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Financial markets stress indicator for Slovenia (FIMSIS)*

Marija Drenkovska[†] Črt Lenarčič[‡]

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Abstract

The Global Financial Crisis (GFC) highlighted the importance of early identification of systemic financial stress and timely macroprudential policy responses. In this context, financial stress indices have become essential tools for monitoring systemic risk in real time. While composite indicators exist for the euro area and several member states, Slovenia has lacked such a measure, primarily due to limited financial market depth and data constraints. This paper introduces the Financial Markets Stress Indicator for Slovenia (FIMSIS), the first composite financial stress indicator developed specifically for the Slovenian financial system. FIMSIS aggregates volatility-based indicators across market segments using three alternative approaches – exponentially weighted moving average (EWMA), multivariate GARCH (BEKK) and principal component analysis (PCA) – allowing for a comparative evaluation of aggregation techniques. The indicator captures both the intensity and systemic dimension of financial stress and is evaluated through robustness checks and regime classification using a Markov-switching model. To assess predictive performance, we apply a Growth-at-Risk framework with Adaptive LASSO and non-crossing constraints. Results confirm FIMSIS's relevance for signalling downside macroeconomic risk.

Keywords: financial systemic stress, financial stress indicator, financial stability, financial system, macroprudential policy.

JEL Classification: E44, G01, G10, G20.

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[†]Banka Slovenije, corresponding author's e-mail account: marija.drenkovska@bsi.si

[‡]Banka Slovenije, author's e-mail account: crt.lenarcic@bsi.si

Non-technical summary

The 2008 global financial crisis (GFC) revealed how quickly financial turmoil can spread from advanced economies to others, affecting even countries with seemingly stable macroeconomic and financial conditions. This experience underscored the importance of timely and reliable tools for tracking financial stress, enabling policymakers to respond swiftly when risks intensify.

One such tool is a composite financial stress indicator, which combines diverse market signals into a single, easy-to-interpret measure of financial market tension. While many countries have developed such indicators, Slovenia has lacked a dedicated, market-based stress indicator – largely due to its smaller, less liquid financial markets and limited availability of consistent data.

This paper addresses that gap by constructing a Financial Market Stress Indicator for Slovenia (FIMSIS), tailored specifically to the structure and data constraints of the Slovenian financial system. FIMSIS is built from key indicators of market volatility, risk premia, and price declines, grouped by financial market segment. These segment-level subindices are then aggregated into a composite indicator using advanced statistical methods grounded in modern portfolio theory, which place greater emphasis on periods of broad-based stress across market segments.

FIMSIS tracks well with known episodes of financial and economic distress in Slovenia, confirming its usefulness as a real-time monitoring tool for systemic stress. Its added value is further demonstrated in a forecasting framework that examines whether FIMSIS can help quantify downside risks to GDP growth. In this setting, certain versions of the indicator perform particularly well – supporting its relevance as an input into macroprudential risk assessment and decision-making.

Povzetek

Globalna finančna kriza leta 2008 je pokazala, kako hitro se lahko finančni pretresi razširijo iz razvitih gospodarstev na preostali svet ter prizadenejo tudi države z na videz stabilnim gospodarskim položajem. Kriza je poudarila potrebo po orodjih ekonomske politike, ki omogočajo sprotno zaznavanje finančnega stresa in tako omogočajo hitrejši in ustreznejši odziv oblikovalcev politik ob povečanju tveganj.

Ena od možnosti so sestavljeni kazalniki finančnega stresa, ki združujejo informacije iz različnih finančnih trgov v enotno in pregledno mero sistemskih napetosti. Medtem ko so številne države takšne kazalnike že razvile, je Slovenija pri tem zaostajala – predvsem zaradi manj razvitih finančnih trgov in omejene dostopnosti tržnih podatkov. S tem prispevkom to vrzel zapolnjujemo z razvojem novega, za slovensko okolje prilagojenega kazalnika finančnega stresa.

Kazalnik stresa finančnih trgov za Slovenijo (FIMSIS) temelji na izboru ključnih tržnih spremenljivk, ki zajemajo štiri glavne segmente finančnega sistema. Iz teh kazalnikov izpeljemo merila stresa, kot so volatilnost, kumulativne izgube in razmiki v donosnosti (spreade), ki jih nato združimo v sestavljene podindekse. Ti so nato združeni v končni kazalnik s pomočjo naprednih statističnih metod, ki temeljijo na sodobni teoriji portfelja. Tak pristop daje večjo težo tistim obdobjem, ko se stres pojavi sočasno v več segmentih finančnega sistema.

Analiza pokaže, da se vrednosti kazalnika FIMSIS dobro ujemajo z znanimi obdobji finančnih pretresov in gospodarskega upada v Sloveniji, kar potrjuje njegovo uporabnost kot orodja za sprotno spremljanje sistemskega tveganja. Uporabnost kazalnika dodatno potrjuje tudi njegova uspešnost pri ocenjevanju repnih tveganj za gospodarsko rast, kar je ključno za presojanje ustreznosti makrobonitetne politike.

1 Introduction

The sudden onset of the 2008 global financial crisis (GFC) and the financial stress triggered by uncertainties in global financial markets, which subsequently spilled over into the real economy, reignited interest in identifying systemic stress and developing early warning indicators. Although the crisis originated in advanced economies, its systemic effects spread globally, impacting even sound economies. From an economic policy perspective, the crucial importance of identifying current and potential future episodes of financial stress became evident. A comprehensive financial stress indicator can serve as a valuable tool for real-time monitoring and assessment of stress levels across the financial system, while also enhancing the statistical reliability and informational value of macroprudential early warning models.

While different stress indicators have been developed and are regularly updated for the euro area and several other countries,[1] Slovenia has been notably absent from such analyses, primarily due to the underdeveloped nature of its financial markets and the unavailability of widely used raw market indicators. To the best of our knowledge, this paper represents the first attempt to construct a composite financial stress indicator specifically for Slovenia. By addressing the unique challenges of data availability and incorporating methodologies adapted to the characteristics of Slovenia's financial markets, we aim to offer a significant contribution to the field of financial stability analysis.

Developing an analytical framework for monitoring financial markets requires identifying the most significant sources of stress that could trigger systemic risks. While individual indicators are valuable, they often generate a large volume of data, complicating analysis. To address this, these indicators are typically aggregated into composite indices, which provide a more comprehensive and clearer assessment of overall stress levels within the financial system. In this paper, we aggregate selected volatility metrics from various sectors of the Slovenian financial system into subindices. These subindices, reflecting developments across different market segments, are then combined into a single composite financial stress indicator - the Financial Markets Stress Indicator for Slovenia (FIMSIS). Composite indices, such as FIMSIS, offer a robust foundation for analysing financial stress and systemic risk (Kota and Saqe, 2013).

In constructing our indicator, we explore a variety of volatility measures and data transformation techniques. We argue that GARCH estimation methods are more effective for

[1] For example, several systemic stress indicators are regularly maintained by the ECB for the euro area and beyond. The CISS (Composite Indicator of Systemic Stress) is calculated on a weekly basis for the euro area as a whole, using 15 mainly market-based indicators grouped into five categories: the financial intermediaries sector, money markets, equity markets, bond markets, and foreign exchange markets (see Holló et al., 2012). The SovCISS, calculated on a monthly basis, focuses on stress in sovereign bond

extracting volatility measures from raw variables compared to simpler approaches. For the aggregation of volatility metrics, we evaluate several methodologies and propose an approach based on modern portfolio theory (MPT). This method incorporates time-varying cross-correlations between subindices, using a dynamic correlation matrix estimated via exponentially weighted moving averages (EWMA). By placing greater weight on stress-dominated episodes, this approach enhances the detection of financial stress periods.

Our methodology draws inspiration from Holló et al. (2012), who developed the CISS indicator. Their work builds on earlier studies, including those by Hakkio and Keeton (2009), Kliesen and Smith (2010), Brave and Butters (2010, 2011), Van Roye (2011), and Oet et al. (2011), which aggregated financial market indicators using factor analysis. We are also influenced by Louzis and Vouldis (2012), who extended Holló et al.'s portfolio-theory-based approach by modelling time-varying cross-correlations with a multivariate GARCH model to measure systemic stress in Greece. Similarly, Iachini and Nobili (2014) constructed a coincident indicator of systemic liquidity risk in Italian financial markets, capturing changes in correlations to identify systemic liquidity events with greater precision.

Building on these foundations, our contribution focuses on developing and evaluating a systemic financial stress indicator specifically tailored to Slovenia's context. In particular, we examine the properties and robustness of FIMSIS by constructing a special case with perfect correlations among subindices, illustrating how ignoring the systemic nature of stress can underestimate the true extent of financial imbalances. We assess the indicator's stability over time and its resilience to the "event reclassification problem" by analysing its recursively constructed counterpart, testing alternative smoothing parameters, and comparing it with other existing indicators. These exercises confirm that FIMSIS is a robust and feasible measure of financial stress in Slovenia. To further gauge its real-time applicability, we construct a chronology of systemic financial events relevant to Slovenia. The results demonstrate that FIMSIS not only aligns with known episodes of elevated financial stress but also effectively captures the systemic dimension of those events.

To further assess whether the peaks in FIMSIS reflect meaningful systemic events, we estimate stress thresholds using an autoregressive Markov-switching model. While our focus is not on forecasting economic crises, we examine whether periods of elevated financial stress identified by FIMSIS coincide with adverse developments in real economic activity. Specifically, we compare the timing of these stress regimes with business cycle phases identified through the modified Bry-Boschan (MBBQ) algorithm.

Finally, we assess the predictive performance of alternative FIMSIS variants in capturing downside macroeconomic risks using the quantile regression framework with Adaptive LASSO and non-crossing constraints proposed by Szendrei and Varga (2023). This Growth-at-Risk application confirms that all FIMSIS variants are relevant predictors of the lower tail of GDP growth, with the EWMA-based variant ($\text{FIMSIS}_{\text{std}}$) achieving the highest forecast accuracy and the BEKK-based version ($\text{FIMSIS}_{\text{BEKK}}$) showing the best in-sample fit.

The proposed composite financial market stress indicator for Slovenia (FIMSIS) enhances the suite of tools and models available for monitoring financial risks and conducting macroprudential analysis. It has the potential to significantly strengthen the existing framework for the positive-neutral countercyclical capital buffer (CCyB). As a macroprudential policy instrument aimed at mitigating systemic risk, Banka Slovenije has already identified key indicators for activating and maintaining the buffer under normal circumstances. FIMSIS, alongside other metrics, can provide critical guidance on the timing of the buffer's release.

This paper proceeds as follows: Section 2 briefly overviews the accepted definitions of systemic financial stress in the relevant literature and discusses the channels through which it affects financial and macroeconomic stability. Section 3 introduces the individual stress indicators for different segments of the financial system and discusses transformation approaches applied on the selected raw indicators. Section 4 discusses the transformation methodology of raw stress indicators, while Section 5 is dedicated to the construction of the subindices and the final aggregation into the composite stress indicator FIMSIS. Section 6 presents a comprehensive evaluation of the FIMSIS indicator, including robustness checks related to its construction (Section 6.1), the identification and validation of systemic stress regimes (Section 6.2) and an assessment of its predictive content for downside macroeconomic risks using quantile LASSO regression (Section 6.3). Following the discussion of policy considerations in Section 7, Section 8 outlines the main limitations, methodological challenges, and potential avenues for future refinement of the FIMSIS framework. We conclude in Section 9.

2 Systemic financial stress and the macro-financial transmission to the real economy

Detecting and quantifying financial stress, along with understanding its systemic risk implications, has become a paramount concern for regulatory authorities, particularly in the aftermath of the 2008 global financial crisis. There is no universally accepted definition of

markets and is available for the euro area as a whole as well as for several euro area and non-euro area EU countries (see Garcia-de-Andoain et al., 2018).

financial stress, as no two episodes of financial stress are exactly the same. In most general terms, financial stress can be thought of as an interruption to the normal functioning of financial markets. Holló (2012) expands this definition, giving it a systemic dimension and interpreting "systemic stress" as *the amount of systemic risk which has already materialised*. In turn, the literature defines "systemic risk" as *the risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially* (De Bandt and Hartmann, 2000; De Bandt, Hartmann and Peydro 2009; ECB 2009; IMF-BIS-FSB 2009).

It is this wider, systemic risk that bears potentially more hazard to the real economy, rather than isolated indices of stress in the financial system. Such stress manifests as a failure of the financial system to fulfil its primary role of efficiently allocating financial resources leading to disruptions in the functioning of financial markets and the intermediation process, which can spill over into the real economy and cause a significant economic slowdown (Hakkio and Keeton, 2009; Balakrishnan et al., 2009). The literature has found significantly larger real costs of downturns that are anticipated by financial stress episodes than the real costs of downturns that were not preceded by financial stress (Claessens et al., 2011; 2012).

There are several channels through which financial distress can impact the real side of the economy. One is the financial accelerator (Bernanke and Gertler, 1995; Bernanke et al., 1999; Kiyotaki and Moore, 1997), which intensifies the impact of negative shocks to borrowers' creditworthiness potentially leading to a credit crunch. The diminished willingness of the financial sector to extend credit to the economy may deepen the contractionary effects on economic output. Another channel is related to factors that affect lenders' balance sheets (for example asset losses or a deterioration in the quality of bank assets). The weakened bank capital may render banks more reluctant to providing capital to the real sector, potentially forcing deleveraging and leading to more severe economic contractions (Bernanke and Lown, 1991; Kashyap and Stein, 1995). Additionally, especially for small open economies with predominantly foreign owned banking systems, the parent banks of the domestic banks can represent an important transmission channel of financial stress from international to domestic financial markets (Dumičić, 2015). Parent banks' difficulties may affect not only the funding costs for their subsidiaries, but also their strategy related to the operations of the subsidiary banks, which can in turn strongly influence the credit activity and real economic developments in the countries (see Balakrishnan et al., 2009, where they show the transmission of financial stress from western European banks to emerging European economies). Finally, a crucial role in shaping the interconnection between the real and financial sectors play the structure and development of the financial system, as weakness in the structure of the financial system contributes to shock propagation (IMF, 2006; Rajan and Zingales, 2003; Illing and Liu, 2006). In Section 6.2, we conduct a brief examination of the link between our proposed composite stress indicator (FIMSIS) and real economic cycle developments.

To design a signalling tool for detecting financial crises and monitoring its build-up phase in a timely manner requires that it i) operationalises the idea of widespread financial instability (horizontal view) and ii) captures the importance of financial stress for the real economy (vertical view). To effectively gauge significant strains within the financial system that can lead to widespread disruption and economic harm, our FIMSIS must encompass the stress levels within its most crucial components, specifically those that pose the highest systemic risk.

3 Variable selection and basic setup

Before constructing the FIMSIS, we first outline the criteria for selecting raw indicators suitable for the timely monitoring of systemic risks. A key requirement for real-time financial stress monitoring is the availability of high-frequency and readily accessible data. At the same time, the primary objective in establishing an analytical framework for detecting and quantifying systemic stress is to develop a comprehensive measure capable of capturing and assessing key stressors emerging from the core components of the financial system-stressors that may ultimately give rise to systemic risk.

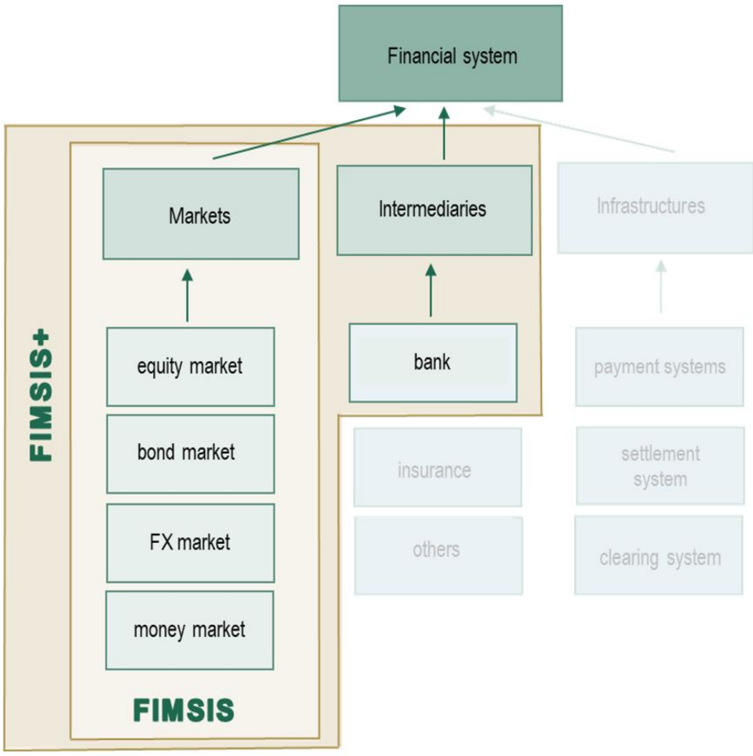
3.1 Criteria for selection raw indicators for timely monitoring of systemic risk

The financial stress literature typically recommends using daily data from the foreign exchange market, securities markets, the money market and the banking sector. As noted by Illing and Liu (2006), such indices are especially useful for analysing developments in highly developed financial markets with a broad range of instruments and corresponding indicators. However, with appropriate adaptation, these indicators can also be applied to less developed financial markets, such as Slovenia's. Our approach is inspired by the work of Dumičić (2015), who constructed financial stress indicators for Croatia, emphasising the importance of selecting market variables appropriate for small, open economies with bank-centric, foreign-owned financial systems and shallow capital markets reliant on foreign financing.

In constructing the FIMSIS, we take into account the structural features of the Slovenian financial market, the broader macro-financial and macroeconomic environment, and the dynamics of external financial markets that can significantly influence domestic financial stability.

Recent work on systemic stress indicators identifies three main building blocks of the financial system: financial markets, financial intermediaries and financial infrastructures (Holló et al., 2012; Oet et al., 2011; Jakubik and Slačik, 2013). In practice, however, due to data limitations, it is often difficult to compute reliable stress indicators for the financial infrastructures segment, which is why it is frequently omitted. Similarly, many small economies with underdeveloped financial markets also face constraints in market data availability when constructing indicators for the intermediaries segment.

Figure 1: Mapping financial system building blocks in the FIMSIS design



Source: Authors' illustration, adapted from Holló et al. (2012).

Our analysis offers two solutions to circumvent these data limitations. First, we construct a composite stress indicator focusing on the financial markets segment, i.e. namely the money market, bond market, equity market, and foreign exchange and commodity market, for which high-frequency market data are available. Second, in addition to the four-segment FIMSIS, we construct a five-segment composite stress indicator at monthly frequency, referred to as FIMSIS+ (see Figure 1). For FIMSIS+, the financial intermediaries segment is added, based on banks' balance sheet data. To accommodate the lower frequency of these data, we use monthly averages of the daily indicators from the financial markets segments included in the four-segment FIMSIS.

3.2 Data and sources for the raw indicators and the derived stress measures

For the construction of FIMSIS, we selected 10 predominantly market-based raw indicators from four financial market segments: (i) the money market, (ii) the bond market, (iii) the equity market, and (iv) the foreign exchange and commodity markets. These include stock indices (the Ljubljana Stock Exchange index, SBITOP and the EuroSTOXX index, which comprises 50 of the largest companies in Europe). Additionally, we use long-term government bond yields, including the Slovenian 10-year government bond and the euro area 10-year benchmark bond. We also include exchange rate data, namely EUR/USD and the nominal effective exchange rate (NEER). In addition to these raw indicators, we include spread-based measures, such as the yield spread between Slovenian and German 10-year government bonds, and the spread between money market rates and short-term government debt instruments like treasury bills. These spread measures are important because they already reflect symptoms of market stress.

Across all segments, we derive three[2] types of stress measures that capture key symptoms of financial distress: volatility, accumulated losses, and market risk premia (i.e. spreads). These stress factors are selected to ensure consistent and comprehensive representation of market dynamics in each segment (Table 1).

While the existing literature provides a wide range of financial indicators to capture different dimensions of financial stress[3] we focus on constructing a narrower set of raw stress indicators specifically tailored to the Slovenian context. This set includes both domestic and international market data, recognising the significant influence that global financial movements exert on small open economies[4] like Slovenia.

Before transforming the predominantly daily raw indicators into volatility measures and scaling them using empirical cumulative distribution functions (ECDFs), the data are aligned to a common sample period from 1 January 2001 to 30 May 2023.[5] This alignment

[2]Although three variables in each market segment should provide complementary information to the composite indicator, a high degree of mutual correlation between them is still expected during episodes of more severe stress disturbances (Holló et al., 2012).

[3]Kliesen et al. (2012) present a detailed review of indicators and methods used for the construction of FSIs. Jakubik and Slačik (2013) provide an example of the construction of financial instability indices for CEE countries, while Holló et al. (2012) and subsequent studies inspired by their work include relevant variables that we also employ in our analysis.

[4]Similar to Dumičić (2015).

[5]This excludes the two CMAX measures, which have been constructed using the entire span of their respective time series.

ensures consistency in the transformation process and comparability of the stress factors derived from the various indicators.

Table 1: Segment-specific stress indicators included in the FIMSIS

Segment	Measure	What it captures	Source
Foreign exchange market	Volatility of EUR/USD exchange rate	turbulence in the main exchange rate	ECB
	Volatility of nominal effective exchange rate	broad volat. to trading partners' base	ECB
	Maximum cumulated loss over a moving two-year window (CMAX) of EUR/USD exchange rate	prolonged depreciation periods (severe impact)	ECB
Money market	Volatility of 3-month SITIBOR/EURIBOR	uncert. in short-term bank funding	ECB
	Spread between 3-month EURIBOR and the issued MF T-bills	tensions between private and sovereign short-term borrowing	ECB, BoS, Min. of Fin.
	Spread between 3-month SITIBOR/EURIBOR and REPO7*/MRO rate	extreme stress (when banks avoid each other and go straight to the CB)	Bloomberg, ECB, BoS
Bond market	Volatility of 10-year government bond	market confidence in SI debt	ECB, BoS
	Volatility of 10-year EA govern. benchmark bond	provides a broader, regional ref.	Bloomberg
	Spread between the German and Slovenian 10-year government bond	SI perceived risk premium vs. a safe haven	Bloomberg
Equity market	Volatility of the SBITOP index	local market stress	Bloomberg
	Maximum cumulated loss over a moving two-year window (CMAX) of SBITOP	sustained price declines (beyond day-to-day noise)	Bloomberg
	Volatility of the EuroSTOXX 50 index	proxy for regional investor sentiment	Bloomberg

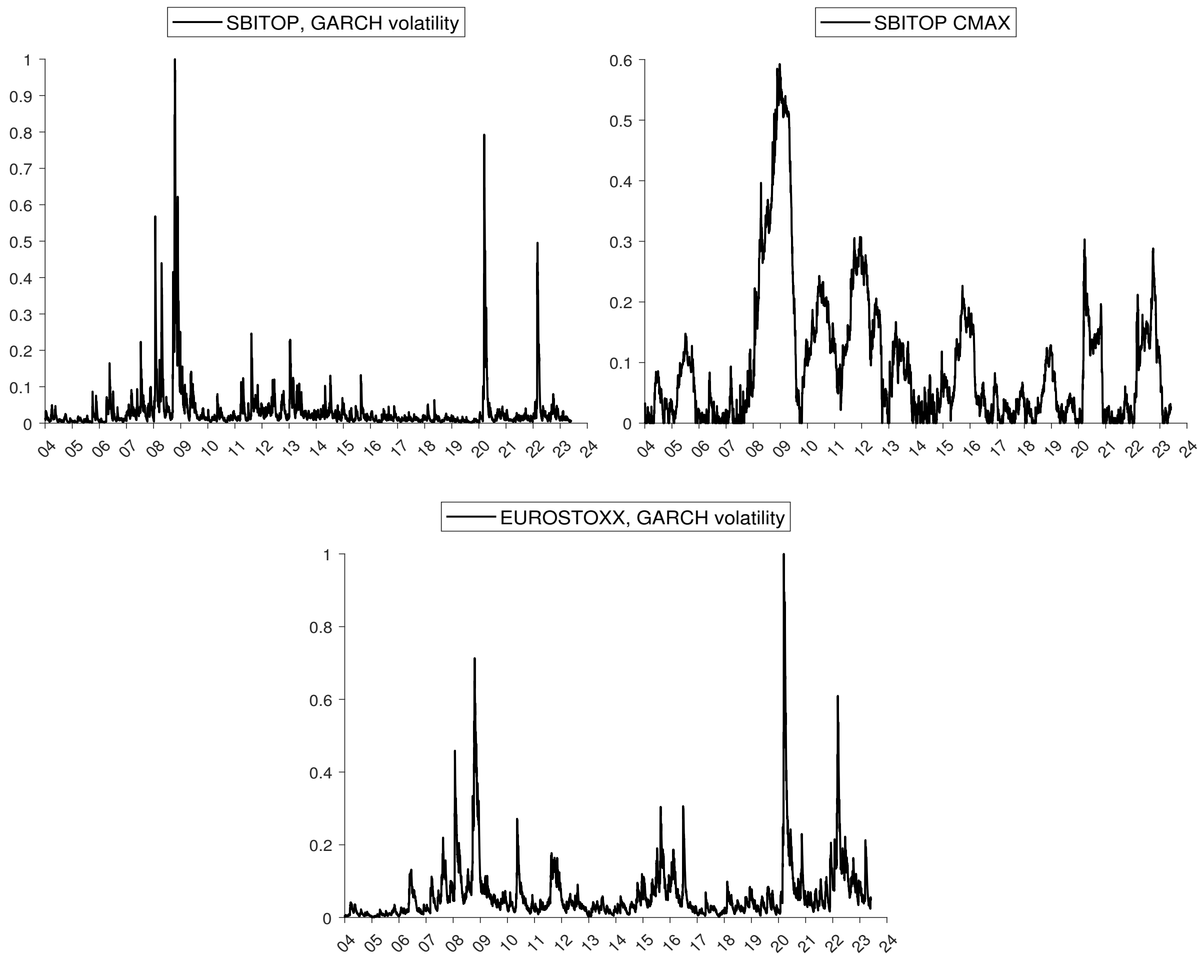
Note: *The 7-day repo rate was the interest rate applied in Banka Slovenije's liquidity-providing operations, functionally analogous to the ECB's Main Refinancing Operations (MRO) rate. This instrument was introduced in 2004 and involved regular auctions through which the central bank supplied liquidity to commercial banks against collateral, typically with a 7-day maturity. Documentation from the Bank's 2006 Annual Report clearly identifies this rate as part of the core set of operational tools used for monetary policy implementation.

3.2.1 Equity market

The link between equity markets and financial stress is well established in the academic literature. Stock market crashes serve as both key indicators and catalysts of financial crises, affecting various aspects of the economy (see, for example, Kindleberger and Aliber, 2005; Mishkin, 1992; Reinhart and Rogoff, 2009). Such crashes can trigger a credit crunch, as financial institutions may incur substantial losses on their equity holdings. This, in turn, can lead to a contraction in credit availability, impacting businesses and households.

Most studies in the literature define an equity crisis as a sharp decline in the overall stock price index. Such a decline may signal greater expected losses, higher dispersion of potential losses (i.e. increased risk) or greater uncertainty about firms' future returns. Although the literature suggests that the positive effects of equity market development on economic growth are limited in countries with underdeveloped markets (see, for example, Levine and Zervos, 1998; Bekaert and Harvey, 2000; Rajan and Zingales, 2003), heightened volatility in stock prices, particularly when driven by instability in other market segments or macroeconomic developments, can still indicate a rising degree of risk and systemic instability in the financial system as a whole.

Figure 2: Equity market volatility indicators



Note: Sample 1 January 2004–30 May 2023.
Source: Authors' calculations.

In constructing our stress indicator, we include three distinct measures aimed at capturing abnormalities in the equity market. These comprise the volatilities of two stock indices (SBITOP and EUROSTOXX 50) and a CMAX transformation of the SBITOP equity index to identify periods of sharp declines in the Slovenian stock market.[6] These three indicators are illustrated in Figure 2, capturing different dimensions of equity market stress.

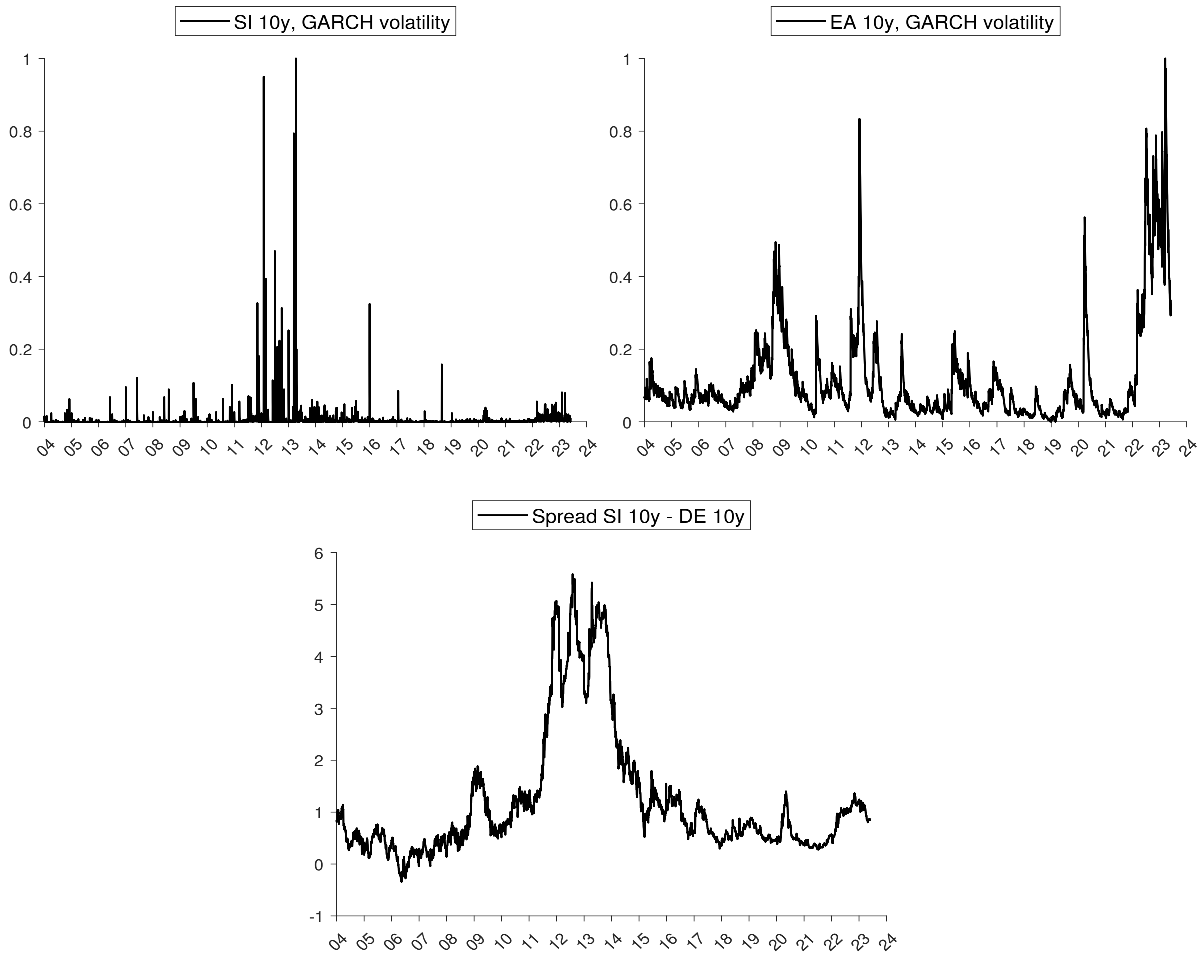
3.2.2 Bond market

Stress in the bond market is most commonly measured in the literature through the yield spread of a particular government bond against a "safe" benchmark bond. This spread is

[6]For more information on the volatility measures used in the construction of FIMSIS, see Section 4.

typically interpreted as a measure of the (excess) default risk premium embedded in the price of the riskier government bond. In a similar manner, stress in the sovereign bond market may manifest through increased price volatility and reduced liquidity in bond trading (Garcia-de-Andoain and Kremer, 2017).

Figure 3: Bond market volatility indicators



Note: Sample 1 January 2004–30 May 2023.
Source: Authors' calculations.

The spread between risky and risk-free bond yields reflects expectations of potential losses. Spreads tend to widen when expectations of future losses increase, as heightened uncertainty affects the shape of the probability distribution, implying a greater dispersion of possible losses. In such circumstances, investors typically move towards safer assets to maintain liquidity and minimise risk exposure. These behaviours serve as indicators of financial stress in the bond market.

The Slovenian debt securities market is characterised by low liquidity, with government bonds comprising the majority of total bond market capitalisation. To capture stress symptoms in this market, we focus on two dimensions: (i) the risk spread between German and Slovenian government bond yields, which reflects the pricing of credit and liquidity risk in the domestic bond market, and (ii) the yield volatilities of both Slovenian and euro area benchmark bonds, which indicate the degree of uncertainty and fragility prevailing in the market (Figure 3).

3.2.3 Foreign exchange (FX) market

Unexpected volatility in the exchange rate generates uncertainty, which affects liquidity and, consequently, the efficiency of the foreign exchange market. As in equity markets, where even small shocks can trigger large price swings, exchange rates can exhibit similarly volatile behaviour. The role of news as the predominant driver of exchange rate movements was emphasised in early studies by Dornbusch (1978) and Frenkel (1981).

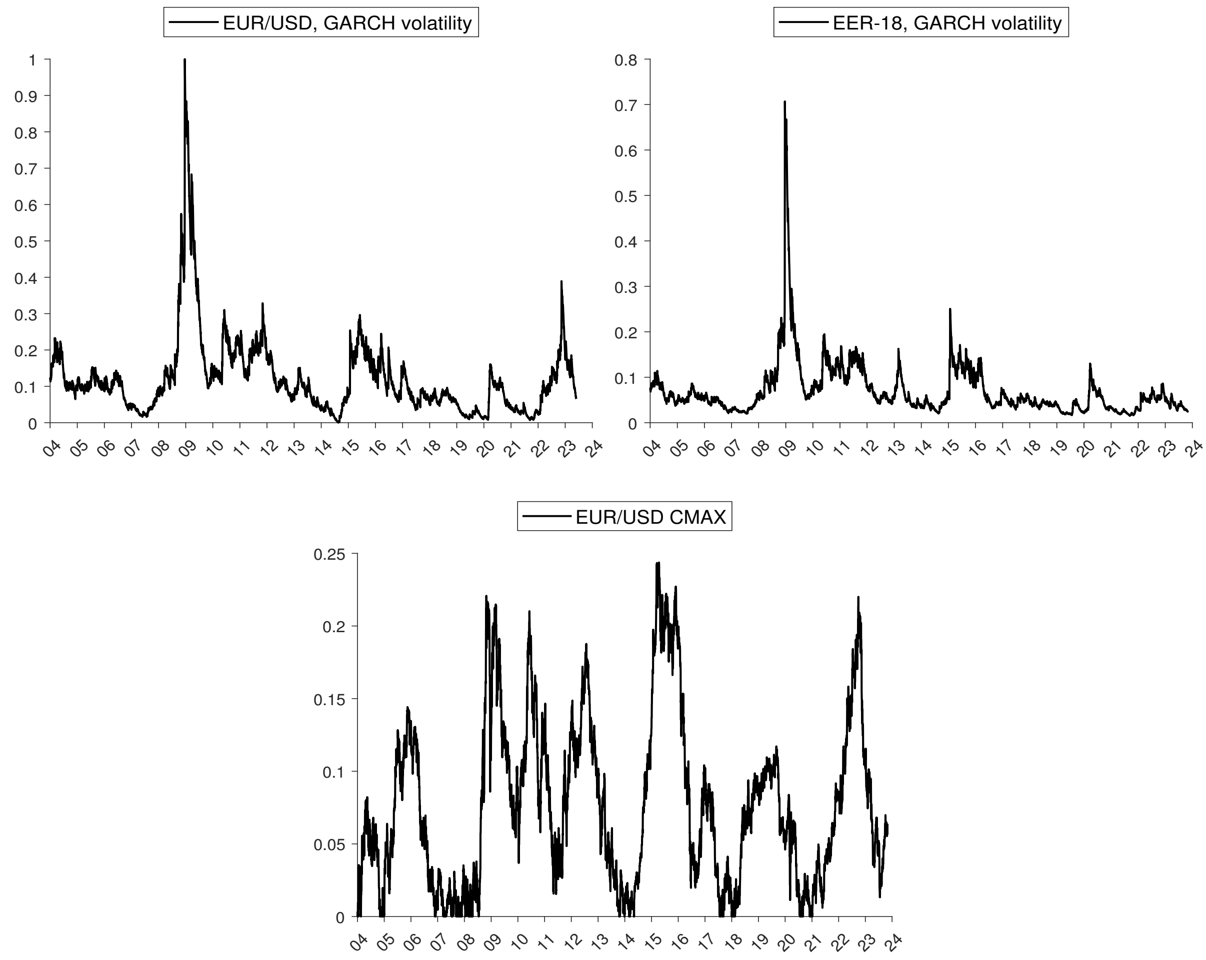
Foreign exchange stress may manifest through different variables, depending on the type of exchange rate regime. The literature on currency crises focuses predominantly on fixed or tightly managed exchange rates. In such cases, stress in the FX market typically leads to substantial devaluations (collapses in currency value), losses in official reserves and/or sharp interest rate increases. For instance, Frankel and Rose (1996) define a currency crisis as a nominal depreciation of at least 25% that exceeds the previous year's change by a margin of at least 10 percentage points. Other studies, such as Kaminsky et al. (1998) and Caramazza et al. (2000), account for potential government intervention during speculative attacks by considering a weighted average of exchange rate changes and reserve losses, with crisis thresholds identified using standard deviations from the mean. Corsetti et al. (1999) follow a similar approach but incorporate multiple thresholds to create a graded stress index.

In our analysis, stress in the foreign exchange market is captured using (i) the volatility of the euro exchange rate vis-à-vis the US dollar, (ii) the volatility of the nominal effective exchange rate (NEER)[7] of the euro against the EER-18[8] group of trading partners, and (iii) the CMAX of the EUR/USD exchange rate (Figure 4).

[7]NEER is a measure of the value of a currency against a weighted average of several foreign currencies. An increase in NEER indicates an appreciation of the local currency against the weighted basket of its trading partners' currencies

[8]The EER-18 group is composed of the non-euro area EU Member States (Bulgaria, Czech Republic, Denmark, Hungary, Poland, Romania and Sweden), plus Australia, Canada, China, Hong Kong, Japan, Norway, Singapore, South Korea, Switzerland, the United Kingdom and the United States.

Figure 4: FX market volatility indicators



Note: Sample 1 January 2004–30 May 2023.
Source: Authors' calculations.

3.2.4 Money market

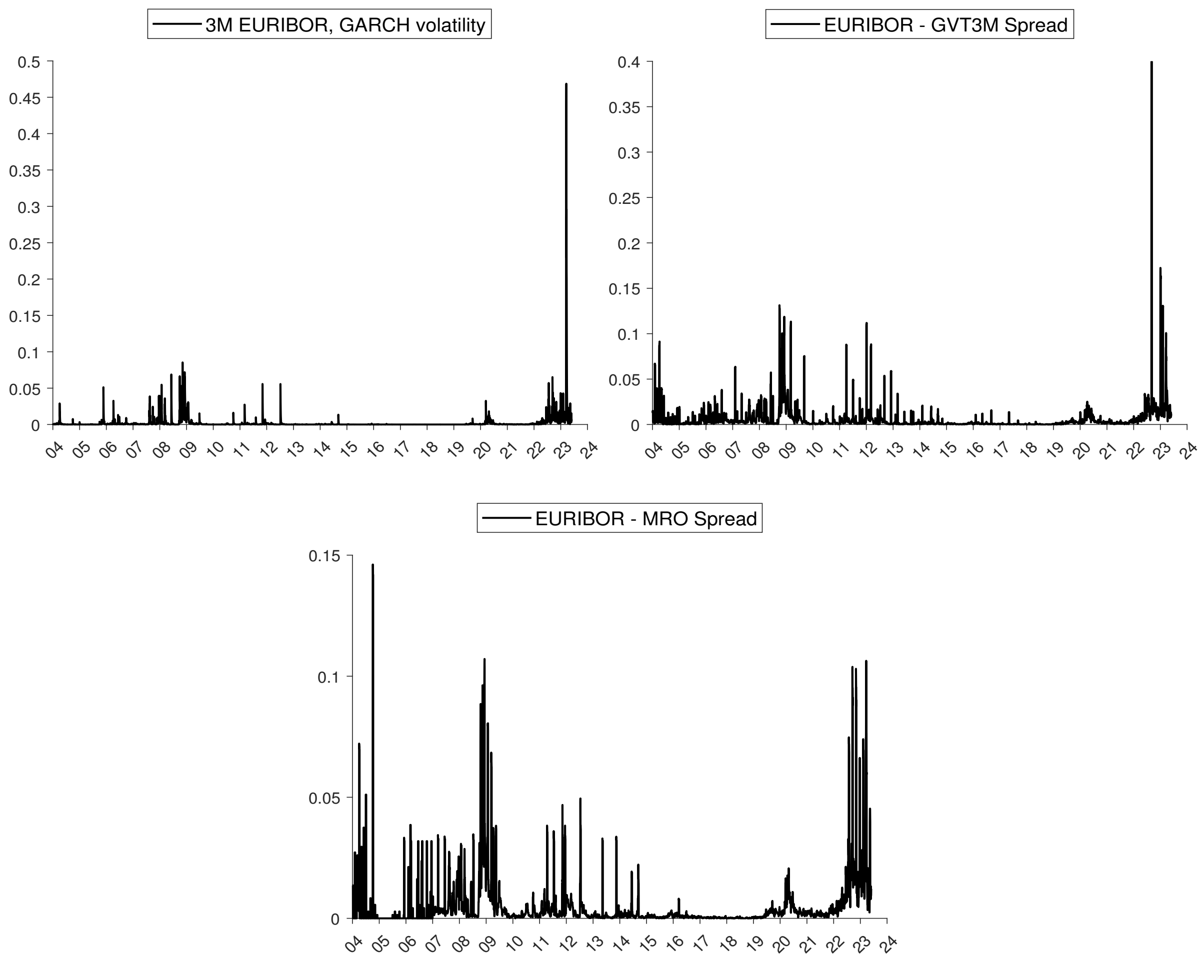
The money market is a primary source of liquidity, i.e. short-term funding, for the financial sector. When money market liquidity declines or the perceived risk of banks being unable to meet their obligations increases, financial stress is expected to rise (Cardarelli et al., 2009). Although this segment has received relatively little attention in the financial stress literature, due to its typically stable functioning, the GFC revealed its vulnerabilities, as noted by Holthausen and Pill (2010).[9]

To capture money market stress, we employ three widely recognised measures in the financial stress literature (Holló et al., 2012; Wen, 2015; Chadwick and Ozturk, 2019; Du-

[9] For a chronology of the phases that the money market underwent following interbank market tensions from August 2007 onward, see the ECB Financial Integration Report (2011).

raković, 2021, among others). The first is the volatility of the 3-month EURIBOR, which reflects the interest rate for short-term unsecured interbank lending in euros. Elevated volatility of this rate indicates heightened uncertainty in the euro area's interbank market. This uncertainty often leads to a flight to quality (e.g. secured lending or risk-free bonds) or a flight to liquidity (e.g. ECB deposits), as asymmetric information increases, an effect noted by Louzis and Vouldis (2012).

Figure 5: Money market volatility indicators



Note: Sample 1 January 2004–30 May 2023.
Source: Authors' calculations.

In addition to interest rate volatility, we calculate two spread-based measures: the spread between the 3-month EURIBOR and the 3-month Slovenian Treasury bill yield, and the spread between the 3-month EURIBOR and the ECB's main refinancing operations (MRO) rate (Figure 5).

The first spread captures the yield differential between an unsecured interbank rate and a near risk-free government rate. It reflects liquidity and counterparty risk in the interbank market (see, e.g., Heider et al., 2015; Acharya and Skeie, 2011), as well as the convenience premium of short-term sovereign paper. It therefore signals flight-to-quality, flight-to-liquidity and adverse selection dynamics in periods of stress. While the 3-month Treasury bill yield is determined by market forces and incorporates counterparty risk, it may not fully reflect funding constraints during times of acute bank illiquidity, especially when asymmetric information limits access to interbank funding. In such situations, the central bank may act as lender of last resort.

This is why the spread between the 3-month EURIBOR and the policy rate may reveal more severe liquidity disturbances than the previous measure. A wider spread generally indicates a higher degree of financial stress.

When constructing indicators for this sector, we take into account that, up to 2007, the interbank money market in Slovenia relied on the SITIBOR rate. This was the rate at which term deposits were offered by one prime bank to another. Given that data for the 3-month SITIBOR are only available at monthly frequency, we use a linear conversion method to derive a daily series, which is then merged with the 3-month EURIBOR data. Similarly, when constructing the key policy rate series, we account for the fact that, from March 2004 onwards, the ECB's MRO replaced Banka Slovenije's 7-day repo rate (REPO7), which had served as the central operational instrument for liquidity provision in the pre-euro period.[10]

3.2.5 Banking segment (financial intermediaries)

As bank loans constitute the bulk of external financing for non-financial corporations in Slovenia, unlike in the US, where this form of financing accounts for only around one quarter of total external financing (Altavilla et al., 2019), we focus on the banking system when selecting variables for the financial intermediaries segment. The banking sector was particularly affected by the GFC, which severely disrupted firms' operations in the absence of well-developed alternative financing sources.

To assess the (in)stability of the banking sector, various methods have been implemented or revisited in both academic and policy circles. In many countries, national banking supervisors use sets of indicators for supervisory risk assessments and early warning systems (EWS).[11] These often involve predicting the likelihood of individual bank distress based on micro-level data. Concerns about systemic stability arise when a significant share of banking assets is at risk or when the probability of distress rises substantially across the

[10]For more details on the key interest rates in Slovenia, see Banka Slovenije's website
[11]Survey provided by Sahajwala and Van den Bergh (2000).

system. Such bottom-up approaches rely heavily on confidential bank-level data.

Another strand of research uses macro-level indicators to assess systemic banking sector soundness. These studies apply quantifiable criteria to identify crisis periods and examine macroeconomic, financial and institutional factors associated with banking distress. Seminal contributions include Demirgüç-Kunt and Detragiache (1998), with further discussion by Davis and Karim (2008). While each crisis is unique, common risk drivers have been identified across countries. These include interest rate, credit, liquidity and market risk (Ergungor and Thompson, 2005). More recent approaches aim to develop indicators of banking stability rather than identify its causes. A notable example is Geršl and Heřmánek (2007), who propose a composite banking stability index and evaluate its methodological strengths and limitations.

The choice of method ultimately depends on the research objective and the characteristics of the available data. In our analysis, we construct a Banking Stability Index (BSI) to assess stress in the financial intermediaries segment. The BSI builds on the approaches used in Ismail et al. (2019) and Duraković (2021) and is based on a subset of widely accepted financial indicators[12] selected with consideration given to sample length and data consistency (see Table 2 for definitions and transformations). The indicator includes three variables that reflect key dimensions of banking sector vulnerability and serve as proxies for three types of systemic risk: (i) liquidity risk, associated with large outflows of deposits;[13] (ii) credit risk , arising from rapid growth in lending to the private sector, which may reflect declining credit standards and/or a higher probability of bad or risky placements (Craig et al., 2005; Davis and Karim, 2008; Gadanecz and Kaushik, 2008); and (iii) foreign exchange risk, as high reliance on external funding increases the banking sector's vulnerability to shifts in investor sentiment, particularly during periods of financial stress or broader global market turbulence (IMF, 2023).[14]

[12]These refer to the financial subset of variables from the macroeconomic framework developed by Demirgüç-Kunt and Detragiache (1998).

[13]Replacing the deposits-to-total assets variable with the first-degree liquidity ratio in the calculation of the BSI yields a highly comparable alternative.

[14]At the end of 2008, banks in Slovenia had to repay EUR 3.8 billion to foreign banks within six months. This represented about a quarter of the banking sector's total debt to foreign banks and eight percent of its total assets. A year earlier, these figures were lower: liabilities with a maturity of up to six months amounted to EUR 2.1 billion, 14.5 percent of the banking sector's debt to foreign banks and 4.9 percent of its total assets (IMF, 2009).

Table 2: Indicators used for the construction of the BSI and the risks that they measure

Financial risk	**Proxy**	**Mnemonic**	**Transformation**
Liquidity risk	Bank real total deposits to total assets	DEP	annual growth rate, normalised
Credit risk	Loans to private sector	LOAN	annual growth rate, normalised
Exchange rate risk	Foreign liabilities	FOREIGN	annual growth rate, normalised

Note: The variable DEP excludes state deposits to avoid volatility related to the major bank restructuring in late 2013, which included state recapitalisation and significant NPL transfers to the Bank Asset Management Company (BAMC). LOAN includes all domestic loans to the non-banking sector. FOREIGN captures foreign bank and non-resident liabilities. *Source*: SORS, Banka Slovenije.

The annual growth rates of these three indicators are used to detect changes in banking sector fragility. Each raw indicator is normalised to the $[0, 1]$ interval using the following transformation, as proposed by Saibal (2011):

$$I_i = \frac{R_i - \min(R_i)}{\max(R_i) - \min(R_i)} \tag{1}$$

where the term R is the raw value and the min/max values denote the bounds for dimension $i \in \{DEP, LOAN, FOREIGN\}$. Higher values of I_i suggest greater vulnerability in that dimension.

The BSI is constructed to increase with growing fragility, reflecting the Euclidean distance from an "ideal point" of stability. For DEP, this ideal is unity; for the other two, it is zero. In n-dimensional space, the BSI is calculated as:

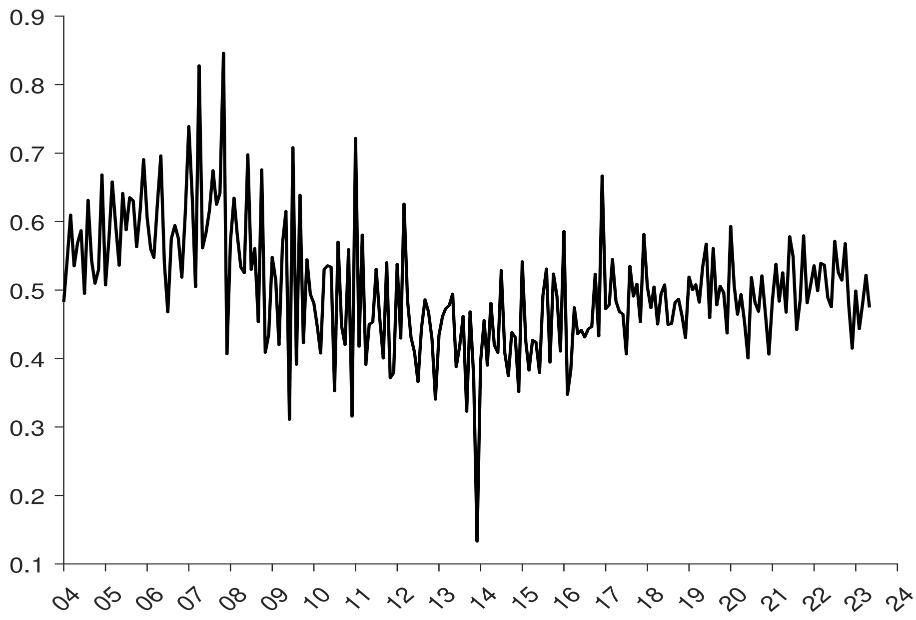
$$BSI = 1 - \frac{\sqrt{\sum_{i=1}^{n} (1 - I_i)^2}}{\sqrt{n}} \tag{2}$$

In our case, with three dimensions:

$$BSI = 1 - \frac{\sqrt{\sum_{i=1}^{n} (1 - R_{DEP})^2 + (R_{LOAN})^2 + (R_{FOREIGN})^2}}{\sqrt{3}} \tag{3}$$

The BSI for Slovenia reached its highest levels in the years leading to the GFC, signalling increased systemic fragility. Conversely, it declined significantly in late 2013, following the recapitalisation of major banks and the transfer of bad assets to BAMC. In subsequent years, the rising share of deposits in bank assets contributed to the stabilisation of the Slovenian banking system. These dynamics are clearly reflected in the evolution of the BSI shown in Figure 6.

Figure 6: Banking stability index (BSI)



Note: Sample 1 January 2004–30 May 2023.
Source: Authors' calculations.

4 Transformation of the raw indicators prior aggregation

4.1 Measures of volatility

As volatility is a latent variable and cannot be directly observed (Pati et al., 2018), various approaches have been developed by academics and practitioners to measure it. Broadly, there are two types of volatility measures: realised (historical) volatility, which is based on past outcomes, and implied volatility, which is derived from pricing models that reflect the market's expectations of future price movements.

In the financial stress literature, the most commonly used approach is the simple historical volatility measure,[15] which can be represented as:

$$\sigma_t^{simple} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} |r_{dt}| \quad (4)$$

where r_{dt} denotes the return on day d in week t and D_{it} is the number of trading days in week t.

However, in practice, financial data often exhibits volatility clustering,[16] meaning that large changes tend to be followed by large changes and small changes by small ones. This violates the assumptions of homoscedasticity and normally distributed errors in many financial models (Brooks, 2008). To account for these features, Bollerslev (1986) and Taylor (1986)[17] developed the GARCH(p,q) model, which allows the conditional variance a variable to depend on past information. Specifically, the model defines the conditional variance as a linear function of the weighted long-run average variance (ω), past short-run shocks (α_j), represented by the lag of the squared residuals ε_t^2, past longer-run shocks (β_j) and conditional variances (σ_j^2):

$$\sigma_t^2 = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (5)$$

In the finance and financial stress indicator literature,[18] implied volatility is most commonly estimated using a GARCH(1,1) model. This approach accounts for volatility clustering by assigning higher weights to recent observations, accommodates fat tails and captures mean reversion in financial data.

We calculate both volatility measures and compare them in Figure 7. The simple volatilities are calculated as the weekly average of absolute daily rate changes, daily yield changes or daily log-returns. Implied volatility is estimated using a standard GARCH(1,1) model, which can be specified as follows:

[15] See, for example, Holló et al. (2012), Louzis and Vouldis (2012), Iachini and Nobili (2014), and many others.

[16] Volatility clustering is observed when large returns are followed by large returns and small returns by small returns, i.e. periods of high volatility tend to be grouped together, as do periods of low volatility.

[17] Engle (1982) developed the Autoregressive Conditional Heteroskedasticity (ARCH) model, which incorporates all past error terms. This was generalised into the GARCH model, independently by Bollerslev (1986) and Taylor (1986), by including lagged terms of the conditional volatility. The conditional variance defined by equation (6) has the property that, if it exists, the unconditional autocorrelation function of ε_t^2 may decay slowly, albeit still exponentially. In the ARCH family, the decay rate is generally too rapid to match the persistence typically observed in financial time series, unless the maximum lag (q) is very large. As GARCH provides a more parsimonious representation of conditional variance than high--order ARCH models, it is preferred in most applications related to financial stress (Teräsvirta, 2006).

[18] See, for example, Cabrera et al. (2014), Wen (2015), Chadwick and Ozturk (2019), Duraković (2021), and others.

Mean equation

$$r_t = \mu + \gamma r_{t-1} + \varepsilon_t \tag{6}$$

Variance equation

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{7}$$

where $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$. If $\alpha_j + \beta_j \leq 1$, the model is weakly stationary (see Allen et al., 2013) and the unconditional variance equals $\sigma_t^2 = \omega/(1 - \alpha_1 - \beta_1)$. Here, r_t is the asset return at time t, μ is the average return, and ε_t is the residual return, defined as:

$$\varepsilon_t = \sigma_t z_t, \quad z_t \sim (0, 1) \tag{8}$$

where z_t is a random variable with zero mean and unit variance and σ_t^2 is conditional standard deviation at time t.[19]

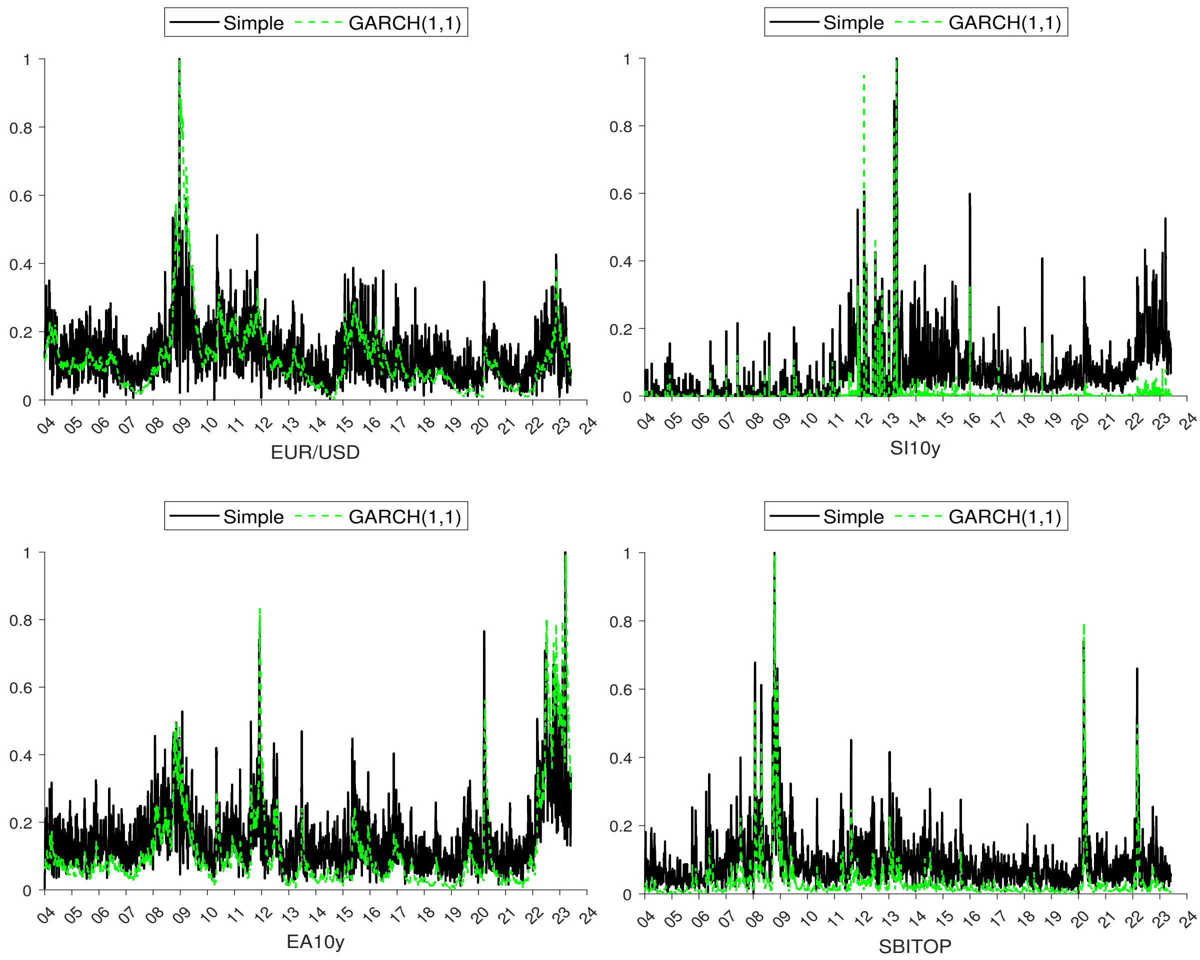
From the comparison of the two volatility measures shown in Figure 7, we observe that GARCH volatilities are smoother than the simple average absolute return measures. The former also appears to correct for outliers, i.e. extremely high volatility of short duration. In general, the GARCH-based measure tends to track the lower bound of the simple volatility series, except during extreme market movements. Nonetheless, both measures exhibit a similar pattern: they react quickly to rising stress and decrease more slowly as market conditions normalise, often with occasional rebounds.

For the construction of FIMSIS, we use implied volatilities estimated via GARCH models, as our diagnostic tests confirm the presence of clustering and heteroscedasticity in the data used to construct the stress indicator.[20]

[19]Engle (1982) assumed that ε_t can be decomposed in this way, implying that $\varepsilon_t \sim (0, h_t)$, typically assumed to follow either a normal or leptokurtic distribution (Teräsvirta, 2006).

[20]The Jarque–Bera tests for normality were derived from the conditional mean equation, alongside tests for heteroscedasticity in the residuals (ARCH LM test).

Figure 7: Two volatility measures



Note: Simple weekly average of absolute daily log returns and weekly average of estimated daily GARCH(1,1) volatilities, both normalised to the same scale. Sample period: 1 January 2004 to 30 May 2023.
Source: Authors' calculations.

The CMAX (Cumulative Maximisation) transformation is a statistical technique commonly used in finance to assess the maximum drawdown, i.e. the greatest peak-to-trough decline in the value of an asset over a specified period. The measure was first proposed by Patel and Sarkar (1998) and has since been further developed in studies aimed at identifying and quantifying periods of financial market stress or sharp declines. In our analysis, we use this measure to date equity market stress by calculating the maximum cumulative loss for the SBITOP index within the past 12 months.

We also apply the CMAX to capture episodes of currency stress in the foreign exchange market, using a moving two-year window (521 working days). The CMAX at time t is defined as:

$$CMAX = \frac{P_t}{\max(P_t, \ldots, P_{t-m})} \tag{9}$$

where P_t is price index at time t, and m is the size of the rolling window. While a window length of 24 months is standard in the literature, the limited data availability in our context necessitates a shorter one. Accordingly, we use a 12-month window (260 working days) for the SBITOP equity index.

4.2 Scaling raw data

A challenging aspect of constructing composite stress indices lies in the aggregation of individual stress indicators. Before aggregation, it is necessary to transform the indicators to a common scale. The most commonly used transformation method, given its simplicity and parsimony, is standardisation:[21] each variable is transformed by subtracting its sample mean and dividing by its standard deviation:

$$z_t = \frac{y_t - \overline{y}}{\sigma_{y_t}} \tag{10}$$

However, the implicit assumption behind the standardisation approach is that the variables are normally distributed. Given that high-frequency financial stress indicators typically exhibit fat tails, results obtained using standardised variables can be sensitive to outliers (Hakkio and Keeton, 2009). This, in turn, may lead to significant revisions of both the resulting subindices and the composite indicator as new data becomes available. These distortions are expected to be more pronounced during extended periods of severe financial stress. We test this hypothesis on Slovenian data by comparing the aggregation of standardised stress indicators using PCA on the one hand and the aggregation of indicators scaled via their ECDFs using the EWMA approach on the other. The results of this comparison are presented in Section 5.2.3.

Another popular approach for scaling raw variables is based on order statistics. This method involves computing the empirical cumulative distribution function (ECDF) of a raw stress indicator and assigning to each observation its corresponding ECDF value. This transformation, following Spanos (1999), is widely used in the literature on composite stress indicators (Holló et al., 2012; Wen, 2015; Chadwick and Ozturk, 2019; etc.). The transformed stress indicator z_t is computed from the raw stress indicator x_t, with

[21] Some aggregation methods do not require the data to be scaled or standardised (for example, in the case of non-Gaussian dynamic factor models).

observations $x_1, x_2, \dots x_t, \dots, x_n$, as follows:

$$z_n = F_n(\chi_n) = \begin{cases} \frac{r}{n} & \text{for} \quad x_{[r]} \le x_t < x_{r+1}, \quad r = 1, 2, \dots, n-1 \\ 1 & \text{for} \quad x_t \ge x_{[n]} \end{cases} \tag{11}$$

Here $x_{[n]}$ is the sample maximum, $x_{[1]}$ the minimum, r is the rank of x_t, and n the total number of observations.[22] To ensure consistency in percentiles, we follow Oet et al. (2011) and generate the CDFs using a common set of dates with full data availability across all indicators included in FIMSIS. This transformation places the raw series on a $[0, 1]$ scale.[23]

Some authors following the Holló et al. (2012) approach define the ECDF transformation using an expanding sample:

$$z_{n+T} = F_{n+T}(\chi_{n+T}) = \begin{cases} \frac{r}{n+T} & \text{for} \quad x_{[r]} \le x_{n+T} < x_{r+1}, \quad r = 1, 2, \dots, n+T-1 \\ 1 & \text{for} \quad x_{n+T} \ge x_{[n+T]} \end{cases} \tag{12}$$

In this recursive formulation, each new observation is added incrementally to the ordered sample. However, because we harmonise the sample start across all raw indicators before normalising them via ECDFs, we do not expect material differences between the recursive and full-sample transformations, as per equation (11). The comparison of FIMSIS based on recursive versus full-sample transformations (starting from January 2006) is discussed in Section 6.1.1.

In our analysis, we employ all three scaling methods to transform the volatility factors before aggregating them into a composite indicator. The results obtained using standardisation and PCA are discussed in Section 5.2.3, while results based on the ECDF (order statistics) transformation are presented in Section 6.1.1.

5 Aggregation of the transformed stress indicators

The aggregation of the standardised stress indicators into a composite indicator (or a subindex) is typically performed either by taking their simple arithmetic average, applying principal component analysis (PCA) or computing a dynamic correlation matrix between

[22] In instances where a value in x_t occurs more than once, the ranking procedure assigns the average rank to each of the repeated observations.

[23] In comparison, when an approximately normally distributed random variable is standardised by

the subindices by means of an exponentially weighted moving average (EWMA) and weighing the subindices with cross correlations between markets, inspired by modern portfolio theory (MPT). In our analysis, we follow the latter approach, as it is the one most commonly used in the financial stress literature.

5.1 Aggregation of the transformed stress indicators in subindices

By deriving volatility measures from the raw indicators and transforming them on the basis of their empirical cumulative distribution function (ECDF), we obtain 12 homogenised stress factors, systematically grouped into four market categories, as shown in Table 1. The aggregation of the three[24] stress factors ($j = 1, 2, 3$) of each market category ($i = 1, 2, 3, 4$) into their respective subindex is done by taking their arithmetic average:

$$s_{i,t} = \frac{1}{3} \sum_{j=1}^{3} z_{i,j,t} \tag{13}$$

In this approach, each of the stress factors is given equal weight, i.e. equal importance, in the subindex. Although one might argue that a drawback of this method is the underlying assumption of normality in the distribution of the variables, it remains an intuitive, comparable and easily implementable technique.

Another commonly employed weighting method within the stress indicators literature is PCA. Unlike the averaging approach, PCA assigns data-driven weights to the stress variables within each subindex. For this reason, PCA can be more sensitive to changes in the subindices' composition over time. As a robustness check, we also aggregated the

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subtracting the mean and dividing by the sample standard deviation, it is expected that approximately 95% of the resulting standardised values will fall within two standard deviations (i.e. between -2 and 2). In contrast, for variables that violate the normality assumption, the range of values that the standardised variable can take becomes unclear. As a result, it is not possible to assert that such variables are transformed onto a consistent or uniform scale.

[24]For consistency, the same number of indicators is included for each market segment. Since the subindices are calculated as simple averages – under the assumption that the transformed indicators are normally distributed –, adding more indicators to a particular market would reduce the variance of the average, and hence the variance of the subindex. The requirement for an equal number of indicators per segment, i.e. the symmetry requirement, is related to the Central Limit Theorem (CLT), which states that the average of independent random variables, regardless of their individual distributions, tends to follow a normal distribution as the number of variables increases. Moreover, the variance of the mean decreases with the number of variables. However, this rationale is rather weak in our context, as raw stress indicators from the same market segment are unlikely to be independent, and the CLT only holds reliably when the number of variables is sufficiently large (typically around 30), which is not the case here. Nevertheless, including several raw indicators per segment allows us to capture diverse sources of information and helps smooth out idiosyncratic noise. A symmetrical setup also ensures that each segment is initially given equal weight in the composite indicator.

stress indicators using PCA and found that, in our case, the resulting subindices are strongly comparable to those obtained using arithmetic averaging.

5.2 Aggregation of subindices into a composite stress indicator

In this section we describe the aggregation approach based on EWMA and MPT, which we use to calculate FIMSIS. We also discuss alternative approaches to constructing the covariance and weighting matrices and examine the comparability of the results with those obtained using simple arithmetic averaging and PCA-based aggregation.

5.2.1 EWMA and portfolio theory

The aggregation methodology proposed by Holló et al. (2012) is inspired by MPT,[25] where the calculation of the overall portfolio risk takes into account not only the variances of the individual asset risks, but also the cross-correlations between them. We follow the same approach in aggregating the subindices into a composite stress indicator. In this case, FIMSIS places greater weight on situations in which high stress prevails across several market segments simultaneously. The more strongly financial stress is correlated across subindices, the more widespread the state of financial instability.

Let the term $\mathbf{w} = (w_1, w_2, w_3, w_4)$ denote the vector of (constant) subindex weights, the term $\mathbf{s}_t = (s_{1,t)}, s_{2,t}, s_{3,t}, s_{4,t})$ the vector of subindices and $\mathbf{C}_t$ the matrix of time-varying cross-correlation coefficients $\rho_{ij,t}$:

$$\mathbf{C}_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \rho_{14,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \rho_{24,t} \\ \rho_{13,t} & \rho_{23,t} & 1 & \rho_{34,t} \\ \rho_{14,t} & \rho_{24,t} & \rho_{34,t} & 1 \end{bmatrix} \tag{14}$$

FIMSIS is computed as continuous, unit-free index bounded by the half-open interval $(0, 1]$ in the following manner:

$$FIMSIS_t = (\mathbf{w} \circ \mathbf{s}_t)\, \mathbf{C}_t\, (\mathbf{w} \circ \mathbf{s}_t)' \tag{15}$$

The operator $\circ$ denotes the Hadamard product, or element wise multiplication. Thus,

[25] An example of the MPT approach to calculating the variance of a portfolio consisting of N securities is provided in Appendix B.

$\mathbf{w} \circ \mathbf{s}_t$ represents the weighted subindices: $\mathbf{w} \circ \mathbf{s}_t = (w_1 s_{1,t}, w_2 s_{2,t}, w_3 s_{3,t}, w_4 s_{4,t})$.

The time-varying cross-correlations, $\rho_{ij,t}$, are estimated recursively on the basis of the EWMA of respective covariances, $\sigma_{ij,t}$,[26] and volatilities, $\sigma^2_{i,t}$,[27] which are approximated in the following way:

$$\sigma_{ij,t} = \lambda \sigma_{ij,t-1} + (1-\lambda)\, \widetilde{s_{i,t}} \widetilde{s_{j,t}} \tag{16}$$

$$\sigma^2_{i,t} = \lambda \sigma^2_{i,t-1} + (1-\lambda)\, \widetilde{s^2_{i,t}} \tag{17}$$

$$\rho_{ij,t} = \frac{\sigma_{ij,t}}{\sigma_{i,t}\sigma_{j,t}} \tag{18}$$

where $i = 1, \ldots, 4, \quad j = 1, \ldots, 4, \quad i \neq j$ and $t = 1, \ldots, T$. The term $\widetilde{s_{i,t}}$ denotes the demeaned subindices obtained by subtracting their "theoretical" median of 0.5: $\widetilde{s_{i,t}} = s_{i,t} - 0.5$).[28]

When relying on the EWMA approach when modelling the covariances, the decay factor, λ, remains constant at 0.93, a value very close to the one proposed by $RiskMetrics^{TM}$ (0.94). The covariances and volatilities are initialised (for $t = 0$, i.e. 1 January 2004) at their average values over the pre-recursion period 1 January 2004 to 1 January 2006.

Subindex weights

Empirically determining the exact relative importance of each stress subindex is not straightforward. For simplicity and broad comparability, subindex weights may be held constant over time and either assumed equal or based on their statistical properties within the sample. Alternatively, they may be derived from rough estimates of the subindices' impact on real economy variables in vector autoregression (VAR) models,[29] as suggested in the literature (Holló et al., 2012; Duraković, 2021[30]) or by solving an optimisation problem involving an index of economic activity, as proposed in Louzis and Vouldis (2012).[31] However, Holló et al. (2012) find that the results obtained using real-impact weights from

[26]This refers to the covariance prediction for the next period ($t + 1$), based on information available up to period t.

[27]Note that the variance of a variable here is simply its covariance with itself ($\sigma_{ii,t} \equiv \sigma^2_{i,t}$)

[28]Since the subindices are arithmetic averages of their ECDFs, their "theoretical" median should approximate that of a CDF, i.e. 0.5, which is confirmed by the Slovenian data for the sample from 1 January 2004 to 30 May 2023 (Table C.1 in Appendix C).

[29]Holló et al. (2012) propose that the subindex weights could also be allowed to vary over time to reflect potential structural changes in the dynamics of the economy.

[30]The authors estimate the weights of the subindices based on an average variance decomposition over a 12-month horizon.

[31]The authors construct an index of economic activity as the first principal component of five monthly variables and estimate the vector of subindex weights by solving a constrained least squares problem.

VAR models are highly comparable to those derived from equal weighting of subindices.

In our analysis, we use constant weighting matrices and approximate them using either the equal-weighting approach (Equation (19)) or the standard deviation-weighted approach (Equation (20)). The former assigns equal weights of 25% to all four subindices, while the latter yields the following weights: bond market: 30%, equity market: 26%, foreign exchange market: 23% and money market: 22%. We find that both approaches result in outcomes that are almost indistinguishable.

The equal-weights matrix is calculated as:

$$\mathbf{W}_{i,j} = \frac{1}{n} \tag{19}$$

where $\mathbf{W}_{i,j}$ is the element in row i and column j of matrix $\mathbf{W}$, and n is the total number of subindices in matrix $\mathbf{S}$, calculated as the product of the number of rows and columns in $\mathbf{S}$.

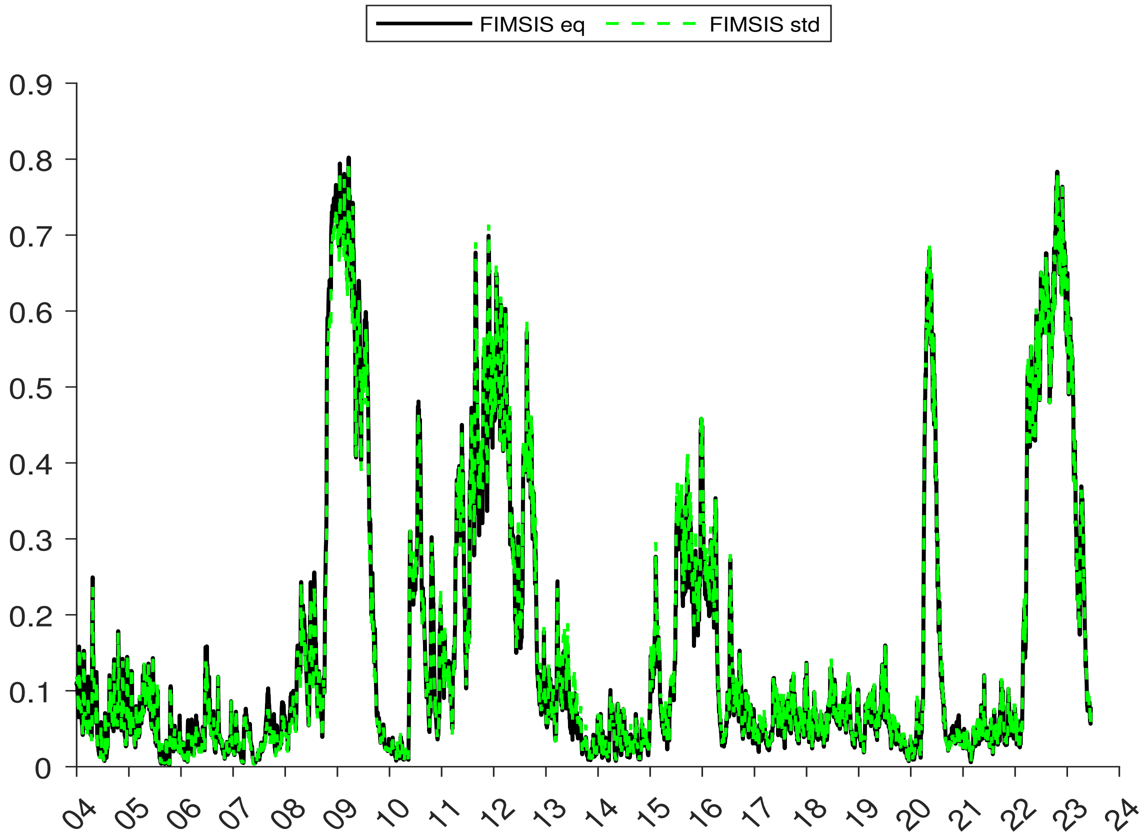
The standard deviation-weights matrix is calculated as:

$$\mathbf{WW}_{i,j} = \frac{1}{k}\frac{1}{\sigma_j} \tag{20}$$

where $k = \sum_{j=1}^{n} \frac{1}{\sigma_j}$ represents the sum of the reciprocals of the standard deviations of the stress factors across all market categories and σ_j is the standard deviation of the j–th stress factor over time.

To evaluate the practical relevance of the weighting choice, we compare the two resulting FIMSIS variants – one based on equal weights ($\text{FIMSIS}_{\text{eq}}$) and the other on inverse standard deviation weights ($\text{FIMSIS}_{\text{std}}$) – over the full sample period. As shown in Figure 8, the two indicators are highly correlated and track financial stress dynamics in a very similar way. This suggests that, in the Slovenian context, the choice between equal and variance-based weighting does not substantially alter the information content of the composite indicator.

Figure 8: Comparison of FIMSIS variants based on different subindex weighting schemes



Source: Authors' calculations.

FIMSIS perfect correlation

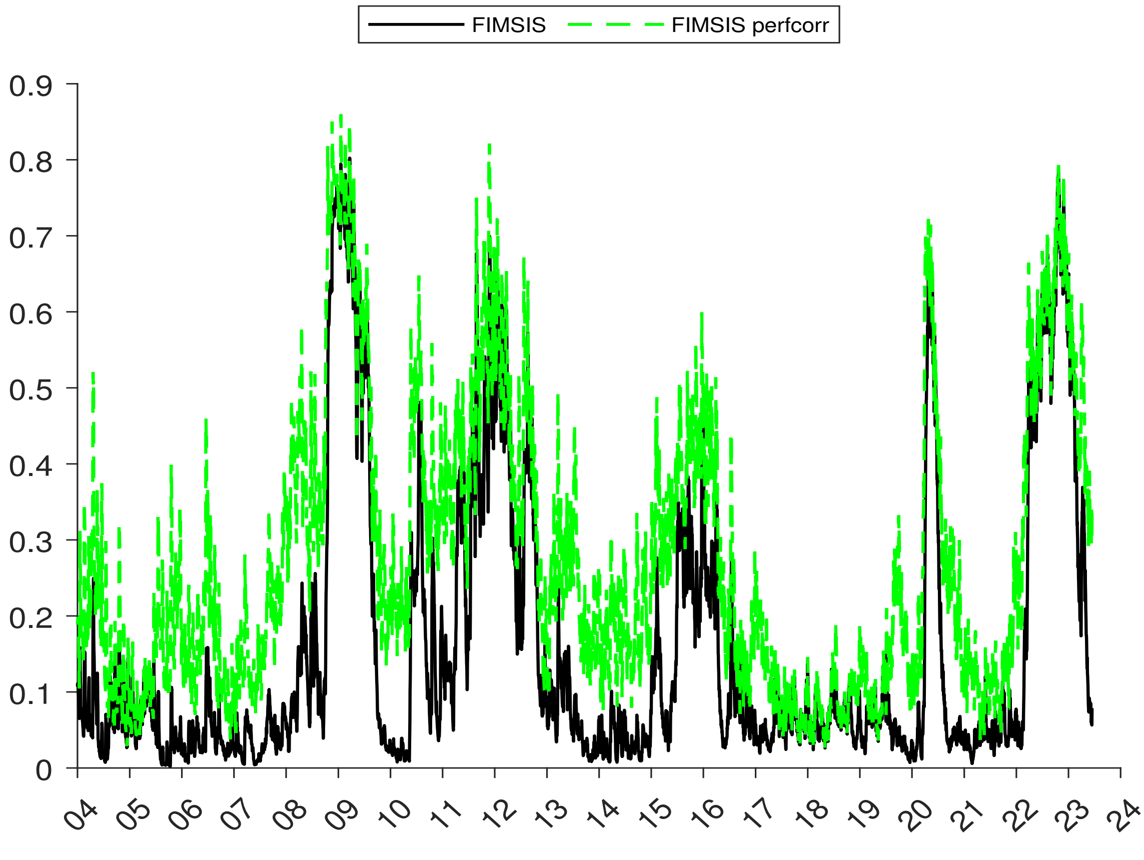
We can explore the properties of FIMSIS by examining special cases of the correlation matrix. In our analysis, the average correlations between any two subindices are positive. One particularly interesting case is when all subindices are perfectly correlated. This corresponds to the square of the simple arithmetic average of the four subindices (i.e. the vector $\mathbf{w} \circ \mathbf{s}_t$). In other words, setting all elements of $\mathbf{C}_t$ equal to 1 implies a situation in which all subindices simultaneously stand at either historically low levels (extreme market tranquillity) or historically high levels (extreme market stress).

$$FIMSIS_t^{perfcorr} = \left(\sum_{j=1}^{4} w_j s_{j,t} \right)^2 \tag{21}$$

Since such scenarios are the exception rather than the norm, a "perfect correlation" version of FIMSIS would be less capable of clearly distinguishing between different levels of systemic stress.

The perfect correlation benchmark defines an upper bound for the FIMSIS indicator. Thus, $\text{FIMSIS}_{\text{perfcorr}}$ represents the maximum value the FIMSIS indicator can attain, given the subindices and their respective weights. This benchmark enables the decomposition of FIMSIS into contributions from each subindex (weighted accordingly) and an overall contribution from cross-correlations, defined as the difference between the squared weighted average of the subindices and the original FIMSIS. Such a decomposition can be particularly useful for regular monitoring exercises conducted as part of financial stability surveillance by macroprudential authorities or other interested stakeholders. Figure 9 and Figure 10 confirm that during crisis periods, the correlation-based FIMSIS converges towards the perfect correlation benchmark as correlations approach unity.[32]

Figure 9: FIMSIS vs FIMSIS "perfect correlation"



Source: Authors' calculations.

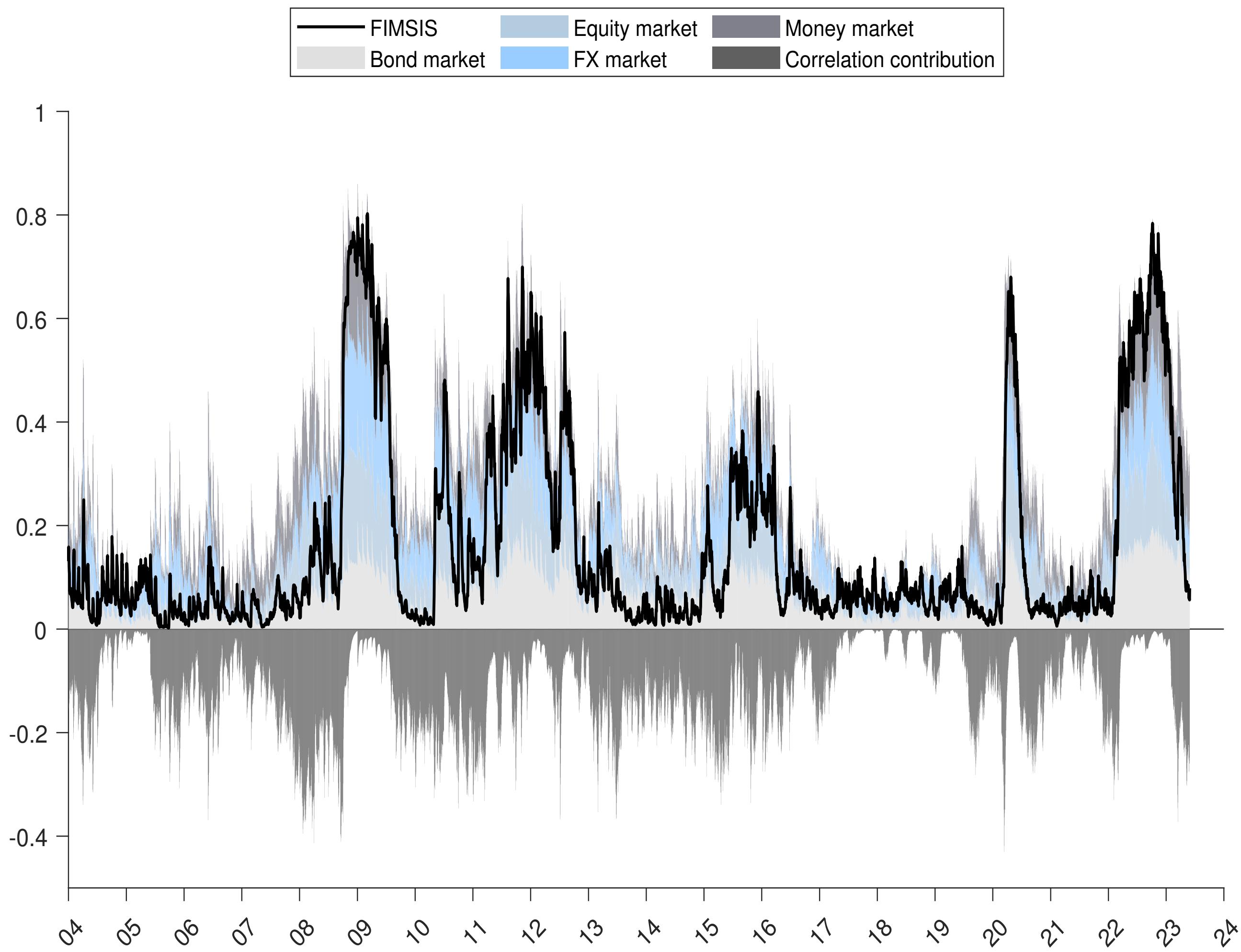
The Slovenian financial market has experienced six systemic stress events in which the correlations between subindices remained, for prolonged periods, close to 1 (i.e. perfect correlation): the GFC; the European sovereign credit risk episode followed by the

[32]The sum of the contributions from each subindex, ignoring their cross-correlations, is represented in the figure by the upper boundary of the light golden area and is thus equivalent to the weighted average of the four subindices. The difference between this perfect correlation FIMSIS and the original (black line) FIMSIS reflects the impact of the cross-correlations and is shown in the figure as the area below the

sovereign debt crisis; Brexit; the COVID-19 crisis; and the recent "polycrisis"[33] (the Russian aggression against Ukraine, followed by the energy crisis and the inflationary shock). These periods correspond to maximum values of the systemic financial stress indicator of approximately 0.8, 0.7, 0.4, 0.7 and 0.8 respectively.

As expected, FIMSIS coincides with the indicator calculated under the assumption of perfect correlation not only when systemic stress is extremely high, but also when it is simultaneously very low across all segments. This confirms that the perfect correlation case may overstate the level of systemic stress during "normal times", when correlations are relatively moderate, thus introducing bias into its informational content under such conditions, as also noted by Louzis and Vouldis (2012).

Figure 10: Decomposition of the composite systemic stress indicator for Slovenia, FIMSIS



Source: Authors' calculations.

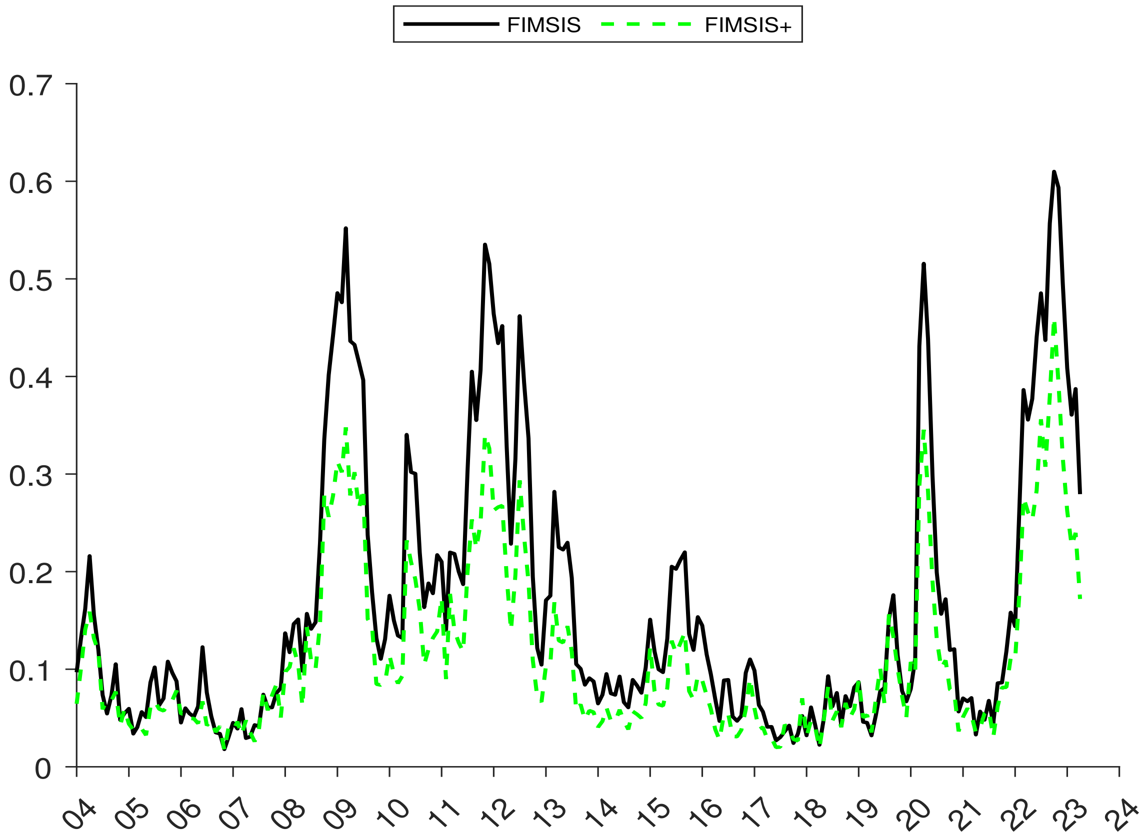
zero line.

[33]First coined in the 1970s, the term "polycrisis" has been popularised by historian Adam Tooze to describe the convergence of multiple crises and was reconceptualised by Lawrence et al. (2024).

Monthly FIMSIS vs FIMSIS+

For each of the financial market segments (money market, bond market, equity market, and the foreign exchange and commodity market), three individual indicators of financial stress are prepared, on the basis of which we compute a stress subindex, except for the financial intermediaries segment, which contains a single constructed indicator. As described in Section 3.2.5, we construct the banking sector fragility index (BSI) exclusively for the purposes of our analysis. The BSI serves as a proxy for the financial intermediaries' stress measure – more specifically, a stress measure for the banking sector (see visualisation in Figure 1).

Figure 11: Monthly frequency indicators FIMSIS and FIMSIS+



Source: Authors' calculations.

The use of high-frequency (daily or weekly) market indicators to gauge stress in the Slovenian financial intermediaries sector quickly encounters problems such as the limited number of listed banks, the near absence of listed bank bonds and the overall shallowness of the domestic capital market. Owing to this lack of data availability, the intermediaries sector is not included in the basic high-frequency FIMSIS. However, we use monthly averages of the original FIMSIS variables to construct the four subindices and combine them with the BSI – the fifth subindex – to construct the monthly-frequency version of the augmented composite indicator of systemic financial stress: FIMSIS+ (see Figure 11).

We observe that the monthly-frequency indicators exhibit less pronounced peaks than the daily FIMSIS. This difference arises from the smoothing effect of the longer aggregation horizon inherent in the monthly indicator. Specifically, as the monthly version aggregates data over a longer time period, short-term fluctuations and noise present in daily data tend to be smoothed out. This averaging process dampens the impact of extreme values or outliers that may occur on specific days, values which are, by contrast, captured by the daily indicator. As a result, sudden spikes in financial stress that occur within a given month may be less pronounced in the monthly version.

Nonetheless, both indicators calculated with monthly frequency data, FIMSIS and FIMSIS+, exhibit consistent responses to stress events. Some differences between the four-segment and five-segment monthly indicators may also stem from divergences in the construction approach of the fifth subindex, although the stationarity conditions required prior to applying the EWMA approach were satisfied, as in the case of FIMSIS.[34]

5.2.2 Dynamic covariance in MGARCH models

In addition to the EWMA model, another class of models commonly used in the financial stress literature for estimating dynamic covariance matrices are the multivariate GARCH (MGARCH) models.[35] The two most widely used variants for estimating conditional covariances and correlations are the BEKK GARCH (the Baba-Engle-Kraft-Kroner GARCH, developed by Engle and Kroner, 1995) and the DCC GARCH (the dynamic conditional correlation GARCH, first proposed by Engle, 2002). Caporin and McAleer (2012) compare the two models and find that they can essentially be used interchangeably for obtaining consistent estimates of dynamic conditional correlations. Based on their findings, and following recent studies that adopt the BEKK approach (see, for example, Louzis and Vouldis, 2012; Iachini and Nobili, 2014; Wen, 2015), we apply the BEKK

[34]As EWMA is, by construction, a regression model, we ensure that weak stationarity assumptions are satisfied before applying it to the subindices (as part of constructing the dynamic covariance matrix). Specifically, the assumption that the first and second moments, as well as autocovariances, are time-invariant is met because the subindices, apart from the BSI subindex, are averages of ECDFs and thus share similar statistical properties. This is supported by the descriptive statistics. From Tables C.1 and C.2 in the Appendix, we observe that the subindices have means of approximately 0.50 (ranging from 0.44 to 0.50 in the case of FIMSIS+) and standard deviations between 0.19 and 0.26 (0.19 to 0.29 for FIMSIS+). Visual inspection of Figures C.1 and C.2 suggests that autocovariances are positive and appear to be time-invariant. We also reject the presence of unit roots in the series.

[35]These models include VECH-GARCH, CCC-GARCH, BEKK-GARCH and DCC-GARCH, which are commonly used for measuring financial risk spillovers and assessing multivariate spillover relationships (see, for example, Jones and Olson, 2012; Zhang et al., 2021).

representation with the simplest specification in which all lags are of order 1, i.e. the BEKK-MGARCH(1,1,1) model.

In its general form a BEKK(p,q,K) model is defined as:

$$\mathbf{\Sigma}_t = \mathbf{C}\mathbf{C}' + \sum_{i=1}^{p}\sum_{k=1}^{K} \mathbf{A}_{ki}^{'}\overline{\mathbf{S}}_{t-i}\overline{\mathbf{S}'}_{t-i}\mathbf{A}_{ki} + \sum_{j=i}^{q}\sum_{k=1}^{K} \mathbf{B}_{kj}^{'}\mathbf{\Sigma}_{t-j}\mathbf{B}_{kj} \tag{22}$$

where $\mathbf{C}$ is an $n \times n$ lower triangular matrix, $\mathbf{A}_{ki}$, $\mathbf{B}_{kj}$ are $n \times n$ parameter matrices, K specifies the generality of the process, while the p and q denote the number of lags used (in our case, $p = q = K$). The parameters of the BEKK[36] model are estimated by maximising the Gaussian likelihood function of the multivariate process.

Although the BEKK model is relatively parsimonious compared with other MGARCH specifications, the number of parameters that must be estimated remains high, even in the bivariate case, as demonstrated by Louzis and Vouldis (2012). For this reason, we impose a diagonal BEKK representation, in which $\mathbf{A}_{ki}$ and $\mathbf{B}_{kj}$ are restricted to diagonal matrices, as in Ding and Engle (2001), thereby reducing the number of parameters to be estimated.

While the EWMA method is found to perform effectively in modelling and forecasting conditional (co)variances,[37] several authors (for example, Louzis and Vouldis, 2012; Wen, 2015[38]) have pointed out its limitations. These include the assumption that shocks in the volatility process persist indefinitely, and the ad hoc selection of the parameter λ, which may not accurately reflect the information content of the data.[39] Another argument in favour of using BEKK GARCH instead of EWMA is that, by construction, it estimates the $\mathbf{C}_t$ on the basis of the information provided by the data.

However, if we expand the expression (22), each covariance entry consists of a constant term, weighted error products and weighted covariances. In this sense, the EWMA model is merely a special case of the scalar BEKK model where $\mathbf{A}' = \sqrt{1-\lambda}\mathbf{I}, \quad \mathbf{B}' = \sqrt{\lambda}\mathbf{I}$.

In our analysis, we compute the correlation matrix, $\mathbf{C}_t$, using both approaches and com-

[36]The most appealing property of the BEKK model is that it ensures the positive definiteness of the conditional covariance matrices, $\mathbf{\Sigma}_t$, by using, as a constant term, the product of two lower triangular matrices (Louzis and Vouldis, 2012).

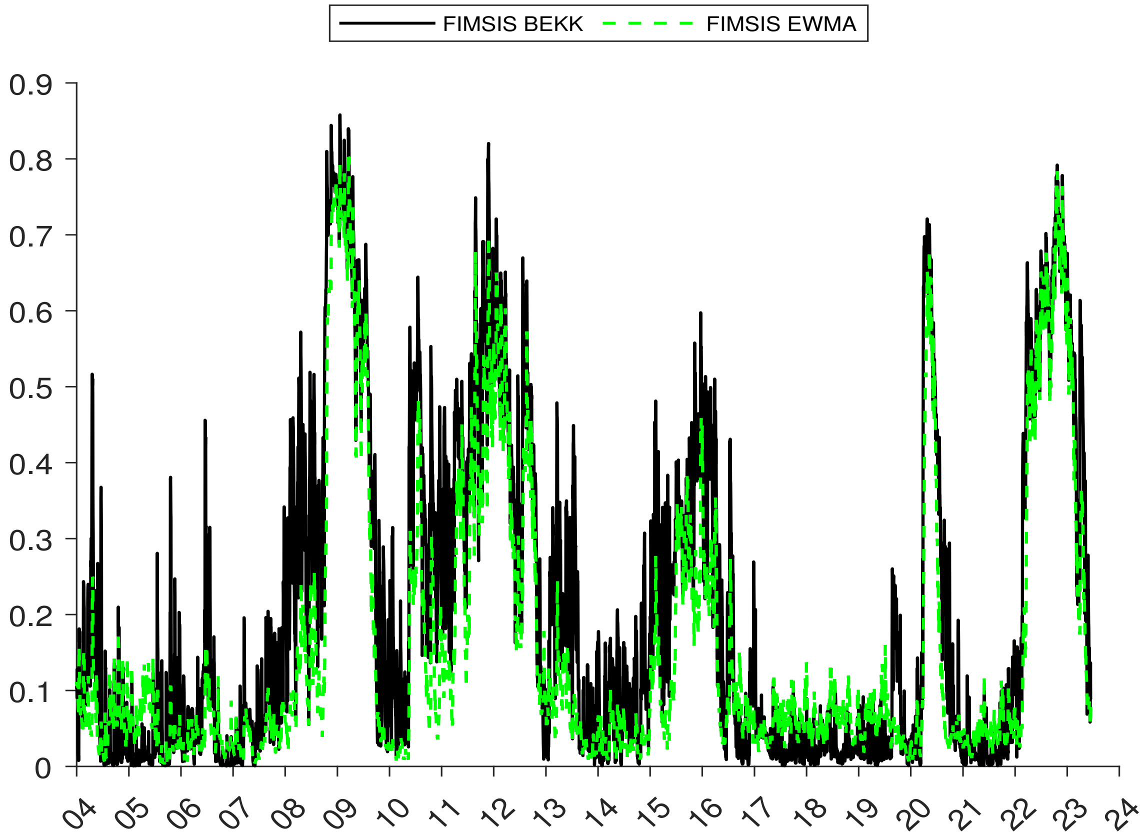
[37]McMillan and Kambouridis (2009) find that the RiskMetrics model performs well in forecasting volatility in small emerging markets and in broader Value-at-Risk (VaR) applications.

[38]Wen (2015) argues that, although the EWMA model is highly parsimonious and estimated using rich datasets, it imposes too many parameter restrictions with limited theoretical justification. He therefore advocates the use of a parametric model instead.

[39]Holló et al. (2012) argue that the EWMA method, when applied to demeaned variables, closely mirrors an IGARCH(1,1) process – a variant of GARCH where shocks have infinite memory.

pare the resulting composite indicators of systemic financial stress in Figure 12. We observe that both indicators respond in the same direction during systemic events. However, the BEKK-based indicator appears to react more strongly in the build-up to the GFC and recedes more gradually in the aftermath of the crisis and later, during the European sovereign credit risk episode.

Figure 12: Comparison of FIMSIS output from two different approaches for the calculation of the time-varying correlation matrix



Source: Authors' calculations.

5.2.3 PCA

PCA applies an orthogonal transformation to convert a set of potentially correlated variables into a set of uncorrelated (orthogonal) principal components. In other words, for each principal component, the procedure determines a weighted linear combination of the original variables that maximises the proportion of total variance explained.[40] The first principal component represents the combination that accounts for the maximum variance in the data, the second component explains the next largest portion and so on. Although

[40]The total variance explained by all principal components equals the total variance of the original variables.

the maximum number of principal components that can be obtained is equal to the number of variables in the set, we expect a single common component to capture financial stress across different financial sectors. This common component forms our $\mathrm{FIMSIS}_{\mathrm{PCA}}$.

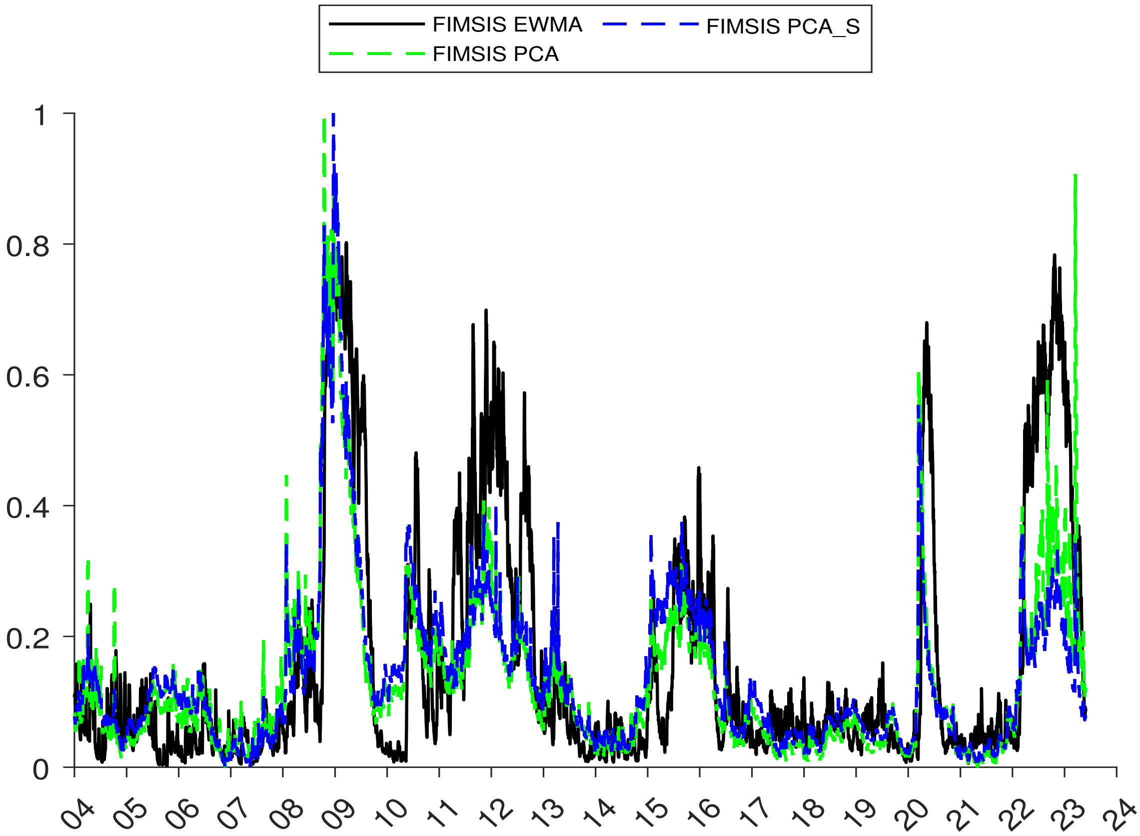
In Figure 13, we compare two composite indicators, FIMSIS, as described in Section 5.2.1 and a composite indicator constructed by PCA. The latter is based on the stress indicators presented in Table 1, which were standardised before entering the analysis. The most notable divergence between the two indicators occurs during the sovereign debt crisis and the polycrisis triggered by the Russian military aggression against Ukraine. These differences may be due to (i) differences in aggregation methods – PCA is applied to all 12 variables, whereas the EWMA-based indicator aggregates the already constructed subindices, and (ii) differences in the weighting approach – PCA assigns higher weights to components that are more correlated with others. In this statistical approach, the resulting weights lack economic interpretation and do not account for the theoretical importance of the original variables (OECD, 2008).

We also include a two-step PCA aggregation variant, denoted $\mathrm{FIMSIS}_{\mathrm{PCA\_S}}$. In this version, PCA is first applied separately to each of the four financial market segments, extracting one component per segment. These intermediate components are then combined into the final indicator by applying PCA again. This approach reflects the structure of the EWMA-based FIMSIS while still benefiting from the dimensionality reduction properties of PCA. It offers an alternative way of grouping stress dynamics without fully flattening sector-specific information into a single aggregation step.

Some authors have pointed out certain disadvantages of using PCA to construct real-time indicators of systemic financial stress. One issue relates to the violation of the normality assumption for the data used in the standardisation step of the analysis. Other authors, for example Oet et al. (2011), note that the weights derived through PCA remain constant over the entire sample, implying stable interdependences among variables even when, in reality, these relationships may be time-varying. This may lead to over- or underestimation of tensions in financial markets during "normal" periods. Varga and Szendrei (2025) also highlight that, due to its stationary nature, such indicators tend to revert to the mean very quickly (unless heteroscedasticity is explicitly allowed for).

Although PCA may, in some instances, be appropriate for real-time monitoring of financial stress, particularly in high-frequency applications and in dynamic financial markets, where it efficiently handles large datasets with minimal computational burden, we opt for the EWMA approach in constructing our systemic stress indicator. This choice is supported by the evaluation results presented in Section 6, where the EWMA-based variant outperforms other versions, including the PCA-based indicator, in terms of forecast accuracy for downside macroeconomic risk. These findings reinforce the suitability of the EWMA methodology for capturing the dynamic and systemic nature of financial stress in the Slovenian context.

Figure 13: Comparison of the composite indicators constructed using two different weighting approaches – EWMA and PCA



Source: Authors' calculations.

6 Evaluation

To evaluate whether FIMSIS accurately captures systemic financial stress in the Slovenian financial system, we adopt a multi-faceted approach combining empirical, qualitative and econometric methods. First, we conduct a series of robustness checks to test the indicator's stability over time and resilience to the event reclassification problem. Second, we assess whether peaks in FIMSIS coincide with well-known episodes of financial stress in Slovenia's recent history. Third, we apply two complementary econometric approaches to identify periods of severe systemic stress: a Markov-switching autoregressive model and a non-parametric method based on the modified Bry–Boschan algorithm. Finally, we evaluate the predictive performance of alternative FIMSIS variants within a Growth-at-Risk (GaR) framework using quantile regression with Adaptive LASSO and non-crossing constraints, focusing on their ability to signal downside risks to economic activity.

6.1 Robustness

As a tool for financial crisis detection and monitoring, FIMSIS must demonstrate stability over time and resilience to the so-called “event reclassification problem”. Without these characteristics, robust historical comparison is not possible, nor is the calculation of meaningful threshold levels for the indicator.

We conduct three exercises to evaluate the robustness of FIMSIS. First, we compute a recursively constructed version of the systemic stress indicator and compare it with the full-sample version. Second, we recalculate FIMSIS using different values of the smoothing parameter (both higher and lower than the baseline) and compare the resulting indices. Third, we compare our FIMSIS with the composite indicator of systemic stress for the euro area, constructed using the same underlying methodology.

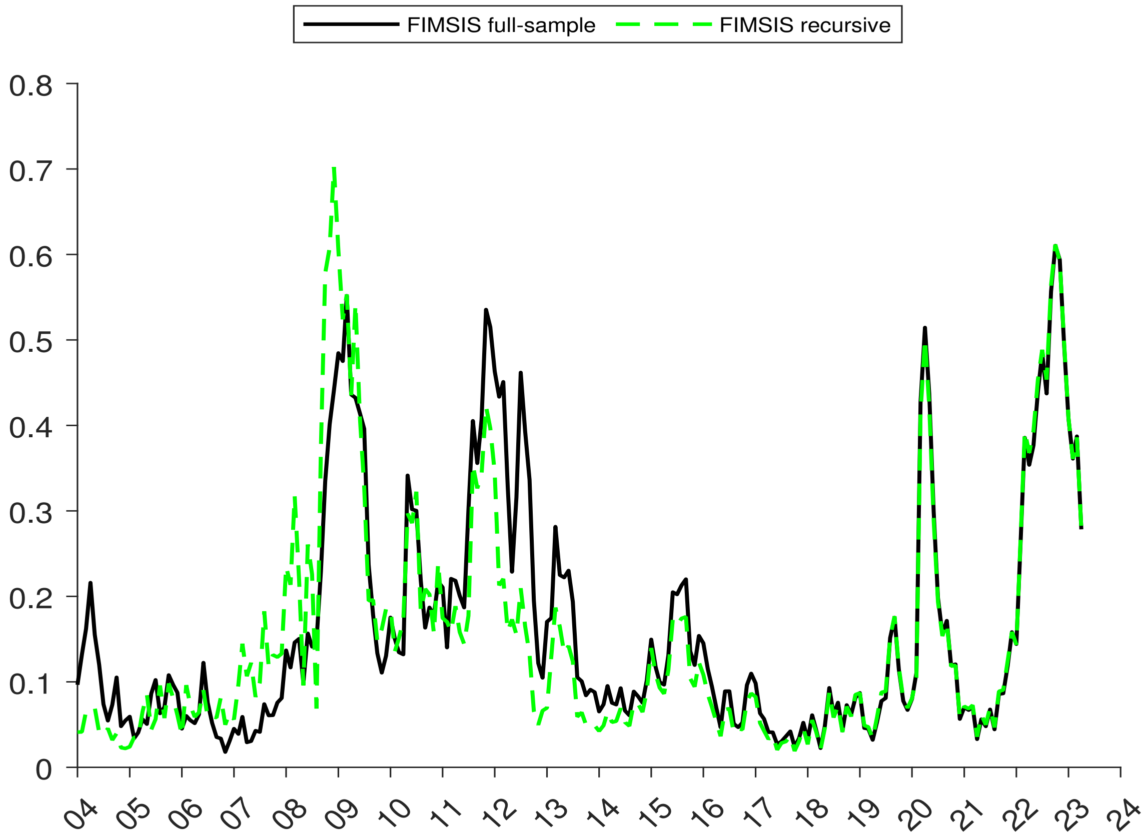
6.1.1 Recursive vs full-sample FIMSIS computation

In Section 4.2, we briefly discussed the differences that may arise due to varying approaches to variable transformation. The rationale for selecting transformation by order statistics, as opposed to standardisation, lies primarily in its ability to enhance the robustness of the resulting subindices and the composite indicator. Here, robustness refers to insensitivity to outliers, which reduces the likelihood of significant revisions as new data become available.

Figure 14 presents the recursively computed FIMSIS in real time, compared with the full-sample version. This was achieved by transforming the selected raw stress indicators according to Equations (11) and (12), based on Slovenian data. The comparison reveals only minor deviations, confirming the robustness of the indicator. Slight differences between the empirical CDFs computed in real time and those obtained from the full data sample are most evident at the beginning of the series. These inconsistencies can largely be attributed to limited data availability and the relative tranquillity of the financial system during the recursion period from June 2004 to June 2006.

Following the onset of the GFC, marked by the collapse of Lehman Brothers, the differences between the recursive and full-sample FIMSIS become negligible. A larger discrepancy appears during the sovereign debt crisis, raising questions about the severity and perception of stress during that period. For the two most recent crises, there is virtually no divergence between the two indicators, as the subindices – transformed using empirical CDFs – demonstrate greater stability. The source of any remaining discrepancies may lie in the dynamic cross-correlations between subindices.

Figure 14: Recursive vs full-sample FIMSIS computation



Note: The figure depicts the transformation of all 12 raw stress indicators when computed recursively (where the recursion starts in January 2006) and non-recursively (full-sample computation).
Source: Authors' calculations.

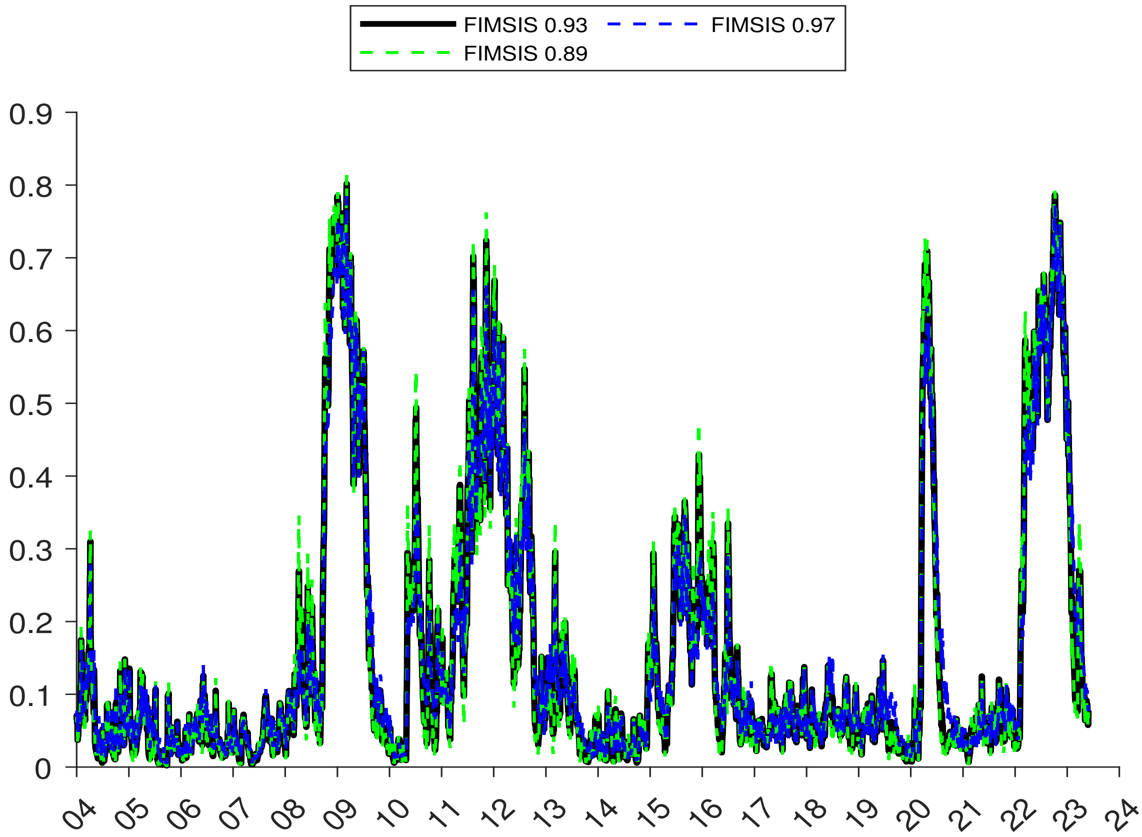
With an average absolute difference of only 0.037 (standard deviation of 0.051) and a mean error of 0.010, we conclude that FIMSIS is a robust statistic over time and is largely unaffected by the event reclassification problem.

6.1.2 Different lambda values

As a second statistical robustness check, we compute the FIMSIS for a range of values of the smoothing parameter λ, which determines the adjustment speed of the estimated time-varying cross-correlations among subindices in response to new information. Figure 15 presents three time series of FIMSIS, each calculated using a different value of λ. As expected, the indicator based on a relatively low smoothing parameter ($\lambda = 0.89$)

displays wider swings and more pronounced spikes than our preferred specification ($\lambda = 0.93$), particularly in response to larger shocks to the Slovenian financial markets. In contrast, with a higher smoothing parameter ($\lambda = 0.97$), we observe somewhat dampened movements in the FIMSIS. Overall, the differences across versions are modest and do not alter the general behaviour of the indicator. Its core informational content, i.e. the broad classification of stress episodes or regimes, which is examined in more detail in the subsequent sections, appears largely unaffected by the choice of λ.

Figure 15: Comparison of FIMSIS for different values of the smoothing parameter λ



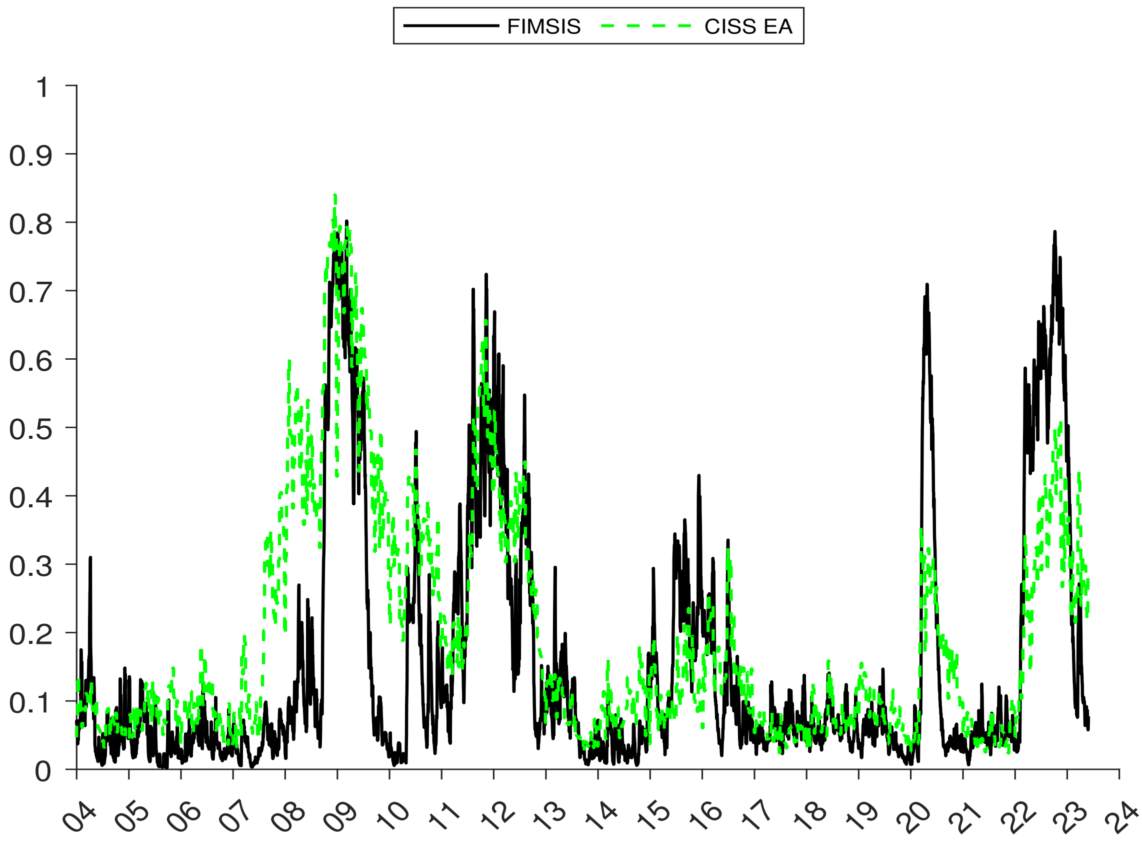
Note: FIMSIS computed for three different values (0.89, 0.93 and 0.97) of the smoothing parameter λ applied in the EWMA estimation of the time-varying cross-correlations. Daily data from January 2004 to 30 May 2023.
Source: Authors' calculations.

6.1.3 Comparison with other stress indicators

As a third robustness check, and given the shared methodological foundations, we compare FIMSIS with the CISS for the euro area. Figure 16 illustrates that both composite indicators exhibit broadly similar behaviour in identifying systemic stress events. However, differences emerge in the timing and intensity of risk materialisation, particularly during the GFC. For example, some euro area countries, particularly those with significant exposure to subprime mortgage-backed securities or highly leveraged financial institutions, experienced earlier and more severe repercussions, which contributed to sharper increases in the euro area CISS.

The CISS signalled its first extreme stress level in August 2007, following the suspension of several BNP Paribas investment funds. The situation was exacerbated by a series of smaller, related credit-loss and write-down events, culminating in the collapse of Bear Stearns in March 2008. This led to another spike in the indicator. When Lehman Brothers filed for bankruptcy in September 2008, the CISS reached its highest value during the GFC – an episode also marked by the highest peak in FIMSIS during the observed period.

Figure 16: Comparison of the Slovenian systemic risk indicators to the euro area CISS



Source: Authors' calculations.

Following the GFC, systemic stress, as captured by FIMSIS, appears to have receded more quickly than in the euro area CISS, which shows a more gradual decline. Apart from differences in underlying data and correlation estimates, this divergence may also reflect structural differences between the economies, exposure to global financial markets and external factors. Similar dynamics can be observed in the trajectories of systemic risk during the COVID-19 pandemic and the recent polycrisis, underscoring the importance of accounting for country-specific features in financial stability analysis.

As the Country-Level Index of Financial Stress (CLIFS), developed by Duprey et al. (2017), is available only at monthly frequency, we compare the three indicators – FIMSIS, CISS and CLIFS – on a monthly basis in Figure D2 in Appendix D. The comparison shows that the Slovenian CLIFS notably diverges from FIMSIS and CISS during the GFC and the European sovereign debt crisis. It also appears to miss the Brexit episode as a stress event (see Figure 17). The difficulty of constructing systemic stress indicators that are timely, robust to reclassification problems and suitable for policymaking has been acknowledged in the literature (e.g. Škrinjarič, 2023; ESRB, 2024).

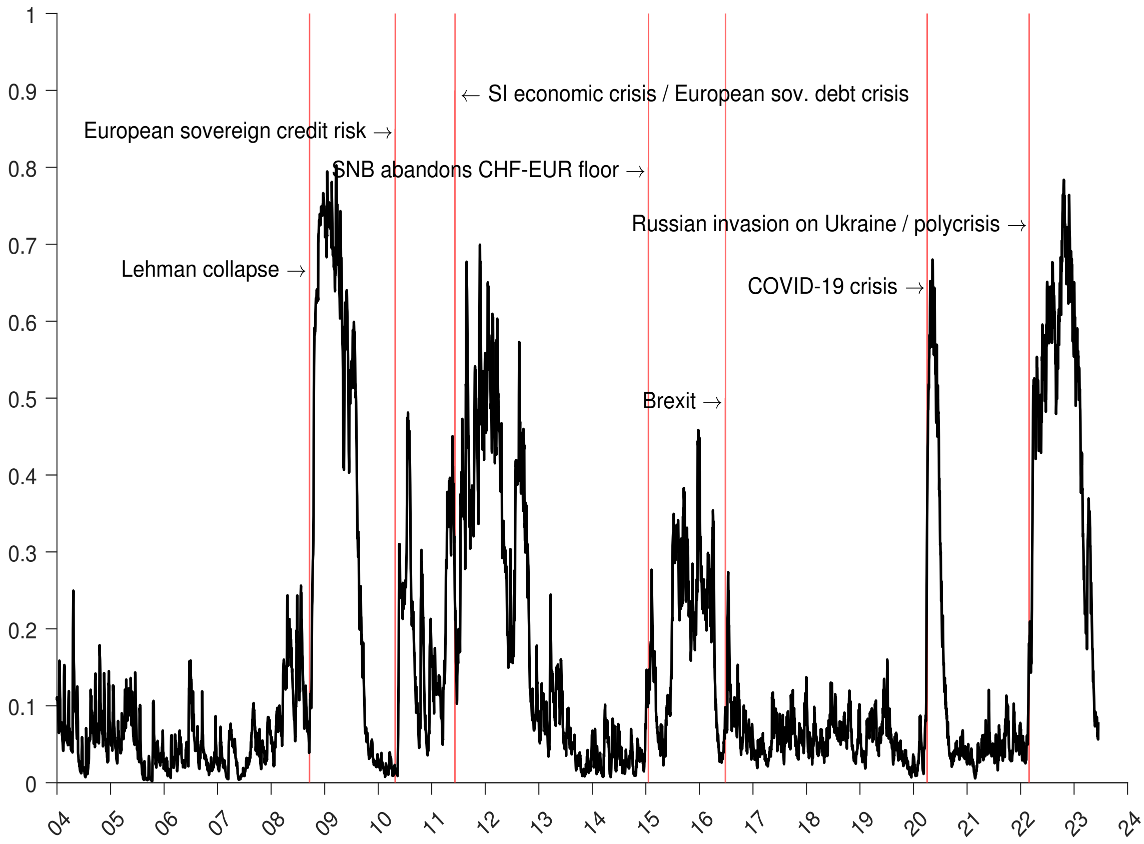
By evaluating the performance of FIMSIS in this section, we aim to assess its plausibility as well as its statistical and econometric credibility. For FIMSIS to serve as a reliable tool for real-time crisis monitoring and informing macroprudential policy, it must pass such empirical and methodological tests.

Unlike indices of economic activity, which can be benchmarked against observable indicators such as GDP or industrial production, there is no direct, observable counterpart for systemic financial stress. Moreover, while business cycle chronologies are typically available or straightforward to construct, crisis chronologies for the financial sector are far more difficult to establish, posing a key challenge in evaluating systemic stress indices. To address this, we construct a chronology of financial crises relevant to the Slovenian financial sector between 2004 and 2023. This enables us to assess whether peaks in FIMSIS are generally aligned with documented historical stress events.

Figure 17 illustrates that the sharpest spikes in the FIMSIS indeed tend to occur around very well-known events which caused, at least temporarily, severe stress in the Slovenian and the financial system of the euro area. The first major stress event in the sample is the outbreak of the GFC, heralded by the collapse of the Lehman Brothers in mid-September 2008. The second notable stress episode began with Greece's request for financial assistance from euro area member states and the International Monetary Fund (IMF), as borrowing costs in financial markets became unsustainable. This event marked the start of the multi-year European sovereign debt crisis, during which several euro area member states (Greece, Portugal, Ireland, Spain and Cyprus) became unable to repay or refinance their government debt or to bail out over-indebted banks under their supervision without third-party support from other euro area countries, the ECB or the IMF.[41]

[41] For more details on the European sovereign debt crisis, see Pierre-Olivier et al. (2022).

Figure 17: FIMSIS and major systemic financial events



Source: Authors' calculations.

A particularly salient event for the Slovenian financial system was the onset of the Slovenian political and economic crisis. The failure of the June 2010 referendums on crisis-response measures deepened economic uncertainty. By the last quarter of 2011, the Slovenian economy had entered a recession, triggered by a combination of fiscal austerity, frozen budget expenditure in late 2011 and a decline in exports. This episode formed part of the broader sovereign debt crisis in Europe.

Another noticeable spike occurs in January 2015, when the Swiss National Bank unexpectedly abandoned its exchange rate floor against the euro, causing a sharp appreciation of the Swiss franc and temporary volatility in European financial markets. Although not systemic in nature, the event highlights FIMSIS's sensitivity to sudden and disruptive market developments

On 23 June 2016, the United Kingdom voted to leave the European Union. This event had a significant impact on European financial markets and is reflected in a marked reaction in FIMSIS. The next sharp increase in systemic risk followed the global outbreak of the COVID-19 pandemic and the containment measures that ensued. In Slovenia, the government declared an epidemic on 12 March 2020.

The final systemic stress event captured by FIMSIS in our sample is the onset of the Russian invasion of Ukraine in February 2022. This episode was followed by a sequence of shocks, commonly referred to as the "polycrisis", including the energy crisis, high inflation and sharp monetary tightening across advanced economies.

Overall, the evidence suggests that all extreme peaks in FIMSIS can be attributed to clearly identifiable stress events, indicating that the indicator does not appear to suffer from Type II errors (i.e. falsely signalling high stress when none occurred). It is, however, more difficult to assess its performance in terms of Type I errors, i.e. whether there were severe crises it failed to capture.

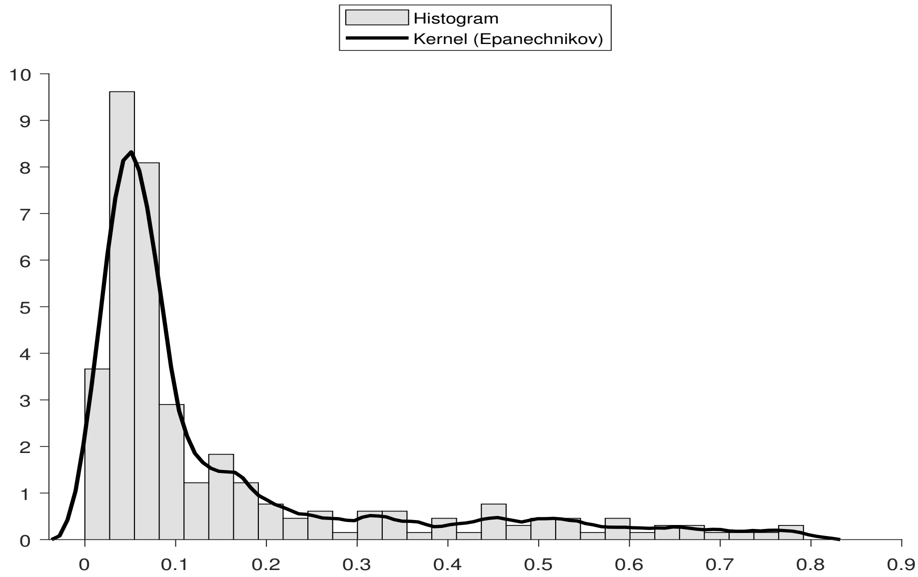
6.2 Regimes and thresholds

The level of stress in the financial system is determined, as proposed by Illing and Liu (2006), by the size of the shock and the degree of interaction with underlying fragilities. These fragilities may refer to structural weaknesses in the financial system, such as market coordination failures, highly asymmetric information flows, inadequate risk management practices and similar vulnerabilities. The severity of systemic events, on the other hand, can be assessed through their impact on consumption, investment, growth or, more broadly, economic welfare (ECB, 2009).

The main objective of a financial stress indicator is to provide a real-time "snapshot" of the prevailing level of stress in the financial system and to assist policymakers in identifying market strains that warrant closer scrutiny. In this context, determining a threshold that signals "severe stress" is not straightforward. Thresholds can either be derived qualitatively, by identifying events that preceded significant increases in the stress indicator, or through statistical and econometric techniques aimed at detecting quantitative thresholds or distinct stress regimes.

A relatively simple and widely applied approach is to classify a situation as "severe" if the indicator exceeds a threshold defined as the historical mean or median plus one (or more) standard deviation(s) (see, for example, Illing and Liu, 2006; Cardarelli et al., 2009). The main challenge with this method lies in selecting, ex ante, the number of standard deviations above the reference point required to signal a stress episode. Moreover, this approach assumes the underlying distribution of the stress indicator is normal – a condition clearly violated in our case (see Figure 18).

Figure 18: Distribution of FIMSIS – histogram and kernel density estimate



Note: Histograms calculated for FIMSIS based on monthly data from January 2004 to May 2023. The smoothed density is obtained using the Epanechnikov kernel. The moments of the empirical distribution indicated in the chart are as follows: mean = 0.1100, median = 0.0813, 90th percentile = 0.2475, 99th percentile = 0.3479.
Source: Authors' calculations.

6.2.1 Regime classification based on an autoregressive Markov-switching model

To address the shortcoming of the historical thresholding approach, we apply an econometric method that endogenously identifies periods of extreme stress in the Slovenian financial system. We follow the methodology of Hollò et al. (2012), employing a regime classification based on an autoregressive Markov-switching model.[42] This approach assumes that the time series properties of the systemic stress indicator are state-dependent, meaning that financial stress exhibits intra-regime persistence, while transitions between regimes occur stochastically.

We estimate several specifications of the following model:

$$F_t = \alpha\left(s_t\right) + \beta\left(s_t\right) F_{t-1} + \sigma\left(s_t\right) \mu_t \quad for \quad s_t \in \{0, 1, 2\} \tag{23}$$

where μ_t are i.i.d. standard normal residuals, and the regime s_t follows an ergodic first-

[42]We apply a modified version of the parametric approach used by Radovan (2023) for dating the business cycle in Slovenia. The terms "stat" and "regime" are used interchangeably throughout the paper. In the context of Markov-switching models, both refer to the unobserved latent condition that governs the time-varying behaviour of the system. This follows standard terminology in the literature (e.g. Hamilton, 1994; Hollò et al., 2012).

order Markov chain with transition probabilities $p(s_i = i|s_{t-1} = j) = p_{i|j}$ collected in the transition matrix $\mathbf{P}$:

$$\mathbf{P} = \begin{bmatrix} p_{0|0} & p_{0|1} & p_{0|2} \\ p_{1|0} & p_{1|1} & p_{1|2} \\ p_{2|0} & p_{2|1} & p_{2|2} \end{bmatrix} = \begin{bmatrix} p_{0|0} & p_{0|1} & p_{0|2} \\ p_{1|0} & p_{1|1} & p_{1|2} \\ 1 - p_{0|0} - p_{1|0} & 1 - p_{0|1} - p_{1|1} & 1 - p_{0|2} - p_{1|2} \end{bmatrix} \tag{24}$$

In the third row, the conditional probabilities are replaced by the standard adding-up constraints, which imply that for a model with three regimes, only six out of nine transition probabilities can be estimated independently. The first-order Markov assumption implies that the probability of the next regime depends solely on the current regime, not on past states (see, e.g., Hamilton, 1994).

We compare three specifications:

- MS(3)-AR(1): A three-regime AR(1) process in which all parameters (intercept, slope and residual variance) vary across regimes.
- MS(3)-DR(1): A dynamic regression model with three regimes in which the intercept and residual variance are regime-dependent but the slope is constant across regimes.
- MS(2)-AR(1): A two-regime AR(1) process with the same structure as model (i) but limited to two states.

  Model fit is evaluated using log-likelihood, AIC, and the Regime Classification Measure (RCM). As shown in Table 3, the MS(3)-AR(1) specification achieves the highest log-likelihood and the lowest AIC among the estimated models, indicating the best overall fit. Although its regime classification measure (RCM) is slightly higher than that of the MS(3)-DR(1) model, the MS(3)-AR(1) model offers a more accurate representation of systemic stress dynamics. Specifically, it tracks FIMSIS values more closely during key stress events (see the top panel of Figure 19) and produces a more plausible time series of regime probabilities. For instance, the MS(3)-AR(1) model clearly distinguishes the global financial crisis (GFC) and the subsequent European sovereign debt crisis as periods of systemic stress. In contrast, the MS(3)-DR(1) model shifts the onset of both crises earlier, classifies Brexit as a systemic event rather than a short-lived stress episode, and fails to recognise the COVID-19 crisis altogether (see Figure D3 in Appendix D).

Table 3: Comparison of different MS-AR models for FIMSIS

Model	Log-likelihood	AIC	RCM
MS(3)-AR(1)	430.3976	-824.7952	14.24
MS(3)-DR(1)	414.3512	-796.7024	11.34
MS(2)-AR(1)	410.8592	-803.7184	17.19

Note: The RCM is the Regime Classification Measure, defined in Equation (25). The model abbreviations are to be interpreted as follows: MS(s) denotes a Markov-switching model with s states; AR(p) refers to an autoregressive model of order p in which both the intercept and slope coefficient can vary across regimes; DR(p) indicates a model in which the slope coefficient is held constant across regimes. Estimates are based on monthly averages of daily data for Slovenia from January 2004 to May 2023.
Source: Authors' calculations.

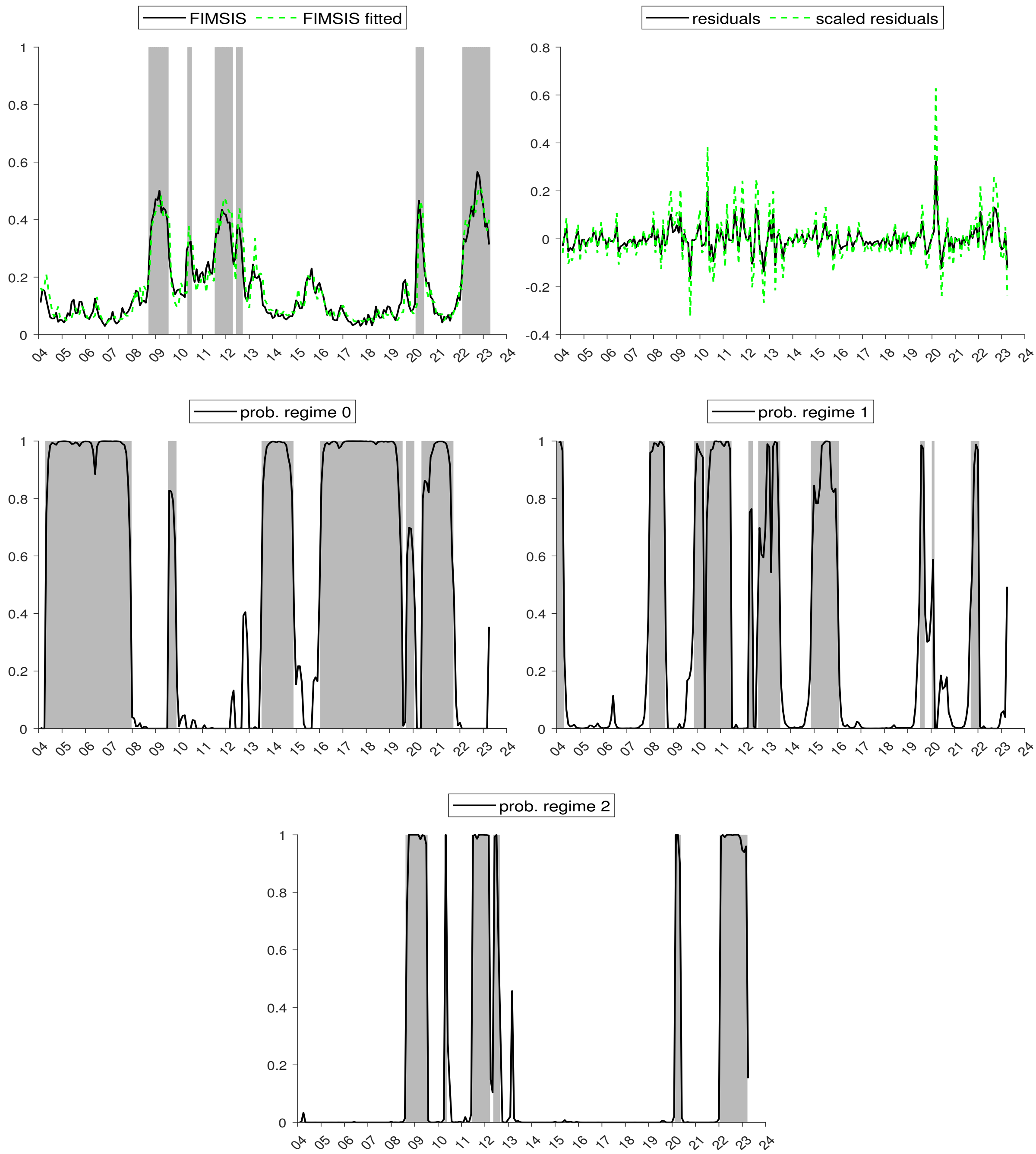
The RCM, introduced by Ang and Bekaert (2002) and adapted for multiple regimes by Baele (2005), is widely used in the financial stress literature (e.g. Hollò et al. 2012; Iachini and Nobili, 2014) to assess the quality of regime inference. It is defined as:

$$RCM(K) = 100 \times \left[1 - \frac{K}{K-1}\frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{K}\left(p_{j,t} - \frac{1}{K}\right)^2\right] \tag{25}$$

where K is the number of regimes, T is the number of observations, and $p_{j,t}$ is the smoothed probability of being in regime j at time t. The RCM is normalised between 0 and 100, where a value of 0 implies perfect regime classification (i.e. one regime receives full probability at each time point), and 100 implies complete uncertainty (equal probability across regimes at all times), which may suggest model misspecification. In our case, all model variants yield relatively low RCM values (ranging from 11.34 to 17.19), confirming a strong ability to distinguish between regimes.

The three-state structure of the MS(3)-AR(1) model provides a meaningful economic classification of systemic stress conditions in Slovenia's financial system. Estimated coefficients and transition dynamics, presented in Tables 4 and 5, confirm clear differences across regimes. The first regime (Regime 0) captures tranquil periods with low volatility and stable financial conditions. The second regime (Regime 1) reflects periods of moderate or elevated stress, typically associated with market turbulence or risk reappraisal that has not yet escalated into a full-blown systemic event. The third regime (Regime 2) corresponds to systemic stress episodes, where financial market disruptions are widespread, volatility is high and stress is persistent. This regime matches well with major crises observed in the Slovenian financial system, as visualised in the smoothed probabilities and demarcation thresholds in Figure 19 and Figure D1.

Figure 19: Fitted values, residuals and smoothed regime probabilities from the MS(3)-AR(1) model



Note: FIMSIS is constructed from daily volatility indicators, averaged to monthly frequency, which are transformed using their empirical cumulative distribution functions (ECDFs) and aggregated into subindices. MS(3)-AR(1) refers to an autoregressive Markov-switching model of order 1, with three regimes applied to FIMSIS. All three parameters (intercept, slope coefficient and variance) are allowed to vary across regimes. The top left panel shows FIMSIS plotted against the model's fitted values while the top right panel compares the raw residuals (right-hand side) with residuals scaled by the respective state-dependent standard deviation (left-hand side). The middle two panels and the bottom panel display the smoothed regime probabilities. Estimates are based on monthly averages of daily data from January 2004 to May 2023.
Source: Authors' calculations.

The three-state structure of the MS(3)-AR(1) model provides a meaningful economic classification of systemic stress conditions in Slovenia's financial system. Estimated coefficients and transition dynamics, presented in Tables 4 and 5, confirm clear differences across regimes. The first regime (Regime 0) captures tranquil periods with low volatility and stable financial conditions. The second regime (Regime 1) reflects periods of moderate or elevated stress, typically associated with market turbulence or risk reappraisal that has not yet escalated into a full-blown systemic event. The third regime (Regime 2) corresponds to systemic stress episodes, where financial market disruptions are widespread, volatility is high and stress is persistent. This regime matches well with major crises observed in the Slovenian financial system, as visualised in the smoothed probabilities and demarcation thresholds in Figure 19 and Figure D1.

The value of the three-regime classification lies in its ability to capture not only the emergence and persistence of systemic stress episodes but also the intermediate phases that may serve as early warning signals or reflect post-crisis normalisation periods. The regime-specific unconditional means, shown in Figure D4, serve as practical demarcation lines that facilitate real-time monitoring and contextual interpretation of current FIMSIS readings.

Table 4: Parameter estimates of the MS(3)-AR(1) model for the FIMSIS

	Coef.	**S.E.**	**p-value**
$\alpha(0)$	0.0257	0.0037	0.000
$\alpha(1)$	0.0657	0.0166	0.000
$\alpha(2)$	0.2332	0.0359	0.000
$\beta(0)$	0.5910	0.0454	0.000
$\beta(1)$	0.6028	0.1080	0.000
$\beta(2)$	0.4886	0.0821	0.000
$\sigma(0)$	0.0004	0.0001	0.000
$\sigma(1)$	0.0012	0.0003	0.000
$\sigma(2)$	0.0034	0.0009	0.000
$\mu(0)$	0.0801		
$\mu(1)$	0.1712		
$\mu(2)$	0.394		

Note: MS(3)-AR(1) denotes an autoregressive Markov-switching model for Slovenian FIMSIS of order 1 with three states. All three parameters (intercept, slope coefficient and variance) are allowed to vary across regimes. The coefficients are defined as in Equations (23) and (24) in the main text. $\mu(s)$ stands for the state-dependent unconditional means for regime s.
Source: Authors' calculations.

Table 5: Transition matrix of the MS(3)-AR(1) model for the FIMSIS (coefficients and p-values)

	Regime $0, t$	**Regime** $1, t$	**Regime** $2, t$
Regime $0, t+1$	0.9629 (0.000)	0.0656 (0.080)	0.0657 (0.224)
Regime $1, t+1$	0.02418 (0.051)	0.8598 (0.000)	0.0861 (0.115)
Regime $2, t+1$	0.01289 (0.635)	0.0746 (0.043)	0.8482 (0.000)

Note: MS(3)-AR(1) denotes an autoregressive Markov-switching model for the FIMSIS of order 1 with 3 states. All three parameters are allowed to switch across regimes. Estimations based on monthly averages of daily data from Jan. 2004 to May 2023.
Source: Authors' calculations.

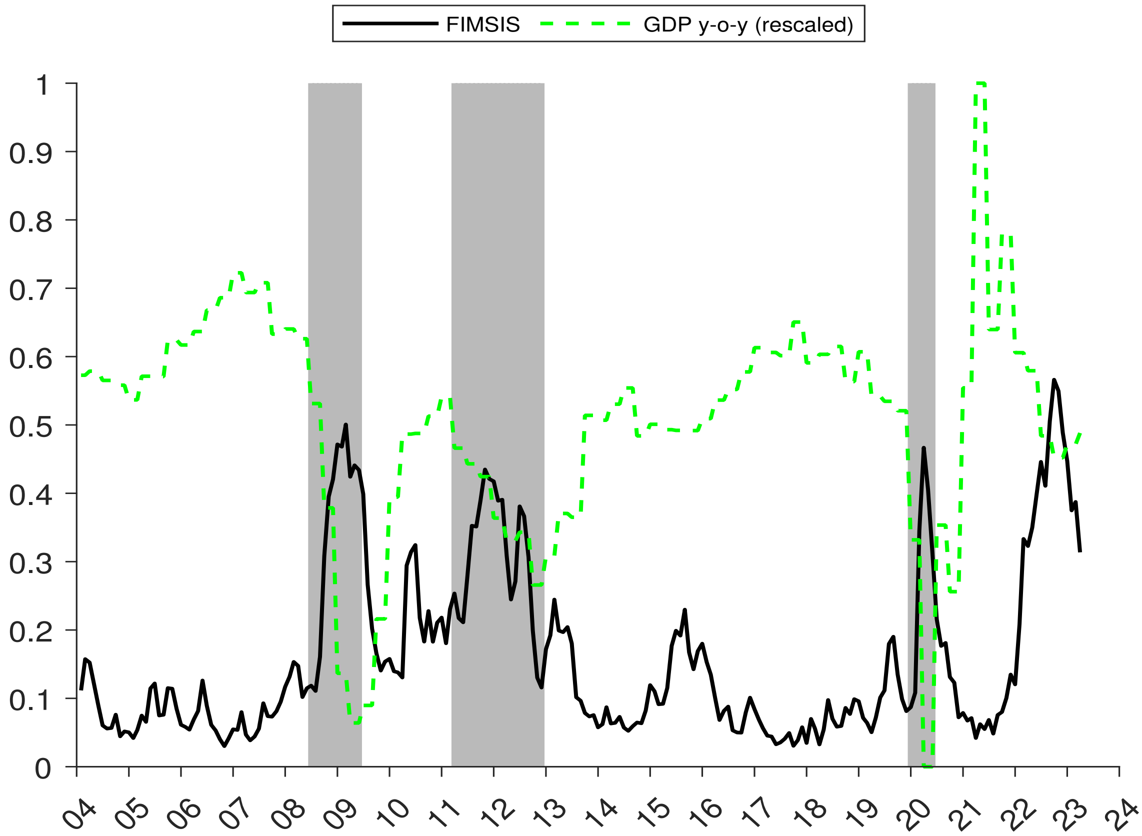
6.2.2 Comparing the endogenous severe stress thresholds with business cycle developments obtained from a non-parametric method

In Section 2, we discussed the channels through which financial distress can affect the real economy. The literature consistently demonstrates that heightened financial stress has adverse effects on economic activity.[43] While not every episode of financial stress leads to an economic downturn or recession, systemic financial stress poses a greater threat, as financial instability tends to propagate across the entire financial system.

We examine the relationship between systemic stress and real economic developments by plotting FIMSIS alongside estimated periods of contraction in Slovenian economic activity. These contraction episodes are identified using a modified Bry–Boschan (MBBQ) algorithm, as proposed by Radovan (2023). The resulting timeline is shown in Figure 20.

[43] Starting from Romer and Romer (2017) in their pioneer work to recent works that confirm the causal effect between financial stress and output loss (see, for example, Ahir et al., 2023).

Figure 20: FIMSIS, estimated contraction period and real GDP growth



Note: Real GDP year-on-year growth is rescaled to the [1, 0] interval for comparability with FIMSIS, which is shown at monthly frequency. Grey-shaded areas indicate estimated contraction periods in the Slovenian economy.
Source: Authors' calculations based on Radovan (2023).

The MBBQ algorithm identifies three contraction periods that coincide with the systemic stress episodes identified by FIMSIS: the GFC, the European sovereign debt crisis and COVID-19. The identification of these events is contingent upon the algorithm's configuration. It is perhaps unsurprising that the "polycrisis" – recognised by FIMSIS as a period of historically high stress – is "overlooked" by the MBBQ algorithm. On the one hand, expansive fiscal measures implemented in response to the pandemic in 2022, as well as energy price mitigation and post-flood reconstruction efforts in 2023, may have prevented the Slovenian economy from entering a contraction phase as defined by the algorithm. On the other, post-pandemic economic activity continued to be supported by robust domestic demand, which was reflected on the production side primarily in the service sector and construction (Banka Slovenije, 2023).

Table 6: Correlation between FIMSIS and real GDP growth

Period	**Full sample**	**Jun. 2007-Jul. 2009**	**Jun. 2007-Dec. 2012**	**Jan. 2013-Dec. 2019**	**Jan. 2020-May 2023**
Correlation	-0.59	-0.73	-0.64	-0.71	-0.58

Source: SORS and authors' calculations.

To quantify the relationship between FIMSIS and real GDP, we look at the correlation between the indicator and the year-on-year growth dynamics of Slovenian real GDP. Table 6 presents the correlation values for the entire sample, for the contraction period during the GFC, for the combined period of the GFC and European sovereign crisis, for the "normal times" between the sovereign crisis and the COVID-19 contraction, and, finally, for the post-COVID period until the end of the sample. The average correlation between FIMSIS and real GDP growth is, as expected, negative, oscillating around -0.6. The strongest negative correlation is observed during the GFC and the longest "normal times" period in the sample, exceeding -0.7.

6.3 Evaluation using quantile LASSO regression

To evaluate the predictive content of alternative financial stress indicators for tail macroeconomic risk, we adopt the quantile regression methodology proposed by Szendrei and Varga (2023). Their approach addresses variable selection in small samples by building on the Bayesian sparsity framework of Kohns and Szendrei (2024), while introducing a frequentist Adaptive LASSO estimator. To ensure monotonicity across the conditional quantile functions, they additionally impose non-crossing constraints, thus avoiding violations of quantile ordering across τ-levels.[44]

This model is particularly suited for growth-at-risk (GaR) applications, where interest lies in understanding how financial stress indicators affect the lower quantiles of the GDP growth distribution. In our setting, the financial stress indicator for Slovenia (FIMSIS) is intended for this purpose, and we examine its performance over forecast horizons of one to four quarters ahead, in line with empirical findings on the relevant signalling horizons of financial stress.

[44] For further methodological details, see Szendrei and Varga (2023)

Table 7: Overview of FIMSIS variants

Mnemonic	**Full name / Description**	**Weighting or Methodology**
$\text{FIMSIS}_{\text{std}}$	Standard deviation-weighted FIMSIS	EWMA-based construction of the dynamic correlation matrix across sub-indicators, which are aggregated using weights based on the inverse of their standard deviations
$\text{FIMSIS}_{\text{eq}}$	Equal-weighted FIMSIS	EWMA-based construction of the dynamic correlation matrix across sub-indicators, which are aggregated with equal weights
$\text{FIMSIS}_{\text{BEKK}}$	FIMSIS with dynamic correlations (BEKK MGARCH)	Covariances and correlations estimated via BEKK-MGARCH(1,1,1), as in Engle and Kroner (1995)
$\text{FIMSIS}_{\text{PCA}}$	PCA-based FIMSIS (all indicators)	The first principal component is extracted from all normalised stress indicators
$\text{FIMSIS}_{\text{PCA\_S}}$	PCA-based FIMSIS (two-step aggregation)	PCA applied first to sub-indicator groups; final indicator constructed by applying PCA to the resulting sub-components

The model specification closely follows Drenkovska and Volčjak (2022), that builds on ESRB (2021), and replaces the financial conditions index (FCI) with FIMSIS. This structure is commonly used in the macroprudential policy literature to evaluate the stance and effectiveness of macroprudential tools, and reflects the prevailing analytical framework used to assess Slovenia's macroprudential stance in a European context. The estimated equation is:

$$\Delta GDP_{t+h}^{(\tau)} = const + \beta_{GDP}^{(\tau)} \Delta GDP_t + \beta_{SRI}^{(\tau)} SRI_t + \beta_{MPI}^{(\tau)} \Delta^{16} MPI_t + \beta_{FIMSIS}^{(\tau)} FIMSIS_t \quad (26)$$

where $\Delta GDP_{t+h}^{(\tau)}$ is the average quarterly GDP growth from t to $t+h$, at quantile τ, with $h = 1, 4$, ΔGDP_t is the quarterly GDP growth at time t, SRI_t is the weighted average of normalised indicators for Slovenia, including the credit-to-GDP gap, debt service ratio, residential real estate price-to-income ratio, residential real estate price growth and current account balance as a percentage of GDP. These indicators capture cyclical systemic risk build-up in the financial system (Lang et al., 2019). $\Delta^{16} MPI_t$ is the overall macroprudential index,[45] cumulative, detrended, 16-period difference. $FIMSIS_t$ is the tested variant of the financial stress indicator for Slovenia ($\text{FIMSIS}_{\text{std}}$, $\text{FIMSIS}_{\text{eq}}$, $\text{FIMSIS}_{\text{BEKK}}$, $\text{FIMSIS}_{\text{PCA}}$ and $\text{FIMSIS}_{\text{PCA\_S}}$)

[45] The macroprudential policy index (MPI) used in the GaR LASSO model is constructed as a cumulative net count of macroprudential actions. It builds on the MaPPED database (Budnik and Kleibl, 2018) and is extended beyond 2018 using the ESRB macroprudential policy database. Since the latter does not classify actions as tightening or loosening, we apply a rule-based approach that replicates the MaPPED classification logic to ensure methodological consistency across the full sample (see Drenkovska, 2025, mimeo, for details). In each quarter, the net effect is calculated as the number of tightening minus relaxation measures, and the MPI is derived as the cumulative sum of these net values.

The model is estimated on quarterly data from 2004Q1 to 2023Q2. To capture the distributional effects across the growth distribution, we estimate quantile regressions for $\tau = 0.1, 0.2, \ldots, 0.9$ using the Adaptive LASSO with non-crossing constraints, following Szendrei and Varga (2023). In this setup:

- Adaptive LASSO applies shrinkage selectively using data-driven penalty weights based on initial (pilot) quantile regressions, reducing bias on large coefficients while enhancing variable selection consistency;
- Non-crossing constraints are implemented through a system of linear inequalities across quantile levels, preserving the logical ordering of conditional quantiles;
- The shrinkage parameter (λ) is selected on a predefined grid using the Bayesian Information Criterion (BIC) to balance in-sample fit and model complexity.

Importantly, our goal is not broad variable selection but targeted testing: each FIMSIS variant is evaluated separately, while the basic specification set variables (lagged GDP growth, the SRI, and the MPI) is always included in the model. These baseline variables, along with the intercept, are excluded from the penalisation process, ensuring the stability and interpretability of the core specification. The choice of baseline variables reflects standard practice in the literature on tail risk analysis in a macroprudential context, where a resilience indicator (MPI) is typically accompanied by a cyclical systemic risk measure and a financial stress indicator to capture the key drivers of macro-financial vulnerability.

To mitigate the well-known issue of shrinkage bias introduced by LASSO, we follow a two-step estimation strategy: after selecting the relevant variables using BIC, we re-estimate the model via unpenalised quantile regression, constraining the coefficients of variables excluded by LASSO to zero. This approach yields unbiased estimates of the conditional quantiles.

As expected, for all FIMSIS variants, the largest negative coefficients are observed at the lowest quantiles ($\tau = 0.1$ and $\tau = 0.2$), confirming their relevance for predicting downside risks. These effects generally diminish at higher quantiles. The coefficient estimates from the BIC-selected model for the analysed horizons are presented in Table D1 in the Appendix.

To assess out-of-sample performance at the one-year-ahead horizon ($h = 4$), we implement a rolling forecast exercise with an initial window of 50 observations, expanding one period at a time. At each step, the full LASSO-based selection and refitting procedure is repeated.

Forecast accuracy is evaluated using the quantile-weighted continuous ranked probability score (qwCRPS) of Gneiting and Ranjan (2011), with emphasis on the left tail.

The predictive performance of each FIMSIS variant is summarised in Table 8, which presents both in-sample fit and out-of-sample forecast accuracy. In-sample fit is assessed using the average absolute error at the 10th conditional quantile (IS10), which captures the alignment between the estimated and realised left-tail outcomes. The BEKK-based variant ($\text{FIMSIS}_{\text{BEKK}}$) shows the best in-sample fit (IS10 = 2.63), only marginally outperforming the EWMA-based variant with standard deviation aggregation ($\text{FIMSIS}_{\text{STD}}$, IS10 = 2.69). These in-sample differences are small, and may well shift under a different sample or evaluation window.

For the one-year-ahead horizon ($h = 4$), the $\text{FIMSIS}_{\text{std}}$ variant delivers the lowest CRPS, both overall and in the left tail, outperforming more complex or dynamic specifications. This suggests that a simple EWMA-based aggregation of stress signals provides a robust and effective summary measure for tail risk forecasting at the one-year-ahead horizon.

Surprisingly, at the one-quarter-ahead horizon ($h = 1$), the FIMSIS+ variant performs best in terms of both overall and left-tail qwCRPS, indicating superior short-term downside risk prediction. This specification includes the banking-sector indicator BSI, which captures financial system vulnerabilities rather than realised stress. The strong near-term performance of the augmented variant (FIMSIS+) may be understood as an additional motivation to further explore the inclusion of the banking system segment in the construction of a comprehensive financial system stress indicator for Slovenia.

Table 8: Predictive performance of the different FIMSIS variants

$h = 4$	$\textbf{FIMSIS}_{\textbf{std}}$	$\textbf{FIMSIS}_{\textbf{eq}}$	$\textbf{FIMSIS}_{\textbf{BEKK}}$	$\textbf{FIMSIS}_{\textbf{PCA}}$	$\textbf{FIMSIS}_{\textbf{PCA\_S}}$	**FIMSIS+**
IS10	2.692	2.694	2.634	2.684	2.736	2.681
IS50	3.303	3.291	3.265	3.277	3.303	3.234
CRPS	0.358	0.364	0.387	0.378	0.368	0.384
qwCRPS (left tail)	0.103	0.106	0.117	0.109	0.107	0.108
$h = 1$	$\textbf{FIMSIS}_{\textbf{std}}$	$\textbf{FIMSIS}_{\textbf{eq}}$	$\textbf{FIMSIS}_{\textbf{BEKK}}$	$\textbf{FIMSIS}_{\textbf{PCA}}$	$\textbf{FIMSIS}_{\textbf{PCA\_S}}$	**FIMSIS+**
IS10	3.385	3.376	3.422	3.367	3.393	3.385
IS50	3.782	3.778	3.748	3.748	3.759	3.738
CRPS	0.864	0.870	0.851	0.823	0.811	0.847
qwCRPS (left tail)	0.275	0.274	0.277	0.267	0.273	0.261

Source: Authors' calculations.

7 Macroprudential policy considerations

In this section, we consider the importance of FIMSIS in the context of macroprudential policy design and implementation. Several key aspects of the macroprudential policy cycle emerge where FIMSIS can serve as a valuable complementary tool. By construction, FIMSIS is well suited to monitor financial market developments and track the build-up or materialisation of systemic risks over time. Timely recognition of changes in financial stress is critical for appropriately calibrating macroprudential instruments – whether to tighten in the face of growing vulnerabilities or to relax measures when risks crystallise and amplify procyclicality.

One specific application is in guiding the release of the countercyclical capital buffer (CCyB) during periods of financial stress. Under the positive neutral CCyB framework of Banka Slovenije,[46] buffer release decisions are tied to the materialisation of systemic risk, including signs of reduced credit intermediation, rising non-performing exposures and declining bank resilience. Recent studies (e.g. De Nora et al., 2020) suggest that market-based stress indicators can provide timely and forward-looking signals to support buffer release decisions in times of stress. FIMSIS, as a composite and systemic-oriented financial market stress indicator, can complement the existing risk and resilience dashboard by enriching the real-time assessment of stress intensity. Its regime-classification framework and signalling performance offer practical advantages for gauging when financial conditions deteriorate sufficiently to justify a relaxation of capital-based macroprudential measures, helping to mitigate credit tightening during downturns.

In a broader policy framework, FIMSIS can also support the assessment of the overall macroprudential stance. This can be done via (i) the growth-at-risk (GaR) approach, where FIMSIS serves as a predictor of downside risks to GDP growth, helping to evaluate how macroprudential tools shape the distribution of future economic outcomes, and (ii) the indicator-based approach, where FIMSIS complements other indicators of risks, resilience and policy stance as part of the risk dashboard used to inform policy decisions.

Beyond its role in monitoring and stance assessment, FIMSIS can contribute to the calibration of specific macroprudential tools, such as capital buffers (e.g. CCyB and sectoral SyRBs) or borrower-based measures (BBMs). For example, sustained periods of elevated stress captured by FIMSIS may inform the timing of buffer adjustments or the need to adapt BBMs to changing risk environments.

All in all, composite financial market stress indicators such as FIMSIS should be seen as evolving tools that complement, rather than replace, expert judgment and other data sources in macroprudential policy. To remain effective, they require regular refinement and updating to reflect the changing structure of financial markets and the emergence of new sources of systemic risk

[46]For more details on the framework, refer to Banka Slovenije's webpage on the Countercyclical capital buffer at www.bsi.si

8 Limitations, challenges, and future refinements

The FIMSIS stress indicator provides a comprehensive framework for capturing financial stress in Slovenia, integrating signals from multiple market segments to capture the broad dynamics of systemic risk. While the methodology ensures consistency with the conceptual design of the CISS and facilitates comparability with existing financial stress indicators used in other countries, certain limitations arise due to data availability and the structural characteristics of the Slovenian financial system. This section outlines key caveats in the current approach and proposes potential directions for future development.

A central conceptual challenge lies in the integration of balance sheet-based indicators, such as those from the Banking Sector Indicator (BSI), alongside market-based measures of realised stress. While balance sheet metrics are informative for identifying vulnerabilities, they are not necessarily reflective of materialised stress. This raises concerns about conceptual consistency when constructing an indicator intended to reflect current stress conditions. Ideally, stress indicators should rely on high-frequency, market-based data that are responsive to real-time financial conditions (Illing and Liu, 2006). However, in financial systems with limited market depth, such as that of Slovenia, key market-based metrics for the banking sector, such as credit default swap (CDS) spreads or Merton model-based distance to default, are either unavailable or unreliable due to the small number of publicly listed banks.

In this context, the inclusion of sector-level balance sheet ratios enhances coverage of the banking sector but introduces a methodological trade-off: while it strengthens structural risk assessment, it may dilute the indicator's sensitivity to acute market disruptions. Future refinements of the FIMSIS+ variant could explore alternative approaches to proxy market-implied stress in the absence of direct indicators. These may include the construction of synthetic CDS spreads, the use of macro-financial stress testing frameworks or extensions of structural credit risk models to estimate default probabilities for non-listed banks (see Segoviano and Goodhart, 2009). Although such methods require additional assumptions, they offer promising avenues for improving stress sensitivity under data constraints.

Future refinements could also explore more flexible aggregation structures, including allowing for an unequal number of indicators across market segments or adjusting the balance between transformation types. These adjustments would enable a more tailored reflection of stress dynamics, especially as data availability improves.

Furthermore, while this study primarily focuses on the construction, classification accuracy and robustness of FIMSIS in identifying financial stress episodes, predictive applications represent a promising area for future research. As an initial step in this direction, we assess the predictive performance of alternative FIMSIS variants using a quantile regression framework with Adaptive LASSO and non-crossing constraints (Szendrei and Varga, 2023), as presented in Section 6.3. Additional extensions could explore the use of MIDAS-based forecasting frameworks that leverage mixed-frequency data to evaluate the ability of FIMSIS to predict macroeconomic outcomes such as GDP or industrial production in real time.

Lastly, a natural extension of the model is to account more explicitly for external risk factors, particularly geopolitical risk, which has become an increasingly important driver of financial stress across countries. Incorporating global risk elements into Banka Slovenije's financial stability toolbox may strengthen the overall risk assessment framework by capturing the interaction between external shocks and domestic financial conditions. Rather than including geopolitical risk as a standalone component, a promising approach could involve modelling its interaction with domestic variables to better understand how external shocks amplify financial stress transmission channels within the Slovenian financial system.

9 Conclusions

The unprecedented period of the recent GFC has shown the need of policymakers taking into account the significance of systemic risks and the consequent sufficient response of relevant economic policies. In order to achieve this timely and efficient response, early and accurate measurements of stress levels must be developed that can help detect systemic stressful episodes in the financial sector. Against this backdrop, in this comprehensive paper, we propose the construction of the FIMSIS stress indicator for Slovenia, which may help to facilitate the real-time monitoring of systemic stress episodes in the Slovenian financial system. The construction of the FIMSIS per se is not trivial. Several aspects have to be considered. The criteria for selection of raw stress indicators must be fulfilled alongside the data and sources availability. The crucial part of the desirable criteria for real-time financial stress monitoring is thus to create a thorough measure that is capable of capturing and assessing the critical stressors that stem from the building blocks of the financial system and could lead to the emergence of systemic risks. Further on, the first transformation of the indicators and the aggregation methodology also affect the characteristics of the composite financial stress indicator. We construct the FIMSIS by applying a dynamic correlation matrix between four subindices (equity market, bond market, FX market and money market), with exponentially weighted moving average (EWMA), while weighing these four subindices with cross correlations between different types of markets using the modern portfolio theory (MPT). Doing this, we also give an extensive overview of the methodology used in the analysis and provide pros and cons with respect to other methodologies utilised in the relevant literature.

The results show that the FIMSIS is a reliable composite financial stress indicator, as i) all of the extreme stress episodes detected in the FIMSIS can be associated with well-known and documented financial stress events, suggesting that it does not suffer from type II errors (falsely reporting a high-stress event), and ii) the highest systemic stress can be also related to the business cycle developments as estimated by a non-parametric MBBQ algorithm. Along these lines, we also provide robustness checks of the proposed measure and discuss possible further extensions of the indicator.

In addition, the decomposition of the indicator into the contributions coming from each of the subindices and the overall contribution from the cross-correlations provides additional information on the behaviour of individual markets and on how the cross-correlations work by amplifying or dampening stressful situations. This decomposition is very helpful for regular monitoring exercises.

Finally, even if all important potential sources of financial stress are sufficiently covered by the composite stress indicators at a given time period, the appropriateness of the methodology and the data entering the composite indicator must still be continuously re-examined and consequently adjusted to reflect the latest trends in the financial system. That said, these measurements have to complement the decisions of policymakers, as they can represent a useful tool to cover several aspects of conducting economic policies. In our case, FIMSIS can be considered as an additional tool to monitor the trends and developments on the financial markets and help the macroprudential policy framework development and its implementation.

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Appendix

A. Proposed variables in the literature for constructing the BSI

Table A.1: Proposed variables for the construction of the BSI

Macroeconomic variables	1. Real GDP growth (%) 2. Change in terms of trade (%) 3. Nominal depreciation (%) 4. Real interest rate (%) 5. Inflation (%) 6. Fiscal surplus/GDP (%)
Financial variables	7. M2/foreign exchange reserves (%) 8. Credit to private sector/GDP(%) 9. Bank liquid reserves/total bank assets (%) 10. Real domestic credit growth (%)
Institutional variables	11. Real GDP per capita (%) 12. Deposit insurance (binary dummy) (%)

Source: Adapted on the basis of Demirgüç-Kunt and Detragiache (1998).

B. Illustration of calculation of the variance of portfolio returns based on MPT

We can illustrate the MPT approach of calculating the variance of a portfolio consisting of N securities with a following example.[47] The portfolio weights, denoted by vector $\mathbf{w}$, sum to 1, such that $\sum_{i=1}^{N} \mathbf{w}_i = 1$.[48] If we denote with $\mathbf{X}$ the vector of returns for the N securities in the portfolio, and with $\mu \equiv (\mathbf{X})$ the expected returns, then we have $\mathbf{R} = \mu'\mathbf{w}$ denoting the expected return on the portfolio. Furthermore, we denote with $\mathbf{\Sigma}$ the covariance matrix for the returns on the assets in the portfolio:

$$\mathbf{\Sigma} = E\left[(\mathbf{X}-\mu)(\mathbf{X}-\mu)'\right] = \begin{bmatrix} \sigma_{11} & \dots & \sigma_{1i} & \dots & \sigma_{1N} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \sigma_{i1} & \dots & \sigma_{ij} & \dots & \sigma_{iN} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \sigma_{N1} & \dots & \sigma_{Nj} & \dots & \sigma_{NN} \end{bmatrix} \tag{B.1}$$

where $\sigma_{ij} = \sigma_i\sigma_j\rho_{ij}$, and ρ_{ij} is the correlation between the returns on securities i and j, X_i and X_j.

The variance of the portfolio returns is then defined as:

$$Var(\mathbf{R}) = \mathbf{w}'\mathbf{\Sigma}\mathbf{w} = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij} = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_i \sigma_j \rho_{ij} \tag{B.2}$$

Both in the literature and in financial markets, it is common to use variance or volatility as risk measurements. One key message from MPT is that the more an asset's return co-moves with that of the rest of the portfolio, the more risk it adds to the portfolio.[49]

The application of modern portfolio theory holds significance for understanding systemic risk and the role of macroprudential authorities. The role of financial stability authorities mirrors that of managing a large fund's risks. Consider, for instance, the analogy[50] of a substantial fund such as a state pension fund, mandated to diversify investments across various economic sectors, including non-financial equities, financial equities, currencies,

[47] The most commonly used representation in the financial stress literature is the vector representation of Markowitz (1952).

[48] Portfolio weights can be negative if investors are allowed to short an asset.

[49] In our exercise in constructing the composite indicator of systemic financial stress, the subindices are treated as individual risky assets and aggregated into an overall portfolio, considering the cross correlation among all individual assets' returns.

[50] The analogy is adapted from Wen (2015).

commodities and bonds. Unlike ETFs (exchange traded funds), mutual funds are not traded on the open market and hence cannot be shorted. Therefore, the portfolio weights have to be non-negative and sum to 1. Similarly, the macroprudential authority cannot simply ignore any particular financial market in their assessment of systemic stress. Their appraisal is very much akin to a risk manager's one that monitors various risk measures, rather than being directly involved in the day-to-day management of a single fund. When these measures, for example portfolio variance, exceed the limit set by the fund's strategy, the risk manager will have to step in and intervene. In the same vein, macroprudential authorities monitor stress in the financial markets in real time, but they have certain policy tools, e.g. the CCyB, to intervene in the financial markets when they deem that existing stress in the financial markets is so high and widespread that it impairs the functioning of the financial system and that the real economy and welfare will suffer (de Bandt and Hartmann, 2000). In this analogy, the macroprudential authorities manage the stress, or realised risk, of the financial system, which can be thought of as a "portfolio" of financial markets. Therefore, the portfolio variance measure may just be suitable for measuring systemic stress.

C. Descriptive statistics of subindices

Table C.1: Descriptive statistics of subindices in FIMSIS

	S1 (bond)	**S2 (equity)**	**S3 (FX)**	**S4 (MMS)**
Mean	0.500070	0.500070	0.500070	0.500070
Median	0.491064	0.479970	0.494160	0.493902
Maximum	0.987194	0.992588	0.987851	0.997326
Minimum	0.079979	0.008819	0.031241	0.007458
Std. Dev.	0.193523	0.225563	0.251605	0.265975

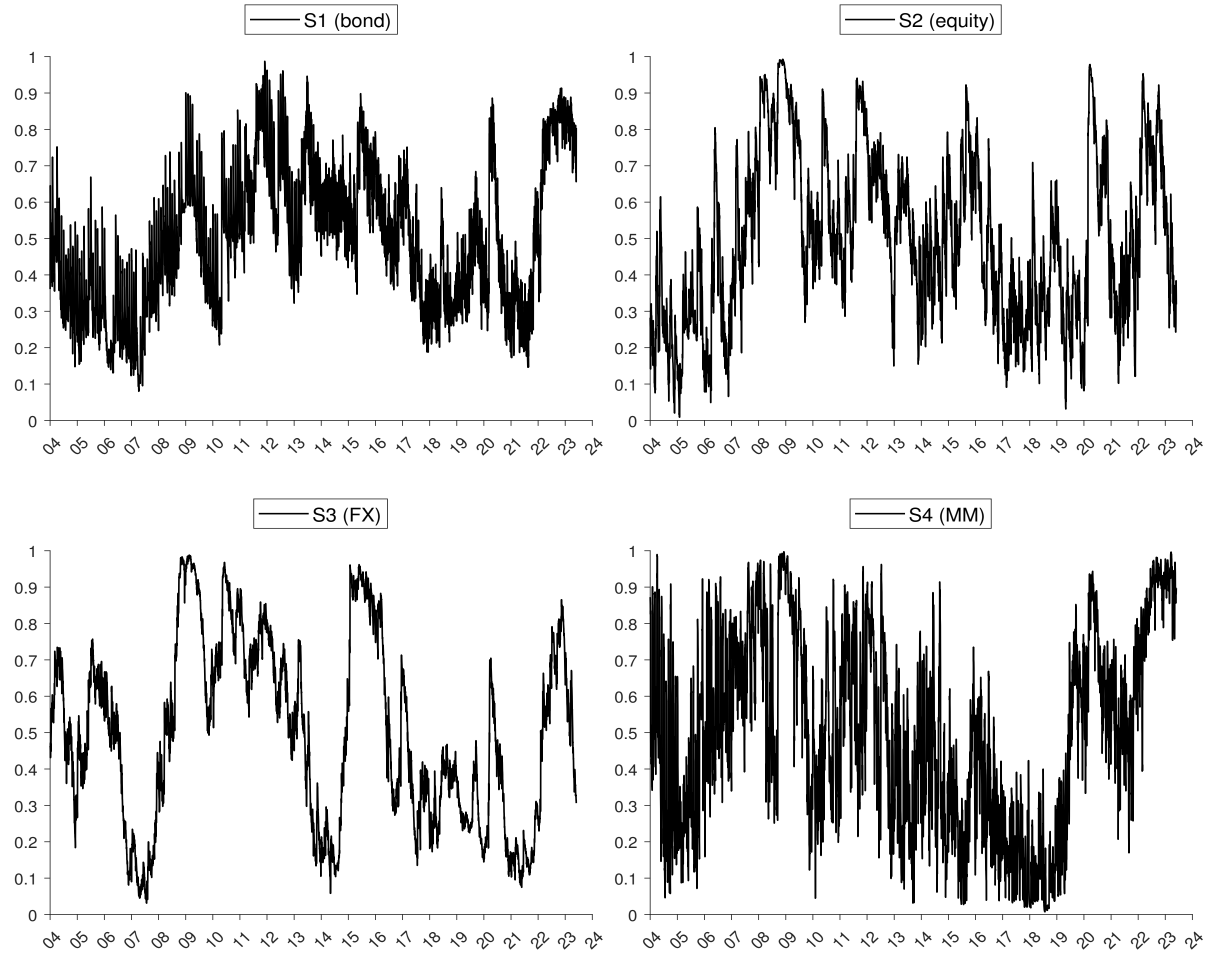
Note: Sample from 1 January to 30 May 2023.

Table C.2: Descriptive statistics of subindices in FIMSIS+

	S1 (bond)	**S2 (equity)**	**S3 (FX)**	**S4 (MMS)**	**S5 (BSI)**
Mean	0.498875	0.500842	0.500811	0.498895	0.443702
Median	0.488889	0.485837	0.493857	0.493349	0.393056
Maximum	0.873056	0.985316	0.982106	0.970471	1.000000
Minimum	0.105695	0.088692	0.057763	0.041889	0.002778
Std. Dev.	0.179931	0.214981	0.249799	0.240195	0.299324

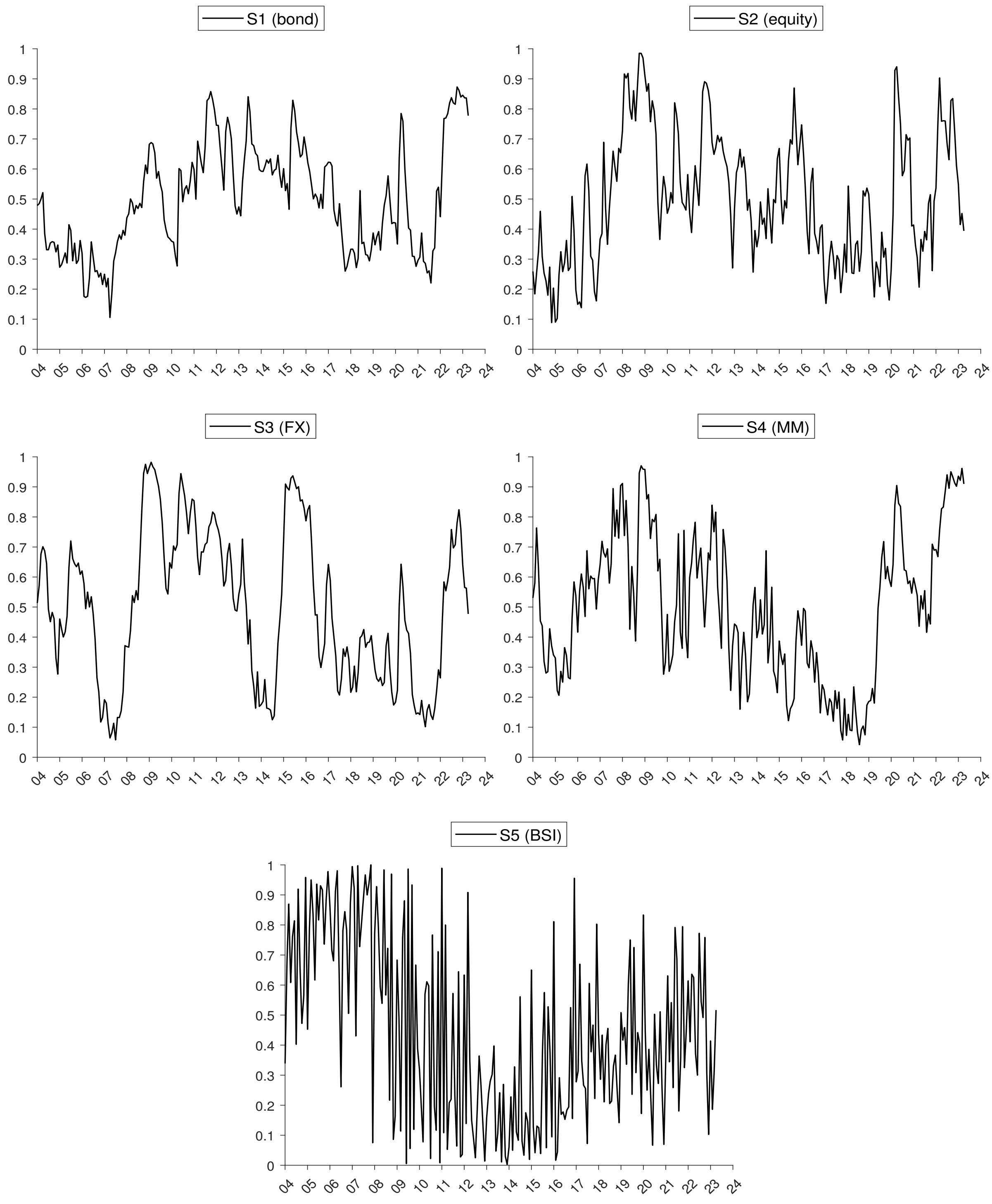
Note: Sample from 1 January to 30 May 2023.

Figure C.1: Subindices of the FIMSIS



Note: Sample from 1 January to 30 May 2023; Based on ADF unit root tests, we reject the H0 and conclude that the series are stationary at the critical level of 0.05.
Source: Authors' calculations.

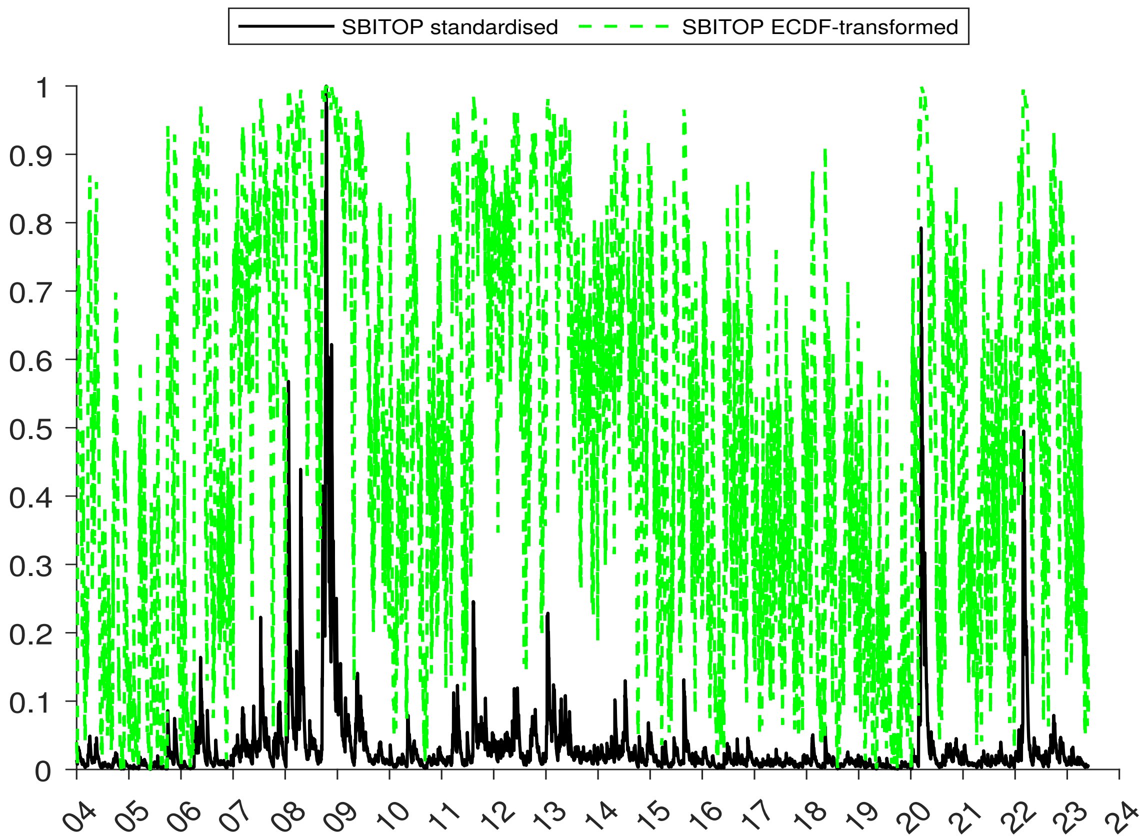
Figure C.2: Subindices of the FIMSIS+



Note: Sample from 1 January to 30 May 2023; Based on ADF unit root tests, we reject the H0 and conclude that the series are stationary at the critical level of 0.05.
Source: Authors' calculations.

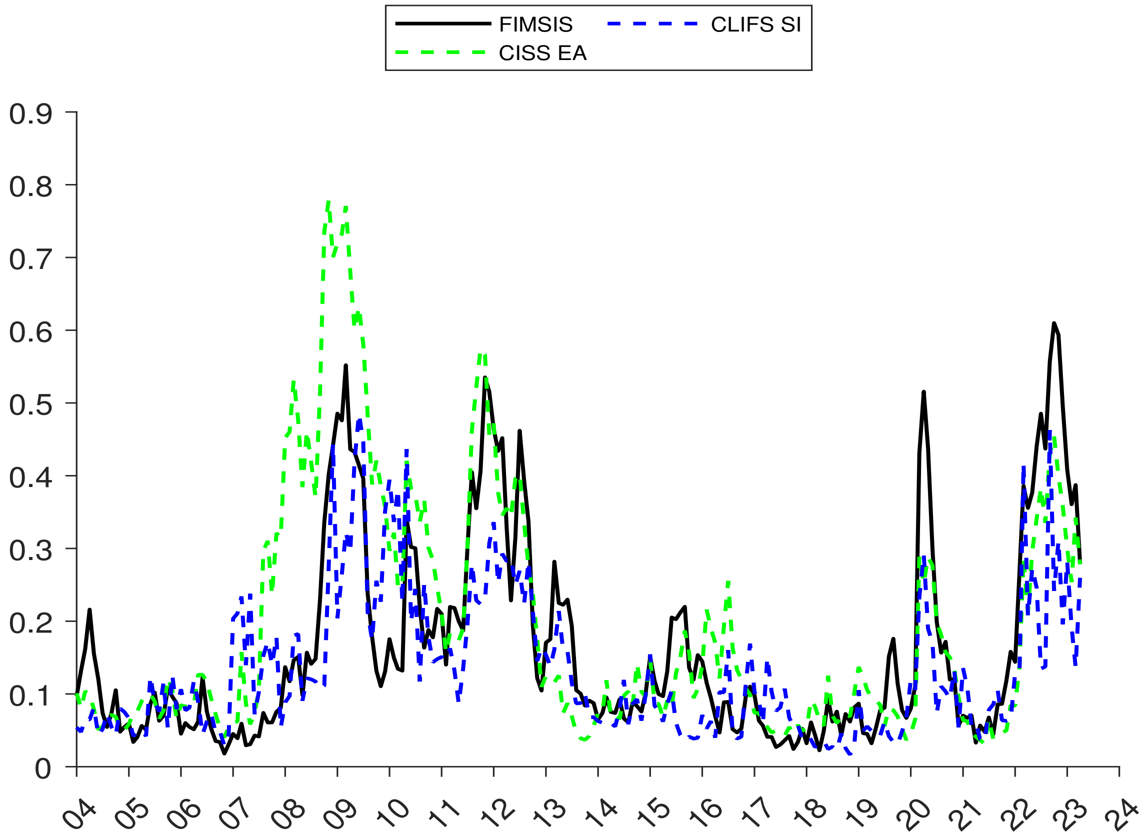
D. Additional figures and results

Figure D.1: Comparison of differently transformed raw indicator (simple standardisation vs. ECDF-based transformation of the SBITOP volatility indicator)



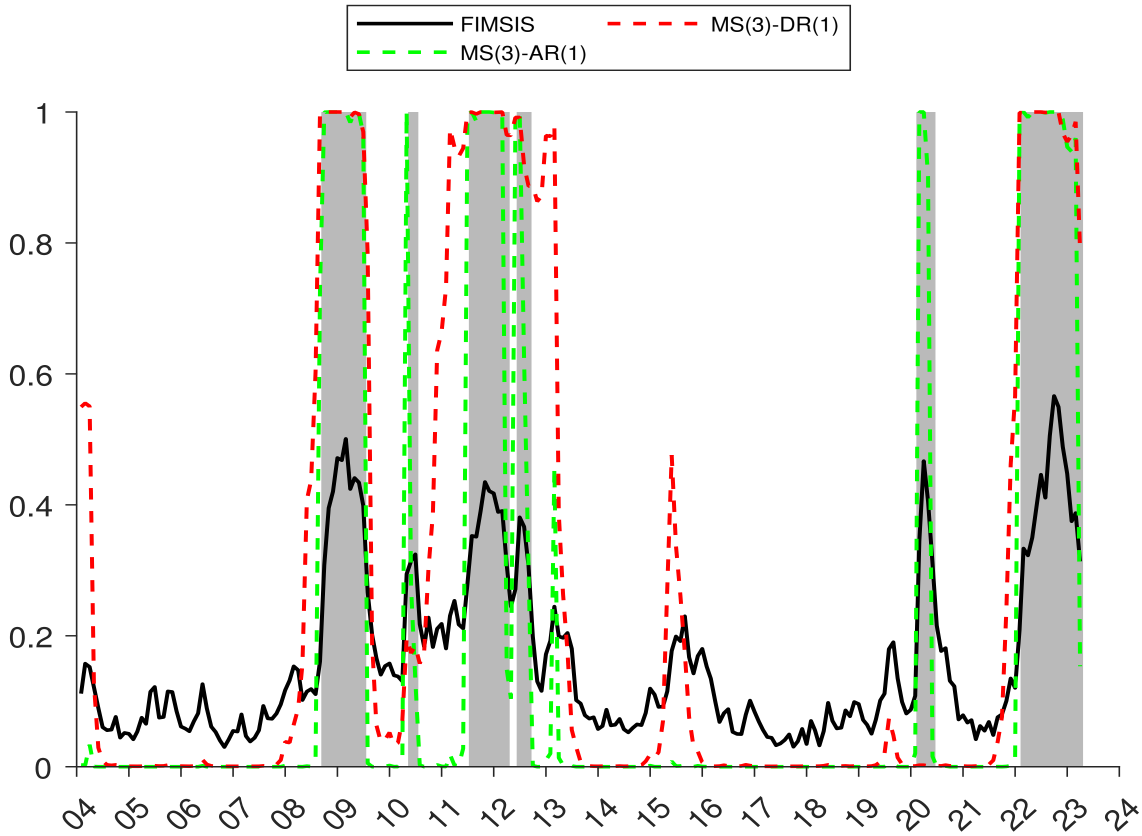
Source: Authors' calculations.

Figure D.2: Comparison of different stress indicators with FIMSIS



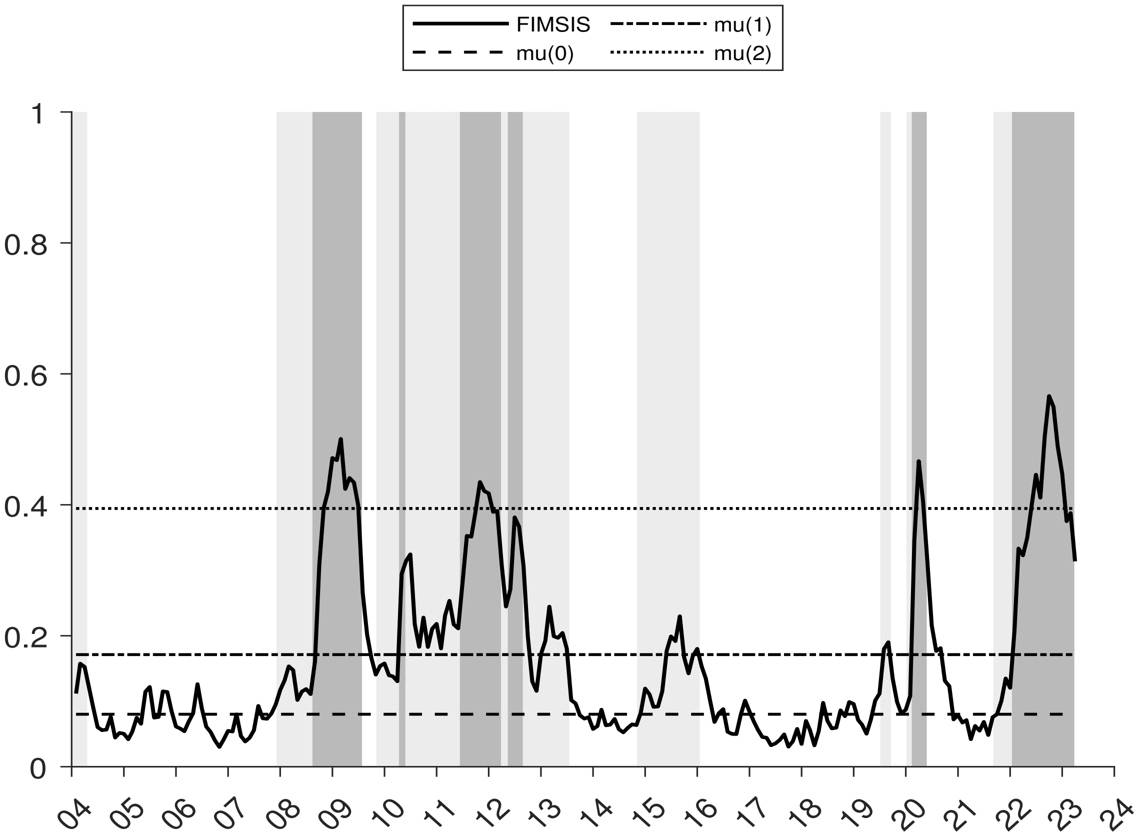
Note: FIMSIS is the monthly version of the original FIMSIS, calculated based on monthly averages of daily volatility factors transformed on the basis of their ECDFs and aggregated in the corresponding subindices before the final aggregation. CISS EA, the composite indicator of systemic stress for the euro area that was developed by Holló et al (2012), is shown in monthly averages of daily values. CLIFS SI a financial stress index measuring stress in the Slovenian financial markets. The financial stress index, CLIFS, is available in monthly frequency only and was developed by Duprey et al. (2017) and measures the stress in financial markets at the country level based on three market segments (equity, bond and foreign exchange) and the cross-correlation among them.
Source: Authors' calculations.

Figure D.3: Comparison of the highest stress regimes of the competing MS-AR models against FIMSIS



Note: FIMSIS is constructed from daily volatility indicators, averaged to monthly frequency, transformed using empirical cumulative distribution functions (ECDFs), and aggregated into subindices. The figure shows smoothed probabilities of Regime 2 from both the benchmark MS(3)-AR(1) model (dashed green line) and the alternative MS(3)-DR(1) model (dashed red line). The grey-shaded areas highlight periods identified as Regime 2 by the benchmark model (MS(3)-AR(1)), aiding visual interpretation of systemic stress phases.
Source: Authors' calculations.

Figure D.4: FIMSIS and the unconditional means from the MS(3)-AR(1) model



Note: MS(3)-AR(1) denotes an autoregressive Markov-switching model for the FIMSIS of order 1 with 3 states. All three parameters are allowed to switch across regimes. Estimations based on monthly averages of daily data from January 2004 to May 2023. The horizontal lines denoted mu(s) represent the three regime-dependent unconditional means from the model. The figure plots FIMSIS together with three horizontal "benchmark" or demarcation lines each representing the unconditional mean of the three different stress regimes. Periods of dominant elevated and extreme levels of stress are highlighted by shadings in light green and dark green, respectively, which allows for easier historical contextualisation of the last FIMSIS values.
Source: Authors' calculations.

Table D.1: Coefficients of the BIC selected model at $h = 1$

τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	-0.8089	-0.3673	0.2285	0.4329	0.6587	0.9304	1.1586	1.5629	1.8773
GDP	-0.4001	-0.449	-0.449	-0.449	-0.449	-0.4681	-0.5134	-0.5856	-0.6481
CCI	-0.0009	-0.0009	0.005	0.0056	0.0056	0.0218	0.0218	0.0218	0.0218
MPI	-0.3119	-0.3119	-0.2604	-0.1801	-0.1162	-0.1384	-0.1384	-0.1384	-0.1384
$\text{FIMSIS}_{\text{std}}$	-1.4861	-1.2469	-0.6911	-0.6911	-0.6126	-0.4946	-0.4946	-0.4449	-0.4449
τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	-0.7844	-0.3143	0.197	0.5001	0.6632	0.902	1.1351	1.5243	1.8429
GDP	-0.3922	-0.4378	-0.4378	-0.4378	-0.4378	-0.438	-0.481	-0.5583	-0.6124
CCI	-0.0084	0.0365	0.0365	0.0365	0.0365	0.0567	0.0476	0.0476	0.0476
MPI	-0.3054	-0.2812	-0.2631	-0.1489	-0.1013	-0.1304	-0.1304	-0.1304	-0.1304
$\text{FIMSIS}_{\text{eq}}$	-1.4249	-1.3076	-0.727	-0.7095	-0.6563	-0.4866	-0.4866	-0.4866	-0.4288
τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	-0.7929	-0.1213	0.2506	0.482	0.7054	0.9134	1.0187	1.3793	1.8675
GDP	-0.3515	-0.3515	-0.3515	-0.3515	-0.3515	-0.381	-0.3906	-0.4622	-0.5352
CCI	0.0254	0.0688	0.0769	0.0769	0.1206	0.1206	0.1206	0.1206	0.1206
MPI	-0.3189	-0.3189	-0.2	-0.1281	-0.0727	-0.0626	-0.0626	-0.0626	-0.0626
$\text{FIMSIS}_{\text{BEKK}}$	-1.3561	-0.7698	-0.7146	-0.6653	-0.6653	-0.6315	-0.5747	-0.5747	-0.455
τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	-0.6082	-0.2248	0.1836	0.4493	0.6916	0.9159	1.2027	1.45	1.8465
GDP	-0.3936	-0.4697	-0.5117	-0.5117	-0.5117	-0.5126	-0.5696	-0.6111	-0.6888
CCI	0.2287	0.2287	0.2287	0.2287	0.2287	0.1303	0.1303	0.109	0.109
MPI	-0.1823	-0.1823	-0.1823	-0.129	-0.0806	-0.0806	-0.0806	-0.0806	-0.0806
$\text{FIMSIS}_{\text{PCA}}$	-1.2462	-1.2462	-1.0441	-0.9102	-0.7873	-0.7441	-0.7441	-0.7441	-0.7388
τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	-0.5491	-0.2667	0.1799	0.5526	0.7099	0.9434	1.2649	1.516	1.7659
GDP	-0.4623	-0.5145	-0.5508	-0.5508	-0.5761	-0.5761	-0.6063	-0.6476	-0.696
CCI	0.1605	0.1497	0.1497	0.1497	0.1497	0.098	0.004	-0.0201	-0.0201
MPI	-0.204	-0.204	-0.204	-0.1463	-0.1421	-0.0868	-0.0868	-0.0868	-0.0896
$\text{FIMSIS}_{\text{PCA\_S}}$	-1.2383	-1.2383	-0.9814	-0.7603	-0.7417	-0.7417	-0.7417	-0.7417	-0.7417
τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	-0.6654	-0.239	0.2319	0.5079	0.718	0.8759	1.0606	1.4022	1.8561
GDP	-0.3804	-0.3804	-0.3804	-0.3804	-0.3816	-0.4064	-0.4385	-0.4764	-0.5287
CCI	0.1032	0.1032	0.1032	0.1032	0.142	0.142	0.142	0.142	0.0885
MPI	-0.3303	-0.2684	-0.2122	-0.1676	-0.116	-0.116	-0.116	-0.116	-0.116
FIMSIS+	-1.4041	-1.1384	-0.8146	-0.6537	-0.6537	-0.6215	-0.5986	-0.4501	-0.3576

Table D.2: Coefficients of the BIC selected model at $h = 4$

τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	-0.7814	-0.1798	0.2301	0.5001	0.7728	0.8839	1.0512	1.1476	1.401
GDP	0.1655	0.1655	0.1655	0.1655	0.1655	0.143	0.1091	0.0896	0.0426
CCI	-0.7135	-0.3901	-0.1736	-0.1101	-0.1101	-0.1101	-0.1101	-0.1101	-0.1101
MPI	-0.3486	-0.3486	-0.3486	-0.3401	-0.3401	-0.3401	-0.3401	-0.3401	-0.3312
$\text{FIMSIS}_{\text{std}}$	-0.5125	-0.5125	-0.5035	-0.3401	0	0	0	0	0
τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	-0.7767	-0.1899	0.2572	0.5436	0.6414	0.8881	1.0548	1.1468	1.4013
GDP	0.1417	0.1417	0.1417	0.1417	0.1417	0.1417	0.1079	0.0892	0.0387
CCI	-0.693	-0.3776	-0.1389	-0.0667	-0.0905	-0.0967	-0.0967	-0.0967	-0.0967
MPI	-0.3342	-0.3342	-0.3342	-0.3246	-0.3246	-0.3246	-0.3246	-0.3246	-0.3225
$\text{FIMSIS}_{\text{eq}}$	-0.5377	-0.5377	-0.5338	-0.3705	-0.2998	0	0	0	0
τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	-0.6487	-0.113	0.1743	0.5079	0.6579	0.8981	0.9673	1.1691	1.4039
GDP	0.0667	0.0667	0.0667	0.0667	0.0667	0.0667	0.0783	0.0783	0.0354
CCI	-0.4285	-0.2364	-0.1406	-0.059	-0.059	-0.059	-0.0509	-0.0509	-0.0383
MPI	-0.4251	-0.353	-0.353	-0.2797	-0.2622	-0.2622	-0.2622	-0.2622	-0.2622
$\text{FIMSIS}_{\text{BEKK}}$	-0.665	-0.665	-0.5548	-0.5548	-0.4469	-0.2041	-0.2041	0	0
τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	-0.6172	-0.2143	0.3992	0.584	0.7066	0.9048	0.9888	1.1554	1.3969
GDP	0.1215	0.1215	0.1215	0.1215	0.1214	0.1015	0.0925	0.0726	0.0237
CCI	-0.4287	-0.2121	-0.0868	-0.0219	-0.0608	-0.0608	-0.0608	-0.0995	-0.0995
MPI	-0.2638	-0.2638	-0.2638	-0.238	-0.2624	-0.2624	-0.2624	-0.2624	-0.2624
$\text{FIMSIS}_{\text{PCA}}$	-0.7225	-0.7224	-0.3185	-0.3185	-0.3186	-0.2124	-0.1705	-0.1705	-0.1705
τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	-0.8074	-0.214	0.2977	0.5777	0.7542	0.8865	1.0493	1.1426	1.3961
GDP	0.197	0.197	0.197	0.197	0.1684	0.1416	0.1086	0.0897	0.0384
CCI	-0.7304	-0.563	-0.2879	-0.1374	-0.1182	-0.1182	-0.1182	-0.1182	-0.1182
MPI	-0.2028	-0.3345	-0.3345	-0.3345	-0.3345	-0.3345	-0.3345	-0.3345	-0.3345
$\text{FIMSIS}_{\text{PCA\_S}}$	0	0	0	0	0	0	0	0	0
τ	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Constant	-0.6117	-0.0779	0.3126	0.3738	0.7137	0.844	0.9766	1.1227	1.2585
GDP	0.0812	0.0812	0.0812	0.0812	0.0812	0.0812	0.0812	0.0703	0.0648
CCI	-0.481	-0.2352	-0.0253	-0.0253	-0.0253	-0.0029	-0.0029	-0.034	-0.0789
MPI	-0.3538	-0.3229	-0.3229	-0.3056	-0.2321	-0.2321	-0.226	-0.2163	-0.2139
FIMSIS+	-0.6065	-0.6065	-0.6065	-0.5891	-0.4389	-0.3546	-0.2426	-0.2471	-0.2248