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# In the Quest of Measuring the Financial Cycle

Miroslav Plašil, Tomáš Konečný, Jakub Seidler, and Petr Hlaváč*


## Abstract

The recent financial crisis has demonstrated the importance of the linkages between the financial sector and the real economy. This paper sets out to develop two complementary methods for assessing the position of the economy in the financial cycle in order to identify emerging imbalances in timely manner. First, we construct a composite indicator using variables representing risk perceptions in the financial sector and calibrate this indicator to capture the credit losses the Czech banking sector experienced during the recent crisis. Second, we focus on the transitions of loans from one risk category to another, which allows us to capture the financial cycle from the perspective of the debt-paying ability of non-financial corporations. Both financial cycle measures can be used by policy makers for a wide range of policy decisions, including that on the setting of the countercyclical capital buffer.

## Abstrakt

Nedávná finanční krize odhalila důležitost vazeb mezi reálnou ekonomikou a finančním sektorem. Tento článek představuje dva vzájemně se doplňující způsoby vyhodnocování pozice ekonomiky v rámci finančního cyklu s cílem včas odhalit vznikající nerovnováhy. Nejdříve je zkonstruován souhrnný indikátor, který kombinuje informace obsažené v proměnných charakterizujících změnu ve vnímání rizik ve finančním systému, přičemž váhy jednotlivých proměnných jsou nastaveny tak, aby indikátor co nejlépe charakterizoval vývoj úvěrových ztrát bankovního sektoru během poslední krize. Za druhé zkoumáme migraci mezi jednotlivými rizikovými kategoriemi úvěrů, což umožňuje popsat finanční cyklus z pohledu schopnosti sektoru nefinančních podniků splácet dluh. Oba indikátory finančního cyklu mohou být využity při rozhodování v oblasti makroobezřetnostní politiky, včetně nastavení proticyklické kapitálové rezervy.



**JEL Codes:** C11, E32, E37, E58.
**Keywords:** Bayesian model averaging, countercyclical capital buffer, credit risk, factor model, financial cycle.


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The views expressed in this paper are those of the authors and not necessarily those of the Czech National Bank.

## Nontechnical Summary

Correctly determining the current phase of the financial cycle is vital for successfully identifying emerging risks, taking timely preventive action and implementing stabilisation policies. Using data on the Czech economy, this paper sets out to propose two complementary methods for assessing the position in the financial cycle in order to identify emerging imbalances in good time and to assist policy makers in activating a new macroprudential tool, the countercyclical capital buffer (CCB).

The first method takes a set of variables measuring swings in risk perceptions and aggregates them into a single composite indicator. Both co-movement of variables and idiosyncratic developments are valuable pieces of information in the macroprudential context. One of the main features of the aggregation method is that it takes into account the time-varying cross-correlation structure of the data. The resulting indicator thus generally takes higher values when the variables reach elevated levels in all monitored segments and the risk build-up signal is stronger. When selecting the candidate variables, we covered the widest possible area of the economy that might be affected by changes in risk perceptions, i.e. the credit demand and supply sides, property prices, debt sustainability, general financial market sentiment and external imbalances. Alongside the time-varying cross-correlation structure, the resulting financial cycle indicator (FCI) employs a system of fixed weights assigned to each variable. These weights were estimated so as to provide optimal predictive performance for loan loss impairment six quarters ahead. Timely identification of risk materialisation is necessary for making timely decisions about the CCB setting.

The second method focuses on the transitions of loans from one risk category to another and captures the financial cycle from the perspective of the debt-paying ability of non-financial corporations. We use individual loan data from the Central Credit Register (CCR) operated by the Czech National Bank to track migration patterns between different credit risk categories of individual loans to extract common components of the migration of loans within the financial cycle. Common components are modelled by means of the hierarchical dynamic factor model, which offers high flexibility through a multilevel structure where a common factor affects all rating classes through rating-specific factors.

In spite of the methodological differences, the outcomes obtained from the two outlined approaches exhibit similar patterns and show that the period of 2005–2008 can be described as an expansionary phase of the financial cycle, with an economic recovery accompanied by gradually rising optimism and risk tolerance. The results of the two methods provide a consistent picture of the Czech financial cycle and at the same time offer complementary guidance on the position of the economy in the financial cycle for the purposes of policy makers' actions.

*Crises and deadlocks when they occur have at least this advantage, that they force us to think.*
Jawaharlal Nehru

# 1. Introduction

Recent developments in the global economy have contributed to the reassessment of some well-established economic notions. Arguably, one of the most conspicuous changes in economic thinking has been that related to the importance of the linkages between the real economy and the financial sector. The recent crisis revealed that as the importance of financial intermediation grows, problems that originate in one part of the economy can spill over more easily to another, thereby magnifying the original negative shocks. To illustrate this link, it suffices to recap the milestones of the Great Recession: a crisis initially linked with the housing market and its financing subsequently turned into an economic crisis and then a debt and banking crisis, which in turn significantly limited the scope for economic recovery. Facing this negative experience, economists have been forced to pay closer attention to the role of financial factors in business fluctuations and their impact on the overall soundness of the economic system. And as a consequence, macroprudential instruments and financial stability issues have become an object of central interest to policy makers.

Although business and financial fluctuations can be seen as very close relatives, they are hardly identical twins. The interactions between the real and financial sectors must be taken on board when analysing the economy; however, one should also be mindful of the differences in their nature, morphology and even timing. The foundations of financial risks and imbalances are laid in good economic times, when expectations are running high. An expansionary phase of the financial cycle, associated with high (or even excessive) credit growth, is often followed by a deterioration in borrowers' ability to repay, growth in non-performing loans and large losses in the banking sector, which together can limit banks' ability to lend to the sound part of the real economy (see also Frait and Komárková, 2012, pp. 12–14).

Correctly determining the current phase of the financial cycle is therefore vital for successfully identifying emerging risks, taking timely preventive action and implementing stabilisation policies. In practice, however, this objective may pose some practical challenges, as the financial cycle is mainly a theoretical quantity lacking a generally accepted empirical counterpart. Although some may favour quite a parsimonious description of the financial cycle defined only in terms of one or very few variables (see, for example, Borio, 2012), relevant features of the cycle are echoed in far more indicators, which may provide some additional refinements. When assessing the current situation, policy makers can simply look at the whole pack of individual indicators to get a basic idea of the cycle in action, but for a more formal quantitative assessment as well as for communication purposes it might still be useful to transform the existing information into a single representative measure.

Using data on the Czech economy, this paper sets out to propose two complementary methods useful for monitoring developments over the financial cycle. Right at the beginning, we stress that the *raison-d'être* of these methods is to assist policy makers in activating and setting the countercyclical capital buffer (CCB). This largely predetermines our modelling choices. In particular, the proposed methods should mainly capture those cyclical risks which can be effectively handled by the CCB, and closer attention is paid to the identification of those phases of the cycle where the need for macroprudential actions is the most urgent (i.e. mainly the build-up phase of the cycle). Conceptually, we follow papers aiming to extract cyclical information from a variety of financial variables (see Ng, 2011, and Hatzius et al., 2010, among others). However, our empirical approach is quite different from the previous literature. To the best of our knowledge, both methods presented below are new in the financial cycle context, either in terms of the methodology applied or in terms of the variables used. We provide a thorough description and motivation for each of the proposed methods in the sections below, so at this stage we confine ourselves to a first-glance introduction. The first method takes a set of variables measuring swings in risk and aggregates them into a single indicator using standard portfolio theory. This methodology was first proposed in the macroprudential context by Holló et al. (2012), who used it to construct a composite indicator of systemic stress (CISS). The second method uses data tracking migrations between different credit risk categories and extracts common components of the migration series by means of factor models.

Although there are some fundamental differences in these two approaches – starting with conceptual differences and continuing with different underlying methodologies and variables (including their frequency and general availability) – they are still quite close to each other in the sense that they try to capture the same elusive phenomenon and have the ambition of assisting policy makers in their decisions. They also document relevant financial cycle indicators which were available when the macroprudential framework in the Czech Republic was established. This is even more relevant in a situation where the apparent macroprudential policy *star on the stage* – the HP filtered credit/GDP gap – delivers highly erratic signals for the Czech economy.[1] Taking this perspective, the integration of these two concepts of the financial cycle under one roof is in our view useful and justified. Moreover, our results show that despite their differences, the proposed methods provide a surprisingly consistent picture of the cycle and might serve as useful complements.

The paper is structured as follows. Section 2 briefly reviews related literature. Section 3 gathers the motivation, description and assessment of the first method, which aggregates selected indicators in a CISS-like fashion (see Holló et al., 2012), while Section 4 provides similar ingredients for the second method, which is based on the modelling of loan risk migration. In Section 5, we briefly sketch out the predictive performance of the proposed financial cycle indicators with respect to GDP growth and credit risk materialisation. Section 6 contains concluding remarks.

## 2. Literature Review

Historically, the financial cycle is considerably less well documented than business fluctuations are and its notion has long wandered from the obscurity to ignorance. For most of the post-war period economic research was practically silent in this regard. Mainstream economics saw the financial system as an amplifier of business fluctuations, just slightly complicating matters at best (e.g. Bernanke et al., 1998), while models ignoring financial variables completely were

[1] Credit-to-GDP measures can deliver highly misleading signals in some countries, as shown in Geršl and Seidler (2011). This is particularly true when the credit aggregate is polluted by structural breaks.

considered a relatively good approximation of reality. One of the few exceptions to the mainstream style was the work by Minsky (1982).

The main impetus for incorporating the financial sector into models (such as DSGE) was the occurrence of the financial crisis in the late 2000s. It turned out that the financial system can be at the centre of a worldwide downturn and be one of the direct causes of subsequent events. The financial crisis made it clear that the research which had been done so far on the identification of the financial cycle and its effects on the real economy was hardly sufficient.

The financial cycle literature, however, has some notable predecessors. In particular, it is important to highlight the work done on early warning indicators. These indicators were constructed to anticipate various kinds of crises, such as currency, debt or banking crises. Since the peaks of financial cycles often coincide with the severest crises, early warning indicators can naturally serve the same purpose as the identification of financial cycles. Krugman (1979) developed early warning indicators to predict currency and balance of payments crises. Kaminsky and Reinhart (1999) and Reinhart and Rogoff (2011) proposed indicators to foresee debt and banking crises. The global financial crisis reawakened interest in this type of analysis, leading to the application of new empirical methods and larger and more detailed panels (see, for example, Laeven and Valencia, 2010, and Babecký et al., 2013). The above-mentioned studies generally find that indicators showing changes in risk aversion (such as the rate of growth in credit to the private sector, debt and debt-servicing ability, property price growth, the tightness of the credit conditions and the current account deficit or government debt level) are suitable indicators of future crises.[2]

The stream of research focusing on the procyclicality of the financial system, which can lead to unexpected boom and bust cycles and amplify economic fluctuations, can also be seen as a close relative of the financial cycle literature. This includes, for example, the papers by Adrian and Shin (2010), Borio et al. (2001), Kashyap and Stein (2004) and White (2006). These studies, however, stayed more or less on the theoretical level and did not provide an unequivocal definition of the financial cycle.

The above theoretical studies are echoed in the empirical works of the authors trying to capture the financial cycle with a particular variable or set of variables. This branch of research has grown to a considerable size. The most parsimonious way of defining the financial cycle empirically, but perhaps incompletely, is to use credit aggregates. For example, Dell'Ariccia et al. (2012) classify an episode as a credit boom simply if (*i*) the annual growth rate of the credit-to-GDP ratio exceeds 10% and the deviation from trend is greater than 1.5 times its standard deviation or (*ii*) the annual growth rate of the credit-to-GDP ratio exceeds 20%. The authors use bank credit in the numerator of the credit-to-GDP ratio and argue that it should be enough to capture the cycle (with one important exception, namely the US). Under this approach, one variable (although calculated from two time series) is sufficient to identify potentially dangerous upswings in the financial cycle, hence the financial cycle is simply a different name for the credit cycle. Similar studies in this respect include Aikman et al. (2010), Mendoza and Terrones (2008) and Schularick and Taylor (2009).

[2] Forward-looking indicators also differ across studies depending on the set of countries examined. For emerging economies foreign exchange reserves and the equilibrium real exchange rate are often appropriate indicators (see, for example, Frankel and Rose, 1996).

To obtain a more realistic picture, single-variable measures of the cycle were later enriched with other supplementary information, in particular that contained in property prices (Borio, 2012, and Drehmann et al., 2012). Borio (2012) argues that credit developments together with property prices represent analytically the smallest set needed to replicate the mutually reinforcing interaction between financing constraints (as represented by credit) and perceptions of values and risks (as represented by property prices). These two quantities tend to move together, mainly at low frequencies, and seem to be fairly good leading indicators of banking crises, especially if used together. This reflects the fact that the credit gap is a rough measure of leverage in the economy, which indicates its loss absorption capacity, and the property price gap indicates the probability and size of the potential price reversal, which is symptomatic of financial crises. Drehmann et al. (2012) also claim that recessions that succeed the peaks of financial cycles tend to be more severe. In this sense, the financial cycle can be thought of as a leading indicator of the business cycle.

The financial cycle as outlined above still exploits only a very limited range of information. On the other side of the imaginary axis, there are methods based on factor models, which frequently utilise more than a dozen time series to identify the cycle. The variables are most often recruited from the area of market prices, lending conditions or quantities related to interest rates (Ng, 2011, Hatzius et al., 2010, and English et al., 2005). Observed correlations between variables can be interpreted as the existence of a common latent factor which forces the variables to co-move. This factor, in turn, can be seen as a good proxy for the financial cycle in action.

Finally, the financial cycle as seen through the accumulation of risk in banks' balance sheets is identified by some authors via migration of loans within risk categories (standard, watch, substandard, doubtful, loss). The credit migration process is often modelled as a state space Markov Chain conditioned on macroeconomic developments and on selected structural characteristics of individual companies, such as indebtedness, interest coverage, gross profit margin and debt-servicing costs (see, among others, Kavvathas, 2001, Bonfirm, 2009, and Banerjee, 2011).[3]

## 3. A CISS-like Financial Cycle Indicator

### 3.1 Motivation and Design

The primary motivation for the first indicator (which we call the FCI for future reference) was to come up with a very simple indicator, one that would be very simple to construct, easy to interpret and well understood by the widest possible audience. Our experience is that "rocket-science" indicators usually fail to hit the intended target, since it is difficult to convey successfully their message to the relevant economic agents. In a similar vein, simpler indicators have a better chance of being employed as a communication vehicle and accepted by the general public. The growing popularity of the CISS indicator in the field of systemic risk measurement gives us some optimism that its underlying methodology goes in the right direction and is fairly easy to

[3] The Markov properties of the migration process can also be examined by analysis of eigenvectors and eigenvalues and analysis of path dependence (Bangia et al., 2002), as well as by semi-parametric regression techniques that address two types of non-Markov effects in rating transitions – duration dependence and dependence on previous rating (Lando and Skødeberg, 2002).

understand. We try to demonstrate that this does not come at the cost of losing good descriptive properties with respect to the financial cycle (its build-up phase in particular).

When proposing an indicator of a cycle, it is first necessary to explain what exactly we want to capture by it. As demonstrated in the previous section, there is hardly a consensus on the definition of the financial cycle. In this section, we stick to the definition adopted by the Czech National Bank in its Financial Stability Reports (for a more detailed account, see Frait and Komárková, 2012, pp. 13–14). This definition is also close in spirit to that in Borio (2012), for example. In what follows, the financial cycle is understood to mean recurrent swings in market participants' attitudes to financial risks, where the swings reflect changes in risk perceptions and value and the reinforcing interactions between them. Falling risk aversion is usually reflected in rapid credit growth, rising asset prices, easy access to external financing and increased investment activity. Conversely, the downward phase of the cycle is accompanied by financing constraints and possible deleveraging in all sectors. Financial developments close to the peak and the trough of the financial cycle can considerably amplify business cycle fluctuations.

Using the above definition, the process of constructing the FCI can be split into two steps. The first step involves selecting relevant variables capturing changes in perceptions of financial risk across various segments of the economy (see section 3.2). In the second step, the variables are combined into a single indicator using a simple aggregation algorithm (see section 3.3). The main focus is placed on timely identification of the build-up phase of systemic risk and its subsequent shift to materialisation, because this is the period when macroprudential intervention is most likely. The idea behind the FCI is to first analyse developments in particular segments of the economy and then make a synthesis in the form of a composite indicator. We note that the synthesis should be made only after a thorough analysis of individual information has been performed. This process thus allows for identification of common movements in the selected indicators while retaining knowledge of idiosyncratic developments in some segments, which may also call for some corrective policy action.[4] The idiosyncratic nature of signals, however, may limit the scope of application of the countercyclical capital buffer, and other macroprudential measures may be preferred in this case.

### 3.2 Variable Selection

Once a researcher opts for one of the existing financial cycle concepts, she should not step out of the outlined territory. In this light, the main criterion for considering a variable a good candidate is that its information content should be in line with the definition of the financial cycle provided above. The way we read the definition suggests that attention should be directed mainly at variables which monitor the *build-up* rather than the *materialisation* of risks. Risk materialisation indicators usually lag behind the cycle, as outlined above, or are even completely inverted in phase, as they often attain their most optimistic levels in the risk accumulation phase.[5]

From this perspective, the variables characterising the financial cycle can be viewed as a set of forward-looking indicators of potential problems in the economy. Indeed, as already suggested,

[4] In contrast to common factor models, idiosyncratic developments should not automatically be seen as noise, as they may still contain valuable information from the macroprudential perspective.

[5] We would argue that bundling together risk accumulation and risk materialisation indicators lacks theoretical interpretation and cannot result in any meaningful measure.

studies on early warning systems generally find that variables connected with changes in risk perceptions – such as the rate of growth of credit to the private sector, the debt and debt-servicing ability of the private sector, property prices, the tightness of the credit conditions and the current account deficit or government debt level – are suitable indicators of future financial crises (see, for example, Leaven and Valencia, 2010, Reinhart and Rogoff, 2011, and Babecký et al., 2013).

The variables used to identify the Czech Republic's position in the credit cycle largely correspond to those listed in the above studies, taking into consideration data availability and quality.[6] We tried to cover the widest possible area of the economy that might be affected by changes in risk appetite, i.e. the credit demand and supply sides, property prices, debt sustainability and general financial market sentiment. Wherever it makes sense, the input variables are compiled separately for the non-financial corporations sector and the household sector to make it easy to distinguish between sectoral tendencies and tendencies at the whole-economy (whole-private-sector) level.

A list of the input variables together with the adjustments made to them can be found in Table 1. The ranking of the variables in the table reflects our expert assessment of their relevance to the identification of the individual phases of the financial cycle (arguably subjective but quite in line with the existing literature), but it also takes into account the quality of the data.[7] A brief rationale for including each variable in the composite indicator is given in the following paragraphs.

***Table 1: Definition of Input Indicators***

| | **Indicator** | **Original units and adjustments made** |
|---|---|---|
| 1 | New bank loans to households | CZK bn, annual moving sum of monthly new loans |
| 2 | New bank loans to non-financial corporations | CZK bn, annual moving sum of monthly new loans |
| 3 | Property prices (inflation) | y-o-y change in price index |
| 4 | Household debt/gross disposable income | bank loans/moving annual total, y-o-y change, % |
| 5 | Non-financial corporations' debt/gross operating surplus | bank loans/moving annual total, y-o-y change, % |
| 6 | Spread between rate on new loans to households and 3M PRIBOR | % p.a., computed from quarterly average rates |
| 7 | Spread between rate on new loans to NFCs and 3M PRIBOR | % p.a., computed from quarterly average rates |
| 8 | PX stock index | three-month average |
| 9 | Adjusted current account deficit/GDP | % p.a., adjusted for reinvestment and transfers |

***Source:*** CNB and CZSO, authors' calculations

### Evolution of (new) Loans to Households and Non-financial Corporations

Many studies have shown that excessive credit growth is one of the best explanatory variables for future problems in the financial sector (see Drehmann and Borio, 2009, and Babecký et al., 2013). This fact is linked with the procyclicality of the financial sector, as economic agents usually display a decreasing ability to recognise risks at times of economic growth and optimistic expectations. Faced with the prospect of rising future incomes, both households and firms are more willing to borrow. Analogously, lenders may be more willing (or may be exposed to strong incentives) to lend to riskier clients. The amount of new bank loans in a given period is used as an indicator of credit growth. Unlike the year-on-year change in the stock of loans, this indicator is not affected by the exclusion of bad loans from banks' balance sheets or by regular repayments of

[6] The choice of variables would be rather different for other countries where the data quality is higher and longer time series for relevant indicators are available. Some very useful variables (e.g. the debt service ratio) could not be used in our case, since the time series necessary for their calculation start only in 2004.

[7] This ranking is used later in simulating the weights of the input variables in the resulting composite indicator (for more details, see section 3.4).

existing loans. The sizeable structural break in the stock of loans within our data sample was also the main reason why indicators such as the credit-to-GDP ratio are not included in the FCI.[8]

**Property Prices (changes in the property price index)**

Many studies consider property market imbalances – associated with sharp growth in residential and commercial property prices – to be a factor that accompanies, or significantly accelerates, the onset of most financial crises (see, for example, Giese et al., 2013, Drehmann et al., 2012, and Allen and Rogoff, 2011). Cheap financing in an optimistic phase of the financial cycle can push demand and prices above a sustainable level. The growth in prices can stimulate further credit expansion as a result of rising collateral value and the income effect on consumers (Bernanke and Gertler, 1995). The return to equilibrium is usually accompanied by negative effects on banks' balance sheets and by investment pessimism. As in Ng (2011), we use the year-on-year change in the property price index to capture imbalances in the property market (the index tracks property transaction prices as monitored by the CZSO on the basis of tax returns).

**Debt Sustainability (ratio of households' debt to gross disposable income, ratio of non-financial corporations' debt to gross operating surplus)**

Rapid growth in the ratio of household debt to gross disposable income can signal that economic agents are overestimating their future ability to repay their debts. Higher growth in debt than in disposable income means that households may spend an increasingly large proportion of their income in the future on repaying their loans. If their income situation turns out worse than they expected, they will often become insolvent. The relationship between households' debt-to-disposable-income ratio and credit risk is described, for example, by Rinaldi and Arellano, 2006.

A similar line of reasoning applies to the ratio of debt to gross operating surplus of non-financial corporations. In this case, moreover, the aspect of debt repayment sustainability is magnified by the fact that firms' total profit, which can be affected by variable or one-off items, does not figure in the denominator. In a converging economy the relative debt level of the private sector is constantly rising, so in this case falling risk aversion is measured using year-on-year changes, i.e. using the rate of growth of debt relative to income. Owing to the short time series available, total debt is proxied by bank loans only. However, as bank loans are the main source of external financing of the real sector, the informative value of these indicators should still be high.

**Lending Conditions**

Lending conditions characterise financial risk perceptions on the credit supply side and feature among the suitable indicators of future crises (Giese et al., 2013). In the growth phase of the cycle, banks may encourage less creditworthy and more risky clients to borrow by offering low interest rates, but they have a tendency to underestimate the level of risk involved. In the risk materialisation phase, by contrast, banks may tighten their lending conditions too much, leading to perceptible constraints on the financing of the sound part of the real sector (a credit crunch). As the bank lending survey in the Czech Republic has too short a history, the lending conditions are approximated using the difference between the interest rate on new loans to households/non-

[8] On the other hand, figures for new credit can be tainted by the phenomenon of loan refinancing, i.e. by the situation where one bank takes over a client's debt from another bank to enlarge its credit portfolio (refinancing becomes part of the "new credit aggregate" despite the fact that no additional credit was extended to the sector in economic terms). Since the available data do not allow the series to be adjusted for this phenomenon, one should take it into account when interpreting the final outcome.

financial corporations and the three-month inter-bank rate (PRIBOR). Plašil et al. (2013) demonstrate that this simple approximation reproduces the results of the euro area survey relatively reliably.

**Stock Index (PX)**

Some studies (see, for example, Borio, 2012) indicate that equity price volatility is not necessarily linked directly with the financial cycle as it is determined more by the business cycle. However, the stock index may complete the overall picture of the nature of market participants' expectations and reveal over-optimism about future asset prices.

**Adjusted Current Account Deficit-to-GDP Ratio**

A current account deficit can be interpreted as meaning that more is invested in the economy than the private sector and the government save together. This may indicate the formation of external imbalances, overheating of the economy, and growth in future problems repaying loans financed by capital inflows from abroad (Giese et al., 2013). The current account also contains the income balance, which in turn has a reinvested earnings item. Countries which in past years attracted high FDI inflows (such as the Czech Republic) may face rising current account deficits due to growth in their income deficits. If, however, such deficits are driven by reinvested earnings the growth is rather optical and does not mean a worsening external imbalance, because the reinvested earnings return to the host economy in the form of FDI. In other words, this is a relatively safe (though not entirely risk-free) source of capital. The current account also contains the balance of current transfers, which is determined primarily by the government sector income item (which often reflects random administrative factors). For this reason, the ratio of the current account to GDP was adjusted for the balance of reinvested earnings and the balance of transfers so as not to be distorted by these factors.

## 3.3 FCI – the Composite Indicator

Before aggregation, the input variables are first transformed into the unit interval (0, 1) using the kernel estimate of the cumulative distribution function (Gaussian kernel). The lowest value of the transformed variable corresponds to the trough of the cycle and the highest value to the peak (see Figure 1).[9] This step represents a form of standardisation of the input variables, making their values mutually comparable. Mapping to the unit interval also facilitates subsequent interpretation of the FCI, as it provides a clearer idea about what is a low value and what is a high one. Note, however, that the transformation is based on historical distributions and as such is sample dependent.[10] As new data arrive, the historical quantiles may change considerably, which in turn implies undesirable ex post revisions of past FCI values in real-time applications. While this may raise some concerns in general, we do not consider it a serious issue in our setting. The main reason for this is that we are chiefly interested in monitoring *future* developments. Given that our sample covers the last credit expansion and the subsequent return to the trough, we tend to argue

[9] The original CISS applies a rather simpler transformation using the empirical cumulative distribution function. Some of the variables (spreads, current account deficit/GDP) had to be multiplied by a coefficient of -1 before the transformation itself so that low financial risk aversion corresponded to higher values for all the variables.

[10] We are not the first to propose a measure of the financial cycle based on the comparison of indicators with their own history and subsequent aggregation – see Rychtárik (2014). However, the mapping and the aggregation algorithm (as well as our conceptual approach to the variable selection) are different in our case.

that all future values are well anchored by the sample.[11] However, even if revisions to the past values of the FCI were to occur in future, the comparison of the actual value with those around the last peak of the cycle would still bear valuable information.

Once the variables have been transformed into the unit interval, the aggregation method can be expressed using the following formula (see Holló et al., 2012)

$$FCI_t = (w \circ s_t)' C_t (w \circ s_t), \tag{1}$$

where a vector of weights, $w = (w_1, w_2, \ldots, w_9)$, indicates the relative importance of the individual variables (subindicators), $s_t = (s_{1,t}, s_{2,t}, \ldots, s_{9,t})$ is the vector of subindicators at time $t$ and $(w \circ s_t)$ represents the element-by-element multiplication of these vectors (also known as the Hadamard-product). Matrix $C_t$ contains the values of the pairwise correlation coefficients $\rho_{t,ij}$ determining how strong the relationship between subindicator $i$ and $j$ is at time $t$. Using aggregation (1), the result is a composite indicator defined on the interval (0, 1). The higher is the indicator, the higher is the degree of financial risk tolerance generally observed among market participants in the economy.

One of the main features of the chosen aggregation method is that it takes account of the time-varying cross-correlation structure of the data. The FCI generally takes higher values when variables are rising across all monitored segments. The stronger are the correlations between all the transformed variables (subindicators), the stronger is the signal sent out by the FCI about overall changes in sentiment over the cycle. This property is useful from the macroprudential perspective, in particular for setting the countercyclical capital buffer. As discussed in previous sections, the latter should be imposed in the event of general growth in cycle-related risks. If the growth is due to only some of the monitored segments (for example, only growth in mortgage loans to households) it may be more appropriate to use a different prudential tool to eliminate the nascent risks.

In addition to the cross-correlation structure, which characterises the interactions between individual segments and thus offers a cross-sectional view of the risks, the resultant aggregation captures the time dimension of risk.[12] The latter is given by the magnitude of the subindicators themselves. Their differing importance can be reflected in the resultant aggregation using a system of weights $w$.

It is useful to demonstrate the properties of the FCI using a simplified example. If the composite indicator were based on the aggregation of just three subindicators, its resultant value could be written in the following form:

---

[11] Current experience seems to support this claim, as ex post revisions of the past values of the FCI were negligible when data for 2013Q4–2014Q4 were added to the sample (not reported).

[12] Definitions of the time and cross-sectional dimension of risk can be found in Frait and Komárková (2012). In this paper, however, the cross-sectional dimension of risk is defined rather differently. The original concept defines the cross-sectional dimension as the degree of financial interconnection between economic agents, which can generate financial risks, whereas here the cross-sectional dimension is taken to mean the degree of interconnection between the various aspects of financial risk, which can amplify the overall level of financial risk.

$$\begin{aligned} FCI_t = {} & \left(w_1 s_{t,1} + w_2 \rho_{t,12} s_{t,2} + w_3 \rho_{t,13} s_{t,3}\right) w_1 s_{t,1} + \\ & + \left(w_1 \rho_{t,12} s_{t,1} + w_2 s_{t,2} + w_3 \rho_{t,23} s_{t,3}\right) w_2 s_{t,2} + \\ & + \underbrace{\left(w_1 \rho_{t,13} s_{t,1} + w_2 \rho_{t,23} s_{t,2} + w_3 s_{t,3}\right)}_{\text{Weight characterising cross-sectional dimension of financial risk}} \underbrace{w_3 s_{t,3}}_{\text{Weight characterising time dimension of financial risk}} \end{aligned} \qquad (2)$$

It is clear from (2) that the total weight of a subindicator in the FCI is given not only by the weights *w* themselves, but also by the value of the expression in parentheses, which in turn depends on the magnitude of the correlations between the given subindicator and other variables. If, for example, subindicator $s_3$ is not correlated with indicators $s_1$ and $s_2$, its contribution to the FCI will be lower. Thus lower correlation represents a negative contribution to the final value of the FCI.

A special case is the situation where the correlation between all the subindicators is equal to one (perfect correlation), so that the FCI attains its upper bound with respect to the values of the subindicators. Comparing the current value of the composite indicator with its hypothetical maximum helps to determine the extent to which the imperfect correlation structure reduces the FCI value, i.e. it allows us to calculate the "signal loss" implied by imperfect synchronisation of individual signals over the cycle. The overall value of the FCI can therefore be broken down into the positive contributions given by the subindicator values and the negative contribution (loss) that depends on the cross-correlation structure of the data. The lower are the observed correlations between the subindicators, the larger is the negative contribution (in absolute terms).

The illustration (2) shows that a set of variables that are strongly positively correlated with each other will have larger positive effect on the final value of the FCI. In other words, variables exhibiting strong co-movement will (other things being constant) contribute most to the value of the FCI. On the contrary, its value can be substantially reduced when developments across segments are mixed and there is no clear signal about the current direction of risk perceptions. This behaviour can be loosely interpreted as meaning that the FCI captures the effect of the latent factor causing the variables to co-move upwards.

Speaking of latent factors, the FCI may offer several advantages over the factor models commonly used to gather information on the co-movement of variables:

- With the short time series typical of most transforming economies, including the Czech Republic, it is difficult to verify (or ensure) the validity of the statistical assumptions needed to estimate factor models. The construction of the FCI may be less problematic in this regard.

- The output in the form of the FCI is more intuitive in nature and more intuitive to interpret, so it is more suitable for communication purposes. The proposed technique makes it easy to break down the indicator into the contributions of individual components and the effect of the correlations between the variables.

- A factor model (or the rather frequently used principal components) seeks to maximally reproduce the variability of the original data with a smaller number of artificial variables. However, this objective does not take into account whether the estimated factors display good predictive properties for some selected variable. By contrast, using an estimated correlation structure, the FCI allows us to set the time weights, *w*, on the variables optimally (in some sense), for example with the objective of best estimating future loan losses. In the case of the FCI, variables that have high loadings on the factor (e.g. the first principal component) can have a minimal weight if they do not help to explain the materialisation of credit risk.

- Basic factor models usually assume a constant cross-correlation structure over time and hence constant relationships between the variables. In the case of the FCI, by contrast, the identification of changes in the cross-correlation structure is an important output, as it helps in identifying the individual phases of the financial cycle and reveals the formation of non-linearities.

### 3.4 FCI – Calibration and Results for the Czech Economy

The Czech data relevant for the FCI do not have too long a history and suffer from structural breaks and lower reporting standards at the beginning of the sample. Constructing the FCI from the time series for the period 2000Q1–2013Q3 offers a reasonable compromise between data length and data quality (see Figure 1). To suppress the effect of the convergence of the Czech economy, variables that display constant upward growth trends due to a low initial level are expressed as year-on-year changes (see Table 1 for the adjustments made).

Synchronisation of variables during the cycle can be demonstrated using historical quantiles. The left panel of Figure 2 shows the number of variables exceeding the 80th quantile in the given period and the right panel depicts the number of variables below the 15th quantile. These quantities might serve as a simple measure of co-movement in the expansionary and recessionary phases respectively. The dynamic nature of the relation between the variables can be readily observed, pointing to a need to model this feature explicitly. Within the FCI methodology this phenomenon is formally captured by time-varying correlations.

The time-varying correlation coefficients were estimated recursively using the exponentially weighted moving average (EWMA) method with smoothing factor $\lambda = 0.94$ (RiskMetrics, 1996). If the covariance $\sigma_{ij}$ and variance $\sigma_i^2$ (or $\sigma_j^2$) at time *t*–1 are known, the correlation coefficient $\rho_{t,ij}$ can be approximated using the following formulas:

$$\sigma_{t,ij} = \lambda\sigma_{t-1,ij} + (1-\lambda)\tilde{s}_{t,i}\tilde{s}_{t,j}$$

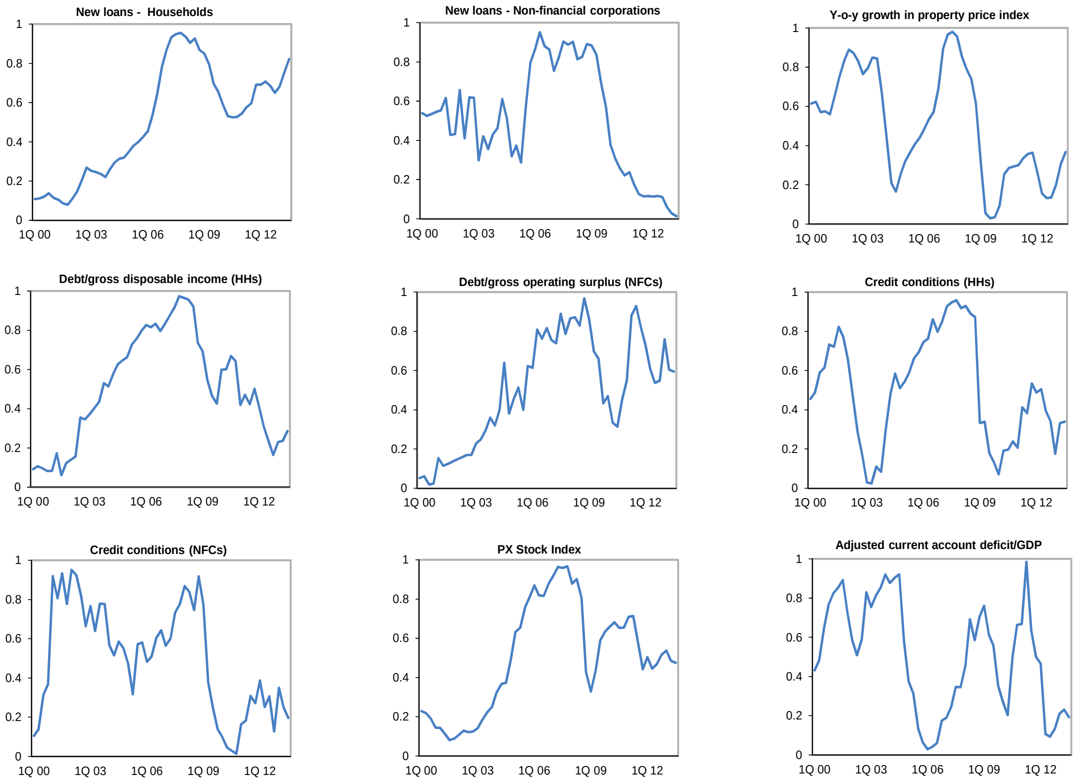
$$\sigma_{t,i}^2 = \lambda\sigma_{t-1,i}^2 + (1-\lambda)\tilde{s}_{t,i}\tilde{s}_{t,i}$$

$$\rho_{t,ij} = \sigma_{t,ij}/(\sigma_{t,i}\sigma_{t,j})$$

where, in line with Holló et al. (2012), $\tilde{s}_{t,i} = (s_{t,i} - 0{,}5)$ denotes the values of the individual subindicators after subtracting their "theoretical" median. The initial values of the correlation coefficients at time $t = 1$ were also estimated using the EWMA method applied to the time series in reverse order from the most recent observation to the oldest.[13]

[13] This is not necessarily a very precise approximation of the initial values, but we are mainly interested in the relative value of the correlations vis-à-vis their value in other periods, rather than their absolute value.

***Figure 1: Input Variables after Their Mapping on Interval (0,1)***




The easiest way to calibrate vector $w$ would be to assign equal weights to each subindicator. However, with regard to the intended use of the FCI for setting the countercyclical buffer, we opt for a more targeted approach which incorporates prior expert knowledge and calibrates the weights of the FCI with respect to its predictive performance in terms of future credit losses. Expert knowledge is expressed in terms of *a priori* constraints on the vector of weights, which can be captured by the following inequality

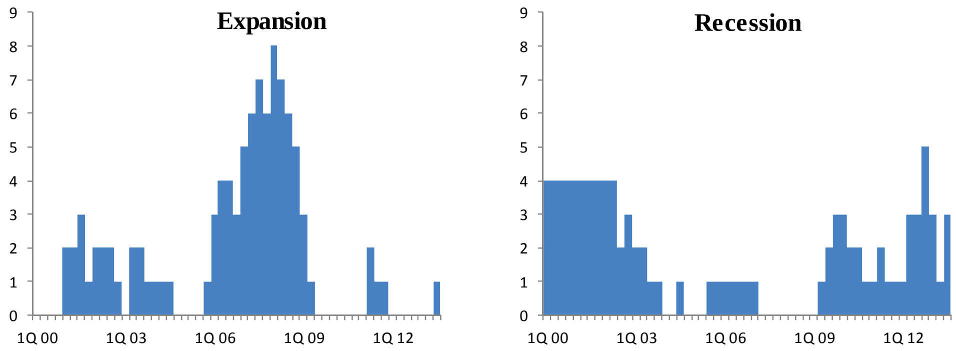
$$w_1 \geq w_2 \geq w_3 \geq \cdots \geq w_9, \tag{3}$$

where the subscripts correspond to the indicator ranking in Table 1. These constraints were imposed in order to reflect current literature and avoid unintuitive results. Note that our *a priori* assessment of the relevance of each variable does not rule out the possibility that all the variables have the same weight.

The final calibration of the vector was determined by means of simulation techniques. A total of 30,000 different weight distributions satisfying (3) were simulated and we chose the vector which, after substitution into equation (1), gave the best predictions of loan loss impairments in the Czech banking sector six quarters ahead (in terms of RMSE).[14] The chosen number of quarters reflects the fact that when a non-zero countercyclical capital buffer is announced, banks need at least one year to implement it. To this period one also needs to add the data publication lag and the time needed to make the decision to set the capital buffer.

[14] As an alternative, the weights were determined with regard to the predictive power of the FCI for the 12-month default rate in the non-financial corporations sector and for the first difference of the ratio of non-performing loans to total loans in the private sector. The results were similar.

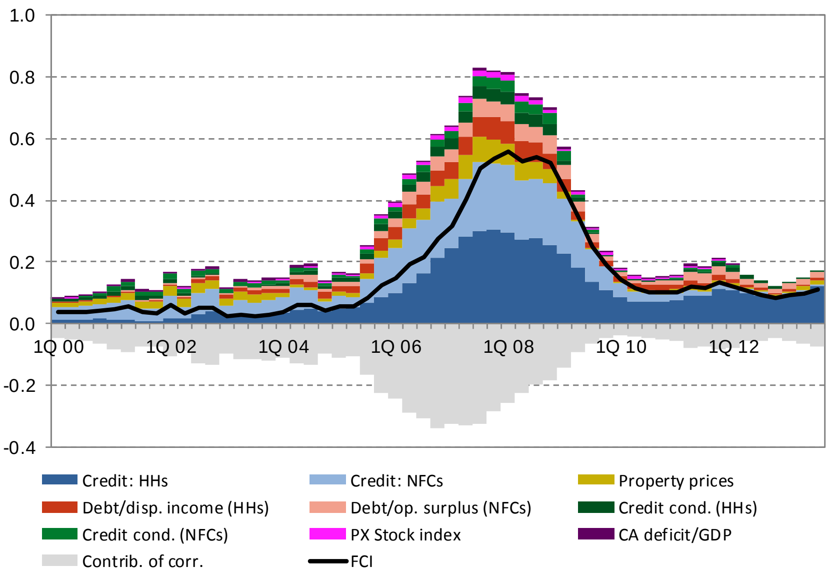
***Figure 2: Simple Descriptive Measures of Co-movement***




***Note:*** Expansion is measured as the number of indicators exceeding the 80th quantile. By contrast, recession is gauged by the number of indicators below the 15th quantile.

The estimated weights[15] $w$ = (0.35 0.27 0.09 0.08 0.07 0.05 0.05 0.02 0.02) indicate that credit dynamics provide the main signal for forecasting the materialisation of financial risks, as loans to households and non-financial corporations together have a weight of over 60% in the composite FCI. Using the estimated weights $w$ and the correlations $C_t$ the FCI values can be obtained according to (1). Figure 3 shows the evolution of the FCI (the black line) along with its decomposition into individual contributions (the bar chart).

***Figure 3: The FCI and its Decomposition***




***Note:*** Minimum FCI = 0, maximum = 1. The negative contribution of the cross-correlation structure to the FCI (the loss due to imperfect correlation of the subindicators) is due to the difference between the current FCI value and the potential upper bound. Highly negative contributions indicate a generally weak correlation between the subindicators, whereas near-zero contributions indicate growing interconnectedness in individual areas of financial risk.

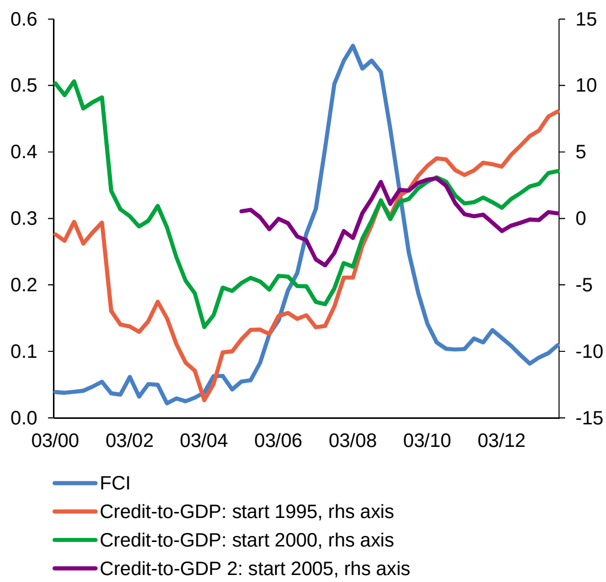
The results show that the FCI was very low until roughly the end of 2005. This reflected high financial risk aversion linked with the late-1990s banking crisis and the subsequent consolidation

[15] The weights are rounded and their order corresponds to that in Table 1. Rounded values were used to calculate the FCI.

of the banking sector, which took until the start of the new millennium to complete. The period of 2005–2008 can be described as an expansionary phase of the financial cycle, with an economic recovery accompanied by gradually rising optimism and risk tolerance. Among other things, the expansion was fostered by growing popularity of mortgage loans along with quite a strong construction boom and growth in property prices.[16] In this period, bank clients showed a greater willingness to borrow despite the risks associated with future debt service. As time went on, this willingness was also fostered by banks themselves through ever weaker lending conditions. Late 2008/early 2009 can be identified as the peak of the cycle. This was followed by a rapid switch to a downward phase of the cycle as a result of (the effects of) the financial crisis impacting on the Czech economy. The latest figures indicate that the Czech economy has been at the bottom of the financial cycle for some time now and is not showing any signs of accumulation of cyclical risks.[17]

The evolution of the FCI from the perspective of the cross-correlation structure and its contributions suggests that in the initial expansion phase (i.e. roughly between 2005 and 2007) the individual subindicators displayed quite mixed trends and the overall correlation between them was relatively low. This hindered growth in the composite indicator and manifested itself in a large difference between the upper bound and the actual value of the FCI (see Figure 3). By contrast, the peak phase of the cycle (2008/2009) was accompanied, in addition to growth in the contributions of the individual subindicators, by overall growth in the pairwise correlations, pushing the FCI value upwards and providing a stronger signal of risk accumulation. The correlations were still rising during the acute phase of the recession, when all the subindicators were falling together.

***Figure 4: Comparison of the FCI and Credit-to-GDP Gaps***




***Note:*** The HP filter with smoothing constant 400,000 was used to obtain the credit-to-GDP gap. Three different starting dates were considered.

[16] Hlaváček and Komárek (2009) point to some overvaluation on the property market in 2007 and 2008. This reflected, among other things, a pre-announced increase in VAT on residential property construction.

[17] In recent years, moreover, the FCI values have been further overestimated due to the phenomenon of mortgage refinancing, which is inflating the total amount of new loans to households. It is not yet possible to fully filter out this effect on the basis of the available statistics.

Overall, the path of the FCI indicator closely matches the retrospective views of experts on cyclical developments and seems to capture global changes in risk perceptions fairly well. To demonstrate its potential in the domain of macroprudential policy it is worth comparing it with the benchmark macroprudential indicator for setting the countercyclical capital buffer rate, namely the HP filtered credit/GDP gap with lambda set to 400,000 (see Figure 4). One can see that the latter is highly misaligned with the generally accepted course of the cycle even if one accounts for the "starting point problem" as proposed in Drehmann and Tsatsaronis (2014).[18] Given the length of the available sample it can hardly be applied in Czech macroprudential practice. On the contrary, the FCI provides a very promising output. This issue is studied more formally in Section 5, where we analyse its predictive properties.

# 4. Financial Cycle and Rating Migrations

This section takes a distinctly different approach to the measurement of the financial cycle and focuses on migration flows between different risk categories and their potential to capture financial cycle fluctuations. The cyclical behaviour of default rates and, more generally, loan migration has been well documented in the literature.[19] Interestingly, it has been shown that this cycle seems to have its own morphology which cannot be fully related to macroeconomic or business cycle developments. Empirical studies employing exclusively observable macroeconomic variables to model default or transition rates have been contested due to the negligible significance of those variables in the model specification. For example, Koopman et al. (2008) and Koopman et al. (2009) estimate an intensity model with observed and unobserved risk factors and show that regressing the "credit risk" cycle exclusively on observable macroeconomic variables results in a dynamically misspecified model. Furthermore, once an unobserved systematic risk factor is added into the model, most macro variables lose their statistical significance.[20] Similarly, Bruche and Aguado (2010) estimate a model of the joint time-variation in default rates and recovery rate distributions via an unobserved Markov chain, which outperforms models driven purely by observed macroeconomic variables. Das et al. (2007) produce evidence that apart from the macroeconomic and other covariates that they use to model default intensities, there are unobserved covariates or factors that drive default probabilities. Hence, given this empirical evidence, latent factor models seem to be a possible tool for evaluating the credit/financial cycle.

## 4.1 Data and Methodology

Our dataset on credit migration contains monthly observations of transition flows over the period 2002m1–2014m3, which were obtained from data in the Czech Central Credit Register (CCR). The CCR is a comprehensive database collecting information on all loans extended by banks to

[18] As a rule of thumb, Drehmann and Tsatsaronis (2014) propose to use credit gaps only when at least 10 years of data are already available for the credit-to-GDP ratio. Another option is to drop the initial data points.

[19] From the literature focusing primarily on credit risk see, for example, Wilson (1997a, b), Nickell et al. (2000) and Bangia et al. (2002). Credit risk studies relying on a duration methodology include Kavvathas (2001), Carling et al. (2002), Couderc and Renault (2005), Duffie et al. (2009) and Figlewski et al. (2012). For research emphasising the macroprudential perspective, see Marcucci and Quagliariello (2009) and references therein.

[20] Stefanescu et al. (2009) allow for a latent factor capturing macroeconomic shocks and find that the model with the best out-of-sample forecasts keeps both the observed macro covariates and the unobserved macroeconomic shock.

non-financial corporations. The ratings follow the official categorisation used by the Czech National Bank, which divides loans into five credit ratings – standard, watch, substandard, doubtful and loss.[21] To get a rough idea of the transition patterns, Table 2 lists the average transition rates over the sample period.

***Table 2: Average Transition Rates between CNB Loan Ratings over 2002m1–2014m3***

| | Standard | Watch | Substandard | Doubtful | Loss |
|---|---|---|---|---|---|
| Standard | 0.993 | 0.005 | 0.001 | 0.000 | 0.000 |
| Watch | 0.061 | 0.907 | 0.022 | 0.002 | 0.001 |
| Substandard | 0.019 | 0.025 | 0.911 | 0.031 | 0.007 |
| Doubtful | 0.009 | 0.005 | 0.024 | 0.893 | 0.062 |
| Loss | 0.001 | 0.000 | 0.001 | 0.001 | 0.997 |

The time series for the individual transition flows were obtained by taking six-month moving averages of the monthly series in order to reduce their volatility. Given that for a specific rating the sum of the transition probabilities must equal 1, we further follow Wei (2003) and additionally transform the transition rates by using the inverse of the cumulative distribution function of the standard normal distribution. This maps the transition probabilities onto the real-line support. For a given rating class and starting with the standard loans category, we thus calculate a z-score for transitions into each of the five categories. We further assume that deviations from the (transformed) long-term mean of the transition probabilities are driven by a common factor and a rating-specific factor (Belkin et al., 1998; Wei, 2003):

$$z_{ij,t} - \bar{z}_{ij} = f\left(F_t, G_{i,t}, \mathbf{\Delta}\right) + \varepsilon_{ij,t}\ ,\ i = 1, \dots, 5\ \ j = 1, \dots, 4\ ,$$

where $z_{ij,t}$ represents the z-score of a transition from rating $i$ to rating $j$ at time $t$, $\bar{z}_{ij}$ is the long-term average, $F_t$ is the common factor and $G_{i,t}$ the rating-specific factor, $\mathbf{\Delta}$ is a vector of unknown parameters (loadings) and $\varepsilon_{ij,t}$ is an idiosyncratic component.[22] Assuming positive loadings, a positive value of factor $G_{i,t}$ means that $z_{ij,t} - \bar{z}_{ij}$ is also more likely to be positive (depending on the shock $\varepsilon_{ij,t}$), i.e. $z_{ij,t}$ tends to exceed the long-term average for the considered transition *i,j*.

A higher value of $j$ for a given $i$ represents a move to a lower rating category (using the notation of Table 2). As each $z_{ij,t}$ is linked to the cumulative distribution function of the standard normal distribution, it can be interpreted as the borderline between transitions from a fixed $i$ to better (or equal) ratings $\tilde{j} \leq j$ and worse ratings $\tilde{j} > j$. Decreasing factor values thus generally imply a shift of transitions towards lower ratings. On the other hand, an increase in the factor loadings shifts the respective z-scores on the standard normal support to the right, ascribing a larger mass to transitions to higher ratings. The estimated factors thus have a straightforward interpretation in terms of the change in the quality of the aggregate credit portfolio and more generally of the credit cycle.

[21] In the following text, categories with riskier loans are referred to as lower ratings (e.g. the loss loans category corresponds to the lowest rating).

[22] Note that the transformation into z-scores creates a new matrix of dimensions K x K-1, where K is the number of rating classes.

We estimate factors $F_t$ and $G_{i,t}$ with the dynamic hierarchical factor by Moench et al. (2013)[23]

$$
\begin{aligned}
&z_{ij,t} - \bar{z}_{ij} = \alpha_{ij} G_{i,t} + \varepsilon_{ij,t}, \\
&G_{i,t} = \beta_i F_t + \varepsilon_{G_{i,t}} \\
&F_t = \gamma_F F_{t-1} + \varepsilon_{F_t} \\
&\varepsilon_{F_t} = \gamma_{e_F} e_{F_{t-1}} + \epsilon_{e_{F_t}}, \qquad \epsilon_{e_{F_t}} \sim N(0, \delta^2_{e_F}) \\
&\varepsilon_{G_{i,t}} = \gamma_{e_{Gi}} \varepsilon_{G_{i,t-1}} + \epsilon_{G_{i,t}}, \qquad \epsilon_{G_{i,t}} \sim N(0, \delta^2_{e_{Gi}}) \qquad i = 1, \dots, 5 \\
&\varepsilon_{ij,t} = \gamma_{\varepsilon_{ij}} \varepsilon_{ij,t-1} + \epsilon_{\varepsilon_{ij,t}}, \qquad \epsilon_{e_{ij,t}} \sim N(0, \delta^2_{e_{ij}}) \qquad j = 1, \dots, 4.
\end{aligned}
$$

The advantage of the hierarchical model structure is its flexibility. In particular, the multilevel model structure assumes that a common factor $F_t$ affects all rating classes through rating-specific factors $G_{i,t}$, which map onto z-score deviations through different loadings for each transition $j$ in a given rating $i$. The rating-specific factors are thus not independent of the common factor $F_t$ and partly reflect economy-wide developments. In other words, each transition probability depends on the global factor approximating the state of the macroeconomy and potentially on the credit cycle (not identified separately). This relationship nonetheless applies only indirectly through the global factor's link to a relevant rating-specific factor. Rating-specific factors might in addition reflect developments in the credit cycle that go beyond the macro or general credit cycle dynamics. The dynamics of rating-specific factors will thus tend to reflect patterns peculiar to the credit cycle as opposed to general macroeconomic trends.

## 4.2 Results

Figure 5 presents the estimated global and rating-specific factors over the sample period. The identification restriction of lower triangular factor loading matrices implies that the systematic factor $F_t$ closely determines (up to the random component $\varepsilon_{F_t}$) the rating-specific factor $G$ for standard loans. Both factors fluctuate around zero, with a more pronounced shift towards higher rating classes only after early 2011, two years after the start of the economic downturn.[24] More importantly, one can observe sharp declines in rating-specific factors located closer to the default boundary, i.e. watch, substandard and doubtful. All three factors follow a declining pattern, i.e. a shift of transitions towards lower categories, over the second half of the sample and in particular after the onset of the economic downturn at the beginning of 2009.

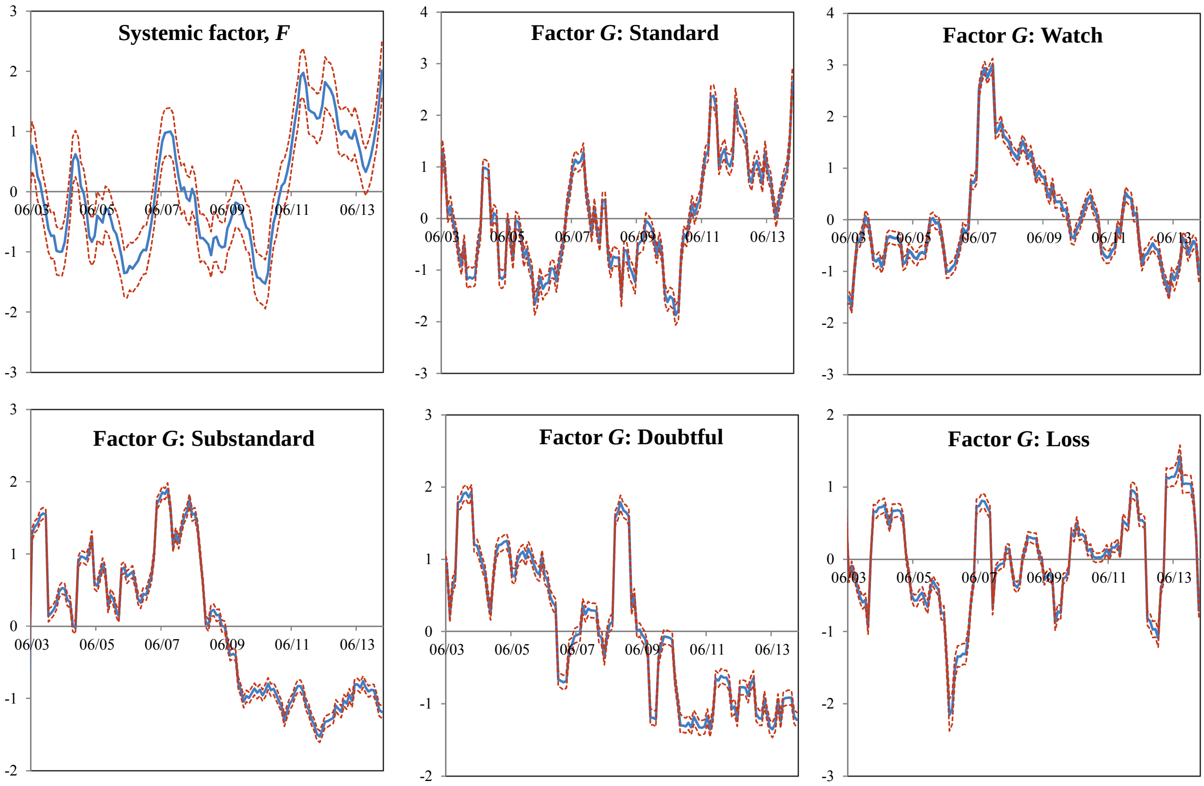
The break occurs with a notable lead for the boundary categories watch and substandard. The two categories represent borderline cases between performing and non-performing loans and their definitions leave some scope for pre-emptive reclassification by banks. In particular, watch loans are performing loans defined as likely to be fully repaid, yet with minor repayment problems, each less than 90 days due.[25] The substandard class refers to impaired loans for which full repayment is uncertain (yet highly likely) and repayment tranches are paid with minor problems, each less than 180 days due. In both cases, banks' expert knowledge of debtors' repayment capacity and more generally of the current phase of the credit cycle might lead to reclassifications even though the portfolio quality has not changed dramatically.

[23] See the Appendix for additional details on the estimation and model identification.

[24] The correlation coefficient between the real GDP y-o-y growth rate and the systemic factor $F$ is $\rho$ = -0.3.

[25] For a full definition of each loan category see Decree No.123/1997 on the prudential business conduct of banks.

***Figure 5: Estimated Systemic and Rating-specific Factors***



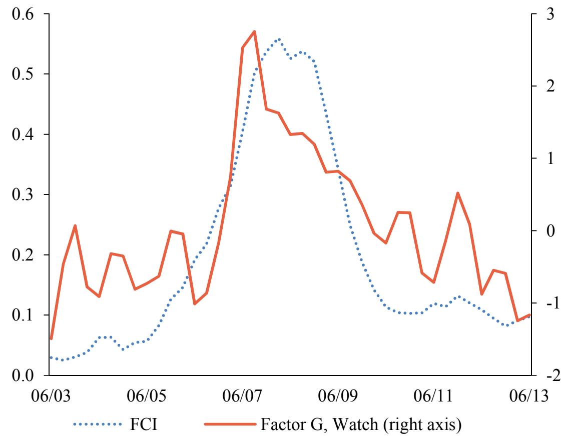

***Note:*** Red dashed lines: 5th and 95th quantile, blue line: mean

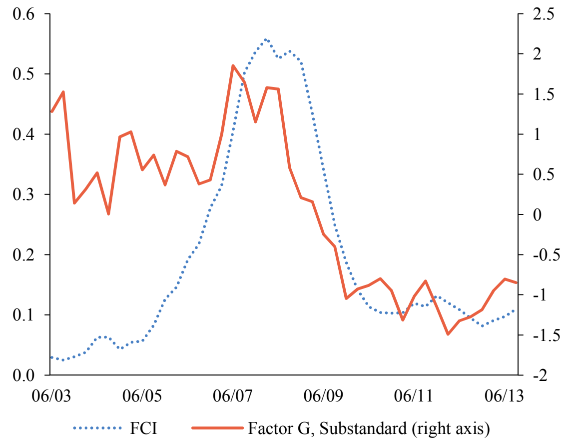
The leading properties of the rating-specific factors on watch and substandard loans are apparent in Figure 6, which compares the factor with the FCI indicator developed in the previous section. Given that the factor loadings on the watch factor are positive except for the loading on the z-score deviation separating standard and watch loans, one can conclude that while the second and third quarters of 2007 were marked by strong inflows into the watch category, from November 2007 onwards the transitions from watch loans started to move dramatically towards the default categories. The left panel of Figure 6 shows that the break coincided with developments in the FCI indicator, which was constructed from a different information set. Furthermore, and similarly to the FCI indicator, the break can be traced to several quarters before the actual increase in the NPLs of the Czech banking sector.

The right panel of Figure 6 compares the FCI indicator with the factor for the substandard category. The difference from the factor on watch loans rests in the level asymmetry before and after the spike in 2007Q4–2008Q4. In the former case, the factor followed a roughly similar path as the FCI indicator and maintained about the same levels before and after the elevated period. By contrast, the factor on substandard loans plummeted after 2008Q4 and remained well below its long-term average over the whole post-crisis period, reflecting a gradual deterioration in the quality of the aggregate credit portfolio. Despite the above-mentioned differences from the factor on watch loans, the results for substandard loans still provide the same qualitative pattern.

The results from the present section thus indicate that factor approximation of rating class dynamics using data from credit registers might provide complementary guidance on the position of the financial cycle. While the information from the global systemic factor does not follow a clear discernible pattern over the sample period, the rating-specific factors for loan classes closest to the default boundary might provide a useful departure point.

***Figure 6: Factor for Watch and Substandard Loans in Comparison with the FCI Indicator***




## 5. What the Proposed Cyclical Measures Can Say about Future Developments

Although the main purpose of the designed measures is different from forecasting, their predictive content with respect to some relevant quantities may be a positive side effect. As stated in Ng (2011), if the measures turn out to perform well for a policy-relevant purpose other than that for which they were constructed, then so much the better. In this section, we provide some elementary insights on this subject. In particular, we analyse the predictive performance of financial cycle measures with respect to growth in GDP and non-performing loans (as representatives of developments in the real economy and credit risk respectively).

The issue of how financial developments amplify fluctuations in the real economy has frequently been investigated (see, for example, Claessens et al., 2011, Ng, 2011, and Havránek et al., 2010), so it is natural to explore this option here. In addition, we analyse the predictive content with respect to growth in NPLs, since a fair estimate of its future path may provide a relevant quantitative link between the risk build-up phase and the size of the subsequent materialisation. This might be particularly useful for decisions on the appropriate policy reaction (for example, that on the setting of the appropriate countercyclical buffer rate).[26]

Given that the FCI measure and the estimated factors for watch and substandard loans exhibited very similar patterns, it might be expected that all of them perform similarly in the forecasting exercise. Since this has been found to be the case, in the following paragraphs we only present the results for the FCI indicator to save space (nevertheless, the results for other measures are available upon request for interested readers).

[26] Note that the weights *w* in the FCI were already chosen optimally with respect to the predictions for loan losses six quarters ahead. As loan losses and NPL growth are clearly correlated, there is a sort of circularity in this exercise. However, *optimal* values (leading to the minimum RMSE) do not necessarily imply *good* predictions. Thus, we still consider it useful to show how *good* the obtained optimum is.

It should be noted that our aim is *not* to obtain the best possible predictions of GDP and NPL growth on the market. Strictly speaking, what we do is not even a forecasting exercise in the real sense, because the estimated values of the proposed measures are based on the whole data set and would have taken different values had they been calculated in real time.[27] The following analysis is thus meant as a quick demonstration of whether the inclusion of financial cycle measures can help explain future developments in the variables under study. To this end, we limit our attention to a suite of very simple single-equation prediction models, which can be expressed in the form:

$$q_{t+h} = \beta c_t + \delta X_t + \varepsilon_t, \tag{4}$$

where $q_{t+h}$ is the variable of interest (either GDP or NPL) predicted at horizon $h$, $c_t$ is a measure of the financial cycle and $X_t$ is a set of additional regressors. In our exercise, we set the horizon $h$ to six quarters, as this is the time necessary for effective use of the countercyclical buffer (see the discussion in subsection 3.4) while it also roughly corresponds to the monetary policy horizon. For the sake of simplicity, we only consider the lags of the variable $q$ as additional regressors $X_t$ (up to the fourth lag). Given this setting, we are *de facto* interested in finding out if the inclusion of the financial cycle measure can bring some additional gains over the information content in the past values of the forecasted variable. To answer this question we use Bayesian model averaging and dynamic model averaging.

To assess the in-sample fit, we employ Bayesian model averaging (BMA; readers unfamiliar with the methodology are referred to Hoeting et al., 1999, and Koop, 2003). As a starting point, we argue that there is considerable prior uncertainty about which model is the "correct" one for predicting $q$ (i.e. GDP or NPL growth). In particular, we do not know if it should contain the financial cycle measure ($\beta \neq 0$) or not ($\beta = 0$) and, similarly, it is not clear whether the financial cycle measure should enter the model separately ($\delta = 0$) or in combination with at least some lagged values of the variable $q$ (some elements of $\delta$ are non-zero). We consider all models formed of any combination of the measure of the financial cycle and four lags of $q$ to be plausible and assume that they all are *a priori* equally likely. The key output of BMA is a posterior model probability for each model considered, which can be interpreted as the probability that the given model is the "correct" one given the observed data. Aggregation of posterior probabilities over all models containing the financial cycle measure then leads to its posterior inclusion probability, i.e. the probability that the measure is included in the model. The BMA results for both GDP and NPL growth are given in Table 3 and Figure 7.

One can clearly see that the posterior inclusion probability (PIP) of the FCI measure virtually equals one in both cases, delivering strong evidence of its good in-sample performance against purely autoregressive models. It is also apparent that the coefficient $\beta$ has the same sign across various model specifications, which is economically appealing (see Figure 7). By contrast, the coefficients $\delta$ frequently change their signs across lags and models, making their interpretation far less intuitive. The overall fit of the model (measured by pseudo R-squared[28]) is quite impressive for NPL growth, suggesting that our financial cycle measure may be very useful in explaining

[27] Splitting the sample into calibration and verification subsamples, however, would hardly have been possible in our conditions due to the short time series available. To obtain reasonable estimates of the cycle we need a span covering expansion and contraction phases. We do not use the vintage data which were available to policy makers at time *t*, either.

[28] Unity minus the posterior variance over the dependent variable.

credit risk materialisation. In the case of GDP growth, the overall predictive performance seems to be quite unsatisfactory even after the inclusion of the financial cycle measure. Besides the fact that it can be difficult to forecast GDP for longer horizons (especially when recession threats are *ante portas*), this may also point to non-linearities in the relation between real and financial developments. Recent experience suggests that they are usually little intertwined in normal times but their interplay may be substantial around the peak of the financial cycle.

***Table 3: BMA Estimates for Model (4)***

**Forecasted Variable: GDP**
(Pseudo R-squared = 0.31)

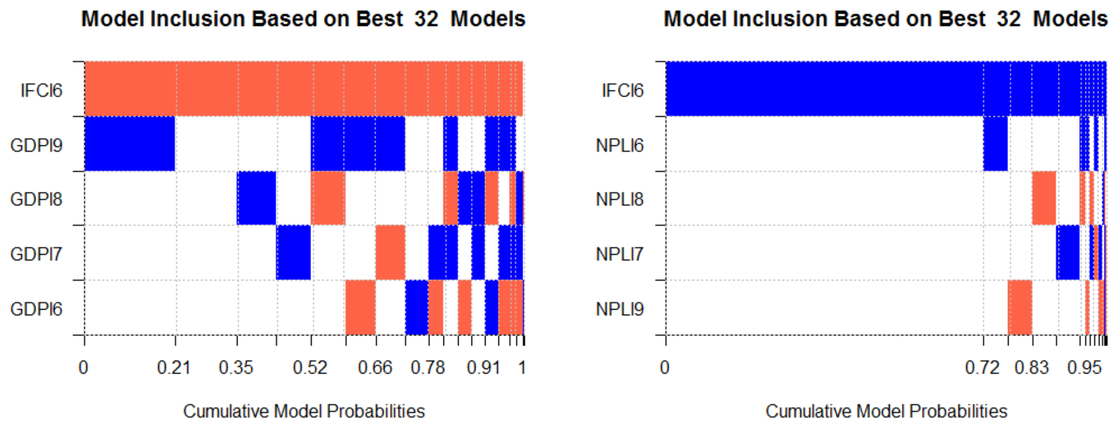
| | PIP | Posterior BMA Mean | Posterior BMA SD | Positive sign certainty |
|---|---|---|---|---|
| FCI_t-6 | 1.00 | -10.77 | 2.66 | 0.00 |
| GDP_t-6 | 0.27 | -0.01 | 0.12 | 0.30 |
| GDP_t-7 | 0.30 | 0.03 | 0.16 | 0.78 |
| GDP_t-8 | 0.32 | 0.00 | 0.18 | 0.52 |
| GDP_t-9 | 0.53 | 0.15 | 0.21 | 1.00 |

**Forecasted Variable: NPL**
(Pseudo R-squared = 0.92)

| | PIP | Posterior BMA Mean | Posterior BMA SD | Positive sign certainty |
|---|---|---|---|---|
| FCI_t-6 | 1.00 | 82.36 | 4.53 | 1.00 |
| NPL_t-6 | 0.09 | 0.01 | 0.04 | 1.00 |
| NPL_t-7 | 0.09 | 0.00 | 0.04 | 0.06 |
| NPL_t-8 | 0.08 | 0.00 | 0.04 | 0.87 |
| NPL_t-9 | 0.08 | 0.00 | 0.02 | 0.02 |

***Note:*** PIP stands for posterior inclusion probability; positive sign certainty (last column) indicates the probability that the coefficient on the given variable takes a positive value.

***Figure 7: Cumulative Posterior Model Probabilities for NPL and GDP Growth***

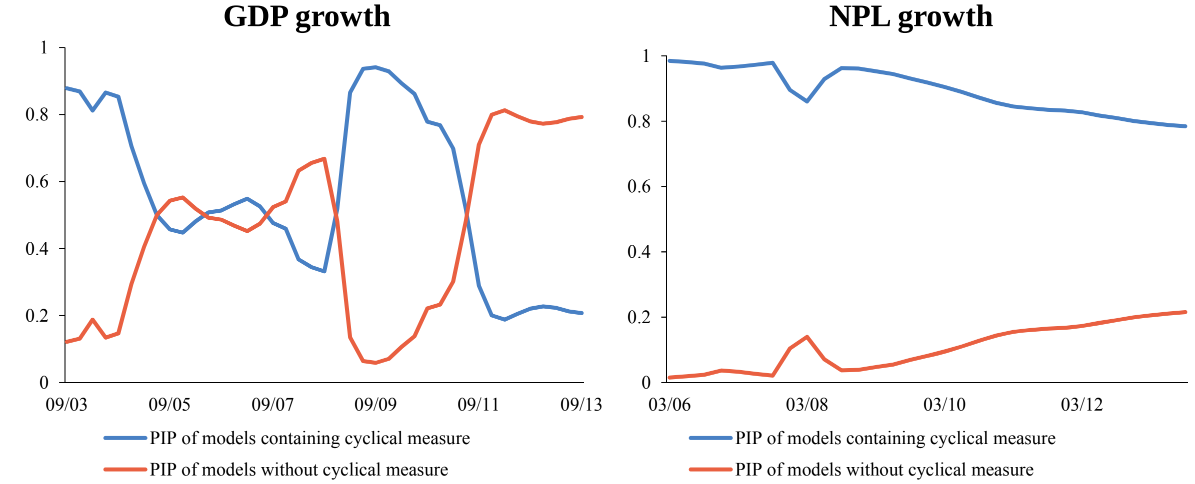



***Note:*** The x-axis shows the cumulative model probabilities of the best 32 models. The models are ordered according to their posterior probabilities, with the best model being on the left (individual models are separated by dashed lines). Blue colour indicates a positive coefficient and red colour a negative coefficient, while white colour denotes the absence of the variable from the given model.

To explore the hypothesis of potential non-linearities a little further, we use the method of dynamic model averaging (DMA; see Raftery et al., 2010, for technical details). It can be seen as an extension of traditional BMA into a time-varying framework, where the parameters $\beta$ and $\delta$ as well as the posterior model probabilities are allowed to change in each time period. As different models can now be preferred in different periods, DMA represents a natural candidate for studying the nature of the non-linearities outlined above. Another feature of DMA is that it uses filtered estimates of $\beta_t$ and $\delta_t$, which brings it closer to the real-time forecasting exercise. The filtered values of the parameters at time $t$ are based solely on the information available up to time $t$. Note that this is very different from the situation we analysed before (the BMA estimates), where the fixed coefficients were estimated using the whole sample. In the case of BMA we analysed the "in-sample" fit, whereas DMA focuses on the one-step-forward "out-of-sample" performance.

Figure 8 depicts the changes in the posterior model probabilities across time. To reduce visual clutter, we only show the aggregate posterior probability for models containing the financial cycle measure vis-à-vis the probability for models without it (effectively, this is the posterior inclusion probability of the cyclical measure vis-à-vis its complement to unity). It is immediately apparent that in the case of NPL growth (left panel), models containing the financial cycle measure convincingly dominate its competitors over the entire sample. This suggests that the measure might be useful for predicting future changes in credit risk in expansionary as well as recessionary phases of the cycle. By contrast, in the case of GDP growth (right panel), the posterior probabilities exhibit a markedly different pattern. It can be seen that the probability of inclusion of the financial cycle measure reaches its peak in the late expansionary phase (in the run-up to recession) and the subsequent recessionary phase. This means that past financial developments contribute considerably to explaining business cycle fluctuations at this time. By contrast, during other periods the models with the cyclical measure performed roughly as well (or as poorly) as the models containing only lagged values, hence they do not show any comparative gains. In the recent past, which can be characterised as a "crawling along the trough" of the financial cycle, they even seem to perform worse than autoregressive models. We interpret these results as evidence of a non-linear relation between financial and business fluctuations, a relation which tends to be strong around the tipping point of the financial cycle and is quite loose otherwise.

***Figure 8: Time-varying Posterior Inclusion probabilities for the FCI***




***Note:*** The time axis is constructed from the perspective of the forecasted variable. For example: the high posterior probability for GDP growth in 2009Q3 means that models containing a measure of the financial cycle can generate a better prediction for this period (using information lagged by six quarters, i.e. information up to 2008Q1).

Overall, we believe that the proposed financial cycle measures withstood the forecasting challenge quite well. If used cautiously, they may provide helpful guidance for macroprudential decisions and, to lesser extent, also for monetary policy decisions. In the latter case this is chiefly true for periods when the financial cycle starts amplifying business fluctuations.

## 6. Conclusions

This paper focuses on modelling of the financial cycle in the Czech economy. While the recent financial crisis has highlighted the importance of relations between business and financial fluctuations, finding a policy-relevant indicator for the financial cycle is still an open problem in the current policy debate. Using data on the Czech economy, this paper proposes two complementary methods for measuring the financial cycle with respect to the setting of the countercyclical buffer.

The first method uses a set of variables capturing swings in attitudes to risk and value and aggregates them into a single indicator using standard portfolio theory. This methodology was first proposed in the macroprudential context by Holló et al. (2012), who construct a composite indicator of systemic stress (CISS). The second method uses data tracking migrations between different credit risk categories and extracts the common components of the migration series by means of factor models.

The results show that the two measures convey a very similar message and confirm that the period of 2005–2008 can be described as an expansionary phase of the financial cycle, with an economic recovery accompanied by gradually rising risk tolerance. In this period, bank clients showed a greater willingness to borrow despite the risks associated with future debt service. As time went on, this willingness was also fostered by banks themselves through ever weaker lending conditions. Late 2008/early 2009 can be identified as the peak of the cycle. This was followed by a rapid switch to a downward phase of the cycle as a result of the financial crisis impacting on the Czech economy. Unlike for the credit-to-GDP gap, these developments closely correspond to economic intuition and are in line with current expert judgement. In this light, the measures may better serve macroprudential purposes than the traditionally used credit-to-GDP gap and may provide policy makers with a useful framework for assessing the financial cycle.

An initial analysis of the predictive content of the cyclical measures suggests that they may contribute to a more precise assessment of future credit risk materialisation in both the expansionary and recessionary phase, and to some extent they may also help to predict developments in the real economy, notably around a tipping point of the financial cycle. This seems to confirm earlier literature on the observed non-linearities in the relation between macroeconomic and financial developments.

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## Appendix: Dynamic Hierarchical Factor Model

Moench et al. (2013) use Markov Chain Monte Carlo (MCMC) methods and generalise the Carter and Kohn (1994) algorithm into settings with a multilevel structure with multiple factors:

Let $\Delta = (\alpha, \beta), \Gamma = \left(\gamma_F, \gamma_{e_F}, \gamma_{e_{Gi}}, \gamma_{\varepsilon_{ij}}\right)$, $\Sigma = (\Sigma_F, \Sigma_G)$.

1) Organise the data into blocks and subblocks of relevant z-score deviations $z_{ij,t} - \bar{z}_{ij}$. Get initial values for $\{G_t\}$ and $\{F_t\}$ using principal components and use them to generate initial values for $\Delta, \Gamma$, and $\Sigma$.

2) Conditional on $\Delta, \Gamma, \Sigma, \{F_t\}$ and the data, draw $\{G_t\}$ for each rating category *b*.

3) Conditional on $\Delta, \Gamma, \Sigma, \{G_t\}$ and the data, draw $\{F_t\}$.

4) Conditional on $\{G_t\}$, and $\{F_t\}$, draw $\Delta, \Gamma$ and $\Sigma$.

5) Return to 2.

Given the parameters and sample data, the Kalman filter is run forwards for periods *t* = 1,.., *T* and then backwards to obtain the factor sequences $\{G_t\}$ and $\{F_t\}$.

In terms of identification, the factors and the loadings are not separately identified. To achieve identification, a lower triangular factor loading matrix is assumed. Furthermore, since we use standardised data, it is assumed that innovations to the factors have fixed variances. For more details see Moench et al. (2013) and references therein.

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