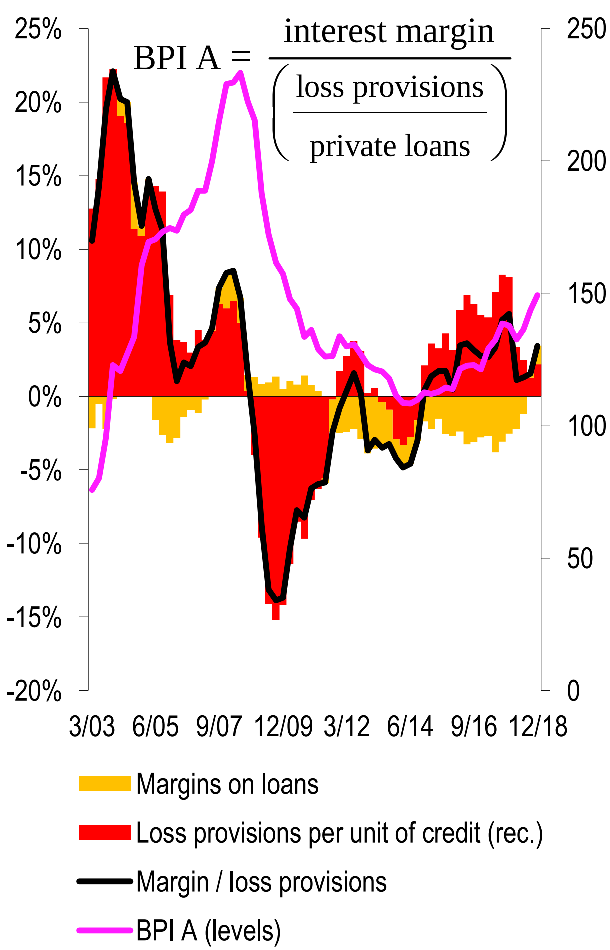
- A = interest margin/loss provisions per unit of credit
  - BPI A monitors whether sufficient provisions are created in relation to the risk premium contained in the interest rate on private loans.
- B = interest profit/loss provisions per unit of credit
  - BPI B increases with increasing loan volume
- C = (interest margin/loss provisions per unit of credit)/(client loans/capital)
  - BPI C should also reflect the procyclicality of risk weights (Brož et al., 2017)

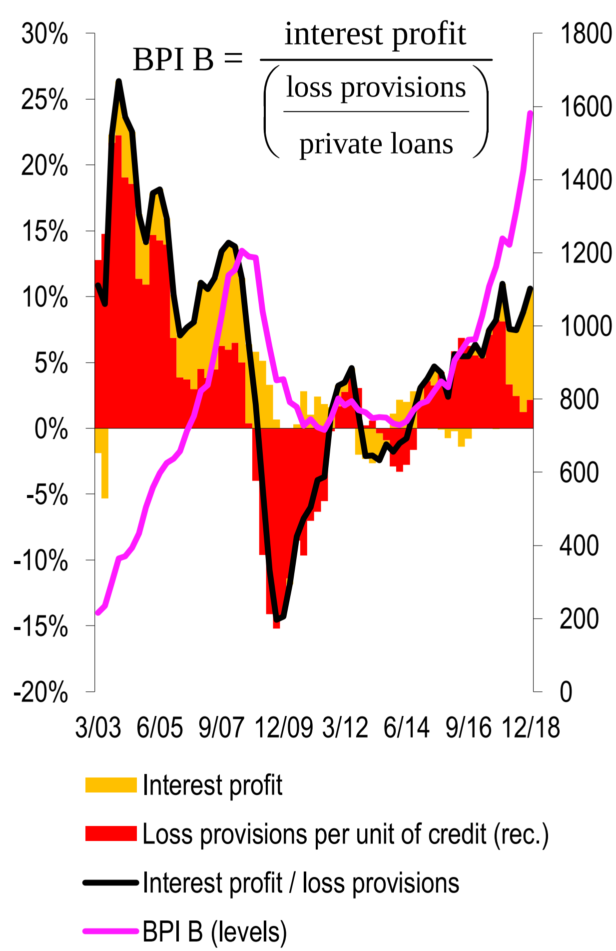


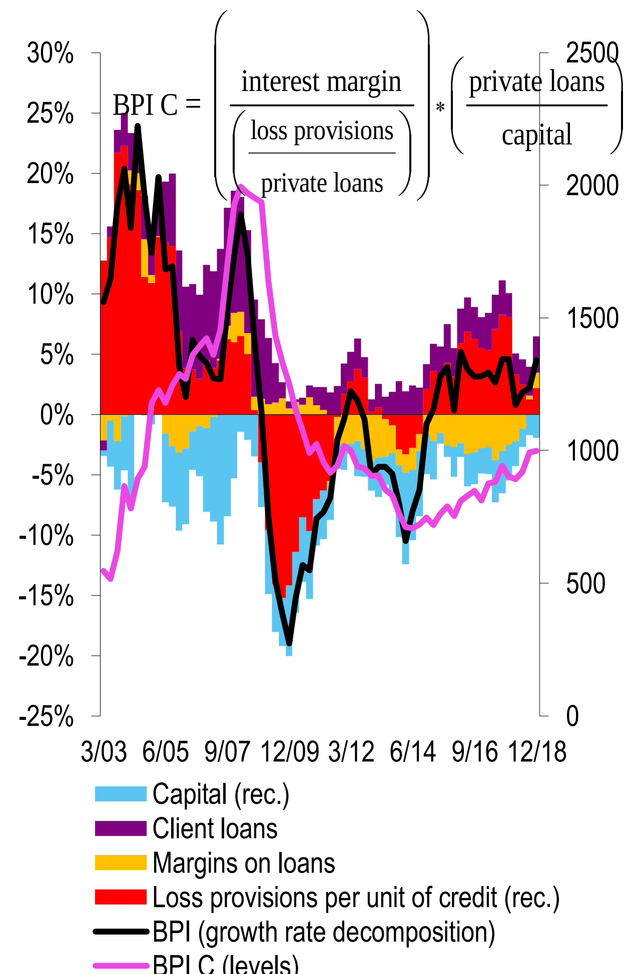



# Decomposing the proposed indicators

- The decomposition of the proposed indicators was performed using the logarithmic function and the values expressed in year-on-year changes.
- For clarity, the elements of the fraction denominator were represented in reciprocal value.



# Evaluation of the proposed BPIs



- Evaluating the performance of the financial cycle indicators is rather complicated
  - Only a handful of episodes of financial stress or even crises
  - Complexity of the financial system
  - Spill-over effects

- It is difficult to evaluate which indicator is good or which of the indicators is "best":
  - Holló et al. (2012) use several econometric exercises
  - Plašil et al. (2015) assesses FCI's ability to predict future losses
  - Several studies use nonlinear models (Brave and Lopez, 2017; Duprey and Klaus, 2017, ...)
  - So ... the more the merrier?

- To test the performance of BPI we use (1) a simple prediction model and (2) a nonlinear Markov-switching model

# (1) Single-equation prediction model

- We test the predictive performance of the proposed BPIs with respect to the accumulation and future materialization of credit risk.
  - First, we analyze the predictive performance of the three versions of the indicator with respect to growth in non-performing loans.
  - Second, we evaluate whether they can capture the early stages of house price growth.

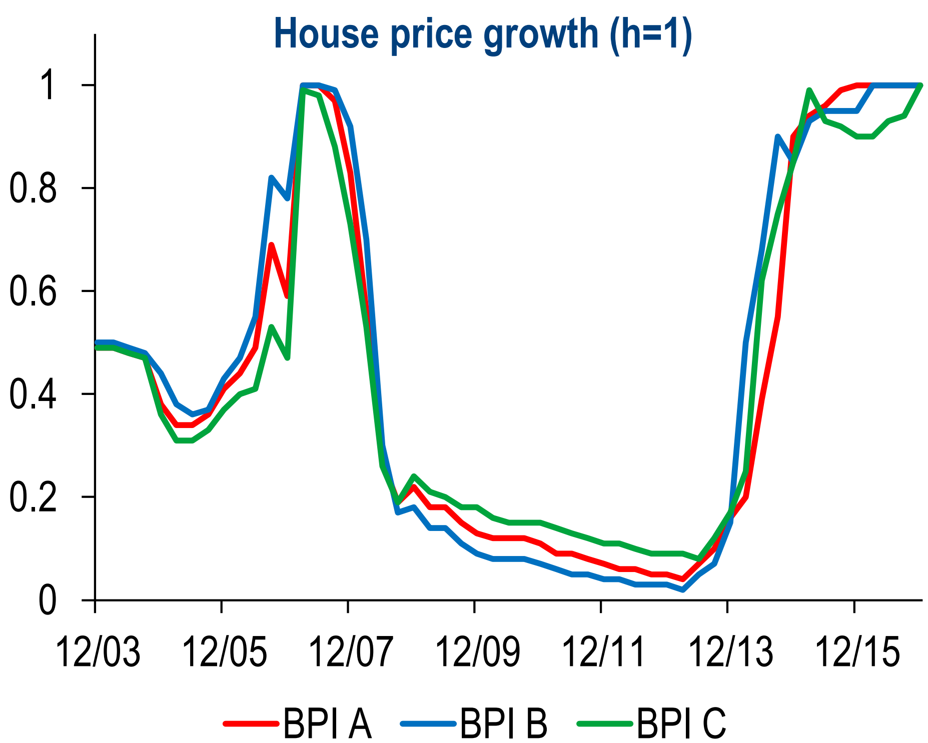
$$Y_{t+h} = \beta_t M_t + \delta_t X_t + \varepsilon_t$$

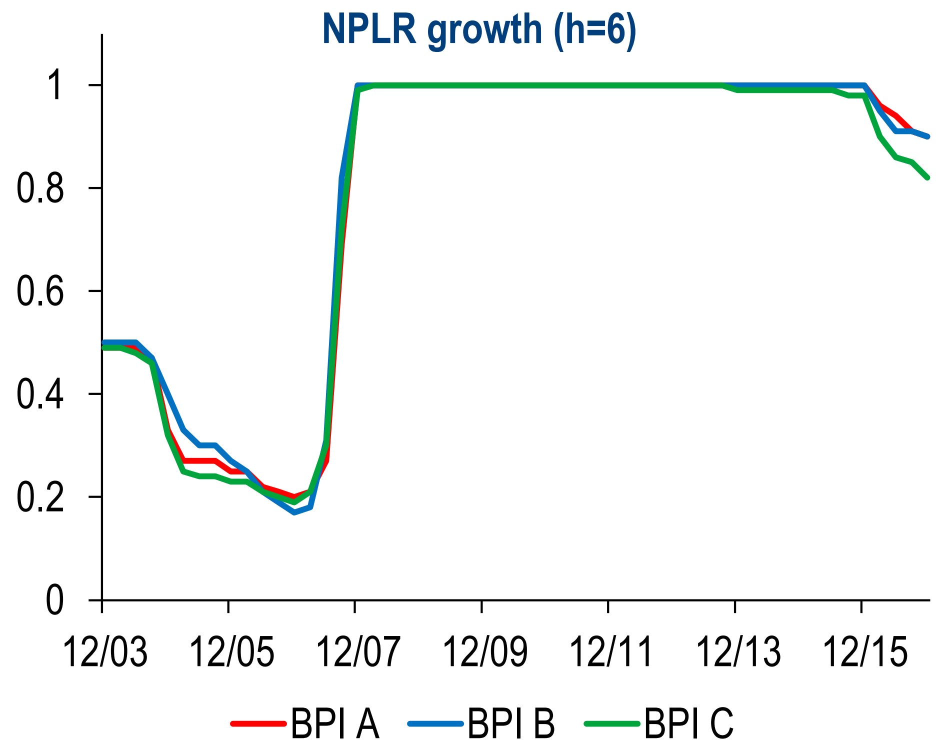
where $y_t$ is the predicted variable (growth of house prices or NPLR) predicted at horizon $h$ using information up to time $t$ , $M_t$ holds the three BPIs (added one-by-one), $X_t$ is a set of additional regressors.

- We use the dynamic model averaging (DMA) method of Raftery et al. (2012).
- In the case of the model forecast of NPL growth, we set $h = 6$
- In the case of the model forecast of house price growth, we set $h = 1$
- The key output of this method is a posterior inclusion probability (PIP), which shows the probability that the measure $M_t$ is included in the "best" model given the available data.

# Time-varying posterior inclusion probabilities for the proposed BPIs

- The two graphs show the evolution of the PIP associated with each BPI




- Models containing any of the BPIs considered contain useful information for the prediction of house prices in the pre-crisis period.
- The high PIP for NPLR growth in 2007Q4 suggests that models containing the BPIs may generate a better prediction for this period (remember that the model uses information lagged by six quarters, i.e., information up to 2006Q2).

# (2) Markov-switching model

- We use the Markov-switching model to assess the ability of an indicator to identify periods of systemic risk build-up, during which the CCyB rate should be increased.
- We estimate a univariate first-order autoregressive Markov-switching model as per Hamilton (1989). Following Brave and Lopez (2017), we use the model to capture the joint dynamics between real GDP and private credit growth while incorporating the different BPI versions into the time-varying transition probability model proposed by Diebold et al. (1994).

$$Y_t = \alpha_S + \beta_S Y_{t-1} + \phi_S X_t + \varepsilon_t$$

$S = (0,1), \varepsilon \sim N(0,1), Y_t = \Delta lnGDP, X_t = \{\Delta lncredit_t, \Delta lncredit_{t-1}\}$

$$\Omega = \begin{bmatrix} \Phi(\delta_0 + \gamma Z_t) & 1 - \Phi(\delta_0 + \gamma Z_t) \\ 1 - \Phi(\delta_1 + \gamma Z_t) & \Phi(\delta_1 + \gamma Z_t) \end{bmatrix}$$

where $\Phi(\delta_{0|1}) = p_{0|1} = Prob(S_t \mid S_{t-1} = 0, X_t, \alpha_S, \beta_S, \phi_S)$ and $Z_t$ holds the proposed BPIs.

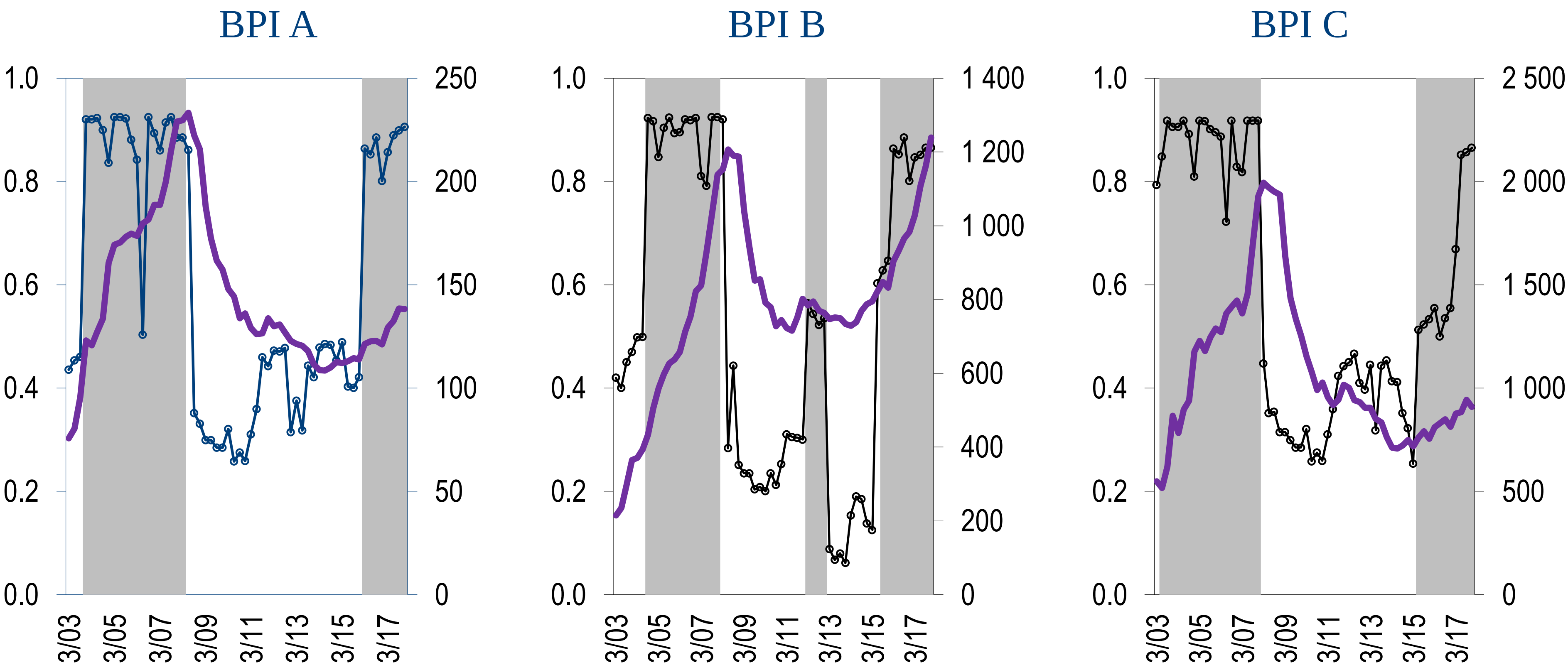
# Parameters and transition probabilities

| Parameters | BPI A | BPI B | BPI C |
|---|---|---|---|
| Dependent variable: real GDP growth | Probabilities | | |
| $\delta_{1\to0}$ | 0.076 | 0.081 | 0.082 |
| $\delta_{0\to1}$ | 0.299 | 0.314 | 0.315 |
| Regime 0 (systemic risk upturn) | | | |
| $\alpha_0$ | **0.042*** (0.011) | **0.032*** (0.008) | 0.001 (0.003) |
| $\beta_0^{GDP(t-1)}$ | **1.638*** (0.250) | **1.393*** (0.232) | **1.396*** (0.238) |
| $\phi_0^{credit(t)}$ | **0.500*** (0.143) | **0.622*** (0.175) | **0.617*** (0.177) |
| $\phi_0^{credit(t-1)}$ | 0.053 (0.013) | 0.060 (0.049) | 0.034 (0.014) |
| Regime 1 (other times) | | | |
| $\alpha_1$ | **0.003*** (0.002) | **0.003*** (0.002) | **0.003*** (0.002) |
| $\beta_1^{GDP(t-1)}$ | **0.327*** (0.100) | **0.393*** (0.106) | **0.387*** (0.109) |
| $\phi_1^{credit(t)}$ | **-0.138*** (0.149) | **-0.204*** (0.119) | **-0.148*** (0.155) |
| $\phi_1^{credit(t-1)}$ | 0.028 (0.049) | 0.048 (0.052) | 0.050 (0.052) |

*Notes:* The table shows the Markov-switching model estimates through the 2003Q1–2017Q4 period. Each column reports the parameter estimates from one of the three model specifications (the model differs by the inclusion of various BPIs). We report the parameter estimates together with their standard deviations. Estimates that are statistically significant at the 10% level or lower are marked with an asterisk and highlighted in bold.

# Smoothed regime probabilities






*Note*: The left-hand vertical axis corresponds to the smoothed probabilities (grey areas) and the one-step-ahead probabilities (solid lines with dots) of the low financial stability regime. The right-hand axis links to the evolution of the BPI, depicted in levels.

- Shaded regions in each panel denote quarters where our filtered probability of the low financial stability state exceeds 50%.
- Two periods of systemic risk build-ups (under regime 0) stand out: 2003–2007 and 2015–2017.

## Conclusion

- We propose a new profit-to-provisioning approach to be used in the decision-making process for setting the CCyB rate.
  - We construct a very simple yet powerful set of banking prudence indicators (BPIs) which should draw attention to the risks of underestimating the expected loss (and overestimating profit) in the banking sector.
- Models containing the BPIs could serve as very good predictors of future credit risk materialization as well as accumulation.
- The BPIs do a reasonably good job in capturing systemic risk build-up periods in the sample data considered.
- We believe that profit-to-provisioning is a suitable approach in general for other national banking sectors based on traditional banking.
- The relevance of the profit-to-provisioning approach and the related set of BPIs should increase after the implementation of IFRS 9.
- The BPIs measure whether banks insure themselves sufficiently against potential credit default over the financial cycle and its application can be broader:
  - BPIs on portfolio level (sectoral systemic risk buffer)
  - BPIs on an individual bank level (microprudential regulation)

## Application in the day-to-day activities of a central bank

- Practical application for setting CCyB rates
- Annually published in the Financial Stability Report and Risks to Financial Stability and Indicators

*Working paper is accessible from CNB WP 5/2018 and ESRB WP No 82*

## Application in research

- May be used as a variable describing the development of the financial cycle (control variable, threshold variable in nonlinear models)

## Future research

- Creating a net-wide public database
- Calibration of the indicator in accordance:
  - with the BCBS methodology.
  - Brave and Lopez (2017) procedure may be useful as well.

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# Thank you for your attention.