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Asymmetric Forecasting of Tail Risk in Micro-Cap Stocks Using Inclusive Finance Factors: Evidence from Explainable Boosting Machines

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Article

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Abstract

This study examines whether inclusive-finance factors contain asymmetric predictive information for Micro-Cap stock tail risk. Motivated by the financing sensitivity of Micro-Cap firms, the study focuses on five inclusive-finance dimensions: financing demand, financing supply, financing price, financing efficiency, and financing risk. Changes in each factor are decomposed into positive and negative components, and an Explainable Boosting Machine (EBM) is employed to compare their out-of-sample forecasting performance. The interpretable structure of EBM is further used to examine nonlinear predictive patterns through Partial Dependence analysis. The results show that the predictive information embedded in inclusive-finance factors is directionally asymmetric. Positive changes in financing demand, financing price, and financing risk provide stronger warning signals for tail risk, whereas negative changes in financing supply and financing efficiency better capture deterioration in the financing environment. The Partial Dependence results further indicate that the relationship between inclusive-finance factors and future tail risk is nonlinear, range-dependent, and directionally heterogeneous. These findings suggest that decomposing inclusive-finance changes into positive and negative components helps reveal predictive information that may be obscured by raw factor levels. Overall, EBM provides both forecasting evidence and interpretable insights for monitoring and managing Micro-Cap stock tail risk.

Keywords: Tail Risk; Micro-Cap Stocks; Inclusive Finance Factors; Asymmetric Forecasting; Explainable Boosting Machines

1. Introduction

Micro-Cap stock tail risk is an important issue in capital-market risk monitoring. Compared with large-cap stocks, micro-cap stocks typically have weaker liquidity, higher information asymmetry, more limited financing channels, and insufficient risk-buffering capacity—these structural vulnerabilities make micro-cap stocks more prone than large-cap stocks to the gradual accumulation of tail risk and its eventual evolution into crash risk when credit conditions tighten, market liquidity declines, investor risk appetite changes, or external shocks intensify (He & Ren, 2023; Hutton et al., 2009; Kelly & Jiang, 2014; Kim et al., 2011;

Schreindorfer, 2020). Therefore, identifying predictive information that can reflect Micro-Cap stock tail risk in advance is important for investors' portfolio management, financing decisions of Micro-Cap business entities, and regulators' risk warning.

The development of inclusive finance provides a new perspective for understanding Micro-Cap stock tail risk. Inclusive finance emphasizes providing effective financial services to Micro-Cap business entities in an affordable and sustainable manner, and can reflect changes in the external financing environment, such as financing availability, financing costs, financing efficiency, and financing risk. Recent studies show that digital inclusive finance can alleviate financing constraints for small and medium-sized enterprises, improve financing accessibility, and affect firm innovation, financing behavior, and capital-market performance (Bu et al., 2024; Guan & Han, 2025; Wang et al., 2025; Zhang & Wang, 2025). However, existing literature pays more attention to the overall effect of inclusive finance or digital finance, and less attention to whether inclusive-finance factors contain differentiated tail-risk predictive information under different directions of change. Increases and decreases in the same inclusive-finance factor may have different economic meanings and may correspond to different risk signals. If only raw levels or symmetric change specifications are used, the predictive information embedded in directional shocks may be obscured. Therefore, this study decomposes inclusive-finance factors into positive and negative changes and examines their asymmetric predictive effects on Micro-Cap stock tail risk.

To identify this nonlinear and asymmetric predictive structure, this study employs the Explainable Boosting Machine (EBM) as the baseline model. EBM is an interpretable glass-box machine learning model in the InterpretML framework. It can decompose predictions into feature-level shape functions while maintaining strong predictive ability (Nori et al., 2019). Its methodological foundation is closely related to generalized additive models and intelligible models. Studies show that additive shape functions can capture complex nonlinear relationships while preserving interpretability (Lou et al., 2012; Lou et al., 2013). In recent years, machine learning methods have been widely used in asset pricing, risk prediction, and financial-market forecasting, and have been shown to capture complex nonlinear relationships that traditional linear models may fail to identify (Gu et al., 2020; Hancock & Khoshgoftaar, 2020). At the same time, interpretable machine learning has been increasingly applied to financial-risk forecasting. Related studies show that interpretable models can not only improve risk prediction but also reveal the contribution of different financial pressures or risk indicators to prediction results (Tang et al., 2024; Weng et al., 2022). For this

study, the advantage of EBM is that it can simultaneously identify nonlinearity, range dependence, and directional heterogeneity between inclusive-finance factors and tail risk, while providing interpretable evidence through native shape functions.

The marginal contributions of this study are mainly reflected in three aspects. First, this study extends inclusive-finance research to the prediction of Micro-Cap stock tail risk in China, linking changes in the Micro-Cap financing environment with capital-market tail-risk warning. China's capital market has a high level of retail investor participation, strong investor sentiment fluctuations, obvious limits to arbitrage, and an evolving institutional environment, which make the tail risk of low-cap stocks more likely to be affected by changes in the financing environment (Han & Shi, 2022; Sun et al., 2024). Second, this study constructs an asymmetric decomposition framework of positive and negative changes, and examines the predictive roles of financing demand, financing supply, financing price, financing efficiency, and financing risk under different directions of change, thereby identifying directional risk information that is difficult to reveal using raw levels. Third, this study applies EBM to the prediction of tail risk using inclusive-finance factors. Beyond out-of-sample forecasting accuracy, it further uses shape functions and Partial Dependence to explain how different directional shocks are mapped into future tail risk. Thus, this study not only provides new predictive evidence for monitoring Micro-Cap stock tail risk, but also offers an interpretable analytical framework for investors, Micro-Cap business entities, and regulators to identify asymmetric risk signals in the financing environment.

2. Literature Review

Research on Micro-Cap stocks usually explains their risk characteristics from the perspectives of firm size, liquidity, information asymmetry, and investor structure. The early size-effect literature shows that small-cap stocks have return-risk characteristics that differ from those of large-cap stocks (Banz, 1981). Subsequent studies on market microstructure and liquidity further demonstrate that transaction costs, bid-ask spreads, turnover, and liquidity risk affect stock returns and risk exposure (Amihud, 2002; Amihud & Mendelson, 1986; Datar et al., 1998; Pástor & Stambaugh, 2003). These issues are generally more pronounced for Micro-Cap stocks, which tend to have weaker trading depth, lower investor attention, limited disclosure quality, and insufficient analyst coverage. As a result, they are more vulnerable to liquidity shocks and investor sentiment. Behavioral finance research also shows that investor sentiment and retail trading generate stronger co-movement and pricing deviations among small-cap stocks, stocks with low institutional ownership, and stocks with higher limits to arbitrage

(Baker & Wurgler, 2006; Kumar & Lee, 2006). In the Chinese market, speculative trading, short-sale constraints, and investor segmentation have also been shown to affect price formation and risk accumulation (Pearson et al., 2021; Xiong & Yu, 2011). More recent evidence further indicates that the tail-risk effect in the Chinese stock market is closely related to investors' irrational biases and limits to arbitrage (Sun et al., 2024), while financing constraints increase firms' future stock price crash risk (He & Ren, 2023). These studies suggest that Micro-Cap stock risk is not driven only by general market volatility, but is also closely related to liquidity, information environment, investor behavior, and financing conditions.

The literature on inclusive finance emphasizes the accessibility, affordability, and effective use of financial services. Allen et al. (2016) discuss the foundations of financial inclusion from the perspective of account ownership and use of formal financial services, while Sarma and Pais (2011) view financial inclusion as an important link between financial development and social inclusion. With the integration of digital technology into the financial system, digital inclusive finance is considered capable of reducing service costs, expanding financial coverage, and alleviating the information asymmetry and insufficient collateral faced by micro and small entities in the traditional financial system (Ozili, 2018; Sahay et al., 2015). Recent studies further show that digital inclusive finance can ease SME financing constraints, improve financing accessibility, and affect firm innovation, financing behavior, and capital-market risk (Bu et al., 2024; Guan & Han, 2025; Wang et al., 2025; Zhang & Wang, 2025). These studies suggest that inclusive finance can affect the operating conditions of micro and small business entities through financing availability, financing costs, financing efficiency, and financing risk. However, the existing literature mainly focuses on the effects of inclusive finance on financing constraints, innovation, or firm performance, and pays less attention to its role as a source of predictive information for capital-market tail risk. This study therefore links the micro-financing environment with Micro-Cap stock tail risk and examines whether inclusive-finance factors provide forward-looking risk signals.

Asymmetric responses in financial markets constitute an important topic in risk research. Black (1976) was among the first to note the asymmetric relationship between stock returns and volatility, where negative shocks tend to trigger stronger volatility responses than positive shocks. Subsequent models, such as EGARCH, GJR-GARCH, and news-impact curves, further characterize the asymmetric effects of good and bad news on conditional volatility (Engle & Ng, 1993; Glosten et al., 1993; Nelson, 1991). Bekaert and Wu (2000) also discuss asymmetric volatility risk at both the market and firm levels. More recently, risk-

forecasting studies have emphasized asymmetric structures in regime switching, risk contagion, and tail dependence. For example, Benaid et al. (2024) examine volatility regimes using Markov-switching GARCH models, while Qiao and Qiao (2024) use Vine Copula methods to analyze risk contagion and tail dependence in portfolio optimization. These studies indicate that increases and decreases in financial variables are often not mirror images of each other. In particular, when risk, liquidity, and investor sentiment change, markets may respond more strongly to stress-type shocks.

In forecasting studies, the idea of asymmetry has been further developed through the decomposition of positive and negative changes. The nonlinear ARDL framework proposed by Shin et al. (2014) identifies short-run and long-run asymmetric effects by decomposing explanatory variables into positive and negative partial sums. Kilian and Vigfusson (2011) also argue that directly assuming symmetric responses to positive and negative macro-financial shocks may lead to misleading conclusions. Risk-forecasting research similarly shows that upside and downside variation, or good and bad volatility, contain different types of information. Patton and Sheppard (2015) show that good volatility and bad volatility differ in volatility persistence and forecasting power. Recent evidence from Ouyang and Lu (2024) demonstrate that decomposing, reconstructing, and integrating financial-risk indicators can improve systemic financial risk prediction. These studies provide a foundation for decomposing inclusive-finance factors into positive and negative changes.

In the context of this study, the asymmetry of inclusive-finance factors has clear economic meaning. Increases and decreases in the same factor may correspond to different signals in the financing environment. Changes in financing costs, credit support, financing efficiency, and financing risk may have different directions or intensities of predictive effects on Micro-Cap stock tail risk. If only raw factor levels or linear symmetric specifications are used, the risk information embedded in directional changes may be obscured. Compared with traditional parametric models, machine-learning forecasting frameworks can more flexibly capture nonlinearity, threshold effects, and range dependence, while interpretable models can further show how directional shocks are mapped into predicted risk levels. Building on the existing literature on financial asymmetry, this study combines positive/negative decomposition with an interpretable forecasting model to identify the asymmetric predictive information of inclusive-finance factors for Micro-Cap stock tail risk.

3. Data and Methods

3.1. Data

This study uses two categories of data: tail-risk measures for the micro cap stock market, and inclusive-finance indices. Tail-risk measures are calculated from daily market data and converted into quarterly indicators, while the inclusive-finance indicators are quarterly series and are matched at the quarterly frequency. The sample period is from 2015Q1 to 2025Q1, with 41 quarterly observations for the original quarterly variables.

The tail-risk measures are constructed from the daily prices of the CSI 2000 Index. The CSI 2000 Index, with index code 932000, selects 2,000 securities with relatively small market capitalization and good liquidity from the Shanghai and Shenzhen A-share markets. The index focuses on Micro-Cap firms and has a distinctive lower-capitalization market style. According to the index profile, the average market capitalization of its constituents is approximately RMB 4.4 billion, and firms with market capitalization below RMB 10 billion account for about 98.25% of the constituents. These features make the CSI 2000 Index an appropriate proxy for China's Micro-Cap stock market and a suitable basis for measuring Micro-Cap stock tail risk. Daily CSI 2000 Index data are obtained from the Wind database. First, the daily logarithmic return is calculated as $r_d = \ln(P_d) - \ln(P_{d-1})$, where P_d denotes the closing price of the CSI 2000 Index on trading day d, and r_d is the daily logarithmic return. The daily loss is then defined as $L_d = -r_d$. For each quarter, the daily loss observations within that quarter are used to compute the tail-risk indicators: ES_{95} and VaR_{95} (Acerbi & Tasche, 2002; Artzner et al., 1999). Specifically, ES_{95} is defined as the average loss conditional on losses exceeding the VaR_{95} threshold: $\mathrm{ES}_{95} = E(L_d \mid L_d \geq \mathrm{VaR}_{95})$. VaR_{95} is defined as the 95th percentile of the quarterly daily loss distribution: $\mathrm{VaR}_{95} = Q_{0.95}(L_d)$. Thus, ES_{95} captures the average severity of losses beyond that threshold, while VaR_{95} measures the tail-loss threshold. These two quarterly variables are used to represent the tail risk of the micro- cap stock market.

The inclusive-finance variables are obtained from the Inclusive Finance Index released by Xinhua Finance (https://indices.cnfin.com/). This study focuses on five financing-related sub-indices: Financing Demand, Financing Supply, Financing Price, Financing Efficiency, and Financing Risk. Financing Demand reflects the strength of financing needs among micro and small enterprises. A higher value generally indicates stronger financing demand, but the direction is economically ambiguous because stronger demand may arise from either expansion needs or liquidity pressure. Financing Supply measures the availability of financial support for micro and small enterprises. A higher value indicates more sufficient credit supply and stronger financial support. Financing Price measures the financing cost faced by micro and small enterprises; a higher value indicates

higher financing costs. Financing Efficiency captures the timeliness and convenience of obtaining financing, with a higher value indicating greater efficiency. Financing Risk reflects risks embedded in the financing process, where a higher value usually indicates higher financing risk.

To capture directional changes in inclusive-finance conditions, each factor is decomposed into positive and negative changes. For a given inclusive-finance factor X_t, the quarterly change is calculated as $\Delta X_t = X_t - X_{t-1}$. The positive component is defined as $\mathrm{POS}_t = \max(\Delta X_t, 0)$, and the negative component is defined as $\mathrm{NEG}_t = \max(-\Delta X_t, 0)$. Here, POS_t captures the magnitude of upward movements in the factor, while NEG_t captures the absolute magnitude of downward movements.

The descriptive statistics (Table 1) indicate that the positive and negative changes in inclusive finance factors exhibit clear asymmetry and volatility. Some indicators, such as financing demand, financing supply, and financing efficiency, show more pronounced positive changes, whereas financing price and financing risk display relatively stronger negative changes. This suggests that different dimensions of inclusive finance experienced heterogeneous adjustment directions and magnitudes during the sample period. In addition, most POS/NEG variables are right-skewed and leptokurtic, indicating that inclusive finance shocks are not evenly distributed but are characterized by occasional large fluctuations. ES 95, as the tail-risk measure, also shows a certain degree of right skewness, suggesting that the tail risk of micro- and small-cap stocks increased markedly in some periods. Overall, these features justify distinguishing between positive and negative changes in inclusive financing factors when examining their asymmetric predictive effects on tail-risk.

Table 1. Descriptive statistics.

Variable	Mean	SD	Min	p50	Max	Skewness	Kurtosis
pos financing demand	5.3093	10.4377	0.0000	0.8200	40.7300	2.4371	7.7432
neg financing demand	4.3925	7.2496	0.0000	0.0000	38.5800	2.8444	13.3846
pos financing supply	4.6113	6.9972	0.0000	1.2800	35.5000	2.5530	11.0893
neg financing supply	2.1538	3.7376	0.0000	0.0000	17.1100	2.1906	7.9977
pos financing price	0.7458	1.9274	0.0000	0.0000	9.1400	2.9856	11.5931
neg financing price	1.5775	2.4625	0.0000	1.0150	13.5100	3.2687	15.4117
pos financing	6.5625	10.7617	0.0000	2.2500	52.0000	2.6013	10.1603

efficiency							
neg financing efficiency	3.6923	7.7672	0.0000	0.0000	28.9900	2.2157	6.9522
pos financing risk	3.0228	6.0381	0.0000	0.0000	26.8300	2.6198	9.8192
neg financing risk	3.6940	5.2494	0.0000	1.6050	26.2400	2.3142	9.7037
ES_{95}	0.0394	0.0177	0.0129	0.0338	0.0816	0.7208	2.5868
VaR_{95}	0.0285	0.0146	0.0103	0.0244	0.0756	1.3661	4.8077

3.2. Explainable Boosting Machine

This section describes the Explainable Boosting Machine (EBM) framework used to evaluate whether inclusive-finance factors contain predictive information for tail risk. EBM is treated as an interpretable additive boosting model (Nori et al., 2019). Its main advantage is that the prediction can be decomposed into feature-specific shape functions, so that forecasting accuracy and economic interpretation can be analyzed within the same framework. The model is implemented under an additive structure without interaction terms, which makes the marginal contribution of each predictor directly observable.

Variable construction and forecasting target. Let y_{t+1} denote the future tail-risk measure to be predicted. The predictors are the inclusive-finance direction-specific factors. For each inclusive-finance factor, the positive component (POS) captures upward movements in the factor, while the negative component (NEG) captures the magnitude of downward movements. Accordingly, the empirical analysis compares three predictor specifications: POS_ONLY, NEG_ONLY, and JOINT. The POS_ONLY uses the positive component, NEG_ONLY uses the negative component, and JOINT includes both POS and NEG.

Additive EBM representation. The general additive form of EBM is expressed as

$$\hat{y}_i = \beta_0 + \sum_{j=1}^{p} f_j\left(z_{ij}\right), \tag{1}$$

where β_0 is the intercept, z_{ij} is the j-th predictor of observation i, and $f_j(\cdot)$ is the learned shape function for predictor j. Since the baseline EBM is estimated without interaction terms, the prediction is fully decomposable into additive main effects.

For the positive-change specification, the model is

$$\hat{y}_{t+h,P} = \beta_0 + f_P(p_t). \tag{2}$$

For the negative-change specification, the model is

$$\hat{y}_{t+h,N} = \beta_0 + f_N(n_t). \tag{3}$$

For the joint asymmetric specification, the model is

$$\hat{y}_{t+h,J} = \beta_0 + f_P(p_t) + f_N(n_t). \tag{4}$$

This structure allows the predictive role of positive and negative changes to be compared directly, because their effects enter the model through separate shape functions.

Cyclic gradient boosting estimation. EBM estimates each shape function through a cyclic gradient boosting procedure. With squared-error loss, the empirical objective is

$$\mathcal{L} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2. \tag{5}$$

The initial prediction is set to the sample mean of the training target:

$$\hat{y}_i^{(0)} = \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i. \tag{6}$$

At boosting round m, the pseudo-residual is the negative gradient of the loss:

$$g_i^{(m)} = y_i - \hat{y}_i^{(m-1)}. \tag{7}$$

For a given feature j, a shallow regression tree or weak learner is fitted to the residuals using only that feature:

$$h_j^{(m)} = \underset{h}{\operatorname{argmin}} \sum_{i=1}^{n} \left(g_i^{(m)} - h(z_{ij})\right)^2. \tag{8}$$

The corresponding feature-specific shape function is updated as

$$f_j^{(m)}(z) = f_j^{(m-1)}(z) + \nu h_j^{(m)}(z), \tag{9}$$

where ν is the learning rate. The model prediction is then updated by adding the latest contribution of the selected feature:

$$\hat{y}_i^{(m)} = \beta_0 + \sum_{j=1}^{p} f_j^{(m)}(z_{ij}). \tag{10}$$

The cyclic boosting process updates one feature function at a time and repeatedly cycles over all features:

$$j_m = 1 + \big((m-1) \bmod p\big). \tag{11}$$

After M boosting rounds, the final EBM predictor is

$$\hat{f}_E(\mathbf{z}_i) = \beta_0 + \sum_{j=1}^{p} f_j^{(M)}(z_{ij}). \tag{12}$$

Because each update is assigned to a specific feature function, the fitted model remains interpretable even though the shape functions are learned flexibly.

Expanding-window forecasting. To evaluate out-of-sample forecasting performance, the model is estimated using an expanding-window scheme. Let s_0 denote the initial training size. At each forecasting step $s \geq s_0$, the training set is

$$\mathcal{D}_s = (\mathbf{z}_t, y_{t+h})_{t=1}^{S}. \tag{13}$$

The EBM fitted on this training window is denoted by

$$\hat{f}_s = E(\mathcal{D}_s). \tag{14}$$

The one-step-ahead out-of-sample prediction is then obtained as

$$\hat{y}_{s+1+h|s} = \hat{f}_s(\mathbf{z}_{s+1}). \tag{15}$$

After the actual observation becomes available, the training window expands and the model is re-estimated:

$$\mathcal{D}_{s+1} = \mathcal{D}_s \cup \{(\mathbf{z}_{s+1}, y_{s+1+h})\}. \tag{16}$$

The out-of-sample forecast error is

$$e_{s+1} = y_{s+1+h} - \hat{y}_{s+1+h|s}. \tag{17}$$

Forecasting error metrics. Forecasting accuracy is evaluated using four standard loss measures. For N out-of-sample forecasts, the mean squared error is

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 . \tag{18}$$

The root mean squared error is

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} . \tag{19}$$

The mean absolute error is

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| . \tag{20}$$

The mean absolute percentage error is

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| . \tag{21}$$

Partial Dependence. Partial Dependence is used to summarize the average marginal predictive pattern of a feature over its observed range. For feature j and grid value v, the Partial Dependence function is

$$\text{PD}_j(v) = \frac{1}{n}\sum_{i=1}^{n}\hat{f}_E\left(v, \mathbf{z}_{i,-j}\right). \tag{22}$$

where $\mathbf{z}_{i,-j}$ denotes all predictors except feature j. Under the additive EBM, however, this expression simplifies to

$$PD_j(v) = \frac{1}{n}\sum_{i=1}^{n}\left[\beta_0 + f_j(v) + \sum_{k\neq j} f_k\left(z_{ik}\right)\right] \tag{23}$$

Therefore,

$$PD_j(v) = f_j(v) + C_j \tag{24}$$

where

$$C_j = \beta_0 + \frac{1}{n}\sum_{i=1}^{n}\sum_{k\neq j} f_k\,(z_{ik}) \tag{25}$$

is a constant independent of v. Thus, the shape, amplitude, and nonlinear pattern of the Partial Dependence curve are fully determined by the native EBM shape function $f_j(v)$. The native shape function is therefore used as the exact feature-specific effect function rather than a post-hoc approximation.

For the asymmetric joint specification, the positive and negative components are represented by two separate native shape functions:

$$S_P(v) = f_P(v) \tag{26}$$

$$S_N(v) = f_N(v) \tag{27}$$

In the asymmetric analysis, these curve summaries help identify whether positive or negative changes have larger predictive amplitude, stronger marginal variation, or more pronounced nonlinear patterns. Therefore, EBM provides both a forecasting model and an interpretable framework for examining the asymmetric predictive content of inclusive-finance factors.

4. Results

4.1. Asymmetric forecasting results

Table 2 presents the out-of-sample forecasting accuracy of the POS and NEG components of inclusive-finance factors for Micro-Cap stock tail risk (ES_{95}). Overall, the results show that the predictive information embedded in inclusive-finance factors is not symmetric across upward and downward movements.

Financing demand's positive changes can be interpreted as a risk-enhancing signal. An increase in financing demand does not necessarily indicate only business expansion; it may also reflect stronger working-capital pressure, tighter liquidity constraints, and greater dependence on external financing among Micro-Cap firms. When financing demand rises rapidly, the market may interpret it as a sign of increasing cash-flow pressure or short-term funding needs, thereby increasing future exposure to tail risk This interpretation is consistent with the financing-constraints literature, which argues that financing constraints make firms' investment and operations more dependent on internal cash flow and more sensitive to changes in external financing conditions (Fazzari et al., 1987; Hirth & Viswanatha, 2011). Smaller firms are also more likely to face financial and institutional constraints, implying that Micro-Cap firms are particularly sensitive to changes in financing demand (Beck et al., 2005).

The negative change in financing supply more directly reflects a deterioration in the financing environment. For Micro-Cap firms, external financing channels are usually more limited, and a contraction in credit support can weaken their liquidity buffers and refinancing capacity. When financing supply declines, firms become more vulnerable to market fluctuations, funding-chain pressure, and

lower investor risk appetite. Therefore, NEG changes in financing supply are more likely to contain predictive information about future increases in tail risk. This mechanism is also consistent with the literature on small-firm financing constraints, which shows that smaller firms are more strongly affected by changes in external financial conditions.

A positive change in financing price represents an increase in financing costs. Higher financing costs compress Micro-Cap firms' profit margins and cash-flow flexibility, while also increasing market concerns about their debt-servicing capacity and operational stability. Since Micro-Cap stocks are more sensitive to changes in financing conditions, increases in financing price are more likely to be transmitted into tail risk. Therefore, POS changes in financing price have stronger risk-predictive implications. From the perspective of financing constraints, rising external financing costs intensify financing frictions, increase firms' dependence on internal funds, and may affect investment and operating decisions.

The negative change in financing efficiency indicates a decline in loan approval speed, funding timeliness, or financing convenience. Even if the total supply of financing does not fall substantially, lower financing efficiency may delay firms' access to funds and reduce their ability to respond to short-term shocks. For Micro-Cap firms that rely more heavily on external financing for working-capital turnover, a decline in financing efficiency can amplify liquidity vulnerability. Thus, NEG changes in financing efficiency are more informative for predicting future tail risk. This channel is consistent with the core idea of the financing-constraints literature: financing frictions are reflected not only in the quantity and cost of external funds, but also in whether firms can obtain external financing in a timely and effective manner.

A positive change in financing risk indicates rising credit risk, default pressure, or financial fragility in the financing process. An increase in this indicator suggests greater uncertainty and higher risk premia in the financing environment, which may intensify investors' concerns about Micro-Cap firms' fundamentals and debt-servicing ability. Therefore, POS changes in financing risk are more likely to serve as forward-looking signals of larger future tail losses.

Overall, the results for the five factors indicate that the predictive effect of inclusive-finance variables on tail risk is mainly reflected in the asymmetry of directional shocks. The POS/NEG decomposition helps uncover risk signals that would be obscured if only raw factor levels were used. Therefore, these findings suggest that Micro-Cap stock tail risk is more sensitive to deteriorations in the financing environment and to financing-pressure shocks, supporting the use of POS/NEG decomposition.

Table 2. out-of-sample forecasting accuracy for tail risk

Factor	POS-MSE	POS-RMSE	POS-MAE	POS-MAPE	NEG-MSE	NEG-RMSE	NEG-MAE	NEG-MAPE
Financing Demand	0.000347	0.018632	0.015513	0.529896	0.000371	0.019267	0.013223	0.437163
Financing Supply	0.000384	0.019603	0.016837	0.598877	0.000257	0.016047	0.013275	0.456699
Financing Price	0.000299	0.017299	0.014260	0.474674	0.000338	0.018396	0.014810	0.460637
Financing Efficiency	0.000331	0.018190	0.015887	0.557833	0.000322	0.017946	0.015039	0.535509
Financing Risk	0.000321	0.017925	0.014573	0.491972	0.000344	0.018543	0.015874	0.556360

4.2. Asymmetric mechanisms

After comparing out-of-sample forecasting accuracy, it is necessary to further examine the Partial Dependence curves. Forecasting accuracy metrics can indicate whether the POS or NEG component has stronger predictive power, but they do not reveal the nonlinear relationship underlying this predictive advantage. Partial Dependence curves provide a direct visualization of how positive and negative changes are separately mapped into the predicted level of future tail risk, thereby helping explain why shocks in one direction contain stronger risk-related information.

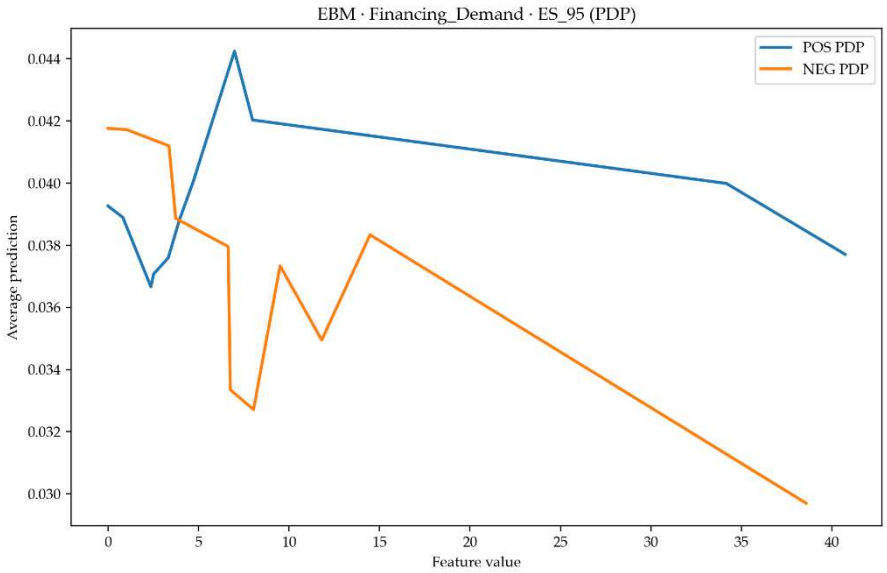


Figure 1. Partial Dependence: Financing Demand.

The Partial Dependence results reflect the average predictive response of the EBM to future tail risk under different magnitudes of financing demand changes. As shown in Figure 1, the mean of the POS component of financing demand is higher than that of the NEG component. This indicates that increases in financing demand were more common during the sample period and exhibited more continuous variation. Building on this distributional feature, the Partial Dependence curve further shows that the POS curve is generally located above the NEG curve, especially over the medium and high ranges of feature values. This suggests that increases in financing demand are associated with a higher model-predicted level of future tail risk, while decreases in financing demand do not generate a comparable risk-enhancing response.

In terms of response magnitude, the POS component exhibits a stronger and more pronounced predictive response. When positive changes in financing demand move from low to moderate levels, the predicted tail risk increases noticeably, indicating that moderate increases in financing demand contain stronger risk-related information. Economically, this range may correspond to the stage at which rising financing demand begins to reveal growing working-capital pressure, stronger dependence on external funding, and tighter cash-flow constraints among Micro-Cap firms. However, when the POS component enters a higher range, the curve does not continue to increase monotonically; instead, it gradually declines while remaining at a relatively high level. One possible interpretation is that extremely high financing demand may already be recognized by the market as a clear risk signal, so that additional increases in financing demand provide less incremental information for tail-risk prediction. In other words, the model suggests a diminishing marginal predictive effect at the upper tail of financing-demand shocks. This pattern indicates that the relationship between financing demand increases and tail risk is not simply linear, but is characterized by threshold-like behavior, range dependence, and nonlinear risk pricing.

By contrast, the NEG curve shows a more persistent downward trend. As the magnitude of negative changes in financing demand increases, the predicted level of tail risk gradually declines. This implies that larger decreases in financing demand do not correspond to stronger tail-risk warnings. Economically, this may reflect an easing of external financing pressure, reduced dependence on external funds, or a narrowing of short-term funding gaps. Overall, positive changes in financing demand better capture the financing pressure and financial vulnerability of Micro-Cap firms, whereas negative changes are more likely to indicate a relaxation of financing pressure. Thus, the two directions of financing demand changes exhibit a clear asymmetric predictive response for tail risk.

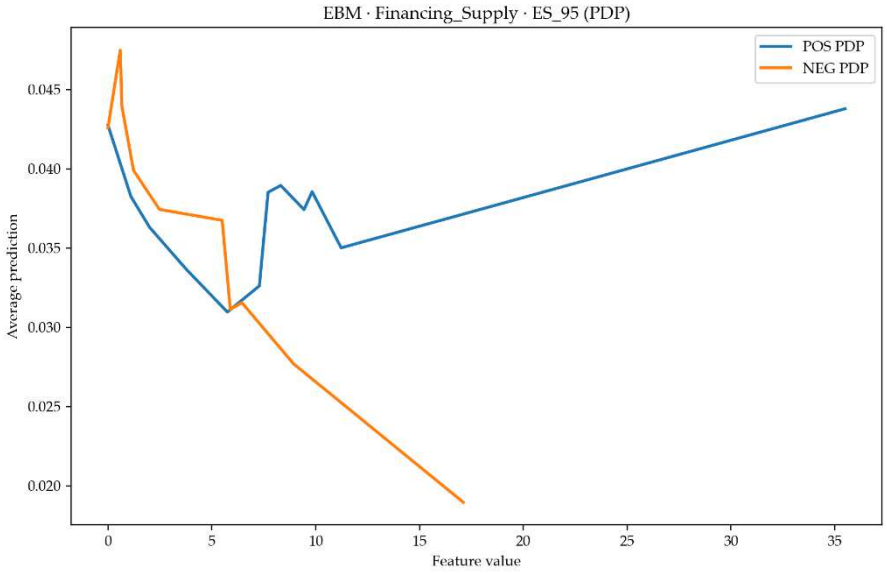


Figure 2. Partial dependence: Financing Supply.

Figure 2 presents the average predictive response of future tail risk to positive and negative changes in financing supply. According to the descriptive statistics in Table 1, the mean of the POS component of financing supply is higher than that of the NEG component, indicating that financing supply expansion was more common during the sample period, whereas financing supply contraction was relatively more intermittent and shock-like. Given this distributional feature, the Partial Dependence curves show that the predictive responses of POS and NEG to tail risk are asymmetric. The POS curve generally follows a pattern of first declining and then rising, whereas the NEG curve displays a more pronounced one-way downward trend. This suggests that the risk information contained in positive and negative changes in financing supply is not simply symmetric.

For the POS curve, positive changes in financing supply are associated with a relatively high predicted tail-risk level at low feature values, followed by a rapid decline and a lower predicted risk level around the medium range. However, when financing supply continues to expand, the predicted risk level gradually rises again. This indicates that an increase in financing supply does not necessarily reduce tail risk in a linear manner. On the one hand, a moderate improvement in financing supply may alleviate funding pressure for Micro-Cap firms and therefore correspond to a lower predicted risk level. On the other hand, excessive expansion in financing supply may reflect credit expansion, rising risk appetite, or accelerated capital allocation, which may push the model-implied tail-risk prediction upward again. Therefore, the POS curve exhibits clear nonlinearity and range dependence.

By contrast, the NEG curve corresponds to a higher predicted risk level in the low-value range and then declines continuously as the magnitude of negative changes in financing supply increases. This pattern suggests that the risk implication of financing supply contraction is not monotonically increasing. A small decline, or the early stage of a decline in financing supply, may be more easily identified by the model as an early signal of a weakening financing environment, thereby corresponding to higher predicted tail risk. However, when the magnitude of negative changes increases further, the predicted risk level instead declines, possibly indicating that the market has already adjusted to the financing contraction, or that a larger contraction corresponds to post-risk-exposure credit tightening and stronger financing constraints. Overall, the POS and NEG curves of financing supply differ clearly in their relative positions, dynamic directions, and nonlinear shapes, indicating that the predictive role of financing supply for Micro-Cap stock tail risk is strongly directional and state-dependent.

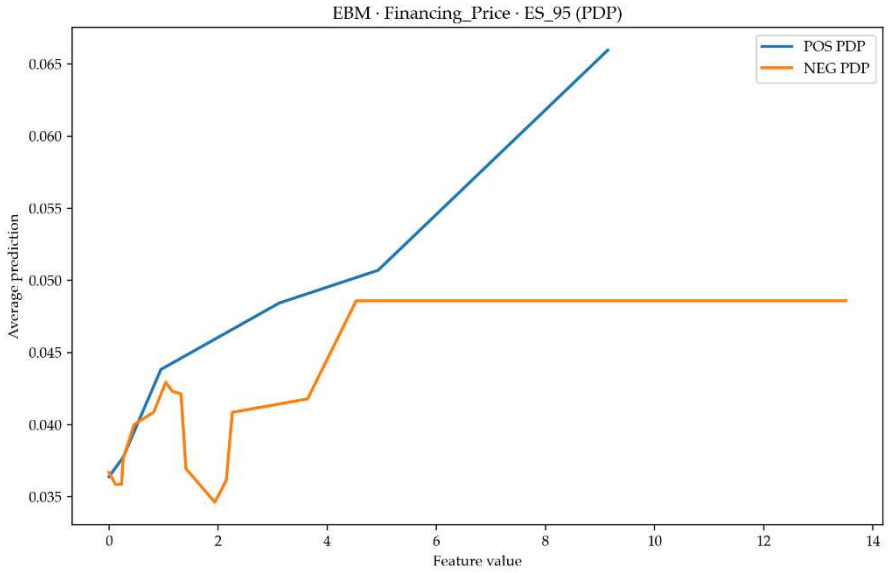


Figure 3. Partial dependence: Financing Price.

Figure 3 presents the average predictive response of future tail risk to positive and negative changes in financing price. Financing price is a negative indicator by nature, as an increase in this factor implies higher financing costs for Micro-Cap firms. Therefore, POS changes carry stronger risk-related implications. As shown in Table 1, the mean of the NEG component of financing price is higher than that of the POS component, indicating that financing price declines were relatively larger during the sample period. However, the Partial Dependence curves show that the POS curve is much steeper and significantly above the NEG curve in the

higher feature-value range. This suggests that although increases in financing price may not be the most frequent or largest changes on average, they generate a stronger predictive response for tail risk.

For the POS curve, positive changes in financing price show a relatively clear upward relationship with future tail risk. As the magnitude of financing price increases expands, the model-predicted tail risk continues to rise. In particular, in the higher range of financing price shocks, the slope of the curve becomes noticeably steeper, indicating that rising financing costs have a strong risk-amplifying effect. Economically, higher financing prices increase the cost of funds for Micro-Cap firms, compress profit margins and cash-flow flexibility, and weaken refinancing capacity. Therefore, when financing costs rise to a relatively high level, the market is more likely to interpret this as a signal of greater financial vulnerability and higher future tail risk.

By contrast, the NEG curve is generally flatter and becomes stable in the higher range of negative changes. Although financing price declines show some fluctuations in the low-value range, the predicted tail-risk level does not continue to decline substantially as the magnitude of price decreases expands; instead, it remains within a relatively stable range. This suggests that although lower financing prices may indicate an improvement in financing costs, their risk-mitigating effect exhibits diminishing marginal predictive response. In other words, declining financing costs may improve the financing environment, but once the decline reaches a certain range, the model does not identify an additional strong reduction in predicted tail risk.

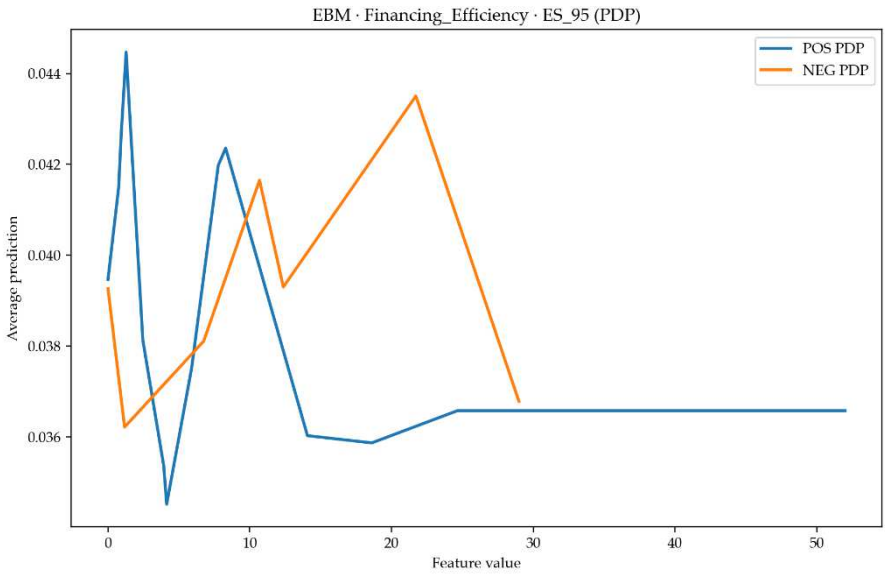


Figure 4. Partial dependence: Financing Efficiency.

Figure 4 presents the average predictive response of future tail risk to positive and negative changes in financing efficiency. The NEG curve rises noticeably in the medium range of feature values, indicating that when financing efficiency declines by a certain magnitude, the model assigns a higher predicted level of tail risk. This suggests that deterioration in financing efficiency is more likely to be identified as a risk signal associated with rising liquidity pressure and stronger financing constraints for Micro-Cap firms.

By contrast, the POS curve tends to remain at a lower and relatively stable predicted risk level in the higher range. This indicates that improvements in financing efficiency do not continuously increase tail risk; instead, they are more likely to reflect an improved financing environment and reduced working-capital pressure. In other words, higher financing efficiency helps lower the model-implied risk level, although this effect is not a simple linear decline but varies across different ranges of feature values.

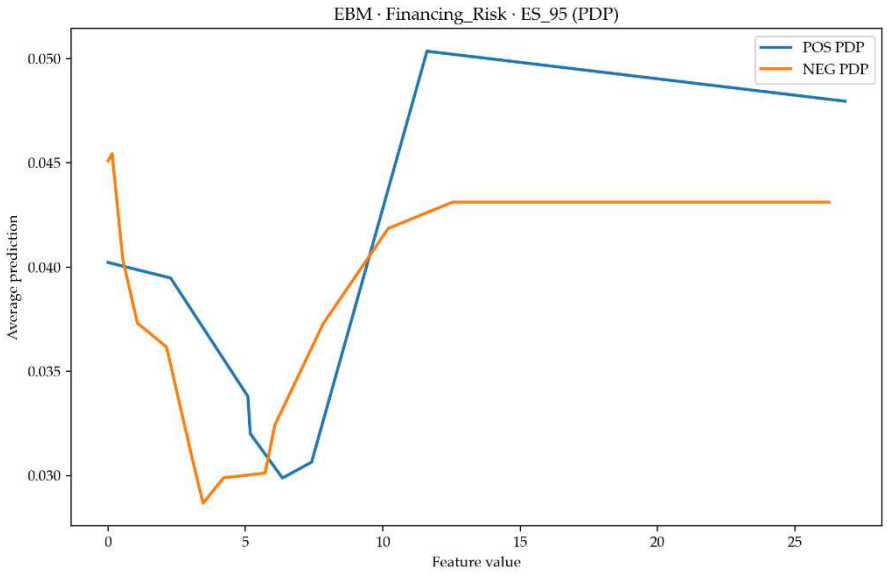


Figure 5. Partial dependence: Financing Risk.

Figure 5 presents the average predictive response of future tail risk to positive and negative changes in financing risk. The POS curve rises sharply in the medium-to-high range and remains at a relatively high predicted risk level, indicating that once financing risk increases beyond a certain magnitude, the model assigns a substantially higher prediction to future tail risk. This suggests that positive changes in financing risk are more likely to be identified as signals of rising financing fragility and increasing risk exposure among Micro-Cap firms. Recent evidence also shows that financing constraints significantly increase firms' future stock price crash risk, indicating a close link between financing fragility and capital-market tail risk (He & Ren, 2023).

By contrast, the NEG curve declines markedly in the low-value range, then gradually rebounds and stabilizes. This indicates that a decline in financing risk is associated with some degree of risk mitigation, but this mitigating effect does not strengthen linearly. Overall, the POS and NEG curves exhibit clear asymmetry: the POS curve corresponds to a higher predicted tail-risk level in the medium-to-high range, whereas the NEG curve mainly shows a pattern of initial decline followed by stabilization. This suggests that increases in financing risk have stronger tail-risk warning value than decreases in financing risk.

4.3. Robustness checks

To further verify the reliability of the baseline results, this study conducts robustness checks from two perspectives: alternative risk measures and alternative model specifications. First, ES_{95} in the baseline analysis is replaced with VaR_{95} to examine whether inclusive-finance factors contain consistent predictive information across different tail-risk measures (please see Table 3). Second, alternative models, including Generalized Additive Model (GAM), Categorical Boosting (CatBoost), and Gaussian Process Regression (GPR), are employed to perform out-of-sample forecasting again, in order to assess whether the baseline EBM results are driven by a specific model specification (please see Table 4). The results show that the relative forecasting performance of POS and NEG components and the main economic interpretations remain broadly consistent across different risk measures and model frameworks. This suggests that the conclusion that inclusive-finance factors asymmetrically predict Micro-Cap stock tail risk is robust.

Table 3. out-of-sample forecasting accuracy for VaR_{95}.

Factor	POS-MSE	POS-RMSE	POS- MAE	POS-MAPE	NEG- MSE	NEG-RMSE	NEG- MAE	NEG-MAPE
Financing Demand	0.000168	0.012956	0.011010	0.473644	0.000201	0.014178	0.009354	0.416389
Financing Supply	0.000191	0.013805	0.011596	0.502015	0.000107	0.010352	0.008543	0.373870
Financing Price	0.000141	0.011880	0.009375	0.379689	0.000168	0.012949	0.009695	0.375034
Financing Efficiency	0.000161	0.012703	0.010867	0.478540	0.000144	0.011993	0.010028	0.456085
Financing	0.000143	0.011978	0.009721	0.406999	0.000155	0.012434	0.010615	0.472837

Factor	POS-MSE	POS-RMSE	POS- MAE	POS-MAPE	NEG- MSE	NEG-RMSE	NEG- MAE	NEG-MAPE
Risk								

Table 4. Alternative model robustness checks

Model	Factor	POS-MSE	POS-RMSE	POS-MAE	POS-MAPE	NEG-MSE	NEG-RMSE	NEG-MAE	NEG-MAPE
GAM	Financing Demand	0.000338	0.018383	0.015365	0.543171	0.000319	0.017858	0.012137	0.383075
GAM	Financing Supply	0.000417	0.020431	0.016956	0.594428	0.000262	0.016176	0.013565	0.448081
GAM	Financing Price	0.000302	0.01737	0.014326	0.487844	0.000313	0.017703	0.014827	0.526708
GAM	Financing Efficiency	0.000321	0.017911	0.015072	0.545288	0.000322	0.017939	0.015006	0.534800
GAM	Financing Risk	0.000324	0.017996	0.014980	0.521939	0.000322	0.017958	0.015196	0.542746
CatBoost	Financing Demand	0.000344	0.018553	0.014909	0.502602	0.000435	0.020864	0.013662	0.467038
CatBoost	Financing Supply	0.000395	0.019864	0.016777	0.595753	0.000207	0.014385	0.012407	0.426921
CatBoost	Financing Price	0.000297	0.017247	0.014031	0.467039	0.000341	0.018477	0.014327	0.433104
CatBoost	Financing Efficiency	0.000356	0.018866	0.016794	0.555006	0.000324	0.018009	0.015113	0.539919
CatBoost	Financing Risk	0.000316	0.017782	0.014063	0.462973	0.000359	0.01894	0.016156	0.543043
GPR	Financing Demand	0.000319	0.017855	0.014958	0.536259	0.000316	0.017773	0.014923	0.535811
GPR	Financing Supply	0.000316	0.017773	0.014923	0.535813	0.000316	0.017772	0.014923	0.535808
GPR	Financing Price	0.000291	0.017053	0.013935	0.472599	0.000321	0.017922	0.015059	0.538863
GPR	Financing Efficiency	0.000322	0.017944	0.015257	0.545459	0.000316	0.017773	0.014923	0.535810

Model	Factor	POS-MSE	POS-RMSE	POS-MAE	POS-MAPE	NEG-MSE	NEG-RMSE	NEG-MAE	NEG-MAPE
GPR	Financing Risk	0.000298	0.017258	0.014119	0.482163	0.000331	0.018192	0.015303	0.553842

5. Conclusions

This study focuses on Micro-Cap stock tail risk and employs the Explainable Boosting Machine (EBM) to examine the asymmetric predictive role of inclusive-finance factors. Specifically, financing demand, financing supply, financing price, financing efficiency, and financing risk are decomposed into positive and negative changes, and their forecasting performance is compared within an out-of-sample forecasting framework. Meanwhile, by taking advantage of the interpretable structure of EBM, Partial Dependence curves are further used to analyze the nonlinear predictive relationship between changes in inclusive-finance factors and future tail risk.

The results show that inclusive-finance factors exhibit clear asymmetric predictive effects on Micro-Cap stock tail risk. Positive changes in financing demand, financing price, and financing risk are more likely to reflect funding pressure, rising financing costs, and greater financing fragility, and therefore contain stronger risk-warning information. In contrast, negative changes in financing supply and financing efficiency better capture deterioration in the financing environment, reflecting credit-support contraction, declining financing convenience, and weakened liquidity buffers. These findings indicate that POS/NEG asymmetric decomposition helps identify the predictive value of inclusive-finance factors more effectively.

The Partial Dependence analysis further shows that the relationship between inclusive-finance factors and future tail risk is not simply linear, but exhibits clear nonlinearity and range dependence. The POS and NEG curves of different factors differ in their relative positions, dynamic trends, and response magnitudes, indicating that increases and decreases in the same factor carry different risk implications in the model. Overall, EBM not only improves out-of-sample forecasting performance but also reveals the nonlinear mechanism through which inclusive-finance factors contribute to tail-risk prediction, providing interpretable evidence for understanding and monitoring Micro-Cap stock tail risk.

Based on the findings that inclusive-finance factors asymmetrically predict Micro-Cap stock tail risk, this study offers the following policy implications. Investors should not focus only on the overall level of inclusive-finance indicators, but should pay closer attention to the risk signals released by their directional changes, especially the tail-risk warning information reflected in rising financing

demand, financing price, and financing risk, as well as declining financing supply and financing efficiency. These signals can be incorporated into portfolio risk monitoring and dynamic allocation decisions for Micro-Cap stocks. Micro-Cap business operators should pay particular attention to funding pressure behind rising financing demand, increasing financing costs, and greater financing risk, while improving cash-flow management and financing stability; they should also enhance financial transparency and credit records to improve financing efficiency. Regulators should improve the inclusive-finance monitoring system from the perspective of asymmetric risk warning. Rather than focusing only on the general development level of inclusive finance, they should closely monitor marginal deterioration signals such as shrinking financing supply, declining financing efficiency, rising financing prices, and increasing financing risk, so as to identify their transmission to Micro-Cap stock tail risk in a timely manner. This would help strengthen capital-market tail-risk prevention while supporting financing accessibility for Micro-Cap business entities.

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Competing Interests/Conflicts Statement

The authors declare no competing interests.

Ethical Approval

This article does not contain any studies with human participants performed by any of the authors.

Informed Consent

Since this article does not contain any studies with human participants performed by any of the authors so therefore it does not require any informed consent.

Authors' Contribution

WG: Conceptualization, Data curation, Methodology, Investigation, Formal analysis, Visualization, Writing-original draft, Funding acquisition, Validation, Investigation; Writing-review & editing;

Data Availability

The data analyzed during this study are included in this published article as a supplementary information file.

Supplementary Files

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