Behind Financial Distress: Involuntary Delisting Risk and Its Broader Asset Pricing Implications

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ABSTRACT

This paper studies the asset pricing implications of involuntary delisting risk, the exogenous component of financial distress risk that remains largely unexplored in prior literature. Applying the data before and after an involuntary delisting policy regime shift in the Chinese stock market at the end of 2020, I document a systematic market-wide effect of the policy tightening, and correspondingly construct a stock-level risk measure using a dynamic logit model. Involuntary delisting risk overshadows firm fundamentals in determining the nature of distress risk. Prior to 2020, when policy strength was relatively weak, the risk of stocks' heterogeneous exposure to future policy regime shift delivered a significant premium, with the long-short portfolio constructed from firms with high versus low involuntary delisting propensity generating an average annualized return of 16.73%, that largely underpinned the size effect. After the strict policy took effect in 2020, as stocks started to face the risk of imminent involuntary delisting, this premium largely disappeared. Finally, I find that involuntary delisting risk significantly influences the short-term return reversal anomaly in the Chinese stock market, both from the time-series and cross-sectional perspectives.

Keywords: Involuntary delisting; Distress risk; Systematic risk; Chinese equity markets; Short-term return reversal; Logistic regression

JEL classification: G12, G14, G18

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I. Introduction

Financial distress risk is conventionally defined by prior researchers as the possibility for a firm to fail its financial obligations and face bankruptcy. To date, the literature has largely evolved along three divergent branches, respectively concluding that distress risk represents: (1) a form of systematic mispricing (e.g., Dichev, 1998; Campbell, Hilscher, and Szilagyi, 2008; George and Hwang, 2010; Gao, Parsons, and Shen, 2018), (2) a distinct systematic risk factor that cannot be explained by existing factor models (e.g., Chava and Purnanandam, 2010; Asis, Chari, and Haas, 2021), or (3) an existing systematic risk behind the Fama-French (1993) SMB and HML factors (e.g., Chan and Chen, 1991; Fama and French, 1996; Vassalou and Xing, 2004; Kapadia, 2011). Despite extensive discussions, a conclusive consensus on its role in the equity market risk-return framework has yet to emerge.

A comprehensive understanding of distress risk requires a panoramic examination of its actual downside outcomes. The consequences of financial distress and bankruptcy are primarily twofold. First, a firm's fundamental value is eroded by financial default, bankruptcy proceedings, and asset liquidation. Second, listed firms in such distress are often subject to involuntary delisting from the secondary stock markets, which strips them of the benefits associated with a listed status and further depresses firm value, while also imposing substantial liquidation costs on shareholders. Although both channels ultimately result in investor losses, there exists fundamental differences: the first channel arises endogenously from a firm's operational and financial fundamentals, whereas the second channel is more exogenously determined by involuntary delisting policies set by the stock exchanges. However, existing literature on distress risk focuses predominantly on the U.S. market, where the overall delisting rate is high and firms encountering financial default and bankruptcy events are typically delisted swiftly, making it difficult to disentangle these two dimensions of risk[1]. This raises a critical question: can the effects of these two channels towards the overall distress risk be separately identified, and to what extent is each of them, especially the involuntary delisting risk channel that has long been understudied in prior research, priced by the market?

In this paper, I use the data from the Chinese stock market to conduct an in-depth analysis towards the role of involuntary delisting risk within distress risk, and further investigate its broader asset pricing implications. The Chinese stock market offers two distinctive features that facilitate the analysis of involuntary delisting and help address the aforementioned research question. Firstly, financial distress and bankruptcy events exhibit very limited co-movement with involuntary delisting events. As summarized and presented in Section IV, only a small fraction of firms that experience bankruptcy ultimately undergo involuntary delisting. Consequently, the endogenous channel of fundamental-based distress risk and the exogenous channel of involuntary delisting risk

[1] As a result, most studies towards financial distress risk largely overlook involuntary delisting events. One exception is Campbell et al. (2008), in which they apply two empirical measures for financial distress in their study towards the U.S. stock market, one based on Chapter 7 & 11 bankruptcy filings and another further including financially-driven delisting. Nevertheless, they did not distinguish the effects of these two types of risk. Coefficients in their predictive models do not differ significantly under the two financial distress measures.

are effectively separable, allowing the effect of each component to be distinctly identified when controlling for the other.

Secondly, the involuntary delisting policies in the Chinese stock market have undergone significant evolution over the past two decades. Although the overall trend has been toward stricter enforcement, regulations prior to 2020 contained a glaring omission: the tolerance for non-recurring profit and loss in income- and profit-related accounting items. This loophole enabled many underperforming firms to avoid involuntary delisting, resulting in an exceptionally low involuntary delisting rate, as emphasized by Lee, Qu, and Shen (2023) and Allen, Qian, Shan, and Zhu (2024). An involuntary delisting policy regime shift occurred at the end of 2020, when non-recurring profit and loss were excluded from relevant accounting items, markedly strengthening involuntary delisting enforcement. Consequently, the annual involuntary delisting rate has gradually risen to levels comparable with those observed in developed stock markets. This transition therefore offers a valuable setting to examine in tandem two distinct types of risk associated with weak and strong involuntary delisting policy regimes. Before the reform, the obvious loophole in the involuntary delisting policy, along with the very few actual involuntary delisting cases, made poorly performing firms bearing negligible immediate involuntary delisting risk but were exposed to the risk of an abrupt policy regime shift at an indeterminate moment in the future. After the reform, with tightened criteria and strengthened enforcement, such firms now face a more direct and immediate risk of being delisted involuntarily — a risk similar to that prevalent in developed markets.

Using China Stock Market & Accounting Research (CSMAR) and Tong Hua Shun (THS) data from 2007 to 2024, I begin with a comprehensive summary of the actual outcomes associated with involuntary delisting and employ an event study methodology to assess the scope of impact of involuntary delisting policies. Findings indicate that involuntary delisting consistently leads to disaster outcomes, characterized by average negative returns of approximately –65%, both before and after the policy regime shift. Furthermore, despite the incidence of involuntary delisting was extremely low prior to 2020 (with only 43 cases recorded between 2007 and 2020), the policy regime shift by the end of 2020 exerted significant short-window effects on systematic risk factors within the CH-4 model (Liu, Stambaugh, and Yuan, 2019). Besides, it influenced the "Special Treated" (ST) stocks and other anomalies linked to involuntary delisting criteria significantly through the channel of systematic risk factor exposure instead of idiosyncratic returns. Based on these findings, I use a Logistic regression model to identify the determinants of involuntarily delisted firms, and corresponding propensity scores are constructed for all stocks to capture their heterogeneous level of involuntary delisting risk.

I further investigate the linkage between corporate bankruptcy events and involuntary delisting outcomes. The analysis reveals that fewer than one-third of firms undergoing bankruptcy were subsequently delisted involuntarily. Notably, market reactions are negative for firms that are eventually delisted, but turn significantly positive for those that avoid involuntary delisting. Building upon this, a one-way sorted portfolio analysis based on fundamental-based distress risk measures,

which are constructed solely from firms' profitability and operational information, yields no significant positive or negative return patterns, indicating that the endogenous channel is not priced by the market. In contrast, portfolios sorted by involuntary delisting risk exhibit a significantly positive return pattern prior to 2020, indicating that the risk of exposure to future policy regime shift is systematically priced. Specifically, the portfolio constructed by longing stocks with involuntary delisting propensity scores in the highest decile and shorting those in the lowest decile earns an annualized return of 16.73% before 2020. This risk premium remains robust after controlling for those fundamental-based distress risk measures in independent double sort tests and Fama-MacBeth (1973) regressions. Following the policy regime shift, under which poorly performing firms directly face involuntary delisting pressure under stricter criteria, involuntary delisting risk no longer delivers any premium.

This newly documented risk premium associated with exposure to future policy regime shift prior to 2020 does not represent an unexplained systematic risk. Within the CH-4 model, this risk premium exhibits no significant unexplained alpha, but displays a statistically and economically significant positive exposure to the SMB factor. On the other hand, I find that variations in the risk loading spread significantly predict returns of the size-sorted long-short portfolio in the Chinese stock market before 2020. Both the long side and the long-short portfolio sorted on firms' market capitalization earn higher returns in months when they carry heavier exposure to the risk of future policy regime shift. This pattern, together with the consistently higher loadings of small firms on involuntary delisting propensity scores relative to large firms, suggests that the risk of exposing to future policy regime shift is one of the underlying drivers of the size effect. However, this mechanism largely disappeared after 2020; since then, stocks in the highest size decile incur a penalty when loading on the risk of imminent involuntary delisting.

Last but not least, I examine the impact of involuntary delisting risk on the short-term return reversal anomaly, which has been documented as significant in the Chinese stock market (see, e.g., Liu et al., 2019; Du, Huang, Liu, Shi, Subrahmanyam, and Zhang, 2025). Returns over the past month, whether oriented from rational risk compensations, fundamental changes or irrational trading behaviors, are inherently linked to the profitability and market trading (particularly regarding nominal share price) requirements prescribed in involuntary delisting policies. Correspondingly, from the time-series perspective, I show that the risk of involuntary delisting significantly weakens stocks' short-term return reversal pattern, after controlling firm fundamentals and other relevant mechanisms. Cross-sectionally, the short-term return reversal long-short portfolio exhibits a moderate, overall positive, but time-varying loading on involuntary delisting risk. Further analysis reveals that, the risk premium from the time-varying exposure to future policy regime shift contributed substantially to the portfolio's positive returns prior to 2020. This also explains the significant (conditional) exposure of short-term return reversal anomaly on the CH-4 SMB factor.

Overall, this paper directly contributes to the aforementioned literature that investigate the nature of financial distress risk. To the best of my knowledge, this is the first study in this field

that disentangles the endogenous and exogenous channels through which distress risk operates. The overall empirical findings suggest that, the endogenous channel itself, driven by firms' operational and financial fundamentals, is not priced by the market. In contrast, the exogenous channel associated with involuntary delisting risk plays a significant role and largely aligns with the literature branch that attributes distress risk to be behind existing systematic risk factors (see, e.g., Chan and Chen, 1991; Fama and French, 1996; Vassalou and Xing, 2004; Kapadia, 2011), under the weak involuntary delisting policy strength prior to 2020.

Especially, this paper extends the debates on distress risk by providing international evidence grounded in the Chinese stock market. Existing studies pay little attention to examine whether their findings and proposed mechanisms established in the U.S. stock market could generalize to other equity markets. One exception is the study conducted by Asis et al. (2021), in which they apply a multi-country dataset containing pooled information from emerging markets in 119 countries. However, such aggregated approaches often fail to account for cross-market heterogeneity in many aspects, such as regulatory policies, listed firm quality, and investor behavior patterns, that may significantly influence how distress risk is priced. Consequently, conclusions drawn from the pooled samples may capture the general patterns but lack the depth and robustness within each market. By contrast, this paper provides a focused and in-depth examination of the Chinese stock market, which is the second largest in the world in terms of total market capitalization (Allen et al., 2024), thereby enhancing the validity and market-specific reliability of the findings.

This paper also adds a new perspective to asset pricing implications of regulatory policies. Different from the extensive literature examining policies and policy-related uncertainty at the macroeconomic level (a branch of research originated from Baker, Bloom, and Davis, 2016), discussions towards the effect of regulatory policies that appear indirect to firm fundamentals on stock pricing are yet to boom. Among emerging discussions, Hsu, Li, and Tsou (2023) focus primarily on the environmental protection regulations and toxic emission control policies, and discover a significant risk premium associated with exposure to environmental policy regime shifts. Similar with their work, my paper also highlights the important role of exposure to future policy regime shifts in a dynamic regulatory framework. Furthermore, Lee et al. (2023) analyze how initial public offering (IPO) control policies affect firm value via reverse merger activities, and Du et al. (2025) investigate the effects of round-lot rules on the differences in pricing patterns between low and high nominal price stocks. This study further extends the discussions towards stock exchange listing and trading policies by examining the substantial pricing impact of involuntary delisting policies.

This paper further adds to the literature on the mechanisms underlying systematic risk factors and asset pricing anomalies. The origins of the size effect have long been discussed among researchers but remain imperfectly understood across markets (for the U.S. stock market, see, e.g., Fama and French, 2015 and Hou, Xue, and Zhang, 2015; for the Chinese stock market, see, e.g., Liu et al., 2019 and Lee et al., 2023). This paper sheds light on one underexplored source of the associated risk premium, from the perspective of exposure to future involuntary delisting policy regime

shifts. Besides, this paper offers a novel perspective on the short-term return reversal anomaly by linking it to exogenous involuntary delisting policy strength, thereby broadening the set of factors known to influence the anomaly — beyond those such as residual return (Da, Liu, and Schaumburg, 2014) and firm fundamental strength (Zhu, Sun, and Chen, 2019) — and extending existing theoretical explanations which primarily focus on retail investor overreaction (e.g., Lehmann, 1990; Jegadeesh and Titman, 1995) and liquidity shocks (e.g., Grossman and Miller, 1988; Nagel, 2012).

The remainder of this paper is organized as follows. Section II outlines the institutional background of involuntary delisting policies in the Chinese stock market and describes the data employed in the analysis. Section III demonstrates the impact of involuntary delisting policy regime shift at the systematic level and correspondingly constructs a firm-level measure of loading on the involuntary delisting risk. Section IV documents a significant premium oriented from the risk of exposing to involuntary delisting policy regime shift, distinguishes it from the fundamental-based distress risk, and validates that it is behind the prevalent size effect. Section V further investigates the effect of involuntary delisting risk on the short-term return reversal anomaly. Section VI concludes.

II. Policy Overview and Data Summary

A. *Involuntary Delisting Policy Dynamics in China*

Since its establishment in 1990, the Chinese stock market operated with weak and ambiguous involuntary delisting policies for about fifteen years. While relevant laws and regulations gradually introduced involuntary delisting criteria based on shareholding structure (i.e., public shareholders' shareholding should not be too small comparing with total issued shares), legal violations (including but not limited to listed firms' financial frauds and information disclosure violations), and firm profitability (primarily focusing on net profit), these standards remained largely qualitative, lacking enforceable quantitative benchmarks. Moreover, even when the criteria had already been triggered, all cases had to be submitted from stock exchanges to the China Securities Regulatory Commission (CSRC) for further review and final decisions. Together, these aspects introduced a significant degree of arbitrariness into the entire involuntary delisting process.

Beginning in 2006, the authority to issue final involuntary delisting decisions was transferred from the CSRC to stock exchanges under the new security law. From 2006 to 2020, quantitative criteria towards involuntary delisting were progressively established and strengthened, as summarized in Table I. Although these criteria aimed to ensure the objectivity and market orientation of involuntary delisting procedures, problems still existed within firms' profitability measures that greatly hindered poorly-performing firms from getting delisted. More specifically, the inclusion of non-recurring profits and losses in net profit calculations allowed firms with little incentive for voluntary delisting to restructure their financial statements — through methods such as debt restructuring, asset sales, and government subsidies — thereby avoiding the triggering of profitability-

based involuntary delisting thresholds. The shortcomings in involuntary delisting policies were not the "elephant in the room"; rather, they had been extensively examined in research papers, investor discussions and analyst reports[2].

Table I. Involuntary Delisting Criteria in Details

This table summarizes criteria towards involuntary delisting for main-board stocks in Shanghai stock exchange and main-board & ChiNext stocks in Shenzhen stock exchange. All the information is manually collected from CSRC and stock exchanges websites.

Time Windows	Shareholding	Legal Violations	Profitability	Market Trading
Before 2000.05	Most criteria were qualitative; final decisions made by CSRC case-by-case; no market trading requirements; listing status suspended if net profit stayed negative for 3 years, and firms got delisted if profitability could not recover in the suspension period; time length of suspension period was not specified			
2000.05 ∼ 2001.02			3-year suspension period	
2001.02 ∼ 2002.01			1-year suspension period	
2002.01 ∼ 2005.12			0.5-year suspension period	
Since 2006.01	Involuntary delisting decisions directly made by stock exchanges in a more quantitative way			
2006.01 ∼ 2012.07			1-year suspension period	
2012.07 ∼ 2014.11			Non-recurring profit & loss not considered in the suspension period Newly Added: Listing status suspended if operational income lower than 10M RMB or net asset stays negative for 2 years	Newly Added: Trading volume lower than 5M shares in 120 trading days; stock price lower than par value in 20 trading days
2014.11 ∼ 2020.12	Newly Added: Shareholder less than 2000 people in 20 trading days	Criteria towards financial fraud & information disclosure violation strengthened		
Since 2021.01	Listing suspension period removed; non-recurring profit & loss no longer considered in firms' net profit			
2021.01 ∼ 2024.04		Overall criteria further strengthened	Adjusted & Strengthened: Directly go delisted if 1. Net asset stays negative for 2 years; or 2. Net profit stays negative and operational income lower than 100M RMB for 2 years	Newly Added: Market cap lower than 300M RMB in 20 trading days Adjusted & Strengthened: Stock price lower than 1 RMB in 20 trading days
After 2024.04		Overall criteria further strengthened	Strengthened: Operational income requirement raised to 300M RMB	Strengthened: Market cap requirement raised to 500M RMB

By the end of 2018, China introduced a registration-based system for IPOs to enhance the efficiency of market-driven capital allocation in its stock markets. In tandem with this reform, corresponding revisions were made towards involuntary delisting policies to facilitate the orderly exit of poorly-performing listed companies. On December 31, 2020, the updated "Rules Governing

[2]The serious defect of involuntary delisting policies was notably documented by researchers prior to 2020. For instance, an earlier working paper version of the study conducted by Allen et al. (2024) - dated back to 2015 and titled "Explaining the Disconnection between China's Economic Growth and Stock Market Performance" - had noted the severity within the policies. Here I also provide several analyst articles (Chinese version) that highlighted shortcomings in involuntary delisting policies to serve as illustrative examples: see, Economic Information Daily (2011), Oriental Morning Post (2012), China Economic Net (2016) and People's Daily Online (2017).

the Listing of Stocks on Shanghai Stock Exchange (December 2020 Revision)" and "Rules Governing the Listing of Stocks on Shenzhen Stock Exchange (December 2020 Revision)" were finalized and formally issued. These regulations substantially tightened involuntary delisting criteria, particularly with regard to profitability requirements. Notably, non-recurring gains and losses were excluded from the measures of net profits or operational incomes, and the maximum period permitted for consecutive loss-making was shortened from four years to two years. The rules were further strengthened in a second amendment issued on April 30, 2024, reflecting continued efforts to improve the quality of listed firms and market discipline.

B. Data Description and Delisting Cases Summary

I obtain listed firms' financial data and stock returns from the CSMAR database. Following Liu et al. (2019), this paper considers stocks listed on the main board of Shanghai Stock Exchange and main board & ChiNext board of Shenzhen Stock Exchange. As summarized in Table I, involuntary delisting policies started to be quantified and authority of involuntary delisting decisions was transferred to stock exchanges since January 2006. To mitigate the potential distortion caused by the historical split-share structure among listed firms before 2007, which aligned managerial incentives poorly with public investors and affected informational efficiency[3], the sample period begins on January 1, 2007 — following the completion of the split-share structure reform and the formal introduction of quantified involuntary delisting policies — and extends through December 31, 2024. For the construction of market returns, CH-4 factors, and other factor & anomaly portfolios, I closely follow the methodology of Liu et al. (2019), except that I include all firms (i.e., without removing the smallest 30% firms ex-ante) across the full sample period. On the other hand, to account for the potential influence of shell value in the Chinese stock market, I construct reverse merge propensity scores for each firm from 2007 to 2020, following the approach of Lee et al. (2023)[4]. Throughout the data preparation & construction process, all accounting and fundamental

[3]Before 2005, two classes of domestic A-shares with otherwise identical rights, tradable and non-tradable, coexist in listed firms in China. The non-tradable shares, which tended to own the largest proportion of a company's total shares in issue, cannot be traded in the secondary market. Shareholders of these non-tradable shares, mainly state, legal persons and other controlling shareholders, therefore could not benefit from capital gains and had weak incentive to improve firm share values or information disclosure quality. The problems caused by the split-share structure are widely documented in the literature (see, e.g., Firth, Lin, and Zou (2010) and Liao, Liu, and Wang (2014)). Specifically, investors in the secondary market largely speculated for short-term returns rather than invested based on firms' fundamentals, leading to chaotic pricing behaviors in the stock market. The Split-Share Structure Reform was launched on April 30, 2005, and mostly completed by early 2007.

[4]This study controls reverse merge propensity within the period 2007-2020 for two reasons. First, this time frame aligns with the sample period examined by Lee et al. (2023). Second, since the registration-based IPO reform was progressively implemented starting in 2018, the difficulty for private firms to go public has decreased substantially in recent years. As shown in Lee et al. (2023), reverse merger activity dropped sharply after 2018. In fact, from 2021 to 2024, only 7 reverse merge cases took place, reflecting a sustained reduction in shell value relevance. Consequently, concerns about shell value in firm valuation, as discussed in Liu et al. (2019), are largely negligible after 2020.

In this study, across all tests within Section IV and V, stocks with reverse merge propensity above the 95th percentile are removed from the analysis at each cross section from 2007 to 2020. This percentile threshold, which results in around 100-200 stocks being removed from each cross section, is large in magnitude comparing with the average size of annual reverse merge activities exhibited in Lee et al. (2023). Most results stay robust if the percentile

variables are appropriately lagged to prevent look-ahead bias [5].

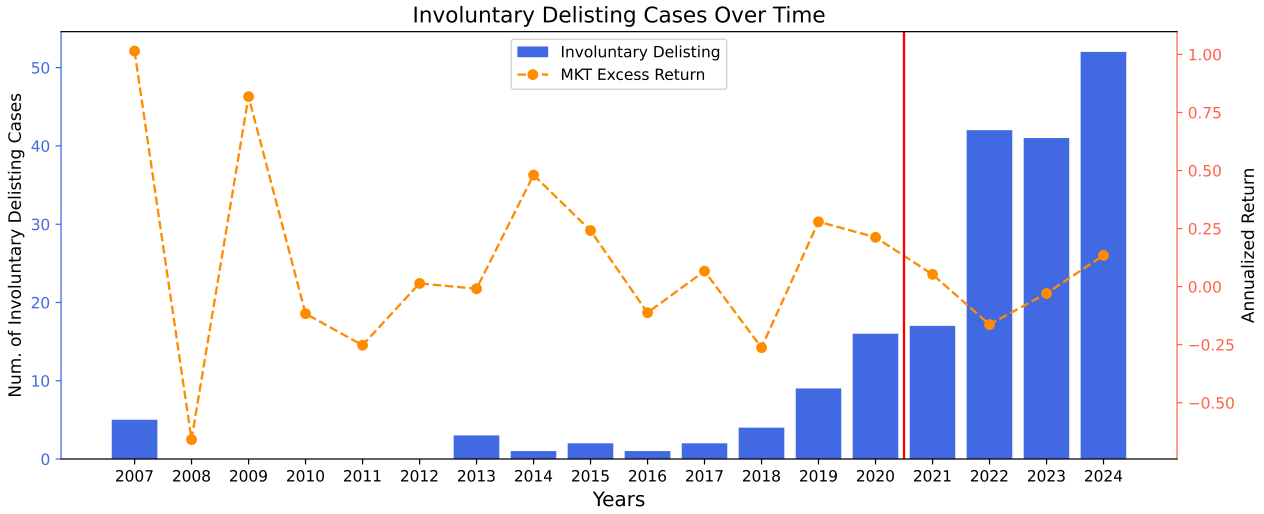


Figure 1. This figure exhibits the amount of involuntary delisting cases over time. The red vertical line indicates the involuntary delisting policy regime shift by the end of 2020. The orange line represents the annualized value-weighted market return in excess of the risk-free rate.

I obtain all delisting samples from the THS iFinD database, a major financial data platform for the Chinese stock market. This database collects all delisting cases among A- & B-shares on Shanghai, Shenzhen and Beijing stock exchanges. This study focuses exclusively on involuntary delisting events. After filtering out delisting cases due to voluntary delisting or merge & acquisition that are not driven by firms' poor performance, a final sample of 195 involuntary delisting cases is identified within the sample period.

Figure 1 visualizes the distribution of these involuntary delisting cases over time. It can be noticed that, the distribution of these cases is largely independent of the overall performance of the stock market, but is instead primarily driven by the policy regime shifts at the end of 2020. Despite several regulatory adjustments prior to 2020, the enforcement of these regulations remained relatively weak, with only 43 cases over the preceding 14 years. In contrast, the regulatory reform enacted at the end of 2020 marked a pronounced regime shift, triggering a substantial increase in enforcement intensity. This is evidenced by 152 firms undergoing involuntary delisting in the subsequent 4 years. Consequently, this study demarcates the end of 2020 as the pivotal point signifying a structural change in the involuntary delisting policy regime.

threshold is further increased, e.g., towards 10%.

[5]Chinese listed firms' accounting year is the calendar year (January 1st — December 31st). Given the common time lags in the release of listed firms' financial reports, following data release requirements in the security law and stock exchanges' regulation files, here I set: from January 1st to April 30th, only data from the third-quarter report of the last year is available; from July 1st to August 31st, only data from the first-quarter report of the current year is available; from October 1st to October 31st, only data from the semi-annual report of the current year is available.

III. Measuring Involuntary Delisting Risk

This section aims to develop a proper risk measure for involuntary delisting. Based on hand-collected data towards involuntary delisting return dynamics and evidence from an event study, the first subsection demonstrates that involuntary delisting functions as a tail risk borne by investors — one that is systematic across the market rather than merely idiosyncratic to those poorest performing stocks. Building on this characterization, the second subsection employs a multivariate logistic regression to construct a firm-level measure of each stock's exposure to such risk.

A. A Deeper Analysis Towards Involuntary Delisting

To examine whether and how involuntary delisting affects stock market pricing patterns, it is useful to first explore the consequences faced by investors in stock delisting events. Contrary to the simplistic view that all delisting events inherently signal corporate failures, voluntary delisting can in fact reflect a strategic repositioning. While listing confers benefits such as access to external financing, lower capital costs, and enhanced reputation (for a more complete summary, see Ritter and Welch, 2002), it also entails costs including agency problems, regulatory burdens, and disclosure requirements. A listed firm could balance benefits and costs and actively choose to delist in order to maximize shareholders' benefits and firm value, as is discussed in Azevedoa, Colakb, Kalak, and Tunaru (2024). In contrast, involuntary delisting is not subject to firm or shareholder discretion. For these firms, the benefits of staying listed likely outweigh the costs, implying that delisting constitutes a value-destroying event. Additionally, liquidity shocks preceding the last trading days can amplify shareholder losses when positions are liquidated. Shumway (1997) documents the significant negative effect of involuntary delisting returns across numerous asset pricing patterns, underscoring that the direct influence of involuntary delisting is both economically meaningful and empirically non-negligible.

Table II reports the return dynamics of involuntarily delisted stocks around their delisting event dates. During the sample period, approximately 90% of these stocks migrated to the National Equities Exchange and Quotations (NEEQ) board following their removals from the main boards or the ChiNext board. Among the 195 delisted stocks examined, investors suffered an average loss of 53% in the six months preceding the final delisting date, followed by an additional 26% loss shortly after the stocks began trading on the NEEQ board — even before accounting for any further losses attributable to potential liquidity constraints. Although the strength of involuntary delisting policies was relatively weak before the end of 2020, the overall negative returns throughout the delisting process are broadly similar in magnitude before and after the policy regime shift. The difference lies in the timing: prior to the policy regime shift, most losses occurred before the final delisting date, while post-delisting returns on NEEQ were marginal and less significant; after the policy regime shift, pre-delisting losses moderated, but the declining trend significantly persisted after moving to NEEQ. Collectively, this significant, substantial decline underscores that

Table II. Involuntary Delisting Return Summary

This table summarizes involuntary delisting returns from 2007 to 2024. Delisting sample data is from the THS iFinD database. Stock return information for the main board and National Equities Exchange and Quotations (NEEQ) board is from the CSMAR database. For all 195 involuntarily delisting cases, their cumulative pre-delisting returns (from day -250 to day -20 & from day -120 to day -20) are reported, with associated t-statistics in parentheses. Besides, in total 174 stocks were transferred to NEEQ board and remained trading. Their cumulative return in the short windows after resuming trading (from day -20 to day +20 & from day -20 to day +60) are reported.

	Before Delisting			**After Listed on NEEQ**		
	Num. of Cases	[-250, -20]	[-120, -20]	Num. of Cases	[-20, 20]	[-20, 60]
Overall	195	-53.44%***	-52.59%***	174	-25.65%***	-23.55%***
		(-22.33)	(-28.18)		(-11.03)	(-7.560)
On & Before Dec 2020	43	-73.16%***	-65.00%***	37	2.44%	8.37%*
		(-20.15)	(-14.90)		(0.672)	(1.795)
After Dec 2020	152	-47.86%***	-49.08%***	137	-33.24%***	-32.18%***
		(-17.52)	(-24.94)		(-13.81)	(-9.466)

Note: *p<0.1; **p<0.05; ***p<0.01

involuntary delisting constitutes a severe tail risk that investors have to bear.

Despite the substantial loss investors may face from involuntary delisting, the proportion of such delisting events remains relatively low even after the regulatory reform by the end of 2020, as is shown in Figure 1. This raises a central question: is involuntary delisting risk merely an idiosyncratic risk confined to the least healthy firms, or has it been systematically priced by the market? In China, listed firms facing imminent risk of involuntary delisting would be designated as "Special Treated" (ST). The ST stocks therefore bear high exposure towards the involuntary delisting policy tightening in the short window by the end of 2020. If involuntary delisting risk is idiosyncratic, ST stocks should exhibit significant returns that are irrelevant and cannot be explained by systematic risk factors in the short window. Conversely, if it is systematically priced, ST stock reactions would be largely accounted for by common risk factors.

Therefore, I employ an event study method to examine the market response to the involuntary delisting policy regime shift implemented on December 31st, 2020, by comparing the performance of ST and non-ST stocks in the immediate trading window surrounding the event. The sample comprises 196 ST stocks and 3,509 non-ST stocks as of the day before the event. The results, presented in the first row of Table III, include raw returns, cumulative abnormal returns adjusted by the CAPM model (CAPM CAR), and cumulative abnormal returns adjusted by the CH-4 model (CH4 CAR) over the short window from day –1 to day +5 relative to the event date. As anticipated, ST stocks underperform non-ST stocks by 7.91% in terms of raw return during this window, a deviation that is statistically significant against the long-term performance trend according to a z-test. However, this underperformance is fully attributable to exposure to systematic risk factors. After removing the exposure towards CH-4 factors, ST stocks instead exhibit a marginal outperformance of 2.87%, which is both economically small and statistically insignificant. These findings indicate that the systematic perspective provides a more compelling explanation for the pricing of

Table III. Stock Market Reaction towards Involuntary Delisting Policy Regime Shift

This table reports value-weighted cumulative stock returns of equity factor & anomaly portfolios around the announcement of the new involuntary delisting policy on Dec 31st, 2020. This table contains factor portfolios derived from the CH-4 model along with three anomalies: the return-on-equity (ROE) anomaly (constructed by longing stocks with ROE in the highest 10% quantile and shorting stocks in the lowest 10% quantile), the nominal price anomaly (constructed by longing stocks with nominal price in the lowest 10% quantile and shorting stocks in the highest 10% quantile), and the special treatment (ST) anomaly (constructed by longing ST stocks and shorting non-ST stocks). Values in this table represent portfolios' short-window returns (in percentage) from day –1 to day +5 relative to the event, with associated two-tailed z-test statistics in parentheses. The population mean and standard deviation used in the two-tailed z-test are constructed using daily portfolio returns from day -252 to day -2. I further adopt a 250-trading day estimation window ending 25 days prior to the event day to construct cumulative abnormal returns (CARs) based on CAPM model and CH-4 model.

	All Stocks			**Excluding ST Stocks**		
Factors & Anomalies	Raw Return	CAPM CAR	CH4 CAR	Raw Return	CAPM CAR	CH4 CAR
ST v.s. non-ST	-7.954^{***}	-5.296^{**}	2.833			
	(-2.906)	(-2.434)	(1.566)			
MKT	6.109			6.182		
	(1.529)			(1.541)		
SMB	-10.343^{***}	-10.163^{***}		-10.198^{***}	-10.168^{***}	
	(-5.183)	(-5.113)		(-5.040)	(-5.031)	
VMG	−2.458	−1.398		−2.336	−1.072	
	(-1.147)	(-0.695)		(-1.018)	(-0.501)	
PMO	-7.200^{**}	-5.728^{**}		-7.257^{**}	-5.880^{**}	
	(-2.325)	(-2.045)		(-2.365)	(-2.100)	
Return on Equity	9.183^{***}	8.103^{***}	−2.749	8.627^{***}	8.139^{***}	−2.933
	(3.003)	(2.905)	(-1.481)	(2.708)	(2.809)	(-1.493)
Nominal Price	-10.304^{***}	-8.273^{***}	4.624^{**}	-10.106^{***}	-7.395^{**}	3.178^{*}
	(-2.958)	(-2.699)	(2.546)	(-2.876)	(-2.539)	(1.798)

Note: *p<0.1; **p<0.05; ***p<0.01

involuntary delisting risk.

To better identify which systematic risk factors are significantly affected and thus more likely to incorporate involuntary delisting risk, I also extend the event study to include the CH-4 model factors, the return-on-equity (ROE) anomaly (examined by Liu et al., 2019), and the nominal price anomaly (discussed by Du et al., 2025). The latter two anomalies are selected specifically because of their direct linkage to the newly tightened involuntary delisting criteria. As is shown in Table III, although the overall market return is positive, small firms significantly underperform large firms by more than 10% in the short window, both in terms of raw return and CAPM-adjusted cumulative abnormal return. Moreover, firms with higher ROE and higher nominal price significantly outperform those with lower ROE and lower nominal price, respectively. All these results remain significant even after excluding all ST stocks. Therefore, the tightening of involuntary delisting criteria exerts its impact predominantly at the systematic level towards the entire market.

B. Involuntary Delisting Risk Measure Construction

Evidence from the preceding subsection suggests adopting a systematic, instead of idiosyncratic, approach to decompose the effects of the strengthened involuntary delisting policy. In principle, the newly tightened criteria apply uniformly to all stocks across exchanges and market boards. However, firms are likely to exhibit heterogeneous levels of exposure to such a policy regime shift. From the results in Table III, it can be noticed that, the ST label cannot fully capture all factors that determine firms' exposure level. Moreover, the ST designation is reserved for stocks at very imminent risk of involuntary delisting and, at any given time, covers only a small fraction of listed firms. Consequently, the simple dummy variable fails to adequately reflect cross-sectional heterogeneity, particularly among the majority of firms with moderate performance.

As introduced in Section II, while the precise timing of the involuntary delisting policy tightening was not pre-announced, deficiencies in the original regulatory framework had long been discovered, acknowledged and discussed among researchers, investors and analysts. Consequently, the substantive measures that would effectively tighten the involuntary delisting criteria were largely anticipated before the actual policy regime shift. Given that a firm with high involuntary delisting risk after 2020 would inherently have high exposure towards potential criteria tightening on or before that year, this study adopts a novel approach to capture such exposure. Specifically, I estimate a logistic regression model using post-policy-change data from 2021 to 2024, and apply the well-trained model to fit the data for both post-policy-change period after 2020 (in sample) and pre-policy-change period on or before 2020 (out of sample). The use of logistic regression models, widely employed in prior research (see, e.g., Campbell et al., 2008; Asis et al., 2021; Lee et al., 2023), allows the incorporation of multiple relevant variables to generate a continuous and time-varying involuntary delisting propensity score towards each stock for further analysis.

To utilize the most influential firm characteristics associated with involuntary delisting, this study begins with the variables derived from and extended beyond the tightened delisting criteria enacted by the end of 2020. The core predictor set includes four key variables: ST status (is_ST), market capitalization ($Size$), nominal price ($Nominal_Price$), and ROE (ROE). ST status dummy directly reflects whether a firm is already in danger of involuntary delisting. ROE measures firms' current profitability level based on non-recurring profit and loss. Market capitalization and nominal price variables are also directly relevant to the market trading criteria towards involuntary delisting. To capture a broader range of delisting criteria, four additional firm characteristics are incorporated: past 12-month turnover ($Turnover$), shareholding ratio of the top-10 shareholders ($Top10_Ratio$), the book-to-market ratio ($Value_BM$), and a state-owned enterprise (SOE) dummy (is_SOE). The first three extend the model's coverage of shareholding structure, market trading and profitability criteria, while the last accounts for potential political supports and downside protections often available to state-owned enterprises, as discussed by Carpenter, Lu, and Whitelaw (2021) and Allen et al. (2024). The analysis uses a pooled panel dataset constructed for the years 2021-2024. In each observation year, the dummy dependent variable equals 1 if a firm encounters involuntary

delisting in that year and 0 otherwise, and all independent variables are measured based on the most recent fiscal year information prior to the observation year.

Table IV. Involuntary Delisting Propensity Logit Model

This table reports the results from a set of logistic regressions. All variables, except dummy variables, are first winsorized at the 1st and 99th percentiles, and then taken logarithm ratio of these variables' original values divided by the cross-sectional median values for each annual dataset. Standard errors are clustered at the year level and reported in parentheses.

	Pooled Logistic Regression Specifications							
Columns	①	②	③	④	⑤	⑥	⑦	⑧
Weight Rebalance	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Const	-7.630***	-9.588***	-7.477***	-9.256***	-4.157***	-8.709***	-3.835***	-8.998***
	(0.392)	(0.289)	(0.452)	(0.327)	(0.479)	(0.468)	(0.588)	(0.246)
is_ST	1.986***	2.180***	2.095***	2.206***	4.110***	5.436***	4.167***	5.535***
	(0.748)	(0.678)	(0.695)	(0.650)	(0.696)	(0.654)	(0.758)	(0.413)
Size	-0.652***	-0.947***	-0.378***	-0.680***	-0.279	-0.568***	0.079	-0.237
	(0.086)	(0.087)	(0.114)	(0.105)	(0.170)	(0.123)	(0.219)	(0.180)
Nominal_Price	-1.938***	-2.144***	-2.000**	-2.223***	-2.444***	-2.895***	-2.537***	-3.230***
	(0.400)	(0.404)	(0.415)	(0.423)	(0.247)	(0.161)	(0.216)	(0.128)
ROE	-0.156***	-0.135***	-0.136***	-0.120***	-0.230***	-0.216**	-0.209***	-0.203***
	(0.051)	(0.020)	(0.042)	(0.023)	(0.056)	(0.059)	(0.053)	(0.050)
Turnover			0.637***	0.569***			0.763**	0.972***
			(0.172)	(0.182)			(0.351)	(0.267)
Top10_Ratio			-0.335	0.005			0.231**	0.908***
			(0.253)	(0.181)			(0.110)	(0.127)
Value_BM			-0.095	-0.091			-0.236**	-0.337*
			(0.110)	(0.121)			(0.170)	(0.183)
is_SOE			-1.191***	-1.221***			-1.674***	-1.693***
			(0.231)	(0.217)			(0.119)	(0.215)
Num. of Label 0 Samples	152							
Num. of Label 1 Samples	16933							
Label 0 Accuracy	99.88%	99.81%	99.83%	99.78%	94.44%	94.80%	94.67%	95.31%
Label 1 Accuracy	22.37%	30.92%	27.63%	30.92%	94.08%	96.71%	96.05%	97.37%
ROC AUC	0.979	0.984	0.982	0.986	0.982	0.986	0.984	0.988
Pseudo R^2	0.496	0.531	0.521	0.550	0.990	0.992	0.991	0.993

Note: 0.5 as the threshold when evaluating prediction accuracy; *p<0.1; **p<0.05; ***p<0.01

Table IV reports the results from the pooled regressions across multiple model specifications. The dataset is notably unbalanced, containing 152 observations with label 1 compared versus 16,933 observations with label 0. Therefore, in addition to the baseline estimation results, results after sample weight rebalancing are also presented. This rebalancing is achieved by adjusting the weights of label 1 observations so that their total weight equals that of label 0 observations in the training sample. As expected, ST status significantly increases involuntary delisting risk across all specifications, while smaller market capitalization, lower nominal price, and poorer profitability (measured by ROE) also significantly predict higher involuntary delisting likelihood. The table further reports prediction accuracy ratios, ROC AUC scores, and Pseudo R^2 for each model specification. Weight rebalancing substantially increases the scale of all prediction values, leading to an increase in accuracy for label 1 samples but a decrease for label 0 samples. Incorporating the four additional predictors yields marginal improvements in overall accuracy for both labels and in Pseudo R^2 val-

ues. Also, consistent with expectations, SOE firms exhibit significantly lower involuntary delisting propensity compared to non-SOE firms.

Table V. Involuntary Delisting Propensity Score Summary Statistics

This table presents summary statistics for estimated delisting propensity scores across the sample periods 2021-01 $\sim$ 2024-12 and 2007-01 $\sim$ 2019-12. For each month, the cross-sectional quantiles of the estimated delisting propensity scores are compiled and summarized herein. Results are presented for both the baseline model and the model incorporating weight rebalancing, corresponding to columns 3 and 7 of Table IV, respectively.

					Without weight rebalancing (%)					
	mean	p1	p5	p10	p25	p50	p75	p90	p95	p99
2021 $\sim$ 2024	1.070	0.0001	0.001	0.002	0.009	0.037	0.164	0.711	2.250	33.81
Before 2021	0.422	0.0004	0.001	0.003	0.010	0.032	0.099	0.338	1.034	10.50
					With weight rebalancing (%)					
	mean	p1	p5	p10	p25	p50	p75	p90	p95	p99
2021 $\sim$ 2024	9.807	0.005	0.027	0.070	0.290	1.260	6.422	28.86	67.77	99.64
Before 2021	7.003	0.012	0.043	0.092	0.303	1.009	3.492	16.67	49.02	93.20

After training the logistic regression models, monthly estimates of involuntary delisting propensity are derived. Specifically, for each month, independent variables are constructed using the most recent trading and accounting data available prior to that month. The datasets are then fed into the well-trained models to generate a delisting propensity score for each stock. Because the dependent variable in the training phase denotes whether a stock will encounter involuntary delisting within the future one year, to prevent any potential look-ahead bias, propensity score estimates for all months in the year 2020 are excluded throughout latter sections. Table V presents summary statistics for the estimated involuntary delisting propensity scores. The estimated propensity scores exhibit positive skewness, with mean values substantially higher than medians in both sub-tables. Compared to the results obtained with weight rebalancing, those without weight rebalancing are notably smaller in magnitude. Both versions, however, display high cross-sectional variance before and after the policy regime shift.

Figure B.1 in Appendix B further exhibits the dynamics of involuntary delisting propensity scores for firms that were involuntarily delisted from 2007 to 2019. Since the policy strength remained weak throughout this period, firms that ultimately faced involuntary delisting are supposed to exhibit extremely high propensity scores. Consistent with this expectation, the scores for these firms show a steady upward trend as they approach their final delisting month, with the average score over the last six months reaching — and often exceeding — the 99th percentile values reported in Table V. This evidence further validates the logistic regression models in effectively capturing a firm's propensity for involuntary delisting under strict criteria after 2020, and thus its exposure to the involuntary delisting policy regime shift before 2020. In latter sections, this study employs propensity score estimates based on the model specification presented in column 3 of Table V[6].

[6]Following prior literature that applies logit model towards unbalanced datasets (e.g., Campbell et al., 2008; Asis

IV. Involuntary Delisting Risk: Mispricing or Systematic Risk?

Given the dynamic evolution of involuntary delisting policies, the involuntary delisting propensity scores constructed in Section III carry distinct economic interpretations across different regulatory periods. Prior to 2020, under the weak involuntary delisting policy regime, a high propensity score naturally reflects a firm's high exposure to a potential policy regime shift at an unforeseen time in the future (termed "exposure risk" hereafter). In contrast, after the policy was tightening since 2021, a high propensity score indicates a direct stress of getting delisted involuntarily (termed "direct delisting risk" hereafter). This section aims to examine the positioning of involuntary delisting risk within the broader risk-return trade-off framework in the equity market. The first subsection compares the pricing patterns of involuntary delisting risk and fundamental-based distress risk, which share certain similarities economically. Results from portfolio sorts and Fama-Macbeth (1973) regressions show a positive premium for loading on the exposure risk but no significant compensation for loading on the direct delisting risk — a pattern distinctly different from that for fundamental-based distress risk. The second subsection further demonstrates that the exposure risk is a systematic risk factor that lies behind the size effect.

A. Involuntary Delisting Risk versus Fundamental-based Distress Risk

Despite the fact that both involuntary delisting risk and fundamental-based distress risk are linked to a firm's current or prospective underperformance, they differ fundamentally in three key dimensions. First, from the perspective of outcome scope, fundamental-based distress risk is defined as the risk of financial default and bankruptcy, while involuntary delisting could be due to financial default and bankruptcy but may also be caused by criteria in other non-profitability aspects exhibited in Table I. Second, for the construction methodology, fundamental-based distress risk are solely measured by firms' endogenous financial and operational fundamental information. Involuntary delisting risk, instead, incorporates broader information related to exogenously determined regulatory requirements. Third, different from the static interpretation of fundamental-based distress risk, the economic implications of involuntary delisting risk evolve dynamically with the policy regime shift, resulting in significant differences before and after 2020. Therefore, it is theoretically meaningful to distinguish and compare these two channels of the financial distress risk.

To validate the previous claim that bankruptcy and involuntary delisting do not often coincide in the Chinese stock market, in Table B.1 in Appendix B I exhibit the annual frequency of listed firms involved in bankruptcy events — including liquidation, reorganization, and conciliation — and track whether and when these firms were delisted involuntarily. Data for listed firms' bankruptcy cases, towards both parent companies and subsidiaries, are collected from the CSMAR database across

et al., 2021; Lee et al., 2023), this paper primarily exhibits results based on propensity score estimates without sample weight rebalancing in subsequent sections. Robustness checks confirm that most findings remain consistent when sample weight rebalancing is applied in the estimation of propensity scores.

the sample period from 2007 to 2024. Although China's Bankruptcy Law took effect in June 2007, very few bankruptcy cases occurred before 2017, with only 6 listed firms having their subsidiaries involved in bankruptcy events. In the full sample, 147 listed firms experienced bankruptcy events towards parent companies, but only 54 listed firms delisted involuntarily after the bankruptcy events. For the other 228 firms having their subsidiaries involved in bankruptcy events, merely 30 listed firms got delisted involuntarily. Given the fact that those involuntary delisting events may be related, but not directly attributed, to preceding bankruptcies, these numbers enhance the argument that the link between bankruptcy and involuntary delisting is notably weak in China.

Table VI. Bankruptcy Events Return Summary

This table summarizes market reactions towards bankruptcy events occurring between 2007 and 2024. The first sub-table is restricted to bankruptcy events involving parent companies only, whereas the second sub-table also incorporates bankruptcy events towards subsidiaries. Within each sub-table, the left panel corresponds to cases where firms subsequently underwent involuntary delisting, and the right panel reflects events where firms remained listed as of the end of 2024. For each event, cumulative stock returns reported are calculated over three pre- and post-announcement windows (60, 120, and 250 days), with associated t-statistics in parentheses.

Only Parent Companies	Delisted (69 events)			Stay Listed (96 events)		
	60d	120d	250d	60d	120d	250d
Before Events	-7.17%*	-15.43%**	-29.27%***	-5.64%*	-15.30%***	-23.09%***
	(-1.740)	(-2.622)	(-5.311)	(-1.730)	(-3.589)	(-5.564)
After Events	-3.97%	-12.43%*	-43.83%***	19.73%***	39.13%***	45.93%***
	(-0.825)	(-1.801)	(-9.256)	(5.149)	(5.030)	(4.519)
Including Subsidiaries	Delisted (153 events)			Stay Listed (452 events)		
	60d	120d	250d	60d	120d	250d
Before Events	-7.26%**	-13.34%***	-27.76%***	-0.38%	-1.65%	-5.59%*
	(-2.519)	(-2.995)	(-7.419)	(-0.309)	(-0.823)	(-1.873)
After Events	-4.60%	-12.99%***	-37.69%***	9.28%***	16.72%***	26.83%***
	(-1.412)	(-3.033)	(-10.18)	(6.898)	(7.093)	(7.974)

Note: *p<0.1; **p<0.05; ***p<0.01

Table VI further presents market reactions towards bankruptcy events among listed firms. Each subtable reports cumulative stock returns before and after event announcement dates, with the left three columns for firms that were eventually delisted involuntarily and the right three columns for those that remained listed through the end of 2024. Although stocks in both groups experienced significant negative returns prior to bankruptcy announcement dates, post-event returns differ sharply depending on eventual involuntary delisting outcomes. Firms that were ultimately delisted continued to exhibit a prolonged and even steeper decline, whereas those that survived from delisting earned significantly positive returns afterward.

This result indicates that, the definitive prospect of future loss from firms' involuntary delisting, instead of firms' current financial distress status, plays a more critical role in pricing distress risk. Given that bankruptcy in the U.S. stock market typically leads to involuntary delisting, which itself is associated with severe negative returns (Shumway, 1997), it can be inferred that much of the prior literature on the pricing of distress risk in the U.S. stock market can address the question towards whether investors have correctly priced performance-based involuntary delisting risk (the

"systematic risk" branch), or, instead, underestimated such risk and thereby overvalued those exposed stocks (the "negative mispricing" branch) — a conjecture that merits further investigation in future research.

In terms of the Chinese stock market, where market reactions towards bankruptcy events are particularly complex, whether and how the fundamental-based distress risk is priced remains an open question. Here I first conduct a univariate portfolio sorting analysis to examine the risk–return pattern. To measure firms' fundamental-based distress risk, I apply several prevalent measures from the literature, including Altman Z-Score (Altman, 1968), Ohlson O-Score (Ohlson, 1980), the downside risk measure RLPM (Miller and Leiblein, 1996) and the distance to default measure MertonDD (Bharath and Shumway, 2008)[7]. All these measures are based exclusively on firms' operational and financial fundamentals and, although possibly tangential to involuntary delisting policies, are not derived from them. Data for all these measures are collected from the CSMAR database across the sample period from 2007 to 2024. For each measure, I construct single-sorted long-short portfolios, with the long (short) side containing stocks with the highest (lowest) risk. Based on the data frequency of these measures, the use of corresponding data is properly lagged and portfolios are rebalanced at the annual frequency.

Results from the single sorting of fundamental-based distress risk portfolios are presented in Table B.2 in Appendix B. Across all measures examined, the long-short portfolios fail to yield statistically significant positive or negative returns. This pattern holds consistently over the entire sample period, as well as within each sub-sample period before and after the regime shift in involuntary delisting policy. Taken together, the findings suggest that the risk of financial distress and bankruptcy is not systematically priced in the Chinese stock market.

Previous findings, on the other hand, reveal the importance of involuntary delisting in determining market reactions. Therefore, to examine how investors price the corresponding risk, I conduct another univariate portfolio sort based on the involuntary delisting propensity scores constructed in Section III. Each month, I form quintile portfolios sorted into five and ten groups with score from low to high. The sample runs from January 2007 to December 2024 and excludes all months in 2020. Sorting portfolios in ascending order allows the long-short portfolios to have positive loading on the exposure risk before the policy regime shift and on the direct delisting risk thereafter. Although the propensity scores are estimated from a model trained on 2021–2024 data — implying that pre-2020 portfolios are largely non-tradable — returns of these sorted portfolios nonetheless effectively capture market pricing patterns related to their exposure risk loadings.

Panels A through C of Table VII report the annualized average excess return, t-statistic, standard deviation, and Sharpe ratio for various quantile portfolios, as well as 80-20 and 90-10 long-short

[7] Campbell et al. (2008) applies a forward-looking predictive model to measure firms' default & bankruptcy probability. The model and method are grounded in U.S. stock market historical data and face challenges in their application to the Chinese stock market. This limitation arises primarily from the extremely limited firm bankruptcy or delisting events prior to 2017, as is exhibited in Table B.1 in Appendix B and Figure 1, making it infeasible to train a valid model across the sample period.

Table VII. Involuntary Delisting Propensity Univariate Portfolio Sorting

This table shows average excess returns for portfolios sorted on involuntary delisting propensity scores estimated in Section III. The sample runs from January 2007 to December 2024 and excludes all months in 2020. Panel A∼C exhibit average excess returns over the risk-free rate (E[R]-R_f), t-statistics in parentheses, standard deviations (Std), and Sharpe ratios (SR) across quantile portfolios and long-short portfolios. Panel D exhibits cumulative returns of long-short portfolios for each year after the policy regime shift. Portfolio returns are value-weighted by firms' market capitalization. All monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns. t-statistics are based on Newey-West (1987) adjustment with 3 lags and small sample correction.

Portfolios	00-10	10-20	20-40	40-60	60-80	80-90	90-100	LS8020	LS9010
Panel A: Full Sample									
E[R]-R_f (%)	2.311	6.063	10.94	13.25	16.13*	17.82*	19.03*	14.79**	16.72**
	(0.330)	(0.968)	(1.458)	(1.497)	(1.725)	(1.775)	(1.820)	(2.202)	(2.290)
Std (%)	0.077	0.071	0.080	0.095	0.101	0.106	0.109	0.072	0.079
SR	0.087	0.245	0.396	0.403	0.462	0.486	0.506	0.594	0.614
Panel B: Before Policy Regime Shift (2007 ∼ 2019)									
E[R]-R_f (%)	4.469	6.629	12.44	15.67	18.40	19.97	21.20*	15.24*	16.73*
	(0.505)	(0.831)	(1.297)	(1.388)	(1.557)	(1.585)	(1.647)	(1.891)	(1.945)
Std (%)	0.083	0.078	0.087	0.104	0.109	0.114	0.116	0.074	0.081
SR	0.156	0.244	0.414	0.437	0.487	0.507	0.527	0.591	0.598
Panel C: After Policy Regime Shift (2021 ∼ 2024)									
E[R]-R_f (%)	-4.704	4.225	6.084	5.400	8.717	10.83	11.99	13.31	16.69
	(-0.646)	(0.689)	(0.888)	(0.647)	(0.855)	(0.885)	(0.794)	(1.169)	(1.234)
Std (%)	0.053	0.042	0.053	0.060	0.068	0.076	0.080	0.063	0.072
SR	-0.258	0.292	0.334	0.261	0.371	0.411	0.434	0.605	0.672

Panel D: Portfolio Returns in 2021 ∼ 2024				
	2021	2022	2023	2024
LS8020	37.56	10.80	6.938	-5.115
LS9010	45.18	13.16	7.956	-2.691

Note: *p<0.1; **p<0.05; ***p<0.01

portfolios. Panel A presents results for the full sample, showing that portfolios with higher involuntary delisting risk loading earn monotonically increasing monthly returns; the 80-20 and 90-10 long-short portfolios deliver statistically significant annualized returns of 14.79% and 16.72%, respectively. Panels B and C further decompose these returns into exposure risk and direct delisting risk components. In the sample period prior to 2020, in which long-short portfolios have positive loading on the exposure risk, portfolio returns remained high and significant. However, following the involuntary delisting policy regime shift, under which stocks start to face the direct delisting risk, the significance of portfolio returns disappears. To better illustrate why portfolio returns in Panel C are economically large yet statistically insignificant, Panel D decomposes the long-short portfolio returns annually from 2021 to 2024. Nearly all positive returns concentrate in 2021, followed by a steady decline in subsequent years. This pattern suggests a gradual market adjustment to the policy regime shift enacted by the end of 2020, which may require time to be fully reflected

in stock pricing dynamics.

Evidence from Table VII supports that exposure to the involuntary delisting policy regime shift represents a systematic risk that positively predicts subsequent stock returns. To validate this predictability is distinct from fundamental-based distress risk, I further conduct independent double sorts and Fama-MacBeth (1973) regressions to observe the predictability patterns after controlling the aforementioned fundamental-based distress risk measures. As shown in Table B.3 in Appendix B, stocks with high exposure risk loadings consistently outperform those with low loadings across different levels of fundamental-based distress risk. Further supporting this, the Fama-Macbeth (1973) regression results in Table B.4 in Appendix B confirms that the predictive power remains significant after controlling for fundamental-based distress risk and industry fixed effects.

Overall, this subsection documents that when the involuntary delisting policy is weakly enforced, stocks with higher exposure to future policy regime shift earn a significant return premium. Moreover, this risk premium is solely determined exogenously, since the cross-sectional return predictability remains strong after various fundamental-based distress risk measures have been well controlled. Conversely, fundamental-based distress risk, defined as the probability of financial default and bankruptcy, is not priced in the Chinese stock market where the linkage between bankruptcy and involuntary delisting is weak. After the involuntary delisting policy is strengthened and stocks originally with high exposure risk now face the direct delisting risk, the previously observed premium disappears entirely.

B. Premium behind the Size Effect

Since the long-short portfolios sorted on the involuntary delisting risk exhibit significant positive return prior to 2020, a natural question follows: is the exposure risk a new systematic risk in the market, or whether it can be adequately explained by well-established systematic risk factors? To address this, I follow the standard procedure and investigate the extent to which the variation in the average returns of the long-short portfolios can be explained by existing factor models. Specifically, I assess risk exposures and pricing errors within the framework of the capital asset pricing model (CAPM) as well as the more recent CH-4 model.

Table B.5 in Appendix B reports the unexplained alphas and estimated exposures towards the prevalent risk factors. The CAPM model cannot explain the significant portfolio returns primarily attributable to the pre-2020 period. However, under the CH-4 model framework, the unexplained alphas are fully absorbed. The portfolio returns exhibit a highly significant exposure to the SMB factor, a significant exposure to the VMG factor, and a marginal exposure to the PMO factor. These exposures align with the construction methodology of the involuntary delisting propensity scores, which heavily incorporate firm size, value, and profitability measures, as demonstrated in Table IV. Overall, the findings suggest that the documented return pattern reflects some known systematic risk factors rather than a distinct new source of systematic risk.

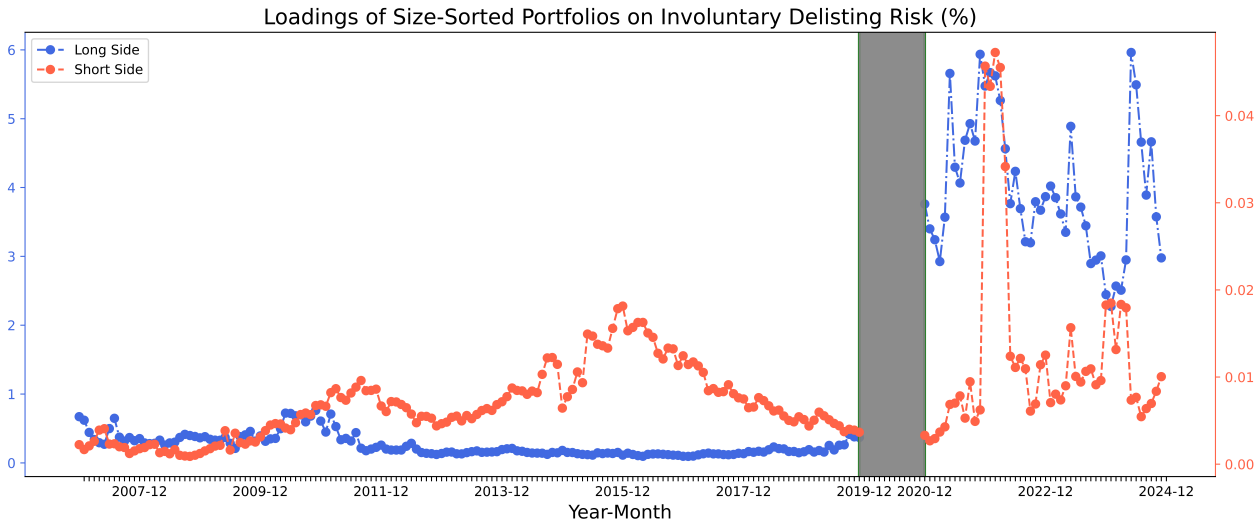


Figure 2. This figure depicts the involuntary delisting propensity score loadings towards size-sorted portfolios. The sample runs from January 2007 to December 2024 and excludes all months in 2020. Each month, two portfolios are formed through cross-sectional sorts on market capitalization: the long side comprises stocks in the lowest decile by market capitalization, while the short side includes those in the highest decile. The portfolio-level loadings are derived from the value-weighted average of individual component stocks' involuntary delisting propensity scores.

This result, on the other hand, sheds light on the possibility that the involuntary delisting risk, especially the exposure risk prior to 2020, could have its premium been concealed within the widely recognized size and/or value factors and neglected by the literature for long. Figure 2 depicts the involuntary delisting propensity score loadings across portfolios sorted by firm size. It can be noticed that, stocks in the lowest decile by market capitalization exhibit on average the involuntary delisting propensity score loading consistently higher than the 75 percentile before 2020, and even reaching the 90 percentile after 2020. Stocks in the highest decile in size, as is expected, have the average delisting propensity score loading much lower in magnitude.

Both portfolios, however, display clear time variation across the sample period. Given that the size-sorted long-short portfolio already has a significant level of loadings on the involuntary delisting risk, if the premium of exposure risk prior to 2020 is indeed embedded within the size effect, a necessary and sufficient condition would be that, the exposure risk should serve as one of the underlying risks that size premium orients from; in other words, time variations in exposure risk loadings should co-move with the returns of the size-sorted portfolios.

Therefore, I use the following regressions to examine the degree of comovement between involuntary delisting risk loadings and size-sorted portfolio returns:

$$R_t = const + \beta \cdot Prop_t \ \ (+\boldsymbol{\beta^C} \cdot Controls_t) + \varepsilon_t \tag{1}$$

$$R_t = const + \beta^{Before} \cdot Prop_t^{Before} + \beta^{After} \cdot Prop_t^{After} \ \ (+\boldsymbol{\beta^C} \cdot Controls_t) + \varepsilon_t \tag{2}$$

The dependent variable denotes the monthly excess returns of three size-sorted portfolios: the long side (containing stocks in the smallest size decile), the short side (containing stocks in the largest size decile), and the corresponding long–short portfolio. The explanatory variable, $Prop_t$, represents the value-weighted average of the component stocks' involuntary delisting propensity scores within the corresponding portfolio; its coefficient reflects the magnitude of return comovement. Equation 1 examines this comovement over the full sample period, whereas Equation 2 further observes whether the comovement pattern differs before and after the involuntary delisting policy regime shift. Additional control variables — including ROE, short-term volatility, accruals, asset growth, and operating income growth — are also constructed at the portfolio level, and incorporated in the regressions to account for potential factors that could possibly contribute to the size premium. Values for the dependent variable and the control variables are constructed prior to the first date of each month.

Table VIII. Size Portfolio Involuntary Delisting Risk Loadings and Future Returns

This table exhibits the time-series regression results of size-sorted portfolio excess returns on involuntary delisting propensity scores and control variables, as specified in Equation 1 and 2. The sample runs from January 2007 to December 2024 and excludes all months in 2020. The long (short) side comprises stocks in the lowest (highest) decile by market capitalization, and the long–short portfolio is thereby formed. Portfolio returns are value-weighted by firms' market capitalization. Each month, all control variables are first winsorized at the 1st and 99th percentiles, and then min-max normalized to the [0,1] interval cross-sectionally. Portfolio-level propensity scores and control variables are derived from value-weighted averages of the individual component stocks' corresponding values. t-statistics are based on Newey-West (1987) adjustment with 3 lags and small sample correction and are reported in parentheses.

Direction	**Long-Short (① ∼ ④)**				**Long Side (⑤ ∼ ⑥)**		**Short Side (⑦ ∼ ⑧)**	
Columns	①	②	③	④	⑤	⑥	⑦	⑧
const	0.024***	0.004	0.020	-0.002	0.009	-0.011	0.035	0.024
	(2.969)	(0.279)	(1.367)	(-0.086)	(0.250)	(-0.312)	(1.430)	(0.805)
β	0.059		0.394		-0.549		-105.85**	
	(0.201)		(0.718)		(-1.135)		(-2.075)	
β^{Before}		8.451*		7.695*		12.62**		10.91
		(1.693)		(1.742)		(2.215)		(0.070)
β^{After}		0.493		0.540		0.078		-114.63**
		(1.250)		(0.976)		(0.138)		(-2.349)
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.019	0.022	0.033	0.067	0.093	0.053	0.058

Note: *p<0.1; **p<0.05; ***p<0.01

The regression results are presented in Table VIII. For the size-sorted long-short portfolio, despite no clear comovement can be obtained over the full sample period, significant comovement exists primarily prior to 2020, as is shown in columns 2 and 4. Economically, during this period, a 0.1% increase in the exposure risk loading spread between the long side and the short side will lead to around 10% additional annualized return for the size-sorted long-short portfolio. This effect is primarily driven by the long side, where a 0.1% rise in exposure risk loading contributes a significant 15.14% increase in annualized return, as is shown in column 6. The short side, on the other hand,

reacts insignificantly with the exposure risk loading. These results strongly validate the role of exposure risk loading in contributing to the size premium. In the post-2020 period, both the long side and the long-short portfolio react weakly towards the direct delisting risk, and the short side is penalized for higher loading on the risk.

In sum, the empirical evidence is consistent with the necessary and sufficient condition supporting the conjecture that exposure risk premium is largely behind the size effect. On the other hand, given the significant exposure of involuntary delisting risk long-short portfolio returns towards the VMG factor, I conduct an additional set of tests to examine whether a similar mechanism underlies the value effect. Specifically, I construct two versions of the value factor using the book-to-market ratio and the earnings-to-price ratio, respectively, analyze the risk loading dynamics of cross-sectionally sorted portfolios, and run similar regressions following Equations 1 and 2. The overall results remain weak and statistically insignificant. Although the value-sorted long-short portfolio exhibits consistently negative loadings on involuntary delisting risk over time, time variations in the loadings within value-sorted quantile portfolios and the long-short portfolios are not significantly priced by the market, either statistically (as indicated by p-values) or economically (in terms of coefficient magnitudes).

V. Effects on the Short-Term Return Reversal Anomaly

This section investigates how exposures to involuntary delisting risk influence the short-term return reversal anomaly in the Chinese stock market. The first subsection adopts the time-series perspective and discovers divergent patterns between stocks with low and high loadings on involuntary delisting risk. The second subsection examines the cross-sectionally sorted portfolios and demonstrates that conditional loadings on the exposure risk effectively explain the significant return of short-term return reversal long-short portfolio.

A. Time-series Analysis

To illustrate why involuntary delisting policies could affect stocks' short-term return reversal pattern, it is essential to first clarify the economic composition of the past-month return. Building on the return decomposition framework proposed by Campbell and Shiller (1988), the past-month return can be separated into an expected return component (reflecting the rational compensation of risk), a cash flow news component, and a discount rate news component. Da et al. (2014) further introduces the residual return component that primarily captures sentiment-driven mispricing or liquidity shocks, by removing the three aforementioned components from the real realized return. While the stochastic discount factor evolves slowly and discount rate news is generally small at the monthly horizon, the remaining three components carry direct implications towards involuntary delisting. Specifically, a negative return from the rational risk compensation or residual return

component would lead to a decline in price and increase the likelihood of violating price-based market trading delisting thresholds. Beyond that, negative cash flow news signals deterioration in a firm's operational fundamentals, further raising the probability of violating the profitability-based delisting criteria. For stocks currently with solid fundamentals and low involuntary delisting risk, a negative return may have negligible effect in leading to involuntary delisting; however, for those already near involuntary delisting boundaries, a negative return can accelerate market consensus that involuntary delisting is imminent, thereby increasing the probability of further negative returns in subsequent months and potentially attenuating or even reversing the short-term return reversal pattern. Similarly, a positive return in this scenario would mitigate the risk of involuntary delisting and prompt positive price adjustments in the following periods.

Existing literature on the short-term return reversal anomaly in the Chinese stock market predominantly focuses on the cross-sectional perspective. Discussions that empirically validate the existence of time-series reversal pattern remains notably scarce. To address this gap, I follow the standard procedure developed by Jegadeesh (1990) to quantify the magnitude and statistical significance of the time-series reversal pattern. Results across the selected sample period, as well as an extended sample period from 2000 to 2024, are reported in Table B.6 in Appendix B. For both sample periods, the reversal pattern is pronounced and statistically significant.

As previously discussed, the evolving nature of involuntary delisting policies implies that both the actual risk of involuntary delisting and the economic interpretation of involuntary delisting propensity scores differ before and after the policy regime shift at the end of 2020. Under the stricter post-2020 regime, the mechanism outlined earlier in this subsection is expected to apply broadly across the stock market, with its influence strengthening as a stock's direct delisting risk rises. In contrast, prior to 2020, the handful of involuntary delisting cases observed were concentrated almost exclusively among stocks with propensity scores around the cross-sectional 99th percentile, as shown in Figure B.1 in Appendix B. This indicates that, under the pre-2020 regime, the proposed mechanism likely is likely relevant only for stocks with the highest involuntary delisting propensity scores; for those with moderate scores, which effectively bore negligible realistic risk of getting delisting involuntarily, the mechanism should not have been operative.

To test the hypothesis, I generally follow the model specification and estimation method applied by Jegadeesh (1990) and design the regression formula as follows:

$$R_{i,t} - E[R_{i,t}] = \alpha_t + \beta_t \cdot R_{i,t-1} + \beta_t^{Prop} \cdot [Prop_{i,t} \cdot R_{i,t-1}] \ \ (+ \boldsymbol{\beta_t^C} \cdot Controls_{i,t}) + \varepsilon_{i,t} \qquad (3)$$

The dependent variable denotes the monthly return of stock i in month t excess of the unconditional expected return of stock i, estimated by the mean monthly return of the stock over the past 12 months prior to month t[8]. The key explanatory variable on the right-hand-side, $[Prop_{i,t} \cdot R_{i,t-1}]$, is

[8] Jegadeesh (1990) applies the mean monthly return of the stock estimated by the mean monthly return from month t+1 to t+60. This method, however, applies the data from the future months that cannot be available at month t. Equation 3 therefore applies the historical mean monthly return in the past 12 months. The corresponding regression results are largely not sensitive to other choices of the mean monthly return construction methods, such

the interaction term between the involuntary delisting propensity score and the past month return; its coefficient reflects the direction and strength of the effect of involuntary delisting risk on stocks' time-series reversal pattern. Additional control variables that could affect stocks' short-term return reversal pattern — including retail investor participation (proxied by abnormal 1-month turnover proposed in Liu et al., 2019), illiquidity, nominal price (discussed by Du et al., 2025), fundamental strength (discussed by Da et al., 2014 and Zhu et al., 2019; proxied by the F-score proposed in Piotroski and So, 2012), firm size, earning-to-price ratio and operational-income-to-asset ratio - are also constructed and controlled in this regression. The regression model is fitted separately for each month, with parameter estimates and test statistics obtained from the time series of monthly cross-sectional regression estimates as in Fama and Macbeth (1973).

Results for the regressions specified in Equation 3 are exhibited in Table IX. Across all columns, the unconditional time-series reversal pattern stays strong and statistically significant, after adding the interaction term and other control variables into the regressions. This persistence holds both before and after the policy regime shift at the end of 2020. In columns 1 and 4, which include the full cross-section of stocks, there exists a significantly positive coefficient for the interaction term which is robust across the pre- and post-2020 periods. However, after excluding stocks with involuntary delisting propensity scores above the 80th cross-sectional percentile[9], the interaction term becomes significant only in the post-2020 period, while it is statistically indistinguishable from 0 prior to 2020. Conversely, when the sample is restricted to stocks with scores above the 80th percentile, the interaction term again displays a positive and statistically significant coefficient throughout the entire sample period, both before and after the policy regime shift.

The estimated coefficients align closely with prior conjectures and are economically large in magnitude. Here I take the coefficient estimations in columns 5 and 6 as an example. Although a strong and robust unconditional short-term return reversal pattern persists across stocks both below and above the 80th cross-sectional percentile of involuntary delisting propensity scores, prior to 2020, only those in the group with higher scores exhibited a positive adjustment toward the reversal trend based on their scores. Specifically, a one-percentage-point increase in the score leads to a positive adjustment of 0.0271 in the reversal coefficient, corresponding to a 26% relative decrease of the short-term return reversal effect. Notably, stocks with involuntary delisting propensity scores exceeding 3.84% no longer exhibit any short-term return reversal pattern. In contrast, no such positive adjustment is observed for stocks with lower scores prior to 2020. However, following the tightening of the involuntary delisting policy at the end of 2020, this positive adjustment becomes evident across all stocks, irrespective of involuntary delisting propensity score-based groups.

This result, together with the pattern of involuntary delisting returns around the event dates (as shown in Table II), sheds light on the behavior how investors trade stocks under different levels of involuntary delisting risk. When involuntary delisting intensity was low prior to 2020, only stocks

as the historical mean monthly return in the past 36 months, or the fitted value obtained from regressing the stock's historical monthly returns on the CH-4 model.

[9]The results remain robust at higher percentile thresholds, such as the 90th percentile.

Table IX. Effect of Delisting Propensity on Time-series Reversal Pattern

This table exhibits the regression results examining the effect of stocks' involuntary delisting propensity towards the time-series short-term return reversal pattern. The sample runs from January 2007 to December 2024 and excludes all months in 2020. The cross-sectional regression model, as specified in Equation 3, is fitted separately for each month using the OLS procedure, with parameter estimates and test statistics obtained from the time series of monthly cross-sectional regression estimates as in Fama and MacBeth (1973). For the sampling method, "All" denotes containing all stocks in the cross-sectional regressions, while "Below 80%" ("Above 80%") denotes containing only stocks with their involuntary delisting propensity below (above) the cross-sectional 80th percentile for each month. All control variables are first winsorized at the 1st and 99th percentiles, and then min-max normalized to the [0,1] interval. t-statistics are based on Newey-West (1987) adjustment with 3 lags and small sample correction and are reported in parentheses.

Columns	①		②		③		④		⑤		⑥	
Sampling Method	All		Below 80%		Above 80%		All		Below 80%		Above 80%	
const	-0.003		-0.005		0.008		0.005		-0.001		0.038^{***}	
	(-0.344)		(-0.682)		(0.853)		(0.529)		(-0.145)		(3.343)	
$R_{i,t-1}$	-0.125^{***}		-0.125^{***}		-0.141^{***}		-0.104^{***}		-0.104^{***}		-0.105^{***}	
	(-17.36)		(-15.73)		(-15.63)		(-15.75)		(-15.07)		(-11.32)	
$[R_{i,t-1}]^{Before}$		-0.126^{***}		-0.122^{***}		-0.144^{***}		-0.104^{***}		-0.102^{***}		-0.104^{***}
		(-16.12)		(-13.79)		(-14.57)		(-15.06)		(-13.78)		(-10.13)
$[R_{i,t-1}]^{After}$		-0.124^{***}		-0.135^{***}		-0.132^{***}		-0.105^{***}		-0.113^{***}		-0.105^{***}
		(-7.137)		(-7.627)		(-6.277)		(-6.165)		(-6.645)		(-5.100)
$Prop_{i,t} \cdot R_{i,t-1}$	4.810^{***}		24.92		4.102^{***}		2.647^{**}		13.89		2.140^{**}	
	(2.752)		(1.373)		(3.050)		(1.999)		(1.337)		(1.993)	
$[Prop_{i,t} \cdot R_{i,t-1}]^{Before}$		6.137^{***}		22.91		5.241^{***}		3.355^{*}		10.70		2.711^{*}
		(2.731)		(0.972)		(3.046)		(1.952)		(0.804)		(1.944)
$[Prop_{i,t} \cdot R_{i,t-1}]^{After}$		0.497^{***}		31.48^{***}		0.403^{***}		0.345^{***}		24.26^{***}		0.284^{***}
		(3.535)		(2.962)		(3.336)		(2.975)		(2.759)		(2.779)
Controls	No		No		No		Yes		Yes		Yes	

Note: *p<0.1; **p<0.05; ***p<0.01

exhibiting extreme involuntary delisting risk were actually delisted — a tendency confirmed by the involuntary delisting propensity score dynamics of pre-2020 delisted firms exhibited in Figure B.1 - and therefore it was relatively easy to distinguish stocks facing tangible involuntary delisting risk from those not at risk. In this regime, investors reacted sharply and with high certainty only toward stocks with extreme involuntary delisting propensity: following a negative past-month return, further declines were highly likely; the price adjustment tended to be strong and largely sufficient, leaving no discernible return pattern after moved to the NEEQ board. For other stocks, the past-month returns were almost unlikely to be related to involuntary delisting, and thus the short-term return reversal pattern remained unaffected by the involuntary delisting risk loading. In contrast, after 2020, the stricter involuntary delisting criteria significantly increased the intensity of involuntary delisting events and broadened the pool of stocks at risk beyond only the most extreme cases. The effect of involuntary delisting propensity on the short-term return reversal pattern therefore expanded to a much wider set of firms. However, the increased uncertainty regarding which specific stocks would ultimately face involuntary delisting weakened the precision and strength of price reactions. When involuntary delisting did occur, the pre-delisting price adjustment often proved insufficient, leading to a continued downward trend in returns after moved to the NEEQ board.

B. Cross-sectional Analysis

The cross-sectional short-term return reversal anomaly is well-documented in the Chinese stock market by Liu et al. (2019), though the same study develops the CH-4 model that can largely explain this effect. To examine this, I construct the short-term return reversal long-short portfolio by longing stocks in the lowest past-month return decile and shorting those in the highest decile, rebalancing monthly. As shown in Table B.7 in Appendix B, the portfolio generates a positive, statistically significant, and economically large raw return. However, columns 2 and 5 indicate that its unexplained component becomes statistically insignificant when factor exposures are adjusted using the CH-4 model. Besides, the portfolio return has statistically significant exposures towards SMB and PMO factors.

The literature discussing the underlying mechanism of cross-sectional short-term return reversal anomaly is primarily divided into two streams. The first, suggested by Lehmann (1990) and Jegadeesh and Titman (1995), attributes the anomaly to retail investors' overreaction to news that affects firms' fundamentals, arguing that prices will temporarily deviate from the correct levels and subsequently revert. The second, notably advanced by Grossman and Miller (1988) and Nagel (2012), emphasizes liquidity shocks: when certain investors face urgent liquidity needs, rational market makers demand a transitory premium, leading to temporary mispricing that later corrects. The PMO factor proposed by Liu et al. (2019) captures retail investors' sentiment trading and can well proxy for the overreaction behavior. To examine whether the aforementioned exposure to the SMB factor stems from the liquidity shock channel, I modify the right-hand-side variables in

columns 3 and 6 to include only the SMB factor, the PMO factor, and the return of an illiquidity-sorted long-short portfolio (constructed by longing the most illiquid stocks and shorting liquid ones). Interestingly, exposure to the illiquidity portfolio shows no significant pattern, whereas exposures to the SMB and PMO factors remain strong and persistent.

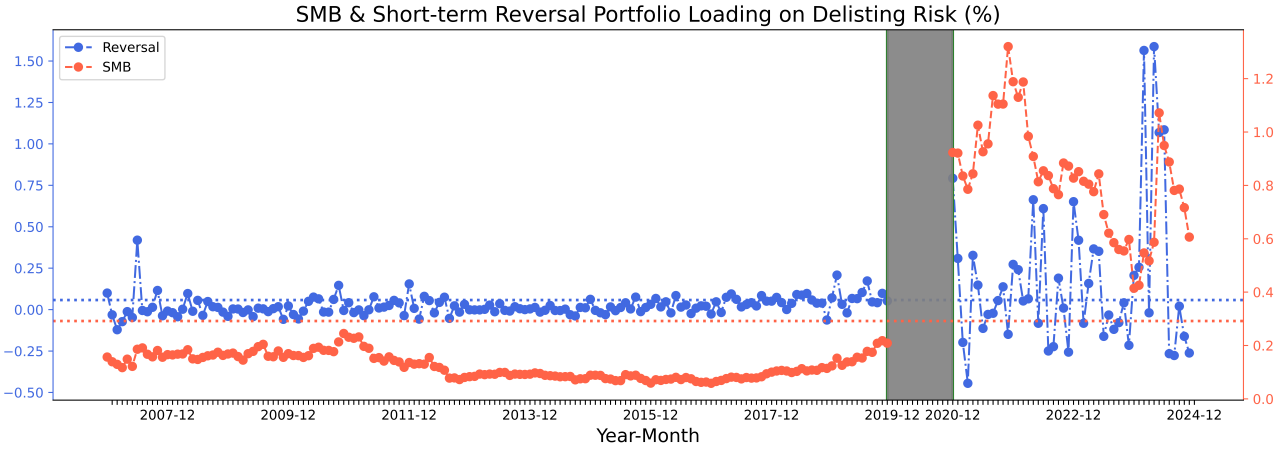


Figure 3. This figure depicts the involuntary delisting propensity score loadings towards short-term return reversal anomaly long-short portfolio and SMB portfolio. The sample runs from January 2007 to December 2024 and excludes all months in 2020. The construction method of these two portfolios follow Liu et al. (2019). Each month, the portfolio-level propensity score loadings are derived from the value-weighted average of the individual component stocks' involuntary delisting propensity scores. Consequently, for each of these two long-short portfolios, its propensity score loading is computed by subtracting the loading of the short side from that of the long side.

As discussed in the previous section, the premium from the exposure risk is largely behind the size effect prior to 2020. Figure 3 depicts the involuntary delisting propensity score loadings for the short-term return reversal long-short portfolio and the SMB factor. The SMB factor demonstrates a stable positive loading over the entire period. The short-term return reversal long-short portfolio, on the other hand, exhibits significant time variation and the average loading above 0. This observation raises a key question: did the overall positive exposure to the involuntary delisting risk contribute to the significantly positive returns of the short-term return reversal anomaly and, consequently, drive its co-movement with the SMB factor, particularly in the pre-2020 period?

If the conjecture holds, returns of the short-term return reversal factor should positively co-vary with its time-varying exposure to involuntary delisting risk. Consequently, a static factor test may fail to fully capture this dynamic component, especially when loading heavily on the exposure risk prior to 2020. To address this, I adopt a conditional factor test framework following the approach of Daniel and Moskowitz (2016), and specify regression models that allow for conditional alphas:

$$\begin{aligned} R_t = const + \mathbf{1}\{Before\}_t \cdot Prop_t \cdot const + \mathbf{1}\{After\}_t \cdot Prop_t \cdot const \\ + \beta^{MKT} \cdot MKT_t + \beta^{SMB} \cdot SMB_t + \beta^{VMG} \cdot VMG_t + \beta^{PMO} \cdot PMO_t + \varepsilon_t \end{aligned} \tag{4}$$

$$R_t = const + \mathbf{1}\{Before\}_t \cdot Prop_t \cdot const + \mathbf{1}\{After\}_t \cdot Prop_t \cdot const + \beta^{SMB} \cdot SMB_t + \beta^{PMO} \cdot PMO_t + \beta^{Illiq} \cdot Illiq_t + \varepsilon_t \quad (5)$$

The dependent variable is the monthly excess return of the short-term return reversal long-short portfolio in month t. $Prop_t$ denotes the loading of the portfolio on the involuntary delisting propensity score in month t. To examine potential structural shifts around 2020, I introduce two indicator variables: $\mathbf{1}\{Before\}_t$, which equals 1 if month t is prior to 2020 and 0 otherwise, and $\mathbf{1}\{After\}_t$, defined analogously for periods after 2020. Equation 4 incorporates factors from the CH-4 model, whereas Equation 5 focuses specifically on the SMB and PMO factors, along with the illiquidity anomaly. In both specifications, the coefficients on the conditional constant terms, $[\mathbf{1}\{Before\}_t \cdot Prop_t]$ and $[\mathbf{1}\{After\}_t \cdot Prop_t]$, are the central focus of the analysis.

Regression results for these two specifications are presented in columns 1 and 4 of Table X, respectively. While the overall returns of the short-term return reversal anomaly can be well explained unconditionally, within months when the reversal portfolio loaded heavily on the exposure risk, the static factor exposure specifications fail to fully capture its time-varying component of risk premium prior to 2020. This leads to a significant and unexplained conditional alpha for the term $[\mathbf{1}\{Before\}_t \cdot Prop_t]$, which is consistent with the previous conjecture. As a comparison, since loading on the directly delisting risk after 2020 no longer brings a premium, the conditional alpha for the term $[\mathbf{1}\{After\}_t \cdot Prop_t]$ is statistically insignificant.

This result naturally leads to an extension of the previous factor test framework, which now allows not only conditional constant terms but also conditional factor exposure terms:

$$\begin{aligned} R_t = const\ (&+\mathbf{1}\{Before\}_t \cdot Prop_t \cdot const + \mathbf{1}\{After\}_t \cdot Prop_t \cdot const) \\ &+ \beta^{MKT} \cdot MKT_t \\ &+ [\beta^{SMB} + \mathbf{1}\{Before\}_t \cdot Prop_t \cdot \beta_1^{SMB} + \mathbf{1}\{After\}_t \cdot Prop_t \cdot \beta_2^{SMB}] \cdot SMB_t \\ &+ \beta^{VMG} \cdot VMG_t \\ &+ [\beta^{PMO} + \mathbf{1}\{Before\}_t \cdot Prop_t \cdot \beta_1^{PMO} + \mathbf{1}\{After\}_t \cdot Prop_t \cdot \beta_2^{PMO}] \cdot PMO_t + \varepsilon_t \end{aligned} \quad (6)$$

$$\begin{aligned} R_t = const\ (&+ \mathbf{1}\{Before\}_t \cdot Prop_t \cdot const + \mathbf{1}\{After\}_t \cdot Prop_t \cdot const) \\ &+ [\beta^{SMB} + \mathbf{1}\{Before\}_t \cdot Prop_t \cdot \beta_1^{SMB} + \mathbf{1}\{After\}_t \cdot Prop_t \cdot \beta_2^{SMB}] \cdot SMB_t \\ &+ [\beta^{PMO} + \mathbf{1}\{Before\}_t \cdot Prop_t \cdot \beta_1^{PMO} + \mathbf{1}\{After\}_t \cdot Prop_t \cdot \beta_2^{PMO}] \cdot PMO_t \\ &+ \beta^{Illiq} \cdot Illiq_t + \varepsilon_t \end{aligned} \quad (7)$$

Here I expand the factor exposure terms for the SMB and PMO factors, as the short-term return reversal anomaly exhibits strong and robust exposures towards these two factors in static settings. All other notations remain consistent with Equations 4 and 5. Under the aforementioned conjecture, the conditional exposure to the SMB factor prior to 2020 - captured by the coefficient on the interaction term $[\mathbf{1}\{Before\}_t \cdot Prop_t \cdot SMB_t]$ - is expected to be positive and significant in explaining

the time-varying component of the short-term return reversal anomaly returns oriented from the exposure risk loading. Correspondingly, the conditional alpha for the term $[\mathbf{1}\{Before\}_t \cdot Prop_t]$ should become statistically insignificant.

Table X. Effect of Delisting Propensity on Cross-sectional Reversal Return Decomposition

This table exhibits the regression results examining whether and how can factors and anomalies explain short-term return reversal anomaly performance under the time-varying involuntary delisting propensity loading. The sample runs from January 2007 to December 2024 and excludes all months in 2020. The regression models for columns 1 and 4 are specified in Equation 4 and 5, respectively. The regression models for columns 2 and 3 are specified in Equation 6. The regression models for columns 5 and 6 are specified in Equation 7. t-statistics are based on Newey-West (1987) adjustment with 3 lags and small sample correction and are reported in parentheses.

Columns	①	②	③	④	⑤	⑥
const	−0.008	−0.001	−0.003	−0.004	0.002	0.0003
	(-1.332)	(-0.253)	(-0.498)	(-0.722)	(0.277)	(0.054)
$[Prop \cdot const]^{Before}$	35.39***		12.32	33.86***		10.28
	(3.616)		(1.174)	(3.395)		(0.999)
$[Prop \cdot const]^{After}$	−0.774		−1.482	−0.851		−1.489
	(-0.870)		(-1.539)	(-0.936)		(-1.555)
MKT	0.109	0.095	0.095			
	(1.387)	(1.136)	(1.159)			
SMB	0.531***	0.355***	0.380***	0.830**	0.582	0.603
	(4.304)	(2.663)	(2.764)	(2.292)	(1.583)	(1.636)
$[Prop \cdot SMB]^{Before}$		705.95***	582.61**		703.72***	601.08**
		(3.174)	(2.240)		(3.129)	(2.339)
$[Prop \cdot SMB]^{After}$		43.38	46.44		43.85	47.60
		(1.139)	(1.476)		(1.206)	(1.620)
VMG	0.351*	0.275	0.293			
	(1.903)	(1.483)	(1.604)			
PMO	0.383***	0.339***	0.344***	0.403***	0.354***	0.358***
	(3.298)	(2.637)	(2.634)	(3.467)	(2.794)	(2.781)
$[Prop \cdot PMO]^{Before}$		91.50	77.23		78.18	66.58
		(0.566)	(0.473)		(0.495)	(0.416)
$[Prop \cdot PMO]^{After}$		−20.05	−6.909		−25.02	−12.40
		(-0.415)	(-0.160)		(-0.537)	(-0.299)
Illiq				−0.319	−0.242	−0.248
				(-1.222)	(-0.916)	(-0.935)
R^2	0.287	0.320	0.326	0.272	0.309	0.315
Note:						*p<0.1; **p<0.05; ***p<0.01

Regression results for these two specifications are reported in columns 2, 3, 5 and 6 of Table X. After adding the conditional factor exposure terms, the estimated alpha terms, particularly the conditional alpha term prior to 2020, are not significantly different from zero anymore. In contrast, the conditional exposure to the SMB factor prior to 2020 exhibits to be highly significant. For numerical illustration, based on the estimates in column 6, a 0.1% loading on the involuntary delisting propensity score by the short-term return reversal long-short portfolio increases the total exposure to the SMB factor to 1.2, doubling its unconditional level. Conversely, a –0.1% loading reduces the overall SMB exposure to nearly zero, effectively eliminating any co-movement pattern. Meanwhile,

the unconditional exposure towards the SMB factor diminishes substantially in magnitude and, in certain specifications, loses statistical significance.

The overall results exhibited in Table X demonstrates that, the short-term return reversal anomaly yields significantly higher returns during periods of positive exposure risk loading prior to the involuntary delisting policy regime shift. This pattern explains the overall positive co-movement between the reversal anomaly and the SMB factor, which itself consistently loads positively on involuntary delisting risk and thus covers the associated exposure risk premium before 2020. However, this linkage is primarily driven by time-varying exposure risk loading; after controlling for this time-varying component, the unconditional exposure term remains only marginally significant. While other mechanisms may exist and contribute to the remaining marginal unconditional co-movement with the SMB factor, current findings have been sufficient to prove the significant role of involuntary delisting risk — particularly the exposure risk premium prior to 2020 — in shaping the returns of the short-term return reversal anomaly.

On the other hand, the conditional exposure to the PMO factor exhibits statistically insignificance both before and after the policy regime shift. In contrast, the unconditional exposure term persists as significant and robust across all model specifications. This outcome is conceptually coherent: the policy regime shift toward involuntary delisting does not meaningfully influence retail investor participation or behavior, and is thus largely unrelated to their overreaction patterns. Consequently, the explanatory power of retail investor overreaction mechanism for the short-term return reversal anomaly remains unaffected by the policy regime shift and continues to hold robustly across both periods.

VI. Conclusion

Beyond the risks arising from firms' deteriorating fundamentals, financial distress risk in many stock markets intrinsically incorporates the latent threat of getting delisted involuntarily. While the former orientates endogenously from firm performance and has been extensively discussed in prior literature, the latter, a more exogenously determined channel, remains largely understudied. Based on the unique policy background and dynamics in the Chinese stock market from 2007 to 2024, this study disentangles these two channels and focuses explicitly on the effects of involuntary delisting risk. In this market where financial default and bankruptcy events are not tightly coupled with involuntary delisting, financially distressed stocks do not invariably earn negative returns unless they face imminent involuntary delisting. Consequently, fundamental-based distress risk is not systematically priced by the market. In contrast, despite involuntary delisting policies formally target only the most severely underperforming companies, they inherently generate systematic effects across all firms — varying with their heterogeneous levels of risk of falling into involuntary delisting. This results in a significant risk premium that extends beyond the traditional fundamental-based distress risk prior to the policy regime shift by the end of 2020.

Moreover, this study explores the broader implications of involuntary delisting risk for the market-wide risk-return relationship. Prior to 2020, the risk of stocks' exposure towards future involuntary delisting policy regime shift did not constitute a new systematic risk factor beyond the CH-4 factors; instead, it served as one of the underlying drivers of the pronounced size effect in the Chinese stock market. After the involuntary delisting policies were tightened, as stocks began to face the risk of imminent involuntary delisting, the associated risk premium no longer existed. Furthermore, involuntary delisting risk significantly shapes stocks' short-term return reversal patterns. From the time-series perspective, a higher risk of imminent involuntary delisting substantially weakens or even reverses stocks' short-term return reversal strength. Cross-sectionally, the short-term return reversal long-short portfolio earned higher returns in months when loading more heavily on the risk of exposing to future policy regime shift before 2020. This explains its significant exposure to the SMB factor, which cannot be explained by other prevalent mechanisms towards the short-term return reversal anomaly.

Findings of this study indicate that trading policies in the secondary stock markets, while not directly related to firms' operational fundamentals, can significantly shape their pricing patterns. Future research could extend this investigation to other asset classes - such as the rapidly expanding cryptocurrency market that is characterized by the frequent listing and delisting of tokens ranging from weak-fundamentals meme coins to mainstream cryptocurrencies across different centralized exchanges - to further examine this mechanism and offer complementary insights.

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Appendix A. Supplementary Material

Supplementary data to this article and relevant codes will be available soon.

Appendix B. Additional Tables and Figures

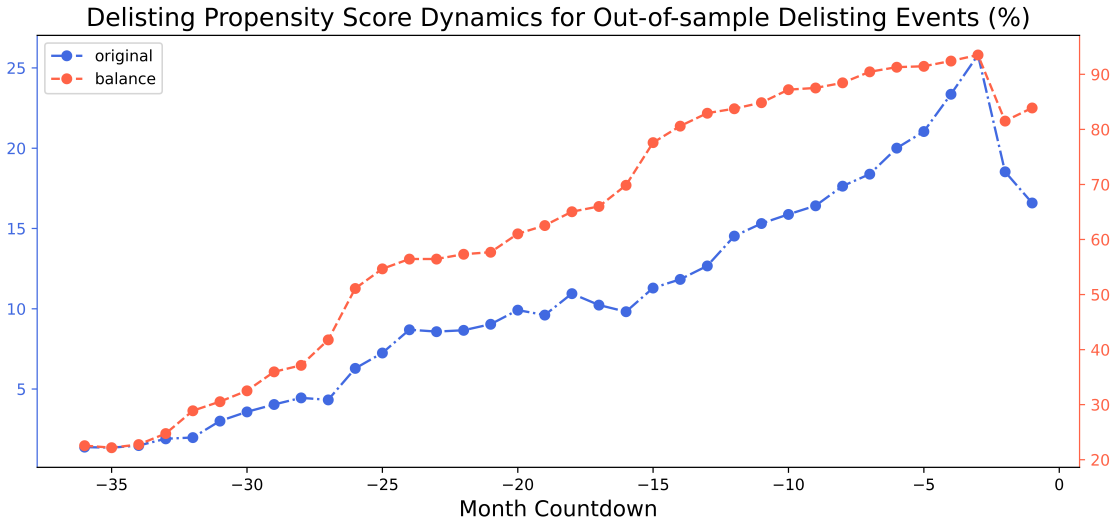


Figure B.1. This figure exhibits the average delisting propensity score dynamics for involuntary delisting cases from 2007 to 2019. For each involuntary delisting stock, its delisting propensity scores in the last 36 months before the final delisting date are collected. The x-axis indicates the monthly countdown steps from month -36 to month -1. y-axes display the equally-weighted average score across all selected stocks at each countdown step. The blue and orange line correspond to scores calculated by the logistic models trained without and with weight rebalancing, respectively.

Table B.1. Bankruptcy Events & Delisting Dynamics

This table presents the annual frequency of listed firms experiencing bankruptcy events and tracks the incidence and timing of any subsequent involuntary delisting from 2007 to 2024. Both sub-tables share a consistent structure: the vertical axis indicates the year of bankruptcy occurrence, while the horizontal axis corresponds to the year of involuntary delisting. To avoid duplication from multiple bankruptcy filings, only the most recent bankruptcy year for each firm is considered and included in the table. The first sub-table is restricted to bankruptcy events involving parent companies only, whereas the second sub-table also incorporates bankruptcy events towards subsidiaries.

Only Parent Companies

	Before 2017	2017	2018	2019	2020	2021	2022	2023	2024	Haven't Delisted	Total
Before 2017	0	0	0	0	0	0	0	0	0	0	0
2017		0	0	0	0	0	0	0	0	1	1
2018			0	0	2	1	0	0	2	0	5
2019				0	3	1	1	1	0	10	16
2020					2	2	1	0	1	11	17
2021						0	8	1	0	18	27
2022							2	10	3	11	26
2023								3	5	17	25
2024									5	25	30

Including Subsidiaries

	Before 2017	2017	2018	2019	2020	2021	2022	2023	2024	Haven't Delisted	Total
Before 2017	0	0	0	0	0	0	0	0	0	6	6
2017		0	0	0	0	0	0	0	0	6	6
2018			0	0	1	2	0	0	1	17	21
2019				2	4	3	1	1	0	34	45
2020					3	6	2	0	2	42	55
2021						1	11	5	1	51	69
2022							3	12	6	39	60
2023								4	6	42	52
2024									7	54	61

Table B.2. Fundamental-based Distress Risk Univariate Portfolio Sorting

This table shows average excess returns for portfolios sorted on different fundamental-based distress risk measures. The sample runs from January 2007 to December 2024. Panel A∼C exhibit average excess returns over the risk-free rate (E[R]-R_f), t-statistics in parentheses, standard deviations (Std), and Sharpe ratios (SR) for long-short portfolios. Based on the definitions of these measures, for Z-Score and MertonDD, the long (short) side contains stocks with lowest (highest) scores in the cross-section; for O-Score and RLPM, the long (short) side contains stocks with highest (lowest) scores in the cross-section. Portfolio returns are value-weighted by firms' market capitalization. All monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns. t-statistics are based on Newey-West (1987) adjustment with 3 lags and small sample correction.

Measures	Z-Score		O-Score		RLPM		MertonDD	
Portfolios	LS8020	LS9010	LS8020	LS9010	LS8020	LS9010	LS8020	LS9010
Panel A: Full Sample								
E[R]-R_f (%)	-1.045	-1.635	2.429	0.690	0.207	-1.205	-2.102	-3.109
	(-0.244)	(-0.330)	(0.536)	(0.133)	(0.056)	(-0.303)	(-0.496)	(-0.639)
Std (%)	0.054	0.062	0.048	0.059	0.043	0.047	0.055	0.066
SR	-0.056	-0.076	0.145	0.033	0.014	-0.075	-0.110	-0.136
Panel B: Before Policy Regime Shift (2007 ∼ 2020)								
E[R]-R_f (%)	-5.141	-5.655	1.510	-1.302	-1.848	-3.531	-1.765	-1.113
	(-1.023)	(-0.951)	(0.292)	(-0.230)	(-0.473)	(-0.844)	(-0.386)	(-0.210)
Std (%)	0.055	0.064	0.046	0.056	0.039	0.042	0.052	0.062
SR	-0.272	-0.256	0.094	-0.067	-0.138	-0.244	-0.098	-0.052
Panel C: After Policy Regime Shift (2021 ∼ 2024)								
E[R]-R_f (%)	13.290**	12.435*	5.646	7.662	7.397	6.934	-3.283	-10.10
	(2.015)	(1.769)	(0.616)	(0.636)	(0.819)	(0.700)	(-0.315)	(-0.896)
Std (%)	0.050	0.055	0.055	0.072	0.055	0.061	0.066	0.080
SR	0.764	0.658	0.299	0.309	0.386	0.329	-0.143	-0.366

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.3. Distress Risk & Delisting Propensity Independent Double Sorting

This table reports average excess returns for five × three portfolios independently double-sorted on involuntary delisting propensity scores estimated in Section III and different fundamental-based distress risk measures. The sample runs from January 2007 to December 2024 and excludes all months in 2020. Based on the definitions of these distress risk measures, for Z-Score and MertonDD, the long (short) side contains stocks with lowest (highest) scores in the cross-section; for O-Score and RLPM, the long (short) side contains stocks with highest (lowest) scores in the cross-section. The first three columns report returns of long-short portfolios formed along the delisting propensity dimension while controlling for distress risk; the remaining five columns report returns of long-short portfolios formed along the distress risk dimension while controlling for delisting propensity. Portfolio returns are value-weighted by firms' market capitalization. All monthly returns are multiplied by 12 to make the magnitude comparable to annualized returns. t-statistics are based on Newey-West (1987) adjustment with 3 lags and small sample correction and are reported in parentheses.

Portfolios	Distress_q1	Distress_q2	Distress_q3	Delist_q1	Delist_q2	Delist_q3	Delist_q4	Delist_q5
Panel A: Z-Score								
Full Sample	11.15*	14.83**	16.80***	-5.407	-1.416	-1.692	-6.778**	0.234
	(1.914)	(2.314)	(2.827)	(-1.429)	(-0.363)	(-0.497)	(-2.038)	(0.090)
2007 ∼ 2019	7.954	15.47**	18.47***	-9.645**	-3.256	-2.369	-7.057*	0.871
	(1.152)	(2.059)	(2.731)	(-2.222)	(-0.687)	(-0.566)	(-1.698)	(0.284)
2021 ∼ 2024	21.55**	12.75	11.35	8.367	4.565	0.510	-5.869	-1.834
	(2.191)	(1.049)	(0.925)	(1.336)	(0.764)	(0.103)	(-1.389)	(-0.390)
Panel B: O-Score								
Full Sample	14.54**	15.09***	14.66***	-1.689	-4.144	-2.251	-3.421*	-1.573
	(2.281)	(2.934)	(2.908)	(-0.449)	(-1.528)	(-0.904)	(-1.687)	(-0.727)
2007 ∼ 2019	14.20*	13.90**	13.86**	-1.205	-3.247	-2.359	-3.612	-1.539
	(1.824)	(2.330)	(2.474)	(-0.272)	(-1.019)	(-0.848)	(-1.597)	(-0.648)
2021 ∼ 2024	15.67	18.95*	17.24	-3.261	-7.058	-1.900	-2.800	-1.685
	(1.606)	(1.911)	(1.550)	(-0.465)	(-1.395)	(-0.342)	(-0.635)	(-0.334)
Panel C: RLPM								
Full Sample	13.18**	12.75**	13.39**	-0.557	-3.325	-1.025	-2.854	-0.355
	(2.247)	(2.252)	(2.486)	(-0.134)	(-1.330)	(-0.366)	(-1.447)	(-0.211)
2007 ∼ 2019	12.61*	12.21*	12.95**	-1.269	-0.974	0.172	-3.366	-0.937
	(1.826)	(1.909)	(2.135)	(-0.254)	(-0.394)	(0.052)	(-1.495)	(-0.518)
2021 ∼ 2024	15.04	14.51	14.82	1.758	-10.97*	-4.917	-1.191	1.537
	(1.383)	(1.207)	(1.279)	(0.259)	(-1.679)	(-0.984)	(-0.290)	(0.379)
Panel D: MertonDD								
Full Sample	13.57**	16.01***	13.09***	-3.724	-6.967**	-2.971	0.046	-4.199**
	(2.057)	(3.241)	(2.593)	(-0.833)	(-2.119)	(-1.112)	(0.017)	(-2.127)
2007 ∼ 2019	12.33	16.54***	12.18**	-3.975	-6.184*	-1.121	0.436	-4.126*
	(1.621)	(2.966)	(2.115)	(-0.794)	(-1.782)	(-0.399)	(0.155)	(-1.948)
2021 ∼ 2024	17.59	14.27	16.06	-2.909	-9.513	-8.983	-1.221	-4.436
	(1.329)	(1.372)	(1.545)	(-0.293)	(-1.130)	(-1.367)	(-0.173)	(-0.908)

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.4. Distress Risk & Delisting Propensity Fama-Macbeth Regressions

This table reports Fama-MacBeth (1973) regressions of individual stock excess returns on involuntary delisting propensity scores after controlling distress risk measures. The sample runs from January 2007 to December 2024 and excludes all months in 2020. I conduct cross-sectional regressions for each month, with monthly returns of individual stocks regressed on estimated involuntary delisting propensity scores and four different distress risk measures respectively known prior to that month. All distress risk measures are first winsorized at the 1st and 99th percentiles and then min-max normalized into [0,1] range for each monthly dataset. I report average slopes for involuntary delisting propensity scores both across all cross-sections and within periods before and after the policy regime shift separately. t-statistics are based on Newey-West (1987) adjustment with 3 lags and small sample correction and are reported in parentheses.

Columns	①	②	③	④	⑤	⑥	⑦	⑧
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Prop	1.252*	0.404*	0.393*	0.426*	1.406*	0.468*	0.714*	0.401*
	(1.651)	(1.728)	(1.781)	(1.894)	(1.946)	(1.939)	(1.938)	(1.663)
$Prop_{before}$	1.628*	0.528*	0.517*	0.558*	1.837**	0.611*	0.928*	0.522*
	(1.650)	(1.738)	(1.806)	(1.915)	(1.962)	(1.955)	(1.941)	(1.667)
$Prop_{after}$	0.031	0.003	-0.008	-0.003	0.004	0.003	0.021	0.008
	(0.557)	(0.063)	(-0.201)	(-0.077)	(0.107)	(0.079)	(0.400)	(0.167)
Z-Score	0.042**	-0.003						
	(1.989)	(-0.967)						
O-Score			0.023**	0.002				
			(1.975)	(0.593)				
RLPM					0.024	0.002		
					(1.636)	(0.432)		
MertonDD							0.033*	-0.003
							(1.734)	(-0.836)

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.5. Asset Pricing Factor Tests

This table shows asset pricing factor tests for long-short portfolios sorted on involuntary delisting propensity scores estimated in Section III. The sample runs from January 2007 to December 2024 and excludes all months in 2020. I perform the time-series regressions of selected portfolios' monthly excess return on the market factor (MKT) as the CAPM model, and on the CH-4 factors (MKT, the size factor - SMB, the value factor - VMG, and the sentiment-based turnover factor - PMO), respectively. For columns 1, 3, 5 and 7, the time-series regression model is specified as: $R_t = \alpha + \beta^{MKT} \cdot R_t^{MKT} (+\beta^{SMB} \cdot R_t^{SMB} + \beta^{VMG} \cdot R_t^{VMG} + \beta^{PMO} \cdot R_t^{PMO}) + \varepsilon_t$. For columns 2, 4, 6 and 8, the time-series regression model is specified as: $R_t = \mathbf{1}\{Before\}_t \cdot \alpha^{Before} + \mathbf{1}\{After\}_t \cdot \alpha^{After} + \beta^{MKT} \cdot R_t^{MKT}$ $(+\beta^{SMB} \cdot R_t^{SMB} + \beta^{VMG} \cdot R_t^{VMG} + \beta^{PMO} \cdot R_t^{PMO}) + \varepsilon_t$. Constant terms are in annualized percentage form. t-statistics are based on Newey-West (1987) adjustment with 3 lags and small sample correction and are reported in parentheses.

Portfolios	LS8020	LS8020	LS8020	LS8020	LS9010	LS9010	LS9010	LS9010
Models	CAPM	CAPM	CH-4	CH-4	CAPM	CAPM	CH-4	CH-4
Columns	①	②	③	④	⑤	⑥	⑦	⑧
α	13.61**		-0.190		15.69**		-0.283	
	(2.156)		(-0.074)		(2.252)		(-0.086)	
α_{before}		13.75*		-0.946		15.41*		-1.511
		(1.822)		(-0.366)		(1.887)		(-0.497)
α_{after}		13.19		2.246		16.58		3.671
		(1.200)		(0.422)		(1.258)		(0.474)
β^{MKT}	0.237**	0.237**	0.057**	0.057**	0.208*	0.208*	0.022	0.022
	(2.217)	(2.216)	(2.128)	(2.114)	(1.826)	(1.826)	(0.663)	(0.666)
β^{SMB}			1.076***	1.077***			1.188***	1.189***
			(18.00)	(18.13)			(18.43)	(18.61)
β^{VMG}			-0.421***	-0.420***			-0.411***	-0.410***
			(-5.067)	(-5.103)			(-3.900)	(-3.942)
β^{PMO}			-0.086**	-0.086**			-0.077*	-0.079*
			(-2.042)	(-2.060)			(-1.854)	(-1.879)
Note:								*p<0.1; **p<0.05; ***p<0.01

Table B.6. Time-series Reversal Baseline Regressions

This table exhibits regression results examining the existence of time-series short-term return reversal pattern in the Chinese stock market. Following Jegadeesh (1990), the cross-sectional regression model, $R_{i,t} - E[R_{i,t}] = \alpha_t + \beta_t \cdot R_{i,t-1} + \varepsilon_{i,t}$, is fitted separately for each month using the OLS procedure, with parameter estimates and test statistics obtained from the time series of monthly cross-sectional regression estimates as in Fama and MacBeth (1973). The unconditional expected return for each stock in month t, $E[R_{i,t}]$, is estimated by the mean monthly return of the stock over the past 12 months prior to month t. The "Full" period starts from January 2000 to December 2024, while the "Selected" period starts from January 2007 to December 2024 and excludes all months in 2020. t-statistics are based on Newey-West (1987) adjustment with 3 lags and small sample correction and are reported in parentheses.

Period	Full	Selected
const	−0.002	−0.003
	(-0.368)	(-0.340)
$R_{i,t-1}$	-0.118^{***}	-0.122^{***}
	(-17.30)	(-16.76)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table B.7. Cross-sectional Reversal Baseline Regressions

This table exhibits asset pricing factor test results for the short-term return reversal anomaly. The "Full" period starts from January 2000 to December 2024, while the "Selected" period starts from January 2007 to December 2024 and excludes all months in 2020. Columns 1 and 4 report the average monthly returns for the long-short portfolio and the corresponding statistical significance levels. For columns 2 and 3, I perform time-series regressions of short-term return reversal anomaly long-short portfolio return on the CH-4 factors (MKT, the size factor - SMB, the value factor - VMG, and the sentiment-based turnover factor - PMO). For columns 5 and 6, I perform time-series regressions of short-term return reversal anomaly long-short portfolio return on the SMB and PMO factors, as well as the illiquidity anomaly long-short portfolio return - Illiq (the construction method also follows Liu et al., 2019). Constant terms are in annualized percentage form. t-statistics are based on Newey-West (1987) adjustment with 3 lags and small sample correction and are reported in parentheses.

Period		Full			Selected	
Columns	①	②	③	④	⑤	⑥
α	10.35^{**}	−3.665	−1.493	16.34^{***}	−2.404	1.213
	(2.333)	(-0.796)	(-0.351)	(2.731)	(-0.359)	(0.192)
β^{MKT}		0.093			0.116	
		(1.511)			(1.424)	
β^{SMB}		0.528^{***}	0.699^{**}		0.525^{***}	0.868^{**}
		(4.795)	(2.423)		(4.119)	(2.411)
β^{VMG}		0.186			0.320^{*}	
		(1.176)			(1.669)	
β^{PMO}		0.413^{***}	0.419^{***}		0.388^{***}	0.409^{***}
		(4.305)	(4.411)		(3.220)	(3.354)
β^{Illiq}			−0.169			−0.338
			(-0.847)			(-1.317)
R^2		0.270	0.262		0.226	0.216
Note:						*p<0.1; **p<0.05; ***p<0.01