Journal of Mathematical Finance and Risk Management
ISSN: 3080-9983 (Print), ISSN: 3080-9991 (Online) | Vol. 2, No. 1, 2026

Corporate Governance Quality and the Persistence of Earnings Volatility

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Abstract: Earnings volatility shapes valuation, credit assessment, and the evaluation of managers, yet little is known about how corporate governance affects its persistence. This paper examines whether governance quality influences not only the level of earnings volatility but also the extent to which volatility shocks carry over into subsequent periods. Using a panel of U.S. listed firms for fiscal years 1990–2014, long-horizon persistence is measured by relating forward five-year earnings volatility to its trailing five-year counterpart, and short-horizon persistence by a panel ARCH-type model of absolute earnings shocks. Governance quality is captured at two levels: firm-level governance failures revealed by SEC Accounting and Auditing Enforcement Releases (AAERs) and the system-wide governance upgrade introduced by the Sarbanes–Oxley Act (SOX) and the 2003 exchange listing standards. Firms with governance failures display higher earnings volatility and substantially stronger long-horizon persistence (0.90 versus 0.48), and the amplification is concentrated before enforcement and among small firms. After the governance reforms, the persistence of annual earnings shocks falls by 21%, shortening their half-life from 1.10 to 0.80 years, and the decline holds across alternative measures, subsamples, firm fixed effects, and a placebo test. The evidence indicates that effective governance accelerates the dissipation of earnings volatility.

Keywords: Corporate governance, earnings volatility, volatility persistence, accounting enforcement, Sarbanes–Oxley Act, panel data.

1. Introduction

Earnings volatility is one of the most closely watched properties of accounting performance. Executives report a strong preference for smooth earnings because volatile earnings are perceived as riskier and harder to predict [1], firms with less volatile cash flows command higher valuations [2], and cash flow volatility is associated with lower investment and higher costs of external capital [3]. Volatile earnings are also less predictable [4], and earnings attributes such as smoothness and persistence are reflected in the cost of equity [5]. Because the generation and reporting of earnings are delegated to managers whose interests can diverge from those of shareholders [6–8], corporate governance is a natural determinant of how volatile earnings are and of how that volatility evolves over time.

A large literature links governance to the level of risk and the variability of performance. Better investor protection is associated with greater value-enhancing risk-taking [9], board size and CEO power shape the variability of corporate performance [10, 11], and corporate risk-taking declined after the Sarbanes–Oxley Act (SOX) [12]. A parallel literature shows that board and audit committee characteristics constrain earnings management [13, 14] and that governance structures relate to a broad set of accounting outcomes [15–17]. These studies, however, treat volatility as a static level. The dynamic dimension, namely how long elevated volatility persists after a shock, has received little attention, even though governance is essentially a corrective system that is expected to act when performance deteriorates [18–20]. If effective boards intervene after volatile performance, volatility shocks should dissipate quickly in well-governed firms; if weak governance allows entrenched managers to maintain risky or opaque practices, volatility should persist.

This paper studies the persistence of earnings volatility as a governance outcome. The analysis uses a public panel of U.S. listed firms for fiscal years 1990–2014 that combines Compustat fundamentals with misstatement indicators derived from SEC Accounting and Auditing Enforcement Releases (AAERs) [21]. Long-horizon persistence is measured by relating earnings volatility over the next five years to volatility over the preceding five years, and short-horizon persistence by an autoregressive model of absolute earnings shocks in the spirit of ARCH models [22, 23]. Governance quality is captured at two levels. At the firm level, governance failures revealed through SEC enforcement identify firms whose monitoring systems failed to prevent material misreporting [24–26]. At the system level, SOX and the 2003 listing standards represent a market-wide upgrade of board independence, audit committee oversight, and executive accountability [27–29].

The results support a governance view of volatility dynamics. Firms with governance failures exhibit higher earnings volatility after controlling for size, leverage, valuation, losses, growth, and year effects. More importantly, their volatility is far more persistent: the long-horizon persistence coefficient is 0.90 for these firms compared with 0.48 for other firms. The amplification is concentrated in the period up to the last misstatement year and fades afterwards, consistent with governance remediation after detection [26], and it is strongest among small firms, where alternative monitoring mechanisms are weaker. At the system level, the persistence of annual earnings shocks declines from 0.53 before SOX to 0.42 after the reforms, a 21% reduction that shortens the half-life of an earnings shock from 1.10 to 0.80 years. The decline holds after excluding the financial crisis, under alternative shock measures and transformations, and with firm fixed effects, whereas a placebo break in 1996 yields the opposite sign.

The paper makes three contributions. First, it introduces

persistence as a distinct dimension of the governance–volatility relation, complementing studies that focus on the level of risk [9, 10, 12]. Second, it provides consistent evidence at both the firm and the system level, connecting research on accounting enforcement [30, 31] with research on governance regulation [27, 32]. Third, it offers practical guidance: the volatility of firms with governance failures should be treated as more durable when forecasting earnings risk, and faster normalization of earnings risk is a tangible benefit of governance reform.

The remainder of the paper is organized as follows. Section II reviews the literature and develops the hypotheses, Section III describes the data and methodology, Section IV presents the empirical results, Section V discusses the implications, and Section VI concludes.

2. Literature Review and Hypotheses

2.1. Corporate Governance and Earnings Volatility

Agency theory predicts that managers who bear undiversifiable employment risk prefer to reduce firm risk [33] or to enjoy a quiet life [34], whereas poorly monitored managers can also pursue risky or opaque strategies that serve private interests [6, 8]. Governance mechanisms, including boards, takeover defenses, and investor protection, discipline these choices [35–37]. Governance quality relates to executive compensation, firm value, and operating performance [38–40], as well as to the variability of outcomes: larger boards produce less variable performance [10], powerful CEOs generate more variable performance [11], and stronger investor protection is associated with greater risk-taking that is value enhancing [9].

Governance also shapes earnings volatility through the reporting channel. Financial accounting information is both an input to and an outcome of the governance system [16, 17]. Independent boards and audit committees curb discretionary accruals [13, 14], governance structures relate to accruals, restatements, and future performance [15], and insiders protected by weak investor rights manage both the level and the variability of reported earnings [41]. Reporting quality is in turn linked to firm-level volatility [42] and to the persistence and predictability of earnings [43, 44]. Managers' incentives to smooth earnings [1, 45] imply that reported volatility reflects both economic risk and reporting choices, and both components fall under the oversight of boards and audit committees.

2.2. Governance Failure and Accounting Enforcement

SEC AAERs identify cases in which firms materially misstated their financial statements. Firms subject to enforcement have fewer outside directors, weaker audit committees, and more frequent CEO–chair duality [24–26], and the likelihood of restatement is lower when boards and audit committees include independent directors with financial expertise [46]. AAERs are therefore widely used to identify failures of the governance and reporting system [30, 31, 47], and recent studies exploit them to build detection models [21], [48]. Enforcement imposes large reputational costs [49], fraud is often revealed by actors outside the formal governance system [50], and sanctioned firms tend to strengthen their boards and audit committees after detection [26].

2.3. The Sarbanes–Oxley Reforms

SOX and the accompanying exchange listing standards required majority-independent boards, fully independent audit committees, executive certification of financial reports, and assessments of internal control [27, 29]. After the reforms, boards became larger and more independent and committees met more often [28], and the effectiveness of the newly mandated outside directors depended on the cost of acquiring information [51]. Accrual-based earnings management declined [32], internal control deficiencies were associated with lower accrual quality and higher firm risk [52, 53], and investment and risk-taking incentives were reduced [12, 54]. The market reaction to the Act and its compliance costs have also been documented [55, 56].

2.4. Persistence of Earnings Volatility and Hypotheses

Profitability mean-reverts [57], and the persistence of earnings depends on their accrual and cash flow composition [58] and on past volatility [4, 59]. Volatility itself clusters over time [22, 23]. We argue that governance determines how long volatility shocks last. Boards respond to risk and poor performance through CEO turnover and strategic change [19], [60], curtailing the policies that generate sustained volatility, and effective oversight of financial reporting limits large positive and negative abnormal accruals [52] as well as manipulation that must later be reversed [25]. Weak governance, in contrast, allows volatile strategies and opaque reporting to continue. Fig. 1 summarizes the framework and the following hypotheses.

H1: Firms with governance failures exhibit higher earnings volatility.

H2: Earnings volatility is more persistent in firms with governance failures.

H3: The persistence of earnings volatility declines after the SOX governance reforms.

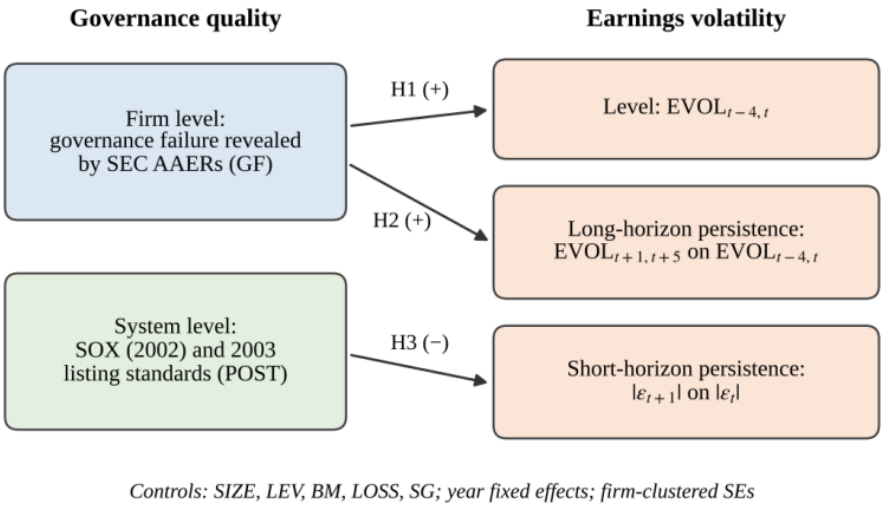


Figure 1. Research framework linking governance quality at the firm and system levels to the level and persistence of earnings volatility.

3. Data and Methodology

3.1. Sample and Data

The analysis uses the public firm-year dataset released by Bao et al. [21], which contains Compustat fundamentals for U.S. listed firms for fiscal years 1990–2014 merged with misstatement indicators based on the AAER database of the Center for Financial Reporting and Management [30]. The raw panel includes 146,045 firm-years of 18,444 firms, of which 964 firm-years of 402 firms are flagged as misstated. We require total assets of at least USD 1 million and construct a complete firm-year grid so that all volatility windows consist of consecutive fiscal years. ROA and the continuous control variables are winsorized at the 1st and 99th percentiles each year. The long-horizon sample contains 27,967 firm-years of 4,453 firms with base years 1994–2009, including 173 firms with governance failures, and the short-horizon sample used for the regime analysis contains 84,432 firm-years of 12,841 firms.

3.2. Earnings Volatility and Its Persistence

Earnings are measured by $ROA_{i,t}$, income before extraordinary items divided by total assets. Long-horizon volatility $EVOL_{i,t}$ is the standard deviation of ROA over years $t-4$ to t, and forward volatility $FEVOL_{i,t}$ is the standard deviation over years $t+1$ to $t+5$. Because the two windows do not overlap, their relation is not mechanical, and its slope measures the persistence of volatility across multi-year regimes. For short-horizon dynamics, we estimate annual cross-sectional regressions

$$ROA_{i,t} = a_t + b_t ROA_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

And define $SHOCK_{i,t} = |\varepsilon_{i,t}|$, the magnitude of the unexpected component of earnings. Analogous to ARCH models [22, 23], the dependence of $SHOCK_{i,t+1}$ on $SHOCK_{i,t}$ measures how strongly volatility clusters from one year to the next.

3.3. Governance Quality

GF_i equals one for firms with at least one AAER-identified misstatement year and zero otherwise. To separate the period of failed governance from the remediation period, GF_{PRE} equals one for years up to and including the firm's last misstatement year, and GF_{POST} equals one for subsequent years [26]. The system-level indicator $POST_t$ equals one for fiscal years from 2003 onward and zero for years up to 2000; the transition years 2001–2002 are excluded. $ACCEL_{i,t}$ equals one when market capitalization is at least USD 75 million, approximating the accelerated-filer threshold that determined the timing of Section 404 compliance [56].

3.4. Empirical Models

H1 is tested with

$$EVOL_{i,t} = \alpha + \theta GF_i + \gamma' X_{i,t} + \mu_t + e_{i,t} \quad (2)$$

And H2 with

$$FEVOL_{i,t} = \alpha + \beta EVOL_{i,t} + \theta GF_i + \lambda(EVOL_{i,t} \times GF_i) + \gamma' X_{i,t} + \mu_t + e_{i,t} \quad (3)$$

Where β is the persistence for firms without governance failures and $\beta + \lambda$ the persistence for firms with failures. H3 is tested with

$$SHOCK_{i,t+1} = \alpha + \rho SHOCK_{i,t} + \kappa(SHOCK_{i,t} \times POST_t) + \gamma' X_{i,t} + \mu_t + e_{i,t} \quad (4)$$

Where ρ and $\rho + \kappa$ are the pre- and post-reform persistence, and the half-life of a shock equals $\ln(0.5)/\ln(\rho)$. The vector X contains firm size (SIZE, the log of total assets), leverage (LEV, total liabilities over total assets), the book-to-market ratio (BM), a loss indicator (LOSS), and sales growth (SG). Year fixed effects μ_t absorb aggregate shocks, including the main effect of $POST_t$. Standard errors are clustered by firm, which accounts for the serial correlation induced by overlapping windows [61].

4. Empirical Results

4.1. Descriptive Statistics

Table I reports descriptive statistics. Earnings volatility is strongly right-skewed: the mean EVOL is 0.105, whereas the median is 0.039, and FEVOL has a mean of 0.126. The average ROA is −4.1%, and 29.6% of firm-years report losses. Firms with governance failures account for 4.6% of the long-horizon sample. Their trailing volatility is similar to that of other firms (0.101 versus 0.105), but their forward volatility is markedly higher (0.147 versus 0.125), an early indication that volatility persists more strongly in these firms. In the short-horizon sample, the mean absolute earnings shock is 0.197, and 61.8% of firm-years meet the accelerated-filer size threshold.

Table I. Descriptive Statistics

Variable	N	Mean	SD	P25	Median	P75
Panel A: Long-horizon sample						
EVOL	27,967	0.104	0.202	0.018	0.039	0.098
FEVOL	27,967	0.126	0.314	0.019	0.041	0.105
ROA	27,967	−0.041	0.407	−0.019	0.036	0.076
SIZE	27,967	5.760	2.459	3.888	5.772	7.548
LEV	27,967	0.547	0.500	0.332	0.515	0.668
BM	27,967	0.544	0.961	0.270	0.489	0.789
LOSS	27,967	0.296	0.456	0.000	0.000	1.000
SG	27,967	0.158	0.669	−0.034	0.075	0.206
GF	27,967	0.046	0.209	0.000	0.000	0.000
Panel B: Short-horizon sample						
$SHOCK_t$	84,432	0.197	0.241	0.060	0.142	0.247
$SHOCK_{t+1}$	84,432	0.225	0.305	0.067	0.159	0.268
ROA	84,432	−0.082	0.504	−0.057	0.028	0.070
POST	84,432	0.500	0.500	0.000	1.000	1.000
ACCEL	84,432	0.618	0.486	0.000	1.000	1.000

Panel A covers the long-horizon sample (base years 1994–2009); Panel B covers the short-horizon regime sample (1991–2000 and 2003–2013). EVOL and FEVOL are standard deviations of ROA over years t−4 to t and t+1 to t+5. SHOCK is the absolute residual from annual cross-sectional AR(1) regressions of ROA.

4.2. Governance Failure and the Level of Earnings Volatility

Column (1) of Table II tests H1. Conditional on firm characteristics and year effects, firms with governance failures have earnings volatility that is 0.030 higher (t = 3.34), which equals about 29% of the sample mean and 78% of the median. The control variables behave as expected: volatility decreases with size and the book-to-market ratio and increases with leverage, losses, and growth. H1 is supported.

4.3. Governance Failure and Long-Horizon Persistence

Column (2) shows that earnings volatility is highly persistent across five-year regimes. The slope of FEVOL on EVOL is 0.505 (t = 12.78), so about half of a cross-sectional difference in volatility carries over into the next five years. Column (3) adds the interaction with GF. Persistence is 0.483 for firms without governance failures, and the interaction is 0.417 (t = 2.19), implying a persistence of 0.900 (t = 4.80) for firms with governance failures. Volatility in these firms is thus carried almost fully into the following five years. Fig. 2 illustrates the result: the binned relation between past and future volatility is considerably steeper for firms with governance failures.

Column (4) separates the governance-failure effect by timing. The interaction equals 0.741 (t = 2.67) for observations up to the last misstatement year and 0.263 (t = 1.24) afterwards. Persistence is therefore concentrated in the period of failed governance and weakens once enforcement has occurred, in line with the evidence that sanctioned firms rebuild their boards and audit committees [26]. H2 is supported.

Table II. Governance Failure, Earnings Volatility, and Long-Horizon Persistence

	(1) EVOL	(2) FEVOL	(3) FEVOL	(4) FEVOL
EVOL		0.505***	0.483***	0.483***
		(12.78)	(12.32)	(12.33)
GF	0.030***		0.008	
	(3.34)		(0.55)	
EVOL×GF			0.417**	
			(2.19)	
GF_{PRE}				−0.012
				(−0.92)
$EVOL \times GF_{PRE}$				0.741***
				(2.67)
GF_{POST}				0.028
				(1.08)
$EVOL \times GF_{POST}$				0.263
				(1.24)
SIZE	−0.030***	−0.021***	−0.021***	−0.021***
	(−26.50)	(−13.37)	(−13.42)	(−13.34)
LEV	0.096***	0.075***	0.075***	0.075***
	(11.67)	(4.66)	(4.67)	(4.70)
BM	−0.017***	−0.002	−0.002	−0.002
	(−6.59)	(−0.57)	(−0.60)	(−0.60)
LOSS	0.086***	0.086***	0.087***	0.087***
	(21.21)	(12.57)	(12.76)	(12.76)
SG	0.035***	0.017**	0.018**	0.018**
	(8.61)	(2.38)	(2.51)	(2.51)
Year FE	Yes	Yes	Yes	Yes
N	27,967	27,967	27,967	27,967
Adj. R^2	0.331	0.285	0.290	0.291

Column (1) uses EVOL as the dependent variable and columns (2)–(4) use FEVOL. t-statistics based on firm-clustered standard errors are in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels.

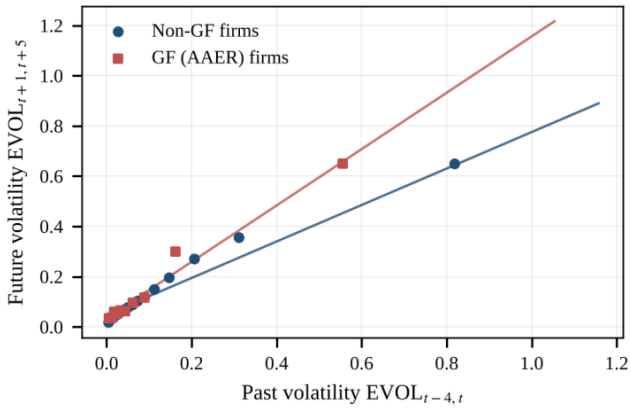


Figure 2. Binned scatter of forward (t+1 to t+5) against trailing (t−4 to t) earnings volatility for firms with and without governance failures, with fitted OLS lines.

4.4. Governance Reforms and Short-Horizon Persistence

Table III reports the short-horizon tests. In column (1), the persistence of absolute earnings shocks is 0.469 (t = 35.34). Column (2) shows that persistence falls from 0.533 before the reforms to 0.421 afterwards (κ = −0.112, t = −4.21), a decline of 21%. Expressed as a half-life, an earnings shock lost half of its magnitude within 1.10 years before SOX and within 0.80 years after it. H3 is supported.

Table III. SOX Reforms and Short-Horizon Persistence of Earnings Shocks

	(1)	(2)	(3)	(4)
SHOCK	0.469***	0.533***	0.535***	0.564***
	(35.34)	(25.14)	(24.56)	(23.43)
SHOCK×POST		−0.112***	−0.113***	−0.105***
		(−4.21)	(−4.13)	(−3.40)
GF			0.011	
			(1.53)	
SHOCK×GF			−0.052	
			(−0.77)	
GF×POST			0.001	
			(0.08)	
SHOCK×POST×GF			0.017	
			(0.18)	
ACCEL				0.018***
				(3.67)
SHOCK×ACCEL				−0.139***
				(−3.01)
ACCEL×POST				0.020**
				(2.39)
SHOCK×POST×ACCEL				−0.023
				(−0.43)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	84,432	84,432	84,432	84,432
Adj. R^2	0.357	0.359	0.359	0.361

The dependent variable is SHOCKt+1; fiscal years 2001–2002 are excluded. Controls are SIZE, LEV, BM, LOSS, and SG; year fixed effects absorb the main effect of POST. t-statistics based on firm-clustered standard errors are in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Columns (3) and (4) examine heterogeneity. The triple interaction with GF is small and insignificant (0.017, t = 0.18), so firms with governance failures do not differ from other firms in year-to-year shock transmission; the governance-failure effect operates on multi-year volatility regimes. In column (4), larger firms exhibit lower persistence (−0.139, t = −3.01), but the post-reform decline does not differ between firms above and below the accelerated-filer threshold (−0.023, t = −0.43). The reduction is thus broad-based, consistent with provisions that applied to all listed firms, such as audit committee independence, executive certification, and board independence requirements, rather than with Section 404 audits, whose timing depended on filer status [55, 56].

Fig. 3 plots persistence coefficients from year-by-year cross-sectional regressions in the spirit of Fama and MacBeth [62]. Persistence averages 0.62 over 1991–2000 and 0.54 over 2003–2013, with a pronounced trough around the reform years and a temporary rise during the 2007–2009 financial crisis. Fig. 4 shows the binned relation between current and next-year shocks: the post-reform line is flatter, particularly for large shocks.

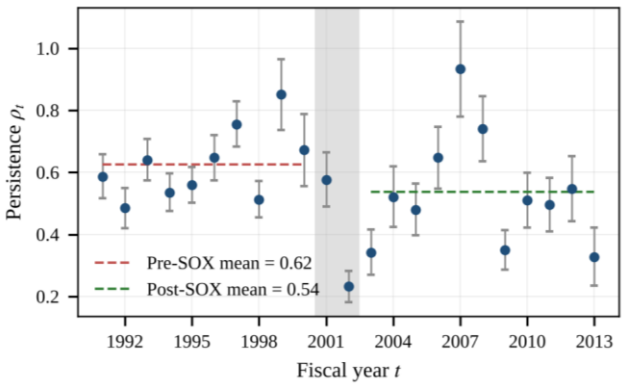


Figure 3. Year-by-year persistence of absolute earnings shocks (slope of |εt+1| on |εt|) with 95% confidence intervals; the shaded area marks the 2001–2002 transition.

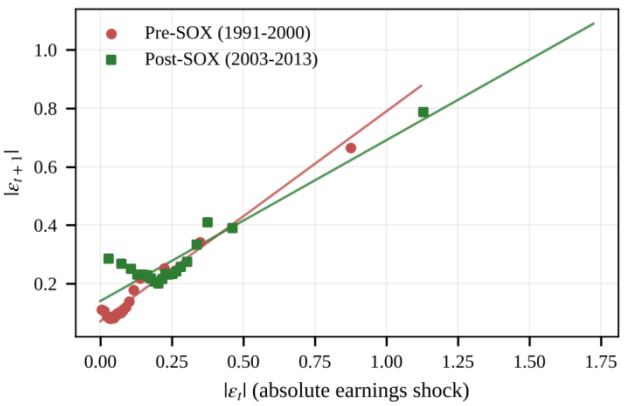


Figure 4. Binned scatter of next-year against current absolute earnings shocks before and after the SOX reforms, with fitted OLS lines.

4.5. Robustness

Table IV reports additional tests. Panel A focuses on the governance-failure interaction. Measuring earnings with net income yields 0.401 (t = 2.15). Removing misstated years from the ROA series raises the interaction to 0.865 (t = 3.40), showing that the result is not produced by the misreported figures themselves. With four-year windows the interaction declines to 0.089 (t = 0.58), which matches column (3) of Table III: governance failure shapes durable multi-year volatility regimes rather than shorter-horizon fluctuations. The effect is concentrated in small firms (0.464, t = 2.18) and is weaker among medium and large firms (0.117, t = 0.87), consistent with internal governance mattering most where external monitoring is limited.

Table IV. Robustness Tests

Specification	Coef.	t	N
Panel A: EVOL×GF in (3)			
Earnings measured as NI/AT	0.401**	2.15	27,967
Misstated years removed from ROA series	0.865***	3.40	27,049
Four-year windows	0.089	0.58	39,626
Small firms (bottom size tercile)	0.464**	2.18	9,317
Medium and large firms	0.117	0.87	18,650
Panel B: SHOCK×POST in (4)			
Excluding 2006–2008	−0.216***	−8.02	72,659
Total assets ≥ USD 10 million	−0.182***	−5.72	75,046
SHOCK = |ΔROA|	−0.082***	−3.57	84,432
Log specification	−0.067***	−6.80	84,432
Percentile-rank specification	−0.058***	−7.26	84,432
Firm and year fixed effects	−0.089***	−2.85	84,432
Placebo break in 1996 (1991–2000)	0.198***	7.25	42,187

All specifications include the control variables and year fixed effects; t-statistics are based on firm-clustered standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel B focuses on the reform interaction. The decline in persistence is larger when the 2006–2008 crisis years are excluded (−0.216, t = −8.02) and when the sample is restricted to firms with assets of at least USD 10 million (−0.182, t = −5.72). It remains significant when the shock is measured as the absolute change in ROA (−0.082, t = −3.57), under log (−0.067, t = −6.80) and percentile-rank (−0.058, t = −7.26) specifications, and with firm and year fixed effects (−0.089, t = −2.85), which absorb time-invariant heterogeneity even though within estimates of dynamic models are attenuated in finite panels [63, 64]. Finally, a placebo break in 1996 within the pre-reform period yields a positive coefficient (0.198, t = 7.25): persistence was rising before SOX, so the post-reform decline is not the continuation of an existing downward trend.

5. Discussion

The results point to two complementary channels through which governance shortens the life of earnings volatility. The first is monitoring and intervention: boards that respond to risk and poor performance replace managers and revise strategies [20, 60], so volatility shocks are absorbed rather than perpetuated. The concentration of the governance-failure effect before enforcement and its attenuation afterwards mirror the documented improvement of boards and audit committees after fraud detection [26]. The second channel is reporting oversight: independent audit committees and effective internal controls limit large abnormal accruals and their later reversals [13, 52], which would otherwise prolong volatile reporting. The post-SOX decline in shock persistence is consistent with both channels, because the reforms strengthened board oversight and reporting accountability for all listed firms [28, 32].

The findings have practical implications. For investors and analysts, volatility forecasts should condition on governance, because past volatility is a much stronger predictor of future volatility in firms with failed oversight [4]. For boards, the evidence highlights the value of timely intervention after volatile periods. For regulators, faster normalization of earnings risk is a benefit of governance reform that complements its documented effects on reporting quality and risk-taking [12, 54]. Future work can extend the framework to direct measures of board structure, to international governance settings [35, 41], and to dynamic panel estimators [64].

6. Conclusion

This paper examines how corporate governance quality affects the persistence of earnings volatility. Using U.S. listed firms over 1990–2014, it shows that firms with governance failures revealed by SEC enforcement have higher and markedly more persistent earnings volatility, with a long-horizon persistence of 0.90 compared with 0.48 for other firms, and that this amplification is concentrated before enforcement and among small firms. At the system level, the persistence of annual earnings shocks fell by 21% after the Sarbanes–Oxley reforms, reducing their half-life from 1.10 to 0.80 years. Together, the results indicate that governance quality determines not only how volatile earnings are but also how quickly volatility dissipates, which makes persistence a useful lens for evaluating governance mechanisms and regulation.

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