# AN INDICATOR OF THE FINANCIAL CYCLE IN THE CZECH ECONOMY

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*This article describes a method for assessing the position of the Czech economy in the financial cycle. On the basis of selected variables tracking risks in the financial sector and the real economy, we construct an indicator aimed at signalling the emergence of future problems in timely fashion. The results show that the indicator is able to capture the individual phases of the financial cycle and predict the size of the banking sector's future loan losses six quarters ahead. Assessing the current position of the Czech economy in the financial cycle is a necessary condition for proper macroprudential policy-making and especially for setting the countercyclical capital buffer.*

## 1. INTRODUCTION

The negative experience of the recent financial crisis has prompted a need for closer study of the linkages between the financial and real sectors. These sectors cannot be analysed separately, as the growing importance of financial intermediation is causing problems to spill over more easily from one part of the economy to another, thereby magnifying the intensity of the original negative shock. Developments in the global economy in recent years clearly illustrate the growing importance of this link: a crisis initially linked with the housing market and its financing subsequently turned into an economic crisis and then a debt and banking crisis. This in turn significantly limited the scope for economic recovery and renewal of financial stability.

These experiences imply a need to study the financial cycle in addition to the economic cycle itself, not least because 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 (for more details, see 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. First among those policies is macroprudential policy, which is aimed at preventing the formation, propagation and materialisation of systemic risks in the financial sector and thereby reducing the probability of financial crises. In practice, however, it is difficult to assess the current position of the economy in the financial cycle because the definition of the financial cycle is itself too vague. The financial cycle is usually described merely as a latent (not directly measurable) process that cannot be associated with a single, specific observable variable. For empirical analysis it is necessary in this situation to construct a suitable indicator that will capture the aggregate tendency of the financial system to behave cyclically and will thus yield information on the position of the economy in the cycle.

This article sets out to present one possible method for measuring the position of the economy in the financial cycle and to evaluate its ability to signal an impending risk of financial instability in advance. The proposed indicator takes into account the requirement that it be practically applicable in macroprudential policy-making, and especially in decision-making on the countercyclical capital buffer rate.[1] Although a single indicator cannot fully substitute for the wide range of analyses needed for such decision-making, it can be taken as a useful starting point for assessing the overall situation.

## 2. DEFINITION OF FINANCIAL CYCLE

The definition of financial cycle used in this article corresponds to that described in previous CNB Financial Stability Reports (see Frait and Komárková, 2011) and, for example, in Borio (2012). In this concept, the financial cycle is understood to mean recurrent swings in the ability of market participants to recognise financial risk. Falling risk aversion is usually reflected in rapid credit growth, rising asset prices, easy access to external financing and increased investment activity.

1 This requirement is important primarily because the traditional method for setting the countercyclical capital buffer and determining its level (implemented in CRD IV and based on estimating the long-term trend in the credit-to-GDP ratio using the HP filter) is not suitable for the Czech economy, as it leads to highly misleading conclusions (Geršl and Seidler, 2011).

In light of the above definition, the identification of the phases of the financial cycle is based solely on a set of variables that captures swings in risk perceptions from over-optimism to under-pessimism. The key to determining the course of the cycle is the fact that changes in sentiment characterise general changes in the behaviour of all market participants and thus take place across various different areas of the economy. The cycle so defined is linked with – but is not entirely identical to – the *financial conditions*, as the latter rather reflect the level of financial stress and the materialisation of risks (Ng, 2011).

With regard to changes in risk sentiment, it is appropriate to describe in more detail the relationship between the cycle as defined above and the materialisation of risks per se. Risk materialisation indicators usually lag behind the cycle, or are even completely inverted in phase, as they often attain their most optimistic levels in the risk accumulation phase. From this perspective, the set of variables characterising the financial cycle can be viewed as a forward-looking indicator of potential problems in the economy. Identification of the financial cycle as we define it is therefore linked to some extent with the issue of early-warning models, which have been examined in many studies in past decades.

Early-warning models were initially used to identify currency crises and balance of payments crises (see, for example, Krugman, 1979) and were subsequently extended to the identification of other sorts of crises, such as banking and debt crises (Kaminsky and Reinhart, 1996; Reinhart and Rogoff, 2011). The global financial crisis generated renewed interest in this type of analysis, leading to the application of new empirical methods and larger and more detailed cross-country time series (see, for example, Leaven and Valencia, 2010, and Babecký et al., 2012).

These studies generally find that suitable indicators of future crises are generally variables connected with changes in risk aversion, such as the rate of growth of credit to the private sector, the debt and debt servicing ability of the private sector, property price growth, the tightness of the credit conditions, and the current account deficit or government debt level.[2]

The variables used to identify the Czech Republic's position in the credit cycle were chosen with due regard to the studies mentioned above. The resulting set of variables (see section 2.1) also took into account the requirement to cover the widest possible area of the economy that might be affected by changes in risk aversion, i.e. the credit demand and supply sides, debt sustainability and general financial market sentiment. The financial cycle indicator should therefore reflect common tendencies in the chosen variables.

## 3. METHOD OF CONSTRUCTION OF THE COMPOSITE INDICATOR

Aggregate information on the comovement of variables is most often gathered on the basis of factor models[3] (see, for example, Ng, 2011). These methods attempt to explain the observed correlations between variables as being a consequence of the existence of underlying factors – in this case the action of the financial cycle. This study, however, proposes a different approach based on the methodology of the composite indicator of systemic stress (CISS; see Holló et al., 2012), which, if one chooses appropriate variables, can also be used to assess the position in the financial cycle and as a basis for discussing the setting of the countercyclical capital buffer (see below). In the text below, we use the abbreviation FCI for our proposed financial cycle indicator in order to differentiate it from the CISS indicator.

The proposed technique may offer several advantages over factor models:

- 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 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.
- The construction of a factor in a factor model is subject to a requirement to faithfully reproduce the variability of

2 Forward-looking indicators can also differ across studies depending on the set of countries examined. For emerging economies one often sees indicators such as the amount of foreign exchange reserves and the equilibrium real exchange rate (see, for example, Frankel and Rose, 1996).

3 Various estimation techniques can be used to estimate a factor model, depending on the nature of the input data and the fulfilment of statistical conditions. The factor characterising the financial cycle is probably most commonly estimated using principal components.

the original data, yet it does not take into account whether the estimated factor displays good predictive properties for the preselected variable. By contrast, the FCI in some sense allows us to set the weights on the variables optimally, for example with regard to the estimate of future loan losses. In the case of the FCI, variables that play a large role in explaining a factor 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.

The process of constructing the FCI can be split into several steps. The first step involves selecting relevant variables capturing changes in perceptions of financial risk across various segments of the economy. In the second step, all the input variables are transformed to make them mutually comparable. Finally, the transformed variables are combined into a single indicator using a simple aggregation algorithm. These steps are described in more detail below.

### 3.1 Selection of variables

The fundamental criteria for choosing the variables were given at the end of section 1. As well as material aspects, however, the availability and information content of the time series also had to be taken into account. Constructing the FCI from the time series for the period 2000 Q1–2013 Q3 offers a suitable compromise between data length and data quality. 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. To suppress the effect of the convergence of the Czech economy, variables that display constant growth trends due to a low initial level are expressed as year-on-year changes. Table 1 lists the input variables together with the adjustments made. The ranking of the variables in the table reflects our subjective assessment of their relevance to the identification of the individual phases of the financial cycle and also reflects the quality of the data.[4] A brief rationale for including each variable in the composite indicator is given in the following paragraphs.

4 This ranking is partially used in setting the weights of the input variables (for more details, see section 2.2).

**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., 2012). This fact is linked with the procyclicality of the financial sector, as economic agents become less prudent 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 suffer from short-sightedness and are willing 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 existing loans.

**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).

**TABLE 1**

**LIST OF INPUT VARIABLES AND MAIN ADJUSTMENTS**

| | Indicator | Original units and adjustments made |
|---|---|---|
| 1 | New bank loans to households | CZK bn, quarterly sum of monthly new loans |
| 2 | New bank loans to non-financial corporations | CZK bn, quarterly 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 50 stock index | three-month average |
| 9 | Adjusted current account deficit/GDP | % p.a., adjusted for reinvestment and transfers |

Source: CNB and CZSO, authors` calculations

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

**Stock index (PX 50)**

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 our overall picture of the nature of market participants' expectations and reveal over-optimism about future asset prices.

**Adjusted current account deficit-to-GDP ratio**

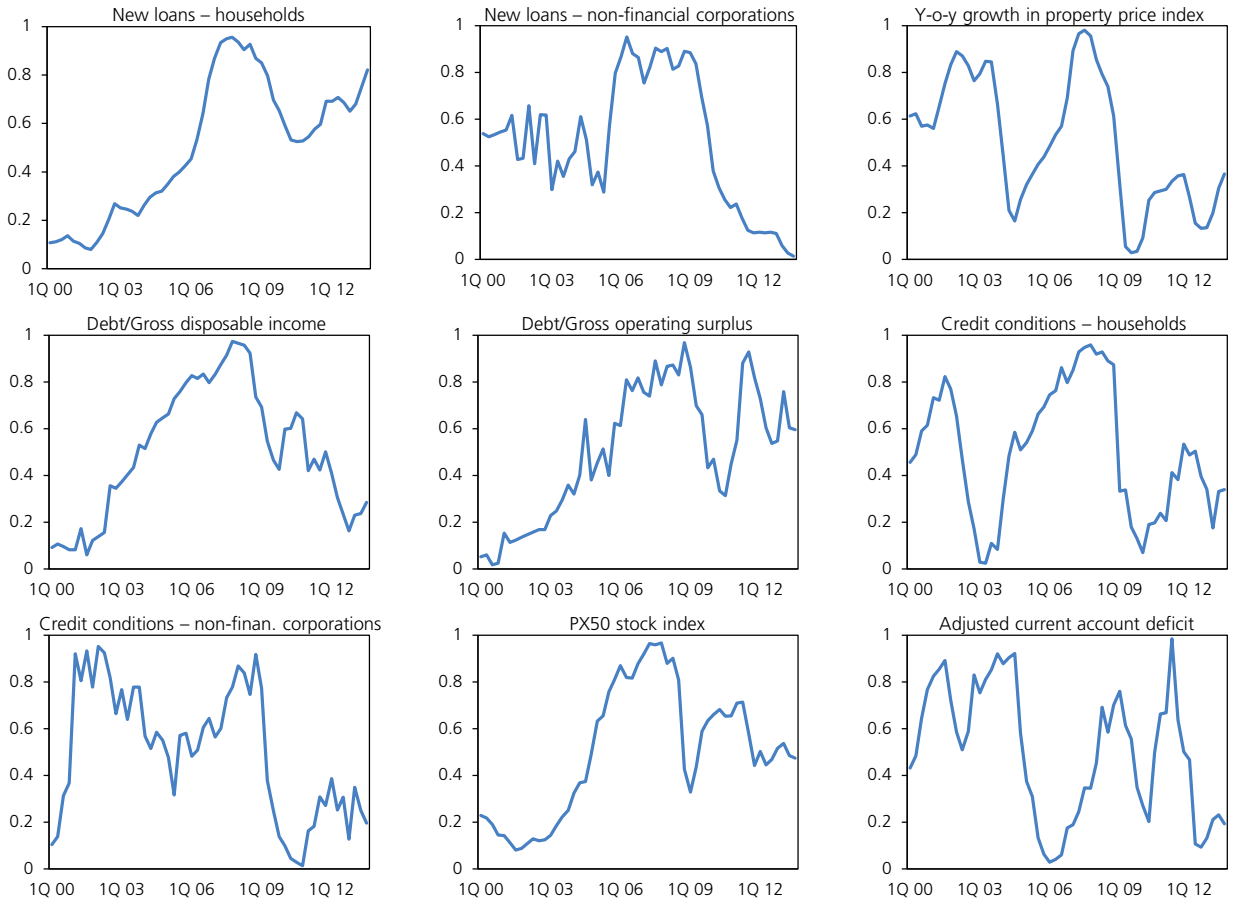
A current account deficit can be interpreted as meaning that more is invested in the economy than the private sector and the government save together. This may indicate the formation of external imbalances, overheating of the economy, and growth in future problems repaying loans financed by capital inflows 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.

### 3.2 Transformation of variables and aggregation method

Before aggregation, the input variables are first tran sformed into the interval (0, 1) using the kernel estimate of the cumulative distribution function (Gaussian kernel) so that the lowest value of the transformed variable corresponds to the trough of the cycle and the highest value

**CHART 1**

**TRANSFORMATION OF INPUT VARIABLES USING THE KERNEL ESTIMATE OF THE CUMULATIVE DISTRIBUTION FUNCTION**
(y-axis: value of transformed indicator, 0 = minimum, 1 = maximum)




Source: CNB and CZSO, authors` calculations

to the peak[5] (see Chart 1). This step ensures that the input variables are homogeneous and comparable. Transformation on a unit interval can also facilitate subsequent interpretation of the FCI, as it provides a clearer idea about what is a low value and what is a high one.

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 optimism is 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 changes in sentiment over the cycle. This property is also useful for setting the countercyclical capital buffer, as 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.[6]

5 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.

6 Clear definitions of the time and cross-sectional dimension of risk can be found in Frait and Komárková (2012). In the present article, however, the cross-sectional dimension of risk is defined rather differently. The original concept defined the cross-sectional dimension as the degree of financial

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. Formally, the aggregation method can be expressed using the following formula (see Holló et al., 2012)

$$IFC_t = (w \circ s_t)' C_t (w \circ s_t), \qquad (1)$$

where $w = (w_1, w_2, \ldots, w_9)$ is a vector indicating the relative importance of the individual 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 (known as the Hadamard-product). Matrix $C_t$ contains the values of the cross-correlation coefficients $\rho_{t,ij}$ determining how strong the relationship between subindicators *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.

The 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 $\tilde{s}_{t,i} = (s_{t,i} - 0{,}5)$ 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, although applied to the time series in reverse order from the most recent observation to the oldest.

The relative weight of the individual subindicators (the vector of weights *w*) was determined by means of simulation techniques. A total of 30,000 different weight distributions were simulated and the vector which, after substitution into equation (1), gave the best predictions (in terms of RMSE) of future loan loss impairments in the Czech banking sector[7] six quarters ahead was chosen. 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 one also needs to add the input data publication lag and the time needed to make the decision to set the capital buffer. Expert knowledge was taken into account *a priori* when estimating the final weights in order to avoid unintuitive results. The *a priori* constraints on the vector of weights can be expressed as an inequality where all the simulated weight distributions must satisfy the condition

$$w_1 \geq w_2 \geq w_3 \geq \cdots \geq w_9,$$

where the indices correspond to the indicator ranking in Table 1. Note that the *a priori* assessment of the relevance of each variable does not rule out the possibility that all the variables have the same weight.

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:

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

It is clear from (2) that the total weight of a subindicator is given – in addition to the weights *w* themselves – by the value of the expression in parentheses, which in turn depends on the magnitude of the correlations between the given subindicator and the other variables in the system under consideration. If, for example, subindicator $s_3$ is not correlated with indicators $s_1$ and $s_2$, its contribution to the FCI will be lower; in the case of a strong negative correlation it will potentially even be negative. This illustration shows that variables that are strongly positively correlated with each other will have the largest positive effect on the final value of the FCI. This can be loosely interpreted as meaning that the FCI, like the factor model,

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.

7 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.

makes it possible to somehow detect the effect of the latent factor causing the variables to co-move.

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 correlation structure influences the final result, or the size of the "loss" caused by imperfect synchronisation of subindicators over the cycle. The overall value of the FCI can therefore be broken down into the 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).

## 4. EVOLUTION OF THE FCI

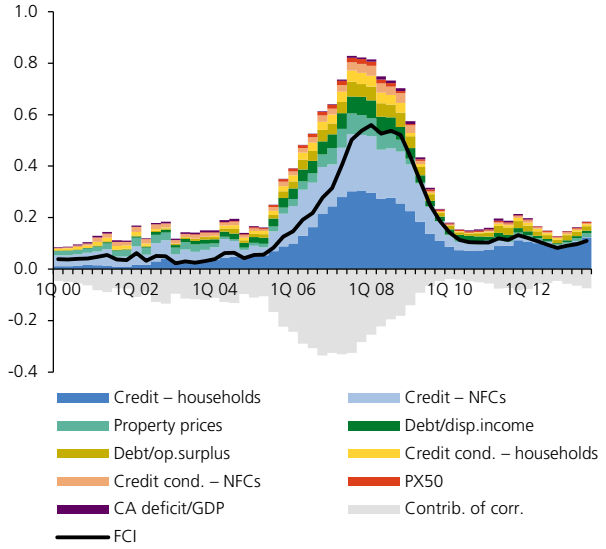
In line with earlier literature, the estimated weights[8] $w$ = (0.35 0.27 0.09 0.08 0.07 0.05 0.05 0.02 0.02) indicate that credit dynamics provide the main signal for forecasting the materialisation of financial risks, as loans to households and non-financial corporations together have a weight of over 60% in the composite FCI. Using the estimated weights $w$ and the correlations $C$ we can obtain the FCI values according to (1). Chart 2 shows the evolution of the FCI (the black line) along with its decomposition into individual contributions (the bar chart).

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 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.[9] 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.[10]

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 (see section 2.2) and the actual value of the FCI (see Chart 2). By contrast, the peak phase of the cycle (2008/2009) was accompanied, in addition to growth

**CHART 2**

**THE FCI AND ITS DECOMPOSITION**
(minimum FCI = 0, maximum = 1)




Source: CNB and CZSO, authors' calculations
Note: The negative contribution of the cross-correlation structure to the FCI value (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.

8 The ordering of the weights corresponds to the ranking of the variables in Table 1. The weights are rounded, and the rounded values were used to calculate the FCI.
9 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.
10 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.

in the contributions of the individual subindicators, by gradual growth in the correlations between them. Even at the peak of the expansion, however, the FCI was fluctuating around 0.6, which is by no means a dramatic figure given the admissible range of (0, 1). The correlations were still rising during the acute phase of the recession, when all the subindicators were falling together.

### 4.1 The FCI and the countercyclical capital buffer

One of the macroprudential tools intended to play a stabilising role in the financial cycle is the countercyclical capital buffer (CCB). Banks should create a CCB at times of excessive credit growth in order to increase the resilience of the banking system at times of falling economic activity and rising loan losses. The greater resilience of banks due to the possibility of partly or fully releasing the CCB is supposed to reduce the risk of a sharp contraction in the credit supply and the transmission of shocks from the financial sector to the real economy.

Because the Basel Committee's baseline method for determining the CCB, which the CNB will have to publish in connection with CRD IV, is not very suitable for the Czech Republic and many other transforming economies (see Geršl and Seidler, 2011), the FCI can be used to obtain aggregate information on the evolution of risks in the domestic economy. In this context, however, it is necessary to verify whether the composite indicator provides a timely signal of future materialisation of the risks and bank losses that the CCB is supposed to cover.

For the sake of simplicity we present only a trivial model between a measure of risk materialisation and the FCI:

$$Materialisation_t = \beta_0 + \beta_1 IFC_{t-6} + u_t, \qquad (3)$$

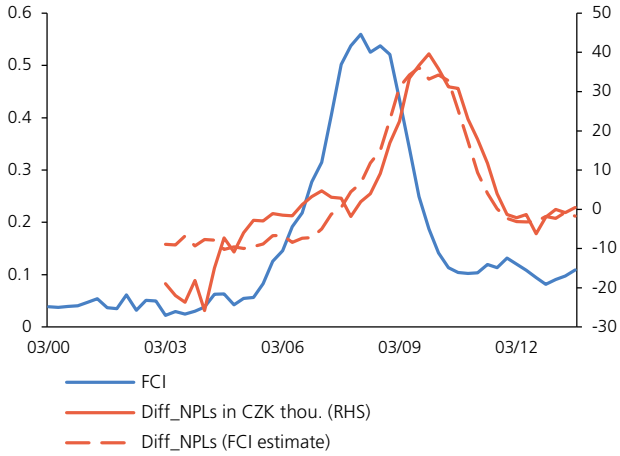
where the measure of risk materialisation at time $t$ (year-on-year differences in NPLs to the private sector[11]) depends only on the FCI lagged by six quarters, $\beta_0$ and $\beta_1$ are regression coefficients and $u_t$ is the error term.

The plots in Chart 3 show that the financial cycle as measured using the FCI is closely linked with future risk materialisation, with the materialisation curve lagging approximately 6–8 quarters behind the financial risk perceptions cycle. This finding is formally confirmed by the estimate of model (3), which, despite its simplicity, is capable of forecasting future changes in NPLs[12] with sufficient accuracy, especially when those changes are positive and imply growth in risk materialisation. On the other hand, the results should be interpreted with caution, as the period under review covers only one financial cycle and the predictive properties of the indicator may change in the future.

**CHART 3**

**THE FCI AND RISK MATERIALISATION**

(FCI value; right-hand scale: CZK billions)




Source: CNB, authors' calculations
Note: The estimate of the FCI for changes in the NPL ratio does not cover the pre-2003 period, when this ratio was significantly affected by the transfer of bad bank loans to a consolidation bank/agency. R-squared is equal to 0.82.

The above results are favourable in terms of the possibility of using the FCI to set a non-zero countercyclical capital buffer, suggesting that it could be applicable in this area. Thanks to its simplicity and good predictive properties, the FCI serves as a starting point for more comprehensive evaluation of the accumulation of financial risks and also as a suitable communication tool.

## 5. CONCLUSION

Successful macroprudential policy requires correct and timely assessment of the position of the economy in the financial cycle. This article described the construction of a composite indicator that captures the accumulation of risks in the financial sector and signals their potential materialisation in advance. To this end, we selected a set of

11 This measure was chosen on account of its easy implementation into the existing bank stress tests, which can be used to determine the necessary capital injection and therefore also to determine the CCB. However, the good predictive ability of the FCI is robust across possible risk materialisation measures such as the 12-month default rate and bank loan losses.

12 R-squared is equal to 0.82.

variables which, according to earlier studies and expert judgement, expresses the cyclical swings in financial risk perceptions in the financial and real sector. Those variables are: credit growth, property prices, lending conditions, debt sustainability in non-financial corporations and households, asset prices and the adjusted current account deficit-to-GDP ratio.

Using these variables we constructed a composite indicator – the FCI – which takes into account the changing cross-correlation structure and takes its highest values at times of rising synchronisation between the monitored variables characterising various aspects of the financial cycle. The weights of the individual variables in the composite indicator are calibrated so that the indicator best identifies the loan impairment losses observed in the Czech banking sector, i.e. the risks in the materialisation phase.

The evolution of the proposed indicator suggests that it identifies the potential future materialisation of credit risks approximately 6–8 quarters ahead. Its simple construction and interpretation makes the FCI a suitable ancillary tool for identifying the phases of the financial cycle in the Czech Republic, which in turn is vital for conducting macroprudential policy and especially for setting the countercyclical capital buffer (see section 5 of this Report).

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