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MEASURING ECONOMIC DISTRESS USING THE CONTINGENT CLAIMS APPROACH

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ABSTRACT

We introduce a new Economic Distress Index (EDI), which incorporates information from all economic sectors as a device for real-time monitoring of financial stability risks in the euro area. Our approach is based on structural models of credit risk and incorporates market and balance sheet information from which we derive distance-to-defaults as uniform risk indicators across economic sectors, which form the basis of the EDI. Monetary financial institutions are the largest contributors to the EDI over the period from 1999 to 2023. In the post-Global Financial Crisis period, non-bank financial intermediaries emerge as the largest contributors to the EDI, consistent with broader developments that have contributed to the growth of non-bank financial intermediation. Using local projections, we show that the EDI also has significant predictive power for macroeconomic developments that originate primarily from high-stress regimes. Finally, we unpack that volatility is clearly the most important driver of the raw risk indicators, accounting on average for almost 80% of the explained variation.

KEYWORDS

Credit risk; Financial accounts; Contingent claims analysis; Systemic risk; Macro-prudential analysis

JEL CODES

C43; C53; E01; E37; E44; G01

1 Introduction

The landscape of the financial system is characterized by complexity and interconnectedness. Historically, however, the analysis of systemic risks has largely focused on the financial sector—especially the banking sector. Following the Global Financial Crisis (GFC) of 2007-08, the prevailing view among policymakers was that the architecture of the financial system plays a pivotal role in shaping systemic risks. Previous literature has emphasized the importance of linkages between different firms and sectors, which can propagate microeconomic shocks throughout the economy and lead to aggregate fluctuations (Gabaix 2011; Acemoglu et al. 2012). This view was often recognized as the main explanation for the propagation of risks through the financial system, leading to the implementation of numerous policy actions (Acemoglu, Ozdaglar, and Tahbaz-Salehi 2015; Farboodi 2023).[1] In addition, regulatory reforms, technological innovation, and the urge to bolster capital market activity in the post-GFC period have contributed to the growth in financial intermediation beyond the conventional banking system perimeter (Acharya, Cetorelli, and Tuckman 2024; European Banking Authority 2024). These developments further reinforce the necessity for a more holistic approach to systemic risk.

In an effort to adopt a more holistic approach to systemic risk and real-time monitoring of the state of the economy, we introduce a new Economic Distress Index (EDI) that incorporates information from all sectors of the economy; including the real economy (i.e., households and non-financial corporations), the public sector (i.e., general government and central banks), and the financial sector (i.e., monetary financial institutions, insurance corporations, pension funds, non-money market investment funds, and other financial intermediaries), in the euro area over a quarter of a century. The EDI is constructed from raw stress indicators based on structural models of credit risk; from this we derive the distance-to-default (DD), which indicates the number of standard deviations by which the market value of assets is away from the default barrier and therefore provides a uniform and easily comparable measure across economic sectors. The index incorporates sector-specific and recursively estimated time-varying systemic risk weights that capture the interdependence between the raw stress indicators across sectors. We document three key insights:

(I) The newly constructed EDI is a real-time monitoring device for the state of the economy that has closely tracked past periods of systemic stress. The EDI is significantly elevated or downward sloping near key events and peaked in late 2008 and early 2009 in the wake of the GFC, followed by the COVID-19 pandemic, and the recent inflation shock. The average conditional probability of being in a low-stress state is 67% and can therefore be considered the default state. However, being in a high-stress state is also relatively prevalent, with an average conditional probability of 24%, which is attributable to the numerous crises of recent years, including the GFC, the sovereign debt crisis, Brexit uncertainty, Trump tariffs, the COVID-19 pandemic, and the inflation shock. We also document that the EDI is correlated with existing indicators of systemic stress, but clearly contains additional information.

(II) Monetary financial institutions (MFIs) are the largest contributors to the EDI over the entire sample period, which is not surprising as the MFI sector forms the core of the euro area financial system and acts as a hub between the economic sectors. However, since the beginning of the rate hike cycle, the

[1] This includes amendments to the Capital Requirements Regulation (EU) No 575/2013 and the Capital Requirements Directive 2013/36/EU in Europe and the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 in the United States.

contribution of the MFI sector to the EDI has tended to decline, suggesting that the financial sector is acting as a shock absorber rather than a shock accelerator during this episode. In addition, in the post-GFC period since 2010, non-bank financial intermediaries (NBFIs) are the main contributors to the EDI, which is in line with broader developments that have contributed to the growth in non-bank financial intermediation post-GFC.

(III) The EDI has significant predictive power for aggregate macroeconomic developments, including key macroeconomic variables for the state of the economy such as industrial production and unemployment rate. The predictive power is asymmetric and arises mainly from high-stress regimes.

To provide additional perspective and considering the importance of each sector for the functioning of the economy, we also examined in detail the raw stress indicators (i.e., DD) for each sector. This is more akin to the conventional approach in the literature, which usually captures certain market or instrument-specific stress symptoms (Chavleishvili and Kremer 2024). In summary, we document that DD has moved sharply around key crisis events such as the GFC and the COVID-19 pandemic, with sometimes heterogeneous responses across economic sectors. The weighted average DD across all sectors is 13.8. We observe substantial level (standard deviation) differences between the different sectors, ranging from 4.9 (1.9) for the MFI sector to 38.6 (9.8) for the households (HH) sector. The reasons for such differences can be wide-ranging and include asset composition, differences in leverage, the regulatory environment, and income stability. Recognizing the substantial level differences between economic sectors, we also unpack the drivers of DD using the Lindeman, Merenda, and Gold (1980) approach, which corresponds to Shapley values—a concept from cooperative game theory. By decomposing the impact of the main drivers of DD—leverage, volatility, and interest rate—we show that asset volatility is clearly the most important driver of DD across all economic sectors, accounting on average for almost 80% of the explained variation. From a theoretical perspective, DD decreases as asset volatility increases. Intuitively, higher volatility implies greater fluctuations in a sector's future asset path, which increases the likelihood that the distress barrier will eventually be reached. By specifying adequate volatility spike scenarios to approximate the impact of a stress state, we observe a 273 point reduction in the average DD to 11.1, a decrease of almost 20.0%.

Related Work. Our paper relates to work in the areas of systemic risk and financial stability; indicators of financial stress, crises, and uncertainty; and real effects of financial distress. Key work in this area include:[2] Adrian and Brunnermeier (2016), Acharya et al. (2017), and Brownlees and Engle (2017) propose measures of systemic risk at the level of individual financial institutions that contribute to financial instability at the level of the financial system. Gilchrist and Zakrajšek (2012) and Saunders et al. (2025) use a bottom-up approach based on corporate bond credit spreads and loan spreads, respectively, to compute an aggregate credit spread index to capture the degree of strains in the financial system. Kritzman et al. (2011) and Billio et al. (2012) proposed systemic risk measures (i.e., 'Absorption Ratio' and 'Cumulative Risk Fraction', respectively) based on a principal component analysis of asset returns by calculating the fraction of the aggregate return variance explained by the largest eigenvectors of the variance-covariance matrix. In Kritzman and Li (2010) and Kritzman et al. (2011), Mahalanobis distance-based measures of 'Financial Turbulence' are proposed to measure uncharacteristic behavior

[2] For a comprehensive survey of systemic risk analytics we refer to Bisias et al. (2012), for an overview of financial stress indices we refer to Chavleishvili and Kremer (2024), and more generally on financial crises to Sufi and Taylor (2022).

in observed asset returns.

Saldías (2013) develops methods for monitoring systemic risk in the European banking system based on forward-looking DD series. Laeven and Valencia (2008), Laeven and Valencia (2013), and Laeven and Valencia (2020, p. 309) construct dummies for systemic banking crises for different countries and time horizons based on either "significant signs of financial distress in the banking system" or "significant banking policy intervention measures in response to significant losses in the banking system." Baron, Verner, and Xiong (2020) combine narrative information and bank equity returns to map banking crises with and without panics.

Starting from the seminal work of Illing and Liu (2006), which proposes a concept for a 'Financial Stress Index' of the Canadian financial system covering broader parts of the financial system including the banking sector, the foreign exchange market, and debt and equity markets, a large number of indices of financial market distress have been proposed. For the US, these include the 'Financial Fragility Indicator' (Nelson and Perli 2007), the 'Kansas City Financial Stress Index' (Hakkio and Keeton 2009), the 'St. Louis Fed's Financial Stress Index' (Kliesen and Smith 2010), the 'National Financial Conditions Index' (Brave and Butters 2011, 2012), the 'Cleveland Financial Stress Index' (Oet, Dooley, and Ong 2015), and the 'Office of Financial Research Stress Index' (Monin 2019). In addition, Van Roye (2014) proposed a financial stress index for Germany, Cardarelli, Elekdag, and Lall (2011) for 17 advanced economies, Vermeulen et al. (2015) for 28 OECD countries, and Groen, Nattinger, and Noble (2020) measure global financial market stress in 46 countries comprising advanced and emerging economies. Grimaldi (2010) introduced a financial stress indicator for the euro area based on 16 market-based financial measures covering corporate bond, government bond, bank, equity, and money markets. Holló, Kremer, and Lo Duca (2012) introduced the 'Composite Indicator of Systemic Stress' based on basic portfolio theory to aggregate individual financial stress measures into market-specific sub-indices (including financial intermediaries, non-financial equity market, bond market, money market, and foreign exchange market) and subsequently into an overall indicator of financial stress. Similar ideas for euro area sovereign bond market stress were extended in Garcia-de-Andoain and Kremer (2017), who developed a 'Composite Indicator of Systemic Sovereign Stress' that incorporates volatility and yield and liquidity spreads into an overall index of sovereign bond market stress. Boyarchenko et al. (2024) propose a 'Corporate Bond Market Distress Index' that captures primary and secondary market measures of corporate bond market functioning. Chavleishvili and Kremer (2024) present a general conceptual and statistical framework for measuring the severity of financial crises in real time and address the construction of different financial stress indices as special cases of the proposed general framework. The main differences between the above stress indices are the selection of indicators, the considerations of extremeness, and the co-dependence between the individual factors (i.e., the weighting schemes).

Romer and Romer (2017) construct a series of financial distress in OECD countries based on narrative reports of country conditions to provide information on the severity and evolution of distress following crises episodes. Finally, Jurado, Ludvigson, and Ng (2015) and Baker, Bloom, and Davis (2016) introduce general uncertainty indicators with the 'Macroeconomic Uncertainty Index' and the 'Economic Policy Uncertainty Index', respectively.

Many of the above indicators also examine the real effects of financial distress and uncertainty and show economically and statistically significant predictive power of measures of financial distress (including, for example, financial stress indices, crisis dummies, systemic risk indicators, or credit spreads) for aggregate macroeconomic outcomes and future economic activity. Thereby, often asymmetric responses are observed, with stronger effects arising mainly from high-stress regimes (see, for example, Bloom (2009), Gilchrist and Zakrajšek (2012), Holló, Kremer, and Lo Duca (2012), Hubrich and Tetlow (2015), Baker, Bloom, and Davis (2016), Romer and Romer (2017), Adrian, Boyarchenko, and Giannone (2019), Alessandri and Mumtaz (2019), Boyarchenko et al. (2024), Chavleishvili and Kremer (2024), and Saunders et al. (2025)).

The main innovation of our proposed EDI as a device for real-time monitoring of the state of the economy is the coverage of all sectors of the economy as defined by the national accounts. This is in contrast to the conventional approach in the literature, which usually only captures certain market or instrument-specific stress symptoms. The raw stress indicators in our approach are derived from structural models of credit risk and therefore provide a unified measure of stress across all economic sectors, rather than simply combining different heterogeneous financial variables from each sector. The input factors for the structural credit risk models combine both market and sectoral balance sheet data. We draw on sectoral balance sheets from the sectoral accounts, which represent a coherent, consistent, and integrated set of macroeconomic accounts for an economy using internationally agreed definitions and accounting rules.

The remainder of this paper proceeds as follows. Section 2 presents the theoretical framework. Section 3 describes our data. Section 4 presents our main empirical results. Section 5 concludes.

2 Theoretical Framework

Our approach is based on contingent claims analysis (CCA), which is a generalization of the option pricing models developed by Black and Scholes (1973) and Merton (1974). CCA provides a framework that combines market and balance sheet information to obtain financial risk indicators. The approach is typically used for individual firms, but we apply the same concepts at a sectoral level by viewing the economy as a series of interconnected balance sheets (Gray, Merton, and Bodie 2010). In this way, the liabilities of a sector can be valued as a contingent claim on the assets of that sector and equity can be modeled as an implicit call option on the assets with a strike price equal to the face value of debt (i.e., the default barrier). The normalized distance between the market value of assets of a given sector and the default barrier is the so-called distance-to-default (DD), which indicates the number of standard deviations by which the market value of assets is away from the default barrier; thus, the measure is easily comparable across sectors. This concept is sometimes also referred to as 'distance-to-distress' and 'distress barrier', respectively. Although distress (e.g., a rating downgrade) usually occurs before a default, it can still have a significant impact on the debtor's business activities. Since we work at sectoral level, a sectoral distress is more conceivable than the default of an entire sector, hence we will use the terms interchangeably.

Formally, following Merton (1974), it is assumed that the market value of a sector's assets V_t follows a geometric Brownian motion:

$$dV_t = \mu V_t dt + \sigma V_t dW_t, \tag{1}$$

where V_t is the total value of the sector's assets, μ is the expected return, σ is the volatility, and W_t is a standard Wiener process. For notational simplicity, we omit in what follows the dependence on the evaluation time t when it is clear from the exposition. It is straightforward to express the value of a sector's equity as a function of the value of the sector's assets and issued debt using the Black-Scholes formula for a call option:

$$E = V\mathcal{N}(d_1) - e^{-rT}F\mathcal{N}(d_2), \tag{2}$$

where E is the market value of the sector's equity (sometimes also referred to as junior claims), F is the face value of the sector's debt, r is the instantaneous risk-free interest rate, $\mathcal{N}$ is the cumulative normal distribution function, d_1 is given by:

$$d_1 = \frac{\ln(V/F) + \left(r + 0.5\sigma_V^2\right)T}{\sigma_V\sqrt{T}}, \tag{3}$$

and d_2 is $d_1 - \sigma_V\sqrt{T}$. Since the value of equity is a function of the sector's assets and time, it follows from Ito's lemma that the sector's equity volatility is related to the sector's asset volatility by:

$$\sigma_E = \left(\frac{V}{E}\right)\frac{\partial E}{\partial V}\sigma_V. \tag{4}$$

From the Black-Scholes-Merton model we know that $\frac{\partial E}{\partial V} = \mathcal{N}(d_1)$, such that:

$$\sigma_E = \left(\frac{V}{E}\right)\mathcal{N}(d_1)\sigma_V. \tag{5}$$

Ultimately, the DD is calculated as:

$$DD = \frac{\ln(V/F) + \left(\mu - 0.5\sigma_V^2\right)T}{\sigma_V\sqrt{T}}, \tag{6}$$

where μ is the asset drift under the physical measure $\mathbb{P}$; to change from the risk-neutral measure $\mathbb{Q}$ to the physical measure $\mathbb{P}$, we specify the following condition: $\mu = r + \lambda\sigma_V$, where λ is the market price of risk. In our implementation, we assume a fixed market price of risk $\lambda = 0.45$, which corresponds to the long-term average calculated by Moody's KMV (Castrén and Kavonius 2009). While the equity E and the corresponding volatility σ_E are easily observable and can be estimated, this is not the case for the required total value of the sector's assets V and the corresponding volatility σ_V. Therefore, we solve Eq. (2) numerically using standard iterative techniques to obtain estimates for V and σ_V. We assume a forecast horizon of 1 year (i.e., $T = 1$), which is standard in the literature.

To provide additional insights, we compute an average distance-to-default (ADD) as the average of the sector-specific DD series weighted by total assets (Saldías 2013):

$$ADD_t = \sum_{i=1}^{N} w_{it}DD_{it}, \tag{7}$$

where DD_{it} is the sector-specific DD series for sector i at time t and w_{it} is the corresponding sector specific weight (i.e., total assets).

As an extension, in the spirit of Guo and Li (2022), we also consider a state-dependent (i.e., regime-switching) geometric Brownian motion:

$$dV_t = \mu V_{s_t} dt + \sigma V_{s_t} dW_t, \tag{8}$$

where $s_t \in \{B, S\}$ reflects the overall state of the economy, which is either in a state of boom B or stress S. Estimating the Merton model iteratively and simultaneously determining the transition rates between the two regimes is computationally complex and, from a systemic risk perspective, the stress state is of greater concern when calculating financial risk indicators. Conditional on the economy remaining in a state of stress during the forecast horizon, we define:

$$DD_S = \frac{\ln(V/F) + \left(\mu_S - 0.5\sigma^2_{V_S}\right)T}{\sigma_{V_S}\sqrt{T}}, \tag{9}$$

where the parameters correspond to our specifications in Eq. (6), but under the assumption of $s = S$. Note that V and F have no state index, as they are based on the currently available information. Therefore, the specification can be understood rather as a stress scenario and not as an estimate of V and F under stress. Since the expected return in our framework is specified as a function of volatility, we are mainly interested in defining adequate measures of volatility spikes to approximate the impact of a stress state. With this aim in mind, we follow two paths to obtain a measure of σ_{E_S} as input to the estimation. The first approach is guided by the marginal expected shortfall specification of Acharya et al. (2017), where $\mathbb{I}_{5\%}$ denotes the set of days with the worst 5% market outcomes at daily frequency (i.e., sectoral returns) for the past calendar year. Consequently, we can specify a sector-specific equity volatility based on these tail days as:

$$\sigma_{E_{tail}} = \mathbb{E}[\sigma_E | \mathbb{I}_{5\%}] = \frac{1}{|\mathbb{I}_{5\%}|} \sum_{\tau \in \mathbb{I}_{5\%}} \sigma_{E_\tau}, \tag{10}$$

where τ indicates a specific day in the set of $\mathbb{I}_{5\%}$. Our second approach is more akin to classical stress tests (Ding et al. 2022), where we define a two standard deviation (SD) volatility spike based on the currently observed 12-month volatilities:

$$\sigma_{E_{shock}} = \sigma_{E_t} + 2 \cdot \mathrm{SD}(\sigma_{E_{t-1,t}}), \tag{11}$$

where the SD is determined over the past calendar year. We use the stressed equity volatility specifications in Eqs. (10) and (11) as inputs to obtain a DD in a stressed state according to Eq. (9), which we refer to as DD_{tail} and DD_{shock}, respectively. Finally, we define the stressed DD as:

$$DD_{stress} = \min(DD_{tail}, DD_{shock}). \tag{12}$$

3 Data

Our paper draws on sectoral balance sheets from the quarterly sectoral accounts, which are derived from the national accounts and published jointly by the ECB and Eurostat. The sectoral accounts provide a coherent, consistent, and integrated set of macroeconomic accounts for an economy using internationally agreed definitions and accounting rules.[3] We obtain data on financial accounts of the euro area aggregate, which provide information on the financial assets and liabilities of different economic sectors for the period from 1999 to 2023.[4] As the data is published with a delay of around one quarter, we shift the sectoral balance sheet data in the empirical exercise by one quarter. However, this is unproblematic as the balance sheets of entire economic sectors move relatively slowly.[5] As the market data (e.g., on volatilities and interest rates) are available at a much higher frequency, we keep the slow-moving balance sheet data constant over the respective quarter and operate at a monthly level in the empirical exercise;[6] this enables better real-time monitoring of the state of the economy by drawing on higher frequency information. Economic sectors include households (HH), monetary financial institutions (MFI), non-bank financial intermediaries (NBFI; i.e., other financial intermediaries, non-money market investment funds, insurance corporations, and pensions funds), non-financial corporations (NFCs), public sector institutions (PUB; i.e., central banks and general government), and the rest of the world (ROW).[7,8] Financial instruments include monetary gold and special drawing rights, currencies, deposits, short and long-term debt securities, short and long-term loans, quoted and unquoted shares, mutual fund shares, insurance reserves, derivatives, and other accounts.

Some sectors in our setting, inter alia, general government and households, do not issue equity, while non-financial corporations usually exhibit a high negative net wealth position—which corresponds to the difference between financial assets and liabilities at the level of an individual sector.[9] For these sectors, we therefore define equity as equity plus net financial wealth position (Castrén and Kavonius 2013). For non-financial corporations, the value of equity is therefore reduced by the negative net financial wealth position, while for households equity is defined solely by the net financial wealth position. For the government sector, junior claims are defined as issued government debt securities plus negative net financial wealth position (Gray, Merton, and Bodie 2010). In addition, we define junior claims for investment funds as investment fund shares and for pension funds as technical reserves and guarantees due to the nature of their business model.

Following the standard convention in the literature, the face value of debt F (i.e., the distress barrier) is specified as short-term liabilities plus half of long-term liabilities. The underlying assumption is that a significant portion of long-term liabilities is not expected to mature during the forecast horizon and therefore does not trigger distress (Nagel and Purnanandam 2020). We have classified monetary gold and special drawing rights, currencies, deposits, short-term debt securities, short-term loans, derivatives, and other accounts as short-term liabilities, while all other instruments are classified as long-term liabilities.

In addition to the balance sheet data, we collect a broad set of market-based data from Refinitiv

[3] We refer to the European System of Accounts (2010) published by Eurostat (2013), which contains the methodological framework for this data.

[4] Alternatively, the analysis can easily be extended to the country level.

[5] Consequently, using this approach we obtain very similar results to when we do not shift the data.

[6] Keeping the balance sheet data constant over the respective quarter can be regarded as unproblematic, as it only serves as a model input in the iterative procedure.

[7] The ROW sector is an important component that closes the system; if the deficits of the domestic borrowing sectors exceed the surpluses of the domestic lending sectors, the remainder must be financed by the ROW.

[8] For brevity, we present the results for the aggregated sectors, i.e., HH, MFI, NBFI, NFC, PUB, and ROW. However, the raw risk indicators are of course estimated at the level of the individual sectors. The DD series for the individual sectors are available from the authors upon request.

[9] We refer to Castrén and Kavonius (2009) for a detailed examination of this aspect.

Table 1. Model Input Summary Statistics

	Mean	SD	Min	Q25	Median	Q75	Max
A. Market Equity (Normalized by Debt)							
MFI	0.08	0.02	0.05	0.06	0.07	0.10	0.13
NBFI	1.30	0.11	1.13	1.21	1.27	1.42	1.48
HH	3.70	0.48	2.80	3.38	3.73	4.01	4.69
NFC	1.54	0.22	1.11	1.37	1.55	1.71	2.02
PUB	0.16	0.02	0.11	0.14	0.16	0.18	0.20
ROW	0.88	0.18	0.60	0.71	0.82	1.07	1.19
B. Equity Volatility							
MFI	0.28	0.12	0.11	0.19	0.26	0.36	0.62
NBFI	0.23	0.07	0.13	0.17	0.22	0.28	0.45
HH	0.06	0.02	0.04	0.04	0.05	0.06	0.11
NFC	0.19	0.07	0.10	0.14	0.19	0.23	0.41
PUB	0.06	0.02	0.04	0.04	0.05	0.06	0.11
ROW	0.15	0.06	0.06	0.10	0.14	0.17	0.37
C. Risk-free Rate							
All	0.02	0.02	-0.01	0.00	0.02	0.03	0.05

Notes for the table. This table shows the model input summary statistics for the entire sample period from 1999 to 2023. The market equity values in Panel A are normalized by the nominal values of debt *F* and can therefore be interpreted as market equity/debt ratios. The equity volatilities in Panel B correspond to 12-month volatilities, i.e., the sector-specific volatilities for the financial (MFI and NBFI) and non-financial (NFC) sectors, the volatility of 10-year German government bonds for the public sector institutions (PUB) and households (HH), and the volatility of the MSCI World for the rest of the world (ROW) sector. The risk-free interest rate in Panel C is approximated by the 12-month EURIBOR.

as input for the equity volatility σ_E in our model. For the financial and non-financial sectors, we obtain 12-month sector-specific volatilities. For public sector institutions and households, we obtain the 12-month volatility of 10-year German government bonds. For the rest of the world sector, we obtain the 12-month volatility of the MSCI world.[10] We also need a measure for the risk-free interest rate. We use the 12-month EURIBOR from Refinitiv as an approximation. Table 1 provides summary statistics on the main inputs used to estimate the DD series.

Finally, we also obtain information on existing indicators of systemic stress, including the Composite Indicator of Systemic Stress (CISS; Holló, Kremer, and Lo Duca (2012)), the Macro Uncertainty indicator (MACROUNC; Jurado, Ludvigson, and Ng (2015)), the Economic Policy Uncertainty index (EPU; Baker, Bloom, and Davis (2016)), the EURO STOXX 50 Volatility index (VSTOXX50), and the Riskspread (i.e., Bbb-Aaa spread). The latter are both sourced from Refinitiv.

4 Results

We first present the DD and stressed DD series in different economic sectors. Next, we unpack the drivers of the DD and examine the impact of the interest rate level and the pass-through rate. Armed with this, we construct an Economic Distress Index (EDI), identify economic distress events, and com-

[10] We obtain qualitatively very similar results if we use estimates of conditional equity volatilities following the procedure described in Nagel and Purnanandam (2020).

pare the new index with contemporaneous market conditions and existing indicators of systemic stress. Finally, we also investigate whether the EDI contains useful information for predicting macroeconomic developments.

4.1 Distance-to-Default and Stressed Distance-to-Default

We report in Table 2 the summary statistics of the model-implied DD series according to Eq. (6) and stressed DD series according to Eq. (9) over the entire sample period. The results in Panel A of Table 2 show that the weighted average DD across all sectors is 13.80, which is the average number of standard deviations by which the market value of assets is away from the default barrier. Relatively high values are not unexpected as we consider the financial sectors, the real economy, public sector institutions, and the rest of the world. However, we also find substantial level differences between the different sectors, ranging from 4.89 for the MFI sector to 38.58 for the HH sector. The reasons for such differences can be wide-ranging and include asset compositions, differences in leverage, the regulatory environment, and income stability. It can also be observed that the standard deviation increases with the level of DD, again with a minimum of 1.92 for the MFI sector and a maximum of 9.78 for the HH sector. Looking at the stressed DD in Panel B of Table 2, we observe a reduction in the average DD by 273 points to 11.07, which corresponds to a decline of almost 20.0%. A volatility spike would lead on average to the highest relative decline in DD for the ROW and MFI sectors at 24.1% and 22.3%, respectively, and the lowest relative decline for the PUB and HH sectors at 17.7% and 18.0%, respectively.

To provide additional insights, we show the time series developments of the DD and stressed DD series in Figure 1. Panel A of Figure 1 shows the developments at an aggregated level together with a 24-month moving average and corresponding confidence bands with two standard deviations. At the aggregate level, DD moved sharply around key crisis events such as the Global Financial Crisis (GFC) of 2007-08, the COVID-19 pandemic or, more recently, the inflation shock and corresponding interest rate hikes. During the GFC, a sharp decline in the DD of more than 12 units can be observed, which was due to high leverage that was exposed by a series of volatility shocks from August 2007 onwards. The high default risk environment persisted until late 2009, even though interest rates were cut sharply at that time and legacy assets shifted from the financial sector to public sector balance sheets. The COVID-19 shock led to a particularly sharp but relatively short-lived decline in DD. From February to March 2020, the sharpest month-on-month decline in the entire sample period was observed at almost 6 units, which is more than ten times the average month-on-month decline in our sample. This is a strong reminder of the high uncertainty in the markets at this time due to a shock outside the financial system perimeter. Already in mid-2021, DD measures exceeded pre-COVID-19 levels; this rapid recovery is probably attributable to the extensive use of COVID-19 moratoria and public guarantees. From December 2021, a rapid decline in the DD can be observed, at a rate faster than during the GFC. This period coincides with the ECB reversing its highly accommodative monetary policy by adjusting its forward guidance in its monetary policy decision of 16 December 2021 and signaling a reduction in the pace of net asset purchases, leading to an increase in the expected path of short-term interest rates (Lane 2023).

In Panel B of Figure 1, we show the parallel evolution of the DD and stressed DD series and the corresponding difference between the two series; the larger the difference, the larger the impact of a volatility spike. The average decline in DD in the stress scenario is 273 points, ranging from 80 to almost 880 points, with relative declines ranging from 7.1% to 45.9%. The year 2021 can be characterized as

Table 2. Model-implied Distance-to-default Series

	Mean	SD	Min	Q25	Median	Q75	Max
A. DD							
Avg.	13.80	3.53	6.72	11.12	13.75	16.99	20.26
MFI	4.89	1.92	1.95	3.33	4.63	6.01	10.52
NBFI	7.67	2.95	2.17	5.75	7.40	9.09	17.66
HH	38.58	9.78	17.38	32.22	38.08	47.21	57.60
NFC	9.44	3.02	3.81	7.16	8.80	11.84	16.64
PUB	21.25	5.20	8.33	17.77	20.97	25.82	32.07
ROW	11.01	4.03	3.80	8.17	10.63	13.56	25.63
B. Stressed DD							
Avg.	11.07	3.06	5.36	8.36	10.95	13.57	17.36
MFI	3.80	1.57	1.26	2.56	3.44	4.57	8.39
NBFI	6.10	2.47	1.45	4.33	5.95	7.47	14.79
HH	31.63	8.49	13.47	24.92	31.64	37.69	47.06
NFC	7.43	2.53	2.81	5.91	6.93	9.17	13.89
PUB	17.48	4.57	6.96	14.20	17.08	20.71	26.90
ROW	8.36	3.10	2.70	6.17	8.06	10.79	16.30

Notes for the table. This table shows the summary statistics of the model-implied estimates for the DD series in Panel A according to Eq. (6) and the stressed DD series in Panel B according to Eq. (9) for the entire sample period from 1999 to 2023. The average sector ('Avg.') is calculated as the average of the sector-specific DD and stressed DD series weighted by total assets.

the year with the largest impact of volatility spikes, implying that additional volatility spikes in this period would have delayed the recovery from the COVID-19 pandemic, as this period also coincides with significant increases in the inflation rate.

In Panels C and D of Figure 1, we show the developments of the DD series across sectors and the dynamics of the DD series as empirical cumulative distributions, which is motivated by the large level differences between sectors. While we observe similar patterns during the GFC, with all sectors reaching one of their lows, there are some notable differences between the sectors over time. For example, looking at the period since December 2021, the lowest standardized levels are clearly observed for the PUB and HH sectors, which are potentially more vulnerable to rate hikes, while comparably high relative DDs are observed for the financial and non-financial sectors.

4.2 Distance-to-Default Drivers

Motivated by the different dynamics between the sectors, we now unpack the drivers of DD. We start with a brief theoretical evaluation of the sensitivity of DD to sector-specific inputs (i.e., leverage and volatility) by taking first- and second-order partial derivatives of Eq. (6):

$$\frac{\partial DD}{\partial\left(\frac{V}{F}\right)} > 0 \quad \text{and} \quad \frac{\partial^2 DD}{\partial\left(\frac{V}{F}\right)^2} < 0 \quad \text{and} \quad \frac{\partial DD}{\partial \sigma_V} < 0 \quad \text{and} \quad \frac{\partial^2 DD}{\partial \sigma_V^2} > 0 \quad \text{and} \quad \frac{\partial^2 DD}{\partial\left(\frac{V}{F}\right)\partial \sigma_V} < 0. \tag{13}$$

In terms of leverage, DD increases as $\left(\frac{V}{F}\right)$ increases, suggesting that a sector becomes safer as the sec-

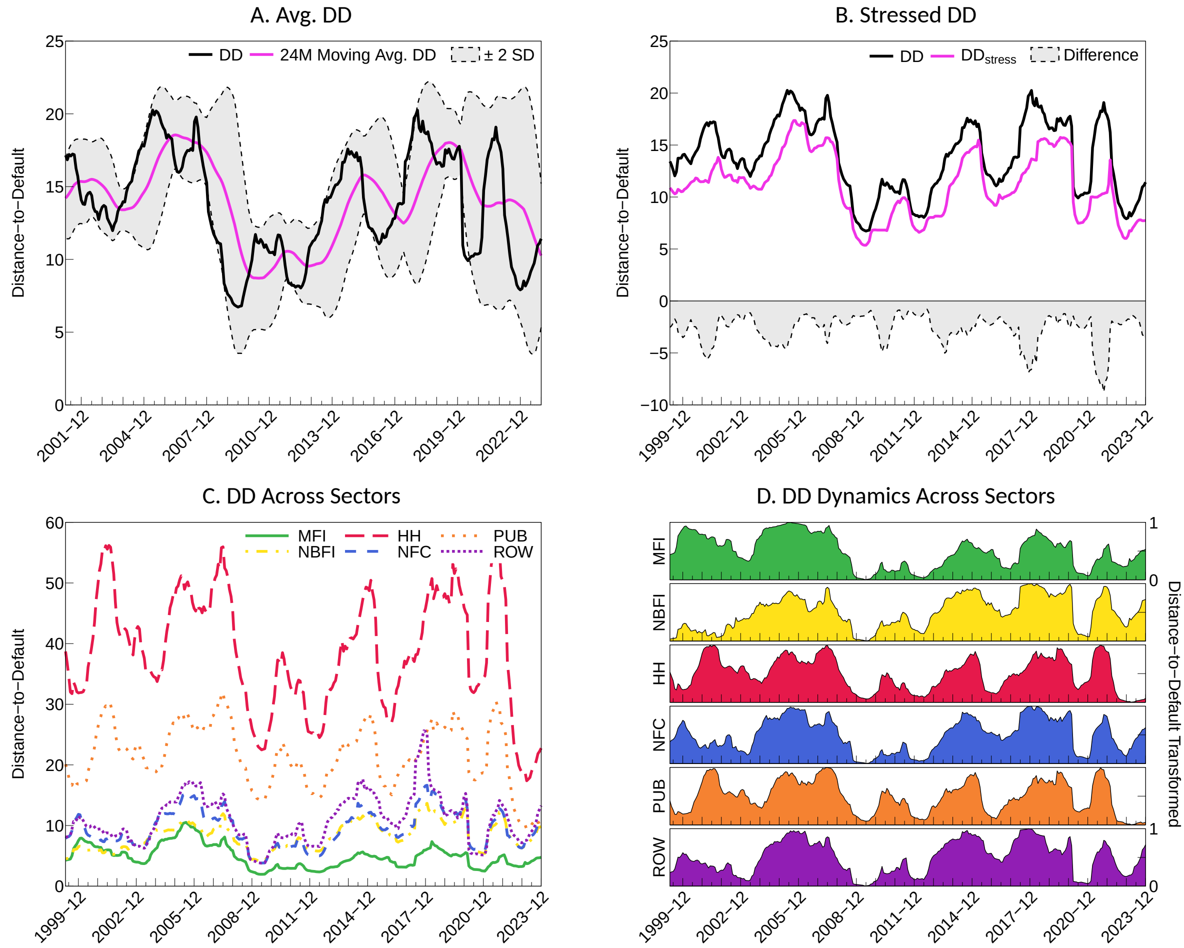

Figure 1. Distance-to-Default

Notes for the figure. This figure shows the DD and stressed DD series. The average DD in Panel A is calculated as the average of the sector-specific DD series weighted by total assets. The average is presented together with a 24-month moving average and corresponding confidence bands with two standard deviations. The parallel development of the DD series according to Eq. (6) and the stressed DD series according to Eq. (9) is shown in Panel B. The development of the DD series by economic sectors is shown in Panel C. The dynamics of the DD series as empirical cumulative distributions are shown in Panel D.

tor's assets increase relative to its debt. The second partial derivative indicates that the marginal utility of an increase in assets decreases with a larger ratio of $\left(\frac{V}{F}\right)$. This observation is reminiscent of ideas in the macro literature by Bernanke, Gertler, and Gilchrist (1999), namely that an increase in the borrower's 'net worth' reduces the expected probability of default and the external finance premium, both of which suggest that the borrower (e.g., sector) becomes safer as assets (i.e., net worth) increases. For volatility, DD decreases as volatility (σ_V) increases. The basic explanation for this is that higher volatility implies greater fluctuations in a sector's future asset path, which increases the likelihood that the distress barrier will eventually be reached. The second partial derivative indicates that the decline in DD accelerates with increasing volatility. The mixed partial derivative suggests that increasing one variable has a decreasing effect on DD when the other variable is also high. For example, an increase in a sector's assets relative to its debt helps less to make the sector safer when volatility is also high, while the negative impact of increased volatility is mitigated when the sector's assets relative to debt are high. Alternatively, one could think of this by defining leverage as debt-to-asset ratio $\left(\frac{F}{V}\right)$ such that a sector becomes more vulnerable to a decline in DD in the event of an increase in volatility if leverage is also high, and vice versa.

Having theoretically examined the sensitivity of DD to sector-specific inputs, we also aim to understand the drivers of DD in a given sector from an empirical perspective. Therefore, we decompose the relative importance of each input factor in a regression model by decomposing the model's total R^2 (Grömping 2007); formally, the R^2 for a model with regressors in set $\mathcal{W}$ can be written as:

$$R^2(\mathcal{W}) = \frac{MSS}{TSS} = \frac{\sum_m (\hat{y}_m - \bar{y})^2}{\sum_m (y_m - \bar{y})^2}, \tag{14}$$

where $R^2(\mathcal{W})$ measures the proportion of variation explained by the regressors in the model, MSS is the model sum of squares (i.e., explained variation), and TSS is the total sum of squares. The incremental R^2 when adding regressors from the set $\mathcal{A}$ to the model with regressors from the set $\mathcal{W}$ is thus given by:

$$\Delta R^2(\mathcal{A}|\mathcal{W}) = R^2(\mathcal{A} \cup \mathcal{W}) - R^2(\mathcal{W}). \tag{15}$$

Assuming uncorrelated regressors, the resulting incremental increase in R^2 could then naturally be interpreted as the corresponding contribution of set $\mathcal{A}$. However, this is typically not the case when relying on empirical data, as the regressors are usually at least modestly correlated and therefore the order of addition of the regressors to the model becomes important. Therefore, we decompose the R^2 into non-negative, non-order-dependent contributions of each input factor by relying on the Lindeman, Merenda, and Gold (1980) (LMG) approach. The general idea of the LMG approach is also based on the incremental R^2, but considers the order of the regressors by averaging over the orders. The order of the regressors in any model is simply a permutation of the variables $x_1, \ldots, x_p$ and is captured by the tuple of indices $\psi = (\psi_1, \ldots, \psi_p)$, where Ψ comprises the set of all permutations.[11] For a given permutation $\psi \in \Psi$, $\mathcal{W}_k(\psi)$ denotes the set of regressors that entered the model before the regressor x_k, which allows us to define the incremental R^2 allocated to the regressor x_k in the permutation ψ as:

$$\Delta R^2(\{x_k\}|\mathcal{W}_k(\psi)) = R^2(\{x_k\} \cup \mathcal{W}_k(\psi)) - R^2(\mathcal{W}_k(\psi)). \tag{16}$$

Finally, the LMG metric for a given regressor x_k is calculated as the average of the incremental R^2 values over all permutations Ψ:

$$LMG(x_k) = \frac{1}{|\Psi|} \sum_{\psi \in \Psi} \Delta R^2(\{x_k\}|\psi). \tag{17}$$

Stufken (1992) showed that this approach is equivalent to the Shapley value calculation—a concept from cooperative game theory—and thus has certain desirable properties and is well embedded in economic theory.[12]

In Table 3, we show the drivers of DD at an aggregate level across sectors; for easier interpretability, the contributions assigned to the input factors are scaled such that they sum to one instead of adding

[11] For p regressors, Ψ contains $p!$ permutations; in the case of three regressors ($p = 3$) there are six different permutations (i.e., $3! = 1 \cdot 2 \cdot 3 = 6$).

[12] Shapley values have recently gained prominence as a tool for interpreting forecasts from so-called 'black-box' models due to the unprecedented rise in machine learning applications. Recent applications include Bali et al. (2023) and Griffin, Hirschey, and Kruger (2023).

Table 3. Distance-to-Default Drivers on Aggregate

	Avg.	MFI	NBFI	HH	NFC	PUB	ROW
Volatility	0.79	0.46	0.80	0.89	0.89	0.82	0.86
Leverage	0.15	0.35	0.13	0.10	0.10	0.14	0.09
Risk-free rate	0.06	0.19	0.07	0.01	0.01	0.04	0.04
R^2	0.88	0.89	0.84	0.90	0.90	0.93	0.83

Notes for the table. This table shows the drivers of DD over the entire sample period by decomposing the relative importance of each input factor in a regression model by decomposing the model's total R^2 based on the Lindeman, Merenda, and Gold (1980) approach. The contributions assigned to each input factor are scaled such that they sum to one instead of adding up to R^2. The average ('Avg.') represents the simple average over all sectors.

up to R^2. On average, a regression of leverage, volatility, and risk-free rate on DD explains 88% of the variation in DD, ranging from 83% to 93%. Volatility is clearly the most important driver of DD, accounting on average for almost 80% of the explained variation and reaching almost 90% in certain sectors. One exception is the MFI sector, for which volatility is the most important factor at only 46%, while leverage at 35% is 20 percentage points more important than for the average sector. The main reason for this is the nature of the MFIs business model, where leverage plays an essential role. The GFC reminded us that too much leverage can be perilous, but MFIs also operate with much lower asset risk, which explains up to 90% of the difference in leverage between MFIs and other firms (Berg and Gider 2017). The risk-free rate has a relatively modest impact at 6% on average, ranging from 1% for HHs and NFCs to 19% for MFIs.

To better understand the dynamics of the input factors, we show in Figure 2 the relative importance assigned to the input factors over time by running 60-month rolling-window regressions; this means that for a given point in time the preceding 60 months are taken into account in the estimation.[13] The error part (i.e., gray) in the figure indicates the unexplained variation, which essentially reflects the residual sum of squares $\sum_m(\hat{y}_m - y_m)^2$. While there are some fluctuations in the dynamics over time, it is clearly evident that for all sectors, volatility is the main driver of DD. However, some notable patterns can also be observed in relation to the other input factors. For the MFI sector, for example, the interest rate component became considerably more important with the onset of the sovereign debt crisis in 2010—sovereign and MFI risks are often closely linked—and peaked exactly six months after Mario Draghi's infamous 'Whatever it takes' speech in July 2012, while its relative importance declined quickly thereafter. By construction, there will be some information lag in the relative importance, but this observation emphasizes how accurately and quickly the information feeds into the metric around key events. This pattern cannot be observed for the recent rate hike period; several factors could explain these differences, such as the fact that MFIs entered this period with a much stronger capital position due to intensive regulatory reforms, which made them less vulnerable to the effects of interest rate hikes, the improved asset quality in MFI loan portfolios, and the sluggish interest rate pass-trough on the liability side of the balance sheet, which has important implications for funding costs and profitability (Messer and Niepmann 2023). For HHs, the importance of leverage $\left(\frac{V}{F}\right)$ increased rapidly in the run-up to the

[13] We have chosen a time horizon of 60 months in order to include a sufficiently large number of observations in the estimation while also being able to examine developments in the run-up to the GFC. Generally, the shorter the selected horizon, the greater the potential fluctuations, and the longer the selected horizon, the more the importance will be smoothed out.

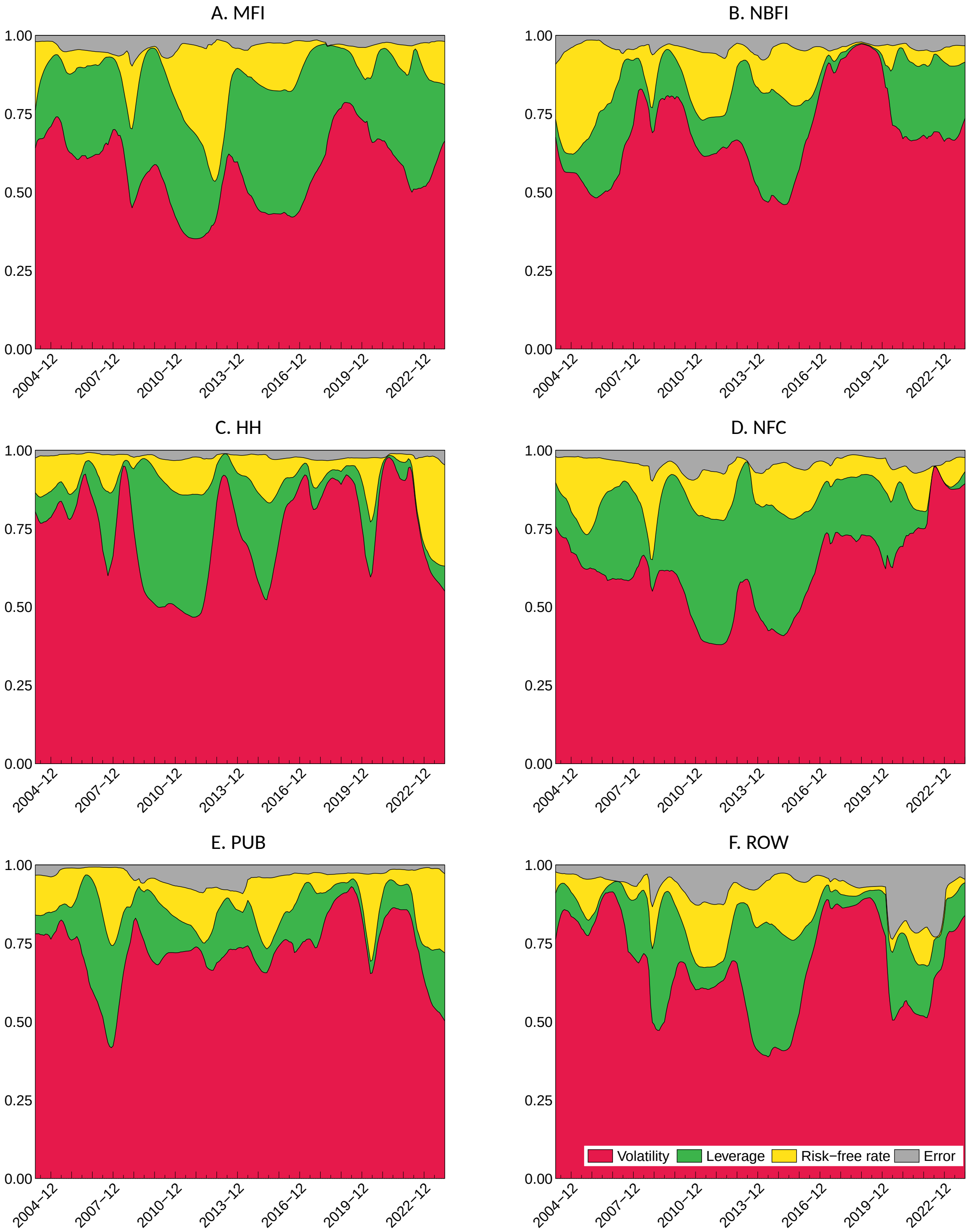

Figure 2. Distance-to-Default Driver Dynamics

Notes for the figure. This figures shows the drivers of DD over time by running 60-month rolling-window regressions. The drivers at each point in time are derived by decomposing the relative importance of each input factor in a regression model by decomposing the model's total R^2 for the preceding 60 months based on the Lindeman, Merenda, and Gold (1980) approach. The error part in the figure indicates the unexplained variation (i.e., residual sum of squares).

GFC and peaked around mid-2009, with the potential drivers being inflated or deflated asset values depending on the period. In addition, the average importance of the interest rate component since the start of the rate hike cycle in July 2022 is more than 20 percentage points higher than the average over all previous periods. A rise in interest rates affects borrowing costs, savings and investment decisions, or makes refinancing more challenging (i.e., on the liability side of the HH balance sheet), which in combination with the sluggish pass-through of policy rates to deposit rates (Messer and Niepmann 2023) on the asset side of the HH balance sheet aggravates the situation.

4.3 Impact of Interest Rate Level and Pass-through Rate

In this section, we substantiate the different effects of pass-through rates on DD in a stylized model. We start again with our expression for DD from Eq. (6), but now assume that assets V and debt F are portfolios of instruments:

$$DD = \frac{\ln(A/P) + \left(\mu - 0.5\sigma_V^2\right)T}{\sigma_V\sqrt{T}}, \text{ with}$$
$$A = \alpha D_A + \beta B_A + \gamma L_A \quad \text{and} \quad P = \delta D_P + \theta B_P + \omega L_P. \tag{18}$$

D, B, and L denote the value of deposits, bonds, and loans on the assets and liabilities side of the balance sheets, respectively, with α, β, γ, δ, θ, and, ω are the weights in the asset-liability mix.[14] Debt instruments (e.g., bonds) can be priced as follows:

$$B = \frac{\mathcal{F}}{(1+r)^n} + C\frac{1-(1+r)^{-n}}{r}, \tag{19}$$

where $\mathcal{F}$ is the face value of debt, C the coupon, r the interest rate, and n the number of periods. Rearranging the terms and introducing a pass-through rate $\varphi \in [0, 1]$, where 0 denotes no pass-through and 1 denotes full pass-through, allows us to show the sensitivity of DD to the interest rate depending on the pass-through rate:

$$B = \mathcal{F}_B + C_B\frac{(1+r)^n - 1}{r}\varphi_B. \tag{20}$$

In order to isolate the effect of the pass-through rate for a particular instrument, we only vary the pass-through rate of one instrument at a time, while we assume a full pass-through for the other instruments; i.e., for bonds, for example, we assume 0 >= φ_B <= 1 and $\varphi_D = \varphi_L = 1$. The same procedure applies to the other instruments. Ultimately, we plug these terms into the expressions for the DD in Eq. (18) and take first-order partial derivatives with respect to: $\frac{\partial DD}{\partial r}$.

Figure 3 shows the results of our stylized example for selected instruments. The values for the asset-liability mix are considered for December 2023, the latest reference date in our sample. We consider a constant volatility of 15% (i.e., around the median in our sample), a coupon rate of 5%, a pass-through rate between 0 and 1, and an interest rate of 0.5% to 5%. We will mainly discuss the observations related to MFIs (Panels A and B) and HH (Panels E and F), since on the asset side MFIs extend a considerable amount of loans to HHs (liability side), which account for about 50% of all long-term loans extended, and on the liability side collect a considerable amount of deposits from HH (asset side), which account for more than one third of all deposits. A sluggish interest rate pass-trough on the liability side (e.g., deposits) of the MFI balance sheet has important implications for funding costs and profitability (Messer

[14] For brevity, we only consider debt instruments in this stylized example, but the same idea can easily be extended to all instruments on the balance sheet.

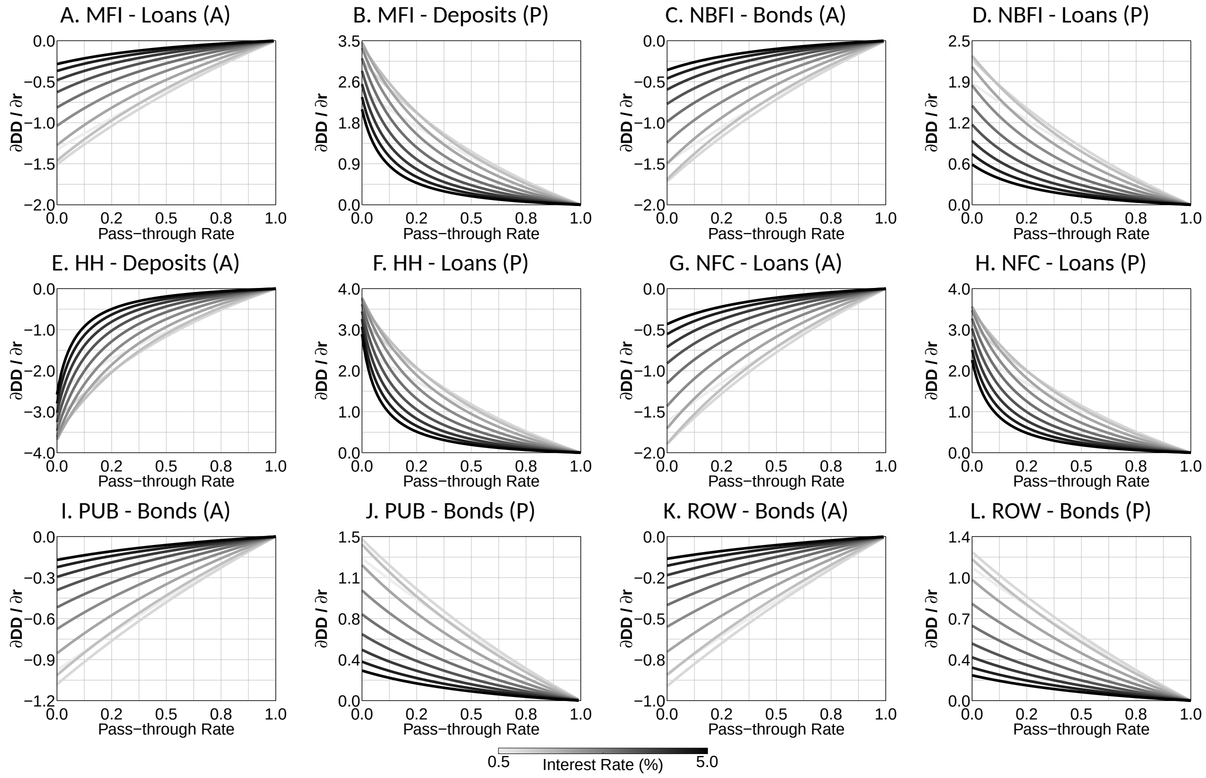

Figure 3. Impact of Interest Rate Level and Pass-through Rate

Notes for the figure. This figure shows the different effects of pass-through rates on DD for selected instruments on the asset (A) and liability (P) side of the sectoral balance sheets. To isolate the effect of the pass-through rate for a particular instrument, we vary only the pass-through rate for one instrument at a time, while assuming full pass-through (i.e., $\varphi = 1$) for the other instruments. The interest rate is varied in steps of 0.5 percentage points, with a darker line indicating a higher interest-rate level.

and Niepmann 2023). Therefore, for MFIs, a low pass-through rate tends to have a positive impact on DD when interest rates rise, i.e., MFIs remain safer as they can still rely on cheaper funding, which is intuitively plausible. For HHs, the opposite is true, i.e., the lower the pass-through rate, the more pronounced the adverse effect on DD, which seems to be more pronounced the lower the interest rate level. This is also intuitively plausible, as an increase in interest rates affects borrowing costs, but at the same time HHs do not benefit from higher interest rate income on their asset side, which reduces their disposable income and thus affects their financial health; this observation is consistent with the observations in the macro-finance literature that shocks to disposable income/financial wealth have a notable impact on financial health (Bernanke, Gertler, and Gilchrist 1999; Hatchondo, Martinez, and Sánchez 2015; Gerardi et al. 2018). The reverse mechanism applies to loans, namely a low pass-through rate has a decreasing effect on DD for MFIs and an increasing effect on DD for HHs.

4.4 Economic Distress Index

In the previous sections, we have mainly discussed financial risk indicators at sectoral level. However, the landscape of the financial system is characterized by complexity and interconnectedness. Therefore, in this section we attempt to take a holistic approach to systemic risk and construct an Economic Distress Index (EDI) that incorporates information from all economic sectors. Such an index can be thought of as a statistical function composed of three main components (Chavleishvili and Kremer 2024): (i) an *N*-

dimensional vector of raw stress indicators (e.g., sectoral DD series), (ii) a conformable vector of weights of the individual raw stress indicators (e.g., relative size of the sectors), and (iii) a vector or matrix of systemic risk weights that captures the co-dependency between the raw stress indicators. Our approach in constructing the EDI is in the spirit of previous work by Holló, Kremer, and Lo Duca (2012) on the Composite Indicator of Systemic Stress (CISS) and Boyarchenko et al. (2024) on the Corporate Bond Market Distress Index (CMDI). We now briefly describe the steps for constructing the EDI.

Distress Indicator Standardization. A sectoral distress is more conceivable than the default of an entire sector. Therefore, we do not use the raw DD series in the construction of the index, but the headroom of our sectoral DD series from Eq. (6) to a divergence of two standard deviations (SD) from the long-run (LR) moving average using an expanding window approach. We calculate the distress metric as: $\mathcal{D}_{it} = (\text{mean}_{\text{LR}}(DD_{i\Delta t}) - 2 \cdot \text{SD}_{\text{LR}}(DD_{i\Delta t})) - DD_{it}$, where Δt denotes the interval of the available DD series up to time t. This is our preferred specification for several reasons; it is arguably more conservative in indicating stress in a sector, it is more akin to classical stress tests, and it is appealing because it is usually desirable for stress indicators to increase with the level of stress (Chavleishvili and Kremer 2024), which is not the case for the raw DD series.[15] However, since we observed large level differences across sectors in Section 4.1, we standardize the distress indicators with the empirical cumulative distribution function (CDF). For a given sector $i \in [0, N]$, the distress series is denoted by $\mathcal{D}_{it}$, with $t = 1, \ldots, T$, and the corresponding ranked series is denoted by $\left(\mathcal{D}_{i[1]}, \ldots, \mathcal{D}_{i[T]}\right)$, with $\mathcal{D}_{i[1]} \leq \mathcal{D}_{i[2]} \leq \cdots \leq \mathcal{D}_{i[T]}$. The standardized distress series z_{it}, with $t = 1, \ldots, T$, can then be obtained by:

$$z_{it} = \hat{F}_{iT}(\mathcal{D}_{it}) = \begin{cases} \frac{\zeta}{T} & \forall \mathcal{D}_{i[\zeta]} \leq \mathcal{D}_{it} < \mathcal{D}_{i[\zeta+1]}, \quad \zeta = 1, 2, \ldots, T-1, \\ 1 & \forall \mathcal{D}_{it} \geq \mathcal{D}_{i[T]}, \\ 0 & \forall \mathcal{D}_{it} < \mathcal{D}_{i[1]}. \end{cases} \tag{21}$$

We compute the empirical CDF using an expanding window approach rather than for the entire sample, which is necessary to avoid a forward-looking bias when tracking market conditions in real time. Our starting window for the transformation covers a 24-month horizon and is subsequently expanded by one month at a time.

Time-varying Correlations. Stress indicators often exhibit strong co-dependence, hence it is important to consider how stress in one sector is related to stress in another sector. This aspect is not taken into account, for example, when calculating the average DD according to Eq. (7). We calculate time-varying correlation weights ρ_{ij} between the economic sectors using rank correlations following Chavleishvili and Kremer (2024). The time-varying correlations are estimated recursively (i.e., in line with our standardization of distress indicators) with exponentially weighted moving averages (EWMA):

$$\begin{aligned} \sigma_{ijt} &= \lambda\sigma_{ijt-1} + (1-\lambda)\tilde{z}_{it}\tilde{z}_{jt}, \quad i, j = 1, \ldots, 6, \\ \sigma^2_{it} &= \lambda\sigma^2_{it-1} + (1-\lambda)\tilde{z}^2_{it}, \\ \rho_{ijt} &= \sigma_{ijt}/\sigma_{it}\sigma_{jt}, \end{aligned} \tag{22}$$

where σ_{ijt} denotes the covariance between the sectors i and j, σ^2_{it} the variance of the sector i, and $\tilde{z}_{it} = (z_{it} - 0.5)$ the standardized distress indicators normalized by their theoretical mean of 0.5. We

[15] However, in unreported analyses, we find that our conclusions remain unchanged if we use the raw DD series.

collect the time-varying correlation coefficients ρ_{ij} in the correlation matrix $\mathcal{R}_t$. In the implementation of the EWMA, we use a constant smoothing factor of $\lambda = 0.9$ (Boyarchenko et al. 2024), which assigns an exponentially decreasing weight to older observations and gives more weight to more recent data.

Index Construction. Now we are armed with all the ingredients to create the EDI that contains information from all sectors as:

$$EDI_t = \sqrt{(w_t \odot z_t)' \mathcal{R}_t (w_t \odot z_t)}, \tag{23}$$

where $z_t = [z_{1t}, \ldots, z_{6t}]'$ is the column-vector of index constituents (i.e., standardized sectoral distress indicators), $w_t = [w_{1t}, \ldots, w_{6t}]'$ is a conformable vector of time-varying weights (i.e., total assets by sector), $\odot$ denotes the element-wise product (i.e., Hadamard product).

Resulting Index. Figure 4 shows the time series of the EDI together with the relative contributions of individual sectors over time. To provide additional perspective, the percentiles of the index distribution over the entire sample period are shown on the right-hand axis. As a starting point for examining the value of the newly constructed index, we assess in Panel A of Figure 4 how well the index tracks past periods of systemic stress. The index is significantly elevated or downward sloping near key events. The highest index value is reached in late 2008 and early 2009 in the wake of the GFC (a and b). The upward trend already began in mid-2005 and accelerated particularly strongly from the second half of 2007. The recovery from the GFC and the accompanying downward trend of the index was halted with the outbreak of the sovereign debt crisis in Europe in April 2010 (c) and only returned to a strong downward trend around Mario Draghi's infamous 'Whatever it takes' speech in July 2012 (d). Around the COVID-19 pandemic (h), by far the largest month-on-month increase of almost 0.50 points was recorded from February to March 2020. To put this into perspective, the average and median increase is 0.031 points (0.025) and 0.020 points (0.019) over the entire sample period (pre-COVID-19). In the wake of the recent inflation shock and the corresponding interest rate hikes (i), a strong upward trend in the index can be observed, which began around the end of 2021. This marks the period when the ECB started to reverse its highly accommodative monetary policy by adjusting its forward guidance in its monetary policy decision of 16 December 2021 (Lane 2023).

Index Contributions. Next, we decompose the most contributing sectors to the EDI in Panel B of Figure 4 by decomposing the square of the index (Boyarchenko et al. 2024); this is appealing because the square of the index allows a linear decomposition as it is additive in the components. Formally, this decomposition can be expressed as follows: $(w_t \odot z_t) \odot \mathcal{R}_t \cdot (w_t \odot z_t)$; for easier interpretability, the contributions associated with the sectors are scaled by the squared index such that they sum to one. Over the entire sample period, the MFI and HH sectors had the highest relative contribution at 0.220 and 0.209, respectively. This is not surprising as the MFI sector forms the core of the euro area financial system and MFIs, as the key financial intermediaries, act as a hub connecting the different sectors of the economy (European Banking Authority 2024). Since the beginning of the rate hike cycle, the contribution of the MFI sector to the EDI has tended to decline, suggesting that the financial sector is acting as a shock absorber rather than a shock accelerator during this episode. The contribution of HHs was particularly high in the run-up to the GFC and somewhat more modest afterwards. Another notable development is the strong increase in the contribution of the NBFI sector since the GFC; while the average contribution up to 2010 was only 0.034, it has been 0.251 since 2010, exceeding the MFI sector by as much as 4.20

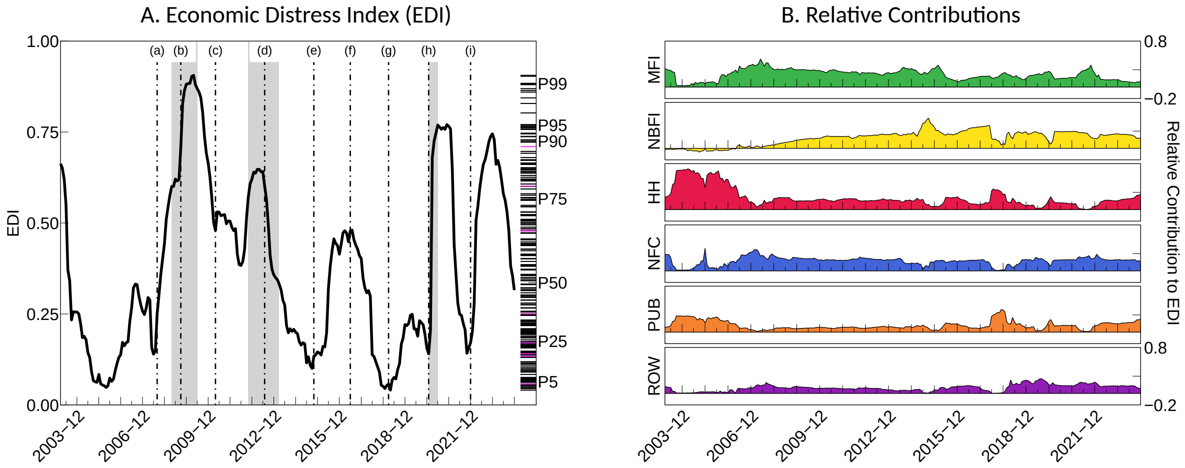

Figure 4. Economic Distress Index

Notes for the figure. This figure shows the monthly time series of the Economic Distress Index (EDI) in Panel A and the corresponding relative contributions to the squared EDI in Panel B. Light gray shaded areas in Panel A indicate recession periods according to the euro area business cycle network. The horizontal dot-dashed lines indicate key events: (a) subprime crisis, (b) Lehman Brothers bankruptcy, (c) European sovereign debt crisis, (d) Mario Draghi's 'Whatever it takes' speech, (e) ECB's asset purchase programmes, (f) Brexit referendum, (g) Trump tariffs, (h) COVID-19 pandemic, and (i) reversal of accommodative monetary policy. The percentiles of the index distribution over the entire sample period are shown on the right-hand axis. The values highlighted in magenta are corresponding to the key events.

points for this period. This is in line with broader developments following the GFC, where technological innovations and regulatory reforms have contributed to growth in financial intermediation outside the banking sector perimeter (Acharya, Cetorelli, and Tuckman 2024; European Banking Authority 2024).

4.5 Identification of Economic Distress Events

For the index to be of practical use, decision-makers need to be able to identify periods of elevated systemic stress and distinguish them from periods of moderate or low systemic stress. As a natural starting point, we attempt to identify in the spirit of Holló, Kremer, and Lo Duca (2012) elevated stress levels more formally by running Markov switching models with up to three latent states (Hamilton 2010):

$$EDI_t = \alpha_{s_t} + \beta_{s_t} EDI_{t-1} + \sigma_{s_t}\epsilon_t, \quad s_t = \{1, 2, 3\}, \tag{24}$$

where EDI_{t-1} is the one-period lagged EDI, β_{s_t} denotes the corresponding slope coefficients, and σ_{s_t} and $\epsilon_t \sim N(0, \sigma^2)$ the respective residual standard deviations and residuals. The intercept term α_{s_t} follows a first-order Markov chain with up to three states, which implies that the future regime is only determined by the current regime, with transition probabilities π_{cf} for the transition from the current state c to the future state f:

$$\begin{bmatrix} \pi_{11} & \pi_{12} & \pi_{13} \\ \pi_{21} & \pi_{22} & \pi_{23} \\ \pi_{31} & \pi_{32} & \pi_{33} \end{bmatrix}. \tag{25}$$

In Table 4, we show standard summary statistics of the different model specifications, including the Log likelihood, Akaike information criterion (AIC), and Bayesian information criterion (BIC). In addition,

Table 4. Specifications of Regime-switching Models

Model	States	Log likelihood	AIC	BIC	RCM
MS-DR(1)	2	-462.96	-919.92	-892.82	21.64
MS-AR(1)	2	-467.95	-927.89	-891.75	23.71
MS-DR(1)	3	-497.75	-987.49	-951.35	12.02

Notes for the table. This table shows different specifications of Markov switching models with up to three states. DR(1) denotes a first-order dynamic regression model in which the slope coefficients are identical between the states. AR(1) denotes a first-order autoregressive model in which the slope coefficients can vary between the states. RCM denotes the refined Regime Classification Measure according to Baele (2005). The RCM measure is bounded between 0 and 100, with a perfect model converging to zero, and a model that cannot distinguish between the states converging to 100.

we also compute the refined Regime Classification Measure (RCM) according to Baele (2005), which essentially measures the regime classification performance of a given model:

$$RCM = 100\left(1 - \frac{\mathcal{S}}{\mathcal{S}-1}\frac{1}{T}\sum_{t=1}^{T}\sum_{s=1}^{\mathcal{S}}\left(\pi_{st} - \frac{1}{\mathcal{S}}\right)^2\right), \tag{26}$$

where $\mathcal{S}$ denotes the number of states, T the number of observations, and π_{st} the smoothed probability of being in state $s = 1, \dots, \mathcal{S}$ at time t. The RCM measure is bounded between 0 and 100, with a perfect model converging to zero, and a model that cannot distinguish between the states converging to 100. With the aim of estimating a parsimonious model, we start by comparing two specifications of Markov switching models with two states. The difference is that in the first specification—first-order dynamic regression (DR(1))—the slope coefficient remains constant between states, whereas in the second specification—first-order autoregressive model (AR(1))—it can vary between states. The model summary statistics are relatively close, but the parsimonious specification appears to have a better regime classification performance, as measured by the RCM. This suggests that state-dependent slope coefficients are less important, which is consistent with previous observations in the literature on systemic stress indices (Holló, Kremer, and Lo Duca 2012). For comparison, we also run a DR(1) with three states; it can be observed that the model with three states leads to considerably better model summary statistics and also achieves a much sharper regime classification at 12.02. In terms of goodness of fit, the correlation between the expected fitted values of the three-state Markov switching model and the realized EDI is 0.98 and the captured variation in the data is 96.01%, suggesting that the model successfully captures the variation in the realized EDI.

In Table 5 we show the estimated parameters and additional metrics of the three-state Markov switching model. The state-dependent intercepts α_s and the corresponding unconditional means differ considerably between the different states, ranging from 0.28 to 0.62. For convenience, we refer to these states as ‘low-stress’, ‘medium-stress’, and ‘high-stress’. The average conditional probability of being in a low-stress state is 67% and can therefore be considered the default state. Being in a high-stress state is also relatively prevalent, with an average conditional probability of 24%, which is likely attributable to the numerous crises of recent years, including the GFC, the sovereign debt crisis, Brexit uncertainty, Trump tariffs, the COVID-19 pandemic, and the inflation shock. The fraction of months in which the most likely regime is in low, medium, and high stress is similar to the average conditional probabilities. The corresponding Markov chain transition probabilities π_{cf} between states are:

$$
\begin{array}{c} \\ s_1 \\ s_2 \\ s_3 \end{array}
\begin{array}{c}
\begin{array}{ccc} s_1 & s_2 & s_3 \end{array} \\
\begin{bmatrix} 0.93 & 0.04 & 0.03 \\ 0.37 & 0.41 & 0.22 \\ 0.08 & 0.09 & 0.84 \end{bmatrix}
\end{array},
$$

which indicates that the low-stress and high-stress states are highly persistent, while the medium-stress state is much less persistent. For a one-month horizon, the probability of remaining in a low-stress (high-stress) regime is 93% (84%), which is intuitively plausible. In addition, it is relatively more likely to move to an intermediate state rather than directly from the low-stress to the high-stress state and vice versa.

Table 5. Results from Estimation of Regime-switching Model

Param.	s_1	s_2	s_3	Metrics	s_1	s_2	s_3
α	0.015	0.043	0.075	Means	0.28	0.44	0.62
	(4.796)	(1.278)	(12.739)	Avg. Prob.	0.67	0.08	0.24
β		0.912		Frac. Months	0.68	0.06	0.26
		(105.456)		Mean RD Prob.	0.97	0.93	0.90
σ	0.023	0.149	0.016	Median RD Prob.	0.99	1.00	0.99

Notes for the table. This table shows the parameter estimates of the three-state Markov switching model according to Eq. (24). s_1, s_2, and s_3 denote low, medium, and high-stress states, respectively. The estimation is based on a first-order dynamic regression model in which the slope coefficients are identical, but the intercepts can vary between states. Means denote the state-dependent unconditional means. Avg. Prob. and Frac. Months denote the average probability and the fraction of months of being in each of the indicated states. Mean RD Prob. and Median RD Prob. denote the average and median probability of the dominant regime.

4.6 Economic Distress and Contemporaneous Market Conditions

We consider the main application of the newly constructed EDI to be real-time monitoring of the state of the economy. Therefore, we now compare the index with existing measures of contemporaneous market conditions and systemic stress in the literature. As a starting point, we look at the correlations between the EDI and existing indicators in Table 6. We find a positive correlation with all indicators, ranging from 0.34 (EPU) to 0.77 (CISS). This suggest that while the EDI correlates with existing indicators from the literature used to measure market conditions, it contains some different information.

To examine the correlations between the indicators more formally, we run regressions of the following form (Boyarchenko et al. 2024):

$$EDI_t = \alpha + \beta EDI_{t-1} + \gamma' \mathcal{M}_t + \epsilon_t, \tag{27}$$

where $\mathcal{M}$ denotes the vector of existing measures of contemporaneous market conditions. Column (1) in Table 7 shows that the EDI is highly persistent, which is consistent with our previous conclusion regarding the transition probabilities between economic states. Furthermore, it can be seen that the additional explanatory power of existing indicators is relatively limited besides the information already contained in the lagged EDI. In column (7), where we consider the full model, the lagged EDI remains both highly statistically and economically significant. The CISS as a market-specific index for the euro

Table 6. Correlation with Existing Indicators

	EDI	CISS	VSTOXX50	Riskspread	MACROUNC	EPU
EDI	1.00					
CISS	0.77	1.00				
VSTOXX50	0.67	0.72	1.00			
Riskspread	0.68	0.80	0.66	1.00		
MACROUNC	0.61	0.47	0.54	0.29	1.00	
EPU	0.34	0.09	0.18	-0.01	0.45	1.00

Notes for the table. This table shows the correlations between the EDI and existing indicators from the literature. CISS refers to the Composite Indicator of Systemic Stress (Holló, Kremer, and Lo Duca 2012), VSTOXX50 to the EURO STOXX 50 Volatility index, Riskspread to the Bbb-Aaa spread, MACROUNC to the Macro Uncertainty indicator (Jurado, Ludvigson, and Ng 2015), and EPU to the Economic Policy Uncertainty index (Baker, Bloom, and Davis 2016). We have divided VSTOXX50 and EPU by 100.

Table 7. EDI and Contemporaneous Market Conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EDI_{t-1}	0.972***	0.864***	0.883***	0.927***	0.916***	0.956***	0.813***
	(0.015)	(0.030)	(0.027)	(0.025)	(0.028)	(0.021)	(0.034)
CISS_t		0.213***					0.159***
		(0.040)					(0.039)
VSTOXX50_t			0.461***				0.277***
			(0.106)				(0.089)
Riskspread_t				0.023***			-0.006
				(0.008)			(0.006)
MACROUNC_t					0.178***		0.061
					(0.066)		(0.039)
EPU_t						0.016*	0.017***
						(0.009)	(0.005)
Adj. R^2	0.950	0.962	0.965	0.953	0.957	0.953	0.972
Obs.	249	249	249	249	249	249	249

Notes for the table. This table shows the estimates of the contemporaneous regressions according to Eq. (27). The dependent variable in all columns is EDI at time t. CISS refers to the Composite Indicator of Systemic Stress (Holló, Kremer, and Lo Duca 2012), VSTOXX50 to the EURO STOXX 50 Volatility index, Riskspread to the Bbb-Aaa spread, MACROUNC to the Macro Uncertainty indicator (Jurado, Ludvigson, and Ng 2015), and EPU to the Economic Policy Uncertainty index (Baker, Bloom, and Davis 2016). We have divided VSTOXX50 and EPU by 100. Newey-West (1987) standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

area, the VSTOXX50, and the EPU also contain some additional explanatory power. This supports the idea that the EDI is correlated with existing indicators but clearly contains additional information for real-time monitoring of the state of the economy.

4.7 Economic Distress and Real Effects

As an extension, we investigate whether the EDI also contains useful information for forecasting macroeconomic developments. To this end, we apply the local projection technique proposed in Jordà (2005) to estimate impulse responses. Our baseline specification is a standard forecasting regression:

$$y_{t+h} = \alpha + \beta\, y_{t-1} + \gamma EDI_t + \delta TS + \nu ROR + \epsilon_{t+h}, \quad h = 0, 1, \ldots, H, \tag{28}$$

where h is the forecast horizon, y is the macroeconomic variable of interest, EDI is the newly constructed Economic Distress Index, TS is the term spread—slope of the yield curve, defined as the difference between the 10-year euro government bond (GDP-weighted) and the 3-month EURIBOR, ROR is the real overnight rate—overnight rate minus realized inflation.[16] The baseline specification is in the spirit of earlier work by Gilchrist and Zakrajšek (2012) and Saunders et al. (2025). We use key macroeconomic variables for the state of the economy, including log industrial production and the unemployment rate, obtained from Eurostat at a monthly frequency in levels, as is standard in applied work (Li, Plagborg-Møller, and Wolf 2024). The impulse response is constructed simply as a sequence of the γ_h's estimated in a series of separate OLS regressions for each forecast horizon h. Since it is conceivable that the impulse responses depend on the state of the economy, the local projection technique can easily be adapted to this nonlinear case where the data are split into two regimes using an indicator variable $\mathbb{I}$. To construct the indicator variable, we use as a threshold the unconditional mean of the medium-stress state in our regime-switching model in Section 4.5.[17] Consequently, the indicator $\mathbb{I} = 1$ if the index is greater or equal to the medium-stress state, and 0 otherwise:

$$\begin{aligned} y_{t+h} = {} & \mathbb{I}_{t-1}[\alpha_A + \beta_A\, y_{t-1} + \gamma_A EDI_t + \delta_A TS + \nu_A ROR] \\ & + (1 - \mathbb{I}_{t-1})[\alpha_B + \beta_B\, y_{t-1} + \gamma_B EDI_t + \delta_B TS + \nu_B ROR] + \epsilon_{t+h}, \quad h = 0, 1, \ldots, H. \end{aligned} \tag{29}$$

To avoid instability in the parameters due to unprecedentedly large movements induced by the COVID-19 pandemic, we estimate the forecasting regressions in line with previous work by Boyarchenko et al. (2024) with data up to 2020.[18] As discussed in Jordà (2005), the local projection technique is subject to serial correlation in the error terms caused by the successive leading of the dependent variable. Therefore, we use Newey-West (1987) standard errors to obtain 95% confidence intervals around the impulse responses.

The impulse responses are shown in Figure 5. Panels A and C indicate that an increase in the EDI has significant predictive power for both macroeconomic variables, with coefficients consistent with economic intuition. An increase in the EDI by one standard deviation is associated with a decrease/increase in the industrial production/unemployment rate by an average of 0.33/0.24 standard deviations, respectively. However, Panels B and D of Figure 5 suggest that the predictive power is asymmetric and mainly stems from shocks in the high-stress regime; this observation is consistent with previous work on the impact of financial shocks on real outputs in times of stress compared to normal times (Holló, Kremer, and Lo Duca 2012; Hubrich and Tetlow 2015; Alessandri and Mumtaz 2019).

[16] The 10-year euro government bond yields are derived from FRED St. Louis, the 3-month EURIBOR from the ECB, the overnight rate—the €uro short-term rate and its predecessor EONIA—from the ECB, and realized inflation is measured using the core consumer price index less food and energy from Eurostat.

[17] The results remain qualitatively unchanged if, for example, we use the unconditional mean of the low-stress state instead.

[18] The fluctuations around the COVID-19 pandemic can be interpreted as outliers. Another approach for dealing with these observations could be to 'de-COVID' the data using the approach of Ng (2021). As we do not see this as the main application of EDI, we keep this avenue open for future research.

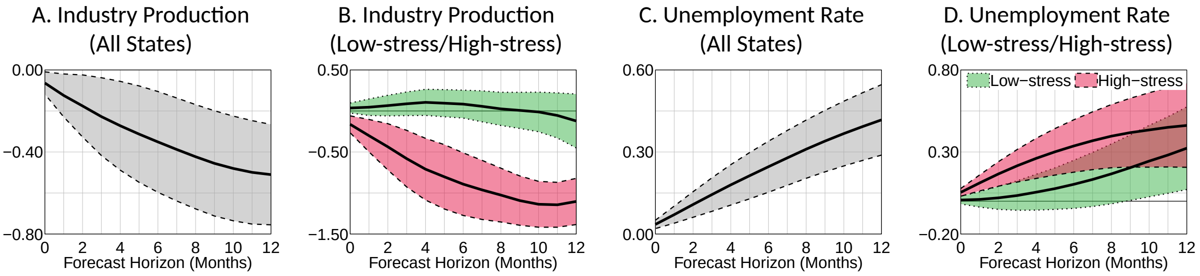

Figure 5. Local Projections

Notes for the figure. This figure shows the impulse responses according to Eqs. (28) and (29) using the local projection technique proposed in Jordà (2005). In each panel, the dependent variable y_{t+h} is the h-month ahead macroeconomic variable (i.e., industrial production and unemployment rate). In Panels A and C we show the impulse responses for the entire sample and in Panels B and D we show the impulse responses separately for low and high-stress states using an indicator variable. The reported coefficients are standardized (solid line). Dotted and dashed shaded areas indicate 95% confidence intervals using Newey-West (1987) standard errors.

5 Conclusion

In this paper, we attempt to take a holistic approach to systemic risk and real-time monitoring of the state of the economy. At the sectoral level, we document that sectoral vulnerabilities, as measured by distance-to-defaults, have moved sharply around key events, that volatility is the most important driver of sectoral vulnerabilities in our setting, and that the pass-through of policy rates has important implications for the financial health of economic sectors. Armed with these insights, we have introduced a new Economic Distress Index (EDI) that incorporates information from all economic sectors as a device for real-time monitoring of the state of the economy in the euro area. The EDI is significantly elevated or downward sloping around key events, monetary financial institutions contribute most to the EDI over the entire sample period, and non-bank financial intermediaries contribute particularly strongly in the aftermath of the Global Financial Crisis since 2010. The main application of the newly constructed index is the real-time monitoring of the state of the economy, but it also shows significant predictive power for macroeconomic developments arising mainly from high-stress regimes.

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