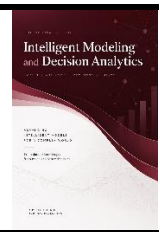


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From Predictive Econometrics to Prescriptive Analytics: A Stochastic Optimization Framework for Asymmetric Cost Behavior

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ABSTRACT

Costs are known to respond asymmetrically to demand, yet the literature remains concentrated in developed markets, relies largely on static models estimated using nominal data, and offers descriptive diagnoses without prescriptive guidance. In high-inflation emerging markets, nominal growth can mask contractions in physical demand, while executives confronting crises receive limited actionable guidance from reported elasticities. This study quantifies the asymmetric real adjustment of administrative and research expenditure in an emerging market and translates the estimated frictions into scenario-based retrenchment policies. The analysis draws on non-financial firms listed in Türkiye over 2002–2025, with all monetary series deflated using the annual consumer price index. Asymmetric elasticities are estimated using two-way fixed effects with Driscoll–Kraay standard errors and complemented by two-step system generalized method of moments estimations. The estimates then enter a stochastic program in which a single ex ante adjustment policy minimizes expected profit loss and capability strain over 2,000 draws from the joint distribution of the elasticity vector, subject to feasibility bounds derived from cost adjustments historically observed under comparable shocks. Administrative costs display moderate and estimator-sensitive stickiness, whereas research expenditure is statistically unresponsive to demand contractions while increasing with demand growth, a difference confirmed by a formal cross-model equality test. No statistically significant moderating effects of leverage or capital intensity on the asymmetry are detected. The resulting policy favors retrenchment primarily through administrative overhead while explicitly accounting for the trade-off between short-term profit protection and long-term organizational resilience. By translating diagnostic elasticities into a stochastic decision framework, the study provides actionable retrenchment guidance for firms operating in volatile, high-inflation economies.

1. Introduction

Following a sequence of compounding macroeconomic shocks, episodic supply-chain disruptions, and severe demand volatility, the ability of corporate decision-makers to rapidly reallocate operational resources has emerged as a central determinant of organizational survival. The sequence of global shocks spanning pandemic aftershocks, geopolitical fragmentation, energy price dislocations, and synchronized inflationary episodes has compressed the time available for managerial response from quarters to weeks [1, 2]. Firms entering such downturns face a destructive

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dilemma. Cutting overhead too deeply sacrifices the organizational capabilities that generate future cash flows, while cutting too little exposes the firm to immediate liquidity pressure. Consequently, navigating these sudden downturns requires managers to make severe structural trade-offs between liquidating short-term overhead to preserve profit margins and shielding strategic investments to secure future competitiveness.

The traditional accounting paradigm, which assumes a mechanistic and symmetric proportionality between sales volume and operational costs, fails to capture these behavioral realities of managerial decision-making under stress. Beginning with the seminal evidence of Anderson *et al.*, [3], the cost behavior literature has documented that costs rise more when activity increases than they fall when activity decreases, a phenomenon known as cost stickiness. Subsequent work attributes this asymmetry to deliberate managerial commitment decisions about idle resources and demonstrates that it varies systematically with adjustment costs, managerial expectations, and institutional settings [4, 5], with recent evidence extending the phenomenon to strategic positioning and research-intensive business models [6, 7]. Extant literature attributes this downward cost rigidity primarily to the severe economic friction of adjustment costs; firing specialized personnel or dismantling research infrastructure during temporary slumps destroys firm-specific capital that is prohibitively expensive to rebuild.

Despite the proliferation of empirical cost behavior studies over the past two decades, the prevailing econometric architectures remain largely static and highly vulnerable to severe endogeneity biases. Budgetary decisions are inherently path-dependent, since each period inherits the commitments of the previous one, and sales and costs are chosen simultaneously within the same managerial plan, so that standard fixed-effects estimators cannot separate the two [5, 8]. The measurement problem is compounded in emerging markets, where nominal accounting series embed inflation noise that masks genuine contractions in physical demand, so that a firm losing real sales volume may still report nominal revenue growth, a distortion that hyperinflation accounting standards have long recognized [9]. Without adequately controlling for unobserved firm-level heterogeneity, the dynamic momentum of prior budgeting, and nominal accounting illusions, static estimators inevitably conflate authentic managerial adjustment frictions with statistical noise.

More fundamentally, the current trajectory of the cost stickiness literature suffers from a structural disconnect between descriptive empirical findings and actionable decision analytics. Two decades of research have established that costs are sticky, yet a chief executive facing a demand collapse gains little guidance on whether research expenditure should be trimmed by five percent or left untouched. The broader analytics literature has long recognized that predictive accuracy alone does not constitute decision support, and that value materializes only when estimated relationships are translated into constrained optimization objects [10–12], a translation increasingly pursued in operations and business analytics but absent from cost behavior research [13, 14]. To bridge this chasm between econometric theory and operational reality, there is a compelling need for hybrid frameworks that translate historical cost elasticities into normative, scenario-based optimization frontiers for strategic resource reallocation.

Motivated by this critical divergence between empirical diagnosis and normative guidance, this study proposes a hybrid analytical framework that explicitly bridges predictive econometrics with stochastic prescriptive optimization. In the first phase, a dynamic panel of non-financial firms listed on Borsa Istanbul over 2002-2025 is estimated through two-way fixed effects with Driscoll-Kraay standard errors, complemented by two-step System GMM dynamic robustness, on fully inflation-adjusted real series, yielding asymmetric cost elasticities for administrative and research expenditure from an estimation design that mitigates unobserved heterogeneity, cross-sectional dependence, dynamic endogeneity, and monetary illusion. In the second phase, these estimates and their joint

sampling uncertainty enter a nonlinear optimization model as stochastic parameters of the objective function, while the feasible region is anchored in the cost adjustments that firms have historically executed during contraction years, so that managerial preferences map onto feasible adjustment bounds for each cost category. By exploiting the high-volatility environment of an emerging market characterized by severe inflationary cycles, this setting provides a noise-filtered laboratory to stress-test the proposed optimization model under authentic macro-shocks.

In the first phase of our methodology, the dynamic estimations document a pronounced functional gradient in cost adjustment. Administrative-cost asymmetry is weak in the fixed-effects benchmark but becomes stronger in the parsimonious System GMM specification, suggesting that administrative adjustment frictions may operate through adjustment dynamics. Research expenditure absorbs expansions with an elasticity of about one half, yet it does not contract during demand declines; the static decline-side elasticity is statistically indistinguishable from zero, while the dynamic estimate is significantly negative, so research budgets behave as quasi-fixed commitments when demand falls. A formal equality test on the common sample of research-active firms confirms that the research asymmetry significantly exceeds the administrative asymmetry. The moderating hypotheses receive limited support. Neither leverage nor capital intensity alters the asymmetry significantly in the dynamic estimations, and nowhere in the estimations does leverage accelerate discretionary cuts, so the creditor-discipline channel documented in covenant violation settings [15] finds no counterpart in this sample.

Transitioning from empirical diagnosis to decision-support in the second phase, the stochastic optimization model quantifies the managerial trade-offs inherent in these empirical boundaries. Under a moderate contraction calibrated to the median realized real sales decline, the optimal administrative cut ranges from about five percent for capability-oriented management to twenty-eight percent for pure profit orientation, the deepest adjustment observed in comparable mild contractions, while research adjustments remain at or around one percent for every preference profile. Under a severe contraction calibrated to the upper quartile of realized declines, profit-oriented policies absorb the shock through historically deep administrative retrenchment of up to forty percent while still capping research reductions near four percent, and balanced or capability-oriented policies reduce that exposure to one percent or less. The resulting efficient frontier prices short-term profit relief in units of long-run resilience, so that the cost of myopic retrenchment becomes a measurable quantity rather than a qualitative warning.

The contributions of this study to the decision-analytics and accounting literatures are threefold. First, on the methodological dimension, the study delivers a dynamic measurement of asymmetric cost behavior in an emerging market in which inflation noise is removed by full deflation and dynamic endogeneity is assessed through complementary dynamic specifications, a combination that prior single-country applications have not jointly addressed. Second, on the theoretical dimension, the evidence shows that the asymmetry is essentially flat across the leverage and capital intensity distributions in dynamic estimations, so that creditor-discipline and asset-specificity accounts find limited support in this setting. Third, on the practical dimension, the study introduces a predictive-to-prescriptive architecture that converts estimated elasticities and their uncertainty into scenario-based decision frontiers, offering managers an operational policy menu rather than a set of historical coefficients. The remainder of this paper proceeds as follows. Section 2 reviews the theoretical underpinnings. Section 3 details the hybrid methodology and optimization architecture. Section 4 presents the empirical estimations and prescriptive scenarios. Section 5 concludes with actionable managerial implications.

2. Theoretical Background and Hypotheses Development

2.1 The Economics of Cost Stickiness and Functional Heterogeneity

For decades, orthodox management accounting operated on the neoclassical premise that organizational costs adjust symmetrically and proportionally to fluctuations in activity volume. Under this mechanical view, resources are assumed to flow frictionlessly in and out of the firm, so that a ten percent contraction in demand triggers the same proportional retrenchment as a ten percent expansion triggers growth. This assumption ignores the economic substance of resource commitments. Hiring, training, severance negotiations, contract terminations, and the dismantling of installed capacity all generate adjustment costs that are not symmetric across directions, because resources acquired cheaply in good times are expensive to dispose of and even more expensive to reacquire [4, 16]. Empirical work on recent regulatory shocks confirms that such frictions intensify when investments are largely irreversible [16]. This traditional assumption was fundamentally challenged by the cost stickiness framework [3], which demonstrated that managers rationally retain slack capacity during demand contractions rather than incur the prohibitive economic frictions of downsizing.

However, treating aggregate operational expenditure as a monolithic construct obscures the profound strategic heterogeneity embedded within different cost functions. Administrative overhead contains layers of genuinely discretionary spending that can be scaled back with modest organizational disruption, whereas research expenditure capitalizes firm-specific human capital whose productivity depends on accumulated, team-embedded tacit knowledge [17]. Recent evidence from research-intensive Japanese firms shows that organizational capital materially amplifies the downward rigidity of administrative spending itself [18], and that sticky research expenditure carries measurable performance consequences in subsequent periods [7]. The dissolution of a research team disperses engineers whose joint problem-solving routines cannot be reconstructed by rehiring strangers, while releasing administrative support staff typically interrupts routines that are codified and recoverable. Dismissing specialized research personnel permanently destroys proprietary, tacit knowledge structures, inherently transforming R&D from a variable period-cost into a quasi-fixed strategic commitment.

Integrating the theory of adjustment frictions with the asset-specificity of research investments, it logically follows that the magnitude of downward rigidity is intrinsically dictated by the functional nature of the resource. Costs that fund replaceable administrative capacity should exhibit moderate asymmetry, whereas costs that fund irreversibly accumulated technological capability should exhibit pronounced asymmetry, since the shadow price of dismantling the latter is systematically higher [6, 7]. Therefore, hypothesizing that technological capabilities constitute the irreducible foundation of future competitiveness, we formally propose the following hypothesis.

Hypothesis 1 (H1). Operational costs exhibit asymmetric stickiness during demand contractions, with Research and Development (R&D) expenditures demonstrating a significantly higher degree of downward rigidity compared to Selling, General, and Administrative (SG&A) costs.

2.2 Firm-Specific Constraints and the Leverage Paradox

While managerial intent to preserve operational capacity drives baseline stickiness, this autonomy is strictly bounded by the pre-existing physical architecture of the firm, most notably its capital intensity. Assets with high specificity cannot be redeployed or liquidated at recoverable prices during downturns, because secondary markets for specialized equipment are thin and fire-sale discounts are severe [19, 20]. Firms burdened with such assets face mechanically higher costs of downward adjustment, and recent sectoral evidence indicates that factor-market frictions propagate this rigidity through labor and housing channels as well [21]. Studies of supply chain alignment further

show that embedded physical commitments transmit sticky behavior across firm boundaries [22]. Thus, high capital intensity mechanically amplifies adjustment costs, effectively forcing constrained managers to absorb temporary financial deterioration rather than liquidate unrecoverable tangible assets.

In stark contrast to physical constraints, the theoretical consensus regarding the moderating role of financial constraints, specifically firm leverage, remains deeply fragmented. One tradition argues that heavy indebtedness disciplines managers through creditor monitoring and covenant pressure, forcing rapid cost retrenchment when demand falls. Evidence from covenant violation settings supports this bank discipline channel, showing that cost stickiness collapses once control rights shift toward creditors [15, 23], and cross-country evidence links constrained financing access to weaker asymmetry [24]. A rival tradition contends that chronically leveraged firms enter crises with their discretionary buffers already exhausted, so that the surviving expenditure base is dominated by the strategic core that cannot be cut without impairing solvency itself. Under this core preservation channel, leverage amplifies rather than attenuates rigidity, and recent distress-focused evidence shows that rigid cost structures interact with distress risk in ways that simple discipline stories cannot absorb [25–27]. This persistent theoretical tension suggests that heavy debt burdens might either enforce myopic cost-cutting through external creditor discipline or, paradoxically, compel firms to fiercely insulate their remaining strategic core at all costs.

Given the robust yet conflicting theoretical justifications in contemporary literature, formulating unidirectional predictions for all constraints would neglect the dual nature of financial distress. Physical constraints admit a clear directional prediction grounded in asset specificity, whereas financial constraints admit two competing channels whose relative strength is an empirical question, particularly in volatile emerging markets where crisis episodes recur with unusual frequency [28]. To empirically resolve this dichotomy within a highly volatile macro-environment, we propose the following competing moderation hypotheses.

Hypothesis 2 (H2). Higher capital intensity structurally exacerbates asymmetric cost behavior, intensifying cost stickiness during demand contractions.

Hypothesis 3 (H3). Financial leverage significantly moderates cost stickiness, either by accelerating downward adjustments through bank discipline or by amplifying the rigidity of strategic investments through core preservation.

2.3 The Prescriptive Void: Bridging Econometrics and Operations Research

Despite the theoretical maturity of the cost stickiness paradigm, empirical validations have historically been compromised by static estimation techniques and the pervasive failure to account for nominal accounting illusions. Systematic reviews of twenty-seven years of research confirm that the field remains dominated by static log-linear panels estimated on undeflated series [28]. This is consequential on two grounds. First, budgetary decisions are path-dependent and jointly determined with sales, so static estimators recover a mixture of genuine frictions and simultaneity bias, a vulnerability that dynamic panel econometrics has long diagnosed [29]. Second, in economies experiencing severe inflationary cycles, nominal accounting growth conflates price drift with physical expansion, so decline indicators computed on undeflated series misclassify crisis years as growth years, and recent evidence from pandemic-affected European samples illustrates how strongly macro conditions distort measured asymmetry [30]. Consequently, isolating authentic managerial discretion demands dynamic estimators applied exclusively to inflation-adjusted, real activity metrics.

However, even when econometric identification challenges are adequately addressed, the resulting parameters remain strictly diagnostic; they explain historical friction but offer no actionable

geometry for impending crises. An estimated elasticity summarizes how the average firm behaved in the average contraction, yet it is silent on the allocation problem that defines managerial work during a downturn, namely how to divide unavoidable retrenchment across heterogeneous cost functions. The decision sciences literature recognizes that diagnostic accuracy is a means rather than an end, and that organizations capture value only when analytical output is embedded into systems that recommend concrete actions [12, 13]. Knowing that R&D is highly sticky provides a Chief Financial Officer with zero normative instruction on the exact percentage by which overhead should be curtailed under a severe, unprecedented macroeconomic shock.

To transcend this diagnostic limitation, contemporary operations research advocates for a structural shift from predictive modeling to prescriptive decision analytics. The defining insight of this literature is that estimated relationships become managerially useful only when they are converted, together with their estimation uncertainty, into the constraints and parameters of an optimization model [10, 11, 31]. Applied to cost adjustment, this conversion yields a decision problem with an inherent trade-off structure, since every incremental unit of short-term profit relief obtained through deeper cuts erodes the organizational capabilities that generate future cash flows. Prescriptive frameworks developed for supply chain and retail operations demonstrate that such trade-offs are best communicated as efficient frontiers rather than point recommendations [14, 32]. By embedding the joint sampling uncertainty of the estimated elasticities in the stochastic objective while deriving feasibility bounds from historically realized adjustments, optimization models empower managers to mathematically balance financial survival against long-term structural resilience.

Synthesizing these theoretical vectors, the cost stickiness paradigm supplies the behavioral primitives, the constraint literature supplies the moderating structure, and the prescriptive analytics literature supplies the decision architecture. What remains absent is an integrated framework that estimates asymmetric cost responses with dynamic, inflation-purged econometrics and then channels the resulting parameters into a stochastic optimization model that prescribes bounded, scenario-specific adjustment policies. The next section develops this integrated methodology, specifying the dynamic panel estimators, the inflation adjustment protocol, and the structure of the prescriptive model that converts econometric evidence into decision frontiers.

3. Methodology

3.1 Research Setting, Sample Selection, and Data Engineering

Following the canonical framework established by Anderson *et al.*, [3], the measurement of organizational activity and resource consumption relies on log-linear response functions. The dependent variables are the year-on-year logarithmic changes in real selling, general, and administrative costs, defined as the sum of marketing, sales, and distribution expenses and general administrative expenses, and in real research and development expenditure. The activity measure is the logarithmic change in real net sales, computed as gross sales minus sales deductions and expressed in constant prices. The asymmetry indicator ($Dec_{\{i,t\}}$) is formulated as a binary dummy variable taking the value of 1 if real net sales strictly decrease compared to the preceding year, and 0 otherwise.

The raw statements are compiled from the annual financial reports of Borsa Istanbul firms. All monetary magnitudes are converted to constant 2001 prices by dividing each series by the annual consumer price index, using the cumulative index with 2001 as the base year, so that real values equal nominal values scaled by the ratio of the current to the base year index for sales, both cost categories, and total assets. Because inflation accounting under TMS 29 applies to reporting periods beginning in 2023, part of the terminal years may already be price adjusted; the uniform deflation is retained to preserve a single measurement basis, and the estimates are materially unchanged when

the 2023-2025 observations are excluded. Firm-years with zero research expenditure are excluded from the research model, since the logarithmic transformation is undefined for zero spending and the research question concerns the adjustment behavior of firms that maintain a research program; this restriction removes 4,849 firm-years and confines the research estimates to the intensive margin of adjustment. To prevent extreme observations from distorting the analysis results, a winsorization of 3 percent at each tail, clipping values below the 3rd and above the 97th percentile, is applied to all continuous variables. The decline indicator and all differenced variables are constructed only from consecutive year pairs, and firm-years with non-consecutive reporting are treated as missing for the differenced variables.

The foundational premise of cost stickiness posits that operational costs adjust asymmetrically to equivalent increases and decreases in activity volume due to the presence of managerial adjustment frictions. The baseline specification formalizes this premise as shown in Eq. (1).

$$\Delta \ln Cost_{i,t} = \beta_0 + \beta_1 \Delta \ln Sales_{i,t} + \beta_2 Dec_{i,t} \times \Delta \ln Sales_{i,t} + \beta_3 Dec_{i,t} + \varepsilon_{i,t} \quad (1)$$

In this formulation, β_1 measures the cost elasticity when sales rise, whereas the sum $\beta_1 + \beta_2$ measures the elasticity when sales fall. The specification additionally includes the decline indicator in levels, so that β_3 absorbs level shifts in cost growth during contraction years and the slope asymmetry is identified cleanly. If managers adjusted resources symmetrically, β_2 would be statistically indistinguishable from zero; a significantly negative interaction coefficient ($\beta_2 < 0$) provides the empirical signature of cost stickiness.

Managerial discretion during demand shocks is rarely unconstrained; it is heavily moderated by firm-specific operational structures and financial obligations. Three constraints enter the specification. Financial leverage (LEV) is the ratio of short-term plus long-term liabilities to total assets and proxies for creditor pressure on discretionary spending. Capital intensity (CI) is the ratio of tangible fixed assets to net sales and captures the degree to which resources are locked into specific physical capital. Firm size (SIZE) is the natural logarithm of real total assets and absorbs scale-related differences in cost structures. When these variables enter the model as moderators of the stickiness term, their scales differ by orders of magnitude, which renders raw interaction coefficients uninformative. To facilitate the interpretation of these interaction effects as per-standard-deviation marginal impacts, the continuous moderating variables are strictly standardized prior to estimation.

3.2 Predictive Analytics: Dynamic Panel Data Estimation

While the static specification introduces the concept of asymmetry, estimating such models with a standard fixed-effects design leaves two identification threats unresolved. Firm fixed effects absorb time-invariant unobserved heterogeneity, but they cannot address the simultaneity between sales and costs, and a lagged dependent variable introduces dynamic panel bias of the Nickell type. Both threats are first-order here. Budgetary allocations are rarely re-optimized from zero each period, because the cost level of each period inherits the commitments, staffing decisions, and project portfolios of the previous one, and sales and costs are determined simultaneously by the same managerial plans, so the activity regressor correlates with the error term by construction. Consequently, failure to control for this dynamic structural momentum inevitably confounds the estimation of true discretionary managerial adjustments.

To address and transparently assess these identification challenges, this study combines two complementary estimators. The benchmark specification is a two-way fixed effects model with firm and year effects, estimated with Driscoll and Kraay [35] standard errors that remain consistent under arbitrary cross-sectional dependence and heteroskedasticity, so that the baseline inferences do not rely on internal instruments. The dynamic extension of the baseline asymmetry equation, specified

in Eq. (2), is estimated under the same fixed effects design and, as a robustness layer that explicitly instruments the endogenous regressors, with the two-step System Generalized Method of Moments (System GMM) developed by Blundell and Bond [33].

$$\Delta \ln Cost_{i,t} = \alpha + \gamma \Delta \ln Cost_{i,t-1} + \beta_1 \Delta \ln Sales_{i,t} + \beta_2 Dec_{i,t} \times \Delta \ln Sales_{i,t} + \beta_3 Dec_{i,t} + \sum_k \theta_k Z_{k,i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

where the lagged dependent variable captures inertia in cost adjustment, Z denotes the vector of firm-level constraints, μ_i represents unobserved firm heterogeneity, and λ_t absorbs macroeconomic shocks common to all firms each year. The lagged dependent variable and real sales growth are treated as endogenous and instrumented with their own lags across the stacked difference and level equations. The decline indicator and its interaction inherit the endogeneity of sales growth, because the indicator is a deterministic sign transformation of the sales change and the interaction is its product with the sales change; the System GMM layer therefore instruments sales growth and the lagged dependent variable in GMM style, while Section 4.2 reports the specification in which the decline indicator and the interaction are additionally instrumented in GMM style, together with difference-in-Hansen tests of the resulting overidentifying restrictions. The constraint variables, firm size, industry, and year dummies enter as standard instruments, and all reported standard errors carry the finite-sample correction of Windmeijer [34]. This specification controls for unobserved firm heterogeneity while capturing the oscillatory adjustment around a target path through the lagged dependent variable.

A critical vulnerability in dynamic panel estimation is the phenomenon of instrument proliferation, which can overfit endogenous variables and weaken the power of specification tests [29]. The instrument strategy is therefore deliberately parsimonious. Lag depth is restricted to the second order for the instrumented variables, and the resulting instrument count is kept comfortably below the number of cross-sectional groups in the benchmark models, 88 instruments against 365 firms in the SG&A equation. In the R&D equation, where the cross-section is smaller, sales growth enters as a standard instrument and GMM-style instruments are reserved for the lagged dependent variable, yielding 57 instruments against 149 firms. Instrument collapsing was examined as an alternative; collapsed specifications proved numerically unstable in this setting, producing erratic point estimates characteristic of weak-instrument bias, and are therefore not retained. The parsimonious uncollapsed design keeps the Hansen J-test informative in the benchmark models, and estimations with deliberately extended instrument sets, including the fully endogenous treatment of the decline-side regressors, are reported as robustness with explicit attention to the instrument-to-group ratio.

To trace the sensitivity of the asymmetry estimates to the identification strategy, the estimations are subjected to a battery of robustness checks. The System GMM layer reported in Section 4.2 re-estimates the dynamic model with the lagged dependent variable and real sales growth instrumented in GMM style. The GMM models are further re-estimated under extended instrument sets, with the decline indicator and its interaction instrumented as endogenous, on undeflated values, and on a subsample that excludes the inflation-accounting years 2023-2025. These exercises map how each asymmetry estimate responds to alternative estimators, instrument matrices, and measurement bases.

3.3 Prescriptive Analytics: The Stochastic Optimization Framework

While the econometric models diagnose the historical magnitude of adjustment frictions, descriptive coefficients alone do not instruct managers on how to reallocate resources during impending macro-shocks. The final methodological layer therefore converts the econometric output

into decision parameters. The estimated elasticities and their joint covariance matrix are lifted from the dynamic fixed effects estimates and embedded as the stochastic parameters of a constrained nonlinear program, while the feasible region of the program is anchored in the distribution of cost adjustments that firms have historically realized.

The core architecture of the prescriptive model is designed to determine the optimal percentage adjustments (ΔCost^*) that minimize a weighted dual-loss function for a firm facing a specific demand contraction (δ). The objective is shown in Eq. (3).

$$\min Z = w_1 \cdot L_1(\Delta\text{SG\&A}, \Delta\text{R\&D}) + w_2 \cdot L_2(\Delta\text{SG\&A}, \Delta\text{R\&D}) \quad (3)$$

with managerial preference weights satisfying $w_1 + w_2 = 1$. The short-term loss $L_1 = 1 - s(\Delta\text{SG\&A}, \Delta\text{R\&D})/s_{\max}$ is a normalized measure of profit relief shortfall, where s denotes realized cost savings as a share of sales, computed as $s = s_{\text{SG\&A}} \cdot (1 - \exp(\Delta\text{SG\&A})) + s_{\text{R\&D}} \cdot (1 - \exp(\Delta\text{R\&D}))$, which converts the log-point decision variables into exact percentage savings of the cost base, with s_j the median share of cost category j in net sales, and $s_{\max}$ denotes the savings attainable at the deepest historically observed adjustment under the same transformation. The long-term loss is the expected capability strain, $L_2 = E_{\theta}[\ell_2(\theta)]$, where the strain function for a given elasticity draw is $\ell_2(\theta) = (\max(|\Delta\text{R\&D}| - m_{\text{R\&D}}(\theta), 0)/|\delta|)^2 + \kappa \cdot (\max(|\Delta\text{SG\&A}| - m_{\text{SG\&A}}(\theta), 0)/|\delta|)^2$, with $m_j(\theta) = \max(-\theta_j \cdot \delta, 0)$. The benchmark against which strain is measured is a marginal flexibility benchmark rather than a full model prediction. The estimated decline-side elasticity $\theta_j = \beta_{1j} + \beta_{2j}$ identifies how much each resource has historically flexed per unit of contraction at the margin, and the strain of a candidate adjustment is the quadratic excess of the cut over that marginal benchmark. The threshold m_j preserves the sign of the predicted response. When the estimated decline-side elasticity is negative, as the point estimate for research expenditure is, the model prediction is a slight cost increase during contractions, so the penalty-free cut capacity m_j is zero and any research cut is treated as strain. Only a genuinely positive downward flexibility earns penalty-free room. The benchmark deliberately excludes the decline-year level shift, the lagged cost dynamics, and the control variables, because it parameterizes the marginal trade-off along which the manager reallocates, not the conditional mean of realized cost growth. The expectation is taken over draws from the joint asymptotic distribution of the elasticity vector, so estimation uncertainty enters the objective rather than the constraint set. The coefficient $\kappa = 0.3$ is a normative preference parameter that weights administrative strain relative to research strain; it is not an estimated quantity, and the sensitivity of the reported prescriptions to κ is documented below. By systematically varying the managerial preference weights between profit orientation and capability retention, the model traces out the full menu of efficient policies rather than a single prescription.

The optimization is not free to invent adjustments that firms have never historically exhibited, and the admissible depth of adjustment is conditioned on the severity of the shock. For each scenario, the lower bound $B_j(\delta)$ is the fifth percentile of the realized cost adjustments observed in contraction years of comparable severity, computed within the half of decline years closest to the scenario shock. For the moderate scenario this yields bounds of -0.331 in log points for SG&A and -0.739 for R&D, corresponding to reductions of about twenty-eight and fifty-two percent of the cost base, while for the severe scenario the bounds are -0.509 and -0.666, about forty and forty-nine percent. These bounds describe what firms have operationally executed under stress of similar magnitude, not the statistical precision of a coefficient, and they are fixed within each simulation. One feature of the slice-specific bounds deserves note. The research bound is shallower in the severe slice than in the mild slice, which reflects the empirical pattern that firms sustaining research programs through the deepest contractions cut research less deeply, not less frequently, than firms in milder contractions. The slices contain 858 and 857 firm-years for SG&A and 345 and 288 for R&D, so the slice quantiles

rest on moderate samples, and in all reported optima the research decision lies far inside the bound, so the inversion does not drive any prescription.

$$\Delta C_j \in [B_j(\delta), 0], \quad B_j(\delta) = Q_{0.05}(\Delta \ln Cost_j \mid Dec = 1, \text{comparable shock severity}) \quad (4)$$

so that admissible adjustments span the range of historically realized retrenchment in each cost category under comparable shocks. Separating feasibility from estimation uncertainty resolves two distinct questions that a single confidence region would conflate. What firms can execute is read from the empirical distribution of realized adjustments in contractions of similar severity, while how damaging a given cut proves to be depends on the estimated elasticities and is averaged over their sampling distribution.

The optimal policies are derived by minimizing the expected objective over two thousand draws from the joint asymptotic distribution of the elasticity vectors, using a fixed random seed and an exhaustive grid search over the feasible rectangle with a step of roughly half a percentage point, so the solutions do not depend on solver tolerances. Because the decision is chosen once before the uncertainty resolves, the program is a sample average approximation of an ex ante stochastic optimization problem with non-anticipative decisions, not a wait-and-see average of draw-specific optima. The scenario magnitudes are taken directly from the empirical distribution of real sales contractions in the sample. The median realized contraction is 13.1 percent and the upper quartile is 24.6 percent, and these quantiles define the moderate and severe scenarios. Reported optima are accompanied by Monte Carlo batch-stability ranges obtained by re-solving the program on forty batches of fifty draws. The accompanying resilience score condenses capability preservation into a single absolute metric, $R(\Delta C) = 1 - (|\Delta R\&D| + \kappa \cdot |\Delta SG\&A|) / (|\bar{B}_{R\&D}| + \kappa \cdot |\bar{B}_{SG\&A}|)$, where the reference bounds $\bar{B}_j$ are the pooled fifth percentiles of realized contraction-year adjustments over all decline years, equal to -0.518 for SG&A and -0.731 for R&D. Because the denominator is fixed across scenarios, the score is measured on a common scale and is directly comparable across scenarios and strategies, equaling one when no adjustment is undertaken and declining toward zero as cuts approach the deepest historically observed levels. The resulting integration of predictive econometrics and stochastic optimization yields a Pareto-efficient policy menu for navigating severe economic contractions.

4. Results

This section presents the empirical findings in two main phases. The first phase covers the descriptive statistics and the panel data estimations, two-way fixed effects with Driscoll-Kraay standard errors complemented by System GMM, to diagnose asymmetric cost behavior. The second phase translates these econometric parameters into a prescriptive decision-support framework using stochastic optimization.

4.1 Descriptive Statistics and Correlation Analysis

Before estimating the dynamic models, we outline the sample distribution and the fundamental characteristics of the data. Table 1 details the sample selection process, the industry breakdown of the estimation panel, and the number of observations available to each estimator, so that the sample underlying every reported model can be traced.

The estimation panel is dominated by industrial firms, which account for 70.7 percent of the observations, while service and technology firms constitute 21.1 and 8.2 percent respectively. This composition reflects the listing structure of Borsa Istanbul and ensures that the estimation is driven by sectors in which operational cost adjustment decisions are most salient. The dynamic samples are smaller than the static panels because the lag structure and the consecutive-reporting requirement

consume observations, and the System GMM layer is further restricted by instrument availability, and the research models are estimated on the subset of firm-years with positive research expenditure, as detailed in Section 3.1.

Table 1
Sample Selection and Industry Distribution

Sample Derivation	Number of Firm-Years	Number of Firms
Initial sample of BIST firms (2002-2025)	8,918	588
Less: Financial institutions and holdings	-2,432	-148
Cleaned non-financial panel with consecutive reporting	6,486	440
Less: Missing data for lagged variables and estimation controls	-2,278	-51
Baseline estimation panel (SG&A, static TWFE)	4,208	389
Estimation Samples by Model	Observations	Firms
SG&A, static TWFE	4,208	389
SG&A, dynamic TWFE	3,682	370
SG&A, System GMM robustness	2,819	365
R&D, static TWFE	1,637	174
R&D, dynamic TWFE	1,389	149
R&D, System GMM robustness	1,056	149
Industry Breakdown (Baseline SG&A Panel)	Observations	Percentage (%)
BIST Industrials	2,974	70.7%
BIST Services	887	21.1%
BIST Technology	347	8.2%
Total	4,208	100.0%

Table 2 presents the descriptive statistics for all dependent, independent, and control variables used in the main estimations. The Variance Inflation Factor (VIF) scores indicate that multicollinearity is not a concern for the model specification.

Table 2
Descriptive Statistics and Multicollinearity Diagnostics

Variable	Mean	Median	Std. Dev.	Min	Max	VIF	N
$\Delta \ln \text{SG\&A}$	0.068	0.046	0.260	-0.509	0.729		4,208
$\Delta \ln \text{R\&D}$	0.105	0.071	0.504	-1.182	1.432		1,637
$\Delta \ln \text{Sales}$	0.055	0.048	0.284	-0.606	0.711	2.27	4,208
Dec	0.408	0.000	0.491	0.000	1.000	2.27	4,208
LEV	0.488	0.483	0.233	0.093	0.974	1.07	4,208
CI	0.666	0.350	0.954	0.007	4.559	1.06	4,208
SIZE	18.263	18.174	1.715	15.083	21.979	1.03	4,208

Note: Dec is an indicator variable set to 1 if sales decrease compared to the previous year, 0 otherwise. LEV is the ratio of total debt to total assets; CI is the ratio of tangible fixed assets to net sales; SIZE is the natural logarithm of total assets. All monetary variables are deflated by the annual consumer price index with 2001 as the base year. The interquartile range of real sales growth runs from -0.101 to 0.212, and the median realized real sales contraction among decline years is 13.1 percent with an upper quartile of 24.6 percent. $\Delta \ln \text{R\&D}$ is available only for firm-years with positive research expenditure. The penultimate column reports variance inflation factors from an auxiliary regression of each determinant on the remaining regressors; the final column reports the number of firm-year observations.

Two features of the distribution stand out. First, real sales declines are far from rare events in this sample, occurring in roughly four out of ten firm-years, which provides substantial identifying variation for the asymmetry tests. Second, research and development expenditure displays visibly wider dispersion than selling, general, and administrative costs, foreshadowing the functional heterogeneity that the dynamic estimations formalize below. Table 3 displays the pairwise

relationships between the variables. As anticipated, the initial correlations indicate a positive and significant relationship between changes in sales and operational costs.

Table 3

Pearson (Below Diagonal) and Spearman (Above Diagonal) Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $\Delta \ln \text{SG\&A}$	1.000	0.250***	0.470***	-0.334***	0.024*	-0.077***	0.073***
(2) $\Delta \ln \text{R\&D}$	0.249***	1.000	0.191***	-0.120***	0.005	-0.005	0.046*
(3) $\Delta \ln \text{Sales}$	0.475***	0.175***	1.000	-0.854***	0.108***	-0.173***	0.038***
(4) Dec	-0.305***	-0.097***	-0.743***	1.000	-0.097***	0.155***	-0.004
(5) LEV	0.009	0.013	0.089***	-0.094***	1.000	-0.243***	0.162***
(6) CI	-0.054***	-0.053**	-0.173***	0.132***	-0.181***	1.000	0.073***
(7) SIZE	0.070***	0.038	0.048***	-0.005	0.151***	-0.032**	1.000

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3 displays the pairwise relationships between the variables, computed on 4,208 firm-year observations. The correlation structure is descriptive rather than evidential. Because the decline indicator is constructed from the sign of the sales change, its strong negative correlation with sales growth is mechanical, and its negative correlation with cost changes cannot by itself establish stickiness, which is a statement about the difference between conditional slopes. Both cost aggregates move positively with sales growth, and leverage and capital intensity correlate with the cost variables only weakly, suggesting that any influence of these constraints operates through the moderation of managerial adjustment decisions rather than through direct level effects.

4.2 Econometric Estimations: Asymmetric Cost Behavior

To map the transition from econometric estimation to decision-making, Figure 1 illustrates the methodological pipeline utilized in this study.

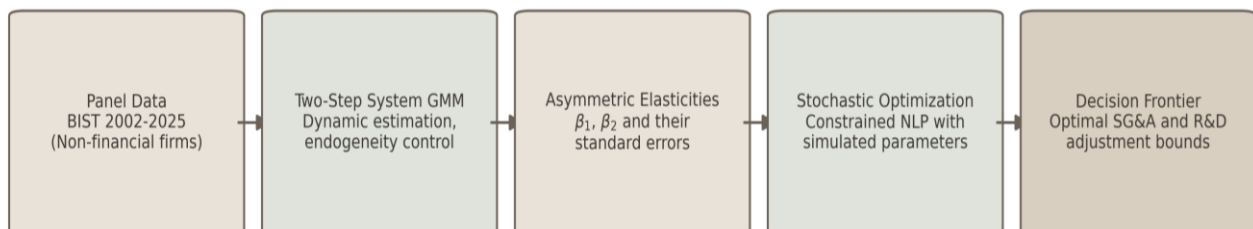


Fig. 1. The Methodological pipeline from predictive econometrics to prescriptive analytics

Table 4 reports the main results from the two-way fixed effects estimations with Driscoll-Kraay standard errors, in both static and dynamic form. The interaction coefficients capture the stickiness of the costs.

The fixed effects design absorbs time-invariant firm heterogeneity and common year shocks, and the Driscoll-Kraay covariance estimator remains consistent under arbitrary cross-sectional dependence, a first-order concern in an emerging market panel exposed to common macroeconomic cycles. All variables enter the models in real terms, so the elasticities describe responses to changes in purchasing-power-adjusted activity rather than nominal inflation-driven movements. The F-statistics confirm the joint significance of the regressors in all four models. Table 4 also reports the decline-side elasticity $\beta_1 + \beta_2$ together with its standard error computed from the full covariance matrix of the estimates, since the sum of two coefficients inherits their covariance and the significance of the components does not by itself establish the significance of the sum.

Table 4

Two-Way Fixed Effects Estimations with Driscoll-Kraay Standard Errors

Variables	Model 1: SG&A (Static)	Model 2: SG&A (Dynamic)	Model 3: R&D (Static)	Model 4: R&D (Dynamic)
L1. $\Delta \ln \text{Cost}$		-0.097*** (0.017)		-0.121*** (0.025)
$\Delta \ln \text{Sales}$	0.398*** (0.040)	0.360*** (0.040)	0.489*** (0.112)	0.466*** (0.129)
$\text{Dec} \times \Delta \ln \text{Sales}$	-0.042 (0.044)	-0.066 (0.052)	-0.655*** (0.216)	-0.737*** (0.139)
Dec	0.009 (0.007)	-0.002 (0.008)	-0.012 (0.048)	-0.043 (0.050)
Decline-side elasticity ($\beta_1 + \beta_2$)	0.356*** (0.032)	0.295*** (0.026)	-0.167 (0.211)	-0.271** (0.112)
LEV	-0.027 (0.025)	-0.063** (0.027)	0.027 (0.136)	-0.036 (0.150)
CI	-0.004 (0.007)	-0.013 (0.009)	-0.101** (0.048)	-0.084 (0.061)
SIZE	0.023 (0.020)	0.051** (0.024)	0.077** (0.036)	0.106*** (0.029)
Firm & Year Effects	Yes	Yes	Yes	Yes
Observations	4,208	3,682	1,637	1,389
R-squared	0.166	0.172	0.029	0.063
F-statistic	125.54***	97.71***	7.06***	11.74***

Note: Driscoll-Kraay standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 5

Dynamic Robustness: System GMM Estimations for Asymmetric Cost Behavior

Variables	Model 1: SG&A Costs	Model 2: R&D Costs
L1. $\Delta \ln \text{Cost}$	-0.025 (0.032)	-0.090* (0.051)
$\Delta \ln \text{Sales}$	0.810*** (0.177)	0.533*** (0.153)
$\text{Dec} \times \Delta \ln \text{Sales}$	-0.505** (0.199)	-0.633** (0.266)
Dec	0.076** (0.033)	-0.005 (0.043)
Decline-side elasticity ($\beta_1 + \beta_2$)	0.305*** (0.055)	-0.100 (0.213)
LEV	-0.016 (0.020)	-0.015 (0.058)
CI	0.005 (0.006)	-0.048 (0.036)
SIZE	0.007** (0.003)	0.026*** (0.008)
Constant	-0.170** (0.072)	-0.489*** (0.148)
Year & Industry Dummies	Yes	Yes
Observations	2,819	1,056
Number of Groups (Firms)	365	149
Number of Instruments	88	57
Wald statistic	1,658.92***	698.54***
AR(1) test (p-value)	0.000	0.000
AR(2) test (p-value)	0.527	0.531
Hansen J-test (p-value)	0.175	0.447

Note: Windmeijer-corrected robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. The decline-side elasticity row reports the sum of the sales-growth and interaction coefficients, with standard errors computed from the full covariance matrix of the estimates, so the row incorporates the covariance between the two components. Year and industry dummies are included in all models.

The results establish a clear functional gradient in asymmetric cost behavior. For selling, general, and administrative costs, the elasticity with respect to rising sales is 0.398 in the static model and 0.360 in the dynamic model, and the interaction coefficient is small and statistically insignificant in both, so the decline-side elasticity of 0.356 statically and 0.295 dynamically remains close to the expansion-side response. Administrative costs therefore display at most mild marginal asymmetry once firm and year effects are flexibly controlled, although the System GMM robustness in Table 5, which explicitly instruments the endogenous regressors, locates a stronger asymmetry that operates through adjustment dynamics rather than through the contemporaneous response.

Research and development expenditure exhibits pronounced asymmetry across the fixed-effects benchmark and parsimonious GMM specifications, although precision weakens in the fully

instrumented model. The upward elasticity is 0.489 in the static model and 0.466 in the dynamic model, while the interaction coefficients of -0.655 and -0.737 are both significant at the one percent level. The decline-side elasticity is statistically indistinguishable from zero in the static model and significantly negative in the dynamic model, which implies that research spending expands with demand growth but does not contract when demand falls. This behavior is consistent with high adjustment costs associated with specialized human capital. Dismissing research personnel or suspending projects destroys firm-specific knowledge that is expensive to rebuild, and managers treat R&D as a quasi-fixed commitment rather than a variable expense. The negative coefficient on the lagged dependent variable in the dynamic models indicates oscillatory adjustment around a target path, reinforcing the interpretation of R&D as a planned, path-dependent investment program rather than a discretionary period expense. Larger firms display faster cost growth conditional on sales, pointing to scale-related expansion of overhead and research programs.

The hypothesis that research expenditure is stickier than administrative expenditure requires a direct comparison rather than a side-by-side reading of two regressions, particularly because the two models are estimated on different samples. A formal equality test is therefore constructed on the common sample of research-active firm-years, stacking both cost aggregates per firm-year and interacting the research indicator with the full set of lower-order terms, the sales slope, the decline indicator, and the decline-side slope. The interaction of the research indicator with the stickiness term is -0.453 with a Driscoll-Kraay standard error of 0.198, rejecting slope equality at the five percent level and confirming that the stronger asymmetry of research expenditure is a property of the same firms observed under the same conditions. The full stacked estimation, including all lower-order interactions, the sample size, the bandwidth, and the tested linear restriction, is reported in Table A3 of the Appendix, and a dynamic variant that adds the lagged cost change yields a larger interaction of -0.588 with a standard error of 0.134, significant at the one percent level. The equality test is a fixed effects construction and does not by itself address dynamic endogeneity, so it complements rather than substitutes for the dynamic estimations. Hypothesis 1 is supported.

To answer the second research question, the baseline specification is augmented with triple interactions between the stickiness term and the two firm-level constraints, leverage and capital intensity, with both moderators entering in lagged form to mitigate the mechanical simultaneity between current sales and current balance-sheet ratios, and standardized so that the coefficients read as per-standard-deviation effects. The full set of estimates appears in Table A1 of the Appendix. The moderating hypotheses are not supported. None of the eight triple interaction terms reaches significance in either the System GMM or the fixed effects estimations, so the data confirm neither that capital intensity deepens stickiness (H2) nor that leverage redirects adjustment (H3). The baseline asymmetry itself survives the inclusion of the interaction terms in every specification. The study finds no statistically significant evidence that leverage accelerates cost reductions in this sample, although the observational design cannot exclude modest effects, so the covenant-based mechanism documented in [15] finds no measurable counterpart here.

To visually interpret the interaction effects, particularly how firm-specific constraints like leverage alter managerial behavior during demand shocks, Figure 2 plots the predictive margins.

The figure illustrates the estimated moderation in economic terms, together with its statistical limits. For firms one standard deviation below and above mean leverage, the predicted paths of research spending diverge modestly on the contraction side, but the ninety-five percent confidence bands overlap almost completely, mirroring the insignificant triple interaction in Table A1. The figure therefore visualizes an upper bound on the leverage channel rather than an established effect, and the prescriptive model in the next section deliberately refrains from conditioning its adjustment bounds on leverage.

Table 5 reports the dynamic robustness layer, the two-step System GMM estimations that explicitly instrument the lagged dependent variable and real sales growth, and the Appendix collects extended instrument sets, alternative measurement bases, and subsample exercises.

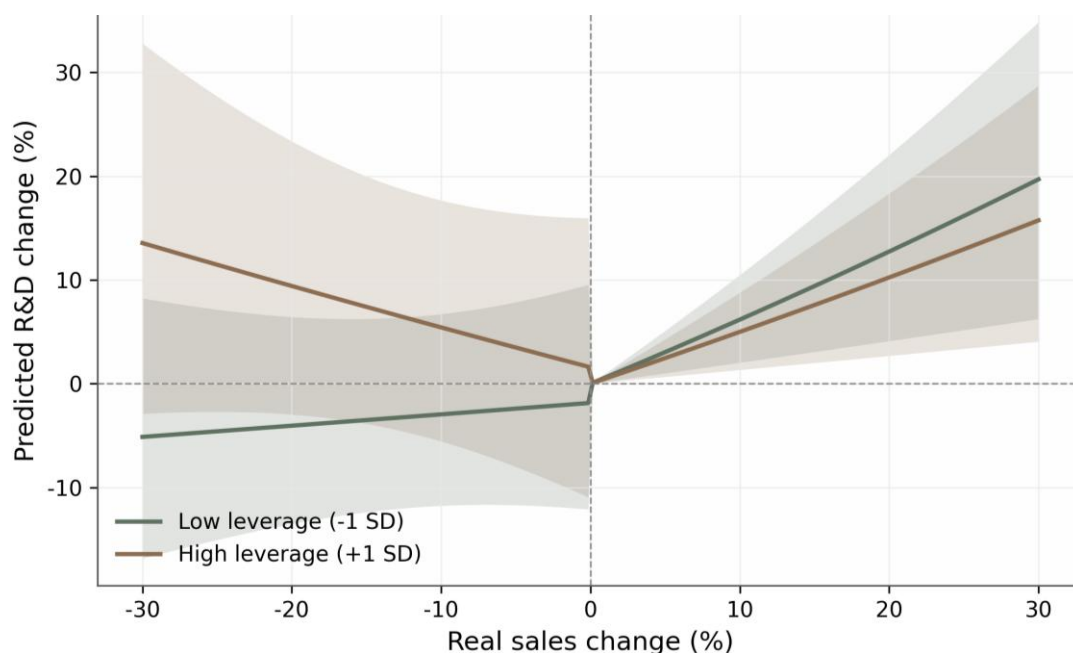


Fig. 2. Marginal effects of sales decline on R&D stickiness by leverage levels (95 percent confidence bands)

The robustness exercises tell different stories for the two cost categories, and the contrast is informative about where the identification burden lies. For research expenditure, the interaction term remains negative, large, and significant in the System GMM layer, under extended instrument sets, and on the subsample excluding the inflation-accounting years, although it loses significance on undeinflated values, where nominal inflation noise dominates the measurement. For administrative costs, the interaction is significant only in the parsimonious System GMM design and is small under fixed effects, so the SG&A asymmetry is estimator-sensitive and may operate through adjustment dynamics. The deflation contrast supports the view that nominal measurement noise attenuates the estimated asymmetry rather than generating it, consistent with the measurement argument in [9]. The final robustness exercise addresses the endogeneity of the decline-side regressors directly by instrumenting the decline indicator and its interaction in GMM style. The difference-in-Hansen test does not reject the overidentifying restrictions introduced by these additional instruments in the SG&A equation ($p = 0.239$), so the instrumented treatment is statistically admissible. The point estimates, however, become imprecise. The SG&A interaction is no longer distinguishable from zero, while the R&D interaction remains negative and large at -0.67 but insignificant, with the instrument count approaching the number of groups in the smaller R&D cross-section, where the near-unity Hansen p -value reflects weak test power under instrument proliferation rather than strong evidence of instrument validity. Internal instruments for a discrete sign transformation and its product with the underlying continuous variable are inherently weak in panels of this size, so this demanding specification constrains precision rather than overturning the benchmark signs. Because the benchmark fixed effects estimates do not rely on internal instruments at all, the main inferences of the study do not depend exclusively on the internally instrumented specification, and the asymmetry claims are framed as convergent evidence across complementary estimators, the fixed effects

benchmark, the parsimonious GMM that mitigates dynamic endogeneity, and the common-sample equality test, rather than as definitive causal elasticities.

4.3 Prescriptive Analytics: Optimization Framework and Scenario Outputs

The econometric coefficients confirm the presence of adjustment costs. Table 6 defines how these parameters are fed into the objective function to minimize both short-term profit loss and long-term capability degradation.

Table 6
Sets, parameters, and decision variables for the prescriptive model

Notation	Type	Description	Source / Estimation Strategy
Sets & Indices			
i, t	Set	Index for firm and time (year)	BIST Panel Data
Parameters			
$\beta_1 = 0.360$ (SG&A), 0.466 (R&D)	Parameter	Upward cost elasticity with respect to real sales growth	Extracted from Table 4 (dynamic TWFE)
$\beta_2 = -0.066$ (SG&A), -0.737 (R&D)	Parameter	Stickiness parameter for sales decline	Extracted from Table 4 (dynamic TWFE)
$\sigma(\beta_1) = 0.040, 0.129$; $\sigma(\beta_2) = 0.052, 0.139$	Parameter	Standard errors of the estimated elasticities; full covariance matrix retained	Extracted from Table 4 (dynamic TWFE)
$\theta = \beta_1 + \beta_2 = 0.295$ (SG&A), -0.271 (R&D)	Parameter	Decline-side elasticity, drawn from its joint asymptotic distribution	Computed from Table 4 with full covariance
$s_{SG\&A} = 0.104$; $s_{R\&D} = 0.005$	Parameter	Median share of each cost category in net sales	BIST panel, decline years
$\kappa = 0.3$	Parameter	Normative weight on administrative strain relative to research strain	Defined by Decision Maker; sensitivity reported in Table A4
$B_{SG\&A}(\delta) = -0.331, -0.509$; $B_{R\&D}(\delta) = -0.739, -0.666$	Bound	Fifth percentile of realized log cost adjustments in contraction years of comparable severity (moderate and severe scenarios)	Historical distribution of $\Delta \ln \text{Cost}$ within shock severity slices
$\bar{B}_{SG\&A} = -0.518$; $\bar{B}_{R\&D} = -0.731$	Reference	Pooled fifth percentiles of realized contraction-year adjustments, fixed across scenarios	Normalizes the resilience score on a common scale
$M = 2,000$; seed = 20240911	Solver	Monte Carlo draws from the joint asymptotic distribution; exhaustive grid search on a 120×120 lattice	Solver setting
w_1	Weight	Managerial preference weight for short-term profit	Defined by Decision Maker (0 to 1)
w_2	Weight	Managerial preference weight for capability retention	$1 - w_1$
δ	Parameter	Demand shock magnitude, set to empirical quantiles of realized real sales contractions	Median -13.1% (moderate); upper quartile -24.6% (severe)
Decision Variables			
$\Delta SG\&A, \Delta R\&D$	Variable	Optimal percentage adjustment in SG&A and R&D	Model Output

The prescriptive model treats the estimated decline-side elasticities as stochastic parameters drawn jointly from their asymptotic distribution. For notational clarity, let $j \in \{SGA, RD\}$ denote the two cost categories and let $\Delta \mathbf{C} = (\Delta C_{SGA}, \Delta C_{RD})$ denote the vector of log cost adjustments. Negative values indicate cost reductions. The decision problem is formulated as the following constrained nonlinear program:

$$\min_{\Delta C_{SGA}, \Delta C_{RD}} Z = w_1 L_1(\Delta C) + w_2 L_2(\Delta C; \delta) \quad (5)$$

subject to

$$B_j(\delta) \leq \Delta C_j \leq 0, \quad j \in \{SGA, RD\}, \quad w_1 + w_2 = 1, \quad w_1, w_2 \geq 0 \quad (6)$$

The scenario-specific lower bound is defined as

$$B_j(\delta) = Q_{0.05}(\Delta \ln Cost_{j,it} \mid Dec_{it} = 1, \delta_{it} \in \mathcal{S}_\delta) \quad (7)$$

where $\mathcal{S}_\delta$ denotes the subset of contraction observations with sales declines comparable in severity to scenario δ . The feasible region therefore tightens or widens with the magnitude of the demand shock.

The short-term loss measures the shortfall between realized savings and the maximum savings attainable within the scenario-specific feasible region:

$$L_1(\Delta C; \delta) = 1 - \frac{s(\Delta C)}{s_{\max}(\delta)} \quad (8)$$

Because the decision variables are expressed as log changes, realized savings as a share of sales are computed using the exact exponential transformation:

$$s(\Delta C) = s_{SGA}(1 - \exp(\Delta C_{SGA})) + s_{RD}(1 - \exp(\Delta C_{RD})) \quad (9)$$

and the maximum feasible savings under scenario δ are

$$s_{\max}(\delta) = s_{SGA}(1 - \exp(B_{SGA}(\delta))) + s_{RD}(1 - \exp(B_{RD}(\delta))) \quad (10)$$

Here, $s_{SGA} = 0.104$ and $s_{RD} = 0.005$ denote the median shares of the respective cost categories in net sales.

The long-term component is the expected capability strain:

$$L_2(\Delta C; \delta) = \mathbb{E}_\theta(\ell_2(\Delta C; \theta, \delta)) \quad (11)$$

where the strain associated with a particular elasticity realization is

$$\ell_2(\Delta C; \theta, \delta) = \left(\frac{\max(|\Delta C_{RD}| - m_{RD}(\theta_{RD}, \delta), 0)}{|\delta|} \right)^2 + \kappa \left(\frac{\max(|\Delta C_{SGA}| - m_{SGA}(\theta_{SGA}, \delta), 0)}{|\delta|} \right)^2 \quad (12)$$

The sign-preserving threshold is

$$m_j(\theta_j, \delta) = \max(-\theta_j \delta, 0), \quad \theta_j = \beta_{1j} + \beta_{2j} \quad (13)$$

This threshold represents the penalty-free downward flexibility implied by the estimated decline-side elasticity. When $\theta_j < 0$ and $\delta < 0$, the estimated response is a cost increase rather than a reduction. In that case, $m_j(\theta_j, \delta) = 0$, and any reduction in that cost category is treated as capability strain. The parameter $\kappa = 0.3$ is a normative weight assigning administrative adjustment strain thirty percent of the weight assigned to research adjustment strain.

The expectation in Equation (9) is approximated with $M = 2\,000$ joint parameter draws:

$$\hat{L}_{2,M}(\Delta C; \delta) = \frac{1}{M} \sum_{m=1}^M \ell_2(\Delta C; \theta^{(m)}, \delta), \quad M = 2\,000 \quad (14)$$

with

$$\theta^{(m)} \sim \mathcal{N}(\hat{\theta}, \hat{\Sigma}_\theta) \quad (15)$$

A single adjustment pair is selected before the elasticity uncertainty is resolved. The resulting formulation is therefore a sample average approximation of an ex ante stochastic optimization problem with non-anticipative decisions, rather than an average of draw-specific, wait-and-see solutions.

Table 7

Optimal cost adjustment frontiers and sensitivity to managerial preferences

Scenario (Sales Shock)	Strategy (w_1, w_2)	Optimal SG&A Adjustment (%)	Optimal R&D Adjustment (%)	Resilience Score	MC Batch-Stability Range, SG&A / R&D (%)
Moderate (-13.1%)	Profit-oriented ($w_1 = 0.9$)	-28.2	-1.2	0.87	-28.2 to -28.2 / -1.2 to -1.2
Moderate (-13.1%)	Balanced ($w_1 = w_2 = 0.5$)	-12.7	0.0	0.95	-12.7 to -12.5 / 0.0 to 0.0
Moderate (-13.1%)	Capability-oriented ($w_1 = 0.1$)	-5.1	0.0	0.98	-5.1 to -5.1 / 0.0 to 0.0
Severe (-24.6%)	Profit-oriented ($w_1 = 0.9$)	-39.9	-3.8	0.78	-39.9 to -39.9 / -3.8 to -3.8
Severe (-24.6%)	Balanced ($w_1 = w_2 = 0.5$)	-27.1	-0.6	0.89	-27.1 to -26.8 / -0.6 to -0.6
Severe (-24.6%)	Capability-oriented ($w_1 = 0.1$)	-10.9	0.0	0.96	-10.9 to -10.5 / 0.0 to 0.0

Note: The moderate and severe sales-shock scenarios correspond to the median (-13.1%) and upper-quartile (-24.6%) real sales contractions in the sample, respectively. For each scenario and cost category, the lower feasibility bound is the fifth percentile of realized log cost adjustments among contraction observations in the half of the decline distribution closest in sales-shock magnitude to that scenario. The corresponding slice sizes are 858 and 857 firm-years for SG&A and 345 and 288 firm-years for R&D in the moderate and severe scenarios, respectively. Monte Carlo batch-stability ranges are obtained from 40 re-solutions using batches of 50 draws.

Calculation details for Table 5:

Because the decision variables are expressed as log changes, the calculations reported below use the exact exponential transformation.

$$s(\Delta C) = s_{SGA}(1 - \exp(\Delta C_{SGA})) + s_{RD}(1 - \exp(\Delta C_{RD})) \quad (14)$$

The maximum savings, s_{max} , are evaluated analogously at the scenario-specific feasibility bounds. Reported cost adjustments are converted from optimal log-point policies into percentage changes in the underlying cost bases as

$$100(\exp(\Delta C_j) - 1) \quad (15)$$

The resilience score is calculated in log-point units as

$$R(\Delta C) = 1 - \frac{|\Delta C_{RD}| + \kappa |\Delta C_{SGA}|}{|\bar{B}_{RD}| + \kappa |\bar{B}_{SGA}|} \quad (16)$$

where $\kappa = 0.3$, $\bar{B}_{SGA} = -0.518$, and $\bar{B}_{RD} = -0.731$. Because the pooled reference bounds are held fixed, resilience scores are measured on a common scale and are directly comparable across scenarios and managerial preference profiles.

Monte Carlo batch-stability ranges show the minimum and maximum re-solved optima obtained from 40 batches of 50 draws from the joint asymptotic distribution of the decline-side elasticities. Each reported optimum is a single ex ante policy that minimizes expected loss over 2,000 joint parameter draws, generated using seed 20240911, on an exhaustive 120×120 decision grid.

The scenario analysis yields differentiated guidance. Under a moderate contraction, the feasible region itself is narrow, and the optimal administrative cut ranges from about five percent for capability-oriented management to twenty-eight percent for pure profit orientation, the deepest adjustment observed in comparable mild contractions, while research adjustments remain at or around one percent across all preference profiles. Under a severe contraction, the qualitative ordering survives at greater depth. Administrative spending absorbs adjustments of up to forty percent of its base, and research reductions remain capped below four percent even for profit-oriented strategies, falling below one percent for balanced profiles and to zero for capability-oriented ones. The resilience score is computed against fixed pooled reference bounds, so it is directly comparable across scenarios; it declines monotonically as the profit weight increases within each scenario and is uniformly lower under the severe shock, confirming that the score tracks absolute capability loss. Sensitivity analysis on the normative weight κ shows that the research prescriptions are stable, while the administrative depth recommended to balanced profiles narrows from forty to twenty-one percent as administrative strain receives a larger penalty, with the full grid reported in Table A4.

Figure 3 maps these boundaries visually, providing a clear Pareto-efficient frontier for decision-makers aiming to balance immediate financial survival with future competitiveness.

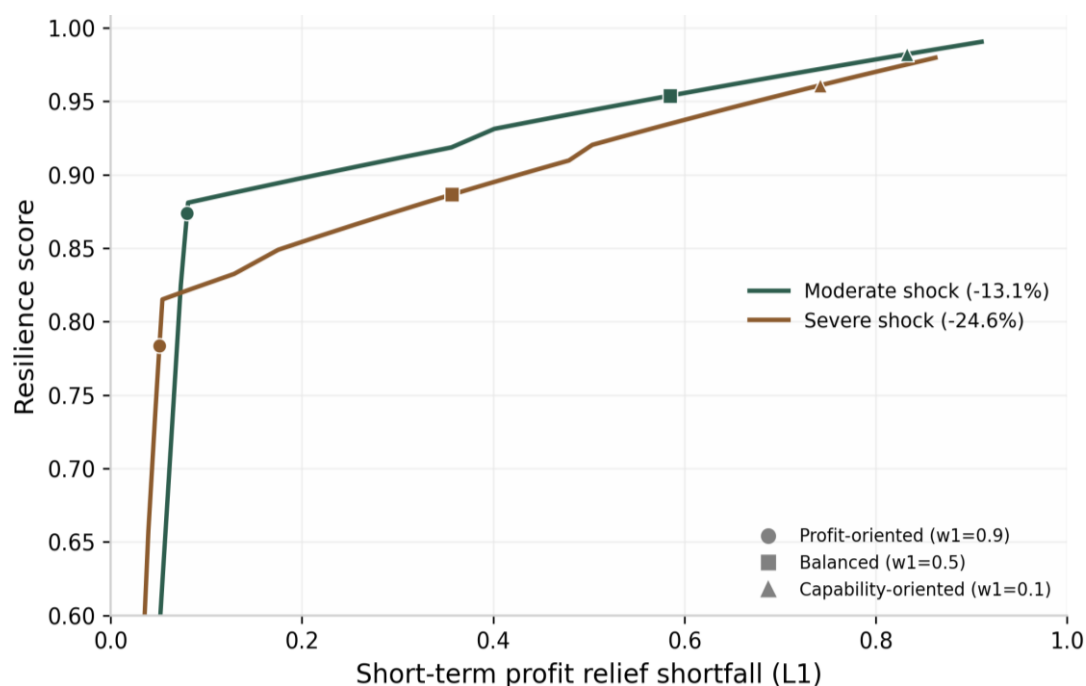


Fig. 3. Efficient cost adjustment frontier

The frontier for the severe shock is steeper at its profit-oriented end, meaning that the last increments of short-term profit relief are purchased at a disproportionate cost to future capability. The moderate-shock frontier sits higher and flatter, indicating that mild contractions can be absorbed with little sacrifice of long-term capability as long as the adjustment is directed toward administrative spending. Managers operating near the balanced region of either frontier secure most of the attainable profit relief while surrendering only a modest share of resilience. This geometry quantifies the adjustment-cost asymmetry estimated in Table 4 and illustrates how the econometric and prescriptive components of the study combine into a unified decision framework.

5. Discussion and Managerial Implications

5.1 Decoding Functional Asymmetry and the Leverage Paradox

The empirical findings indicate that organizational cost structures in emerging markets do not contract symmetrically during macroeconomic demand shocks. Beyond this general asymmetry, the results highlight a distinct functional variation. Administrative overhead exhibits a sluggish downward adjustment that operates through adjustment dynamics, whereas research expenditure does not contract during demand declines; its static decline-side elasticity is statistically indistinguishable from zero and the dynamic estimate is significantly negative. This pattern is consistent with human capital and tacit knowledge theories of cost behavior [7]. Unlike codified administrative routines that can be temporarily suspended and later restored with standard operating procedures, research productivity relies on continuous, path-dependent experimentation and team-embedded synergies. Dismantling such deeply integrated innovation networks to satisfy short-term earnings targets irreversibly destroys the firm's technological trajectory. Recent longitudinal evidence on workforce preservation supports this interpretation; firms that retain core employees through recessions tend to exhibit higher survival rates, as firm-specific knowledge remains intact during recovery periods [36]. Overall, the evidence suggests that managerial adjustment costs are closely associated with the functional irreversibility of the underlying resources.

The moderating hypotheses receive limited support, and that null result disciplines the interpretation. Physical constraints do not measurably deepen the asymmetry in either estimator, even though asset-specificity arguments predict that capital-intensive firms, facing illiquid secondary markets and severe liquidation discounts, should adjust more rigidly [19, 20]. The defensible conclusion is narrow. In this sample, the asymmetry is large, systematic, and essentially flat across the leverage and capital intensity distributions, so whatever generates the rigidity operates at the level of the cost function itself rather than through the balance-sheet margins examined here. Studies that detect significant moderation typically exploit finer constraint measures, such as covenant violations or refinancing events [15, 23], which the present data do not observe.

The leverage results stand in contrast to the covenant-based creditor-discipline narrative, under which indebted firms retrench aggressively once creditor control tightens [15]. No acceleration of cost cuts appears at any point of the leverage distribution in this sample, in either estimator. The observational design does not identify the mechanism behind this absence, and competing accounts remain open. Firms may preserve their research core because its liquidation value is low, creditors in bank-based systems may tolerate capability retention, or leveraged firms may simply have exhausted their discretionary buffers before the shock arrives [24, 27]. The study finds no statistically significant evidence that leverage accelerates cost reductions in this emerging-market sample, and the observational design cannot exclude modest effects below the detection threshold of the data.

5.2 Prescriptive Analytics: The Strategic Policy Menu

While diagnosing historical cost rigidity contributes to the theoretical accounting literature, predictive parameters provide limited normative guidance during an active economic crisis. Decision-makers facing demand shocks require systematic frameworks to allocate unavoidable retrenchment across cost functions with varying adjustment frictions. The proposed prescriptive framework converts estimated elasticities and their joint uncertainty into an expected-loss objective, while the feasible region is anchored in the deepest adjustments that comparable firms have historically executed. This separation matters for interpretability. Estimation uncertainty governs how damaging a cut is expected to be, historical behavior governs how deep a cut may go, and the resulting recommendations avoid the fragility of deterministic calculators built on point estimates [10, 14].

The generated policy frontiers demonstrate that the optimal allocation of retrenchment depends on the magnitude of the macroeconomic shock. Under a moderate contraction calibrated to the median realized decline, the optimization concentrates the adjustment overwhelmingly on administrative spending for every preference profile, because the feasible savings from research budgets are negligible relative to their expected capability cost, and even strongly profit-oriented management is directed to keep research reductions at or around one percent. For mild contractions, the framework therefore focuses financial relief efforts on administrative overhead while nearly insulating ongoing research projects, allowing the organization to absorb the shock through its most recoverable cost structures.

As contraction severity escalates to the upper quartile of realized declines, the efficient frontier steepens, and the trade-off between immediate relief and future capability becomes visible. Strategies that maximize short-term profit drive the resilience score down to just above three quarters of its no-adjustment value, while balanced policies cap research reductions below one percent and capability-oriented policies at essentially zero. Capital market evidence aligns with this ordering, as investors penalize managers who cut research expenditure to meet short-term earnings targets [37]. The geometry of the frontier makes the cost of myopia explicit in resilience units rather than leaving it as a qualitative warning.

This prescriptive architecture implies that there is no single optimal adjustment policy; rather, choices depend on organizational risk appetite and governance structures. Boards of directors can utilize the efficient frontier as a benchmarking tool to evaluate realized retrenchment patterns against scenario-bounded reference policies, helping to identify short-term deviations before they erode long-term capability. Furthermore, from a practical implementation standpoint, translating these policy frontiers into routine corporate governance requires embedding such stochastic frameworks directly into enterprise risk management systems. Integrating the prescriptive boundaries developed in this study into intelligent enterprise resource planning architectures would allow financial controllers to stress-test their budgets against multiple macroeconomic scenarios in real time, so that strategic boundaries, specifically the preservation of research teams, are protected against generalized, across-the-board cost-cutting mandates triggered by sudden revenue shortfalls.

5.3 Limitations and Avenues for Future Research

The prescriptive outputs should be interpreted within the empirical boundaries of the study. First, the estimations rely on data from a single emerging market, and the elasticities may not fully generalize to low-inflation environments with different labor market frictions. Second, the administrative-cost asymmetry is estimator-sensitive, and the stickiness estimates are further sensitive to the endogeneity treatment of the decline-side regressors, whose fully instrumented estimation is constrained by weak internal instruments, so prescriptions drawn from these elasticities should be read with that fragility in mind. Third, the research expenditure model conditions on firms maintaining active research programs, so the findings relate to the intensive margin of adjustment rather than the decision to initiate or terminate research; two-part or hurdle specifications could extend the analysis to the extensive margin. Fourth, the capability weight κ in the objective function is a normative parameter chosen by the decision-maker, and the prescriptions are scenario illustrations rather than measured welfare optima. Finally, the optimization addresses a single-period shock, and multi-period recovery trajectories remain outside the current objective function.

These limitations outline avenues for future research in accounting and decision analytics. Future studies could re-estimate asymmetric elasticities using machine learning architectures, which have shown utility in capturing complex, nonlinear financial relationships [38]. Such approaches might yield firm-specific, real-time stickiness forecasts to complement sample-average parameters.

Additionally, future research could integrate the prescriptive model within the agentic analytics paradigm, where generative systems couple estimation and scenario simulation into continuous decision support [39]. Ultimately, by shifting the focus from explaining historical cost rigidity to prescribing proactive adjustment policies, this framework provides a structured decision-support architecture for navigating volatile economic environments.

6. Conclusion

The defining challenge of corporate crisis management lies not merely in predicting the magnitude of an impending demand shock, but in determining how to allocate unavoidable financial retrenchment across operations with different adjustment frictions. This study addresses this challenge with an integrated framework that bridges the predictive diagnostics of econometric cost behavior with prescriptive optimization. Using inflation-adjusted dynamic panel estimations from an emerging market, the empirical phase establishes a strong asymmetry for research expenditure that is broadly robust across the principal specifications, whose decline-side elasticity is statistically indistinguishable from zero in the static model and significantly negative in the dynamic model, while the administrative-cost asymmetry is weaker and estimator-sensitive, gaining significance only in the parsimonious dynamic specification; this functional gradient survives a formal equality test, while leverage and capital intensity leave the asymmetry essentially unchanged. The prescriptive phase translates these elasticities and their joint uncertainty into a scenario-based policy menu whose feasibility region is anchored in historically realized adjustments. The resulting frontiers indicate that mild contractions are best absorbed through administrative cost reductions, whereas severe systemic shocks force a trade-off in which aggressive short-term profit relief is purchased with measurable losses in long-run organizational resilience. By shifting the analytical emphasis from explaining historical cost stickiness to prescribing scenario-bounded adjustment policies, the framework offers executives, boards, and creditors a structured architecture for navigating volatile economic environments.

Appendix

Table A1

Moderating Effects of Leverage and Capital Intensity on Cost Stickiness

Specification	Dec $\times$ $\Delta \ln \text{Sales}$	Dec $\times$ $\Delta \ln \text{Sales} \times Z$	Hansen (p)	AR(1) (p)	AR(2) (p)	N
GMM, SG&A, Z = LEV	-0.447** (0.216)	0.008 (0.066)	0.165	0.000	0.561	2,819
GMM, SG&A, Z = CI	-0.512*** (0.185)	0.096 (0.078)	0.291	0.000	0.525	2,819
GMM, R&D, Z = LEV	-0.672** (0.265)	-0.186 (0.262)	0.459	0.000	0.513	1,056
GMM, R&D, Z = CI	-0.650** (0.282)	-0.071 (0.203)	0.440	0.000	0.531	1,056
TWFE, SG&A, Z = LEV	-0.042 (0.045)	-0.043 (0.040)				4,208
TWFE, SG&A, Z = CI	-0.054 (0.040)	0.007 (0.062)				4,208
TWFE, R&D, Z = LEV	-0.649*** (0.226)	0.009 (0.142)				1,637
TWFE, R&D, Z = CI	-0.597*** (0.229)	-0.150 (0.118)				1,637

Note: Z denotes the moderating variable, leverage or capital intensity, entering in lagged and standardized form, so the triple interaction coefficients read as per-standard-deviation effects. Windmeijer-corrected standard errors in parentheses for the GMM models; Driscoll-Kraay standard errors in parentheses for the TWFE models. The Hansen and Arellano-Bond serial correlation tests apply only to the GMM estimations and are not defined for the static TWFE models. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table A2

Additional Robustness: Alternative Instrument Sets, Dynamic TWFE, and Uninflated Values

Specification	Model 1: SG&A Costs	Model 2: R&D Costs
GMM with extended instrument set		
L1. $\Delta \ln \text{Cost}$	-0.044* (0.027)	-0.115*** (0.040)
$\Delta \ln \text{Sales}$	0.501*** (0.133)	0.460*** (0.122)
$\text{Dec} \times \Delta \ln \text{Sales}$ (Stickiness)	-0.171 (0.153)	-0.494** (0.221)
Number of Instruments	118	72
AR(1) test (p-value)	0.000	0.000
AR(2) test (p-value)	0.436	0.365
Hansen J-test (p-value)	0.202	0.739
Dynamic TWFE with Driscoll-Kraay SE		
L1. $\Delta \ln \text{Cost}$	-0.109*** (0.028)	-0.187*** (0.030)
$\text{Dec} \times \Delta \ln \text{Sales}$ (Stickiness)	-0.024 (0.050)	-0.728*** (0.143)
Observations	3,819	1,463
GMM on uninflated values		
L1. $\Delta \ln \text{Cost}$	-0.026 (0.033)	-0.086* (0.052)
$\Delta \ln \text{Sales}$	0.770*** (0.142)	0.448*** (0.110)
$\text{Dec} \times \Delta \ln \text{Sales}$ (Stickiness)	-0.384* (0.202)	-0.336 (0.489)
Number of Instruments	88	57
AR(1) test (p-value)	0.000	0.000
AR(2) test (p-value)	0.255	0.487
Hansen J-test (p-value)	0.159	0.456
GMM excluding 2023-2025		
$\text{Dec} \times \Delta \ln \text{Sales}$ (Stickiness)	-0.396* (0.216)	-0.542* (0.316)
Observations	2,071	760
GMM with endogenous Dec and $\text{Dec} \times \Delta \ln \text{Sales}$		
L1. $\Delta \ln \text{Cost}$	-0.003 (0.031)	-0.136*** (0.044)
$\Delta \ln \text{Sales}$	0.389*** (0.148)	0.624* (0.326)
$\text{Dec} \times \Delta \ln \text{Sales}$ (Stickiness)	-0.026 (0.237)	-0.672 (0.615)
Number of Instruments	150	143
AR(1) test (p-value)	0.000	0.000
AR(2) test (p-value)	0.868	0.316
Hansen J-test (p-value)	0.131	0.977
Difference-in-Hansen (p-value)	0.239	0.993

Note: Windmeijer-corrected robust standard errors are reported in parentheses for the GMM models and Driscoll-Kraay standard errors for the dynamic TWFE model. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. Extended instrument sets widen the lag depth of the GMM-style instruments to orders two and three. The block excluding 2023-2025 removes the inflation-accounting years. The final block instruments the decline indicator and its interaction in GMM style, with lag depth two for SG&A and three for R&D to keep the instrument count below the number of groups; the difference-in-Hansen statistic tests the overidentifying restrictions introduced by the additional instruments against the benchmark specification. The dynamic TWFE block re-estimates the main dynamic specification of Table 4 but constructs the lagged dependent variable from the most recent available observation instead of requiring strictly consecutive annual observations, which enlarges the estimation samples to 3,819 and 1,463 firm-years; the R&D interaction is essentially unchanged in sign, magnitude, and significance, and the SG&A interaction remains statistically insignificant under both lag constructions.

Table A3

Common-Sample Equality Test for the Functional Gradient

Variables	Static Stacked TWFE	Dynamic Stacked TWFE
L1. $\Delta \ln \text{Cost}$		-0.151*** (0.027)
$\Delta \ln \text{Sales}$	0.477*** (0.085)	0.462*** (0.060)
Dec	0.024 (0.016)	0.018 (0.012)
$\text{Dec} \times \Delta \ln \text{Sales}$	-0.092 (0.106)	-0.071 (0.120)
R&D indicator	0.000 (0.029)	-0.005 (0.027)
$\text{R\&D} \times \Delta \ln \text{Sales}$	0.010 (0.123)	0.053 (0.100)
$\text{R\&D} \times \text{Dec}$	-0.004 (0.052)	-0.016 (0.059)

Table A3

Continued

Variables	Static Stacked TWFE	Dynamic Stacked TWFE
R&D × Dec × ΔlnSales	-0.453** (0.198)	-0.588*** (0.134)
LEV	0.006 (0.078)	-0.039 (0.073)
CI	-0.068** (0.034)	-0.075* (0.042)
SIZE	0.065*** (0.021)	0.080*** (0.019)
Firm & Year Effects	Yes	Yes
Observations	3,274	2,926
Driscoll-Kraay bandwidth	3	3
Tested linear restriction: R&D × Dec × ΔlnSales = 0 (p-value)	0.023	0.000

Note: Both columns stack the SG&A and R&D cost changes of the same firm-years, restricting the sample to firm-years with positive research expenditure, and interact a research indicator with the sales slope, the decline indicator, and their interaction, so the coefficient on the triple interaction is the difference between the R&D and SG&A decline-side slopes estimated on identical firm-years. Firm and year effects are included in both columns; the dynamic column adds the lagged cost change. Driscoll-Kraay standard errors with bandwidth three are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

Table A4

Sensitivity of Optimal Policies to the Strain Weight κ

Specification	Moderate shock	Severe shock
$\kappa = 0.1$		
Profit-oriented	-28.2 / -1.2 (0.94)	-39.9 / -3.8 (0.88)
Balanced	-24.7 / 0.0 (0.96)	-39.9 / -0.6 (0.93)
Capability-oriented	-7.2 / 0.0 (0.99)	-15.7 / 0.0 (0.98)
$\kappa = 0.3$ (baseline)		
Profit-oriented	-28.2 / -1.2 (0.87)	-39.9 / -3.8 (0.78)
Balanced	-12.7 / 0.0 (0.95)	-27.1 / -0.6 (0.89)
Capability-oriented	-5.1 / 0.0 (0.98)	-10.9 / 0.0 (0.96)
$\kappa = 0.5$		
Profit-oriented	-28.2 / -1.2 (0.82)	-39.9 / -3.8 (0.70)
Balanced	-9.5 / 0.0 (0.95)	-21.0 / -0.6 (0.88)
Capability-oriented	-4.6 / 0.0 (0.98)	-9.8 / 0.0 (0.95)

Note: Each cell reports the optimal SG&A and R&D adjustments in percent of the cost base, followed by the resilience score in parentheses. Policies minimize expected loss over 2,000 draws from the joint asymptotic distribution of the decline-side elasticities on the same 120 × 120 grid as Table 6. The resilience score in each block is computed with the matching κ against the fixed pooled reference bounds, so scores are comparable within a block and across scenarios.

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Conflicts of Interest

The authors declare no conflicts of interest.

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