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Looser, tighter, clearer: a new Financial Conditions Index for the euro area

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Abstract

Financial Conditions Indices (FCIs) are a widely used tool for assessing the broader monetary policy stance beyond the central bank's direct control. This paper presents a novel vector autoregressive (VAR) model that includes key macroeconomic variables and maps financial variables into a single index, named *Macro-Finance FCI*. The VAR coefficients and the FCI weights are estimated jointly in one step, ensuring a model-consistent macro-finance feedback. The model-implied long-run mean of the index provides a neutral benchmark to which financial conditions converge when inflation is at target and output is at potential. For the euro area, the proposed FCI incorporates nine asset prices – including risk-free rates, sovereign spreads, risk assets, and the exchange rate – and assigns a dominant role to nominal interest rates. It outperforms existing indices in out-of-sample forecasts of inflation and output. A structural identification of supply, demand, and financial shocks indicates that financial conditions require up to one year to transmit to the real economy and almost up to two years to inflation.

Keywords: financial conditions index, monetary policy, structural macro-finance VAR.

JEL codes: C32, E44, E52.

Non-technical summary

Central banks have a natural interest in assessing how accommodative or restrictive monetary policy and financial markets more broadly are for macroeconomic developments. For that purpose, Financial Conditions Indices (FCIs) summarise the overall state of financial markets by aggregating information from a wide range of asset prices – including risk-free interest rates, sovereign and corporate credit spreads, equity prices and exchange rates. For central bankers constantly faced with changing asset prices, the conceptual appeal of FCIs is that they map these numerous changes into a single meaningful metric. As such, FCIs extend the concept of the monetary policy stance to a wider set of financial markets and beyond the level of accommodation or restrictiveness that is under the central bank's direct control. Akin to a stance measure, loose (or tight) financial conditions tend to stimulate (or dampen) economic activity and inflation. Thus, monitoring financial conditions has become an essential ingredient for the conduct of monetary policy at central banks.

Despite their widespread use, existing FCIs face important challenges related to their construction. Most importantly, existing methods either do not include any feedback from macroeconomic variables in estimating each financial variable's contribution to the overall index or do so only in various sub-models without ensuring consistency. The key contribution of this paper is a novel method for estimating an FCI within a single macro-finance vector autoregressive (VAR) framework – giving rise to its label as Macro-Finance FCI. *The estimation method maintains the comprehensible design of the FCI as a linear combination of observable financial market data, while fully incorporating a mutual feedback between macro and financial variables based on one coherent model with endogenous variable selection. The VAR setup makes standard VAR techniques applicable for inference, including impulse responses, decompositions, forecasting and structural identification. Eventually, the Macro-Finance FCI is the by-product of jointly estimating the VAR parameters and FCI weights.*

The novel methodology provides a clear interpretation of the FCI, is fully transparent, straightforward to implement and comes with a number of further benefits. While other FCIs typically link financial conditions only to one macro variable, the new method makes it possible to simultaneously incorporate several macroeconomic variables of interest. The VAR setup also provides a model-implied unconditional mean which serves as benchmark towards which the included variables convergence in the long run. Furthermore, the method is designed to incorporate financial variables with as little transformation as possible and to produce an index with a unit and scale similar to a policy rate. In fact, the textbook macro VAR with inflation, output, and a policy rate is a nested special case in which the FCI loads only onto the policy rate. As a result, the new FCI is interpretable as a broader stance measure of monetary policy and, during the lower bound episode, even as a shadow policy rate.

Empirically, the estimated Macro-Finance FCI for the euro area spans key asset classes and, even though estimated with monthly frequency, can be applied to daily financial data for real-time policy purposes. The decomposition is economically intuitive: policy rate movements set the broad direction outside the lower bound episode, while long-term and real rates, credit spreads, equity valuations and the euro affect financial conditions consistent with major euro area macroeconomic events. The new FCI also beats other euro area FCIs in out-of-sample forecasts. Its model-implied mean results in meaningful periods of looser and tighter financial conditions relative to the neutral benchmark. A structural identification of supply, demand and financial shocks reveals that financial conditions require up to one year to transmit to the real economy and almost up to two years to inflation.

1 Introduction

Central banks have a natural interest in assessing how accommodative or restrictive monetary policy and financial markets more broadly are for macroeconomic developments. For that purpose, Financial Conditions Indices (FCIs) summarise the overall state of financial markets by aggregating information from a wide range of asset prices – including risk-free interest rates, sovereign and corporate credit spreads, equity prices and exchange rates. For central bankers constantly faced with changing asset prices, the conceptual appeal of FCIs is that they map these numerous changes into a single meaningful metric. As such, FCIs extend the concept of the monetary policy stance to a wider set of financial markets and beyond the degree of accommodation or restrictiveness that is under the central bank's direct control. Akin to a stance measure, loose (or tight) financial conditions tend to stimulate (or dampen) economic activity and inflation. Thus, monitoring financial conditions has become an essential ingredient for the conduct of monetary policy at central banks.

Despite their widespread use, existing FCIs face important challenges related to their construction. The two most common approaches in the literature can be classified into two categories: elasticity-based and statistical-based methods. Elasticity-based methods treat the FCI as a weighted average of observable financial variables, with weights often being calibrated or derived from separately estimated elasticities of macroeconomic outcomes with respect to financial variables.[1] The aggregation into an FCI occurs subsequently, without ensuring consistency across the various sub-models. Statistical-based methods, instead, typically rely on latent factor models, extracting common components from large sets of financial variables and linking them to macroeconomic outcomes only ex post.[2] As a result, these FCIs are purely based on financial market data, without feedback from macro variables, and are often not able to attach weights to the input data, making them less appealing for policy applications. Both approaches are limited by the separation of financial and macroeconomic estimation steps and the lack of a selection procedure for financial variables that enter the FCI.

[1] Examples of elasticity-based FCIs that focus on the US include the Goldman Sachs FCI (GS-FCI) developed by Dudley and Hatzius (2000), the OECD-FCI of Guichard et al. (2009), and the Fed's Financial Conditions Impulse on Growth (FCI-G) of Ajello et al. (2023). Stehn et al. (2019) extended the GS-FCI and Gasparini et al. (2025) the FCI-G to the euro area.

[2] Examples of statistical-based FCIs include the IMF-FCI using principal component analysis (IMF, 2017), the Chicago Fed's National Financial Conditions Index (NFCI) and its adjusted version (ANFCI) by Brave and Kelley (2017), Koop and Korobilis (2014) using a time-varying factor-augmented VAR method as well as Morana (2024) and Lombardi et al. (2025) using dynamic factor models.

The key contribution of this paper is a novel method for estimating an index of financial conditions within a single macro-finance vector autoregressive (VAR) framework, giving rise to its label as *Macro-Finance FCI*. The estimation method maintains the comprehensible design of the FCI as a linear combination of observable financial market data, while fully incorporating a mutual feedback between key macro and financial variables based on one coherent model. The estimation in one step includes the endogenous selection of financial variables entering the FCI by determining their weights simultaneously. The VAR setup makes standard VAR techniques applicable for inference, including impulse responses, decompositions, forecasting, and structural identification. Ultimately, the Macro-Finance FCI is a by-product of jointly estimating the VAR parameters and FCI weights.

The novel methodology provides a clear interpretation of the FCI, is fully transparent, straightforward to implement and comes with a number of further benefits. While other FCIs typically link financial conditions only to one macro variable (mostly economic growth), the new method makes it possible to simultaneously incorporate several macroeconomic variables of interest. The VAR setup also provides a model-implied unconditional mean which serves as benchmark towards which the included variables convergence in the long run. By including inflation and the output gap, the model mean of the FCI receives an interpretation as a neutral level that is consistent with inflation at target and output at potential, similar to the FCI* concept of Caballero et al. (2025). Likewise, the set of potential financial variables can be easily modified for specific policy applications, making the new method a convenient tool for monetary policy preparation. Furthermore, the method is designed to incorporate financial variables with as little transformation as possible and to produce an index with a unit and scale similar to a policy rate. In fact, the textbook macro VAR with inflation, output, and a policy rate is a nested special case in which the FCI loads only onto the policy rate. As a result, the new FCI is interpretable as a broader stance measure of monetary policy and, during the lower bound episode, even as a shadow policy rate.

Table 1 summarises the key conceptual and methodological differences between the Macro-Finance FCI and those existing in the literature. Unlike traditional indices, the Macro-Finance FCI is estimated within a single macro-finance VAR framework, where its weights are endogenously determined to maximise explanatory power. The resulting index is the best linear combination of financial variables to describe the dynamics of macroeconomic variables and financial conditions. This design not only strengthens macro-financial coherence but also enhances

Table 1: Methodological comparison of FCI estimation methods

	Elasticity-based	**Statistical-based**	**Macro-Finance FCI**
FCI	weighted average of financial variables	latent factor underlying financial variables	weighted average of financial variables
Weights	two-step procedure: estimate/calibrate elasticities from multiple bivariate models, aggregate ex-post	two-step procedure: extract latent factor and loadings from financial data, validate macro relevance ex-post	one-step procedure: joint estimation within single macro-finance VAR
Macro-finance feedback	feedback at sub-models but no consistency ensured across models	no direct macro feedback in estimation step	fully incorporated mutual feedback
Interpretability	lack of estimation transparency and model consistency	unclear or limited economic interpretation of latent factors	best linear combination of financial variables to describe macro dynamics

interpretability, as the contribution of each financial variable can be transparently assessed. The new method mitigates estimation challenges common in large-scale models by embedding the FCI as a single observed variable within a standard VAR. Because financial asset prices are highly correlated, multi-collinearity can undermine the reliability of statistical inference (Swiston, 2008; Kozak et al., 2020). In choosing the financial variables, the risk of over-fitting needs to be balanced against the risk of omitted-variable bias due to excessive parsimony (Ericsson et al., 1998; English et al., 2005; Lack, 2003). In the estimation of the Macro-Finance FCI, multi-collinearity is addressed by means of a generalised ridge penalty. In contrast, a common strategy in elasticity-based methods is to estimate a series of two-variable models, typically pairing one macroeconomic variable with one financial variable, and to assign index weights based on the magnitude of the resulting impulse responses. This approach, however, lacks cross-equation consistency as financial variables are treated in isolation, and interactions among them are ignored. The index is thus assembled ex post from weights derived across multiple disconnected models rather than estimated within a unified multivariate framework. Moreover, while the two-variable VAR framework allows for some feedback between financial and macroeconomic variables, this feedback is partial and fragmented across models, limiting its ability to capture integrated macro-financial dynamics.

The Macro-Finance FCI framework is estimated with maximum likelihood for the euro area, using monthly data from January 2007 until December 2025. Headline inflation and an estimated output gap measure for the euro area are included as key macroeconomic variables. A number of key empirical results stand out. First, nominal interest rates matter the most in steering financial conditions in the euro area. The €STR receives the highest weight, closely followed by the 10-year nominal interest rate. Equity price valuations, based on the cyclically adjusted price-earnings ratio, also play an important role, especially around the global financial crisis. The nominal effective exchange rate of the euro matters at the margin. Sovereign and corporate bond spreads were particularly relevant during the European sovereign debt crisis. Unlike other FCIs, the new index also includes real interest rates, which became relevant when nominal rates were constrained during the lower bound episode. Second, the Macro-Finance FCI shows dynamics that are similar in sample to those of other indices for the euro area. It reached its loosest level in 2021 before tightening rapidly until 2023. Importantly, the new index outperforms other indices in out-of-sample forecasts of inflation and output, emphasising the advantage of the coherent macro-finance approach. Third, taking into account the model-implied mean, the new FCI provides meaningful episodes of looser and tighter financial conditionals relative to neutral, converging closer towards neutral by the end of 2025. Fourth, a structural identification of supply, demand, and financial shocks reveals that financial conditions require up to one year to transmit to the real economy and almost up to two years to inflation. Based on the shock identification, a historical decomposition suggests that the pandemic was characterised by a mix of negative demand and supply shocks and restrictive financial shocks. With the onset of the inflation surge, supply and demand shocks dominated, while financial shocks subsided.

The remainder of the paper is structured as follows. Section 2 reviews the related literature and puts the contribution into a historical policy context. Section 3 introduces the theoretical and empirical methodology. Section 4 reports the estimated Macro-Finance FCI for the euro area, including a comparison to other FCIs and to a principal component analysis as well as a structural identification. Section 5 concludes.

2 Related literature

This paper contributes to the vast literature on dimensionality-reduction techniques for the purpose of estimating financial conditions that matter for the macroeconomy. The concept of an FCI has its roots in the earlier Monetary Conditions Indices (MCIs), which gained prominence in the 1990s, particularly in small open economies. MCIs were deliberately simple, typically combining the short-term policy rate and the exchange rate (Lack, 2003). For example, Freedman (1994) constructed an MCI for Canada by combining the policy rate with a trade-weighted exchange rate index, assigning fixed weights based on the estimated relative impact of each variable on output. More recently, Mojon et al. (2025) estimated a new MCI that integrates the short-term interest rate and the size of the central bank balance sheet within a Bayesian VAR (BVAR) framework, thereby capturing both conventional and unconventional monetary policy decisions.[3]

In the late 1990s and early 2000s, researchers and policymakers began expanding the scope of MCIs by incorporating additional financial variables such as equity prices, housing prices, and credit spreads. This expansion reflected a growing recognition that macroeconomic activity is influenced by broader financial conditions operating through multiple channels beyond interest rates and exchange rates. As these indices began encompassing a wider range of asset classes, they gradually evolved into what is now referred to as FCIs. Early contributions include Goodhart et al. (2001), who developed an extended index for the US economy, and Mayes and Virén (2001), who constructed indices for several European countries and showed that asset prices provide valuable information for forecasting macroeconomic developments.

These early FCIs were typically constructed using either reduced-form econometric techniques or semi-structural macroeconomic models, both of which assigned weights to selected financial variables. In the reduced-form tradition, weights were often estimated via ordinary least squares (OLS), while vector autoregressions (VARs) were primarily employed to analyse the dynamic effects of financial variables through impulse response functions (e.g., Goodhart et al., 2001; Mayes and Virén, 2001; Gauthier et al., 2004; Swiston, 2008). In parallel, semi-structural FCIs, like the index developed at the OECD by Guichard et al. (2009) and the Fed's Financial Conditions Impulse on Growth (FCI-G) of Ajello et al. (2023), derived weights from calibrated macroeconomic models, often incorporating expert judgment regarding the elasticities of financial variables with respect to economic activity. In both approaches, the objective was to construct a single summary measure of financial conditions by combining variables such as interest rates, exchange rates, credit spreads, and equity prices, under the premise that these jointly shape aggregate demand through channels including interest rate transmission, wealth effects, and credit supply dynamics. The use of fully structural models to estimate FCI weights has been limited, with Goodhart and Hofmann (2000) being a notable example.

[3] Their methodology is conceptually close to the VAR-based dimensionality-reduction approach presented in this paper, although only applied to a pair of variables instead of to a more general set of variables.

Over time, FCIs have become more sophisticated as researchers sought to overcome early limitations – an effort that gained urgency following the Global Financial Crisis (GFC), which underscored the need to broaden the set of financial variables considered (Wacker et al., 2014). To address multi-collinearity, data-reduction techniques such as principal component analysis (PCA) and factor models became standard. For instance, Hatzius et al. (2010) used a factor analysis to construct a US FCI from 57 financial series, including interest rates, credit spreads, asset prices, and survey indicators. For Europe, Angelopoulou et al. (2014) applied PCA to more than 20 financial price, quantity, and survey variables selected on theoretical grounds. Other notable PCA-based FCIs include Bloomberg's Financial Conditions Index and the cross-country indices of Erdem and Tsatsaronis (2013), who demonstrate superior forecasting performance for real GDP. Adrian et al. (2023) constructed their Volatility Financial Conditions Index (VFCI) by extracting the first principal component from a broad set of financial variables and embedding it in a heteroscedastic framework to estimate the conditional volatility of GDP.

Dynamic factor FCIs likewise extract latent common components from a broad set of financial variables. Matheson (2012) shows that dynamic factor-based FCIs significantly improve GDP forecasting in both the euro area and the United States, underscoring their value as forward-looking indicators of macroeconomic conditions.[4] Within this framework, the Chicago Fed's National Financial Conditions Index (NFCI), developed by Brave and Butters (2011), estimates a single dynamic factor summarising financial conditions, together with an adjusted version (ANFCI) that controls for the macroeconomic environment – namely, contemporaneous and lagged economic activity and inflation, thereby isolating the pure evolution of financial conditions.[5] Both indices draw on 105 financial indicators, grouped into three key categories: risk, credit, and leverage. More recently, Lombardi et al. (2025) employ a dynamic factor model to extract two latent dimensions of financial conditions: a safe yield factor and a risk factor. Both factors exhibit strong predictive power for key macroeconomic variables, and monetary policy is found to exert a persistent influence on each.

While PCA- and factor-based FCIs efficiently condense large sets of financial information, their weights are statistically determined and often lack direct macroeconomic interpretation unless validated ex-post (Ajello et al., 2023; Borraccia et al., 2023; Lombardi et al., 2025). The

[4]Examples of dynamic factor model (DFM) FCIs include Darracq Pariès et al. (2014) for the euro area and Metiu (2022) for Germany.

[5]The ANFCI estimation was further refined by Brave and Kelley (2017).

extracted factors are typically chosen to explain the maximum variance in the financial dataset, rather than to maximise relevance for macroeconomic outcomes such as growth or inflation – an alignment that is assessed only after estimation. This disconnect stands in contrast to earlier approaches, such as VAR- and impulse response–based methods, which sought to quantify directly the effects of financial variables on real activity (e.g., Swiston, 2008; English et al., 2005). Consequently, factor-based indices may respond to shifts in latent financial structures that are difficult to interpret or attribute to specific shocks, complicating the identification of the drivers of tightening or easing in financial conditions. Interpretability thus remains a central limitation: PCA loadings and latent factors are inherently abstract, making it difficult to pinpoint which financial instruments or markets are driving the index at any given time. Unlike these statistical approaches, Arrigoni et al. (2020) argue that FCIs defined as the average of observable data with weights based on economic judgment rather than estimation perform better along several dimensions.

In settings with large cross-sectional information sets, two other widely used dimensionality-reduction approaches are factor-augmented VAR (FAVAR) models and multivariate autoregressive index (MAI) models. Following Bernanke et al., 2005, FAVARs address the curse of dimensionality by summarising large datasets with a small number of latent factors. While the FCI framework presented in this papers bears similarities with FAVARs, the causality between financial variables and the FCI is reversed. Rather than being driven directly by observable financial variables, the FCI from a FAVAR as in Koop and Korobilis (2014) is a latent factor that is driving financial variables, hampering a straightforward interpretation of what this factor is. The less widely-used MAI models, introduced by Reinsel (1983), instead treat the relevant factors (or indices) as observable linear combinations of underlying variables (Carriero et al., 2016), which is closest to the approach presented in this paper. The key difference is that MAI models typically apply the dimensionality reduction only to the lag structure of the endogenous VAR variables and not to the contemporaneous variables. As such, MAI models rather connect to the literature on large-scale VAR models which seek to jointly model business and financial cycles (Berger et al., 2022). Yet rather than modelling the full macro-financial system, the focus of this paper is on extracting a single index that summarises the information contained in financial market variables in a way that maximises their explanatory power for the dynamics of macroeconomic variables and financial conditions, while preserving full transparency and tractability of the weights and contributions of each financial variable.

Finally, financial conditions are shaped not only by exogenous market developments but also by monetary policy itself (see, e.g., Ajello et al., 2023). Central banks influence financial conditions directly through policy rate changes and indirectly by affecting term premia, credit spreads, and risk appetite more broadly (Borio and Zhu, 2012; Gertler and Karadi, 2015). Building on this perspective, a growing literature has emphasised the role of FCIs as potential anchors for monetary policy decisions. For example, Caballero and Simsek (2024) propose an optimal target level of FCI ($\overline{\text{FCI}}$), while Caballero et al. (2025) introduce the concept of a neutral level of financial conditions (FCI^*) – an alternative to the natural rate of interest – defined as the level of financial conditions consistent with closing the expected output gap.

3 Methodology

This section presents the methodological framework used to construct and estimate a new financial conditions index (FCI). The goal is to obtain an easily interpretable index within one macro-finance model such that it features a model-consistent mutual feedback between macroeconomic and financial variables – giving rise to its label as *Macro-Finance FCI*. For that purpose, the theoretical starting point is a large-scale joint vector autoregressive (VAR) process that governs the evolution of key macroeconomic variables and a potentially large set of financial variables. Within this system, the Macro-Finance FCI is defined as the linear combination of financial variables that best describes the joint dynamics of macroeconomic variables and financial conditions. This definition makes it possible to collapse the initial and large-scale VAR model to a much more tractable small-scale VAR model, providing the new index along the way. The VAR parameters and the weights of the constituent financial variables entering the FCI are estimated jointly in one step. With this estimation at hand, typical VAR inferences based on one coherent model are possible.

3.1 Macro-Finance VAR

Consider a setting in which macroeconomic and financial variables of interest evolve according to a joint VAR process. The N macroeconomic variables are collected in $M_t = (M_{1,t}, \dots, M_{N,t})'$ and the set of K financial variables in $Z_t = (Z_{1,t}, \dots, Z_{K,t})'$. The $(N+K) \times 1$

vector of endogenous variables as $Y_t = \left(M_t', Z_t'\right)'$ is assumed to follow the standard VAR process

$$Y_t = \mu + \Phi Y_{t-1} + \Sigma e_t, \tag{1}$$

where μ is an $(N+K)\times 1$ vector of constants, Φ is an $(N+K)\times(N+K)$ matrix of autoregressive coefficients, and Σ is an $(N+K)\times(N+K)$ loading matrix that maps the structural shocks e_t into reduced-form innovations. Assume further that $e_t \sim \mathcal{N}(0, I_{N+K})$, which implies the conditional covariance matrix of the reduced-form innovations to be $\Omega = \Sigma\Sigma'$. The choice of one lag is made for illustrative purposes only. The setting easily generalises to any number of lags, as will be done in the estimation in Section 3.2.

The estimation of the full-scale VAR in equation (1) is theoretically feasible but creates empirical challenges as the number of highly correlated variables grows large. Furthermore, the original VAR leaves the aggregation of financial variables into an FCI unresolved. Assume instead that financial conditions are summarised by a one-dimensional index $F_t = \alpha' Z_t$ with $\alpha = (\alpha_1, \dots, \alpha_K)'$. This assumption adopts the common representation of financial conditions indices as a weighted average of financial variables, in which α_i marks the weight of each constituent financial variable $Z_{i,t}$. Importantly, the assumption that the financial variables only matter in this specific linear combination in the VAR is taken as a premise, on which the very idea of an index as a summary statistic rests, rather than as a testable hypothesis.

To see how an FCI as linear combination of financial variables simplifies the original model, define a $(N+1)\times(N+K)$ mapping matrix Γ such that

$$\Gamma Y_t = \underbrace{\begin{pmatrix} \mathbf{I}_N & \mathbf{0}_{N\times K} \\ \mathbf{0}_{1\times N} & \alpha' \end{pmatrix}}_{\equiv \Gamma} \begin{pmatrix} M_t \\ Z_t \end{pmatrix} = \begin{pmatrix} M_t \\ \alpha' Z_t \end{pmatrix} = \begin{pmatrix} M_t \\ F_t \end{pmatrix} \equiv \tilde{Y}_t. \tag{2}$$

The mapping matrix Γ keeps the macro variables one-by-one and collapses all financial variables into one linear combination using the weights in α. The vector of endogenous variables reduces from Y_t to $\tilde{Y}_t$. Under an intuitiv set of parameter constraints, pre-multiplying the initial VAR in equation (1) by the mapping matrix Γ yields a lower-dimensional representation of the model, which takes again the form of a standard VAR process.

$$\begin{aligned} & Y_t = \mu + \Phi Y_{t-1} + \Sigma e_t \\ \Leftrightarrow \quad & \Gamma Y_t = \Gamma\mu + \Gamma\Phi Y_{t-1} + \Gamma\Sigma e_t \\ \Leftrightarrow \quad & \Gamma Y_t = \Gamma\mu + \tilde{\Phi}\Gamma Y_{t-1} + \tilde{\Sigma}\Gamma e_t \\ \Leftrightarrow \quad & \tilde{Y}_t = \tilde{\mu} + \tilde{\Phi}\tilde{Y}_{t-1} + \tilde{\Sigma}\tilde{e}_t \end{aligned} \tag{3}$$

In these steps, the following non-trivial matrix transformations are used: Any matrix A that is pre-multiplied by Γ turns into a lower-dimension $\tilde{A}$ post-multiplied by Γ, that is $\Gamma A = \tilde{A}\Gamma$. These transformations are not valid in general because Γ is not square and invertible, but require the assumption that financial variables share the same combined parameters in the VAR, once appropriately scaled by each variable's weight in the FCI.[6] More formally:

Assumption 1 (Linearity)**.** *The VAR parameters loading on financial variables and their shocks are the same once appropriately scaled by the FCI weights* α*. For the first* N *rows in* Φ *and* Σ *related to the macro variables, it holds that* $\frac{\phi_{M,Z_i}}{\alpha_i} = \tilde{\phi}_{M,F}$ *and* $\frac{\sigma_{M,Z_i}}{\alpha_i} = \tilde{\sigma}_{M,F}$ $\forall i \in \{1, \ldots, K\}$*. For the last* K *rows in* Φ *and* Σ *related to the financial variables, it holds that* $\sum_{k=1}^{K} \frac{\alpha_k \phi_{Z_k,Z_i}}{\alpha_i} = \tilde{\phi}_{F,F}$ *and* $\sum_{k=1}^{K} \frac{\alpha_k \sigma_{Z_k,Z_i}}{\alpha_i} = \tilde{\sigma}_{F,F}$ $\forall i \in \{1, \ldots, K\}$ *.*

Appendix A.1 illustrates the exact parameter constraints and matrix transformations in a tractable example. The intuition underlying Assumption 1 is that all financial variables and their shocks share the same impact on macroeconomic variables, once scaled by the relevant weight, such that their aggregated impact can be represented by a single variable, coined financial conditions index. Likewise, each financial variable's and its shock's scaled impact on the linear combination making up the FCI is the same, too. Without doubt, these are strong assumptions, but they resemble very much the idea underlying the concept of an FCI.

A key feature of the new VAR is that the left-hand side variable F_t is itself a function of parameters, namely α. Since the usual VAR parameters are obviously dependent on the left-hand side variables, the dependency of F_t on α creates a mutual link between the VAR parameters and the weights. The parameters in the small-scale VAR in equation (3) are linked to the original VAR in equation (1) via Assumption 1 and via the following remaining

[6] If Γ was invertible, it would be straightforward to define $\Gamma A = \Gamma A(\Gamma^{-1}\Gamma) = (\Gamma A \Gamma^{-1})\Gamma = \tilde{A}\Gamma$ for any Γ. Another trivial solution could arise if A was rank-deficient, which is not assumed for Φ or Σ.

definitions, which require no further assumption:[7]

$$
\begin{aligned}
\begin{pmatrix} M_t \\ F_t \end{pmatrix} &= \begin{pmatrix} \mu_M \\ \tilde{\mu}_F \end{pmatrix} + \begin{pmatrix} \phi_{M,M} & \tilde{\phi}_{M,F} \\ \tilde{\phi}_{F,M} & \tilde{\phi}_{F,F} \end{pmatrix} \begin{pmatrix} M_{t-1} \\ F_{t-1} \end{pmatrix} + \begin{pmatrix} \sigma_{M,M} & \tilde{\sigma}_{M,F} \\ \tilde{\sigma}_{F,M} & \tilde{\sigma}_{F,F} \end{pmatrix} \begin{pmatrix} e_t^M \\ e_t^F \end{pmatrix} \\
F_t &\equiv \alpha_1 Z_{1,t} + \ldots + \alpha_K Z_{K,t} \\
\tilde{\mu}_F &\equiv \alpha_1 \mu_{Z_1} + \ldots + \alpha_K \mu_{Z_K} \\
\tilde{\phi}_{F,M} &\equiv \alpha_1 \phi_{Z_1,M} + \ldots + \alpha_K \phi_{Z_K,M} \\
\tilde{\sigma}_{F,M} &\equiv \alpha_1 \sigma_{Z_1,M} + \ldots + \alpha_K \sigma_{Z_K,M} \\
e_t^F &\equiv \alpha_1 e_t^{Z_1} + \ldots + \alpha_K e_t^{Z_K}
\end{aligned} \tag{4}
$$

Since the model is assumed to have normally distributed error terms, its dynamics are fully described by the first and second moments of the system. For the dynamics of the macroeconomic variables M_t and the aggregate index F_t, the large- and small-scale VAR representations in equations (1) and (3) are equivalent as long as two conditions are met. First, Assumption 1 ensures the preservation of the appropriate mean. Second, for the variance, the linearity assumption alone would only ensure $\Gamma\Omega\Gamma' = \Gamma\Sigma\Sigma'\Gamma' = \tilde{\Sigma}\Gamma\Gamma'\tilde{\Sigma}' \neq \tilde{\Omega}$. Thus, for the covariance matrix of the small-scale VAR to fulfil $\tilde{\Omega} = \tilde{\Sigma}\tilde{\Sigma}'$ it also requires row-orthonormality of Γ, leading to an intuitive implication for the weights α contained in Γ. Formally:

Assumption 2 (Orthonormality)**.** *The mapping matrix* Γ *is row-orthonormal. Using the definition of* Γ *in equation* (2)*, this results in*

$$
\Gamma\Gamma' = \begin{pmatrix} \mathbf{I}_N & \mathbf{0}_{N\times K} \\ \mathbf{0}_{1\times N} & \alpha'\alpha \end{pmatrix} = \begin{pmatrix} \mathbf{I}_N & \mathbf{0}_{N\times K} \\ \mathbf{0}_{1\times N} & 1 \end{pmatrix} = \mathbf{I}, \tag{5}
$$

which implies the norm constraint $||\alpha||_2^2 = 1$ *to be binding.*

In other words, the squared weights need to sum to one, that is $\sum_{i=1}^{K} \alpha_i^2 = 1$. This means that each weight α_i – once squared – is closer to the relative weight (or share) of the corresponding financial variable in the total variance of the FCI, rather than the share of each financial variable in the level of the FCI. This distinction is important when comparing the weights with those of other FCIs in the literature, which typically sum to one directly.

[7]Note that μ_M, $\phi_{M,M}$ and $\sigma_{M,M}$ remain unchanged from the original VAR.

Overall, the reduced VAR maintains all relevant information from the original VAR, while achieving a substantial reduction in dimensionality. It delivers the same macroeconomic dynamics while drastically reducing the number of parameters to be estimated – an important benefit when financial variables are highly correlated and large in number relative to the available sample size. Another key benefit of the reduced system is the introduction of weights which determine the new FCI as a meaningful linear combination of financial variables, providing a natural decomposition of the index into the contributions from the constituent variables. One downside of the dimensionality reduction is that the parameters governing the financial variables of the original VAR are not recoverable from the reduced-form parameters. Because the mapping matrix Γ is not invertible, the transformations $\mu \mapsto \tilde{\mu}$, $\Phi \mapsto \tilde{\Phi}$ and $\Sigma \mapsto \tilde{\Sigma}$ are not invertible either. Yet for the purpose of estimating the FCI, knowing the original parameters provides no economic insight.

On a final note, FCIs that are constructed as a linear combination of financial variables bear resemblance to a principal component analysis (PCA). However, there is a key conceptual distinction. A PCA assigns weights to the constituent variables so as to maximise the explained variation across the financial variables themselves, without reference to their macroeconomic implications. By contrast, the weights α in the new FCI are determined endogenously within a macro-finance model and therefore reflect the relevance of each financial variable for explaining the joint dynamics of both macroeconomic variables and financial conditions. Unlike in a PCA, a financial variable that explains a lot of the financial variation but adds no value to the macro dynamics may receive a small weight in the estimation of the FCI. In this sense, the Macro-Finance FCI features a model-consistent mutual feedback between macroeconomic and financial variables as well as between the VAR parameters and the FCI weights. The new FCI framework also bears similarities with factor-augmented VAR (FAVAR) models. In those models, the estimated FCI is one of the latent factors which describe the dynamics of chosen macroeconomic and financial variables. Yet, the causality is reversed: The FCI presented in this paper is driven directly by observable financial variables, making an intuitive interpretation and decomposition possible, while in a FAVAR some latent factor is driving financial variables, hampering a straightforward interpretation and application for policy purposes.

3.2 Estimation

For the description of the estimation, the VAR is generalised to any number of lags, indicated by P, with a more compact notation of the coefficient matrix $\Phi = [\Phi_1, \ldots, \Phi_P]$ and the variable vector $X_{t-1} = [Y'_{t-1}, \ldots, Y'_{t-P}]'$. Vector μ and covariance matrix $\Omega = \Sigma\Sigma'$ remain unchanged.

$$Y_t = \mu + \sum_{p=1}^{P} \Phi_p Y_{t-p} + \Sigma e_t = \mu + \Phi X_{t-1} + \Sigma e_t \tag{6}$$

The conditional distribution of the original large-scale VAR in equation (6) is given by $Y_t \sim \mathcal{N}(\mu + \Phi X_{t-1}, \Omega)$. In general, the distribution of a linear transformation of the form ΓY_t equals $\Gamma Y_t \sim \mathcal{N}(\Gamma\mu + \Gamma\Phi X_{t-1}, \Gamma\Omega\Gamma')$. In the specific setup of the macro-finance VAR introduced in Section 3.1, this distribution admits a more compact representation using reduced-form parameters: $\tilde{Y}_t \sim \mathcal{N}(\tilde{\mu} + \tilde{\Phi}\tilde{X}_{t-1}, \tilde{\Omega})$. The mapping of original to reduced-form parameters follows the linearity Assumption 1 and the logic presented around equation (4).

The set of parameters $\Theta = \{\tilde{\mu}, \tilde{\Phi}, \tilde{\Omega}, \Gamma\}$ is estimated with maximum likelihood subject to the norm constraint on the weights, $||\alpha||_2^2 = 1$, which are included in the mapping matrix Γ as defined in equation (2). The norm constraint results from the orthonormality Assumption 2 on the mapping matrix Γ. Given an observation Y_t of the observable data, the log-likelihood of the corresponding lower-dimensional representation $\tilde{Y}_t = \Gamma Y_t$, conditional on the past $\tilde{X}_{t-1}$ (or equivalently, ΓX_{t-1}), and as a function of the reduced-form parameters Θ is given by:

$$\begin{aligned} \mathcal{L}_t(\Theta) &= \log\left(p(\tilde{Y}_t = \Gamma Y_t \mid X_{t-1}; \Theta)\right) \\ &= -\frac{M+1}{2}\log(2\pi) - \frac{1}{2}\log|\tilde{\Omega}| - \frac{1}{2}\left(\Gamma Y_t - \tilde{\mu} - \tilde{\Phi}\Gamma X_{t-1}\right)' \tilde{\Omega}^{-1} \left(\Gamma Y_t - \tilde{\mu} - \tilde{\Phi}\Gamma X_{t-1}\right) \end{aligned} \tag{7}$$

When estimating the model parameters, it is essential that the linear transformation defined by Γ is scale-invariant. That is, the projection of Y_t into the lower-dimensional space $\tilde{Y}_t = \Gamma Y_t$ should only provide a direction of the projection but not a length. Without scale invariance, the likelihood could be arbitrarily increased by multiplying Γ with some constant.[8] In the setup presented in Section 3.1, the scale invariance of Γ is conveniently already ensured due to

[8]This issue becomes evident when expressing the likelihood in terms of the original parameters. Suppose Γ is multiplied by a scalar s in the likelihood function, such that $\mathcal{L}_t(\mu, \Phi, \Sigma, s\Gamma) = -\log(2\pi) - \frac{1}{2}\log(|s\Gamma\Omega\Gamma' s|) - \frac{1}{2}(s\Gamma Y_t - s\Gamma\mu - s\Gamma\Phi X_{t-1})'(s\Gamma\Omega\Gamma' s)^{-1}(s\Gamma Y_t - s\Gamma\mu - s\Gamma\Phi X_{t-1})$. The s cancels everywhere except in the determinant where a s^2 term remains, rendering the estimation of Γ impossible. Even when estimating the reduced-form parameters only, as in equation (7), an unconstrained Γ leads to numerical instability.

the row-orthonormality Assumption 2. Despite the unusual appearance of Γ in the likelihood function, Appendix A.2 shows that estimating equation (7) via maximum likelihood provides unbiased estimates of all parameters by means of a Monte Carlo simulation. Importantly, for a given set of financial variables, it is possible to find the optimal Γ that maximises the likelihood, even though Γ changes the left-hand side variable Y_t. However, the joint likelihood cannot be used to compare models with different sets of financial variables, as discussed in Section 4.2.

The optimisation of the joint log-likelihood includes a generalised ridge penalty to deal with issues of multi-collinearity among the financial variables in the FCI. Formally:

$$\min_{\Theta} \sum_{t=P+1}^{T} -\mathcal{L}_t(\Theta) + \lambda\gamma \quad \text{s.t.} \quad ||\alpha||_2^2 = 1 \tag{8}$$

The parameter λ governs the strength of the penalty term γ. Note that the norm constraint on α already enforces a regular ridge penalty on the weights with infinite strength. Yet, the regular ridge penalty treats all variables the same, regardless of their scale and co-movement with other variables. In the empirical implementation, a generalised ridge penalty of the form $\gamma = \alpha' C^{-1} \alpha$ is added, where the precision matrix $C = \text{Cov}(Z_t)$ is the sample covariance matrix of the financial variables. As a result, the penalty applies more strongly to weights whose variables are more strongly correlated and, by using the covariance, it also accounts for differences in the scales of financial variables. A practical implication of the generalised ridge penalty is that there is no need to standardise the input variables. The choice of λ is a practical one: It should be as low as possible but as high as necessary to mitigate obvious multi-collinearity issues. For example, when including a full term-structure of interest rates, the weights should display smooth changes along maturities. Oscillating weights of neighbouring maturities would be a sign of a too small penalty. In the empirical part, λ is set to 77.

Eventually, the resulting Macro-Finance FCI is a by-product of estimating the parameters Θ and is the linear combination of financial variables that best explains the joint dynamics of the macroeconomic variables and financial conditions. Note that the textbook VAR that uses some short-term nominal interest rate instead of the FCI is simply a nested special case as long as that interest rate is among the set of financial variables entering the index. If the interest rate alone were to provide the best in-sample fit, the estimation approach would set its weight accordingly. In addition, Section 4.5 carries out an out-of-sample forecasting comparison.

4 Results

The theoretical framework outlined in Section 3 is applied to the euro area in an estimation with monthly data from January 2007 to December 2025. The following set of results are obtained with $P = 2$ lags in the VAR, supported by two out of three information criteria (BIC and HQIC suggest two lags, whereas the more permissive AIC suggests three).

4.1 Data

The estimation sample covers key business cycles for the euro area, including the global financial crisis, the European sovereign debt crisis, the lower bound episode, the Covid-19 pandemic and the inflation surge. To deal with the extraordinary impact of the Covid-19 pandemic, the observations from March to June 2020 are excluded from the likelihood evaluation. The sample does not include the early years of the euro area as – in particular – financial markets were arguably in a different regime for a protracted period. The macroeconomic set of variables included in the estimation consists of headline inflation and the output gap. Appendix A.3 lists the raw data information in Table A.2. Headline inflation is defined as the deviation of the year-on-year growth rate of euro area HICP from target:

$$\pi_t = 100 \times \left[\log(\text{HICP}_t) - \log(\text{HICP}_{t-12})\right] - \pi_t^{target}. \tag{9}$$

The inflation target is set to 1.9% before July 2021 and to 2.0% thereafter, reflecting the ECB's move from an inflation target of below, but close to, 2% to a symmetric 2% inflation target as a result of a strategy review (ECB, 2021).[9] Real economic activity is measured with an output gap calculated from interpolated quarterly real euro area GDP:[10]

$$x_t = 100 \times \left[\log GDP_t^{interp} - \log GDP_t^{trend}\right]. \tag{10}$$

The interpolation of quarterly to monthly GDP follows the disaggregation method implemented by Sax and Steiner (2013), while the decomposition of the monthly series into trend and cycle

[9]The calibration to 1.9% before July 2021 is in line with point estimates of the ECB's perceived inflation target at the time (see, e.g., Bletzinger and Wieland, 2017).

[10]Alternative specifications using more readily available data, such as the composite PMI or industrial production, lead to similar results.

components results from the filtering method of Hamilton (2018).[11]

The set of potential financial variables are daily traded asset prices. Whereas the estimation makes use of end-of-month values, the FCI can be calculated daily by applying the estimated weights to daily financial data, thereby maximising the usefulness for policy purposes. Four categories of financial variables are assessed for inclusion in the FCI, of which only a subset will make it into the final index: (1) nominal and real risk-free interest rates, with real rates obtained by subtracting the maturity-matching inflation-linked swap rate from the OIS rate; (2) euro area sovereign spreads; (3) risky assets, including corporate bond spreads and various equity price measures; and (4) euro exchange rates against major currencies. The eventual selection of financial variables is guided by data availability, economic relevance, and a deliberate balance between model fit and parsimony. Starting from a large set of variables, including the full term structure of nominal and real interest rates in spot and forward space, several sovereign and corporate bond spreads, different equity price valuation metrics and various euro exchange rates in effective and bilateral terms, the final choice is determined endogenously through the estimation procedure, with the objective of explaining the dynamics of macroeconomic variables and financial conditions as accurately as possible while relying on the smallest feasible set of financial variables.

The data transformation of financial variables is kept to a minimum for the sake of simplicity and comparability between variables. Rates, yields, and spreads are expressed in percent without transformation, while equity valuation ratios and exchange rates are expressed as percentage deviations from their sample means. As a result, the Macro-Finance FCI inherits a meaningful unit and scale measured in percent, facilitating an interpretation that is intuitive and directly comparable to an interest rate.

4.2 Baseline specification

The selection of financial variables cannot be based on a comparison of the joint likelihood in equation (7) for different model specifications because the left-hand side variable F_t that is included in $\tilde{Y}_t$ (resulting from the pre-multiplication of the data vector Y_t with the mapping matrix Γ) changes as the set of financial variables changes. As in any other regression, it is not

[11] The chosen temporal disaggregation method is *Denton-Cholette*. For Hamilton's filter the recommended look-back horizon of two years ($h = 24$) and four lags ($p = 4$) is used as the data is already stationary.

admissible to compare models in terms of fit when the endogenous variable changes. To still guide the variable selection with a measure of fit the model comparison is conducted on the basis of the conditional likelihood of the macro variables alone. The conditional distribution of macroeconomic variables M_t given F_t and X_{t-1} is

$$\mathcal{L}_t^{(M|F)} = -\frac{N}{2}\log(2\pi) - \frac{1}{2}\log\left|\Omega_{M|F}\right| - \frac{1}{2}\left(M_t - \hat{\mu}_t\right)' \Omega_{M|F}^{-1}\left(M_t - \hat{\mu}_t\right), \tag{11}$$

where the conditional moments of the distribution are given by:

$$\hat{\mu}_t = \mu_M + \Phi_M X_{t-1} + \Omega_{M,F}\Omega_{F,F}^{-1}\left(F_t - \mu_F - \Phi_F X_{t-1}\right)$$
$$\Omega_{M|F} = \Omega_{M,M} - \Omega_{M,F}\Omega_{F,F}^{-1}\Omega_{F,M}.$$

The partitioning of $\mu_\bullet$, $\Phi_\bullet$ and $\Omega_{\bullet,\bullet}$ refers to the corresponding elements of M_t and F_t respectively as indicated in the subscripts. The financial variable selection is eventually based on maximising equation (11), whereas the parameters are optimised over equation (8).

The final baseline specification of the Macro-Finance FCI comprises nine asset prices spanning key segments of financial markets. The estimated FCI weights are shown in Table 2, while the corresponding VAR estimates are presented in Table 3 of Section 4.4. Specifically, the new index includes the €STR overnight rate, the 10-year nominal overnight index swap (OIS) rate, the 1-year forward 1-year real OIS rate, and the 5-year real OIS rate. In addition, it incorporates 2-year and 10-year GDP-weighted euro area sovereign bond spreads relative to their OIS benchmarks, investment-grade corporate bond spreads, the cyclically adjusted price-to-earnings (CAPE) ratio for euro area equities, and the nominal effective exchange rate (NEER) of the euro. Appendix A.3 plots the data in Figure A.2 and lists further details about the raw data in Table A.3.

It is evident from the point estimates in Table 2 that risk-free interest rates play a dominant role in shaping financial conditions. Yet, these estimates do not fully reveal the relative importance of each variable for two reasons. First, the coefficients do not sum to one – only their squares do. For comparability with other FCIs, Table 2 and Figure 1 show relative weights that are rescaled to sum to one in absolute terms. The relative weights of the Macro-Finance FCI place much greater emphasis on short-term interest rates than other euro area FCIs do, at the cost of lower relative weights for sovereign spreads, equity valuations and the euro (see

Table 2: Estimates of FCI weights

Variable	Point estimate	Std. Dev.	Relative weight (%)	MVC (%)
€STR	0.631	0.147	25.321	31.739
OIS 10y	0.520	0.221	20.886	23.820
Real OIS 1y1y	0.287	0.222	11.524	9.493
Real OIS 5y	0.351	0.299	14.089	12.385
Sov. spread 2y	0.151	0.214	6.058	0.427
Sov. spread 10y	0.212	0.313	8.494	0.646
Corp. spread	0.227	0.178	9.115	2.609
CAPE	−0.038	0.006	−1.512	−14.745
NEER	0.075	0.016	3.000	4.136

Notes: The point estimate and its standard deviation (based on the outer product of gradients) refer to the estimated weights α, estimated jointly with the VAR coefficients. The relative weight rescales the point estimates so that they sum to one in absolute terms. The marginal variance contribution (MVC) takes the variation and co-movement of variables into account and is also rescaled to sum to one in absolute terms.

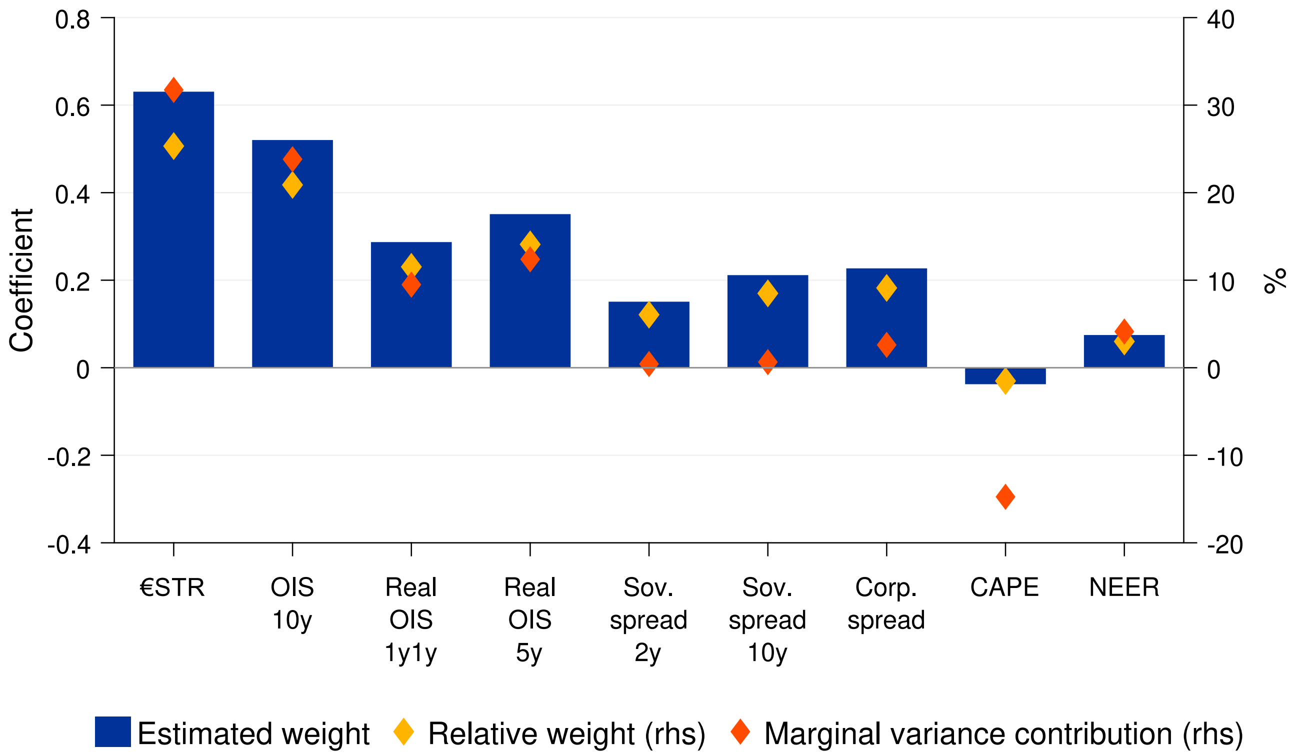
for comparison, Stehn et al., 2019; Arrigoni et al., 2020). Second, the input variables differ in scale and co-movement among each other. For example, a variable with a small coefficient may still contribute significantly to the overall index if it is very volatile or if it is typically associated with changes in other variables. To take these effects into account, the marginal variance contribution (MVC) of variable i measures the change of the FCI's variance if its weight α_i increases, factoring in the covariance of all variables. As the sum of all MVCs adds up to the total variance of the index by definition, the reported values are normalised to shares:

$$\text{MCV}_i = \frac{\alpha_i \left(\alpha' C\right)_i}{\sum_{j=1}^{K} \left| \alpha_j \left(\alpha' C\right)_j \right|} \tag{12}$$

Vector α contains the estimated weights and $C = Cov(Z_t)$ denotes the covariance matrix of financial variables that enter the FCI. This adjustment, shown as red diamonds in Figure 1, reveals in particular that the large volatility of the CAPE ratio makes it account for a substantially larger share of the FCI's variance than suggested by its relatively small coefficient.

Importantly, with regard to the sign of the weights, all estimated weights, except for the CAPE ratio, are positive, implying that an increase in these variables raises the FCI. In economic terms, higher yields, wider spreads and a stronger euro tend to tighten financial conditions in the euro area, whereas higher equity valuations lead to a loosening. In terms of statistical significance, Table 2 suggests that real rates as well as sovereign and corporate spreads are not significant on their own. Yet, a joint test of significance for each group of real

Figure 1: Estimates of FCI weights

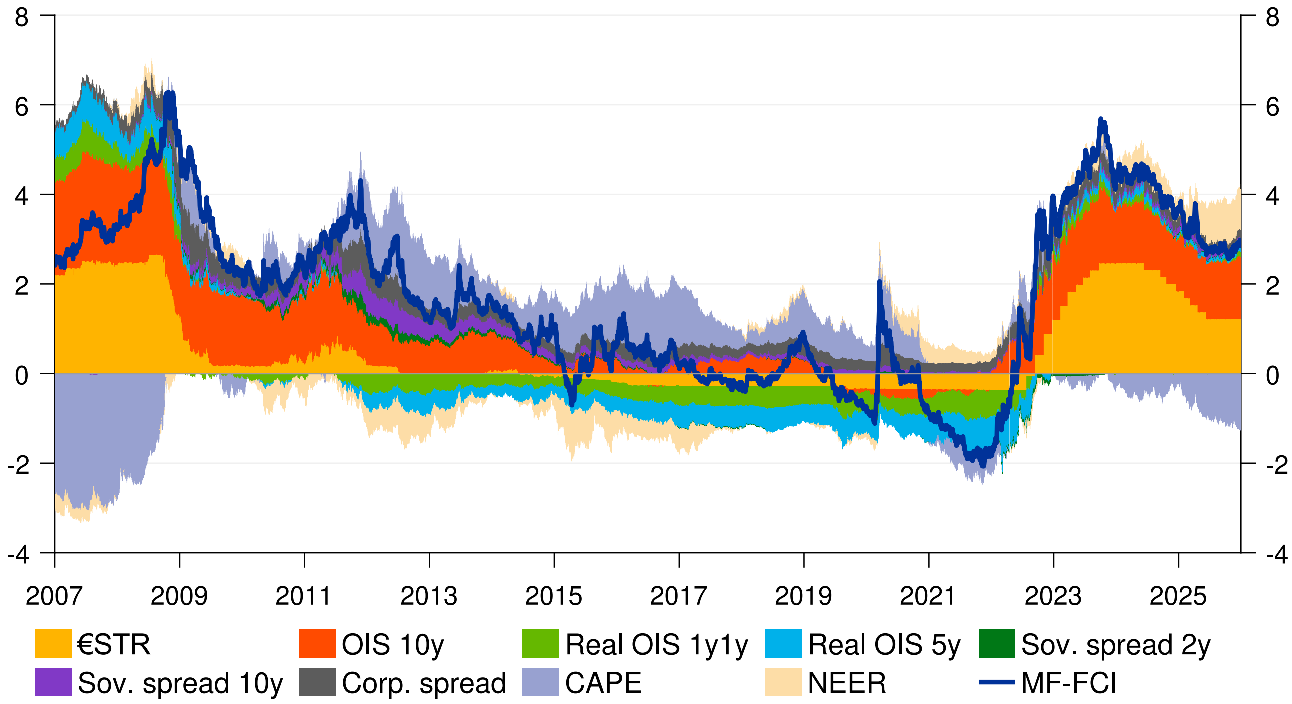


Note: The blue bars show the estimated coefficients of the variables entering the Macro-Finance FCI. Yellow markers show the relative coefficients and red diamonds the marginal variance contribution to the overall variation of the FCI, both normalised to sum to one in absolute terms.

rates and spreads rejects their exclusion from the FCI. In fact, both real rates and spreads played a particular role during a subset of the estimation sample. Adding real rates on top of nominal rates ensures that the FCI reflects looser financial conditions than would be implied by nominal rates alone while they were constrained by the lower bound.

The resulting estimated Macro-Finance FCI provides an intuitive time series of financial conditions in the euro area and a meaningful decomposition into its constituent variables over time. Figure 2 plots the Macro-Finance FCI and its decomposition in daily frequency from 2007 until 2025, obtained by applying the estimated coefficients of the monthly model to daily observations of the constituent variables. The €STR sets the general direction of the index, except during the effective lower bound episode, when the 10-year OIS rate captured the accommodative effects of forward guidance and quantitative easing, and real rates gained importance. In late 2021, as inflation accelerated, the FCI reached its historical trough, before rising sharply ahead of the first interest rate hike in July 2022. The two most pronounced peaks occurred in late 2008, preceding the global financial crisis, and in late 2023, following the decline of euro area inflation from its peak in October 2022, consistent with the broader monetary policy

Figure 2: The Macro-Finance FCI and its decomposition



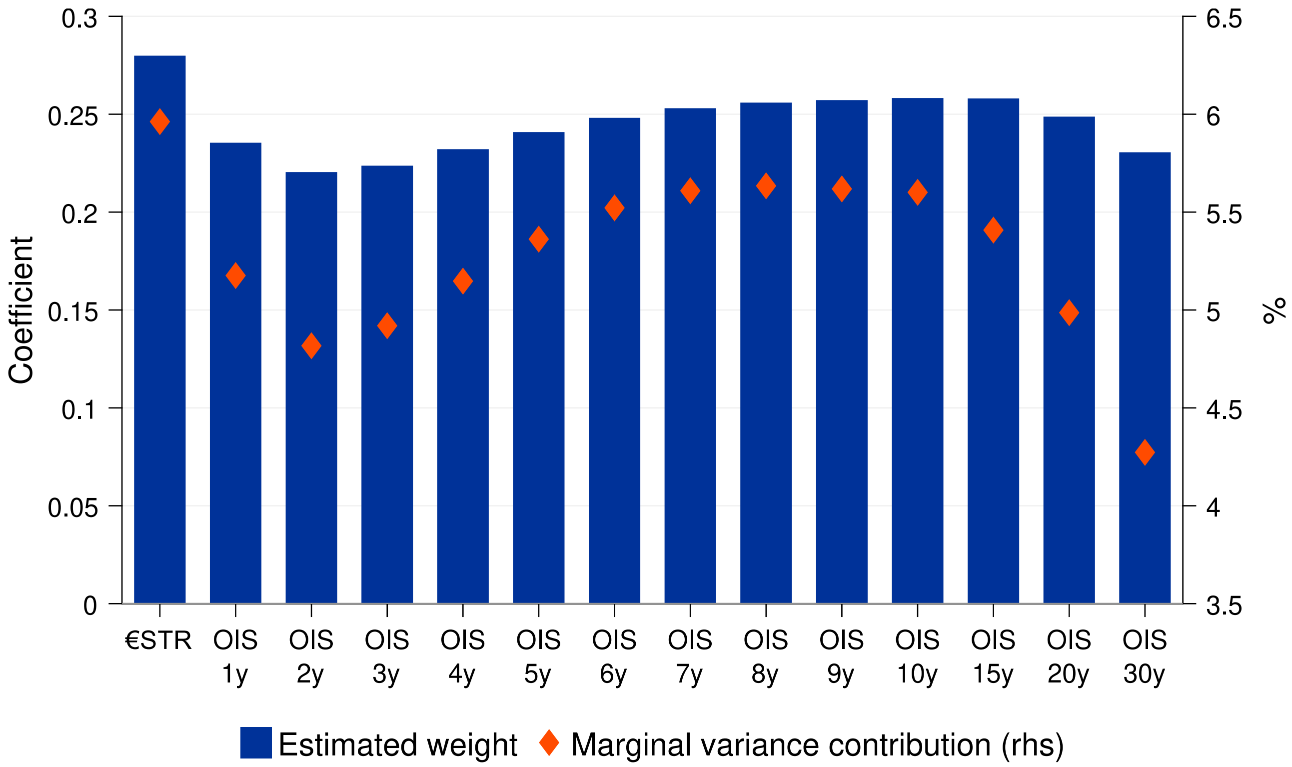
Note: The chart shows the daily Macro-Finance FCI and its decomposition obtained by applying the parameters of the monthly model estimated over January 2007 to December 2025 to daily data.

cycle. Sovereign and corporate bond spreads made their strongest contributions in 2012 during the European sovereign debt crisis. Equity valuations substantially eased financial conditions ahead of the global financial crisis and again more recently, although they exerted a tightening effect during much of the interim decade. The euro contributed predominantly negatively to financial conditions until 2018 but exerted thereafter a tightening influence, with a particularly strong effect over 2025, reflecting its sharp appreciation against the US dollar amid trade tensions. Overall, the estimated dynamics of the Macro-Finance FCI, together with its scale and unit, make it comparable to a policy rate and suggest an interpretation as a broader stance measure or as a shadow policy rate during the lower bound episode.

4.3 Alternative specifications

The one-step estimation approach makes it straightforward to conduct one-off exercises to examine the selection of financial variables and their average effects. Two such exercises are presented here. A recurring policy question, for instance, revolves around which asset prices matter most for the transmission of monetary policy decisions to the real economy. While the selection of financial variables and their weights in the baseline specification already provide

Figure 3: Term structure of nominal coefficients

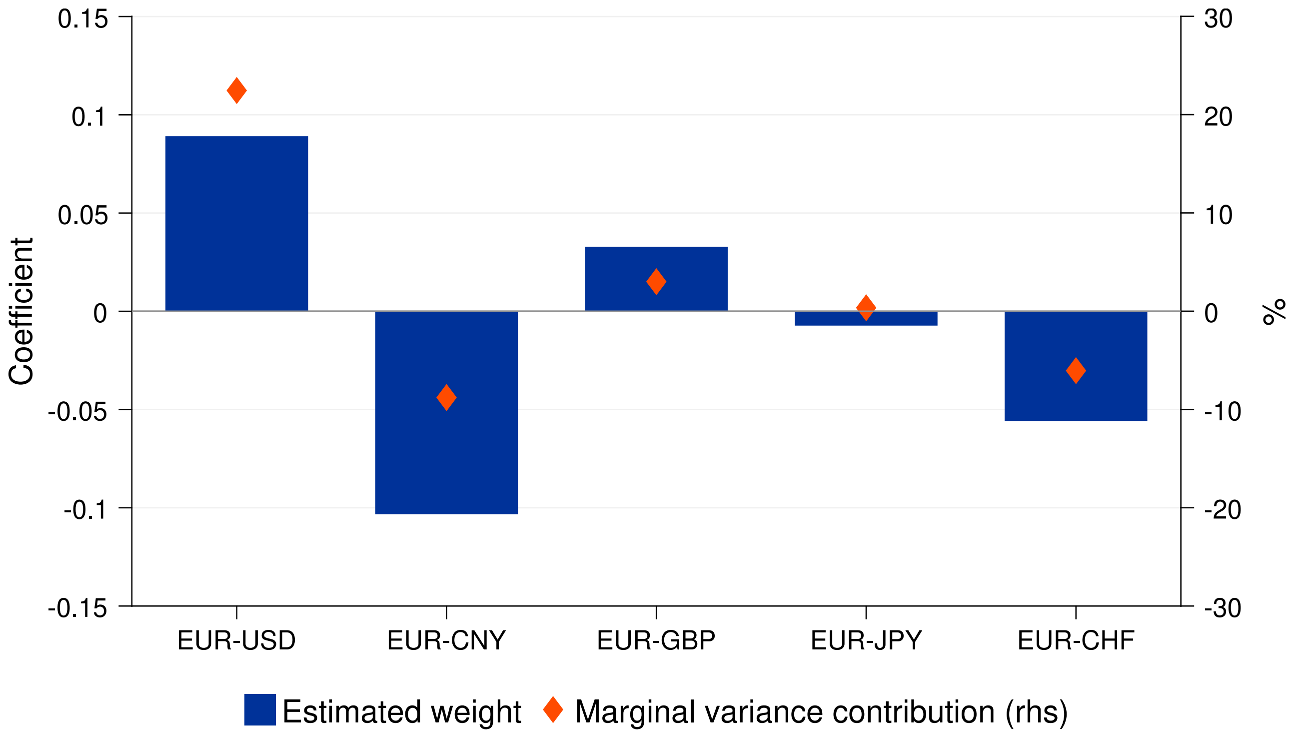


Note: Estimated coefficients are obtained from an extended version of the baseline specification of the MF-FCI, including the full term structure of nominal rates. Red diamonds show the marginal variance contribution to the overall variation of the MF-FCI, normalised to sum to one in absolute terms.

a first answer to this question, an extended specification includes the full term-structure of nominal OIS rates up to 30 years. This extension illustrates the advantage of the one-step estimation approach which helps the researcher in the selection of variables. Figure 3 shows that the coefficients along the term structure obey a bi-modal shape. The overnight maturity receives the highest weight, whereas the second peak occurs at the 10-year maturity. When comparing marginal variance contributions to account for variation and co-movements across variables, the ordering along the term structure remains, albeit with smaller differences. Even though clearly all maturities influence financial conditions, once the €STR and the 10-year OIS rate are included, the additional explanatory power of the remaining maturities does not justify their inclusion in the baseline index – following the variable selection explained around equation (11) in Section 4.2. Due to the high multi-collinearity of nominal rates, incorporating the full term structure would require a stronger shrinkage via the generalised ridge penalty without improving the conditional likelihood of the macro variables. The other variables in the baseline specification are selected through similar steps.

Another type of exercise helps understand the coefficients of the baseline. These coefficients

Figure 4: Coefficients of bilateral exchange rates



Note: Estimated coefficients are obtained from an extended version of the baseline specification of the MF-FCI, substituting the NEER with bilateral exchange rates of the euro. Red diamonds show the marginal variance contribution to the overall variation of the MF-FCI, normalised to sum to one in absolute terms.

do not only resemble average effects over the sample from 2007 until 2025, but possibly also across underlying variables. In the case of the NEER, another model specification substitutes it with bilateral exchange rates of the euro (Figure 4). The positive average coefficient of the NEER is primarily driven by the EUR-USD, pointing to the importance of the USD for global financial markets and the relevance of a stronger euro relative to the US dollar (higher EUR-USD) as dampener of the domestic economy via lower exports to the US. A stronger euro relative to Chinese renminbi (higher EUR-CNY) makes imports from China less expensive, indicating a loosening of financial conditions. A stronger Swiss Franc (lower EUR-CHF) is associated with a global flight-to-safety, adding to a tightening of financial conditions.

4.4 Neutral benchmark

The joint estimation of the macro-finance VAR delivers the estimated weights shown in Table 2 of Section 4.2 as well as the VAR coefficients shown in Table 3. With these estimates at hand, standard VAR techniques are applicable for inference. Importantly, the parameter uncertainty of the VAR coefficients are linked to the uncertainty of the FCI weights via their

Table 3: Estimates of VAR coefficients

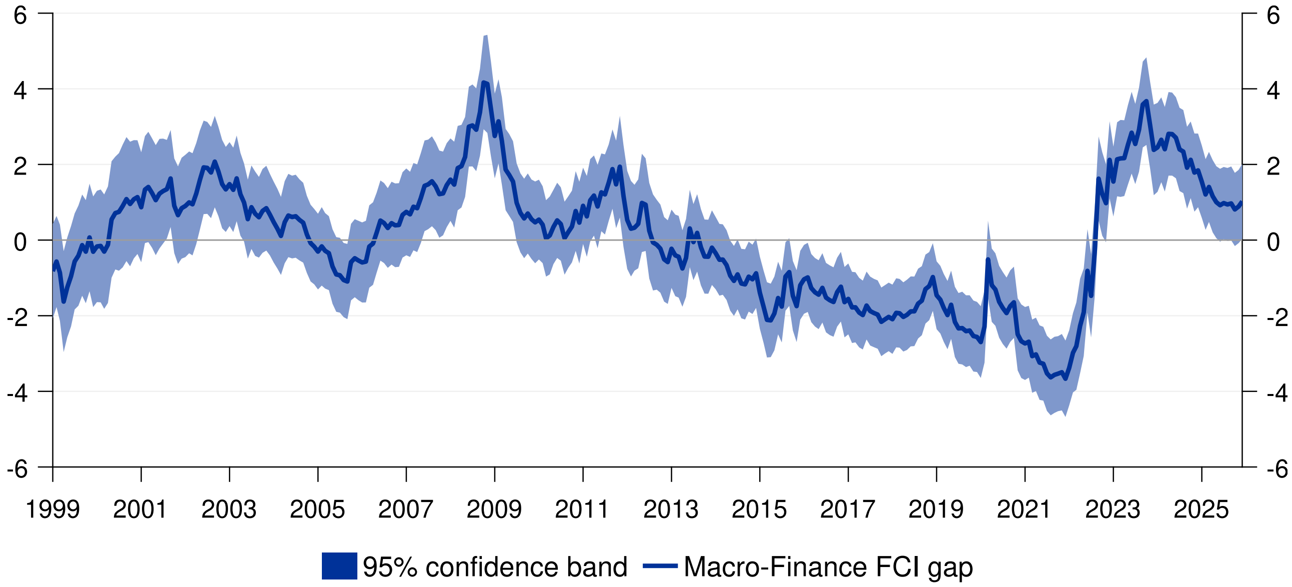
Variable	HICP	GDP	FCI
HICP(-1)	1.1800	0.2264	0.1204
	(0.071)	(0.176)	(0.119)
GDP(-1)	0.0333	1.3780	0.0319
	(0.026)	(0.039)	(0.039)
FCI(-1)	−0.0665	−0.1985	0.8699
	(0.075)	(0.158)	(0.098)
HICP(-2)	−0.1891	−0.1230	−0.0631
	(0.072)	(0.177)	(0.121)
GDP(-2)	−0.0300	−0.4787	−0.0183
	(0.019)	(0.034)	(0.038)
FCI(-2)	0.0130	0.0905	0.0959
	(0.076)	(0.151)	(0.095)
constant	0.0970	0.2149	0.0655
	(0.040)	(0.122)	(0.053)
Model mean	−0.0748	0.0961	1.8290
	(0.604)	(0.902)	(0.555)

Notes: The shown VAR coefficients are the point estimates obtained from a joint estimation with FCI weights over the monthly sample from 2007 until 2025. The model mean refers to the implied unconditional mean of the VAR. Numbers in parentheses denote standard deviations of the parameter estimation uncertainty obtained via the outer product of gradients.

joint estimation. Thus, any inference reflects the entire uncertainty of the model. This full incorporation of the mutual feedback between the VAR coefficients and the FCI weights is unique among existing FCI estimation techniques.

The VAR setup makes it possible to calculate the unconditional mean as implied by the model estimates. For the inflation gap and the output gap, the estimated model mean is close to zero. Together with their wide estimation uncertainty (shown in parentheses in Table 3), the model means confirm the interpretation of inflation and output as gaps from their target and potential, respectively. For the FCI, the model mean turns out to be 1.83%. The value as such has little meaning as it resembles an average of each of the nine constituent variables in the FCI. The current approach does not try to pin down a neutral level for each variable, which may not even exist for some or may be unobservable and time-varying for others, such as the short-term neutral rate i^* and its real counterpart, the natural rate r^*. What is more important is that the model mean provides a benchmark level for the overall FCI to judge

Figure 5: The Macro-Finance FCI in deviation from neutral



Note: The chart plots the monthly Macro-Finance FCI in deviation from its model-implied neutral benchmark (the level to which the FCI converges when inflation is at target and output is at potential) together with parameter estimation uncertainty obtained by the delta method. Values before the estimation sample from 2007 to 2025 are calculated back and make use of backcasted real rates taken from Burban and Schupp (2023).

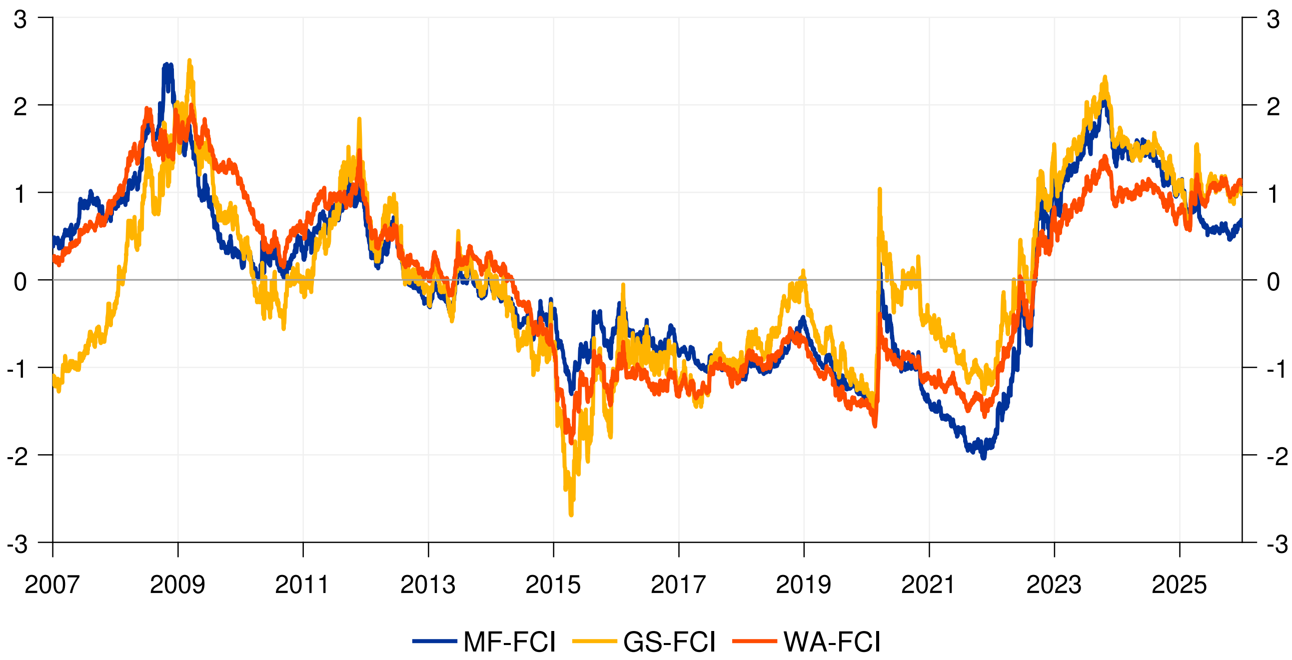
whether financial conditions are loose or tight for macroeconomic dynamics. Without this benchmark, the level of the FCI would be difficult to interpret in those terms. Caballero et al. (2025) present a similar concept of a neutral FCI, yet in a semi-structural macro model in the spirit of Laubach and Williams (2003). The VAR setup makes the notion of the model mean as neutral benchmark very intuitive because it is the value to which the FCI converges as the inflation and output gaps are closed – that is, as inflation is at target and output at potential. Figure 5 plots the Macro-Finance FCI in deviation from its model-implied long-run mean together with a confidence band, reflecting parameter estimation uncertainty of all parameters in the model. Thus, the confidence band expresses uncertainty about both the estimated FCI and its estimated neutral benchmark. The FCI is shown in monthly frequency and calculated back until the inception of the euro in 1999, which requires backcasts of real rates before 2006 taken from Burban and Schupp (2023). In terms of statistical significance, financial conditions are estimated to have been clearly tighter than neutral after the global financial crisis and clearly looser than neutral between 2015 and 2021. In the wake of the inflation surge in 2022, the estimated FCI marked a strong tightening, before converging closer towards neutral by the end of 2025.

One caveat in the interpretation is that the model mean, by construction of the VAR, is constant and cannot reflect changing neutral levels over time. This is why the dynamics of the FCI over time provide a clearer and less disputable guidepost of financial conditions than the distance to the neutral benchmark. Also, the FCI can be at neutral even if some constituent variables are not believed to be at their neutral levels as long as their tightening and loosening effects offset each other.

4.5 Model comparison

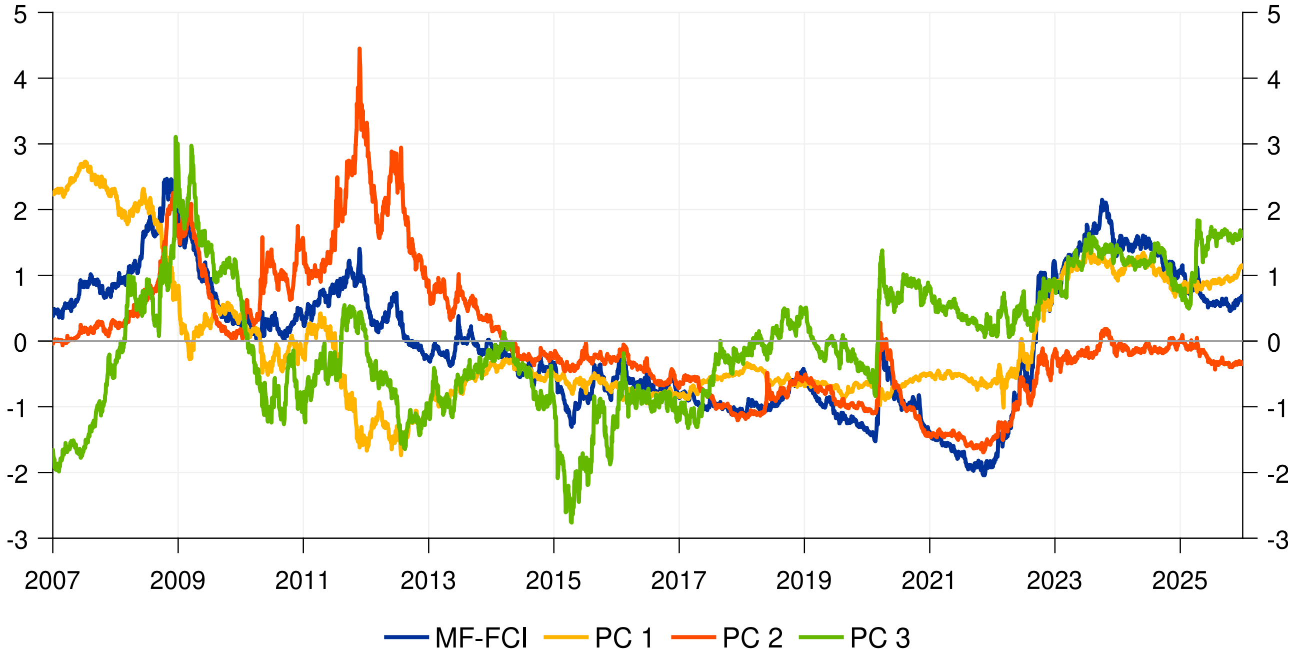
The Macro-Finance FCI co-moves closely with other readily-available euro area FCIs – specifically, the Goldman Sachs FCI (GS-FCI) based on Stehn et al. (2019) and the weighted-average FCI (WA-FCI) developed by Arrigoni et al. (2020). Two notable exceptions are the run up to the global financial crisis and the recent inflation surge, during which the Macro-Finance FCI tightened the most from historically loose levels (Figure 6). For most of the sample, it shows the least volatile daily changes of the three indices, reflecting its relatively lower weights on equity prices and the euro exchange rate, the explicit inclusion of real interest rates, and a comparatively higher weight on the policy rate. At the same time, the Macro-Finance FCI captures the rapid tightening from record-low levels in late 2022 more distinctly. The pairwise

Figure 6: Comparison with other FCIs



Note: The chart compares the daily Macro-Finance FCI with the Goldman Sachs euro area FCI (GS FCI) by Stehn et al. (2019) and the Weighted Average-FCI (WA-FCI) by Arrigoni et al. (2020). All FCIs are normalised to a z-score over the shown sample.

Figure 7: Comparison with PCA



Note: The chart plots the daily Macro-Finance FCI and the first three principal components extracted from the financial variables entering the FCI. All series are normalised to a z-score over the shown sample.

correlations are high and stand at 0.93 with the WA-FCI and 0.83 with the GS-FCI. In terms of daily changes, the pairwise correlation declines to around 0.7 with both.

As discussed in Section 3.1, the Macro-Finance VAR resembles similarities with a principal component analysis, with the major difference that the weights of the FCI are not only estimated to explain the variation within financial variables but also to explain macroeconomic dynamics. A comparison with a simple principal component analysis of the underlying financial variables shows that the Macro-Finance FCI largely spans the first three principal components (Figure 7). Its pairwise correlation with the first two principal components is 0.67 and 0.64, respectively, and only 0.43 with the third. The Macro-Finance FCI co-moves with the first principal component over medium-run swings – most notably around the global financial crisis and again during the 2022–24 tightening. Sudden and sharp movements line up with the second and third principal components, especially during the euro area sovereign debt episode (2011–12) and the early pandemic. The pairwise correlation of daily changes is generally lower and highest for the second, middle for the third and lowest for the first principal component. Outside such stress episodes the Macro-Finance FCI is smoother than the individual principal components, but during the inflation surge it rises more than any of them. Overall, the Macro-Finance FCI behaves like a low-noise combination of a level factor (first principal component)

Table 4: Comparison of forecasting performance

	MSFE				APL			
	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
Headline inflation								
€STR	1.06	1.10	1.15	1.17	0.98	0.92	0.92	0.95
GS-FCI	1.02	1.04	1.06	1.07	0.99	0.95	0.91	0.92
WA-FCI	1.03	1.07	1.11	1.12	0.99	0.94	0.92	0.95
PC1	1.05	1.10	1.15	1.16	0.98	0.92	0.89	0.93
PC2	1.03	1.07	1.11	1.13	1.01	0.98	0.97	0.98
PC3	1.06	1.10	1.15	1.17	0.98	0.92	0.87	0.92
MF-FCI	0.50	0.86	1.19	1.55	0.77	0.43	0.32	0.24
Output gap								
€STR	1.05	1.08	1.09	1.12	0.97	1.01	1.01	1.00
GS-FCI	1.02	1.02	1.02	1.02	0.93	0.92	0.90	0.90
WA-FCI	1.02	1.02	1.02	1.00	0.95	0.96	0.97	0.97
PC1	1.04	1.06	1.06	1.08	0.97	1.01	1.01	1.01
PC2	1.00	1.01	1.01	1.00	1.00	1.03	1.06	1.07
PC3	1.03	1.06	1.07	1.10	0.97	1.00	0.99	0.99
MF-FCI	1.13	2.24	3.22	3.54	0.41	0.21	0.14	0.12

Notes: The table compares the Mean Squared Forecast Error (MSFE) and the Average Predictive Likelihood (APL). The values for the Macro-Finance FCI show the actual performance, whereas all other values are in relative terms to it. A relative MSFE above 1 and a relative APL below 1 indicate a relatively worse performance. The training sample is from January 2007 to March 2021 (75% of the estimation sample), leaving April 2021 to December 2025 for the evaluation sample. The forecast horizon is one to four months ahead.

with a transitory slope or stress component (second and third principal components). Akin to this notion, Lombardi et al. (2025) identify a two-factor FCI for the euro area, comprising a level and stress contribution.

Concerning the comparison of fit of macroeconomic variables when replacing the estimated Macro-Finance FCI with other FCIs or principal components in the VAR, the in-sample fit is by design the highest for the Macro-Finance FCI. The FCI weights are estimated to create the linear combination of financial variables that delivers the best fit of the included macroeconomic variables and financial conditions. A more suitable test for comparing different FCIs is an out-of-sample forecast exercise. Table 4 reports the forecasting performance for both headline inflation and the output gap, with the accuracy measured using the mean squared forecast error (MSFE) and the average predictive likelihood (APL) in relative terms to the performance of the Macro-Finance FCI. The evaluation is conducted for forecasts one to four months ahead. The table also includes the first three principal components and the plain €STR, which is a special case of setting the weight of the €STR equal to one in the new framework. The Macro-Finance FCI consistently outperforms all other measures. The MSFE is the lowest for both headline inflation and the output gap at any horizon, while the APL is the highest for both variables at almost all horizons. The superior performance supports the innovative methodology underlying the Macro-Finance FCI approach, which fully incorporates the mutual feedback between macroeconomic and financial variables.

4.6 Structural identification

To obtain a structural interpretation of the VAR, its residuals are identified as economic shocks with sign and zero restrictions that are common to the literature. Following standard techniques, the estimated reduced-form covariance matrix $\tilde{\Omega}$ of equation (3) is decomposed into a lower Cholesky matrix L such that $LL' = \tilde{\Omega}$. Any row-orthonormal matrix Q can be used to rotate L without invalidating the reduced-form estimates as $LQ(LQ)' = L(QQ')L' = LL' = \tilde{\Omega}$.

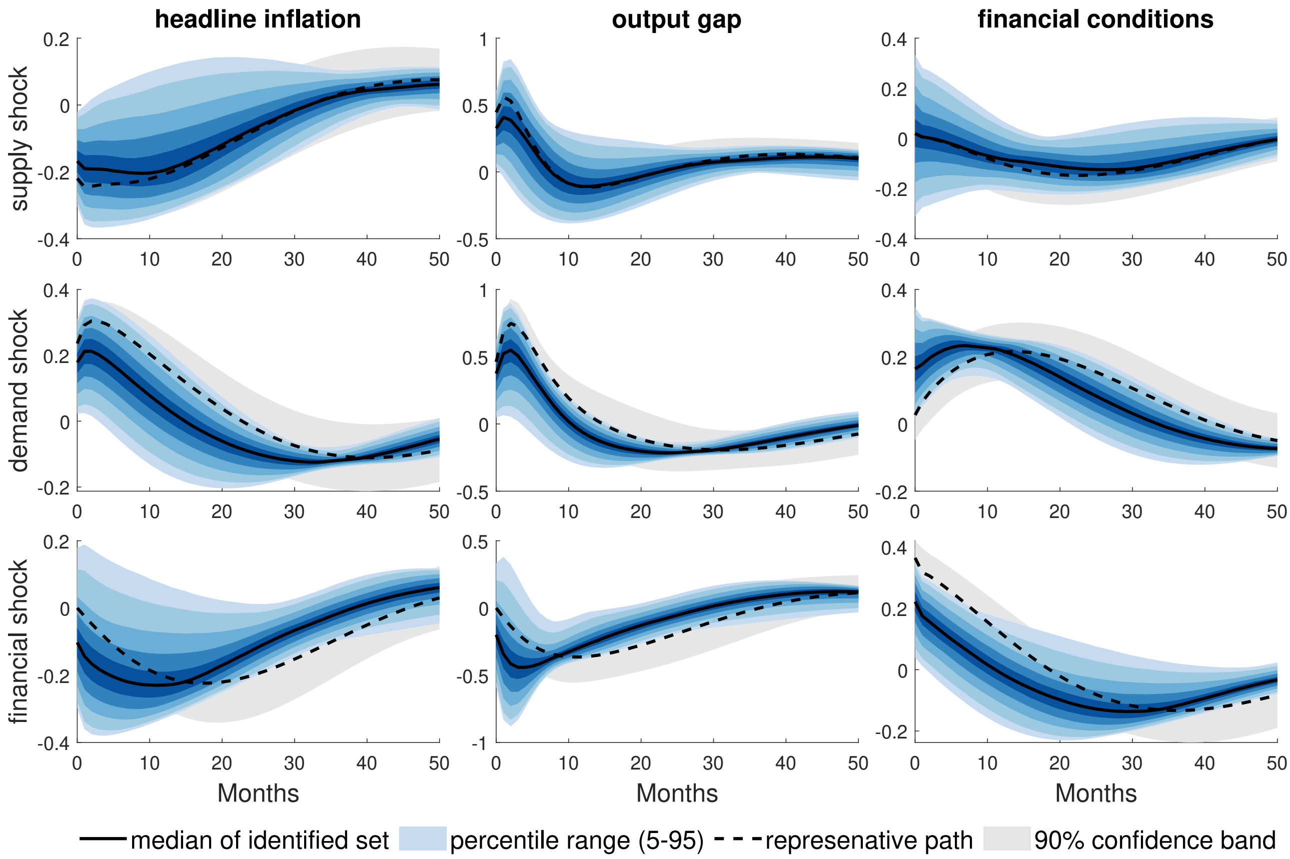
In a first step, a feasible set of random rotation matrices Q is obtained by defining two structural shocks. A shock to which inflation and output react with opposite sign on impact is classified as supply shock, leaving financial conditions unconstrained to tolerate the notion of a looking-through reaction. A shock to which inflation and output as well as financial conditions react with the same sign on impact is classified as demand shock. The third shock is unidentified at this stage. Figure 8 shows the median and percentiles of the identified set of impulse responses based on 10,000 successful random draws of Q. The third row referring to the yet unidentified shock is indicative that this shock bears similarities with a monetary policy shock or, in the case of financial conditions, to a financial shock more broadly. Headline inflation and the output gap tend to move in opposite direction to financial conditions, which is a result of the model and is not imposed. In a second step, the economic interpretation of the third shock as financial shock is sharpened by imposing zero restrictions for inflation and

Table 5: Structural identification scheme

	headline inflation	output gap	financial conditions
supply shock	-	+	?
demand shock	+	+	+
financial shock	0	0	+

Notes: The table reports the scheme to identify structural shocks. A +, −, or 0 imply a positive, negative or no reaction on impact to the indicated shock, whereas a ? imposes no constraint.

Figure 8: Structural impulse responses

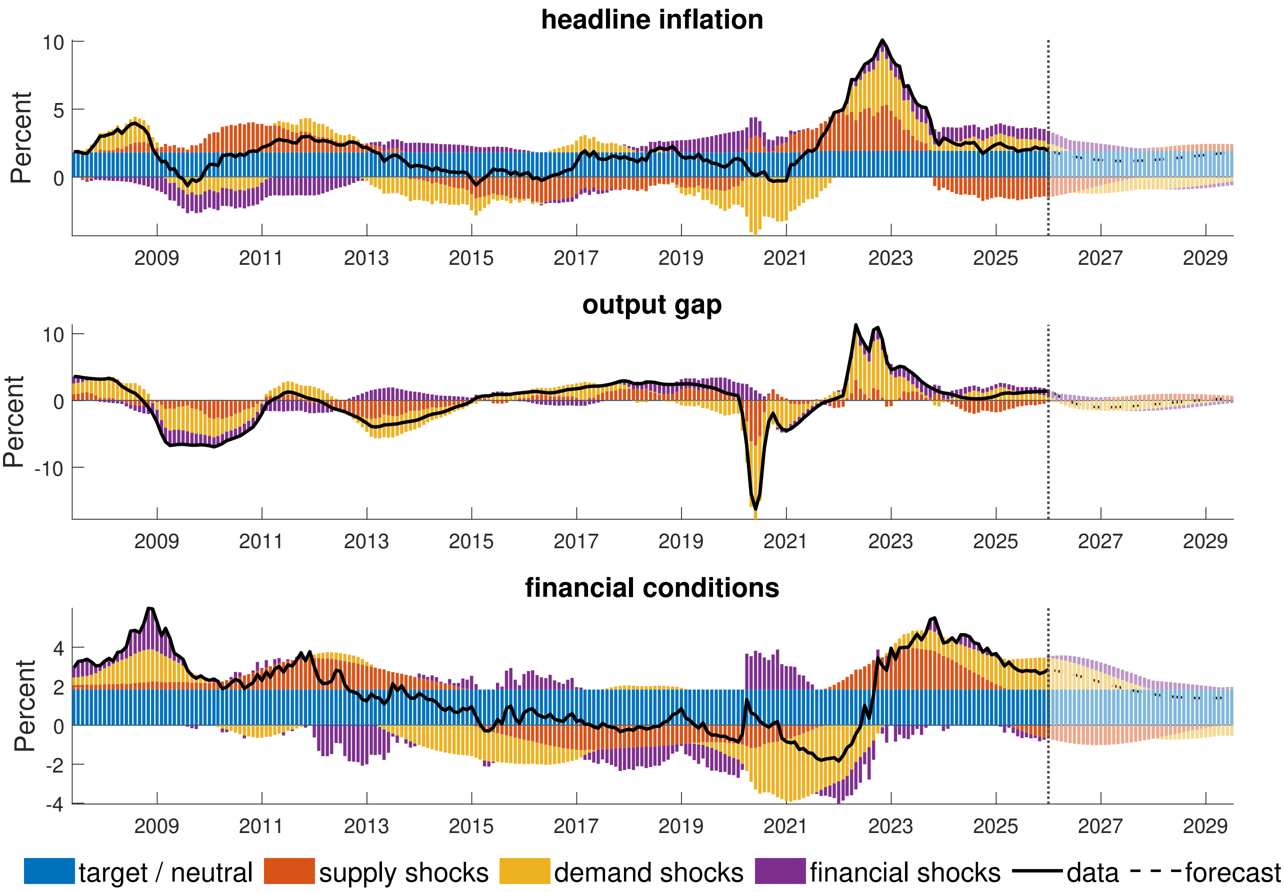


Note: The chart plots impulse responses to supply, demand, and financial shocks, respectively, of one standard deviation. The median and percentile ranges refer to the identified set of supply and demand shocks using sign restrictions (with the third shock unidentified), whereas the representative path adds zero restrictions to identify the financial shock. The confidence band shows the parameter estimation uncertainty of the representative path.

output on impact of the shock. The representative path in Figure 8 is the single draw of Q that is closest in a least-square sense to the median of impulse responses from all rotation matrices that satisfy both sign and zero restrictions (see Table 5). The confidence bands refer to the estimation uncertainty of the representative path based on the parameter uncertainty of VAR coefficients and FCI weights, using the outer product of gradients.

Looking at the representative path in Figure 8, a supply shock of one standard deviation leads to an immediate and persistent decline of headline inflation by about 0.2 percentage points, whereas the output gap increases by up to 0.5 percentage points with less persistency. Financial conditions do neither tighten nor loosen, strengthening their interpretation as a broader monetary policy stance that looks through supply shocks. Based on the estimated dynamics, inflation and output stabilise without an extra impulse from financial conditions as the supply shock fades. By contrast, a demand shock leads to similar reactions of inflation and

Figure 9: Historical decompositions



Note: The shocks are identified with sign and zero restrictions. The initial conditions of the decomposition are distributed across shocks according to their share in the long-run Forecast Error Variance Decomposition. The forecast is made as of end-2025, assuming no further shocks. Headline inflation includes the ECB's target.

output in terms of magnitude and dynamics but with the sign of inflation aligned to output. As a result, financial conditions clearly tighten, yet with some lagged response. The tightening peaks at 0.2 percentage points after about a year. Financial conditions take some time to fully incorporate the shock and then accompany the fading out of the demand shock so as to stabilise inflation and output. Finally, a financial shock leads to an immediate tightening of financial conditions of around 0.4 percentage points. By design, inflation and output show no reaction on impact, but both decline visibly over time as the financial shock is being transmitted through the economy. The trough of the inflation response is at -0.2 percentage points and for the output gap at -0.4 percentage points. Consistent with economic reasoning and findings in the literature, the full transmission to the output gap takes up to one year, while the reaction of inflation bottoms out roughly one additional year later.

The impulse responses provide a good understanding of the general economic relationships between the variables and the structural shocks in the VAR. To learn the actual relevance of each shock as a driver of the variables in the economy over time, the residuals of the estimated VAR can be used to back out the time series of structural shocks corresponding to each successful rotation matrix Q. The resulting historical decomposition of the VAR is plotted in Figure 9 and is based on the average of successful rotations. A number of explanatory messages stand out. The global financial crisis marked a strong financial crisis which put a strain on inflation and output in the years thereafter. Throughout the lower bound episode, accommodative financial shocks increasingly supported real activity and subsequently inflation. The Covid-19 pandemic was characterised by a mix of strongly negative demand and supply shocks as well as strongly restrictive financial shocks, with the latter quickly turning accommodative. During the inflation surge, supply and demand shocks dominated, while financial shocks subsided.

Finally, the VAR and its historical decomposition can be used to construct forecasts as of the end of the estimation sample in December 2025. At that point in time, the fading out of demand and supply shocks point to a mild future decline of output and inflation below target as well as to a continuation of a decline of financial conditions towards neutral.

5 Conclusion

This paper develops a new method for estimating a financial conditions index by embedding the index directly into a macro-finance VAR model and estimating its weights jointly with the VAR coefficients in a joint estimation step. This approach provides several benefits. First, it ensures a model-consistent macro–finance feedback: the index is identified to explain the joint dynamics of macroeconomic variables and financial conditions, rather than being linked to macroeconomic outcomes only ex-post or via separated sub-models. Second, it enhances interpretability. The contribution of each financial variable is transparent via the estimated weights and the index inherits a meaningful unit and scale, similar to a policy rate. Third, it improves tractability. In endogenously collapsing a large set of financial variables into a single index, the approach mitigates multi-collinearity issues while preserving a cross-equation coherence. Fourth, the estimation within a VAR makes standard inference techniques possible. The unconditional mean of the VAR serves as benchmark in which inflation is at target, output at potential and financial conditions at neutral.

Empirically, the estimated Macro-Finance FCI for the euro area spans key asset classes and, even though estimated with monthly frequency, can be applied to daily financial data for real-time policy purposes. The decomposition is economically intuitive: policy rate movements set the broad direction outside the lower bound episode, while long-term and real rates, credit spreads, equity valuations and the euro affect financial conditions consistent with major euro area macroeconomic events. The new FCI also beats other euro area FCIs in out-of-sample forecasts. A structural identification of supply, demand and financial shocks reveals that financial conditions require up to one year to transmit to the real economy and almost up to two years to inflation.

The new framework lends itself for a number of further refinements. The set of macroeconomic and financial variables can be easily broadened within this straightforward estimation setup. Also the estimation of a Macro-Finance FCI for other economies is a worthwhile consideration. It would also be of great interest to study whether the FCI weights differ over time, depending on the economic environment. Finally, the estimation technique can be applied to derive other indices, for example related to financial stability. We leave these considerations for future work.

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Appendix

A.1 Illustration

For full clarity about the dimension reduction presented around equation (3), we illustrate the mathematical steps in a small fictional macro-finance VAR of one macro variable and two financial variables and with one lag. The two financial variables shall be weighted and summed to make up a financial conditions index. The illustration easily extends to several macro and financial variables and more lags. The VAR uses the same specifications as in the main text.

$$Y_t = \mu + \Phi Y_{t-1} + \Sigma e_t \tag{A.1}$$

$$Y_t = \begin{pmatrix} \pi_t \\ i_t \\ r_t \end{pmatrix} = \begin{pmatrix} \mu_\pi \\ \mu_i \\ \mu_r \end{pmatrix} + \begin{pmatrix} \phi_{\pi,\pi} & \phi_{\pi,i} & \phi_{\pi,r} \\ \phi_{i,\pi} & \phi_{i,i} & \phi_{i,r} \\ \phi_{r,\pi} & \phi_{r,i} & \phi_{r,r} \end{pmatrix} \begin{pmatrix} \pi_{t-1} \\ i_{t-1} \\ r_{t-1} \end{pmatrix} + \begin{pmatrix} \sigma_{\pi,\pi} & \sigma_{\pi,i} & \sigma_{\pi,r} \\ \sigma_{i,\pi} & \sigma_{i,i} & \sigma_{i,r} \\ \sigma_{r,\pi} & \sigma_{r,i} & \sigma_{r,r} \end{pmatrix} \begin{pmatrix} e_t^\pi \\ e_t^i \\ e_t^r \end{pmatrix} \tag{A.2}$$

Pre-multiply equation (A.2) with the appropriately defined mapping matrix Γ to get $\Gamma Y_t = \tilde{Y}_t$:

$$\begin{aligned} \underbrace{\begin{pmatrix} 1 & 0 & 0 \\ 0 & \alpha_i & \alpha_r \end{pmatrix}}_{\Gamma} \begin{pmatrix} \pi_t \\ i_t \\ r_t \end{pmatrix} = & \begin{pmatrix} 1 & 0 & 0 \\ 0 & \alpha_i & \alpha_r \end{pmatrix} \begin{pmatrix} \mu_\pi \\ \mu_i \\ \mu_r \end{pmatrix} + \begin{pmatrix} 1 & 0 & 0 \\ 0 & \alpha_i & \alpha_r \end{pmatrix} \begin{pmatrix} \phi_{\pi,\pi} & \phi_{\pi,i} & \phi_{\pi,r} \\ \phi_{i,\pi} & \phi_{i,i} & \phi_{i,r} \\ \phi_{r,\pi} & \phi_{r,i} & \phi_{r,r} \end{pmatrix} \begin{pmatrix} \pi_{t-1} \\ i_{t-1} \\ r_{t-1} \end{pmatrix} \\ & + \begin{pmatrix} 1 & 0 & 0 \\ 0 & \alpha_i & \alpha_r \end{pmatrix} \begin{pmatrix} \sigma_{\pi,\pi} & \sigma_{\pi,i} & \sigma_{\pi,r} \\ \sigma_{i,\pi} & \sigma_{i,i} & \sigma_{i,r} \\ \sigma_{r,\pi} & \sigma_{r,i} & \sigma_{r,r} \end{pmatrix} \begin{pmatrix} e_t^\pi \\ e_t^i \\ e_t^r \end{pmatrix} \end{aligned} \tag{A.3}$$

$$
\begin{aligned}
\Leftrightarrow \quad \begin{pmatrix} \pi_t \\ \alpha_i i_t + \alpha_r r_t \end{pmatrix} = \; & \begin{pmatrix} \mu_\pi \\ \alpha_i \mu_i + \alpha_r \mu_r \end{pmatrix} \\
& + \begin{pmatrix} \phi_{\pi,\pi} & \phi_{\pi,i} & \phi_{\pi,r} \\ \alpha_i \phi_{i,\pi} + \alpha_r \phi_{r,\pi} & \alpha_i \phi_{i,i} + \alpha_r \phi_{r,i} & \alpha_i \phi_{i,r} + \alpha_r \phi_{r,r} \end{pmatrix} \begin{pmatrix} \pi_{t-1} \\ i_{t-1} \\ r_{t-1} \end{pmatrix} \\
& + \begin{pmatrix} \sigma_{\pi,\pi} & \sigma_{\pi,i} & \sigma_{\pi,r} \\ \alpha_i \sigma_{i,\pi} + \alpha_r \sigma_{r,\pi} & \alpha_i \sigma_{i,i} + \alpha_r \sigma_{r,i} & \alpha_i \sigma_{i,r} + \alpha_r \sigma_{r,r} \end{pmatrix} \begin{pmatrix} e_t^\pi \\ e_t^i \\ e_t^r \end{pmatrix} \qquad \text{(A.4)}
\end{aligned}
$$

$$
\begin{aligned}
\Leftrightarrow \quad \begin{pmatrix} \pi_t \\ \alpha_i i_t + \alpha_r r_t \end{pmatrix} = \; & \begin{pmatrix} \mu_\pi \\ \alpha_i \mu_i + \alpha_r \mu_r \end{pmatrix} \\
& + \begin{pmatrix} \phi_{\pi,\pi} \pi_{t-1} + \frac{\phi_{\pi,i}}{\alpha_i} \alpha_i i_{t-1} + \frac{\phi_{\pi,r}}{\alpha_r} \alpha_r r_{t-1} \\ (\alpha_i \phi_{i,\pi} + \alpha_r \phi_{r,\pi}) \pi_{t-1} + \frac{\alpha_i \phi_{i,i} + \alpha_r \phi_{r,i}}{\alpha_i} \alpha_i i_{t-1} + \frac{\alpha_i \phi_{i,r} + \alpha_r \phi_{r,r}}{\alpha_r} \alpha_r r_{t-1} \end{pmatrix} \\
& + \begin{pmatrix} \sigma_{\pi,\pi} e_t^\pi + \frac{\sigma_{\pi,i}}{\alpha_i} \alpha_i e_t^i + \frac{\sigma_{\pi,r}}{\alpha_r} \alpha_r e_t^r \\ (\alpha_i \sigma_{i,\pi} + \alpha_r \sigma_{r,\pi}) e_t^\pi + \frac{\alpha_i \sigma_{i,i} + \alpha_r \sigma_{r,i}}{\alpha_i} \alpha_i e_t^i + \frac{\alpha_i \sigma_{i,r} + \alpha_r \sigma_{r,r}}{\alpha_r} \alpha_r e_t^r \end{pmatrix} \qquad \text{(A.5)}
\end{aligned}
$$

$$
\begin{aligned}
\Leftrightarrow \quad \begin{pmatrix} \pi_t \\ \alpha_i i_t + \alpha_r r_t \end{pmatrix} = \; & \begin{pmatrix} \mu_\pi \\ \alpha_i \mu_i + \alpha_r \mu_r \end{pmatrix} \\
& + \begin{pmatrix} \phi_{\pi,\pi} \pi_{t-1} + \phi_{\pi,f} (\alpha_i i_{t-1} + \alpha_r r_{t-1}) \\ (\alpha_i \phi_{i,\pi} + \alpha_r \phi_{r,\pi}) \pi_{t-1} + \phi_{f,f} (\alpha_i i_{t-1} + \alpha_r r_{t-1}) \end{pmatrix} \\
& + \begin{pmatrix} \sigma_{\pi,\pi} e_t^\pi + \sigma_{\pi,f} (\alpha_i e_t^i + \alpha_r e_t^r) \\ (\alpha_i \sigma_{i,\pi} + \alpha_r \sigma_{r,\pi}) e_t^\pi + \sigma_{f,f} (\alpha_i e_t^i + \alpha_r e_t^r) \end{pmatrix} \qquad \text{(A.6)}
\end{aligned}
$$

$$
\Leftrightarrow \quad \begin{pmatrix} \pi_t \\ \alpha_i i_t + \alpha_r r_t \end{pmatrix} = \begin{pmatrix} \mu_\pi \\ \mu_f \end{pmatrix} + \begin{pmatrix} \phi_{\pi,\pi} \pi_{t-1} + \phi_{\pi,f} f_{t-1} \\ \phi_{f,\pi} \pi_{t-1} + \phi_{f,f} f_{t-1} \end{pmatrix} + \begin{pmatrix} \sigma_{\pi,\pi} e_t^\pi + \sigma_{\pi,f} e_t^f \\ \sigma_{f,\pi} e_t^\pi + \sigma_{f,f} e_t^f \end{pmatrix} \qquad \text{(A.7)}
$$

$$
\Leftrightarrow \quad \begin{pmatrix} \pi_t \\ f_t \end{pmatrix} = \begin{pmatrix} \mu_\pi \\ \mu_f \end{pmatrix} + \begin{pmatrix} \phi_{\pi,\pi} & \phi_{\pi,f} \\ \phi_{f,\pi} & \phi_{f,f} \end{pmatrix} \begin{pmatrix} \pi_{t-1} \\ f_{t-1} \end{pmatrix} + \begin{pmatrix} \sigma_{\pi,\pi} & \sigma_{\pi,f} \\ \sigma_{f,\pi} & \sigma_{f,f} \end{pmatrix} \begin{pmatrix} e_t^\pi \\ e_t^f \end{pmatrix} \qquad \text{(A.8)}
$$

$$
\Leftrightarrow \quad \tilde{Y}_t = \tilde{\mu} + \tilde{\Phi} \tilde{Y}_{t-1} + \tilde{\Sigma} \tilde{e}_t \qquad \text{(A.9)}
$$

Along those steps, we introduced the following linear parameter constraints (Assumption 1):

$$\phi_{\pi,f} \equiv \frac{\phi_{\pi,i}}{\alpha_i} = \frac{\phi_{\pi,r}}{\alpha_r} \tag{A.10}$$

$$\phi_{f,f} \equiv \frac{\alpha_i\phi_{i,i} + \alpha_r\phi_{r,i}}{\alpha_i} = \frac{\alpha_i\phi_{i,r} + \alpha_r\phi_{r,r}}{\alpha_r} \tag{A.11}$$

$$\sigma_{\pi,f} \equiv \frac{\sigma_{\pi,i}}{\alpha_i} = \frac{\sigma_{\pi,r}}{\alpha_r} \tag{A.12}$$

$$\sigma_{f,f} \equiv \frac{\alpha_i\sigma_{i,i} + \alpha_r\sigma_{r,i}}{\alpha_i} = \frac{\alpha_i\sigma_{i,r} + \alpha_r\sigma_{r,r}}{\alpha_r}. \tag{A.13}$$

In our notation, $\phi_{\bullet,\bullet}$ elements form the matrix Φ and $\sigma_{\bullet,\bullet}$ elements form the matrix Σ of the covariance matrix $\Omega = \Sigma\Sigma'$, to which the $\omega_{\bullet,\bullet}$ elements belong accordingly. Furthermore, as defined in equation (4), all remaining FCI-related variables and parameters are redefined – without further implications – as linear combinations of the financial constituents:

$$f_t \equiv \alpha_i i_t + \alpha_r r_t \tag{A.14}$$

$$\mu_f \equiv \alpha_i\mu_i + \alpha_r\mu_r \tag{A.15}$$

$$\phi_{f,\pi} \equiv \alpha_i\phi_{i,\pi} + \alpha_r\phi_{r,\pi} \tag{A.16}$$

$$e_t^f \equiv \alpha_i e_t^i + \alpha_r e_t^r \tag{A.17}$$

$$\sigma_{f,\pi} \equiv \alpha_i\sigma_{i,\pi} + \alpha_r\sigma_{r,\pi}. \tag{A.18}$$

A.2 Simulation

The dimension-reduction from the large-scale VAR in equation (1) to the small-scale VAR in equation (3) via the mapping matrix Γ leads to the unusual appearance of Γ in the likelihood function as specified in equation (7). As discussed in Section 3.1, linearity Assumption 1 and orthonormality Assumption 2 together ensure the equivalence of the two VARs. This equivalence allows us to estimate the VAR coefficients jointly with the FCI weights. To test the estimation approach presented in Section 3.2 empirically, we run a Monte Carlo exercise in which we simulate the small fictional macro-finance VAR specified in Section A.1. We choose the original VAR parameters such that both assumptions are satisfied and set $\alpha_i = 0.6$. As a result of Assumption 2, $\alpha_r = \sqrt{(1-\alpha_r^2)} = 0.8$. We use the fictional VAR to simulate 10,000 paths of the macro variable and the two financial variables with 240 observations each. This sample size corresponds to 20 years of monthly data, similar to our true data set. Then, we apply our approach to estimate the reduced-form parameters of the small-scale VAR, featuring the FCI, jointly with the FCI weights in one step via maximum likelihood estimation.

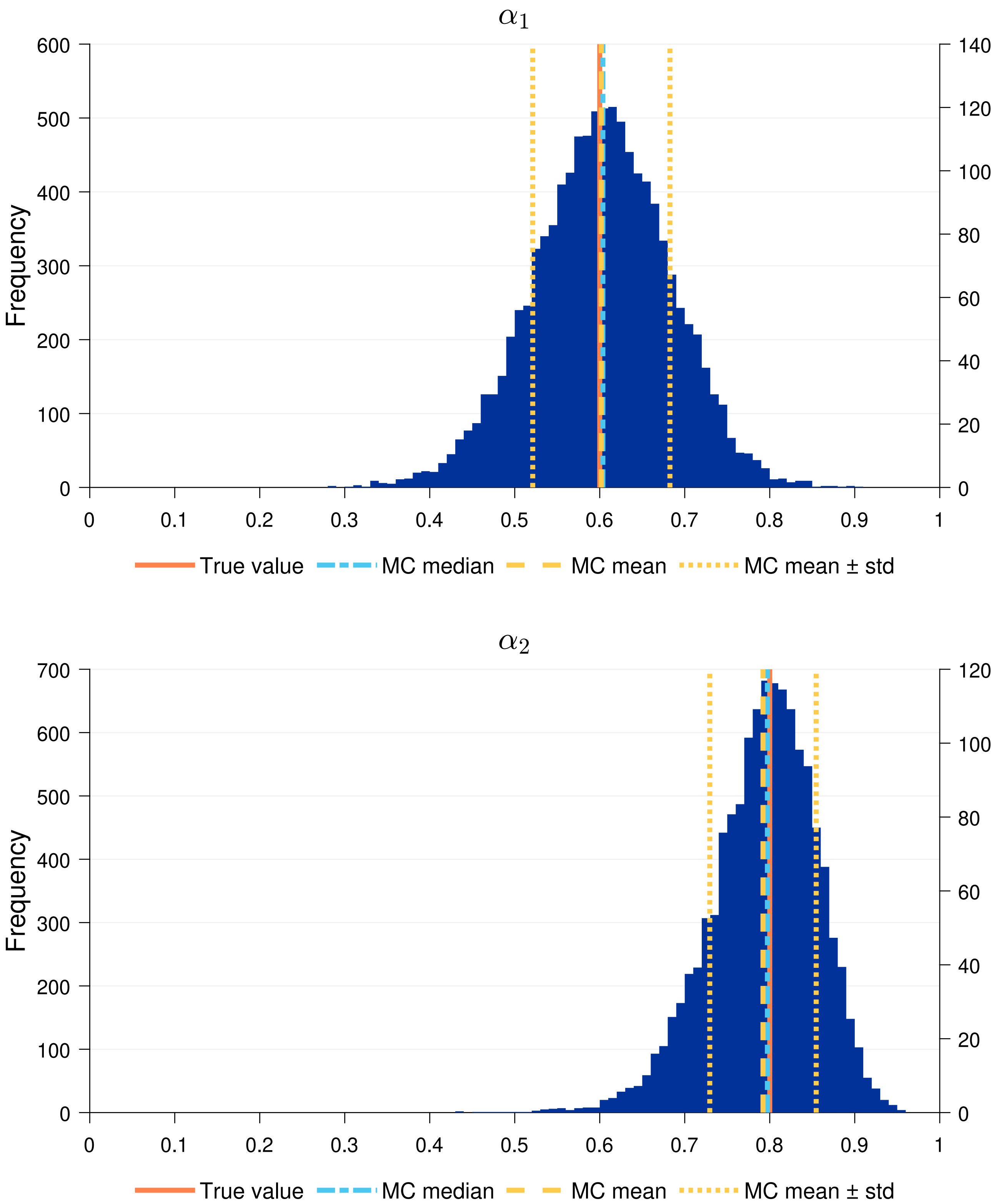
Table A.1 shows the true values of the VAR parameters and the FCI weights, alongside summary statistics of the simulation. Note that the true FCI-related values are implied as linear combinations of the original parameters (not shown) of the full system, in line with Assumption 1. The estimation approach produces unbiased estimates of the true parameters. The sampling distributions of all parameters are centred around the true values and show reasonable standard errors. Figure A.1 illustrates the full sampling distribution of the weights.

Table A.1: Monte Carlo estimates of VAR and FCI parameters

Parameter	True value	Simulation				
		mean	std. dev.	P05	median	P95
μ_π	0.050	0.051	0.046	-0.024	0.051	0.129
μ_f	0.040	0.046	0.023	0.010	0.045	0.085
$\phi_{\pi,\pi}$	0.500	0.496	0.036	0.433	0.498	0.552
$\phi_{\pi,f}$	-0.833	-0.848	0.060	-0.954	-0.846	-0.754
$\phi_{f,\pi}$	0.200	0.199	0.017	0.169	0.200	0.226
$\phi_{f,f}$	1.167	1.160	0.029	1.110	1.161	1.206
$\omega_{\pi,\pi}$	0.444	0.440	0.040	0.376	0.438	0.507
$\omega_{\pi,f} = \omega_{f,\pi}$	0.000	-0.001	0.014	-0.024	-0.001	0.022
$\omega_{f,f}$	0.111	0.109	0.010	0.093	0.109	0.126
α_i	0.600	0.602	0.081	0.466	0.604	0.731
α_r	0.800	0.792	0.063	0.682	0.797	0.885

Notes: The parameter estimates are based on 10,000 Monte Carlo simulations of a fictional VAR with three variables, one representing a macro variable and two representing financial variables entering the FCI.

Figure A.1: Monte Carlo estimates



Note: The estimates of weights α are based on 10,000 Monte Carlo simulations of three fictional variables, one representing a macro variable and two representing financial variables entering the FCI.

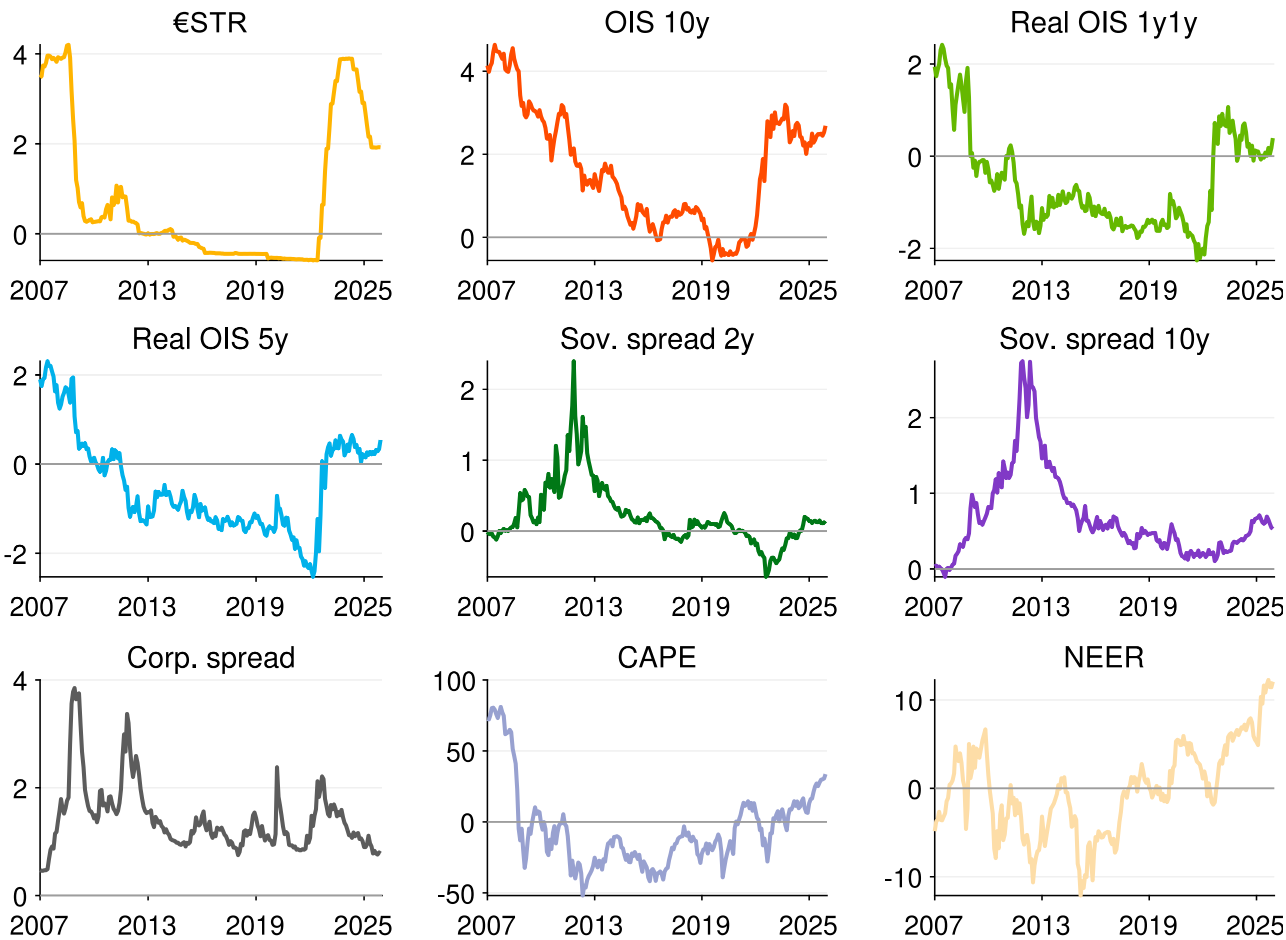
A.3 Data sources

Table A.2: Macroeconomic variables and data sources

Variable	Definition	Source
HICP	Euro area (changing composition) - HICP - Overall index, Neither seasonally nor working day adjusted	Eurostat
GDP	Gross domestic product at market prices - Euro area 20 (fixed composition) as of 1 January 2023 - Domestic (home or reference area), Total economy, Euro, Chain linked volume (rebased), Calendar and seasonally adjusted data	Eurostat

Note: HICP is sampled at a monthly frequency and GDP at quarterly frequency, both in levels.

Figure A.2: Time series of financial variables



Note: Financial variables are sampled at a daily frequency and depending on the data type, daily observations are transformed to monthly frequency using the last available daily value of each month. Before September 2021, EONIA instead of €STR is used, adjusted for the fixed EONIA-€STR spread of 8.5 basis points.

Table A.3: Financial variables and data sources

Variable	Definition	Source
€STR*	Euro short-term rate-Volume-weighted trimmed mean rate—Unsecured—Overnight-Borrowing—Financial corporations	ECB SDW
OIS rates*	Euro area (changing composition)—Overnight interest rate swaps—EUR Overnight Index Swap (ESTR)—Historical close—Euro	Bloomberg Finance L.P.
ILS rates	Euro area (changing composition)—Interest rate swaps—Euro Inflation Linked Interest Rate Swap—Middle—Euro	LSEG
Real rates	OIS rates minus ILS rates	Authors' calculation
Sovereign yields	Euro Area Government Benchmark Bond, GDP Weighted—Yield. Euro area (changing composition)—Benchmark bond	ECB SDW
Sovereign spreads	Euro Area Sovereign yields minus OIS rates*	Authors' calculation
Corporate bond spreads	ICE BofA Euro Corporate Index Bond Index—Option adjusted spread	LSEG
Market Equity Index	EMU-DS Market Equity Index—Historical close	LSEG
Price-to-earnings (PE) ratio	Euro area (changing composition)—Equity/index—EMU-DS Market Equity Index—Price earning ratio—Euro, provided by ECB	LSEG
CAPE	Cyclically adjusted price-to-earnings ratio constructed as the EMU-DS index divided by the trailing 10-year moving average of earnings, where earnings are backed out from the price-to-earnings ratio	Authors' calculation
NEER	ECB Nominal effective exchange rate of the Euro	ECB SDW

Note: Financial variables are sampled at a daily frequency and depending on the data type, daily observations are transformed to monthly frequency using the last available daily value of each month.
*Before September 2021, EONIA is used, adjusted for the fixed EONIA-€STR spread of 8.5 basis points.

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