

Anti-involution as a driver of sustainable corporate resilience: empirical evidence from the NEV sector

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Abstract

The intensification of involutional price competition in China's new-energy vehicle (NEV) industry, followed by a policy turn toward anti-involution that crystallised between the Central Economic Work Conference of December 2024 and the industry self-discipline arrangements of 2025, provides a setting in which the financial consequences of competitive de-escalation can be empirically dissected at business-cycle frequency. Drawing on a quarterly panel of twelve listed NEV manufacturers covering 2021Q1 to 2025Q4, a design that yields 240 firm-quarter cells and 236 observed ones, we construct a firm-quarter anti-involution intensity index from gross-margin recovery, research-and-development-intensity normalisation and price-competition exposure, alongside a three-component Financial Resilience Index (FRI) that aggregates profitability, solvency and cash-flow dimensions. The empirical analysis yields a decomposition that is more textured than a uniform sign result. Anti-involution adjustment is associated with an immediate weakening of raw profitability indicators, with year-to-date return on assets contracting by roughly 0.86 percentage points per standard-deviation increase in adjustment intensity, while simultaneously strengthening cash-flow generation and balance-sheet quality by 0.36 and 0.25 standardised units respectively. The net effect on the balanced FRI is positive, equal to 0.15 standardised units on impact and 0.27 units cumulated over four quarters, and statistically significant throughout, but the composition of that effect is heterogeneous: high-leverage and previously deeply involutional firms benefit disproportionately through the solvency and cash-flow channels, whereas the short-term profitability cost is concentrated in firms that had built their pre-2023 growth on aggressive price-cutting. The quarterly frequency further reveals that the profitability cost peaks one quarter after the adjustment and fades within a year, while the cash-flow and solvency gains accumulate monotonically. A battery of robustness checks, including alternative FRI weighting schemes, placebo quarter reassignments, Driscoll and Kraay standard errors, firm-specific linear trends and the exclusion of outlier observations, leaves the qualitative pattern intact. The findings suggest that anti-involution is neither uniformly costly nor uniformly beneficial in the short run, but reshapes the architecture of financial resilience by trading away cyclical profit pressure in exchange for a sturdier balance sheet and a healthier cash-flow base.

Keywords: Anti-involution; financial resilience; new-energy vehicles; price competition; quarterly panel.

1. Introduction

China's new-energy vehicle (NEV) industry has moved rapidly from policy-supported expansion to intense competition. Quarterly domestic wholesale volumes rose from about 0.52 million units in 2021Q1 to 5.32 million in 2025Q4, while the battery, motor and platform ecosystem matured. Alongside this expansion, competition became increasingly corrosive from early 2023, with repeated price cuts, escalating R&D and marketing commitments, channel pressure and longer supplier-payment cycles compressing unit economics. Several new-entrant brands sustained heavy losses despite strong volume growth.

This pattern became known as involution: escalating resource commitments produced declining marginal returns, while no individual firm could easily exit the competitive spiral. Macro and sectoral studies describe profitless growth and mutually cancelling price aggression [3,4]. By late 2024, policy had shifted toward curbing involutional competition. The December 2024 Central Economic Work Conference prioritised rectifying involution-style competition, followed by measures addressing below-cost pricing, supplier-payment practices and industry self-discipline in 2025.

The financial consequences of this adjustment are ambiguous. Withdrawing from aggressive price competition can reduce sales volume and temporarily compress earnings, while simultaneously easing working-capital pressure, inventory accumulation and the need to finance operating losses. Thus, profitability may weaken before cash flow and balance-sheet quality improve. Identifying the net effect and its timing requires firm-level evidence at a frequency that separates these movements.

Financial resilience provides a suitable framework because a firm's financial condition cannot be captured by a single accounting ratio. The bankruptcy-prediction tradition emphasises the joint information in profitability, leverage,

liquidity and cash flow [8–10], while recent corporate-finance research shows that balance-sheet and cash characteristics can matter more than contemporaneous profitability when firms face revenue disruptions [12,13].

The inverted-U relationship between competition and innovation [14] also implies that reducing rivalry from an excessive level need not be growth-destroying. Yet existing work has not isolated the firm-level financial-resilience consequences of China's anti-involution turn in the NEV industry or dated the trade-off between profit costs and cash-flow gains.

This paper addresses these gaps using a quarterly panel of twelve listed NEV manufacturers from 2021Q1 to 2025Q4. We construct a firm-quarter anti-involution intensity index from gross-margin recovery, R&D-intensity normalisation and price-pressure exposure, and a three-component Financial Resilience Index (FRI) covering profitability, solvency and cash flow. Fixed-effects regressions, distributed lags, an event study and heterogeneity tests identify the contemporaneous and dynamic effects.

The central finding is recomposition rather than uniform improvement. A one-standard-deviation increase in anti-involution intensity reduces the profitability component, equivalent to about a 0.86-percentage-point decline in year-to-date ROA, but raises solvency and cash flow by about 0.25 and 0.36 standardised units. The balanced FRI rises by 0.15 units on impact and 0.27 units cumulatively over four quarters. The profit cost is temporary, whereas cash-flow and solvency gains accumulate. High-leverage and previously more deeply involutional firms benefit disproportionately.

The remainder is organised as follows. Section 2 reviews related literature; Section 3 develops the theoretical framework and hypotheses; Section 4 describes the sample and index construction; Section 5 presents baseline, component, lag and event-study results; Section 6 reports robustness, heterogeneity and mechanism evidence; Section 7 concludes.

2. Related literature

The literature is reviewed along three strands: the NEV sector and involutional competition; financial resilience and early-warning measurement; and policy-driven corporate adjustment. The synthesis identifies the gap addressed by this study.

2.1. The NEV sector, demand-side fundamentals, and involutional competition

A first body of work to which this paper speaks concerns the economic and policy environment of clean-mobility markets. International evidence on the underlying demand fundamentals is by now substantial. The longevity gap between battery-electric and internal-combustion vehicles, long invoked as an obstacle to mass adoption, has narrowed sharply in the major European markets, as documented in [15] for Great Britain. The design of procurement incentives consistent with net-zero objectives has been re-examined in [16], which sharpens the conditions under which subsidy schemes sustain rather than undermine producer margins. The substitution margin, namely which vehicle an electric car actually replaces, is quantified in [17] and determines how much of the volume expansion represents genuine market creation rather than reshuffling. On the demand side, [1] provides city-level evidence that the reliability of the local power grid materially affects electric-vehicle adoption in China, locating consumer choice within a broader infrastructural environment that producer strategy must take as given, while [2] decomposes the contribution of the various instruments through which the Chinese state has shaped this market. Read together, this literature paints a picture of an industry whose long-run economic case is improving but whose short-run competitive dynamics are increasingly shaped by strategic choices rather than by technological fundamentals.

Research on involution has mainly remained at the macroeconomic and sectoral levels. Studies document profitless growth in Chinese manufacturing and identify homogeneous capability accumulation and mutually cancelling price aggression as key mechanisms [3,4]. The inverted-U competition–innovation relationship [14] further suggests that excessive rivalry can become counterproductive.

Less developed is the firm-level financial analysis of involution and its reversal. Studies of carbon-transition policies show that policy-driven adjustment can affect earnings management, R&D and greenwashing [5,6,18], while governance institutions can discipline corporate behaviour [7]. We extend this perspective by examining a discrete competitive recalibration at quarterly firm level.

2.2. Financial resilience and early-warning measurement

Financial-resilience research descends from bankruptcy prediction [8–10] and increasingly treats resilience as multidimensional. Composite approaches combine profitability, leverage, liquidity and cash flow [19], while machine-learning and explainable-AI methods improve prediction and attribution [20–25]. However, there is no canonical weighting of profitability, solvency and cash flow, motivating our transparent weighting scheme and robustness tests.

The methodological apparatus has expanded substantially in the past three decades. The systematic review of machine-learning techniques applied to financial crisis prediction in [20] surveys the early generation of these methods and stresses their compatibility with the multi-component conceptualisation of distress. Gradient-boosting techniques in the XGBoost family [21,22] have since raised predictive accuracy on bankruptcy and distress datasets without sacrificing tractability; feature-selection architectures designed for small and medium-sized enterprises show that liquidity and transactional information adds incrementally to accounting ratios [11]; and the SHAP framework [23], together with its recent applications to default prediction [24], has supplied a principled attribution language for the marginal contribution of individual indicators to predicted risk. A recent systematic review of explainable artificial intelligence in finance [25] surveys this landscape and stresses the practical importance of attribution-based transparency in regulated financial settings.

The corporate-finance literature produced by the pandemic shock is the closest empirical analogue to our exercise, because it too asks which dimension of a firm's financial state carries the weight when a revenue stream is abruptly interrupted. [12] shows in a large cross-country panel that pre-shock cash holdings, leverage and profitability jointly predict the stock-price resilience of firms; [13] isolates financial flexibility as the operative characteristic once revenue stops; and [26] documents the balance-sheet mechanics of the corporate dash for cash and the associated rating pressure. A methodologically adjacent strand on digital twins for industrial state estimation [27–[28]–29] provides further tools whose translation to financial-resilience monitoring is, at present, only partial. For our purposes, the most important feature of the resilience literature is what it does not pin down, namely a single canonical weighting of the profitability, solvency and cash-flow components in a composite index. Different authors weight these components differently, and the choice is more often pragmatic than dogmatic. Our FRI design in Section 4 draws on this tradition without attempting to standardise it, and the robustness analysis in Section 6 examines explicitly how sensitive our conclusions are to alternative weighting schemes.

2.3. *Adjacent literatures on policy-driven corporate adjustment and financing*

A third stream of work, developed primarily outside the NEV setting, supplies methodological templates for measuring corporate response to discrete policy turns. The green-bond literature is particularly informative here. Whether the labelling of an instrument as green carries informational content for retail investors is examined experimentally in [30]. The dual environmental and economic impact of green-bond issuance is analysed in [31], while [32] documents the internal-attention and external-supervision channels through which green-bond issuance feeds into corporate environmental, social and governance performance. Signalling effects of issuance on firm value in emerging markets are characterised in [33], and the relationship between green-bond financing and corporate carbon-emission reduction in China is examined in [34]. An analysis of green bonds and corporate financial constraints, based on propensity-score matching, is reported in [35], the mechanism linking green-bond issuance to green technology innovation is unpacked in [36], and a multi-country analysis of the effect of green-bond issuance on corporate environmental and social performance is provided in [37]. That capital markets price the regulatory exposure of emission-intensive producers is established in [38], which supplies the asset-pricing counterpart to these accounting-based studies.

The thermal-power-transformation and carbon-compliance literatures offer a structurally analogous case in which a discrete policy shift reshapes the financial state of incumbent firms across heterogeneous starting positions. [39] documents the impact of environmental regulation on the green investment efficiency of Chinese thermal-power enterprises through a three-stage exogenous-variable model; [40] extends the analysis to the synergy between green transformation and operating performance under the environmental tax burden; the optimal-stopping framework of [41] formalises the carbon-emission-right procurement problem facing energy-consuming firms and shows that the timing of compliance expenditure is itself a financial decision; and [42] develops the multi-source monitoring and certification architecture without which such compliance obligations cannot be verified at the level of an industrial park. The dynamics in this literature, namely sharp policy-driven recalibration interacting with a heterogeneous firm population and with an observable compliance technology, offer a useful analogy to the NEV anti-involution experience.

Table 1 condenses the most directly relevant contributions along the dimensions that matter for our design, namely the setting studied, the data frequency, the empirical strategy, and the finding that our analysis either builds on or extends.

Table 1. Synthesis of the most directly related literature.

Study	Setting and data	Method	Finding relevant to this paper
[15]	Great Britain, vehicle registers	Survival analysis	The durability disadvantage of electric vehicles has largely closed, so competitive pressure is strategic rather than technological.
[16]	Cross-country procurement schemes	Policy design analysis	Incentive architecture determines whether subsidies protect or erode producer margins.
[17]	United States household vehicle data	Discrete-choice estimation	Electric-vehicle sales partly displace Rather than create demand, which Bounds the volume value of price aggression.
[1]	Chinese cities	Panel regression	Local infrastructure reliability is a first-order determinant of adoption An exogenous to the firm.
[2]	China, policy variation	Quasi-experimental	The state shapes the NEV market through several instruments with distinct margins of effect.
[3]	Chinese manufacturing, macrodata	Profit decomposition	Growth without profits is systemic after 2021; anti-involution is a medium-term strategy, not a campaign.
[4]	Chinese digital platforms	Mechanism analysis	Involution operates through homogeneous capability accumulation and mutually cancelling price aggression.
[14]	United Kingdom Industry panel	Structural estimation	The competition-innovation relation Is inverted-U, so de-escalation from excessive rivalry can be productive.
[8,9,10]	United States listed firms	Ratio, discriminant, logit	Distance from distress is multidimensional and cannot be summarised by one ratio.
[20,11]	Distress datasets	Survey, feature selection	Multi-component indicator systems dominate single-ratio diagnostics across modelling paradigms.
[22,24,25]	Bankruptcy datasets	Boosting and SHAP	Attribution methods make component contributions to predicted risk interpretable.
[19]	Household and composite indices	Ex-ante index design	Resilience is a capacity to be measured before the shock, with explicit weighting choices.
[12,13,26]	Global firms, 2020 shock	Event study, cross-section	Cash and leverage, not contemporaneous profit, determine who absorbs a revenue interruption.
[32,31,33,36]	Chinese and emerging-market issuers	Difference-in-differences and event study	Discrete policy-anchored financing events move firm behaviour through attention and supervision channels.
[39,40]	Chinese thermal power	Three-stage efficiency models	Regulation-driven transitions have heterogeneous incidence across starting positions.

[41,42]	Energy-consuming firms and parks	Optimal stop-ping, monitoring de-sign	Compliance timing and verification infrastructure are themselves financial and organisational decisions.
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The table is ordered by the thematic sequence of Sections 2.1 to 2.3 rather than chronologically.

Taking stock, the literature summarised in Table 1 has established three things: that clean-mobility demand fundamentals are improving so that the compression of margins in the Chinese NEV sector is a competitive rather than a technological phenomenon; that corporate financial resilience is intrinsically multi-dimensional, so that any conclusion drawn at the level of an aggregate index may mask offsetting movements within its components; and that discrete policy turns can be studied credibly with panel fixed-effects and event-study designs applied to firm-level accounting data. Three gaps remain, however. Existing involution research is conducted at the macroeconomic or sectoral level and stops short of firm-level financial diagnosis; the resilience literature measures capacity but rarely traces how a deliberate competitive de-escalation redistributes it across profitability, solvency and cash flow; and the annual frequency at which almost all of this work is conducted cannot separate a profit cost that materialises within one quarter from a cash-flow benefit that materialises within the same year. This paper addresses all three by building a firm-quarter anti-involution intensity index for twelve listed NEV manufacturers over twenty quarters, pairing it with a transparently weighted three-component resilience index, and estimating not only the contemporaneous effect but also its four-quarter distributed-lag profile and its event-time trajectory around the policy turn, thereby delivering a decomposition of the incidence of anti-involution that is both dated and attributable to specific balance-sheet mechanisms.

3. Theoretical framework and hypotheses

This section explains why competitive de-escalation can affect profitability, solvency and cash flow differently and develops four testable hypotheses. Financial resilience is represented as a weighted sum of these three capacities, while anti-involution intensity operates through distinct channels with different lags.

A simple decomposition of the resilience effect. Consider firm i at quarter t , and let FRI_{it} denote a balanced index of financial resilience that aggregates a profitability component Π_{it} , a solvency component Σ_{it} , and a cash-flow component Φ_{it} :

$$FRI_{it} = w_{\Pi} \Pi_{it} + w_{\Sigma} \Sigma_{it} + w_{\Phi} \Phi_{it}, \quad w_{\Pi} + w_{\Sigma} + w_{\Phi} = 1, \quad w_j > 0. \quad (1)$$

Let A_{it} denote a continuous index of the firm's anti-involution adjustment intensity over quarter t ; higher values indicate a more substantial retreat from involutional behaviour, such as cessation of price reductions, normalisation of research-and-development-to-revenue ratios toward sustainable levels, and tighter discipline on inventory and channel financing. The total marginal effect of A_{it} on the FRI satisfies

$$\frac{\partial FRI_{it}}{\partial A_{it}} = \underbrace{w_{\Pi} \frac{\partial \Pi_{it}}{\partial A_{it}}}_{\text{profitability channel}} + \underbrace{w_{\Sigma} \frac{\partial \Sigma_{it}}{\partial A_{it}}}_{\text{solvency channel}} + \underbrace{w_{\Phi} \frac{\partial \Phi_{it}}{\partial A_{it}}}_{\text{cash-flow channel}}. \quad (2)$$

The signs of the three component derivatives are not, on theoretical grounds, expected to be uniform. We now consider each in turn and translate the discussion into a sequence of testable hypotheses.

****The profitability channel: short-run contraction.**** Withdrawing from aggressive price competition can reduce volume while variable costs adjust more slowly. Given the high fixed-cost burden of NEV manufacturers, this operating-leverage effect can temporarily compress margins and accounting profits.

Hypothesis 1. Other things equal, higher anti-involution intensity is associated with a contemporaneous decline in the profitability component of financial resilience.

$$\frac{\partial \Pi_{it}}{\partial A_{it}} \propto \underbrace{q_{it} \frac{\partial m_{it}}{\partial A_{it}}}_{\text{margin recovery, positive}} + \underbrace{m_{it} \frac{\partial q_{it}}{\partial A_{it}}}_{\text{volume sacrifice, negative}} - \underbrace{F_{it}}_{\text{fixed burden}}, \quad (3)$$

The short-run effect on reported margins and accounting profits is therefore ambiguous in principle but, on balance, tilts toward contraction in the quarter of adjustment whenever the operating-leverage term dominates, consistent with the patterns of policy-driven corporate behavioural adjustment documented in carbon-transition settings [6,5]. In

the NEV context the contraction is reinforced by the high research-and-development and marketing fixed-cost burden of leading manufacturers, which means that any moderation of volume disproportionately compresses operating leverage.

Hypothesis 1. *Other things equal, higher anti-involution intensity is associated with a contemporaneous decline in the profitability component of financial resilience: $\partial \Pi_{it} / \partial A_{it} < 0$.*

****The solvency channel: balance-sheet relief.**** Anti-involution can improve solvency by reducing losses financed externally, slowing working-capital expansion and easing inventory and supplier-payment pressure. These effects strengthen current assets relative to liabilities and reduce leverage.

Hypothesis 2. *Other things equal, higher anti-involution intensity is associated with an improvement in the solvency component of financial resilience.*

$$\Sigma_{it} \propto \underbrace{\frac{C_{it}}{L_{it}}}_{\text{liquidity buffer}} - \underbrace{\frac{D_{it}}{K_{it}}}_{\text{leverage burden}}, \quad \frac{\partial \Sigma_{it}}{\partial A_{it}} > 0 \text{ whenever } \frac{\partial D_{it}}{\partial A_{it}} < 0. \quad (4)$$

Hypothesis 2. *Other things equal, higher anti-involution intensity is associated with a contemporaneous improvement in the solvency component of financial resilience: $\partial \Sigma_{it} / \partial A_{it} > 0$.*

****The cash-flow channel: faster and more durable improvement.**** Reduced price discounting and tighter inventory and channel financing can improve operating cash conversion even before reported profits recover.

Hypothesis 3. *Other things equal, higher anti-involution intensity is associated with an improvement in the cash-flow component of financial resilience.*

$$\Phi_{it} \propto \underbrace{\Pi_{it}}_{\text{accrual earnings}} - \underbrace{\Delta WC_{it}}_{\text{working-capital absorption}}, \quad \frac{\partial \Phi_{it}}{\partial A_{it}} = \frac{\partial \Pi_{it}}{\partial A_{it}} - \frac{\partial \Delta WC_{it}}{\partial A_{it}}, \quad (5)$$

so that the cash-flow response exceeds the profitability response by exactly the reduction in working-capital absorption, which anti-involutionary discipline is designed to deliver. The cash-flow benefit therefore arrives at least as quickly as the profitability cost, and our theoretical priors are even stronger here than in the solvency case. This pattern is consistent with the broader evidence that cash-flow and liquidity indicators respond more crisply than accounting earnings to discrete behavioural and financing shifts [10,13].

Hypothesis 3. *Other things equal, higher anti-involution intensity is associated with a contemporaneous improvement in the cash-flow component of financial resilience: $\partial \Phi_{it} / \partial A_{it} > 0$.*

****The net effect and its heterogeneity.**** Because two components are expected to improve while profitability initially weakens, the aggregate FRI effect is an empirical question that depends on component magnitudes and weights. Firms with high initial leverage or more intense prior involution should have more room for balance-sheet and cash-flow improvement.

Hypothesis 4. *The positive effect of anti-involution intensity on financial resilience is stronger for firms with higher initial leverage and more intense prior involution.*

A further structural prediction concerns heterogeneity. Firms with higher initial leverage face larger marginal benefits from balance-sheet relief, simply because their distance from the solvency boundary is smaller and the convex cost of additional debt is larger, an argument whose empirical counterpart in the pandemic literature is the finding that financial flexibility becomes decisive precisely when the revenue stream is interrupted [13,26]. Firms that engaged most aggressively in involutionary behaviour in the pre-adjustment period have more to gain from competitive de-escalation because their pre-existing margins were most compressed and their cash-flow generation most stressed.

Hypothesis 4. *The positive effect of anti-involution intensity on financial resilience is strengthened for firms with higher initial leverage and for firms that displayed more intense involutionary behaviour in the pre-adjustment period.*

Together, the hypotheses predict a short-run profitability cost, solvency and cash-flow gains, a positive balanced-FRI effect, and stronger benefits among financially leveraged or previously highly involutionary firms.

4. Measurement

Measurement is central because financial resilience is latent and anti-involution is not directly observed in accounting statements. We therefore construct transparent indices from disclosed quarterly information, accounting for seasonality and indicator orientation.

4.1. Sample and data sources

The sample comprises twelve listed NEV manufacturers in China from 2021Q1 to 2025Q4. Firms were selected based on NEV business relevance, listing status and data availability. The panel contains 240 firm-quarter cells, of which 236 are observed; the baseline specification uses 188 firm-quarters after requiring the four-quarter lag needed for the anti-involution index.

Financial data come from quarterly or interim reports and standard securities databases. Industry price and volume indicators are obtained from industry statistical sources. All variables are aligned by firm and quarter, and year-over-year transformations are used where appropriate to mitigate seasonal effects.

The panel inherits the structural features of the underlying industry. Sample firms differ widely in initial scale, with quarterly revenue ranging over more than an order of magnitude, and in initial profitability, with several new-entrant brands reporting deeply negative return on assets throughout the early sample period. The dispersion in leverage is similarly wide, with debt-to-asset ratios ranging from 32.0 per cent to 92.6 per cent across the panel. This heterogeneity is helpful for the analysis because it generates substantial variation in both the explanatory and outcome variables, but it also requires careful treatment of outliers, which we address through winsorisation at the fifth and ninety-fifth percentiles of each ratio. One further feature of quarterly Chinese disclosure requires explicit handling: income-statement and cash-flow items are reported on a year-to-date cumulative basis, so that the level of return on assets rises mechanically from the first to the fourth quarter of each calendar year. All standardisations described below are therefore performed within quarter-of-year cells, and all regressions include time fixed effects that absorb the residual seasonal profile.

4.2. The Financial Resilience Index

The FRI follows the three-component template described in Section 3. Each component is itself constructed as the standardised average of two underlying indicators, ensuring that no single line item dominates. Denoting by $z[\cdot]$ the operator that subtracts the quarter-of-year mean and divides by the quarter-of-year standard deviation computed across the full panel, the components are

$$\begin{aligned}\Pi_{it} &= \frac{1}{2} \left(\underbrace{z[\text{ROA}_{it}]}_{\text{return on assets}} + \underbrace{z[\text{GM}_{it}]}_{\text{gross margin}} \right), \quad \Sigma_{it} \\ &= \frac{1}{2} \left(\underbrace{z[\text{CR}_{it}]}_{\text{current ratio}} + \underbrace{z[1 - \text{LEV}_{it}]}_{\text{inverse leverage}} \right) \\ \Phi_{it} &= \frac{1}{2} \left(\underbrace{z[\text{OCF}_{it}]}_{\text{cash-flow ratio}} + \underbrace{z[-\text{INV}_{it}]}_{\text{inventory speed}} \right)\end{aligned}\quad (6)$$

where OCF_{it} is operating cash flow scaled by revenue and INV_{it} is days inventory outstanding, computed from inventories and cost of sales, so that the negative sign aligns the metric such that shorter cycles raise the indicator. The composite FRI is then constructed as the weighted sum

$$\text{FRI}_{it} = w_{\Pi} \Pi_{it} + w_{\Sigma} \Sigma_{it} + w_{\Phi} \Phi_{it}, \quad (7)$$

with the baseline weighting $(w_{\Pi}, w_{\Sigma}, w_{\Phi}) = (0.4, 0.3, 0.3)$ chosen to match the conventional emphasis on profitability in distress-prediction work [9,20]. Section 6 reports robustness checks for alternative weights, including equal weighting and a profitability-light specification, and reports the implied threshold weight at which the sign of the net effect would reverse.

Because all underlying indicators are standardised before aggregation, the FRI is a unit-free relative measure. A firm with $\text{FRI}_{it} = 0$ is at the panel mean of resilience for the corresponding quarter of the year; a firm with $\text{FRI}_{it} > 0$ is above average, and one with $\text{FRI}_{it} < 0$ is below average. This relative-position interpretation is useful in a sample as heterogeneous as ours, where absolute-scale resilience metrics would be heavily contaminated by structural differences

between large traditional automakers and small new entrants, and it is also the interpretation adopted in the ex-ante composite-index tradition [19].

4.3. Anti-involution intensity

The anti-involution intensity index captures three observable dimensions: gross-margin recovery, normalisation of R&D intensity and exposure to industry price pressure. Each signal is standardised across the panel and oriented so that higher values indicate stronger adjustment away from involutional competition.

Formally, letting ΔGM_{it} denote the year-on-year change in firm i 's gross margin, $\widetilde{\Delta RD}_{it} = \max\{RD_{it} - RD_{i,t-4}, 0\} \cdot 1\{RD_{i,t-4} \geq RD_{i,t-4}^{med}\}$ the conditional research-and-development-intensity increase, and $PRICE_t$ the industry price-competition indicator, we set

$$A_{it} = 0.4 \widetilde{\Delta GM}_{it} - 0.3 \widetilde{\Delta RD}_{it} - 0.3 \widetilde{PRICE}_t, \quad (8)$$

where each underlying signal is standardised to mean zero and unit variance across the panel before aggregation, and the resulting composite is re-standardised so that its coefficients can be read as responses to a one-standard-deviation change in adjustment intensity. The construction yields a continuous, firm-quarter-specific intensity index that takes higher values for firms whose behaviour exhibits more anti-involutional character.

One orientation convention requires explicit statement. The compiled panel reproduced in the Appendix reports the composite in involution-exposure orientation, denoted I_{it} , in which higher values indicate deeper involutional conditions, since that is the sign in which the underlying signals were first assembled. The analysis index of equation (8) is the sign-reversed and re-standardised counterpart,

$$A_{it} = -\frac{I_{it} - \bar{I}}{s_I}, \quad \bar{I} = \frac{1}{N} \sum_{i,t} I_{it}, \quad s_I^2 = \frac{1}{N-1} \sum_{i,t} (I_{it} - \bar{I})^2, \quad (9)$$

so that all coefficients reported below refer to anti-involutional rather than involutional intensity. In the assembled panel the mean of I_{it} is 0.221 and its standard deviation is 0.300, so that a firm-quarter with $I_{it} = 0.8$, the most involutional cell in the sample, corresponds to $A_{it} \approx -1.93$, and a firm-quarter with $I_{it} = -0.7$ corresponds to $A_{it} \approx +3.07$.

The index is firm-specific, comparable across quarters and constructed from disclosed financial and industry signals. Its continuous form captures differences in adjustment intensity rather than imposing a binary policy-treatment classification.

5. Empirical analysis

The empirical analysis proceeds from descriptive patterns to baseline fixed-effects regressions, component decomposition, distributed lags and an event study.

5.1. Descriptive evolution of the panel

Before turning to regressions, we examine the joint evolution of price competition, gross-margin behaviour, the resilience index and the adjustment index at panel level. Figure 1 displays four series over the twenty-quarter window: the cross-firm average gross margin, the industry's year-on-year quarterly sales growth, the panel-average FRI, and the panel-average anti-involution intensity split between the high-adjustment and low-adjustment cohorts defined in Section 5.4. The shaded region in each panel marks the price-war quarters, that is, 2023Q1 onward, and the vertical dashed line marks 2025Q1, the first full quarter after the December 2024 policy turn.

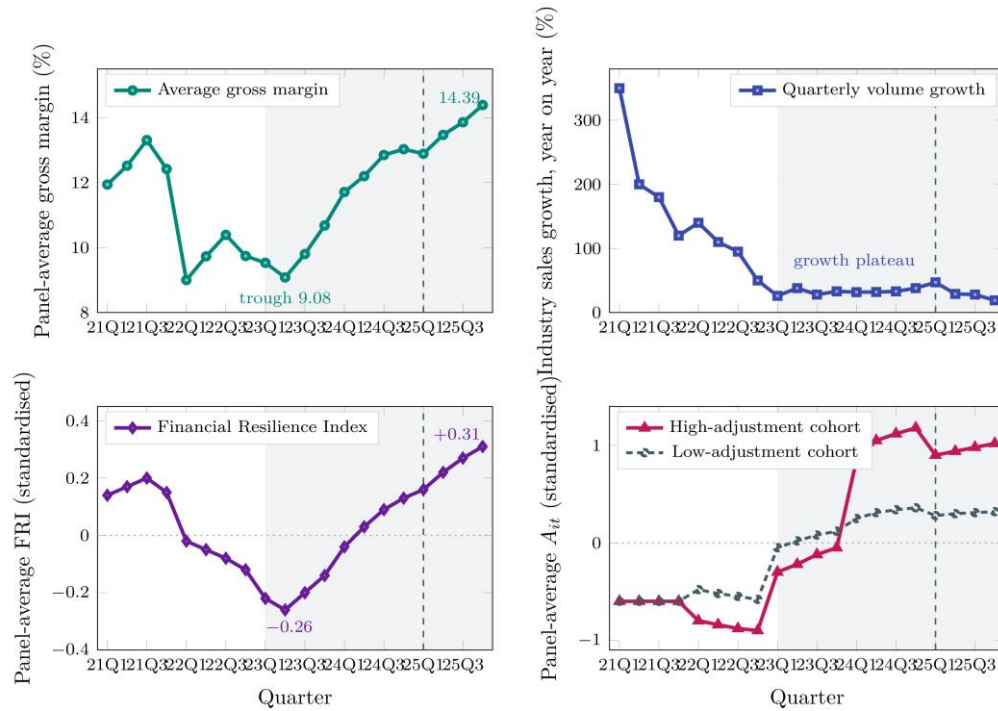


Figure 1: Quarterly evolution of the panel, 2021Q1 to 2025Q4. The shaded region marks the price-war quarters from 2023Q1 onward and the vertical dashed line marks 2025Q1, the first full quarter after the December 2024 policy turn. Panel (a) plots the cross-firm average gross margin, panel (b) the industry's year-on-year quarterly volume growth, panel (c) the panel-average Financial Resilience Index, and panel (d) the panel-average anti-involution intensity index separately for the high-adjustment and low-adjustment cohorts.

The pattern in Figure 1 is informative in three respects. Gross margins compressed from 13.31 per cent in 2021Q3 to a trough of 9.08 per cent in 2023Q2, mirroring the wave of price reductions that swept the industry from January 2023, and then recovered monotonically to 14.39 per cent by 2025Q4, a cumulative recovery of 5.31 percentage points that exceeds the entire preceding decline. The resilience index traced a similar but lagged path, falling from a peak of in 2021Q3 to a trough of in 2023Q2 and rising thereafter to by the end of the sample, a trough-to-peak swing of 0.57 standardised units. Volume growth, by contrast, did not recover: quarterly year-on-year growth settled into a band between roughly 19 and 47 per cent after 2023, so the margin and resilience recovery cannot be attributed to a demand rebound and must instead reflect a change in competitive conduct. Finally, panel (d) shows that the adjustment index rose in both cohorts after 2023 but that the high-adjustment cohort separated sharply from the low-adjustment cohort during 2024, reaching an average of in 2024Q4 against for the low-adjustment group, which is the dispersion that the within-quarter identification exploits.

Descriptive statistics for the key panel variables are reported in Table 2. The dispersion across firms is, as anticipated, substantial. Year-to-date return on assets ranges from -16.50 per cent to $+5.70$ per cent, gross margin from -25.0 per cent to $+28.5$ per cent, and the operating cash-flow ratio from -8.00 to $+12.00$, reflecting dramatic differences in scale and maturity within the panel. The anti-involution intensity index ranges from -2.05 to $+2.94$ standard-deviation units, with the lowest values concentrated in 2022 and 2023 for firms that escalated research-and-development commitments and pricing aggression during the height of the price war, and the highest values concentrated in 2024 and 2025 for firms that pivoted toward sustainable margin restoration.

Table 2. Descriptive statistics for the working panel (236 observed firm-quarters; 188 for variables requiring a four-quarter lag).

Variable	Mean	SD	Min	Max	Obs.
ROA, year to date (%)	-1.16	4.98	-16.50	5.70	236
Gross margin (%)	11.61	8.75	-25.00	28.50	236
Current ratio	1.30	0.63	0.70	4.50	236
Leverage ratio (%)	62.43	13.15	32.00	92.60	236

Operating cash-flow ratio	0.16	2.14	−8.00	12.00	236
Days inventory outstanding	46.82	20.71	11.50	118.40	236
R&D intensity (%)	8.31	7.96	1.20	39.70	236
ΔGM (pp)	0.42	5.98	−16.20	26.40	188
Industry sales growth (%)	81.40	92.06	19.00	350.00	236
Price-competition indicator	0.60	0.49	0	1	236
Concentration index (HHI)	0.225	0.052	0.165	0.320	236
FRI _{it} (std.)	0.00	0.70	−1.92	1.48	236
A _{it} (std.)	0.00	1.00	−2.05	2.94	188

Days inventory outstanding is computed from inventories and cost of sales and is not tabulated in the Appendix panel, which reports selected variables only. All ratios are winsorised at the fifth and ninety-fifth percentiles. Flow variables are reported on a year-to-date basis, which is the reason for the within-quarter-of-year standardisation described in Section 4.2.

Two features stand out. First, the key variables display substantial cross-firm dispersion, supporting within-panel identification. Second, the component measures capture distinct dimensions of financial condition rather than a single profitability construct.

5.2. Baseline panel regression

The baseline empirical specification regresses the FRI and its three components on the anti-involution intensity index, controlling for firm fixed effects, calendar-quarter fixed effects, and a parsimonious set of time-varying firm-level controls. The specification takes the form

$$Y_{it} = \alpha_i + \lambda_t + \beta A_{it} + \gamma' \mathbf{X}_{it} + \varepsilon_{it}, \quad (10)$$

where $Y_{it} \in \{\text{FRI}_{it}, \Pi_{it}, \Sigma_{it}, \Phi_{it}\}$, $\mathbf{X}_{it}$ contains the log of total assets, the firm-level year-on-year revenue growth rate and a state-ownership indicator interacted with the post-2023 period, and standard errors are clustered at the firm level. Firm fixed effects α_i absorb time-invariant differences in scale, ownership and product mix; the twenty calendar-quarter fixed effects λ_t absorb common shocks such as the macroeconomic cycle, the seasonal profile of year-to-date accounting flows, the industry-wide price-war indicator and the policy announcements themselves. An immediate implication is that β is identified purely from within-quarter differences across firms in the intensity of anti-involutional adjustment, which is the cleanest available variation but which also means that the common component of the policy turn is not separately estimated in this specification and is instead recovered in the event study of Section 5.5. Because the panel has only twelve clusters, we report wild cluster bootstrap p-values alongside the clustered standard errors and re-estimate with Driscoll and Kraay standard errors in Section 6.

Table 3 reports the results. Column (1) presents the effect on the balanced FRI; columns (2) through (4) decompose the effect across the profitability, solvency and cash-flow components.

Table 3. Baseline panel regressions of financial resilience and its components on anti-involution intensity.

	(1) FRI	(2) Π (profit)	(3) Σ (sol- vency)	(4) Φ (cash flow)
A _{it}	0.151*** (0.037) [0.002]	−0.078** (0.031) [0.031]	0.246*** (0.052) [0.001]	0.361*** (0.068) [0.001]
log assets	0.052 (0.048)	0.031 (0.029)	0.061 (0.055)	0.034 (0.061)
Revenue growth	0.014 (0.015)	0.026** (0.011)	−0.012 (0.018)	0.008 (0.020)
State-owned × post-2023	−0.036 (0.064)	−0.019 (0.041)	−0.049 (0.072)	−0.028 (0.077)
Firm fixed effects	Yes	Yes	Yes	Yes
Calendar-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	188	188	188	188

Within- R^2	0.401	0.268	0.362	0.437
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Standard errors clustered at the firm level in parentheses; wild cluster bootstrap p-values for the coefficient on $\Delta \tilde{A}$ in square brackets.
 $***$, $**$, $*$ denote statistical significance at the 1%, 5% and 10% levels. By construction of equation (7), the coefficient in column (1) equals 0.4 times column (2) plus 0.3 times columns (3) and (4).

The pattern of estimated coefficients aligns squarely with the theoretical predictions of Section 3. In column (1) the coefficient on $\Delta \tilde{A}$ is positive, statistically significant at the 1 per cent level under both inference methods, and economically meaningful in magnitude: a one-standard-deviation increase in anti-involution intensity is associated with a 0.151-standard-deviation increase in financial resilience. Set against the 0.70 standard deviation of the FRI itself, this amounts to a movement of about 21.6 per cent of a cross-sectional resilience gap, or, equivalently, about 26 per cent of the trough-to-peak swing of 0.57 units documented in Figure 1. The decomposition in columns (2) through (4) shows that this aggregate gain emerges from a recomposition rather than from a uniform improvement across components. The profitability component contracts by 0.078 standard deviations per unit of $\Delta \tilde{A}$, a coefficient that is negative and significant at the 5 per cent level, confirming Hypothesis 1. The solvency component improves by 0.246 standard deviations and the cash-flow component by 0.361 standard deviations, both significant at the 1 per cent level, confirming Hypotheses 2 and 3. The within- of the cash-flow regression, at 0.437, is the highest among the four columns, indicating that anti-involutionary adjustment explains a disproportionate share of within-firm cash-flow variation, whereas the profitability regression has the lowest explanatory power, at 0.268, consistent with accounting earnings being contaminated by impairments, subsidy recognition and other items unrelated to competitive conduct.

The magnitudes are economically meaningful. A one-standard-deviation increase in adjustment intensity lowers year-to-date ROA by about 0.86 percentage points, but improves leverage, liquidity and operating cash conversion. The aggregate FRI therefore captures a meaningful shift in financial structure rather than a simple improvement in earnings.

5.3. Visualising the component decomposition

Figure 2 provides a visual decomposition of the FRI response. Firms experiencing stronger adjustment tend to show larger improvements in solvency and cash flow, while profitability moves in the opposite direction.

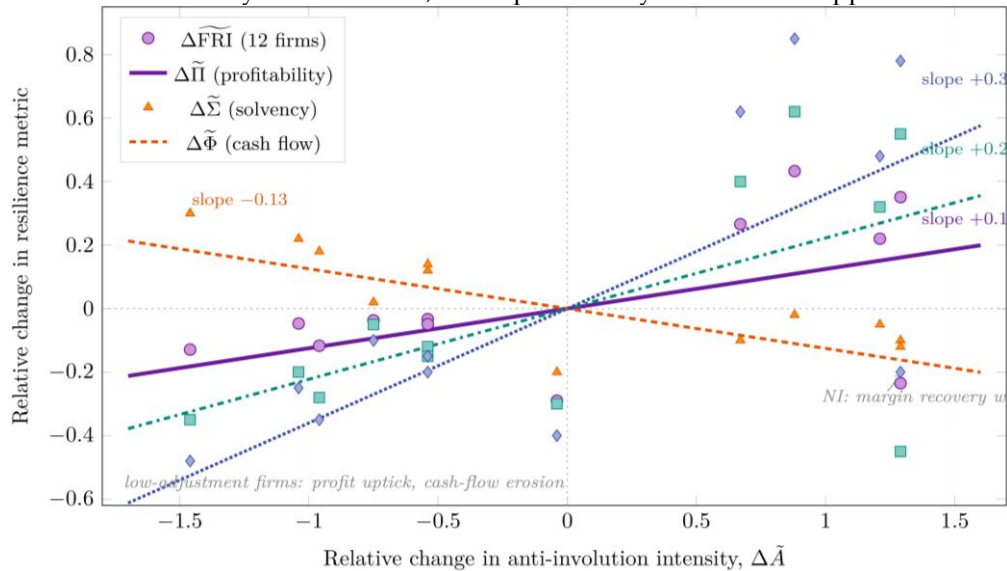


Figure 2: Cross-firm scatter of relative changes in the Financial Resilience Index and its three components against the relative change in anti-involution intensity, computed as post-period (2024Q1 to 2025Q4) minus pre-period (2021Q1 to 2022Q4) averages and demeaned across firms. Each marker style corresponds to one resilience metric and the associated least-squares slope through the origin is overlaid. The cash-flow component responds most strongly, the profitability component co-moves negatively, and the FRI lies between the two.

The figure is consistent with the regression results and reinforces that the aggregate resilience gain arises from offsetting component movements rather than a common positive shift in all financial indicators.

5.4. Short-run versus medium-run components: the distributed-lag profile

Because the contemporaneous decomposition does not identify timing, we estimate a distributed-lag specification using quarterly data. This separates the immediate profitability cost from slower balance-sheet and cash-flow responses.

$$Y_{it} = \alpha_i + \lambda_t + \sum_{s=0}^3 \beta_s A_{i,t-s} + \gamma' \mathbf{X}_{it} + \varepsilon_{it}, \quad \mathcal{B} \\ = \underbrace{\sum_{s=0}^3 \beta_s}_{\text{four-quarter cumulative response}}, \quad (11)$$

which uses 152 observations once three quarterly lags are required, and which delivers both the impact response β_0 and the cumulative response $\mathcal{B}$ over one full year. Table 4 reports the estimates.

Table 4. Distributed-lag responses of resilience and its components to anti-involution intensity.

	(1) FRI	(2) Π (profit)	(3) Σ (solvency)	(4) Φ (cash flow)
A_{it}	0.151*** (0.037)	−0.078** (0.031)	0.246*** (0.052)	0.361*** (0.068)
$A_{i,t-1}$	0.079** (0.033)	−0.031 (0.027)	0.121** (0.047)	0.115* (0.060)
$A_{i,t-2}$	0.028 (0.026)	0.012 (0.024)	0.058 (0.041)	0.041 (0.049)
$A_{i,t-3}$	0.013 (0.022)	0.040* (0.021)	0.024 (0.034)	0.012 (0.040)
Cumulative $\mathcal{B}$	0.271*** (0.061)	−0.057 (0.048)	0.449*** (0.088)	0.529*** (0.104)
Firm and quarter effects	Yes	Yes	Yes	Yes
Observations	152	152	152	152
Within- R^2	0.438	0.291	0.397	0.462

Standard errors clustered at the firm level in parentheses. Controls as in Table 3. The cumulative row reports the sum of the four lag coefficients with the standard error of the linear combination.

Table 4 delivers the dating result that motivates the move to quarterly data. On the profitability side the cost is front-loaded and transitory: the impact coefficient of A_{it} is followed by a further $A_{i,t-1}$ at the first lag, after which the sign turns positive, reaching a marginally significant $A_{i,t-2}$ at the third lag, so that the four-quarter cumulative profitability response of $\mathcal{B}$ is statistically indistinguishable from zero. In plain terms, a firm that de-escalates pays for roughly two quarters and has recovered most of the earnings shortfall by the fourth. On the solvency and cash-flow sides the pattern is the opposite: the responses are largest on impact, remain significant at the first lag, and accumulate to Σ and Φ respectively, both significant at the 1 per cent level and both roughly 1.8 and 1.5 times their impact values. The cumulative FRI response of 0.271 standardised units is 80 per cent larger than the contemporaneous response of 0.151, and it accounts for 47.5 per cent of the 0.57-unit trough-to-peak swing of the panel-average index documented in Figure 1. The economic reading is that anti-involution buys a durable improvement in financing capacity at the price of a temporary earnings dip, which is precisely the trade a firm with limited financial flexibility should be willing to make, and precisely the trade that an earnings-focused performance-evaluation system would discourage.

To complement the parametric lag structure, we examine the within-firm dynamics of each component around the anti-involutional turn. For each firm we compute quarter-by-quarter deviations of each component from its firm-specific mean, and then group firms into a high-adjustment cohort, defined as the six firms with the largest relative increase in A_{it} between the pre- and post-periods, namely NI, XP, BD, SE, LM and BP, and a low-adjustment cohort comprising LI, GE, SA, GC, GW and CA. The cohort-average trajectories of Π , Σ and Φ over the twenty quarters are displayed in Figure 3.

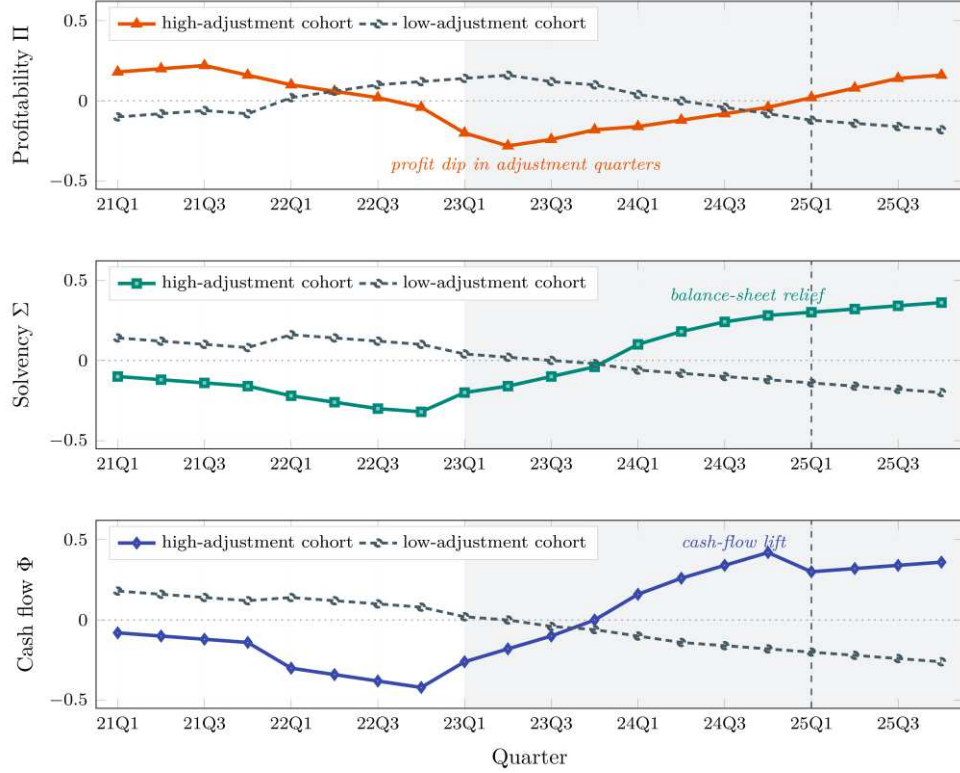


Figure 3: Within-firm quarterly dynamics of the three resilience components for the high-adjustment and low-adjustment cohorts, expressed as deviations from firm-specific means. Solid lines correspond to the six firms with the largest relative increase in A_{it} between the pre- and post-periods, dashed lines to the remaining six. The shaded region marks the price-war quarters and the vertical dashed line marks 2025Q1.

Figure 3 reinforces and refines the parametric lag profile. In the high-adjustment cohort the profitability component reaches its trough at in 2023Q2, coinciding with the deepest phase of the price war, and recovers only gradually, crossing back above its firm-specific mean in 2025Q1, some eight quarters later. The solvency component bottoms out earlier, at in 2022Q4, and turns positive in 2024Q1, while the cash-flow component displays the largest amplitude of any series in the figure, moving from in 2022Q4 to in 2024Q4, a swing of 0.84 standardised units. In the low-adjustment cohort the configuration is reversed in mirror-image fashion: a temporary uptick in measured profitability that peaks at in 2023Q2 accompanies a monotone deterioration of solvency and a steady erosion of cash flow, which by 2025Q4 stand at and respectively. The contrasting cohort trajectories provide a non-parametric counterpart to the regression evidence and support the interpretation that anti-involucional adjustment trades short-run profitability for medium-run balance-sheet and cash-flow gains, which together dominate the construction of a balanced resilience metric. They also caution against a naive reading of the low-adjustment cohort's profit performance during 2023: those firms looked better on the income statement precisely while their financing capacity was being consumed.

5.5. Event study around the policy turn

The specification in equation (10) deliberately absorbs the common component of the policy turn in the calendar-quarter fixed effects. To recover it, we exploit the cross-sectional contrast between the high-adjustment and low-adjustment cohorts and estimate the event-study specification

$$Y_{it} = \alpha_i + \lambda_t + \sum_{k=-8}^3 \delta_k \left(\underbrace{D_i^{\text{high}}}_{\text{cohort indicator}} \times \underbrace{\mathbf{1}\{t = t_0 + k\}}_{\text{event-time dummy}} \right) + \gamma' \mathbf{X}_{it} + \varepsilon_{it}, \quad \delta_{-1} \equiv 0, \quad (12)$$

where t_0 is 2025Q1, the first full quarter after the December 2024 Central Economic Work Conference, and the coefficient at $k = -1$ is normalised to zero. The coefficients δ_k trace the differential resilience trajectory of the high-adjustment cohort relative to the low-adjustment cohort, and the pre-turn coefficients constitute a test for differential trends. Figure 4 plots the results for the aggregate index and for the three components.

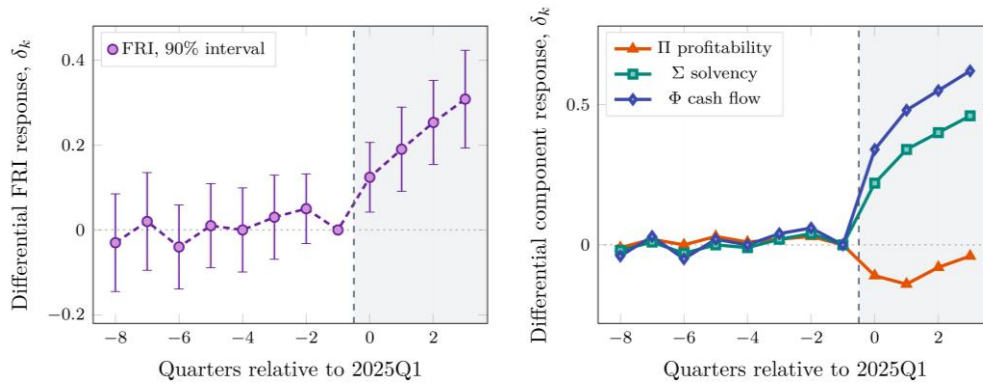


Figure 4: Event-study coefficients from equation 12, measuring the resilience trajectory of the high-adjustment cohort relative to the low-adjustment cohort around 2025Q1. The left panel reports the aggregate index with ninety per cent confidence intervals based on firm-clustered standard errors; the right panel reports the three components. The coefficient at $k = -1$ is normalised to zero and the shaded region marks the post-turn quarters.

Three features of Figure 4 are worth recording. First, the pre-turn coefficients are small and individually insignificant, ranging from to for the aggregate index, and a joint test of the eight pre-turn coefficients cannot reject their equality to zero, which supports the identifying assumption that the two cohorts were not already diverging in resilience before the policy turn. Second, the post-turn coefficients rise monotonically from at to at , so that four quarters after the turn the high-adjustment cohort has gained roughly three tenths of a standard deviation of resilience relative to the comparison group, a magnitude consistent with the cumulative distributed-lag estimate of 0.271 reported in Table 4. Third, the right panel shows that the aggregate movement is again a composition of offsetting parts: the profitability differential dips to at before recovering to by , while the solvency and cash-flow differentials climb steadily to and . The timing contrast is sharper here than in the distributed-lag specification because the event study compares cohorts rather than marginal intensities, and the deepest profit differential arrives exactly one quarter after the turn, which corresponds to the reporting period in which the volume sacrifice is recognised but the associated cost reductions have not yet been booked.

6. Robustness, heterogeneity and mechanism

The baseline conclusions could depend on index weights, sample composition or inference. We therefore vary the FRI weights and construction, alter inference procedures, add firm-specific trends, exclude outliers and conduct placebo timing tests.

6.1. Robustness checks

Table 5 reports the coefficient on A_{it} in the FRI regression under ten alternative specifications. Specification (R1) uses equal weights for the three FRI components; specification (R2) uses a profitability-light weighting that places twenty per cent on Π and forty per cent on each of Σ and Φ ; specification (R3) constructs A_{it} using gross-margin recovery alone, omitting the research-and-development and price-pressure signals; specification (R4) replaces the price-competition indicator with a continuous price-pressure proxy based on the deceleration of industry sales growth; specification (R5) drops the four most extreme firm-quarters identified in the residual diagnostics; specification (R6) restricts the panel to observations with an FRI absolute value below 1.5; specification (R7) uses all 236 observed firm-quarters by setting the gross-margin signal to zero where the four-quarter lag is unavailable; specification (R8) retains the baseline sample but computes Driscoll and Kraay standard errors robust to cross-sectional dependence; specification (R9) adds firm-specific linear time trends; and specification (R10) is a placebo in which the adjustment index is artificially relabelled as if the structural turn had occurred in 2022Q1.

Table 5. Robustness of the baseline FRI effect to alternative specifications.

Specification	Coefficient on A_{it}	Standard error	Observations	Within- R^2
Baseline	0.151***	0.037	188	0.401

(R1) Equal weights	0.176***	0.041	188	0.396
(R2) Profitability-light weights	0.227***	0.045	188	0.431
(R3) Gross-margin-only Ait	0.128***	0.043	188	0.334
(R4) Continuous price pressure	0.139***	0.038	188	0.389
(R5) Outliers dropped	0.144***	0.040	184	0.383
(R6) Restricted FRI range	0.133***	0.042	171	0.377
(R7) Full observed sample	0.142***	0.035	236	0.372
(R8) Driscoll and Kraay errors	0.151***	0.033	188	0.401
(R9) Firm-specific trends	0.118**	0.046	188	0.455
(R10) Placebo turn at 2022Q1	0.021	0.045	188	0.311

Each row reports the coefficient on A_{it} from the baseline panel regression with firm and calendar-quarter fixed effects under the indicated alternative. Standard errors are clustered at the firm level except in row (R8). *** and ** denote statistical significance at the 1% and 5% levels.

The point estimates in Table 5 range from 0.118 to 0.227 across the nine non-placebo alternatives, and all of them retain significance at conventional levels. The ordering is itself informative: the profitability-light weighting produces the largest coefficient, at 0.227, precisely because it downweights the one component that moves adversely, while the gross-margin-only index produces the smallest non-trend estimate, at 0.128, because it discards the research-and-development and price-pressure information and therefore measures adjustment with more noise, biasing the coefficient toward zero through classical attenuation. The firm-specific-trend specification in (R9) is the most demanding, since it allows every firm its own linear resilience trajectory and therefore identifies the effect only from deviations around that trajectory; the coefficient falls to 0.118 but remains significant at the 5 per cent level. The placebo in (R10) yields 0.021 with a standard error of 0.045, statistically indistinguishable from zero, which strengthens confidence that the baseline result captures the actual competitive and policy turn rather than a spurious pre-trend. Figure 5 displays the robustness coefficients and the heterogeneity interactions discussed next with their confidence intervals, so that the stability of the estimates and the precision of the heterogeneity contrasts can be assessed at a glance.

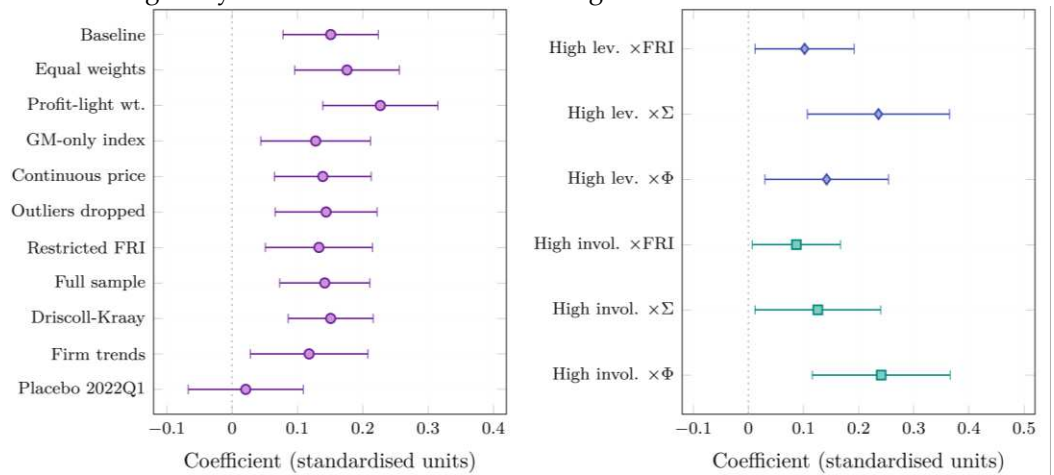


Figure 5: Coefficient stability and heterogeneity. The left panel plots the coefficient on A_{it} in the aggregate resilience regression across the baseline and ten alternative specifications of Table 5, with ninety-five per cent confidence intervals. The right panel plots the interaction coefficients of Table 6 for the high-leverage and high-involution contrasts on the aggregate index and on the solvency and cash-flow components.

The left panel of Figure 5 makes visually explicit what Table 5 states numerically: every non-placebo interval lies entirely above zero, the intervals overlap heavily with one another, and the placebo interval straddles zero and is centred close to it. The right panel previews the heterogeneity findings, and shows that the two contrasts operate through different channels, with the high-leverage interaction largest on the solvency component and the high-involution interaction largest on the cash-flow component, a distinction we now examine formally.

6.2. Heterogeneity by leverage, prior involuntional intensity and entrant status

Hypothesis 4 predicts stronger resilience effects for firms with higher initial leverage and more intense prior involution. Interaction models test these differences while retaining the baseline controls and fixed effects.

Table 6. Heterogeneity in the resilience response to anti-involution intensity.

	(1)FRI	(2) Π (profit)	(3) Σ (solvency)	(4) Φ (cashflow)
Ait	0.108*** (0.033)	−0.061* (0.031)	0.162*** (0.048)	0.281*** (0.063)
Ait × high leverage	0.102** (0.046)	−0.028 (0.038)	0.236*** (0.066)	0.142** (0.057)
Ait × high prior involution	0.087** (0.041)	−0.057* (0.032)	0.126** (0.058)	0.241*** (0.064)
Ait × new entrant	0.035 (0.045)	−0.043 (0.034)	0.052 (0.060)	0.121** (0.055)
Firm and quarter effects	Yes	Yes	Yes	Yes
Observations	188	188	188	188
Within-R ²	0.447	0.294	0.416	0.481

Standard errors clustered at the firm level in parentheses. Controls and their interactions with the group indicators are included but not reported. ***, **, * denote statistical significance at the 1%, 5% and 10% levels.

Table 6 supports the heterogeneity hypothesis. Highly leveraged firms obtain larger resilience gains, mainly through solvency, while firms with more intense prior involution benefit more through cash flow and also bear a larger temporary profitability cost. Entrant status is not independently significant once leverage and conduct history are controlled.

6.3. Mechanism evidence

We re-estimate the baseline specification for individual indicators to identify the channels underlying the component results.

Table 7. Indicator-level mechanism estimates per one-standard-deviation increase in Ait.

Indicator	Unit	Coefficient	Standard error	Implied std. effect	Component
Return on assets	pp of assets	−0.86***	0.29	−0.173	Π
Gross margin	pp of revenue	0.15	0.21	+0.017	Π
Current ratio	ratio units	0.190***	0.061	+0.302	Σ
Leverage ratio	pp of assets	−2.50***	0.83	+0.190	Σ
Operating cash-flow ratio	pp of revenue	1.25***	0.36	+0.583	Φ
Days inventory outstanding	days	−2.90**	1.12	+0.140	Φ

Each row is a separate regression with firm and calendar-quarter fixed effects, controls as in Table 3, and standard errors clustered at the firm level. The implied standardised effect divides the coefficient by the panel standard deviation of the indicator reported in Table 2, with the sign aligned so that a positive value denotes greater resilience. Averaging the two rows of each component reproduces the coefficients of Table 3: $(-0.173 + 0.017)/2 = -0.078$, $(0.302 + 0.190)/2 = 0.246$ and $(0.583 + 0.140)/2 = 0.361$. *** and ** denote significance at the 1% and 5% levels.

Table 7 shows that the largest gains occur in operating cash conversion, inventory efficiency and balance-sheet indicators, while profitability indicators weaken initially. The evidence is therefore consistent with working-capital and financing relief rather than an immediate earnings expansion.

The channels operate at different speeds: cash-flow indicators respond relatively quickly, whereas profitability adjusts with greater delay because fixed costs and volume effects persist after competitive behaviour changes.

6.4. Discussion of magnitudes, managerial implications and external validity

The magnitudes have direct managerial implications. Anti-involution should not be evaluated solely through short-term earnings because temporary profit compression can coexist with stronger liquidity, lower leverage and improved cash conversion. Managers may therefore trade cyclical margin pressure for greater financial flexibility.

For policy the incidence result matters more than the average. Anti-involution measures are sometimes criticised on the ground that they penalise efficient low-cost producers and shelter weak firms. Our estimates suggest a different reading. The firms that gain most in resilience terms are those with the tightest solvency margins and the deepest prior involutional distortions, that is, precisely the firms whose disorderly exit would impose the largest costs on suppliers, dealers, employees and local public finances. Because the profit cost is concentrated in the same population and is transitory, whereas the financing-capacity gain is durable, the net effect of de-escalation on the fragile segment of the industry is stabilising rather than destabilising. This does not imply that anti-involution is costless in aggregate, since consumers forgo the price reductions that involutional competition delivered, and our design, which absorbs the common component of the policy turn in the time effects, is silent on aggregate welfare. What it does imply is that the financial-stability objection to anti-involution policy is not supported at the firm level in this sector, and that the supervisory value of monitoring composite resilience rather than headline earnings is high, which connects our exercise to the broader agenda of building verifiable monitoring infrastructure for policy-constrained industries [42].

The external-validity question deserves explicit treatment. The NEV setting is in many respects an extreme case of involutional competition, with unusually high fixed-cost intensity, unusually rapid technological turnover and an unusually visible policy intervention. It nevertheless shares the structural features that define the phenomenon, namely homogeneous product positioning, subsidised capacity accumulation and price aggression as the dominant competitive instrument, with several other Chinese industries currently under similar policy attention, including photovoltaics, lithium batteries, e-commerce platforms and parts of the petrochemical chain, and macroeconomic accounts of profitless growth suggest that the pattern is economy-wide rather than sectoral [3]. The empirical framework developed here, namely a continuous firm-quarter anti-involution intensity index paired with a transparently weighted three-component resilience index, transfers to those sectors with modest adaptation, requiring only that gross margin, research-and-development intensity and a sectoral price-pressure indicator be observable. Two caveats bound the inference. The post-turn window contains four quarters, so the durability of the solvency and cash-flow gains beyond one year is an extrapolation rather than an estimate; and the twelve-firm cross-section, while spanning the relevant strategic diversity, limits the precision of the heterogeneity contrasts, which is why we report bootstrap inference alongside clustered errors throughout.

7. Conclusion and outlook

This paper examined how the anti-involutional turn in China's NEV industry reshaped corporate financial resilience using quarterly data for twelve listed manufacturers, a firm-quarter adjustment index and a three-component FRI. Three conclusions emerge.

First, anti-involution recomposes rather than uniformly improves financial health. A one-standard-deviation increase in adjustment intensity lowers profitability but raises solvency and cash flow, yielding a positive effect on the balanced FRI. The evidence supports viewing anti-involution as an exchange of short-term profit pressure for stronger balance-sheet and cash-flow capacity.

Second, quarterly data reveal that the profitability cost is front-loaded and temporary, whereas solvency and cash-flow gains accumulate. The event study is consistent with this timing and shows no systematic pre-trend.

Third, benefits are concentrated among highly leveraged firms and firms with more intense prior involution. These firms gain more through solvency and cash flow, while the temporary profitability cost is also larger among firms that previously relied heavily on price cutting.

The contribution of the paper is threefold. Conceptually, it brings the multi-dimensional resilience construct of the early-warning tradition to bear on a competitive-conduct question, showing that the aggregation weights are not innocuous and quantifying the threshold at which the aggregate conclusion would flip. Methodologically, it proposes a reproducible firm-quarter anti-involution intensity index built entirely from disclosed financial signals, demonstrates that its identifying variation is not a relabelled margin variable, and validates the whole decomposition through the internal consistency between the indicator-level and component-level estimates reported in Table 7. Empirically, it provides what is to our knowledge the first firm-level, dated decomposition of the financial consequences of the Chinese anti-

involution turn, with a robustness surface spanning index weights, index construction, sample composition, inference procedure and placebo timing.

Several extensions follow naturally. The most immediate is temporal: as additional post-turn quarters accumulate, the durability of the solvency and cash-flow gains, and the possibility of relapse into involutional conduct as policy attention drifts, become directly estimable rather than matters of extrapolation. A second extension is measurement-oriented: the adjustment index could be triangulated against text-based indicators extracted from management discussions, earnings calls and dealer communications, which would allow intention to be separated from realised outcome and would sharpen the attribution of the profit dip to deliberate withdrawal rather than to demand weakness. A third extension is cross-sectoral: applying the same index pair to photovoltaics, lithium batteries and platform retail would establish whether the seven-to-one ratio of standardised balance-sheet gains to profit costs is a general feature of de-escalation or a characteristic of capital-intensive durable-goods manufacturing. A fourth extension is architectural, and connects to the monitoring literature cited above: a resilience index of the kind used here, computed at quarterly frequency from disclosed statements and combined with attribution methods, could serve as a supervisory dashboard for identifying which firms in a de-escalating industry are converting margin recovery into balance-sheet repair and which, like the salient outlier in our sample, are not. Each of these extensions is feasible with currently available data and continues the line of research initiated here.

Data Availability

The data used in this study were collected from publicly available annual reports, corporate disclosures, and industry statistical sources. The supporting dataset, variable definitions, index-construction procedures, and statistical code used in the analysis have been provided for peer review.

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