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Predicting Corporate Financial Distress Using an Ensemble Machine Learning Model Integrating Financial Ratios and Macroeconomic Indicators

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Abstract
Corporate distress models built on accounting ratios alone treat every firm-year as if it were drawn from the same economic environment, yet default clusters sharply in downturns and tightening cycles. This paper develops a stacked ensemble that combines a regularized logistic regression, a random forest, XGBoost and LightGBM through an out-of-fold logistic meta-learner, and feeds it twelve firm-level financial ratios together with eight macroeconomic indicators (GDP growth, inflation, the policy rate and its change, the credit spread, unemployment and its change, and exchange-rate depreciation). The model is estimated on a firm-year panel of 54,750 observations on 5,398 firms over 2003 to 2022 generated by a calibrated data-generating process that embeds the leverage thresholds, liquidity cliffs and rate-sensitivity interactions reported in the empirical literature, and it is evaluated on a strictly out-of-time test window (2017 to 2022) that contains an unseen recession year.
On the test window the ensemble with macroeconomic inputs reaches an AUC of 0.852 (95% bootstrap interval 0.836 to 0.867) against 0.842 for a ratios-only logistic benchmark, and raises the share of distressed firms captured in the riskiest decile from 55.0% to 57.5%. Adding macroeconomic indicators improves the ensemble's AUC by 0.007 (interval 0.0003 to 0.013) and its average precision from 0.318 to 0.342. Tree-based SHAP decomposition attributes about one third of predictive signal to macroeconomic variables, led by GDP growth and the change in unemployment. The gains are concentrated where linear models are misspecified: under a purely linear benchmark design the ensemble offers no advantage over logistic regression, although macroeconomic inputs still help. A notable cost is calibration in the recession year, where the macro-augmented ensemble overstates the realized distress rate (24.4% predicted against 13.8% observed). We argue that macro-augmented ensembles are best used for ranking and early warning, with explicit recalibration or scenario overlays when the macroeconomic state lies near the edge of the training history.

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1. Introduction

1.1. Background and Motivation

Forecasting which firms will fall into financial distress is one of the oldest applied problems in empirical finance. Lenders price and ration credit on it, auditors use it in going-concern judgments, supervisors use it to anticipate loan losses, and investors use it to avoid the well-documented underperformance of distressed equities (Campbell, Hilscher and Szilagyi, 2008) [76]. Banks increasingly embed such models in data-driven risk evaluation, supervisory reporting and portfolio oversight (Akomolafe and Agu, 2019b; Mensah *et al*., 2019a; Mensah *et al*., 2023) [30, 147, 149]. The canonical tools, Beaver's (1966) [65] univariate ratio analysis, Altman's (1968) [41] Z-score and Ohlson's (1980) logit model, share a common premise: that the information needed to separate healthy from failing firms is contained in a small set of accounting ratios describing liquidity, profitability, leverage, activity and solvency.

Two lines of subsequent work have challenged that premise from different directions. The first argues that the functional form is too restrictive. Ratios interact and act non-linearly: high leverage is far more dangerous when interest coverage is thin, and weak liquidity matters more when credit markets are closed. Machine learning methods, especially tree ensembles, can learn such structure without the analyst specifying it, and comparative studies have repeatedly found that bagged and boosted trees outperform discriminant analysis and logistic regression in bankruptcy and credit-scoring tasks (Kumar and Ravi, 2007; Lessmann *et al*., 2015; Barboza, Kimura and Altman, 2017; Jones, Johnstone and Wilson, 2017) [63, 113, 123, 136], and recent reviews of credit risk and loan-default analytics in retail, SME and commercial lending reach the same conclusion (Ashore-Onisemo *et al*., 2020; Mensah *et al*., 2022; Okoli, Pedro, *et al*., 2022) [53, 148, 176].

The second line argues that the information set is too narrow. Default rates are strongly counter-cyclical, and firm-level ratios observed at fiscal year end can lag the deterioration of the environment in which the firm will try to refinance. Models that add macroeconomic covariates, such as output growth, interest rates and credit spreads, have been shown to improve both discrimination and the stability of predictions through the cycle (Mensah, 1984; Duffie, Saita and Wang, 2007; Bonfim, 2009; Tinoco and Wilson, 2013) [72, 85, 151, 213]. The point is sharper in emerging markets, where exchange-rate, interest-rate and payment-system shocks are larger and digital lending is extending credit to firms with short histories (Uzondu *et al*., 2020; Okafor *et al*., 2021; Akomolafe *et al*., 2023; Pedro *et al*., 2024) [32, 171, 201, 234].

These two lines are rarely joined. Most machine learning studies of distress use purely firm-level features, often on cross-sectional samples in which every firm shares the same macroeconomic history, so macroeconomic variables cannot be identified. Conversely, studies that add macroeconomic variables usually keep a linear hazard or logit specification. This leaves open three questions that matter for practice: whether an ensemble learner extracts more value from macroeconomic information than a linear model does, whether the improvement survives a genuinely out-of-time test that includes a downturn the model has not seen, and what the macroeconomic inputs do to the calibration of predicted probabilities, which lenders and supervisors use directly.

This paper addresses those questions. We build a stacked ensemble (Wolpert, 1992; Breiman, 1996) [73, 236] of four heterogeneous base learners and train it on twelve financial ratios plus eight macroeconomic indicators. We evaluate it against single learners and against the same ensemble without macroeconomic inputs on a firm-year panel with a strict chronological split. Because the purpose is to isolate the mechanisms by which ensembles and macroeconomic data add value, the panel is generated from a transparent, calibrated data-generating process (DGP) whose properties are known, and we report a second, purely linear DGP as a benchmark. This design lets us state precisely when the ensemble should and should not beat a logit, something that is difficult to establish on a single proprietary dataset.

The paper makes four contributions. First, it provides a reproducible protocol for integrating time-varying macroeconomic indicators into a stacked distress ensemble while preventing look-ahead bias, through lagged macro inputs, firm-grouped out-of-fold stacking and an out-of-time test window. Second, it quantifies the separate contributions of model flexibility and of macroeconomic information using paired bootstrap tests. Third, it uses SHAP values (Lundberg and Lee, 2017) [137] to decompose predictive signal between firm-level and economy-wide sources. Fourth, it documents a calibration trade-off in a recession year that has received little attention in the machine learning distress literature and proposes practical remedies.

The remainder of the paper is organized as follows. The rest of this introduction reviews and synthesizes the literature (Section 1.2) and presents the conceptual model and hypotheses (Section 1.3). Section 2 describes the research method: the data, variables and sample design, the base learners and stacked ensemble, and the evaluation protocol. Section 3 presents and discusses the results, including robustness checks and the theoretical, practical and policy implications. Section 4 concludes and sets out the limitations of the study and directions for future research.

1.2. Literature Review and Synthesis

1.2.1 Accounting-Based Distress Models

Beaver (1966) [65] showed that individual ratios, especially cash flow to total debt, diverge between failing and surviving firms several years before failure. Altman (1968) [41] combined five ratios (working capital, retained earnings, EBIT, market equity relative to liabilities, and sales, each scaled appropriately) in a multiple discriminant function, the Z-score, which remains a reference point more than fifty years later (Altman *et al*., 2017) [42]. Ohlson (1980) [169] replaced discriminant analysis with logistic regression, which yields probabilities directly and relaxes distributional assumptions, and Zmijewski (1984) [239] proposed a probit alternative while highlighting choice-based sampling bias. Shumway (2001) [211] demonstrated that static single-period models are inconsistent when firms are observed repeatedly and recast distress prediction as a discrete-time hazard model estimated as a multi-period logit on firm-years, the design adopted in this paper.

1.2.2 Market and Macroeconomic Information

Accounting ratios are backward-looking and published with a lag. Shumway (2001) [211] and Campbell *et al*. (2008) [76] showed that market-based variables such as equity returns and volatility add predictive power. A parallel literature links default to the economic cycle. Mensah (1984) [151] documented that the coefficients of ratio-based models are not stationary across economic regimes. Duffie *et al*. (2007) [85] modeled default intensities as functions of both firm-specific covariates and macroeconomic state variables, including interest rates, and found that macro variables materially shift the term structure of default probabilities. Bonfim (2009) [72] found that macroeconomic dynamics improve the explanation of firm credit risk beyond firm characteristics, and Tinoco and Wilson (2013) [213] showed that adding inflation and interest-rate variables to accounting and market data improves the accuracy of distress models for listed UK firms.

Recent applied work, much of it from emerging and Sub-Saharan African markets, extends this perspective to the financial infrastructure through which macroeconomic conditions reach firms. Studies model remittance liquidity, cross-border payment interoperability, regulatory adaptation and the continuity of financial services, and use econometric models to anticipate technology adoption and labor-market adjustment in transitional economies (Adesuyi, Akomolafe,

et al., 2023; Akomolafe *et al*., 2023; Akomolafe *et al*., 2024a; Anichukwueze *et al*., 2021; Fadero *et al*., 2020; Komi and Adamolekun, 2024; Olaogun *et al*., 2023; Osuji *et al*., 2021; Oteri and Chibwaye, 2022) [8, 32, 36, 46, 102, 121, 183, 197, 198]. Others show how exchange-rate and commodity-price volatility, changes in fiscal legislation, access to finance, climate-linked financing and the digital transformation of banks and capital markets condition firm outcomes and the information available to lenders (Agboada *et al*., 2020; Akinola *et al*., 2020; Asibor *et al*., 2021; Mbonu *et al*., 2021a; Michael and Ogunsola, 2019a; Oluwo *et al*., 2022; Sakyi *et al*., 2024a; Sanni and Attah, 2023a; Ukadike, 2022) [14, 23, 54, 141, 152, 184, 206, 207, 224]. These settings, where macroeconomic shocks are larger and more frequent, are precisely where integrating macroeconomic indicators into distress models should matter most.

1.2.3 Machine Learning and Ensemble Methods

Neural networks, support vector machines and decision trees entered the distress literature in the 1990s, and surveys such as Kumar and Ravi (2007) [123] and Bellovary, Giacomino and Akers (2007) [68] catalogue the resulting comparisons. Ensembles have become the most consistently strong performers. Random forests (Breiman, 2001) [74] reduce variance by averaging de-correlated trees, while gradient boosting implementations such as XGBoost (Chen and Guestrin, 2016) [78] and LightGBM (Ke *et al*., 2017) [115] reduce bias by fitting trees sequentially to residual errors. Nanni and Lumini (2009) [156], Kim and Kang (2010) [116] and Zięba, Tomczak and Tomczak (2016) [238] reported gains from ensembles in bankruptcy prediction, Barboza *et al*. (2017) [63] found bagging, boosting and random forests superior to traditional models on North American firms, and Carmona, Climent and Momparler (2019) [77] applied XGBoost to bank failure. In a large benchmark of credit-scoring classifiers, Lessmann *et al*. (2015) [136] found that heterogeneous ensembles were among the best performers.

Stacked generalization (Wolpert, 1992; Breiman, 1996) [73, 236] combines heterogeneous learners through a second-stage model trained on their out-of-sample predictions. It is attractive for distress prediction because the base learners have complementary strengths: a logit extrapolates smoothly, a random forest is robust to noisy ratios, and boosting captures sharp interactions.

Beyond finance, predictive and early-warning models built on machine learning and deep learning have been applied to operational resource allocation and capacity planning, predictive maintenance, condition monitoring and digital twins, interpretable failure prediction for energy assets, renewable and load forecasting, schedule risk, carbon accounting, environmental and public-health risk prediction, enterprise technology risk and supply-disruption early warning (Adaramola *et al*., 2018; Adeyelu, 2018; Ahmed *et al*., 2020; Atakpa, Abolaji, and Abetoh, 2024; Azeez and Badmus, 2024b; Ebisi *et al*., 2024; Edivri and Oteri, 2022; Eze *et al*., 2022a; Ezeugwa *et al*., 2023b; Filani *et al*., 2022; Ilodigwe and Adesemoye, 2024a; Komi and Adamolekun, 2021; Komi and Adeniji, 2023; Komi, 2021; Komi, 2023; Kumuyi *et al*., 2024a; Lamidi and Olamide, 2018; Lamidi, 2023; Mayo *et al*., 2021; Nwangwu *et al*., 2020; Ogunnowo *et al*., 2020; Ogunnowo *et al*., 2024c; Okojie *et al*., 2023; Okwesa *et al*., 2024; Oparah *et al*., 2021; Oparah *et al*., 2022; Oparah *et al*., 2024; Shittu and Shittu, 2024; Sunday *et al*., 2020; Tonoyan *et al*., 2024a; Unamma *et al*., 2018b; Upreti and Oteri, 2023; Zhou *et al*., 2024), and to customer retention, demand forecasting, marketing return measurement and supply chain analytics (Aifuwa *et al*., 2020; Akin-Oluyomi and Akhigbe, 2023c; Akin-Oluyomi *et al*., 2023; Akinleye and Adeyoyin, 2022a; Anene and Clement, 2022; Basnet *et al*., 2021; Ebisi *et al*., 2021; Ezeako *et al*., 2024; Oghenemaiga *et al*., 2024; Ogundairo and Ayivi-Donkor, 2023a; Okonkwo *et al*., 2024c; Oziri *et al*., 2020; Rukh *et al*., 2023a; Rukh *et al*., 2023b; Rukh *et al*., 2024; Sanni *et al*., 2020a; Tonoyan *et al*., 2022a; Wedraogo and Sanni, 2024) [20, 22, 24, 43, 64, 87, 97, 164, 165, 178, 199, 202, 203, 204, 208, 216, 235]. Studies of feature selection and predictive modeling in clinical, educational and agricultural settings (Aliliele *et al*., 2023c; Atakpa and Abolaji, 2021; Joseph and Uzondu, 2024a; Michael and Ogunsola, 2021c; Michael and Ogunsola, 2023a; Michael and Ogunsola, 2023c) [40, 57, 114, 153, 154, 155], and of anomaly, threat and malware detection and adversarial machine learning in cybersecurity (Adebayo *et al*., 2022; Adebayo, Adegbite, and Ahmed, 2023; Akeju *et al*., 2018; Idika *et al*., 2021; Okwesa *et al*., 2020) [4, 5, 21, 107, 182], confront the same trade-offs between interpretability, class imbalance and generalization that recur in distress prediction. Work on human-in-the-loop learning and natural language processing of financial records (Iziduh *et al*., 2020; Ladapo *et al*., 2022) [112, 125] points to ways of combining model output with analyst judgment.

1.2.4 Applied Credit Risk and Default Analytics

A large recent applied literature brings machine learning directly to credit risk and loan default. Systematic reviews and conceptual studies of retail, SME and commercial lending document a shift from traditional scorecards toward machine learning classifiers used for early-warning detection, recovery optimization and credit portfolio growth in emerging markets (Ashore-Onisemo *et al*., 2020; Mensah *et al*., 2022; Okoli, Pedro, *et al*., 2022; Uzondu *et al*., 2020) [53, 148, 176, 234]. Related work examines how fintech-enabled transaction banking, digital lending, financial inclusion, relationship banking, CRM-based lending forecasts and data-driven small-business operations change the composition and observability of borrowers (Agboada *et al*., 2018; Agboada *et al*., 2022; Dada *et al*., 2021b; Eyetsemitan *et al*., 2024b; Ezeako *et al*., 2019; Okafor *et al*., 2021; Pedro *et al*., 2024) [15, 16, 80, 95, 98, 171, 201], which raises the value of models that can learn from heterogeneous and partially observed firms.

At the institutional level, studies develop data-driven risk evaluation models for emerging-market financial institutions, asset-liability and interest-rate risk modeling, enterprise risk management and capital allocation, capital adequacy optimization, operational resilience, and risk-based internal control and governance (Akomolafe and Agu, 2019a; Akomolafe and Agu, 2019b; Ashore-Onisemo and Unamma, 2022a; Mensah *et al*., 2019a; Mensah *et al*., 2019b; Mensah *et al*., 2023; Okafor, Osuji, and Dako, 2024) [29, 30, 50, 147, 149, 150, 172]. Parallel contributions address machine learning in insurance underwriting, risk scoring for cross-border payment transactions and correspondent-banking controls (Adesuyi *et al*., 2024; Okafor, Farounbi, *et al*., 2024; Oluwo

et al., 2024) [9, 170, 185], as well as the effects of climate-risk disclosure on bank valuation and financial stability (Kinyanjui *et al*., 2021) [117]. Interest-rate and capital-market conditions run through much of this work, reinforcing the case for joining macroeconomic indicators to firm-level credit models.

1.2.5 Predictive Financial Analytics in Corporate Finance

Because distress is ultimately a failure of liquidity and cash generation, research on predictive financial analytics within firms bears directly on the choice of predictors. Studies of predictive cash flow and working capital modeling, multinational cash consolidation and FX risk control, predictive budgeting and integrated financial data management show that forward-looking cash and liquidity measures carry information beyond static balance-sheet ratios (Adesuyi *et al*., 2022; Agu *et al*., 2023b; Dada *et al*., 2021a; Oduleye and Medon, 2023a; Tonoyan *et al*., 2021b) [11, 18, 79, 162, 215], which motivates the inclusion of operating cash flow and liquidity ratios in this paper. Machine learning has also been applied to strategic financial forecasting, revenue projection, cost optimization, valuation and scenario analysis under uncertainty (Lawal and Oduleye, 2019b; Medon and Oduleye, 2024; Oduleye and Medon, 2023b; Tonoyan *et al*., 2021a; Tonoyan *et al*., 2022c; Unamma, 2022) [131, 146, 163, 214, 218, 226].

A broader body of work links financial analytics to capital allocation, profitability, enterprise value, portfolio optimization and capital structure decisions (Filani *et al*., 2023; Ilesanmi *et al*., 2024; Isiekwu *et al*., 2021; Lawal and Oduleye, 2018a; Lawal and Oduleye, 2021a; Lawal and Oduleye, 2021b; Lawal and Oduleye, 2023a; Lawal and Oduleye, 2023b; Medon and Oduleye, 2023; Okoli *et al*., 2024; Tonoyan *et al*., 2023; Ukadike and Ibeh, 2023) [106, 109, 111, 128, 132, 133, 134, 135, 145, 175, 219, 225], and to cost governance, variance analysis, performance monitoring, revenue optimization and procurement-related financial risk (Adesuyi, Kalu, and Walawalkar, 2023; Akin-Oluyomi *et al*., 2020; Akomolafe *et al*., 2022; Aliliele *et al*., 2024; Anene *et al*., 2023; Ashore-Onisemo and Iziduh, 2024; Bello *et al*., 2023; Bola-Sadipe *et al*., 2023; Nnabueze *et al*., 2024; Oduleye and Medon, 2021; Okoli *et al*., 2020; Tonoyan *et al*., 2022b; Tonoyan *et al*., 2024b) [10, 26, 34, 38, 44, 49, 67, 70, 158, 161, 174, 217, 221]. Studies of accounting systems, financial reporting and compliance, tax and transfer-pricing governance, reconciliation controls and reporting data quality (Akomolafe and Agu, 2019c; Alieme *et al*., 2022; Bola-Sadipe *et al*., 2019; Bola-Sadipe *et al*., 2022; Dogbatsey and Ebhojie, 2018; Dogbatsey *et al*., 2019; Ebhojie *et al*., 2023a; Lawal and Oduleye, 2018b; Lawal and Oduleye, 2019a; Medon and Oduleye, 2022; Unamma *et al*., 2019a; Unamma, Okwesa, and Iwuanyanwu, 2021) [31, 37, 69, 71, 81, 82, 86, 129, 130, 144, 229, 230] bear on a practical constraint of every ratio-based model: its predictions are only as reliable as the financial statements from which the ratios are computed.

1.2.6 Adjacent Evidence from Fraud Detection and Audit Analytics

Fraud detection and anti-money-laundering analytics share the core statistical problem of distress prediction: identifying a rare and costly event from noisy financial records. Reviews and models of machine learning for fraud detection in banking systems, data-mining techniques for fraud, synthetic-identity fraud, adaptive transaction risk scoring, anti-money laundering and financial-crime prevention (Atakpa and Abetoh, 2022; Atakpa, 2021; Elebe *et al*., 2023; Fadayomi *et al*., 2021; Fadayomi *et al*., 2024; Ominyi and Anichukwueze, 2021; Unamma, Iziduh, and Okwesa, 2021) [55, 56, 94, 100, 101, 189, 229] repeatedly confront class imbalance, threshold selection and drift, the same issues this paper addresses through PR-AUC, out-of-fold threshold selection and out-of-time testing.

The adjacent literature is completed by predictive and data-driven auditing in public, health and corporate settings, and SOX and risk-based audit frameworks (Abetoh and Atakpa, 2022; Abetoh and Atakpa, 2024; Adelanwa *et al*., 2023b; Agu *et al*., 2023a; Akomolafe and Agu, 2018; Akomolafe *et al*., 2023a; Ashore-Onisemo and Unamma, 2022b; Atakpa, Abetoh, and Akeju, 2024; Ekechi *et al*., 2022; Okoli, Kinyanjui, *et al*., 2022; Okwesa and Ashore-Onisemo, 2023) [1, 2, 7, 17, 28, 32, 51, 60, 93, 176, 179]; investment-risk models for venture capital and private equity (Eboh and Aliliele, 2023; Eboh and Aliliele, 2024) [89, 90]; anomaly detection in financial time series and compliance data streams (Atakpa and Fobellah, 2023; Mbonu *et al*., 2021; Ominyi *et al*., 2024a; Uchechi, Ominyi, Anichukwueze, and Jones, 2022) [59, 141, 192, 222]; and quantitative risk-assessment frameworks for enterprise, cyber, supplier and public-private partnership risk (Adebayo, Adepoju, and Ozowara, 2023; Agbabiaka *et al*., 2019; Akin-Oluyomi *et al*., 2023b; Akomolafe *et al*., 2023b; Dosunmu and Ogundele, 2019; Dosunmu and Ogundele, 2024b; Falemi *et al*., 2024; Ike *et al*., 2024a; Mbonu *et al*., 2022a) [6, 13, 25, 33, 83, 84, 103, 108, 143].

1.2.7 Literature Synthesis and Research Gaps

Table 1 synthesizes the seven streams reviewed above. Read together, they converge on three propositions. First, accounting ratios describing liquidity, profitability, leverage and cash generation remain the core of any distress model. Second, the economic environment shifts both the level of default risk and the way ratios should be read, which implies interaction rather than simple additive effects. Third, flexible learners, and ensembles in particular, rank risk better than linear models in most comparisons, yet the applied literature that deploys them, much of it from emerging markets, is largely conceptual and seldom tests models out of time.

Table 1: Synthesis of the literature

Research stream	Representative studies	What it establishes	What remains open (addressed here)
Accounting-ratio models	Beaver (1966) [65]; Altman (1968) [41]; Ohlson (1980) [169]; Zmijewski (1984) [239]; Shumway (2001) [211]	Ratios separate failing from healthy firms; firm-year hazard design	Linear form; no role for the economic environment
Market and macroeconomic information	Mensah (1984) [151]; Duffie *et al.* (2007) [85]; Campbell *et al.* (2008) [76]; Bonfim (2009) [72]; Tinoco and Wilson (2013) [213]	Macro conditions shift default risk and model stability	Mostly linear specifications; interactions untested
Machine learning and ensembles	Breiman (2001) [74]; Lessmann *et al.* (2015) [136]; Zięba *et al.* (2016) [238]; Barboza *et al.* (2017) [63]; Jones *et al.* (2017) [113]	Bagging, boosting and stacking outperform linear models	Rarely include time-varying macro data; often random splits
Applied credit and default analytics	Ashore-Onisemo *et al.* (2020) [53]; Uzondu *et al.* (2020) [234]; Mensah *et al.* (2022) [148]; Okoli, Pedro, *et al.* (2022); Pedro *et al.* (2024) [201]	Machine learning for default early warning in emerging-market lending	Largely conceptual; little out-of-time evidence
Predictive financial analytics	Tonoyan *et al.* (2021b) [215]; Oduleye and Medon (2023a) [162]; Medon and Oduleye (2024) [146]	Cash-flow and forecasting information is forward-looking	Not linked to a distress hazard
Fraud and audit analytics	Unamma, Iziduh, and Okwesa (2021) [229]; Atakpa and Abetoh (2022) [56]; Fadayomi *et al.* (2024) [101]	Methods for rare events, thresholds and drift	Different target event
Explainability and model governance	Lundberg and Lee (2017) [137]; Ominyi and Anichukwueze (2023) [190]; Unamma and Ashore-Onisemo (2023) [227]	Need for interpretable, auditable models	Calibration under regime change underexplored

Note: Full citations for each stream are given in Sections 1.2.1 to 1.2.6.

Three gaps follow. Machine learning distress studies seldom include time-varying macroeconomic indicators, and when they do they rarely test performance out of time. The contribution of model flexibility is seldom separated from the contribution of richer information. And evaluation usually centers on accuracy or AUC, leaving the calibration of predicted probabilities, which matters for pricing and provisioning, largely unexamined. The conceptual model in Section 1.3 is built to address all three.

1.3. Conceptual Model and Hypotheses

1.3.1 Conceptual Framework

Figure 1 sets out the conceptual model. Distress in year *t+1* is the outcome of a firm's financial condition at *t*, captured by its ratios, operating in an economic environment at *t*, captured by macroeconomic indicators. The environment plays two roles. It has a *direct* effect, raising or lowering the risk faced by every firm, and a *conditioning* effect, changing how much a given ratio matters: high leverage is more dangerous when rates are rising, and thin liquidity is more dangerous when credit spreads widen. Both sets of inputs feed four heterogeneous base learners whose out-of-fold predictions are combined by a logistic meta-learner. The output is a probability that is evaluated for ranking and for calibration, and decomposed with SHAP values into the contributions of ratios and macroeconomic indicators.

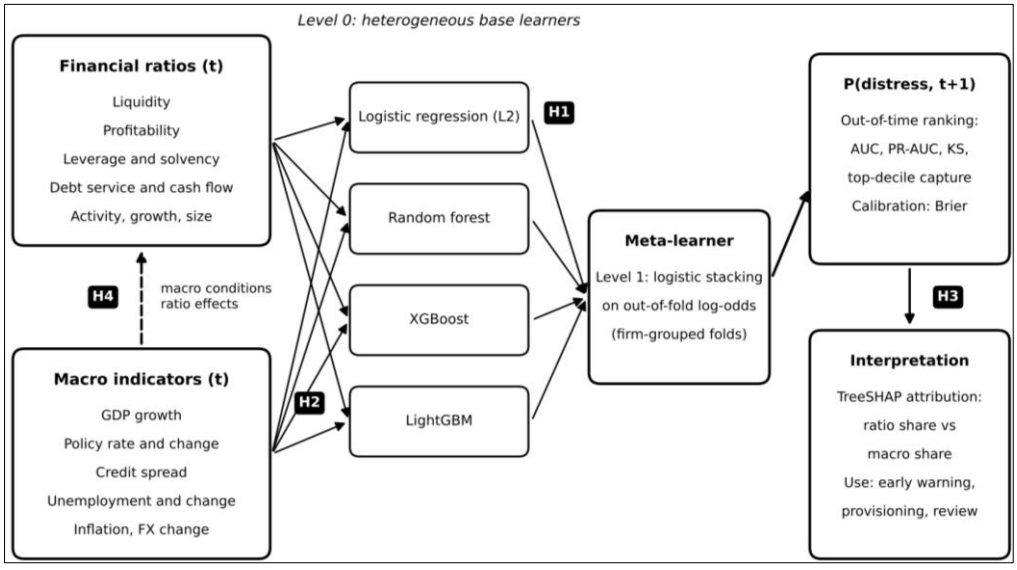


Fig 1: Conceptual model. Solid arrows show the flow of information through the stacked ensemble; the dashed arrow shows the conditioning effect of the macroeconomic environment on ratio effects. Labels H1 to H4 mark where each hypothesis is tested.

1.3.2 Hypotheses

The framework yields four testable hypotheses. Because the conditioning effect produces thresholds and interactions that a linear logit cannot represent without explicit specification, a flexible ensemble should rank firms better (H1). Because part of next year's environment is foreshadowed by current macroeconomic indicators, adding them should improve out-of-time discrimination (H2) and should account for a material share of the model's signal (H3). Finally, if the ensemble's advantage comes from learning non-linear structure, it should disappear when that structure is absent (H4).

- **H1.** A stacked ensemble discriminates distressed from healthy firms better than a logistic regression on the same inputs.
- **H2.** Adding macroeconomic indicators improves the out-of-time discrimination of the ensemble relative to ratios alone.
- **H3.** Macroeconomic indicators account for a material share of the ensemble's predictive signal.
- **H4.** The advantage of the ensemble over a logit depends on the presence of non-linear and interaction effects in the true distress process.

2. Research Method

2.1. Research Design and Panel Data

We construct a firm-year panel covering observation years 2003 to 2022, so that distress outcomes span 2004 to 2023. The panel is produced by a calibrated data-generating process rather than drawn from a commercial database, for two reasons. First, the paper's central questions concern mechanisms (whether flexibility or information drives gains, and under what structure of the true hazard) and these can only be answered cleanly when the true process is known and can be varied. Second, a fully specified DGP makes every number in the paper reproducible from the accompanying code. The cost is external validity, which we discuss in Section 4.1, while Section 4.2 sets out the protocol for replication on Compustat, Orbis or exchange-listed samples. Each firm carries a latent financial-health state h_{it} that evolves as a persistent autoregressive process (coefficient 0.82) and is shocked each year by a sector-specific response to the macroeconomic environment and by an idiosyncratic disturbance. Six sectors (manufacturing, retail, energy, technology, construction and services) differ in their sensitivity to output growth and to changes in the policy rate, with construction and retail the most cyclical. Observed ratios are noisy, partly firm-specific functions of the latent state. Firms that become distressed exit the panel and are replaced by new entrants, together with modest net entry each year, so the panel is unbalanced in the way real listed-firm panels are. The macroeconomic path is a stylized annual series that reproduces the main features of a developed economy over the period: a pre-2008 expansion, a severe financial-crisis contraction with a spike in credit spreads in 2008 and 2009, a long low-rate recovery, a sharp pandemic-type contraction in 2020, a rebound in 2021 and an inflation and tightening episode in 2022 and 2023. Because the test window contains the 2020 contraction, the model must forecast through a downturn whose macroeconomic configuration differs from the one it learned in training.

2.2. Definition of Financial Distress

The dependent variable $Distress_{i,t+1}$ equals one if firm *i* enters financial distress during year *t+1* and zero otherwise. In applied work this event is typically defined as a bankruptcy filing, delisting for financial reasons, a debt default or restructuring, or a combination of an interest coverage ratio below one with negative equity growth for two consecutive years (Tinoco and Wilson, 2013) [213]. In the DGP the event is drawn from a firm-year hazard described in Section 2.4. All predictors are measured at fiscal year end *t*, so the model forecasts one year ahead using only information available at the forecast date.

2.3. Predictors

Table 2 defines the predictors. The twelve financial ratios cover the five dimensions emphasized since Altman (1968) [41] and Ohlson (1980) [169]: liquidity, profitability, leverage, activity and size, plus cash flow and growth; cash flow and working-capital measures are included because predictive cash-flow research shows they lead deterioration in reported profitability (Tonoyan *et al*., 2021b; Oduleye and Medon, 2023a) [162, 215]. The eight macroeconomic indicators capture output (real GDP growth), prices (inflation), the cost and direction of monetary policy (the policy rate and its annual change), funding conditions (the corporate credit spread), labor-market slack (unemployment and its change) and external pressure (currency depreciation). Five sector indicators complete the feature set.

Table 2: Variable definitions

Variable	Definition	Group	Expected sign
WC/TA	Working capital / total assets	Liquidity	(-)
Current ratio	Current assets / current liabilities	Liquidity	(-)
RE/TA	Retained earnings / total assets	Profitability (cumulative)	(-)
EBIT/TA	Earnings before interest and taxes / total assets	Profitability	(-)
NI/TA	Net income / total assets	Profitability	(-)
MVE/TL	Market value of equity / total liabilities	Solvency	(-)
TL/TA	Total liabilities / total assets	Leverage	(+)
Interest coverage	EBIT / interest expense	Debt service	(-)
CFO/TL	Operating cash flow / total liabilities	Cash flow	(-)
Sales/TA	Sales / total assets	Activity	(-)
Sales growth	Annual change in sales	Growth	(-)
Log TA	Natural log of total assets	Size	(-)
GDP growth	Real GDP growth, year t (%)	Macro: output	(-)
Inflation	Consumer price inflation, year t (%)	Macro: prices	(+/-)
Policy rate	Central bank policy rate, year t (%)	Macro: monetary	(+)
Change in policy rate	Policy rate, t minus t-1 (pp)	Macro: monetary	(+)
Credit spread	Corporate minus government bond yield (pp)	Macro: funding	(+)
Unemployment	Unemployment rate, year t (%)	Macro: labor	(+)
Change in unemployment	Unemployment, t minus t-1 (pp)	Macro: labor	(+)
FX depreciation	Annual change in exchange rate (%)	Macro: external	(+)

Note: TA = total assets; TL = total liabilities. All ratios are winsorized at the 1st and 99th percentiles of the training sample. Five sector dummies (reference: construction) are also included.

2.4. The Distress Process

In the main (non-linear) design, the log-odds of distress in *t+1* depend on the latent health state, on observed leverage and liquidity, on the macroeconomic environment, and on four interaction terms of the kind documented in the literature: (i) a leverage threshold whose penalty switches on when total liabilities exceed 80% of assets in a high or rising rate environment; (ii) a liquidity cliff in which a current ratio below one is dangerous only when credit spreads are wide or output is about to contract; (iii) a compound operating shock when negative EBIT coincides with falling sales; and (iv) a refinancing squeeze when interest coverage below 1.5 meets a sharp increase in the policy rate. Part of the macroeconomic driver is next year's outcome (for example, next year's GDP growth), which is not observable at the forecast date. This reproduces a real-world feature: current macroeconomic indicators are informative about, but do not fully reveal, the environment in which refinancing will happen.

The benchmark (linear) design uses the same panel mechanics and the same macroeconomic path but removes the four interaction terms and the threshold effects, so that the true log-odds are close to linear in the observed predictors. The comparison between the two designs is the basis for H4.

2.5. Sample and Descriptive Statistics

The non-linear design yields 54,750 firm-years on 5,398 distinct firms, with 2,510 distress events, an unconditional rate of 4.58%. Distress is strongly cyclical (Figure 2): the annual rate is between 0.7% and 3.2% in normal years but rises to 12.0% for observation year 2008 and to 34.2% for 2009, reflecting the deliberately severe financial-crisis stress episode in the DGP, and to 13.8% for 2020. Sectors are evenly represented, each accounting for between 15.6% and 17.9% of observations.

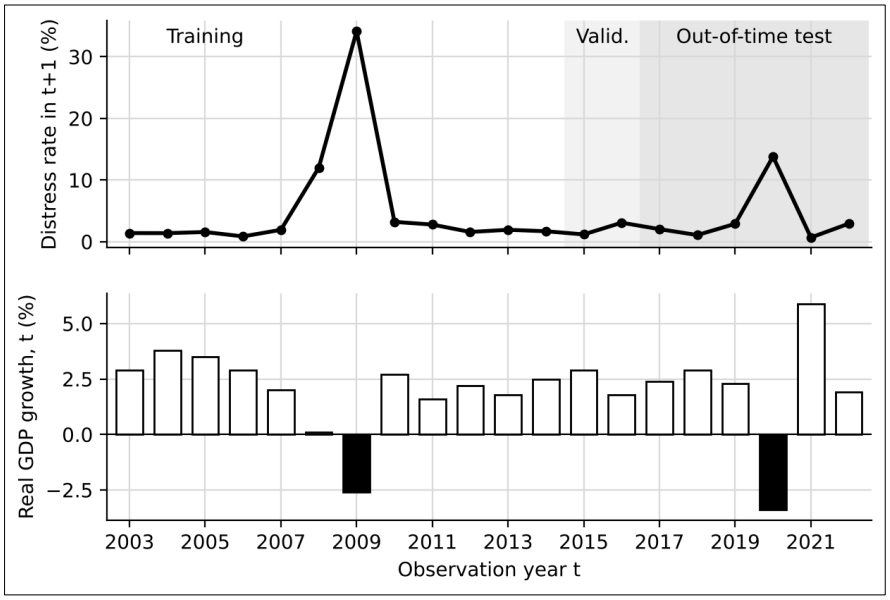


Fig 2: Distress rate by observation year (top) and real GDP growth (bottom). Shading marks the training, validation and out-of-time test windows. Contraction years are highlighted.

Table 3 reports summary statistics. Every ratio differs between the two groups in the expected direction. Distressed firm-years have far thinner working capital (2.8% of assets against 11.8%), near-zero operating profitability (EBIT/TA of 0.1% against 6.9%), heavier leverage (67.5% against 52.0%), a current ratio barely above one, and interest coverage close to zero. Size differs only slightly, which is consistent with size acting mainly through its interaction with other characteristics.

Table 3: Descriptive statistics, full sample

Variable	Mean	Std. dev.	Median	Mean (healthy)	Mean (distressed)
WC/TA	0.114	0.081	0.114	0.118	0.028
Current ratio	1.633	0.662	1.506	1.656	1.149
RE/TA	0.176	0.150	0.178	0.183	0.040
EBIT/TA	0.066	0.056	0.067	0.069	0.001
NI/TA	0.056	0.060	0.057	0.059	-0.010
MVE/TL	1.980	1.255	1.658	2.025	1.031
TL/TA	0.527	0.150	0.527	0.520	0.675
Interest coverage	3.618	3.604	3.054	3.787	0.118
CFO/TL	0.223	0.200	0.184	0.231	0.059
Sales/TA	1.018	0.309	1.017	1.024	0.892
Sales growth	0.027	0.123	0.028	0.030	-0.038
Log TA	6.298	1.593	6.296	6.306	6.147

Note: 54,750 firm-years, of which 2,510 distressed. Ratios winsorized at the 1st and 99th percentiles. The macroeconomic series (20 annual observations, 2003 to 2022) have the following means and ranges: GDP growth 2.00% (-3.4 to 5.9), inflation 2.48% (-0.3 to 8.0), policy rate 1.31% (0.1 to 5.0), credit spread 1.14 pp (0.7 to 2.7), unemployment 6.02% (3.6 to 9.6), FX depreciation 0.95% (-4.0 to 9.0).

2.6. Chronological Split

To mimic real deployment, the sample is split by time rather than at random. Observation years 2003 to 2014 form the training window (31,650 firm-years, 1,706 events, 5.39%), 2015 to 2016 the validation window (5,625 firm-years, 120 events, 2.13%), and 2017 to 2022 the out-of-time test window (17,475 firm-years, 684 events, 3.91%). The test window is never touched during model building. The training window contains the financial-crisis episode; the test window contains the 2020 contraction, which the model has not seen and which has a different macroeconomic signature (a deeper output drop and a smaller spread widening).

2.7. Pre-Processing

Missing values (about 3% of observations for cash flow, interest coverage and sales growth, introduced at random) are imputed with the training-window median. Ratios are winsorized at the 1st and 99th training percentiles, and the same bounds are applied to the validation and test windows. Macroeconomic indicators enter at their year-t values, which are known at the forecast date; no future macroeconomic value is used as an input. Continuous inputs are standardized for the logistic model only, since tree learners are invariant to monotone transformations.

2.8. Base Learners

Logistic Regression

The benchmark is the multi-period logit of Shumway (2001) [211], estimated with an L_2 penalty (inverse strength $C = 0.5$):

$$P\,(Distress_{i,t+1} = 1 \mid x_{it}) = 1 / [1 + \exp(-(\beta_0 + \beta' x_{it}))] \quad (1)$$

where x_{it} stacks the firm ratios, macroeconomic indicators and sector dummies.

Random Forest

A random forest (Breiman, 2001) [74] of 300 trees, each grown on a 50% bootstrap sample with 40% of features considered at each split and a minimum of 20 observations per leaf. Averaging de-correlated trees makes it robust to noisy ratios and outliers.

Gradient Boosting: XGBoost and LightGBM

Gradient boosting builds an additive model of M trees f_m fitted sequentially to the gradient of the log-loss:

$$F_M(x) = \Sigma_{m=1..M}\, \eta\, f_m(x), \text{ minimizing } \Sigma_i\, \ell(y_i, F(x_i)) + \Sigma_m\, \Omega(f_m) \quad (2)$$

with learning rate η and a complexity penalty Ω on the number of leaves and leaf weights. XGBoost (Chen and Guestrin, 2016) [78] uses depth-wise growth (maximum depth 4, 600 rounds, $\eta = 0.03$, row and column subsampling of 0.8, L_2 penalty 2.0, minimum child weight 5). LightGBM (Ke *et al*., 2017) [115] uses leaf-wise growth with histogram-based splits (15 leaves, 600 rounds, $\eta = 0.03$, minimum 40 observations per leaf). Including both adds diversity, since their growth strategies produce differently shaped trees.

2.9. Stacked Ensemble

Let $p_k(x)$ denote the probability from base learner $k = 1, ..., 4$. The stacked ensemble combines them on the log-odds scale through a logistic meta-learner:

$$p_{stack}(x) = \Lambda(\, \alpha_0 + \Sigma_k\, \alpha_k \,\text{logit}(p_k(x))\,) \quad (3)$$

where Λ is the logistic function. The weights α_k must be learned on predictions the base learners did not see in training, otherwise the meta-learner rewards overfitting. We therefore pool the training and validation windows and generate out-of-fold predictions with five-fold *stratified group* cross-validation in which all observations of a firm fall in the same fold. Grouping by firm is essential: with persistent firm characteristics, random row-level folds leak information about the same firm across folds and inflate out-of-fold accuracy. The base learners are then refitted on the full pooled sample to produce test-window predictions. For comparison we also report a soft-voting ensemble that averages the four probabilities with equal weights.

2.10. Model Specifications

Each of the six models (four base learners, soft voting and stacking) is estimated twice: with financial ratios and sector dummies only (*ratios only*), and with financial ratios, sector dummies and the eight macroeconomic indicators (*ratios + macro*). This two-by-six design separates the effect of the learning algorithm (H1) from the effect of the information set (H2).

2.11. Evaluation Metrics

Because distress is rare (3.91% of test observations), accuracy is uninformative. We report five complementary metrics:

- AUC, the area under the ROC curve, the probability that a randomly chosen distressed firm-year is ranked above a randomly chosen healthy one (Fawcett, 2006) [104].
- PR-AUC (average precision), which focuses on the minority class and is more informative than AUC under heavy imbalance (Saito and Rehmsmeier, 2015) [205], a point also stressed in fraud-detection studies that face similar class ratios (Unamma, Iziduh, and Okwesa, 2021; Atakpa and Abetoh, 2022) [56, 229].
- The Brier score, the mean squared error of predicted probabilities, which penalizes miscalibration (Brier, 1950) [75].
- The Kolmogorov-Smirnov (KS) statistic, the maximum separation between the cumulative score distributions of the two classes, widely used in credit risk.
- Top-decile capture, the share of all distress events found among the 10% of firm-years with the highest predicted risk, which corresponds to a fixed review budget.

We also report a confusion matrix at a decision threshold chosen to maximize F1 on the out-of-fold training predictions, so that no test information is used, following the practice of adaptive risk-scoring systems that fix operating thresholds before deployment (Fadayomi *et al*., 2024) [101]. Statistical significance of AUC differences is assessed with a paired bootstrap of 1,000 resamples of test firm-years (Efron and Tibshirani, 1993) [92]; because the same resample is used for both models, the interval of the difference accounts for the strong correlation between their predictions.

2.12. Interpretability

We explain the ensemble using exact TreeSHAP values (Lundberg *et al*., 2020) [138] computed from the XGBoost component, which receives a substantial meta-weight.

Interpretable machine learning is increasingly expected of early-warning and credit models, both for analyst trust and for fairness and model-risk review (Komi and Adamolekun, 2021; Ominyi and Anichukwueze, 2023; Unamma and Ashore-Onisemo, 2023) [120, 190, 227]. For a prediction $F(x)$, the SHAP values φ_j satisfy

$$F(x) = \varphi_0 + \Sigma_j \varphi_j(x) \quad (4)$$

where φ_j is the contribution of feature j in log-odds units, defined as its average marginal contribution over all feature orderings (Lundberg and Lee, 2017) [137]. The mean absolute SHAP value over the test window measures global importance, and summing it within feature groups measures the share of signal attributable to financial ratios, macroeconomic indicators and sector.

2.13. Software and Reproducibility

The data-generating process, model estimation, bootstrap tests and figures are implemented in Python (scikit-learn 1.9, XGBoost 3.4, LightGBM 4.7) with fixed random seeds, so every reported number can be reproduced. Code is available from the author on request.

3. Results and Discussion

3.1. Out-Of-Time Predictive Performance

Table 4 reports test-window performance for all twelve model-feature combinations. Three patterns stand out. First, the stacked ensemble with macroeconomic indicators is the best or tied for best on every ranking metric: AUC 0.852, PR-AUC 0.342, KS 0.558 and top-decile capture of 57.5%. Second, with ratios only, the single tree learners do not beat the logit on AUC, and only the ensembles improve on it; combining learners matters more than choosing any single one. Third, adding macroeconomic indicators lifts every tree-based model and both ensembles, with the largest gains in PR-AUC (for the stacked ensemble from 0.318 to 0.342, a relative gain of 7.4%) rather than in AUC, indicating that macro information sharpens the ranking at the top of the risk distribution where it matters most for review.

Table 4: Out-of-time test performance, 2017 to 2022 (17,475 firm-years, 684 events)

Model	Features	AUC	PR-AUC	Brier	KS	Top-10% capture
Logistic regression	Ratios only	0.842	0.306	0.0318	0.551	55.0%
Random forest	Ratios only	0.842	0.312	0.0315	0.545	54.4%
XGBoost	Ratios only	0.838	0.312	0.0316	0.536	56.1%
LightGBM	Ratios only	0.836	0.311	0.0317	0.526	54.4%
Soft-voting ensemble	Ratios only	0.845	0.318	0.0314	0.552	55.8%
Stacked ensemble	Ratios only	0.845	0.318	0.0314	0.555	56.6%
Logistic regression	Ratios + macro	0.844	0.315	0.0496	0.539	54.4%
Random forest	Ratios + macro	0.843	0.342	0.0314	0.550	57.5%
XGBoost	Ratios + macro	0.851	0.343	0.0310	0.553	57.2%
LightGBM	Ratios + macro	0.851	0.340	0.0318	0.553	57.3%
Soft-voting ensemble	Ratios + macro	0.851	0.341	0.0332	0.557	56.6%
Stacked ensemble	Ratios + macro	0.852	0.342	0.0330	0.558	57.5%

Note: Higher is better for all metrics except the Brier score. The unconditional test distress rate (the PR-AUC of a random ranking) is 0.039. Top-10% capture is the share of all test distress events falling in the decile of firm-years with the highest predicted probability.

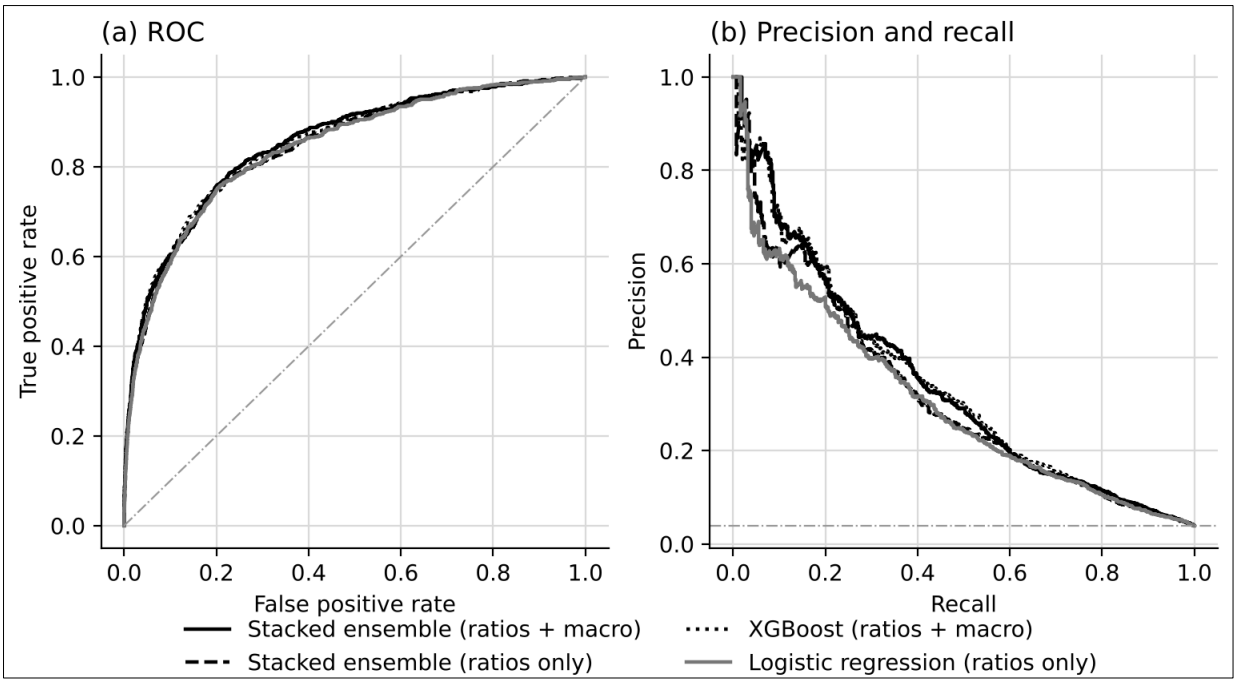


Fig 3: ROC curves (a) and precision-recall curves (b) on the out-of-time test window. The curves nearly coincide in ROC space; the separation is visible in the high-precision, low-recall region of panel (b), where the macro-augmented models identify the most clearly distressed firms with fewer false alarms.

Figure 3 illustrates why AUC differences are modest. The ROC curves overlap almost everywhere because all models, including the logit, rank the bulk of clearly healthy and clearly weak firms correctly. The macro-augmented models separate in the precision-recall plane at low recall, which is exactly the region in which a lender with a fixed review capacity operates.

3.2. Statistical Significance

Table 5 reports paired bootstrap tests. The stacked ensemble's improvement over a logistic regression with the same inputs is +0.008 AUC with a 95% interval of 0.004 to 0.012 that excludes zero in all 1,000 resamples, supporting H1. Adding macroeconomic indicators to the ensemble improves AUC by +0.007 (interval 0.0003 to 0.013, with 2.1% of resamples showing no gain), supporting H2. By contrast, the stacked ensemble is statistically indistinguishable from XGBoost alone (+0.001, interval -0.004 to 0.006). The ensemble's practical value over its best member is therefore robustness, since it does not require choosing the right learner in advance, rather than a large accuracy gain.

Table 5: Paired bootstrap comparison of test AUC (1,000 resamples)

Comparison	AUC difference	95% interval	Share of resamples with difference at or below 0
Stacked (ratios + macro) vs. logit (ratios + macro)	+0.0078	[0.0036, 0.0122]	0.000
Stacked (ratios + macro) vs. stacked (ratios only)	+0.0066	[0.0003, 0.0132]	0.021
Stacked (ratios + macro) vs. XGBoost (ratios + macro)	+0.0011	[-0.0035, 0.0056]	0.298

Note: Level AUCs with 95% bootstrap intervals: stacked (ratios + macro) 0.852 [0.836, 0.867]; stacked (ratios only) 0.845 [0.828, 0.860]; logit (ratios only) 0.842 [0.825, 0.859].

3.3. Classification at an Operating Threshold

At the F1-maximizing threshold of 0.24, chosen on out-of-fold training predictions, the macro-augmented stacked ensemble flags 1,186 firm-years (6.8% of the test window). It correctly identifies 343 of 684 distress events (recall 50.1%) with precision of 28.9%, about 7.4 times the base rate, and specificity of 95.0% (Table 6). For a like-for-like comparison, flagging the same 6.8% of firm-years with the ratios-only logit identifies 45.9% of events with 26.5% precision. At an equal review budget, the ensemble therefore catches roughly 29 additional distressed firms over the six test years, an improvement of the kind that early-warning and recovery programs in commercial lending are designed to exploit (Okoli, Pedro, *et al*., 2022) [176], or about one in every thirteen that the benchmark misses.

Table 6: Confusion matrix, stacked ensemble (ratios + macro), threshold 0.24

	Predicted distressed	Predicted healthy	Total
Actually distressed	343 (TP)	341 (FN)	684
Actually healthy	843 (FP)	15,948 (TN)	16,791
Total	1,186	16,289	17,475

Note: Recall 50.1%; precision 28.9%; specificity 95.0%; F1 0.367.

3.4. Meta-Learner Weights

The fitted stacking weights reveal how the ensemble uses its members. With macroeconomic inputs the meta-learner spreads weight across all four learners (random forest 0.335, logistic regression 0.264, XGBoost 0.216, LightGBM 0.176). With ratios only it leans more on the logit (0.389) and almost ignores LightGBM (0.051). This shift is informative: once macroeconomic variables enter, the regime-dependent interactions in the data become learnable, and the meta-learner moves weight toward the tree learners that can represent them.

3.5. What Drives the Predictions

Figure 4 ranks features by mean absolute SHAP value. GDP growth is the single most influential input (0.572 log-odds on average), roughly twice the next feature. This is not because it discriminates between firms in a given year, since it is identical for all firms in a year, but because it shifts the level of risk for every firm in a downturn and conditions how the ratios are read. The firm-level ranking is led by the current ratio (0.286), leverage (0.206), market equity to liabilities (0.191) and operating cash flow to liabilities (0.187), consistent with the liquidity, leverage and solvency dimensions emphasized since Beaver (1966) [65] and Altman (1968) [41]. The change in unemployment (0.152) ranks seventh and the credit spread (0.074) fourteenth.

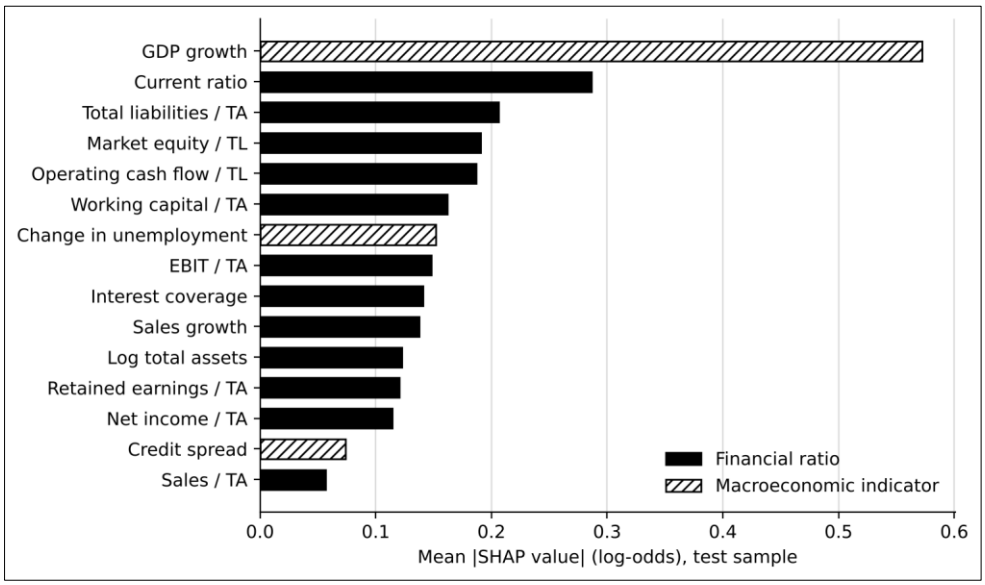


Fig 4: Global feature importance: mean absolute SHAP value on the test window, XGBoost component of the macro-augmented ensemble (top 15 features).

Summing within groups, financial ratios account for 63.6% of total mean absolute SHAP, macroeconomic indicators for 33.4% and sector for 3.0%. Macroeconomic indicators thus carry about one third of the signal used by the model, supporting H3. The two shares answer different questions: ratios determine *which* firms are at risk, while macroeconomic indicators determine *how much* risk the whole cross-section faces.

3.6. Performance Through the Cycle

Table 7 and Figure 5 break test performance down by year. Discrimination is consistently higher for the macro-augmented ensemble, which has the highest AUC in five of six years. The most revealing pattern, however, concerns the level of predicted risk. In normal years the macro-augmented ensemble tracks the observed distress rate closely, whereas the ratios-only ensemble overstates it in most normal years, by up to about one percentage point, because it has absorbed the training-window average, inflated by the crisis, as a constant. In the 2020 contraction the two err in opposite directions: the ratios-only ensemble under-reacts (11.3% predicted against 13.8% observed) because balance sheets at the end of 2020 do not yet fully reflect the shock, while the macro-augmented ensemble over-reacts (24.4%) because the only comparable contraction in training, 2009, coincided with a much larger credit-spread shock and a far higher distress rate.

Table 7: Test performance by observation year

Year	Firm-years	Events	Observed rate	Mean predicted: stacked, ratios only	Mean predicted: stacked, ratios + macro	AUC: logit, ratios only	AUC: stacked, ratios + macro
2017	2,850	58	2.0%	2.9%	1.8%	0.792	0.793
2018	2,875	31	1.1%	2.4%	1.4%	0.727	0.766
2019	2,900	84	2.9%	2.6%	1.8%	0.702	0.710
2020	2,925	404	13.8%	11.3%	24.4%	0.797	0.813
2021	2,950	20	0.7%	1.7%	1.5%	0.742	0.772
2022	2,975	87	2.9%	3.0%	2.4%	0.814	0.816

Note: Within-year AUCs are lower than the pooled AUC because pooling across years adds the between-year variation in distress rates, which the models partly capture.

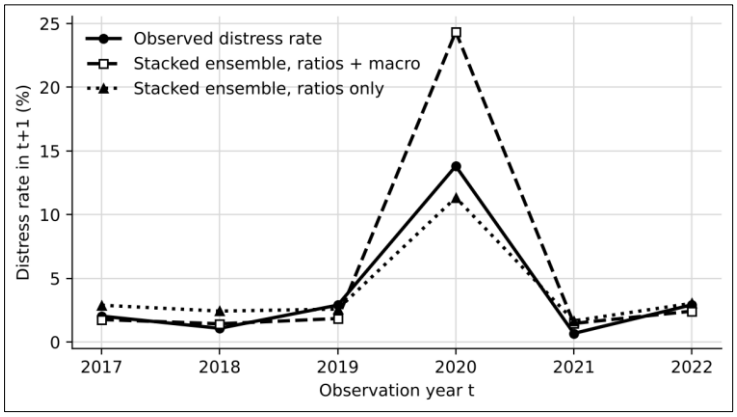


Fig 5: Observed and mean predicted distress rate by test year.

This calibration gap explains the one metric on which the macro-augmented models do not win in Table 4: the Brier score. Excluding 2020, the macro-augmented stacked ensemble has the lowest Brier score of all specifications (0.0179 against 0.0185 for both the ratios-only ensemble and logit), along with the highest AUC (0.779 against 0.775 and 0.771). In 2020 alone its Brier score is 0.108 against 0.096 for the ratios-only ensemble. The macro-augmented logit is worst of all in 2020 (Brier 0.206), because a linear model extrapolates the GDP coefficient to an output drop larger than any it observed.

3.7. Robustness: When Does the Ensemble Help?

To test H4 we re-estimate all models on the benchmark linear DGP, in which the true log-odds are approximately linear in the observed predictors and contain no threshold or interaction effects, keeping the panel mechanics, macroeconomic path and sample split unchanged. Table 8 compares the key results.

The results support H4 directly. In the linear design the ensemble's advantage over the logit vanishes (difference 0.000, interval -0.001 to 0.001) and the meta-learner places 80% of its weight on the logistic regression, effectively learning that the simple model is correctly specified. Stacking thus adapts gracefully: it does not lose accuracy when flexibility is unnecessary, which is a practical argument for its use when the true structure is unknown.

The value of macroeconomic information, on the other hand, is not tied to model flexibility. In the linear design macroeconomic indicators improve AUC by 0.014 for both the logit and the ensemble, a larger gain than in the main design. The reason is that in the non-linear design part of the macroeconomic effect operates through interactions with firm ratios, and the ratios-only tree learners already capture part of it indirectly, so the measured increment from adding macro variables is smaller.

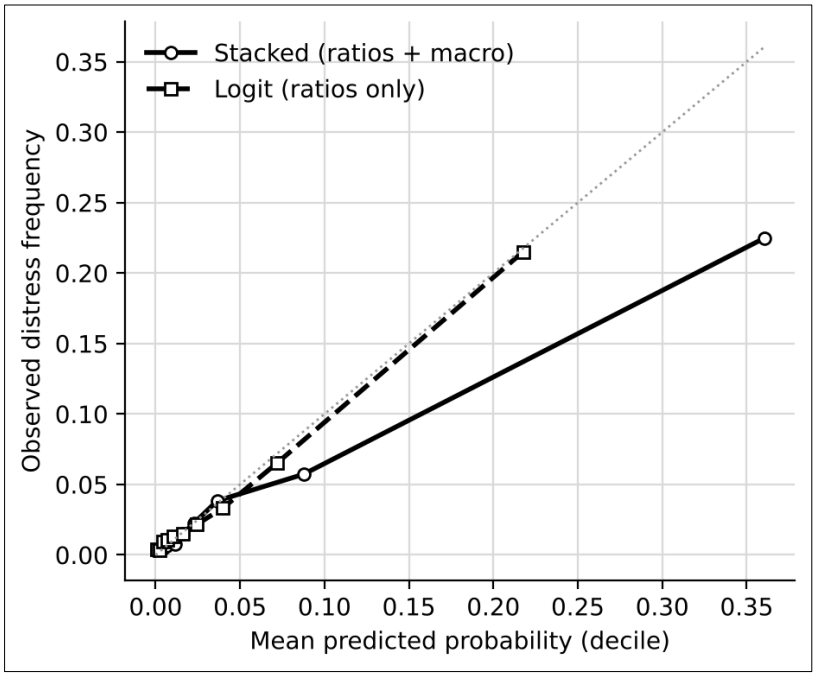


Fig 6: Reliability diagram on the full test window, by decile of predicted probability. Points above the diagonal indicate under-prediction; points below indicate over-prediction. The top decile of the macro-augmented ensemble (95% of which are 2020 observations) predicts 36.1% against an observed 22.5%, while the ratios-only logit is close to the diagonal in that decile (21.8% against 21.5%).

Table 8: Main design versus linear benchmark design (test-window AUC)

Specification	Non-linear design (main)	Linear benchmark design
Logistic regression, ratios only	0.842	0.819
Logistic regression, ratios + macro	0.844	0.833
XGBoost, ratios + macro	0.851	0.829
Stacked ensemble, ratios only	0.845	0.819
Stacked ensemble, ratios + macro	0.852	0.833
Ensemble minus logit (both ratios + macro), 95% interval	+0.008 [0.004, 0.012]	0.000 [-0.001, 0.001]
Macro gain for ensemble, 95% interval	+0.007 [0.0003, 0.013]	+0.014 [0.007, 0.021]
Meta-weight on logistic regression	0.26	0.80
Macro share of mean absolute SHAP	33.4%	27.9%

3.8. Interpreting the Gains

The improvements reported here are modest in AUC terms, between 0.007 and 0.010, and it is worth being clear about why that is the realistic expectation. Financial ratios are already strong predictors; the ratios-only logit reaches 0.842. The remaining errors are concentrated in firms whose ratios look acceptable at year end but which are exposed to a deterioration in conditions over the following year. That is exactly where macroeconomic information and interaction-aware learners help, and the effect is visible in the measures that focus on the top of the risk ranking: PR-AUC rises by 7.4% and the ensemble identifies about one in thirteen of the distressed firms that a logit misses at the same review budget.

For a lender or supervisor, gains of this size at the high-risk end translate into material differences in losses avoided.

Against the hypotheses of Section 1.3, the evidence supports all four. The stacked ensemble outperforms a logit on the same inputs (H1); macroeconomic indicators improve out-of-time discrimination (H2) and account for about one third of the signal (H3); and the ensemble's advantage appears only when the distress process contains threshold and interaction effects (H4). These results are consistent with the comparative evidence that ensembles outperform linear models (Lessmann *et al*., 2015; Barboza, Kimura and Altman, 2017; Jones, Johnstone and Wilson, 2017) [63, 113, 136] and with the evidence that macroeconomic information matters for default (Duffie, Saita and Wang, 2007; Tinoco and Wilson, 2013) [85, 213], while showing that the two gains have different sources: flexibility pays off only where the true process is non-linear, whereas macroeconomic information helps regardless.

3.9. The Calibration Trade-Off

The 2020 result is the paper's most practically important finding. Macroeconomic inputs let the model react to a downturn immediately, before balance sheets deteriorate, which is the whole point of including them. But the model can only learn the mapping from the macroeconomic state to the distress level from the downturns in its training history. With one prior crisis in the sample, it reads any deep contraction as a repeat of that crisis. Tree models cannot extrapolate beyond the training range, so they map the new state to the nearest region seen in training; linear models do extrapolate, and in this case extrapolate worse. Neither is a reliable guide to the level of distress in a novel downturn whose transmission differs, for example because of policy support. Studies of climate-related financial risk in banking make a similar observation: the transmission of a shock depends on policy and market responses that historical data cannot fully capture (Kinyanjui *et al*., 2021) [117].

We draw three practical recommendations. First, use macro-augmented ensembles primarily for *ranking*, where they are consistently superior, and treat their probability level with caution when the macroeconomic state is near or beyond the edge of the training data. Second, recalibrate the level, for example by re-estimating the meta-learner's intercept on the most recent realized distress rate or by applying Platt or isotonic recalibration to recent data (Niculescu-Mizil and Caruana, 2005) [157]. Third, combine the model with expert scenario overlays, as supervisory stress-testing and enterprise risk frameworks already do (Mensah *et al*., 2019a; Mensah *et al*., 2019b) [149, 150], so that information about policy support or the nature of the shock can adjust the macro mapping.

3.10. Implications

3.10.1 Theoretical implications

The study refines the theory of distress prediction in two ways. First, it treats the economic environment as a moderator of ratio effects, not merely an additional covariate, and shows that this conditioning structure is what allows flexible learners to outperform linear models. Second, it separates two sources of predictive gain, model flexibility and information, which earlier comparisons have usually confounded. A practical corollary for researchers is that head-to-head comparisons of learners on a single dataset should not be read as general: whether an ensemble beats a logit depends on the structure of the true distress process, which the stacking weights themselves can help diagnose.

3.10.2 Practical Implications

- **For lenders and credit analysts**, the ensemble offers a better-ordered watch list at a fixed review budget, with SHAP explanations that can be reported at firm level to satisfy model-risk and explainability requirements.
- **For auditors**, the model can serve as an independent, quantitative input to going-concern assessments, flagging firms whose position looks fragile given the economic environment even when their ratios look adequate in isolation.
- **For corporate managers and boards**, the decomposition into firm-level and macroeconomic drivers indicates which risks are under management control (liquidity, leverage, cash generation) and which require hedging, refinancing ahead of tightening cycles or contingency planning.

3.10.3 Policy and Regulatory Implications

- **For supervisors and central banks**, the macro-augmented model links the cross-section of firm risk to the economic outlook, making it usable for forward-looking provisioning and macro-prudential monitoring, provided the calibration caveat is managed.
- **For model-risk and AI governance**, the calibration failure in the recession year shows why validation should include out-of-time and stress-period tests, not only pooled accuracy, and why probability levels should be monitored and recalibrated when the macroeconomic state moves outside the training range.

Deploying such a model also falls within a growing governance literature. Work on algorithmic accountability, model risk management, responsible AI governance structures, fairness and bias auditing of credit decision models, adaptive control of AI in financial compliance environments, automated model evaluation and readiness for AI regulation (Annan, 2024; Ashore-Onisemo *et al*., 2024; Nwakamma *et al*., 2024a; Ominyi and Anichukwueze, 2023; Ominyi and Anichukwueze, 2024; Ominyi *et al*., 2024b; Sanni *et al*., 2022; Unamma and Ashore-Onisemo, 2023; Unamma *et al*., 2022) [48, 49, 159, 190, 191, 193, 209, 226, 227] emphasizes documentation, explainability and independent validation, which the SHAP decomposition and out-of-time protocol used here are designed to support. Related studies on technology-risk controls, cybersecurity and data-privacy governance in financial institutions, cross-border compliance, and the organizational conditions for sound investment decisions (Aliliele *et al*., 2023b; Anichukwueze *et al*., 2020; Annan, 2022; Atakpa and Abolaji, 2022; Bello *et al*., 2024; Mbonu *et al*., 2018; Oguntegbe *et al*., 2023; Okwesa *et al*., 2023; Ominyi and Anichukwueze, 2020; Ominyi, 2020; Ominyi, 2021; Ozowara *et al*., 2022; Uchechi, Ominyi, Anichukwueze, and Uzougbo, 2022) [39, 45, 47, 58, 66, 140, 168, 179, 186, 187, 188, 200, 222] describe the operational environment in which distress models must be implemented.

4. Conclusion

This paper set out to determine whether integrating macroeconomic indicators into an ensemble machine learning model improves the prediction of corporate financial

distress, and why. A stacked ensemble of logistic regression, random forest, XGBoost and LightGBM, given twelve financial ratios and eight macroeconomic indicators, delivered the strongest out-of-time ranking performance (AUC 0.852, PR-AUC 0.342, top-decile capture 57.5%), significantly better than a logit on the same inputs and better than the same ensemble without macroeconomic data. Macroeconomic variables, led by GDP growth and the change in unemployment, account for about one third of the model's predictive signal. The ensemble's advantage over a logit appears only when the distress process contains threshold and interaction effects, and the stacking weights adapt accordingly, shifting toward the logit when the true structure is linear. The value of macroeconomic information is present in both cases.

The benefit comes with a responsibility. A model that reacts to the economy will also over-react when the economy moves into territory its history does not cover. Used as a ranking and early-warning tool, recalibrated regularly and paired with scenario judgment in unusual downturns, a macro-augmented ensemble offers a meaningful and interpretable improvement over ratio-based models that have served the field since the 1960s, and a practical complement to the predictive risk analytics now being adopted by lenders and financial institutions (Mensah *et al*., 2022; Okoli, Pedro, *et al*., 2022; Medon and Oduleye, 2024) [146, 148, 176].

4.1. Limitations

The principal limitation of this study is that the evidence comes from a calibrated data-generating process rather than from observed firms. The design deliberately builds in non-linear and macro-interaction effects drawn from the literature, so the magnitudes reported here describe what an ensemble can gain *when such structure is present*, not how much structure exists in any particular market. The size of the macroeconomic contribution likewise depends on how strongly the true process loads on the cycle. The 2009 stress episode in the panel is also more severe than in most real samples, which amplifies the 2020 over-reaction. Other limitations are that the panel contains no market-based variables such as equity volatility, which are known to be informative (Campbell *et al*., 2008) [76], that macroeconomic indicators enter as annual national aggregates rather than sector- or region-specific series, and that one-year-ahead forecasts do not address the timing of distress beyond the next year.

4.2. Future Research

The first priority for future research is replication on observed data, following the same protocol: (i) assemble firm-years from Compustat, Orbis or an exchange-listed sample with a distress flag based on bankruptcy filings, delistings or the interest-coverage definition in Section 2.2; (ii) merge macroeconomic series from national statistics, the central bank and the IMF or World Bank at their year-*t* values; (iii) split chronologically so that at least one downturn falls in the test window; (iv) estimate base learners with firm-grouped out-of-fold stacking; and (v) report the full set of metrics in Section 2.11 together with year-by-year calibration.

Beyond replication, five extensions are particularly promising:

- **Emerging-market samples**, where currency and inflation shocks are larger and more frequent and where macroeconomic effects on payments and firm finance are already documented (Asibor *et al*., 2021; Oteri and Chibwaye, 2022; Akomolafe *et al*., 2023) [32, 54, 198].
- **Richer information sets**, adding market-based variables such as equity volatility (Campbell *et al*., 2008) [76] and textual information from annual reports and news.
- **Sector- and region-specific macroeconomic series**, which would sharpen the conditioning effect for firms whose exposure differs from the national aggregate.
- **Multi-horizon and survival formulations**, predicting the timing of distress over several years rather than a one-year event.
- **Calibration under regime change**, testing dynamic recalibration, scenario overlays and uncertainty quantification so that probability levels remain reliable in downturns unlike those seen in training.

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