# WORKING PAPER SERIES 10

2019

Martin Hodula, Simona Malovaná, Jan Frait

Introducing a New Index of Households' Macroeconomic Conditions

CZECH NATIONAL BANK

# WORKING PAPER SERIES

**Introducing a New Index of Households' Macroeconomic Conditions**

Martin Hodula
Simona Malovaná
Jan Frait

10/2019

Reviewed by: Adam Geršl (Joint Vienna Institute)
Karel Brůna (University of Economics, Prague)
Jan Šolc (Czech National Bank)

Project Coordinator: Dominika Ehrenbergerová

# Introducing a New Index of Households' Macroeconomic Conditions

Martin Hodula, Simona Malovaná, and Jan Frait*

## Abstract

We construct a novel index of households' macroeconomic conditions for 22 high-income European countries between 2002 Q1 and 2018 Q4. The resulting index is in line with the broad features of the countries' business cycles and captures households' economic well-being. We discuss the complementary character of the proposed index in relation to widely employed survey-based consumer confidence indicators. We show that households' expectations are tightly linked to current macroeconomic conditions. This finding echoes the literature linking consumer attitudes and economic development. In a single-country case study, we provide empirical evidence that links the proposed index to new credit extended to households. The evidence suggests that households need a longer period of good macroeconomic conditions to decide to take on a mortgage than they do in the case of a consumer loan.

## Abstrakt

Vytváříme nový index makroekonomických podmínek domácností pro 22 vysokopříjmových evropských zemí za období mezi prvním čtvrtletím 2002 a čtvrtým čtvrtletím 2018. Výsledný index je v souladu se všeobecnými charakteristikami hospodářského cyklu v daných zemích a zachycuje ekonomický blahobyt domácností. Zabýváme se komplementární povahou navrhovaného indexu ve vztahu k obecně využívaným indikátorům spotřebitelské důvěry založeným na výběrových šetřeních. Ukazujeme, že očekávání domácností jsou úzce spjata s aktuálními makroekonomickými podmínkami. Toto zjištění je v souladu s odbornou literaturou, která propojuje postoje spotřebitelů a ekonomický vývoj. V případové studii zaměřené na jednu zemi empiricky dokládáme vazbu mezi navrhovaným indexem a novými úvěry poskytnutými domácnostem. Naše zjištění naznačují, že domácnosti potřebují delší období příznivých makroekonomických podmínek k tomu, aby se rozhodly vzít si hypotéku, než k tomu, aby se rozhodly vzít si spotřebitelský úvěr.

**JEL Codes:** F12, F41, F43.

**Keywords:** Composite index, factor analysis, households' confidence, loan growth.

* Martin Hodula, Czech National Bank (martin.hodula@cnb.cz) and Technical University of Ostrava.
Simona Malovaná, Czech National Bank (simona.malovana@cnb.cz).
Jan Frait, Czech National Bank (jan.frait@cnb.cz) and University of Finance and Administration in Prague.
The authors would like to thank Karel Brůna, Dominika Ehrenbergerová, Adam Geršl, Tomáš Nidetzký, and Jan Šolc for useful comments. The views expressed in this paper are those of the authors and not necessarily those of the Czech National Bank. All errors and omissions remain the fault of the authors.

# 1. Introduction

Following the Global Financial Crisis (GFC), researchers have turned their focus to expectational factors contributing to credit booms while leaving aside the assumptions of rational behavior and rational expectations. Fuster et al. (2010) propose a natural expectations concept. Households tend to have wrong beliefs about the true development of fundamental factors and over-estimate the persistence of favorable conditions. As a result, they can be excessively optimistic in good times and pessimistic in bad times. Boom and bust cycles then follow. Similarly, Bordalo et al. (2018) present a model with diagnostic expectations in which agents tend to overweight future outcomes that they have anticipated in light of current data. Foote et al. (2012) go even further and state that the facts refute the popular story that the GFC resulted from finance industry insiders deceiving uninformed mortgage borrowers and investors. Instead, they argue that borrowers and investors made decisions that were rational and logical given their ex post overly optimistic beliefs about the development of house prices.

The concept of extrapolative expectations – originally developed to explain asset price drifts (Schiller, 2000) – clarifies that expectations formed by extrapolating recent trends can become temporarily self-fulfilling. This particular concept can also be applied to households' economic well-being. For example, the combination of fast income growth and low interest rates can give rise to optimistic expectations that can be gradually extrapolated to the view that the good times will last "forever". Households can then be inclined to tolerate a much higher level of indebtedness. If these optimistic expectations are accompanied by steady growth in housing prices, the overall level of debt can shoot up in a relatively short period. This way of forming expectations is an outcome of the constrained rationality of households. Households are ready to accept that the fast income growth is just temporary and will converge to more normal levels in the long run. At the same time, households tend to underrate the probability that a period of abnormal income growth will be followed by a subnormal one.

We contribute to the literature by investigating key macroeconomic factors affecting households' economic well-being. To overcome the shortcomings of single indicators such as disposable income, wages, and savings, we propose a composite index that captures the development of the overall macroeconomic conditions faced by households. The index combines eleven macroeconomic variables most commonly found in the literature that jointly drive consumer confidence and expectations. We refer to this index as the Households' Macroeconomic Conditions Index (henceforth H-MCI). The index is constructed for 22 high-income OECD countries in Europe at quarterly frequency between 2002 and 2018.

Following recent theoretical literature on credit cycles and the formation of asset bubbles (Nofsinger, 2012; De Stefani, 2017; Bordalo et al., 2018; Angelico, 2018), we provide a single-country case study to offer some deeper understanding of, and economic intuition for, the values of the index and its relationship with credit dynamics. Specifically, we use data for the Czech economy in a dynamic model averaging framework. Our estimates show that households generally need a longer period of good macroeconomic conditions to decide to take on a mortgage than they do in the case of a consumer loan.

The remainder of the paper is structured as follows. Section 2 discusses the existing literature. Sections 3 presents the methodology and data used to construct the index and provides a comparison of the new index with the OECD consumer confidence index. Section 4 uses the index and investigates empirically its ability to predict the evolution of new loans and consumption expenditure in a case study analysis for the Czech Republic. Section 5 concludes.

## 2. Consumer Confidence Indicators: A Short Review

Empirical studies focused on households' expectations generally rely on consumer confidence indicators, which, in turn, are mostly based on information obtained from household surveys. Consumer confidence surveys, which are regularly conducted in at least 45 countries (Curtin, 2007), have been used to provide stakeholders, particularly government policymakers and business leaders, with timely and important information on consumer attitudes and perceptions. Multiple studies have focused on linking consumer confidence and consumption growth. Mishkin (1978) reported that the Index of Consumer Sentiment published by the University of Michigan possesses good explanatory power for changes in durable goods. Acemoglu and Scott (1994) found that consumer confidence is a leading indicator of future consumption growth in the United Kingdom. Delorme, et al. (2001) conducted a study on consumer confidence and rational expectations in the United States compared with the United Kingdom. Mehra and Martin (2003) found that consumer confidence is a significant predictor for consumer spending. Using regional data, Garrett et al. (2005) showed that consumer confidence helped in predicting retail spending in the US. Other empirical studies researching the predictive power of consumer confidence indicators include Belessiotis (1996), Kwan and Cotsomitis (2006), Souleles (2004), Vuchelen (2004), and many others.

More recently, researchers have switched their focus to using consumer confidence indicators to explain credit dynamics. Kłopocka (2017) shows that consumer confidence indexes have strong predictive power for future household borrowing. De Stefani (2017) documents that expectations of US households contain a component of systematic extrapolative bias which is inconsistent with full-information rational expectations theory. He shows that a change in house price expectations has substantial effects on mortgage leverage, which increases whenever there is an expected increase in home equity. Angelico (2018) provides empirical evidence that survey data on expectations have strong predictive power for the dynamics of household debt. She shows that beliefs depart from rationality at the aggregate level in a way coherent with the hypothesis of natural expectations. A positive shock to income first generates a boom, since households fail to forecast long-run income and get over-indebted. Eventually, expectations adjust and a bust leading to a debt decline follows.

However, there are at least three dilemmas associated with the reliability of consumer confidence indicators. First, given the general disunity of economists on the question of economic agents' rationality, it remains an open question whether consumer surveys reflect a rational or irrational assessment of households' expectations of future economic developments. This remains a fruitful ground for future research. Second, the question of whether to focus on changes in levels or to consider changes between periods when analyzing consumer confidence indicators' values is not fully resolved. Third, it is not clear whether to focus on the actual values or the expectations of agents. In this spirit, Ludvigson (2004) assessed the relationship between consumer confidence indicators and the real economy. His results suggest that widely used consumer-based indexes contain some information on future aggregate consumption spending, but most of this information is already contained in other economic and financial indicators. According to his findings, "independent" additional information from consumer surveys only explains a relatively small proportion of changes in future consumer spending.

There are also several practical disadvantages with the data acquisition methods used to calculate consumer confidence indicators. First, the selected households may not be fully representative of the entire population, so there may be selection bias. Second, not all respondents will complete the survey in any given period. Third, consumer confidence indicators are based solely on the answers to the questions asked during the survey, and other aspects of consumer confidence are not captured. Fourth, there is a risk that respondents will not provide honest answers or give enough time to the questionnaire.

For the above-stated reasons, it is appropriate to look for alternative ways of expressing consumer confidence. One possibility is to create a composite index from information contained in commonly available macroeconomic indicators. Since some studies state that households commonly extrapolate recent and current macroeconomic conditions to the future (Bordalo et al., 2018), such a composite data-based indicator could serve as a useful approximation of households perceptions' of macroeconomic conditions.

## 3. The Households' Macroeconomic Conditions Index (H-MCI)

Rich and extensive data are available to analyze the household sector in developed economies. Researchers and policymakers have access to both stock and flow data from a wide range of sources. However, interpreting the information contained in these variables may sometimes be difficult, because different variables may offer conflicting information about economic developments and overall market sentiment. Moreover, obtaining the required information can be complicated by the specific characteristics of the individual time series. Reliance on one indicator may thus be misleading when assessing conditions in the household sector (or any other sector of the economy). For this reason, many economists argue in favor of using a composite indicator which provides a broader view of the conditions in the selected sector. This approach is widely applied in analyses of, for example, the labor market (Chung et al., 2015; Willis and Hakkio, 2014; Armstrong et al., 2016), monetary policy (Babecká-Kucharčuková et al., 2016; Frait and Malovaná, 2017), and financial stress (Kremer, et al., 2012).

The proposed H-MCI uses the information contained in various economic aggregates, households' disposable income, labor market indicators, asset prices, interest rates, and external environment indicators. These variables form a comprehensive set of indicators reflecting the overall macroeconomic conditions faced by households. They come from a range of sources but are, in general, publicly available, so our proposed indicator is transparent and replicable by other researchers.

Table 1 provides an overview of the time series that enter the composite index, along with their definitions and sources. We use a total of eleven variables, drawn mainly from the databases of the OECD, the Bank for International Settlements, and the ECB.[1] Data for some countries were extracted directly from national statistical office or central bank databases. Table A1 offers

[1] Note that only variables that cover a sufficiently wide range of countries over a sufficiently long time period are selected. As a result, a number of potentially useful indicators could not be included. Still, the databases consist of key proxy variables that are well established in the literature.

summary statistics for the individual time series. The dataset can be divided into five logical blocks. Block I describes the development of the economic aggregates and the income of households. Gross domestic product and its growth is one of the most widely quoted indicators of economic performance. Still, it may not fully reflect households' economic conditions, especially in the short run. Therefore, it is supplemented by gross disposable income and gross savings to get a better picture of households' well-being and living standards. Block II captures the labor market situation. Compensation of employees and the number of employees provide a further indication of households' economic well-being and may signal potential vulnerabilities. Block III shows the evolution of interest rates on consumer loans and mortgages. The lending rate directly influences households' access to credit. Since households perceive higher lending rates negatively, these variables enter the estimate at reciprocal value. Block IV shows asset price developments. Historically, real estate developments are a key indicator of households' financial vulnerability. Block V approximates the development of the external environment. For economies with a high level of openness, the evolution of exchange rates and the terms of trade could represent a significant force affecting domestic households' economic conditions.

***Table 1: Data Used to Estimate the H-MCI***

| Block | ID | Description | Source | Units |
|---|---|---|---|---|
| I | 1 | Gross domestic product, current prices, annual levels, seasonally adjusted | OECD | National currency, millions |
| | 2 | Gross disposable income, households and non-profit institutions serving households, current prices, quarterly levels, seasonally adjusted* | OECD | National currency, millions |
| | 3 | Gross savings, households and non-profit institutions serving households, current prices, quarterly levels, seasonally adjusted* | OECD | National currency, millions |
| II | 4 | Compensation of employees, households, current prices, quarterly levels, seasonally adjusted | OECD | National currency, millions |
| | 5 | Average registered number of employees, seasonally adjusted | OECD | Thousand persons |
| III | 6 | Bank interest rates on consumer loans, households, outstanding amounts | ECB, national statistical office or central bank | % pa |
| | 7 | Bank lending rate on loans for house purchase, households, outstanding amounts | ECB, national statistical office or central bank | % pa |
| IV | 8 | Residential property prices, nominal, broadest available (i.e., all types of dwelling) | BIS, ECB | 2010=100 |
| | 9 | Share price index | BIS | 2010=100 |
| V | 10 | BIS effective exchange rates, nominal, broad index, quarterly averages | BIS | 2010=100 |
| | 11 | Terms of trade, calculated as ratio of export prices to import prices, exports/imports of goods and services, seasonally adjusted | OECD | 2010=100 |

Our original sample comprised 26 high-income OECD countries in Europe as defined by the World Bank.[2] Due to data availability we ended up with a weakly unbalanced panel of 22 countries with a time span of 2002 Q1–2018 Q4. Table 2 provides the final list of countries

[2] See, for example, World Bank (2018a, 2018b).

together with an indication of whether the country is categorized as advanced, is a member of the European Union, and is part of the euro area. Overall, the sample can be considered relatively homogeneous and thus ready to use in a joint empirical framework.

***Table 2: Estimation Sample***

| | | OECD | IMF AE | EU | EA | | | OECD | IMF AE | EU | EA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | Austria | Y | Y | Y | Y | IE | Ireland | Y | Y | Y | Y |
| BE | Belgium | Y | Y | Y | Y | IT | Italy | Y | Y | Y | Y |
| CZ | Czechia | Y | 2009 | 2004 | N | LV | Latvia | 2016 | 2014 | 2004 | 2014 |
| DE | Germany | Y | Y | Y | Y | NL | Netherlands | Y | Y | Y | Y |
| DK | Denmark | Y | Y | Y | N | NO | Norway | Y | Y | N | N |
| EE | Estonia | 2010 | 2011 | 2004 | 2011 | PL | Poland | Y | N | 2004 | N |
| ES | Spain | Y | Y | Y | Y | PT | Portugal | Y | Y | Y | Y |
| FI | Finland | Y | Y | Y | Y | SE | Sweden | Y | Y | Y | N |
| FR | France | Y | Y | Y | Y | SK | Slovakia | Y | 2009 | 2004 | 2009 |
| GR | Greece | Y | Y | Y | Y | SL | Slovenia | 2010 | 2007 | 2004 | 2007 |
| HU | Hungary | N | N | 2004 | N | UK | United Kingdom | Y | Y | Y | Y |

***Note:*** * Cubic interpolation is used to transform the frequency from annual to quarterly for EE, HU, LV, SK, and SL.

AE – advanced economy as categorized by the IMF. Y/N indicates that the country does/does not belong to that category for the whole sample period (2001Q1–2018Q4); a specific year indicates the year of entry.

### 3.1 Factor Model Estimation Procedure

There are several approaches that allow a large number of time series to be combined into a single composite index. In the case of the indicator presented in this paper, we use factor model estimation. Factor analysis allows for a large number of time series to be expressed as only a handful of components (factors). The aim of factor analysis is to identify the number of significant factors and to estimate the values of each of the factors for all the observable time series, i.e., to describe the time series using the estimated factors. In this respect, factor analysis can also be seen as a method for reducing the data scale.

We construct two state-space representations of a factor model. The first one is a fairly standard factor model which describes a direct linear relationship between the $N$-dimensional vector of observable variables and an $M$-dimensional random vector of originally unobservable factors $F = (F_1, \dots, F_m)$. In this case, the observable variables enter the model in annual growth rates, except for lending rates, which are left in levels.[3] The first specification can be written as follows:

$$X_t = \Lambda F_t + \varepsilon_t \sim N(0, R), \tag{1}$$

$$F_t = \sum_{i=1}^{p} A_i \, F_{t-1} + u_i \sim N(0, Q), \tag{2}$$

where $\Lambda$ is a matrix of factor loadings, $A_i$ is a matrix of autoregressive coefficients for $p$ lags, and $\varepsilon_t, u_t$ are i.i.d. Gaussian error terms.

The second factor model specification takes a step further and introduces an additional two equations decomposing the observable variables into a trend and cycle component. The factors are

[3] All variables are standardized using their long-run mean and standard deviation.

then related to the unobserved cycle (gap) component of the observable variables. By doing so, we keep the information about the level of a given variable, which, in some cases, might be of great importance. Let us elaborate using a simple example from the labor market. Picture a situation in which the labor market grows for several years in a row to the point where it becomes exhausted by insufficient supply. At this point, the number of employees might not change on a year-to-year basis, but the country's labor market would still be exhausted by significant upward pressures on wages. Such a situation would be difficult to capture by year-to-year dynamics. The second specification can be written as follows:

$$X_t = \widehat{X_t} + X_t^*, \tag{3}$$

$$\widehat{X_t} = \Lambda F_t + \varepsilon_t \sim N(0, R), \tag{4}$$

$$F_t = \sum_{i=1}^{p} A_i F_{t-1} + u_i \sim N(0, Q), \tag{5}$$

$$X_t^* = X_{t-1}^* + \eta_t \sim N(0, H), \tag{6}$$

which can be rewritten in state-space form as follows:

$$X_t = BZ_t, \tag{7}$$

$$Z_t = CZ_{t-1} + \Pi_t, \tag{8}$$

where $Z_t = \left[\widehat{X_t}, X_t^*, F_{t+1}\right]$, $B = [I_{NxN}, I_{NxN}, 0_{NxM}]$,

$$C = \begin{bmatrix} 0_{NxN} & 0_{NxN} & \Lambda \\ 0_{NxN} & I_{NxN} & 0_{NxM} \\ 0_{MxN} & 0_{MxN} & A \end{bmatrix} \text{ and } \Pi_t \sim N(0, \begin{bmatrix} R & 0_{NxN} & 0_{NxM} \\ 0_{NxN} & I_{NxN} & 0_{NxM} \\ 0_{MxN} & 0_{MxN} & Q \end{bmatrix}).$$

The variables decomposed into trend and cycle components within the model are gross domestic product, gross disposable income, gross savings, compensation of employees, number of employees, and property prices. Except for lending rates, the remaining variables (the share price index, effective exchange rates, and terms of trade) are in annual growth rates.[4]

Both factor models are estimated using the Kalman filter.[5] The optimal number of factors to estimate is based on parallel analysis[6] and an assessment of the percentage of the variance explained by the factors estimated[7] (see Table A2 in the Appendix). The optimal number of lags is set based on the Schwarz information criterion. Based on the statistical tests, our baseline model

[4] In this case again, all variables are standardized using their long-run mean and standard deviation.

[5] The initial conditions are set as follows. Firstly, we estimate Λ and F by applying principal component analysis to the covariance matrix of X (the first factor model) or $\hat{X}$ (the second factor model); $\hat{X}$ is estimated using a simple Hodrick-Prescott filter with lambda equal to 1,600. Secondly, we obtain A and Q by estimating a vector autoregression (VAR) model on $\hat{F}$; R and H are set to be identity matrices.

[6] The results of the parallel analysis are not reported, but are available upon request.

[7] We set the threshold level of the variance explained to at least 70%. This condition is satisfied by models with three estimated factors for all sample countries. Hair et al. (2012) state that the acceptable variance explained in the social sciences for a construct to be valid is 60%. By extracting information from 803 substantive factor analyses, Peterson (2000) shows that the average percentage of the variance accounted for is about 60%.

specification is a factor model with three factors and one lag.[8] The final indexes are robust to the inclusion of additional factors, as the variance explained by three factors is already high. The index is also relatively robust to the exclusion of the third factor, as most of the variance is explained by the first two factors in most cases.

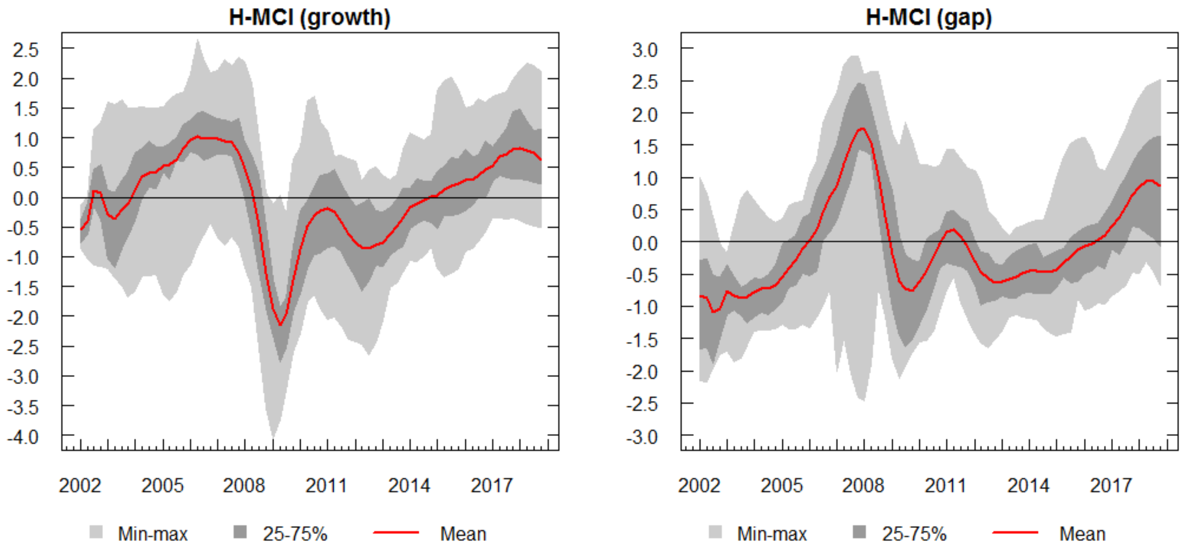
The paths of the resulting growth and gap versions of the H-MCI are shown in Figure 1. The synthetic indicator is constructed for each country in the sample as a weighted average of the individual factors, with the weights corresponding to the percentage of the total data variability explained by the factors. The resulting index is then standardized.[9] This means that for each estimate the long-term mean is zero. Positive values signal favorable macroeconomic conditions (above-average conditions) and negative values unfavorable macroeconomic conditions (below-average conditions). These are then reflected in households' optimism or pessimism about the future economic outlook. The more distant the indicator is from zero, the more optimistic/pessimistic the outlook is. As is apparent from the graph, the H-MCI describes households' evolving macroeconomic conditions across countries fairly well. At the beginning of the period under review, macroeconomic conditions were affected by the echoes of the Dot-com bubble burst and the resulting decline in aggregate demand. During the Great Moderation that followed, we see a gradual increase in the H-MCI values, reflecting a general improvement in households' conditions and perception of their economic situation. In this context, long-lasting accommodative monetary policy was found to be one of the significant factors in the accumulation of imbalances that led to the GFC outbreak (Obstfeld and Rogoff, 2009; White, 2009[10]). In particular, Maddaloni and Peydró (2013) and Jiménez et al. (2014) explain how low short-term rates helped to boost credit and macroeconomic dynamics through their contribution to the softening of lending standards during the pre-GFC times. The favorable macroeconomic conditions were shattered with the onset of the GFC in 2008–2009, and the negative mood persisted essentially until the end of 2014. Since 2015, optimism has prevailed in the H-MCI, which reached the pre-GFC levels at the end of 2017. This rise in optimism has been fed mostly by favorable macroeconomic developments, but also by a long period of historically low interest rates.

[8] We do not record any missing data in our sample. Since we work with aggregate time series for the entire economy, we do not winsorize the data.

[9] The index is standardized using the z-score formula. The z-score is calculated for each country as the difference between the actual value of the H-MCI and its long-run average divided by its long-run standard deviation; it expresses the distance of the index in a given year from its historical mean expressed in terms of the number of standard deviations. This allows its relative position in relation to the historical data to be assessed. As the number is based on the assumption of a normal distribution, 68% of the outcomes are going to be no more than one standard deviation unit away from the mean, and 95% of the outcomes are going to be no more than two standard deviation units away from the mean.

[10] Schularick and Taylor (2012) look at the issue of monetary policy, credit booms, and subsequent episodes of financial instability from a much longer historical perspective.

***Figure 1: The H-MCI for Selected Countries***




***Note:*** The index is standardized using its long-run mean and standard deviation; the vertical axis shows the standard deviations. The H-MCIs for individual countries are depicted in Figure A2 in Appendix A.

## 3.2 Comparison of the H-MCI and the Consumer Confidence Index

Despite the widespread use of surveys of consumer confidence in various economic applications, the mechanisms by which households' attitudes influence the real economy are rarely discussed. One may thus ask whether consumer confidence indicators contain meaningful and independent information about economic developments, or if they just repackage the information already contained in basic economic indicators. This issue was addressed in Ludvigson (2004) and more recently in Barnes and Olivei (2017). There is a consensus that the role of consumer sentiment in consumption is typically small from an economic standpoint, even if often statistically significant. One might argue that the CCI possesses some time advantage over macroeconomic indicators, which are often revised. The CCI can thus be considered a better real-time predictor. However, we show that the CCI loads on current macroeconomic data and thus uses the same historical information subject to revisions. It is thus expected to perform equally well or badly as macroeconomic indicators.

To give this body of literature some justice, we briefly compare the economic outcomes of the two H-MCIs and the consumer confidence index (CCI) published by the OECD. The CCI is calculated as a simple average of answers to questions regarding respondents' past and future (expected) financial situation, expected economic situation, and unemployment expectations. The CCI is thus constructed as forward-looking, since the questions dealing with expectations over the next 12 months are strongly favored (three to one).

When looking at the evolution of the two H-MCIs and the CCI, we spot a significant correlation between the two types of index for a majority of countries in the sample (see Figures A2 and A3 and Table A3). The correlation is generally higher when both indexes are considered at time $t$, but one must keep in mind that the CCI is meant to be forward-looking (four quarters ahead). This explains why the correlation remains strong even when we consider the lagged H-MCI $(t + 4)$

and the CCI ($t$). Overall, this supports the view that households' optimistic/pessimistic expectations captured in the CCI are tightly linked to the current development of macroeconomic conditions. We further check whether the simple bivariate statistics can survive increasingly demanding statistical tests.

Table 2 shows how well the CCI can be explained by the lead and lagged values of the H-MCI. It serves as a natural check of whether the responses of economic agents are built on the current, expected, or past values of the basic macroeconomic aggregates that form the H-MCI. The independent variables include up to four lags and leads of the H-MCI. For each specification, we present the parameter estimate and the adjusted R-squared statistic to see how well the H-MCI can explain the formation of CCI values.

The results point to several key findings related to the growth version of the H-MCI. First, the growth version of the H-MCI has significant explanatory power for the CCI at all leads and up to two lags. The highest parameter values and R-squared are reported for the H-MCI at time $t$ or $t+1$, while the lowest are found for the lagged H-MCI values ($t-4$). This confirms that the forward-looking CCI loads on current values of economic variables. Second, the fact that the model's explanatory power decreases with the lag of the H-MCI means that households' expectations are not all that adaptive. In another words, households value current economic information more than past economic information. This echoes the fact that the current H-MCI values explain a significantly larger portion of the CCI than the lagged values (43% vs 19% on average). Third, increasing the lead of the H-MCI modestly increases the explanatory power for the CCI values. At time $t+2$, the H-MCI tends to explain over 50% of the CCI variation. This shows that households tend to extrapolate expectations of current economic conditions into the future.

The gap version of the H-MCI has much lower explanatory power than the growth version at its current value and at lagged values. This significantly limits the ability of this version to be used as an alternative to the CCI or, in general, as a leading indicator of households' macroeconomic conditions. However, the gap version of the H-MCI may still serve well as a backward-looking indicator, because it is able to capture the conditions ex post. Its main value added is that it takes into consideration long-run trends and the deviation from these trends. Nevertheless, this feature possibly also explains why the index is not forward-looking and reliable at the end of the sample period.[11]

[11] Any filtration technique trying to separate the trend from the cyclical component suffers to some extent from end-point bias.

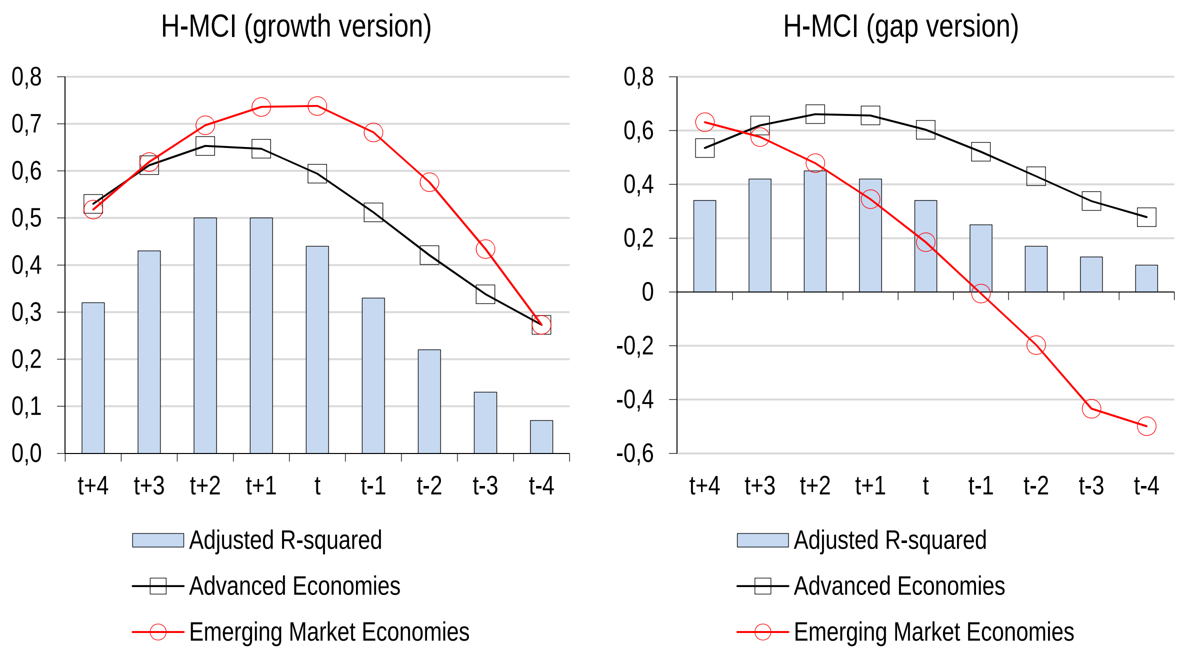
***Table 2: Relationship between the H-MCI and the CCI at Different Lags and Leads***

| *Dependent variable: Consumer Confidence Index (CCI)* | *Parameter* | *Adj. $R^2$* | *No. of Obs.* |
|---|---|---|---|
| | H-MCI (growth version) | | |
| H-MCI (t+4) | 0.528*** (0.022) | 0.32 | 1,173 |
| H-MCI (t+3) | 0.613*** (0.02) | 0.43 | 1,194 |
| H-MCI (t+2) | 0.660*** (0.019) | 0.50 | 1,215 |
| H-MCI (t+1) | 0.662*** (0.019) | 0.50 | 1,236 |
| H-MCI (t) | 0.618*** (0.02) | 0.43 | 1,257 |
| H-MCI (t-1) | 0.541*** (0.022) | 0.33 | 1,236 |
| H-MCI (t-2) | 0.448*** (0.024) | 0.22 | 1,215 |
| H-MCI (t-3) | 0.354*** (0.025) | 0.13 | 1,194 |
| H-MCI (t-4) | 0.273*** (0.026) | 0.07 | 1,173 |
| | H-MCI (gap version) | | |
| H-MCI (t+4) | 0.569*** (0.024) | 0.32 | 1,189 |
| H-MCI (t+3) | 0.539*** (0.024) | 0.28 | 1,210 |
| H-MCI (t+2) | 0.461*** (0.026) | 0.20 | 1,231 |
| H-MCI (t+1) | 0.341*** (0.027) | 0.10 | 1,252 |
| H-MCI (t) | 0.196*** (0.028) | 0.02 | 1,273 |
| H-MCI (t-1) | 0.042 (0.029) | 0.02 | 1,252 |
| H-MCI (t-2) | -0.105*** (0.029) | 0.01 | 1,231 |
| H-MCI (t-3) | -0.226*** (0.029) | 0.03 | 1,210 |
| H-MCI (t-4) | -0.307*** (0.029) | 0.07 | 1,189 |

***Note:*** This table presents estimates based on panel data regression with country fixed effects for 21 countries between 2002 Q1 and 2018 Q4 (see Figure A2 in Appendix A for the individual time series). The specification is as follows: $CCI_{i,t} = \alpha HMCI_{i,t-p} + v_i + \varepsilon_{i,t}$, where $p = -4, -3, \ldots, 4$; the panel is weakly unbalanced. Standard errors are reported in parentheses. ***, **, and * denote the 1%, 5%, and 10% significance levels.

Figure 2 shows the evolution of the model parameters when differentiating between the sample of advanced and emerging market economies. This empirical exercise is meant to reflect the fact that emerging markets have been widely understood to have higher stock price volatility, weaker market efficiency, lower liquidity, and higher macroeconomic and policy uncertainty. "Animal spirits" might thus influence the real economy more than in advanced economies. Interestingly, our estimates argue against a significant role of sentiment (as determined by consumer opinion) and in favor of extrapolative expectations in both advanced and emerging market economies. The parameter values and the adjusted R-squared remain high when considering current values of the growth version of the H-MCI, which supports our previous statements. The negative coefficient estimates of the gap version of the H-MCI at higher lags are driven mainly by emerging market economies. This may point to the difficulty of separating trend and gap components in economies whose convergence is not finished yet and whose data series are usually shorter.

***Figure 2: Relationship between the H-MCI and the CCI at Different Lags and Leads – Advanced Economies vs Emerging Market Economies***




***Note:*** The figure sums up the estimates based on panel data regression with fixed effects.

## 4. Case Study Analysis: The H-MCI and Credit Dynamics in the Czech Republic

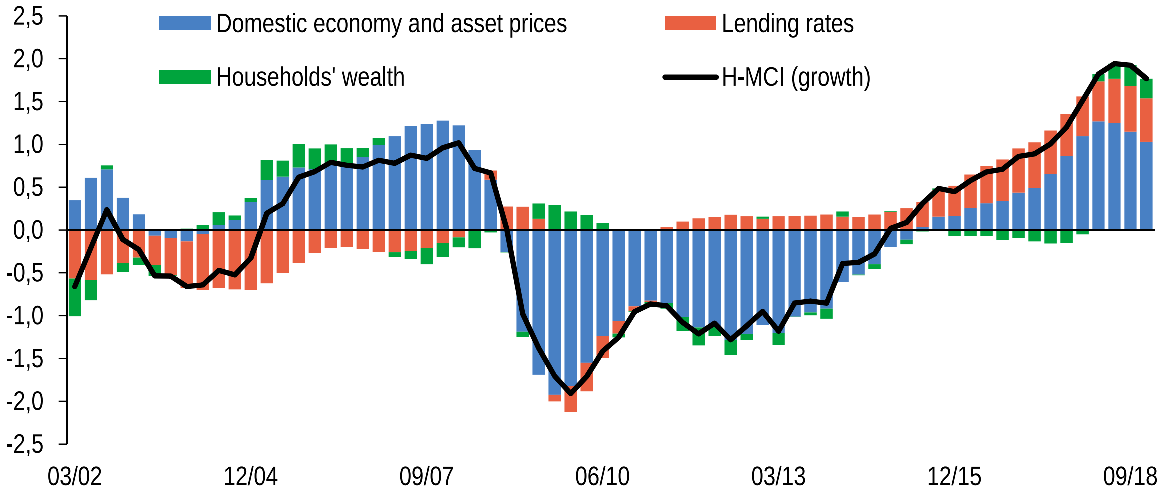
This section turns to a case study of the Czech Republic to offer some deeper understanding of, and economic intuition for, the values of the H-MCI and its relationship with credit dynamics. After a period of transformation in the early 1990s, the Czech Republic went through a deep banking crisis during 1996–2000. Since then, the economy has gone through a full business and financial cycle. It was hit by the GFC, which resulted in a short recession and a partial loss of confidence. Since the Czech Republic is a small open economy, the slowdown in GDP growth was caused predominantly by economic spillovers from its trading partners, while the Czech financial sector remained sound throughout the recession. Given the structure of the economy, which is largely export-oriented, it would be interesting to see (among other things) to what extent the domestic macroeconomic conditions, as captured by the H-MCI, are affected by external developments. Because the growth version of the H-MCI possesses more favorable forward-looking features than the gap version, we focus solely on the growth version of the index.

Figure 3 shows the contributions of the individual estimated factors to the aggregate H-MCI.[12] From that and a visual inspection of the raw time series (see Figure C2 in Appendix C), we can draw conclusions about their possible interpretation. To lay some statistical support, we also

[12] Results of robustness and sensitivity tests of the H-MCI estimation can be found in Appendix D.

check for correlations of sub-groups of variables with the estimated factors. It seems that Factor 1 captures the evolution of major macroeconomic aggregates and asset prices. In the context of the period analyzed, it captures the typical situation in a period of prosperity where GDP, employment, wages – and, with them, disposable income – are rising. The increasing income and wealth lead to growth in property prices and stock prices. Factor 1 strongly follows the development of the economy and contributes significantly to the growth in the overall index. Factor 2 captures the development of lending rates and the echoes from the domestic labor market in the form of employment growth. As such, it has been contributing to growth in the overall index since the second half of 2011, when interest rates reached all-time lows compressed to all-time lows. It has been gaining momentum since 2013, and its contribution remains high until the end of the period analyzed. Factor 3 loads on households' savings, disposable income, and share prices, but given the structure of the financial system, which is largely bank-based, and the relative conservativeness of Czech households, its contribution to the overall index is minor.

***Figure 3: H-MCI Decomposition for the Czech Republic***




***Note:*** The vertical axis reflects the standard deviation. The graph depicts the growth version of the H-MCI.

To explore the relationship between the H-MCI and credit dynamics, we resort to a simple forecasting exercise. Specifically, we use the method of dynamic model averaging (DMA), originally introduced for engineering applications in Raftery et al. (2010). Koop and Korobilis (2011, 2012) were among the first to implement DMA in an economic application to forecast US and UK inflation. DMA consists of many time-varying coefficient regression models formed from all possible combinations of the predictors available to the practitioner. It allows the forecasting model to change over time while allowing the coefficients in each model to evolve over time. It can be seen as an extension of the more traditional Bayesian model averaging (BMA) into a time-varying framework. Our baseline prediction model takes on the following form:

$$y_t = z_t^{(k)} \xi_t^{(k)} + \varepsilon_t^{(k)}, \tag{6}$$

$$\xi_{t+1}^{(k)} = \xi_t^{(k)} + \eta_t^{(k)}, \tag{7}$$

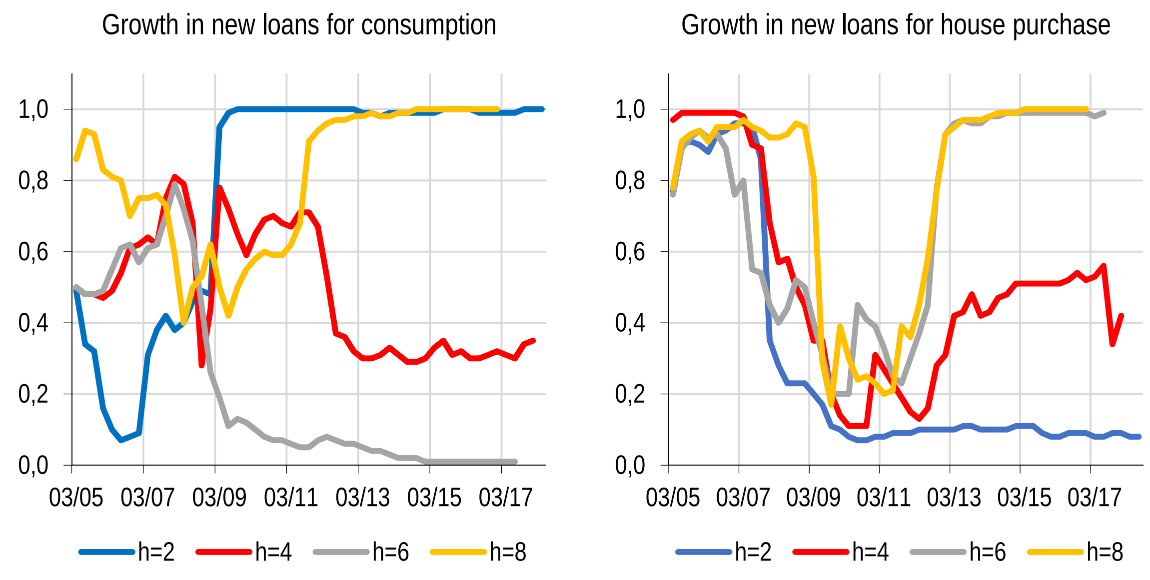
where $y_t$ is the dependent variable to be forecasted. In our application, $y_t$ is the annual growth rate of new loans to households. We differentiate between types of loans, i.e., we consider two separate models for consumer loans and mortgages. Additionally, we consider consumer spending as a forecasted variable. $z_t^{(k)}$ for $k = 1,2, \ldots, K$ denotes a specific predictor set. We consider the

H-MCI and past values of the predicted variable as potential predictors (up to lag four). In the end, we are merely interested in finding out if the inclusion of the H-MCI yields any additional gains over the information content in the past values of the forecasted variables. $\varepsilon_t^{(k)}, \eta_t^{(k)}$ are error terms that are $N\left(0, V_t^{(k)}\right)$ and $N\left(0, W_t^{(k)}\right)$ respectively. Details on the estimation procedure are available in Appendix D.

The main outcome from DMA is a posterior inclusion probability (PIP). The PIP refers to the sum of the probabilities $\left(\xi_{t|t-1,k}\right)$ that a given predictor will be included among the set of viable predictors in the forecasting model $k(k = 1,2, \dots, K)$ of DMA at time $t$. In other words, the higher is the value of PIP, the more forecasting weight is assigned to the given predictor and the higher forecasting power that predictor has.

Figure 3 shows the estimated PIP values and their development across time for models with different forecasted horizons. To reduce visual cluster, we only report PIP values for models containing the H-MCI as a predictor and omit the rest. From visual exploration, it is apparent that there are some differences between the models predicting growth of consumer loans and mortgages. Specifically, the H-MCI is found to be a dominant predictor of consumer loan growth at short horizons (up to three quarters) and of mortgage growth at long horizons (from six quarters up). This shows that households generally need a longer period of good macroeconomic conditions to decide to take on a mortgage than they do in the case of a consumer loan.

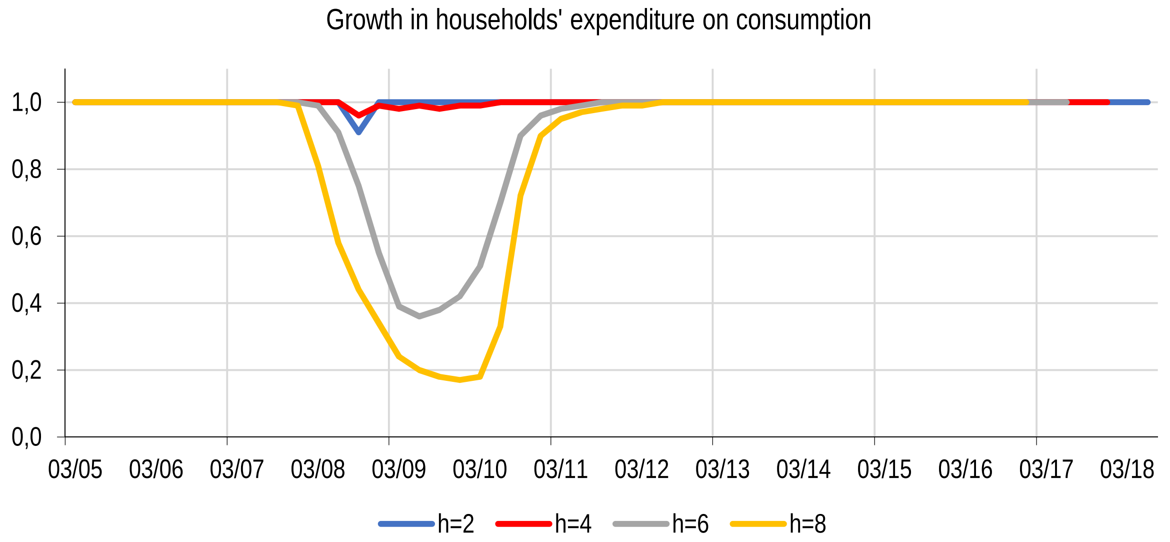
***Figure 3: Posterior Inclusion Probabilities for Credit Models Containing the H-MCI***




***Note:*** The time axis corresponds to the forecasted variable. The raw credit data in levels are transformed before estimation using 12-month moving averages to overcome their seasonality patterns. The data enter the estimation in annual growth rates.

Motivated by the large body of literature that discusses the role of consumers' attitudes in their consumption behavior, we check the predictive power of our proposed index in relation to the growth in the consumption expenditure of households. This exercise mimics the previous one, i.e., lagged values of consumption growth are the competitor of the H-MCI. As is apparent from the PIP values (Figure 4), models containing the H-MCI convincingly dominate their competitors over the entire sample. The PIP decreases sometime around the GFC, which means the H-MCI performed worse during this period than the lagged values of consumer expenditure. This is not surprising given the growing body of literature that discusses the role of non-fundamental factors in explaining households' consumption behavior (Dees and Brinca, 2013; Bailey et al., 2017).

***Figure 4: Posterior Inclusion Probabilities for Consumption Models Containing the H-MCI***




***Note:*** The time axis corresponds to the forecasted variable. The data enter the estimation in annual growth rates.

## 5. Conclusion

In the paper, we construct a novel index of households' macroeconomic conditions (the H-MCI) for 22 high-income OECD countries in Europe at quarterly frequency between 2002 and 2018. The proposed index combines the information contained in various economic aggregates, households' disposable income, labor market indicators, asset prices, interest rates, and external environment indicators. The variables come from a range of sources but are, in general, publicly available, so our proposed index is transparent and replicable by other researchers. We demonstrate that the evolution of the H-MCI is in line with the broad characteristics of the business cycle. The index is robust to variable and estimator choice and to the estimation period. Overall, the index is an improvement over the traditional measures of households' economic conditions. As such, it may be used in various empirical exercises analyzing or controlling for the impact of households' macroeconomic conditions.

We discuss the favorable statistical characteristics of the proposed index in relation to widely employed consumer confidence indexes. In a simple empirical framework, we compare the outcomes of the H-MCI and the popular consumer confidence index (CCI) published by the OECD. We report a strong correlation when considering the contemporaneous relationship between the two indexes. We find support for the view that the CCI contains some new information, but most of this information is already contained in the other economic and financial indicators that form the H-MCI. In other words, we show that the CCI loads on current macroeconomic data and thus uses the same historical information subject to revisions.

As an example of potential application, we use the index in a single-country case study. Specifically, we test its ability to predict the evolution of new loans extended to households in the Czech Republic. In the process, we differentiate between consumer loans and mortgages, since they represent different decision-making processes of households. We find that the predictive performance of the H-MCI is high for consumer loans at short horizons. In the case of mortgages, we report quite the opposite. At short horizons, the H-MCI performs equally as well (or badly) as a simple autoregressive process. However, at longer horizons, we find the H-MCI to be a dominant predictor of growth in new mortgages, suggesting a need for a longer period of good macroeconomic conditions for households to take on a mortgage.

In a potential extension of our work, one might follow the rich discussion on the role of non-fundamental (rational or irrational) drivers of economic development. The decision of households regarding their indebtedness can be influenced by both fundamental and non-fundamental factors. For example, a long period of "good times" may give the illusion that these times will continue into the future and that the inevitable turn in the cycle will not occur or will occur further in the future or to a lesser extent. Such extrapolative expectations cannot be considered fully rational and can encourage households to become over-indebted. Taken as such, the deviations of consumer attitudes from fundamental drivers (H-MCI) of credit dynamics may reflect the uncertainty surrounding the economic environment.

## References


ACEMOGLU, S. AND A. SCOTT (1994): "Consumer Confidence and Rational Expectations: Are Agents' Beliefs Consistent with the Theory?" *Economic Journal* 104(422), pp. 1–19.

ANGELICO, C. (2018): "Household Expectations and the Credit Cycle." Paper presented at the CEPR European Conference on Household Finance 2018. Available at: https://cepr.org/sites/default/files/Angelico_august.pdf

ARMSTRONG, J., G. KAMBER, AND Ö. KARAGEDIKLI (2016): "Developing a Labour Utilisation Composite Index for New Zealand." Analytical Notes 2016/04, Reserve Bank of New Zealand.

BABECKÁ-KUCHARČUKOVÁ, O., P. CLAYES, AND B. VAŠÍČEK (2016): "Spillover of the ECB's Monetary Policy Outside the Euro Area: How Different Is Conventional from Unconventional Policy?" *Journal of Policy Modelling* 38(2), pp. 199–225.

BAILEY, M., E. DÁVILA, T. KUCHLER, AND J. STROEBEL (2017): "House Price Beliefs and Mortgage Leverage Choice." NBER Working Paper 24091, National Bureau of Economic Research.

BARNES M. L. AND G. P. OLIVEI (2017): "Consumer Attitudes and Their Forecasting Power for Consumer Spending." *Journal of Money, Credit and Banking* 49(4), pp. 1031–1058.

BELESSIOTIS, T. (1996): "Consumer Confidence and Consumer Spending in France." Economic Papers 116, European Commission.

BORDALO, P., N. GENNAIOLI, AND A. SHLEIFER (2018): "Diagnostic Expectations and Credit Cycles." *Journal of Finance* 73(1), pp. 199–227.

CHUNG, H., B. C. FALLICK, C. J. NEKARDA, AND D. RATNER (2015): "Assessing the Change in Labor Market Conditions." Working Paper 1438, Federal Reserve Bank of Cleveland.

CURTIN, R. (2007): "Consumer Sentiment Surveys: Worldwide Review and Assessment." *Journal of Business Cycle Measurement and Analysis* 2007(1), pp. 7–42.

DE STEFANI, A. (2017): "Waves of Optimism: House Price History, Biased Expectations and Credit Cycles." ESE Discussion Paper Series, No. 282, Edinburgh School of Economics, University of Edinburgh.

DEES, S. AND P. S. BRINCA (2013): "Consumer Confidence as a Predictor of Consumption Spending: Evidence for the United States and the Euro Area." *International Economics* 134, pp. 1–14.

DELORME, C., D. KAMERSCHEN, AND L. VOEKS (2001): "Consumer Confidence and Rational Expectations in the United States Compared with the United Kingdom." *Applied Economics* 33, pp. 863–869.

FOOTE, C., K. S. GERARDI, AND P. S. WILLEN (2012): "Why Did So Many People Make So Many Ex Post Bad Decisions? The Causes of the Foreclosure Crisis." NBER Working Paper 18082, National Bureau of Economic Research.

FRAIT, J. AND S. MALOVANÁ (2017): "Monetary Policy and Macroprudential Policy: Rivals or Teammates?" *Journal of Financial Stability* 32, pp. 1–16.

FUSTER, A., D. LAIBSON, AND B. MENDEL (2010): "Natural Expectations and Macroeconomic Fluctuations." *Journal of Economic Perspectives* 24(4), pp. 67–84.

GARRETT, T. A., R. HERNÁNDEZ-MURILLO, AND M. T. OWYANG (2005): "Does Consumer Sentiment Predict Regional Consumption?" *Federal Reserve Bank of St. Louis Review* 87, pp. 123–135.

HAIR, J. F., W. C. BLACK, B. J. BABIN, AND R. E. ANDERSON (2012): "Multivariate Data Analysis, 7th Edition." *Pearson*, ISBN 13: 978-1-292-02190-4.

JIMÉNEZ, G., S. ONGENA, J. PEYDRO, AND J. SAURINA (2014): "Hazardous Times for Monetary Policy: What Do Twenty-three Million Bank Loans Say about the Effects of Monetary Policy on Credit Risk-Taking?" *Econometrica* 82(2), pp. 463–505.

KŁOPOCKA, A. (2017): "Does Consumer Confidence Forecast Household Saving and Borrowing Behavior? Evidence for Poland." *Social Indicators Research* 133(2), pp. 693–717.

KOOP, G. AND D. KOROBILIS (2011): "UK Macroeconomic Forecasting with Many Predictors: Which Models Forecast Best and When Do They Do So?" *Economic Modelling* 28(5), pp. 2307–2318.

KOOP, G. AND D. KOROBILIS (2012): "Forecasting Inflation Using Dynamic Model Averaging." *International Economic Review* 53(3), pp. 867–886.

KREMER, M., M. LO DUCA, AND H. DÁNIEL (2012): "CISS – A Composite Indicator of Systemic Stress in the Financial System." Working Paper Series 1426, European Central Bank.

KWAN, A. C. AND J. A. COTSOMITIS (2006): "The Usefulness of Consumer Confidence in Forecasting Household Spending in Canada: A National and Regional Analysis." *Economic Inquiry* 44, pp. 185–197.

LUDVIGSON, C. (2004): "Consumer Confidence and Consumer Spending." *Journal of Economic Perspectives* 18(2), pp. 29–50.

MADDALONI, A. AND J.-L. PEYDRÓ (2013): "Monetary Policy, Macroprudential Policy, and Banking Stability: Evidence from the Euro Area." *International Journal of Central Banking* 9(1), pp. 121–169.

MEHRA, Y. P. AND E. W. MARTIN (2003): "Why Does Consumer Sentiment Predict Household Spending?" *Economic Quarterly* 89 (fall), pp. 51–67.

MISHKIN, F. S. (1978): "Consumer Sentiment and Spending on Durable Goods." *Brookings Papers on Economic Activity* 1:1978, pp. 217–232.

NOFSINGER, J. R. (2012): "Household Behavior and Boom/Bust Cycles." *Journal of Financial Stability* 8(3), pp. 161–173.

OBSTFELD, M. AND K. ROGOFF (2009): "Global Imbalances and the Financial Crisis: Products of Common Causes." CEPR Discussion Papers 7606, Centre for Economic Policy Research.

PETERSON, R. A. (2000): "A Meta-Analysis of Variance Accounted for and Factor Loadings in Exploratory Factor Analysis." *Marketing Letters* 11(3), pp. 261–275.

RAFTERY, A. E., M. KARNY, AND P. ETTLER (2010): "Online Prediction Under Model Uncertainty via Dynamic Model Averaging: Application to Cold Rolling Mill." *Technometrics* 52, pp. 52–56.

SCHILLER, R. (2000): "Measuring Bubble Expectations and Investor Confidence." *Journal of Psychology and Financial Markets* 1, pp. 49–60.

SCHULARICK, M. AND A. M. TAYLOR (2012): "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008." *American Economic Review* 102(2), pp. 1029–1061.

SOULELES, N. S. (2004): "Consumer Sentiment: Its Rationality and Usefulness in Forecasting Expenditure – Evidence from the Michigan Micro Data." NBER Working Paper 8410, National Bureau of Economic Research.

VUCHELEN, J. (2004): "Consumer Sentiment and Macroeconomic Forecasts." *Journal of Economic Psychology* 25(4), pp. 493–506.

WHITE, W. (2009): "Should Monetary Policy 'Lean or Clean'?" Working Paper 34, Federal Reserve Bank of Dallas.

WILLIS, J. L. AND C. S. HAKKIO (2014): "Kansas City Fed's Labor Market Conditions Indicators (LMCI)." *Macro Bulletin*, pp. 1–2.

WORLD BANK (2018a): "Doing Business 2019 Fact Sheet: OECD High-Income." World Bank. Retrieved December 1, 2019. Available at: https://www.doingbusiness.org/content/dam/doingBusiness/media/Fact-Sheets/DB19/FactSheet_DoingBusiness2019_OECD_Eng.pdf

WORLD BANK (2018b): "Doing Business 2019 Regional Profile: OECD High Income." World Bank. Retrieved December 1, 2019. Available at: https://www.doingbusiness.org/content/dam/doingBusiness/media/Profiles/Regional/DB2019/OECD-High-Income.pdf

# Appendix A: Factor Model

## A. 1 Data

*Table A1: Summary Statistics of Variables Entering the Factor Model*

| ID | 1 | | 2 | | 3 | | 4 | | 5 | | 6 | | 7 | | 8 | | 9 | | 10 | | 11 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | GDP (YoY growth, %) | | GDI (YoY growth, %) | | GS (YoY growth, %) | | Compensation (YoY growth, %) | | Employment (YoY growth, %) | | Lending rate cons. loans (% pa) | | Lending rate housing loans (% pa) | | Property prices (YoY growth, %) | | Share prices (YoY growth, %) | | NEER (YoY growth, %) | | ToT (YoY growth, %) | |
| | Mean | St.Dev. | Mean | St.Dev. | Mean | St.Dev. | Mean | St.Dev. | Mean | St.Dev. | Mean | St.Dev. | Mean | St.Dev. | Mean | St.Dev. | Mean | St.Dev. | Mean | St.Dev. | Mean | St.Dev. |
| AT | 3.4 | 2.0 | 3.1 | 2.2 | 3.0 | 12.0 | 3.5 | 1.3 | 0.9 | 0.7 | 4.7 | 1.3 | 3.4 | 1.3 | 4.4 | 3.5 | 10.1 | 26.0 | 0.3 | 1.9 | -0.2 | 1.2 |
| BE | 3.3 | 1.9 | 2.9 | 1.9 | 0.6 | 8.7 | 3.0 | 1.6 | 0.9 | 0.7 | 5.7 | 1.1 | 3.9 | 1.0 | 4.4 | 3.7 | 6.3 | 20.6 | 0.6 | 2.5 | -0.3 | 1.5 |
| CZ | 4.4 | 3.3 | 4.0 | 2.5 | 4.7 | 14.5 | 5.1 | 3.5 | 0.7 | 1.1 | 13.6 | 1.2 | 4.7 | 1.3 | 6.6 | 11.2 | 9.0 | 24.8 | 2.4 | 5.6 | 0.1 | 1.9 |
| DE | 2.7 | 2.3 | 2.3 | 1.2 | 3.3 | 3.1 | 2.8 | 1.7 | 0.8 | 0.7 | 5.8 | 0.9 | 4.4 | 1.0 | 2.2 | 2.9 | 7.1 | 20.2 | 0.6 | 3.2 | 0.1 | 2.0 |
| DK | 2.9 | 2.5 | 3.4 | 3.7 | 28.3 | 90.7 | 3.1 | 2.0 | 0.3 | 1.5 | 6.1 | 1.4 | 5.1 | 1.4 | 4.4 | 8.7 | 10.2 | 21.8 | 0.7 | 2.7 | 0.5 | 1.4 |
| EE | 7.0 | 8.9 | 7.2 | 7.2 | -53.4 | 485.5 | 7.9 | 9.4 | 0.7 | 4.2 | 8.5 | 1.6 | 2.9 | 1.4 | 7.3 | 19.0 | 10.6 | 31.2 | 0.5 | 2.2 | 0.6 | 1.7 |
| ES | 3.1 | 3.9 | 2.8 | 3.5 | 4.5 | 34.7 | 2.7 | 4.6 | 0.8 | 3.2 | 5.9 | 0.4 | 3.0 | 1.3 | 3.1 | 9.5 | 4.0 | 20.5 | 0.5 | 2.2 | -0.1 | 2.4 |
| FI | 2.9 | 3.2 | 3.4 | 2.2 | 11.4 | 48.0 | 2.9 | 2.3 | 0.7 | 1.5 | 4.2 | 1.1 | 2.5 | 1.3 | 3.2 | 3.6 | 4.9 | 20.6 | 0.8 | 2.8 | -0.7 | 2.2 |
| FR | 2.5 | 1.9 | 2.4 | 1.7 | 2.2 | 6.5 | 2.6 | 1.1 | 0.5 | 0.6 | 6.0 | 1.2 | 3.9 | 0.9 | 4.1 | 6.3 | 5.0 | 18.1 | 0.5 | 2.6 | 0.0 | 1.7 |
| GR | 1.1 | 5.8 | 0.7 | 7.1 | -12.0 | 364.7 | 1.6 | 7.6 | -0.2 | 2.9 | 10.7 | 0.9 | 3.9 | 1.1 | -0.3 | 7.4 | -1.3 | 32.0 | 0.7 | 2.3 | 0.3 | 2.4 |
| HU | 5.2 | 3.5 | 4.6 | 2.5 | 7.5 | 16.6 | 4.8 | 3.5 | 1.0 | 2.0 | 7.1 | 0.9 | 4.9 | 1.2 | 4.4 | 8.1 | 12.6 | 29.4 | -1.5 | 5.3 | -0.3 | 1.4 |
| IE | 6.0 | 9.4 | 3.7 | 5.1 | 12.3 | 33.5 | 4.1 | 5.9 | 1.5 | 3.5 | 6.5 | 1.0 | 3.3 | 0.8 | 2.9 | 12.5 | 5.9 | 24.0 | 0.9 | 4.0 | -0.6 | 2.6 |
| IT | 1.7 | 2.3 | 1.5 | 2.1 | -0.7 | 10.1 | 2.2 | 2.2 | 0.3 | 1.2 | 5.9 | 0.9 | 3.7 | 1.1 | 0.9 | 4.3 | 2.2 | 19.8 | 0.6 | 2.7 | -0.1 | 2.8 |
| LV | 5.4 | 12.6 | 5.3 | 10.8 | -83.3 | 939.8 | 7.1 | 15.9 | -0.9 | 5.2 | 8.6 | 2.5 | 3.4 | 1.3 | 3.5 | 17.5 | 8.4 | 27.5 | 0.5 | 1.8 | 0.8 | 3.4 |
| NL | 2.8 | 2.4 | 2.3 | 1.9 | 5.6 | 17.9 | 2.5 | 1.9 | 0.6 | 1.3 | 5.5 | 0.8 | 4.5 | 0.6 | 1.8 | 4.7 | 4.2 | 19.3 | 0.6 | 2.9 | -0.1 | 1.0 |
| NO | 5.4 | 5.4 | 5.1 | 3.1 | 9.5 | 28.5 | 5.4 | 2.8 | 1.2 | 1.4 | 5.8 | 1.8 | 4.0 | 1.2 | 6.1 | 4.8 | 15.8 | 25.3 | -0.9 | 5.5 | 2.2 | 10.1 |
| PL | 6.0 | 2.7 | 5.3 | 2.4 | 15.4 | 68.7 | 6.6 | 3.3 | 1.2 | 1.8 | 11.7 | 2.6 | 5.3 | 1.3 | 6.9 | 19.7 | 9.0 | 26.3 | 0.0 | 7.5 | 0.3 | 2.7 |
| PT | 2.3 | 2.9 | 2.1 | 2.9 | 3.2 | 39.5 | 1.8 | 3.5 | -0.2 | 2.1 | 8.0 | 0.6 | 2.8 | 1.5 | 1.2 | 5.2 | 5.6 | 20.2 | 0.4 | 1.3 | 0.4 | 2.1 |
| SE | 4.0 | 2.7 | 4.5 | 1.5 | 12.7 | 16.4 | 4.4 | 1.9 | 1.2 | 1.2 | 6.1 | 1.1 | 3.1 | 1.1 | 6.5 | 5.1 | 9.1 | 20.0 | -0.5 | 5.4 | -0.1 | 1.0 |
| SK | 4.6 | 4.8 | 4.5 | 3.4 | 6.9 | 14.2 | 5.7 | 3.5 | 1.2 | 2.1 | 9.4 | 2.1 | 4.5 | 1.3 | 5.5 | 11.4 | -0.7 | 16.2 | 2.1 | 4.4 | -0.8 | 0.9 |
| SL | 2.5 | 3.9 | 2.6 | 3.1 | 1.0 | 12.6 | 2.7 | 4.1 | 0.6 | 2.0 | 5.8 | 0.9 | 3.4 | 1.4 | 0.3 | 6.7 | -5.0 | 22.2 | 0.3 | 1.5 | -0.1 | 2.1 |
| UK | 3.8 | 2.0 | 3.7 | 1.5 | 4.0 | 21.9 | 3.8 | 2.4 | 0.9 | 0.9 | 8.0 | 1.1 | 4.2 | 1.3 | 5.5 | 7.0 | 1.9 | 14.3 | -1.2 | 6.1 | 0.5 | 1.7 |

***Note:*** For exact definitions and data sources, see Table 1.

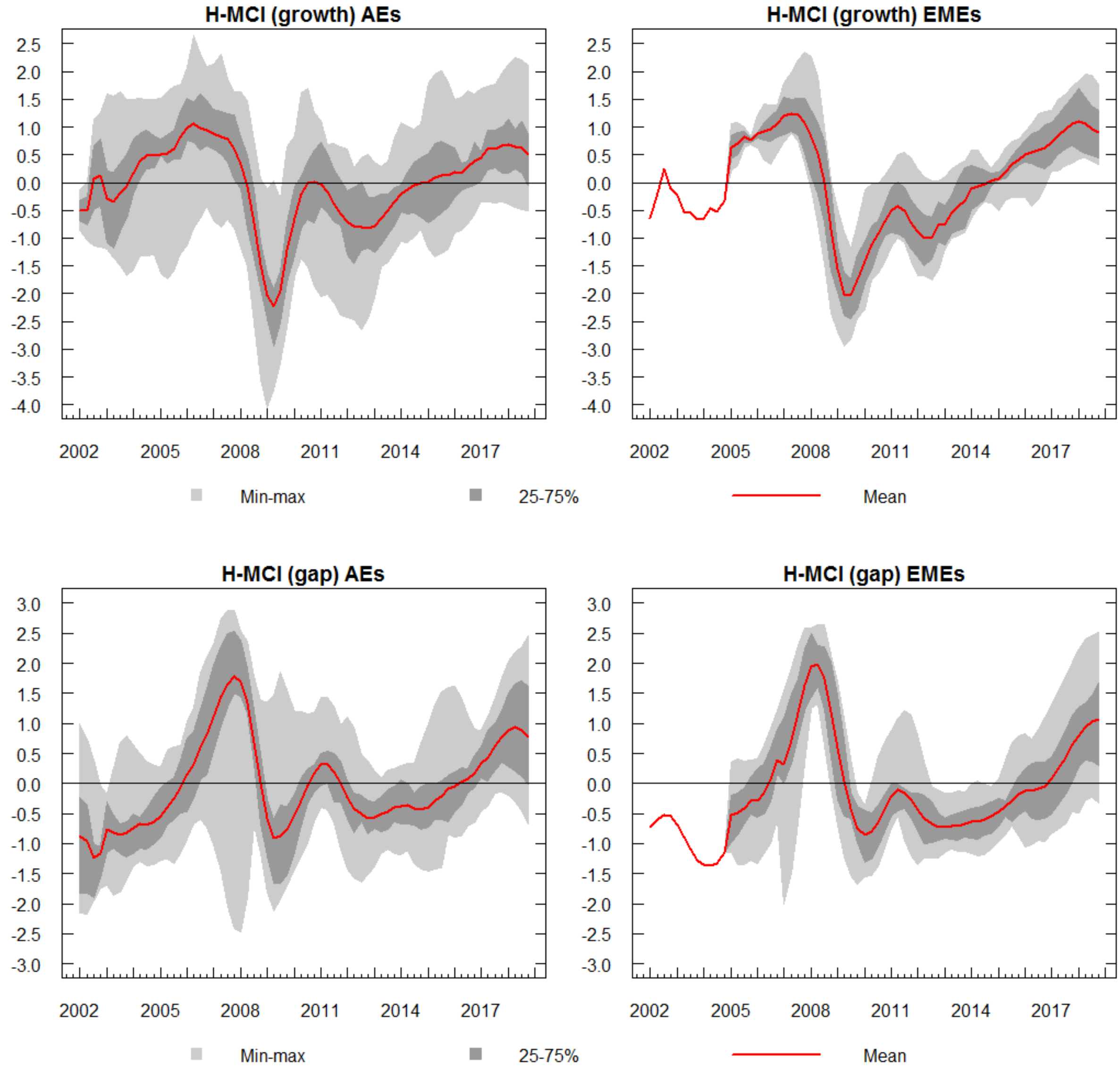
## A. 2 Statistical Tests

***Table A2: Cumulative Percentage of the Variance Explained by Individual Factors***

| | Estimation with growth rates | | | Estimation with gaps | | |
|---|---|---|---|---|---|---|
| | F1 | F2 | F3 | F1 | F2 | F3 |
| AT | 41% | 65% | 81% | 41% | 68% | 86% |
| BE | 46% | 66% | 78% | 45% | 73% | 92% |
| CZ | 39% | 66% | 81% | 44% | 73% | 88% |
| DE | 53% | 67% | 80% | 46% | 71% | 85% |
| DK | 30% | 53% | 73% | 35% | 59% | 74% |
| EE | 34% | 58% | 76% | 31% | 58% | 79% |
| ES | 46% | 67% | 83% | 44% | 72% | 92% |
| FI | 28% | 50% | 67% | 39% | 63% | 79% |
| FR | 37% | 68% | 83% | 34% | 57% | 81% |
| GR | 40% | 65% | 80% | 45% | 64% | 81% |
| HU | 36% | 59% | 73% | 49% | 74% | 89% |
| IE | 28% | 53% | 74% | 44% | 63% | 79% |
| IT | 47% | 65% | 82% | 39% | 67% | 84% |
| LV | 38% | 67% | 86% | 42% | 66% | 85% |
| NL | 40% | 67% | 83% | 38% | 74% | 84% |
| NO | 38% | 63% | 77% | 37% | 69% | 83% |
| PL | 32% | 56% | 73% | 46% | 72% | 86% |
| PT | 33% | 57% | 71% | 45% | 68% | 80% |
| SE | 41% | 64% | 77% | 58% | 80% | 92% |
| SK | 46% | 68% | 84% | 48% | 65% | 80% |
| SL | 43% | 68% | 82% | 38% | 64% | 88% |
| UK | 38% | 61% | 72% | 35% | 65% | 83% |

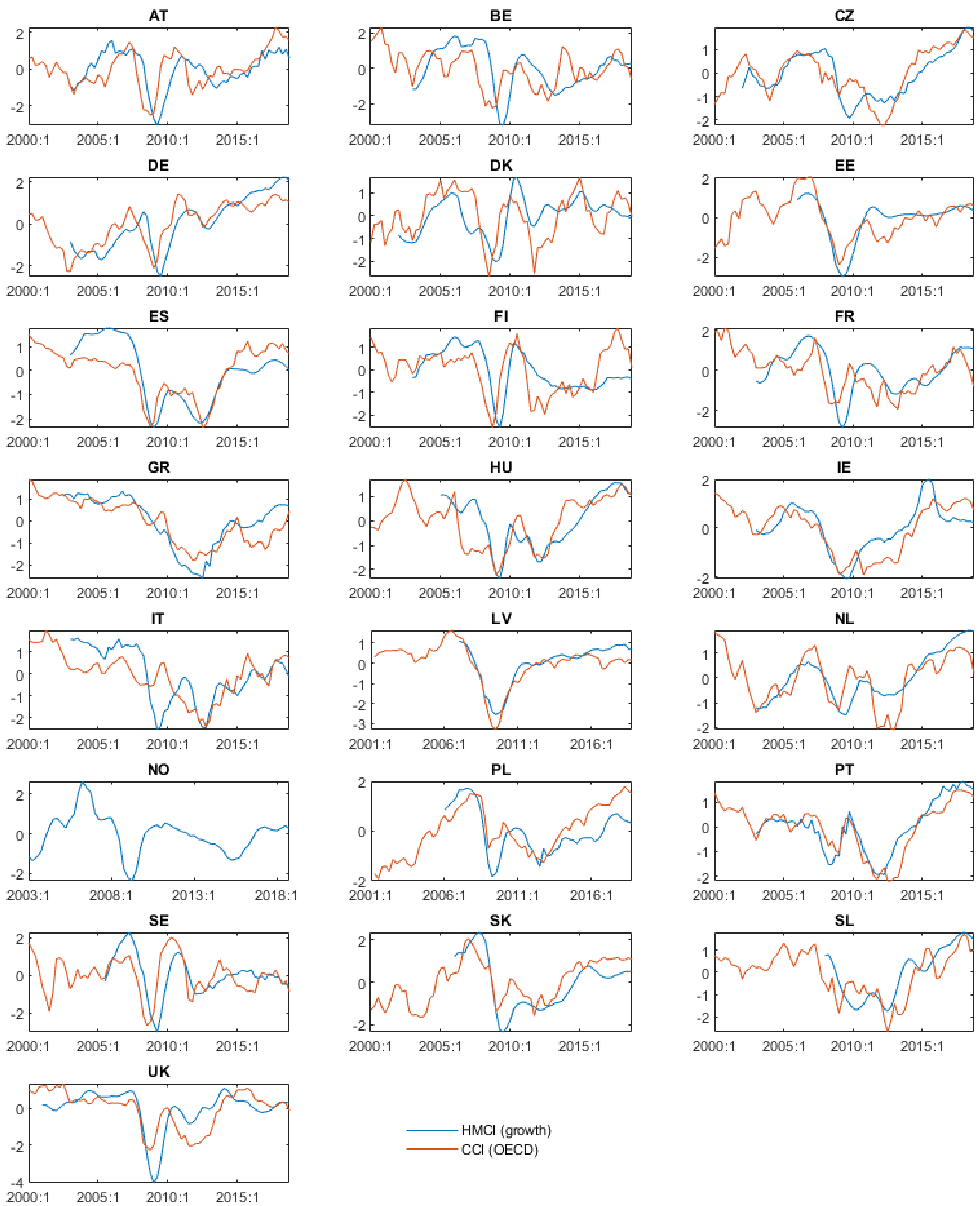
## A. 3 H-MCI Values for Selected EU Countries

***Figure A1: The H-MCI for Selected Countries***



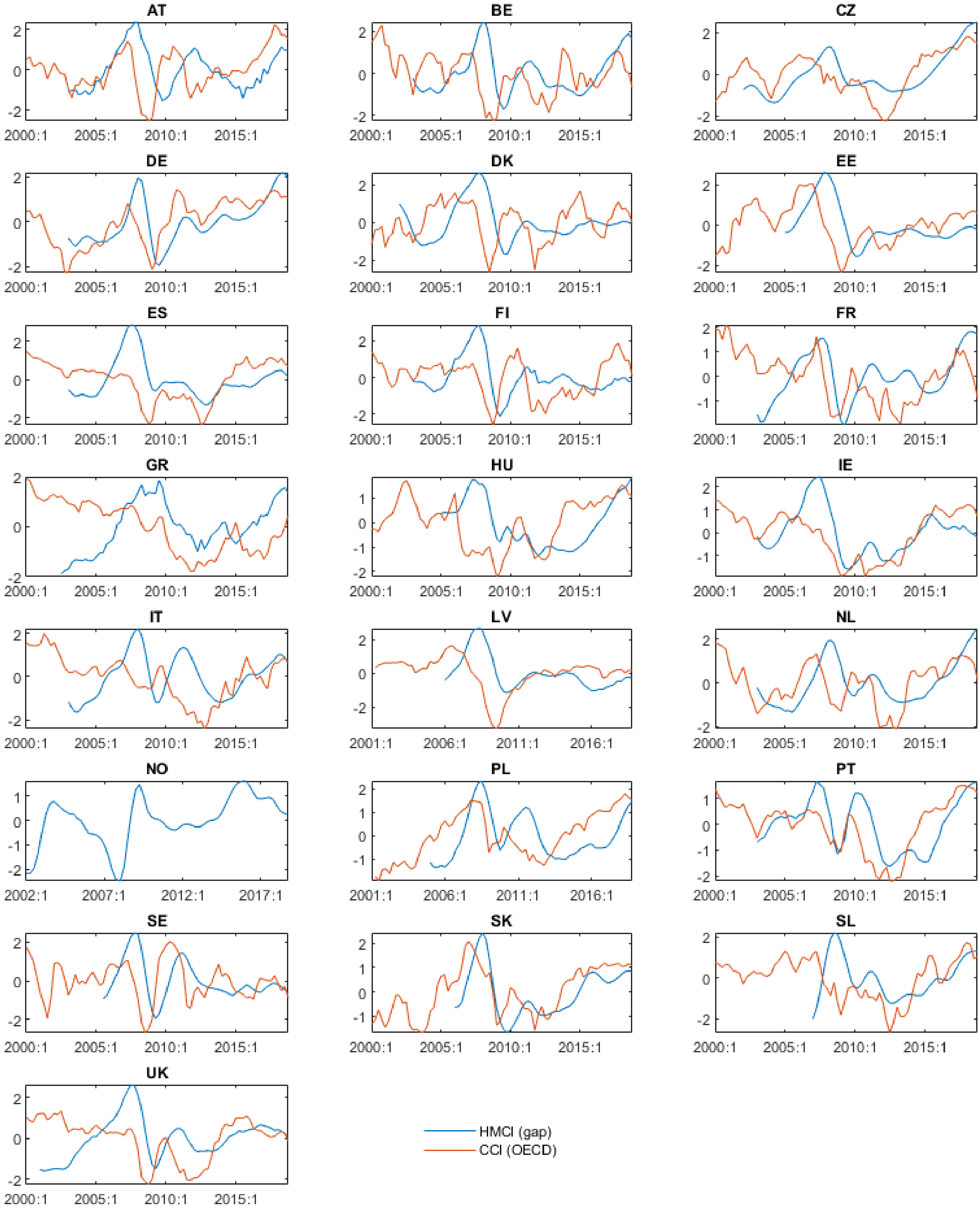

***Note:*** The index is standardized using its long-run mean and standard deviation; the vertical axis shows the standard deviations. The H-MCIs for individual countries are depicted in Figure A2 in Appendix A. AEs – advanced economies as categorized by the IMF for the whole sample period (AT, BE, DE, DK, ES, FI, FR, GR, IE, IT, NL, NO, PT, SE, UK); EMEs – emerging market economies (CZ, EE, HU, LV, PL, SK, SL).

***Figure A2: The H-MCI for Selected European OECD Countries (Estimated with Annual Growth Rates)***




***Note:*** The vertical axis reflects the standard deviation. Estimates with three factors.

***Figure A3: The H-MCI for Selected European OECD Countries (Estimated with Gaps for Selected Variables)***




***Note:*** The vertical axis reflects the standard deviation. Estimates with three factors.

***Table A3: Correlations***

| | HMCI growth (t) vs CCI (t) | HMCI growth (t+4) vs CCI (t) | HMCI gap (t) vs CCI (t) | HMCI gap (t+4) vs CCI (t) | HMCI growth (t) vs HMCI gap (t) |
|---|---|---|---|---|---|
| AT | 0.51*** (4.63) | 0.56*** (5.35) | 0.09 (0.75) | 0.60*** (5.95) | 0.47*** (4.24) |
| BE | 0.25** (2.01) | 0.66*** (6.85) | -0.11 (-0.89) | 0.46*** (4.10) | 0.62*** (6.21) |
| CZ | 0.79*** (10.63) | 0.76*** (9.36) | 0.61*** (6.17) | 0.71*** (8.12) | 0.79*** (10.51) |
| DK | 0.49*** (4.63) | 0.21* (1.70) | -0.06 (-0.50) | 0.61*** (6.26) | -0.20* (-1.69) |
| EE | 0.78*** (9.08) | 0.46*** (3.65) | 0.22 (1.63) | 0.83*** (10.97) | 0.13 (0.89) |
| FI | 0.41*** (3.49) | 0.57*** (5.39) | 0.03 (0.23) | 0.45*** (3.97) | 0.66*** (7.01) |
| FR | 0.58*** (5.54) | 0.58*** (5.63) | 0.22* (1.73) | 0.30** (2.51) | 0.77*** (9.36) |
| DE | 0.79*** (10.37) | 0.87*** (13.80) | 0.56*** (5.32) | 0.71*** (8.04) | 0.83*** (11.78) |
| GR | 0.85*** (12.82) | 0.65*** (6.84) | -0.15 (-1.25) | -0.20* (-1.67) | -0.03 (-0.27) |
| HU | 0.69*** (6.95) | 0.67*** (6.93) | 0.13 (0.97) | 0.37*** (2.92) | 0.69*** (7.13) |
| IE | 0.78*** (9.92) | 0.53*** (4.93) | 0.53*** (4.89) | 0.65*** (6.72) | 0.59*** (5.85) |
| IT | 0.58*** (5.60) | 0.66** (6.85) | -0.03 (-0.27) | 0.27** (2.22) | 0.14 (1.12) |
| LV | 0.94*** (19.23) | 0.58*** (4.78) | -0.04 (-0.30) | 0.51*** (4.22) | -0.09 (-0.63) |
| NL | 0.73*** (8.40) | 0.56*** (5.34) | 0.31** (2.60 | 0.77*** (9.55) | 0.51*** (4.58) |
| PL | 0.71*** (7.18) | 0.31** (2.32) | 0.23* (1.75) | 0.60*** (5.47) | 0.23 (1.67) |
| PT | 0.88*** (14.78) | 0.53*** (4.94) | 0.57*** (5.40) | 0.70*** (7.82) | 0.43*** (3.71) |
| SK | 0.82*** (10.24) | 0.66*** (6.13) | 0.71*** (7.05) | 0.79*** (9.20) | 0.86*** (11.97) |
| SL | 0.73*** (6.96) | 0.56*** (4.39) | 0.20 (1.39) | 0.49*** (3.83) | 0.46*** (3.31) |
| ES | 0.76*** (9.26) | 0.63*** (6.43) | 0.14 (1.07) | 0.31** (2.54) | 0.33*** (2.73) |
| SE | 0.48*** (3.95) | 0.53*** (4.53) | -0.06 (0.48) | 0.71*** (7.18) | 0.70*** (7.13) |
| UK | 0.59*** (6.12) | 0.31*** (2.71) | -0.03 (-0.25) | 0.17 (1.41) | 0.30*** (2.66) |

***Note:*** T-values in brackets. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

## Appendix B: Dynamic Model Averaging

Given $m$ predictors, the total number of possible combinations of forecasting models is $K = 2^m$. DMA incorporates the uncertainty factors from these $K = 2^m$ models as follows:

$$\hat{y}_t = \sum_{k=1}^{K} y_{(t|\mathrm{t-1,k})} z_{t-1}^{(k)\prime}\, \xi_{t-1}^{(k)}, \tag{B.1}$$

where the probability of model $k$ is $y_{(t|\mathrm{t-1,k})} = Prob(L_t|Y^{t-1})$. $L_t \in \{1,2,\dots,K\}$ denotes which model applies in each time period. DMA obtains the forecasting result at any point in time by taking the average of all the $K$ models according to their historical forecasting performances $y_{(t|\mathrm{t-1,k})}$.

The estimation procedure introduced in Raftery et al. (2010) is rather straightforward and is based on the Kalman filter method. The initial assumption is that $\xi_{t-1}^{(k)}$ is independent and identically distributed and can be determined separately only if $L_{t-1} = k$. Raftery et al. (2010) then consider a so-called forgetting factor $\lambda$. The forgetting factor is used to simplify the calculation of $\xi_{t-1}^{(k)}$, where it assigns period $j$ weight $\lambda^j$ from the starting period. $\lambda$ is also used to simplify the covariance matrix of $\xi_{t-1}^{(k)}$. The whole process is described as follows:

$$\xi_{t|t-1}^{(k)} = \xi_{t-1|t-1}^{(k)}, \tag{B.2}$$

$$\Sigma_{t|t-1}^{(k)} = \frac{1}{\lambda}\Sigma_{t-1|t-1}^{(k)}, \tag{B.3}$$

where $\Sigma_{t|t-1}^{(k)}$ is the covariance matrix. DMA estimates its parameters by the following equations:

$$\hat{\xi}_{t|t}^{(k)} = \hat{\xi}_{t-1|t-1}^{(k)} + \Sigma_{t|t-1}^{(k)} z_{t-1}^{(k)\prime}\left(V_t^{(k)} + x_{t-1}^{(k)\prime}\Sigma_{t|t-1}^{(k)} x_{t-1}^{(k)}\right)^{-1}\left(y_t - x_{t-1}^{(k)\prime}\hat{\xi}_{t-1}^{(k)}\right), \tag{B.4}$$

$$\Sigma_{t|t}^{(k)} = \Sigma_{t|t-1}^{(k)} - \Sigma_{t|t-1}^{(k)} z_{t-1}^{(k)\prime}\left(V_t^{(k)} + x_{t-1}^{(k)\prime}\Sigma_{t|t-1}^{(k)} x_{t-1}^{(k)}\right)^{-1} z_{t-1}^{(k)}\Sigma_{t|t-1}^{(k)}, \tag{B.5}$$

where eq. (B.3) is solved by using the forgetting factor $\lambda$ with $W_t^{(k)} = (\lambda^{-1} - 1)\Sigma_{t|t-1}^{(k)}$. It is common to choose a value of $\lambda$ near one, suggesting gradual evolution of the coefficients.

A second forgetting factor $\alpha$ is used to reduce the calculation time and error in eq. (B.1). If we were to use a transition matrix of probability, we would have to consider $K = 2^m$ model combinations with $m$ predictors at each time point. For large $m$, the computational burden would be too large. Raftery et al. (2010) suggest replacing the model prediction equation:

$$y_{t|\mathrm{t-1,k}} = \sum_{l=1}^{K} y_{t-1|\mathrm{t-1,l}}\, p_{k,l}, \tag{B.6}$$

with

$$y_{t|\mathrm{t-1,k}} = \frac{y_{t-1|\mathrm{t-1,k}}^{\alpha}}{\sum_{l=1}^{K} y_{t-1|\mathrm{t-1,l}}^{\alpha}}, \tag{B.7}$$

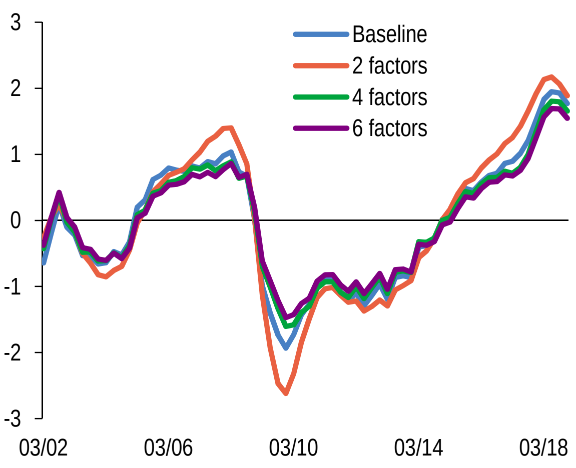
where $\alpha$ is set to a value near one in a similar spirit to that of $\lambda$. In fact, Raftery et al. (2010) indicate that if $\alpha = \lambda = 1$, then DMA can be treated as BMA without any forgetting. In our application, we follow Raftery et al. (2010) and Koop and Korobilis (2012) and use a constant forgetting factor of $\lambda = \alpha = 0.99$ in each period. This means setting a rather non-informative prior over the models $y_{0|0,\mathrm{k}} = 1/K$ (initially, all models are equally likely) and a relatively diffuse prior on the initial conditions of the states $\xi_0^{(k)} \sim N(0,100)$.

## Appendix C: Robustness Checks and Individual Factors for the Czech Republic Case Study

The robustness and sensitivity analysis of the selected model specification for calculating the H-MCI is performed with respect to the number of factors and the estimation period. Firstly, a different number of estimated factors does not significantly change the result of the index. Secondly, the index is also robust to shortening the estimation period.

***Figure C1: Robustness Checks***

a) Different number of estimated factors




b) Historical simulations

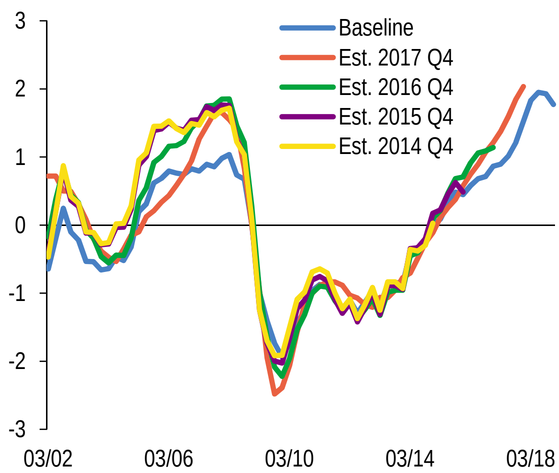
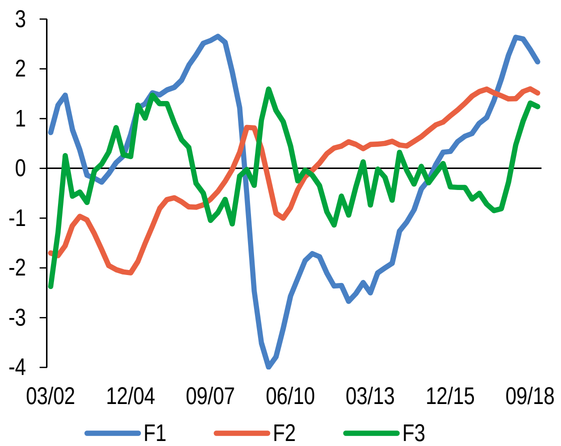



***Figure C2: Development and Correlation Analysis of the Estimated Factors***

a) Development of estimated factors




b) Correlations of estimated factors and underlying data

| ID | Variable | F1 | F2 | F3 |
|---|---|---|---|---|
| 1 | GDP | 0.81*** | -0.26** | -0.07 |
| 2 | GDI | 0.82*** | -0.13 | 0.36*** |
| 3 | GS | 0.12 | -0.10 | 0.78*** |
| 4 | Compensation | 0.94*** | -0.12 | -0.09 |
| 5 | Employment | 0.65*** | 0.40*** | -0.20 |
| 6 | Lending rate CL | 0.59*** | 0.55*** | 0.06 |
| 7 | Lending rate HL | 0.17 | 0.89*** | 0.06 |
| 8 | Property prices | 0.72*** | -0.09 | -0.50*** |
| 9 | Share prices | 0.31** | -0.61*** | 0.41*** |
| 10 | NEER | 0.60*** | -0.29** | -0.09 |
| 11 | ToT | -0.06 | -0.12 | -0.34*** |

***Note:*** Factors are not standardized. Growth version of the H-MCI. Except for lending rates, the data in panel b) are in growth rates.

| CNB Working Paper Series (since 2018) | | |
|---|---|---|
| 10/2019 | Martin Hodula<br>Simona Malovaná<br>Jan Frait | *Introducing a new index of households' macroeconomic conditions* |
| 9/2019 | Jiří Panoš<br>Petr Polák | *How to improve the model selection procedure in a stress-testing framework?* |
| 8/2019 | Sebastian Gechert<br>Tomáš Havránek<br>Zuzana Iršová<br>Dominika Kolcunová | *Death to the Cobb-Douglas production function? A quantitative survey of the capital-labor substitution elasticity* |
| 7/2019 | Alexis Derviz | *Coexistence of physical and crypto assets in a stochastic endogenous growth model* |
| 6/2019 | Dominika Ehrenbergerová<br>Simona Malovaná | *Introducing macro-financial variables into semi-structural model* |
| 5/2019 | Martin Hodula | *Monetary policy and shadow banking: Trapped between a rock and a hard place* |
| 4/2019 | Simona Malovaná<br>Žaneta Tesařová | *Banks' credit losses and provisioning over the business cycle: Implications for IFRS 9* |
| 3/2019 | Aleš Bulíř<br>Jan Vlček | *Monetary policy is not always systematic and data-driven: Evidence from the yield curve* |
| 2/2019 | Dominika Kolcunová<br>Simona Malovaná | *The effect of higher capital requirements on bank lending: The capital surplus matters* |
| 1/2019 | Jaromír Baxa<br>Tomáš Šestořád | *The Czech exchange rate floor: Depreciation without inflation?* |
| 19/2018 | Jan Brůha<br>Jaromír Tonner | *Independent monetary policy versus common currency: The macroeconomic analysis for the Czech Republic through lens of an applied DSGE model* |
| 18/2018 | Tomáš Adam<br>Filip Novotný | *Assessing the external demand of the Czech economy: Nowcasting foreign GDP using bridge equations* |
| 17/2018 | Kamil Galuščák<br>Jan Šolc<br>Pawel Strzelecki | *Labour market flows over the business cycle: The role of the participation margin* |
| 16/2018 | Martin Hodula | *Off the radar: Exploring the rise of shadow banking in the EU* |
| 15/2018 | Lukáš Pfeifer<br>Martin Hodula<br>Libor Holub<br>Zdeněk Pikhart | *The leverage ratio and its impact on capital regulation* |
| 14/2018 | Martin Gürtler | *What influences private investment? The case of the Czech Republic* |
| 13/2018 | Václav Hausenblas<br>Jitka Lešanovská | *How do large banking groups manage the efficiency of their subsidiaries? Evidence from CEE* |
| 12/2018 | Simona Malovaná | *The pro-cyclicality of risk weights for credit exposures in the Czech Republic* |
| 11/2018 | Tibor Hlédik<br>Karel Musil<br>Jakub Ryšánek<br>Jaromír Tonner | *A macroeconomic forecasting model of the fixed exchange rate regime for the oil-rich Kazakh economy* |

| | | |
|---|---|---|
| 10/2018 | Michal Franta<br>Tomáš Holub<br>Branislav Saxa | *Balance sheet implications of the Czech National Bank's exchange rate commitment* |
| 9/2018 | Dominika Kolcunová<br>Tomáš Havránek | *Estimating the effective lower bound on the Czech National Bank's policy rate* |
| 8/2018 | Volha Audzei<br>Sergey Slobodyan | *Sparse restricted perception equilibrium* |
| 7/2018 | Tibor Hlédik<br>Jan Vlček | *Quantifying the natural rate of interest in a small open economy – The Czech case* |
| 6/2018 | Václav Brož<br>Michal Hlaváček | *What drives distributional dynamics of client interest rates on consumer loans in the Czech Republic? A bank-level analysis* |
| 5/2018 | Lukáš Pfeifer<br>Martin Hodula | *Profit-to-provisioning approach for setting the countercyclical capital buffer: The Czech example* |
| 4/2018 | Ivan Sutóris | *Asset prices in a production economy with long run and idiosyncratic risk* |
| 3/2018 | Michal Franta | *The likelihood of effective lower bound events* |
| 2/2018 | Soňa Benecká<br>Ludmila Fadejeva<br>Martin Feldkircher | *Spillovers from euro area monetary policy: A focus on emerging Europe* |
| 1/2018 | Jan Babecký<br>Clémence Berson<br>Ludmila Fadejeva<br>Ana Lamo<br>Petra Marotzke<br>Fernando Martins<br>Pawel Strzelecki | *Non-base wage components as a source of wage adaptability to shocks: Evidence from European firms, 2010-2013* |

| **CNB RESEARCH AND POLICY NOTES (SINCE 2018)** | | |
|---|---|---|
| 2/2019 | Jan Filáček<br>Ivan Sutóris | *Inflation targeting flexibility: The CNB's reaction function under scrutiny* |
| 1/2019 | Iveta Polášková<br>Luboš Komárek<br>Michal Škoda | *The contemporary role of gold in central banks' balance sheets* |
| 1/2018 | Mojmír Hampl<br>Tomáš Havránek | *Central bank financial strength and inflation: A meta-analysis* |

| **CNB ECONOMIC RESEARCH BULLETIN (SINCE 2018)** | |
|---|---|
| November 2018 | *Interest rates* |
| May 2018 | *Risk-sensitive capital regulation* |

Czech National Bank
Economic Research Division
Na Příkopě 28, 115 03 Praha 1
Czech Republic
phone: +420 2 244 12 321
fax: +420 2 244 12 329
http://www.cnb.cz
e-mail: research@cnb.cz
ISSN 1803-7070