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Financial Conditions In Europe: Dynamics, Drivers, And Macroeconomic Implications

Giovanni Borraccia, Raphael Espinoza, Vincenzo Guzzo, Fuda Jiang, Romain Lafarguette, Vina Nguyen, Miguel Segoviano, and Phillippe Wingender

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Prepared by Giovanni Borraccia, Raphael Espinoza, Vincenzo Guzzo, Fuda Jiang, Romain Lafarguette, Vina Nguyen, Miguel Segoviano, and Phillippe Wingender*

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ABSTRACT: We develop a new measure of financial conditions (FCs) that targets the growth of financial liabilities using the partial least square methodology. We then estimate financial condition indexes (FCIs) across European economies, both at the aggregate and sectoral levels. We decompose the changes in FCs into several factors including credit availability and costs, price of risk, policy stance, and funding constraints. Our results show that FCs loosened during the pandemic thanks to policy support but started to tighten significantly since mid-2021. Using the inverse probability weighting method over the sample period from 2000 to 2023, we find that a shift from a neutral to a tight FCI regime such as the ongoing episode for most European countries will on average lower output and inflation by 2.2 percent and 0.7 percentage points respectively and increase unemployment by 0.3 percentage points over a three-year horizon.

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Glossary

ECB European Central Bank

FC Financial Conditions

FCI Financial Condition Index

GARCH Generalized Auto-Regressive Conditional Heteroskedasticity

GFC Global Financial Crisis

GG General Government

HH Households

IPW Inverse Probability Weighting

NFC Non-financial Corporates

OLS Ordinary Least Square

PCA Principal Component Analysis

PLS Partial Least Square

Executive Summary

The disinflation challenge and rapid monetary policy tightening in Europe has rekindled interest in analytical frameworks to assess the evolution of financial conditions (FCs)—the availability and cost of funding—as well as their drivers and impact on economic activity.

This paper introduces a new indicator of financial conditions, a Financial Conditions Index (FCI), that captures the availability and affordability of financing, while estimating the effect of changes in financial conditions on economic activity, including output, inflation, and unemployment. The FCI is constructed for a broad range of European (both Euro area and non-Euro area) countries, disaggregated by countries as well as economic sectors.

After loosening in 2020, the estimated FCI began tightening mid-2021, with funding constraints becoming more binding in Europe. Conditions tightened further in 2022, after the start of Russia's war in Ukraine, as spreads widened and volatility across asset classes increased, reflecting a higher market price of risk. The monetary policy stance also turned significantly tighter—as the European Central Bank (ECB) and other central banks started hiking policy rates in pursuit of price stability. And as monetary policy tightened, so did the credit availability and costs, along with rising household and corporate lending rates, lower stock prices, higher government bond yields. The pace of tightening in FCs started slowing down in late-2022 as retreating energy prices lowered market perceptions of risk and volatility.

The recent and ongoing tightening in financial conditions is broad-based across sectors and countries, even though not to the same extent across the latter. FCs have tightened for both households and corporations. In contrast with previous financial cycles when increased government borrowing acted as an offsetting force, conditions have also tightened for governments. While the policy tightening cycle is synchronized across countries, having affected both Euro and non-Euro area European economies, the extent of tightening has been different, even within the euro area.

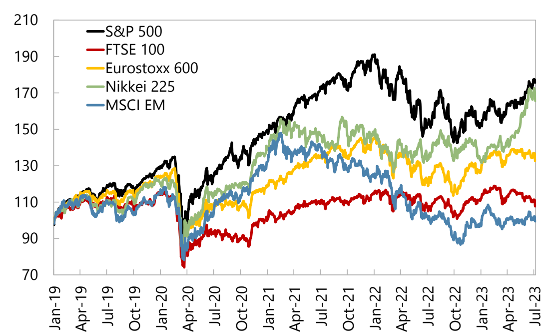
Over the sample period from 2000 to 2023, the tightening in FCs, including the recent shift to tighter FCs since mid-2021, is expected to lower output and inflation, while raising unemployment. Over a three-year horizon, tighter FCs are estimated to lower real GDP by 2.2 percent and inflation by 0.7 percentage points, while increasing the unemployment rate by about 0.3 percentage points.

The following findings of the analysis are relevant for policy choices and deserve further exploration in future work. First, the divergence in estimated FCs across countries underscores how monetary policy tightening may have heterogenous effects across Europe, indicating the benefits of using multiple policy levers—including fiscal and macroprudential policy—as complementary tools in pursuit of macroeconomic stability. Relatedly, differences in FCs across sectors also point to the need of carefully calibrating macroprudential policies in line with developments in specific sectors, to contain the buildup of future financial fragilities. Second, while tighter monetary policy results in tighter FCs in the near term, the analysis suggests that the impact is temporary, as bringing inflation under control eventually reduces price of risk; hence, possibly supporting a normalization and loosening of FCs down the line. Finally, the results also suggest that elevated government debt ratios may constrain funding, contributing to tighter FCs.

I. Introduction

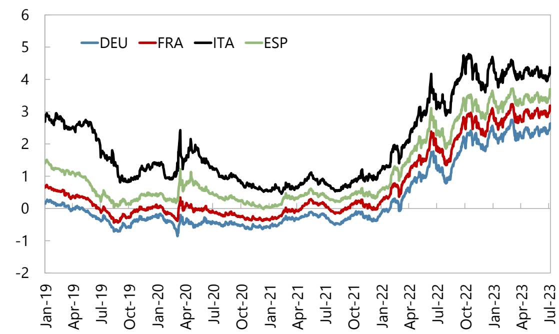
Following a favorable funding environment during the pandemic, access to credit tightened in Europe during 2022. Boosted by stimulative monetary, fiscal and macroprudential policies adopted in response to the pandemic, access to credit in Europe remained healthy through late 2021. However, with the start of the war in Ukraine, the availability and affordability of funding deteriorated significantly. Risk premia and market volatility jumped amid geopolitical tensions and expectations that monetary policy accommodation would be withdrawn to counter inflation pressures. Equity prices fell, sovereign bond yields increased, and bank spreads widened. In turn, higher funding costs fed through into higher corporate and consumer lending rates, making it costlier and more difficult for firms and households to access credit. In emerging markets, challenging market conditions came alongside a contraction in portfolio flows and currency depreciations, increasing the burden of repaying FX debt and further weighing on public and private balance sheets.

Global Equity Market Indices
(Index, Jan. 2, 2019 = 100)



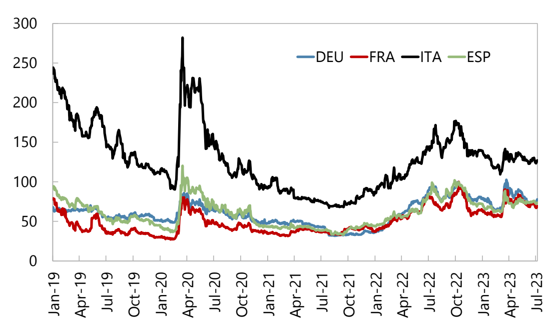
Source: Bloomberg.

10-year Government Bond Yields - Euro Area
(Percent)



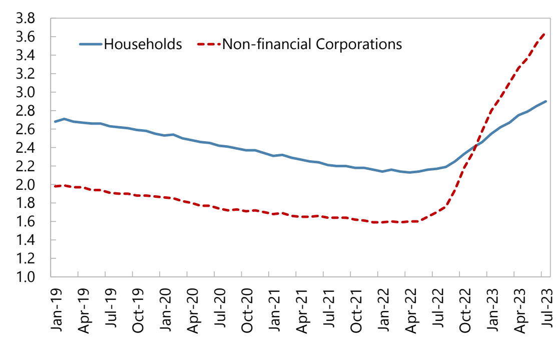
Source: Bloomberg.

5-Year European Bank CDS Spreads 1/
(Basis points)



Source: Bloomberg.
1/ Average of available G-SIBSs CDS.

Lending Rates - Euro Area
(Percent)



Sources: ECB; and Haver Analytics.

Against this background, policymakers should ensure that credit provision continues, while avoiding working at cross-purposes with other policy objectives. While policies should safeguard adequate provision of credit to viable households and firms, such actions should not undermine the ongoing efforts to normalize monetary policy—in response to high inflation—and to promote fiscal consolidation—to reduce public debt vulnerabilities. Macro-financial policies should also ensure that adequate buffers remain in place and prevent the buildup of future market fragilities and financial risks.

Striking the right policy balance is a challenging task as policymakers are faced with important trade-offs. In guiding policymakers, this paper aims to tackle three fundamental questions: (i) how financial conditions, which in the literature are loosely defined as "conditions for the provision of credit," can be best characterized; (ii) what factors drive financial conditions; and (iii) how financial conditions impact economic activity. At the current juncture, characterized by more restrained access to credit, finding answers to each of these high-level questions entails addressing the following more specific issues:

- How tight are current financial conditions in Europe? How do they compare with previous credit cycles?
- What is driving the tightening in financial conditions? How significant is the role of the policy stance?
- Is the ongoing tightening cycle broadly uniform across countries and sectors or are some regions and sectors experiencing more restrictive financial conditions compared to others? And, if so, what is driving these divergences?
- Finally, what are the effects of tighter financial conditions on growth, inflation, and the labor market?

The objective of this paper is to shed light on the above issues by constructing a financial condition index with strong statistical properties and simple economic interpretations. Despite a growing list of FCIs, including for European countries, the literature has not settled on an indicator that can also be used to measure the effect of changes in financial conditions on economic activity (see Box 1).[1] This paper intends to address this gap by introducing an indicator that captures the availability and affordability of financing, while estimating the causal effect of changes in financial conditions on economic activity. The paper's contributions are the following:

- It provides a new methodology to construct an FCI, consistent with the definition of financial conditions as the availability and affordability of financing.
- Building on a comprehensive dataset, it estimates FCIs for a broad range of European (both Euro area and non-Euro area) countries, disaggregated by countries as well as economic sectors.
- It estimates the causal impact of changes in the proposed FCI on key macroeconomic variables, including output, inflation, and unemployment using an approach that corrects for the potential endogeneity of the FCI.

The rest of the paper is organized as follows: section 2 defines financial conditions, reviews the relevant literature, and introduces the conceptual framework to think about the different drivers of financial conditions; section 3 presents the database and the methodology used to estimate the proposed FCI as well as the framework to assess the impact of financial conditions on key macroeconomic variables; section 4 describes the relevant findings; section 5 discusses policy implications and how an understanding of the current state of financial conditions may help calibrate an appropriate macro-policy mix; and suggests possible extensions of the analysis presented in the paper.

[1] Box 3.1 of the April 2017 GFSR Chapter 3 provides a nice summary of the evolution of financial condition indexes in the literature. We will summarize other indexes by methodologies in Box 1.

II. The Concept of Financial Conditions

Financial conditions in this paper are defined as the availability and affordability of financing to the main sectors of the economy. In line with IMF GFSR 2017 Chapter 3, the FCI proposed in this paper aims to capture the *"costs, conditions, and availability of funds to the economy".* However, compared to other FCIs*,* the index is constructed for the whole economy or for each of its main sectors, i.e., households, firms, and the general government.

Different approaches to defining financial conditions can be found in the literature. While the concept of financial conditions is commonly used in the empirical macro-financial literature, the specific measures of availability and affordability of credit, as well as the forms of financing—equity, bond, bank lending—and the relative importance of these measures, differ across studies and often depend on the country, the period and the sectors of the economy that are the focus of analysis in different papers. Stremmel (2015) finds that the index that best fits the financial cycle in Europe is based on private credit and house prices, in line with Borio (2014). Deghi, Welz and Zochowski (2018) extend a standard set of financial indicators for the euro area by including variables capturing spillover and contagion risk and find that this indicator provides accurate near-term predictions of deep recessions. Schüler, Hiebert and Peltonen (2015) also found that within Europe, whereas some countries' financial cycles are very closely related (Belgium, the UK, Sweden, Finland, Spain, Ireland), other countries (including Germany) are rather weakly related to other countries. Box 1 reviews in greater detail alternative FCIs.

Views about the interaction between financial conditions and the state of the economy have evolved over time. The post-GFC literature has highlighted how changes in financial conditions can amplify economic booms and busts, and possibly lead to financial distress with systemic implications and feedback effects from the macroeconomy back to financial conditions (see Brunnermeier et al. 2009; Adrian and Shin 2010). Financial conditions can change because of changes in valuations—including those driven by monetary policy—in the attitude towards risk, and due to financing constraints. Changes in economic conditions, such as higher macroeconomic uncertainty, may worsen the asymmetric information between creditors and borrowers, thus hindering financial intermediation. Stress in financial intermediaries and financial markets can affect the availability of credit to firms and households with negative impact to aggregate demand. Such stress can also amplify financial imbalances and liquidity mismatches within the financial sector and propagate distress due to direct exposures among financial intermediaries (Allen and Gale 2000; Freixas et al. 2000; Cifuentes et al. 2005). It can also operate through indirect effects, for example, fire sales, especially in the presence of collateral constraints (Lorenzoni 2000; Cont and Shanning 2017), which could reinforce financing constraints in a downturn. These complex interactions can lead to sudden and non-linear distress dynamics.

An FCI should encompass a wide array of price and quantity indicators. While most FCIs in the literature include only indicators of volatility, term premia and credit spreads, as they are good near-term predicator of crises (Brave and Butters, 2012), these market stress measures are not sufficient to capture the broader availability and affordability of financing. Therefore, additional variables should be considered when building FCIs, including indicators of:

- *Monetary conditions* that encompass policy rates and monetary aggregates, as these aim to capture how monetary policy impacts growth (Friedman and Kuttner 1992). In open economies, this group of indicators should include exchange rate movements given their relevance as channel of transmission of monetary policy (Ericsson and others 1998).

- *Credit aggregates* capture the capacity of the financial system to finance the economy. These include capital adequacy of banks, indices of the stringency of credit standards (e.g., issuance of asset-backed securities, senior loan officer surveys) and measures of leverage (e.g., the credit/GDP gap, Borio 2014).
- *Equity and bond prices* measure the cost of market financing and have been shown to predict economic activity. In addition to prices, other useful variables include the slope of the yield curve (Stock and Watson 1989); and measures of credit risk (e.g., the spread of commercial paper over treasury yields, Friedman and Kuttner 1992) which have been found to be good predictors of recessions.

The transmission channels of monetary policy provide a basic framework to conceptualize the main channels through which financial conditions operate. As monetary policy rates change, so do money market rates and, bank lending and deposit rates. Changes in policy rates also influence expectations of future interest rates, which, in turn, affect long-term government bond yields and exchange rates. Depending on the degree of market development, the impact of policy rates on market expectations has broader implications for asset prices, including equity prices and corporate bond prices. In turn, changes in interest rates and collateral values influence savings and investment decisions of households and firms and affect borrowers' ability to repay existing loans and banks' willingness to extend new credit.

The interaction among these transmission channels is complex and affected by institutional arrangements and financial market structures. The provision of credit could be constrained by administrative measures as well as all forms of information asymmetries, or, in contrast, it could be encouraged by government guarantees and regulatory forbearance, as observed in the policy response to the COVID pandemic. Similarly, in less developed capital markets the propagation of shocks may be slower, whereas more sophisticated financial systems may amplify the impact of asset prices on financial conditions and thus economic activity. These effects may rapidly unwind non-linear effects, especially at times of market turmoil.

This paper aggregates relevant individual financial indicators into five broad categories of drivers. To facilitate the economic interpretation of financial conditions, indicators are grouped into five key macroeconomic drivers, reflecting the transmission channels through which indicators may work and their complex interactions. These include the following (see Annex I for a comprehensive list of all variables included and their corresponding aggregation in drivers):

- *Credit availability and costs.* This reflects the terms on which households and non-financial corporates have access to credit, including mortgage and consumer lending rates as well as corporate lending rates. It also relates to prices affecting valuations of financial and real assets, such as stock prices, long-term government bond yields, and house prices.
- *External conditions.* This driver includes select variables which fall outside the scope of domestic financial systems, including exchanges rates, cross-border financial linkages. For European, non-euro are countries these include German benchmark government bond yields as well as the ECB policy rate.
- *Funding constraints*. This groups broadly refers to restrictions to financial intermediation, thus encompassing various Financial Soundness Indicators (FSI), including NPL ratios, capital ratios, interest rate margins, return on assets, and return on equity. It also includes financial sector's market capitalization as well as stocks of outstanding debt across sectors.

- *Policy stance.* This driver reflects central bank rates and other indicators which may be affected more directly by monetary and financial policy decisions, such as interbank rates, deposit rates, short-term government bond yields. It also features monetary aggregates as well as shadow rates to deal with interest rates close to the zero lower bound during most of the reference period.
- *Price of risk.* This driver captures risk premia and market volatility. Therefore, government and corporate bond spreads, interest rate swap spreads, and CDS spreads are included in this group, alongside various measures of stock and bond market volatility.

III. Constructing Robust and Economically Interpretable FCIs

The proposed FCI is statistically robust and economically interpretable. The data and the econometric techniques to build the index and to quantify the impact of financial conditions on macroeconomic aggregates are presented in this section.

A. The Data

As a first step, this work builds a comprehensive database of macro-financial variables. These variables aim to capture all the relevant transmission channels identified in the previous section and reflect the availability and affordability of funding in the European economy, disaggregated by countries, country groups[2] as well as institutional sectors, including households (HH), non-financial corporates (NFC) and the general government (GG).

The data include high- and low frequency indicators. High-frequency indicators include stock price indexes, bond yields, CDS spreads, as well as measures of market volatility among various indicators. Low-frequency indicators include lending surveys and several FSIs. All variables are averaged over the course of the quarter. Year-on-year HICP inflation levels across countries are also included as high inflation has had some impact on the nominal growth of liabilities.[3] The complete list of indicators is presented in Annex I.[4]

B. Constructing the FCI

In the next step, the dataset is reduced into a composite indicator of financial conditions. Unlike most traditional data reduction methods, where an FCI is extracted from an atheoretical relationship among the data, the adopted methodology relies on a *supervised* learning algorithm, the Partial Least Squares (PLS) estimation (see Annex II for a technical discussion of the PLS approach).

[2] The countries covered in the analysis include: i) Euro-area: Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Slovenia, and Spain; and ii) non-Euro-area: Croatia (through end 2021), Czech Republic, Hungary and Poland and Israel.

[3] In assessing the contributions of groups of indicators, we subtract first the contribution of inflation and then add the indicators' contribution by groups.

[4] For non-stationary indicators the trend is removed either using the HP filter or a linear trend.

Box 1. Alternative Methodologies to Construct FCIs

A. Macro-based FCIs with Regressions

Weighted averages of financial indicators were initially used to summarize information about financial conditions. The weights were obtained via standard Ordinary Least Square (OLS) regressions (Gauthier, Graham, and Liu, 2004, the Monetary Conditions Index by the Bank of Canada). Others proposed the estimation of the IS curve to construct FCIs via regression methods (Goodhart and Hofmann (2001), Mayes and Viren (2001). In the same vein, some papers use Vector Autoregressions (VAR) by mixing target variables such as credit or inflation with a set of financial variables whose Impulse Response Functions are then aggregated to create an FCI (Batini and Turnbull (2002), Gauthier, Graham, and Liu (2004), Swiston (2008)). Estimating FCIs via VARs allows to account for the impact of shocks to financial variables on other variables in the system and purging them to retrieve the "pure" financial cycle.

Regression-based FCIs are easy to interpret because they derive from a macro model but face several shortcomings. In an IS curve, they represent the linear combination of financial variables that best explain the dynamic of investment/savings. In a VAR, FCIs represent the "pure financial cycle," in theory, purging from endogeneity and feedback loops, depending on the degree of identification. However, the macro-model approach suffers from two major shortcomings: (1) the set of variables are limited, as adding dozen of regressors in a VAR or an OLS increases parametric noise and estimator variances; and (2) as often with financial variables, severe multicollinearity issues arise. To use macro-model based FCIs, one must rely on theories, selecting only what one considers the most relevant variables and assuming an unambiguous transmission of monetary policy. As the financial system becomes more complex, the macro-model approach suffers from a specification bias and will miss a substantial part of the financial cycle. Besides, VAR-based FCIs are expected to "purge" the financial cycle from some simultaneity bias (e.g., due to the macro-financial feedback loop) but good instruments are hard to find. VAR also relies on arbitrary Cholesky decompositions, which offer a relatively poor identification and does not guarantee that causal effects are adequately identified (see Stock and Watson (2001) for a discussion). Because of these shortcomings, the use of macro-based FCIs has become less popular after the global financial crisis.

B. Data-Reduction FCIs

The opposite approach, an atheoretical and purely data-driven approach, is to estimate FCIs through data reduction methods. These reduced-form FCIs often rely on some form of PCA or factor model, where the first (in most cases) component/factor is interpreted as the FCI. This approach was popularized by Hatzius et al. (2010) who estimated an FCI for the U.S. using 57 variables, starting from the 1970s. The Chicago Fed constructs an FCI by taking the first component of a PCA estimated on 105 financial variables (Brave and Kelly, 2017). The ECB constructs FCIs for the euro area and selected European countries by taking the first three principal components on a PCA estimated over 24 variables (Angelopoulou, Balfoussia, and Gibson (2012)). The Global Financial Stability Report of the IMF uses PCA-based methods to compute FCIs over 29 systemically important jurisdictions (see IMF GFSR, online annex 2.1, 2021). The weights of the components are fixed over time to allow better tractability. The components include policy rates, spreads, exchange rates, asset prices (equity, housing), and volatility measures. Other researchers have used PCA-based approaches to estimate FCIs for a wide range of countries such as the United Kingdom (Aikman et al., 2018), China (Zheng and Yu, 2014), India (Khundrakpam, Kavediya, and Anthony, 2017), a set of developed and emerging markets (US, Japan, China, Brazil, Russia, Turkey, etc. in Nicoletti, Wacker, and Lodge, 2014), Colombia (Gómez, Murcia, and Zamudio, 2011), South Africa (Klein, Gumata, and Ndou, 2012)). The financial industry routinely produces PCA or factor based FCIs (Deutsche Bank, JP Morgan).

The advantage and disadvantage of PCA or factor analysis is that these approaches are agnostic, "letting data speak." These approaches offer the possibility to potentially capture a wide range of effects as the number of variables can be large. Linear data reduction is a simple and is widely available on many statistical packages. However, aggregating many variables into one metric without a target or anchor complicates the interpretation. The first components will weigh the set of variables that explain the most common variance across all the indicators regardless of whether this variance is relevant for the policymakers. For instance, in a country where funding from banks dominates market funding, giving a high weight to the principal component of volatile market variables may not be appropriate. In addition, the loadings (the coefficients of the linear combination of variables) are hard to interpret. Contrary to the coefficients of linear regressions that represent a "ceteris paribus" marginal effect, the loadings in a PCA or a latent factor model are simple linear combination coefficients; hence, they embed the impact of other variables.

C. Hybrid FCI Models: Supervised Data Reduction Methods

Attempts to overcome the abovementioned drawbacks have resulted in hybrid approaches that aim to keep the interpretability of macro-based FCIs, while remaining data driven. Koop and Korobilis (2014) propose a TVP-FAVAR model (Time-Varying Parameters Factor Augmented Vector AutoRegression). The financial cycle is purged from the standard business macro-cycle model via a VAR model, and the FCI is estimated through a latent factor model with time-varying parameters, thereby allowing the weights of the different variables to change over time. The IMF has used the TVP-FAVAR model to estimate FCIs over many countries (Elekdag et al., 2018). However, the TVP-FAVAR model is initialized with a PCA. In the end, the authors noticed very few differences with a standard PCA, despite a substantial increase in complexity. For this reason, the recent IMF GFSR versions use simple PCA instead of a TVP-FAVAR model (see IMF 2021). Using a two-step approach, **Goldman Sachs Index** aggregates from 6 categories whose weights are determined by their impact on GDP growth over the following 4 quarters using a stylized macro model. The result is a heavy weight on corporate and sovereign spreads (for the euro area, such weight would make up 40 percent of the index).

Major central banks are investing more efforts into improving FCIs using hybrid approaches.

US Fed researchers recently designed a Bayesian VAR with a shrinkage algorithm, to include a large number of financial variables into a full-fledged macroeconomic model (Crump et al., 2021). This approach has many advantages as it captures many transmission channels while accommodating 31 variables. However, it relies on a quite complex multi-layer Bayesian approach with shrinkage, depends on some non-obvious modelling choices (for instance, the choice of priors or the treatment of the Bayesian hyper-parameters) and requires a high familiarity with Bayesian econometrics for fine-tuning and interpretation.

Bank of France and the Bundesbank implemented approaches involving two-step process (Petronevich and Sahuc 2019, Metiu 2022). For the Bank of France, in the first step, 18 financial series are combined into 6 main factors (the first 6 components of the PCA). Then, for each of the 6 components, the authors fit a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and estimate the conditional volatility. The conditional volatility of each factor serves to compute a weight (the more volatile, the higher the weight), which is then used to aggregate the six PCA components into one. The general idea is to combine PCA but to use components' own conditional variance instead of their variance explained in the projection (as in a standard PCA). It, therefore, helps to "recover" higher-order factors into the FCI instead of just taking the first one. While the method is appealing, it is not clear that weighting the factors by their volatility is desirable. It will give more importance to certain factors (typically market ones) over more stable ones (e.g., balance sheets variables). Volatile financial variables may not represent financial conditions more adequately. Similarly, from about 70 financial variables, the Bundesbank aggregate into 6 sub-indicators using PCA, and then aggregate into one single FCI with time-varying weights. The weights also capture the time-varying correlation structure of the sub-indicators.

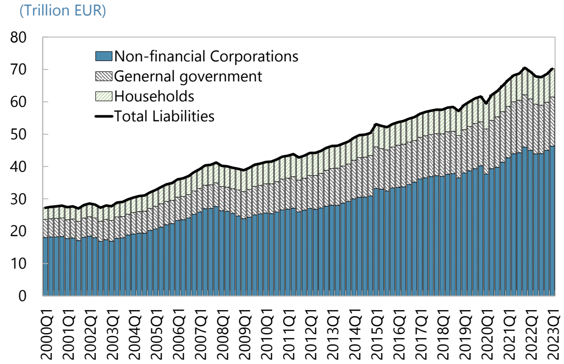
The PLS bears some resemblance to Principal Component Analysis (PCA) in that it does not impose a subjective selection of the variables involved. However, the PLS *anchors* the estimated relationships to a *target variable* (see Wold et al. 2001 for a PLS review). Other FCI techniques proposed in the literature are presented in Box 1.

The chosen target variable is the growth rate of total financial liabilities for the main sectors of the economy. This quarterly year-on-year variable: (i) reflects the availability and affordability of funding to all economic agents, including households (HH), non-financial corporates (NFC), and the general government (GG); (ii) encompasses different types of liabilities, including loans and debt securities; and (iii) is readily available from quarterly financial accounts that are consistent across countries. We construct FCIs for each economic sector, i.e., HH, NFC and GG. We then aggregate the HH and NFC FCIs into a private sector FCI, which constitutes the basis for the analysis in this paper and it is presented throughout the paper in all charts. For each target variable, each PLS regression produces a regression score reflecting the explanatory power of the indicators. Based on this score, we choose the best specification which includes two quarters' lagged values for each indicator.

The composition of financial liabilities varies markedly across sectors. A visual inspection of the data reveals that NFCs account for the largest share of financial liabilities, and they are the most dynamic sector, in other words the sector with the largest contribution to the change in overall financial liabilities. Loans are by far the most relevant source of funding for households, while NFCs rely on a mix of equity and investment fund shares, loans, and debt securities. Household liabilities tend to move much more slowly given the longer maturities of mortgage loans and react to monetary policy with longer lags. Conversely, corporate liabilities are more volatile and have declined rapidly during 2022. General government financial liabilities have generally played a countercyclical role, although not in 2022. During the GFC, when credit to NFCs collapsed, government funding increased significantly to counter the economic downturn. Similarly, during the pandemic, fiscal policy also turned markedly expansionary. However, in 2022 government liabilities contracted in sync with private sector liabilities.

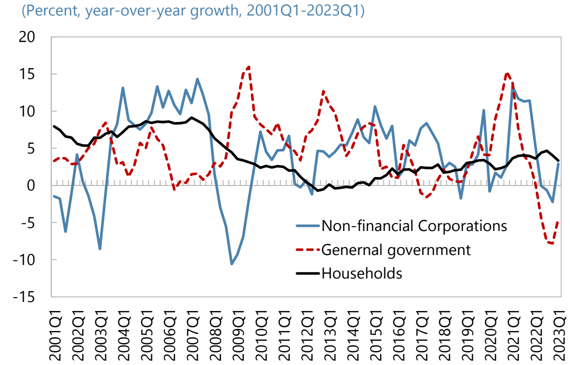
The use of the PLS approach in constructing FCIs offers several important benefits. These include its interpretability, flexibility, and statistical properties. More specifically:

Euro Area Total Liabilities
(Trillion EUR)



Sources: ECB; and Haver Analytics.

Euro Area Financial Liabilities - Growth by Sector
(Percent, year-over-year growth, 2001Q1-2023Q1)



Sources: ECB; and Haver Analytics.

- PLS is designed to handle a large number of highly collinear variables via linear projections.[5]

- PLS allows for economic interpretation by linking explanatory variables to a target variable. The variables carrying the highest loadings in the framework are those having the best predictive power for the development of financial liabilities.

- A *supervised* PLS approach, as opposed to an *unsupervised* PCA, also helps ensure comparability across FCIs by using an anchor variable that is standardized and consistent across countries (even though the observations are country-specific).

- Similarly, the PLS approach offers the possibility of estimating FCIs by sectors, using sector-specific financial liabilities. Other PLS-based FCIs have been shown to have good statistical performances compared to other techniques.[6]

C. Assessing the Impact of FCIs on the Real Economy

The relationship between FCIs and output is affected by different sources of endogeneity. One key contribution of this paper is to assess the causal effect of changes in financial conditions. This is a challenging task because the relationship between FCIs and output is affected by different sources of endogeneity, including policy endogeneity and market expectation effects:

- **Policy endogeneity effects.** When output growth decelerates below potential and expected inflation falls below target, policies would typically turn looser, for instance through lower policy rates. Given the inclusion of policy rates and other policy variables in the FCI, all else being equal, looser financial conditions would thus be associated with weak output growth (and low inflation), at odds with the expectation that looser financial conditions would boost growth. Conversely, when output growth accelerates above potential, policies would turn tighter. Tighter financial conditions would be associated with strong growth (and high inflation), at odds with the expectation that tighter financial conditions would depress growth.

- **Market expectation effects.** An FCI, however, is a complex indicator, aggregating not only policy variables but also several market indicators, including for instance stock prices and corporate spreads that move in anticipation of future economic developments. For instance, when output growth accelerates, stock prices would typically go up, reflecting higher expected corporate earnings. Given the inclusion of stock prices and other market variables in the FCI, all else being equal, looser financial conditions would be associated with strong growth. While this correlation is as expected, estimations in this case would reflect reverse causality from growth to financial conditions. Conversely, when growth decelerates, stock prices would go down. Tighter financial conditions would be associated with weak growth, again implying reverse causality.

[5] This allows “one step” regressions, in contrast to other methodologies that require multiple steps and may compound estimation errors. Moreover, PLS regressions produce regression scores that allow the choice of the best specification with the highest score.

[6] Researchers at the Bank of England (Kapetanios, Price, and Young, 2018) show that PLS-based FCIs for the United Kingdom outperform PCA-based FCIs in forecasting monthly GDP. Moreover, PLS-based FCIs can be used to improve the identification of credit supply shocks in a SVAR. Similarly, Duo and Wang (2016) estimate PLS-based FCIs for the United States and show that these outperform PCA-based FCIs in out-of-sample GDP forecasting setups.

In the sample under consideration, market expectation effects tend to dominate policy endogeneity effects, with loose financial conditions associated on average with stronger growth (see Table 1).

Table 1. Unconditional Averages of Growth in Different FCI Regimes

Mean annualized q/q real GDP growth (in percent)	Loose FCI	Neutral FCI	Tight FCI
Lag 1	3.5	2.0	1.0
Lag 2	3.5	2.2	1.0
Lag 3	3.3	2.0	1.5
Lag 4	2.7	2.3	1.8

Source: Author's calculations.

This paper resorts to a treatment effects approach to identify the causal impact of financial conditions amid these sources of endogeneity. The treatment effects approach used in this paper is the Inverse Probability Weighting (IPW). Treatment effects approaches allow the study of causal effects without assuming a specific functional form.[7] Moreover, the combination of these approaches with regression adjustment methods produces robust estimators (Annex III includes a technical presentation).

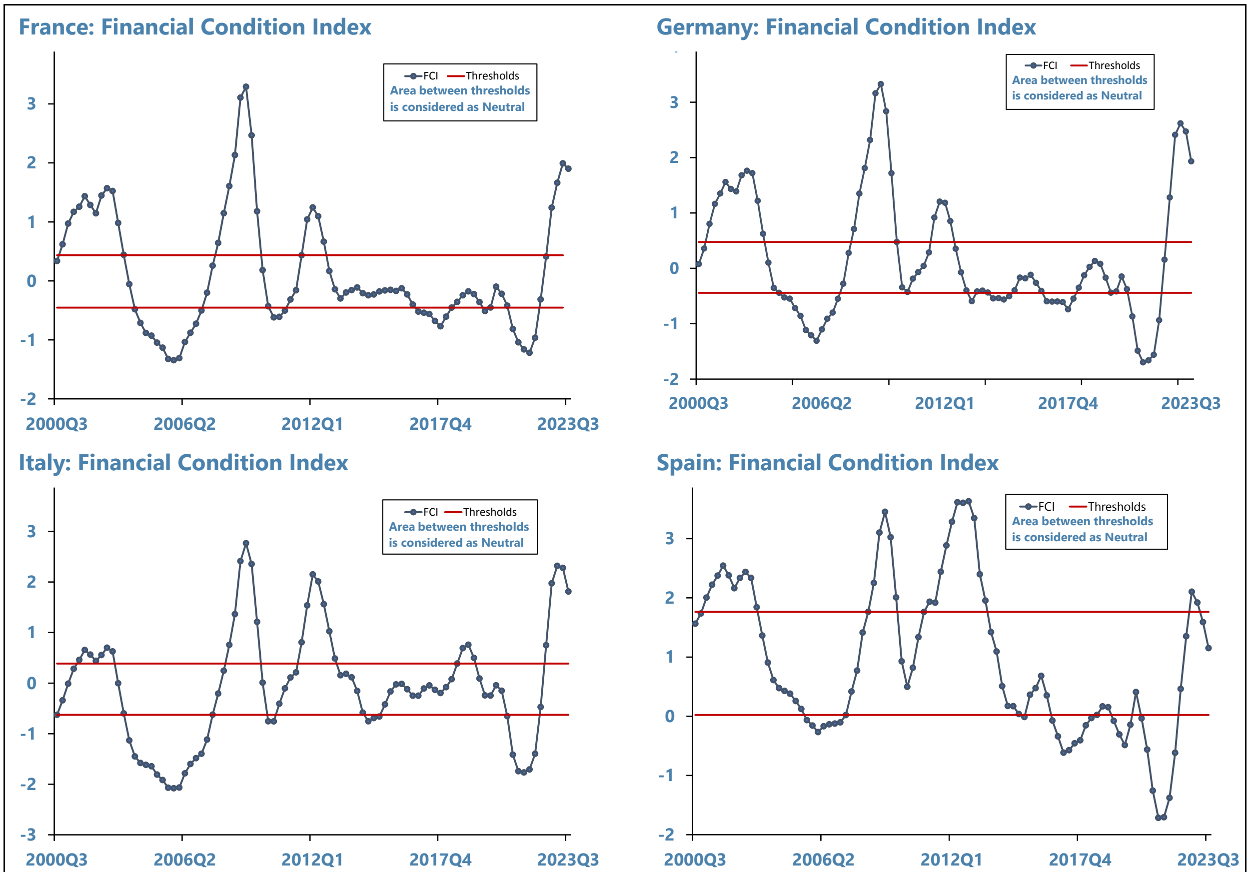
The implementation of the IPW involves the following two steps:

- **Discretization of FCIs.** A continuous FCI is discretized to identify three regimes: tight, neutral, and loose. Using the historical distribution of the FCI for each country over the past 10-20 years, we assign thresholds so that well-known episodes of tight FCs (GFC and European sovereign debt crisis) are assigned to the tight regime, whereas post-crisis periods of more accommodative policies are assigned to the loose regime. Consistent with historical observations, thresholds are assumed such that on average 30 percent of the time the FCI is in a neutral regime, 40 percent in a loose regime, and 30 percent in a tight regime.[8] Numerical thresholds may change from one country to another to match this distribution.
- **Reweighting observations.** As market expectation effects tend to dominate policy endogeneity effects in the sample under consideration, strong growth is more likely to be observed in the "treatment" group, i.e., loose FCI. Therefore, these observations are overrepresented in the sample, compared to the true population. This would produce biased estimators. The IPW allows to reweight the sample and give less weight to these observations, ensuring that estimates of the impact of loose

[7] Treatment effects approaches were initially developed in the context of labor market and program evaluation (Ashenfelter 1978, Lalonde 1986, Card and Sullivan 1988, Heckman, Ichimura, and Todd 1997, Angrist 1998; see also Imbens 2004 and Imbens and Wooldridge 2009 for literature reviews. However, it has been increasingly used in macroeconomics, including in studies on the impact of monetary policy (Angrist, Jordà and Kuersteiner 2018), on fiscal multipliers (Jordà and Taylor 2016), on linkages between democracy and growth (Acemoglu, Naidu, Restrepo, and Robinson 2019), and on the effectiveness of fiscal rules (Caselli and Wingender 2021)

[8] Broadly comparable thresholds can be drawn from the Basel Committee's guidance on the requirements for capital buffer add-ons. This indicates that, according to the historical distribution of credit gaps for all European countries, credit was tight, neutral, or loose for 40, 25 or 35 percent of the time.

financial conditions on macroeconomic aggregates, i.e., output, unemployment, and inflation are unbiased.[9]



Source: Author's calculations.
Note: 2023Q2 and 2023Q3 are forecasts.

IV. Results: Financial Conditions in Europe

Financial conditions in Europe have gone through sustained loosening and tightening periods, in line with the dynamics of financial liabilities. According to the estimated FCIs, between 2003 and 2006 financial conditions loosened substantially. Then, conditions tightened rapidly during the GFC, mainly driven by a decline in the availability of credit and a rise in its cost.[10] During the European sovereign debt crisis, wider government bond spreads in the euro area periphery as well as growing concerns about public debt financing

[9] Observations that associate high growth and tight FCI can be defined as "control" group. The unbiased impact of financial conditions will be the difference between the average predicted outcome under the control group and the average predicted outcome under the treatment group with reweighted observations.

[10] The turnaround in US house prices, partly related to a tightening cycle in monetary policy, was the initial trigger of the tightening in financial conditions at the time of the GFC. The crisis, which was rooted in the US subprime market, quickly led to a collapse in the value of mortgage- and asset-backed securities and disruptions in interbank markets, before spilling over to global equity and credit markets and raising broader solvency concerns for systemically important financial institutions after the collapse of Lehman Brothers.

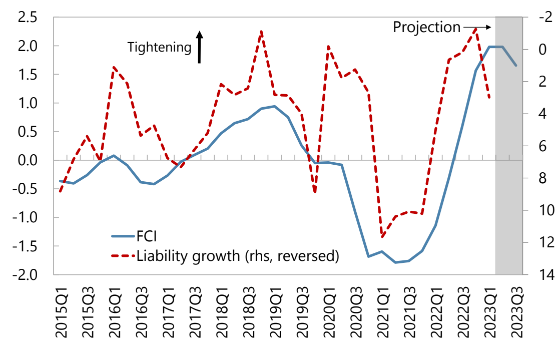
and sovereign default risks had a significant impact on financial conditions. It was only through major central bank liquidity provision and unprecedented government interventions that financial conditions were loosened again and confidence in the financial system restored.

At the onset of the pandemic, financial conditions loosened significantly, reflecting the exceptional policy support deployed in this period. Uncertainty about the pandemic and its impact on economic activity resulted in a spike of the price of risk. However, the outpouring of monetary and fiscal support resulted in a loosening environment up until the end of 2020. In this period, the increase in government funding more than offset private sector deleveraging.

But in 2021–22, financial conditions tightened significantly. In line with the sharp drop in the growth rate of financial liabilities, financial conditions started tightening significantly in 2021 and continued in early 2022 with the onset of Russia's war in Ukraine. The rate of tightening then moderated somewhat in late 2022.

Euro Area: FCI and Liability Growth

(Index; percent)



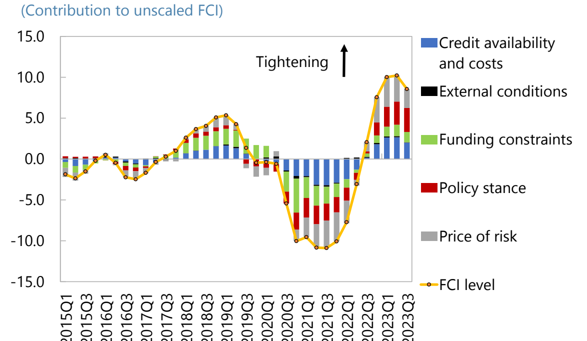
Sources: Author's calculations.

Initially, in 2021, tighter funding constraints were the main drivers of financial conditions. An analysis of the key drivers introduced in section 2 shows that that the pandemic-induced rise in public and private debt ratios, increasingly acted as a funding constraint, while higher commodity prices weighed adversely on financial flows. In contrast, favorable stock market conditions were still providing a mildly loosening contribution to financial conditions during this phase.

After the start of the war in Ukraine, lower availability, and higher cost of credit as well as a higher price of risk compounded the effect of tighter funding constraints. In February 2022, as the war started, the price of risk jumped, reflecting wider spreads and higher market volatility across a variety of financial asset classes. The policy stance turned decisively tighter, as the ECB and other central banks started hiking rates to keep inflation expectations anchored. And, as monetary policy tightened, so did the availability and cost of credit, with rising household and corporate lending rates, lower stock prices, higher government bond yields all contributing to more restrictive financial conditions.

Euro Area: FCI level

(Contribution to unscaled FCI)

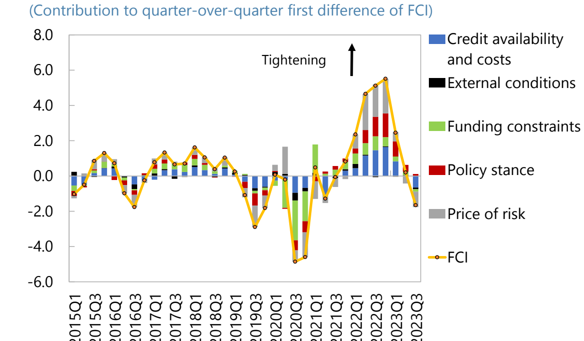


Sources: Author's calculations.

Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Euro Area: FCI Changes

(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.

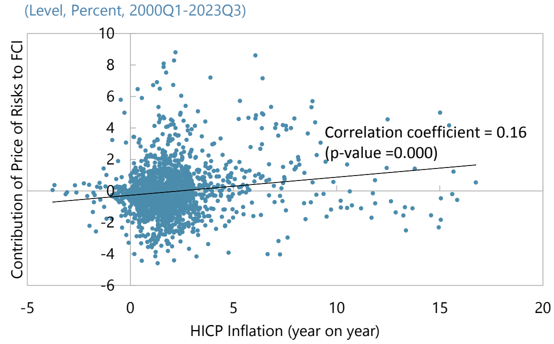
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

The pace of tightening has started to slow down in late 2022. While financial conditions significantly tightened in 2022, the rate of tightening exhibits early signs of moderation. This slowdown has taken hold as the rise in lending rates as well as government and corporate yields—which had weighed adversely on the credit availability and costs—starts decelerating.

Our analysis indicates that the price of risk tends to rise with inflation, but tighter monetary policy weakens the impact of inflation on the price of risk. The unconditional correlation between the level of HICP inflation and the price of risk across countries over time is positive and significant. A panel regression using data for Italy, Germany, Spain, and France shows that a higher price of risk comes along with higher inflation, but this relationship is weakened with a tighter policy stance. That is, while tighter monetary policy may result in tighter FCs in the near term, these results suggest that this effect may be temporary, as a tighter policy stance would eventually reduce the impact of inflation on the price of risk; hence, possibly supporting looser FCs. Further analysis would be needed to confirm the significance of this channel.

Contribution of Risk and Inflation Level

(Level, Percent, 2000Q1-2023Q3)



Sources: Author's Calculation.
Note: 2023Q2 and 2023Q3 are forecasts.

The Impact of Policy Stance on the Inflation-Price of Risks Linkage

	(1)	(2)
	D.Price of risk	*D.Price of risk*
HICP Inflation	**0.114*****	**0.139****
	(0.0392)	(0.0377)
D.Policy stance		**0.802*****
		(0.105)
HICP Inflation # D.Policy stance		**-0.0972*****
		(0.0253)
Observations	363	363
Adjusted R-squared	0.90	0.92

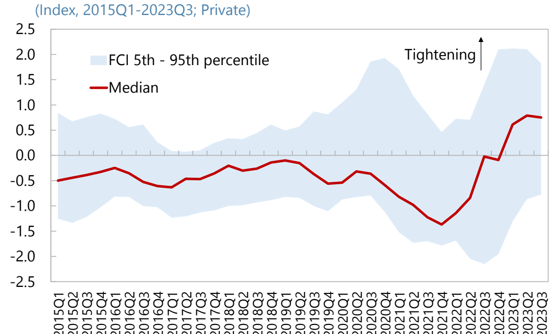
Country and time fixed effects are included. Contributions are expressed in first differences. 4 quarter lags of inflation are included. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Source: Author's calculations.

Cross-country divergences in FCs have increased. The current tightening cycle is broad-based across countries, having affected both Euro and non-Euro European economies; however, dispersion across FCs shows a growing heterogeneity across countries from 2022. For some countries, including Italy and Spain, the

Euro Area: Financial Condition across Member States

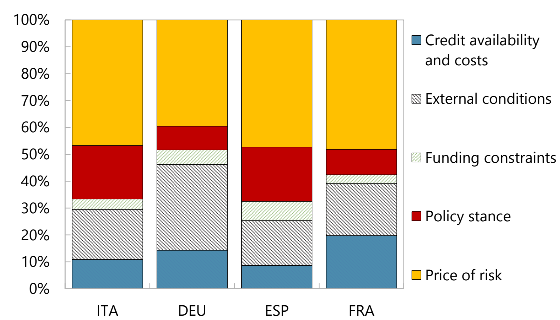
(Index, 2015Q1-2023Q3; Private)



Source: Author's calculations.
Note: 2023Q2 and 2023Q3 are forecasts.

Drivers of FCIs across Countries

(Average 2022Q3 - 2023Q3)



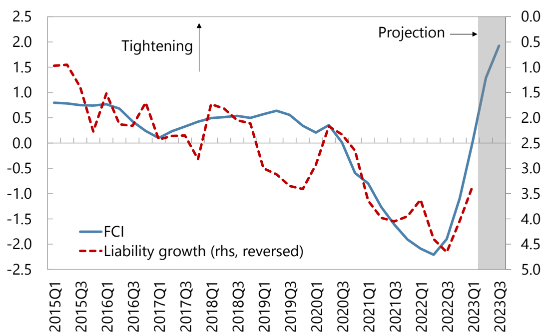
Sources: Author's calculations.
Note: 2023Q2 and 2023Q3 are forecasts.

policy stance driver is etimated to have had a larger impact in FCs.

Cross-sector comparisons show that both households and firms are facing tighter financial conditions but driven by different factors. To have a better understanding of the FCI, we analyze FCs for the individual sectors, i.e., HHs, NFCs. While financial liabilities for HHs and NFCs were still growing during the first half of 2022, financial conditions started tightening for NFCs in 2022Q2, followed by HHs later in the year. For HHs, the tightening was mainly driven by the tighter policy stance as well as the lower credit availability and higher costs, in turn determined by higher lending rates. For the corporate sector, the price of risk, led by widening corporate spreads and rising volatility, played a more prominent role.

Euro Area Households FCI and Liability Growth

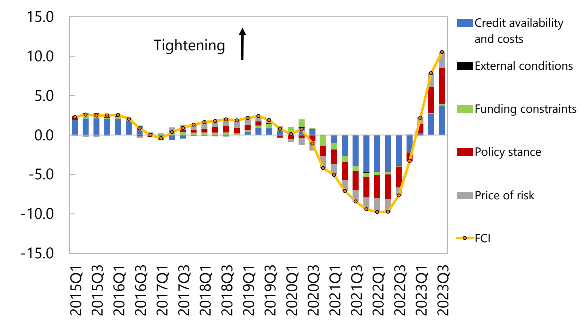
(Index; percent)



Sources: Author's calculations.

Euro Area Contributing Factors to Household FCI

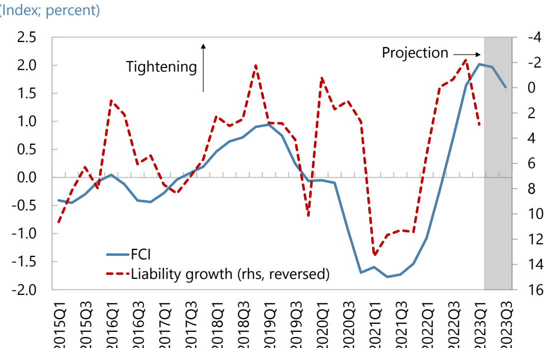
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Euro Area Nonfinancial Corporations FCI and Liability Growth

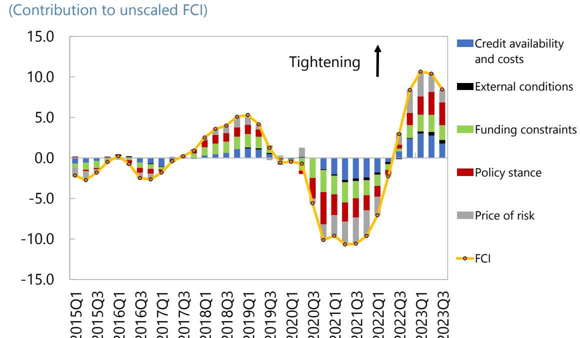
(Index; percent)



Sources: Author's calculations.

Euro Area Contributing Factors to Nonfinancial Corporations FCI

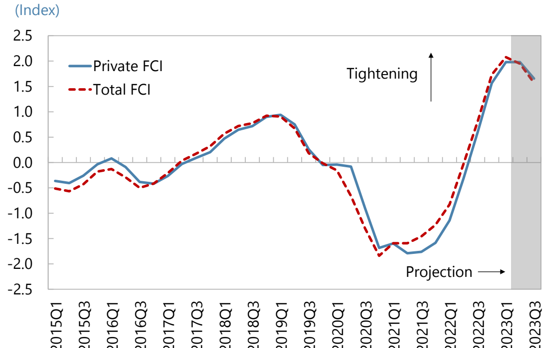
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Euro Area Private Sectors FCI and Total FCI

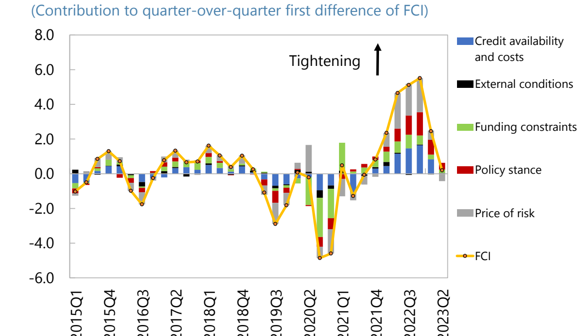
(Index)



Sources: Author's calculations.

Euro Area Private Sectors FCI Changes

(Contribution to quarter-over-quarter first difference of FCI)

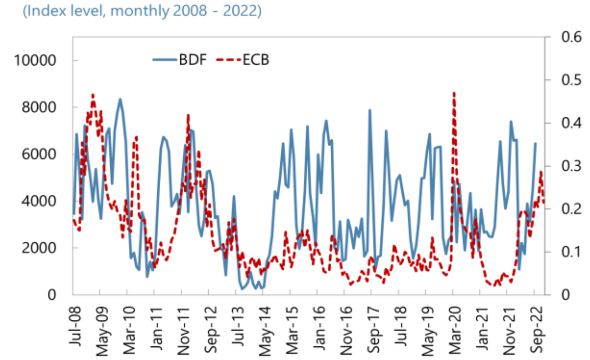


Sources: Author's calculations.
Notes: FCI is not scaled.

In the near term, conditions will likely remain tight, in line with survey data. While falling energy prices have fueled a correction in global long-term yields and boosted equity prices, a tight monetary policy stance and funding constraints from banks are still affecting financial conditions, especially for the household sector. These results are also consistent with the findings of the July 2023 euro area Bank Lending Survey (BLS) indicating tighter credit standards and deteriorating bank funding.

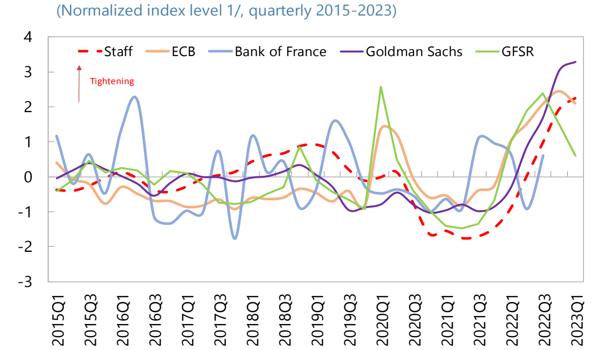
Consistent with our results, other estimated FCIs also point to a tightening of financial conditions through the end of 2022, with some important differences. For example, the ECB publishes monthly country-level indexes of financial stress focusing on three market segments: equity, bond, and foreign exchange (see Duprey and Klaus 2015). The Bank of France's FCI is based on eighteen financial series combined in six main factors (Box 1). The Goldman Sachs Index attributes a large weight (almost 40 percent) to corporate spreads. Methodological differences and focus on largely market-based variables result in much more volatile series (especially the Bank of France's FCI). The IMF GFSR FCI, which includes price and volatility variables but does not feature quantity measures, exhibited a sharper easing of financial conditions in late 2022. These acute episodes of stress do not happen so frequently, as shown in Ahir et al. (2023) and Adrian et al. (2023). Consequently, these indicators are geared towards capturing short-term gyrations in financial conditions, whereas the FCI proposed in this paper—which is anchored to quarterly financial accounts and incorporates a wide set of market and non-market-based indicators—identifies longer term financial cycles, whose assessment is particularly relevant for macroeconomic and policy implications. Our index can capture periods of tight financial conditions that do not coincide with a crisis episode. These periods happen much more frequently in our sample.

Comparison of FCIs
(Index level, monthly 2008 - 2022)



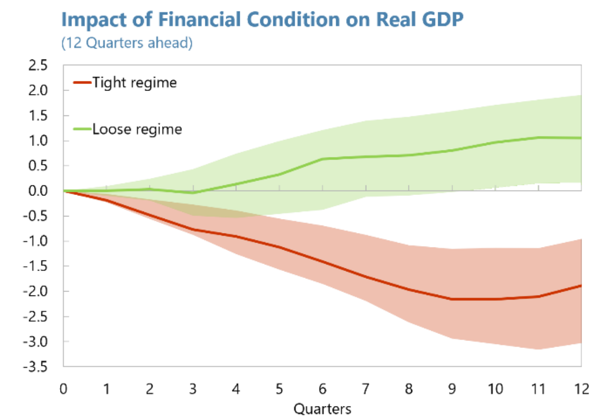
Sources: Bank of France, ECB

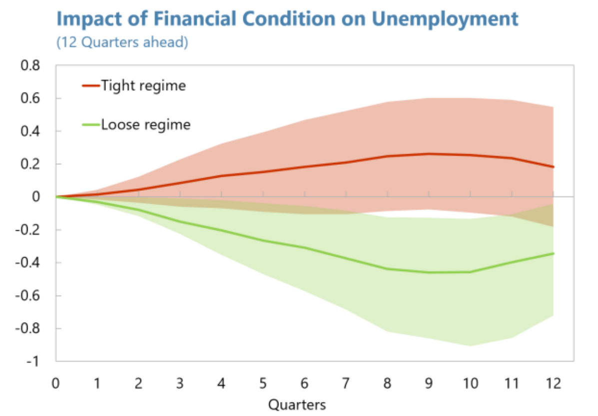
Comparison of FCIs
(Normalized index level 1/, quarterly 2015-2023)



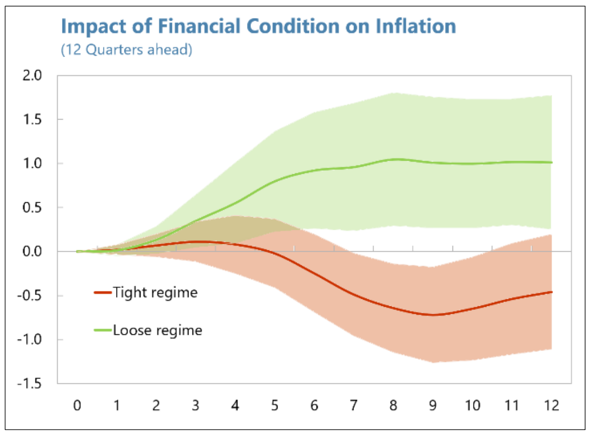
Sources: ECB, Goldman Sachs, Bank of France, IMF, Authors' calculations
1/ for comparison, all indexes are scaled so the averages for 2015-2022 equal zero.

The ongoing tightening in financial conditions is expected to lower output and raise unemployment. Almost all euro area countries' FCIs have been tightening with countries accounting for 91 percent of the euro area GDP having entered a significantly tight regime. Based on estimates across all euro area countries and selected emerging European countries since 2000, on average, switching to a tight regime could lower output by 2.2 percent and raise the unemployment rate by 0.3 percentage points over three years. Our indexes capture long periods of elevated tightening or loosening. The indices are normalized by means and standard deviations. The cumulative tightening since mid-2021 is on average about 2.5 standard deviations although the magnitude varies across countries.[11] All else equal, the current tightening in financial conditions will put a drag on output through 2025, with an average impact of around three quarters of a percentage point during 2023.





Tighter financial conditions are also expected to lower inflation. The response of inflation to changing FCI regimes shows that tightening FCIs can reduce inflation on average by 0.3 percentage points and up to 0.7 percentage points after 3 years. Our estimates show a sacrifice ratio between 3 and 4, which is in line with the literature (Coibion (2012), CEE model in Lawrence et al. (2005), Blanchard et al. (2016), Gertler (2015), Romer and Romer (2014)). However, the impact on inflation is more difficult to quantify for several reasons. The lack of variability in historical inflation rates in the euro area is a challenge to generate a full distribution of outcomes with different regimes of financial conditions.



Moreover, as it is well-known in the macroeconomic literature, policies aiming to tighten financial conditions often occur at the same time when inflation is high. While this has led to the price puzzle in which the empirical results show a tightening of monetary policy to increase inflation at least initially, to some extent, IPW can control for this endogeneity issue over a three-year horizon.

V. Policy Implications and Conclusions

This paper presents a novel Financial Conditions Index. This indicator is designed to assess the *costs, conditions, and availability* of funds to the economy. Additionally, it investigates the potential relationship between fluctuations in financial conditions and various economic indicators such as output, inflation, and unemployment. The FCI is computed for a broad set of European countries, encompassing both those within and outside the Euro area, and further breaks down the analysis by individual countries and economic sectors.

[11] Hites et al, (2023) finds that a one-standard deviation increase in the financial stress indicator across a worldwide sample is associated with a reduction in the level of output by 0.8 percent and an increase in unemployment rate by 0.1 percentage point after a year. After one year, a shift in regime reduces output by 0.9 percent and increases unemployment rate by 0.06 percentage point.

The tightening in FCs is expected to lower output and inflation, while raising unemployment. Based on historical data from 2000 to 2023Q3, a shift from a neutral to a tight FCI regime, which happens around 30 percent of the time tighter FCs are estimated to lower real GDP by 2.2 percent and inflation by 0.7 percentage points, while increasing the unemployment rate by about 0.3 percentage points over a three-year horizon. During 2021–22, more than 90 percent of the countries in our sample have entered a tight regime by historical standards.

The results include several findings relevant for the choice of policies.

- The divergence in estimated FCIs across countries highlights the heterogenous impact of monetary policy tightening in Europe, and the benefits of taking macroeconomic stability into account when setting fiscal and macroprudential policies.
- Differences across HH and NFC FCs emphasize the importance of carefully calibrating macroprudential policies in accordance with developments in individual sectors, to mitigate the potential risk of creating future fragilities.
- While tighter monetary policy initially leads to tighter FCs, the analysis indicates that this effect is transitory. As policies successfully rein in inflation, the price of risk can decrease over time, ultimately resulting in looser FCs.
- The results also indicate that high government debt ratios could potentially limit available financing, which in turn, may result in more restrictive FCs.

Possible extensions of this work may further explore spillovers of the financial cycle. Among its main contributions, this paper estimates the effect of changes in financial conditions on key macroeconomic variables. Further analysis could investigate the impact of a tightening financial cycle on vulnerabilities in the financial sector, their dynamics, and broader financial stability implications.

Annex I. List of FCI indicators

Driver	Variable[1]	Source
Credit availability and costs	Interest Rates of Loans to HHs	National Authorities; ECB; Haver Analytics
	Interest Rates of Mortgages to HHs	National Authorities; ECB; Haver Analytics
	Interest Rates of Consumer Credit & Other Lending to HHs	National Authorities; ECB; Haver Analytics
	Rates on Outstanding Loans to NFCs	National Authorities; ECB; Haver Analytics
	Commodity Index	Bloomberg; Haver Analytics
	10-Year Government Bond Yield	Refinitiv; Haver Analytics
	Housing Prices	Eurostat; Haver Analytics
	Lending Conditions	ECB; Haver Analytics
	Stock Price Index	National Authorities; Financial Times; Haver Analytics
	Brent Crude Oil*	Financial Times; Haver Analytics
	Euro Area 10-Year Yield Curve Spot Rate*	ECB; Bloomberg
	Stock Trading Volume	Bloomberg
External conditions	Bank Linkages Ratio	BIS; Eurostat
	USD/EUR Exchange Rate	Bloomberg
	Germany: 2-Year Government Bond Yield	Refinitiv; Haver Analytics
	Germany: 2-Year Government Bond Yield Volatility	Refinitiv; Haver Analytics
	Germany: 10-Year Government Bond Yield	Refinitiv; Haver Analytics
	Nominal Effective Exchange Rate	IMF; Haver Analytics
Funding constraints	LTV Ratio	ECB; Haver Analytics
	Government Debt Service	ECB; Haver Analytics
	Non-performing Loans to Total Gross Loans	IMF FSI
	Interest Margin to Gross Income	IMF FSI
	Return on Assets	IMF FSI
	Return on Equity	IMF FSI
	Household Debt to GDP	IMF FSI
	Regulatory Capital to Risk-Weighted Assets	IMF FSI
	MSCI Financials Index	Bloomberg
	Liquid Assets to Short-Term Liabilities	IMF FSI; Haver Analytics
	General Government Debt Outstanding*	Eurostat; Haver Analytics
	Nonfinancial Corporations Debt Outstanding*	Eurostat; Haver Analytics
	Financial Corporations Debt Outstanding*	Eurostat; Haver Analytics
	Household Debt Outstanding*	Eurostat; Haver Analytics
	GG interest expense/revenue ratio	WEO

Driver	Variable [1]	Source
Policy stance	Households Deposit Rate	ECB; Haver Analytics
	NFCs Deposit Rate	ECB; Haver Analytics
	Policy Rate 2/	National Authorities; Haver Analytics
	Euro Area: Main Refinancing Rate 3/	ECB; Haver Analytics
	Euro Area: Euro Short-term Rate (€STR) 3/	ECB; Haver Analytics
	Euro Area: Shadow Short Rate Point Estimates 3/	LJK Limited; Haver Analytics
	Wu-Xia Shadow ECB Rate 3/	Prof. Jing Cynthia Wu of Chicago Booth; Haver Analytics
	2-Year Government Bond Yield	Bloomberg
	1-Month Overnight Interest Rate Swap Close	Refinitiv; Haver Analytics
	Money Supply M1*	ECB; Haver Analytics
	Money Supply M3*	ECB; Haver Analytics
	3-Month Yield Curve Spot Rate*	Bloomberg; ECB
	2-Year Yield Curve Spot Rate*	Bloomberg; ECB
Price of risk	5-Year CDS Premium	DataStream
	iBoxx EUR Non-Sovereigns BBB	IHS Markit; Haver Analytics
	iBoxx EUR Non-Sovereigns AAA	IHS Markit; Haver Analytics
	EUR Swap Annual 5-Year vs 6-Month	Bloomberg
	Germany: 10-Year Government Bond Yield Volatility	Refinitiv; Haver Analytics
	2-Year Government Bond Yield Volatility	Refinitiv; Haver Analytics
	10-Year Government Bond Yield Volatility	Refinitiv; Haver Analytics
	2-Year Government Bond Spread	Refinitiv; Haver Analytics
	10-Year Government Bond Spread	Refinitiv; Haver Analytics
	3-Month Interbank Offer Rate	Tullett Prebon Information; Haver Analytics
	LIBOR-OIS Spread	Bloomberg
	Stock Price Volatility Index	National Authorities; Financial Times; Haver Analytics
	10-Year Interest Rate Swap	Tullett Prebon Information; Haver Analytics
	EURO STOXX 50 Volatility Index	STOXX Limited; Haver Analytics
	EURO FTSE Volatility Index*	Financial Times; Haver Analytics
	United States CBOE Volatility Index	Wall Street Journal; Haver Analytics

1/ Data availability may differ among countries; daily and monthly data are converted to quarterly.

2/ Used for non-EA countries.

3/ Categorized as Policy stance for EA countries, External conditions for non-EA countries.

* Used for EA aggregate only.

Annex II. Partial Least Square

The PLS estimator, also called Partial Least Squares Regression - PLSR, models the covariance between two sets of data, Y and X. It goes beyond OLS and other traditional regression techniques as it also models the structure of the Y and X matrices. PLS is useful to analyze data with many collinear variables, potentially noisy, and even with incomplete observations. While an OLS suffers from efficiency losses as the degree of collinearity among variables increases, the precision of the PLS coefficients improves with the number of regressors. Therefore, the PLS algorithm is particularly well suited for estimating FCIs that rely on a large set of highly related financial variables, potentially polluted with substantial market and idiosyncratic noises. Contrary to an OLS estimator which projects Y on the subspace of X, the PLS maximizes the covariance between Y and X in a latent structure. This latent structure allows to circumvent the collinearity issue and operate a projection on a more suitable subspace than the original set of X. The algorithm constructs weights, scores, and loadings as linear combinations of the datasets. Formally, the PLS decomposes the X and Y matrices as follows:[1]

$$X = TP'_X + E_X$$
$$Y = UP'_Y + E_Y$$

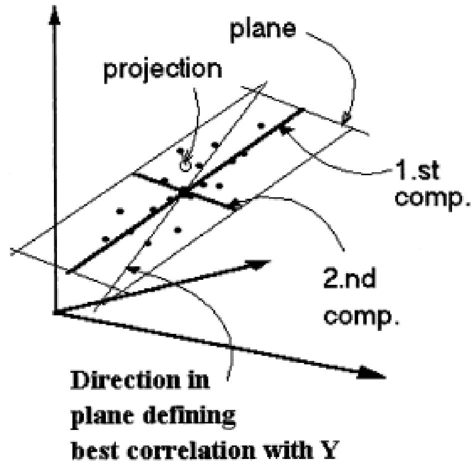
- T and U are the scores of X and Y. They represent the latent structure.
- P'_X and P'_y are the loadings of X and Y respectively i.e., the projection of X and Y on the latent structure.
- E_X and E_Y are the error terms, assume to be independent and identically distributed random variables.

The PLS algorithm estimates the scores and loadings recursively, depending on the number of components chosen. Components in a PLS are conceptually similar to those of a PCA, as they represent recursive orthogonal projections, with the first component capturing most of the covariance explained (variance in the case of a PCA), then the second being orthogonal to the first and explaining most of the remaining covariance, etc.

The PLS algorithm starts by initializing a candidate score vector U for Y (most software implementations use a column of Y to kickstart the algorithm). Then, based on the candidate score:

[1] We follow in this paragraph the presentation done by Wold, Sjöström, and Eriksson (2001)

Annex II Figure 1. Geometrical Representation of PLS Projection



Source: World et all. 2001

- Compute the loadings of X as $P_X = X'\ T(T'\ T)^{-1}$
- Compute the loadings of Y as $P_Y = Y'T(T'\ T)^{-1}$
- Update the score of Y as $U = YP_Y/(P'_Y P_Y)^{-1}$
- Repeat this process until convergence of the series of Y scores $(U_{1,\dots,k})$ where k is the number of iterations
- Once the convergence is achieved, the first component is fully estimated. Hence, the X matrix with the orthogonal residual $E_X = X - TP'_X$ [2]

These components are, together, an approximation of X, orthogonal to each other, and contain as much unique variance of X as possible. This approach resembles the PCA, which also extracts orthogonal components to maximize the projected variance of X. However, an important aspect of PLS is that the X scores are also good estimates of Y when they are multiplied by the loadings of Y: $Y = TP'_Y + F$ (a formal proof is available in Delaigle and Hall (2012)). Because of this property, the PLS can in fine be expressed as a linear decomposition of Y as a function of X:

$$Y = XWP'_Y + F = XB + F$$

Therefore, the PLS approach combines two objectives: it provides a data reduction of the matrix X into a fewer set of components while ensuring that the X scores are well correlated with the Y matrix.

Conceptually, the PLS projection can be broadly understood as a standard linear projection (like an OLS) on a latent structure, as presented in the figure above.

Number of Components

Following the practice adopted in the PCA-based literature, we decided to use only the first PLS component to construct the FCIs. While this approach is ad-hoc, it has many advantages: first, it offers a clean interpretability, as the first component is the one maximizing the covariance between Y *and* X while reducing the information in X. The following orthogonal components of the PLS (the second, the third, etc.) are also linear combinations of the same variables, but with different loadings. Unless there is a clear-cut differentiation between the two set of weights (for instance, the weights on the first components being predominantly on banking variables and the weights of the second on market variables), the interpretation is very complicated. Besides, providing two FCIs might be confusing, especially as the second component mechanically explains less variance than the first. From an economic perspective, it is more intuitive to change the supervising variable (the Y) to create a distinct FCI with a different interpretation, rather than extracting multiple components.

[2] The Python implementation of the PLS used for this paper is publicly available on https://romainlafarguette.github.io/software/

In this paper, in our main specification, our target variable Y is the year-on-year growth rate of financial liabilities of the private sector (households and firms). We also consider this growth rate of financial liabilities for each of the following sectors: household, firm, government. For our X matrix, we include all the variables listed in Annex I. The variables are all detrended and normalized to be stationary.

Annex III. Inverse Probability Weighting

We provide here a brief overview of the estimation framework. Let y_t be the outcome variable of interest (e.g. GDP growth, inflation, or unemployment). The model intends to relate y_t to D_t, a discretized version of changes in financial condition index, which can take values d_L, d_C, d_T based on whether the index changes or remains constant across two consecutive quarters. Let also z_t be a vector of predetermined variables that are relevant in predicting both D_t and y_t.

Changes in financial conditions D_t can be thought of as being determined by both observed (z_t) and unobserved (ε_t) components. We use a multinomial logit where the probability of receiving treatment d_j conditional on covariates z_t, and among observations that received either treatment d_j or the control treatment d_C, is given by

$$\Pr\left(D_t = d_j \middle| z_t; j = \{d_j, d_c\}\right) = \Lambda\left(z_t \gamma^j + \varepsilon_t\right). \tag{1}$$

From Eq. (1), we can recover the propensity score

$$\hat{p}\left(d_j | z_t\right) = \Lambda\left(z_t \hat{\gamma}^j\right),$$

which is the probability of financial conditions changing by d_j, conditional on covariates z_t.

We also estimate the outcome equation at horizon h separately by treatment group

$$y_{t+h|j} = z_t \Gamma^j + e_t^j, \tag{2}$$

where et is an error term. Estimates from Eq. (1) and (2) are used to form a doubly-robust causal estimate below.

Regression Adjustment, Inverse Probability Weighting Estimator

Under the unconfoundedness assumption, a causal estimate θ_h^j of the impact of financial conditions on y_t at horizon h can be recovered by comparing average outcomes across levels of D_t using reweighted and adjusted data:

$$\theta_h^j = E\left[\hat{y}_{t+h|j}\left(\frac{1\{D_t = d_j\}}{\hat{p}(z_t)} - \frac{1\{D_t = d_0\}}{(1 - \hat{p}(z_t))}\right)\right], \tag{3}$$

where $\hat{p}(z_t)$ is the predicted probability of financial conditions changing to $D_t = d_j$ conditional on z_t and $\hat{y}_{t+h}$ the predicted outcome at horizon h conditional on covariates at time t (Hirano, Imbens and Ridder 2003).

Intuitively, when computing the expected value of GDP growth for observations for which financial conditions loosened $(D_t = d_L)$, the average outcome can be biased because observations for which financial conditions are loosening are likely to be also observations for which growth is also high. The logit model of equation (1) is therefore used to explain how likely it is that $D_t = d_L$ in a given time period, conditional on observable factors z_t. In the estimation of θ_h^j, more weight should be given to observations that occur 'as a surprise', i.e. to observations where, although $D_t = d_j$ the model predicted likelihood $\hat{p}\left(d_j | z_t\right)$ of this happening was low. A similar adjustment to the outcome is also done by replacing y_{t+h} with its predicted value $\hat{y}_{t+h|j} = z_t \hat{\Gamma}^j$.

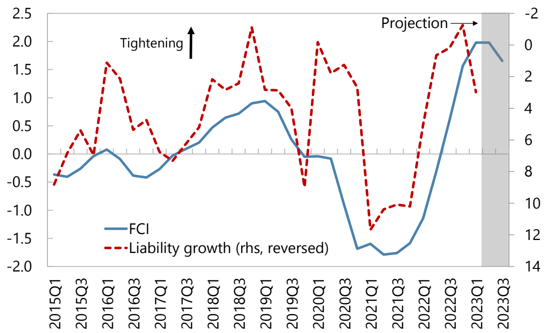
Our outcome variables are real GDP, year-on-year core inflation, and unemployment rates. Our control variables are all the lagged values, the real effective exchange rate, output gap, government balances, and current account balances as percent of GDP.

The success of the inverse probability weighting procedure at satisfying the unconfoundedness assumption can be assessed by looking at the impulse response functions in Figure X and Y. Notably, after the adjustments made to the data with the estimator, the difference between GDP growth, unemployment and inflation across FCI regimes vanishes in period 0, before the FCI can impact the outcomes of interest. This suggests that we are able to compare outcomes for growth, unemployment and inflation on samples that are otherwise the same except for the FCI treatment (tight or loose).

Annex IV. Individual Country Results

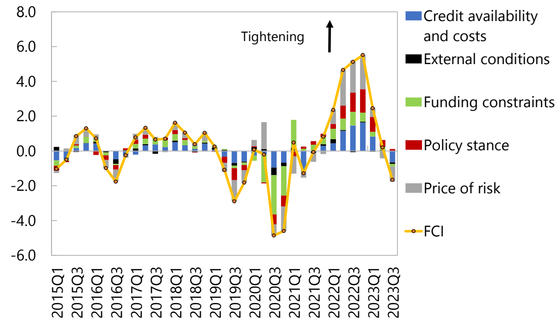
FCI—Euro Area

Euro Area: FCI and Liability Growth
(Index; percent)



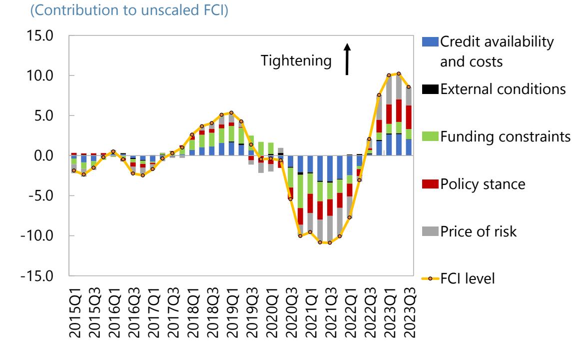
Sources: Author's calculations.

Euro Area: FCI Changes
(Contribution to quarter-over-quarter first difference of FCI)



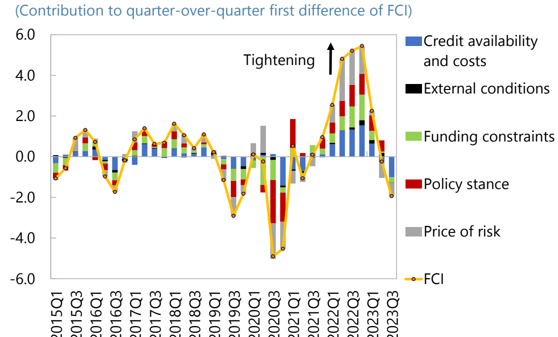
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Euro Area: FCI level
(Contribution to unscaled FCI)



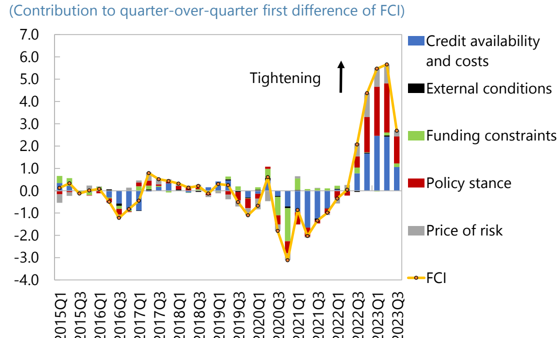
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Euro Area: FCI Changes - Nonfinancial Corporations
(Contribution to quarter-over-quarter first difference of FCI)



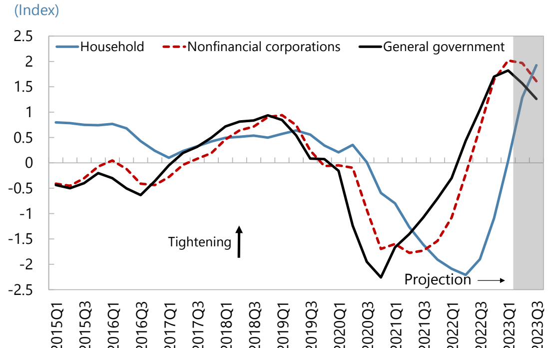
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Euro Area: FCI Changes - Households
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Euro Area: FCI by Sectors
(Index)

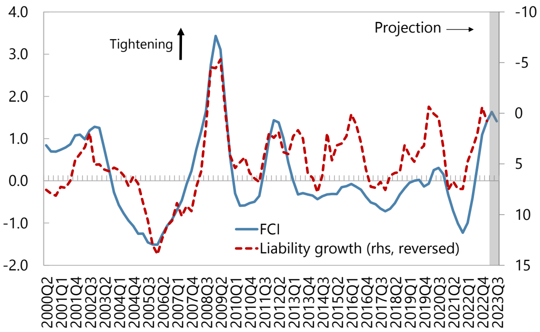


Sources: Author's calculations.

FCI—Austria

Austria: FCI and Liability Growth

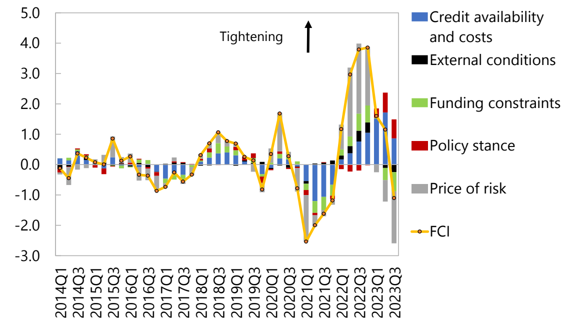
(Index; percent)



Sources: Author's calculations.

Austria: FCI Changes

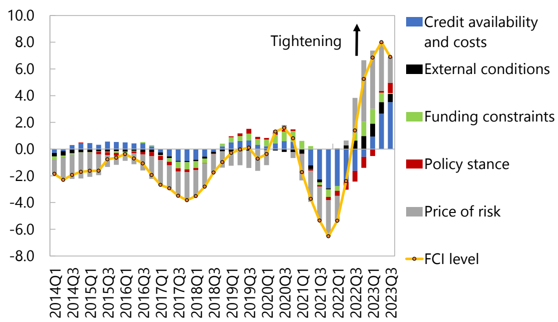
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Austria: FCI level

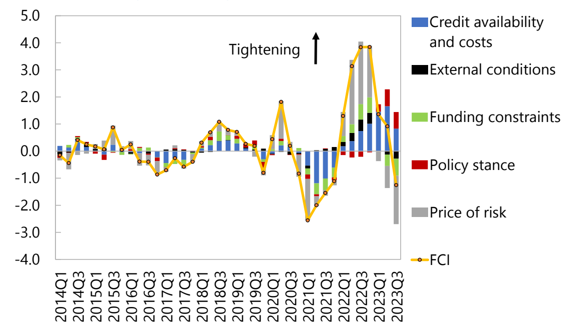
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Austria: FCI Changes - Nonfinancial Corporations

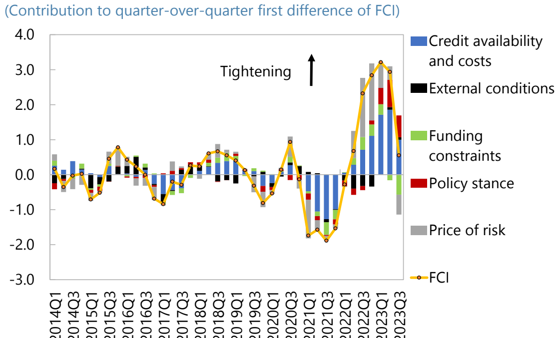
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Austria: FCI Changes - Households

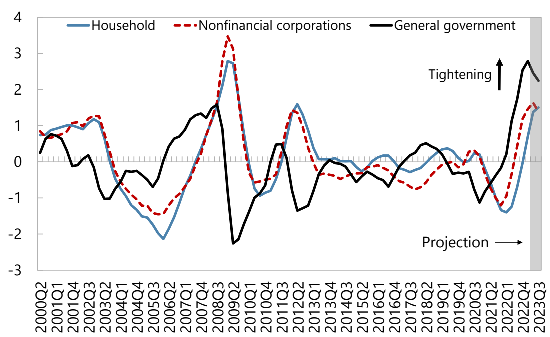
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Austria: FCI by Sectors

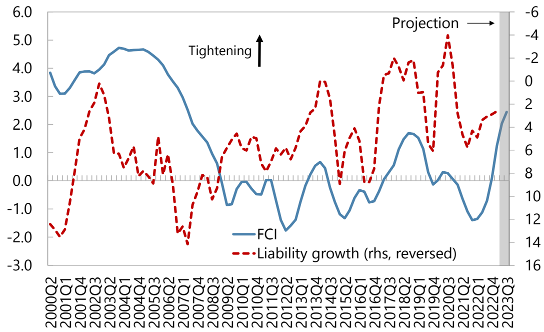
(Index)



Sources: Author's calculations.

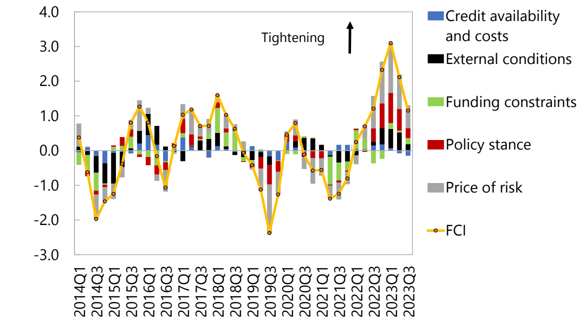
FCI—Belgium

Belgium: FCI and Liability Growth
(Index; percent)



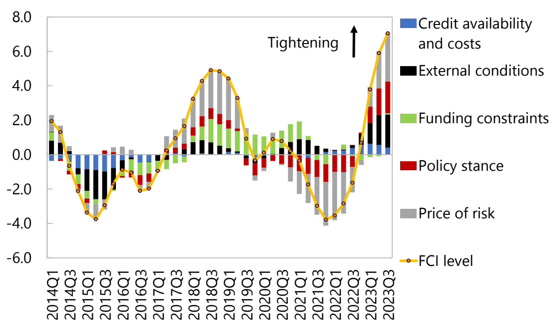
Sources: Author's calculations.

Belgium: FCI Changes
(Contribution to quarter-over-quarter first difference of FCI)



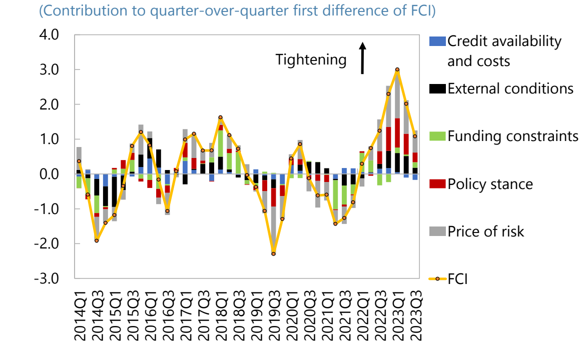
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Belgium: FCI level
(Contribution to unscaled FCI)



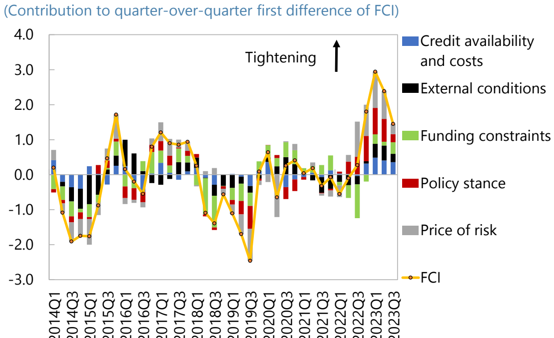
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Belgium: FCI Changes - Nonfinancial Corporations
(Contribution to quarter-over-quarter first difference of FCI)



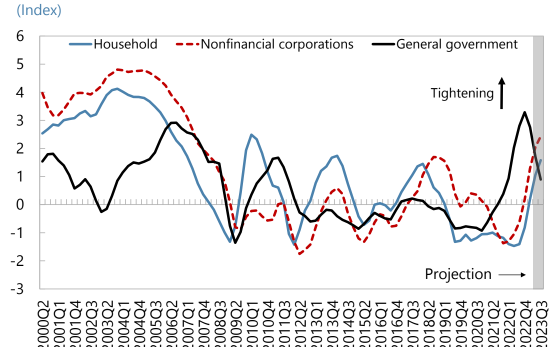
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Belgium: FCI Changes - Households
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

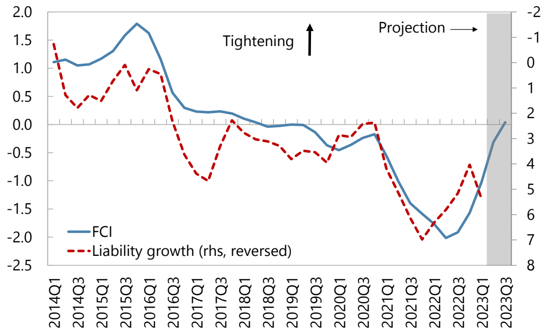
Belgium: FCI by Sectors
(Index)



Sources: Author's calculations.

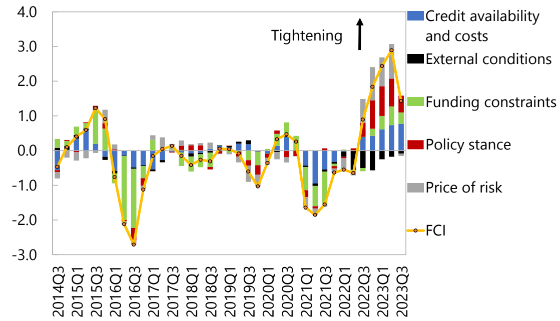
FCI—Croatia

Croatia: FCI and Liability Growth
(Index; percent)



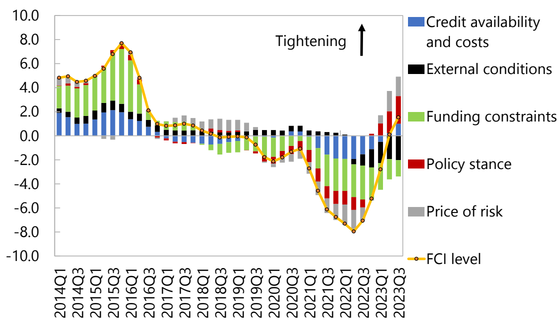
Sources: Author's calculations.

Croatia: FCI Changes
(Contribution to quarter-over-quarter first difference of FCI)



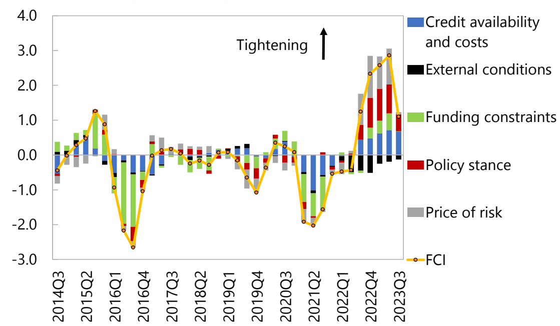
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Croatia: FCI level
(Contribution to unscaled FCI)



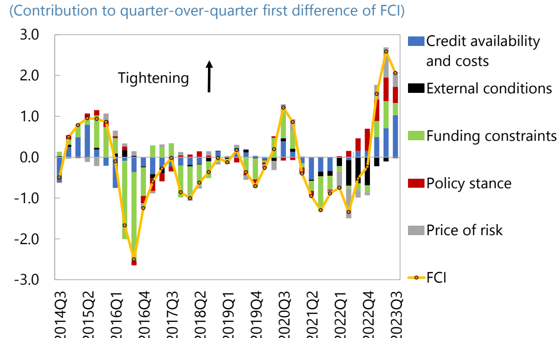
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Croatia: FCI Changes - Nonfinancial Corporations
(Contribution to quarter-over-quarter first difference of FCI)



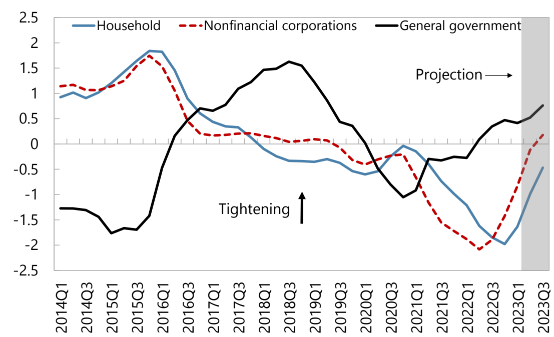
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Croatia: FCI Changes - Households
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Croatia: FCI by Sectors
(Index)

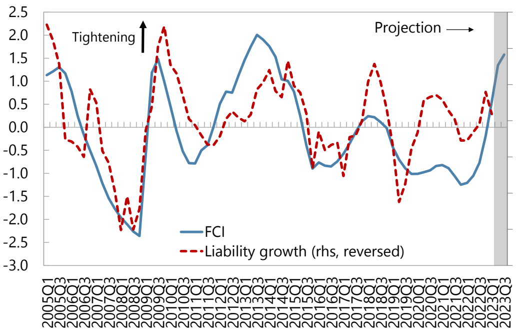


Sources: Author's calculations.

FCI—Cyprus

Cyprus: FCI and Liability Growth

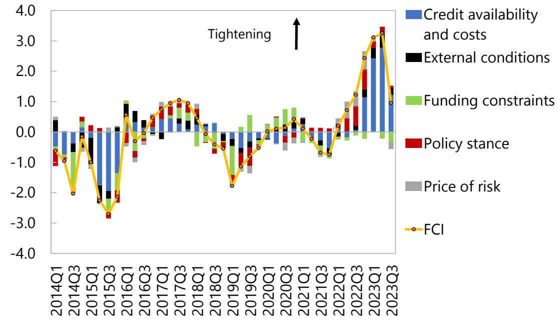
(Index; percent)



Sources: Author's calculations.

Cyprus: FCI Changes

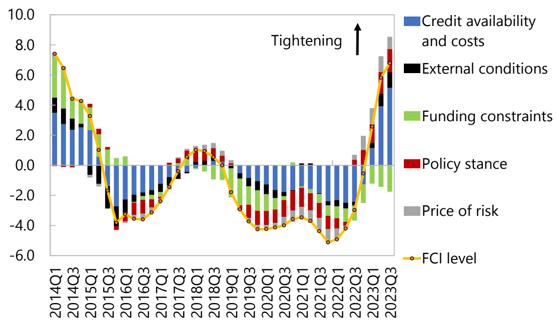
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Cyprus: FCI level

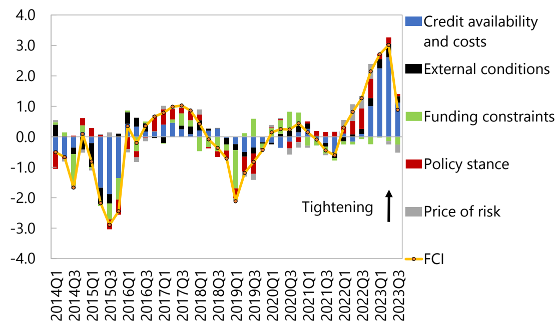
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Cyprus: FCI Changes - Nonfinancial Corporations

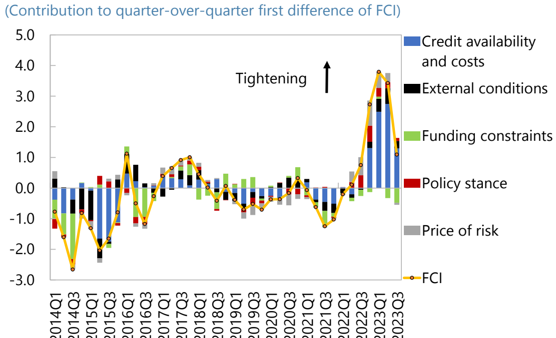
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Cyprus: FCI Changes - Households

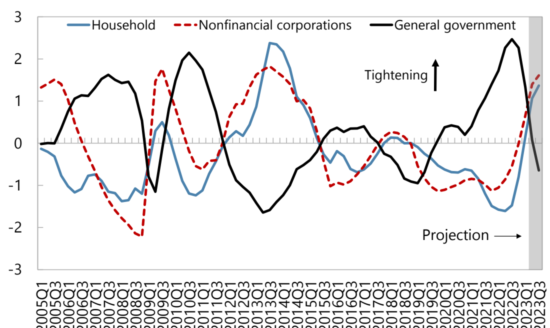
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Cyprus: FCI by Sectors

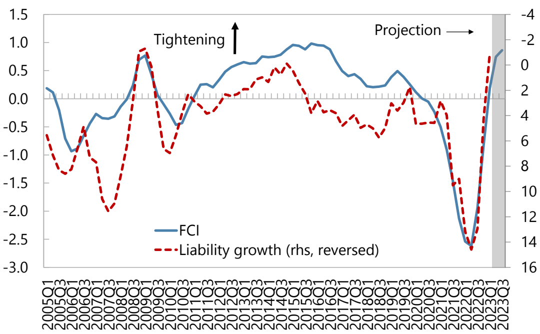
(Index)



Sources: Author's calculations.

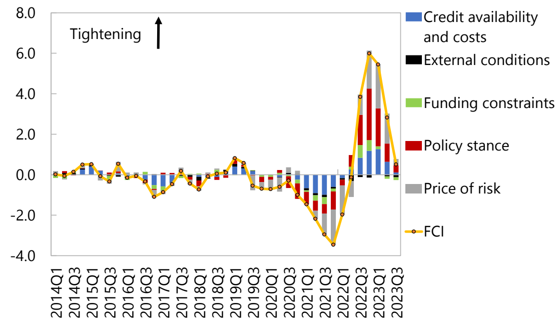
FCI—Czech Republic

Czech Republic: FCI and Liability Growth
(Index; percent)



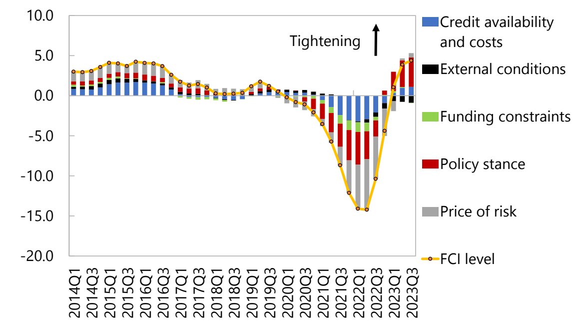
Sources: Author's calculations.

Czech Republic: FCI Changes
(Contribution to quarter-over-quarter first difference of FCI)



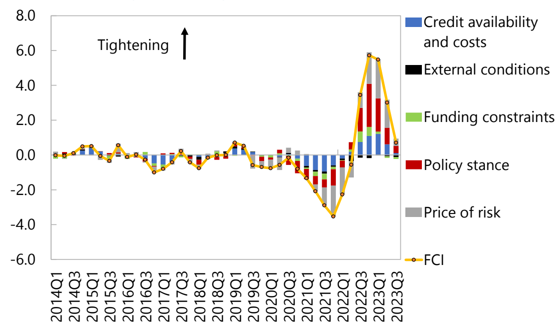
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Czech Republic: FCI level
(Contribution to unscaled FCI)



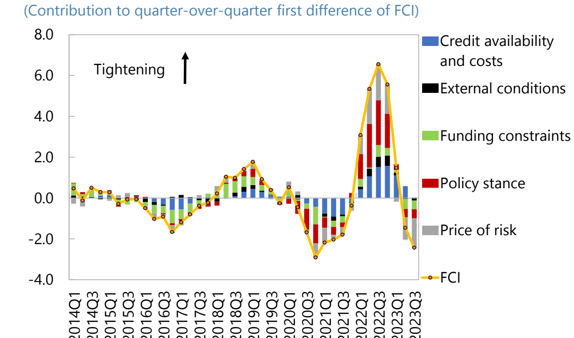
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Czech Republic: FCI Changes - Nonfinancial Corporations
(Contribution to quarter-over-quarter first difference of FCI)



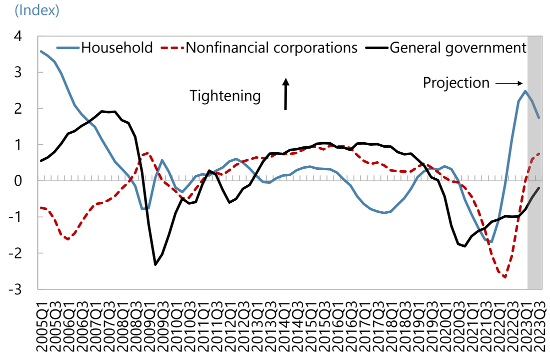
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Czech Republic: FCI Changes - Households
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Czech Republic: FCI by Sectors
(Index)

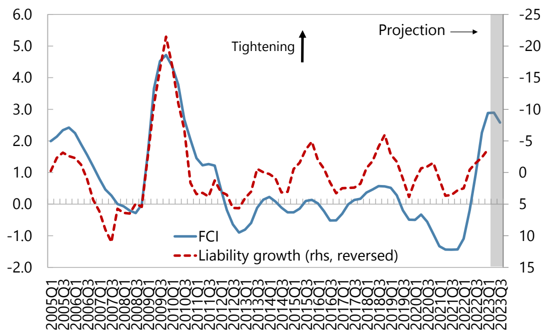


Sources: Author's calculations.

FCI—Estonia

Estonia: FCI and Liability Growth

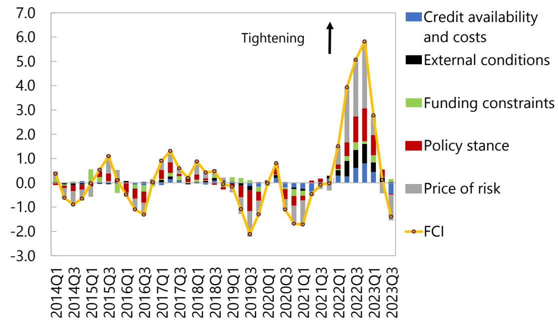
(Index; percent)



Sources: Author's calculations.

Estonia: FCI Changes

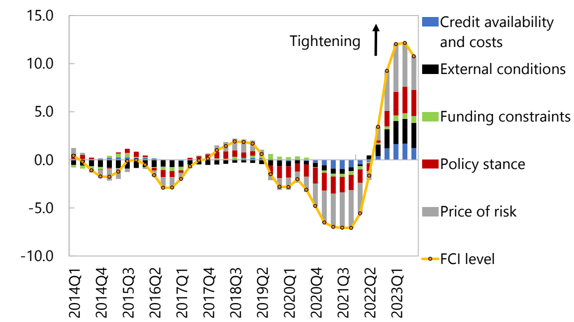
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Estonia: FCI level

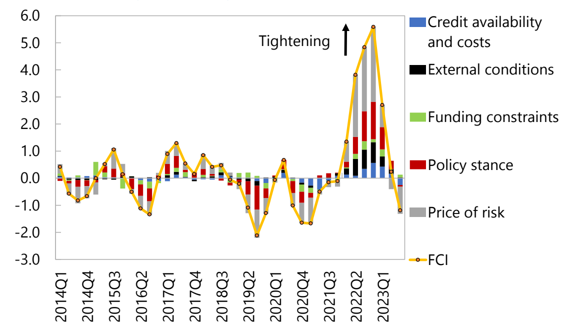
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Estonia: FCI Changes - Nonfinancial Corporations

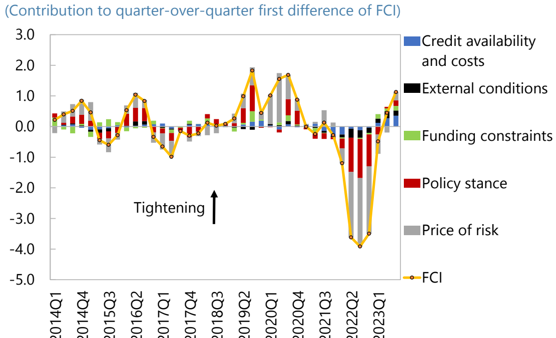
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Estonia: FCI Changes - Households

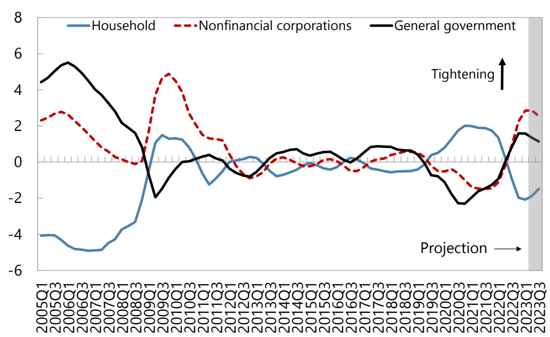
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

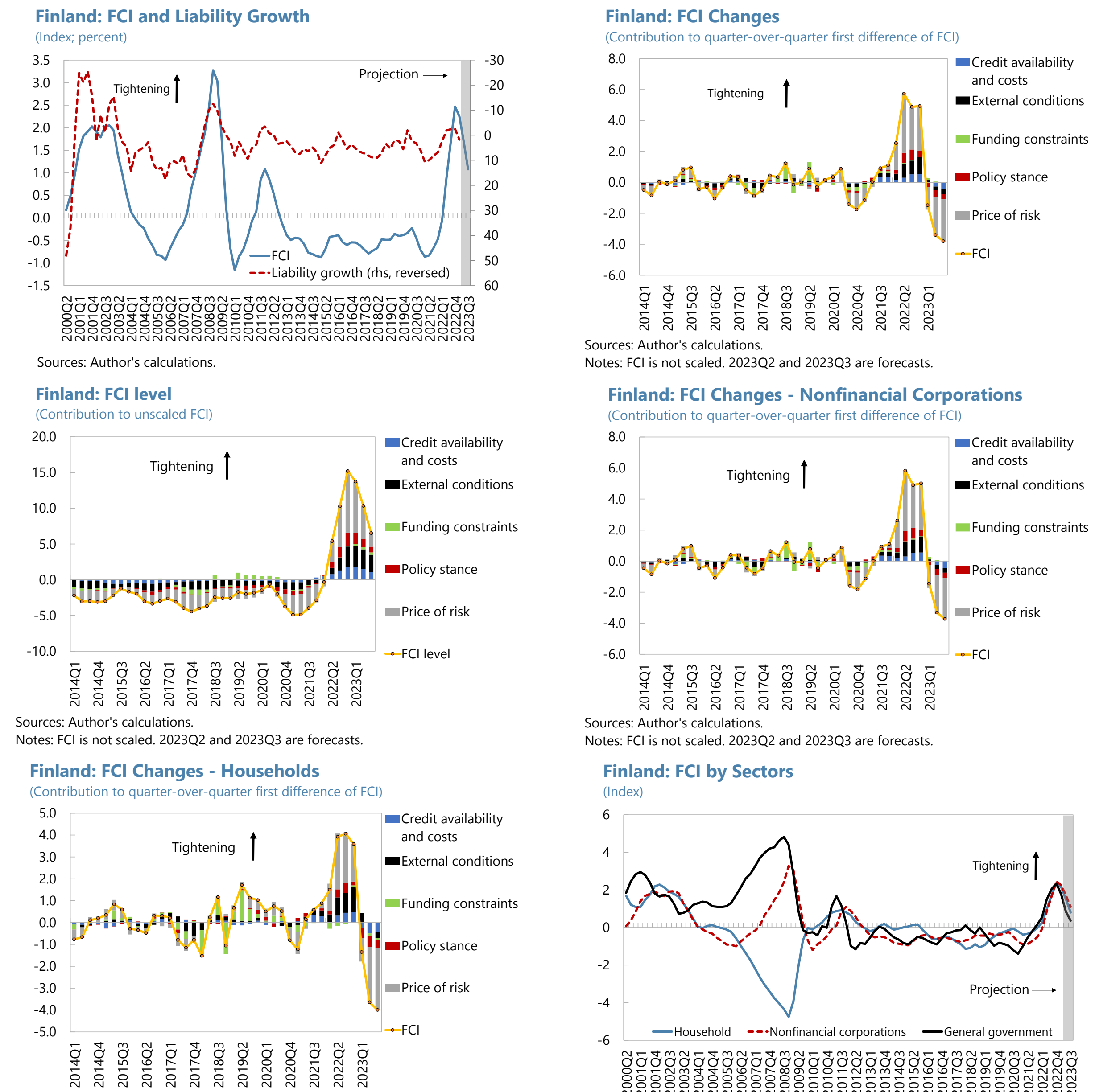
Estonia: FCI by Sectors

(Index)



Sources: Author's calculations.

FCI—Finland



Finland: FCI and Liability Growth — Sources: Author's calculations.

Finland: FCI Changes — Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Finland: FCI level — Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

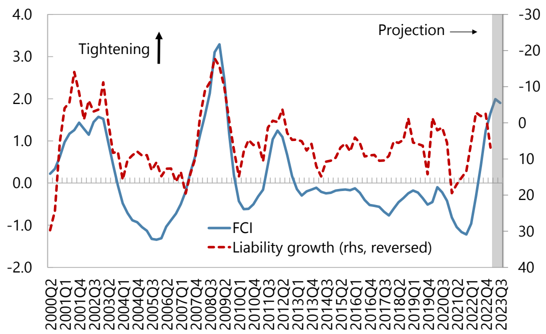
Finland: FCI Changes - Nonfinancial Corporations — Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Finland: FCI Changes - Households — Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Finland: FCI by Sectors — Sources: Author's calculations.

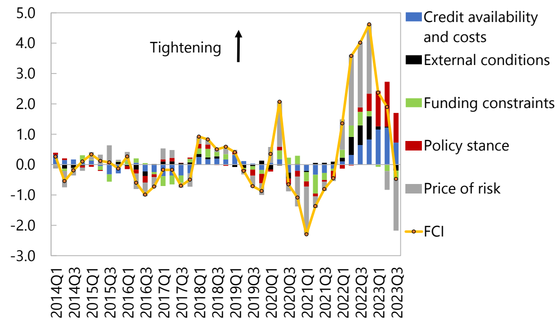
FCI—France

France: FCI and Liability Growth
(Index; percent)



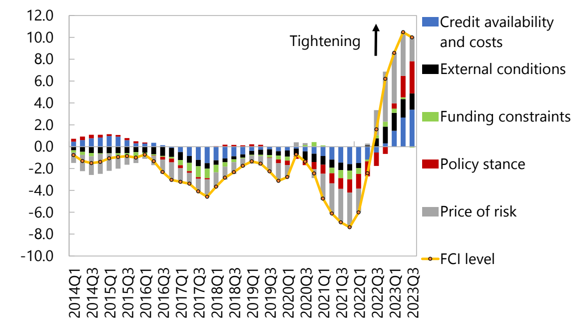
Sources: Author's calculations.

France: FCI Changes
(Contribution to quarter-over-quarter first difference of FCI)



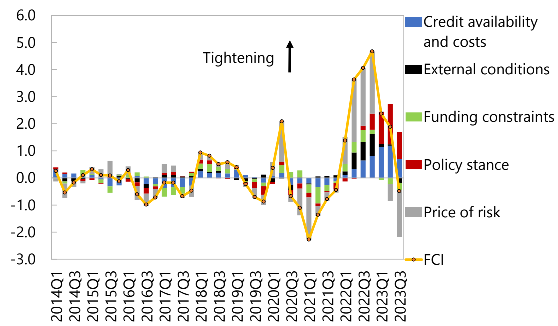
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

France: FCI level
(Contribution to unscaled FCI)



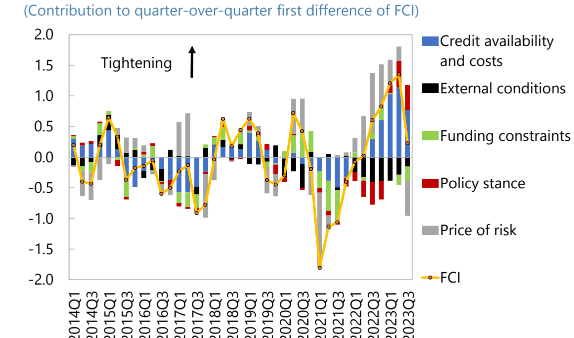
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

France: FCI Changes - Nonfinancial Corporations
(Contribution to quarter-over-quarter first difference of FCI)



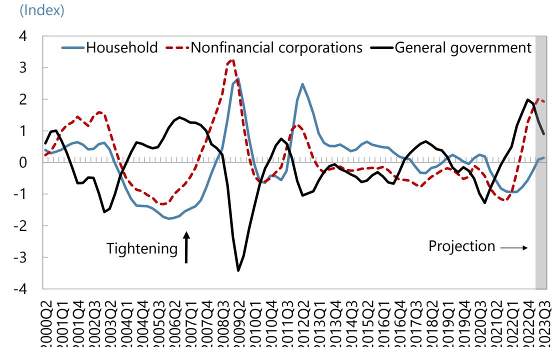
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

France: FCI Changes - Households
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

France: FCI by Sectors
(Index)

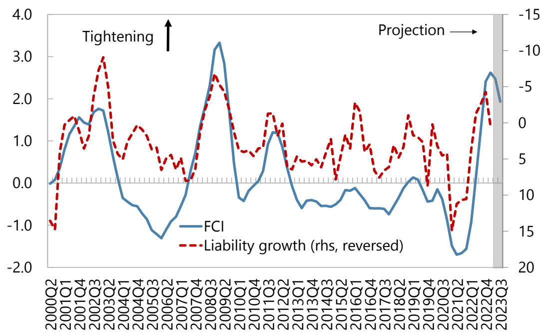


Sources: Author's calculations.

FCI—Germany

Germany: FCI and Liability Growth

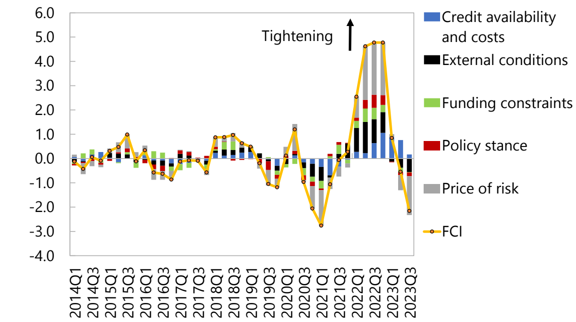
(Index; percent)



Sources: Author's calculations.

Germany: FCI Changes

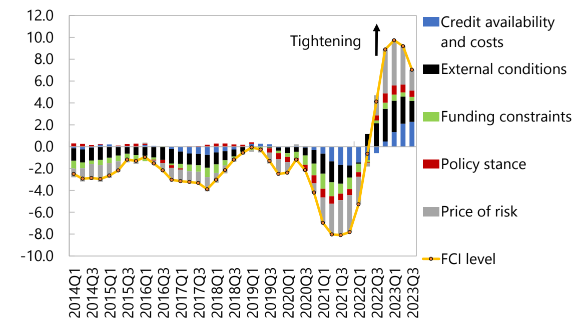
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Germany: FCI level

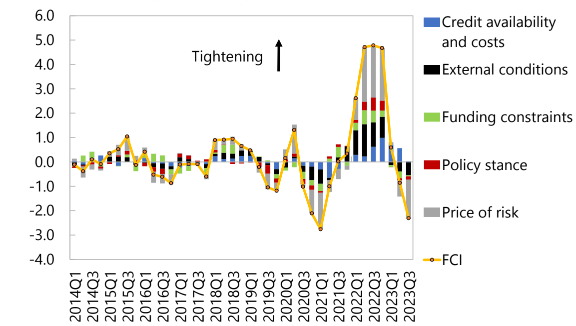
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Germany: FCI Changes - Nonfinancial Corporations

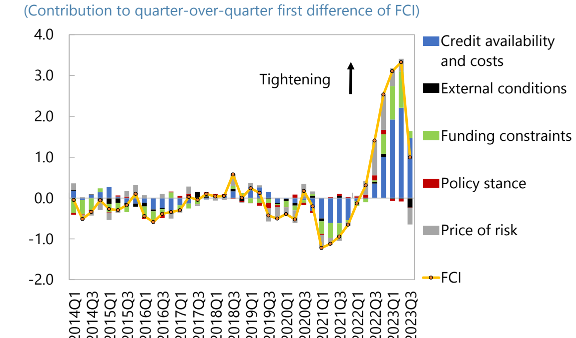
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Germany: FCI Changes - Households

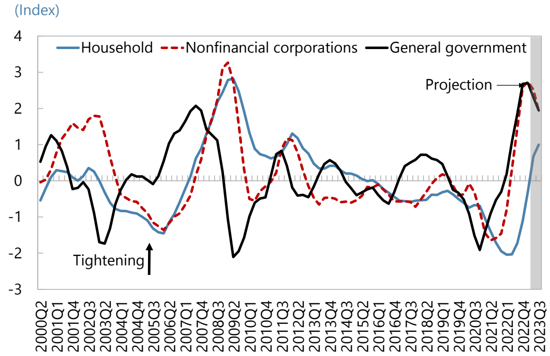
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Germany: FCI by Sectors

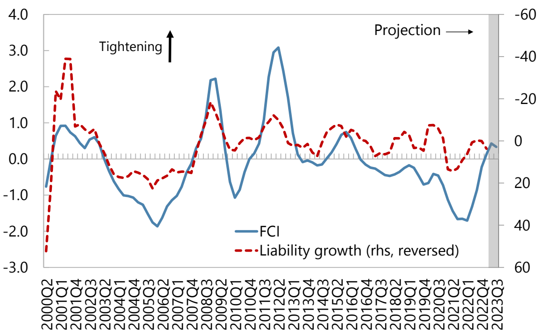
(Index)



Sources: Author's calculations.

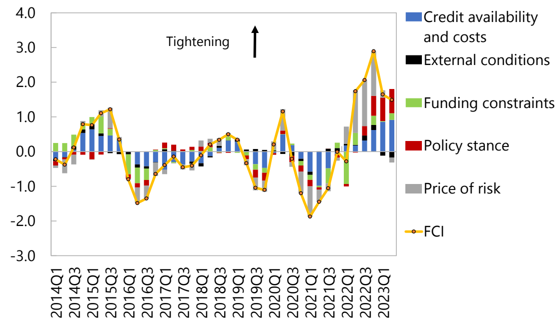
FCI—Greece

Greece: FCI and Liability Growth
(Index; percent)



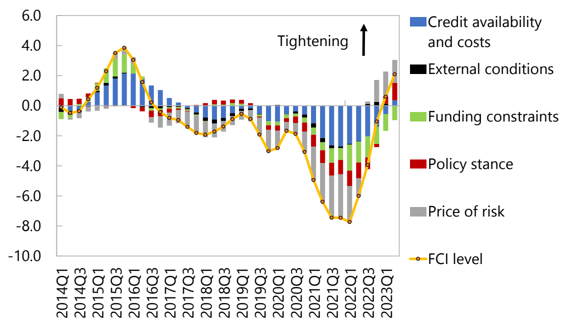
Sources: Author's calculations.

Greece: FCI Changes
(Contribution to quarter-over-quarter first difference of FCI)



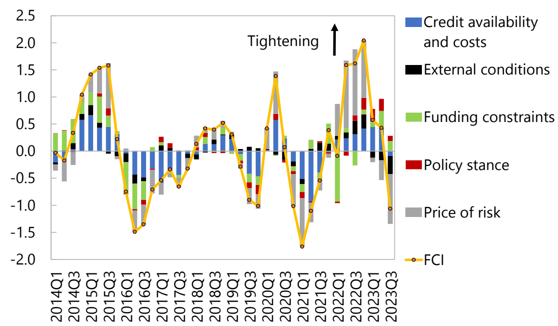
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Greece: FCI level
(Contribution to unscaled FCI)



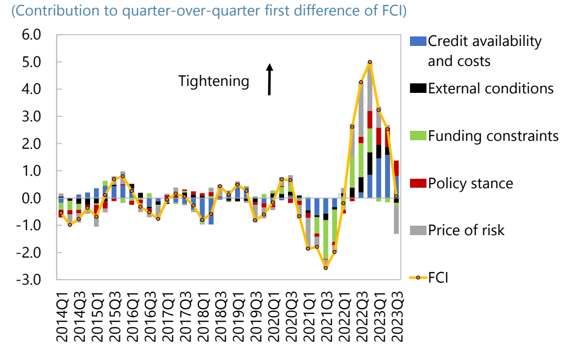
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Greece: FCI Changes - Nonfinancial Corporations
(Contribution to quarter-over-quarter first difference of FCI)



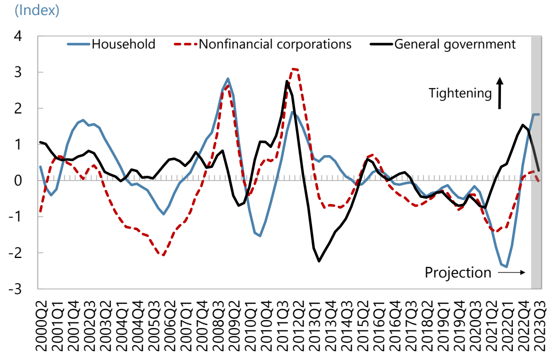
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Greece: FCI Changes - Households
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Greece: FCI by Sectors
(Index)

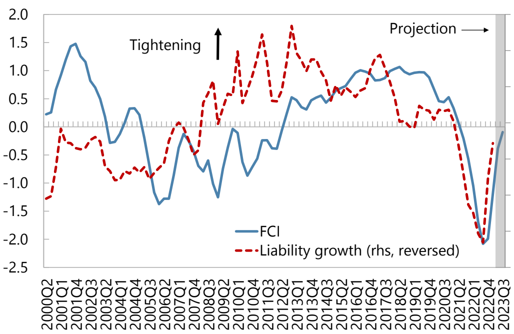


Sources: Author's calculations.

FCI—Hungary

Hungary: FCI and Liability Growth

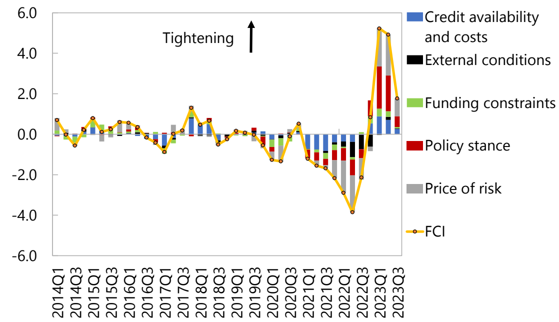
(Index; percent)



Sources: Author's calculations.

Hungary: FCI Changes

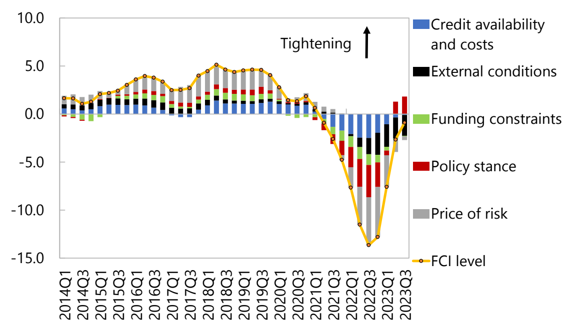
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Hungary: FCI level

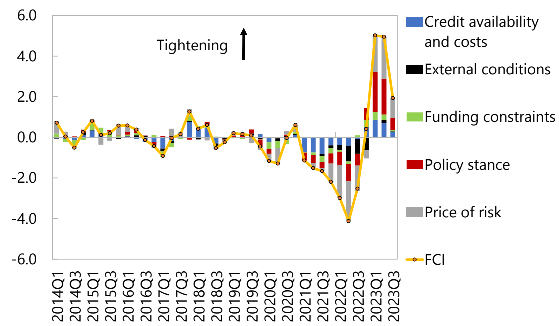
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Hungary: FCI Changes - Nonfinancial Corporations

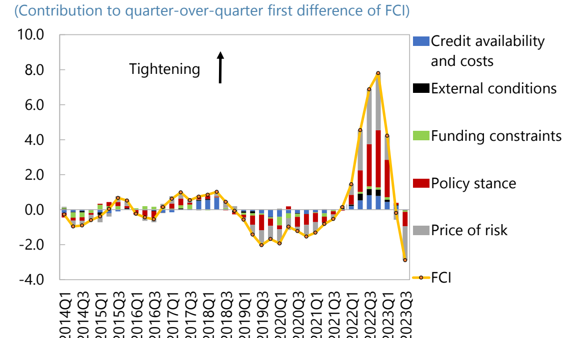
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Hungary: FCI Changes - Households

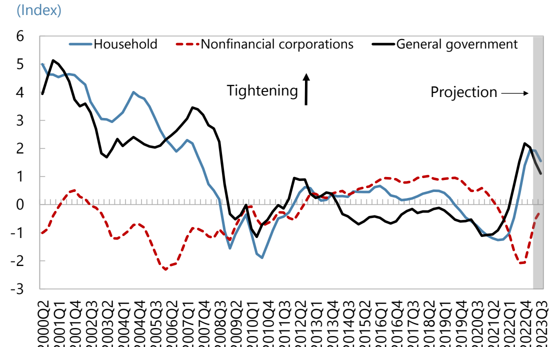
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Hungary: FCI by Sectors

(Index)

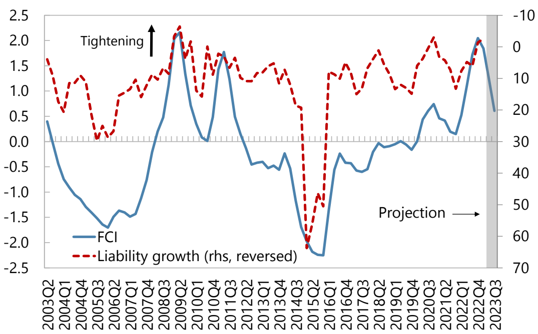


Sources: Author's calculations.

FCI—Ireland

Ireland: FCI and Liability Growth

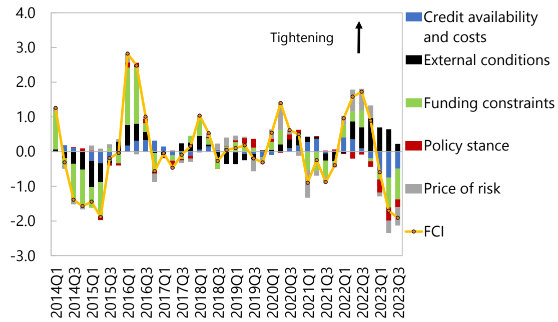
(Index; percent)



Sources: Author's calculations.

Ireland: FCI Changes

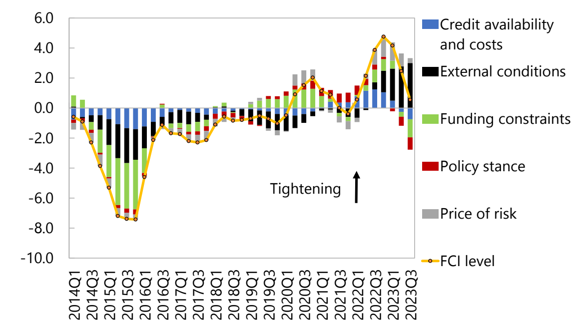
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Ireland: FCI level

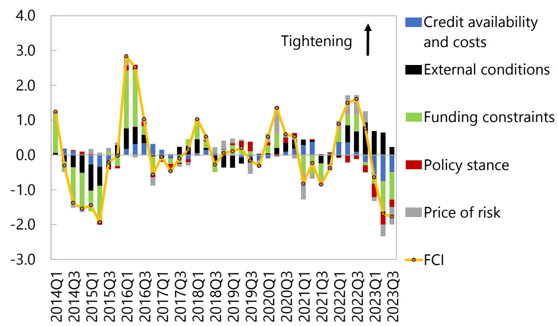
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Ireland: FCI Changes - Nonfinancial Corporations

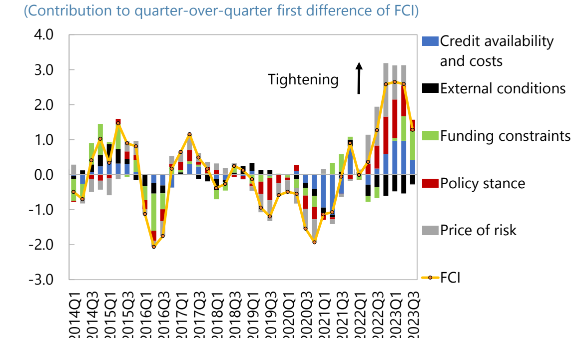
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Ireland: FCI Changes - Households

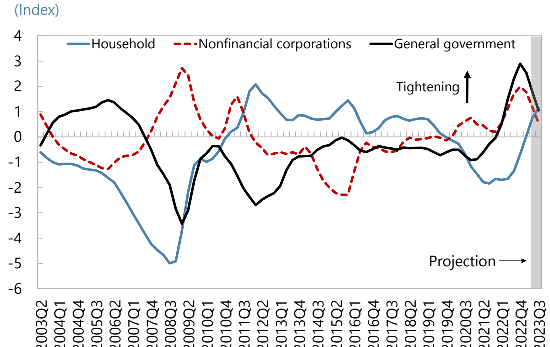
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Ireland: FCI by Sectors

(Index)

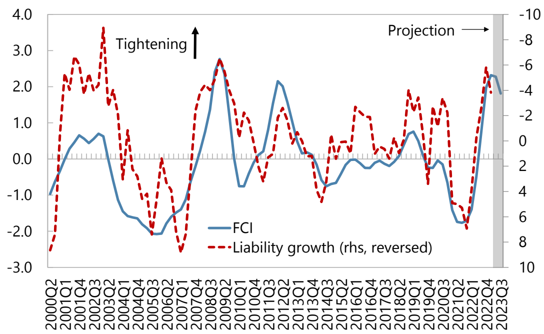


Sources: Author's calculations.

FCI—Italy

Italy: FCI and Liability Growth

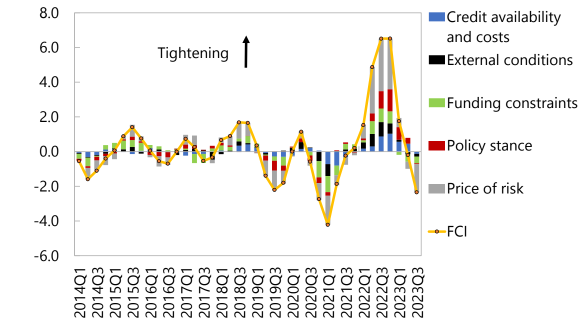
(Index; percent)



Sources: Author's calculations.

Italy: FCI Changes

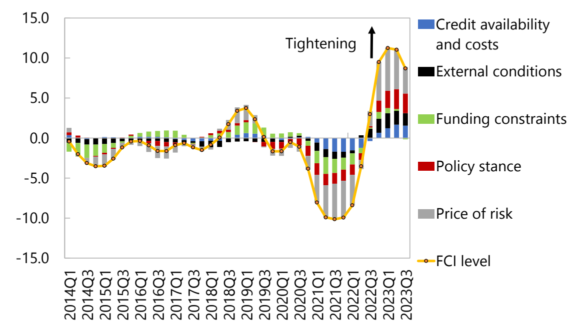
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Italy: FCI level

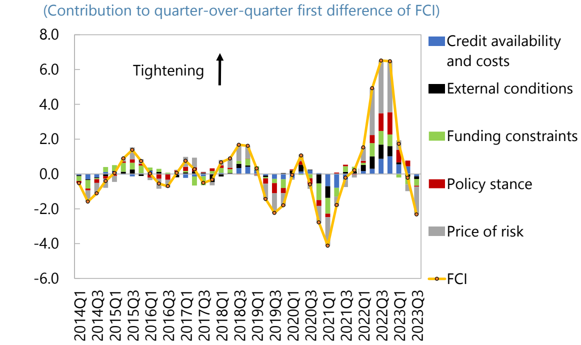
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Italy: FCI Changes - Nonfinancial Corporations

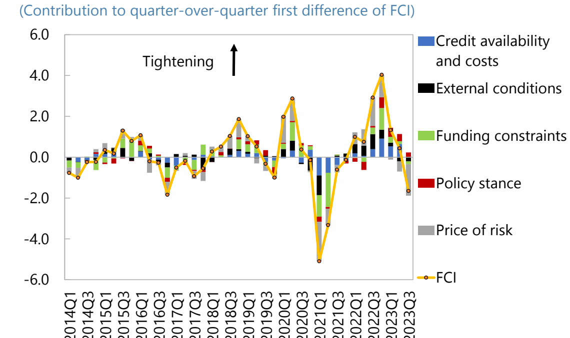
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Italy: FCI Changes - Households

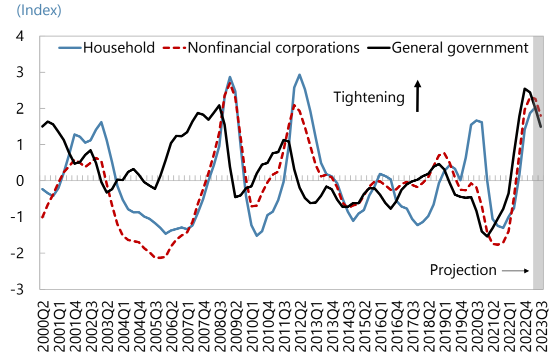
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Italy: FCI by Sectors

(Index)

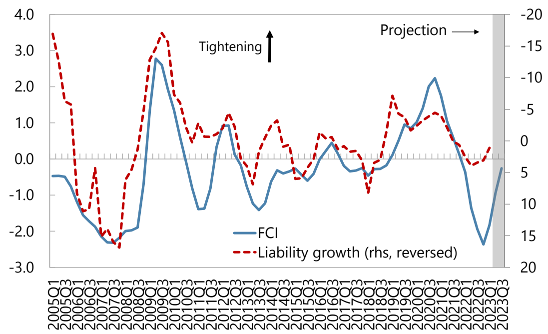


Sources: Author's calculations.

FCI—Latvia

Latvia: FCI and Liability Growth

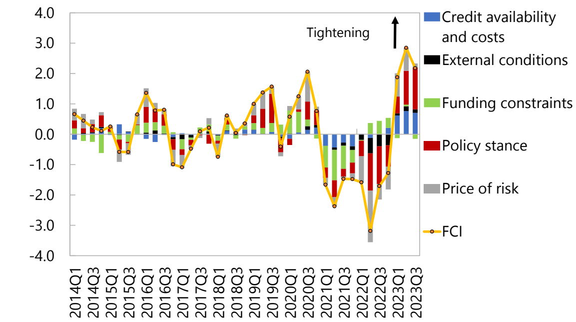
(Index; percent)



Sources: Author's calculations.

Latvia: FCI Changes

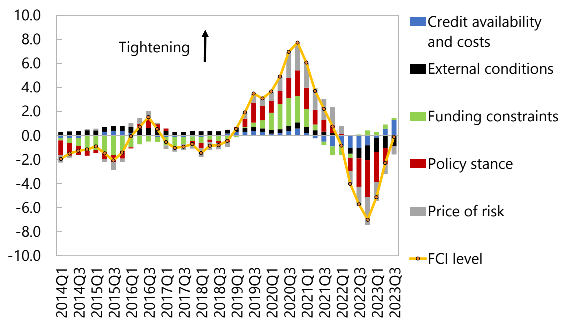
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Latvia: FCI level

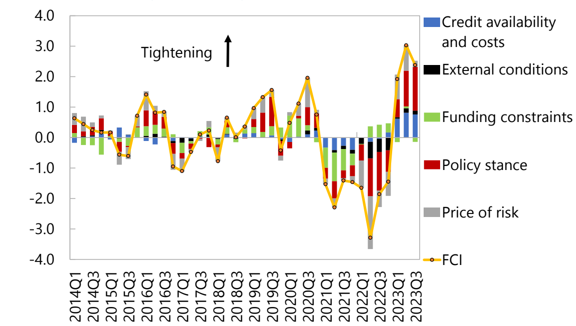
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Latvia: FCI Changes - Nonfinancial Corporations

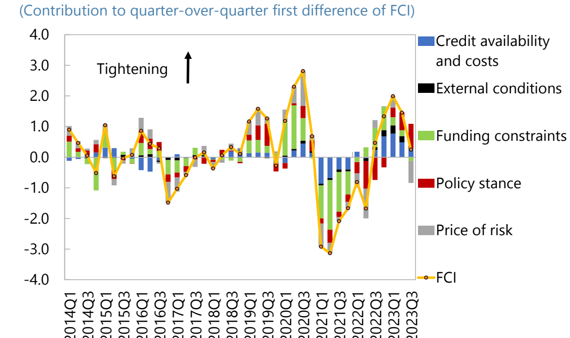
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Latvia: FCI Changes - Households

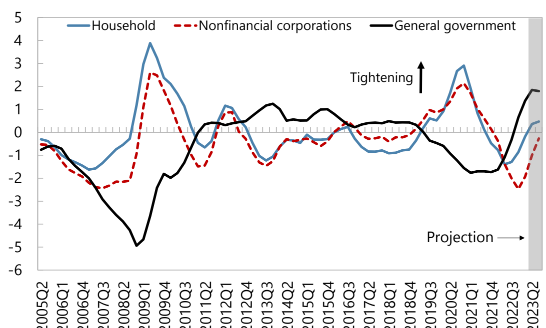
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Latvia: FCI by Sectors

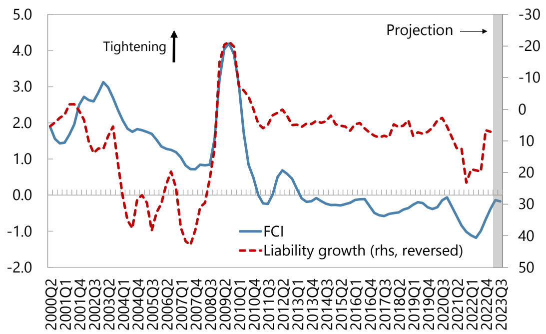
(Index)



Sources: Author's calculations.

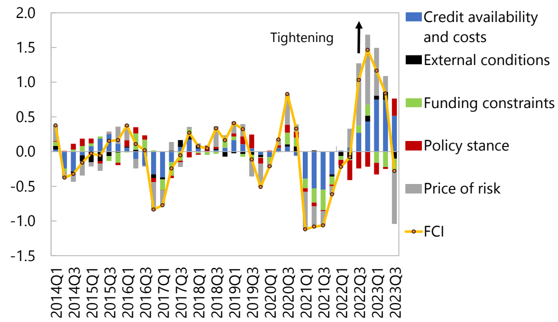
FCI—Lithuania

Lithuania: FCI and Liability Growth
(Index; percent)



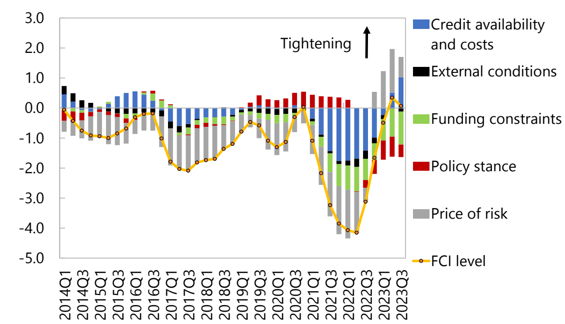
Sources: Author's calculations.

Lithuania: FCI Changes
(Contribution to quarter-over-quarter first difference of FCI)



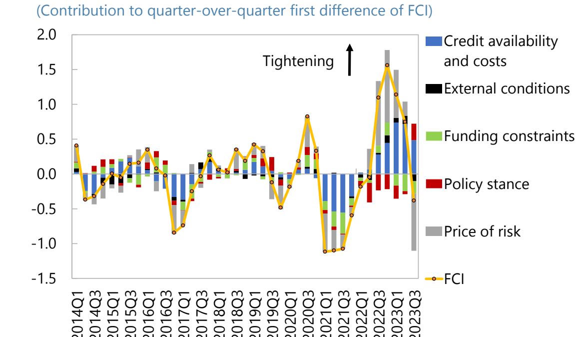
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Lithuania: FCI level
(Contribution to unscaled FCI)



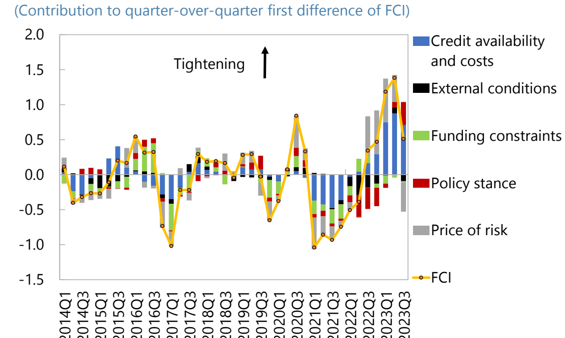
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Lithuania: FCI Changes - Nonfinancial Corporations
(Contribution to quarter-over-quarter first difference of FCI)



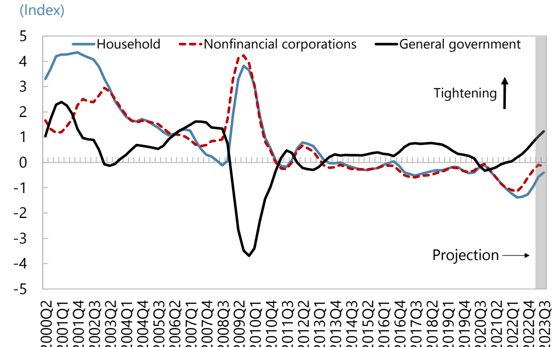
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Lithuania: FCI Changes - Households
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Lithuania: FCI by Sectors
(Index)

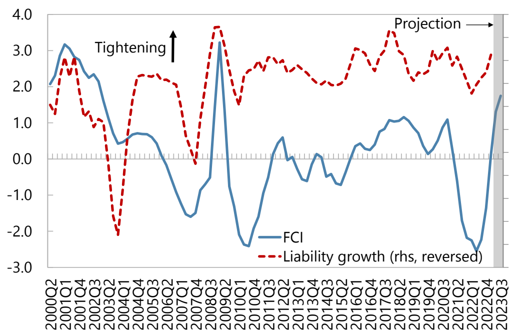


Sources: Author's calculations.

FCI—Luxembourg

Luxembourg: FCI and Liability Growth

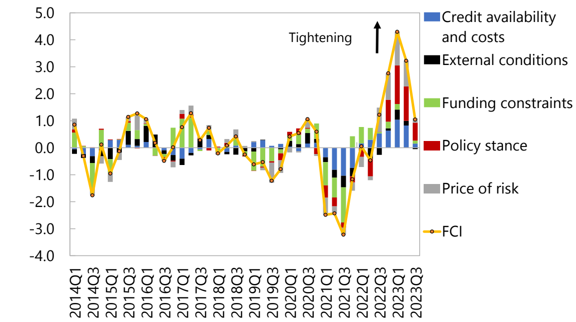
(Index; percent)



Sources: Author's calculations.

Luxembourg: FCI Changes

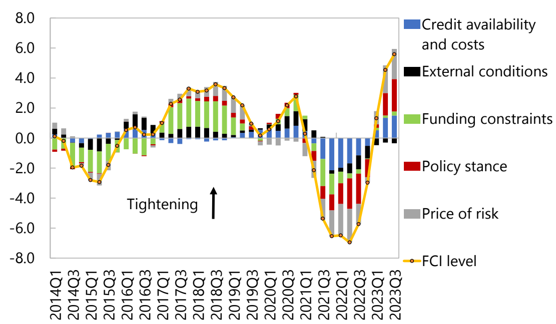
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Luxembourg: FCI level

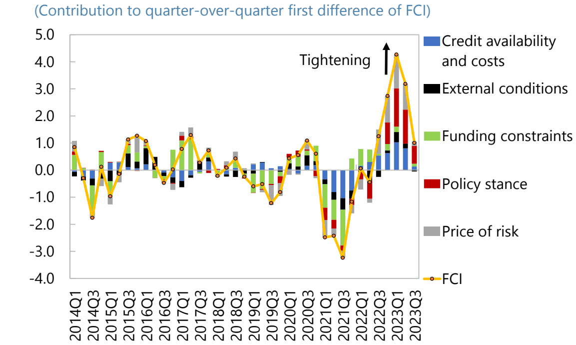
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Luxembourg: FCI Changes - Nonfinancial Corporations

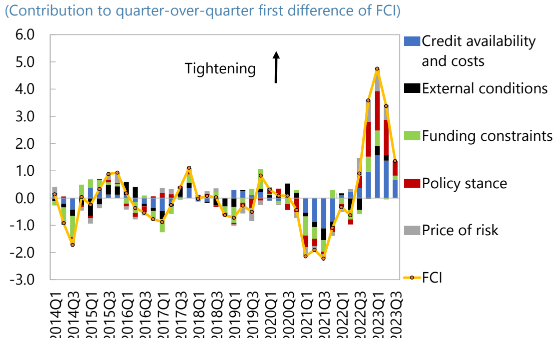
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Luxembourg: FCI Changes - Households

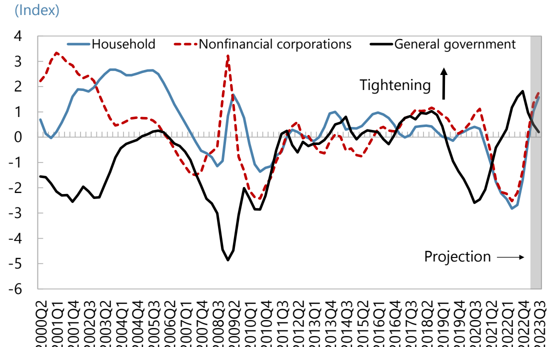
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Luxembourg: FCI by Sectors

(Index)

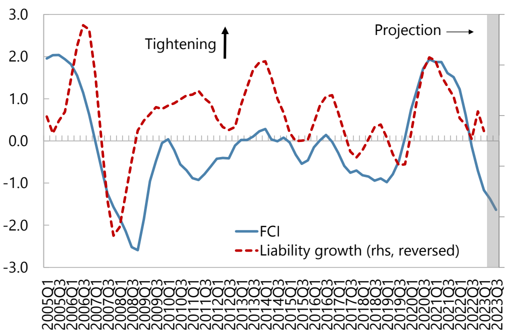


Sources: Author's calculations.

FCI—Malta

Malta: FCI and Liability Growth

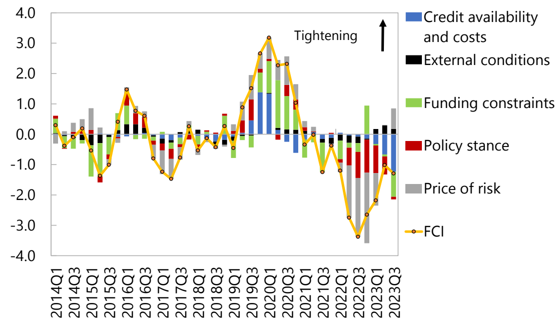
(Index; percent)



Sources: Author's calculations.

Malta: FCI Changes

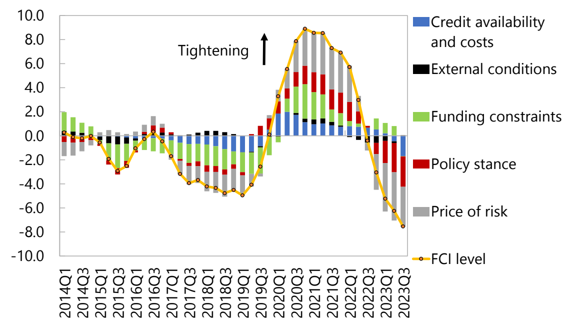
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Malta: FCI level

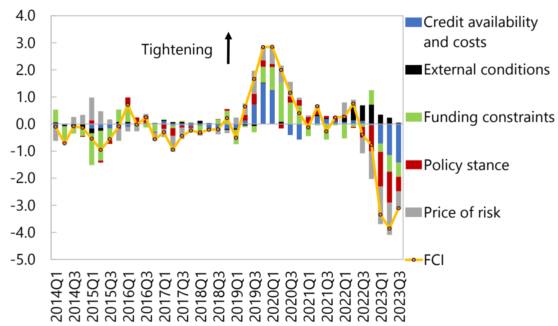
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Malta: FCI Changes - Nonfinancial Corporations

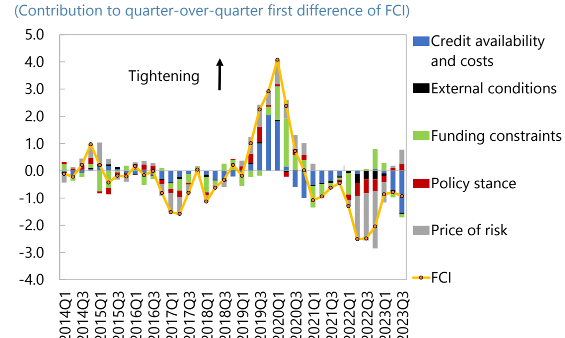
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Malta: FCI Changes - Households

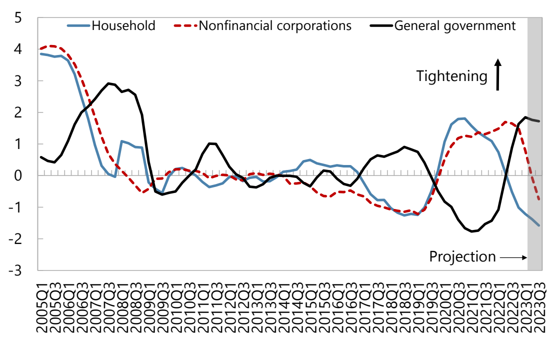
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

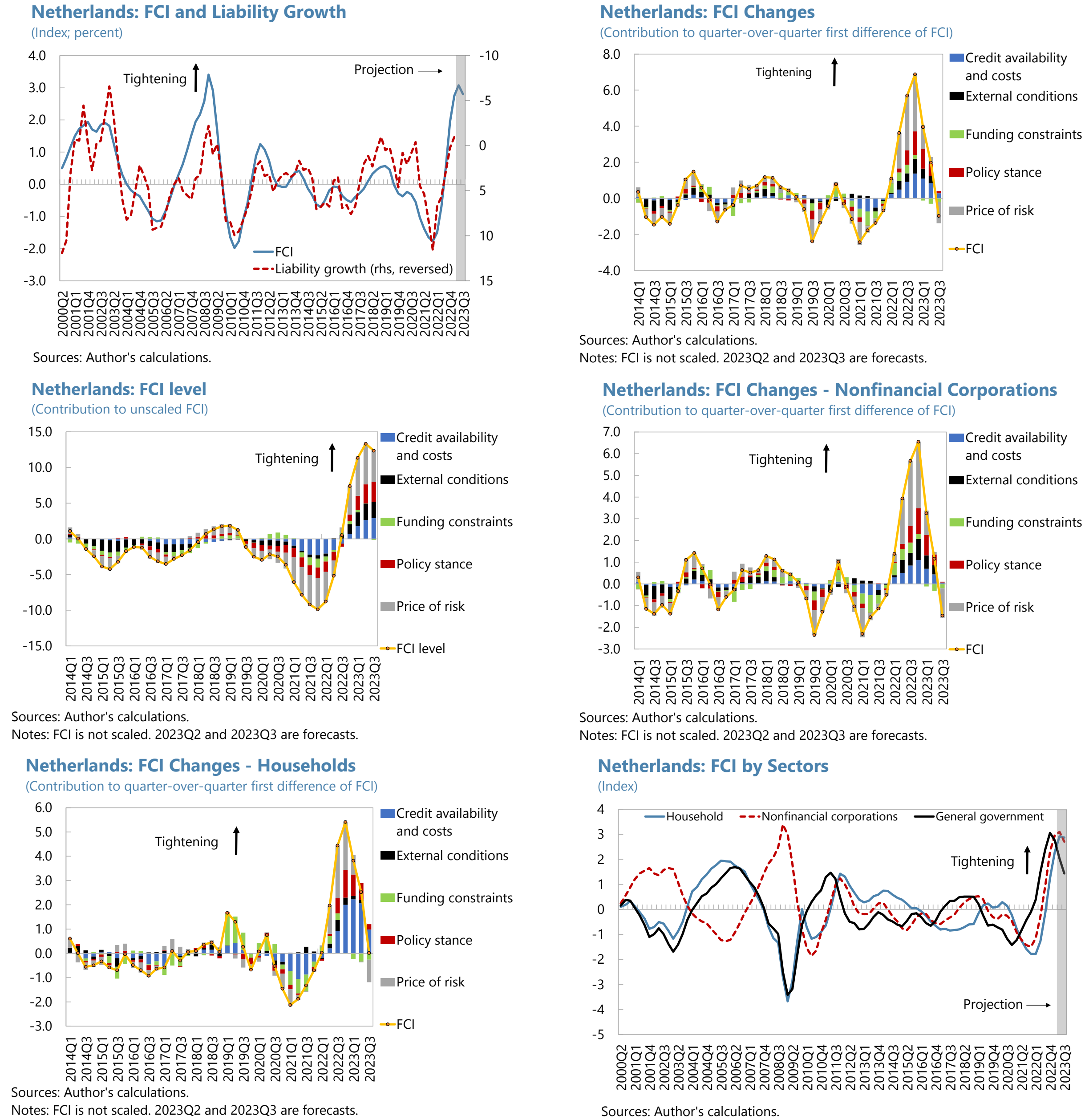
Malta: FCI by Sectors

(Index)



Sources: Author's calculations.

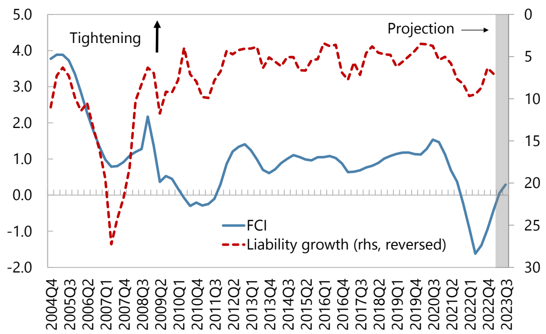
FCI—Netherlands



FCI—Poland

Poland: FCI and Liability Growth

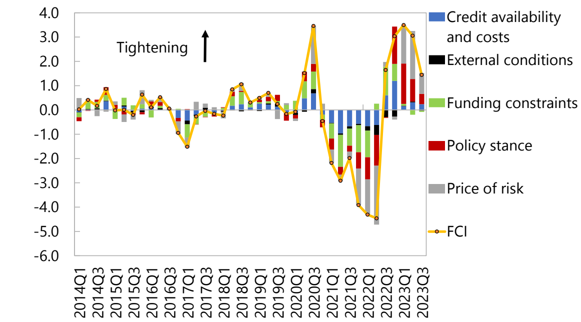
(Index; percent)



Sources: Author's calculations.

Poland: FCI Changes

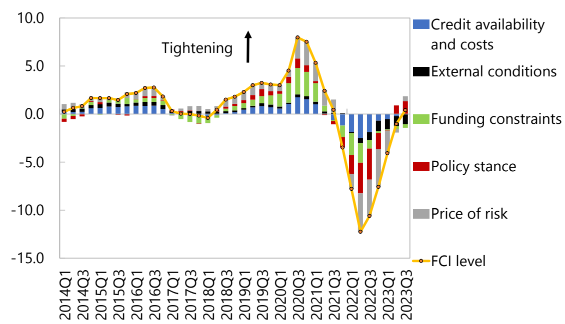
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Poland: FCI level

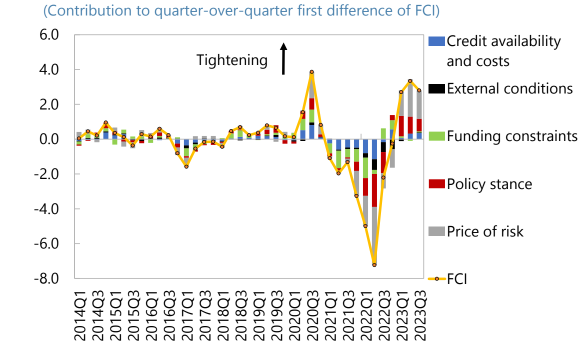
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Poland: FCI Changes - Nonfinancial Corporations

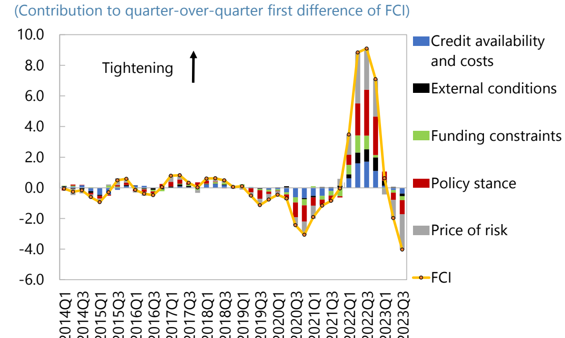
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Poland: FCI Changes - Households

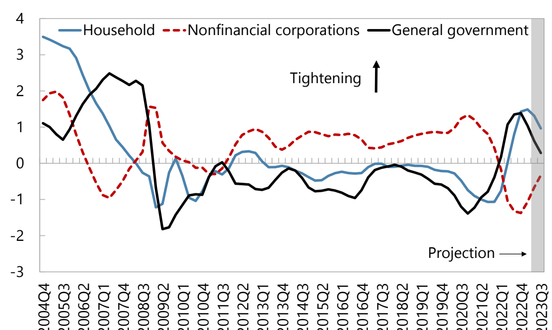
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Poland: FCI by Sectors

(Index)

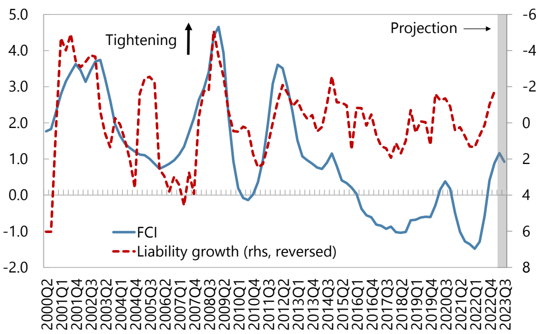


Sources: Author's calculations.

FCI—Portugal

Portugal: FCI and Liability Growth

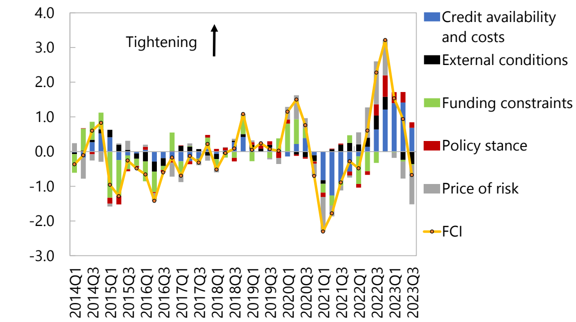
(Index; percent)



Sources: Author's calculations.

Portugal: FCI Changes

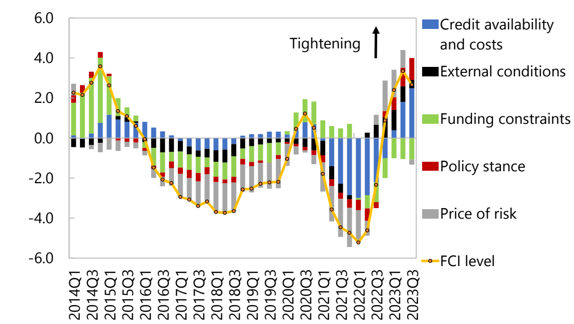
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Portugal: FCI level

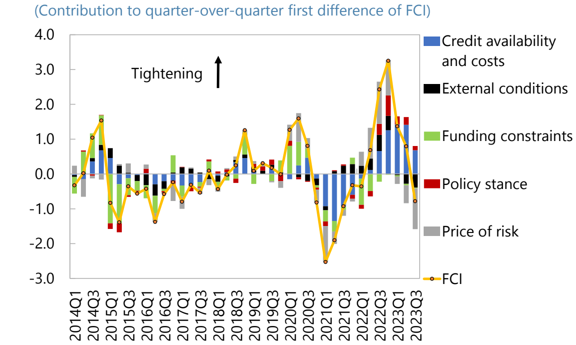
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Portugal: FCI Changes - Nonfinancial Corporations

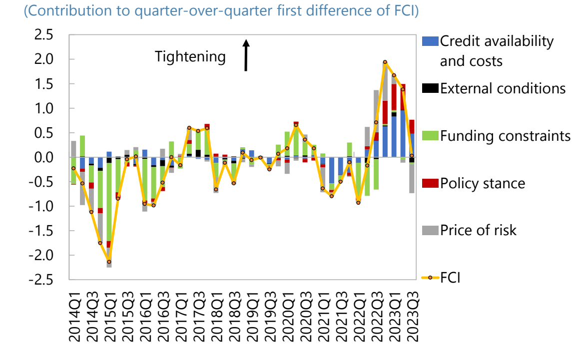
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Portugal: FCI Changes - Households

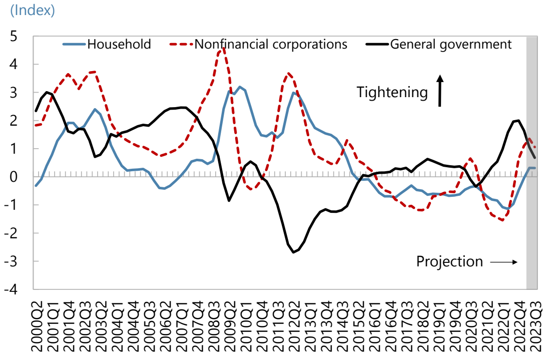
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Portugal: FCI by Sectors

(Index)

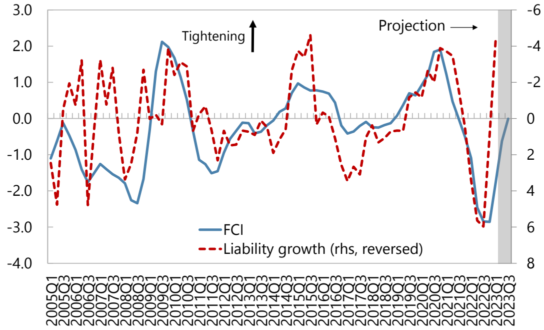


Sources: Author's calculations.

FCI—Slovakia

Slovakia: FCI and Liability Growth

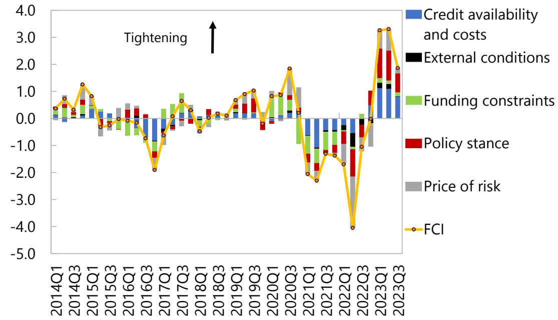
(Index; percent)



Sources: Author's calculations.

Slovakia: FCI Changes

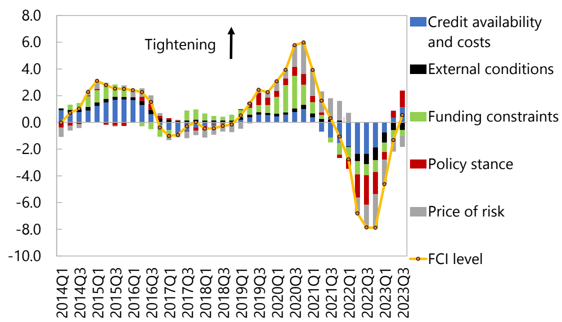
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Slovakia: FCI level

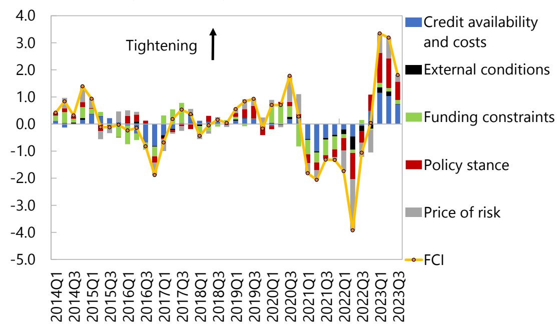
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Slovakia: FCI Changes - Nonfinancial Corporations

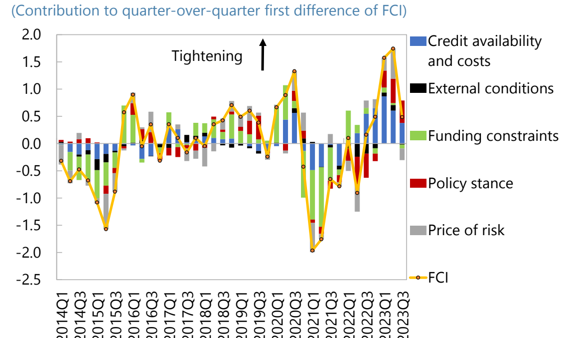
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Slovakia: FCI Changes - Households

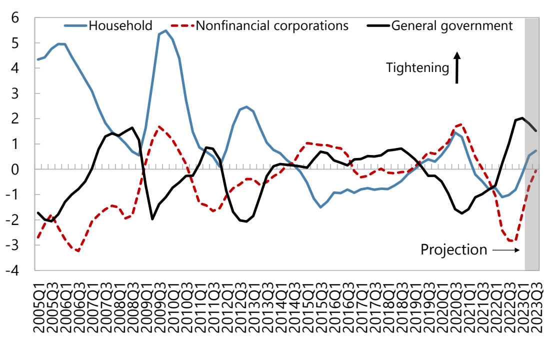
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Slovakia: FCI by Sectors

(Index)

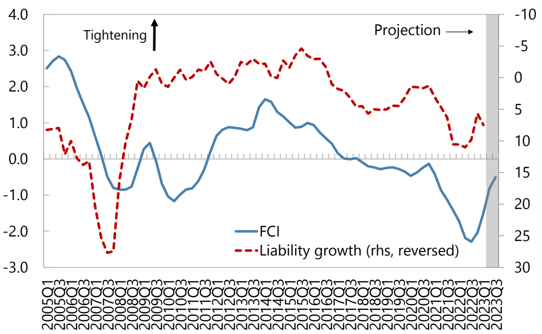


Sources: Author's calculations.

FCI—Slovenia

Slovenia: FCI and Liability Growth

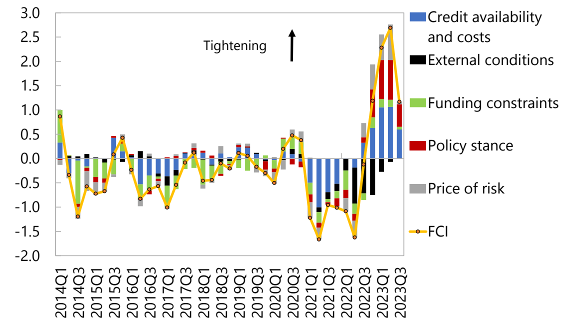
(Index; percent)



Sources: Author's calculations.

Slovenia: FCI Changes

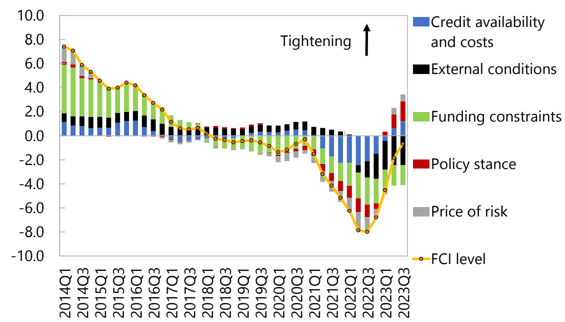
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Slovenia: FCI level

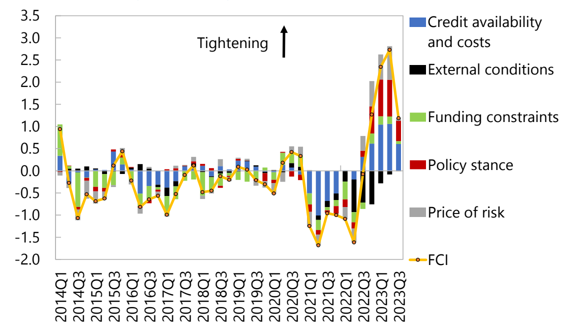
(Contribution to unscaled FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Slovenia: FCI Changes - Nonfinancial Corporations

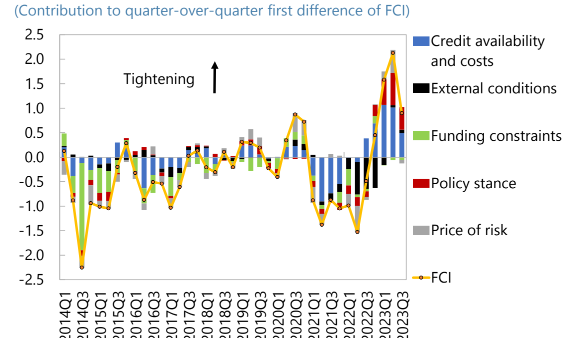
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Slovenia: FCI Changes - Households

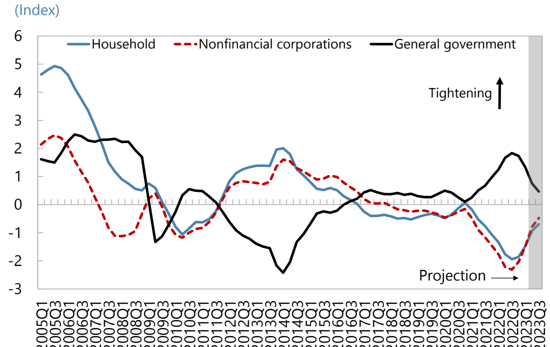
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Slovenia: FCI by Sectors

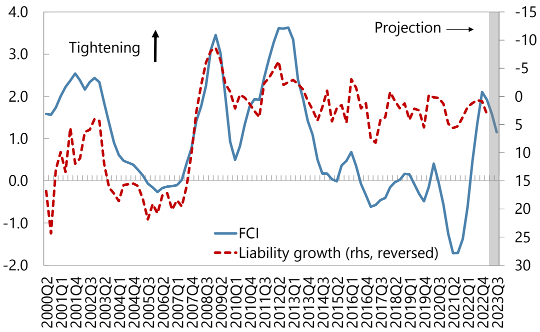
(Index)



Sources: Author's calculations.

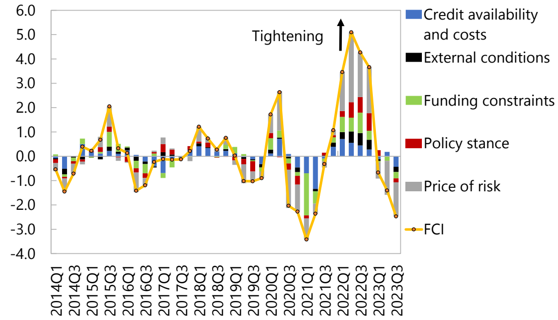
FCI—Spain

Spain: FCI and Liability Growth
(Index; percent)



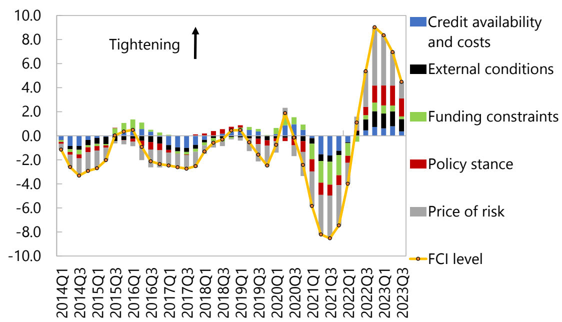
Sources: Author's calculations.

Spain: FCI Changes
(Contribution to quarter-over-quarter first difference of FCI)



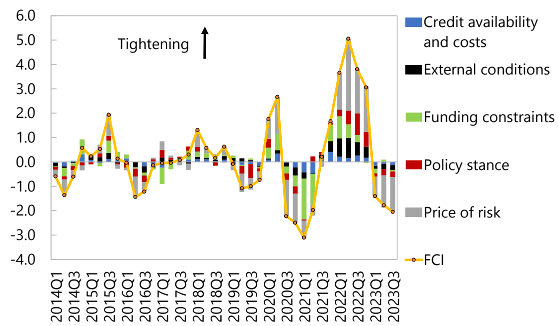
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Spain: FCI level
(Contribution to unscaled FCI)



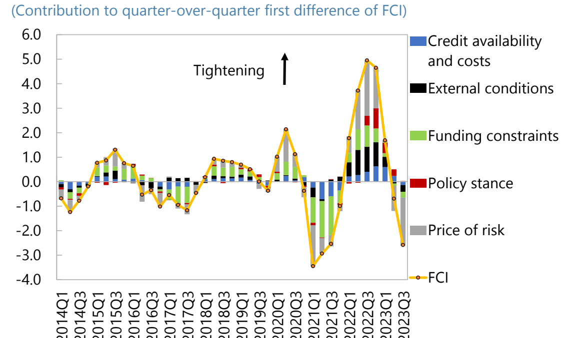
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Spain: FCI Changes - Nonfinancial Corporations
(Contribution to quarter-over-quarter first difference of FCI)



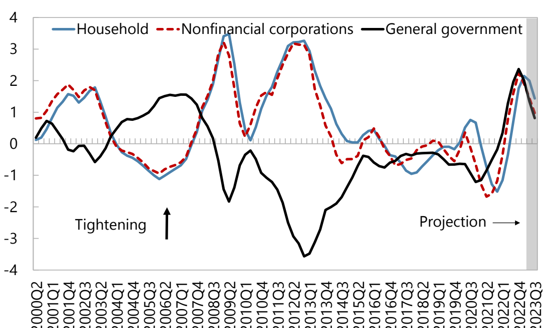
Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Spain: FCI Changes - Households
(Contribution to quarter-over-quarter first difference of FCI)



Sources: Author's calculations.
Notes: FCI is not scaled. 2023Q2 and 2023Q3 are forecasts.

Spain: FCI by Sectors
(Index)



Sources: Author's calculations.

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