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The Financial Cycle Index of Ukraine

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Abstract

This study introduces the financial cycle index as a means to identify the position of the Ukrainian economy in the financial cycle. The index encompasses 16 indicators aggregated into four subindices that capture cyclical systemic risks stemming from the immoderate debt burden of the private sector, the easing of lending conditions, excessive growth of real estate prices, and macroeconomic imbalances. This financial cycle measure can be used as one of a number of guidelines when making policy decisions on the use of countercyclical prudential instruments to prevent the accumulation of cyclical systemic risks and to stabilize the financial system in a timely manner.

Keywords: financial cycle, credit-to-GDP gap, financial cycle index, countercyclical capital buffer

JEL Codes: E32, E51, E58, G01, G21

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1. Introduction

Macroprudential policy aims to ensure financial stability by preventing the accumulation and materialization of systemic risks. It relates closely to reducing the procyclical vulnerabilities of the financial system. Procyclicality refers to the fluctuations of financial variables around a trend during the economic cycle (Landau, 2009), which can magnify risks to economic growth. Regulators face the challenge of identifying the cyclical fluctuations.

This study introduces the financial cycle index (FCI) to identify the position of the Ukrainian economy in the financial cycle. The FCI is based on 16 indicators from four broad areas: the debt burden of the private sector, credit conditions and demand, the housing market, and the real economy. More specifically, the indicators capture cyclical systemic risks related to the immoderate debt burden of the private sector, the easing of lending conditions, excessive growth in real estate prices, and macroeconomic imbalances. The measure of the financial cycle presented here can be used as a quantitative guide to implement macroprudential policy tools to prevent the accumulation and mitigate cyclical systemic risks, in particular the countercyclical capital buffer.

The paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the methodology used in the FCI's composition. Section 4 describes how the FCI is estimated, and gives its properties. Section 5 provides conclusions.

2. Literature Review

The procyclical behavior of the financial system is a central issue when it comes to promoting the system's stability. Landau (2009) states that procyclicality refers to the tendency of financial variables to fluctuate around a trend during the economic cycle. Another meaning of this phenomenon is how banking shocks propagate through the real economy (Andrieș and Sprincean, 2021). Vulnerabilities arising from procyclicality are associated with amplifying fluctuations of economic activity (Geršl and Jakubík, 2010) via reinforcing interactions between the financial sector and the real economy (Minsky, 1982; Kindleberger, 2000; BIS, 2010a).

This study contributes to the extensive literature on *the indicators of financial system procyclicality*.

One of the main indicators of the financial cycle discussed in the literature is *credit* (Reinhart and Rogoff, 2009; Schularick and Taylor, 2012; Jordà et al., 2013). The upswing of the financial cycle often sees rapid growth in lending, which positively affects investment and economic growth. Simultaneously, in times of economic growth, economic agents can significantly increase their debt burden, underestimating risks (notably, this may be associated with obtaining foreign currency loans in cases where the borrower does not have income in foreign currency). At the same time, banks tend to lend to riskier borrowers, overestimating their future income. This situation often leads to a deterioration in the ability of debtors to repay their loans and, as a result, to an increase in non-performing bank loans and consequent losses for the banks, which can in turn worsen their ability to lend to the real economy and, as a result, reduce the lending supply (Plašil et al., 2014). Thus, an additional source of financial procyclicality is the propensity of financial market participants to underestimate risk during booms, which contributes to strong credit growth, collateral overvaluation, the easing of lending standards, and financial institutions holding relatively low capital and provisions (Borio et al., 2001). High procyclicality in bank loan loss provisioning is undesirable from a financial stability perspective, as it can be a driver of cyclical loan supply as well, and a drop in bank equity during economic downturns can lead to a credit crunch (Huizinga and Laeven, 2019).

Although we know the dramatic consequences of credit booms, not all of them cause subsequent financial crises (Mendoza and Terrones, 2008; Dell'Ariccia et al., 2016; Gorton and Ordoñez, 2016). In this regard, *asset prices* could complement credit to capture the financial cycle, as their changes influence borrowers' ability to borrow through their net worth (Kelly et al., 2011) and collateral value (Schüler et al., 20204; Schüler et al., 2017) consider asset price indicators as house, equity, and bond prices. Borio and Drehmann (2009), Schüler et al. (2017) suggest that the joint fluctuations of credit and asset prices perform reasonably well as pointers to potential bank distress ahead of a crisis. Claessens et al. (2009, 2012) indicate that recessions accompanied by house and equity price busts tend to be longer and deeper, while recoveries combined with rapid growth in credit and house prices tend to be stronger. Pouvelle (2012) shows that stock price growth has a significant effect on lending growth, and, by contrast, housing price growth only has a notable effect during periods of financial instability. Hiebert et al. (2015) point out that credit and asset price indicators for G-7 countries exhibit considerable cyclical cohesion, which is most evident over the long term. Drehmann et al. (2012) find that combinations of credit and property prices best capture financial cycles, while equity prices do not fit the picture well. Jordà et al. (2015) reveal that asset price bubbles increase financial crisis risks when fueled by credit booms. The authors specify credit-financed housing price bubbles as a particularly dangerous phenomenon. Jordà et al. (2014, 2015) conclude that financial stability risks have been increasingly linked to real estate lending booms, which are typically followed by deeper recessions and slower recoveries.

Athanasoglou and Daniilidis (2011) note that *credit standards* are also procyclical. ECB (2009) indicates that bank lending conditions are considerably softened during the business cycle's upturn, and tightened in the downturn, which has significant implications for credit and, potentially, for output growth as well.

This paper also adds to the existing literature on *financial cycle composite indicators*.

One way to identify the economy's position within the financial cycle is to construct financial cycle composite measures. Lang et al. (2019) propose a domestic cyclical systemic risk indicator (d-SRI) that captures risks stemming from domestic credit, real estate markets, asset prices, and external imbalances. This indicator, designed for euro area countries, along with Denmark, Sweden, and the United Kingdom, is intended to signal financial crisis vulnerabilities sufficiently in advance for mitigating macroprudential policy actions to be taken. On average, the d-SRI increases on several years before the onset of systemic financial crises. Stemmel (2015) find the best-fitted synthetic financial cycle measure for 11 European countries (Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Spain, and the United Kingdom), which includes the credit to gross domestic product (GDP) ratio, credit growth, and the house-prices-to-income ratio. This study also suggests that financial cycles are highly correlated during periods of stress, and diverge during booms. Russo (2022) describes two indicators to measure the financial cycle in France, with one covering short cycles (two to eight years) and the other covering longer cycles (eight to 25 years), to analyze the build-up or reduction of financial risks over different timeframes and provide insights into the various factors driving the cycle, such as credit to corporates and households, share and housing prices, and bond yields.

In contrast to advanced economies, financial cycle indicators for emerging markets are described insufficiently. The literature mainly characterizes indicators within the financial cycle measures. Methods to extract the cyclical component from short time series with numerous structural breaks are still being discussed.

In Slovakia, a financial cycle indicator called Cyclogram was developed in addition to the standard credit-to-GDP gap measure (Rychtárik, 2018). The Cyclogram is based on 13 indicators within five categories: lending market, indebtedness, risk appetite, property market, and macroeconomy. Kupkovič and Šuster (2020) propose another composite financial cycle measure for the Slovak economy from input indicators such as credit growth, house prices, debt burden, credit standards, interest rate spreads, and current account deficit-to-GDP ratio. The authors consider endogenous co-movement between input indicators, and focus solely on the build-up phase. Plašil et al. (2014, 2016) propose a composite indicator of systemic stress (CISS) for assessing the economy's position in the financial cycle to identify emerging imbalances in a timely manner. The indicators comprising the CISS track the evolution of loans to the private sector, property prices, debt sustainability, lending conditions, the stock index, and the adjusted current account deficit to GDP ratio. The authors note that the CISS fully corresponds to retrospective expert views on cyclical developments, and reflects the changes in risk perceptions in the Czech economy very well.

The abovementioned highlights the importance of studying the financial cycle and identifying the economy's position within it. Knowing the economy's position within the financial cycle enables the level of systemic cyclical risks to be determined, and the appropriate countercyclical macroprudential instruments and stabilization policies to be applied in a timely manner.

3. FCI Composition Methodology

We follow the definition of the financial cycle of Borio et al. (2001), which means the sequence of rapid expansion in credit and asset prices, often accompanied by a relaxation of price and non-price terms in access to external funding. Borio (2014), in his influential paper, also indicates that the financial cycle has a much lower frequency than the business cycle, and its peaks are closely associated with financial crises. Financial cycles also tend to be longer, deeper, and sharper than business cycles (Claessens et al., 2012; Drehmann et al., 2012). Moreover, business and financial cycles are likely more pronounced in emerging markets than in advanced countries (Claessens et al., 2012).

3.1. Selection of Indicators

When selecting indicators that characterize financial cycle developments and that track vulnerabilities arising from macroeconomic activity in Ukraine, we aimed to capture the main indicators of the financial system's procyclicality, as discussed in the literature (see Section 2). These are the debt burden on the private sector, credit conditions and demand, housing prices, and the state of the real economy. The dynamics of these indicators are shown on in Appendix A.

Private Sector Debt Burden

To estimate excessive credit growth, we include the *credit-to-GDP gap* ("credit gap" or "Basel gap") proposed by Borio and Lowe (2002) measured as the deviation of the credit-to-GDP ratio from its long-term trend as estimated by a one-sided Hodrick-Prescott (HP) filter. The credit gap shows not only the growth in private sector debt relative to economic growth expressed in terms of GDP, but also whether the difference in their respective growth rates is widening or shrinking. That is, the deviation of the credit-to-GDP ratio from its long-term trend is linked to situations in which new debt does not sufficiently contribute to GDP growth (Rychtárik, 2014). The credit-to-GDP ratio also indicates the ability to repay a given stock of loans, as GDP relates to private sector income (Geršl and Seidler, 2012). Extensive empirical literature has demonstrated the reliability of the credit gap's early warning properties (Borio and Drehmann, 2009; Drehmann et al., 2010; Drehmann et al., 2012). Based on these grounds, the Basel Committee on Banking Supervision (BCBS) has adopted the credit gap as a common starting point for countercyclical buffer decisions, with the caveat that buffer guidance does not always work well in all jurisdictions at all times (BIS, 2010).

Nevertheless, the credit gap has been criticized as an indicator for determining the build-up phase of the financial cycle, and because of the measurement problems related to assessing trends with a one-sided HP filter. Critics argue that it does not necessarily align with the equilibrium level of private credit in the economy (Drehmann et al., 2010; Drehmann and Tsatsaronis, 2014; Geršl and Seidler, 2012). For this reason, several authors apply a structural approach, using models in which credit is associated with fundamental variables (Baba et al., 2020; Galán and Mencía, 2018; Geršl and Seidler, 2012; Juselius et al., 2017; Lang and Welz, 2018). However, this approach also faces limitations related to model specification, sample composition, and estimation techniques (Baba et al., 2020). Since the credit-to-GDP ratio inherently normalizes credit volume relative to the economy's size (Jokipii et al., 2020), Geršl and Seidler (2012) also analyze credit gaps with alternative denominators such as financial assets and total assets of the private sector. This approach partially addresses the issue of comparing stock and flow variables, as GDP as a flow variable is potentially more volatile than credit stock (Rychtárik, 2014).

Another limitation of the credit gap relates to its conflicting signals when credit growth exceeds GDP growth, which may indicate financial deepening – particularly relevant for emerging countries where the credit market is converging to its equilibrium level. The ratio also could increase due to a rapid decrease of GDP, providing false signals of excessive borrowing (Baba et al., 2020; Galán and Mencía, 2018; Geršl and Seidler, 2012). Rychtárik (2014) also mentions that credit-to-GDP does not indicate any excessiveness if credit is growing faster than GDP, but it is not accelerating; in addition, possible changes in the loan stock due to non-performing loan write-offs or sell-offs can be misinterpreted as deleveraging. To address credit stock data distortion due to the sharp rise of non-performing loans during the Ukraine's 2014–2016 banking crisis, and further write-offs, we incorporate credit flow indicators such as *new lending to corporations and households to GDP* ratios. We avoid including new lending as the only indicator of a credit gap, as this indicator also has its drawbacks. For example, it includes a significant amount of short loans to large companies that are constantly repaid, i.e. are in permanent circulation. This indicator also gives a misleading signal about increasing risks of excessive lending in 2019–2021, while this period saw a recovery in credit growth after a previous drop.

Thus, as we calculate subindices by taking the simple average of the underlying indicators, we include metrics that can complement each other and capture diverse signals of change in the financial cycle.

Furthermore, the credit gap is based on the aggregate stock of credit, while imbalances can build up in individual segments. Understanding the source of vulnerabilities is critical for appropriate policy response (Baba et al., 2020). To address the lack of sectoral details, we incorporate *credit-to-GDP* separately *for households and corporates*. We also complement credit measures with the *credit to private sector to GDP ratio,* as corporates in the previous indicator also encompass state-owned entities.

A further area of critique widely discussed in the literature concerns the potential measurement problems from estimating the long-term trend component using the HP filter. As most of the indicators enter the FCI in terms of gaps, which are also calculated using the same filter as the credit-to-GDP ratio, understanding of limitations and drawbacks of this statistical approach is of great importance. The first challenge is linked to the length of the underlying time series, which can affect trend estimates considerably (Lang et al., 2019;

Jokipii et al., 2020). Drehmann and Tsatsaronis (2014) point out that at least 20-year data series are needed to assess the signaling capacity of the credit gap properly. This issue is particularly relevant for emerging market economies, where statistics have not been available for a long period of time. The second concern relates to structural breaks or crises in the data, which can cause substantial distortion in the credit gap's performance. The estimates of the HP filter are also very sensitive to the chosen smoothing parameter (lambda) which is directly connected to the debate on the credit cycle duration. BIS (2010b) recommends setting the lambda to 400,000, based on the empirical results of Drehmann et al. (2010) and proceeding from the fact that the credit cycle is longer than the business cycle. Several authors argue in favor of lambda adaptation for specific countries (Galati et al., 2016; Galán, 2019). Another major drawback is the so-called downward bias risk – during a pronounced and long credit boom-bust cycle, the credit gap appears to underestimate cyclical systemic risks (Baba et al., 2020; Jokipii et al., 2020). Trend estimations are also substantially affected by the data's starting point (Drehmann and Tsatsaronis, 2014). Finally, the credit gap estimations with the HP filter suffer from the well-known "end-point bias" problem. This means that estimates of the trend at the end of the sample can change substantially as future data become available. According to BCBS guidance, the trend is estimated using a one-sided HP filter (real-time estimates) based only on backward-looking data. While this solves to some extent the problem arising from a two-sided HP filter based on ex-post measures, the trend estimates are still affected by the end-point problem (Edge and Meisenzahl, 2011; Geršl and Seidler, 2012; Drehmann and Tsatsaronis, 2014; Baba et al., 2020; Jokipii et al., 2020).

Despite its weaknesses, the credit gap is a reliable measure of the financial cycle, which can be included in the macroprudential framework with careful interpretation and in conjunction with an analysis of other risk indicators. Following the practice of other countries, as outlined, for example, in BIS (2017), we supplement our financial cycle index with other indicators of financial system procyclicality.

Drehmann and Juselius (2012) show that the debt service ratio provides a very accurate early warning signal up to one to two years in advance of systemic banking crises. Therefore, we added *the debt service ratio for households (DSR)* as a supplementary indicator of private sector debt burden to reveal potential credit risks associated with retail lending. This measure reflects the share of income used to repay principal and interest, thereby showing the ability of households to meet their debt obligations given their level of disposable income.

Following Drehmann et al. (2015), we calculate the DSR based on aggregate level data, making the simplified assumption that debt servicing costs (principal and interest) are paid in equal installments over the life of the loan, as follows:

$$DSR_t = \frac{\frac{i_t}{4} \cdot \frac{D_t}{\sum_{\mathrm{j}=1}^{4} I_{t-j+1}/4}}{1-(1+\frac{i_t}{4})^{-\frac{m_t}{3}}} = \frac{i_t \cdot \frac{D_t}{\sum_{\mathrm{j}=1}^{4} I_{t-j+1}}}{1-(1+\frac{i_t}{4})^{-\frac{m_t}{3}}}, \quad (1)$$

where D_t denotes the total debt on loans in quarter t, I_t denotes the household disposable income in quarter t, i_t is the annualized interest rate on the loan stock in quarter t, and m_t is the average remaining maturity of loans in months in quarter t.

The growth of the DSR indicates an increase in households' debt burden and, accordingly, their vulnerability to a decline in income. This indicator also provides insight into how interest rates and maturities affect the debt burden non-linearly. Changes in the DSR, as well as in the credit gap, can be associated not only with an increase in lending activity, but also with a revaluation of debt in foreign currency.

At the same time, the higher the debt-related payments, the lower borrowers' spending. For example, during financial booms, rising asset prices increase the value of collateral, making it easier to borrow. However, higher debt means greater costs associated with servicing it. This suppresses spending, which offsets the effect of the rise in new lending, and eventually the boom tapers off. It then takes time for DSR, and hence spending, to normalize, even if interest rates fall, since the principal still needs to be paid down. Thus, DSR is an important procyclical indicator that links the debt burden and the real economy and describes the financial cycle (Drehmann et al., 2015).

Credit Conditions and Demand

Credit conditions are covered by nominal interest rates on new loans to corporations and households. Higher interest rates are associated with the contraction phase of the financial cycle.

Credit standards indicators for corporations and households are sourced from the NBU's Bank Lending Survey (BLS). They are based on answers to two questions: How did lending standards change in the past quarter, and how does the bank plan to change the lending standards over the next quarter? A positive indicator value reflects a tightening of lending standards, and a negative value – a weakening. Given the differences in the trends of consumer and mortgage lending in Ukraine, the change in standards for approving applications for each of them is considered separately.

To capture *credit demand*, we use the NBU's BLS indicators for corporations and households calculated on the basis of answers to the following questions: Did the banks experience higher or lower demand in the past quarter, and what do they expect for the next quarter? A positive value of the indicator corresponds to an increase in credit activity, while a negative value corresponds to a decrease in the demand for loans. Changes in household demand for consumer and mortgage loans are considered separately.

We also include the *Google Trends indicator*, which provides insights into public interest in credit, in particular, showing how frequently the search term "credit" in Ukrainian is searched for with Google across Ukraine over a specified time period. This indicator reflects the relative popularity of the search term and ranges from 0 to 100, with zero being very low popularity, and 100 being the maximum.

Housing Market

For asset prices, we include the development of house prices by using indicators for residential property in the primary market in Kyiv such as *real house prices*, the *house price to income ratio*, and the *house price to rent ratio*. The house price to income ratio reflects the affordability of residential real estate for the population. In contrast, the house price to rent ratio measures the relative affordability of buying a house versus renting it. High values of these indicators usually indicate an overheating of the real estate market linked to the boom stage of the financial cycle.

Real Economy

The real economy is represented by the *output gap*[6] and the *current account balance as a percentage of nominal GDP*. The output gap is a key indicator that reflects the economy's position at a particular stage of the business cycle. The current account balance to GDP ratio can indicate there is excessive financing of expenditures and investments in the economy through inflows from abroad, which can lead to the buildup of external imbalances, and potential problems with the repayment of loans financed by foreign capital.

3.2. Variable Transformation and Aggregation

Data on the indicators in the FCI are derived from statistics of the NBU, the State Statistics Service of Ukraine, and real estate agencies. Despite some data limitations, we were able to receive sufficiently long time series. The data period for most indicators is from 2009, and for some even from 2001 – apart from those based on the NBU's Bank Lending Survey, which starts at the end of 2011. The sample ends in Q3 2024.

[6] A detailed description of the methodology for calculating the output gap is presented in the NBU Inflation report, October 2021.

Table 1 presents the FCI's underlying indicators within the four subindices, and indicates the transformations performed before they enter the index.

Several indicators are smoothed using a four-quarter moving average method. Considering that some variables rise in the upward phase of the financial cycle, while others fall, the latter are included in an inverted form (interest rates on loans) or with an inverse sign (the ratio of the current account balance to GDP, credit standards). This operation is necessary in order to bring all indicators to the same direction of development, that is, the higher the indicator value, the greater the risk.

Table 1. FCI Composition

Subindices	Indicators included	Transformations made	Start date
Debt burden of private sector	Corporate credit to GDP gap	Credit adjusted by exchange rate, HP filtered, standardized	Q1 2007
	Household credit to GDP gap	Credit adjusted by exchange rate, HP filtered, standardized	Q1 2006
	Credit to private sector to GDP gap	Credit adjusted by exchange rate, HP filtered, standardized	Q4 2002
	New lending to corporations to GDP gap	HP filtered, standardized	Q1 2009
	New lending to households to GDP gap	HP filtered, standardized	Q1 2009
	Debt service ratio gap for households	HP filtered, standardized	Q1 2009
Credit conditions and demand	Interest rate on new loans to corporations gap	4Q moving average, inverted, HP filtered, standardized	Q1 2009
	Interest rate on new loans to households gap	4Q moving average, inverted, HP filtered, standardized	Q1 2009
	Average of past and expected change in credit standards to corporations and households	4Q moving average, sign inverted, standardized	Q4 2011
	Average of past and expected credit demand indicator for corporations and households	4Q moving average, standardized	Q4 2011
	Google Trends indicator	4Q moving average, standardized	Q4 2004
Housing market	Real primary house price gap	Exchange rate and CPI adjusted, 4Q moving average, HP filtered, standardized	Q1 2003
	House price to income gap (primary market)	Exchange rate adjusted, 4Q moving average, HP filtered, standardized	Q1 2003
	House price to rent gap (primary market)	Exchange rate adjusted, 4Q moving average, HP filtered, standardized	Q1 2009
Real economy	Output gap	4Q moving average, standardized	Q1 2004
	Current account balance to GDP	Sign inverted, standardized	Q4 2001

Notes: Data on credit standards and demand are derived from the NBU Bank Lending Survey. All HP filtered indicators use a lambda of 25,000.

Abbreviations: HP, Hodrick–Prescott; 4Q, four-quarter; CPI, consumer price index; GDP, gross domestic product.

Credit stock variables are adjusted for changes in the exchange rate due to the rather high level of loan dollarization[7], as well as housing market indicators, since housing prices and rents are generally quoted in US dollars. Currency depreciation could lead to an increase in indicators such as credit-to-GDP or house prices, erroneously indicating a continuation of financial expansion, whereas it is likely the beginning of a downturn. Even if house prices or rents in US dollars fall, prices in national currency may rise due to devaluation. Therefore, the dynamics of these variables in the national currency do not always adequately reflect the state of the market.

Since we proceed from the fact that the procyclicality of financial systems is closely related to fluctuations in financial variables around trends during the economic cycle, most of the indicators included in the index are expressed as deviations from their trends, that is, in terms of gaps. To calculate gaps, we first estimate the trend components of the FCI's underlying indicators using a HP filter. We apply different HP filters with various lambdas to compose indices, so as to see which one more accurately describes the phases of the financial cycle and more reliably points to impending financial crises. The use of different variations of the HP filter is also aimed at addressing the measurement problems associated with this filter, as described in Section 3.1. We begin with, the FCI is assessed by applying a one-sided HP filter as prescribed by BIS (2010a). Then, we turn to considering estimates using a two-sided HP filter. Additionally, we apply both filters recursively, as suggested by Geršl and Seidler (2012), i.e. each past period using only the observations that were available in that period. For example, when performing recursive estimations for the sample from Q4 2001 to Q3 2024, we first determine the trend for Q4 2001 to Q3 2011, which is selected because not all data series are available for that period. Next, we evaluate the trends sequentially for Q4 2001 to Q4 2011, Q4 2001 to Q1 2012, etc. up to Q4 2011 to Q3 2024, i.e. adding one observation at a time. We retrieve the last point from each trend estimated in this way and add it sequentially to the trend determined for the period of Q4 2001 to Q3 2011. We thus create an index that is no longer modified retrospectively. Analyzing the resulting indices, we conclude that the index estimated by a two-sided HP filter with a smoothing parameter lambda of 25,000 best captures the financial cycle.

The gap is defined as the difference between the observed values and the trend components for variables that are expressed as percentages or ratios, such as credit-to-GDP and price-to-income ratios. For variables expressed as indices, such as the real house price index, the gap needs to be calculated as a percentage of the trend value. Indicators that are not subject to a trend, i.e. BLS-based indicators, Google Trends indicator, the output gap, and the current account balance-to-GDP ratio, are not detrended.

Next, the variables in gaps and the not-detrended indicators are rescaled to bring them to a similar dimension as the same mean (zero) and the degree of variability. For this purpose, we applied standardization by subtracting the mean from the current observations and

[7] At the end of Q3 2024, the level of loan dollarization was 24.4%, and mainly applied to corporate loans. For households, this is a legacy problem, as new loans must be issued solely in national currency.

dividing by the standard deviation. As a result, all variables entered into the FCI are roughly between -2 and +2, and centered at zero.

The final FCI is set as an arithmetic average of the four subindices, calculated as the arithmetic average of the underlying indicators. Considering the residual volatility of the constructed FCI during the year, the index is smoothed by the HP filter with a lambda parameter of 100, which corresponds to the annual data frequency. To evaluate the contribution of each subindex, the individual subindicators were adjusted by the difference between the unsmoothed and smoothed FCIs as follows:

$$FCI_{i,t}^{adj} = FCI_{i,t} + \frac{FCI_t^{\lambda=100} - FCI_t}{4}, \tag{2}$$

where $FCI_{i,t}^{adj}$ denotes the contribution of subindex i in quarter t adjusted by the smoothing of the overall FCI, $FCI_{i,t}$ denotes subindex i in quarter t, $FCI_t^{\lambda=100}$ denotes the FCI in quarter t, smoothed by an HP filter with a lambda of 100, and FCI_t is the unsmoothed FCI in quarter t.

The final FCI is understood to mean a weighted average of the ultimate indicators used, with implicit weights given by the equal weight of the four subindices and the number of indicators within one subindex.

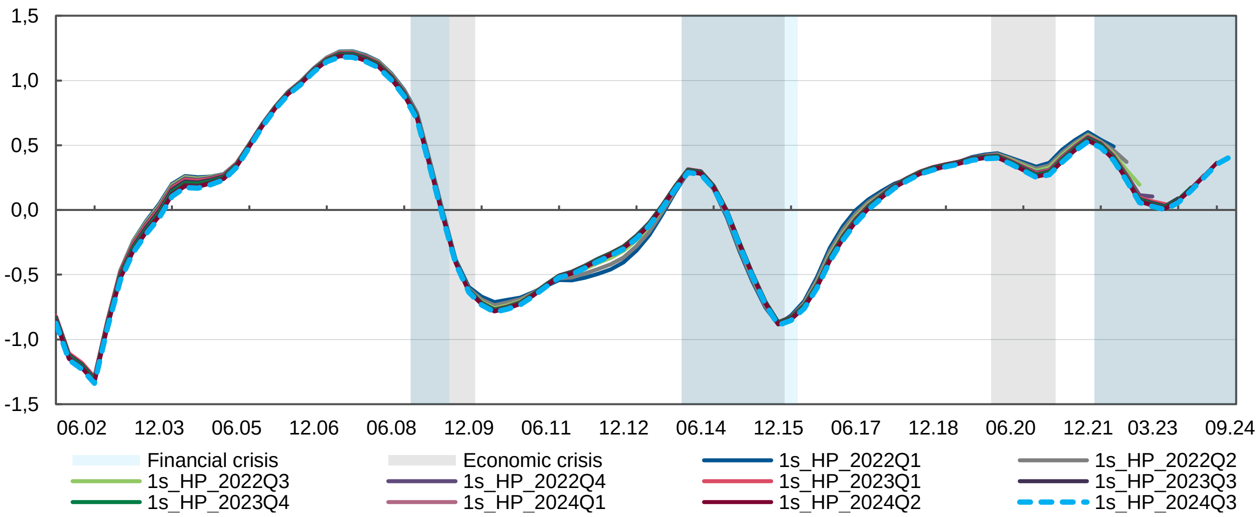
4. FCI Estimation and Its Properties

In this section, we present a step-by-step estimation of the FCI and analyze the results obtained. Following Drehmann and Juselius (2014), we proceed from several principles when calculating the FCI and evaluating its properties. The first principle is timing, which means that the index should provide early warning signals well before a crisis, as banks need time to raise additional capital – notably two-three years as suggested by BIS (2010b). The second is stability, implying that signals should not constantly switch between a crisis and non-crisis, hindering proper policy decisions. The third is easy interpretability, indicating that index dynamics should be clearly understandable for policymakers.

We start our analysis by assessing the FCI with a one-sided HP filter as prescribed by BCBS (BIS, 2010). BCBS recommends a smoothing parameter of 400,000, which is rationalized that credit cycles are on average about four times longer than standard business cycles, and crises tend to occur once every 20–25 years (Drehmann et al., 2010). Such a large parameter appears inappropriate for our sample, which is only about 20 years in total. To set a proper lambda, we look at the FCIs estimated with different smoothing parameters of 1,600, 25,000, and 125,000, which turn out to be quite close to each other (see Appendix B, panel A). Thus, the lambda of 25,000 is chosen to reflect the average estimate.

We also estimate the FCIs for samples with different end points over the past two years to examine the backward revision of the trend (see Figure 1). The constructed indices are in close proximity, although the end-point problem is slightly visible. Going forward, we increase the number of time ranges. The results of this exercise are given in Appendix C, where each figure presents FCI estimates for different samples starting from Q4 2001 to Q3 2011, and then adding one observation at a time sequentially, i.e. Q4 2001 to Q4 2011, Q4 2001 to Q1 2012, etc. up to Q4 2011 to Q3 2024. Since the color of the lines becomes darker as the time window expands, the retrospective shift of indices becomes more noticeable. Thus, the results suggest that real-time estimates vary to some extent in retrospect, but not as much as when looking at the range of the last few years. However, this index is generally not considered suitable due to its volatility. Smoothness, which cannot be determined by highly volatile indicators, is crucial in policy decision-making, and is therefore one of the criteria for good composite cyclical indicators. The indicator is smoothed to eliminate redundant fluctuations and show only long-term cyclical movements, as opposed to noisy series, which can make the leading signal ambiguous. For this reason, we next look at the indices estimated by other filters.

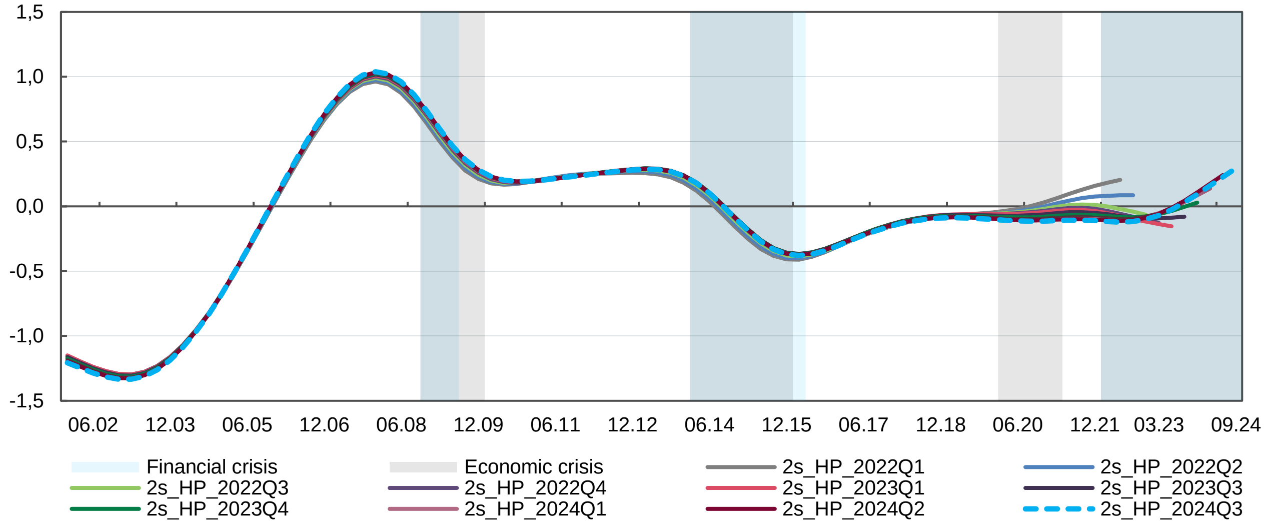
Figure 1. The FCIs Estimated by a One-Sided HP Filter for Samples with Different End Points



Notes: In the notations of data series, 1s_HP means that the FCI is estimated using a one-sided HP filter, the date in the format of 202XQY indicates the end point of the estimated sample.

As expected, the FCIs constructed with a two-sided HP filter demonstrate end-point bias that is more pronounced than the estimates of a one-sided filter (see Figure 2 and Appendix C, right hand panel). On the other hand, the volatility is reduced, and the index captures the financial cycle quite well, which we will look closely at later. To address the problem of backward revision, we alternatively apply both HP filters with observations added recursively, as described in Section 3.2.

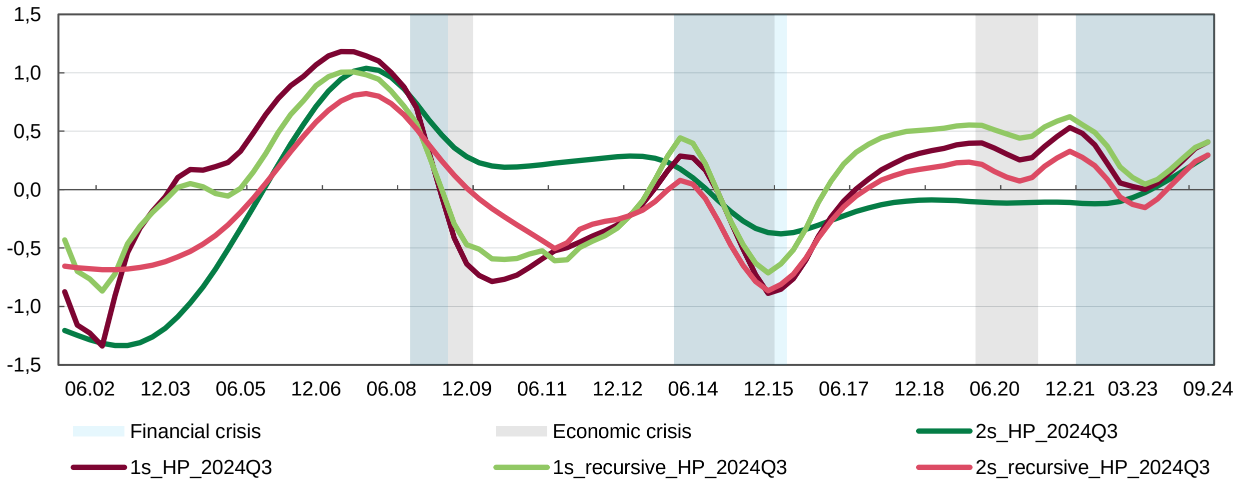
Figure 2. The FCIs Estimated by a Two-Sided HP Filter for Samples with Different End Points



Notes: In the notations of data series, 2s_HP means that the FCI is estimated using a two-sided HP filter, the date in the format of 202XQY indicates the end point of the estimated sample.

Figure 3 plots the FCIs estimated using one-sided and two-sided HP filters and their recursive versions with a smoothing parameter of 25,000 for the Q4 2001 to Q3 2024 sample. As mentioned in Section 3.2, the FCI is centered around 0 and fluctuates roughly between -2 and +2 as all underlying series are standardized. However, as shown in Figure 3, its variability over time is lower, as averaging and the additional smoothing tend to reduce the variance.

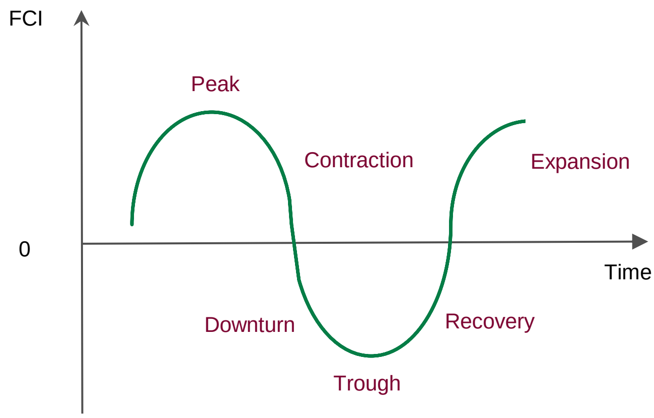
Figure 3. The FCIs Estimated by Different HP Filters



Notes: The notations of data series mean the following: 1s_HP – one-sided HP filter, 1s_HP_recursive – one-sided HP filter applied recursively, 2s_HP – two-sided HP filter, 2s_HP_recursive – two-sided HP filter applied recursively. The date 2024Q3 indicates the end point of the estimated sample.

Figure 4 shows FCI evolution through the financial cycle phases. A value around 0 reflects cyclically neutral times, while descending positive values after the peak point at the contraction phase of the financial cycle, and descending negative values indicate a financial downturn. Ascending negative values correspond to the recovery period after through. Ascending positive FCI values characterize the expansion phase of the financial cycle.

Figure 4. FCI Evolution Depending on Financial Cycle Phases



As illustrated in Figure 3, the highest level of about 1.0 is achieved in 2007, at the peak of the financial cycle preceding the Global Financial Crisis (GFC). The FCIs generally have an upward trend well ahead of the GFC. However, the one-sided filters suggested that the countercyclical capital buffer (CCyB) should be accumulated by Q1 2004, whereas the two-sided filters indicated a much later onset – by Q1 2006. Given the necessary time for decision-making and the subsequent buffer accumulation by banks, these early signals before the GFC appear well-timed. The FCIs then indicate a contraction phase and a following financial downturn – apart from the index estimated by a two-sided HP filter, which smoothly transitions into a mild expansion without entering a downturn. Next, the indices estimated by a one-sided HP filter and its recursive version point to a recovery phase followed by expansion before the deepest financial crises in Ukraine of 2014 to 2016, whereas the index calculated using the recursive version of a two-sided HP filter does not turn into expansion after recovery. Then, all indices point to a downturn phase during the crisis, and after this, the dynamics of the indices diverge. The index based on a two-sided HP filter, whose fall through the crisis was the smallest of all ones, begins a slow recovery and has been at levels just under zero since 2018 until Q3 2023. All other indices recover until Q3 2017 at the latest and then are in the expansion phase until the end of 2021, after which they gradually decline to almost zero in 2023. Between 2017 and 2024, Ukraine experienced two crises that were not accompanied by financial distress – the COVID-19-related economic crisis in 2020–2021, and the ongoing crisis since 2022. The FCI does not indicate a buildup of cyclical systemic risks ahead of these crises due to the nature of their causes. To understand whether there was an accumulation of cyclical risks within this period, we will briefly recall the main economic and financial development trends in these years.

In 2017, the banking sector was recovering from the previous financial crisis. Banks had stable funding and resumed lending. At the same time, private sector credit penetration remained very low. Interest rates on loans gradually decreased but remained quite high. The financial system's overall level of systemic risks was low, while slow economic growth hampered its development. In 2018, the macroeconomic environment became more favorable, with no significant internal or external shocks affecting the banking sector. Due to inflation risks, the NBU increased the key policy rate throughout the year, and, accordingly, loan interest rates went up again. Banks raised funds and were lending more actively. However, lending was subject to limitations due to high interest rates, a lack of high-quality corporate borrowers, and weak demand from households for loans – other than unsecured consumer ones. The banking sector risks associated with excessive lending were low in this period. In 2019, inflation entered the target range set by the NBU, and the key policy rate was cut, which contributed to a decrease in loan interest rates. Unsecured consumer lending surged, and the banks relaxed their retail lending standards. However, these loans amounted to only about 5% of GDP, and this credit growth did not pose a systemic risk to the banking system.

The banks entered the COVID-19-related crisis of 2020–2021 without noticeable imbalances, and with sufficient capital and high liquidity. The economy began to expand in Q3 2020, supported by strong domestic demand and favorable conditions in Ukraine's key export markets. However, the recovery slowed at the end of 2021, primarily due to rising energy prices. A further reduction in interest rates on loans contributed to the development of lending. In 2021, the banks' corporate loan portfolio in national currency increased by more than 40% year-on-year. Consumer lending returned to pre-crisis growth rates. Mortgages also grew rapidly, although mortgage credit lending remained conservative. Nevertheless, such credit growth cannot be considered excessive due to the rather low level of lending penetration, as illustrated by the dynamics of the credit-to-GDP ratio during this period (see Appendix A).

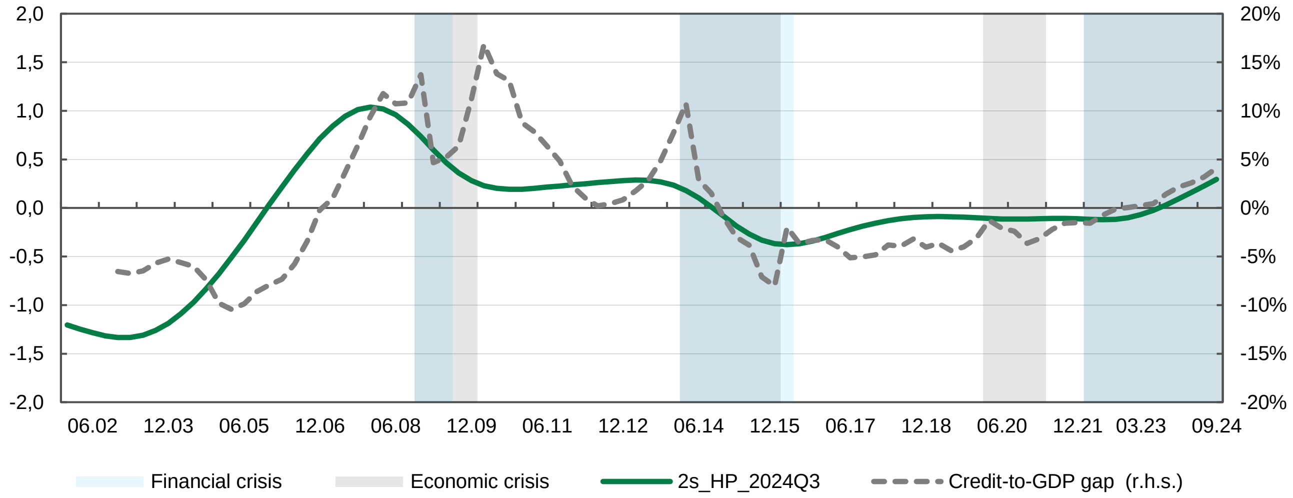
Since early 2022, the Ukrainian economy has plummeted. The NBU took immediate measures to maintain the resilience of the financial system and stability in the foreign exchange market. Significant international financial assistance helps to cover the state budget deficit and support the balance of payments and international reserves. The banking system is successfully resisting the challenges that have arisen: the banks are operating without interruption, maintaining their liquidity and continuing to lend. There are no significant outflows of deposits. The banks recognized large credit losses, but the sector has remained profitable.

Considering the above, we conclude that, in the period from 2017 to 2024, there was no accumulation of cyclical systemic risks that could be associated with the turning of the financial cycle to the expansion phase, even given the fact that some vulnerabilities continued to persist during the specific period, not having been addressed after the crisis of 2014–2016. Only when the index is estimated by a two-sided HP filter does it not exhibit false signals of systemic cyclical risk buildup prior to these two crises of 2020–2021 and 2022–2025, which we view as a positive outcome.

When comparing the dynamics of the resulting index and the credit-to-GDP gap (see Figure 5), we note that the FCI reveals the accumulation of risks earlier and its dynamics is less volatile.

With this in view, we conclude that the index calculated using a two-sided HP filter most reliably describes the financial cycle.

Figure 5. The FCI Estimated by a Two-Sided HP Filter and Credit-to-GDP Ratio



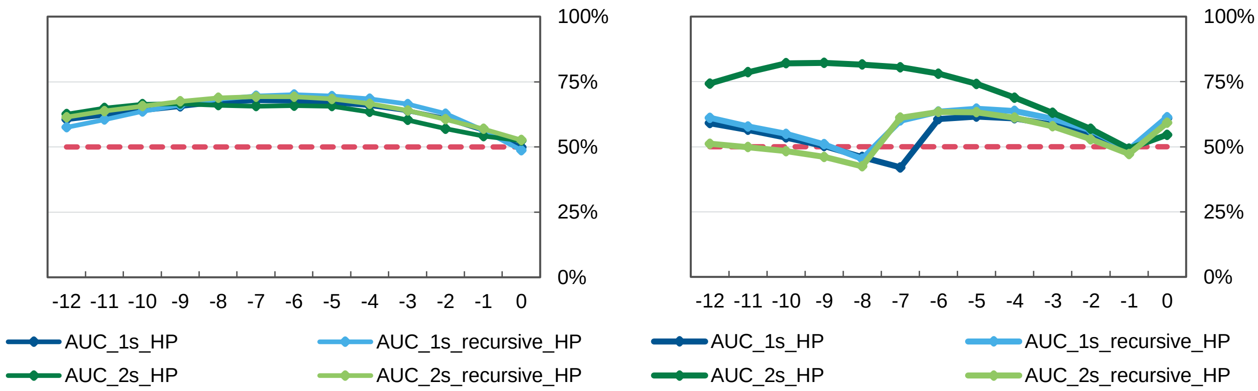
Notes: The notations of the FCI data series are as follows: 2s_HP – two-sided HP filter. The date 2024Q3 indicates the end point of the estimated sample. Credit-to-GDP gap is calculated using credit to private sector adjusted by exchange rate.

4.1. Testing The Predictive Properties of the FCI

Assessing the probability of crisis. Following Drehmann and Juselius (2014) and Lang et al. (2019), we analyze the early warning properties of FCIs using the area under the curve (AUC). AUC is calculated on the basis of logit models, where the dependent variable is the financial crisis event, which equals 1 if the crisis occurs, and 0 if does not; and the independent variable is the FCI. Crisis events correspond to the financial crises in Ukraine, which are set following the methodology of Filatov (2021). An AUC value of 0.5 indicates a random guess. The greater the AUC is from 0.5, the better the signaling performance of the indicator.

The results are presented in Figure 6 and Appendix D. The figures display the AUC values for four FCIs estimated with different HP filters over 12 quarters prior to a financial crisis. We consider two samples: the whole available data period Q1 2001 to Q3 2024 and the period before the crisis of 2022–2025, implying that it was caused by reasons other than financial ones. Surprisingly, the results suggest weaker forecast performance for the period of Q1 2001 to Q4 2021, except with a two-sided HP filter, although it would seem that given the non-financial causes of the 2022–2025 crisis in Ukraine, the results should be the opposite. Considering the period of Q1 2001 to Q3 2024, the AUC estimates for forecast horizons between one and two years prior to a crisis have superior performance. In general, the other indices yield very similar dynamics over the entire horizon and demonstrate AUC values in a range of 0.67–0.7 over the period from one to two years, indicating an acceptable signaling capacity.

Figure 6. AUCs for the FCIs Estimated with Different HP Filters on Different Samples, quarters



A. Data sample Q1 2001 to Q3 2024

B. Data sample Q1 2001 to Q4 2021

Notes: The horizontal axis is the forecast horizon in quarters before financial crises. The vertical axis is the AUC. A dashed pink line indicates AUC value of 0.5, which means a random guess.

Thus, we analyzed the evolution of indices constructed in alternative ways, using all available historical information on the selected horizon. The index based on a recursive two-sided HP filter fails to provide a reliable signal before the deep Ukrainian banking crisis of 2014–2016, which is a serious limitation. A one-sided HP filter and its recursive version provide advance signals of impending crises. However, the rather high estimates prior to crises that were not related to financial causes, in 2020–2021 and 2022–2025 (almost reaching levels before the GFC) do not seem justified, as at that time critical accumulations of cyclical systemic risks and vulnerabilities were not observed to such an extent. The index estimated using a one-sided HP filter varies reasonably in retrospect but cannot be accepted due to its volatility. In contrast, while the FCI estimated with a two-sided HP filter is subject to the end-point bias, it powerfully signals the buildup of cyclical risks and is also well smoothed, which is why we chose this index.

Assessing the severity of crisis. We further investigate the predictive properties of the FCI for crises of different severities, which is proxied by various depths of output decline. We hypothesize that the index has predictive power in the short term, indicating a relatively short financial cycle in Ukraine, with the strongest impact on the left tail of the GDP growth rate distribution.

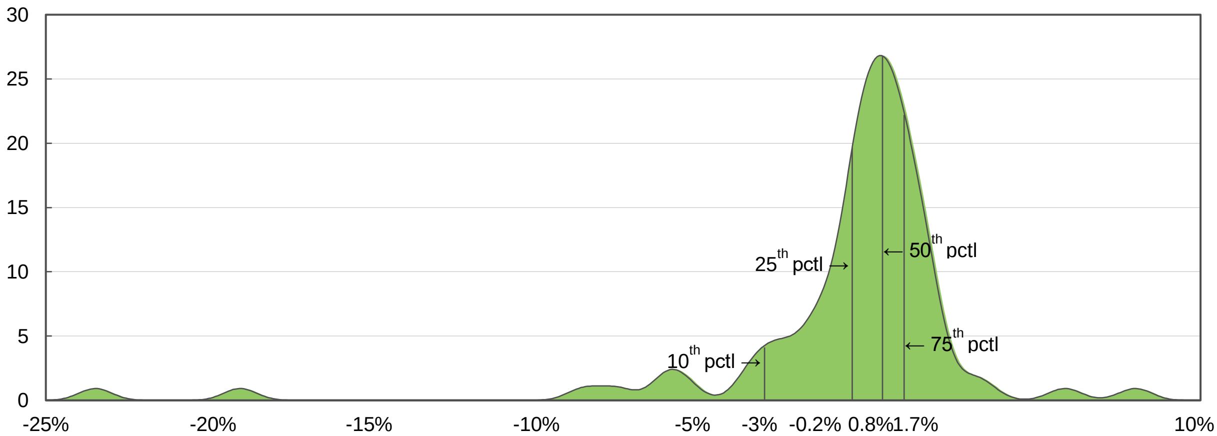
For this purpose, we estimate quantile regressions following Lang et al. (2019):

$$Y_{t+h}(\tau) = \alpha + \beta(\tau) \cdot FCI_t + \sum_{i=0}^{3} \gamma_i(\tau) \cdot Y_{t-i}, \tag{3}$$

where FCI_t is the index in quarter t, Y_t denotes the seasonally adjusted real GDP growth rate in quarter t, measured as percentage change from the previous quarter, h is a prediction horizon from 1 to 12 quarters; and τ is the percentile of the real GDP growth rate.

The actual distribution of quarterly real GDP growth in Ukraine for the period of Q4 2002 to Q3 2024 is shown in Figure 7. The left tail of the distribution is assumed to be at the 10th and 25th percentile levels, implying falls in GDP of 3% and 0.2% or more, respectively. We include GDP growth rate in the right-hand side part of the regression, with lags from 0 to 3 to control for the effects of other omitted variables besides the index. We also run regressions with lags of the FCI, but the resulting estimates are statistically insignificant.

Figure 7. Distribution of Real GDP Growth Rates in Ukraine for Q4 2002 to Q3 20242



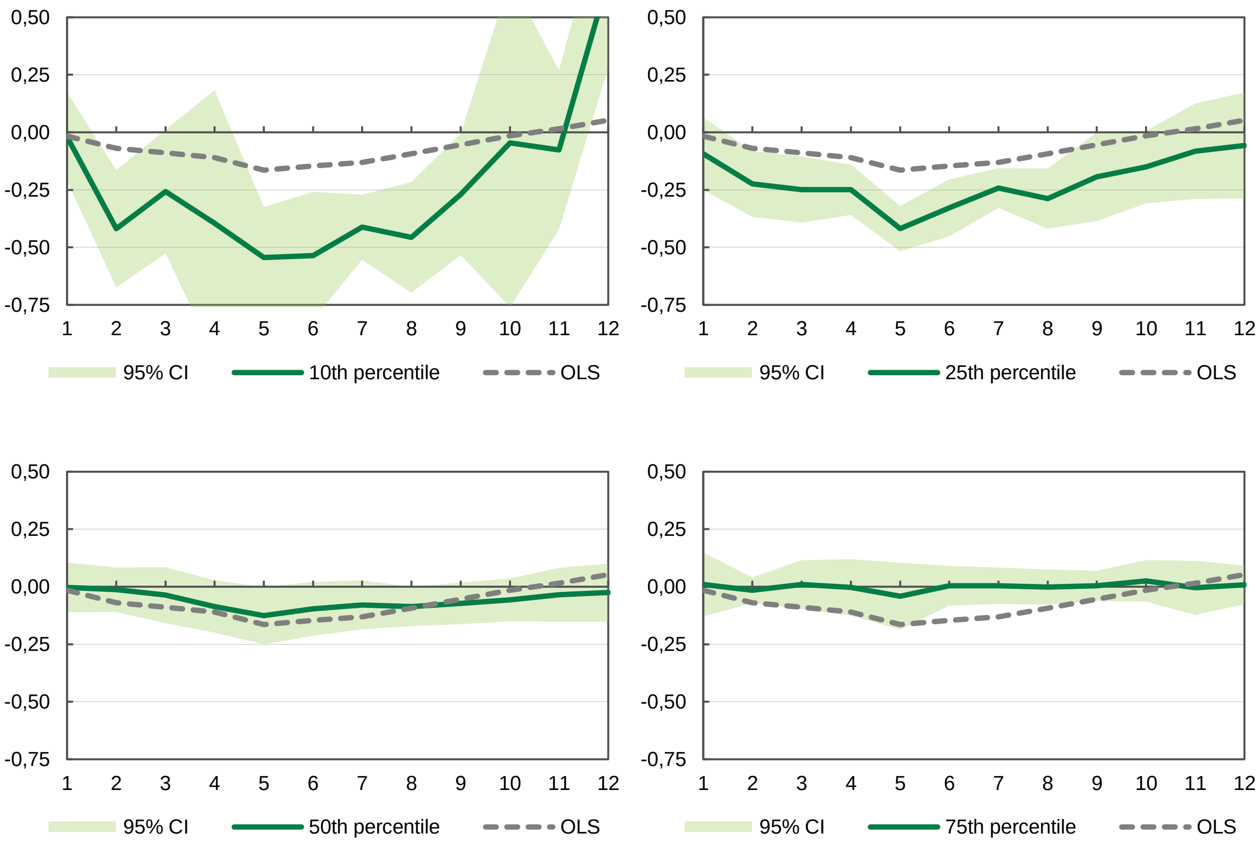
Notes: The figure displays the density function of real GDP growth. The horizontal axis indicates the quarterly seasonally adjusted real GDP growth rate, measured as a percentage change over the previous quarter. Abbreviations: pctl, percentile; GDP, gross domestic product.

Figure 8 plots the impulse responses of the quarterly seasonally adjusted real GDP growth rate, measured as percentage change from the previous quarter, at the 10th, 25th, 50th and 75th percentiles respectively to a 0.1 unit increase in the FCI, with 95% confidence intervals.

For a horizon of two to nine quarters (apart from quarters three and four, estimates of which are statistically insignificant), the reduction in the 10th percentile of the real GDP growth distribution is around 0.4 percentage points. For the 25th percentile, a statistically significant decline of around 0.3 percentage points is observed from quarters two through nine. For the 50th percentile, the statistically significant effects (in quarters five and eight) are weaker, around 0.1 percentage points. The results are statistically insignificant for the 75th percentile.

The resulting estimates support the hypothesis of there being a strong impact already in the short run, as well as a larger effect in the left tail of the GDP distribution. Generally, the results align with those obtained by Lang et al. (2019). The main difference is in the horizon, over which we can see the impact of the FCI on the left-hand side of the GDP distribution. While Lang et al. (2019) find that the effect is strongest in two to three years, our calculations show that a strong effect starts in the first year. This could point to a relatively short financial cycle in Ukraine, which appears reasonable for an emerging market.

Figure 8. Response of Real GDP Growth Distribution to Increase in the FCI

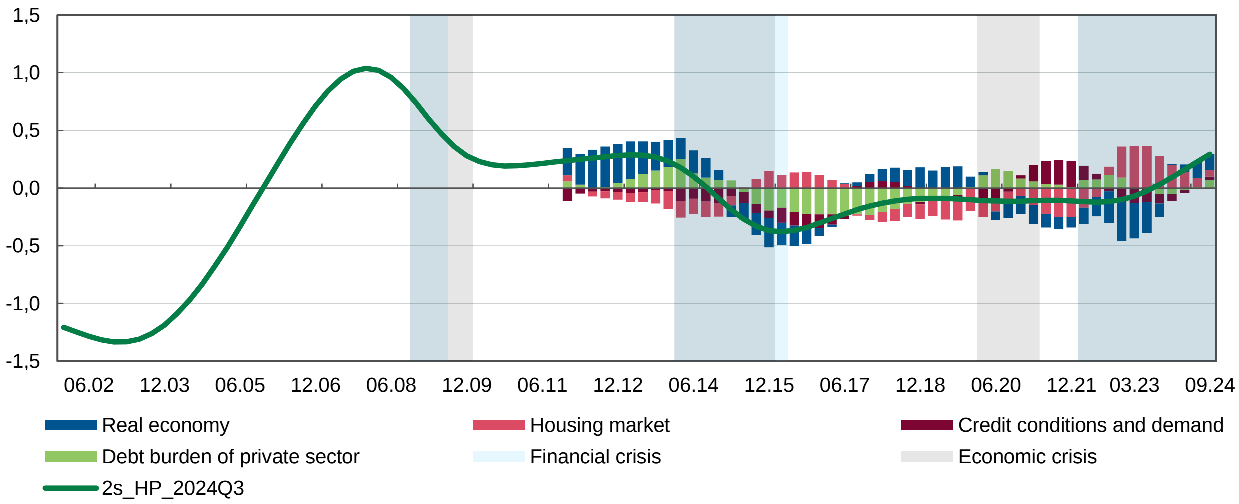


Notes: The horizontal axis is the forecast horizon in quarters. The green solid lines indicate the impulse responses of the quarterly seasonally adjusted real GDP growth rate, measured as percentage change from the previous quarter, at the 10th, 25th, 50th and 75th percentiles respectively (in percentage points) to a 0.1 unit increase in the FCI. Light green areas denote 95% confidence intervals. The gray dashed line shows the response of the average real GDP growth rate, derived from ordinary least squares (OLS) estimates, over the forecast horizon.

4.2. FCI Decomposition

Figure 9 depicts the FCI estimated by a two-sided HP filter with a smoothing parameter of 25,000 and the contributions of the four subindices. The contributions are calculated starting from Q4 2011, as all underlying indicators are available only from this period. Before that, the FCI is based on those indicators available in certain quarters. Given the standardization of all variables entering the index, a varying number of indicators in the FCI across periods is not a large problem per se, but should be considered when looking at the whole evolution of the FCI. For example, in 2001–2003, the FCI is based on only two variables – the credit-to-GDP gap and the current account balance-to-GDP ratio; from 2004, the output gap is added, and from 2006, the sectoral credit-to-GDP gaps are included. From 2009, most indicators have been available, except those from the NBU's Bank Lending Survey, which started in 2011.

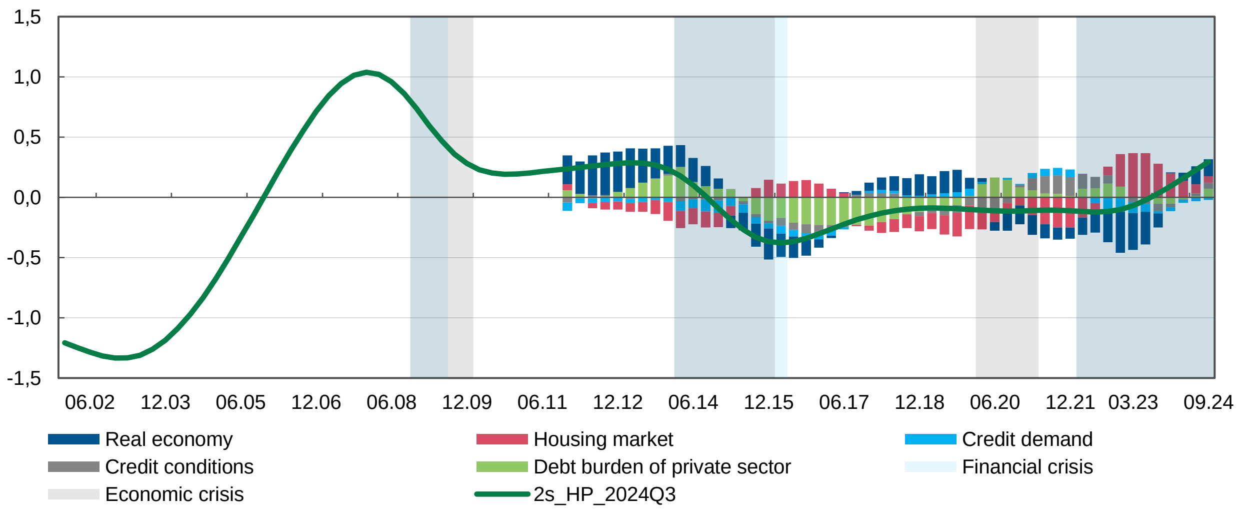
Figure 9. The FCI Estimated by a Two-Sided HP Filter with Subindices



Notes: The notations of the FCI data series are as follows: 2s_HP – two-sided HP filter. The date 2024Q3 indicates the end point of the estimated sample.

In the subindex on credit conditions and demand, the interest rates on new loans and credit standard indicator reflect the willingness of banks to lend, while the two other indicators reflect demand for credit. To enhance interpretability, we display the contribution of the supply and demand factors separately in Figure 10.

Figure 10. The FCI Estimated by a Two-Sided HP Filter with Subindices



Notes: The notations of the FCI data series are as follows: 2s_HP – two-sided HP filter. The date 2024Q3 indicates the end point of the estimated sample.

5. The FCI and Countercyclical Capital Buffer Calibration

According to BIS (2010b), the primary aim of the CCyB is to ensure that the banking sector in aggregate has enough capital to help maintain the flow of credit in the economy without its solvency being questioned when the broader financial system experiences stress after a period of excess credit growth. The CCyB can also dampen the credit cycle during an economic upturn, as banks can tighten the credit supply to meet higher capital requirements. A desirable feature of the guidelines used to make CCyB decisions is to signal the turning point of the financial cycle early enough, as countercyclical macroprudential instruments are implemented with a long lag. Notably, banks are given one year from the announcement of a change in the CCyB to adjust to its new level.

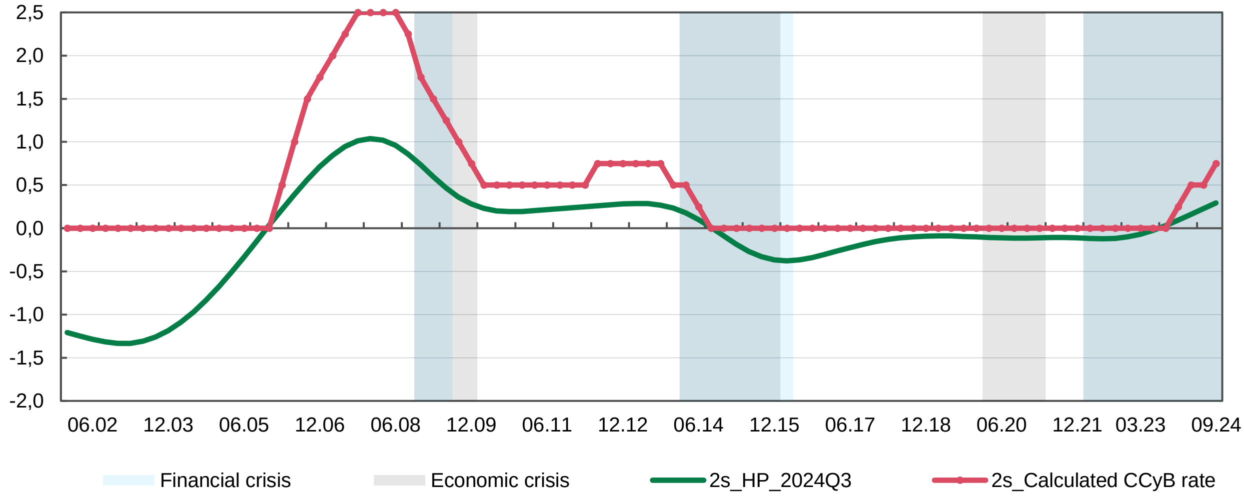
The CCyB is an instrument that needs to be activated in financial upturns, so once the FCI crosses zero and either remains at that level or continues increasing, a positive CCyB rate should be put in place. If the FCI increases further, the CCyB should increase correspondingly, up to the Basel III recommended upper limit of 2.5% of risk-weighted assets. However, Basel III allows the countries to go above 2.5% in the case of strong financial upturns, with a large accumulation of systemic risk.

In line with the experience of other central banks, when using a financial cycle indicator to calibrate the CCyB, heuristically, this knowledge about past levels can be used to calibrate the CCyB rate as follows: in 2007, if the CCyB regime had been in place, it would have been good to have had it at the highest level of 2.5%. Thus, a FCI level of 1 would correspond to a CCyB rate of 2.5%, while a cyclically neutral FCI level of 0 would correspond to a 0% CCyB. The formula giving the CCyB rate corresponding to the FCI level is as follows:

$$CCyB_t = \max\{2.5 \cdot FCI_t, 0\}, \tag{4}$$

However, the calculated values of the CCyB (see Figure 11) should only be used as an indicative rate. As argued by Drehmann and Tsatsaronis (2014), the CCyB should not be anchored mechanically to the credit-to-GDP gap, since no indicator is infallible, policy decision-making requires judgment, and combinations of measures work better than individual indicators. Similarly, we accept the FCI as one of the guidelines when making a decision on setting the CCyB, but not the only one, especially given the end-point bias problem. To make the FCI a reliable guide for macroprudential policy decisions, a wide range of indicators characterizing the level of credit risks in bank portfolios, the dynamics of capital adequacy standards, the results of stress testing, and the effect of other macroprudential instruments must be considered.

Figure 11. Calculated CCyB Rates Based on the FCI Estimated by a Two-Sided HP Filter



Notes: The notations of the FCI data series are as follows: 2s_HP – two-sided HP filter. The date 2024Q3 indicates the end point of the estimated sample. The calculated CCyB rates are rounded to 0.25% and capped at 2.5%.

6. Conclusions

In this study, we present the FCI as a means of identifying where the Ukrainian economy is in the financial cycle. The FCI is based on 16 indicators aggregated into four subindices to capture systemic risks related to excessive credit growth, immoderate easing of lending conditions, the state of the real estate market, and macroeconomic imbalances. Since we proceed from the fact that the procyclicality of financial systems is closely related to fluctuations in financial variables around trends during the economic cycle, most of the indicators included in the index are expressed in terms of gaps – that is, deviations from their trends.

To compose the index, we apply one- and two-sided HP filters with various lambdas, and their recursive versions, to see which one more accurately describes the phases of the financial cycle. The FCI estimated by a two-sided HP filter is subject to the end-point bias, but it strongly signals rising cyclical risks and is well smoothed, which is why we chose this index.

We accept the presented FCI as one of the guidelines for making a decision on setting the CCyB. To make the FCI a reliable guide for macroprudential policy decisions, a wide range of indicators characterizing the level of credit risk in bank portfolios, the dynamics of capital adequacy standards, the results of stress testing, and the effect of other macroprudential instruments must be considered.

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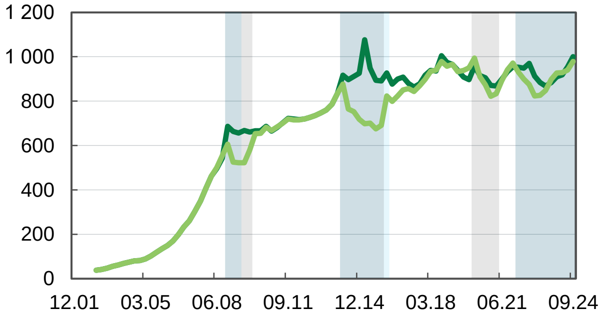
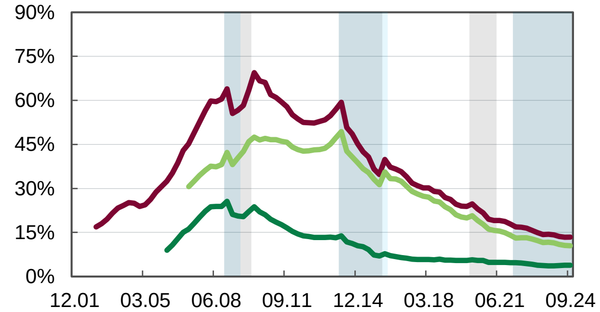
APPENDICES

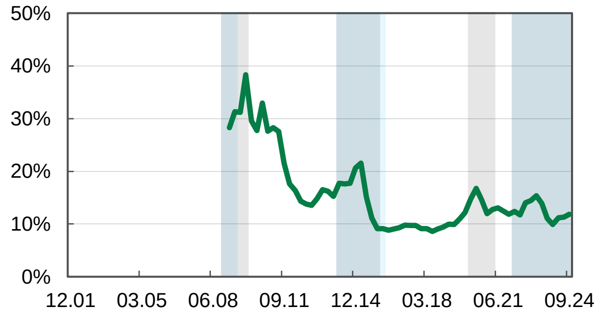
APPENDIX A. Dynamics of Indicators within the FCI



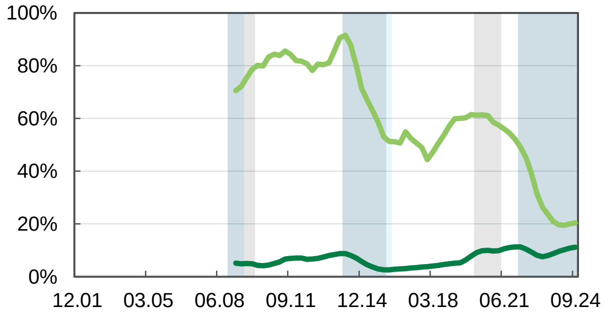
Credit to private sector, UAH billion
Credit to private sector, exchange rate adjusted, UAH billion



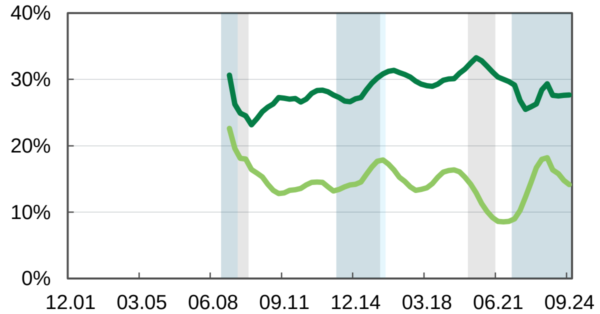
Credit to private sector, exchange rate adjusted, to GDP
Household credit, exchange rate adjusted, to GDP
Corporate credit, exchange rate adjusted, to GDP



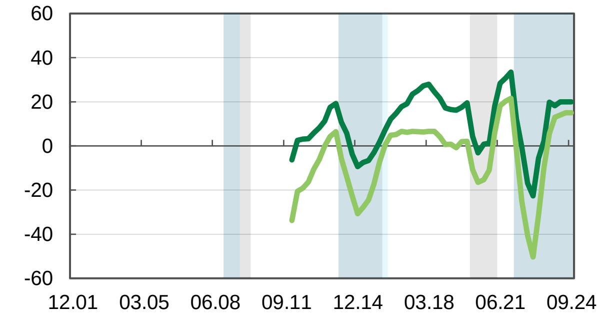
Debt service ratio for households



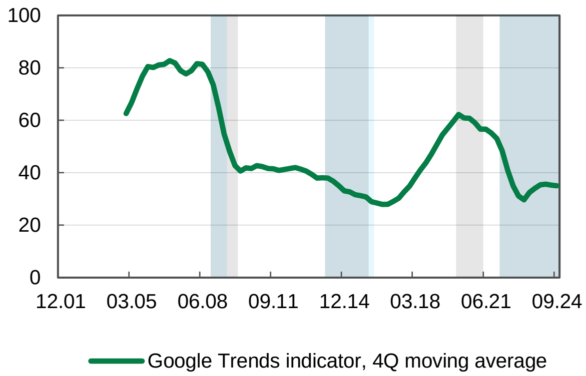
New lending to households to GDP
New lending to corporations to GDP

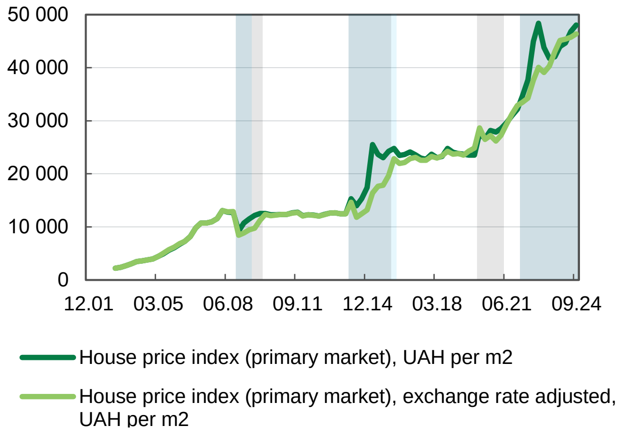


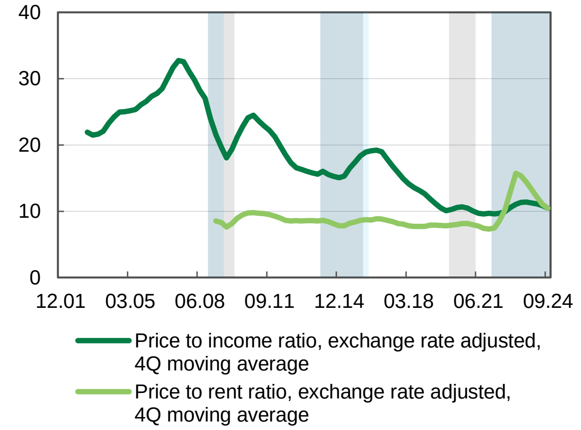
Interest rates on new loans to households, 4Q moving average
Interest rates on new loans to corporations, 4Q moving average

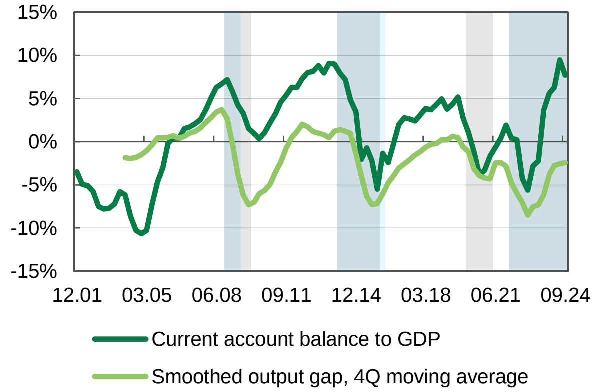


Average of past and expected credit demand for corporations and households, 4Q moving average
Average of past and expected change in credit standards to corporations and households, 4Q moving average



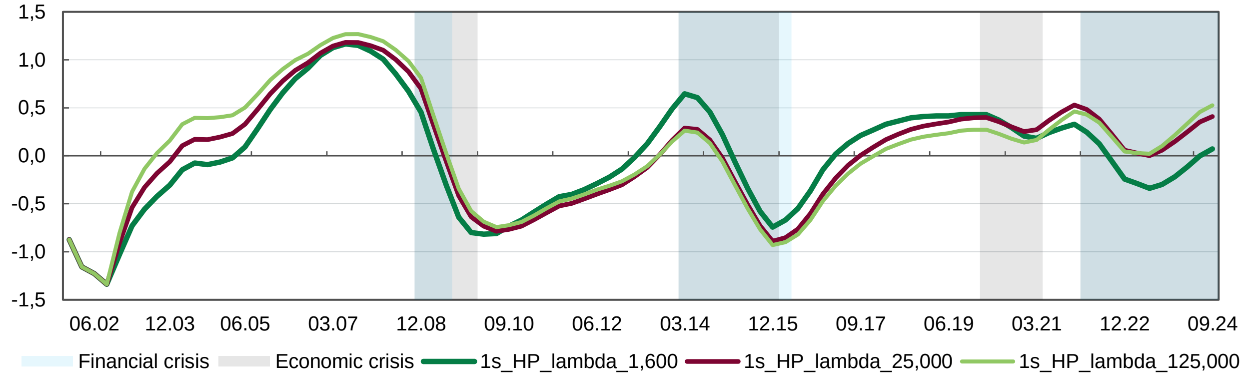




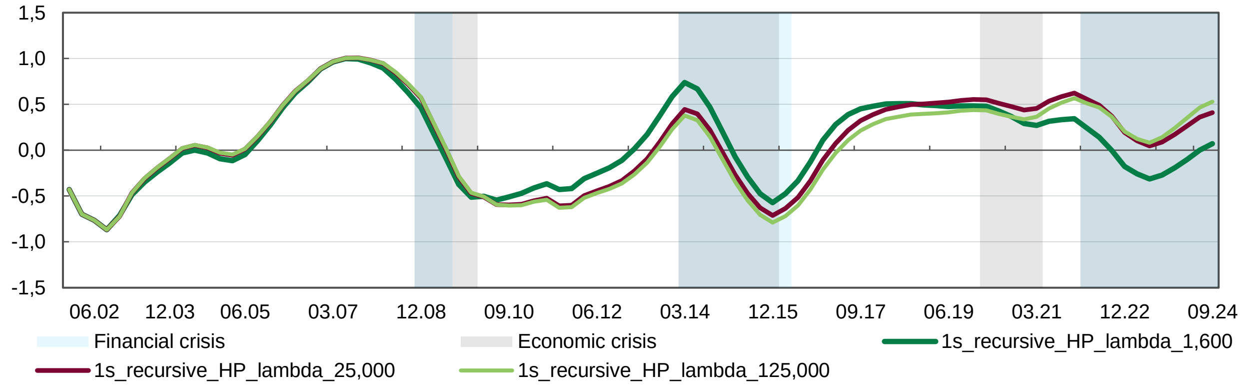


Notes: A positive value of the credit standards indicator reflects their tightening, a negative value – a weakening. A positive value of the demand indicator corresponds to an increase in credit activity, a negative value corresponds to a decrease in the demand for loans. The blue bars indicate financial crisis periods, the grey bars – economic crisis periods.

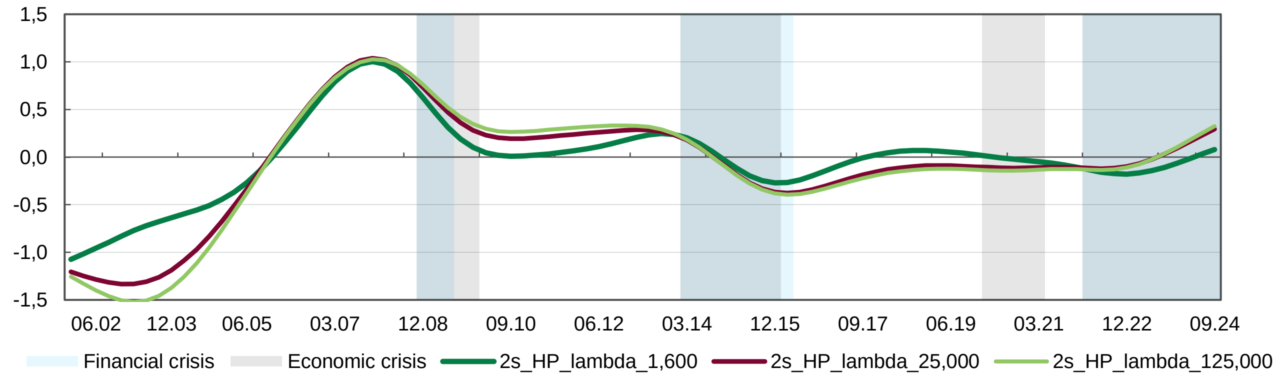
APPENDIX B. The FCIs Estimated with Different HP Filters with Different Smoothing Parameters



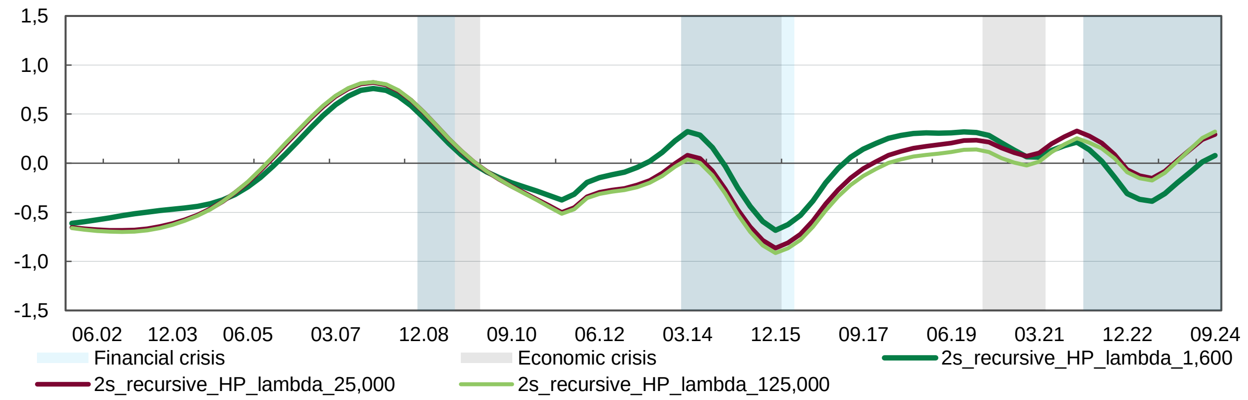
A. One-sided HP filter



B. Recursive one-sided HP filter



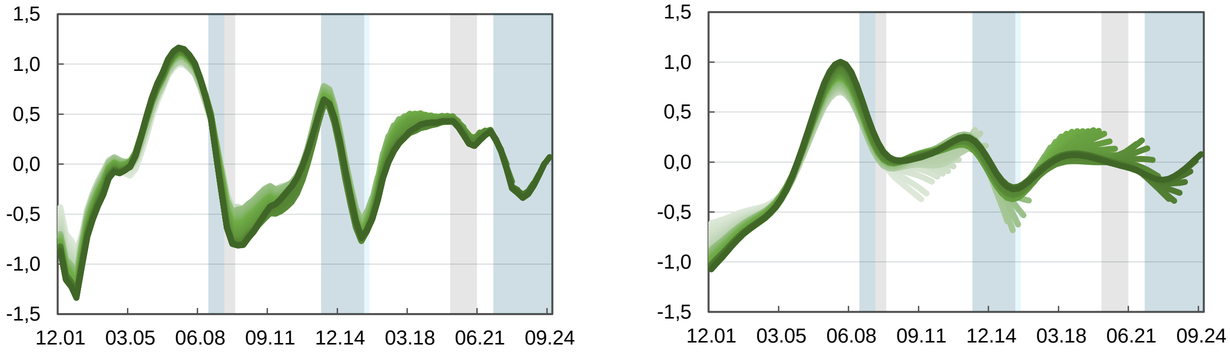
C. Two-sided HP filter



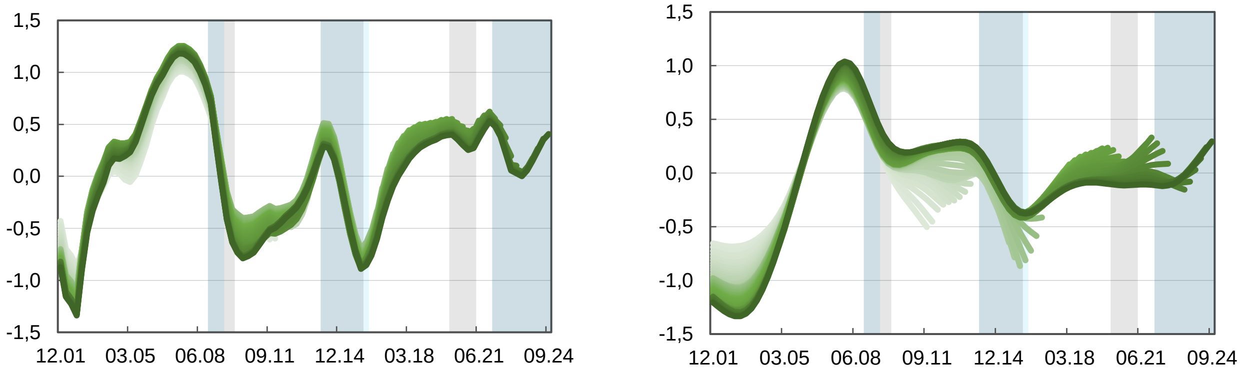
D. Recursive two-sided HP filter

APPENDIX C. The FCIs Estimated on Different Samples Using Different HP Filters with Different Smoothing Parameters

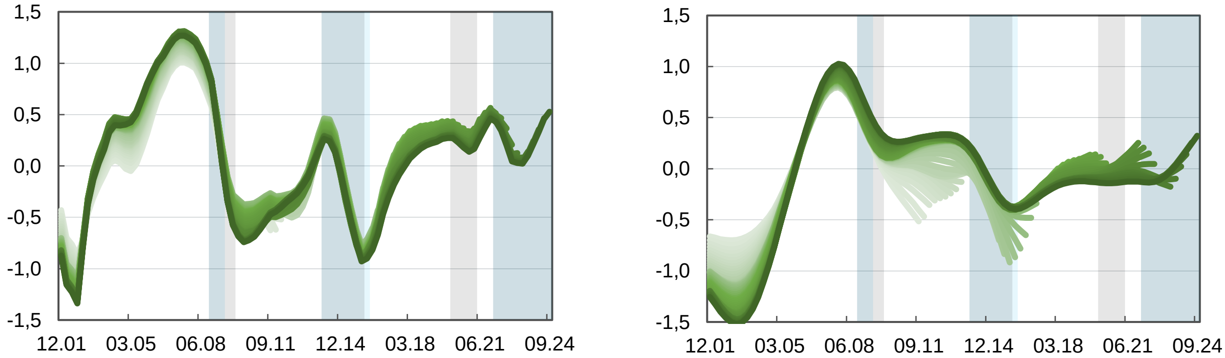
One-sided HP filter Two-sided HP filter



A. Lambda = 1,600



B. Lambda = 25,000



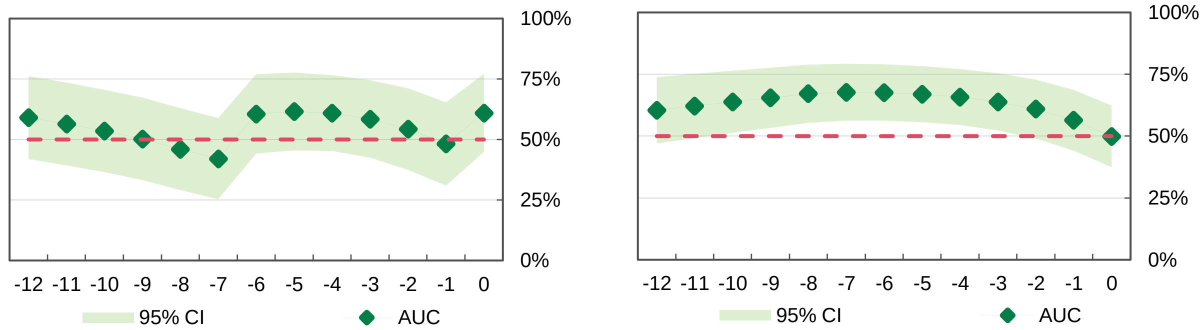
C. Lambda = 125,000

Notes: Each figure depicts FCI estimates for different samples starting from Q4 2001 to Q3 2011 and then adding one observation at a time sequentially, i.e. Q4 2001 to Q4 2011, Q4 2001 to Q1 2012, etc. until Q4 2011 to Q3 2024. The colors of the lines become darker as the time span expands. The blue bars indicate financial crisis periods, the grey bars – economic crisis periods.

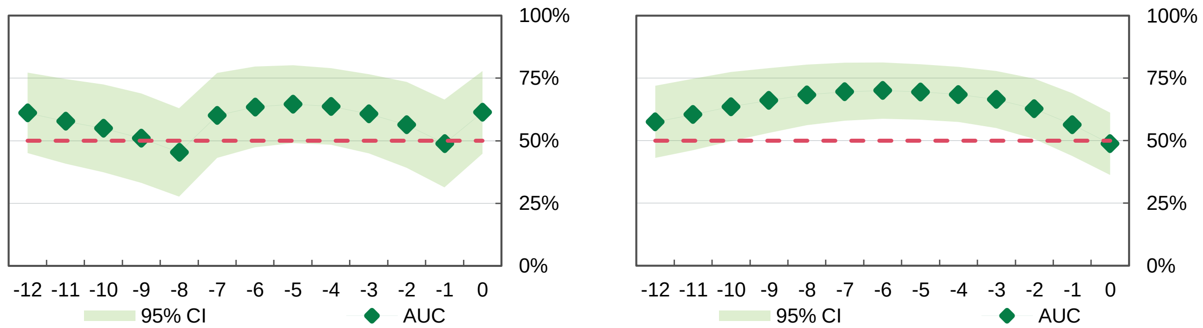
APPENDIX D. AUCs for the FCIs Estimated on Different Samples and Using Different HP Filters

Data sample Q1 2001–Q4 2021

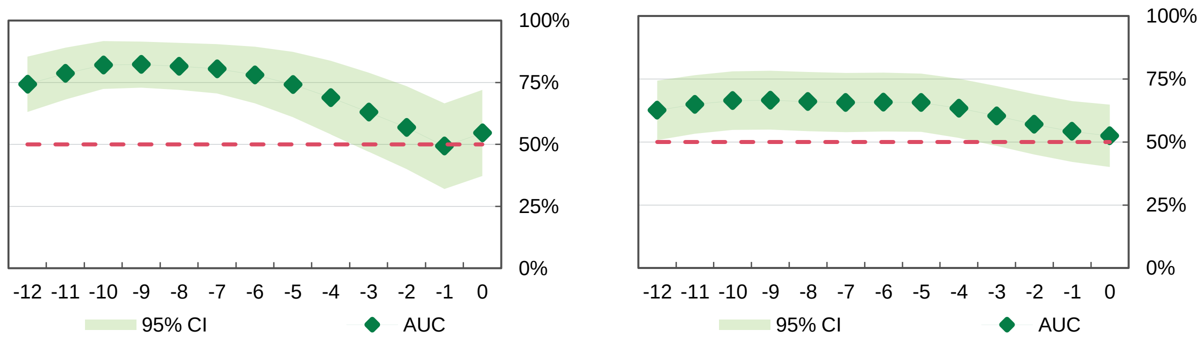
Data sample Q1 2001–Q3 2024



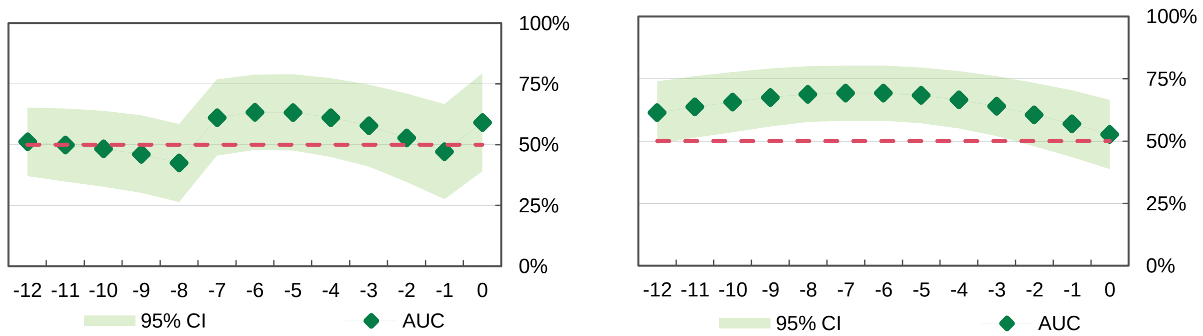
A. One-sided HP filter



B. Recursive one-sided HP filter



C. Two-sided HP filter



D. Recursive two-sided HP filter

Notes: The horizontal axis is the forecast horizon in quarters before financial crises. The vertical axis is the AUC. The AUC is calculated on the basis of a logit model where the dependent variable is the crisis event, which equals 1 if a crisis occurs, and 0 if it does not, and the independent variable is the FCI. Financial crisis periods for Ukraine are set following the methodology of Filatov (2021). The dashed pink line indicates an AUC value of 0.5, meaning a random guess.