Financial Conditions and the Macroeconomy: A Two-Factor View*

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Abstract

We construct a new financial conditions index for the United States based on a dynamic factor model applied to a broad set of financial prices and yields. The resulting two latent factors capture, respectively, the general level of safe interest rates and an overall measure of perceived and priced financial risk. Analysing the interaction between these factors and the macroeconomy, we find that: (i) both factors are affected significantly by monetary policy; (ii) positive shifts in both factors lead to a persistent contraction in economic activity; (iii) relative to the safe interest rates factor, the risk–related factor exhibits stronger predictive power for economic activity. Our results are consistent with both the demand and the credit channels of monetary policy being at work, and emphasize that isolating movements in safe interest rates from shifts in perceived financial risk is essential to accurately assess the transmission of financial conditions to economic activity.

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"[...] financial conditions affect households' and firms' saving and investment plans, and, therefore, play a key role in influencing economic activity and the economic outlook. This is why the evaluation of financial conditions is so crucial in the conduct of monetary policy."
William C. Dudley, 2017

1 Introduction

Financial conditions faced by agents in the economy play a pivotal role as an intermediate step of the monetary transmission mechanism. While central banks ultimately aim to stabilise inflation and real activity around desired targets, they do so by steering firms' and households' incentives to invest and save. These decisions are shaped by the cost and accessibility of financing. Therefore, closely monitoring financial conditions – broadly defined as the financing costs faced by firms and households – is essential for evaluating the stance of monetary policy and its transmission to the broader economy.

Formally evaluating how monetary policy transmits to financial conditions and how these affect the macroeconomic outlook is, however, far from straightforward. One challenge is that the notion of "financial conditions", by its own nature, represents a multi-faceted concept, so that measuring it entails at least some ad-hoc choices. In general terms, the ensuing financial condition indices (or FCIs) can be thought of as weighted averages of a certain set of financial prices (reflecting interest rates on various types of short and long-term funding instruments, some of which safe while others reflecting a compensation of risk of various types). Yet the weights, and the "representative" prices themselves are subject to individual choices, which are bound to lead to different results. The measures of financial conditions that are available off-the-shelf give different indications depending on the datasets on which they are based, and on the methodologies on which they rely upon.[1] And even more importantly, prevailing indices often suffer from a not fully transparent construction methodology, which makes it difficult to understand and rationalise the drivers of their dynamics and, consequently, their transmission to the macroeconomy.[2]

In this paper, we introduce a new financial condition index constructed using a dynamic factor model that has several desirable features. First, it relies on a compact and transparent construction methodology, hence avoiding the black-box nature of some of the existing approaches. Moreover, working with a dynamic factor model enables us to rely on a rich dataset of prices representing various segments of financial markets, whose contributions can be summarised through a few homogeneous subcomponents (factors), determined by the joint dynamics of the

[1] For example, financial conditions indices such as the one by the Goldman Sachs or by the Federal Reserve Board typically give a significant weight to "safe" government bond yields, while indices geared more towards financial stress (e.g. the Bloomberg FCI) rely more squarely on riskier segments of the monetary transmission mechanism.

[2] This is especially the case for the Goldman Sachs FCI: while the underlying variables and the associated weights are publicly available, the way the former are constructed and the latter estimated is less clear, and is documented only in relatively generic terms.

data. These factors are determined as to be maximally representative of the dataset in terms of the overall share of variance that they can explain. The different factors end up capturing specific aspects of financial conditions, and have an easy and intuitive economic interpretation – a desirable feature for the purpose of economic and financial monitoring.

It turns out that the dataset has a very clear and distinctive factor structure: the first factor relates mainly to the overall level of interest rates, especially those on government bonds – hence we label it "safe yields factor"; the second factor reflects mainly spreads, risky yields and returns on equities – hence we label it "risk factor". Importantly, this factor structure emerges naturally from the data, without imposing any identifying assumptions related to orthogonality of the blocs in the dataset, or to the relationship between the factors and economic activity.

Yet such a natural factor structure also has a meaningful relation to financial and economic activity. We show that both factors anticipate macroeconomic developments, but the "risk factor" has a higher predictive power for economic activity over a horizon of one year. Hence, if one wants to come up with a synthetic "headline" index that maximises predictive power for a specific macro variable, as the popular Goldman Sachs index does for GDP growth, the "risk factor" would receive a relatively larger weight.

The relative prominence of the "risk factor" in terms of its forecasting performance suggests that risk shocks are a key driver of macroeconomic developments. To explore this further, we build on the SVAR specification in Gilchrist and Zakrajšek (2012) and demonstrate that substituting their measure of safe long-term interest rates (10-year government bond yield) and risk measures (the excess bond premium) with our first and second factors, respectively, yields results that align closely, both qualitatively and quantitatively, with theirs. Specifically, we find that shocks to the "risk factor" lead to a significant and persistent contraction in real activity and inflation, while also prompting a monetary policy response in the form of cuts in short-term rates.

Using our second factor as a risk variable in the VAR offers two distinct advantages. First, it integrates a broader concept of financial conditions – recently highlighted as critical for monetary transmission – into a comprehensive and well-established empirical framework (see, e.g., Caballero et al., 2024). Second, through the factor loadings, it allows us to disentangle and trace the contributions of developments in various financial market segments in driving risk shocks.

In a subsequent step, we modify the Cholesky ordering in Gilchrist and Zakrajšek (2012)'s specification to identify a safe interest rate shock. We find that a positive shock to the first factor similarly results in a persistent decline in real activity and inflation, mirroring the effects of a standard monetary policy shock (*e.g.*, Bernanke and Blinder (1992), Christiano et al. (2005), Ramey (2016)).

Next, we examine how monetary policy transmits differently through each of the factors by means of local projections on off-the-shelf monetary shocks identified at high frequency. Here we rely on the monetary policy shocks by Jarociński and Karadi (2020) that strip out possible central bank information effects. Results suggest that monetary policy transmits through both factors in a significant and persistent way.

Finally we showcase some additional results that should help convincing the reader of the robustness of our approach: i) estimates for selected euro area countries, for which the same factor structure we found for the US emerges naturally; ii) additional results including a bloc of FX-related variables, which appears to emerge as a separate stand-alone factor.

The remainder of the paper is organised as follows. Section 2 gives an overview of existing financial condition indices and reviews the related literature. Section 3 focuses on the construction of the FCI: we discuss the logic underlying our selection of series, and show how these are modelled through a dynamic factor model, producing two distinct and highly intuitive factors. Section 4 illustrates the predictive power of the factors for key macroeconomic variables, and suggests how to combine them via different weighting schemes. Section 5 relies on SVAR methods to illustrate the transmission of shocks to each of the two factors to credit aggregates, real activity and inflation. The fifth section elaborates on the transmission of monetary policy shocks to the factors. A battery of robustness checks follow in Section 6 – including on the role of FX markets, before we conclude.

2 Review of financial condition indices and related literature

In this section we start with a brief review of leading existing FCIs and the methodologies underlying them. We then turn to a discussion of related theoretical and empirical academic studies that, like us, study the broader macroeconomic implications of shifts in financial conditions.

Methodological FCI studies. Over the past two decades, a growing literature has sought to construct Financial Conditions Indices (FCIs) that provide a summary measure of the cost and availability of finance across economic agents. FCIs vary widely in terms of purpose, coverage, and methodology (Table 1).

A first key point of differentiation lies in their intended use: (i) some indices are designed to forecast macroeconomic outcomes, (ii) others to assess the relative tightness of financial conditions by historical standards, while (iii) others still are primarily geared towards monitoring financial stress. For example, the Goldman Sachs FCI aggregates five core financial variables—short- and long-term interest rates, corporate spreads, equity prices, and exchange rates—and calibrates their weights based on their estimated effects on GDP over a one-year horizon (Hatzius et al., 2017a). Likewise, the OECD FCI assigns weights to eight indicators based on their regression-estimated effects on the output gap (Davis et al., 2016a). In a similar vein, the FCI provided by the U.S. Federal Reserve Board (FRBUS) aims to forecast the impact of monetary policy on real activity by mimicking the transmission of monetary policy through different markets in a way that is consistent with the workhorse FRBUS model.

By contrast, other indices, such as the Chicago Fed's National Financial Conditions Index (NFCI) or the IMF's FCIs, are more statistically-driven and aim at capturing the tightness of financial conditions by historical standards. The NFCI for example is based on a principal components analysis on over 100 financial time series spanning money, credit, and equity markets. The IMF's FCI also relies on a principal components methodology applied to both financial prices and spreads (International Monetary Fund, 2017).

Another set of indices seek to measure financial stress instead of broad financial conditions. Hence they give prominence to various interest rate spreads or measures of risk such as implied volatility. In this category, some indices such as the Bloomberg FCI or the Asian Development Bank (ADB) Financial Stress Indices (FSIs) are based on a few variables from various financial markets deemed representative for the financial system as a whole, while others, such as the St. Louis Fed FSI or the Composite Indicator of Systemic Stress (CISS) of the ECB are based on a wider set of credit spreads and market volatility measures.

A second key point of differentiation of existing indices is their country coverage. Some indices are available for a wide range of countries (*e.g.* GS FCIs, OECD FCIs, IMF FCIs), while others focus on one specific country (*e.g.* FRBUS FCI, NFCI, St. Louis Fed FSI, Reserve Bank of Australia FCI).

Finally, a third key point of differentiation of existing indices is the methodology used to combine individual series into a composite index. In some cases, the individual weights are set to maximise the impact of financial conditions on GDP over a certain horizon (e.g. in the GSFCI), to replicate the impact certain variables have on GDP in the context of a broader structural model (e.g. the Fed Board's FCI), or are based on reduced-form demand equations (e.g. Mayes and Virén (2001), Goodhart and Hofmann (2003)). Other approaches use instead statistical methods to compute the weights, ranging from simple equal weights (e.g. the Bloomberg FCI) to more elaborate statistical methods (e.g. the Chicago Fed FCI uses weights that are maximally representative of the data matrix being used as input; the CISS incorporates time-varying cross-correlations to capture systemic risk dynamics (Chavleishvili and Kremer, 2023a)).

Our contribution to this strand of literature lies in proposing a financial conditions index that addresses both the measurement and interpretability challenges inherent in prior approaches. Specifically, our model relies on a dynamic factor model (DFM) estimated on a broad panel of financial variables. The model identifies two economically meaningful latent factors: (i) a "safe yields" factor capturing movements in risk-free interest rates (particularly government bonds), and (ii) a "risk" factor associated with credit spreads, risky bond yields, and equity market conditions.[3] Identifying a two-factor structure represents a crucial innovation. It provides a transparent decomposition of financial conditions into components aligned with monetary policy stance and perceived financial risk. The separation is not only theoretically grounded—in the spirit of financial accelerator models (Bernanke et al., 1999b)—but also empirically

[3] While this two-factor structure appears relatively robust across countries,

validated. We show that the risk factor has greater predictive power than the safe yields factor across multiple horizons and economic aggregates, including credit, investment, and output growth.

While other institutions have employed dynamic factor models to construct FCIs, their indices are based on a single latent index and hence stop short of separating the two structural components we uncover in a manner that facilitates macroeconomic inference and policy analysis. For instance, the IMF constructed such DFMs for the United States, euro area (International Monetary Fund, 2016) and the Asian economies (Beaton et al., 2016), while the Reserve Bank of Australia used a similar approach for the Australian economy (Reserve Bank of Australia, 2021).

Table 1: Overview of Existing Financial Conditions Indices

Index name	Main purpose	Methodology & Coverage
Goldman Sachs FCIs	Impact of financial conditions on GDP growth	Five variables: nominal short-term rate, nominal long-term rate, corporate spread, equity price, trade-weighted exchange rate. A sixth variable for some countries: sovereign spread (EA countries), debt-weighted FX rate (some EMEs). Weights based on one-year GDP impact. *Daily frequency; AEs and EMEs; Since 1980s for most AEs and 2000s for most EMEs.*
OECD FCIs	Impact of financial conditions on GDP growth	Eight variables: real short-term rate, real long-term rate, real effective exchange rate, loan survey results, real house prices, real share prices, bond yield spreads between corporate and public bonds. Weights based on 1/1.5 years GDP impact. *Quarterly frequency; Seven OECD countries; Since 1995.*

IMF FCIs	Tightness of financial conditions by historical standards	Eleven variables: real short-term rate, interbank spread, term spread, sovereign local debt spread, sovereign dollar debt spread, corporate local currency spread, corporate dollar debt spread, equity price, equity volatility, exchange rate, real house price. Weights based on principal components analysis. *Monthly frequency; AEs and EMEs; From 1990 to 2017, depending on data availability.*
ADB FSIs	Financial conditions / financial stress	Five variables covering four major financial markets: banking sector, foreign exchange market, equity market, debt market. Weights based on equal variance and principal components analysis. *Daily frequency; AEs and EMEs; Since mid-1990s.*
Bloomberg FCIs	Financial stress	Ten variables from money, bond, and equity markets. Equal weights. *Daily frequency; US, EA, GB; Since early 1990s.*
CISS	Systemic financial stress / financial crisis risk	Fifteen variables capturing stress in money, bond, equity and foreign exchange markets. Time-varying cross-correlations as systemic weights; more weight to periods with systemic stress. *Daily frequency; AEs and China; Time coverage varies widely.*

Source: Based on Avalos et al. (2023). See Hatzius et al. (2017b), Hatzius and Stehn (2018) for the GS-FCI; Davis et al. (2016b) for the OECD FCI; International Monetary Fund (2018) for the IMF FCI; Park and Mercado (2014) for the ADB FSI; Bloomberg for the BFCI; Chavleishvili and Kremer (2023b), Duprey (2020) for the CISS.

Studies with a conceptual focus. The interest in financial conditions is not restricted to policy circles but there has also been a growing academic literature stressing their conceptual importance. In a broad sense, the conceptual relevance of financial conditions in macroeconomic models stems from the presence of financial frictions Bernanke and Blinder (1992); Gilchrist and Zakrajšek (2012). But contributions in which financial conditions are modelled explicitly are only recent.

Caballero et al. (2024), for instance, provide a rationale for central banks to target such indices and not only to monitor them. Specifically, they develop a "risk-centric" New-Keynesian model in which noise shocks to financial markets propagate to the real economy through a broad Financial Conditions Index. Because arbitrageurs are reluctant to lean against such noise in the presence of aggregate return volatility, the authors show that it is optimal for the central bank to announce a soft, temporary target for the FCI and to adjust the policy rate so as to keep the realised FCI close to that target. This strategy – dubbed financial-conditions targeting — reduces FCI volatility and delivers sizable gains in output-gap stabilisation, even though stabilising financial conditions is not an objective per se.

Furthermore, Aikman et al. (2020) use a FCI to provide empirical evidence that the transmission of shocks to financial conditions depends on the state of the credit cycle. Using U.S. data from 1975-2014, they show that looser financial conditions boost output and inflation when the non-financial credit-to-GDP gap is below trend, but generate a boom-bust pattern (short-run expansion followed by recession) when the gap is above trend. Their results underscore that an FCI's macro-predictive power hinges on the prevailing level of private-sector leverage, and that policymakers may need to pair FCI monitoring with indicators of credit imbalances—an approach that aligns with our own two-factor index design.

3 Financial conditions through the prism of a dynamic factor model

3.1 Modeling philosophy

As indicated above, the main guiding principles when devising our index are threefold: i) the idea is to broadly capture the cost and ease of financing faced by key agents in the economy (financial intermediaries, firms, households and the government), while ii) at the same time being transparent in how the contributing series are processed, and easy-to-interpret in terms of the results, and iii) being meaningfully related to subsequent macroeconomic developments (in particular, when it comes to credit and investment). The first criterion relates to our choice of the types of variables, the second to the choice of methodology when constructing our index, and the third to our approach of validating the index and assessing its relevance.

3.2 Data

The first necessary step in constructing an FCI is to select a relevant set of contributing series.[4] Relying on a dynamic factor model enables us to be less selective, and picking instead a

[4] A detailed list of the series used for the construction of our index is available in Appendix A.

relatively large set of series. Through this choice, we want to reflect all the different facets of the monetary transmission mechanism. More precisely, we aim at giving a role to a wide selection of interest rates and prices faced by different agents in the economy along the various steps of the monetary transmission mechanism. Even though we will not impose any bloc structure on the dynamic factor model itself, it is nevertheless useful to describe the series we choose according to a taxonomy that is meant to reflect these different steps. We collect data at daily frequency, starting on 2 January 2002, until 5 February 2025. We illustrate the methodology using the United States as a key benchmark, but our results extend easily to other countries, and further below we will also present results for the euro area.

The first segment of the transmission of monetary policy from the interest rates controlled by the central bank to key funding costs faced by agents in the economy takes place in the money market segment. Accordingly, our *first* bloc (which we label "short-term funding") includes daily data on the effective FFR, as well as 3-month T-bills, interbank and OIS rates, as well as and rates on commercial papers (for financial and non-financial corporations) and certificates of deposits, all at a 3-month maturity. Some of these short-term rates are close to risk-free while others contain some compensation for liquidity and credit risk.

The *second* bloc, labeled "government bond yields", covers risk-free bond yields at longer maturities, that is, longer-term financing costs by the government. Accordingly, it includes the longer-end of the yield curve of government bonds, from 1-year to 10-year maturity, as well as inflation-linked bonds of corresponding maturities.

In the *third* bloc, we move to consider "risky bond yields" that corporations with bond market access face when funding themselves over longer-horizons. These rates reflect a compensation for credit risk and we consider the yields on corporate bonds of different ratings (AAA, BBB, investment-grade and high-yield) here.

The *fourth* bloc, similarly, deals with various "spreads". Here we include term spreads on government bonds yields (10Y-3M and 10Y-2Y), the investment-grade and high-yield corporate bond spread, as well as spreads between commercial paper and OIS rates.

The *fifth* bloc covers "equity markets". It includes total returns on the S&P500 as well as on the sub-index that refers to banks and other financial institutions, plus various valuation ratios. Regarding the latter we use price-to-earnings and price-to-book ratios, as well as the dividend yield.

Finally, the *sixth* bloc comprises various "bank rates" that capture borrowing rates by households and smaller firms: prime rates, rates on loans to small businesses, as well as 15-year and 30-year mortgage rates; note this latter bloc is only observed at monthly frequency.

Developments in foreign exchange markets can play an important contribution to overall financial conditions Avdjiev et al. (2019a). But for the United States, which we use as a benchmark for our illustration here, it is not obvious that this is the case. Therefore, we opted for not including them in our baseline specification. That said, we show evidence on how an additional FX-related bloc would affect the results in the robustness section below.

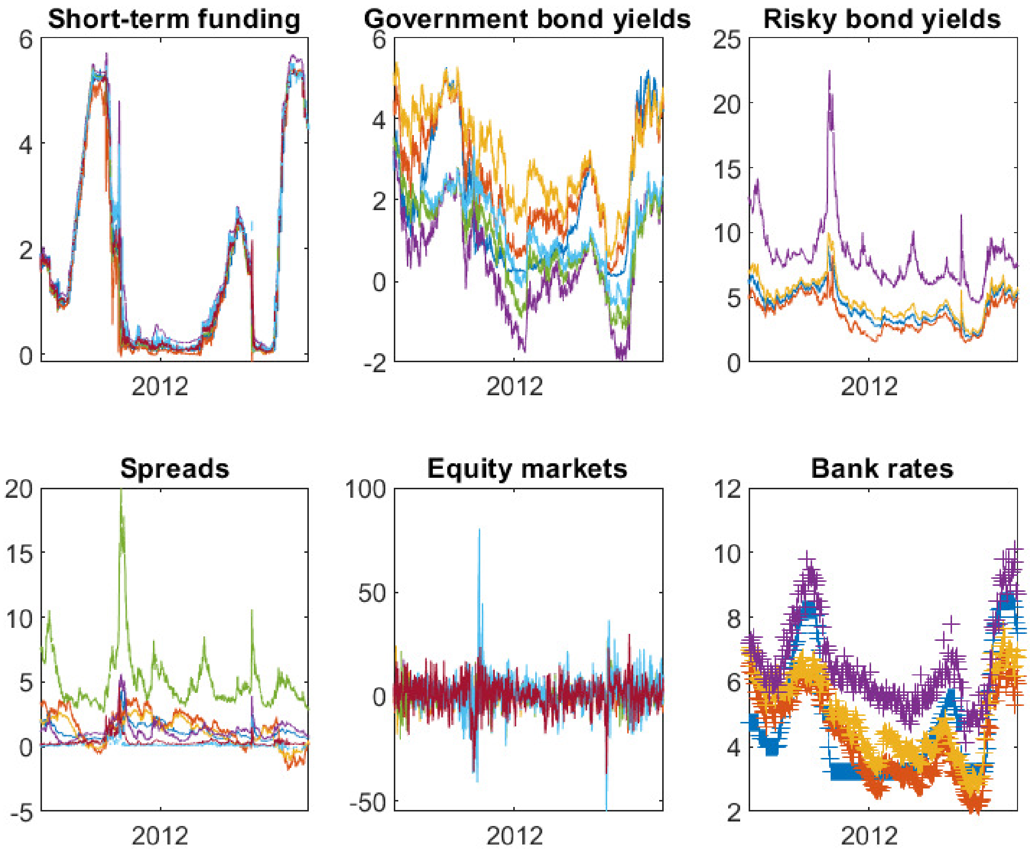

Figure 1: The contributing series to financial conditions

Notes: The figure shows the "ingredients" that serve as input to the dynamic factor model, organised in conceptually homogenous blocs. The "bank rates" bloc is marked with crosses as the data is only available at monthly frequency.

3.3 A dynamic factor model for mixed-frequency data

Dynamic factor models are particularly useful in the analysis of large datasets such as the one we encounter in our financial conditions setup. They reduce the data dimension by extracting a small number of common components out of a large amount of available information. The common components, or factors, are chosen in such a way as to maximise the proportion of total variability of the dataset they can explain.

Let $X_{1:T}$ be a K-dimensional multiple time series with T observations, some of which are missing. We write its factor representation as:

$$X_t = \Lambda F_t + e_t, \qquad e_t \sim N(0, R) \tag{1}$$

where F_t is an $r \times 1$ vector of factors, Λ is the $K \times r$ matrix which contains the factor loadings, and the errors e_t are idiosyncratic components, orthogonal to the factors F_t; their covariance matrix R is assumed to be diagonal.[5]

The factors F_t are unobserved and must be estimated. We assume that the common factors follow a VAR process of order p:

$$F_t = \sum_{i=1}^{p} A_i F_{t-i} + u_t, \qquad u_t \sim N(0, Q) \tag{2}$$

so that the resulting dynamic factor model can be cast and estimated in state-space form. We refer the reader to the Annex for additional details on the estimation procedure itself.

3.4 The factor structure

Running the dynamic factor model on our dataset of financial input variables described above reveals a strikingly clear and intuitive factor structure. The first two factors explain over 60% of the total variance, and the loadings have a very distinctive pattern. More specifically, the first factor loads positively on all the "rates" blocs, especially the safe ones (Figure 2, blue bars). Hence, it can be thought of as a summary measure of the prevailing level of interest rates. The second factor, instead, loads distinctively on risky assets, that is, corporate bonds, risky spreads and equity market variables. If anything, it loads negatively on short-term rates, highlighting the endogenous monetary policy easing that is typically elicited by the occurrence of financial stress.

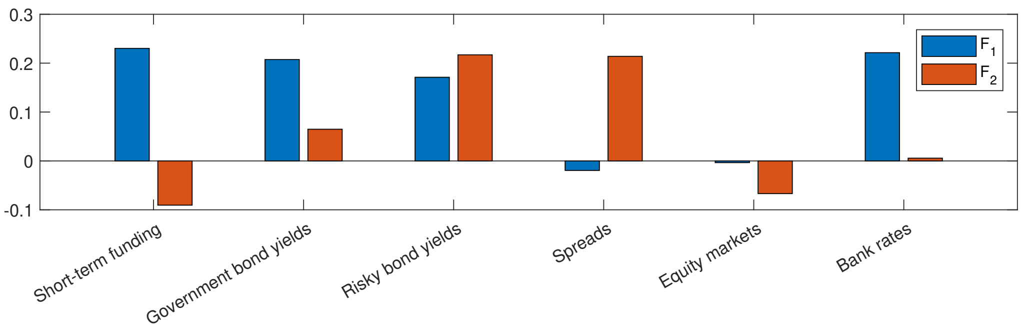

Figure 2: Average factor loadings on the blocs of variables

Notes: The figure shows the average factor loadings on the first and the second dynamic factor for the different blocs of variables.

The time-series evolution of the two factors (Figure 3) is also quite telling on their relative roles. Factor 1 by and large tracks the monetary policy cycle: it increases during the 2004-06

[5] Note that this assumption corresponds to an exact factor model. While in practice the error components may not be orthogonal to each other and can contain residual correlations that are not explained by the factors, Doz et al. (2011) show that in the presence of weak cross-correlations the estimation of factors is still consistent. Bańbura and Modugno (2014) also provide algorithms to deal with serially correlated error terms.

policy rate hike, to then plummet swiftly during the Great Financial Crisis (GFC), and then decline gradually as unconventional policy measures were deployed to bring down borrowing costs in the economy. The post-pandemic easing represents another phase in which the first factor declines to even lower levels than in the post-GFC on the back of monetary easing, to then swiftly increase in parallel with the surge of inflation and the associated policy tightening. In terms of the contributions, the bulk of the dynamics of factor 1 is driven by short-term funding costs and government bond yields.

The dynamics of the second factor instead reflects the evolution of attitudes towards risk. The period around the GFC stands out here, but also the prolonged period of risk-taking in the run-up to it. Note also how the second factor briefly spikes at the onset of the pandemic, to be rapidly undone by the swift and substantial support provided by monetary and fiscal authorities. In terms of the contributors, during the GFC both risky yields, spreads and equity prices contribute positively and lead to a tightening of financial conditions as embodied in factor 2. But during the risk-taking phase preceding it, as well as over the most recent period, it is mainly compressed spreads that weigh negatively on the second factor.

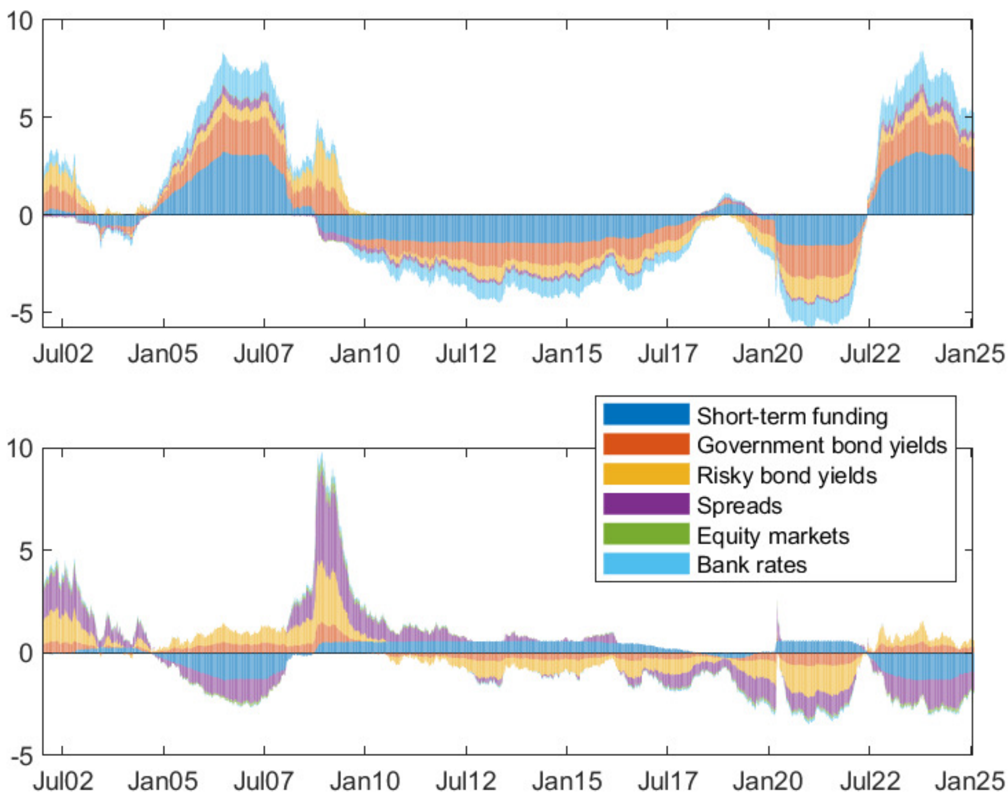

Figure 3: Decomposition of the two factors into contributions from the different blocs.

Notes: The figure shows the two estimated factors, decomposed according to the contributions coming from each bloc of variables.

4 The Factors and Economic Activity

Equipped with the two factors summarising financial conditions, we now examine how their dynamics embed information relevant for anticipating subsequent economic activity. As a first step, we use simple predictive regressions to investigate the predictive power of the two factors for a set of macroeconomic indicators that are key to the transmission of monetary policy: credit, investment, GDP growth and inflation. As a by-product, these forecasts will also yield weights that one can use to combine the two factors into a single composite indicator of financial conditions. As a second step, we rely on a standard macro VAR augmented by our first and second factor to capture safe interest rate levels and financial risks, respectively. Based on this VAR setup, with identified structural shocks, we assess how safe interest rate shocks and risk-related shocks transmit to the real economy, credit, asset prices and inflation through the two factors.

4.1 Predictive Regression Results

To assess the predictive ability of the financial condition components plotted in Figure 3 on various measures of economic activity, we proceed in two stages. First, we estimate the following univariate forecasting regression:

$$\Delta^h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \epsilon_{t+h}, \tag{3}$$

where $\Delta^h Y_{t+h} \equiv \frac{400}{h+1} ln\left(\frac{Y_{t+h}}{Y_{t-1}}\right)$, $h \geq 0$ is the forecast horizon (either one or four quarters,in the regressions below). Y denotes, in turn, one the following (quarterly) measures of economic activity: total credit to private non-financial sector, real fixed business investment, real GDP, nominal GDP deflator and core PCE index. The forecasting regression is estimated by ordinary least squares (OLS), features four lags of the dependent variable and the standard errors are computed à la Newey-West to ensure robustness to serial correlation.

In a second stage, we compute the partial R^2 of each of the two factors in the forecasting Equation in (3) by running the following regression

$$\widehat{\epsilon}_{t+h} = \alpha_1 + \gamma_i FC_t(i) + \varepsilon_{t+h}, \tag{4}$$

where $\widehat{\epsilon}_{t+h}$ are the residuals of the forecasting regression (3) and $FC_t(i)$ denotes one of the two financial conditions factors. To assess the marginal significance of the two factors as predictors, we report estimates of the regression coefficients γ_i as well as their statistical significance. Regression (4) is also estimated by OLS, with standard errors computed based on Newey-West.

Table 2 shows the predictive content of the two factors for each measure of economic activity. The table is organised in two subpanels, each reporting results for the short- and the long-term forecast horizons, respectively. Within each subpanel, the first and second columns report results for the first and second factors, respectively.

Financial indicator	Horizon: one quarter		Horizon: one year	
A. Credit growth				
F1	-0.08	—	-0.11	—
	[-1.39]		[-1.47]	
F2	—	−0.23**	—	−0.24**
		[-2.23]		[-2.26]
Partial R^2	0.03	0.13	0.04	0.12
B. Investment growth				
F1	−0.17	—	−0.30	—
	[−0.96]		[−1.53]	
F2	—	−0.95**	—	−0.74**
		[−2.23]		[−2.17]
Partial R^2	0.01	0.18	0.04	0.14
C. Real GDP growth				
F1	-0.8	—	−0.12**	—
	[-0.9]		[-2.02]	
F2	—	−0.46***	—	−0.20**
		[-3.30]		[-2.01]
Partial R^2	0.01	0.16	0.06	0.10
D.Nominal GDP deflator growth				
F1	-0.53	—	−0.06	—
	[-1.62]		[-1.44]	
F2	—	−0.11**	—	−0.14***
		[-2.56]		[-2.84]
Partial R^2	0.03	0.09	0.04	0.13
E. Core PCE inflation				
F1	0.02	—	0.003	—
	[0.09]		[0.11]	
F2	—	−0.04	—	−0.08**
		[-1.26]		[-2.62]
Partial R^2	0.0036	0.01	-0.01	0.08

Table 2: The Predictive Power of Financial Conditions for Economic Activity

Notes: The table reports the partial R^2 values from regressions of the residuals of the forecasting regression (3) on each of the two financial condition factors, as specified in (4). The corresponding estimates for coefficients $\gamma(i)$ are also reported in each case. The sample period is 2001:Q1–2024:Q3. Standard errors are computed using the Newey-West method. Statistical significance at 1%/5% level indicated with */** respectively.

For the three measures of *real* economic activity (credit growth, investment growth and real

GDP growth), the second factor emerges as a statistically significant marginal predictor across all variables and horizons, whereas the first factor is significant only in forecasting real GDP growth at the one-year-ahead horizon.[6] Consistent with these findings, the partial R^2 values associated with the second factor exceed those of the first factor at both horizons, with the difference being larger at the shorter horizon.

Results paint a similar picture for the two inflation measures derived based on the nominal GDP deflator and on the core PCE index. The second factor emerges as a statistically significant marginal predictor for nominal GDP deflator at both horizons and its sign is negative, suggesting that a rise in financial risk perceptions and attitudes (as gauged by the second factor) is associated with lower inflation. The sign of the first factor is also negative, but its marginal predictive power is not statistically significant. The findings are further corroborated by the higher partial R^2 values characterizing the second factor compared to the first factor. The results for core PCE inflation suggest a muted relation between financial conditions and core inflation at the short horizon, with the marginal predictive power of the second factor becoming significant only at the longer horizon.

Overall, the findings of the forecasting exercise suggests that both financial factors have a meaningful relation to subsequent economic activity, over and above that contained in lagged values of the dependent variable. Nevertheless, the second factor emerges as the one with the strongest predictive content, at both short and long horizons.

Toward a headline index. The forecasting exercise also serves as a benchmark to construct composite financial condition indices that are informative about the future path of a specific economic variable at a given horizon: such composite indices can be computed as weighted sums of the two factors. More precisely, we assign to the first factor a weight equal to one, and to the second factor a weight equal to the ratio of its partial R^2 to that of the first factor. According to the values reported in Table 2, the relative weights attributed to the "risk factor" are all greater than one, though their magnitude varies across variables and across forecast horizons. For example, the relative weight of the risk factor is larger when it comes to the prediction of credit and investment growth, rather than that of GDP.

Figures 4 and 5 display such composite indices in the particular case of investment for the one-quarter-ahead and for the one-year-ahead horizons, respectively. In both figures, the weighted composite index (red solid line) exhibits a stronger negative comovement with future investment growth (green solid line) than a plain, unweighted index (blue solid line). In other words, the composite indices are more informative about the future expected dynamics of investment.[7]

[6] In the Annex we show that these results also hold when controlling for other common predictors of GDP, such as the term spread.

[7] This is also true relatively to the second factor taken separately.

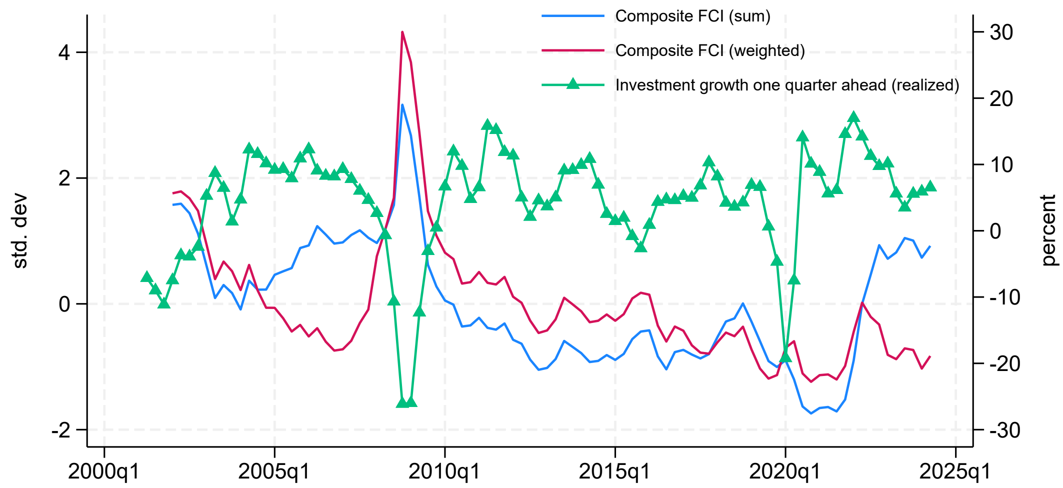

Figure 4: Composite financial conditions indices (FCI): investment growth one-quarter-ahead

Notes: The figure displays the composite financial indices constructed as the sum (blue solid line) and as the weighted sum (red solid line) of the two financial conditions factors. In the weighted composite index the second factor is weighted by the ratio of the partial R^2 of the second factor to that of the first factor in the forecasting regression of the one-quarter ahead investment growth (3). The resulting weight on the second factor is 18. The two composite indices are plotted against the realized investment growth one-quarter-ahead (green solid line). The figure shows that the weighted composite index exhibits a stronger negative comovement with future investment growth. Composite financial condition indices are reported in standard deviations (left axis). Investment growth is expressed in percent (right axis).

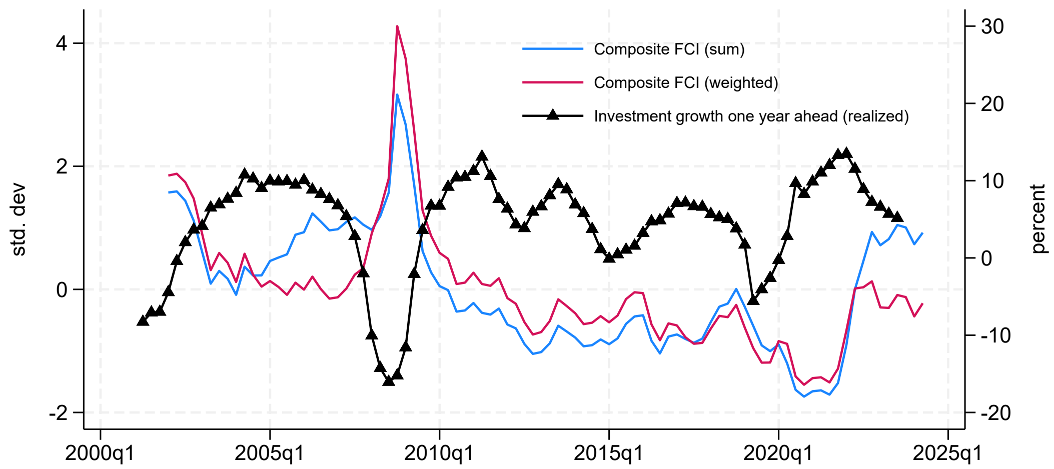

Figure 5: Composite financial conditions indices (FCI): investment growth one-year-ahead

Notes: The figure displays the composite financial indices constructed as the sum (blue solid line) and as the weighted sum (red solid line) of the two financial conditions factors. In the weighted composite index the second factor is weighted by the ratio of the partial R^2 of the second factor to that of the first factor in the forecasting regression of the one-quarter ahead investment growth (3). The resulting weight on the second factor is 3.6. The two composite indices are plotted against the realized investment growth one-quarter-ahead (green solid line). The figure shows that the weighted composite index exhibits a stronger negative comovement with future investment growth. Composite financial condition indices are reported in standard deviations (left axis). Investment growth is expressed in percent (right axis).

According to the composite weighted indices, financial conditions were exceptionally loose (i.e. below average values) between 2005 and 2009, while according to equally-weighted indices they were exceptionally tight (above average values). Thus, the assessment based on weighted indices tracks more accurately the subsequent actual expansion in investment observed during that period.

The statistical significance and magnitude of the estimated coefficients of the two factors in our forecasting exercise point to an economically significant link between current financial conditions and future economic activity. One related question, which we will explore in the following section, is therefore how, and through which channels, shocks to financial conditions affect economic activity.

4.2 Quantile Regression Results

We complement the evidence about the basic (linear) predictive properties of the two factors with a non-linear exercise, where we focus more specifically on the prediction of extreme events through quantile regressions. This exercise builds on the seminal paper by Adrian et al. (2019), in which extreme financial tightness – as measured by the Chicago Fed FCI – is shown to be a significant predictor of the left tail of GDP growth in the US. More precisely, we take the Adrian et al. (2019) quantile regressions for one-quarter-ahead and four-quarter-ahead GDP, and replace the Chicago Fed NFCI with our two factors.[8]

Results suggest that the effects of a tightening in financial conditions depend on the underlying driver. When changes in financial conditions occur through F_1, the predictive power for the tails of GDP growth is only marginally different from that of a linear model: in the left-hand panel of Figure 6, the green and black lines are nearly parallel to the OLS regression (blue line). If anything, high values of F_1 are associated to (marginally) larger GDP losses, while at the same time low values correspond to (marginally) higher GDP growth compared to what is predicted by a linear model. By contrast, a tightening occurring through the second factor (right-hand panel) has a much stronger bearing on downside risks to GDP growth. While the upper fifth percentile is not affected by higher values of F_2, the lower fifth percentile is, highlighting that a tightening of the second factor increase the risks of a large GDP contraction over a one-year horizon.

4.3 The macroeconomic effects of shocks to financial conditions

To study the macroeconomic effects of shocks to the two financial condition factors, we use the structural SVAR framework featuring macro-financial variables developed by Gilchrist and Zakrajšek (2012) and proceed in two steps. First, we compare the responses of macroeconomic

[8]To run the quantile regressions on a sample size that is sufficiently long as to enable a correct representation of the tails of the distribution, we extended our factor decomposition further back in time, starting in 1986; see Section 6.3 for further technical details on such extension.

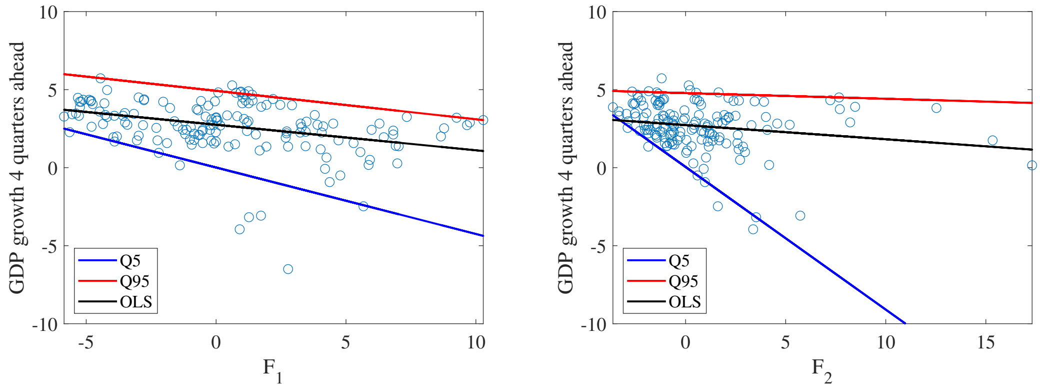

Figure 6: Quantile regressions

Note: The figure shows the univariate quantile regressions of four-quarters ahead real GDP growth on current real GDP growth and F_1 (left panel) and F_2 (right panel).

variables to a financial shock in their original specification to those of a shock in our "risk factor". Second, we change the Cholesky ordering in the original specification so as to be able to identify the effects of a shock in the first financial conditions factor, and we use the ensuing specification to study the dynamic macro-economic effects of a shock to "safe rates".

A financial shock. As argued above, the second factor primarily captures how market participants perceive and price financial risks, and movements in this factor anticipate those of key indicators of economic activity, at least in a pure forecasting sense. The corresponding causal question relates to the effects that a shock to the second factor (or, in other words, an exogenous increase in financial risk) has on key macroeconomic variables.

To answer this question, we build on the structural SVAR framework featuring macro-financial variables developed by Gilchrist and Zakrajšek (2012), introducing minimal modifications to preserve comparability with their results. Specifically, we adapt the original specification along three dimensions. First, we replace the excess bond premium with the second financial conditions factor (hereafter, F2), and the ten-year-treasury-bond yield by the first financial conditions factor (hereafter, F1) which loads mostly on the levels of short and long-term interest rates. Second, we replace the effective federal funds rate with the one-year government bond yield as in Gertler and Karadi (2015) to account for the effects of zero lower bound during the estimation period. Third, in line with our forecasting exercise in the previous section, we add the log-difference of total credit to non-financial institutions as an additional variable.

Given these adjustments, our SVAR includes the following set of variables (in this order): (i) the log-difference of real personal consumption expenditures (PCE); (ii) the log-difference of real business fixed investment (BFI); (iii) the log-difference of real GDP; (iv) inflation as measured by the log-difference of the GDP price deflator; (v) the log-difference of real total credit to the private nonfinancial sector; (vi) the quarterly average of F2; (vii) the quarterly (value-weighted) excess stock market return from CRSP; (viii) the quarterly average of F1; and (ix) the quarterly average of the one-year-treasury yield.

The identifying assumption implied by the recursive ordering of the model is that shocks to F2 affect economic activity and inflation with a lag, while safe interest rates (as captured by the one-year-treasury-yield and the first financial condition factor) and stock prices can react contemporaneously to such a financial risk disturbance; the estimation period spans over 2002:Q1 to 2024:Q4, using two lags of each endogenous variable.[9]

Figure 8 depicts the impulse response functions of the endogenous variables to an orthogonalised shock to F2. An unanticipated increase of one standard deviation in F2 leads to a significant reduction in real economic activity, with consumption, investment, output and total credit, all falling over the next several quarters. The macroeconomic consequences of this adverse financial shock are substantial; the level of real GDP bottoms out about 0.5% percentage point below trend one quarter after the shock, while the drop in investment is much more severe and persistent. The resulting economic slack leads to a substantial disinflation over time. In response to these adverse economic developments, monetary policy is eased significantly, as evidenced by the decline in the one year bond yield that commences about one quarter after the initial impact of the shock; this is also matched by a milder decline in F1, driven by the effects of the monetary policy easing on the yield curve. Despite the reduction in short term rates, the stock market experiences a significant drop.

The macroeconomic dynamics reported above are consistent with the notion that F2 provides a timely and useful gauge of supply conditions in credit and other key financing segments. Specifically, an increase in F2, akin to a tightening in the supply of credit, causes a drop in asset prices and a contraction in economic activity as predicted by the “financial accelerator" literature (*e.g.* Bernanke and Gertler (1995), Kiyotaki and Moore (1997), Bernanke et al. (1999a)).

Notably, all dynamic responses to a shock in F2 follow a similar pattern as those to a shock in the Gilchrist and Zakrajšek (2012) excess bond premium variable. This lines up very well with the fact that F2 loads mainly on spreads and with its initial interpretation as a gauge for risk attitudes and perceptions. Yet, in contrast to the credit spread index, the use of our factor also leaves room for other determinants of risk attitudes – for example equity market valuations – that partly contribute to F2 to play a role. Also note that the response of F1 to the risk shock is similar to that of the one year rate in the current specification, and to that of the ten-year treasury yield in the original Gilchrist and Zakrajšek (2012) specification. These findings are in line with F1 loading mostly on short-term funding costs and the government bond yield curve, and hence mainly reflecting the level of long- and short-term safe interest rates faced by the government, as opposed to the borrowing costs of private agents that would also incorporate a compensation for credit risk.

A safe rate shock. To identify the macroeconomic effects of a shock to the first financial condition factor, we switch F1 with F2 in the recursive VAR specification. The identifying

[9]The beginning of the sample is constrained by the availability of the financial conditions series.

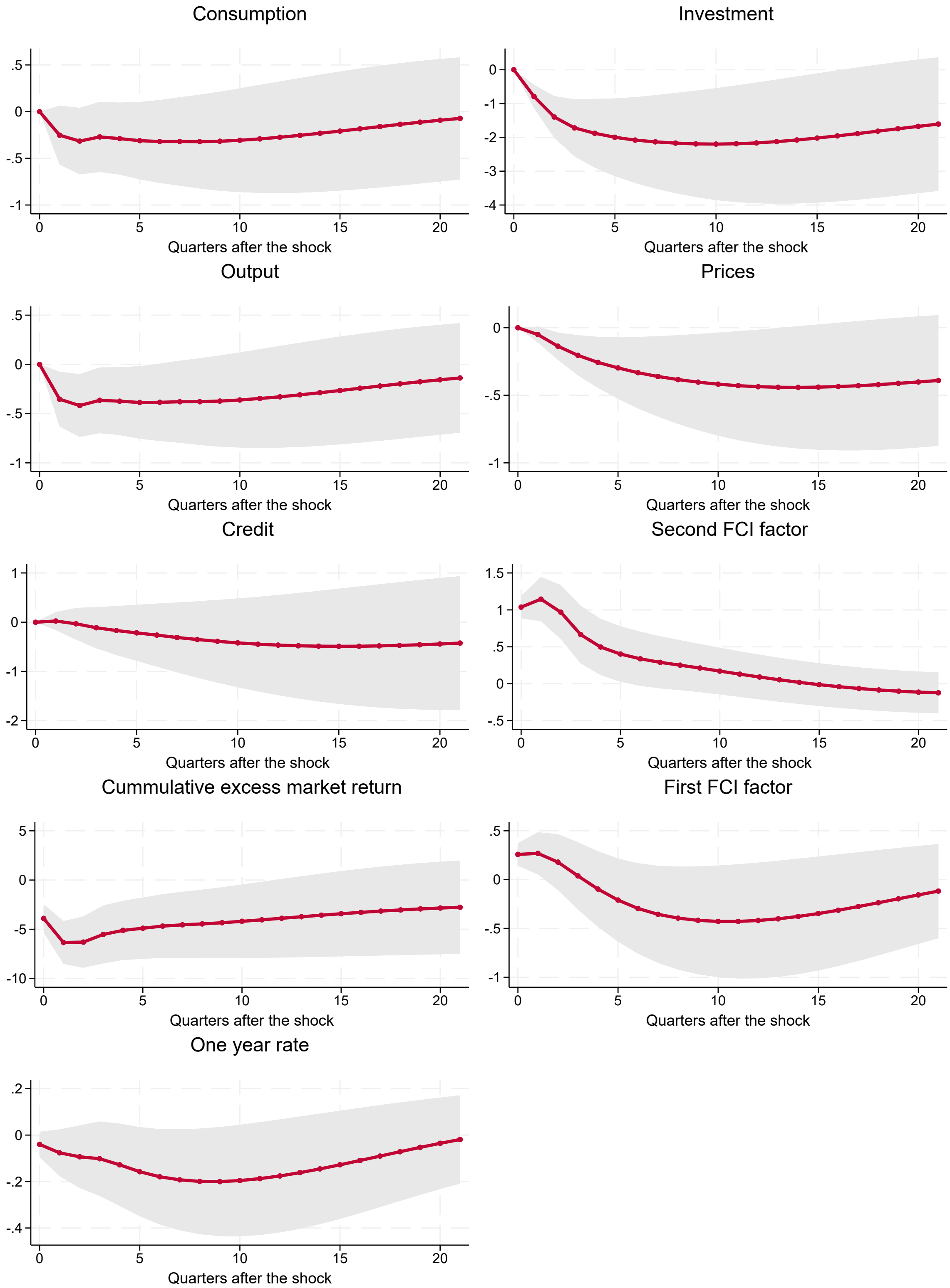

Figure 7: Macroeconomic effects of a financial shock

Notes: The figure depicts the impulse responses to a one-standard-deviation orthogonalised shock to the second financial conditions factor gauging financial stress (see text for details). The responses of consumption, investment, credit and output growth and that of the excess market return have been accumulated. Shaded bands denote 95-percent confidence intervals based on 2,000 bootstrap replications.

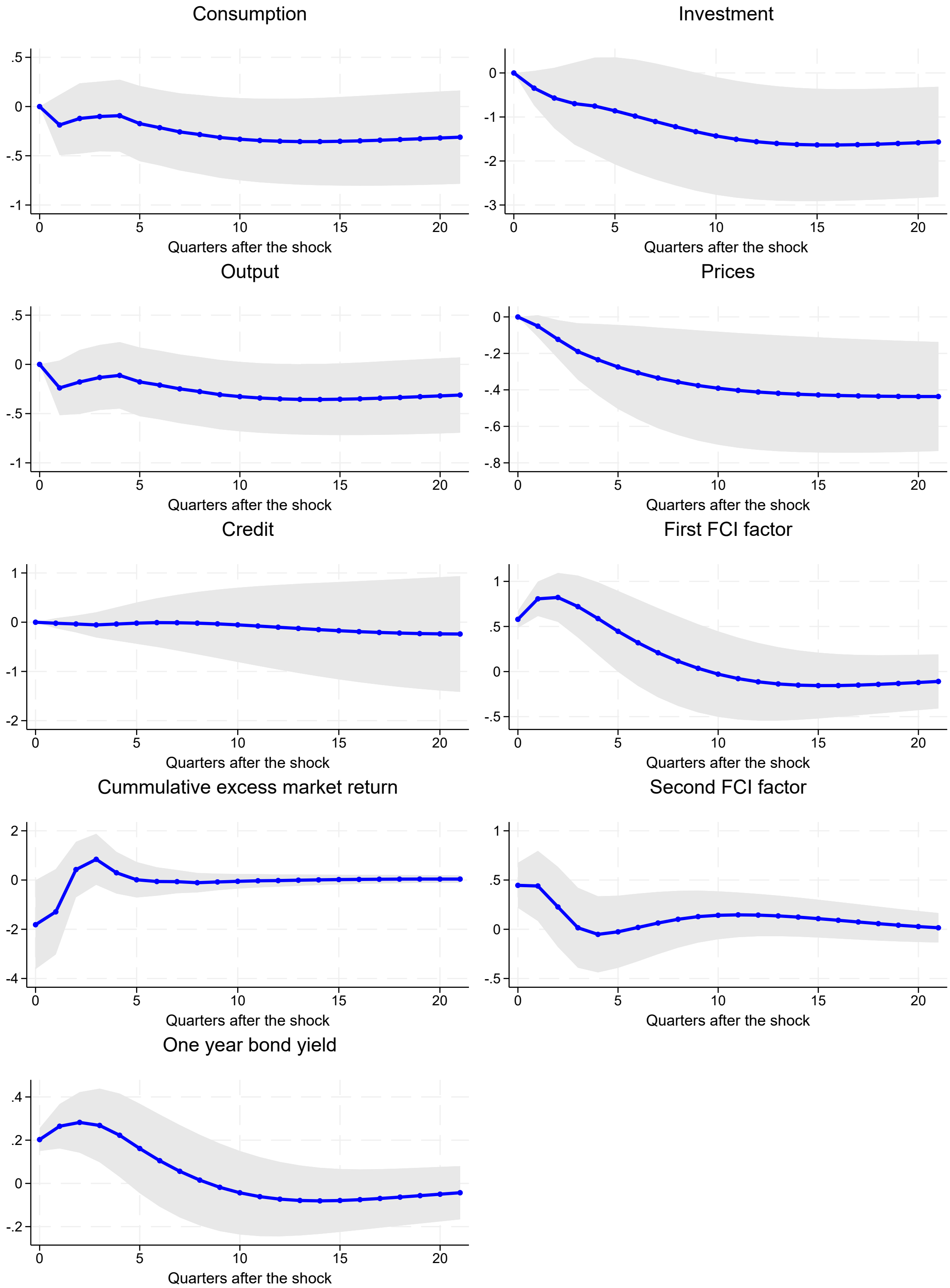

Figure 8: Macroeconomic effects of a safe rate shock

Notes: The figure depicts the impulse responses to a one-standard-deviation orthogonalised shock to the first financial conditions factor gauging safe interest rate levels at different maturities (see text for details). The responses of consumption, investment, credit and output growth have been accumulated. Shaded bands denote 95-percent confidence intervals based on 2,000 bootstrap replications.

assumption implied by this new recursive ordering is that shocks to safe interest rates affect economic activity and inflation with a lag, while they may affect contemporaneously the stock market, the level of financial stress, and the policy rate.

The dynamic responses to a "safe-rate" shock are plotted in Figure 8 and show that a positive shift in F1 induces a persistent contraction in real economic activity, credit and prices. The estimated dynamic impact on economic activity is akin that of a monetary policy shock, as identified by the macroeconomic literature (*e.g.* Bernanke and Blinder (1992), Christiano et al. (2005), Ramey (2016)). Notably, the estimation results do not feature any price puzzle, despite the absence of commodity prices in our specification.[10] This is consistent with F1 incorporating forward-looking information about future states of the economy (unlike the policy rate).[11]

The rise in "safe-rates" further reduces stock market returns and raises credit spreads and financial market volatility as captured by the second financial condition factor, albeit these effects on financial markets are shorter-lived than those on the real economic activity and prices. Finally, the short-term rate follows the same pattern as the "safe rate" factor. Results are robust to dropping the safe rate from the VAR specification.

5 Transmission of Monetary Policy to Financial Conditions

The results showcased in the previous section underscore that developments in the two factors affect real activity and inflation. It is therefore important to assess the extent to which monetary policy has a grip on the factors. This section takes a first look at how monetary policy transmits to the two financial conditions factors.

To do so, we estimate separately the dynamic responses of each factor to monetary policy surprises identified at high-frequency using Jordà (2005)'s local projection approach. That is, for each forecast horizon $h = 0, ..., H-1$ we run a separate regression of factors F_1 and F_2 on a high-frequency identified monetary policy surprise (mps_t), and a vector of control variables $\mathbf{x}_t$:

$$F^{(1,2)}_{t+h} - F^{(1,2)}_{t-1} = \alpha_h + \beta_h \cdot mps_t + \mathbf{A_h} \cdot \mathbf{x}_t + e_{t+h}, \tag{5}$$

where $F^{(1,2)}_{t+h}$ denotes the value of the dependent variable (one of our two FCI factors) h periods after the monetary policy shock, the coefficient β_h gives the response of the dependent variable at time $t+h$ to a shock at time t, the coefficient γ_h captures the additional size-dependent effect

[10] The "price puzzle", a term coined by Eichenbaum (1992), refers to a common result in monetary VARs that contractionary monetary policy shocks appear to raise the price level in the short-run. This feature is thought to be the result of typical VARs not including all relevant information for forecasting future inflation. Under this hypothesis, the identified policy shocks include not only the exogenous shocks to policy but also the endogenous policy responses to forecasts of future inflation. In this context, Sims (1992) showed that the price puzzle was substantially reduced if commodity prices, often a harbinger of future inflation, were included in the VAR.

[11] Running a specification with consumption, investment, output, prices, credit and the federal funds rate or the one-year government bond yield does feature a "price puzzle" consistent with previous findings in the literature.

at time $t+h$ to a shock at time t, $\mathbf{A_h}$ is the coefficient matrix of control variables at horizon h (to be described shortly), and e_{t+h} is the regression residual at horizon h. As before, we report Newey-West standard errors to account for serial correlation.

Following Ramey (2016), we include in the vector of control variables $\mathbf{x}_t$ lags of the dependent variable, contemporaneous and lagged values of the log-transformed CPI, of the unemployment rate, of the log-transformed industrial production, and of the Commodity Price Index.[12] We choose the number of lags optimally based on the AIC criterion, namely two lags for the specification for factor one and two lags for the specification for factor two. We use the series of monetary policy surprises from Jarociński and Karadi (2020) that are purged from any potential central bank information effects. Our estimation period runs from 2002:Q1-2019:Q4 because the series of the two financial conditions factors begins in 2002:Q1 and that of high-frequency monetary policy surprises ends in 2019:Q4. Note that as the sample ends in 2019:Q4, no observation from the COVID-19 period is included in the estimation. The LP coefficients are therefore identified from a single, stable regime, uncontaminated by the structural break triggered by the pandemic and the attendant policy interventions.

Figure 9 reports the dynamic responses of the first factor (panel (a)) and of the sector factor (panel (b)) to a positive monetary policy surprise.

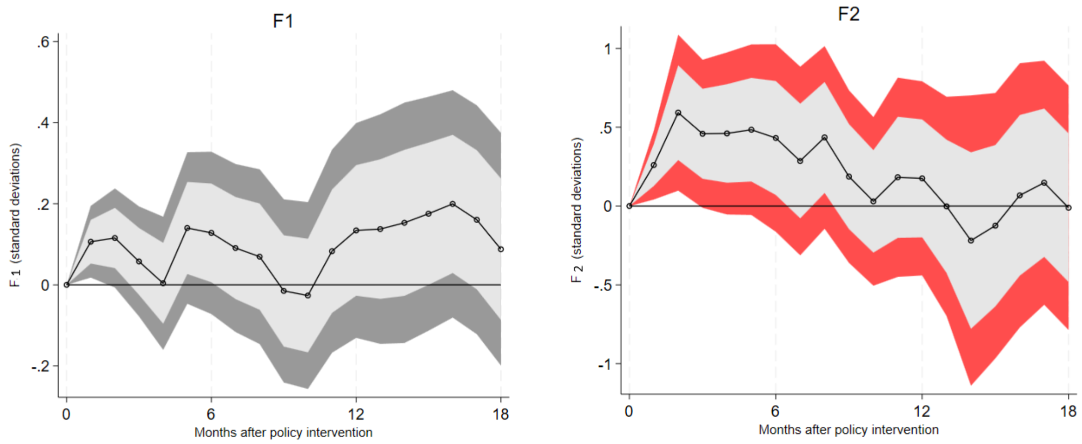

Figure 9: Dynamic responses of financial conditions to a monetary policy surprise

Notes: The figure depicts the impulse responses of the first financial conditions factor (panel (a)) and of the second financial conditions factor (panel (b)) to a 25 basis points positive monetary policy surprise. The impulse responses are estimated based on the LP specification in (8) and are built by reporting the estimated coefficient β at different horizons $h = 0, 1, 2, \ldots$. Shaded bands denote 90-percent confidence intervals and are built using Newey-West standard errors.

The figure highlights that the effect of monetary policy on both factors goes in the expected direction, *i.e.* a monetary policy tightening works to increase both the level of safe interest rates in the economy, as well as agents' risk perceptions and attitudes. Overall, the results are consistent with the operation of both an interest rate channel (as captured by factor one) and a

[12]All these variables are retrieved from the FRED database of the Federal Reserve Bank of St. Louis.

credit channel (as captured by factor two) of monetary policy transmission, and with the latter channel being relatively stronger.

6 Additional results and robustness

In this section we present a set of additional results that help shed light on the properties of our dynamic factor based approach to measuring FCIs. We will first show that the factor structure is robust to the inclusion of a set of additional variables, using an "FX bloc" as a specific example. We will then show results for a selection of large euro area countries, highlighting that the factor structure is similar to that we identified for the United States.

6.1 The choice of variables and the role of exchange rates

To be sure, the factor structure emerging naturally form the data series that are fed to the dynamic factor model is naturally sensitive to the choice of input variables. Obviously, if one were to only provide the algorithm with yields on government bonds, the second factor will not reflect risky assets but, most likely, some key feature of the yield curve, i.e. its slope. This is why it is so important to come up with a curated selection of input series, reflecting all the different facets of financial conditions—a process we have approached with a lot of care in this work.

In our selection, one potentially missing bloc of variables relates to the foreign exchange market. Given the safe haven status enjoyed by USD-denominated assets, the USD exchange rate can be viewed as a barometer of risk appetite at the global level (Avdjiev et al., 2019a). In a similar vein, tensions emerging in FX markets, e.g. an unwinding of carry trades, or a widening of the cross-currency bases, can be a harbinger of financial tensions and funding strains, and hence have a bearing on overall financial conditions.

To test the robustness of our results and the factor structure, we re-ran the estimation, including a set of FX-related variables: the USD broad nominal effective exchange rate (NEER), an index of carry trade profitability and the 3-month and 3-year cross-currency bases against the JPY and the CHF. Running the dynamic factor model with this additional bloc of variables does not alter the results: as the left-hand panel of Figure 10 shows, the factor structure is by and large the same as the one in our baseline specification (Figure 2), even if the share of the total variance explained by the two factors drops by about 10%. The FX bloc does not play a prominent role, yet shows a positive loading on the second factor, highlighting the fact that a USD appreciation and a widening of cross-currency bases are associated with an overall tightening of financial conditions Avdjiev et al. (2019b); Kroencke et al. (2021).

That said, capturing in full the role played by the FX bloc may require a richer factor structure. If one allows for a third factor, it turns out that it would mainly load on the FX bloc (Figure 10, right-hand panel) and explain an additional 10% of the total variance. This finding is in line with the intuition that, at least in the case of the United States, the FX bloc may have its own dynamics and hence contribute only marginally to our two-factor view of financial conditions. Yet for smaller open economies the FX bloc is likely to play a much larger role as a key contributor to the risk factor.

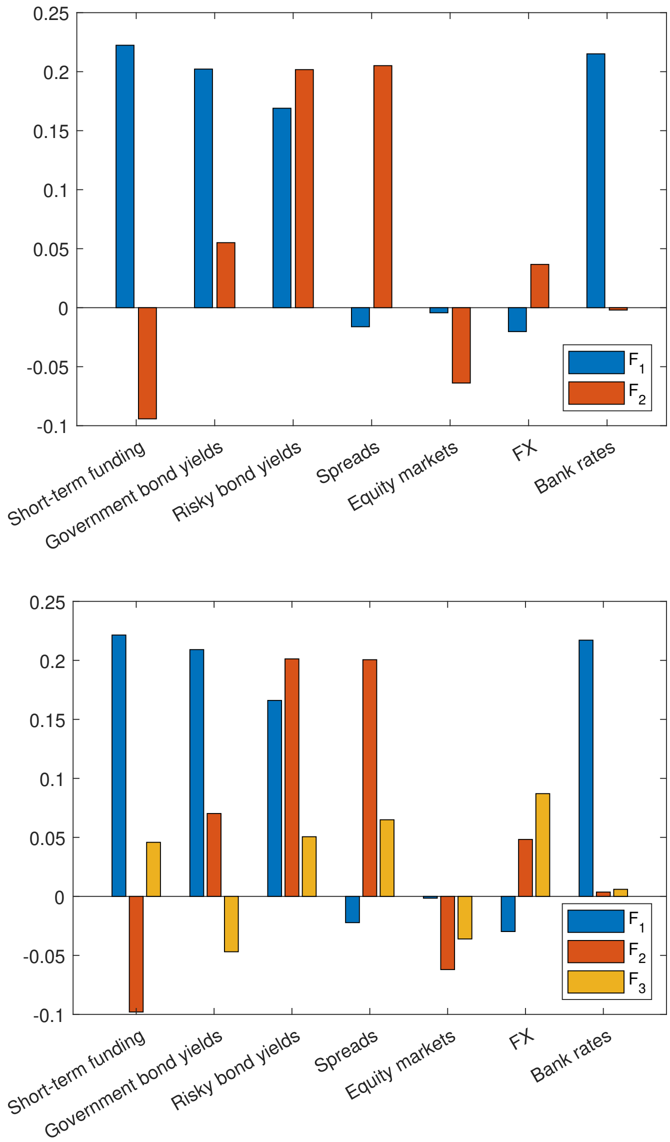

Figure 10: Average factor loadings on the blocs of variables

Notes: The figure shows the average factor loadings on each bloc of variables in the case where an FX bloc is included; the left-hand panel sticks to two factors, while the right-hand panel allows for a third one.

6.2 Results for euro area countries

We used the United States as a baseline case to illustrate the features of our factor decomposition, but results can be promptly and easily extended to other countries. In this respect, it is important to remark that, in spite of differences in the data, the two-factor structure that we highlighted for the United States also emerges naturally from the data of other countries.

For example, we collected a dataset with a similar structure for various euro area countries. Results confirm the emergence of a two-factor structure, where the first factor relates to the level of rates, and the second one to risk attitudes and perceptions. Given the common monetary policy, the first factor is broadly similar across countries. But interestingly, the second factor is not, and rather reflects country-specific developments, especially so during the euro area crisis.

Figure 11 illustrates this point by juxtaposing the factor decomposition of Germany and Italy.

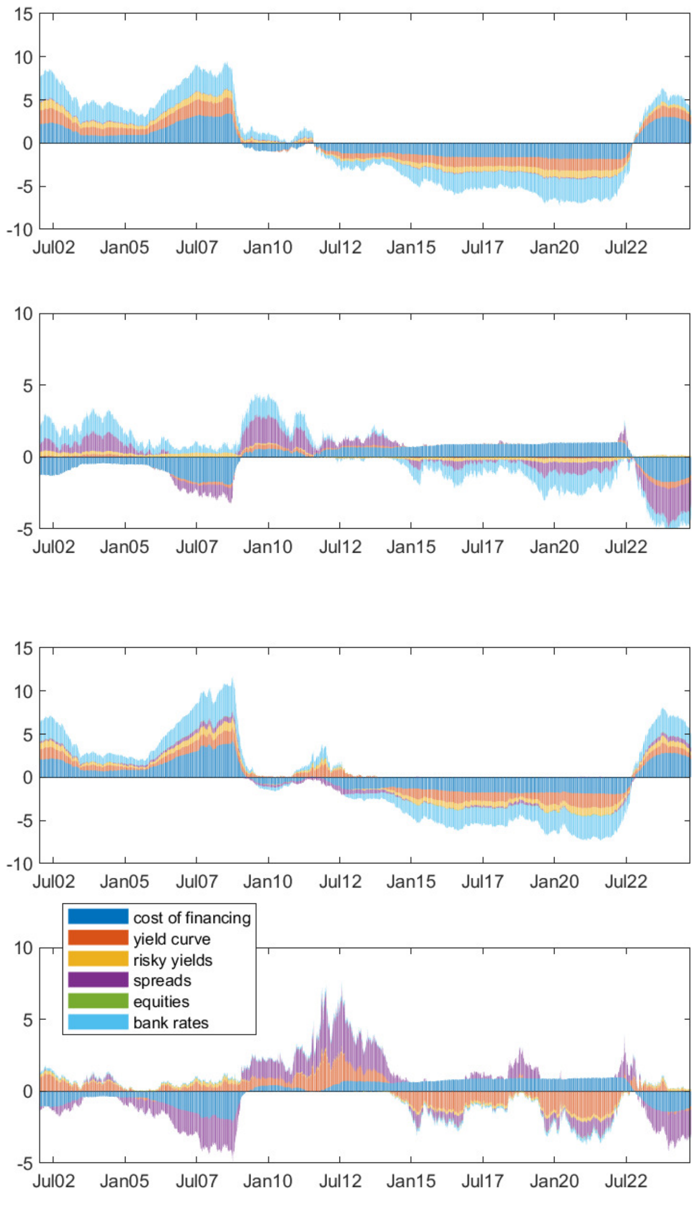

Figure 11: Decomposition of the two factors for Italy and Germany.

Notes: The figure shows the decomposition of the two factors into the components attributed to each bloc of variables for Italy (top panel) and Germany (bottom panel).

In Germany, the second factor moves rather smoothly, and increases at the onset of the GFC due to higher spreads. In the case of Italy, the second factor is more volatile, and starts increasing in 2010, as concerns over fiscal positions start mounting. Related, note that in the case of Italy, the yield curve significantly contributes to the second factor, on top of spreads. This may indicate that at times the government bond curve in Italy has been susceptible to shifts in credit risk. And negative contributions from the yield curve bloc are indeed a key driver of the decline in the second factor following Mario Draghi's "whatever it takes" announcement.

6.3 Extending the factor decomposition further back in time

Our main baseline estimates above start in 2002. This choice is motivated with data availability – quite a number of key time series, most notably many of the spreads, are not available before the early 2000s. Yet since the EM algorithm would in principle fill the values of the missing series, it is in principle possible to extend the estimates further back in time. One difficulty, though comes from the downward trend in interest rates throughout the 1980s and the 1990s. Dynamic factor models are designed for stationary input series, and are not designed to handle (common) trends in the input series.[13]

To remove the trend from the interest rate series and extend our estimates further back in time, we first extract a nominal trend by applying the Baxter and King band-pass filter with cutoff parameters of 10 and 4320 days to the Fed funds rate series; we then subtract the trend component from the other interest rate series in the input data matrix. Results are not very different form the baseline. While the first factor shows some dissimilarities during the post-GFC years, the dynamics of the second factor is nearly identical (Figure 12).

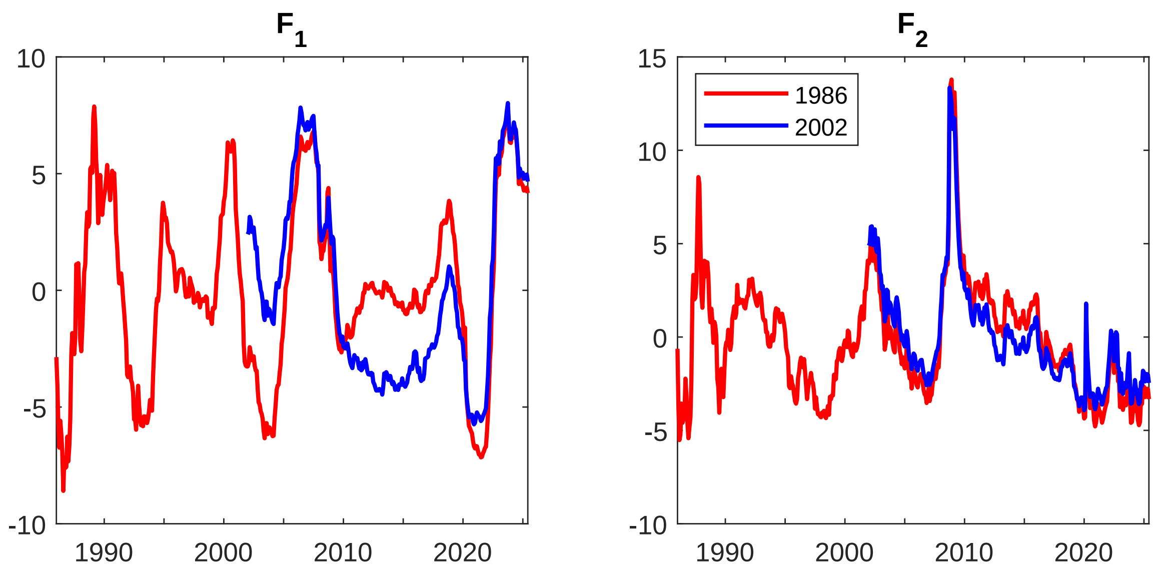

Figure 12: Robustness to an earlier starting date

Note: The figure compares the first and second factor extracted, respectively, using data starting in 2002 (blue lines) and 1986 (red lines).

[13]For a discussion and an extension to trending data, see Kaufmann and Strachan (2024).

7 Conclusion

In this paper we laid out a novel financial conditions index based on a dynamic factor model, designed to provide a transparent and broad-based summary measure of financial conditions in the economy. Using a rich dataset of financial market indicators, we extract two key latent factors: one capturing the level of safe interest rates and another capturing broader risk conditions across markets.

We then studied the interplay of the two factors with the macroeconomy. Our findings reveal that both factors possess significant predictive power for key macroeconomic aggregates, including credit growth, investment, gross domestic product and inflation. Furthermore, monetary policy affects persistently both factors, while positive shifts in the latter lead to persistent contractions in economic activity. Our results are thus consistent with both the demand and the credit channels of monetary policy being at work.

Finally, to further enhance the practical use of the factors, we showed how composite indices can be constructed by taking weighted sums of the two factors, where the weights are calibrated to maximize the predictive power for specific macroeconomic outcomes, such as credit growth or investment. Future research could extend this framework to a richer factor structure or incorporate international spillovers through foreign exchange dynamics, particularly given the global role of the U.S. dollar in financial markets.

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Appendix
Financial Conditions and the Macroeconomy: A Two-Factor View

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A Appendix

A1 Data sources

Series	Frequency	Transformation	Source
Effective FFR	Daily	Level	FRED
3-month T-bill rate	Daily	Level	FRED
Interbank rate	Daily	Level	FRED
OIS rate	Daily	Level	FRED
3-month CP (financial, non-financial)	Daily	Level	FRED
Certificates of deposit (3-month)	Daily	Level	FRED
Govt bond yields (1Y–10Y)	Daily	Level	FRED
Inflation-linked bonds	Daily	Level	FRED
Corporate bond yields (AAA, BBB, IG, HY)	Daily	Level	FRED
Govt bond term spreads (10Y–3M, 10Y–2Y)	Daily	Spread	FRED
Corporate bond spreads (IG, HY)	Daily	Spread	FRED
CP–OIS spreads	Daily	Spread	FRED
S&P500 total return	Daily	Return	CRSP
Financial sector return index	Daily	Return	CRSP
P/E, P/B ratios, dividend yield	Daily	Ratio	Bloomberg/FRED
Prime rate	Monthly	Level	FRED
Small business loan rates	Monthly	Level	FRED
15Y, 30Y mortgage rates	Monthly	Level	FRED

Table A.1: Data series used in the Dynamic Factor Model (DFM)

Series	Frequency	Transformation	Source
Real GDP	Quarterly	Log-difference	BEA
Business fixed investment	Quarterly	Log-difference	BEA
Total credit to non-financial sector	Quarterly	Log-difference	BIS
FCI Factors 1 & 2	Quarterly	Standardized	Authors' calculations

Table A.2: Data series used in the Forecasting Regressions

Series	Frequency	Transformation	Source
Real PCE	Quarterly	Log-difference	BEA
Business fixed investment	Quarterly	Log-difference	BEA
Real GDP	Quarterly	Log-difference	BEA
GDP deflator	Quarterly	Log-difference	BEA
Total credit (private nonfinancial)	Quarterly	Log-difference	BIS
F2 (Risk factor)	Quarterly	Standardized	Authors' calculations
Excess stock return	Quarterly	Return	CRSP
F1 (Safe rate factor)	Quarterly	Standardized	Authors' calculations
1Y Treasury yield	Quarterly	Level	FRED

Table A.3: Data series used in the SVAR (Shock to Financial Risk)

Series	Frequency	Transformation	Source
F1, F2	Monthly	Standardized	Authors' calculations
Monetary policy surprises	Event-based	Summed at the month level	Jarocinski & Karadi (2020)
CPI	Monthly	Log	FRED
Unemployment rate	Monthly	Level	FRED
Industrial production	Monthly	Log	FRED
Commodity Price Index	Monthly	Log	FRED

Table A.4: Data series used in the Local Projection (Monetary Policy Transmission)

Series	Frequency	Transformation	Source
USD Broad NEER	Daily	Index	BIS
Carry trade profitability index	Daily	Index	Authors' calculations
3M, 3Y cross-currency basis (JPY, CHF)	Daily	Basis spread	BIS

Table A.5: Data series used in the Robustness Check – FX Bloc

A2 Estimating the dynamic factor model

This Annex provides further details on the estimation procedure of the dynamic factor model.

Let $\Theta = (\Lambda, A, R, Q)$ be a vector of the unknown parameters, where A is a vector stacking all A_i's, $i = 1, \ldots, p$, then the log-likelihood function take the form:

$$\ell(X_{1:T}, F_{1:T}, \Theta) = N - \frac{T}{2}\log|Q| - \frac{1}{2}\sum_{t=1}^{T}(F_t - \sum_{i=1}^{p} A_i F_{t-i})' Q^{-1}(F_t - \sum_{i=1}^{p} A_i F_{t-i}) \quad \text{(A.1)}$$

$$-\frac{T}{2}\log|R| - \frac{1}{2}\sum_{t=1}^{T}(X_t - \Lambda F_t)' R^{-1}(X_t - \Lambda F_t) \quad \text{(A.2)}$$

The log-likelihood function (A.1) can in normal circumstances be evaluated using the Kalman filter, and maximised to obtain estimates of the unknown parameters Doz et al. (2011). Yet evaluating the likelihood function (A.1) is not possible when the data matrix $X_{1:T}$ has missing entries. To overcome this problem, Bańbura and Modugno (2014) propose the use of the generalised expectation maximisation (EM) algorithm of Dempster et al. (2018).

The EM algorithm proceeds as follows. First, one substitutes the missing entries in $X_{1:T}$ with arbitrary initial values $z^{(0)}$ and constructs the matrix $X^{(0)}_{1:T}$, which is subject to the standard treatment of unobserved-components models. It is therefore possible to apply the Kalman filter, based on an arbitrary initial parameter vector $\Theta^{(0)}$, on $X^{(0)}_{1:T}$ to filter out the unobservable factors. More precisely, the Kalman filter provides the expected value of the latent factors, conditional on the available observations and $z^{(0)}$:

$$\hat{F}^{(0)}_t = E_{\Theta^{(0)}}[F_t|\tilde{X}_{1:T}, z^{(0)}] \quad \text{(A.3)}$$

This allows evaluating and maximising the likelihood function – which also turns out to be conditional on the arbitrary starting values $z^{(0)}$ – to produce a first estimate of the parameter vector $\hat{\Theta}^{(1)}$. This is sometimes referred to as the initialisation step. One can then replace the initial guess for the missing observations $z^{(0)}$ with their expected values, which are obtained by evaluating (1) at the parameter estimates $\hat{\Theta}^{(1)}$, this is known as the expectations step. Equivalently, this amounts to computing the expected value of the likelihood, conditional on the available data $\tilde{X_{1:T}}$. This can be written as:

$$\ell(\Theta, \hat{\Theta}^{(1)}) = E_{\hat{\Theta}^{(1)}}[\ell(X_{1:T}, F_{1:T}, \Theta)|\tilde{X}_{1:T})] \quad \text{(A.4)}$$

The expectations step produces a new guess for the missing observations $z^{(1)}$, which enables the construction of a new full data matrix $X^{(1)}_{1:T}$. We apply the Kalman filter again and maximise the likelihood function to obtain $\hat{\Theta}^{(2)}$ in the maximisation step:

$$\hat{\Theta}^{(2)} = \text{argmax}_{\Theta}\ell(\Theta, \hat{\Theta}^{(1)}) \quad \text{(A.5)}$$

The process is iterated until convergence at j-th iteration (i.e. until the distance between $\hat{\Theta}^{(j)}$ and $\hat{\Theta}^{(j-1)}$, becomes negligible), yielding a vector of parameter estimates $\hat{\Theta}^{*}$. Conditional on $\hat{\Theta}^{*}$, one can run once again the Kalman filter and obtain the moments of the latent factors, notably their expected value:

$$\hat{F}_t^{*} = E_{\hat{\Theta}^{*}}[F_t|\tilde{X}_{1:T}] \tag{A.6}$$