DEUTSCHE BUNDESBANK
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Technical Paper

A composite indicator of financial conditions for Germany

03/2022

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Non-technical summary

Composite indicators that summarize information from a broad range of financial variables are used for macroprudential surveillance of the financial system on a regular basis. Composite indicators of financial stress, for example, measure systemic risks in various financial market segments by condensing information on asset price-based variables, such as yield spreads and asset price volatilities. Composite indicators of financial conditions, by contrast, are broader in scope than financial stress indicators. In addition to financial market data, they usually also contain quantity-based measures and other macro-financial indicators that capture information from different segments of the financial system, e.g., on financial intermediaries and the non-financial sector. Composite indicators of financial conditions may thus prove particularly useful in obtaining information about the state of the financial system in a timely fashion.

In its Financial Stability Review 2022, the Deutsche Bundesbank analyses financial conditions in the financial system based on a new Composite Indicator of Financial Conditions (CIFC). This paper presents the methodology to compute this indicator. The CIFC aggregates six subindicators, three of which are comparable to the components *credit risk*, *liquidity risk* und *market risk* of the financial stress indicator of the Bundesbank. Three additional subindicators capture financial conditions in the German government bond market (subindicator *Bund yield curve*) and the banking sector as well as the non-financial private sector (subindicators *money and credit volumes* and *bank lending behaviour*). The subindicators are estimated from a battery of financial variables (70 in total) using principal component analysis, and they are aggregated into a single composite indicator, the CIFC, using time-varying weights. The weights capture the time-varying correlation structure of the subindicators. The CIFC is computed from January 2003 onwards at a monthly frequency. It thus provides a timely gauge of financial conditions in the German financial system.

The results indicate that since 2003 there were four episodes of tight financial conditions in Germany. These coincided with the financial crisis of the early 2000s, the 2008 global financial crisis, the euro area sovereign debt crisis of the early 2010s and the COVID-19 recession in 2020. The composite indicator is currently below the levels of past financial crises. It nevertheless recently reached a level last seen during the outbreak of the COVID-19 pandemic. Macroeconometric model estimates show that disturbances within the financial system had a relatively strong influence on financial conditions in the past.

Nichttechnische Zusammenfassung

Zusammengesetzte Indikatoren, die Informationen aus einem breiten Spektrum von Finanzvariablen zusammenfassen, werden zur makroprudenziellen Überwachung des Finanzsystems regelmäßig verwendet. Ein Beispiel dafür sind Finanzstressindikatoren. Sie messen systemische Risiken in verschiedenen Finanzmarktsegmenten, indem sie vermögenspreisbasierte Variablen wie Vermögenspreisvolatilitäten und Renditespreads in einen Gesamtindikator verdichten. Zusammengesetzte Indikatoren für finanzielle Bedingungen sind dagegen breiter angelegt als Finanzstressindikatoren. Neben Marktdaten enthalten sie in der Regel auch mengenbasierte Kennzahlen und andere makrofinanzielle Indikatoren, die Informationen aus verschiedenen Segmenten des Finanzsystems erfassen, wie etwa zu Finanzintermediären und dem nichtfinanziellen Privatsektor. Zusammengesetzte Indikatoren für finanzielle Bedingungen können sich daher als besonders nützlich erweisen, um zeitnahe Informationen zum Zustand des Finanzsystems zu liefern.

In ihrem Finanzstabilitätsbericht 2022 analysiert die Deutsche Bundesbank finanzielle Bedingungen im Finanzsystem anhand eines neuen Gesamtindikators für finanzielle Bedingungen (Composite Indicator of Financial Conditions, CIFC). In diesem Papier wird die Methodik zur Berechnung dieses Indikators beschrieben. Der CIFC aggregiert sechs Teilindikatoren, von denen drei vergleichbar sind mit den Komponenten *Kreditrisiko*, *Liquiditätsrisiko* und *Marktrisiko* des Finanzstressindikators der Bundesbank. Drei weitere Teilindikatoren erfassen die finanziellen Bedingungen auf dem deutschen Staatsanleihemarkt (Teilindikator *Bundesanleihe-Zinsstrukturkurve*) und dem Bankensektor sowie dem nichtfinanziellen Privatsektor (Teilindikatoren *Geld- und Kreditmengen* und *Kreditvergabeverhalten der Banken*). Die Teilindikatoren werden aus einer Reihe von Finanzvariablen (insgesamt 70) unter Verwendung der Hauptkomponentenanalyse geschätzt und mit Hilfe von zeitvariablen Gewichten zu einem zusammengesetzten Indikator, dem CIFC, zusammengefasst. Die Gewichte spiegeln die zeitvariable Korrelationsstruktur der Teilindikatoren wider. Der CIFC wird ab Januar 2003 monatlich berechnet. Er liefert damit ein zeitnahes Maß für finanzielle Bedingungen im deutschen Finanzsystem.

Die Ergebnisse zeigen, dass es in Deutschland seit 2003 vier Episoden angespannter finanzieller Bedingungen gab. Diese fielen zeitlich mit der Finanzkrise Anfang der 2000er Jahre, der globalen Finanzkrise 2008, der Staatsschuldenkrise im Euroraum Anfang der 2010er Jahre und der Corona-Rezession im Jahr 2020 zusammen. Der Indikator liegt am aktuellen Rand zwar unter dem Niveau vergangener Finanzkrisen. Jedoch erreichte er jüngst ein Niveau, das zuletzt zu Beginn der Corona-Pandemie zu beobachten war. Schätzungen eines makroökonometrischen Modells zeigen, dass Störungen innerhalb des Finanzsystems in der Vergangenheit einen vergleichsweise starken Einfluss auf die finanziellen Bedingungen hatten.

A composite indicator of financial conditions for Germany*

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November 14, 2022

Abstract

This paper proposes a composite indicator of financial conditions for Germany. The composite indicator distills information from large amounts of data covering different segments of the German financial system into a summary measure of financial conditions. This measure is constructed from 70 individual financial indicators for the period between January 2003 and June 2022. The findings show that there were four main episodes of tight financial conditions in Germany, which coincide with the financial crisis of the early 2000s, the 2008 global financial crisis, the euro area sovereign debt crisis of the early 2010s and the COVID-19 recession in 2020. Recent readings of the composite indicator point to tighter-than-average financial conditions in the first half of 2022. Estimates from a structural vector autoregression indicate that financial shocks account for a relatively large part of the variation in financial conditions, while macroeconomic shocks play a smaller role.

JEL classification: E44, E51, G12, G17

Keywords: diffusion index, factor model, financial conditions, financial stability

*The author thanks Yiran Wei for excellent research assistance. The views expressed are those of the author and do not necessarily represent the views of the Deutsche Bundesbank or the Eurosystem.

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1 Introduction

Adverse financial shocks can have detrimental effects on the real economy. A reminder of this was the 2008 financial crisis, which spread from the U.S. subprime mortgage market to nearly all segments of the global financial system, leading to a broad-based deterioration in financial conditions and a severe recession worldwide. The crisis and ensuing recession underscored that financial conditions play a crucial role for macroeconomic fluctuations. Monitoring financial conditions is thus of central importance to economists and macroprudential policymakers concerned with safeguarding financial stability.

Composite indicators that summarise information from a broad range of financial variables may prove particularly useful in tracking the state of financial conditions in a timely fashion. Composite indicators of financial stress, for example, measure contemporanous systemic stress in financial markets by condensing information on asset price-based indicators, such as yield spreads and asset price volatilities.[1] Composite indicators of financial conditions, by contrast, are broader in scope than financial stress indicators. In addition to financial market data, they usually also contain quantity-based measures and other macro-financial indicators that capture information from different segments of the financial system – e.g., financial markets, intermediaries, and the non-financial sector.[2] To date, there is no broad-based composite indicator of financial conditions for Germany. Some of the existing composite indicators are narrower in scope and restrict their focus on financial stress, such as the Bundesbank's financial stress indicator (see Deutsche Bundesbank, 2019) and the CLIFS index for Germany (see Duprey et al., 2017). Others, including the Bundesbank's early warning indicator (see Deutsche Bundesbank, 2017; Beutel et al., 2019) and the financial cycle indicator proposed by Schüler et al. (2020), track the build-up rather than the materialisation of financial vulnerabilities.

In its Financial Stability Review 2022, the Deutsche Bundesbank analyses financial conditions in the financial system based on a new composite indicator of financial conditions (CIFC) for Germany (see Deutsche Bundesbank, 2022). This paper presents the methodology to compute this indicator. The CIFC distills information from large amounts of financial data covering different segments of the financial system, such as the government bond market, the stock market, the foreign exchange market, the banking sector, and the non-financial private sector, into a summary measure of financial conditions. I construct this new composite indicator from a battery of individual financial indicators (70 in total), selected based on earlier studies.[3] To

[1] See, e.g., the Composite Indicator of Systemic Stress (CISS) proposed by Holló et al. (2012) for the euro area and the Country-Level Index of Financial Stress (CLIFS) developed by Duprey et al. (2017) for members of the European Union.

[2] See, e.g., the financial conditions indicators proposed by Hatzius et al. (2010), Brave and Butters (2011) and Koop and Korobilis (2014) for the United States, the indicator proposed by Moccero et al. (2014) for the euro area, and the indicators published regularly by the International Monetary Fund (IMF) for advanced and emerging economies (e.g., International Monetary Fund, 2022, page 6).

[3] The coverage of individual indicators is comparable to, e.g., the U.S. National Financial Conditions Index of the Federal Reserve Bank of Chicago (Brave and Butters, 2011).

construct the CIFC, I first estimate six subindicators of financial conditions (SIFCs) that measure different dimensions of financial conditions. The SIFCs are estimated from subsets of individual indicators using principal components (Stock and Watson, 2002). In a second step, I aggregate the SIFCs into a single composite indicator using time-varying weights that capture the changing correlation structure between the SIFCs (see also Holló et al., 2012; Schüler et al., 2020). At each point in time, SIFCs that co-move more strongly receive a larger weight, while SIFCs that behave in an idiosyncratic way receive a lower weight. The CIFC is computed from January 2003 onwards at a monthly frequency. It thus provides a timely gauge of financial conditions in the German financial system.

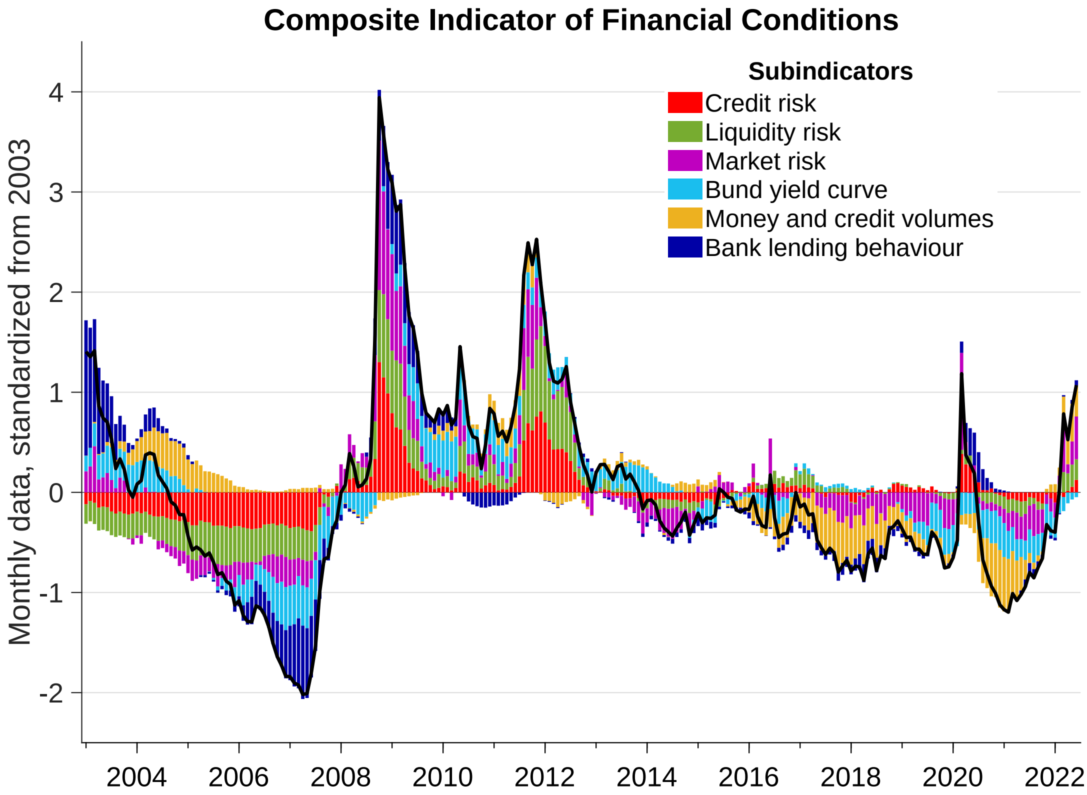


Figure 1: **Composite indicator of financial conditions for Germany**

Note: This figure depicts the composite indicator of financial conditions (CIFC) and its subindicators for Germany. Source: Bank for International Settlements, Banque de France, Bloomberg Finance L.P., Deutsche Bundesbank, European Central Bank and own calculations. Sample: 2003:M1-2022:M6. The CIFC is the weighted sum of six subindicators of financial conditions (SIFCs) that capture different dimensions of financial conditions. For details on data and variable transformations, see Table 1. The CIFC is standardized from 2003:M1 with mean equal to zero and standard deviation equal to one. An increase in any of the SIFCs indicates a tightening in the corresponding dimension of financial conditions. An increase in the CIFC indicates a tightening in overall financial conditions. Positive (negative) values of each SIFC indicate that the corresponding dimension of financial conditions is tighter (looser) than average. Positive (negative) values of the CIFC indicate that financial conditions are overall tighter (looser) than average.

The CIFC indicates that in the last two decades there were four main episodes of tight financial conditions in Germany (see Figure 1). The first episode occured in the early 2000s, and it coincides with a period identified by Lo Duca et al. (2017) as a systemic financial crisis originating in the domestic financial system. This episode saw a considerable financial tightening, particuary in bank lending conditions. In contrast to the first episode, the remaining three episodes were of international origin. The 2008 global financial crisis represents the second episode, the third episode occurred during the euro area sovereign debt crisis in the early 2010s, and the fourth occurred during the COVID-19 crisis in the first half of 2020. Distress in financial markets was the main driver of tight financial conditions during these last three episodes. Since early 2021 there has been a considerable, broad-based tightening in financial conditions. By June 2022, the CIFC reached a level comparable to that of the COVID-19 crisis. Nevertheless, it was still clearly below levels of past financial crises. Economic downside risks arising from geopolitical tensions are a likely factor behind this recent tightening.

The existing literature suggests that financial conditions are interlinked with macroeconomic fluctuations. For instance, empirical evidence shows that macroeconomic tail risks significantly increase when financial conditions tighten (e.g., Adrian et al., 2019). Moreover, studies find that financial shocks account for a large share of the fluctuations in output and other macroeconomic variables in DSGE models and structural vector autoregressions (SVARs) (e.g., Christiano et al., 2014; Prieto et al., 2016; Furlanetto et al., 2019). Armed with a new measure of financial conditions, I investigate the relationship between financial conditions and macroeconomic fluctuations by estimating a structural VAR model that includes the CIFC and macroeconomic variables for the German economy. The model features five structural shocks: an aggregate supply shock, an aggregate demand shock, a monetary shock, an investment shock and a financial shock. The shocks are identified using the sign restrictions proposed by Furlanetto et al. (2019). The model estimates indicate that financial shocks drive the bulk of the variation in the CIFC, with demand shocks and investment shocks also playing a role. Despite being unrestricted in the estimation, the response of the CIFC to a financial shock is statistically significant and strongly counter-cyclical. A positive financial shock generates a significant decrease in the CIFC, indicating a loosening in financial conditions during a financial boom. A financial bust, in turn, leads to a significant tightening in financial conditions.

The remainder of the paper is organised as follows. Section 2 describes the econometric approach to constructing the new composite indicator. The main empirical results are presented in Sections 3 and 4. Finally, Section 5 concludes.

2 Methodology

Let $\boldsymbol{X}_t = [x_{1,t}, \ldots, x_{N,t}]$ denote an $N \times 1$ vector of financial time series observed over the period $t = 1, 2, \ldots, T$. Each time series in $\boldsymbol{X}_t$ is standardised by subtracting the sample mean from the series and then dividing by the sample standard deviation. That is, I compute $z_{i,t} = (x_{i,t} - \bar{x}_i)/\sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_{i,t} - \bar{x}_i)^2}$, where $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$ for $i = 1, \ldots, N$. I collect the standardised time series in the $N \times 1$ vector $\boldsymbol{Z}_t = [z_{1,t}, \ldots, z_{N,t}]$. I partition $\boldsymbol{Z}_t$ into M subvectors $\boldsymbol{Z}_t^j$ of size $N^j \times 1$ (where $\boldsymbol{Z}_t^j \in \boldsymbol{Z}_t$ for $j = 1, \ldots, M$). The j^{th} subvector $\boldsymbol{Z}_t^j$ contains a set of individual financial indicators that are used to compute the SIFC that captures the j^{th} dimension of financial conditions.

The $M = 6$ subindicators measure different dimensions of financial conditions. Three of the subindicators capture credit, liquidity and market risk in the equity, bond, foreign exchange and interbank markets, using time series that are used in composite indicators of financial stress (e.g., Holló et al., 2012; Duprey et al., 2017; Deutsche Bundesbank, 2019). Specifically, the first subindicator measures *credit risk* in the financial markets based on five credit spread series. It captures counterparty risk in the secured and unsecured segments of the interbank market using the three-month Euribor-Eurepo spread and the six-month Euribor-Bund spread, respectively. In addition, it contains credit spreads for banks and non-financial corporations proposed by Gilchrist and Mojon (2018), which are the average spreads on the bond yields of German financial and non-financial corporations relative to the yield on Bunds of matched maturities. Finally, it contains the spread between the long-term interest rates for mortgage loans with maturities of over 10 years relative to 10-year Bund yields as a measure of mortgage debtors' credit default risk. These five credit spread series are collected into the subvector $\boldsymbol{Z}_t^1$.

The second subindicator measures *liquidity risk* in the foreign exchange and government bond markets based on three time series. In particular, it contains the EUR/USD cross-currency basis swap spread as a measure of liquidity risk in the foreign exchange market, the spread between the yields on 5-year bonds issued by the KfW and 5-year Bund yields and the spread between 5-year yields on public sector *Pfandbriefe* and Bund yields of matching maturity as measures of liquidity risk in different segments of the sovereign bond market. I collect these series into the subvector $\boldsymbol{Z}_t^2$.

The third subindicator measures financial *market risk* based on 14 variables that include implied and realized equity market volatilities, a measure for the equity market variance risk premium, realized Bund yield volatilities at various maturities from three-months to thirty years, the correlation between DAX returns and yields on 10-year government bonds, implied and realized exchange-rate volatilities of the euro relative to the U.S. dollar the Japanese yen and the British pound, and the realized volatility of the interest rate on long-term mortgage loans. These variables are collected into the subvector $\boldsymbol{Z}_t^3$.

In addition to indicators derived from risky asset prices, existing financial conditions indicators also contain information on the term structure of government bond yields (e.g., Hatzius et al., 2010; Brave and Butters, 2011; Moccero et al., 2014; Koop and Korobilis, 2014). Studies have shown that the term structure can be characterized by the level, slope and curvature of the yield curve (e.g., Diebold and Li, 2006). Hence, the fourth subindicator measures the German *Bund yield curve* based on variables that capture its level, slope and curvature. Instead of estimating yield curve factors from an affine term structure model, I calculate their empirical counterparts directly using yields and spreads of different maturities as defined in Diebold and

Li (2006). In particular, the level of the Bund yield curve is measured by 10-year and 30-year Bund yields. The slope of the yield curve is measured by the term spread between 10-year and 3-month Bund yields, the term spread between 10-year and 2-year Bund yields, the term spread between 30-year and 3-month Bund yields, and the term spread between 30-year and 2-year Bund yields. Finally, the curvature of the yield curve is measured by two times the 2-year Bund yields minus the sum of 10-year and 3-month Bund yields. These variables are collected into the subvector $\boldsymbol{Z}_t^4$.

Given that financial intermediaries play a substantial role in the German financial system, I compute two additional subindicators that capture financial conditions beyond the financial markets. The fifth subindicator measures the amount of credit and liquidity in the financial system and the degree of financial intermediary leverage, in line with the existing literature (e.g., Hatzius et al., 2010; Brave and Butters, 2011; Moccero et al., 2014). It is based on nine quantity indicators for year-on-year changes in *money and credit volumes*, including changes in loans by monetary financial institution (MFIs) to other MFIs, MFI loans to non-financial corporations (NFCs) and MFI loans to households (HHs), the ratios of MFI loans to MFIs, NFCs and HHs relative to MFIs' total assets, total credit to NFCs, and monetary aggregates (M1 and M3). I collect these variables into the subvector $\boldsymbol{Z}_t^5$.

Financial conditions indicators for the U.S. typically include measures of banks' lending conditions based on data from the Senior Loan Officer Opinion Survey on Bank Lending Practices (e.g., Hatzius et al., 2010; Brave and Butters, 2011; Koop and Korobilis, 2014). In accordance with this literature, the sixth subindicator contains survey-based measures of changes in bank lending conditions. In particular, it measures *bank lending behaviour* based on 32 indicators from the German responses to the euro area Bank Lending Survey (BLS). The BLS is a quarterly survey on bank lending conditions in the member states of the euro area, conducted by the national central banks in collaboration with the European Central Bank (ECB). It provides information on bank lending conditions based on qualitative questions on past and expected future lending policies addressed to senior loan officers of participating banks.[4] I use data from the BLS that capture lending standards and the individual factors driving changes in those standards, as well as loan demand for banks domiciled in Germany. These variables are collected into the subvector $\boldsymbol{Z}_t^6$.

The subvector $\boldsymbol{Z}_t^j$ is assumed to admit an approximate factor model representation (Stock and Watson, 2002):

$$\boldsymbol{Z}_t^j = \boldsymbol{\Lambda}^j \boldsymbol{F}_t^j + \boldsymbol{W}_t^j, \tag{1}$$

where $\boldsymbol{F}_t^j$ is a $r^j \times 1$ vector of common factors, $\boldsymbol{\Lambda}^j$ is an $N^j \times r^j$ matrix of factor loadings, and $\boldsymbol{W}_t^j$ is an $N^j \times 1$ vector of idiosyncratic components. $\boldsymbol{F}_t^j$ are mutually orthogonal and uncorrelated with $\boldsymbol{W}_t^j$. The idiosyncratic components $\boldsymbol{W}_t^j$ are stationary with zero mean, and they may

[4]For further information, see: https://www.bundesbank.de/en/tasks/monetary-policy/economic-analyses/-/bank-lending-survey-for-germany-618070.

exhibit weak cross-sectional and serial correlation. Without loss of generality, the number of factors is set to $r^j = 1$ for all $j = 1, \ldots, M$. Hence, the factor F_t^j is of dimension 1×1 in period t, with an $N^j \times 1$ vector of factor loadings $\boldsymbol{\lambda}^j$. Factors and loadings are consistently estimated using principal components (Stock and Watson, 2002). The factor F_t^j is thus estimated as the first principal component extracted from the subvector $\boldsymbol{Z}_t^j$, and it represents the j^{th} SIFC.

Factors and loadings are only identified up to sign. I thus normalize each factor and its loadings such that an increase in the factor is associated with a tightening in the corresponding dimension of financial conditions. This normalization is implemented by verifying the sign of the loading on one of the variables in each subvector $\boldsymbol{Z}_t^j$.[5] I reverse the sign of the corresponding factor and all of its loadings if the sign of the estimated loadings violates the normalising assumptions.

I collect the factors F_t^j into an $1 \times M$ vector $\boldsymbol{F}_t = [F_t^1, F_t^2, \ldots, F_t^M]$ and compute the CIFC by taking the weighted sum of the factors:

$$CIFC_t = \boldsymbol{F}_t \boldsymbol{w}_t^{'}, \tag{2}$$

where $\boldsymbol{w}_t$ is an $1 \times M$ vector of time-varying weights that sum to M in each period t. The weights reflect the changing correlation structure between the factors (see also Holló et al., 2012; Schüler et al., 2020). Specifically, following Schüler et al. (2020), the weights I use in the aggregation scheme exploit *positive* time-varying correlations between factor pairs, implying that factor whose movements are positively related receive higher weights in the aggregation.[6] Let $\mathbf{C}_t$ denote an $M \times M$ matrix of time-varying cross-correlation coefficients with diagonal elements equal to one and off-diagonal elements $c_{jk,t}$ (where $j = 1, \ldots, M$, $k = 1, \ldots, M$ and $j \neq k$) given by:

$$c_{jk,t} = \begin{cases} \rho_{jk,t} = \frac{\sigma_{jk,t}}{\sqrt{\sigma_{jj,t}\sigma_{kk,t}}} & \text{if } \sigma_{jk,t} \geq 0 \\ 0 & \text{if } \sigma_{jk,t} < 0 \end{cases}, \tag{3}$$

where following Holló et al. (2012), the time-varying cross-correlations $\rho_{jk,t}$ are estimated recursively on the basis of exponentially-weighted moving averages (EWMA) of respective co-

[5] I impose the convention that the credit risk subindicator loads positively on the Euribor-Bund spread, the liquidity risk subindicator loads positively on the EUR/USD cross-currency basis swap spread, the market risk subindicator loads positively on the VDAX implied volatility index, the yield curve subindicator loads positively on the 10-year minus 3-month term spread, the money and credit subindicator loads negatively on the year-on-year growth rate of the (MFI loans to MFIs)/(total assets)-ratio, and finally, the bank lending behavior subindicator loads positively on the BLS variable measuring the net percent of survey respondents that expect their bank's credit standards as applied to the approval of loans or credit lines to enterprises to tighten over the next three months (Question 8 in the BLS).

[6] I conduct a robustness exercise using different weighting methods and find that the resulting indicators are qualitatively and quantitatively very similar and highly correlated.

variances $\sigma_{jk,t}$ and volatilities $\sigma_{jj,t}$ and $\sigma_{kk,t}$. That is,

$$\sigma_{jk,t} = \gamma\sigma_{jk,t-1} + (1-\gamma)(F_t^j - \bar{F}_t^j)(F_t^k - \bar{F}_t^k),$$
$$\sigma_{jj,t} = \gamma\sigma_{jj,t-1} + (1-\gamma)(F_t^j - \bar{F}_t^j)^2 \quad \text{and} \quad \sigma_{kk,t} = \gamma\sigma_{kk,t-1} + (1-\gamma)(F_t^k - \bar{F}_t^k)^2,$$

where $\bar{F}_t^j = \frac{1}{T}\sum_{t=1}^T F_t^j$ and $\bar{F}_t^k = \frac{1}{T}\sum_{t=1}^T F_t^k$, and γ is the smoothing parameter that I set to $\gamma = 0.90$.[7] The factor weights are then given by:

$$\boldsymbol{w}_t = \frac{\boldsymbol{\iota}'\mathbf{C}_t}{\boldsymbol{\iota}'\mathbf{C}_t\boldsymbol{\iota}}, \tag{4}$$

where $\boldsymbol{\iota}$ is a vector of ones of dimension $M \times 1$ (see Schüler et al., 2020).

3 CIFC estimates

3.1 Data and factor model estimates

The CIFC is constructed from a balanced monthly panel that consists of 70 individual financial indicators for the period between January 2003 and June 2022. Individual indicators are derived from a large sample of financial time series for Germany and a few additional series for the euro area. The raw variables are available at a daily, monthly and quarterly frequency. Daily data are summed up or averaged within the month, depending on the variable considered.[8] Quarterly data are interpolated using the cubic convolution method. The sample starts in 2003:M1 because observations are not available prior that date for a large part of the sample. For some of the time series, observations are missing at the end of the sample.[9] I replace the missing observations with values obtained from a recursive multi-step forecast with an autoregressive model of order one (AR(1) model). In Appendix A, I present a sensitivity exercise which shows that the AR(1) model produces superior forecasts compared to a factor-augmented AR(1) model and the expectation-maximisation algorithm proposed by Stock and Watson (2008).

Table 1 provides a comprehensive list of the individual financial indicators used to construct the CIFC, grouped into six categories. The table also contains information on the data transformation applied to each indicator, the frequency at which the time series are available, the date of the last available observation for each indicator at the time of writing, the estimated factor loadings, and the variance share explained by the first principal component, i.e., the amount of variation in the data attributable to variation in the SIFC over the sample period 2003:M1-

[7]The smoothing parameter I use with monthly data is slightly smaller than the $\gamma = 0.93$ used in Holló et al. (2012) for daily data and the $\gamma = 0.89$ used by Schüler et al. (2020) for quarterly data. Varying γ in the parameter range used by earlier studies leads to negligible differences in the estimated time-varying weights.

[8]E.g., monthly sovereign bond yields are obtained by averaging daily yields, while monthly realized sovereign bond yield volatilities are computed as the sum of squared daily yields.

[9]At the time of writing, there are nine raw time series (i.e., series from which the individual financial indicators are constructed) for which observations are not available up to 2022:M6.

2022:M6.

Table 1 indicates that the first three SIFCs load positively on all spreads and volatilities included into their calculation. Hence, an increase in one of the first three SIFCs implies a tightening in the credit, liquidity or market risk component of the CIFC, respectively. The SIFCs explain a large amount of the variation in most yield spreads and volatilities, highlighting that financial market indicators exhibit a high degree of co-movement.

The fourth SIFC loads positively on the level and the slope of the yield curve, and it loads negatively on its curvature. Moreover, it explains a large share of yield-curve variation, particularly of variation in term spreads. This is consistent with the empirical evidence that yields on long-term bonds tend to be countercyclical, while they tend to be procyclical at the short end of the yield curve, implying that the yield curve slopes upward and term premia are high in recessions (Ang et al., 2006).[10] Recessions, in turn, go hand-in-hand with tight financial conditions (Bernanke et al., 1999).

The fifth SIFC, comprising money and credit volumes, loads negatively on all quantity indicators included, indicating that financial conditions loosen when the growth rate of monetary aggregates, credit volumes and financial intermediary leverage accelerates. This is consistent with the empirical evidence that credit and leverage booms are associated with a build-up of financial vulnerabilities that can lead to financial crises (Gourinchas and Obstfeld, 2012; Schularick and Taylor, 2012). The factor explains a large amount of the variation in bank and non-bank credit to NFCs and bank loans to MFIs, while it explains less of the variation in bank loans to HHs and in the variance of narrow money growth.

Finally, the sixth SIFC, which captures bank lending behavior, loads positively on bank lending standards as measured by the BLS, and it loads negatively on almost all BLS-based measures of loan demand.[11] This is consistent with a tightening in bank lending standards and a decrease in demand for bank loans indicating a tightening in financial conditions. The factor explains a high degree of variation in lending standards for nonfinancial corporate and consumer loans, while it explains less of the variation in standards and demand for mortgage loans.

3.2 Baseline CIFC estimates

Figure 1 depicts the new composite indicator of financial conditions for Germany, estimated for the 2003:M1-2022:M6 period. The figure also shows the contributions of the six subindicators to the CIFC at each point in time. The CIFC has a mean equal to zero and standard deviation

[10] While an upward sloping yield curve can indicate that the economy is in a recession, a downward sloping yield curve can predict that a recession will occur at some point in the future (e.g., Hamilton and Kim, 2002, and the references therein).

[11] One exception is mortgage loan demand from households which, however, is a highly idiosyncratic variable. More generally, variables related to the housing market turn out to be rather idiosyncratic, as also indicated by the relatively low variance share for the mortgage-Bund spread in the first SIFC, for the realized volatility of the mortgage rate in the third SIFC, and for MFI loans to HHs relative to total assets in the fifth SIFC.

Indicator	Transf.	Freq.	End date	Loading	Variance share (%)
SIFC: Credit risk					
Euribor-Bund spread 6m	a	d	2022:M6	0.91	84
Euribor-repo spread 3m	a	d	2022:M6	0.80	65
NFC-Bund spread	a	m	2022:M6	0.93	86
Bank-Bund spread	a	m	2022:M6	0.84	71
Mortgage-Bund spread 10y	a	m	2022:M6	0.52	28
SIFC: Liquidity risk					
Cross-currency basis swap EUR/USD	a	d	2022:M6	0.91	83
KfW-Bund spread 5y	a	d	2022:M6	0.93	87
Pfandbrief-Bund spread	a	d	2022:M6	0.97	95
SIFC: Market risk					
Implied volatility VDAX	a	d	2022:M6	0.85	72
Realized volatility DAX	a	d	2022:M6	0.84	71
Variance risk premium DAX	a	m	2022:M6	0.66	44
Realized volatility financial subindex	a	d	2022:M6	0.84	71
Realized volatility Bund 10y	a	d	2022:M6	0.82	67
Realized volatility Bund 2y	a	d	2022:M6	0.71	51
Realized volatility Bund 30y	a	d	2022:M6	0.80	65
Realized volatility Bund 3m	a	d	2022:M6	0.73	53
Correlation DAX vs. Bund 10y	a	d	2022:M6	0.37	14
Implied volatility EUR/GBP	a	d	2022:M6	0.73	53
Implied volatility EUR/JPY	a	d	2022:M6	0.84	70
Implied volatility EUR/USD	a	d	2022:M6	0.85	72
Realized volatility EUR/USD	a	d	2022:M6	0.80	64
Realized volatility mortgage rate	a	m	2022:M6	0.29	8
SIFC: Bund yield curve					
Yield curve: slope 10y-3m	a	d	2022:M6	0.93	88
Yield curve: slope 10y-2y	a	d	2022:M6	0.99	99
Yield curve: slope 30y-3m	a	d	2022:M6	0.98	96
Yield curve: slope 30y-2y	a	d	2022:M6	0.98	96
Yield curve: curvature 2*2y-(10y+3m)	a	d	2022:M6	-0.84	71
Yield curve: level 10y	c	d	2022:M6	0.03	0
Yield curve: level 30y	c	d	2022:M6	0.31	10
SIFC: Money and credit volumes					
MFI loans to MFIs/Total assets	b	m	2022:M5	-0.69	48
MFI loans to NFCs/Total assets	b	m	2022:M5	-0.52	27
MFI loans to HHs/Total assets	b	m	2022:M5	-0.27	7
Total credit to NFCs; real	b	q	2021:Q4	-0.79	63
MFI loans to MFIs; real	b	m	2022:M5	-0.63	40
MFI loans to NFCs; real	b	m	2022:M5	-0.77	60
MFI loans to HHs; real	b	m	2022:M5	-0.64	41
M3; real	b	m	2022:M4	-0.53	28
M1; real	b	m	2022:M4	-0.19	4

Table 1: **Individual financial indicators**

Note: See next page.

Indicator	Transf.	Freq.	End date	Loading	Variance share (%)
SIFC: Bank lending behaviour					
S^f NFC	a	q	2022:Q2	0.79	63
S^b NFC	a	q	2022:Q2	0.85	72
S^b NFC industry-specific situation	a	q	2022:Q2	0.91	84
S^b NFC capital position	a	q	2022:Q2	0.77	59
S^b NFC competition from banks	a	q	2022:Q2	0.60	36
S^b NFC general economic situation	a	q	2022:Q2	0.94	88
S^b NFC competition from market financing	a	q	2022:Q2	0.26	7
S^b NFC competition from non-banks	a	q	2022:Q2	0.08	1
S^b NFC liquidity position	a	q	2022:Q2	0.44	20
S^b NFC risk on collateral demanded	a	q	2022:Q2	0.76	59
S^b NFC access to market financing	a	q	2022:Q2	0.63	40
S^f HH-HP	a	q	2022:Q2	0.46	21
S^b HH-HP	a	q	2022:Q2	0.68	46
S^b HH-HP competition from banks	a	q	2022:Q2	0.46	21
S^b HH-HP general economic situation	a	q	2022:Q2	0.83	70
S^b HH-HP competition from non-banks	a	q	2022:Q2	0.47	22
S^b HH-HP balance sheet constraints	a	q	2022:Q1	0.55	30
S^f HH-CC	a	q	2022:Q2	0.69	48
S^b HH-CC	a	q	2022:Q2	0.82	67
S^b HH-CC competition from banks	a	q	2022:Q2	0.54	30
S^b HH-CC economic situation and outlook	a	q	2022:Q2	0.85	73
S^b HH-CC competition from non-banks	a	q	2022:Q2	0.39	15
S^b HH-CC borrower creditworthiness	a	q	2022:Q2	0.73	53
S^b HH-CC balance sheet constraints	a	q	2022:Q1	0.38	15
S^b HH-CC risk on collateral demanded	a	q	2022:Q2	0.55	30
S^b HH-HP housing market prospects	a	q	2022:Q2	0.74	55
D^b HH-CC	a	q	2022:Q2	-0.33	11
D^b HH-HP	a	q	2022:Q2	0.04	0
D^b NFC	a	q	2022:Q2	-0.34	12
D^f HH-CC	a	q	2022:Q2	-0.54	29
D^f HH-HP	a	q	2022:Q2	-0.54	29
D^f NFC	a	q	2022:Q2	-0.42	18

Table 1: **Individual financial indicators – Continued**

Note: Transformation: a: no transformation, b: year-on-year log-difference, c: linear detrending. Frequency: d: daily, m: monthly, q: quarterly. End date: the date of the last available observation for each indicator (data collected in early July 2022). Loading: factor loading on the first principal component estimated over the period 2003m1-2022m6. Var. share: variance share explained by the first principal component in percent of the financial indicator's total sample variance. Abbreviations: 3m: 3-months, 6m: 6-months, 2y: 2-year, 5y: 5-year, 10y: 10-year, 30y: 30-year, CC: consumer credit, D^b: loan demad (backward-looking for past three months), D^f: loan demand (forward-looking for next three months), DAX and VDAX: German stock market index DAX and its implied volatility index VDAX, EUR: euro, GBP: British Pound, HHs: household, HP: house purchase, JPY: Japanese Yen, KfW: German Development Bank (*Kreditanstalt für Wiederaufbau*), MFI: monetary financial institution, NFC: non-financial corporation, S^b: lending standards (backward-looking for past three months), S^f: lending standards (forward-looking for next three months), USD: US-Dollar.

equal to one. An increase in the CIFC indicates a tightening in overall financial conditions, while an increase in any of the SIFCs indicates a tightening in the corresponding dimension of financial conditions. Positive (negative) values of the CIFC indicate that financial conditions are overall tighter (looser) than average. Similarly, positive (negative) values of each SIFC indicate that the corresponding dimension of financial conditions is tighter (looser) than average.

From a historical perspective, the CIFC indicates that in the past there were four episodes of remarkably tight financial conditions. The first of these coincides with the German financial crisis of the early 2000s. I find that tight financial conditions during this episode were mainly attributable to tight bank lending conditions and shrinking money and credit volumes. This finding is consistent with the crisis classification of the European Systemic Risk Board (ESRB), according to which the 2001-2003 financial crisis originated in the domestic financial system (see Lo Duca et al., 2017). By contrast, the remaining three episodes were of international origin.

The second episode occurred during the 2008 global financial crisis. The CIFC indicates that financial conditions in Germany were exceptionally loose in the years before the crisis, reaching a level of nearly two standard deviations below the mean in early 2007. Financial conditions began to rapidly tighten from Spring 2007 onwards. The CIFC then reached its maximum at nearly four standard deviations above its mean in October 2008, indicating exceptionally tight financial conditions in the crisis, which were primarily driven by stress in financial markets as captured by the credit, liquidity and market risk subindicators. Tighter-than-average bank lending conditions were also a contributing factor. These results are consistent with the crisis classification of the ESRB, according to which the 2008 financial crisis was not of domestic origin in Germany but instead was imported from abroad through strains in international capital markets and the global banking system (see Lo Duca et al., 2017).

The third episode of tight financial conditions occurred during the euro area sovereign debt crisis of the early 2010s, while the fourth episode occurred during the COVID-19 crisis in the first half of 2020. Distress in financial markets was the main driver of tight financial conditions during both of these episodes. Finally, there has been a considerable tightening in financial conditions since the beginning of 2021. This tightening has been broad based, with all subindicators contributing to an increase in the CIFC. By June 2022, the CIFC reached a level comparable to that of the COVID-19 crisis. Nevertheless, it was still clearly below levels of past financial crises. A likely factor behind this broad-based tightening is downside risk to economic activity resulting from geopolitical tensions.

3.3 Robustness

Robustness to calculation of weights. The CIFC is computed as the weighted sum of subindicators with weights based on time-varying correlations between the subindicators, as described in Section 2. Figure 2 shows the estimated time-varying weights. The weights fluctuate in the region between 0.25 and 1.5. The first three SIFCs receive weights above one more often than the last three SIFCs.

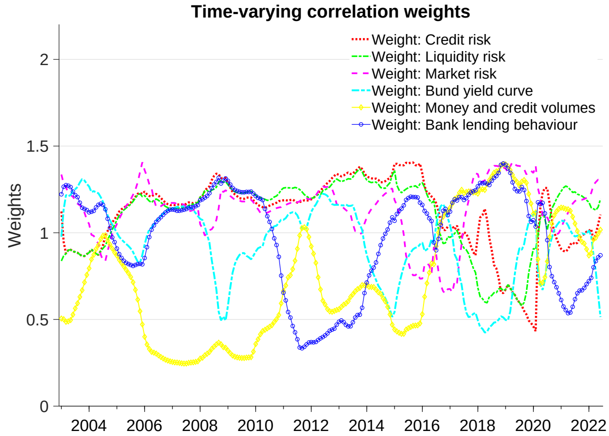


Figure 2: **Subindicator weights based on time-varying correlations**

Note: This figure depicts the weights of each subindicator based on time-varying correlations between the subindicators. Source: Bank for International Settlements, Banque de France, Bloomberg Finance L.P., Deutsche Bundesbank, European Central Bank and own calculations. Sample: 2003:M1-2022:M6. The weights are given by Equation (4), and their estimation follows the approach proposed by Schüler et al. (2020).

The estimation of the CIFC is robust to the weighting scheme used. Figure 3 depicts the baseline CIFC computed as the weighted sum of subindicators with time-varying weights (black solid line), the CIFC computed as the unweighted sum of the subindicators, i.e., with constant equal weights (blue dotted line), and the CIFC computed as the weighted sum of subindicators with weights based on the loadings on the first principal component (PC) extracted from the six subindicators (red dashed-dotted line). The sample correlation coefficient between the baseline CIFC and the CIFC computed with constant equal weights is equal to 0.99. The correlation coefficient between the baseline CIFC and the CIFC computed with constant PC weights is equal to 0.97. The correlation coefficient between the CIFCs calculated with constant equal weights and with constant PC weights is equal to 0.96.

Robustness to forecasting method. The estimated CIFC is robust to the method used to forecast the underlying financial time series. Time series for which observations are not available up to the most recent month are forecasted using three different methods. After obtaining the forecasts for each time series, the forecasted series are used to construct the individual financial indicators that enter the calculation of the CIFC. The first method is a recursive multi-step forecast with an AR(1) model. The second method is a recursive multi-step forecast with a factor-augmented AR(1) model. The factor used in this latter model is the first principal component extracted from a balanced data set containing first differences of all the raw series for which data are available for the entire sample period. The third method is the expectation-maximisation algorithm proposed by Stock and Watson (2002), which fills data gaps by exploiting the factor structure of the data. Figure 4 depicts the CIFC for the period between 2021:M6

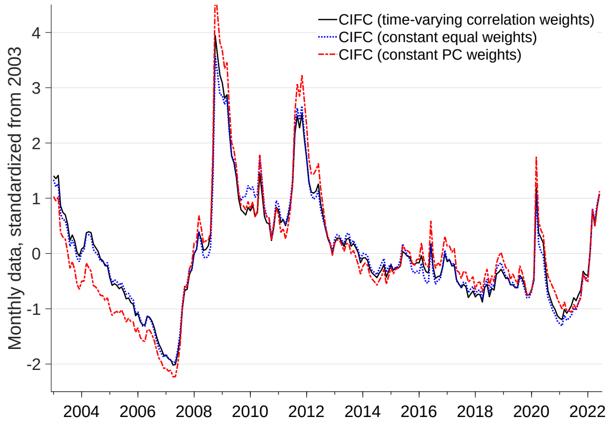


Figure 3: **CIFC: Robustness to calculation of weights**

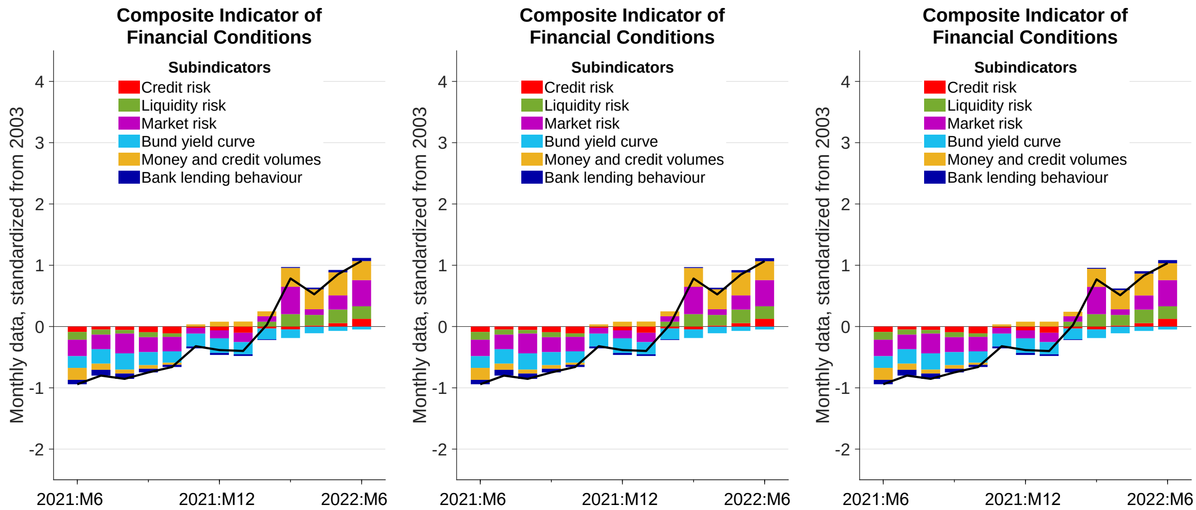
Note: This figure depicts the baseline CIFC computed as the weighted sum of subindicators with weights based on time-varying correlations between the subindicators (black solid line), the CIFC computed as the unweighted sum of the subindicators, i.e., with constant equal weights (blue dotted line), and the CIFC computed as the weighted sum of subindicators with weights based on the loadings on the first principal component (PC) extracted from the six subindicators (red dashed-dotted line). Source: Bank for International Settlements, Banque de France, Bloomberg Finance L.P., Deutsche Bundesbank, European Central Bank and own calculations. Sample: 2003:M1-2022:M6.

and 2022:M6 calculated from data forecasted using these three different forecasting methods. Forecasted values of certain variables are used from 2022:M1 onwards.[12] The majority of forecasted series are used to calculate the money and credit volumes SIFC. The figure shows that the forecasting method used has no material impact on the contribution of this SIFC to the overall indicator and, as a result, the CIFC is robust to the forecasting method used.

Robustness to expanding samples. To investigate the stability of the CIFC and its subindicators over time, I estimate the subindicators from factor models estimated over recursively expanding samples. I also compute recursive estimates of the CIFC with weights estimated using Equation (4) for recursively expanding samples. Expanding window estimation proceeds by first estimating each factor model over a five-year (60 months) window between 2003:M1 and 2007:M12, and then reestimating the factors by recurively adding one month to the estimation sample, such that the last expanding-window estimate coincides with the full-sample estimate for the 2003:M1-2022:M6 period.

For each subindicator, Figure 5 shows the full-sample estimate, estimates from recursively expanding windows, the cross-sectional mean over expanding window estimates for each period and the cross-sectional median over expanding window estimates for each period. The subindicators market risk and bank lending behaviour are estimated with the highest precision over recursively expanding windows. Their expanding-window estimates are very close to the full-sample estimate already in the early part of the sample, and they are virtually identical to the full-sample estimate after the early 2010s. Their factor loadings estimated over recursively

[12]See Appendix A for the list of forecasted series.



(a) AR(1) **(b)** Factor-augmented AR(1) **(c)** EM algorithm

Figure 4: **CIFC: Robustness to forecasting method used**

Note: This figure depicts the composite indicator of financial conditions (CIFC) for Germany, calculated from data forecasted using three different methods. Source: Bank for International Settlements, Banque de France, Bloomberg Finance L.P., Deutsche Bundesbank, European Central Bank and own calculations. Sample: 2003:M1-2022:M6. Panel (a): Time series for which observations are not available up to the most recent month are forecasted using a recursive multi-step forecast with an AR(1) model. Panel (b): Time series for which observations are not available up to the most recent month are forecasted using a recursive multi-step forecast with a factor-augmented AR(1) model. The factor used in the forecast is the first principal component extracted from a balanced data set containing first differences of all the raw series for which data are available for the entire sample period. Panel (c): Time series for which observations are not available up to the most recent month are nowcasted using the expectation-maximisation algorithm proposed by Stock and Watson (2002). After obtaining the nowcasts for each time series, the forecasted series are used to construct the individual financial indicators that enter the calculation of the CIFC. For further details, see Appendix A.

expanding windows are also relatively stable, as shown in Figure 6. The subindicators credit risk and liquidity risk are subject to relatively large revisions up to 2009, after which they resemble more closely their full-sample estimate. Their loadings are somewhat less stable over time, as shown in Figure 6. The factors and loadings of the Bund yield curve subindicator and especially the money and credit subindicator are subject to larger revisions over time. However, the dispersion of the factor estimates decreases over time and the expanding-window estimates are aligned with the full-sample estimate over the last part of the sample. For the Bund yield curve, the instability is driven by changing loadings on the yield curve level, while the loadings on money and credit volumes change particularly after the COVID-19 shock in 2020.

Finally, Figure 7 depicts the CIFC estimated over the full sample and over recursively expanding windows. For the first part of the sample, instability in the subindicator estimates translates to instability in the estimated CIFC. The estimates become considerably more stable in the second part of the sample, however. Revisions of the CIFC over time are relatively minor from around 2012 onwards, as more observations become available for estimation.

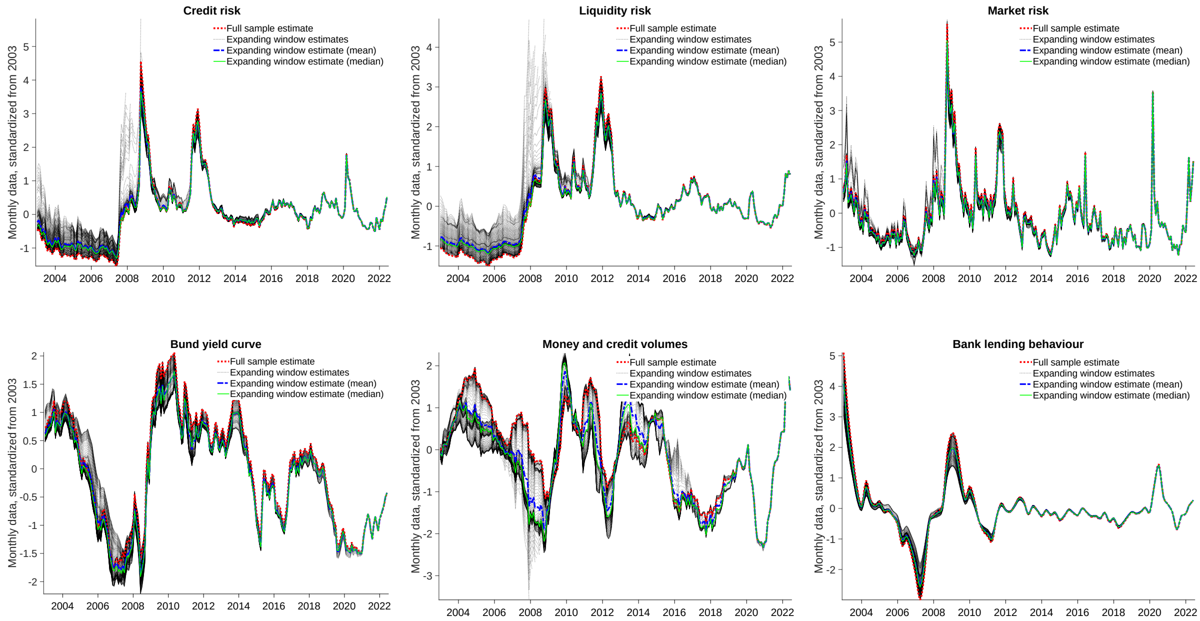


Figure 5: **Expanding window estimates of subindicators**

Note: This figure shows, for each subindicator, the full-sample estimate between 2003:M1 and 2022:M6 (red dotted line), estimates from recursively expanding windows (black dotted lines), the cross-sectional mean over the expanding window estimates for each period between 2003:M1 and 2022:M6 (blue dashed line), and the cross-sectional median over the expanding window estimates for each period between 2003:M1 and 2022:M6 (green solid line). Expanding window estimation proceeds by first estimating each factor model over a five-year (60 months) window beginning in 2003:M1, and then reestimating the factors by recurively adding one month to the estimation sample, such that the last expanding-window estimate coincides with the full-sample estimate. Source: Bank for International Settlements, Banque de France, Bloomberg Finance L.P., Deutsche Bundesbank, European Central Bank and own calculations. Sample: 2003:M1-2022:M6.

3.4 Comparison with other composite indicators

In this section, I compare the CIFC to some other widely used composite financial indicators. First, the CIFC is compared to the Bundesbank's weekly financial stress indicator (FSI) (see Deutsche Bundesbank, 2019). There is some overlap between the data used to compute the Bundesbank's FSI and the credit risk, liquidity risk and market risk subindicators of the CIFC. It is thus not surprising that the correlation-weighted sum of the three subindicators is closely correlated with the FSI, as illustrated in Figure 8 (left panel). The correlation between the two composite indicators equals to 0.96. The liquidity risk subindicator of the CIFC and its FSI counterpart are virtually identical, with a correlation coefficient equal to 0.99. There is, however, also a very close association between the credit risk and market risk subindicators and their FSI counterparts, with a correlation of 0.90 and 0.93, respectively. Minor differences exist due to partly different underlying indicators used to construct the subindicators.

Second, I compare the CIFC to two other widely used composite financial indicators: the U.S. National Financial Conditions Index (NFCI) of the Federal Reserve Bank of Chicago and

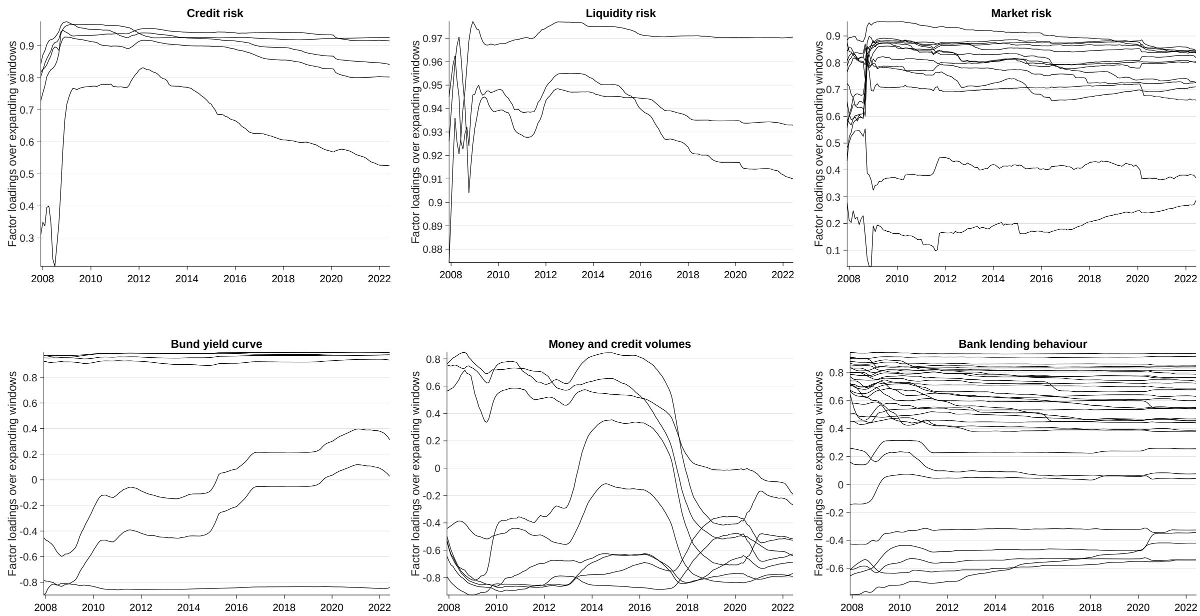


Figure 6: **Expanding window estimates of factor loadings**

Note: This figure shows, for each subindicator, the factor loadings estimated from recursively expanding windows. Expanding window estimation proceeds by first estimating each factor model over a five-year (60 months) window beginning in 2003:M1, and then reestimating the factors by recurively adding one month to the estimation sample, such that the last expanding-window estimate coincides with the full-sample estimate. Source: Bank for International Settlements, Banque de France, Bloomberg Finance L.P., Deutsche Bundesbank, European Central Bank and own calculations. Sample: 2003:M1-2022:M6.

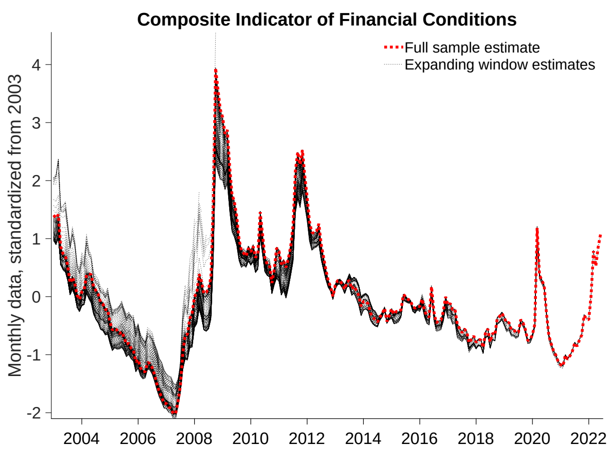


Figure 7: **Expanding window estimates of the CIFC**

Note: This figure shows the full-sample estimate of the CIFC between 2003:M1 and 2022:M6 (thick red dotted line) and the CIFC estimated over recursively expanding windows (thin black dotted lines). Expanding window estimation proceeds by first estimating the CIFC over a five-year (60 months) window beginning in 2003:M1, and then reestimating it by recurively adding one month to the estimation sample, such that the last expanding-window estimate coincides with the full-sample estimate. Source: Bank for International Settlements, Banque de France, Bloomberg Finance L.P., Deutsche Bundesbank, European Central Bank and own calculations. Sample: 2003:M1-2022:M6.

the euro area Composite Indicator of Systemic Stress (CISS) of the European Central Bank. The NFCI is a weekly indicator of U.S. financial conditions in money markets, debt and equity markets and the traditional and "shadow" banking systems, computed from 100 individual indicators (Brave and Butters, 2011). The CISS is a daily financial stress indicator for the euro area, computed using 15 raw, mainly market-based financial stress measures that are split equally into five categories, namely the financial intermediaries sector, money markets, equity markets, bond markets and foreign exchange markets (Holló et al., 2012). The CISS can thus be seen as a relatively narrow measure of financial conditions compared to the CIFC and the U.S. NFCI.

Figure 8 (right panel) shows the CIFC together with monthly averages of the NFCI and the CISS. Financial conditions in Germany strongly co-vary with financial conditions in the United States and the euro area. Specifically, the correlation between the CIFC and the NFCI equals to 0.66, while the correlation between the CIFC and the CISS equals to 0.78. All three composite indicators tighten during the global financial crisis, the euro area sovereign debt crisis and the COVID-19 crisis, as well as at the current juncture. The CIFC deviates from the other indicators only in the 2000s when it is mainly driven by domestic factors. These findings are consistent with, e.g., Rey (2015) and Miranda-Agrippino and Rey (2020, 2021), who find evidence for global co-movement in gross capital flows, banking sector leverage, credit, and asset prices, suggesting that financial conditions are for a large part determined globally rather than at the national level.

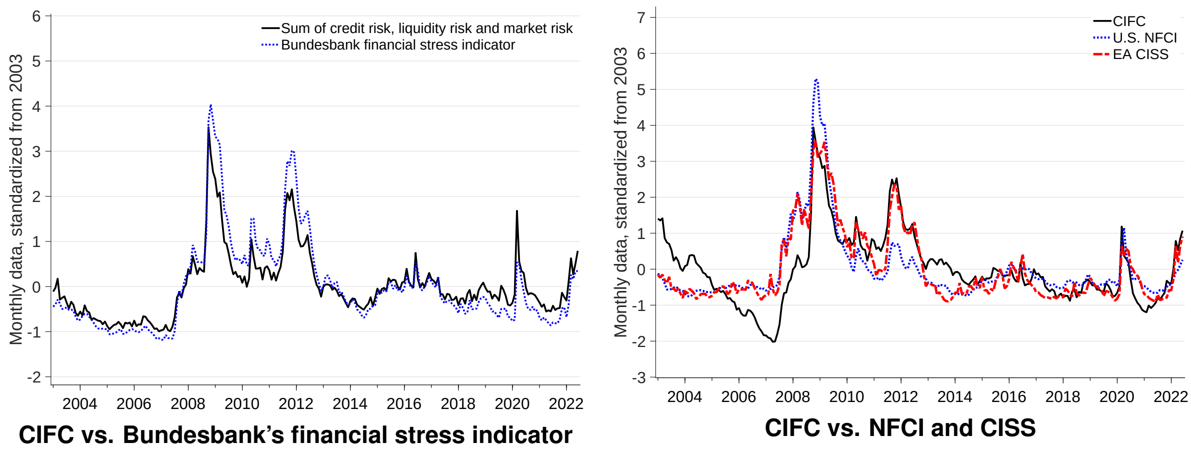


Figure 8: **Comparison with other composite indicators**

Note: Left panel: The sum of the subindicators credit risk, liquidity risk and market risk of the CIFC (black solid line), together with monthly averages of the Bundesbank's weekly financial stress indicator (blue dotted line). Righ panel: CIFC (black solid line), together with the U.S. National Financial Conditions Index (NFCI) of the Federal Reserve Bank of Chicago (blue dotted line), and the euro area Composite Indicator of Systemic Stress (CISS) of the European Central Bank (red dashed line). Source: Bank for International Settlements, Banque de France, Bloomberg Finance L.P., Deutsche Bundesbank, Federal Reserve Bank of St. Louis, ECB Statistical Data Warehouse and own calculations. Sample: 2003:M1-2022:M6. All series are standardized from 2003:M1 with mean equal to zero and standard deviation equal to one.

4 Structural VAR estimates

Existing evidence shows that financial factors play an important part in macroeconomic fluctuations in the United States. For instance, empirical estimates obtained from DSGE and SVAR models attribute a relatively large share of the fluctuations in U.S. output and other macroeconomic variables to financial shocks (e.g., Christiano et al., 2014; Prieto et al., 2016; Furlanetto et al., 2019). Moreover, U.S. financial conditions are strongly counter-cyclical (Furlanetto et al., 2019), and a tightening in U.S. financial conditions foreshadows higher macroeconomic downside risks (Adrian et al., 2019). Having obtained a comprehensive measure of financial conditions for the German economy, I now study whether financial factors play an equally important role in economic fluctuations in Germany.

To assess the relationship between financial conditions and macroeconomic fluctuations, I estimate an SVAR model that closely follows the empirical exercise in Furlanetto et al. (2019). Specifically, consider the following VAR in reduced form:

$$\boldsymbol{y}_t = \boldsymbol{\mu} + \mathbf{B}_1 \boldsymbol{y}_{t-1} + \cdots + \mathbf{B}_p \boldsymbol{y}_{t-p} + \boldsymbol{u}_t, \tag{5}$$

where $\boldsymbol{y}_t$ is an $n \times 1$ vector of endogenous variables observed in period $t = 1, \ldots, T$, $\boldsymbol{\mu}$ is an $n \times 1$ vector of constants, $\mathbf{B}_i$ are $n \times n$ coefficient matrices for $i = 1, ..., p$ lags, and $\boldsymbol{u}_t$ is an $n \times 1$ vector of reduced-form errors with $n \times n$ variance-covariance matrix $\boldsymbol{\Sigma_u} = E[\boldsymbol{u}_t, \boldsymbol{u}_t']$. The VAR includes the following six endogenous variables for the German economy: the log of industrial production, the log of the consumer price index, the monetary policy rate[13], the log of investment[14], the log of the stock market index DAX (deflated by the consumer price index) and the CIFC. The model is estimated for the period between 2003:M1 and 2019:M3, using six lags of the endogenous variables. The last observation is constrained by the availability of investment data.

There exists a linear mapping between the reduced-form errors $\boldsymbol{u}_t$ and an $n \times 1$ vector of mutually independent structural shocks, ε_t, given by $\boldsymbol{u}_t = \mathbf{A}\varepsilon_t$ with $E(\varepsilon_t \varepsilon_t') = \mathbf{I}$. Following Furlanetto et al. (2019), I identify five structural shocks: an aggregate supply shock, an aggregate demand shock, a monetary shock, an investment shock (i.e., a shock to the supply of capital), and a financial shock (i.e., a shock to the demand for capital). A sixth shock is included to match the number of shocks with the number of endogenous variables. This shock does not satisfy the restrictions imposed on the other five shocks, and it captures the residual dynamics in the system. Table 2 summarises the sign restrictions used, which are imposed on the impact

[13] As a measure of the monetary policy rate, I use the shadow short rate for the euro area proposed by Krippner (2015), which is designed to also account for the stance of monetary policy during the period when the short-term interest rate is constrained by the zero lower bound. The shadow rate was retrieved in August 2022 from https://www.ljkmfa.com/.

[14] I measure investment by gross fixed capital formation (price adjusted). This is a quarterly time series that I interpolate to the monthly frequency using the cubic convolution method.

effects of the shocks. Following Furlanetto et al. (2019), a positive financial shock is assumed to generate an investment boom and a stock market boom, and the restrictions associated with the financial shock are consistent with various DSGE models (e.g., Christiano et al., 2014). The response of the CIFC to a financial shock is left unrestricted. However, a positive financial shock is expected to lower the CIFC.

	Supply	Demand	Monetary	Investment	Financial
Industrial production	$+$	$+$	$+$	$+$	$+$
Consumer prices	$-$	$+$	$+$	$+$	$+$
Monetary policy rate	NA	$+$	$-$	$+$	$+$
Investment/production ratio	NA	$-$	NA	$+$	$+$
Stock prices	$+$	NA	NA	$-$	$+$
CIFC	NA	NA	NA	NA	NA

Table 2: **Sign restrictions in the structural VAR model**

Note: The table describes the sign restrictions used for each variable or ratio (in rows) to identified shocks (in columns) in the structural VAR model. The restrictions are based on Furlanetto et al. (2019), and they are imposed on the impact effects of the shocks. NA indicates that the response of the variable is left unrestricted.

The sign restrictions are implemented using the method proposed by Rubio-Ramirez et al. (2010). Specifically, rotation matrices are drawn until 500 of them yield shocks that are consistent with the sign restrictions. The median target approach by Fry and Pagan (2011) is adopted to pick among the 500 rotations the one which yields impulse responses that are closest to the median response. This rotation matrix is subsequently used to produce the bootstrap replications for inference. I then keep 2000 bootstrap replications that satisfy the sign restrictions.

Figure 9 depicts the impulse responses of the endogenous variables for the German economy to a positive financial shock, that is, to an unexpected increase in the demand for capital associated with an investment and stock market boom. The estimated effects are consistent with the results obtained by Furlanetto et al. (2019) for the U.S. economy. A positive financial shock leads to a statistically significant and hump-shaped increase in industrial production and investment relative to their baseline level. The shock also generates a statistically significant boom in the stock market, an increase in consumer prices, and a tightening in the monetary policy rate. The estimated effects are relatively persistent and last for at least one year, although the sign restrictions are imposed only on impact. Despite being unrestricted in the estimation, the response of the CIFC is statistically significant and strongly counter-cyclical. This validates the estimated financial shock, and it indicates that financial conditions significantly loosen during a financial boom. A negative financial shock associated with a financial bust, in turn, leads to a significant tightening in financial conditions.

Financial shocks drive the bulk of the variation in the CIFC on impact, as indicated by the forecast error variance decomposition reported in Table 3. Financial shocks are also responsi-

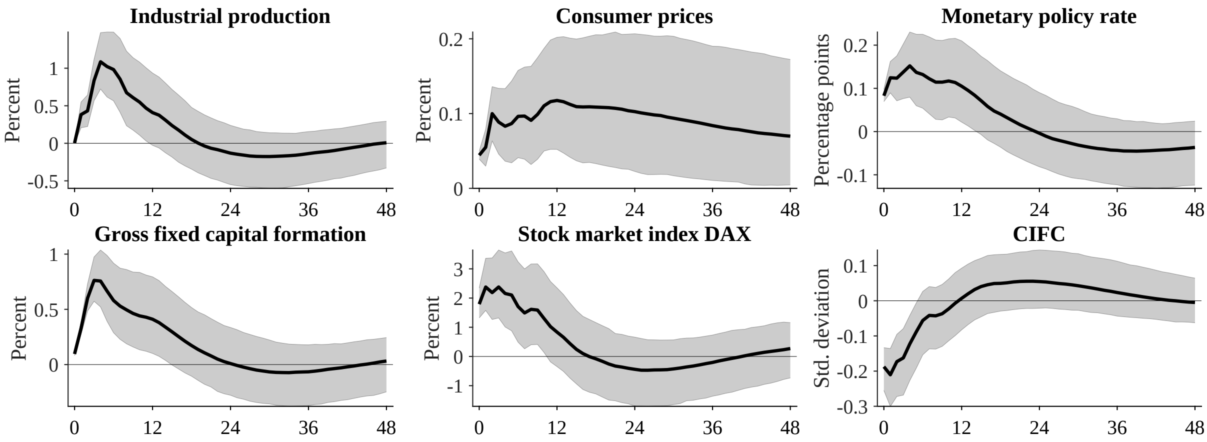


Figure 9: **Impulse responses to a financial shock**

Note: This figure depicts the impulse response functions of endogenous variables to a one-standard-deviation positive financial shock, identified using sign restrictions (see Furlanetto et al., 2019, and Table 2). Shaded areas represent the 95 percent confidence intervals based on 2000 bootstrap replications. The VAR model is estimated for the period between 2003:M1 and 2019:M3, using six lags. Impulse responses are computed for 48 months.

ble for around 30 percent of the variation in the CIFC at a horizon of one to four years. On top of that, more than 20 percent of the variation in the CIFC is attributable to investment shocks and demand shocks at horizons associated with business cycle frequencies. By contrast, supply shocks and monetary shocks play a relatively minor role in the forecast error variance of the CIFC.

Months after shock	Supply	Demand	Monetary	Investment	Financial	Residual
0	0.31	3.70	2.05	25.16	66.40	0.28
12	3.64	17.17	4.38	27.20	35.68	4.30
24	5.10	21.45	4.74	24.55	30.90	5.32
36	5.84	20.68	5.42	22.83	31.05	6.06
48	6.02	20.41	5.83	22.46	30.68	6.23

Table 3: **Forecast error variance decomposition for the CIFC**

Note: This table reports the contribution (in percent) of each of the six shocks identified in the structural VAR to the forecast error variance of the CIFC on impact and at the 12, 24, 36 and 48 months horizon. The variance decompositions are based at each horizon on the median bootstrap draw that satisfies the sign restrictions.

5 Conclusion

Composite indicators, which aggregate information from a wide range of financial variables, can prove particularly useful in assessing the state of the financial system. For example, composite financial stress indicators combine asset price-based variables such as yield spreads and asset price volatilities into an overall measure of systemic risk in various financial market segments. Composite financial conditions indicators, by contrast, are broader than financial stress indicators and typically include, in addition to market data, quantity-based metrics and other macro-financial indicators that capture information from different segments of the financial system, such as financial intermediaries and the non-financial private sector. The composite indicator of financial conditions (CIFC) for Germany introduced in this paper is such a measure.

The CIFC combines information from large amounts of financial data covering different segments of the financial system into a summary measure of financing conditions. It aggregates six sub-indicators, three of which measure stress in financial markets along the dimensions of ”credit risk”, ”liquidity risk” and ”market risk”. Three further subindicators capture financial conditions in the German government bond market (subindicator ”Bund yield curve”) and the banking sector as well as the nonfinancial private sector (subindicators ”money and credit volumes” and ”bank lending behavior”). The subindicators are estimated from a large set of financial indicators (70 in total) using principal component analysis. The CIFC is the weighted sum of the subindicators, where the weights reflect the time-varying correlation structure of the subindicators.

The CIFC is constructed for the period between January 2003 and June 2022. The estimates indicate that in the past there were four main episodes of tight financial conditions in Germany, including the German financial crisis of the early 2000s, the 2008 global financial crisis, the euro area soveregn debt crisis of the early 2010s and the COVID-19 recession in 2020. Recent readings of the composite indicator point to tighter-than-average financial conditions in the first half of 2022. Estimates from a structural vector autoregression indicate that financial shocks drive the bulk of the variation in financial conditions, with demand shocks and investment shocks also playing a role. In addition, the estimates show that an adverse financial shock leads to a statistically significant tightening in financial conditions.

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A Forecasting exercise

The CIFC is estimated for the period between January 2003 and June 2022. For some of the time series, observations are missing for one or more months at the end of the sample. Specifically, at the time of writing, there are nine time series for which observations are not available up to June 2022. These are: total credit to NFCs, MFI loans to MFIs, MFI loans to NFCs, MFI loans to HHs, narrow money M1, M3 broad money M3, total assets of MFIs and two variables from the BLS that measure the contribution of banks' cost of funds and balance sheet constraints to credit standards for loans to households for consumer credit on the one hand, and for house purchase on the other hand. The column "End date" in Table 1 indicates until when observations for each of these variables are available.

For estimation of the CIFC a balanced monthly panel is required. Thus, the missing observations must be replaced with predicted values. I obtain these values using recursive multi-step forecasts that involve using a one-step forecasting model multiple times. First, I transform each variable to (log) first differences. Next, I obtain the one-month-ahead prediction from the forecasting model. This prediction is then used as an observation input in order to obtain a prediction for the second month, and so on until the last month. Finally, I cumulate the (log) first differences back to levels, starting from the first observation in the sample in levels.[15]

This section presents a horse race of several forecasting methods for the nine variables listed above. The benchmark method is a recursive multi-step forecast obtained from an AR(1) model. Forecasts obtained from this model are compared to forecasts from an AR(3) model, an AR(12) model, a factor-augmented AR(1) model, a factor-augmented AR(3) model, a factor-augmented AR(12) model and the expectation-maximisation algorithm proposed by Stock and Watson (2008), which exploits the factor structure of the data to fill in missing values. For the factor-augmented AR (FAAR) model, the factor is the first principal component estimated from the subset of first-differenced variables that are available for the full sample. Since the factor is available for the entire time period, its contemporaneous values are used for prediction, complementing the AR term in a nowcasting fashion (Stock and Watson, 2008).

The horse race takes the form of a pseudo out-of-sample forecasting exercise that starts from τ months ago. Using the forecasting methods listed above, I obtain m-months-ahead predictions for recursively expanding windows up to the most recent observation, and I compute the root-mean-square error (RMSE) between values predicted by the model and the values

[15] It is important to note that I forecast the raw time series used to construct the individual financial indicators listed in Table 1 and not the financial indicators themselves. That is, for instance, instead of forecasting the ratio of MFI loans to NFCs relative to MFIs' total assets, I perform a forecast separately for MFI loans to NFCs and for total assets, and then I construct their ratio.

Table 4: RMSE (1 month ahead, 120 months ago)

Variable name	AR(1)	AR(3)	AR(12)	FAAR(1)	FAAR(3)	FAAR(12)	EM
x_bls_supply_hhcc_re_de	0.209	0.458	0.633	0.234	0.458	0.633	0.342
x_bls_supply_hhhp_re_de	0.473	1.103	1.026	0.475	1.098	1.024	0.702
x_bnk_loansfin_de	32.219	30.736	36.544	32.202	30.769	37.407	32.540
x_bnk_loansnfc_de	3.910	3.736	3.901	3.958	3.792	3.928	4.037
x_bnk_loanshh_de	2.977	2.677	2.656	2.993	2.688	2.660	3.660
x_m1_sa_de	12.116	12.074	12.364	11.930	11.845	12.243	12.067
x_m3_sa_de	15.089	15.341	16.505	15.035	15.217	16.783	15.302
x_bnk_assets_de	87.707	87.774	92.863	87.428	87.579	92.120	85.132
x_credit_nfc_de	5.962	14.184	12.146	5.932	14.205	12.140	9.624
RMSE relative to the AR(1) case							
x_bls_supply_hhcc_re_de	1.000	2.189	3.028	1.118	2.190	3.026	1.636
x_bls_supply_hhhp_re_de	1.000	2.333	2.171	1.005	2.323	2.167	1.485
x_bnk_loansfin_de	1.000	0.954	1.134	0.999	0.955	1.161	1.010
x_bnk_loansnfc_de	1.000	0.955	0.998	1.012	0.970	1.005	1.032
x_bnk_loanshh_de	1.000	0.899	0.892	1.005	0.903	0.893	1.229
x_m1_sa_de	1.000	0.996	1.020	0.985	0.978	1.010	0.996
x_m3_sa_de	1.000	1.017	1.094	0.996	1.009	1.112	1.014
x_bnk_assets_de	1.000	1.001	1.059	0.997	0.999	1.050	0.971
x_credit_nfc_de	1.000	2.379	2.037	0.995	2.383	2.036	1.614

Note: This table reports RMSEs and relative RMSEs for the following nine variables: the contribution of banks' cost of funds and balance sheet constraints to credit standards for loans to households for consumer credit reported in the BLS (x_bls_supply_hhcc_re_de); the contribution of banks' cost of funds and balance sheet constraints to credit standards for loans to households for house purchase reported in the BLS (x_bls_supply_hhhp_re_de); MFI loans to MFIs (x_bnk_loansfin_de); MFI loans to NFCs (x_bnk_loansnfc_de); MFI loans to HHs (x_bnk_loanshh_de); narrow money M1 (x_m1_sa_de); M3 broad money M3 (x_m3_sa_de); total credit to NFCs (x_credit_nfc_de) and total assets of MFIs (x_bnk_assets_de). The benchmark method is a recursive multi-step forecast obtained from an AR(1) model. Forecasts obtained from this model are compared to forecasts from an AR(3) model, an AR(12) model, a factor-augmented AR(1) model (Stock and Watson, 2008), a factor-augmented AR(3) model, a factor-augmented AR(12) model and the expectation-maximisation (EM) algorithm proposed by Stock and Watson (2008).

observed, which is given by:

$$RMSE_i = \sqrt{\frac{1}{\tau}\sum_{t=1}^{\tau}(\hat{x}_{i,t} - x_{i,t})^2} \tag{6}$$

where i stands for the ith variable. The RMSE calculation starts from $\tau = 120$ months ago, $\hat{x}_{i,t}$ is the predicted value and $x_{i,t}$ is the observed value. Tables 4, 5 and 6 report RMSEs and relative RMSEs for each variable obtained from forecasts with m equal to one-, three- and six-months ahead, respectively. Overall, there is overwhelming evidence in favour of the most simple AR(1) model. This outperforms the other models in most settings considered. I thus use this as the baseline to produce forecasts as inputs to the calculation of the CIFC. Nevertheless, differences between the CIFC estimated based on forecasts obtained from either of these methods are negligibly small, as shown in Figure 4.

Table 5: RMSE (3 month ahead, 120 months ago)

Variable name	AR(1)			AR(3)			AR(12)		
x_bls_supply_hhcc_re_de	0.208	0.512	0.819	0.472	1.095	1.162	0.654	1.159	1.724
x_bls_supply_hhhp_re_de	0.469	1.149	1.808	1.096	2.593	2.780	1.026	1.761	2.518
x_bnk_loansfin_de	32.088	47.607	58.675	30.697	44.119	52.865	36.401	51.645	67.095
x_bnk_loansnfc_de	3.894	5.977	8.060	3.721	5.531	7.340	3.885	5.748	7.479
x_bnk_loanshh_de	2.961	5.549	8.101	2.668	4.498	6.218	2.643	4.425	5.994
x_m1_sa_de	12.136	18.201	22.597	12.073	18.009	22.184	12.402	18.535	23.734
x_m3_sa_de	15.018	22.169	27.201	15.260	22.568	27.530	16.416	23.602	29.661
x_bnk_assets_de	89.932	129.445	163.782	89.467	126.171	160.849	94.749	129.832	162.045
x_credit_nfc_de	5.926	15.429	25.927	14.078	35.449	39.601	12.091	22.236	32.538
RMSE relative to the AR(1) case									
x_bls_supply_hhcc_re_de	1.000	1.000	1.000	2.267	2.140	1.419	3.141	2.265	2.106
x_bls_supply_hhhp_re_de	1.000	1.000	1.000	2.336	2.257	1.538	2.187	1.532	1.393
x_bnk_loansfin_de	1.000	1.000	1.000	0.957	0.927	0.901	1.134	1.085	1.144
x_bnk_loansnfc_de	1.000	1.000	1.000	0.956	0.925	0.911	0.998	0.962	0.928
x_bnk_loanshh_de	1.000	1.000	1.000	0.901	0.811	0.768	0.893	0.797	0.740
x_m1_sa_de	1.000	1.000	1.000	0.995	0.989	0.982	1.022	1.018	1.050
x_m3_sa_de	1.000	1.000	1.000	1.016	1.018	1.012	1.093	1.065	1.090
x_bnk_assets_de	1.000	1.000	1.000	0.995	0.975	0.982	1.054	1.003	0.989
x_credit_nfc_de	1.000	1.000	1.000	2.376	2.298	1.527	2.040	1.441	1.255

Variable name	FAAR(1)			FAAR(3)			FAAR(12)		
x_bls_supply_hhcc_re_de	0.232	0.536	0.841	0.472	1.095	1.162	0.654	1.157	1.725
x_bls_supply_hhhp_re_de	0.471	1.148	1.801	1.091	2.587	2.776	1.024	1.744	2.526
x_bnk_loansfin_de	32.096	48.030	60.244	30.747	44.452	54.237	37.280	53.350	69.484
x_bnk_loansnfc_de	3.943	6.022	8.099	3.778	5.581	7.386	3.912	5.769	7.502
x_bnk_loanshh_de	2.979	5.573	8.127	2.681	4.514	6.267	2.648	4.436	6.015
x_m1_sa_de	11.951	18.386	23.133	11.846	18.011	22.464	12.292	18.923	24.446
x_m3_sa_de	14.963	22.343	27.529	15.137	22.501	27.456	16.699	23.890	30.196
x_bnk_assets_de	89.974	127.338	161.681	89.600	123.872	158.665	94.227	128.211	160.650
x_credit_nfc_de	5.896	15.342	25.770	14.099	35.508	39.659	12.086	22.238	32.517
RMSE relative to the AR(1) case									
x_bls_supply_hhcc_re_de	1.115	1.048	1.028	2.268	2.140	1.419	3.138	2.261	2.106
x_bls_supply_hhhp_re_de	1.005	0.999	0.997	2.326	2.251	1.536	2.183	1.518	1.397
x_bnk_loansfin_de	1.000	1.009	1.027	0.958	0.934	0.924	1.162	1.121	1.184
x_bnk_loansnfc_de	1.012	1.008	1.005	0.970	0.934	0.916	1.005	0.965	0.931
x_bnk_loanshh_de	1.006	1.004	1.003	0.905	0.814	0.774	0.894	0.799	0.742
x_m1_sa_de	0.985	1.010	1.024	0.976	0.990	0.994	1.013	1.040	1.082
x_m3_sa_de	0.996	1.008	1.012	1.008	1.015	1.009	1.112	1.078	1.110
x_bnk_assets_de	1.000	0.984	0.987	0.996	0.957	0.969	1.048	0.990	0.981
x_credit_nfc_de	0.995	0.994	0.994	2.379	2.301	1.530	2.040	1.441	1.254

Variable name	EM		
x_bls_supply_hhcc_re_de	0.339	0.637	0.885
x_bls_supply_hhhp_re_de	0.698	1.286	1.728
x_bnk_loansfin_de	32.380	48.774	63.227
x_bnk_loansnfc_de	4.016	6.223	8.412
x_bnk_loanshh_de	3.623	6.600	9.443
x_m1_sa_de	12.038	18.845	23.727
x_m3_sa_de	15.148	22.909	28.156
x_bnk_assets_de	87.102	121.914	155.644
x_credit_nfc_de	9.570	18.097	25.202
RMSE relative to the AR(1) case			
x_bls_supply_hhcc_re_de	1.628	1.244	1.081
x_bls_supply_hhhp_re_de	1.488	1.119	0.956
x_bnk_loansfin_de	1.009	1.024	1.078
x_bnk_loansnfc_de	1.031	1.041	1.044
x_bnk_loanshh_de	1.224	1.189	1.166
x_m1_sa_de	0.992	1.035	1.050
x_m3_sa_de	1.009	1.033	1.035
x_bnk_assets_de	0.969	0.942	0.950
x_credit_nfc_de	1.615	1.173	0.972

Note: See Table 4.

Table 6: RMSE (6 month ahead, 120 months ago)

Variable name	AR(1)						AR(3)						AR(12)					
x_bls_supply_hhcc_re_de	0.252	0.600	0.924	1.188	1.408	1.613	0.638	1.506	1.595	1.442	2.353	3.636	0.730	1.308	1.925	2.141	2.565	2.853
x_bls_supply_hhhp_re_de	0.474	1.153	1.802	2.299	2.626	2.833	1.116	2.631	2.807	2.775	3.817	5.684	1.030	1.751	2.488	2.640	2.797	2.826
x_bnk_loansfin_de	31.720	47.842	59.306	76.184	92.895	107.485	30.294	43.977	53.139	69.627	86.268	100.276	37.582	53.634	69.181	85.687	104.684	117.717
x_bnk_loansnfc_de	3.794	5.883	7.999	10.127	12.345	14.484	3.645	5.475	7.304	9.142	11.104	13.045	3.833	5.710	7.406	9.202	11.080	12.690
x_bnk_loanshh_de	2.918	5.417	7.891	10.685	13.581	16.116	2.521	4.168	5.768	7.715	9.783	11.428	2.612	4.346	5.882	7.576	9.359	11.162
x_m1_sa_de	11.462	17.010	22.038	26.859	31.244	35.631	11.377	16.792	21.613	26.168	30.335	34.594	11.891	17.698	23.417	28.372	32.934	37.155
x_m3_sa_de	14.571	21.684	26.902	31.896	37.029	41.773	14.743	21.999	27.196	32.002	36.949	41.276	16.109	23.233	29.390	34.784	39.711	44.504
x_bnk_assets_de	88.146	128.709	163.218	205.631	244.003	276.302	88.042	126.063	160.489	203.381	240.585	271.752	93.209	131.214	163.264	197.499	230.344	259.505
x_credit_nfc_de	5.870	15.279	25.661	35.084	43.150	50.044	13.934	35.076	39.170	39.603	54.251	92.251	12.118	22.137	32.305	36.825	43.436	51.328
RMSE relative to the AR(1) case																		
x_bls_supply_hhcc_re_de	1.000	1.000	1.000	1.000	1.000	1.000	2.528	2.511	1.725	1.214	1.671	2.254	2.894	2.181	2.083	1.802	1.821	1.768
x_bls_supply_hhhp_re_de	1.000	1.000	1.000	1.000	1.000	1.000	2.356	2.282	1.558	1.207	1.454	2.006	2.176	1.519	1.381	1.148	1.065	0.998
x_bnk_loansfin_de	1.000	1.000	1.000	1.000	1.000	1.000	0.955	0.919	0.896	0.914	0.929	0.933	1.185	1.121	1.167	1.125	1.127	1.095
x_bnk_loansnfc_de	1.000	1.000	1.000	1.000	1.000	1.000	0.961	0.931	0.913	0.903	0.899	0.901	1.010	0.971	0.926	0.909	0.898	0.876
x_bnk_loanshh_de	1.000	1.000	1.000	1.000	1.000	1.000	0.864	0.769	0.731	0.722	0.720	0.709	0.895	0.802	0.745	0.709	0.689	0.693
x_m1_sa_de	1.000	1.000	1.000	1.000	1.000	1.000	0.993	0.987	0.981	0.974	0.971	0.971	1.037	1.040	1.063	1.056	1.054	1.043
x_m3_sa_de	1.000	1.000	1.000	1.000	1.000	1.000	1.012	1.015	1.011	1.003	0.998	0.988	1.106	1.071	1.092	1.091	1.072	1.065
x_bnk_assets_de	1.000	1.000	1.000	1.000	1.000	1.000	0.999	0.979	0.983	0.989	0.986	0.984	1.057	1.019	1.000	0.960	0.944	0.939
x_credit_nfc_de	1.000	1.000	1.000	1.000	1.000	1.000	2.374	2.296	1.526	1.129	1.257	1.843	2.064	1.449	1.259	1.050	1.007	1.026

Variable name	FAAR(1)						FAAR(3)						FAAR(12)					
x_bls_supply_hhcc_re_de	0.271	0.615	0.935	1.197	1.409	1.604	0.637	1.504	1.593	1.441	2.350	3.626	0.729	1.305	1.926	2.136	2.565	2.845
x_bls_supply_hhhp_re_de	0.476	1.151	1.795	2.286	2.612	2.825	1.111	2.624	2.803	2.773	3.805	5.710	1.028	1.734	2.497	2.630	2.811	2.835
x_bnk_loansfin_de	31.193	47.805	60.837	78.227	94.769	109.557	29.666	43.617	54.401	71.400	87.768	102.071	37.917	55.039	71.443	87.389	106.345	120.015
x_bnk_loansnfc_de	3.814	5.904	8.036	10.152	12.343	14.433	3.677	5.505	7.350	9.174	11.099	12.962	3.854	5.728	7.426	9.214	11.086	12.682
x_bnk_loanshh_de	2.934	5.437	7.919	10.733	13.611	16.141	2.545	4.197	5.823	7.821	9.844	11.482	2.615	4.355	5.903	7.614	9.386	11.177
x_m1_sa_de	10.875	16.975	22.568	27.481	32.211	36.782	10.687	16.535	21.864	26.497	31.154	35.748	11.474	17.914	24.136	29.014	33.772	38.003
x_m3_sa_de	14.117	21.704	27.211	32.217	37.620	42.500	14.179	21.774	27.100	31.806	37.103	41.680	16.118	23.383	29.905	35.371	40.430	45.290
x_bnk_assets_de	86.905	125.591	160.887	204.161	241.293	273.839	86.942	122.956	158.123	201.777	237.584	269.386	91.807	128.993	161.461	196.605	228.333	257.750
x_credit_nfc_de	5.841	15.193	25.506	34.860	42.846	49.670	13.955	35.134	39.227	39.669	54.357	92.480	12.113	22.139	32.283	36.836	43.404	51.336
RMSE relative to the AR(1) case																		
x_bls_supply_hhcc_re_de	1.074	1.025	1.011	1.008	1.000	0.994	2.526	2.508	1.723	1.213	1.669	2.248	2.891	2.177	2.084	1.797	1.821	1.764
x_bls_supply_hhhp_re_de	1.004	0.999	0.996	0.995	0.995	0.997	2.345	2.276	1.556	1.206	1.449	2.015	2.172	1.504	1.385	1.144	1.071	1.001
x_bnk_loansfin_de	0.983	0.999	1.026	1.027	1.020	1.019	0.935	0.912	0.917	0.937	0.945	0.950	1.195	1.150	1.205	1.147	1.145	1.117
x_bnk_loansnfc_de	1.005	1.004	1.005	1.002	1.000	0.996	0.969	0.936	0.919	0.906	0.899	0.895	1.016	0.974	0.928	0.910	0.898	0.876
x_bnk_loanshh_de	1.005	1.004	1.003	1.005	1.002	1.002	0.872	0.775	0.738	0.732	0.725	0.712	0.896	0.804	0.748	0.713	0.691	0.694
x_m1_sa_de	0.949	0.998	1.024	1.023	1.031	1.032	0.932	0.972	0.992	0.987	0.997	1.003	1.001	1.053	1.095	1.080	1.081	1.067
x_m3_sa_de	0.969	1.001	1.011	1.010	1.016	1.017	0.973	1.004	1.007	0.997	1.002	0.998	1.106	1.078	1.112	1.109	1.092	1.084
x_bnk_assets_de	0.986	0.976	0.986	0.993	0.989	0.991	0.986	0.955	0.969	0.981	0.974	0.975	1.042	1.002	0.989	0.956	0.936	0.933
x_credit_nfc_de	0.995	0.994	0.994	0.994	0.993	0.993	2.377	2.300	1.529	1.131	1.260	1.848	2.063	1.449	1.258	1.050	1.006	1.026

Variable name	EM					
x_bls_supply_hhcc_re_de	0.348	0.647	0.892	1.089	1.257	1.415
x_bls_supply_hhhp_re_de	0.697	1.279	1.713	2.005	2.189	2.310
x_bnk_loansfin_de	31.948	49.179	63.883	81.053	97.378	112.619
x_bnk_loansnfc_de	3.887	6.125	8.339	10.485	12.641	14.723
x_bnk_loanshh_de	3.529	6.389	9.181	12.079	14.996	17.811
x_m1_sa_de	10.844	16.936	22.781	28.311	33.705	39.082
x_m3_sa_de	14.334	21.946	27.527	32.761	38.461	43.859
x_bnk_assets_de	84.649	121.480	156.475	197.079	231.077	262.454
x_credit_nfc_de	9.462	17.895	24.932	30.508	34.920	38.504
RMSE relative to the AR(1) case						
x_bls_supply_hhcc_re_de	1.380	1.079	0.965	0.916	0.893	0.877
x_bls_supply_hhhp_re_de	1.472	1.110	0.951	0.872	0.834	0.816
x_bnk_loansfin_de	1.007	1.028	1.077	1.064	1.048	1.048
x_bnk_loansnfc_de	1.025	1.041	1.043	1.035	1.024	1.017
x_bnk_loanshh_de	1.209	1.179	1.163	1.130	1.104	1.105
x_m1_sa_de	0.946	0.996	1.034	1.054	1.079	1.097
x_m3_sa_de	0.984	1.012	1.023	1.027	1.039	1.050
x_bnk_assets_de	0.960	0.944	0.959	0.958	0.947	0.950
x_credit_nfc_de	1.612	1.171	0.972	0.870	0.809	0.769

Note: See Table 4.