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A quantile probability model for sectoral corporate defaults in Europe

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Abstract

Conventional credit risk models understate tail risk by centering on mean default probabilities and neglecting distributional and sectoral heterogeneity. We propose a Quantile Probability of Default (QPD) framework based on unconditional quantile regressions estimated on flow default rates from five million non-financial firms across nine countries, conditioned on macro- and sectoral scenario covariates standard in stress testing. The tail exhibits three- to five-fold stronger sensitivity than at the median, revealing non-linearities and asymmetric sectoral propagation of credit risk. We validate the performance of our model across crisis periods and benchmark models to confirm the framework's robustness and prudential efficiency. Under the European Central Banks's 2025 increasing geopolitical and trade tensions scenario, the QPD identifies higher tail vulnerabilities in construction, trade, hospitality, and real estate. The framework embeds distributional estimation into stress testing, advancing scenario-based assessment of sectoral credit risk for policy and prudential applications.

Non-Technical Summary

This paper introduces a new framework to measure sector-level corporate credit risk in the euro area and to improve its integration into banking stress-testing. It proposes a "quantile probability of default" (QPD) model that uses quantile regression techniques to estimate the full distribution of sectoral default rates, rather than a single conditional mean. This distributional perspective allows the authors to characterise not only average default risk but also tail behaviour and sector-specific vulnerabilities under adverse macro-financial scenarios, including those driven by geopolitical and trade tensions.

Empirically, the paper assembles a new panel of sectoral flow default rates using firm-level balance sheet information from the Orbis database for roughly five million non-financial firms in nine euro area countries over 1999–2023. Defaults are identified using a balance-sheet-based criterion à la Gourinchas et al. (2020), whereby a firm is classified as defaulted once internal cash flow fails to cover financial expenses in two consecutive years, so that the measure captures persistent rather than transitory liquidity stress. Firm-level indicators are aggregated to country–sector "flow" default rates, interpreted as empirical hazard rates for new defaults. Descriptive evidence reveals strong cyclical variation and pronounced cross-sector heterogeneity: construction, tourism, real estate and other cyclical sectors display higher and more volatile default rates than utilities or some business and professional services, and high energy-intensive manufacturing is systematically riskier than low energy-intensive manufacturing.

The QPD model relates these sectoral default rates to a set of macro-financial variables that are chosen to coincide with those used in euro-area stress-testing scenarios: real sectoral Gross Value Added (GVA), unemployment, short- and long-term interest rates, the term spread, equity prices and property prices. Methodologically, the paper adopts an unconditional quantile regression framework with sector–country fixed effects, implemented via recentered influence functions. This allows the authors to estimate how macro-financial shocks affect different quantiles (e.g., the median, 70th or 90th percentile) of the sectoral default-rate distribution, while controlling for time-invariant heterogeneity across sector–country pairs. The results point to economically meaningful non-linearities: the response of default rates to adverse movements in unemployment, long-term interest rates or GVA is significantly larger in the upper tail of the distribution than around the median, implying that macro-financial shocks have disproportionately severe effects in already stressed states.

A series of validation exercises demonstrates that the QPD model satisfies key criteria for stress-testing use. In-sample, euro-area aggregate PDs, obtained by GVA-weighting sectoral QPD estimates, track realised default rates closely and reproduce the spikes associated with the global financial crisis and the euro area sovereign debt crisis. Realised defaults tend to lie between the model's 50th and 70th percentiles in tranquil periods and move closer to higher quantiles during crises, consistent with the intended interpretation of the quantile dimension. Out-of-sample projection exercises, in which the model is estimated only on data available up to a given year and then conditioned on realised macro-financial paths over a three-year horizon, indicate that QPD-based forecasts match both the direction and approximate magnitude of subsequent default episodes and outperform simple benchmark models, while maintaining a conservative bias desirable from a supervisory perspective.

The paper's main scenario application is an adverse trade-tension shock aligned with the severe macro-financial scenario in the European Central Banks's (ECB) June 2025 Broad Macroeconomic Projection Exercise and the 2025 EU-wide stress test. The scenario features a sizeable and persistent increase in US tariffs on euro-area exports, symmetric EU retaliation, and persistently high trade policy uncertainty, which together depress global investment, euro-area exports and domestic demand. Feeding the corresponding paths for GDP, unemployment, interest rates and sectoral GVA into the QPD model yields a cross-section of sectoral PDs at different quantiles over a three-year horizon. The model projects a sizeable increase in PDs relative to the 2024 baseline, especially in the first year of the scenario, and a widening dispersion between quantiles, reflecting greater sensitivity in the upper tail of the distribution. Vulnerabilities are highly uneven across sectors: construction, wholesale and retail trade, accommodation and food services, real estate and arts and entertainment record the strongest increases in tail PDs, whereas information and communication, transport and utilities show more muted responses.

As a background, the QPD framework has served as the ECB's benchmark model for assessing the credit risk of non-financial corporations since 2022, supporting the 2023 and 2025 EU-wide stress tests. Its implementation followed detailed scrutiny and approval by designated and competent authorities and is embedded within a regular validation and governance structure. The framework extends the ECB's ongoing programme to advance top-down credit risk modelling, initiated by the Financial Stability Committee's Working Group on Stress Testing (now the Task Force on Top-Down Models). Since 2018, this initiative has progressively enhanced the methodological foundation of benchmark models, strengthened validation practices, and adjusted to evolving challenges such as the COVID-19 shock and the increasing need for sector-specific and climate-related risk analysis. Through close cooperation among institutions within the Single Supervisory Mechanism and the European System of Central Banks, these developments have established a coherent and empirically grounded modelling framework that supports consistent, policy-relevant assessment of credit risk across the EU financial system.

From a policy standpoint, the QPD framework delivers three main contributions. First, by modelling the full distribution of sectoral default risk, it allows supervisors and central banks to trace how vulnerabilities evolve not only on average but also in the tail, which is crucial for assessing financial stability under severe but plausible scenarios. Second, the country- and sector-level granularity reveals pockets of risk that are obscured in aggregate PD measures, thereby supporting a more targeted calibration of macroprudential instruments and supervisory follow-up, for example by linking sectoral PDs to banks' credit portfolios. Third, the methodology is directly compatible with existing Eurosystem stress-testing frameworks, since it uses the same macro-financial scenario variables and can be run as a modular "challenger" model alongside existing top-down benchmarks; indeed, the QPD has already been deployed in the Eurosystem stress tests of 2023 and 2025. More broadly, the paper illustrates how distributional methods from the quantile-regression literature can be integrated into macro-prudential analysis to better capture non-linearities, heterogeneity and tail risk in corporate credit dynamics.

1 Introduction

The accurate assessment of corporate default risk is crucial for financial stability and prudent risk management. Traditional credit risk models, which often assume linear responses to macroeconomic shocks, have shown significant limitations in capturing the true extent of vulnerabilities exposed by geopolitical tensions, trade wars, and abrupt economic disruptions. Recent episodes, such as the escalation of global trade conflicts and the COVID-19 pandemic, have highlighted the heterogeneous and non-linear effects in which different sectors and firms respond to exogenous shocks, showing the inadequacy of conventional, mean-based stress testing frameworks. In this context, there is a pressing need for advanced modelling approaches that can account for sectoral heterogeneity, firm-level characteristics, and the full distribution of risk, particularly under scenarios of geopolitical and macroeconomic uncertainty.

The motivation for this study arises from the growing recognition that linear stress testing frameworks systematically underestimate tail risks and fail to capture the cross-sectoral heterogeneity that emerges during episodes of geopolitical turmoil and trade fragmentation. For example, sectors highly reliant on geopolitically sensitive trade corridors or exposed to sudden tariff escalations can experience exponentially higher default probabilities, particularly in the upper quantiles of the risk distribution, i.e., risks that are often discarded by models focusing solely on average effects. The introduction of non-linear modelling techniques, such as quantile regression, enables a more granular analysis of how shocks propagate through the corporate sector, revealing pockets of vulnerability that may otherwise remain undetected. This is especially relevant in the wake of recent policy developments, such as the imposition and reciprocation of tariffs by major economies, which have further intensified global economic uncertainty and exposed the limitations of traditional credit risk benchmarks. By integrating quantile-based responses into stress testing frameworks, this research aims to provide regulators and financial institutions with more robust tools to anticipate and manage the non-linear effects of geopolitical and trade-related shocks, ultimately enhancing the resilience of the banking sector.

In this paper, we develop a quantile regression model to estimate probabilities of default (PD). We estimate the model on granular data of sectoral defaults to introduce a two-dimensional approach that captures non-linearities and sectoral heterogeneity across countries. Based on corporate balance sheet data, we calculate a measure of corporate default that incorporates firm liquidity and financial expenses. We aggregate firm-level information to country-sector flow default rates, which form our dependent variables in the regression. In a second step, the country-sector flow default rates are regressed on a selection of macro-financial variables. In order to use the approach as a stress test model in the Eurosystem's exercises, we restrict the choice of the macroeconomic variables not only in terms of their significance for estimating corporate PDs, but also to comply with scenario availability of the stress test. The resulting quantile regression model for probabilities of default (QPD) is able to estimate the sensitivity of corporate sectoral defaults across the whole distribution of observed defaults. Model estimations are therefore capturing sectoral heterogeneity and tail-risks. We validate the model in terms of predictive power as well as sufficient conservativeness for stress test applications.

The fitted QPD reveals heterogeneity across sectors not only in terms of level-differences, but also in the non-linear response of PDs to an adverse shock. A scenario application of rising

geopolitical and trade tensions between the United States and the euro area illustrates our findings. Non-linear responses to such a scenario vary across sectors, meaning that the QPD delivers additional insights for identifying risks to financial stability.

As a background, the proposed QPD framework has served as the benchmark model for non-financial corporations' PDs in European Union (EU) -wide stress tests since 2022 (including the 2023 and 2025 exercises). Prior to implementation, the framework was reviewed and discussed with designated and competent authorities and underwent their scrutiny as part of the European Central Bank's (ECB) approval process for credit risk benchmarks. It is now embedded in a comprehensive, regular validation and governance framework. The development of this framework builds on the ECB's long-standing efforts to advance top-down credit risk modelling (Budnik et al., 2024). Since 2018, the ECB Financial Stability Committee's Working Group on Stress Testing (now Task Force on Top-Down Models) has operationalised state-of-the-art methodologies to enhance the analytical foundations of the EU-wide stress testing framework. This workstream has progressively refined benchmark models, strengthened validation procedures, and adapted rapidly to emerging challenges—most notably the COVID-19 shock and the growing relevance of climate-related and sector-level risks. The mandate of the working group encompassed the development of operational tools grounded in stress-testing experience, academic research, and frameworks used by EU central banks and supervisory authorities. Its efforts combined methodological innovation with a strong policy orientation, ensuring that new models were both analytically robust and readily implementable. Emphasis was placed on rigorous validation, regular review by competent authorities, and coherence with evolving macroprudential policy mandates. Beyond model development, the group played a central role in fostering cooperation among institutions within the Single Supervisory Mechanism and the European System of Central Banks. It provided a platform for analytical exchange, policy dialogue, and data sharing among experts across member institutions. As the first EU initiative to coordinate modelling expertise on this scale, the group substantially strengthened the network of practitioners advancing stress-testing methods and risk assessment tools, achieving results that exceeded its initial mandate.

The QPD can be used not only for stress test but also for a variety of impact analyses. The multi-dimensional design can be leveraged for policy design, which requires decomposing bank balance sheets in terms of counterparty vulnerabilities. QPD estimations, therefore, inform the process of calibrating macroprudential policy as well as supervisory regulation

1.1 Literature Review

The estimation of the PD has undergone a significant transformation over recent decades, driven by regulatory developments and advances in quantitative modelling. Accurate PD measurement is fundamental to credit risk management, underpinning regulatory capital frameworks, loan pricing, and stress testing. Previous models, notably the logistic regression approach of Ohlson (1980) and the structural framework of Merton (1974), established the initial methodologies for the estimation of default risk. However, these foundational models have faced criticism for their reliance on point estimates and their inherent procyclicality, which can result in the underestimation of risk during economic expansions and overestimation during downturns

(Carlehed and Petrov, 2012; Taylor, 2015)). This cyclical bias, as highlighted by Borio et al. (2001), poses a threat to financial stability by amplifying the effects of the business cycle.

In response, regulatory reforms, most notably Basel II and III, have mandated the adoption of forward-looking, internal PD models designed to capture the impact of adverse economic scenarios (Basel Committee on Banking Supervision, 2019). Despite these advances, recent ECB stress tests have exposed the limitations of conventional bank PD models, particularly their inability to account for sectoral heterogeneity and firm-specific vulnerabilities that become pronounced during periods of economic stress (European Central Bank, 2021; Budnik et al., 2024). The COVID-19 pandemic, for instance, revealed substantial differences in corporate sector responses to exogenous shocks. This highlighted the need for modelling frameworks capable of decomposing sectoral sensitivity to shocks at the firm level and capturing the non-linearities inherent in a heterogeneous corporate landscape.

In recent years, research has shifted from mean-based models to approaches capturing the full distribution of default risk. Quantile regression, introduced by Koenker and Bassett (1978), has gained prominence in the study of how macroeconomic and firm-specific factors affect PD throughout the risk spectrum. Extensions to panel data (Lamarche, 2010; Canay, 2011; Machado and Santos Silva, 2019) have further enabled the control of unobserved heterogeneity at the firm level over time. However, systematic analysis of how macroeconomic shocks propagate through the PD distribution within panel frameworks remains limited, and most validation efforts remain focused on the accuracy of the mean prediction (Jacobs, 2022).

The literature highlights the importance of macroeconomic and monetary policy shocks in shaping corporate credit risk. Seminal work (Bernanke and Gertler, 1995; Mishkin, 1995; Bernanke et al., 1999) demonstrates how such shocks influence creditworthiness via their effects on asset values, cash flows, and credit supply. Empirical studies confirm that contractionary monetary or supply shocks markedly increase average PDs, especially for smaller or financially constrained firms (Pesaran et al., 2006; Palazzo and Yamarthy, 2022; Anderson and Cesa-Bianchi, 2024). Research also shows that financially fragile firms—those with high leverage or limited liquidity—are more vulnerable to adverse shocks, while cash reserves buffer against default risk (Durante et al., 2022).

Much of this work, however, relies on indirect proxies for credit risk, such as credit spreads or default swap indices, and often focuses on listed firms. Recent studies address these gaps by using direct measures of PD and broadening the scope to include both listed and unlisted firms, offering a more comprehensive view of corporate risk. Growing interest also lies in disentangling the effects of different macroeconomic shocks—demand, supply, and monetary policy—on default risk and in understanding their timing and magnitude across firms.

In response, research has increasingly embraced distributional modelling approaches. This shift is motivated by evidence from related fields, such as Adrian et al. (2019) on GDP growth and Krüger and Rösch (2017) on loss given default, which highlight the importance of capturing non-linearities and tail risks under stress scenarios. While some studies explore non-linear dynamics in macroeconomic time series (Azzalini and Capitanio, 2003), research explicitly addressing non-linearities in firm-level default probabilities remains sparse. Notable recent contributions, such as Cathcart et al. (2020), emphasize the role of leverage in shaping default risk

for small and medium-sized enterprises.

Thus, quantile regression emerges as a powerful tool for studying covariate effects throughout the risk distribution rather than at the mean alone (Koenker and Bassett, 1978). Its extensions to panel data (Canay, 2011; Lamarche, 2010; Machado and Santos Silva, 2019) enhance its applicability, enabling analysis of borrower heterogeneity. However, while these methodological advances improve our understanding of default risk, systematic investigations of macroeconomic shocks across the PD distribution and panel contexts remain underexplored. Most validation frameworks continue to emphasize the accuracy of mean prediction, limiting insight into the calibration of the full distribution (Jacobs, 2022).

In summary, the literature highlights the necessity for credit risk models that can accommodate non-linearities, firm-level heterogeneity, and the full impact of macroeconomic shocks. Quantile panel regressions as implemented in this work offers an avenue for providing a more nuanced and policy-relevant understanding of default risk across diverse economic environments.

The remainder of this paper is structured as follows. Section 2 details the data used in the analysis, while Section 3 outlines the modelling framework. Section 4 and 5 discuss the performance of the model, and Section 6 presents the application to a trade stress and geopolitical tension scenario. Finally, Section 7 concludes.

2 Data

2.1 Corporate Firm Default Rates Using Orbis

Our approach uses corporate financial data from the Orbis Global Database,[1] which provides harmonised balance sheet and income statement information, together with basic firm descriptors, for around five million companies over the period 1999–2023. Corporate accounts are cleaned and standardised following the procedure in Kalemli-Özcan et al. (2024), applied to the Orbis vintage available in June 2025.

The empirical analysis focuses on nine euro area economies - Belgium, Germany, Spain, France, Greece, Italy, Portugal, Slovenia, and Slovakia - selected to ensure robust sectoral coverage and statistical reliability for estimating firm-level defaults. Country inclusion rests on three technical criteria: (i) membership of the euro area to ensure monetary policy homogeneity and consistent macroeconomic shock exposure; (ii) adequate firm-level observations across all NACE Rev.2 letter-level sectors to support reliable estimation of within-sector default hazard rates;[2] and (iii) sufficient Orbis coverage such that the standardised data cleaning protocol of Kalemli-Özcan et al. (2024) generates representative sectoral aggregates, with post-cleaning firm counts per country-sector-year cell exceeding 100 observations and sectoral coverage surpassing 85% of NACE letter categories.[3]

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[1]Orbis Global Database, Moody's (formerly Bureau van Dijk).

[2]Sector C (manufacturing) is further disaggregated into energy-intensive sub-industries (NACE 19-26, basic metals, chemicals, non-metallic minerals) and non-intensive categories based on Eurostat energy intensity thresholds; financial intermediation (sector L) is excluded to avoid endogenous balance sheet feedback.

[3]We implement the comprehensive cleaning procedure of Kalemli-Özcan et al. (2024), encompassing global ultimate owner (GUO) identification via ownership chain consolidation, activity status verification through revenue and employment filters, balance sheet consistency checks (assets > 0, liabilities matching equity), and outlier winsorisation at the 1st/99th percentiles. While adhering strictly to their methodology, we do not claim

To construct a balance-sheet-based measure of firm default, we adopt the methodology of Gourinchas et al. (2020), which identifies liquidity distress through the firm's capacity to service financial expenses from internal cash flows over time. A firm i is classified as being in default in year t if cash, cash-equivalents and cash flow (say cash sum) fail to cover financial expenses in two consecutive years, $t-1$ and t.[4] This generates a binary default indicator $DF_{i,s,c,t} \in \{0,1\}$ for firm i in sector s, country c, and year t, where the indicator equals 1 if the firm is in default and 0 otherwise.

$$DF_{i,s,c,t} = \mathbf{1}\left(\text{CF}_{i,s,c,t} < \text{FE}_{i,s,c,t} \ \wedge \ \text{CF}_{i,s,c,t-1} < \text{FE}_{i,s,c,t-1}\right), \qquad (1)$$

where $\text{CF}_{i,s,c,t}$ denotes cash sum and $\text{FE}_{i,s,c,t}$ financial expenses in year t, and $\mathbf{1}(\cdot)$ is the indicator function returning 1 if the condition holds and 0 otherwise. This consecutive-periods requirement mitigates transitory liquidity shocks and captures persistent financial distress.

This firm-level indicator enables construction of sectoral flow default rates (FDRs), $FlowDF_{s,c,t}$, which measure the hazard rate of new defaults within each country-sector-year cell:

$$FlowDF_{s,c,t} = \frac{\sum_{i \in \mathcal{I}_{s,c}} DF_{i,s,c,t}}{\sum_{i \in \mathcal{I}_{s,c}}(1 - DF_{i,s,c,t-1})}, \qquad (2)$$

where $\mathcal{I}_{s,c}$ denotes the set of active firms in sector s and country c. The denominator captures the population at risk (non-defaulted firms from $t-1$). The flow default rate equals the ratio of the number of newly defaulted companies per country and sector at time t over the total number of non-defaulted companies in the respective country and sector pair relative to the previous year. As discussed in Budnik et al. (2024), this definition can be interpreted as the relative frequency of defaulted firms and serves as an empirical proxy of sectoral probabilities of default based on firm's defaults, observable via firm characteristics. This flow measure, rather than stock defaults, appropriately proxies time-varying sectoral default rates for stress testing applications, as it reflects the marginal incidence of distress conditional on prior survival. The resulting flow default rate country-sector panel subsequently forms the basis of the quantile PD model discussed in Section 3.

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to replicate the scale or proprietary validation of their dataset. Country selection prioritises economies where these filters yield statistically meaningful sectoral representation, as documented in their coverage diagnostics.

[4] Cash flow is computed as after-tax profits plus depreciation, both measured at financial year-end.

Figure 1: Cross-sectoral distribution of flow default rates
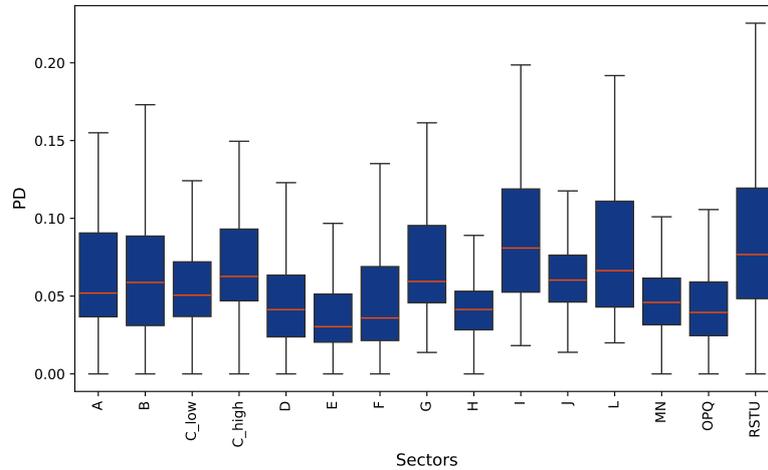
Note: Letter labels are based on NACE Rev 2 and are disaggregated into high and low energy intensive sub-sectors for Manufacturing (C) and condensed to one Science and Administration sector (M and N), one Public, Educational and Human and Social Work activities (O,P and Q) and one Arts, Other and Home Production and Extraterritorial services sector (R,S,T and U). Other sectors are referred to by the following letters: Agriculture (A), Mining and Quarrying (B), Energy services (D), Water and Sewage services (E), Construction (F), Wholesale and Retail (G), Transportation (H), Accommodation and Food (I), Information Technologies and Communication (J), Real Estate (L). Financial Services (K) is omitted for the analysis. The black line within the box represents the median, the blue box represents the inter-quartile range and the outer lower and upper black line represent the 1st and 99th percentile respectively.

Figure 1 presents the cross-sectoral variation in the resulting default rates over the panel horizon. It shows some cross-sector heterogeneity in flow default rates over the sample period with median default rates clustering between roughly 3–7% across most sectors, but both the level and dispersion of default risk vary markedly along the cross-section. Manufacturing is characterised by a clear within-sector gradient: high energy-intensive manufacturing (C_high) displays higher medians and wider interquartile ranges than low energy-intensive manufacturing (C_low), consistent with greater exposure to cost and demand shocks. Cyclical and investment-oriented sectors such as construction and real-estate–related activities (RSTU) exhibit the highest upper tails, whereas primary sectors (A) and non-market services (OPQ) show more compressed distributions. Overall, the boxplots indicate that both the level and volatility of firm default risk are systematically sector-dependent, providing ample cross-sectional variation for identifying sectoral sensitivities to macro-financial shocks.

When looking at Table 1, summarising the average sectoral flow default rates across major macroeconomic regimes, it is clear that default risk is cyclical. For almost all sectors, flow default rates are lowest in the pre-GFC and "stagflation" period (1999–2007 and 2013–2019) and spike during systemic stress episodes: the Global Financial Crisis (GFC, 2008–2009) and the subsequent Sovereign debt crisis (2010–2012). Second, there is pronounced and persistent heterogeneity across sectors. Tourism and transport-related services (I) and construction/real estate (RSTU) display the highest default rates throughout, indicating both structurally higher risk and greater sensitivity to macro-financial shocks. By contrast, utilities and energy (E), and some business and professional services (MN), feature comparatively low default rates. Manufacturing high energy-intensive manufacturing (C_high) consistently exhibits higher default rates than low energy-intensive manufacturing (C_low), especially during the GFC and sovereign cri-

sis, consistent with greater exposure to cost and demand shocks. Finally, as expected, Covid-19 period does not generate a uniform surge in observed corporate defaults reflecting the extensive policy support and moratoria that muted realised defaults, particularly in sectors heavily targeted by fiscal and credit support schemes. Overall, the table indicates that both the level and volatility of default risk are sector- and regime-dependent, providing rich cross-sectional and time-series variation to identify heterogeneous responses to macro-financial shocks in the subsequent econometric analysis.

Table 1: Average sectoral flow default rate by macroeconomic period

Period Sector	Pre-GFC (1999-2007)	GFC (2008-2009)	Sov. Crisis (2010-2012)	Stagflation (2013–2019)	Covid 19 (2020–2021)
A	0.06	0.07	0.07	0.06	0.04
	(0.04)	(0.05)	(0.04)	(0.03)	(0.02)
B	0.05	0.05	0.08	0.07	0.05
	(0.02)	(0.04)	(0.05)	(0.04)	(0.04)
C_{low}	0.05	0.07	0.08	0.06	0.04
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)
C_{high}	0.07	0.08	0.09	0.06	0.04
	(0.04)	(0.03)	(0.04)	(0.02)	(0.02)
D	0.03	0.05	0.06	0.05	0.03
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
E	0.03	0.05	0.05	0.03	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
F	0.05	0.07	0.09	0.04	0.02
	(0.04)	(0.04)	(0.06)	(0.03)	(0.01)
G	0.07	0.09	0.10	0.06	0.04
	(0.04)	(0.03)	(0.04)	(0.02)	(0.02)
H	0.04	0.06	0.06	0.04	0.03
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
I	0.08	0.12	0.12	0.09	0.09
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
J	0.07	0.07	0.08	0.06	0.04
	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)
L	0.07	0.11	0.12	0.07	0.05
	(0.04)	(0.05)	(0.06)	(0.04)	(0.02)
MN	0.04	0.06	0.06	0.05	0.04
	(0.02)	(0.02)	(0.02)	(0.01)	(0.03)
OPQ	0.04	0.04	0.05	0.04	0.04
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
RSTU	0.08	0.11	0.12	0.10	0.08
	(0.04)	(0.06)	(0.08)	(0.07)	(0.05)

Note: Flow default rates measure the new corporate defaults within each country-sector-year, calculated as the ratio of newly defaulted firms to surviving firms from the previous period. Data cover nine euro area countries (1999–2021), excluding financial intermediation (sector K). Sectors follow NACE Rev. 2 letter codes with manufacturing (C) split into low (C_{low}) and high (C_{high}) energy-intensive sub-sectors; other sectors are: A (Agriculture), B (Mining), D (Energy), E (Utilities), F (Construction), G (Wholesale/Retail), H (Transport), I (Accommodation/Food), J (ICT), L (Real Estate), MN (Professional/Scientific), OPQ (Public Services), RSTU (Arts/Real Estate-Related). Standard deviations in parentheses. Standard deviations are in parentheses.

2.2 Macroeconomic, Sectoral and Scenario Data

To model sectoral default probabilities based on macroeconomic dynamics, we focus on both aggregate country-level and sectoral variation. We supplement the default rate panel with macroeconomic variables — GDP, unemployment rate, property price indices, stock price index, and long- and short-term rates — all sourced from the OECD and ECB Data Portal as publicly available at country-level. At the country-sector level, we incorporate historical gross value-added (GVA) data from Oxford Economics to capture sectoral business cycle dynamics.

As detailed in Section 3, the choice of macroeconomic variables for modelling is constrained

by the macro-financial scenario used in stress tests. Euro area stress test exercises typically include real GDP, inflation, unemployment rates, real estate prices, stock prices, exchange rates, interest rates, and real GVA for selected economic sectors, spanning a three-year horizon. In this paper, we use an adverse scenario with a special focus on geopolitical tensions, particularly the looming US-Europe trade war (Figure 2).[5]

Figure 2: Severe scenario gross value added (average 2025-2027)
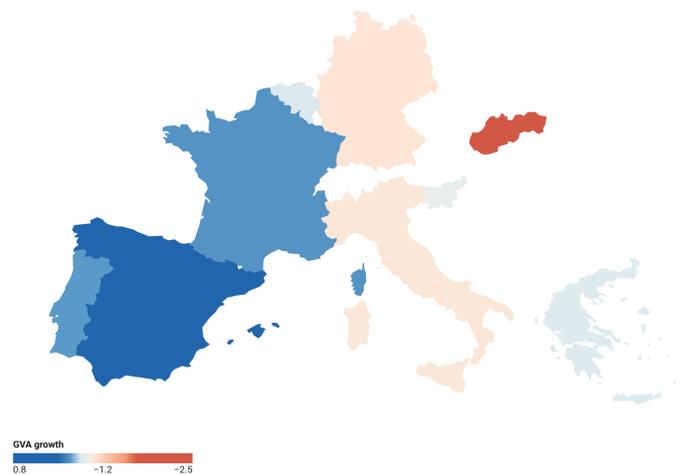
Note: Sectoral gross value added (average 2025-2027) of the ECB's June 2025 Broad Macroeconomic Projection Exercise (BMPE) severe scenario, as detailed in Box 2.

Table 2 summarises the key assumptions, macroeconomic outcomes, transmission channels and sectoral implications of the severe scenario from the ECB's June 2025 Broad Macroeconomic Projection Exercise (BMPE), as described in Box 2. PD estimates in this paper are derived under a sensitivity scenario that assumes a further 10 pp bilateral tariff increase on euro area exports to the US, relative to the adverse scenario of the 2025 EU-wide stress test. The scenario assumes US tariffs on euro area exports revert to "2 April reciprocal" levels (effective rate of ∼28%, up from 10% in the baseline), implying a 20 pp bilateral increase relative to the baseline when embedded in the 2025 EU-wide stress test adverse scenario. This incorporates an additional 1.2-percentage-point output loss relative to the BMPE baseline, on top of the stress test's existing 6.2% cumulative GDP decline over three years (from a 10% bilateral tariff assumption).[6] Symmetric EU retaliation is assumed, alongside persistently elevated US-China tariffs (∼120%, without the baseline's 90-day pause) and trade policy uncertainty that triggers financial market corrections, deteriorating asset quality, and rising bank funding costs.

The scenario's transmission operates primarily through four channels, ranked by impact (see Table 2). First, capital goods exports suffer most acutely as global firms postpone investment

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[5]More details are available in Box 2 in European Central Bank (2025a) and macro-financial scenario in European Systemic Risk Board (2025).

[6]The 2025 stress test adverse scenario already assumes a 10% bilateral tariff level, projecting a 6.2% cumulative GDP decline over three years. Under the severe BMPE scenario, the materialisation of additional tariffs implies a further 1.2 pp output loss relative to the BMPE baseline — embedded into the stress test adverse scenario to ensure consistency with ECB official projections, leading to an assumed 20 pp bilateral tariff increase relative to the baseline.

amid uncertainty, with peak effects in 2026, a critical hit given the euro area's export specialisation. Second, direct tariff effects erode price competitiveness in the US market. Third, domestic investment weakens as firms delay capex. Fourth, consumption softens via precautionary saving and lower confidence.

At the sectoral level, the tariff-induced slowdown propagates most severely to agriculture, mining, manufacturing, energy, utilities, and construction, sectors that are both externally vulnerable and central to economic activity via their disproportionate GVA shares. These amplify aggregate GDP losses and, through supply-chain linkages, constrain downstream services and trade-intensive industries. Consequently, in this higher-uncertainty environment, PDs rise further, with these GVA-intensive sectors driving the bulk of credit risk increases as macro-financial conditions deteriorate, driven primarily by a tariff-induced slowdown propagating through vulnerable sectoral channels. The EU-wide adverse scenario is further exacerbated by financial stability tail risks from trade disputes and policy uncertainty, which undermine financial market confidence, trigger disorderly corrections and promote rising bank funding costs alongside deteriorating asset quality.

Table 2: Scenario key assumptions, macroeconomic outcomes and transmission channels

US tariff shock (+10pp bilateral) embedded in 2025 EU-wide stress test adverse scenario	
Tariff assumptions and macroeconomic context	
US tariffs on EU	+10pp bilateral increase. In the context of the 2025 EU-wide stress test, this implies an assumed 20 pp bilateral tariff increase relative to the baseline, embedding a further 1.2 pp incremental output loss on top of the stress test adverse scenario.
EU retaliation	Symmetric response assumed; no negotiated settlement.
US-China tariffs	Remain at ~120% effective rate (no 90-day pause); adds geopolitical uncertainty.
Trade policy uncertainty	Uncertainty remains persistently high (2025–27), with no improvement as seen in the baseline. Ongoing geopolitical and trade tensions undermine market confidence, triggering a disorderly correction, weakening asset quality and increasing banks' funding costs.
Transmission channels (ordered by impact)	
1. Capital goods exports	Dominant channel: global investment postponement sharply cuts euro area capital goods demand (key euro area export); peaks in 2026.
2. Direct tariff effect	EU-US tariffs erode price competitiveness of euro area goods in the US, hitting export volumes and net trade contribution to GDP.
3. Domestic investment	Uncertainty suppresses euro area investment amid unclear trade/demand outlook.
4. Consumption	Precautionary saving and lower consumer confidence.
Sectoral and PD impact	
Exposed sectors	Agriculture, mining, manufacturing, energy, utilities, construction hit hardest; amplify shock via GVA linkages, amplifying the transmission of tariff shocks to the wider economy.
GVA amplifier	Exposed sectors represent a disproportionate share of total GVA, so shocks to their output and investment have broad macroeconomic spillovers. Declines in their GVA directly reduce overall GDP growth and, via supply-chain linkages, dampen activity in downstream services and trade-related industries.
PD increase	GVA from affected sectors drive credit risk surge.

Notes: Further details are available in (European Central Bank, 2025b) and (European Central Bank, 2025a).

3 Model

Koenker and Hallock (2001) first introduced quantile regressions as a means to study non-linearities across the distribution of an outcome conditional on its covariates and expanded this seminal body of work to Conditional Quantile Regression (CQR) for panels in Koenker (2004). They typically treat fixed effects as nuisance location-shifts and estimate them jointly with slope parameters. Canay (2011) simplifies this by "demeaning" under the assumption of pure location effects, obtaining asymptotically consistent and normal estimators. Machado and Santos Silva (2019) propose CQR method-of-moments estimators accommodating multiple high-dimensional fixed effects that would generally serve our application well. However, a potential drawback to the conditional quantile approach is the interpretation of the coefficient estimates per quantile, since they are conditional on the distribution of independent variables[7]

In parallel, the subsequent extensions to various panel applications also involve Unconditional Quantile Regression (UQR), which, in contrast, target marginal distributional effects via recentered influence-function (RIF) methods developed by Firpo et al. (2009) and later extended to panel settings by Powell (2022) and Rios-Avila and Maroto (2024). Powell (2022) specifically proposes a Quantile Regression Fixed Effects estimator that conditions on fixed effects for identification but yields unconditional quantile treatment effects consistent in small-T panels. Rios-Avila (2020); Rios-Avila and Maroto (2024) extends and implements RIFs in a multidimensional panel fixed effect setting.

While this overview is by no means exhaustive, it illustrates the choice an applied researcher has to make. Similar to Rios-Avila (2020); Rios-Avila and Maroto (2024) we implement a RIF based model as it offers a simple linear probabilistic implementation and interpretation at every estimated quantile, unconditional of the distribution of the macroeconomic variables of interest. We also compare our outcomes to a CQR based implementation and discuss the benefits and drawbacks of coefficient interpretation of both in more detail in Section A. For a given scenario this yields an interpretation of fitted values as a default probability distribution unconditional of a *specific* macroeconomic environment but as impact of a respective scenario. In addition, and importantly for our setting, it allows to control for fixed effects a various level. As previously discussed, it has become apparent in the pandemic and during the recent US-presidency, that idiosyncratic shocks to different sectors can play an important role in the assessment of credit risk. Therefore, accounting for unobservables across the distribution of economic sectors is represents one of the key objectives. The proposed specification takes the following form:

$$PD_{s,c,t} = \alpha(\tau) + \beta_1(\tau)Z_{s,c,t} + \beta_2(\tau)X_{c,t} + (\tau)C_{s,c} + \varepsilon_{s,c,t} \tag{3}$$

Equation 3 Models the τ-th unconditional quantile of the dependent variable $PD_{s,c,t}$, which denotes the probability of default for sector s in country c at time t[8]. The specification includes a quantile-specific intercept $\alpha(\tau)$, sector- and country-specific log GVA $Z_{s,c,t}$ with corresponding quantile-varying coefficients $\beta_1(\tau)$, and a vector of country-level macro-financial variables $X_{c,t}$, that contains Unemployment, The 3-month/10-year yield spread, the long term rate, the log-

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[7]Conditional quantile regressions based on method of moments require specific assumptions on the independent variables' properties.

[8]As discussed, we use flow default rates to estimate the model. Fitted values can then be interpreted as PD.

Stock Index, and the log Private Property Price Index. All variables are first-differenced. Sector and country fixed effects $C_{s,c}(\tau)$ are included to account for time-invariant unobserved heterogeneity across sector-country pairs. $\varepsilon_{i,t}$ is the residual term and is assumed to satisfy the standard condition $Q_\varepsilon(\tau \mid Z_{s,c,t}, X_{c,t}) = 0$. We omit 2020 (the onset of the Covid pandemic) from the estimation sample. By allowing all parameters to vary with τ, the model captures potential heterogeneity in the relationship between country and sector outcomes and the outcome across the distribution of $PD_{s,c,t}$.

Table 3: Regression results across different quantiles

Quantile PD	(1) 50th	(2) 70th	(3) 90th
$\Delta lnGVA$	-0.0641***	-0.0605***	-0.0877***
	(0.0101)	(0.0142)	(0.0335)
$\Delta longRate$	0.0411	0.383***	1.005***
	(0.0801)	(0.113)	(0.267)
ΔUR	0.307***	0.795***	1.800***
	(0.0504)	(0.0710)	(0.168)
$\Delta lnStockIndex$	-0.00798**	-0.0166***	-0.0390***
	(0.00365)	(0.00513)	(0.0122)
$\Delta lnPorpertyIndex$	-0.195***	-0.259***	-0.347***
	(0.0177)	(0.0250)	(0.0592)
$\Delta YCSpread$	-0.0558	-0.363***	-1.016***
	(0.0814)	(0.115)	(0.271)
Constant	6.103***	8.382***	13.78***
	(0.0957)	(0.135)	(0.319)
Observations	2,568	2,568	2,568
R-squared	0.388	0.387	0.269
Country FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes

Note: Estimates from (1), (2) and (3) respect to the 50th, 70th, and 90th quantiles of country-sector flow default rates (1999–2023, excluding 2020). All regressors are first-differenced. Δln GVA is the country-sector gross value added (in log terms); ΔUR is the country unemployment rate; ΔlongRate is the 10-year government bond yield; ΔlnStockIndex and ΔlnPropertyIndex are country-level equity and private property price indices (in log terms); ΔYCSpread is the 10-year minus 3-month yield curve slope. Sector-country fixed effects control for time-invariant unobserved heterogeneity. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3 displays the coefficient estimates for three select quantiles: the median, the 75th and the 90th. For simplicity, we proceed by discussing the respective three quantiles throughout the rest of the paper even though every quantile can be fitted in theory. As the coefficients display, non-linearity across quantiles is present. While the unexplained part captured by the constant also grows, one can observe varying degrees of non-linearity in the coefficient at the respective quantiles. While GVA, the long term rate or the stock price index appear to not move much within the upper inter-quartile range, all three increase significantly in the 90th quantile. The unemployment rate coefficient increases almost linear while others like the spread increase almost exponentially.

4 Model Performance

This section present a set of validation exercises for the quantile PD model. A stress testing model needs to fulfil a series of requirements that need to be validated ahead of application. Adequate models for stress testing need to be (i) sufficiently conservative in crisis episodes, (ii) strongly correlated with the dynamics of macroeconomic scenario variables and (iii) have predictive power for forecasting.

We evaluate the first two requirements to stress test models by comparing the projected PDs across different quantiles over time to the observed flow default rates from the data. Further, predicted PDs' correlation with the macroeconomic scenario variables are tested. To evaluate the forecasting performance of the model, we perform an out-of-sample test. The test relies on pseudo out-of-sample projections, where the current model specification is estimated based on the data up to a past reference date. The projections from the model are then assessed against the actual realisations of the outcome variables. This type of analysis is a relevant criterion for phasing-in new models or fine-tuning the existing setups. This analysis considers projections based on the already realised macro-financial variables over a three-year horizon. We can further benchmark the forecasting performance against a random walk with a drift, which is often used in time series analysis as a necessary condition for validation. In this context, the random walk model generates a naive projection dictation that the best forecast of the future PDs is the current observed PD.

Finally, we can compare the outcomes of the QPD model against an established and frequently used model in stress testing, the Bayesian Model Averaging (BMA) approach (Gross and Población, 2015), to verify that the generated PDs on aggregate compare to alternative estimations.

Figure 3: Quantile PDs and realised default rate flows across years
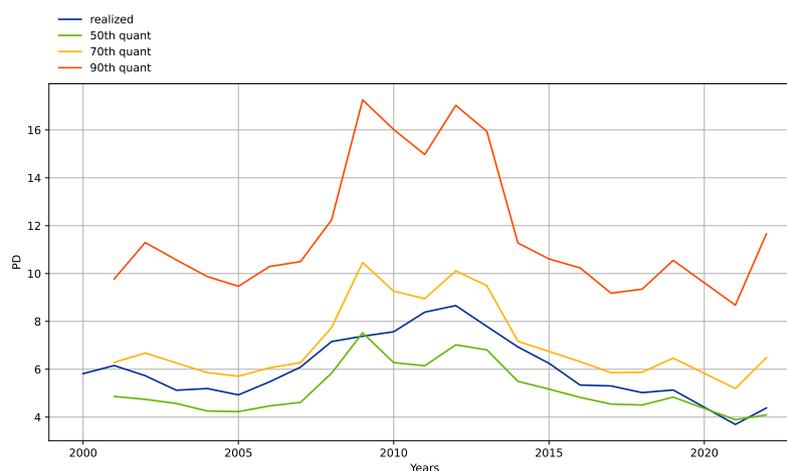
Note: The figure plots realised default rate flows (blue) against the model predicted average PDs at quantile 50,70, and 90. Fitted values are based on the model estimated using the full sample. The PD is in percentage (%).

We begin by evaluating the overall fitted PDs against the realised flow default rates. PD's are aggregated to euro area-level by weighting the respective sectoral PDs with the GVA contri-

bution within each country and subsequently take the mean across all sample countries[9] Figure 3 shows a strong correlation between realised and projected PDs. The estimated values at the 50th, 70th and 90th quantile all capture spikes in corporate defaults during the GFC as well as the euro sovereign debt crisis. As expected, the non-linear nature of PDs reveals varying proximity of observed PDs to different quantiles. While during recessions and recoveries, observed PDs are closer to the 70th quantile, calmer macroeconomic episodes are characterised by observed PDs that are closer to the estimated 50th quantile. This is particularly true for the period of low interest rates and quantitative easing policies in the euro area. Figure 3 therefore does not only provide evidence on the correlation between realised and estimated PDs, but also shows that estimating PDs at the full distribution of observed values enables the model to capture non-linear dynamics during crisis episodes over the different quantiles.

Compared to macroeconomic variables, the projected PDs also show a strong correlation in particular to recession and recovery dynamics. Figure 4 shows the estimated 50th quantile against realised values of GDP growth and the unemployment rate. The estimated values at the 50th quantile are sensitive to changes in the macroeconomic environment. They capture larger contractions in GDP growth and reflect longer term trends in the unemployment rate.

Figure 4: 50th quantile PDs and realised macroeconomic variables across years
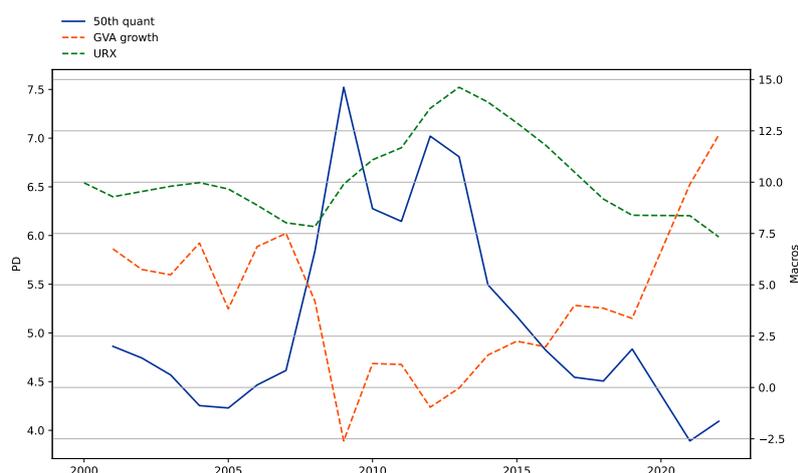
Note: The LHS scale is for fitted PD in percentage, the RHS scale is for both the unemployment rate and GVA in percentage.

The out-of-sample projections are conditioned on the realised macro-financial indicators. The model is estimated up to a certain point within the sample and then projects three years forward using the realised macroeconomic variables. By repeating this process multiple times, we can observe the performance of the model with increasing data availability and through different financial episodes. We start by estimating the model up to 2010, which on one hand gives the model a minimum of 10 years of time series for estimation, but more importantly includes a crisis episode in the estimation. Including crisis episodes is important when estimating stress test models, as it gives the opportunity to sensitize the coefficients to abnormal macroeconomic realisations. Figure 5 demonstrates a conservative yet adequate forecasting

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[9]We also use varying other aggregation approaches but rely on a simple method for the illustrative purpose here. Ideally, of course, country-sector PDs are not aggregated in a granular application.

performance of the model compared to realised default rates. The projections closely track the realised corporate default rates in the out-of-sample periods, indicating the model's ability to forecast corporate defaults. The out-of-sample predictions coincide in terms of direction and magnitude with the realised values. Further, they show a slightly greater and more contemporary reaction to macroeconomic dynamics than the realised values, which is desirable for a stress test model that aims to capture the conservative impact of a macroeconomic scenario over only three years. While this objective poses a trade-off between forecasting performance and sufficient conservativeness of stress test models, Figure 5 maintains realistically forecasted values in terms of direction.

Figure 5: Out-of-sample performance of the 50th quantile regression
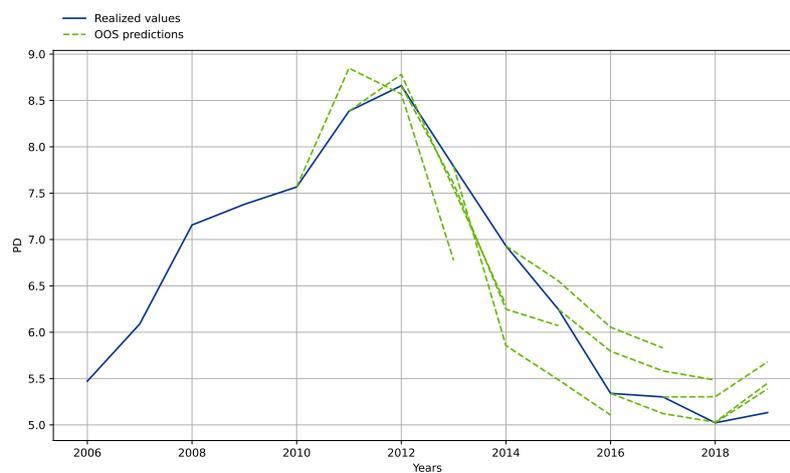
Note: The green lines represent the fitted average PDs for the median based on the model being estimated until the respctive yellow line's starting point and for three years ahead (sector country gva weighted).

The QPD outperforms the standard benchmark model of past PDs with the addition of a random term in the 50th and the 70th quantile. In Table 4, we show the root mean squared errors (RMSE) of the model against the RMSE of a naive random walk approach. The Naive model is constructed by taking the past period PD and adding a random term, which is normally distributed with 0 mean and the standard deviation of the observed PD distribution. We iterate this process for three consecutive years and compare the results. The respective opposite values from the QPD model are generated by estimating the model up to a point in time and then projecting three years out of sample, using realized macroeconomic variables. Table 4 shows the results for the years 2018-2021. RMSE of the QPD model are on average smaller over the 3-year projection horizon than those of the naive model. The ratio of QPD RMSEs over the naive model RMSEs, also called Theil's U, puts those figures into relation; the QPD model outperforms the naive model by about 40%.

Finally, we can compare the outcome of the QPD to the benchmark model for stress testing until 2023, the BMA approach. For this purpose, we estimate the standard ECB BMA model and the QPD for the 2021 EU-wide stress test scenario, baseline and adverse. Figure 6 shows the interquartile range and the median PDs estimated by both models. For the purpose of comparing the BMA, a macro-model estimated for each euro area country, the granular PD projections from our model have been aggregated to country-level. We can state that the

Table 4: Root mean square error of QPD at different quantiles and a naive random walk model, 2018-2021

	Naive Model	**QPD 50th quant.**	**QPD 70th quant.**
RMSE	1.158	0.728	0.662
Theils U		.628	.578

Note: The generation of random moments is calibrated using the standard normal distribution with zero mean and the standard deviation of the observed PD distribution. The QPD is estimated up until 2017, projected values for 2018-2021 are calculated using realised macroeconomic variables for the period.

QPD estimates compare reasonably well to the BMA approach. In the baseline scenario, the interquartile range is close to identical, while the overall level of PDs from the quantile model is more conservative. In the adverse scenario, QPD estimated are relatively less dispersed than the BMA. The compression of the PD distribution takes place in the right tail, with the 75th percentile estimates for the QPD being relatively lower than the BMA projections.

Figure 6: Projections for the stress test 2023 baseline and adverse scenario for the QPD and the BMA model
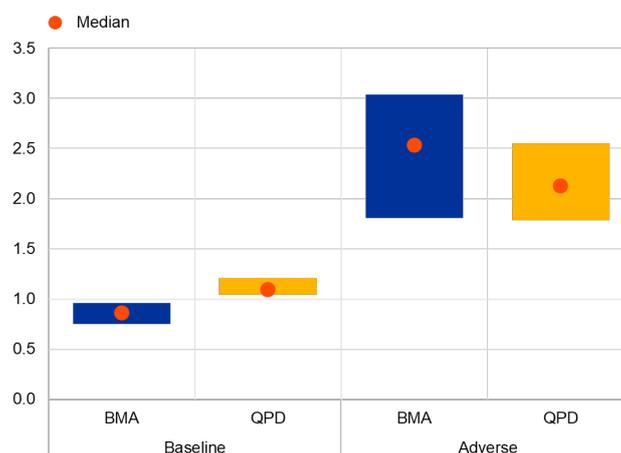
Note: The blue and yellow bars show the interquartile range for the BMA and the QPD models respectively. Red dots indicate the median. PDs on the y-axis are modelled projections based on the baseline and adverse scenario of the euro area stress test 2023.

5   Non-linear and sectoral features of the model

The major novelty of our approach lies in the combination of non-linear estimation approaches with granular data on sectoral PDs across euro area countries. While it is established that default rates can observe non-linear dynamics in crisis episodes, this non-linearity can vary across sectors. Our model captures this dimension of heterogeneity in its predictions and can identify sectors that are more vulnerable to shocks than others. Figure 7 depicts the relationship between estimated PDs in different quantiles and GVA growth at sectoral level. The sensitivity of estimated PDs and GVA growth increases over quantiles, with the lowest relationship in the 50th quantile and the highest in the 90th quantile. The slope of simple univariate regression lines of PDs on GVA growth is significantly more negative for the upper quantiles. That means that PDs at different quantiles, while having a level difference to start with, also reveal different

sensitivities to the direction of a shock. The key take-away is that PD increases when the model is estimated at the tail are significantly more severe during a shock.

Figure 7: Estimated PDs vs. GVA growth over different quantiles
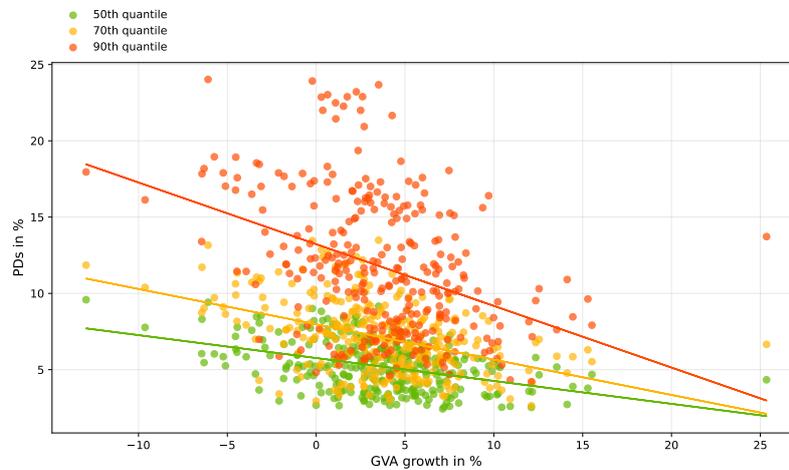
Note: The solid lines are the regression lines for GVA growth obtained from the fully specified quantile regression at the respective quantile.

At a sectoral level, we observe a higher sensitivity of estimated PDs to macroeconomic changes when the model is estimated at the tail. Decomposing this effect along the sectoral dimension reveals that this is more true for some sectors than for others. We take the difference between estimated PDs at the 90th quantile and the 50th quantile and compare them across sectors (Figure 8). We can see that the interquartile range is particularly high for a group of sectors, and relatively contained for others. Specifically, the real estate sector, arts & entertainment, accommodation and construction are the most exposed sectors to macroeconomic shocks. Other sectors, such as Technology, Transportation, Energy, Science and Public administration reveal less cross-quantile differentiation. This classification into vulnerable and less vulnerable sectors coincides to a large part with typically cyclical industries in terms of revenue.

Figure 8: Differences between estimated PDs at the 90th and 50th quantile across sectors
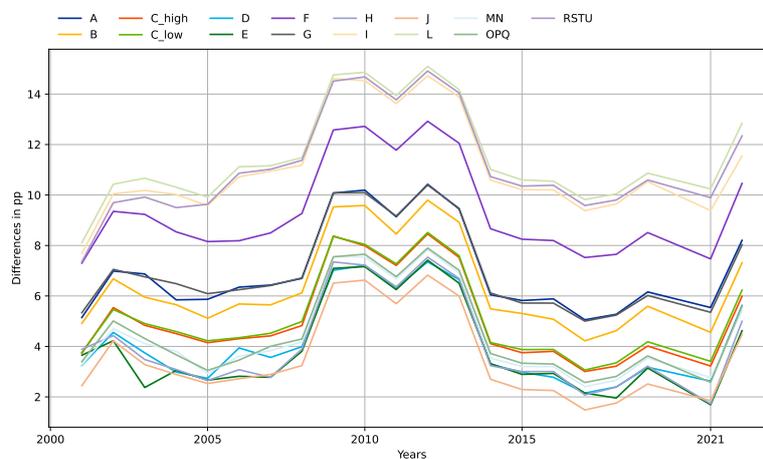

Note: The graph details sectoral heterogeniety in scenario sensitivities.

6 An adverse sectoral trade scenario application

Finally, we inspect sectoral corporate defaults based on an adverse geopolitical scenario for the years 2025 to 2027. Using different quantiles will help to identify heterogenous sensitivities of sectors to the scenario. As discussed in Section 3 the fitted PDs are a function of the stressed macroeconomic variables that form part of our model.

Results for the scenario dependent projections are shown in figures 9 - 11. Figure 9 shows a strong increase in PDs from the baseline year 2024 to the first scenario year 2025, which realises the greatest shock to macroeconomic variables in the scenario. Additionally, to the shift in terms of PD levels, the dispersion across quantiles widens. This reflects the higher sensitivity of the model estimated at the tail of the PD distribution to macroeconomic shocks. With the scenario recovery in years 2026 and 2027, levels and cross-quantile dispersion contract as well. Ultimately, the projected PDs end up at levels above the baseline, which reflects well the dynamic of the scenario.

Figure 9: Scenario dependent PDs across scenario years
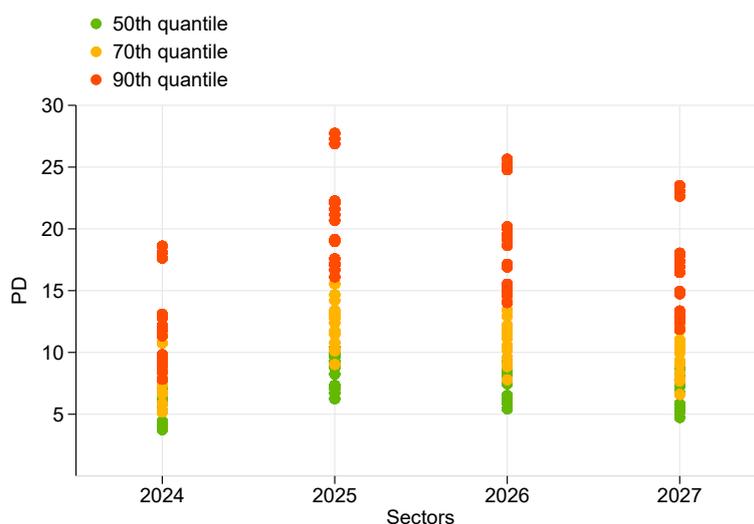
Note: Sector averages, weighted by country-level gross value added.

We can further observe stronger cross-sectoral heterogeneity in the upper quantiles. Figure 10 shows the 3-year scenario dependent projections of PDs across different sectors. The sensitivity of the tail of the PD distribution against macroeconomic shocks varies greatly across sectors. Construction, Wholesale and Retail trade, Accommodation, Real Estate and Entertainment are the most vulnerable sectors to a geopolitical scenario with trade disruptions.

Figure 11 displays a three-dimensional surface plot illustrating the evolution of projected probabilities of default across sectors, quantiles, and scenario years. Each layer represents the PDs at the fitted i-th quantiles across the three-year scenario horizon and all sectors, with the vertical distance between surfaces reflecting the widening and heterogeneous dispersion of default risk across quantiles under adverse macroeconomic conditions. The figure highlights pronounced cross-sector heterogeneity in the response of corporate default risk to the scenario:

sectors such as construction, wholesale and retail trade, accommodation and food services, and real estate exhibit higher PD levels and stronger cross-quantile variation, whereas sectors such as information and communication, transport, and utilities show comparatively smaller dispersion. Overall, the distributional framework captures both sectoral differences in the transmission of macro-financial shocks and the amplification of default risk in the upper tail of the distribution.

Figure 10: Scenario dependent PDs across sectors
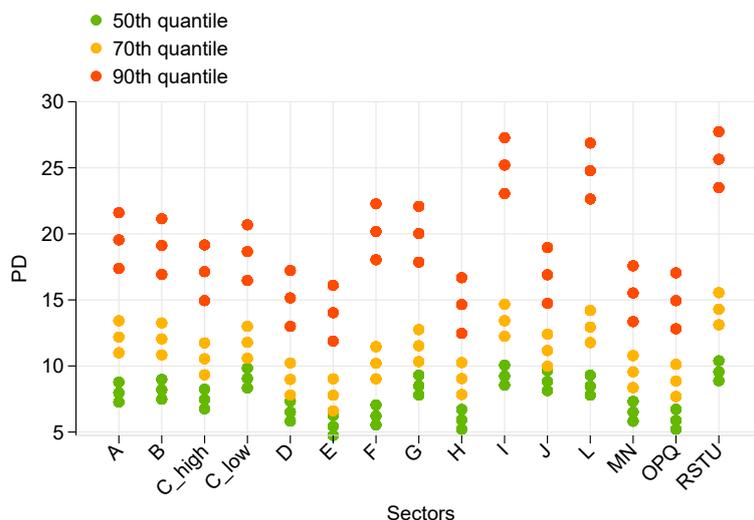
Note: Country averages weighted by gross value added.

Figure 11: Scenario based quantile PDs over a three year simulation horizon
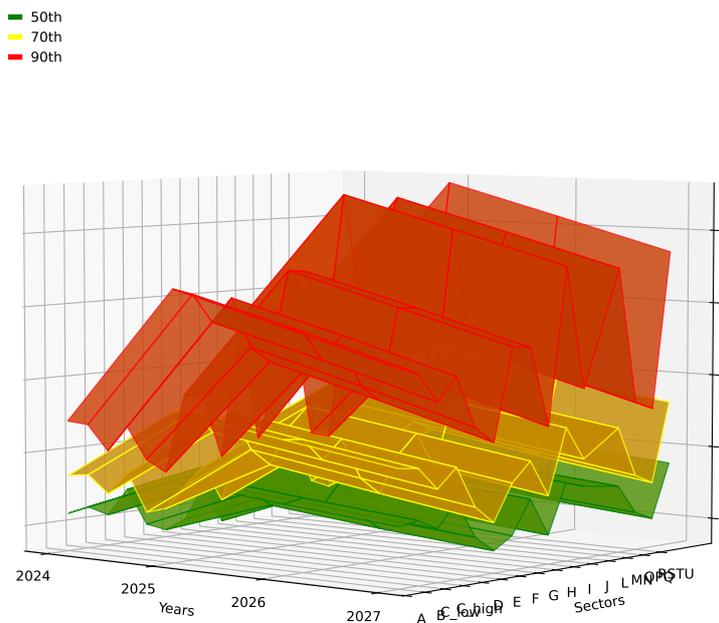
Note: Surface spanned by years (x-axis), sectors (y-axis) and PDs (z-axis).

7 Conclusion

This paper introduced a new framework to measure sector-level corporate credit risk in the euro area using quantile regressions. It introduces a QPD model that estimates the full distribution of sectoral default rates, rather than a single mean, thereby capturing tail risks and heterogeneity across sectors.

The empirical basis is a new panel of sectoral flow default rates for nine euro area countries over 1999–2023 (except 2020), constructed from Orbis firm-level balance sheet data using a cash-flow-based default definition in the spirit of Gourinchas et al. (2020). Aggregating firm-level indicators yields country–sector hazard-type default rates that are strongly cyclical and highly heterogeneous, with construction, tourism and real estate exhibiting systematically higher and more volatile defaults than utilities or business services. Energy-intensive manufacturing is more vulnerable than less energy-intensive manufacturing.

We estimates an unconditional quantile regression with sector–country fixed effects and relating sectoral default rates to the macro-financial variables used in euro-area stress tests (unemployment, interest rates, term spread, equity and property prices) and sectoral GVA. Coefficients are allowed to vary across quantiles, allowing the model to trace how the sensitivity to macro-financial shocks changes along the default-rate distribution. The results show pronounced non-linearities: the impact of adverse movements in unemployment, GVA and asset prices is larger in the upper tail than at the median, implying that macro-financial shocks are disproportionately damaging when underlying risk is already high.

Validation exercises confirm that GVA-weighted QPD estimates track realised euro-area default rates well, reproducing the spikes during the global financial crisis and the sovereign debt crisis. Average realised defaults lie around the 50th quantile in normal times and move towards the 70th quantile in crises. Out-of-sample projections based on realised macroeconomic paths match both the direction and approximate magnitude of subsequent default episodes and outperform simple benchmarks, with a conservative bias suitable for stress-testing.

An application to a severe geopolitical risk and trade-tension scenario, aligned with the ECB's June 2025 projections and the 2025 EU-wide stress test, shows sizeable increases in tail PDs, especially in construction, wholesale and retail trade, accommodation and food services, real estate and arts and entertainment, whereas information and communication or utilities are less affected. Overall, the QPD framework demonstrates how panel quantile methods can be used to embed non-linearities, sectoral heterogeneity and tail risk into solvency stress tests and to link scenario-driven PD distributions more explicitly to banks' sectoral and country exposures.

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A Conditional Quantile Regressions

To model the distribution of sectoral default rates conditional on a given set of macroeconomic conditions, we also estimate a conditional quantile regression (CQR) specification. The interpretation in the coefficients and distributional implications for PDs vary In contrast to unconditional quantile approaches, CQR directly characterizes the conditional distribution $Q_{PD}(\tau \mid X_{s,c,t})$, thereby allowing macro scenario variables to shift not the marginal quantile value but the entire distribution of default probabilities, however, only when keeping other variables fixed. This framework follows the Growth-at-Risk approach of Adrian et al. (2019), who estimate the conditional distribution of GDP growth to assess downside risks under different financial conditions. Analogously, our CQR specification interprets tail quantiles of sectoral default rates as state-dependent risk measures, *conditional* on the macroeconomic and sectoral environment. Using a method of moments approach following Machado and Santos Silva (2019) and analogously to Equation 3, we estimate:

$$Q_{PD_{s,c,t}}(\tau \mid Z_{s,c,t}, X_{c,t}, C_{s,c}) = \alpha(\tau) + \beta_1(\tau)Z_{s,c,t} + \beta_2(\tau)X_{c,t} + \gamma(\tau)C_{s,c}, \tag{4}$$

Table 5 displays the results

Table 5: Conditional quantile regression results across different quantiles

Quantile PD	(1) 50th	(2) 70th	(3) 90th
$\Delta \ln GVA$	-0.0590***	-0.0554***	-0.0500***
	(0.0094)	(0.0122)	(0.0180)
$\Delta longRate$	0.1526**	0.2891***	0.4912***
	(0.0740)	(0.0957)	(0.1416)
ΔUR	0.5055***	0.5917***	0.7193***
	(0.0495)	(0.0640)	(0.0947)
$\Delta \ln StockIndex$	-0.0104***	-0.0180***	-0.0293***
	(0.0032)	(0.0042)	(0.0062)
$\Delta \ln PropertyIndex$	-0.1794***	-0.1763***	-0.1717***
	(0.0140)	(0.0181)	(0.0268)
$\Delta YCSpread$	-0.1301*	-0.2729***	-0.4843***
	(0.0753)	(0.0974)	(0.1441)
Constant	6.8395***	8.2861***	10.4285***
	(0.0916)	(0.1077)	(0.1553)
Observations	2,568	2,568	2,568
Country FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes

Note: Estimates from (1), (2) and (3) correspond to the 50th, 70th, and 90th **conditional** quantiles of country-sector flow default rates (1999–2023, excluding 2020). All regressors are first-differenced. $\Delta \ln GVA$ is the country-sector gross value added (in log terms); ΔUR is the country unemployment rate; $\Delta longRate$ is the 10-year government bond yield; $\Delta \ln StockIndex$ and $\Delta \ln PropertyIndex$ are country-level equity and private property price indices (in log terms); $\Delta YCSpread$ is the 10-year minus 3-month yield curve slope. Sector-country fixed effects control for time-invariant unobserved heterogeneity. Coefficients and standard errors are multiplied by 100. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Across the conditional quantiles, some variables show stronger non-linear effects, while others are close to linear, broadly mirroring the UQR specification. In the CQR, GVA growth and residential property prices are fairly linear: their coefficients are sizeable but relatively stable

across the 50th, 70th, and 90th conditional quantiles (GVA around -0.06 to -0.05, property prices around -0.18 to -0.17), implying that a given change in real activity or house prices shifts the whole conditional distribution of default rates almost in parallel rather than disproportionately affecting the tail. By contrast, the unemployment rate, the long-term interest rate, the yield curve spread and the stock market price index display more pronounced non-linearity: their absolute coefficients roughly double or more between the median and the 90th conditional quantile (e.g. Δur from about 0.51 to 0.72, Δltn from 0.15 to 0.49, the spread from -0.13 to -0.48, the stock index from -0.01 to -0.03). This means that tightening financial conditions and rising unemployment have relatively modest effects on average default rates but disproportionately reprice the upper tail—high-risk country-sector cells which see much larger changes in their conditional default quantiles. The UQR results tell a similar story at the level of the unconditional PD distribution: unemployment, long rates, the yield spread, and equities all have much larger effects at the 90th unconditional quantile than at the median, whereas GVA and property prices remain important but more evenly distributed across quantiles. Put differently, GVA and house prices act mostly as level shifters of the default distribution (conditional and unconditional), while unemployment, rates, the curve, and equities are the more significant drivers of tail risk, with effects that become stronger as one moves from the centre to the upper end of the default-rate distribution.

B Linear Probability Default Model

We also implement the same baseline specification but as linear probability model using ordinairy least squares:

$$PD_{s,c,t} = \alpha + \beta_1 Z_{s,c,t} + \beta_2 X_{c,t} + C_{s,c} + \varepsilon_{s,c,t}. \tag{5}$$

Table 6 highlights the coefficient estimates relative to the quantile approach. In most cases they lie between the 50th and 70th.

Table 6: Regression results: quantile and mean regressions

PD	(1) 50th quantile	(2) 70th quantile	(3) 90th quantile	(4) Mean
$\Delta \ln GVA$	-0.0641***	-0.0605***	-0.0877***	-0.0583***
	(0.0101)	(0.0142)	(0.0335)	(0.00873)
$\Delta longRate$	0.0411	0.383***	1.005***	0.1796**
	(0.0801)	(0.113)	(0.267)	(0.0695)
ΔUR	0.307***	0.795***	1.800***	0.5225***
	(0.0504)	(0.0710)	(0.168)	(0.0437)
$\Delta \ln StockIndex$	-0.00798**	-0.0166***	-0.0390***	-0.0119***
	(0.00365)	(0.00513)	(0.0122)	(0.00316)
$\Delta \ln PropertyIndex$	-0.195***	-0.259***	-0.347***	-0.1788***
	(0.0177)	(0.0250)	(0.0592)	(0.0154)
$\Delta YCSpread$	-0.0558	-0.363***	-1.016***	-0.1583**
	(0.0814)	(0.115)	(0.271)	(0.0707)
Constant	6.103***	8.382***	13.78***	7.125***
	(0.0957)	(0.135)	(0.319)	(0.0831)
Observations	2,568	2,568	2,568	2,568
R-squared	0.388	0.387	0.269	0.508
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes

Note: Estimates from columns (1)–(3) correspond to the 50th, 70th, and 90th quantiles of country-sector flow default rates (1999–2023, excluding 2020); column (4) reports the mean regression. All regressors first-differenced. $\Delta \ln$ GVA: country-sector log gross value added; ΔUR: country unemployment rate; ΔlongRate: 10-year government bond yield; ΔlnStockIndex, ΔlnPropertyIndex: country-level log equity and private property price indices; ΔYCSpread: 10-year minus 3-month yield curve slope. Sector-country fixed effects included. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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