

Beyond the Ivory Tower: The Dual Expertise of Academic Directors in Deterring Corporate Violations

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Abstract

This study investigates the impact of academic independent directors with relevant industry expertise (*AID_Exp*) on corporate violations. Using a comprehensive panel of U.S. firms from 2000 to 2024, we find a robust, negative, and economically significant relationship between the board presence of *AID_Exp* and the likelihood and severity of corporate violations. This finding supports a dual toolkit theory, wherein *AID_Exp* directors possess both the strong reputational incentives of an academic to monitor and the practical industry expertise to effectively detect complex, non-obvious misconduct. We find this effect is concentrated in Social and Governance-related violations and is driven entirely by firms in high-risk sin and politically sensitive industries. We further explore the mechanisms driving this effect, finding the relationship is mediated by improved external monitoring (higher institutional ownership) and enhanced internal assurance (engagement of a CSR auditor). The negative impact is also amplified by a complementary internal governance ecosystem, including strong ESG performance, a dedicated CSR committee, a corporate governance board committee (CGBC), and transparent CSR reporting. Conversely, the effect is significantly weakened in environments with high state-level corruption. Overall, academic independent directors are valuable for stakeholders through monitoring and compliance by highlighting their knowledge and specialized skills.

Keywords: Academic Independent Directors, Industry Expertise, Corporate Violations, Corporate Governance, Sustainability

Introduction

The significant costs of corporate misconduct, which include severe financial penalties, shareholder value destruction, and the erosion of public trust (Paruchuri, Hoempler, Cowen, Cannella & Nahm, 2024), place an immense responsibility on the board of directors. As the firm's primary internal monitoring mechanism, boards are tasked with deterring and detecting such malfeasance, often by strengthening board independence (Neville, Byron, Post, and Ward, 2019; Finkelstein, Hambrick, & Cannella, 2009). Within this context, the appointment of university professors, or academic independent directors (AIDs), has become a prevalent governance strategy. This practice is notably common in the United States, where approximately 40% of S&P 1,500 firms appointed at least one professor to their board between 1998 and 2011 (Francis, Hasan, and Wu, 2015). Such appointments are often perceived as strategic moves to enhance reputational capital; a prominent illustration occurred in the wake of the Enron scandal, when Eli Lilly appointed Harvard economics professor Martin Feldstein in a move widely viewed as an effort to restore the board's credibility (White, Woidtke, Black & Schweitzer, 2014).

This focus on board-level monitoring complements a rich body of upper echelons theory (UET) literature, which investigates how the specific traits of CEOs influence misconduct. This research has shown that firm outcomes are linked to executive traits such as age (Davidson, 2022; Zahra, Priem, & Rasheed, 2005) and personality (Schrand & Zechman, 2012). Most relevant to our study, prior work has established a direct link between a CEO's academic experience and a reduced likelihood of financial fraud (Wang et al., 2021). Our study builds directly on this finding, extending this "leader attributes" logic from the CEO to the board. We argue that this effect is even more potent in the context of an independent director, whose academic training can be used as an active monitoring tool.

However, the role of academic independent directors (AIDs) in corporate governance presents a significant puzzle. On one hand, their strong reputational incentives (Pang, Zhang & Zhou, 2020; Quan & Li, 2017) and training in critical thinking (Jin, Su, Wang & Xiao, 2022) position them as ideal, objective monitors. A body of empirical work supports this, linking AIDs to reduced financial statement fraud (Wen, Li, Huang and Zhu, 2025) and enhanced CSR (Cho, Jung, Kwak, Lee & Yoo, 2017). On the other hand, a compelling critique argues that AIDs are "ivory tower" directors. This view holds that their lack of practical industry experience (Jiang & Murphy, 2007) and "narrow or theoretical" expertise (Francis et al., 2015) makes them incapable of detecting sophisticated, real-world misconduct. This leaves a critical, unresolved question: Are AIDs effective monitors in practice, and what separates an effective academic monitor from an ineffective one?

This paper argues that these mixed findings stem from a critical omitted factor: the role of industry expertise. We resolve this puzzle by proposing a dual toolkit theory. We argue that effective monitoring requires both the incentive to act and the ability to detect. An academic without industry experience has the incentive (reputation) but lacks the practical ability, earning them the "ivory tower" label. Conversely, an industry expert may have the ability but lack the critical independence of an academic. We propose that it is the synergy of these two traits that creates a superior monitor. This monitor possesses both the academic's reputational incentive to act as a monitor and the practitioner's technical knowledge to know where to look and how to detect sophisticated, industry-specific violations. This study, therefore, hypothesizes that AIDs with relevant industry expertise reduce the firm's likelihood of engaging in corporate violations.

We test this hypothesis using a comprehensive sample of U.S. firms from 2000 to 2024. Our primary analysis reveals a robust and statistically significant negative association between the presence of academic independent directors with relevant industry expertise and the probability and severity of corporate violations. This core result supports our central theory: it is this specific combination of academic rigor and practical industry knowledge that creates an effective monitor. This finding helps resolve the tension in the prior literature. It suggests that the documented failures of AIDs (Francis et al., 2015) may be driven by those without industry expertise, while the documented successes (Jin et al., 2022) are likely driven by those with it. This effect is not only statistically significant but also economically meaningful. Adding just one such director to a typical board is associated with a 9.28% reduction in future violations relative to the sample mean.

Our analysis of the mechanisms reveals how this reduction in misconduct is achieved and when it is most effective. First, we find that the relationship is significantly mediated by the firm's governance monitoring; Academic independent directors with relevant industrial expertise appear to reduce violations by helping to attract higher levels of institutional ownership (external monitoring) and by promoting the engagement of a CSR auditor (internal monitoring). Second, our moderation analyses show that academic independent directors with relevant industry expertise's effectiveness is significantly amplified by other strong, complementary governance structures. The violation-reducing effect is stronger in firms with high ESG performance, a dedicated CSR committee, a corporate governance's board committee (CGBC), and those that regularly publish CSR report. Conversely, we find that the directors' efforts can be undermined by the external environment: the violation-reducing effect of academic independent director with relevant industrial expertise is significantly weakened in firms operating in states with high levels of public corruption.

We further explore the heterogeneity of this monitoring effect. We find that the violation-reducing impact of academic independent director with relevant industrial expertise is not uniform across all types of misconduct. The effect is concentrated in ESG-related violations and is particularly strong for social and governance-related misconduct, while the impact on environmental violations is substantially weaker. This finding aligns with the industry-specific nature of the effect. Most notably, a sub-sample analysis reveals that the results are driven almost entirely by firms in high-risk sectors. Academic independent director with relevant industrial expertise significantly reduces violations only in 'sin' and politically sensitive industries; we find no significant effect in other industries. This suggests that the specialized expertise of academic independent director with relevant industrial expertise is most critical in contexts where the risks of social and governance-related misconduct are most salient.

To address potential endogeneity concerns, we employ a comprehensive empirical strategy. First, we use a two-stage least squares (2SLS) instrumental variable (IV) approach. Following Jin et al. (2022), we use the state-level number of higher education institutions as an instrument, which is predicated on the finding that firms often recruit academic directors from local universities. Second, we utilize matching methods, including propensity score matching (PSM) and entropy balancing, to construct comparable treatment and control groups based on observable firm characteristics. Third, we employ a Difference-in-Differences (DID) analysis using the 2006 SEC adoption of Regulation S-K, Item 407, as an exogenous shock. This regulation imposed new disclosure requirements on NASDAQ firms (the treatment group) but was largely redundant for NYSE firms (the control group). Finally, we confirm the robustness of our main findings through supplementary analyses, using alternative measures for both corporate violations and our independent variable.

This study's primary contribution is to the unsettled debate on the role of academic directors. We seek to reconcile the mixed findings of prior literatures (Francis et al., 2015; Jin et al., 2022) by moving beyond the binary question of "Are AIDs effective?" We specify the critical condition under which they are: relevant industry expertise. By identifying this dual toolkit as the key factor, we shift the research question from "Are AIDs good monitors?" to "Which AIDs are good monitors and why?"

Second, we contribute to the broader literature on corporate governance and misconduct. While prior work has focused on general board independence or financial expertise (Agrawal & Chadha, 2009), we respond to calls for a more refined view of director attributes. We show that the specific 'dual toolkit' of an academic independent director with relevant industrial expertise is a critical factor in a board's ability to deter complex corporate violations, particularly in opaque, high-risk industries.

From a practical standpoint, our findings offer specific, actionable guidance for corporate boards and nominating committees. For firms seeking to genuinely enhance monitoring, particularly those in high-risk 'sin' or politically-sensitive industries, our results suggest that simply appointing a high-profile academic director is an insufficient governance strategy. The true value is unlocked by appointing an academic who also possesses deep, relevant industry expertise. This provides a clear, actionable characteristic for boards. Furthermore, our findings caution that this appointment is not a panacea. The value of these specialized directors is maximized when they are embedded within a strong, supportive

governance ecosystem, such as through a dedicated CSR or Corporate Governance committee to empower their oversight.

Finally, this study contributes to the broader discussion on sustainable development. By demonstrating the tangible value of advanced, specialized education in improving corporate integrity, our work speaks to UN Sustainable Development Goal 4 (Quality Education). Moreover, by identifying a governance mechanism that reduces corporate misconduct and strengthens corporate accountability, our findings directly support the aims of UN SDG 16 (Peace, Justice, and Strong Institutions).

The remainder of this paper is organized as follows. Section 2 presents literature review and hypothesis development. Section 3 presents the data and methodology. Section 4 presents results and discussions. Finally, Section 5 presents the conclusion.

Theoretical Underpinning, Literature Review, and Hypothesis Development

The separation of ownership and control, a core concept in agency theory, creates opportunities for managers to engage in opportunistic behaviors that can range from shirking to outright fraud and other corporate violations (Jensen & Meckling, 1976). These violations impose severe costs on firms, including direct financial penalties, reputational damage, and a loss of investor confidence. The board of directors serves as the primary internal governance mechanism to mitigate these agency costs by monitoring management on behalf of shareholders (Fama & Jensen, 1983).

A rich body of upper echelons theory (UET) literature has investigated how the specific traits of CEOs influence the likelihood of corporate misconduct (Sun, Liu, Li, Wang, & Luo, 2024). UET posits that firm outcomes are a reflection of its leaders' values and cognitive bases. For instance, firms committing violations tend to have younger managers (Davidson, 2022; Zahra et al., 2005). Personality also plays a role, as overconfident and narcissistic CEOs are more prone to misstatements and violations (Schrand & Zechman, 2012; Harrison et al., 2018; Scotter and Roglio, 2020), while religious CEOs are less likely to violate regulations (McGuire et al., 2012).

The literature also demonstrates that a CEO's life experiences are significant (Davidson et al., 2015; Troy et al., 2011). Most relevant to our study, prior work has established a link between a CEO's academic experience and a reduced likelihood of financial fraud (Wang et al., 2021; Sun et al., 2024). Our study builds directly on this finding, arguing that this effect is even more potent in the context of an independent director. While a CEO's academic background may enhance their own ethical framework, an academic director's training can be used as an active monitoring tool, allowing them to better scrutinize management and deter the very misconduct this literature identifies.

An extensive literature has likewise examined how board composition, particularly independence, influences monitoring effectiveness. However, empirical findings are mixed, suggesting that mere independence is often insufficient for effective oversight (Duchin et al., 2010). This insufficiency finding has shifted research focus toward the specific skills, incentives, and attributes of individual directors. This includes studies on financial expertise (Agrawal & Chadha, 2009) and, more recently, director gender, which finds that female board members are associated with fewer environmental violations (Liu, 2018; Carter, Shank, & Wynter, 2024). Our study contributes to this "director attributes" literature by focusing on a unique and increasingly common profile: the academic director (AID).

Theoretically, AIDs represent ideal monitors, an argument grounded in upper echelons theory and supported by agency and human capital theories. We extend UET's logic to the board, arguing that an AID's specific 'upper echelon' traits, shaped by their unique career and training, make them superior monitors. This effectiveness operates through two complementary mechanisms: First, agency theory explains their powerful incentives for monitoring. AIDs' primary careers and reputations are built outside the boardroom, making them less susceptible to managerial influence and social capture (Jiang & Murphy, 2007). Furthermore, they face significant reputational punishment for corporate failures, providing a powerful, incentive-based argument for diligent monitoring (Quan & Li, 2017). Second, human capital theory explains their distinct ability or skill set (Crook et al., 2011; Gerhart & Feng, 2021). Their academic training emphasizes analytical rigor, objective risk analysis, and ethical decision-making. Empirical evidence

supports this view, linking AIDs to improved financial reporting quality (Jin et al., 2022), enhanced CSR performance (Cho et al., 2017), and a lower likelihood of financial statement fraud (Wen et al., 2025).

However, this "incentive" argument is challenged by a "capability" critique. Critics argue that AIDs are "ivory tower" directors whose theoretical knowledge is detached from the practical realities of a complex firm (Francis et al., 2015). This lack of direct industry experience may limit their ability to contribute to strategy or, more importantly, to identify sophisticated, industry-specific methods of misconduct (Jiang & Murphy, 2007). A generalist monitor, even one with strong incentives, may be unable to detect "red flags" in operational reports that an industry veteran would immediately recognize.

This literature, therefore, presents a tension: AIDs may have the incentive to monitor but lack the ability. We propose to resolve this tension by introducing academic independent director with relevant industrial expertise (*AID_Exp*) as a distinct category. We argue that effective monitoring requires both the incentive to challenge management and the ability to detect misconduct. The *AID_Exp* is unique, possessing a dual toolkit: the academic's reputational incentive and independent mindset, combined with the practitioner's technical knowledge to know where to look and how to detect sophisticated violations. We argue this synergy creates a superior monitor, one who is uniquely positioned to deter and detect complex violations. Therefore, we hypothesize:

H1: *The presence of academic independent directors with relevant industry expertise on a board is negatively associated with corporate violations.*

We propose two primary channels through which *AID_Exp* reduce misconduct, focusing on how they enhance the firm's overall monitoring environment. First, we posit an external, market-based channel. The appointment of an *AID_Exp* sends a credible signal to the market. While appointing any AID may be seen as "window dressing," appointing one with deep industry expertise signals a serious commitment to substantive governance. This certification effect can attract sophisticated, long-term investors, particularly institutional investors, who value such credible signals (Delgado-García et al., 2010). These institutional investors then bring their own significant monitoring resources to bear, creating a second layer of oversight that further deters managerial opportunism.

Second, we propose an internal, process-based channel. Prior work links AIDs, with their strong reputational concerns, to greater CSR engagement (Cho et al., 2017). We argue that *AID_Exp* use their dual toolkit to move this beyond simple engagement to tangible assurance. Their academic rigor demands data and verification, while their industry expertise allows them to understand what should be measured. This combination likely leads them to champion the engagement of an external CSR auditor to provide independent assurance over non-financial data. This assurance process enhances transparency and accountability, making it more difficult for firms to hide misconduct.

H2a: *The negative association between AID_Exp and corporate violations is mediated by an increase in institutional ownership.*

H2b: *The negative association between AID_Exp and corporate violations is mediated by the adoption of a CSR audit.*

We further hypothesize that the effectiveness of an *AID_Exp* is contingent on their environment. An *AID_Exp* does not act in a vacuum. Effective governance is not merely the sum of its parts, but a system of complementary mechanisms (Aguilera et al., 2008). The human capital of a director and the firm's formal governance processes can be seen as such complements. We propose this complementarity is twofold. First, it relates to the firm's cultural commitment to ESG. Strong ESG performance has emerged as a key driver of long-term value by signaling a commitment to sustainable growth (Ren, Zheng & Zhao, 2023). We argue that the principled, long-term perspective of an academic director aligns naturally with this ethos. In fact, prior literature suggests that an academic on the board can lend significant credibility to a firm's ESG initiatives, mitigating stakeholder concerns about "greenwashing" (Zhang et al., 2018). This creates a powerful synergy: in a high-ESG firm, the *AID_Exp*'s monitoring is amplified by the firm's transparent and aligned culture.

Second, this complementarity is structural. Formal governance structures provide the platform and information flow necessary for an *AID_Exp* to be effective. A dedicated CSR committee or corporate governance board committee (*CGBC*), for example, provides a formal venue for directors to specialize, process complex information, and apply their expertise, a structure shown to enhance oversight effectiveness (Eberhardt-Toth, 2017). Likewise, the regular publication of a CSR report creates a more transparent information environment, which is fundamental for monitoring (Reid, Ringel, & Pendleton, 2024). These mechanisms signal a corporate culture that is receptive to monitoring. In such an environment, the *AID_Exp* is not a lone voice but an empowered expert. These structures provide the formal platform and information flow necessary for them to raise concerns and ensure they are addressed, thereby amplifying their monitoring effectiveness.

H3: *The negative association between AID_Exp and corporate violations is stronger in firms with complementary internal governance structures*

Conversely, the external environment can constrain the effectiveness of even the most diligent monitor. We argue that a high-corruption environment, in particular, can undermine internal governance. Prior research establishes a strong link between a local culture of corruption and a higher incidence of corporate misconduct, including earnings management, accounting fraud, and opportunistic insider trading (Liu, 2016). Such an environment often normalizes corrupt behaviors. In a high-corruption setting (e.g., a state with a high rate of public official convictions), the "rules of the game" are different. The potential for collusion between managers and external parties is higher, and the legal or political channels for addressing misconduct may be compromised or ineffective. In such a setting, the monitoring efforts of an internal director, even a specialized *AID_Exp*, may be rendered inert. Their ability to credibly threaten to (or appeal to) external enforcement bodies is severely diminished, thus constraining their ultimate power to effect change.

H4: *The negative association between AID_Exp and corporate violations is weaker for firms operating in states with high levels of corruption.*

Finally, we argue that the dual toolkit of an *AID_Exp* is a specialized tool, most valuable for reducing specific types of misconduct. We posit that their effectiveness is concentrated in the complex, non-financial, and ethically-laden Environmental, Social, and Governance (ESG) domain. Prior literature already establishes a strong theoretical link between generalist academic directors and ESG-related outcomes. AIDs are associated with enhanced CSR performance (Cho et al., 2017), improved financial reporting quality (Jin et al., 2022), a key pillar of Governance and are perceived by stakeholders as lending credibility to a firm's ESG initiatives (Zhang et al., 2018).

This suggests that the academic's training with its emphasis on analytical rigor, long-term perspectives, and objective reasoning, is naturally suited to the challenges of ESG oversight. We argue that the *AID_Exp*'s industry expertise amplifies this natural inclination. Their dual toolkit makes them uniquely qualified to monitor the complex, industry-specific risks embedded in ESG, such as supply chain labor practices (Social), carbon accounting (Environmental), or board oversight failures (Governance). In contrast, other forms of misconduct (e.g., anti-trust, market collusion) may be more related to competitive strategy or legal-centric issues, falling outside this specialized domain. We therefore hypothesize that the violation-reducing effect of *AID_Exp* will be concentrated in violations related to ESG.

H5: *The negative association between AID_Exp and corporate violations is stronger for ESG-related violations than for non-ESG-related violations.*

Building on this specialization argument, we argue this specialized monitoring is most critical in industries where the a priori risk of ESG-related misconduct is highest. Firms in "sin and "politically sensitive" industries, for example, face intense, persistent scrutiny and reputational risk related to complex social and governance issues. Prior literature has defined sin industries as those with harmful societal effects, such as alcohol, tobacco, and gaming (Hong and Kacperczyk, 2009), and politically sensitive industries as those close to political debate, such as defense, guns, and natural resources (Hong and Kostovetsky, 2012).

In these high-risk, high-scrutiny environments, the advanced monitoring capability of an *AID_Exp* is crucial for navigating complex compliance regimes and public-relations landmines. Conversely, in safer industries where the risk of such specific misconduct is lower, the monitoring provided by a generalist board may be sufficient.

H6: The negative association between AID_Exp and corporate violations is stronger for firms in sin or political-sensitive industries.

Data and Methodologies

Sample and Data

Our sample is constructed by merging data from several sources for U.S. firms from 2000 to 2024. We obtain director-level data, used to identify our *AID_Exp* variable and other board characteristics, from the BoardEx database. All firm-level financial data for our control variables are sourced from Capital IQ. ESG performance data and information on CSR committees and reports are drawn from Refinitiv Eikon. Finally, institutional ownership data are collected from Thomson Reuters 13f filings. Data on state-level corruptions are obtained from U.S. department of justice, criminal division website.

Our key dependent variable, corporate violations, using the Good Jobs First "Violation Tracker" database. This is the first comprehensive database of corporate crime and misconduct (Duong, Khalifa, Sheikhabaei, & Sualihu, 2024). The data are collected from a comprehensive repository of U.S. corporate enforcement actions, aggregating records from over 40 federal regulatory agencies and all divisions of the Department of Justice since the year 2000. Additionally, the database incorporates cases initiated by State Attorneys General and selected state regulatory bodies. Collectively, the dataset comprises more than 557,000 civil and criminal cases brought against firms since 2000. The database also excludes violations where the penalties are lower than \$5,000 throughout the sample period and does not include corporations without violations. It means all observations in the database do not have zero values. On the other hand, the database includes a broad range of different types of corporate violations, where prior literatures (Karpoff, Koester, Lee, and Martin, 2017; Oberheim, Davies, Giese, Kluin, & Lord, 2025) focused on specific type. For our sample, we include all types of violations and additionally further hand-categorize the violation types into a sub-category of ESG and non-ESG violation types. The data are recorded at the establishment level, which we then aggregate to the firm level for our analysis.

To construct the final sample, we mitigate the influence of potential outliers by winsorizing all continuous variables at the 1st and 99th percentiles. After merging all data sources and applying these filters, our final sample comprises 10,713 unique firms, resulting in an unbalanced panel of 116,991 firm-year observations from 2000 to 2024, Appendix D reports the unique firms for each sample year. The summary statistics for our variables are reported in Table 1.

Variable Definition and Measurement

Prior literature on corporate misconduct has employed a wide array of proxies, including fraud (Uzun, Szewczyk, and Varma, 2004), legal penalties (Murphy, Shrieves, and Tibbs, 2009), earnings management, opportunistic insider trading, options backdating, accounting fraud (Liu, 2016), restatements, securities class action lawsuits, accounting and auditing enforcement releases (AAERs) (Karpoff et al., 2017), penalizations by the China Securities Regulatory Commission (CSRC) (Dong, Han, Ke, and Chan, 2018), and collusion (Ferrés and Marcet, 2021). Building on studies that aggregate these events (Zaman et al., 2021), we source our data from the Good Jobs First "Violation Tracker" database.

We construct our corporate misconduct measures consistent with a wide body of recent literature (Raghunandan, 2024; Christensen, 2017; Campbell & Shang, 2022; Murphy et al., 2009; Chen et al., 2025). Our primary dependent variable, *ln_violation*, is the natural logarithm of one plus the total number of violations a firm incurs in a given year. We use this measure to capture the severity of misconduct. For robustness, we employ several alternative measures: a simple count of violations (*Violation*); a two-year violation count (*Violation2*) dummy variable for the presence of violation in year *t* (*Violation_dum*), dummy for the presence of violation in year *t* or *t+1* regardless of when the detection occurs (*Violation_dum2*); and

multiple penalty-based measures, including the total penalty in millions (*Penalty*), its log-transformed value (*ln_penalty*), and penalties scaled by equity, sales, and assets (*Adj_penalty*). Following prior studies (Chen et al, 2025; Heese and Pérez-Cavazos, 2020), if Violation Tracker reports no offenses for a firm-year, we set violations and penalties to zero. Finally, to test our hypotheses on violation types (H5), we categorize the violation data into each ESG pillars-related (Environmental, Social, Governance) and non-ESG violations. Detailed variables definitions are reported in Appendix A.

Our primary explanatory variable, *AID_Exp*, measures the proportion of board by academic independent directors who also possess relevant industry expertise. We construct this variable by first identifying directors who meet three distinct criteria: (1) they are independent directors; (2) they are an 'academic' (proxied by holding a PhD); and (3) they have 'relevant industry experience' (proxied by prior employment in the firm's two-digit SIC code industry). The *AID_Exp* variable is the total count of directors who satisfy all three conditions, divided by the total number of directors on the board. For example, Adobe Inc in 2010 and Gilead Sciences Inc in 2023 both had two such directors on their boards with no violations recorded, yielding *AID_Exp* values of 0.20 (2/10) and 0.22 (2/9), respectively. This variable construction process is detailed in Appendix B.

For our mediation analyses (H2), Institutional Ownership (*IO*) is the percentage of shares held by 13f institutional investors, and *CSR_audit* is a dummy variable equal to 1 if the firm obtains external assurance for its CSR report. For our moderation analyses (H3, H4), *CSR_committee*, *CGBC*, and *CSR_report* are dummy variables indicating the presence of a dedicated CSR committee, a corporate governance committee, and regular sustainability report, respectively. Corruption is a state-level corruption index.

To isolate our variable of interest from confounding factors, our models include a comprehensive set of controls. We control for firm-specific characteristics, including firm size, cash-to-assets ratio, Tobin's Q, ROA, R&D intensity, leverage, and market competition (HHI). We also control for board characteristics, including board independence, average director age and tenure, board size, and CEO duality. All specifications incorporate industry and year fixed effects to absorb unobserved time-invariant industry factors and macroeconomic trends. To ensure robust statistical inferences, standard errors are clustered at the firm level to correct for serial auto-correlation.

Model Selection

To examine the effect of academic independent directors with relevant industrial expertise (*AID_Exp*) on corporate misconduct, we estimate the regression as follows:

$$\ln_violation_{i,t+1} = \alpha_0 + \beta_1 * AID_Exp_{i,t} + \beta_2 * Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (1)$$

Where the dependent variable, *ln_violation*, is the natural logarithm of one plus the total violations for firm *i* in year *t+1*. Our primary variable of interest, *AID_Exp* represents the proportion of academic independent directors with relevant industry expertise on the board in year *t*. We lag all independent and control variables by one year relative to the dependent variable. This lag structure is our first step in mitigating endogeneity, specifically by reducing concerns of reverse causality. *Controls* is a vector represent firm and corporate governance characteristics. The symbols γ , δ , and ε denote the industry-fixed effects, year-fixed effects, and the regression error terms, respectively.

While this industry-fixed effects model provides a stringent test, we acknowledge that the coefficient may still be subject to endogeneity concerns, such as from time-varying omitted variables or reverse causality. We address these concerns comprehensively in our empirical results section through a multi-pronged identification strategy, including instrumental variable (IV), matching, and difference-in-differences (DID) analyses.

Descriptive Statistics

Table 1 presents the summary statistics for our sample of 116,991 firm-year observations. Our dependent variables illustrate that corporate misconduct is a relatively rare but severe event. The *Violation_dum* variable indicates that 11% of our firm-year observations record at least one violation. The underlying raw count, *Violation*, has a mean of 0.326 and is highly skewed, which is typical for such data; both the median

and 75th percentile are zero. The maximum value of *Violation* is 9.00, indicating significant severity at the upper tail of the distribution. This skewness supports our use of the log-transformed measure, *ln_violation*, as our primary dependent variable.

[Insert Table 1]

Regarding our key governance controls, the mean for board independence is 0.809, a figure consistent with recent findings by Treepongkaruna, Kyaw, and Jiraporn (2024), who report a mean of approximately 0.80 using U.S. data from a similar period (2002–2019). Our primary independent variable, *AID_Exp*, is a rare attribute. The mean value of 0.020 indicates that directors with this dual toolkit comprise, on average, 2% of the board. The distribution is also highly skewed, with a median and 75th percentile of zero, suggesting that at least three-quarters of the firm-year observations have no such director. The 99th percentile of *AID_Exp* is 0.333, indicating that even in firms that appoint *AID_Exp*, they rarely constitute more than a third of the board.

[Insert Table 2]

Table 2 presents the Pearson correlation matrix for our key variables. We observe a preliminary negative and significant correlation between *AID_Exp* and *ln_violation*, as well as our other violation measures, providing initial univariate support for H1. *AID_Exp* is positively correlated with firm size, board size, and board independence. This is consistent with the notion that larger, more heavily monitored firms are also more likely to appoint specialized directors.

Empirical Results Analysis

AID_Exp and Corporate Violations

Table 3 presents the baseline regression results for our primary hypothesis. We estimate a series of models, beginning with a simple bivariate regression in Column 1 and incrementally adding controls, culminating in our full specification in Column 5. In Column 1, the coefficient on *AID_Exp* is negative and highly significant, providing preliminary support for H1. In our full model (Column 5), which includes comprehensive firm and board-level controls as well as industry and year fixed effects, the coefficient on *AID_Exp* remains negative and highly statistically significant ($\beta = -0.103$, $t = -6.804$).

This core result provides strong support for H1 and our dual toolkit hypothesis. This finding is consistent with upper echelons theory (UET), as it demonstrates that a specific, refined 'upper echelon' characteristic (*AID_Exp*) is a significant predictor of firm outcomes (i.e., reduced violations). More specifically, it validates our integrated theoretical framework: the *AID_Exp* appears to possess both the superior human capital (the 'ability' to monitor from their dual training) and the stronger agency-based incentives (the 'willingness' to monitor from their reputational concerns). Our findings contribute to and align with prior literature that links AIDs to enhanced oversight, such as improved CSR performance (Cho et al., 2017), reduced stock price crash risk (Jin et al., 2022), and a lower incidence of financial statement fraud (Wen et al., 2025).

[Insert Table 3]

Based on our full specification in Column (5), this effect is not only statistically robust but also economically meaningful. We assess the economic magnitude in two ways. First, a one-standard-deviation increase in *AID_Exp* (an increase of 0.070) is associated with a 0.00721 unit reduction in *ln_violation* (0.070×-0.103). Relative to the sample mean of *ln_violation* (0.139), this represents a 5.19% reduction in future violations ($-0.00721 / 0.139$). Second, to provide a more intuitive interpretation, we estimate the effect of adding one *AID_Exp* to a firm with the median board size of 8. This change corresponds to an increase of 0.125 in our *AID_Exp* variable ($1/8$). This shift is associated with a 0.0129 unit reduction in the

log of violations (0.125*-0.103). This translates to a 9.28% reduction relative to the sample mean (-0.0129/0.139), indicating an economically significant effect.

To validate that our *AID_Exp* variable captures a unique synergy, we conduct a horse race regression (Table 4) to test our dual toolkit hypothesis against the competing ivory tower critique.

[Insert Table 4]

The results provide direct support for this critique. In Column (3), the *Academic_independent* variable, representing the "ivory tower" director with incentives but no industry capability is statistically insignificant. This finding is crucial: it suggests that an academic's reputational incentives, in isolation, provide no significant monitoring benefit, aligning with the argument that their theoretical knowledge is detached from practical realities (Francis et al., 2015). In contrast, Column (5) presents the horse race analysis with our *AID_Exp* variable, which represents the director who has bridged the gap between theory and practice. The results are striking. The general academic variable becomes insignificant, while the expert variable remains significant. Most importantly, our *AID_Exp* variable is negative and highly significant and its coefficient magnitude is more than double that of the general expert. This strongly supports our dual toolkit theory. The data shows that while general expertise is beneficial, the ivory tower critique is valid (pure academics are ineffective). It is only the *AID_Exp*, the specific director who combines academic rigor with practical expertise that creates a superior monitoring effect.

Potential Mechanisms

Having established a robust negative association between *AID_Exp* and corporate violations, we now explore the mechanisms that underpin this relationship. This section investigates two key questions: how *AID_Exp* reduces violations (mediation) and when this effect is strongest (moderation).

First, we test our mediation channels, which propose two distinct monitoring pathways. We posit that *AID_Exp* enhances both the external and internal monitoring environment. For the external monitoring channel, we argued that the dual toolkit sends a credible signal of high-quality governance, which in turn attracts sophisticated Institutional Investors (Delgado-García et al., 2010). These investors then serve as active, external monitors. For the internal monitoring channel, we argued that an *AID_Exp*'s academic skepticism and reputational concerns (Cho et al., 2017) would lead them to demand tangible proof of compliance, specifically by championing an external CSR auditor. We therefore test *IO* and *CSR_audit* as our two key mediators.

Second, we investigate the boundary conditions that govern this relationship by testing our moderation hypotheses. We argued that the *AID_Exp*'s effectiveness is contingent on its operating environment. For H3, we test for governance complementarity. We hypothesize that the *AID_Exp*'s monitoring is amplified when embedded in a supportive internal ecosystem (Aguilera et al., 2008), such as one with a dedicated CSR committee, corporate governance board committee (*CGBC*), better ESG performance and having CSR report disclosure. For H4, we test for external constraints. We hypothesize that the *AID_Exp*'s effect is weakened in a high-corruption external environment, where the legal channels for addressing misconduct are compromised (Liu, 2016). The following sections present the results for these analyses.

We test our mediating hypotheses (H2a and H2b) using a three-step path analysis, with the results presented in Table 5. The findings support both the external, market-based channel and the internal, process-based channel.

[Insert Table 5]

We first examine the external monitoring channel (H2a). Column 2 tests the first path, revealing that *AID_Exp* is positively and significantly associated with future institutional ownership ($t = 4.389$). This finding supports our hypothesis that *AID_Exp* acts as a certification effect, signaling high-quality governance that is valued by sophisticated investors (Delgado-García et al., 2010). Column 3 presents the

full model, which includes both *AID_Exp* and the mediator. The mediator *IO* is negative and highly significant ($t = -11.714$), confirming its role as an effective external monitor. In this model, the direct effect of *AID_Exp* also remains significant ($t = -6.126$). The simultaneous significance of each path confirms the presence of an indirect effect, indicating that *AID_Exp* reduces misconduct in part by attracting these sophisticated external monitors, who then add their own layer of scrutiny.

We find a similar pattern for the internal monitoring channel (H2b), which we test on the firm-year observations for which *CSR_audit* data is available. Column 4 shows that *AID_Exp* is positively and significantly associated with the likelihood of engaging an external CSR auditor ($t = 2.428$). This supports our dual toolkit argument: the academic's reputational concerns (Cho et al., 2017) and analytical rigor lead them to demand tangible, third-party assurance rather than relying solely on internal reports. In the full model in Column 5, the *CSR_audit* mediator is, as hypothesized, negative and significant ($t = -2.995$). The direct effect of *AID_Exp* also remains significant ($t = -2.396$). The simultaneous significance of each path indicates a mediation effect, confirming that *AID_Exp* also reduces violations by enhancing the firm's internal transparency and assurance processes.

We next test our moderating hypotheses (H3 and H4), which posit that the effectiveness of *AID_Exp* is contingent on the firm's internal and external environment. We augment our baseline specification by introducing an interaction term. The model is specified as:

$$\ln_violation_{i,t+1} = \alpha_0 + \beta_1 * AID_Exp_{it} + \beta_2 * Moderators_{it} + \beta_3(AID_Exp_{it} \times Moderators_{it}) + \beta_2 * Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (2)$$

This model retains all control variables and fixed effects from Model (1). The coefficient of primary interest is β_3 on the interaction term, which captures the moderating effect of firm's internal and external environment separately. The results of this moderation analysis are presented in Table 6.

[Insert Table 6]

Columns 1 through 4 tests for internal governance complementarity (H3). We find that the interaction terms for *AID_Exp* with *ESG* ($t = -8.687$), *CSR_committee* ($t = -7.725$), *CGBC* ($t = -2.299$), and *CSR_report* ($t = -8.617$) are all negative and highly significant. This consistent finding supports our governance complementarity argument (Aguilera et al., 2008).

The results suggest two types of amplification. First, a high ESG score signals a cultural alignment, a corporate environment already committed to sustainable growth (Ren et al., 2023). In this context, the *AID_Exp*'s efforts are not met with resistance but are amplified, lending further credibility to the firm's ESG initiatives (Zhang et al., 2018). Second, the presence of a CSR committee, CGBC, or CSR report disclosure provides the structural alignment. These mechanisms create the formal platforms (Eberhardt-Toth, 2017) and transparent information environment (Reid et al., 2024) that empower the *AID_Exp* to translate their expertise into effective oversight.

Conversely, Column 5 tests for external constraints (H4). We find that the interaction term *Corruption***AID* is positive and significant ($t = 4.544$). This finding strongly supports our hypothesis. The positive sign indicates that as state-level corruption increases, the negative (beneficial) effect of *AID_Exp* on violations is significantly weakened (it moves closer to zero). This suggests that even a highly effective internal monitor can be constrained when operating in a dysfunctional institutional environment where the formal channels for addressing misconduct are compromised (Liu, 2016).

Heterogeneity Analysis

While the preceding analyses establish a robust, average negative association between *AID_Exp* and corporate violations, these findings may not apply uniformly across all contexts. To advance our theoretical understanding, this section explores heterogeneity in the *AID_Exp* effect. We test two specific, theory-driven hypotheses: first, whether the dual toolkit of *AID_Exp* is specialized for a particular type of misconduct (H5), and second, whether its effectiveness is concentrated in specific high-risk industry environments (H6).

[Insert Table 7]

Table 7 presents the results for H5, which posits that the *AID_Exp*'s dual toolkit is a specialized tool concentrated in the complex ESG domain. The findings provide strong support for this hypothesis. In Panel A Column 1, the coefficient on aggregate ESG violations is negative and highly significant ($t = -6.853$). In stark contrast, Panel A Column 5 shows that the effect of *AID_Exp* on non-ESG violations is statistically insignificant ($t = 0.451$). This strongly suggests that the violation-reducing effect of *AID_Exp* is driven entirely by their impact on ESG-related misconduct. We also employ the same method for the penalty-based measures, and we found the results is robust in Panel B. This result aligns perfectly with our theoretical framework. The academic's training is naturally suited to the long-term, ethically-laden, and analytical nature of ESG. This is consistent with prior work linking AIDs to enhanced CSR performance (Cho et al., 2017) and lending credibility to sustainability initiatives (Zhang et al., 2018).

We examine this effect further by categorizing both violations and penalty-based measures into each ESG pillars, which reveals an interesting result. The violation-reducing effect is strongest for social violations ($t = -5.326$) and governance violations ($t = -4.247$). The effect on environmental violations is also negative but only marginally significant ($t = -1.924$). This pattern provides a clear window into how the dual toolkit functions. The strong governance finding directly supports literature linking AIDs to improved financial reporting quality (Jin et al., 2022). It suggests the *AID_Exp*'s academic rigor and expert knowledge are most effective for monitoring complex, opaque issues like accounting practices and internal controls. Similarly, social issues (e.g., product safety, supply chain ethics) are often highly industry-specific and prone to "social-washing," making the dual toolkit essential for effective oversight. The weaker, though still significant, effect on environmental violations ($t = -1.924$) suggests a potential boundary to this expertise. Deep environmental compliance often involves highly technical engineering or scientific knowledge (e.g., chemical process safety, emissions technology). It is plausible that this type of oversight requires a different specialization (e.g., an engineer or scientist director) than the "academic rigor + industry management" profile that *AID_Exp* captures, thus refining our understanding of which ESG risks the dual toolkit is best equipped to mitigate.

We next explore whether the value of this specialized monitoring is contingent on the industry risk environment. To test this, we identify two high-risk sectors: sin industries (e.g., alcohol, tobacco, gaming), which face persistent societal scrutiny for their perceived harmful effects, and politically sensitive industries (e.g., defense, guns, natural resources), which are deeply entwined with political debate and regulation. We then run separate regressions on the high-risk sectors comparing with other sectors.

[Insert Table 8]

Table 8 presents the results of this heterogeneity analysis. The contrast is stark. In Column 2, which restricts the sample to sin and politically sensitive industries, the coefficient on *AID_Exp* is negative and highly significant ($t = -9.176$). In Column 1, which includes all other industries, the effect is statistically insignificant ($t = -1.395$).

This finding provides powerful confirmation of our specialization hypothesis (H6). It suggests that the *AID_Exp*'s monitoring value is not universal but is concentrated in high-stakes environments where specific ESG risks are endemic. Prior literature defines "Sin" industries (e.g., alcohol, tobacco, gaming) as those facing persistent societal scrutiny for perceived harmful effects (Hong and Kacperczyk, 2009), and "Politically Sensitive" industries (e.g., defense, natural resources) as those deeply entwined with political regulation (Hong and Kostovetsky, 2012). In these environments, firms face intense reputational risk and complex compliance regimes. Our results indicate that the advanced monitoring capability of the dual toolkit that combines academic rigor with industry knowledge, is crucial, and perhaps "super effective," for navigating these public-relations landmines. Conversely, in safer industries where the risk profile is lower, the monitoring provided by a generalist board appears sufficient.

Endogeneity

While our baseline results are robust to a comprehensive set of controls and fixed effects, we acknowledge that endogeneity concerns, specifically reverse causality and selection bias may persist. To address these concerns and strengthen our causal claims, we employ a two-stage least squares (2SLS) instrumental variable (IV) approach.

Following Jin et al. (2022), we exploit the local supply of academic talent as a source of exogenous variation. We construct two state-level instruments using data hand-collected from the National Center for Education Statistics (NCES): (1) *ln_total*, defined as the natural logarithm of the total number of post-secondary institutions in the firm's headquarters state; and (2) *ln_higher_edu*, defined as the natural logarithm of the number of PhD-granting institutions in that state. The economic rationale is straightforward: firms face lower search costs and stronger network ties when recruiting from local universities, making them more likely to appoint local academic directors. However, the aggregate number of universities in a state should have no direct theoretical link to a specific firm's propensity for corporate violations, satisfying the exclusion restriction. We estimate the model in two stages:

$$AID_exp_{i,t+1} = \alpha_0 + \beta_1 * IV_{st} + \beta_2 * Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (3)$$

$$ln_violation_{i,t+1} = \alpha_0 + \beta_1 * AID_Exp_{i,t} + \beta_2 * Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (4)$$

In the first stage (Model 3), we predict the endogenous *AID_Exp* variable using our instruments. A positive and significant coefficient β_1 would confirm the instrument's relevance. In the second stage (Equation 3), we replace the actual *AID_Exp* with its predicted value $\widehat{AID_Exp}$. A negative and significant coefficient β_1 in the second stage regression would confirm that our main finding holds even after isolating the exogenous variation in director appointments.

[Insert Table 9]

Table 9 presents the results of this analysis. Columns 1 and 3 report the first-stage estimates. Both instruments, *ln_total* ($t = 10.809$) and *ln_higher_edu* ($t = 9.022$), are strong, positive predictors of *AID_Exp*, confirming that the local academic supply significantly influences board composition. Columns 2 and 4 report the second-stage results. Crucially, the coefficient on the instrumented *AID_Exp* variable remains negative and statistically significant in both specifications. This consistency with our baseline results mitigates concerns that our findings are driven by endogeneity and supports a causal interpretation of the *AID_Exp* effect.

Our second approach to mitigate concerns regarding selection bias on observables by constructing a more comparable sample group using matching techniques (Rosenbaum and Rubin, 1983). We first employ propensity score matching (PSM), following Jin et al. (2022), we define a treatment group of firms in the top quartile of AID presence and matching them to a control group based on the full set of firm and board characteristic covariates such as *Firm_size*, *Tobin's_Q*, *ROA*, *R&D*, *Leverage*, *Competition*, *BI*, *Director_age*, *Director_tenure*, *Board_size*, and *CEO_Duality*. To ensure our results are not sensitive to the matching algorithm, we implement multiple techniques such as nearest neighbor, caliper, kernel, Mahalanobis, and radius matching and re-estimate our baseline model (Model 1) on each resulting sample. Table 10, Panel A, shows the covariate balance before and after matching. Prior to matching, significant differences existed between the two groups; after matching, these differences are eliminated, and the most t-tests become insignificant, indicating that covariate balance has been successfully achieved, thus making both groups more comparable. The regression results in Panel B, estimated on the various matched samples, consistently show that *AID_Exp* is negatively and significantly associated with corporate violations, reinforcing our main conclusions.

[Insert Table 10]

As an alternative strategy to mitigate selection bias, we apply entropy balancing (Hainmueller, 2012). This technique eliminates the need for iterative balance checking by directly adjusting control unit

weights to exactly match the covariate moments (e.g., means and variances) of the treatment group. The results are presented in Table 10 column 7. Table in Appendix C demonstrates the effectiveness of the reweighting, as the means of the covariates are nearly identical between the groups post-weighting. Using the entropy-balanced sample, confirm that the positive and significant relationship between *AID_Exp* and violations holds, further mitigating concerns of selection bias.

To more directly address endogeneity concerns, we utilize a Difference-in-Differences (DID) framework that exploits the SEC's 2006 adoption of Regulation S-K, Item 407, as a quasi-natural experiment. This regulation mandated detailed new disclosures regarding director qualifications and independence. Crucially, this rule created an exogenous shock to the information environment rather than to board composition itself. The new requirements were largely redundant for NYSE-listed firms, which were already subject to the stringent governance disclosures of NYSE Section 303A. However, for NASDAQ-listed firms, which faced less rigorous disclosure requirements at the time, Regulation S-K imposed a significant new transparency burden.

This regulatory asymmetry allows us to use NYSE firms as the control group and NASDAQ firms as the treatment group. Our identification strategy relies on the "unveiling" hypothesis. Following the Sarbanes-Oxley Act (SOX) of 2002, firms rapidly added independent directors, many of whom were "qualified directors" (Duchin et al., 2010) or PhD holders (Kim et al., 2016). We posit that many NASDAQ firms already possessed valuable *AID_Exp*, but their specific expertise was not fully visible to the market or external monitors due to weaker disclosure rules. The 2006 shock exogenously forced NASDAQ firms to reveal these qualifications. We argue that this sudden transparency allowed the market and external monitors to properly identify and value the pre-existing *AID_Exp*, thereby strengthening the external monitoring environment and leading to a relative decrease in corporate misconduct. Following the logic, we specify the DID model as:

$$\ln_violation_{i,t+1} = \alpha_0 + \beta_1(Treat_i \times Post_t) + \beta_2 * Treat_i + \beta_3 * Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (5)$$

In this specification, $Treat_i$ is a dummy variable equal to one for firms traded on NASDAQ and zero for firms traded on the NYSE. $Post_t$ is a dummy variable equal to one for the period from 2006 onwards, and zero otherwise. The interaction term, $Treat_i \times Post_t$, captures the DID estimate. We retain the full set of firm and board controls, along with industry and year fixed effects, from our baseline model. The coefficient of interest, β , measures the differential change in corporate violations for the treatment group relative to the control group in the post-event period.

[Insert Table 11]

The results of the DID test are presented in Table 11. Consistent with our hypothesis, we find a negative and significant coefficient on the interaction term ($Treat \times Post$). This indicates that NASDAQ firms experienced a more pronounced decrease in corporate violations following the 2006 disclosure mandate relative to their NYSE counterparts. This finding strengthens our causal claims by suggesting that the violation-reducing effect is not driven by endogenous director appointments, but rather by the exogenous revelation of director expertise, which enhanced the monitoring environment. We provide the test for the parallel assumption in Appendix E.

Robustness Tests

To ensure the robustness of our findings, we subject our baseline results to a series of rigorous robustness tests. These analyses are designed to address potential biases and to evaluate the consistency of our findings across alternative specifications. Specifically, we conduct a lead-lag analysis to test for persistence and reverse causality, employ alternative measures for both our independent and dependent variables, and re-estimate our models after excluding regulated industries (financials and utilities). Each test is motivated by specific econometric concerns and aims to strengthen the validity of the observed relationship between *AID_Exp* and corporate violations.

Temporal Dynamics: Lead-Lag Analysis

To verify that our baseline results are not driven by short-term fluctuations or simultaneous reverse causality (e.g., firms hiring directors after a violation), we examine the temporal dynamics of the *AID_Exp* effect. We re-estimate our baseline model (Equation 1) by replacing the dependent variable with corporate violations in subsequent years, ranging from $t+1$ to $t+3$.

[Insert Table 12]

The results, presented in Table 10, demonstrate a remarkable persistence in the governance benefits of *AID_Exp*. The coefficient on *AID_Exp* remains negative and statistically significant across all six future periods tested ($t+1$ to $t+6$). Notably, the magnitude of the effect remains stable and even slightly increases over time. This enduring significance confirms that the violation-reducing effect of *AID_Exp* is not merely a transient phenomenon but a long-term improvement in governance quality. Furthermore, the fact that the director's presence in year t strongly predicts lower violations six years into the future significantly mitigates concerns that our results are driven by simultaneous reverse causality.

Alternative Measures

While our primary measure of corporate violations (*ln_Violation*) is standard in the literature, we re-estimate our baseline model using a battery of alternative metrics to ensure our results are not sensitive to variable construction. We employ: a simple count of violations (*Violation*); a two-year cumulative violation count (*Violation2*); a dummy variable for the presence of a violation in year t (*Violation_dum*); a dummy for the presence of a violation in year t or $t+1$ (*Violation_dum2*); and multiple penalty-based measures, including total penalties in millions (*Penalty*), its log-transformed value (*ln_penalty*), and penalties scaled by equity, sales, and assets (*Adj_penalty*)

[Insert Table 13]

Table 13 reports the results of these robustness tests. The negative and significant coefficient on *AID_Exp* holds across all alternative specifications. This consistency confirms that our main finding is robust to the choice of dependent variable measurement.

To further validate our dual toolkit hypothesis, we re-estimate our baseline model using alternative definitions of our key independent variable. We compare our main measure (*AID_Exp*) against: a dummy variable for the presence of an AID with relevant industry experience (*AID_Exp_2*); a measure for academic independent directors without industry experience (*AID*); a measure for non-academic independent directors with industry experience (*ID_Exp*); and a dummy for the presence of such directors (*ID_Exp2*).

[Insert Table 14]

Table 14 presents the results. Consistent with our theoretical framework, we find that the coefficient for AIDs without relevant industry expertise is statistically insignificant. This null result reinforces our central argument: academic independence alone is insufficient for effective monitoring; it is the combination with industry expertise that drives the reduction in corporate violations.

Excluding Regulated Industries

Finally, we address the concern that our results may be driven by the unique regulatory environments of the financial and utilities sectors. To mitigate this potential noise, we exclude firms in these industries (SIC codes 6000-6999 and 4900-4999) and re-estimate our baseline model.

[Insert Table 15]

Table 15 presents the results for this subsample. We observe that the negative effect of *AID_Exp* on corporate violations remains robust and statistically significant, confirming that our findings are generalizable and not an artifact of specific regulatory regimes.

Conclusion

This study investigates the impact of academic independent directors with relevant industry expertise (*AID_Exp*) on corporate violations. Motivated by the mixed findings in prior literature, where academic directors possess the reputational incentive to monitor but are often critiqued for lacking the practical ability, which we resolve this tension by introducing the dual toolkit theory. Grounded in Upper Echelons Theory, we argue that the specific cognitive and experiential background of the *AID_Exp* creates a superior monitor. Using a comprehensive sample of U.S. firms from 2000 to 2024, we find robust evidence that a greater board presence of *AID_Exp* is negatively associated with the likelihood and severity of corporate violations.

Our analysis of the mechanisms reveals a refined story of how this governance effect is achieved. We identify two complementary channels that align with our theoretical framework. First, consistent with Agency Theory, *AID_Exp* reduce violations by enhancing external monitoring; their presence signals high-quality governance, attracting sophisticated Institutional Investors who add a layer of market discipline. Second, consistent with Human Capital Theory, they utilize their specialized skills to enhance internal monitoring processes, specifically by championing the engagement of external CSR auditors to verify non-financial compliance.

However, we demonstrate that this effectiveness is not absolute; it is deeply contingent on the firm's environment. We find strong evidence of governance complementarity: the violation-reducing effect of *AID_Exp* is significantly amplified when embedded within a strong internal ecosystem, characterized by high ESG performance, a dedicated CSR committee, a CGBC, or transparent CSR reporting. Conversely, their efforts can be constrained or rendered inert by a corrupt external (state-level) environment. Most critically, we show that *AID_Exp* are specialized monitors. Their dual toolkit is not a generalist solution; its impact is concentrated on the complex, opaque social and governance violations they are uniquely qualified to understand, and their value is realized almost exclusively in high-risk sin and politically sensitive industries.

These findings are robust to a comprehensive suite of endogeneity tests, including a 2SLS instrumental variable approach based on the local supply of academic talent, propensity score matching (PSM), entropy balancing, and a difference-in-differences (DID) analysis exploiting the 2006 Regulation S-K disclosure shock.

This study offers several implications for across different aspects. Theoretically, we contribute to the corporate governance literature by identifying a new type of high-value director that bridge the gap between academic expertise and industrial expertise. For policymakers and manager, our findings provide robust evidences to further support global sustainability goals. By demonstrating that advanced academic education is a key driver of ethical leadership, our work validates the importance of SDG 4. Furthermore, by identifying a specific governance mechanism that significantly reduces corporate misconduct, our findings offer a direct support to SDG 16.

Finally, we highlight the unique and superior value of independent directors when they are equipped with both academic and industrial expertise compared to general directors. While general independent directors may be sufficient, our evidence suggests that adding such directors equipped with both academic rigor and industry expertise creates great values in corporate governance. This specialized combination allows them to more explicitly improve the firms overall monitoring activities, leading to a significance reduction in probability of corporate violations.

Conflicts of Interest

The authors declare no conflicts of interest.

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Appendix A: Variable Definitions

Variable name	Definition	Source
<i>Violation</i>	A simple count of violations	Violation Tracker
<i>Violation2</i>	A two-year violation counts	Violation Tracker
<i>Violation_dum</i>	Dummy indicator for the presence of violation in year t	Violation Tracker
<i>Violation_dum2</i>	Dummy indicator for the presence of violation in year t or $t+1$ regardless of when decision occurs	Violation Tracker
<i>ln_violation</i>	Natural logarithm 1+ count of violations	Violation Tracker
<i>ln_penalty</i>	Natural logarithm 1+ amount of penalties	Violation Tracker
<i>ln_penalty2</i>	Natural logarithm of 1+ the total value of penalties for violations in 2005 dollars	Violation Tracker
<i>Penalty</i>	Total penalties in millions USD	Violation Tracker
<i>Adj_penalty</i>	Ratio of legal penalties to equitycap	Violation Tracker
<i>Adj_penalty2</i>	Ratio of legal penalties to sales	Violation Tracker
<i>Adj_penalty3</i>	Ratio of legal penalties to total asset	Violation Tracker
<i>AID_Exp</i>	The percentage of independent directors with an academic background that has industry experience as current firm's sector scaled by the board size	BoardEx
<i>AID_Exp2</i>	Dummy 1 if have <i>AID_Exp</i>	BoardEx
<i>BI</i>	The percentage of independent directors scaled by the board size	BoardEx
<i>Director_Age</i>	Average director's age in the board	BoardEx
<i>Director_Tenure</i>	Average director's tenure in the board	BoardEx
<i>Board_Size</i>	Total number of directors in the boardroom	BoardEx
<i>CEO_Duality</i>	Dummy variable that equal one if the CEO and chairman are the same person	BoardEx
<i>Firm_Size</i>	Natural logarithm of total assets.	Capital IQ
<i>Tobin_Q</i>	Following Maury (2006), Tobin's q is the market value of common equity plus the book value of total assets minus common equity and deferred taxes divided by the book value of total assets.	Capital IQ
<i>ROA</i>	The ratio of EBIT on total assets.	Capital IQ
<i>Leverage</i>	Total debt (long-term debt and debt in current liabilities) divided by total assets.	Capital IQ
<i>IO</i>	The percentage of shares held by institutional investors.	13f Thomson Reuters
<i>Competition</i>	Following Hou and Robinson (2006), industry competition is captured using the HHI. Higher values of HHI indicate less competition.	Capital IQ
<i>IO</i>	Percentage of institutional holdings	LSEG
<i>CSR_audit</i>	Does the company have an external auditor of its CSR/H&S/Sustainability report?	LSEG
<i>ESG</i>	Refinitiv eikon's datastream's ESG score	LSEG
<i>CGBC</i>	Does the company have a corporate governance board committee?	LSEG

<i>CSR_report</i>	Does the company publish a separate CSR/H&S/Sustainability report or publish a section in its annual report on CSR/H&S/Sustainability?	LSEG
<i>Corruption</i>	State-level corruption index	U.S. department of justice
<i>Total_Edu</i>	Natural logarithm of total post-secondary educational institution (both public and private)	NCES
<i>Total_Higher_Edu</i>	Natural logarithm of total higher post-secondary educational institution (both public and private)	NCES

Appendix B: Identification for *AID_Exp*

Our primary variable of interest measures the proportion of independent directors who are academics with relevant industry experience. The variable is constructed from director-level data sourced from BoardEx. The process begins by creating three director-level dummy variables.

First, a director is classified as independent based on their designation in BoardEx (*Independent* = 1). Second, a director is classified as an academic (*Academic_i* = 1) from the year they obtain a PhD. We identify these individuals by filtering the "qualification" field in BoardEx for keywords start with “PhD” and “Post Doc” such as “PhD” and its variations “PhD (ABD)”, “PhD (Cum Laude Hons)”, “PhD (Distinction)”, “PhD (Hons)”, “PhD (Magna Cum Laude)”, “PhD (cum laude)”, “PhD (summa cum laude)”, “Post Doctoral Fellowship”, “Post Doctoral Studies” and “Post Doctorate Degree”. Third, a director is coded as having relevant industry expertise (*IndustryExp_i* = 1) if their prior employment history includes non-directorial roles at a firm operating within the same two-digit SIC code as the focal firm. Excluding prior board memberships ensures the measure captures hands-on operational or executive experience rather than purely governance experience.

From these director-level indicators, we construct our firm-year level variable, *AID_Exp*. It is calculated as the number of directors for whom all three conditions (Independent, Academic, and Industry Experience) are met, scaled by the total number of directors (*N*) on the board:

$$AID_exp = \frac{\sum_{i=1}^N (Academic_i \times Independent_i \times IndustryExp_i)}{N}$$

This construction yields a proportion that is comparable across firms with different board sizes.

Appendix C: Entropy Balancing Statistics

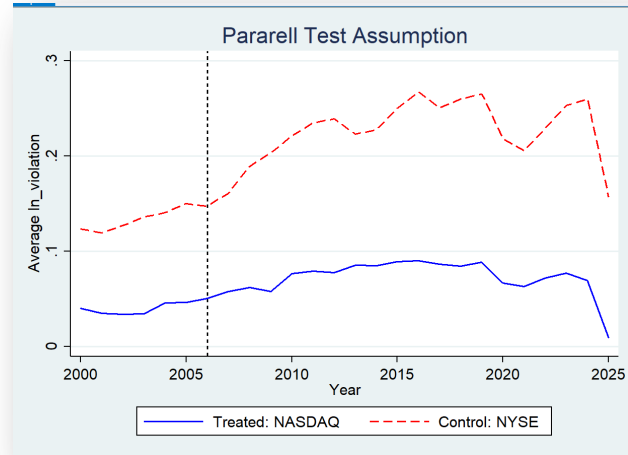
	Before Weighting						After Weighting					
	Treat			Control			Treat			Control		
	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness
total_boar~e	8.66	6.765	0.6908	8.339	9.226	0.2996	8.66	6.765	0.6908	8.66	9.215	0.4295
board_inde~e	0.8377	0.008579	-1.235	0.8085	0.01653	-1.749	0.8377	0.008579	-1.235	0.8377	0.00941	-1.164
bx_direct~ge	60.28	28.67	-0.02087	60.51	36.25	-0.1716	60.28	28.67	-0.02087	60.28	33.33	-0.09798
bx_direct~re	9.237	16.98	0.8727	10.68	23.86	0.7221	9.237	16.98	0.8727	9.237	18.67	0.8728
bx_ceo_dua~y	0.1563	0.1319	1.893	0.2061	0.1636	1.453	0.1563	0.1319	1.893	0.1563	0.1319	1.893
ln_at	5.974	4.722	0.592	6.398	4.65	0.07596	5.974	4.722	0.592	5.974	5.654	0.2931
tobinq	2.665	3.989	1.88	1.916	2.521	2.994	2.665	3.989	1.88	2.665	5.268	1.9
roa	-0.2029	0.1336	-1.485	-0.03664	0.05819	-3.29	-0.2029	0.1336	-1.485	-0.2029	0.1813	-1.501
rdint	0.1765	0.03467	1.168	0.04034	0.008989	3.831	0.1765	0.03467	1.168	0.1765	0.05244	1.101
lev	0.3913	0.05861	0.4595	0.507	0.05829	-0.02439	0.3913	0.05861	0.4595	0.3913	0.05357	0.4835
competition	7.838	35.72	5.566	7.708	105.8	4.423	7.838	35.72	5.566	7.838	85.52	5.005

Appendix D: Number of Unique Firms Per Year

Year	No of Unique Firms
2000	4,457
2001	4,608
2002	4,809
2003	5,053
2004	5,266
2005	5,332
2006	5,204
2007	5,069
2008	4,717
2009	4,537
2010	4,481
2011	4,434
2012	4,375
2013	4,457
2014	4,594
2015	4,512
2016	4,359
2017	4,366
2018	4,387
2019	4,347
2020	4,579
2021	5,011
2022	4,838
2023	4,610
2024	4,470

Appendix E: Parallel Test Assumption

	(1)
	$\ln \text{ violation}_{t+1}$
<i>before3</i>	0.056*** (3.308)
<i>before2</i>	0.024 (1.436)
<i>before1</i>	0.037** (2.179)
<i>current</i>	-0.003 (-0.171)
<i>after1</i>	-0.024 (-1.229)
<i>after2</i>	-0.051** (-2.562)
<i>after3</i>	-0.057*** (-2.645)
<i>Board_size</i>	0.011*** (16.816)
<i>BI</i>	-0.025** (-2.319)
<i>Director_age</i>	0.003*** (11.646)
<i>Director_tenure</i>	0.006*** (16.937)
<i>CEO_duality</i>	0.023*** (5.443)
<i>Firm_size</i>	0.082*** (60.950)
<i>Tobin_Q</i>	0.005*** (7.517)
<i>ROA</i>	-0.125*** (-23.086)
<i>RND</i>	0.086*** (7.735)
<i>Lev</i>	-0.002 (-0.298)
<i>competition</i>	-0.004*** (-8.330)
Constant	-0.657*** (-35.321)
Industry FE	Yes
Year FE	Yes
SEs clustered at firm-year	Yes



Observations	77052
Adjusted R-squared	0.335

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Table 1. Summary Statistics

This table reports descriptive statistics for all variables utilized in our empirical models, based on a sample spanning from 2000 to 2024. For comprehensive definitions of each variable, please refer to Appendix A.

Variable	Obs	Mean	STD	Min	P1	P25	P50	P75	P99	Max
<i>Violation</i>	116,991	0.326	1.264	0.000	0.000	0.000	0.000	0.000	9.000	9.000
<i>Violation2</i>	116,991	0.645	2.385	0.000	0.000	0.000	0.000	0.000	17.000	17.000
<i>Violation_dum</i>	116,991	0.110	0.312	0.000	0.000	0.000	0.000	0.000	1.000	1.000
<i>Violation_dum2</i>	116,991	0.143	0.350	0.000	0.000	0.000	0.000	0.000	1.000	1.000
<i>ln_violation</i>	116,991	0.139	0.463	0.000	0.000	0.000	0.000	0.000	2.303	5.673
<i>ln_penalty</i>	116,991	1.329	3.913	0.000	0.000	0.000	0.000	0.000	16.757	24.034
<i>ln_penalty2</i>	116,872	1.335	3.929	0.000	0.000	0.000	0.000	0.000	16.798	24.070
<i>Penalty</i>	116,991	0.308	2.132	0.000	0.000	0.000	0.000	0.000	18.943	18.943
<i>AID</i>	116,991	0.072	0.132	0.000	0.000	0.000	0.000	0.111	0.556	1.000
<i>AID_Exp</i>	116,991	0.020	0.070	0.000	0.000	0.000	0.000	0.000	0.333	1.000
<i>F_AID</i>	116,991	0.011	0.045	0.000	0.000	0.000	0.000	0.000	0.200	1.000
<i>F_AID_Exp</i>	116,991	0.003	0.022	0.000	0.000	0.000	0.000	0.000	0.111	1.000
<i>F_ID</i>	116,991	0.115	0.136	0.000	0.000	0.000	0.100	0.200	0.500	1.000
<i>BI</i>	116,991	0.809	0.152	0.000	0.000	0.750	0.857	0.900	1.000	1.000
<i>Director_age</i>	116,583	60.321	6.158	43.500	43.500	56.571	60.667	64.286	77.000	77.000
<i>Director_tenure</i>	116,619	10.485	4.865	2.500	2.500	6.833	9.800	13.375	25.667	25.667
<i>Board_size</i>	116,991	8.164	3.410	1.000	1.000	6.000	8.000	10.000	18.000	18.000
<i>CEO_duality</i>	116,619	0.193	0.395	0.000	0.000	0.000	0.000	0.000	1.000	1.000
<i>Firm_size</i>	116,991	6.739	2.299	0.002	1.974	5.134	6.705	8.237	12.462	15.203
<i>Tobin_Q</i>	93,091	1.951	1.627	0.536	0.536	1.031	1.371	2.172	10.362	10.362
<i>COA</i>	115,436	0.145	0.188	0.000	0.000	0.022	0.071	0.188	0.904	0.904
<i>ROA</i>	105,854	-0.051	0.256	-1.402	-1.402	-0.047	0.019	0.063	0.298	0.298
<i>ROE</i>	105,714	-0.128	0.820	-5.524	-5.524	-0.104	0.065	0.146	1.469	1.469
<i>RND</i>	116,991	0.049	0.111	0.000	0.000	0.000	0.000	0.042	0.649	0.649
<i>Lev</i>	116,991	0.533	0.256	0.036	0.036	0.330	0.539	0.739	0.964	0.964
<i>Competition</i>	116,858	9.548	12.374	1.000	1.000	3.243	5.761	10.434	75.297	75.297

Table 2. Correlation matrix

This table reports Pearson correlation analysis of all core variables utilized in our empirical models.

Variables	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13
(1) ln_violation	1												
(2) AID_exp	-0.057***	1											
(3) BI	0.084***	0.061***	1										
(4) Director_afe	0.139***	-0.021***	0.135***	1									
(5) Director_tenure	0.091***	-0.101***	-0.038***	0.286***	1								
(6) Board_size	0.253***	-0.040***	0.222***	0.220***	0.111***	1							
(7) CEO_duality	0.083***	-0.051***	-0.109***	0.016***	0.077***	0.138***	1						
(8) Firm_Size	0.320***	-0.108***	0.158***	0.181***	0.055***	0.342***	0.075***	1					
(9) Tobin_Q	-0.052***	0.153***	-0.039***	-0.101***	-0.080***	-0.089***	-0.006*	-0.211***	1				
(10) ROA	0.116***	-0.219***	0.025***	0.103***	0.255***	0.095***	0.048***	0.411***	-0.165***	1			
(11) RND	-0.111***	0.391***	0.016***	-0.104***	-0.182***	-0.113***	-0.065***	-0.368***	0.335***	-0.641***	1		
(12) Lev	0.114***	-0.178***	0.101***	0.089***	0.070***	0.284***	0.027***	0.440***	-0.237***	0.094***	-0.260***	1	
(13) Competition	-0.089***	-0.030***	0.023***	0.064***	0.062***	0.094***	-0.001	0.157***	-0.109***	0.022***	-0.083***	0.184***	1

Table 3. Baseline regressions

This table reports the regression results of academic independent directors with relevant industry expertise (*AID_Exp*) on corporate violations (*ln_violation*). All of the explanatory variables are lagged by 1 year period to mitigate the reverse causality issues. t-statistics are shown in parentheses. *p < .1; **p < .05; ***p < .01.

	(1)	(2)	(3)	(4)	(5)
	<i>ln_violation_{t+1}</i>	<i>ln_violation_{t+1}</i>	<i>ln_violation_{t+1}</i>	<i>ln_violation_{t+1}</i>	<i>ln_violation_{t+1}</i>
<i>AID_Exp</i>	-0.392*** (-18.120)	-0.065*** (-6.117)	-0.122*** (-8.126)	-0.049*** (-4.347)	-0.103*** (-6.804)
<i>Firm_size</i>			0.092*** (73.449)		0.082*** (62.047)
<i>Tobin_Q</i>			0.005*** (7.789)		0.005*** (7.665)
<i>ROA</i>			-0.107*** (-20.273)		-0.124*** (-22.966)
<i>RND</i>			0.117*** (10.559)		0.094*** (8.402)
<i>Lev</i>			-0.005 (-0.724)		-0.003 (-0.479)
<i>Competition</i>			-0.005*** (-9.666)		-0.004*** (-8.271)
<i>Board_size</i>				0.032*** (62.467)	0.011*** (16.742)
<i>BI</i>				0.073*** (10.403)	-0.022** (-2.007)
<i>Director_age</i>				0.003*** (13.326)	0.003*** (11.582)
<i>Director_tenure</i>				0.006*** (22.361)	0.006*** (16.887)
<i>CEO_duality</i>				0.051*** (13.276)	0.023*** (5.330)
Constant	0.155*** (101.703)	0.149*** (110.455)	-0.394*** (-47.993)	-0.415*** (-31.634)	-0.657*** (-35.826)
Industry FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
SEs clustered at firm-year	No	Yes	Yes	Yes	Yes
Observations	105014	105012	77202	104650	77071
Adjusted R-squared	0.003	0.194	0.327	0.252	0.335

Table 4. Horse race analysis

This table reports the results of horse race regressions comparing *AID_Exp* against its constituent parts, including dummy academic directors (*Academic*), dummy expert directors (*Expert*), dummy academic independent directors (*Academic_Independent*), and dummy independent expert directors (*Expert_Independent*). All models include firm and board controls, as well as industry and year fixed effects. t-statistics are shown in parentheses. *p < .1; **p < .05; ***p < .01.

	(1)	(2)	(3)	(4)	(5)
	<i>ln violation_{t+1}</i>	<i>ln violation_{t+1}</i>	<i>ln violation_{t+1}</i>	<i>ln violation_{t+1}</i>	<i>ln violation_{t+1}</i>
<i>Academic</i>	-0.006* (-1.762)				-0.004 (-1.024)
<i>Expert</i>		-0.028*** (-7.249)			-0.026*** (-6.871)
<i>Academic_Independent</i>			-0.003 (-0.829)		
<i>Expert_independent</i>				-0.028*** (-7.249)	
<i>AID_Exp</i>					-0.067*** (-4.038)
<i>Board_size</i>	0.011*** (16.843)	0.012*** (17.520)	0.011*** (16.729)	0.012*** (17.520)	0.012*** (17.383)
<i>BI</i>	-0.024** (-2.214)	-0.014 (-1.282)	-0.024** (-2.192)	-0.014 (-1.282)	-0.012 (-1.111)
<i>Director_age</i>	0.003*** (11.715)	0.003*** (11.363)	0.003*** (11.606)	0.003*** (11.363)	0.003*** (11.460)
<i>Director_tenure</i>	0.006*** (16.937)	0.006*** (16.885)	0.006*** (16.961)	0.006*** (16.885)	0.006*** (16.819)
<i>CEO_duality</i>	0.023*** (5.358)	0.023*** (5.289)	0.023*** (5.371)	0.023*** (5.289)	0.023*** (5.246)
<i>Firm_size</i>	0.082*** (61.918)	0.082*** (62.033)	0.082*** (61.930)	0.082*** (62.033)	0.082*** (61.980)
<i>Tobin_Q</i>	0.005*** (7.778)	0.006*** (7.932)	0.005*** (7.752)	0.006*** (7.932)	0.005*** (7.895)
<i>ROA</i>	-0.125*** (-23.210)	-0.125*** (-23.093)	-0.125*** (-23.168)	-0.125*** (-23.093)	-0.124*** (-23.005)
<i>RND</i>	0.088*** (7.823)	0.091*** (8.194)	0.086*** (7.690)	0.091*** (8.194)	0.099*** (8.796)
<i>Lev</i>	-0.003 (-0.391)	-0.003 (-0.443)	-0.002 (-0.320)	-0.003 (-0.443)	-0.005 (-0.645)
<i>Competition</i>	-0.004*** (-8.279)	-0.004*** (-8.300)	-0.004*** (-8.297)	-0.004*** (-8.300)	-0.004*** (-8.261)
Constant	-0.660*** (-35.886)	-0.653*** (-35.740)	-0.658*** (-35.708)	-0.653*** (-35.740)	-0.656*** (-35.795)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes	Yes
Observations	77071	77071	77071	77071	77071

Adjusted R-squared	0.335	0.336	0.335	0.336	0.336
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Table 5. Channel test: Path analysis

This table reports the results of the mediation analysis testing two channels: external monitoring via institutional ownership (*IO*) and internal monitoring via CSR auditors (*CSR_audit*). The models utilize a causal-steps approach to test the indirect effect of *AID_Exp* on corporate violations through these mediators. t-statistics are shown in parentheses. *p < .1; **p < .05; ***p < .01.

	(1) <i>ln violation_{t+1}</i>	(2) <i>IO_{t+1}</i>	(3) <i>ln violation_{t+1}</i>	(4) <i>CSR_audit_{t+1}</i>	(5) <i>ln violation_{t+1}</i>
<i>AID_Exp</i>	-0.103*** (-6.804)	0.110*** (4.433)	-0.094*** (-6.127)	0.370** (2.428)	-0.604** (-2.396)
<i>IO</i>			-0.075*** (-11.722)		
<i>CSR_audit</i>					-0.083*** (-2.995)
<i>Board_size</i>	0.011*** (16.742)	0.007*** (12.691)	0.012*** (17.408)	0.001 (0.468)	0.008* (1.887)
<i>BI</i>	-0.022** (-2.007)	0.214*** (20.416)	0.006 (0.531)	0.120* (1.776)	0.186 (1.361)
<i>Director_age</i>	0.003*** (11.582)	-0.002*** (-8.697)	0.003*** (10.838)	-0.003 (-1.454)	0.016*** (5.135)
<i>Director_tenure</i>	0.006*** (16.887)	0.002*** (5.147)	0.006*** (16.989)	0.003 (1.359)	-0.000 (-0.100)
<i>CEO_duality</i>	0.023*** (5.330)	0.004 (1.276)	0.024*** (5.462)	-0.009 (-0.668)	-0.003 (-0.124)
<i>Firm_size</i>	0.082*** (62.047)	0.090*** (79.586)	0.091*** (56.727)	0.075*** (11.139)	0.230*** (18.409)
<i>Tobin_Q</i>	0.005*** (7.665)	0.024*** (22.948)	0.006*** (8.472)	0.019*** (3.498)	0.012 (1.519)
<i>ROA</i>	-0.124*** (-22.966)	0.160*** (20.045)	-0.119*** (-21.397)	0.105 (1.375)	0.012 (0.095)
<i>RND</i>	0.094*** (8.402)	0.171*** (8.168)	0.112*** (9.732)	0.418* (1.810)	0.030 (0.104)
<i>Lev</i>	-0.003 (-0.479)	-0.123*** (-16.265)	-0.017** (-2.385)	-0.033 (-0.791)	0.091 (1.258)
<i>Competition</i>	-0.004*** (-8.271)	0.002** (2.184)	-0.004*** (-7.988)	-0.006** (-2.096)	0.001 (0.176)
Constant	-0.657*** (-35.826)	-0.131*** (-7.430)	-0.697*** (-35.781)	-0.281** (-2.214)	-2.680*** (-11.370)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes	Yes
Observations	77071	71983	74883	4886	4903
Adjusted R-squared	0.335	0.326	0.341	0.485	0.600

Table 6. Channel test: Moderation analysis

This table reports the regression results for the moderating effects of internal governance structures (ESG performance, CSR committee, Corporate Governance Board Committee, CSR report) and external constraints (state-level corruption) on the relationship between *AID_Exp* and corporate violations. t-statistics are shown in parentheses. *p < .1; **p < .05; ***p < .01.

	(1)	(2)	(3)	(4)	(5)
	<i>ln violation_{t+1}</i>	<i>ln violation_{t+1}</i>	<i>ln violation_{t+1}</i>	<i>ln violation_{t+1}</i>	<i>ln violation_{t+1}</i>
<i>AID_Exp</i>	0.694*** (7.559)	-0.033 (-0.837)	0.077 (0.570)	-0.013 (-0.315)	-0.231*** (-8.595)
<i>ESG</i>	0.002*** (6.225)				
<i>ESG_aid</i>	-0.026*** (-8.687)				
<i>CSR_committee</i>		0.052*** (4.708)			
<i>CSR_aid</i>		-0.910*** (-7.725)			
<i>CGBC</i>			0.072*** (4.844)		
<i>CGBC_aid</i>			-0.316** (-2.299)		
<i>CSR_report</i>				0.053*** (4.642)	
<i>Report_aid</i>				-1.107*** (-8.617)	
<i>Corruption</i>					-0.000*** (-3.410)
<i>Corruption_aid</i>					0.002*** (4.544)
<i>Board_size</i>	0.016*** (9.028)	0.013*** (7.118)	0.013*** (7.050)	0.013*** (7.368)	0.009*** (10.533)
<i>BI</i>	0.012 (0.270)	-0.003 (-0.068)	-0.003 (-0.062)	-0.001 (-0.019)	-0.038*** (-2.603)
<i>Director_age</i>	0.009*** (9.849)	0.009*** (10.424)	0.009*** (10.404)	0.010*** (10.698)	0.003*** (10.725)
<i>Director_tenure</i>	-0.001 (-1.190)	-0.004*** (-2.915)	-0.003*** (-2.577)	-0.003*** (-2.770)	0.005*** (13.828)
<i>CEO_duality</i>	0.045*** (4.212)	0.039*** (3.646)	0.039*** (3.600)	0.039*** (3.573)	0.019*** (4.293)
<i>Firm_size</i>	0.123*** (28.744)	0.140*** (34.434)	0.144*** (37.621)	0.139*** (33.899)	0.097*** (65.489)
<i>Tobin_Q</i>	0.008*** (4.190)	0.007*** (3.375)	0.007*** (3.268)	0.007*** (3.480)	0.004*** (5.833)
<i>ROA</i>	-0.218*** (-8.984)	-0.245*** (-9.718)	-0.249*** (-9.825)	-0.246*** (-9.625)	-0.143*** (-23.601)
<i>RND</i>	0.114***	0.142***	0.155***	0.126***	0.122***

	(2.597)	(3.084)	(3.363)	(2.721)	(9.798)
<i>Lev</i>	0.003	-0.015	-0.018	-0.014	-0.014*
	(0.118)	(-0.701)	(-0.835)	(-0.632)	(-1.808)
<i>Competition</i>	0.003**	0.003*	0.002	0.003*	-0.005***
	(2.058)	(1.754)	(1.578)	(1.867)	(-9.058)
Constant	-1.392***	-1.424***	-1.500***	-1.441***	-0.701***
	(-20.200)	(-20.338)	(-21.592)	(-20.448)	(-31.628)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes	Yes
Observations	21069	20367	20388	20277	70137
Adjusted R-squared	0.513	0.527	0.526	0.528	0.356

Table 7. Heterogeneity analysis: Violation categories

This table reports the regression results examining the effect of *AID_Exp* on different classifications of corporate violations and penalties, specifically disaggregating into ESG-related violations (Environmental, Social, Governance) and non-ESG violations. Panel A reports the violation-based measures and panel B reports the penalty-based measures. t-statistics are shown in parentheses. *p < .1; **p < .05; ***p < .01.

Panel A. Violation-based measures

	(1)	(2)	(3)	(4)	(5)
	<i>ln esg vio_{t+1}</i>	<i>ln e vio_{t+1}</i>	<i>ln s vio_{t+1}</i>	<i>ln g vio_{t+1}</i>	<i>ln o vio_{t+1}</i>
<i>AID_Exp</i>	-0.088*** (-6.853)	-0.013* (-1.924)	-0.042*** (-5.326)	-0.033*** (-4.247)	0.001 (0.451)
<i>Board_size</i>	0.009*** (16.156)	0.002*** (7.230)	0.005*** (10.482)	0.003*** (7.372)	0.000** (2.374)
<i>BI</i>	-0.018* (-1.870)	0.015*** (3.271)	-0.016** (-2.175)	-0.017*** (-3.184)	0.000 (0.186)
<i>Director_age</i>	0.002*** (11.277)	0.001*** (6.467)	0.001*** (4.410)	0.001*** (8.351)	0.000 (0.755)
<i>Director_tenure</i>	0.005*** (16.646)	0.001*** (6.188)	0.003*** (11.641)	0.001*** (7.853)	0.000* (1.926)
<i>CEO_duality</i>	0.017*** (4.492)	0.004* (1.932)	0.004 (1.226)	0.009*** (4.007)	-0.001** (-2.062)
<i>Firm_size</i>	0.067*** (58.465)	0.015*** (26.270)	0.025*** (30.380)	0.027*** (32.292)	0.001*** (6.669)
<i>Tobin_Q</i>	0.004*** (7.433)	-0.000 (-0.511)	0.003*** (7.067)	0.001*** (3.667)	0.000** (2.509)
<i>ROA</i>	-0.099*** (-21.118)	-0.025*** (-11.767)	-0.029*** (-8.728)	-0.044*** (-16.397)	-0.001*** (-2.739)
<i>RND</i>	0.076*** (8.025)	0.023*** (6.227)	0.035*** (5.236)	0.018*** (3.601)	-0.000 (-0.193)
<i>Lev</i>	-0.002 (-0.405)	-0.012*** (-3.686)	0.017*** (3.802)	-0.008** (-2.065)	-0.000 (-0.158)
<i>Competition</i>	-0.004*** (-8.510)	0.000 (0.535)	-0.003*** (-8.145)	-0.001*** (-5.803)	0.000 (0.806)
Constant	-0.542*** (-34.115)	-0.145*** (-17.921)	-0.186*** (-15.715)	-0.211*** (-21.850)	-0.006*** (-4.354)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes	Yes
Observations	77071	77071	77071	77071	77071
Adjusted R-squared	0.314	0.142	0.224	0.127	0.005

Panel B. Penalty-based measures

	(1)	(2)	(3)	(4)	(5)
	<i>ln esg pen_{t+1}</i>	<i>ln e pen_{t+1}</i>	<i>ln s pen_{t+1}</i>	<i>ln g pen_{t+1}</i>	<i>ln o pen_{t+1}</i>
<i>AID_Exp</i>	-0.090*** (-4.281)	-0.010* (-1.887)	-0.014*** (-3.022)	-0.066*** (-3.341)	0.001 (0.022)

<i>Board_size</i>	0.005*** (6.697)	0.001*** (3.774)	0.000* (1.745)	0.004*** (5.382)	0.002** (1.986)
<i>BI</i>	-0.056*** (-5.299)	0.003 (0.939)	-0.007*** (-3.107)	-0.052*** (-5.358)	-0.002 (-0.200)
<i>Director_age</i>	0.002*** (7.238)	0.000*** (3.833)	0.000 (1.551)	0.001*** (6.060)	0.000 (0.896)
<i>Director_tenure</i>	0.001*** (3.277)	0.000*** (2.632)	0.000** (2.053)	0.001** (1.993)	0.001 (1.461)
<i>CEO_duality</i>	0.015*** (3.102)	0.001 (0.662)	0.000 (0.305)	0.014*** (3.042)	-0.011** (-2.187)
<i>Firm_size</i>	0.057*** (26.938)	0.006*** (11.898)	0.005*** (9.520)	0.046*** (22.582)	0.014*** (6.895)
<i>Tobin_Q</i>	0.003*** (3.035)	-0.000 (-0.412)	0.001** (2.284)	0.002** (2.370)	0.003*** (2.600)
<i>ROA</i>	-0.074*** (-12.819)	-0.011*** (-6.985)	-0.002 (-1.501)	-0.061*** (-11.405)	-0.022*** (-2.994)
<i>RND</i>	0.024* (1.847)	0.014*** (5.787)	0.005** (1.963)	0.005 (0.378)	-0.012 (-0.718)
<i>Lev</i>	-0.019** (-2.197)	-0.010*** (-3.011)	0.008*** (3.450)	-0.017** (-2.271)	0.004 (0.382)
<i>Competition</i>	-0.003*** (-5.052)	0.000 (0.250)	-0.000** (-2.536)	-0.002*** (-5.221)	0.000 (0.513)
Constant	-0.399*** (-19.454)	-0.060*** (-8.695)	-0.033*** (-6.003)	-0.305*** (-16.244)	-0.109*** (-4.223)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes	Yes
Observations	77071	77071	77071	77071	77071
Adjusted R-squared	0.093	0.075	0.029	0.073	0.004

Table 8. Heterogeneity analysis: Industry context

This table reports the regression results of subsample analyses splitting firms into sin and politically sensitive industries versus all other industries to test the specialization hypothesis. t-statistics are shown in parentheses. *p < .1; **p < .05; ***p < .01.

	Not (1) <i>ln violation_{t+1}</i>	Sin & Political sensitive industries (2) <i>ln violation_{t+1}</i>
<i>AID_Exp</i>	-0.037 (-1.395)	-0.176*** (-9.176)
<i>Board_size</i>	0.009*** (13.094)	0.016*** (10.116)
<i>BI</i>	-0.021* (-1.771)	-0.026 (-1.036)
<i>Director_age</i>	0.002*** (8.119)	0.005*** (8.571)
<i>Director_tenure</i>	0.006*** (16.430)	0.005*** (6.118)
<i>CEO_duality</i>	0.016*** (3.477)	0.046*** (4.168)
<i>Firm_size</i>	0.075*** (52.362)	0.106*** (33.453)
<i>Tobin_Q</i>	0.005*** (5.802)	0.007*** (5.626)
<i>ROA</i>	-0.108*** (-17.049)	-0.187*** (-16.663)
<i>RND</i>	0.143*** (8.999)	0.051*** (2.845)
<i>Lev</i>	0.033*** (4.033)	-0.101*** (-7.298)
<i>Competition</i>	-0.004*** (-8.153)	-0.008*** (-4.039)
Constant	-0.585*** (-29.389)	-0.878*** (-20.050)
Industry FE	Yes	Yes
Year FE	Yes	Yes
SEs clustered at firm-year	Yes	Yes
Observations	59898	17173
Adjusted R-squared	0.322	0.378

Table 9. Instrumental variable (2SLS) analysis

This table reports the results of the two-stage least squares (2SLS) regressions. Columns (1) and (3) report the first-stage results predicting *AID_Exp* using state-level education instruments (*ln_total* and *ln_higher_edu*). Columns (2) and (4) report the second-stage results of the instrumented *AID_Exp* on corporate violations. t-statistics are shown in parentheses. *p < .1; **p < .05; ***p < .01.

	(1) <i>AID_Exp_{t+1}</i>	(2) <i>ln_violation_{t+1}</i>	(3) <i>AID_Exp_{t+1}</i>	(4) <i>ln_violation_{t+1}</i>
<i>ln_total</i>	0.003*** (10.809)			
<i>aid_hat1</i>		-2.025*** (-3.105)		
<i>ln_higher_edu</i>			0.003*** (9.022)	
<i>aid_hat2</i>				-2.753*** (-2.909)
<i>Board_size</i>	-0.000 (-0.389)	0.009*** (10.250)	0.000 (0.167)	0.010*** (8.843)
<i>BI</i>	0.021*** (10.668)	0.005 (0.262)	0.026*** (9.334)	0.065* (1.927)
<i>Director_age</i>	0.000 (0.545)	0.003*** (10.499)	0.000 (1.312)	0.004*** (10.297)
<i>Director_tenure</i>	-0.000*** (-6.433)	0.005*** (10.818)	-0.000*** (-5.614)	0.004*** (6.507)
<i>CEO_duality</i>	-0.003*** (-5.887)	0.015*** (3.109)	-0.002*** (-4.050)	0.029*** (4.249)
<i>Firm_size</i>	0.001*** (9.986)	0.100*** (54.305)	0.001*** (6.429)	0.112*** (48.601)
<i>Tobin_Q</i>	-0.001** (-2.491)	0.003*** (4.048)	-0.001** (-2.127)	-0.000 (-0.194)
<i>ROA</i>	0.011*** (6.457)	-0.119*** (-13.029)	0.014*** (6.253)	-0.151*** (-9.495)
<i>RND</i>	0.088*** (15.583)	0.296*** (4.933)	0.085*** (11.970)	0.337*** (4.004)
<i>Lev</i>	-0.014*** (-10.867)	-0.039*** (-3.286)	-0.011*** (-6.774)	-0.054*** (-3.605)
<i>Competition</i>	0.000** (1.967)	-0.005*** (-8.298)	0.000 (0.701)	-0.004*** (-4.841)
Constant	-0.017*** (-5.102)	-0.710*** (-31.681)	-0.014*** (-3.413)	-0.899*** (-27.524)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes
Observations	67380	67380	44737	44737
Adjusted R-squared	0.327	0.352	0.355	0.378

Table 10. Propensity score matching (PSM)

This table reports the propensity score matching (PSM) analysis. The covariates used for matching include all of the board and firm characteristics. Panel A reports the statistic before and after matching. Panel B reports the regression results using the matched sample. All of the explanatory variables are lagged by 1 year period to mitigate the reverse causality issues. t-statistics are shown in parentheses. * $p < .1$; ** $p < .05$; *** $p < .01$.

Panel A. Statistics before and after matching

Variable	Before Matching						After Matching					
	Mean		t-test		V(T)/V(C)		Mean		t-test		V(T)/V(C)	
	Treated	Control	%bias	t	p> t		Treated	Control	%bias	t	p> t	
<i>Board_size</i>	8.5079	8.1209	12.1	12.18	0	0.69*	8.6602	8.5865	2.6	1.91	0.056	0.73*
<i>BI</i>	0.83842	0.80542	25	23.35	0	0.42*	0.83766	0.83292	4.2	3.62	0	0.86*
<i>Director_age</i>	60.199	60.336	-2.3	-2.39	0.02	0.78*	60.275	60.142	2.3	1.76	0.078	0.85*
<i>Director_tenure</i>	9.1937	10.646	-32	-32.14	0	0.70*	9.2371	9.1844	1.2	0.92	0.356	0.93*
<i>CEO_duality</i>	0.15151	0.19824	-12.3	-12.7	0	.	0.15628	0.14849	2	1.59	0.112	.
<i>Firm_size</i>	6.2538	6.7988	-23.4	-25.48	0	1.07*	5.9744	5.8814	4.3	3.01	0.003	0.84*
<i>Tobin_Q</i>	2.643	1.8585	44	48.04	0	1.66*	2.6647	2.8451	-10	-5.99	0	0.69*
<i>ROA</i>	-0.18905	-0.03205	-52.1	-65.93	0	2.36*	-0.20289	-0.2012	-0.5	-0.32	0.75	0.77*
<i>RND</i>	0.16565	0.035	90.8	135.22	0	4.23*	0.1765	0.17566	0.6	0.31	0.755	0.80*
<i>Lev</i>	0.41133	0.54821	-54.5	-58.09	0	0.97	0.39131	0.38046	4.5	3.36	0.001	1.09*
<i>Competition</i>	8.4675	9.6819	-11.4	-10.53	0	0.38*	7.8384	7.5547	3.4	2.9	0.004	0.53*

Panel B. Regressions using the matched sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\ln \text{violation}_{t+1}$	$\ln \text{violation}_{t+1}$	$\ln \text{violation}_{t+1}$	$\ln \text{violation}_{t+1}$	$\ln \text{violation}_{t+1}$	$\ln \text{violation}_{t+1}$	$\ln \text{violation}_{t+1}$
<i>AID_Exp</i>	-0.052*** (-3.838)	-0.052*** (-3.838)	-0.057*** (-4.512)	-0.057*** (-4.512)	-0.030** (-2.294)	-0.057*** (-4.512)	-0.041*** (-3.090)
<i>Board_size</i>	0.012*** (8.516)	0.012*** (8.516)	0.011*** (12.241)	0.011*** (12.241)	0.013*** (8.786)	0.011*** (12.241)	0.010*** (17.507)
<i>BI</i>	-0.068*** (-2.642)	-0.068*** (-2.642)	-0.028* (-1.804)	-0.028* (-1.804)	-0.089*** (-3.272)	-0.028* (-1.804)	-0.026* (-1.805)
<i>Director_age</i>	0.003*** (6.886)	0.003*** (6.886)	0.004*** (11.347)	0.004*** (11.347)	0.003*** (6.873)	0.004*** (11.347)	0.004*** (12.739)
<i>Director_tenure</i>	0.000 (0.106)	0.000 (0.106)	0.003*** (5.259)	0.003*** (5.259)	-0.000 (-0.499)	0.003*** (5.259)	0.003*** (6.876)
<i>CEO_duality</i>	0.020** (2.081)	0.020** (2.081)	0.024*** (3.991)	0.024*** (3.991)	0.020** (2.114)	0.024*** (3.991)	0.024*** (6.628)
<i>Firm_size</i>	0.059*** (19.262)	0.059*** (19.262)	0.070*** (35.152)	0.070*** (35.152)	0.060*** (18.928)	0.070*** (35.152)	0.073*** (74.148)
<i>Tobin_Q</i>	-0.002** (-2.224)	-0.002** (-2.224)	-0.001 (-1.120)	-0.001 (-1.120)	-0.002*** (-2.974)	-0.001 (-1.120)	-0.001 (-1.488)
<i>ROA</i>	-0.086*** (-10.772)	-0.086*** (-10.772)	-0.107*** (-17.787)	-0.107*** (-17.787)	-0.096*** (-11.445)	-0.107*** (-17.787)	-0.106*** (-17.327)
<i>RND</i>	0.059*** (3.774)	0.059*** (3.774)	0.096*** (7.673)	0.096*** (7.673)	0.030* (1.948)	0.096*** (7.673)	0.102*** (8.067)
<i>Lev</i>	0.003 (0.234)	0.003 (0.234)	0.008 (1.047)	0.008 (1.047)	-0.000 (-0.004)	0.008 (1.047)	0.009 (1.259)

<i>Competition</i>	0.000	0.000	-0.003***	-0.003***	0.000	-0.003***	-0.003***
	(0.089)	(0.089)	(-3.310)	(-3.310)	(0.194)	(-3.310)	(-4.947)
Constant	-0.512***	-0.512***	-0.616***	-0.616***	-0.513***	-0.616***	-0.658***
	(-12.589)	(-12.589)	(-24.469)	(-24.469)	(-12.048)	(-24.469)	(-18.487)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16521	16521	77071	77071	15877	77071	77074
Adjusted R-squared	0.443	0.443	0.392	0.392	0.454	0.392	0.407

Table 11. Difference-in-Differences (DID) analysis

This table reports the results of a Difference-in-Differences (DID) analysis exploiting the 2006 SEC Regulation S-K, Item 407 as an exogenous shock. The treatment group (*Treat*) consists of firms listed on NASDAQ, while the control group consists of firms listed on the NYSE. The post-regulation period (*Post*) is a dummy variable equal to one for years 2006 and onwards, and zero otherwise. The interaction term ($Treat \times Post$) captures the DID estimate. t-statistics are shown in parentheses. *p < .1; **p < .05; ***p < .01.

	1Y	2Y	3Y	4Y	5Y	Full sample
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln violation_{t+1}$	$\ln violation_{t+1}$	$\ln violation_{t+1}$	$\ln violation_{t+1}$	$\ln violation_{t+1}$	$\ln violation_{t+1}$
<i>TreatxPost</i>	-0.049** (-2.215)	-0.060*** (-2.930)	-0.059*** (-3.767)	-0.074*** (-5.489)	-0.082*** (-6.864)	-0.117*** (-13.595)
<i>Nasdaq</i>	0.021 (1.046)	0.027 (1.400)	0.027* (1.934)	0.032*** (2.738)	0.033*** (3.269)	0.066*** (8.333)
<i>Board_size</i>	0.013*** (5.678)	0.013*** (6.334)	0.012*** (7.393)	0.012*** (8.588)	0.012*** (9.622)	0.011*** (14.368)
<i>BI</i>	-0.051 (-1.303)	-0.019 (-0.532)	-0.027 (-0.924)	-0.028 (-1.133)	-0.017 (-0.787)	-0.013 (-0.945)
<i>Director_age</i>	0.002** (2.185)	0.002*** (2.796)	0.002*** (3.748)	0.002*** (4.040)	0.002*** (4.549)	0.003*** (9.961)
<i>Director_tenure</i>	0.006*** (6.173)	0.006*** (6.321)	0.006*** (7.510)	0.006*** (9.545)	0.006*** (10.523)	0.006*** (14.793)
<i>CEO_duality</i>	0.005 (0.398)	0.012 (0.989)	0.004 (0.407)	0.003 (0.407)	0.010 (1.357)	0.028*** (5.619)
<i>Firm_size</i>	0.088*** (18.381)	0.090*** (21.497)	0.093*** (26.581)	0.093*** (30.202)	0.091*** (33.552)	0.091*** (54.263)
<i>Tobin_Q</i>	0.007*** (3.231)	0.007*** (3.487)	0.008*** (4.623)	0.008*** (5.562)	0.008*** (5.842)	0.004*** (5.055)
<i>ROA</i>	-0.094*** (-3.561)	-0.082*** (-4.112)	-0.087*** (-5.371)	-0.097*** (-6.952)	-0.088*** (-7.651)	-0.145*** (-19.607)
<i>RND</i>	0.141*** (3.038)	0.150*** (3.743)	0.149*** (4.572)	0.147*** (5.209)	0.162*** (6.593)	0.113*** (7.604)
<i>Lev</i>	-0.070*** (-3.059)	-0.048** (-2.358)	-0.038** (-2.235)	-0.042*** (-2.809)	-0.025* (-1.861)	-0.006 (-0.691)
<i>Competition</i>	-0.002 (-0.336)	0.002 (0.937)	0.001 (0.670)	0.001 (0.827)	-0.000 (-0.078)	-0.004*** (-7.419)
Constant	-0.618*** (-8.153)	-0.705*** (-11.081)	-0.716*** (-13.738)	-0.715*** (-15.917)	-0.709*** (-17.935)	-0.734*** (-30.099)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8002	10568	15866	20991	26079	63612
Adjusted R-squared	0.343	0.355	0.354	0.351	0.351	0.363

Table 12. Robustness: Lead-lag analysis

This table reports the results of robustness tests for lead-lag analysis, re-estimating the baseline model for future periods $t+1$ through $t+3$ to confirm the long-term effect of *AID_Exp* on corporate violations. t-statistics are shown in parentheses. * $p < .1$; ** $p < .05$; *** $p < .01$.

	(1)	(2)	(3)	(4)
	$\ln \text{ violation}_t$	$\ln \text{ violation}_{t+1}$	$\ln \text{ violation}_{t+2}$	$\ln \text{ violation}_{t+3}$
<i>AID_Exp</i>	-0.105*** (-7.719)	-0.103*** (-6.804)	-0.113*** (-6.759)	-0.122*** (-6.695)
<i>Board_size</i>	0.011*** (18.186)	0.011*** (16.742)	0.012*** (16.399)	0.012*** (15.228)
<i>BI</i>	-0.020** (-2.012)	-0.022** (-2.007)	-0.023* (-1.907)	-0.025* (-1.948)
<i>Director_age</i>	0.003*** (12.010)	0.003*** (11.582)	0.003*** (11.099)	0.003*** (10.583)
<i>Director_tenure</i>	0.006*** (19.285)	0.006*** (16.887)	0.005*** (14.326)	0.005*** (11.564)
<i>CEO_duality</i>	0.024*** (5.901)	0.023*** (5.330)	0.024*** (5.302)	0.026*** (5.319)
<i>Firm_size</i>	0.079*** (64.177)	0.082*** (62.047)	0.084*** (60.158)	0.087*** (58.050)
<i>Tobin_Q</i>	0.005*** (7.733)	0.005*** (7.665)	0.006*** (8.328)	0.007*** (8.259)
<i>ROA</i>	-0.126*** (-25.648)	-0.124*** (-22.966)	-0.118*** (-19.861)	-0.117*** (-17.885)
<i>RND</i>	0.082*** (8.394)	0.094*** (8.402)	0.108*** (8.646)	0.114*** (8.159)
<i>Lev</i>	-0.008 (-1.258)	-0.003 (-0.479)	-0.005 (-0.631)	-0.001 (-0.164)
<i>Competition</i>	-0.004*** (-8.609)	-0.004*** (-8.271)	-0.004*** (-7.788)	-0.004*** (-7.064)
Constant	-0.633*** (-37.544)	-0.657*** (-35.826)	-0.674*** (-34.102)	-0.687*** (-32.009)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes
Observations	86226	77071	69170	62030
Adjusted R-squared	0.329	0.335	0.344	0.351

Table 13. Robustness: Alternative dependent variables

This table reports the regression results using alternative measures of corporate violations, Panel A include violation counts (*Violation*, *Violation2*), binary indicators (*Violation_dum*, *Violation_dum2*), and Panel B include various penalty-based measures (*Penalty*, *ln_penalty*, *Adj_penalty*). t-statistics are shown in parentheses. *p < .1; **p < .05; ***p < .01.

Panel A. Violation-based measures

	(1)	(2)	(3)	(4)
	<i>ln violation_{t+1}</i>	<i>Violation2_{t+1}</i>	<i>Violation_dum_{t+1}</i>	<i>Violation_dum2_{t+1}</i>
<i>AID_Exp</i>	-0.254*** (-6.062)	-0.512*** (-6.501)	-0.066*** (-5.788)	-0.084*** (-6.408)
<i>Board_size</i>	0.027*** (14.225)	0.055*** (15.584)	0.009*** (19.261)	0.011*** (22.194)
<i>BI</i>	-0.067** (-2.184)	-0.118** (-2.035)	-0.008 (-1.008)	-0.005 (-0.581)
<i>Director_age</i>	0.008*** (11.497)	0.015*** (11.690)	0.002*** (8.722)	0.002*** (8.607)
<i>Director_tenure</i>	0.012*** (12.558)	0.024*** (14.227)	0.006*** (23.148)	0.008*** (29.646)
<i>CEO_duality</i>	0.071*** (5.799)	0.149*** (6.614)	0.013*** (4.625)	0.013*** (4.211)
<i>Firm_size</i>	0.211*** (54.409)	0.412*** (57.125)	0.053*** (68.004)	0.064*** (76.365)
<i>Tobin_Q</i>	0.010*** (5.438)	0.019*** (5.445)	0.005*** (8.918)	0.007*** (11.336)
<i>ROA</i>	-0.334*** (-22.314)	-0.654*** (-23.158)	-0.073*** (-19.650)	-0.078*** (-18.767)
<i>RND</i>	0.292*** (9.313)	0.593*** (9.960)	0.030*** (3.805)	0.024*** (2.589)
<i>Lev</i>	-0.031 (-1.555)	-0.073** (-1.978)	0.008* (1.669)	0.009* (1.697)
<i>Competition</i>	-0.011*** (-7.652)	-0.021*** (-8.201)	-0.003*** (-7.526)	-0.004*** (-8.076)
Constant	-1.692*** (-32.863)	-3.302*** (-34.343)	-0.428*** (-34.287)	-0.508*** (-36.819)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes
Observations	77071	77071	77071	77071
Adjusted R-squared	0.305	0.334	0.305	0.351

Panel B. Penalty-based measures

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Penalty_{t+1}</i>	<i>ln_penalty_{t+1}</i>	<i>ln_penalty2_{t+1}</i>	<i>Adj_penalty_{t+1}</i>	<i>Adj_penalty2_{t+1}</i>	<i>Adj_penalty3_{t+1}</i>
<i>AID_Exp</i>	-0.492*** (-5.463)	-0.917*** (-6.203)	-0.913*** (-6.148)	-27.028*** (-2.682)	-47.788*** (-3.486)	-22.692*** (-3.591)

<i>Board_size</i>	0.026*** (7.423)	0.107*** (18.537)	0.108*** (18.570)	2.125*** (5.156)	2.367*** (5.065)	1.575*** (6.582)
<i>BI</i>	-0.258*** (-5.282)	-0.236** (-2.522)	-0.238** (-2.530)	-18.287*** (-2.840)	-27.157*** (-3.786)	-7.096* (-1.881)
<i>Director_age</i>	0.009*** (6.945)	0.022*** (9.827)	0.022*** (9.835)	0.573*** (3.747)	0.508*** (2.905)	0.370*** (4.049)
<i>Director_tenure</i>	0.005*** (3.294)	0.062*** (20.800)	0.063*** (20.838)	0.911*** (4.329)	1.205*** (5.120)	0.881*** (6.937)
<i>CEO_duality</i>	0.088*** (3.831)	0.178*** (4.921)	0.180*** (4.970)	3.271 (1.228)	5.258* (1.780)	2.309 (1.448)
<i>Firm_size</i>	0.288*** (33.312)	0.727*** (66.210)	0.730*** (66.242)	19.787*** (24.199)	25.166*** (25.707)	12.152*** (25.387)
<i>Tobin_Q</i>	0.014*** (3.545)	0.057*** (8.510)	0.057*** (8.553)	-2.477*** (-6.642)	0.245 (0.444)	0.901*** (3.012)
<i>ROA</i>	-0.408*** (-15.944)	-1.003*** (-21.515)	-1.012*** (-21.632)	-35.287*** (-11.439)	-30.551*** (-8.253)	-11.028*** (-5.874)
<i>RND</i>	0.130** (2.260)	0.458*** (4.448)	0.458*** (4.443)	-0.366 (-0.058)	9.195 (1.020)	3.629 (0.835)
<i>Lev</i>	-0.061 (-1.617)	0.059 (0.949)	0.060 (0.956)	20.243*** (4.318)	1.321 (0.245)	7.259*** (2.629)
<i>Competition</i>	-0.012*** (-5.071)	-0.038*** (-7.944)	-0.037*** (-7.769)	-0.545* (-1.772)	-0.663** (-1.969)	-0.344** (-2.023)
Constant	-2.004*** (-21.365)	-5.662*** (-36.043)	-5.697*** (-36.083)	-132.962*** (-12.053)	-155.244*** (-12.308)	-93.091*** (-14.161)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77071	77071	76978	76275	74632	77071
Adjusted R-squared	0.118	0.306	0.306	0.061	0.055	0.065

Table 14. Robustness: Alternative independent variables

This table reports the regression results using alternative definitions of the independent variable, comparing *AID_Exp* against academic directors without industry experience (*AID*), expert independent directors (*ID_Exp*), and dummy variable specifications. t-statistics are shown in parentheses. *p < .1; **p < .05; ***p < .01.

	(1)	(2)	(3)	(4)
	<i>ln violation_{t+1}</i>	<i>ln violation_{t+1}</i>	<i>ln violation_{t+1}</i>	<i>ln violation_{t+1}</i>
<i>AID_Exp2</i>	-0.139*** (-3.218)			
<i>AID</i>		-0.164 (-1.601)		
<i>ID_Exp</i>			-0.748*** (-10.337)	
<i>ID_Exp2</i>				-0.124*** (-4.036)
<i>Board_size</i>	0.109*** (18.755)	0.107*** (18.491)	0.108*** (18.685)	0.112*** (18.801)
<i>BI</i>	-0.249*** (-2.662)	-0.246*** (-2.613)	-0.101 (-1.061)	-0.214** (-2.267)
<i>Director_age</i>	0.022*** (9.829)	0.022*** (9.930)	0.020*** (9.186)	0.022*** (9.696)
<i>Director_tenure</i>	0.063*** (20.822)	0.063*** (20.849)	0.062*** (20.681)	0.063*** (20.835)
<i>CEO_duality</i>	0.178*** (4.933)	0.179*** (4.957)	0.173*** (4.806)	0.178*** (4.924)
<i>Firm_size</i>	0.727*** (66.263)	0.727*** (66.149)	0.726*** (66.258)	0.726*** (66.178)
<i>Tobin_Q</i>	0.057*** (8.577)	0.057*** (8.575)	0.057*** (8.507)	0.058*** (8.665)
<i>ROA</i>	-1.006*** (-21.589)	-1.011*** (-21.701)	-0.987*** (-21.196)	-1.009*** (-21.666)
<i>RND</i>	0.431*** (4.162)	0.398*** (3.859)	0.555*** (5.353)	0.408*** (3.948)
<i>Lev</i>	0.064 (1.019)	0.067 (1.075)	0.053 (0.848)	0.067 (1.071)
<i>Competition</i>	-0.038*** (-7.960)	-0.038*** (-7.964)	-0.037*** (-7.887)	-0.038*** (-7.976)
Constant	-5.668*** (-36.089)	-5.675*** (-36.173)	-5.587*** (-35.683)	-5.642*** (-35.960)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes
Observations	77071	77071	77071	77071
Adjusted R-squared	0.306	0.306	0.307	0.306

Table 15. Robustness: Excluding regulated industries

This table reports the regression results of *AID_Exp* on corporate violations after excluding firms in the financial (SIC 6000-6999) and utilities (SIC 4900-4999) industries. Panel A reports the violation-based measures and panel B reports the penalty-based measures. t-statistics are shown in parentheses. *p < .1; **p < .05; ***p < .01.

Panel A. Violation-based measures

	(1)	(2)	(3)	(4)
	<i>ln_violation_{t+1}</i>	<i>Violation2_{t+1}</i>	<i>Violation_dum_{t+1}</i>	<i>Violation_dum2_{t+1}</i>
<i>AID_Exp</i>	-0.291*** (-7.149)	-0.586*** (-7.640)	-0.072*** (-6.277)	-0.089*** (-6.714)
<i>Board_size</i>	0.030*** (13.808)	0.060*** (15.074)	0.009*** (17.611)	0.011*** (20.230)
<i>BI</i>	-0.013 (-0.415)	-0.015 (-0.253)	0.000 (0.057)	0.004 (0.422)
<i>Director_age</i>	0.007*** (9.641)	0.014*** (9.756)	0.001*** (7.482)	0.002*** (7.569)
<i>Director_tenure</i>	0.012*** (11.411)	0.025*** (13.093)	0.006*** (21.325)	0.008*** (27.314)
<i>CEO_duality</i>	0.103*** (7.721)	0.214*** (8.638)	0.016*** (4.988)	0.015*** (4.312)
<i>Firm_size</i>	0.205*** (50.657)	0.400*** (53.321)	0.053*** (60.992)	0.063*** (68.513)
<i>Tobin_Q</i>	0.008*** (4.267)	0.015*** (4.156)	0.004*** (7.897)	0.006*** (10.169)
<i>ROA</i>	-0.323*** (-21.294)	-0.635*** (-22.220)	-0.072*** (-18.890)	-0.078*** (-18.177)
<i>RND</i>	0.291*** (9.092)	0.596*** (9.803)	0.030*** (3.747)	0.025*** (2.663)
<i>Lev</i>	-0.037* (-1.850)	-0.081** (-2.216)	0.005 (0.952)	0.006 (1.023)
<i>Competition</i>	-0.010*** (-3.745)	-0.023*** (-4.621)	-0.002*** (-3.628)	-0.003*** (-4.362)
Constant	-1.653*** (-30.125)	-3.214*** (-31.352)	-0.423*** (-31.154)	-0.502*** (-33.562)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes
Observations	64805	64805	64805	64805
Adjusted R-squared	0.320	0.349	0.306	0.353

Panel B. Penalty-based measures

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Penalty_{t+1}</i>	<i>ln_penalty_{t+1}</i>	<i>ln_penalty2_{t+1}</i>	<i>Adj_penalty_{t+1}</i>	<i>Adj_penalty2_{t+1}</i>	<i>Adj_penalty3_{t+1}</i>
<i>AID_Exp</i>	-0.493*** (-5.525)	-0.987*** (-6.691)	-0.982*** (-6.626)	-23.373** (-2.321)	-44.453*** (-3.266)	-22.611*** (-3.540)
<i>Board_size</i>	0.027*** (7.041)	0.111*** (17.192)	0.112*** (17.236)	2.163*** (4.914)	2.312*** (4.733)	1.574*** (5.849)

<i>BI</i>	-0.197*** (-4.022)	-0.124 (-1.251)	-0.127 (-1.279)	-9.958 (-1.556)	-17.340** (-2.459)	-5.528 (-1.395)
<i>Director_age</i>	0.008*** (6.052)	0.021*** (8.538)	0.021*** (8.521)	0.510*** (3.189)	0.413** (2.255)	0.357*** (3.562)
<i>Director_tenure</i>	0.006*** (3.473)	0.065*** (19.303)	0.065*** (19.369)	0.840*** (3.711)	1.128*** (4.456)	0.810*** (5.663)
<i>CEO_duality</i>	0.094*** (3.871)	0.211*** (5.401)	0.214*** (5.453)	4.184 (1.502)	5.250* (1.719)	3.180* (1.825)
<i>Firm_size</i>	0.269*** (30.015)	0.709*** (60.548)	0.711*** (60.560)	17.136*** (21.133)	21.487*** (22.230)	12.213*** (23.285)
<i>Tobin_Q</i>	0.011*** (2.740)	0.051*** (7.424)	0.052*** (7.468)	-2.565*** (-6.733)	0.150 (0.266)	0.880*** (2.847)
<i>ROA</i>	-0.359*** (-14.553)	-0.970*** (-20.465)	-0.980*** (-20.593)	-28.367*** (-9.500)	-20.802*** (-5.867)	-11.093*** (-5.834)
<i>RND</i>	0.111* (1.932)	0.447*** (4.287)	0.447*** (4.280)	-5.359 (-0.850)	1.993 (0.221)	3.048 (0.694)
<i>Lev</i>	0.007 (0.190)	0.048 (0.733)	0.048 (0.736)	23.970*** (5.183)	7.042 (1.309)	7.003** (2.413)
<i>Competition</i>	-0.010** (-2.355)	-0.029*** (-3.547)	-0.028*** (-3.485)	0.126 (0.241)	0.053 (0.090)	-0.226 (-0.702)
Constant	-1.930*** (-19.854)	-5.545*** (-33.005)	-5.574*** (-33.012)	-122.186*** (-10.709)	-138.733*** (-10.736)	-91.160*** (-12.788)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SEs clustered at firm-year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64805	64805	64716	64659	62438	64805
Adjusted R-squared	0.122	0.311	0.311	0.058	0.049	0.064