2026

Essays on leadership and workforce dynamics in operations

BOSTON UNIVERSITY

QUESTROM SCHOOL OF BUSINESS

Dissertation

ESSAYS ON LEADERSHIP AND WORKFORCE DYNAMICS IN OPERATIONS

by

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B.S., Tufts University, 2020

Submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

2026

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Acknowledgments

I am deeply grateful to my dissertation committee for their mentorship, rigor, and generosity throughout my doctoral journey. I owe my deepest thanks to my advisor, Professor Marcus Bellamy, for his unwavering guidance, high standards, and consistent encouragement. His insight has shaped not only this dissertation but also how I think as a scholar. I am equally thankful to Professor Dokyun (DK) Lee and Professor Gerry Tsoukalas for their thoughtful feedback, incisive questions, and intellectual support across all stages of this work. Their perspectives strengthened each essay and challenged me to communicate my ideas with greater clarity and precision.

I am especially thankful to my co-author, colleague, and friend, Richard Yuze Li. Our collaboration has been one of the most meaningful parts of my PhD experience. I have benefited enormously from his creativity, discipline, and generosity. Many of the ideas in this dissertation were sharpened through our conversations, and I am grateful for his partnership and friendship.

I am also grateful to the Questrom doctoral community. I want to thank my cohort and close peers — Jinyuan Zhang, Linghui Feng, and Fanying Chen — for their support, candor, and camaraderie. The PhD journey can be intellectually demanding and emotionally challenging; their encouragement made it lighter and more joyful. I am thankful as well to the faculty and staff at the Questrom School of Business for creating a supportive environment in which I could grow as a researcher and teacher.

Finally, I would like to thank my family and partner for their unconditional love and patience. Their belief in me made this dissertation possible. This work is as much theirs as it is mine.

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ABSTRACT

This dissertation examines how leadership composition, operational governance mechanisms, and workforce dynamics jointly shape the design and performance of organizational operating systems. Across three essays, I advance a people-centric perspective on operations management: operational systems are not purely technical infrastructures but are shaped by the individuals who design, govern, and participate in them.

The first essay studies how board gender representation influences environmental innovation through internal operational mechanisms. Using panel data on U.S. public firms, I show that board female representation increases environmental innovation primarily when women constitute a majority of the workforce. The mechanism operates through the adoption of environmental management systems (EMS), which embed environmental monitoring and performance evaluation into operational routines. While gender-diverse boards are more likely to adopt EMS, these systems translate into innovation mainly in female-majority workforces, where employees appear more responsive to governance signals emphasizing environmental priorities.

The second essay examines responsible supplier governance in supply-chain operations. I document that the presence of a female Chief Supply Chain Officer (CSCO) strengthens supplier monitoring systems and increases the likelihood that firms terminate noncompliant suppliers. This enforcement effect is amplified when sustainability performance is embedded in executive compensation, highlighting how leadership authority and incentive alignment jointly influence operational control systems within supply networks.

The third essay investigates workforce instability as an operational risk. I conceptualize "talent drain" as reductions in employee inflow or increases in voluntary outflow and examine how capital markets respond to signals of workforce instability. Leveraging the arrival of initial Glassdoor reviews as an information shock, I show that investors reprice firms' risk exposure when employee sentiment becomes publicly observable. I further construct text-based talent drain indices using machine learning techniques that provide incremental predictive power for future workforce attrition.

Together, these essays demonstrate how leadership characteristics, governance structures, and workforce sentiment shape operational systems, with important implications for innovation, supply-chain governance, and organizational risk.

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List of Abbreviations

2SLS	Two-Stage Least Squares
ATT	Average Treatment Effect on the Treated
AUC	Area Under the Curve
BFR	Board Female Representation
BTM	Book-to-Market
CEM	Coarsened Exact Matching
CEO	Chief Executive Officer
COO	Chief Operating Officer
CSCO	Chief Supply Chain Officer
CSI	Corporate Social Irresponsibility
CSR	Corporate Social Responsibility
EMPSTK	Employee Stock Ownership
EMS	Environmental Management System
ESG	Environmental, Social, and Governance
EXEOPT	Executive Stock Options
FE	Fixed Effects
FMW	Female-Majority Workforce
HDBSCAN	Hierarchical Density-Based Spatial Clustering of Applications with Noise
IV	Instrumental Variables
NLTK	Natural Language Toolkit
OLS	Ordinary Least Squares
PSM	Propensity Score Matching
ROA	Return on Assets
SA Index	Hadlock-Pierce Financial Constraints Index
SIC	Standard Industrial Classification
TD	Talent Drain
UGC	User-Generated Content
UMAP	Uniform Manifold Approximation and Projection
WFR	Workforce Female Ratio

Chapter 1

Introduction

Organizations increasingly operate in environments where financial performance, sustainability, and workforce resilience must be managed jointly rather than in isolation. Boards and executives are expected to deliver competitive outcomes while responding to stakeholder demands on environmental stewardship, responsible supply-chain practices, and employee well-being. At the same time, digital information channels have reduced the lag between organizational events and external evaluation, making firms more exposed to reputational and human-capital risks. These developments raise a core operations question: how do governance design, organizational composition, and information environments jointly shape operational outcomes?

This dissertation addresses that question through three essays at the intersection of operations management, organizational design, and human capital. Across the three studies, I examine how leadership structure and workforce conditions affect environmental innovation, how supply-chain leadership and incentive systems shape responsible supplier governance, and how employee-generated information influences investor perceptions of talent-drain risk. Although each essay focuses on a distinct outcome, they share a common logic: formal governance mechanisms affect performance through operational channels, and those channels are conditioned by organizational context.

The first essay studies board female representation and environmental innovation.

It shows that greater board female representation is associated with stronger environmental innovation, but that this association is contingent on workforce gender composition. The evidence further identifies environmental management system adoption as a mechanism through which board-level governance priorities are translated into employee-level operational behavior. The findings indicate that governance diversity is most effective when it is reinforced by internal organizational alignment.

The second essay examines responsible supplier governance through the lens of supply-chain leadership. It documents that female chief supply chain officer presence is associated with stronger supplier monitoring structures and, through those structures, a higher likelihood of formal termination provisions for non-compliant suppliers. The essay also shows that female CEO leadership and female compensation-committee leadership are linked to greater appointment of female CSCOs, and that sustainability-linked executive compensation strengthens the relationship between supply-chain leadership and supplier governance outcomes. These results highlight the role of authority allocation and incentive alignment in shaping inter-organizational governance choices.

The third essay focuses on talent-drain risk and the information content of employee voice. Using the initiation of Glassdoor review coverage as a quasi-experimental information shock, it shows that investor risk perceptions change when a new employee-information channel becomes salient, especially when the initial signal is ambiguous. The essay also develops an explainable text-based prediction framework showing that employee-review content provides incremental power for forecasting future inflow reduction and outflow increase. This demonstrates that employee-generated information is not only reputationally relevant but also operationally predictive.

Taken together, the dissertation contributes in three ways. First, it provides evidence that leadership and governance attributes matter for operational outcomes through specific organizational mechanisms rather than through symbolic effects alone. Second, it shows that internal context, including workforce composition and incentive structures, is central to whether governance initiatives produce measurable impact. Third, it expands the information set of operations research by incorporating employee-generated digital signals into risk assessment and managerial decision support.

From a managerial perspective, the results imply that firms should avoid one-dimensional governance interventions. Board and executive diversity initiatives are most effective when paired with operational systems that enable implementation and with incentive structures that reward intended behaviors. In supply networks, responsible governance requires both monitoring architecture and credible escalation mechanisms. In workforce strategy, employee-review platforms should be treated as early-warning systems for human-capital instability rather than as passive reputation channels.

The remainder of this dissertation is organized as follows. Chapter 2 examines board gender representation, environmental management systems, and environmental innovation. Chapter 3 investigates female supply-chain leadership, executive compensation design, and responsible supplier governance. Chapter 4 analyzes talent-drain risk perception and text-based prediction using employee-generated information. Chapter 5 concludes with cross-essay implications, limitations, and directions for future research.

Chapter 2

Board Gender Diversity and Environmental Innovation: The Role of Environmental Management System and Workforce Composition

2.1 Introduction

Firms increasingly face pressure from regulators, investors, and consumers to integrate environmental sustainability into their operational strategies. A key manifestation of this shift is environmental innovation, defined as the development of products and processes that reduce resource use and environmental externalities. While environmental innovation is widely recognized as critical for sustainable competitive advantage, it often arises from incremental experimentation embedded in day-to-day operational processes rather than from top-down strategic decisions. This raises an important organizational question: what governance and operational conditions enable firms to translate sustainability priorities into environmentally innovative outcomes?

Board female representation (BFR) has emerged as a potential driver of environmental innovation because gender is systematically associated with differences in environmental preferences and governance priorities. Recent evidence documents a robust "eco-gender gap," whereby female decision-makers place greater weight on environmental protection, while male decision-makers prioritize economic growth and energy production (Hsu et al., 2025). This preference difference extends to corporate settings: female directors are more likely to support environmentally friendly business operations and to endorse investments in environmental protection, even when such investments involve short-term economic costs. As a result, greater female board representation shifts governance priorities toward sustainability, increasing firms' willingness to undertake long-horizon environmental investments that require sustained resource commitment and operational change.

Importantly, gender is not merely a proxy for other observable board characteristics. Employing a rich set of director demographics and board attributes, Hsu et al. (2025) show that none consistently supersedes the share of female directors in explaining corporate environmental performance. This evidence suggests that gender captures a unique set of values and decision-making orientations that are difficult to observe directly but nonetheless shape corporate strategy. In this sense, gender diversity represents a holistic dimension of board composition that uniquely influences how firms evaluate tradeoffs between environmental and economic objectives. Consistent with this perspective, firms with more women on their boards exhibit stronger environmental innovation outcomes (Nadeem et al., 2020; Bazel-Shoham et al., 2024). Yet the mechanisms through which gender representation at the board level translates into environmentally innovative outcomes inside the firm remain poorly understood. Environmental innovation rarely originates from boardroom decisions themselves; instead, it emerges from employees' discretionary experimentation embedded in operational processes (Ramus and Steger, 2000). Governance priorities therefore influence environmental innovation only insofar as they shape the operational systems through which employees monitor environmental performance and implement sustainability initiatives.

Adopting an operations management perspective, we argue that one such system is the environmental management system (EMS). EMS adoption represents an organizational capability that embeds environmental monitoring, data collection, and performance evaluation into operational routines (Melnyk et al., 2003). These systems institutionalize environmental management practices by establishing procedures for identifying environmental impacts, tracking performance metrics, and enabling continuous improvement. In doing so, EMS provide the operational infrastructure through which employees can identify opportunities for environmental improvement and experiment with environmentally beneficial practices. In this sense, EMS translate governance priorities into concrete organizational processes that enable employee-driven environmental innovation.

Why, then, should BFR increase the likelihood that firms adopt such environmental management capabilities? Building on the preference-based argument above, we posit that boards with higher female representation are more likely to prioritize environmental monitoring and accountability, thereby increasing the adoption of formal systems that support environmental oversight. However, the effectiveness of these governance signals depends critically on the workforce context in which they are implemented. Drawing on social identity theory (Ashforth and Mael, 1989), employees are more likely to identify with leaders who share salient identity attributes. When women constitute a majority of the workforce, higher BFR strengthens the perceived legitimacy of sustainability priorities promoted by the board, thereby increasing employee engagement in environmental initiatives embedded within EMS. Because EMS integrate environmental information into day-to-day operations, this heightened engagement translates into greater experimentation and implementation of environmentally innovative processes and products. In contrast, when women are underrepresented in the workforce, the same governance signals may generate weaker engagement or resistance, limiting the extent to which EMS-enabled initiatives translate into environmental innovation. Workforce gender composition therefore shapes the conditions under which governance diversity translates into operational outcomes.

We test these ideas using panel data on U.S. public firms from 2011–2023 constructed from Refinitiv ESG, Compustat, and BoardEx. Our empirical strategy combines fixed-effects regressions with instrumental-variable estimation to address potential endogeneity in BFR. Specifically, we instrument firm-level BFR using industry-level and state-level peer BFR measures. To examine the proposed mechanism, we estimate a fixed-effects logit model predicting EMS adoption and a fixed-effects OLS model linking EMS adoption to environmental innovation conditional on workforce gender composition.

Our results reveal three key patterns that support the proposed mechanism. First, firms with higher BFR are significantly more likely to adopt EMS, suggesting that gender-diverse boards are more inclined to establish formal environmental monitoring and governance capabilities. Second, EMS adoption is positively associated with environmental innovation, indicating that these systems provide the operational infrastructure through which employees generate and implement environmentally beneficial improvements. Third, the effectiveness of this mechanism depends on workforce gender composition: EMS adoption translates into environmental innovation primarily when women constitute the majority of the workforce, and consistent with this pattern, BFR enhances environmental innovation only in female-majority workforce settings. Taken together, these findings suggest that governance diversity influences environmental innovation through the adoption of environmental management systems, while workforce gender composition determines when these operational systems translate into employee-driven innovation outcomes.

This study contributes to operations management research in three ways. First, it advances the literature on inclusive operations by showing that the operational impact of governance diversity operates through environmental management capabilities and depends on workforce composition. Second, it contributes to sustainable operations research by identifying EMS adoption as an operational capability through which governance priorities shape environmental innovation. Third, the study bridges corporate governance and people-centric operations by demonstrating how board composition interacts with workforce demographics to influence environmental innovation outcomes.

The findings also have managerial implications. Rather than treating board diversity as a stand-alone governance reform, firms should consider how board composition interacts with workforce demographics and operational systems. In organizations where women constitute a substantial share of employees, increasing BFR can significantly enhance environmental innovation by strengthening environmental management capabilities and employee engagement in sustainability initiatives. In contrast, in male-dominated settings, increasing board gender diversity alone may yield more limited environmental innovation gains unless accompanied by complementary organizational changes.

The remainder of the paper proceeds as follows. Section 2.2 develops the theoretical framework and hypotheses. Section 2.3 describes the data and sample construction. Section 2.4 defines the variables and presents summary statistics and correlations. Section 2.5 outlines the empirical strategy. Section 2.6 presents the results, followed by supplementary analyses in Section 2.7. Section 2.8 discusses theoretical and managerial implications, and Section 2.9 concludes with limitations and directions for future research.

2.2 Literature Review and Hypotheses Development

2.2.1 Why Gender Diversity Specifically?

A central theoretical question in our setting is why gender diversity, as opposed to other dimensions of board diversity, should exert a distinct influence on environmental innovation. We build our argument on recent evidence documenting a robust "eco-gender gap," whereby female decision-makers place systematically greater weight on environmental protection, while male decision-makers prioritize economic growth and energy production (Hsu et al., 2025). This preference difference extends to corporate settings: female directors are more likely to support environmentally friendly business practices and to endorse investments in environmental protection, even when such investments involve short-term economic costs. As a result, greater female board representation shifts governance priorities toward sustainability, increasing firms' willingness to undertake long-horizon environmental investments that require sustained resource commitment and operational change.

Importantly, gender is not merely a proxy for other observable board characteristics. Employing a rich set of director demographics and board attributes, Hsu et al. (2025) show that none consistently supersedes the share of female directors in explaining corporate environmental performance. This evidence suggests that gender captures a unique set of values and decision-making orientations that are difficult to observe directly but nonetheless shape corporate strategy. In this sense, gender diversity represents a holistic dimension of board composition that uniquely influences how firms evaluate tradeoffs between environmental and economic objectives, providing a strong theoretical foundation for our focus on board gender diversity as a key driver of environmental innovation.

2.2.2 BFR, Workforce Gender Ratio, and Environmental Innovation

Prior research points to a link between BFR and environmental innovation. For example, firms with more women on the board tend to achieve higher rates of green innovation (Nadeem et al., 2020). Studies have also found that this positive link can depend on external cultural context, such as being stronger in traditionally masculine societies (Bazel-Shoham et al., 2024). However, less attention has been paid to the intra-organizational context in which this relationship unfolds. In line with calls in operations management to consider people-centric factors in operational outcomes (Corbett et al., 2025), we focus on how a firm's own workforce composition may condition the impact of board gender diversity on environmental innovation.

Within organizations, the inclusion of women in leadership positions can trigger complex social dynamics. Past work shows that incumbent male directors often perceive new female directors as out-group members (Knippen et al., 2019). In response to external pressures (such as gender quota regulations) to add women to boards, male directors have been found to increase board size to accommodate a female director rather than replacing a male, thereby preserving their in-group dominance. This practice leaves many female directors in a token position with limited influence (e.g., they are less likely to be assigned to key board committees). Notably, evidence suggests that a critical mass of women may be needed to overcome tokenism. Wowak et al. (2021) find that having at least two female directors is necessary to significantly hasten high-severity product recalls, an important operational decision, whereas a lone female director has limited effect. Similarly, firms with two or more women on the board are markedly more likely to adopt sustainable supply chain practices (Gull et al., 2023). These findings underscore that simply adding one woman may not suffice; sufficient female representation is needed to influence organizational outcomes.

Stakeholder reactions to increased BFR are also context-dependent. Some investors interpret the appointment of female directors as a signal that the firm is prioritizing social goals at the expense of shareholder value, reacting negatively to BFR (Solal and Snellman, 2019). For instance, when firms prominently tout diversity credentials, investors may penalize female director appointments, perceiving a potential trade-off with profit goals. Other evidence, however, indicates more favorable responses under certain conditions: shareholders on average register less dissent toward female director candidates than male ones, especially in firms that previously had few women on the board (Mitra et al., 2021). This pattern suggests that when a firm faces a legitimacy threat in terms of social responsibility, adding female directors can actually bolster shareholder support. These mixed external reactions mirror the broader theme that the impact of diversity is contingent on context, reinforcing the importance of examining internal conditions such as the employee demographic context.

Employees' perceptions of female leadership can sometimes be prone to systematic biases that differ by the employees' own gender. Experimental and field evidence demonstrates that male subordinates tend to evaluate female leaders more harshly than male leaders, whereas female subordinates do not show such bias (De Paola et al., 2022). Specifically, the authors find that even when teams led by women outperformed those led by men, male team members rated female leaders as less effective than they rated male leaders. Similarly, an analysis of anonymous employee ratings on Glassdoor shows that firms with female CEOs receive lower approval on average, driven entirely by male employees' lower ratings of female leaders (Brenner et al., 2023). Such gender-biased perceptions are also evident in people-centric operations contexts. Wang et al. (2023) document that in online education operations, male instructors disproportionately favor answering questions posed by male students, whereas female instructors exhibit no such bias, indicating male in-group favoritism in work interactions. Likewise, Son et al. (2024) show that simply revealing an employee's gender can alter customer behavior in service exchanges, underscoring how gender mismatch can provoke biased responses even in operational settings. These findings all point to the potential for resistance or diminished support when a female leader directs a male-majority workforce.

The above dynamics can be understood through the lens of group competition theory (Blumer, 1958). According to this perspective, members of a dominant group may react negatively toward members of a subordinate group when they perceive a threat to their status. In corporate settings, male employees' heightened dislike of female leaders can stem from fear that women will encroach on roles traditionally held by men. On the other hand, female employees are likely to respond positively to female leadership due to identification and role modeling. De Paola et al. (2022) show that female subordinates both perform better and evaluate their leaders more favorably when those leaders are women, underscoring a "role-model" mechanism whereby gender alignment fosters identification, trust, and mentoring opportunities. Moving further up the ranks, findings of such a response at the workforce level can possibly translate similarly at the board level. This would imply an opportunity for a board with greater female representation to be perceived as more inspirational and legitimate by women deeper in the organizational hierarchy, thereby heightening receptivity to board-driven initiatives.

This role-model effect is salient in work concerning gender differences in innovation: experimental research finds that when women decision-makers are salient, other women become more open to innovation. For instance, when female innovators know that an evaluation panel has a higher proportion of female judges, they exhibit significantly less avoidance of novel ideas, leading to greater innovation success (Jin and Chua, 2024). Following a logic similar to findings that female online freelancers demonstrate "innovation avoidance" when they perceive a high level of country-level masculinity, female employees may likewise withhold acting on innovative ideas when they perceive low female representation on the board, and vice versa. Evidence from idea-evaluation settings shows that the presence of more women on selection panels curbs the tendency to shy away from novel ideas, and it further reveals that this benefit weakens in societies that score high on cultural masculinity (Jin and Chua, 2024). Translating these insights to the corporate arena, we posit that the gender climate established by the board of directors serves as a critical backdrop for female employees' creative expression. A board dominated by masculine norms can signal to women that creativity is judged through a gender-stereotypical lens, prompting them—often subconsciously—to steer clear of bold or unconventional proposals. A more gender-balanced board projects a different signal: stereotypes lose traction, and female employees feel safer advancing novel ideas. Accordingly, the gender climate at the board level becomes a pivotal contextual cue that influences whether women bring their full creative potential to the firm's innovation efforts.

This theoretical reasoning implies a certain extent of employee awareness of the board of directors. We find some qualitative and textual analysis on the plausibility of employees being aware of their firms' board gender composition. From a qualitative perspective, researchers have formally codified interview documentation to arrive at implications for female identity and organizational context in the workplace. A codified interview study of German stock-listed companies by Kirsch (2022) gathers 60 semi-structured interviews—balanced between 30 female and 30 male directors—spanning 90 boards that vary in ownership structure and company size (small cap-large cap). Using both interview transcription and documentary data, the study finds that roughly 60% of female directors deliberately heighten their visibility to the workforce by speaking at internal events, contributing to company newsletters, and mentoring junior women, thereby providing direct informational channels through which employees can observe who occupies board seats. Complementing this, we analyzed 1,080 Glassdoor reviews that mention the board of directors and found that 11.7% also include gender-related language. Of these, 7.1% contain specific, verifiable observations—e.g., "all-male board" or "finally two women on the board"—indicating clear employee awareness of the board's gender makeup. The triangulation of codified interview evidence (revealing purposeful visibility practices) with independent employee discourse (revealing accurate, composition-specific observations) suggests that deliberate efforts are being made by a company's board of directors to enhance exposure to rank-and-file employees.[1]

Building on this logic and similar to people-centric operations management research highlighting the performance impact of leader–team disability status alignment (Cole et al., 2024), we anticipate that the effect of board gender diversity on environmental innovation depends on the workforce gender composition. Thus, we posit that a gender-diverse board is most likely to foster environmental innovation when the workforce is predominantly female, whereas it may encounter resistance—and diminished returns—in male-majority settings. Formally:

Hypothesis 1. The BFR–environmental innovation relationship is more positive in a female-majority workforce than in a male-majority workforce.

[1]Exemplary reviews demonstrating workforce knowledge of board gender makeup: "I love the fact that you have two female board members." "The company boasts about its 20% of women on the board of directors and that women make $1.03 to each $1 that men make but this is primarily because women and people of color at PGE are underemployed." "Oleg is a terrible CEO who gripes about wokeness- moved the company to AZ to be close to his home and avoid women on the board Lack of diversity inclusion see there are only seven reviews from women." "[T]here is no female representation on the board of directors and only two females at the executive level (one of which is an assistant secretary)." "This was the only company in 2020 to launch and IPO with an ALL MALE Board of Directors." "One woman on the Board of Directors."

2.2.3 BFR–Environmental Innovation Relationship among Female-Majority Workforce: The Role of Environmental Management Systems

We conceptualize EMS adoption as the development of an organizational capability for systematically collecting, monitoring, and governing environmental information. Melnyk et al. (2003) define an EMS as a formal system that integrates procedures for training personnel and monitoring, summarizing, and reporting environmental performance information, thereby enabling firms to manage environmental impacts through structured operational routines. Similarly, Bellamy et al. (2020) characterize environmental management systems as administrative environmental innovations that institutionalize environmental policies, establish measurable objectives, and create processes for tracking and improving environmental outcomes. Under the ISO 14001 framework, EMS implementation follows a structured cycle of leadership commitment, environmental planning, operational implementation, monitoring, and management review, requiring organizations to establish procedures for identifying environmental aspects, collecting environmental data, and evaluating performance.[2] Implementing such systems therefore requires governance support for environmental monitoring, information processing, and continuous improvement activities.

Higher BFR can strengthen these governance incentives. Prior research shows that female directors place greater emphasis on environmental protection and are more likely to advocate governance mechanisms that improve environmental oversight (Hsu et al., 2025). Firms with higher BFR exhibit stronger environmental performance and greater adoption of E&S-related governance practices (Hsu et al., 2025). In addition, increases in BFR make firms more likely to establish board-level E&S committees

[2] See EMS Under ISO 14001.

and to place women on monitoring committees that oversee sustainability initiatives (Ginglinger and Raskopf, 2023). Such governance structures can facilitate EMS adoption by translating board environmental priorities into operational monitoring systems. During the ISO 14001 process, these committees can oversee the identification of environmental aspects, monitor the establishment of environmental objectives and procedures, and ensure that environmental performance information is reviewed at the leadership level. By strengthening the board's orientation toward environmental monitoring and governance, higher BFR increases the likelihood that firms invest in formal systems that support environmental information collection, monitoring, and operational control. Formally, we hypothesize

Hypothesis 2a. Higher BFR increases the likelihood that a firm adopts an EMS.

Environmental management systems influence environmental outcomes primarily through employee behavior. Cantor et al. (2012) show that organizational environmental management practices shape employees' perceptions that the firm values environmentally responsible behaviors, which increases employees' affective commitment to environmental initiatives and encourages them to engage in environmental activities such as promoting environmental programs, participating in environmental management efforts, and proposing environmentally oriented improvements. Building on this insight, we argue that employee engagement constitutes the critical behavioral mechanism linking EMS adoption to environmental innovation. By embedding environmental performance data into operational routines, EMS create opportunities for improvement; however, whether these opportunities translate into innovation depends on employees' willingness to act on them. Greater engagement motivates employees to identify inefficiencies, experiment with alternative processes, and propose environmentally focused improvements, thereby generating environmental innovation. In contrast, when employee engagement is low, an EMS is more likely to produce compliance-oriented behaviors, such as monitoring and reporting, without substantive environmental innovation.

The extent to which employees engage in environmental initiatives embedded within EMS depends on the demographic context of the workforce. As discussed earlier, female employees may respond more positively to signals of female leadership due to identification and role-model mechanisms. Greater BFR can signal to female employees that their perspectives are valued within the organization, increasing their engagement in sustainability-oriented initiatives and their willingness to propose environmentally focused improvements. Because EMS adoption provides the operational infrastructure through which environmental information is translated into actionable improvements, this engagement channel becomes particularly important for converting environmental management practices into innovation outcomes. When women constitute the majority of the workforce, the alignment between board gender composition and workforce demographics strengthens employee engagement in environmental initiatives, thereby amplifying the translation of EMS adoption into environmental innovation. In contrast, when women are underrepresented in the workforce, the same governance signals may generate weaker engagement or even resistance, limiting the extent to which EMS-enabled initiatives produce environmental innovation outcomes. Accordingly, we posit:

Hypothesis 2b. EMS adoption enhances a firm's environmental innovation, particularly when women constitute the majority of the workforce.

The hypotheses are summarized in the conceptual model in Figure 2·1.

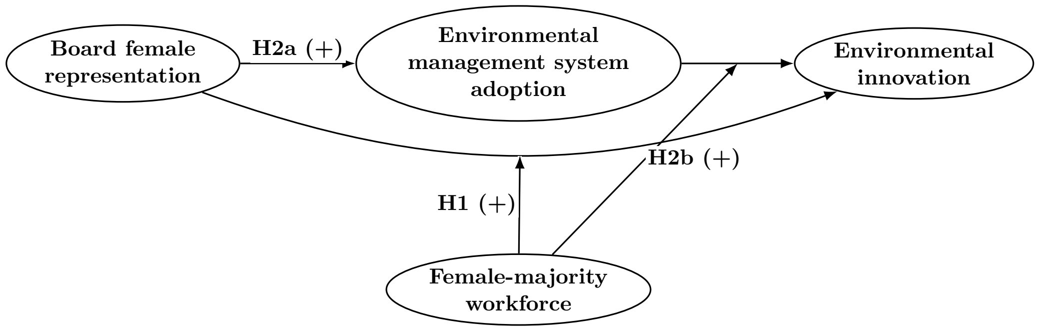

Figure 2·1: Conceptual Model

2.3 Data Sources and Sample

2.3.1 Refinitiv ESG

The Refinitiv ESG database encapsulates time-series data on a firm's environmental, social, and governance (ESG) activities dating back to 2002. As of 2022, the database has a firm universe comprising over 12,500 firms globally, covering 85% of the global market cap.[3] Refinitiv's approach to due diligence and risk management incorporates data from various human intelligence sources, leveraging insights from investigative journalists, compliance professionals, and industry experts. This structured data is integrated into the World-Check database, accredited with the ISAE 3000 standard, an international standard for assurance over non-financial information. This accreditation ensures that the data processes and controls in place are robust and reliable.

In terms of data quality, Refinitiv owns a global network of data analysts who manually collect and input more than 630 raw data points from both firms' own corporate disclosures (e.g., annual reports, sustainability reports, and websites) and various third-party sources (e.g., non-governmental organization (NGO) websites, major news sources) into an automated data production pipeline equipped with over 400 error check logics. Post-production involves about 300 automated quality checks

[3] https://www.lseg.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

in the data collection tool, addressing interconnected data points, negative screening, and verification of both quantitative and qualitative data consistency. Independent audits conducted daily provide detailed examination and critical evaluation of data points, supplemented by weekly reporting and root cause analysis to refine production processes. Finally, management reviews, including monthly in-depth quality analyses and the creation of new validation checks based on continuous learning and feedback, solidify the database's reliability.

The Refinitiv ESG database's computational hierarchy is as follows: a sustainability performance measure is determined for each firm in the environmental, social, and governance areas, referred to as pillars. There are ten dimensions underlying the environmental (dimensions: Emissions, Innovation, Resource Use), social (dimensions: Community, Human Rights, Product Responsibility, Workforce), and governance (dimensions: Management, Shareholders, CSR strategy) areas. Each dimension is operationalized by some subset of the initial data pool determined by each data point's availability and universal relevance to all firms in the Refinitiv's firm universe. The set of data points corresponding to each dimension is used to compute the dimension score. For each dimension, there is a set of themes and each theme, when possible, is operationalized by a specific data point. For each data point corresponding to a theme, an industry-specific magnitude weight is assigned to reflect the relative importance of the theme to that industry group; the weighted points are then averaged to produce a dimension score.

For this study, we use the Innovation dimension score as our measure of a firm's environmental-innovation performance. In Refinitiv, the Innovation dimension aggregates data drawn from items such as: percentage of revenue derived from green products or services; R&D spending on products and services that improve environmental impact; share of total energy generated from renewable sources; disclosure of eco-designed product lines; reporting of products with positive environmental effects (e.g., noise-reducing technologies); adherence to the Equator Principles for project finance; evaluation of projects on biodiversity criteria; and initiatives to supply organic or other environmentally preferable products. The full list of data points that constitute the Innovation score, as well as a sample of raw observations for several of these items, is provided in the E-companion (Tables EC.1-EC.6).

2.3.2 Compustat North America Database

Firm-level financial information is drawn from Compustat North America. More specifically, select data retrieved from the Fundamentals Annual and Financial Ratios Firm Level databases are used as firm-level financial controls for econometric analyses.

2.3.3 BoardEx Database

The BoardEx database is the most comprehensive database providing biographical data such as age, gender, positions held, educational qualifications, prior professional experience, compensations and stock holdings, and professional networks on 1.7 million corporate executives and board members from over 2.2 million listed, unlisted, educational, and NGO organizations. Compared to competing data vendors such as Compustat Execucomp and ISS (formerly Riskmetrics), BoardEx has a greater regional and company coverage.

2.3.4 Sample Construction

Our sample construction proceeds in several steps. First, we obtain firm-year observations from Refinitiv ESG covering the period 2011–2023. We retain observations with non-missing values for environmental innovation, board female representation (BFR), the share of female employees in the workforce (WFR), the share of female executives, average board tenure, board size, the percentage of independent directors, the presence of sustainability-related compensation incentives, the presence of a CSR or sustainability committee, and whether the CEO also serves on the board. Following common practice, we exclude financial firms (two-digit SIC codes 60–69) because their regulatory environment and financial structure differ substantially from those of non-financial firms.

Next, we merge these observations with financial information from Compustat, including firm size (log total assets), capital expenditures (log), return on equity, the cash ratio, and the debt-to-equity ratio. We then merge the resulting dataset with board demographic information from BoardEx to construct a measure of board age diversity, giving rise to the baseline sample.

For the analysis of H1, we further merge the baseline sample with non-missing values for two instrumental variables constructed from Refinitiv ESG: the industry-average level of BFR and the state-average level of BFR among firms headquartered in the same U.S. state. To avoid mechanical relevance, both IVs are computed using the leave-out-the-focal-firm approach. The final sample for H1 consists of 2,811 firm-year observations spanning 53 industries.

For the analysis of H2, we merge the baseline sample with information on whether a firm adopts an EMS (e.g., ISO 14001 certification) from Refinitiv ESG. The final sample for H2 contains 3,220 firm-year observations across 57 industries.

2.4 Measures

Table 2.1: Variable Definitions and Data Sources

Variable	Definition & Measure	Data Source
Independent Variable		
BFR	Percentage of board members who are female.	Refinitiv ESG
Moderating Variable		
FemaleMajorityWorkforce	Dummy =1 if female workforce share > 50%.	Refinitiv ESG
Mediating Variable		
EMS	Dummy =1 if a firm adopts an environmental management system (e.g., ISO 14001).	Refinitiv ESG
Control Variable		
TotalAssets_log	ln(total assets).	Compustat (Fundamentals Annual)
CapitalExpenditures_log	ln(capital expenditures).	Compustat (Fundamentals Annual)
ReturnOnEquity	Return on equity.	Compustat (Financial Ratios)
CashRatio	Cash / total liabilities.	Compustat (Financial Ratios)
DebtEquityRatio	Long-term debt / total equity.	Compustat (Financial Ratios)
CeoBoardMember	Dummy =1 if CEO also sits on the board.	Refinitiv ESG

Continued on next page

Table 2.1 (continued from previous page)

Variable	Definition	Data Source
CsrSustainabilityCommittee	Dummy =1 if firm has CSR committee/team at board or senior-management level.	Refinitiv ESG
Sustainability-CompensationIncentives	Dummy =1 if executive compensation is tied to CSR/ESG targets.	Refinitiv ESG
IndependentBoardMembers	Percentage of independent directors.	Refinitiv ESG
BoardSize	Board size (count).	Refinitiv ESG
AverageBoardTenure	Average director tenure (years).	Refinitiv ESG
ExecutiveMembersGender-DiversityPercent	Share of executives who are female.	Refinitiv ESG
WFR	Share of workforce that is female.	Refinitiv ESG
BoardAgeDiversity	Std. dev. of directors' ages.	BoardEx
Instrument		
IndustryAverageBFR	Industry-average BFR (2-digit SIC, focal firm's BFR excluded).	Refinitiv ESG
HQStateAverageBFR	Average BFR of peer firms headquartered in the same U.S. state as a focal firm (focal firm's BFR excluded).	Refinitiv ESG

Continued on next page

Table 2.1 (continued from previous page)

Variable	Definition	Data Source
Dependent Variable		
EnvironmentalInnovation	Composite score capturing a firm's capability to reduce customers' environmental burden and create green market opportunities (eco-products, processes).	Refinitiv ESG

Table 2.2: Summary Statistics: H1

	N	mean	sd	skewness	min	q25	median	q75	max
Independent Variable									
BFR	2811	27.04	9.98	0.29	0	20	27.27	33.33	66.67
Moderating Variable									
FemaleMajorityWorkforce	2811	0.15	0.36	1.92	0	0	0	0	1
Instruments									
IndustryAverageBFR	2811	20.20	7.03	-0.70	1.32	15.77	21.98	25.56	37.80
HQStateAverageBFR	2811	21.50	6.14	-0.26	0	17.26	22.17	25.33	35.83
Control Variables									
WFR	2811	33.68	15.74	0.83	0.84	22.53	30	43	92
ExecutiveMembersGenderDiversityPercent	2811	19.89	13.75	0.46	0	11.11	20	28.57	75
TotalAssets_log	2811	9.25	1.59	-0.13	3.44	8.10	9.28	10.41	13.04
CapitalExpenditures_log	2811	8.36	0.41	2.57	8.09	8.11	8.19	8.42	11.11
ReturnOnEquity	2811	0.15	0.45	0.54	-8.79	0.04	0.12	0.24	6.52
CashRatio	2811	0.33	0.88	9.64	0	0.05	0.13	0.31	17.34
DebtEquityRatio	2811	1.31	4.70	27.91	0	0.38	0.70	1.23	186.42
CeoBoardMember	2811	0.99	0.09	-10.91	0	1	1	1	1
CsrSustainabilityCommittee	2811	0.99	0.11	-9.21	0	1	1	1	1
SustainabilityCompensationIncentives	2811	0.48	0.50	0.09	0	0	0	1	1
IndependentBoardMembers	2811	84.71	8.92	-1.90	28.57	80	87.50	90.91	100
BoardSize	2811	10.61	3.59	20.99	4	9	11	12	138
AverageBoardTenure	2811	8.18	3.02	0.58	0	6.22	7.98	9.80	20.81
BoardAgeDiversity	2811	7.39	2.25	0.78	2.01	5.77	7	8.66	17.58
Dependent Variable									
EnvironmentalInnovation	2811	0.38	0.31	0.20	0	0	0.38	0.61	1

All non-integer results recorded with two decimal places.

Table 2.3: Summary Statistics: H2

	N	mean	sd	skewness	min	q25	median	q75	max
Independent Variable									
BFR	3220	26.21	10.08	0.30	0	20	25	33.33	66.67
Mediating Variable									
EMS	3220	0.74	0.44	-1.11	0	0	1	1	1
Moderating Variable									
FemaleMajorityWorkforce	3220	0.16	0.36	1.87	0	0	0	0	1
Control Variables									
WFR	3220	33.73	15.73	0.81	0.84	22.59	30	44	92
ExecutiveMembersGenderDiversityPercent	3220	19.60	13.56	0.49	0	11.11	18.18	28.57	75
TotalAssets_log	3220	9.30	1.57	-0.14	3.44	8.19	9.34	10.44	13.53
CapitalExpenditures_log	3220	8.37	0.41	2.51	8.09	8.12	8.19	8.44	11.11
ReturnOnEquity	3220	0.16	0.44	0.98	-8.79	0.05	0.12	0.23	6.52
CashRatio	3220	0.32	0.84	9.82	0	0.05	0.12	0.30	17.34
DebtEquityRatio	3220	1.31	5.21	26.23	0	0.38	0.68	1.19	186.42
CeoBoardMember	3220	0.99	0.09	-11.21	0	1	1	1	1
CsrSustainabilityCommittee	3220	0.99	0.12	-8.09	0	1	1	1	1
SustainabilityCompensationIncentives	3220	0.49	0.50	0.04	0	0	0	1	1
IndependentBoardMembers	3220	84.71	8.82	-1.88	28.57	80	87.50	90.91	100
BoardSize	3220	10.67	3.45	20.69	4	9	11	12	138
AverageBoardTenure	3220	8.27	3.01	0.55	0	6.33	8.08	9.88	20.81
BoardAgeDiversity	3220	7.35	2.21	0.80	2.01	5.78	6.99	8.57	17.58
Dependent Variable									
EnvironmentalInnovation	3220	0.38	0.31	0.19	0	0	0.38	0.62	1

All non-integer results recorded with two decimal places.

Table 2.4: Correlation Matrix: H1

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 BFR_{t-1}																			
2 WFR_{t-1}	0.29***																		
3 $FemaleMajorityWorkforce_{t-1}$	0.20***	0.75***																	
4 $IndustryAverageBFR_{t-1}$	0.38***	0.13***	0.10***																
5 $HQStateAverageBFR_{t-1}$	0.39***	0.14***	0.09***	0.79***															
6 $ExecutiveMembersGenderDiversityPercent_{t-1}$	0.30***	0.14***	0.12***	0.16***	0.13***														
7 $TotalAssets\_log_{t-1}$	0.01	-0.08***	-0.12***	-0.23***	-0.29***	0.07***													
8 $CapitalExpenditures\_log_{t-1}$	-0.01	-0.14***	-0.14***	-0.18***	-0.24***	0.00	0.72***												
9 $CashRatio_{t-1}$	0.00	0.09***	0.08***	0.04*	0.14***	-0.02	-0.29***	-0.11***											
10 $ReturnOnEquity_{t-1}$	0.05**	0.02	-0.03	-0.02	-0.02	0.09***	0.14***	0.05**	-0.11***										
11 $DebtEquityRatio_{t-1}$	0.03	0.06**	0.04*	0.05**	0.02	0.05*	0.01	-0.02	-0.06**	0.01									
12 $CeoBoardMember_{t-1}$	0.04*	0.00	0.04*	-0.02	-0.01	0.02	0.01	0.00	-0.10***	-0.01	-0.01								
13 $CsrSustainabilityCommittee_{t-1}$	0.03	0.01	0.01	0.12***	0.09***	0.01	0.01	-0.01	0.00	-0.02	0.01	0.03							
14 $SustainabilityCompensationIncentives_{t-1}$	0.04*	-0.17***	-0.07***	0.02	-0.02	0.07***	0.24***	0.22***	-0.12***	-0.03	0.03	0.04*	0.02						
15 $IndependentBoardMembers_{t-1}$	0.16***	-0.06***	-0.05**	-0.01	0.00	0.13***	0.14***	0.07***	-0.08***	0.08***	0.02	0.08***	0.09***	0.15***					
16 $BoardSize_{t-1}$	-0.02	0.03	-0.01	-0.10***	-0.14***	0.05**	0.35***	0.19***	-0.12***	0.06***	0.01	0.02	0.00	0.09***	0.02				
17 $AverageBoardTenure_{t-1}$	-0.05**	0.06**	0.03	-0.06***	-0.07***	-0.03	0.05*	0.01	-0.04*	0.09***	-0.04*	0.05*	0.00	-0.03	-0.10***	0.08***			
18 $BoardAgeDiversity_{t-1}$	-0.08***	0.10***	0.07***	0.07***	0.09***	-0.06**	-0.16***	-0.15***	0.05**	-0.07***	0.04*	-0.05**	-0.04*	-0.09***	-0.28***	-0.02	0.01		
19 $ESGInnovationScore_{t}$	0.01	-0.19***	-0.20***	-0.02	-0.07***	0.00	0.28***	0.21***	-0.14***	0.10***	-0.01	0.00	0.04*	0.08***	0.08***	0.13***	0.11***	-0.10***	

Notes: All non-integer results are recorded with two decimal places; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 2.5: Correlation Matrix: H2

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 BFR_{t-1}																		
2 WFR_{t-1}	0.28***																	
3 $FemaleMajorityWorkforce_{t-1}$	0.19***	0.75***																
4 EMS_{t-1}	0.25***	0.03	0.03															
5 $ExecutiveMembersGenderDiversityPercent_{t-1}$	0.30***	0.13***	0.12***	0.05**														
6 $TotalAssets\_log_{t-1}$	0.00	-0.06***	-0.10***	0.05**	0.08***													
7 $CapitalExpenditures\_log_{t-1}$	-0.01	-0.13***	-0.12***	0.03	0.01	0.72***												
8 $CashRatio_{t-1}$	0.00	0.08***	0.06***	-0.06***	-0.01	-0.27***	-0.11***											
9 $ReturnOnEquity_{t-1}$	0.06**	0.03	-0.02	0.04*	0.10***	0.14***	0.04*	-0.10***										
10 $DebtEquityRatio_{t-1}$	0.04*	0.04*	0.03	0.02	0.06**	0.02	-0.02	-0.05**	0.12***									
11 $CeoBoardMember_{t-1}$	0.04*	0.00	0.04*	0.01	0.02	0.01	0.00	-0.09***	0.01	-0.01								
12 $CsrSustainabilityCommittee_{t-1}$	0.04*	0.00	0.01	0.05**	0.02	-0.01	-0.03	0.00	-0.01	0.01	0.02							
13 $SustainabilityCompensationIncentives_{t-1}$	0.01	-0.17***	-0.07***	0.08***	0.06***	0.25***	0.23***	-0.12***	-0.03	0.03	0.03	0.01						
14 $IndependentBoardMembers_{t-1}$	0.16***	-0.06***	-0.05**	0.03	0.14***	0.14***	0.07***	-0.08***	0.08***	0.01	0.06***	0.08***	0.15***					
15 $BoardSize_{t-1}$	-0.02	0.03	-0.01	-0.03	0.05**	0.36***	0.21***	-0.13***	0.07***	0.01	0.03	-0.01	0.09***	0.02				
16 $AverageBoardTenure_{t-1}$	-0.06***	0.07***	0.03	0.00	-0.03*	0.04*	0.00	-0.03	0.09***	-0.04*	0.05**	-0.03	-0.04*	-0.10***	0.09***			
17 $BoardAgeDiversity_{t-1}$	-0.08***	0.07***	0.05**	-0.03	-0.06***	-0.16***	-0.15***	0.06***	-0.07***	0.03	-0.05**	-0.03	-0.10***	-0.29***	-0.02	0.01		
18 $ESGInnovationScore_{t}$	0.02	-0.18***	-0.20***	0.02	0.00	0.28***	0.22***	-0.13***	0.09***	-0.02	0.00	0.03	0.08***	0.07***	0.13***	0.11***	-0.10***	

Notes: All non-integer results are recorded with two decimal places; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

2.5 Empirical Strategy

We examine how BFR and workforce gender composition relate to corporate environmental innovation using panel data on U.S. public firms from 2011–2023. Our empirical strategy proceeds in two stages corresponding to our hypotheses. All specifications exploit within-firm variation and include firm, industry, and year fixed effects. Standard errors are clustered at the firm level to account for serial correlation and persistent shocks within firms over time.

2.5.1 Hypothesis 1

Fixed-Effects OLS

Hypothesis 1 predicts that the relationship between BFR and environmental innovation is more positive when women constitute a majority of the workforce. We test this moderation prediction using a fixed-effects OLS specification that includes an interaction between lagged BFR and a female-majority workforce indicator:

$$\begin{aligned} \mathrm{EI}_{it} = {} & \beta_1 \mathrm{BFR}_{i,t-1} + \beta_2 \mathrm{FMW}_{i,t-1} + \beta_3 \big(\mathrm{BFR}_{i,t-1} \times \mathrm{FMW}_{i,t-1}\big) \\ & + \mathbf{X}_{i,t-1}\boldsymbol{\gamma} + \mu_i + \lambda_j + \tau_t + \varepsilon_{it}. \end{aligned} \tag{2.1}$$

Here, EI_{it} denotes environmental innovation and $\mathrm{FMW}_{i,t-1}$ is the female-majority workforce indicator. μ_i represents firm fixed effects, λ_j denotes two-digit SIC industry fixed effects, and τ_t captures year effects. $\mathbf{X}_{i,t-1}$ is a vector of lagged control variables. The coefficient β_3 measures whether the marginal effect of BFR on environmental innovation differs between female-majority and male-majority workforces.

Instrumental Variables (2SLS)

Although the fixed-effects model accounts for time-invariant heterogeneity, BFR may remain endogenous due to omitted time-varying factors. To address this concern, we estimate a two-stage least squares (2SLS) model that instruments for both $\mathrm{BFR}_{i,t-1}$ and its interaction with the female-majority workforce indicator.

Specifically, we instrument $\mathrm{BFR}_{i,t-1}$ using the lagged industry-average level of BFR, excluding the focal firm's BFR. Because the interaction term is also endogenous, we instrument $\mathrm{BFR}_{i,t-1} \times \mathrm{FMW}_{i,t-1}$ using the interaction between the industry-average BFR and the female-majority workforce indicator. This yields a just-identified system with two endogenous regressors and two excluded instruments.

Instrument relevance is assessed using first-stage diagnostics that evaluate the strength of the relationship between the instruments and the endogenous regressors. In the first stage, the excluded instruments exhibit substantial explanatory power for both endogenous variables. The cluster-robust first-stage Wald statistics equal 10.43 ($p < 0.001$) for $\mathrm{BFR}_{i,t-1}$ and 24.05 ($p < 0.001$) for the interaction term.

Moreover, following Stock and Yogo (2002), we compare the Cragg–Donald statistic to the size-based critical values for weak instruments. For a specification with two endogenous regressors and two instruments, the Stock–Yogo critical value for limiting the maximal size distortion of the Wald test to 10% is 7.03. Our Cragg–Donald statistic equals 30.1, which substantially exceeds this threshold, suggesting that weak-instrument concerns are unlikely to materially distort statistical inference in our setting.

As a robustness check, we re-estimate the model using an alternative instrument constructed from the average BFR of firms headquartered in the same U.S. state as the focal firm, excluding the focal firm's BFR. The results remain consistent, and the corresponding first-stage statistics continue to exceed standard weak-instrument thresholds (Wald statistics of 10.35 ($p < 0.001$) and 17.59 ($p < 0.001$); Cragg–Donald statistic of 27.5).

2.5.2 Hypothesis 2

Hypothesis 2 proposes that environmental management systems (EMS) constitute a mechanism linking board gender diversity to environmental innovation.

First Stage of the Mechanism

We first examine whether greater BFR increases the likelihood that a firm adopts an EMS. Because EMS adoption is a binary variable, we estimate a fixed-effects logit model:

$$\Pr(\mathrm{EMS}_{i,t-1} = 1) = \Lambda\Big(\alpha_1 \mathrm{BFR}_{i,t-1} + \mathbf{X}_{i,t-1}\boldsymbol{\delta} + \mu_i + \lambda_j + \tau_t\Big), \tag{2.2}$$

where $\Lambda(\cdot)$ denotes the logistic link function and the control variables and fixed effects are defined as in Equation (2.1).

Second Stage of the Mechanism

Next, we examine whether environmental management systems contribute to environmental innovation and whether this effect differs across workforce gender compositions. We estimate the following fixed-effects OLS specification:

$$\begin{aligned} \mathrm{EI}_{it} = {} & \theta_1 \mathrm{BFR}_{i,t-1} + \theta_2 \mathrm{EMS}_{i,t-1} + \theta_3 \big(\mathrm{EMS}_{i,t-1} \times \mathrm{FMW}_{i,t-1}\big) \\ & + \mathbf{X}_{i,t-1}\boldsymbol{\kappa} + \mu_i + \lambda_j + \tau_t + \eta_{it}. \end{aligned} \tag{2.3}$$

The coefficient θ_2 captures the average relationship between EMS adoption and environmental innovation, while θ_3 tests whether the effect of EMS differs depending on workforce gender composition.

2.6 Results

Table 2.6 provides initial support for Hypothesis 1. The interaction between lagged BFR and the female-majority workforce indicator is positive and statistically significant, suggesting that the relationship between BFR and environmental innovation is more favorable when women make up the majority of employees. At the same time, the standalone coefficient on BFR is negative and weakly significant, indicating that in firms without female-majority workforces, greater BFR is not associated with higher environmental innovation. Taken together, these estimates are consistent with the idea that workforce gender composition conditions when BFR is most beneficial.

To complement our primary specification based on a binary moderator, we conduct a secondary analysis that models workforce gender composition (WFR) as a continuous variable with a quadratic term. This specification allows us to relax the discrete majority threshold and examine whether the moderating role of workforce composition follows a more flexible, non-linear pattern.

The results are reported in Table 2.7. The interaction between BFR and the squared term of WFR is positive and statistically significant, while the linear interaction term is negative. This pattern implies a non-linear moderating effect of workforce gender composition on the relationship between board gender diversity and environmental innovation. Specifically, the marginal effect of BFR on environmental innovation is attenuated at intermediate levels of WFR (WFR $= \sim 22\%$) and increases as workforce composition becomes more skewed.

Importantly, the economically meaningful portion of this pattern occurs at higher levels of workforce female representation. In this region, the marginal effect of BFR becomes stronger, consistent with a "critical mass" interpretation whereby greater demographic alignment between the board and workforce enhances the operational effectiveness of governance initiatives. In contrast, at lower levels of WFR, the estimated marginal effects remain small and statistically indistinguishable from zero, suggesting limited operational translation of board-level diversity in such contexts.

Taken together, this continuous specification reinforces our main findings from the binary moderator analysis. While the quadratic model uncovers a non-linear pattern, it converges on the same substantive conclusion: the positive impact of board gender diversity on environmental innovation is concentrated in contexts where female representation in the workforce is sufficiently high to support effective implementation. This finding also mitigates concerns that the binary specification imposes an arbitrary threshold, as the continuous analysis yields consistent qualitative insights.

The IV-2SLS results in Table 2.8 reinforce this conclusion. In the second stage, the coefficient on the instrumented interaction term remains positive and significant, while the coefficient on instrumented BFR alone is not statistically different from zero. This pattern suggests that the positive governance effect emerges primarily in firms with female-majority workforces. The first-stage results further indicate that the excluded instruments are relevant predictors of both endogenous regressors. The first-stage Wald statistics exceed 10 for both endogenous variables, and the Cragg–Donald statistic is 30.1, reducing concerns that the findings are driven by weak instruments.

Table 2.9 shows that the main result is robust to an alternative instrument based on state-level peer BFR. The interaction term remains positive and statistically significant, although somewhat smaller in magnitude, and the first-stage diagnostics continue to exceed conventional weak-instrument thresholds. The main effect of instrumented BFR becomes negative and significant in this alternative specification, but the overall pattern remains the same: the estimated effect of BFR is more positive in firms with female-majority workforces than in those without them.

The Hypothesis 2 results shed light on a possible operations mechanism. Table 2.10 shows that higher BFR is associated with a greater likelihood of adopting an EMS, providing support for the first part of the mechanism. Table 2.11 then shows that EMS adoption is associated with higher environmental innovation specifically in female-majority firms, as indicated by the positive and significant interaction between EMS and the female-majority workforce indicator. The standalone EMS coefficient is near zero, suggesting that formal environmental systems do not uniformly translate into environmental innovation outcomes; rather, their effectiveness appears to depend on workforce gender representation. Overall, these findings are consistent with the view that female-majority workforces strengthen the conditions under which both BFR and EMS adoption translate into greater environmental innovation.

Table 2.6: FE-OLS Results of Hypothesis 1

Dependent Variable:	$\text{ESGInnovationScore}_t$
BFR_{t-1}	-0.0009
	(0.0008)
WFR_{t-1}	0.0023
	(0.0022)
$\text{FemaleMajorityWorkforce}_{t-1}$	-0.1108
	(0.0817)
$\text{BFR}_{t-1} \times \text{FemaleMajorityWorkforce}_{t-1}$	0.0046^{**}
	(0.0023)
$\text{ExecutiveMembersGenderDiversityPercent}_{t-1}$	-0.0007
	(0.0008)

Continued on next page

Table 2.6: FE-OLS Results of Hypothesis 1 (continued)

Dependent Variable:	$\text{ESGInnovationScore}_t$
$\text{TotalAssets\_log}_{t-1}$	0.0250
	(0.0256)
$\text{CapitalExpenditures\_log}_{t-1}$	0.1507^{**}
	(0.0686)
CashRatio_{t-1}	-0.0014
	(0.0096)
$\text{ReturnOnEquity}_{t-1}$	0.0166
	(0.0107)
$\text{DebtEquityRatio}_{t-1}$	0.0004
	(0.0005)
$\text{CeoBoardMember}_{t-1}$	-0.0268
	(0.0321)
$\text{CsrSustainabilityCommittee}_{t-1}$	0.0500
	(0.0397)
$\text{SustainabilityCompensationIncentives}_{t-1}$	0.0229^{*}
	(0.0128)
$\text{IndependentBoardMembers}_{t-1}$	-0.0011
	(0.0009)
BoardSize_{t-1}	-0.0001
	(0.0008)
$\text{AverageBoardTenure}_{t-1}$	-0.0092^{**}
	(0.0046)
$\text{BoardAgeDiversity}_{t-1}$	0.0019
	(0.0039)
Firm FE	Yes

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Table 2.6: FE-OLS Results of Hypothesis 1 (continued)

Dependent Variable:	$\text{ESGInnovationScore}_t$
Industry FE	Yes
Year FE	Yes
Observations	2,811
R^2	0.8819
Within R^2	0.0455

Standard errors clustered at the firm (ticker) level are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 2.7: FE-OLS Results with Continuous Workforce Gender Composition

Dependent Variable:	$\text{ESGInnovationScore}_t$
BFR_{t-1}	0.0004
	(0.0028)
WFR_{t-1}	0.0079
	(0.0064)
WFR^2_{t-1}	-0.0001
	(8.35×10^{-5})
$\text{BFR}_{t-1} \times \text{WFR}_{t-1}$	-0.0002
	(0.0002)
$\text{BFR}_{t-1} \times \text{WFR}^2_{t-1}$	$4.52 \times 10^{-6*}$
	(2.35×10^{-6})
$\text{ExecutiveMembersGenderDiversityPercent}_{t-1}$	-0.0007
	(0.0008)
$\text{TotalAssets\_log}_{t-1}$	0.0230

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Table 2.7: FE-OLS Results with Continuous Workforce Gender Composition (continued)

Dependent Variable:	$\text{ESGInnovationScore}_t$
	(0.0256)
$\text{CapitalExpenditures\_log}_{t-1}$	0.1518^{**}
	(0.0688)
CashRatio_{t-1}	-0.0024
	(0.0092)
$\text{ReturnOnEquity}_{t-1}$	0.0166
	(0.0108)
$\text{DebtEquityRatio}_{t-1}$	0.0004
	(0.0004)
$\text{CeoBoardMember}_{t-1}$	-0.0313
	(0.0327)
$\text{CsrSustainabilityCommittee}_{t-1}$	0.0483
	(0.0397)
$\text{SustainabilityCompensationIncentives}_{t-1}$	0.0232^{*}
	(0.0127)
$\text{IndependentBoardMembers}_{t-1}$	-0.0011
	(0.0009)
BoardSize_{t-1}	-3.48×10^{-5}
	(0.0009)
$\text{AverageBoardTenure}_{t-1}$	-0.0092^{**}
	(0.0046)
$\text{BoardAgeDiversity}_{t-1}$	0.0017
	(0.0039)
Firm FE	Yes
Industry FE	Yes

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Table 2.7: FE-OLS Results with Continuous Workforce Gender Composition (continued)

Dependent Variable:	$\text{ESGInnovationScore}_t$
Year FE	Yes
Observations	2,811
R^2	0.8828
Within R^2	0.0530

Standard errors clustered at the firm (ticker) level are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 2.8: IV-2SLS Results of Hypothesis 1

	First Stage BFR_{t-1}	First Stage $\text{BFR}_{t-1}\times$ $\text{FemaleMajority}_{t-1}$	Second Stage ESGInnovation Score_t
$\text{IndustryAverageBFR}_{t-1}$	0.554***	0.042	
	(0.122)	(0.049)	
$\text{IndustryAverageBFR}_{t-1}\times$ $\text{FemaleMajority}_{t-1}$	-0.124	0.550***	
	(0.091)	(0.081)	
$\widehat{BFR}_{t-1}$			0.0075
			(0.0075)
$\widehat{BFR}_{t-1}\times$ $\text{FemaleMajority}_{t-1}$			0.0146**
			(0.0065)
WFR_{t-1}	0.189***	-0.002	0.0003
	(0.057)	(0.020)	(0.0024)
FemaleMajority Workforce_{t-1}	2.076	19.25***	-0.0896
	(1.835)	(1.640)	(0.0682)

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Table 2.8: IV-2SLS Results of Hypothesis 1 (continued)

	First Stage BFR_{t-1}	First Stage $BFR_{t-1}\times$ $FemaleMajority_{t-1}$	Second Stage ESGInnovation $Score_t$
ExecutiveMembers $GenderDiversityPercent_{t-1}$	-0.010	-0.002	-0.0006
	(0.022)	(0.010)	(0.0008)
$TotalAssets\_log_{t-1}$	-1.489	0.198	0.0291
	(1.049)	(0.241)	(0.0274)
$CapitalExpenditures\_log_{t-1}$	-0.820	-0.061	0.1622**
	(2.055)	(0.242)	(0.0723)
$CashRatio_{t-1}$	1.013	0.112	-0.0100
	(0.687)	(0.219)	(0.0135)
$ReturnOnEquity_{t-1}$	0.128	-0.034	0.0156
	(0.571)	(0.125)	(0.0128)
$DebtEquityRatio_{t-1}$	-0.003	0.005	0.0003
	(0.016)	(0.010)	(0.0005)
$CeoBoardMember_{t-1}$	-1.624	-1.208	0.0026
	(2.459)	(1.101)	(0.0376)
CsrSustainability $Committee_{t-1}$	-0.642	-0.553	0.0601
	(1.635)	(0.537)	(0.0403)
Sustainability $CompensationIncentives_{t-1}$	0.078	-0.102	0.0228*
	(0.456)	(0.120)	(0.0134)
Independent $BoardMembers_{t-1}$	0.106***	0.009	-0.0021
	(0.040)	(0.013)	(0.0014)
$BoardSize_{t-1}$	-0.098***	-0.035	0.0008
	(0.033)	(0.024)	(0.0011)
$AverageBoardTenure_{t-1}$	-0.413***	-0.046	-0.0056
	(0.159)	(0.052)	(0.0057)
$BoardAgeDiversity_{t-1}$	-0.217	-0.127**	0.0057

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Table 2.8: IV-2SLS Results of Hypothesis 1 (continued)

	First Stage BFR_{t-1}	First Stage $BFR_{t-1} \times$ $FemaleMajority_{t-1}$	Second Stage ESGInnovation $Score_t$
	(0.163)	(0.064)	(0.0046)
Firm FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	2,811	2,811	2,811
R^2	0.82453	0.9831	0.8835
Within R^2	0.06311	0.7815	0.05851
First-stage Wald statistic	10.43	24.05	

Standard errors clustered at the firm (ticker) level are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The Cragg–Donald statistic equals 30.1. For a specification with two endogenous regressors and two instruments, the Stock-Yogo critical value for limiting the maximal size distortion of the Wald test to 10% is 7.03. Because the reported statistic exceeds this threshold, weak-instrument concerns are unlikely to materially affect statistical inference.

Table 2.9: IV-2SLS Results of Hypothesis 1 (Alternative IV)

	First Stage BFR_{t-1}	First Stage $BFR_{t-1} \times$ $FemaleMajority_{t-1}$	Second Stage ESGInnovation $Score_t$
$HQStateAverageBFR_{t-1}$	0.5469***	-0.0654*	
	(0.1007)	(0.0396)	
$HQAverageBFR_{t-1} \times$ $FemaleMajority_{t-1}$	-0.0941	0.6495***	
	(0.1129)	(0.0986)	

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Table 2.9: IV-2SLS Results of Hypothesis 1 (Alternative IV) (continued)

	First Stage BFR_{t-1}	First Stage $BFR_{t-1}\times$ FemaleMajority$_{t-1}$	Second Stage ESGInnovation Score$_t$
$\widehat{BFR}_{t-1}$			-0.007
			(0.008)
$\widehat{BFR}_{t-1}\times$ FemaleMajority$_{t-1}$			0.0088**
			(0.0038)
WFR_{t-1}	0.1936***	-0.0083	0.0046*
	(0.0508)	(0.0265)	(0.0024)
FemaleMajority Workforce$_{t-1}$	0.6716	14.79***	-0.0788
	(2.142)	(2.085)	(0.0557)
ExecutiveMembers GenderDiversityPercent$_{t-1}$	0.0175	0.0154	-0.0006
	(0.0190)	(0.0100)	(0.0007)
TotalAssets_log$_{t-1}$	-1.243	0.5527	0.0086
	(0.8841)	(0.3418)	(0.0254)
CapitalExpenditures_log$_{t-1}$	-0.9941	-0.2197	0.1448**
	(1.817)	(0.3654)	(0.0694)
CashRatio$_{t-1}$	0.9826	0.0296	0.0098
	(0.6146)	(0.1849)	(0.0139)
ReturnOnEquity$_{t-1}$	0.2909	-0.0962	0.0182
	(0.4774)	(0.1398)	(0.0116)
DebtEquityRatio$_{t-1}$	0.0082	0.0092	0.0002
	(0.0136)	(0.0116)	(0.0003)
CeoBoardMember$_{t-1}$	-0.2781	-0.7875	-0.0260
	(2.409)	(1.020)	(0.0500)
CsrSustainability Committee$_{t-1}$	-0.7467	-0.3424	0.0679
	(1.537)	(0.3164)	(0.0517)

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Table 2.9: IV-2SLS Results of Hypothesis 1 (Alternative IV) (continued)

	First Stage BFR_{t-1}	First Stage $BFR_{t-1} \times$ $FemaleMajority_{t-1}$	Second Stage ESGInnovation $Score_t$
Sustainability $CompensationIncentives_{t-1}$	0.3482	0.0298	0.0280^{**}
	(0.3978)	(0.1309)	(0.0126)
Independent $BoardMembers_{t-1}$	0.1019^{***}	0.0187	0.0011
	(0.0355)	(0.0133)	(0.0011)
$BoardSize_{t-1}$	-0.0864^{***}	-0.0187	-0.0014
	(0.0286)	(0.0199)	(0.0011)
$AverageBoardTenure_{t-1}$	-0.2483^{*}	0.0640	-0.0097^{**}
	(0.1484)	(0.0742)	(0.0046)
$BoardAgeDiversity_{t-1}$	-0.1209	-0.0585	-0.0012
	(0.1448)	(0.0647)	(0.0040)
Firm FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	2811	2811	2811
R^2	0.8242	0.9827	0.8827
Within R^2	0.06142	0.7766	0.5221
First-stage Wald statistic	10.35	17.59	

Standard errors clustered at the firm (ticker) level are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The Cragg–Donald statistic equals 27.5. For a specification with two endogenous regressors and two instruments, the Stock-Yogo critical value for limiting the maximal size distortion of the Wald test to 10% is 7.03. Because the reported statistic exceeds this threshold, weak-instrument concerns are unlikely to materially affect statistical inference.

Table 2.10: FE-Logit Results of Hypothesis 2a

Dependent Variable:	EMS_{t-1}
BFR_{t-1}	0.1438^{***}
	(0.0171)
WFR_{t-1}	-0.0472^{*}
	(0.0279)
$ExecutiveMembersGenderDiversityPercent_{t-1}$	-0.0176
	(0.0116)
$TotalAssets\_log_{t-1}$	-0.2989
	(0.4962)
$CapitalExpenditures\_log_{t-1}$	0.2676
	(0.8112)
$CashRatio_{t-1}$	-0.1941
	(0.5501)
$ReturnOnEquity_{t-1}$	0.0871
	(0.3900)
$DebtEquityRatio_{t-1}$	0.0025
	(0.0242)
$CeoBoardMember_{t-1}$	-0.7346
	(1.3480)
$CsrSustainabilityCommittee_{t-1}$	0.2078
	(0.7873)
$SustainabilityCompensationIncentives_{t-1}$	0.1862
	(0.2271)
$IndependentBoardMembers_{t-1}$	-0.0317^{*}
	(0.0165)
$BoardSize_{t-1}$	-0.0334

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Table 2.10: FE-Logit Results of Hypothesis 2a (continued)

Dependent Variable:	EMS_{t-1}
	(0.0218)
$\text{AverageBoardTenure}_{t-1}$	0.1076^{*}
	(0.0624)
$\text{BoardAgeDiversity}_{t-1}$	-0.0498
	(0.0598)
Firm FE	Yes
Industry FE	Yes
Year FE	Yes
Observations	3,220
Squared correlation	0.5028
Pseudo R^2	0.4869
BIC	9,306.5

Standard errors clustered at the firm (ticker) level are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 2.11: FE-OLS Results of Hypothesis 2b

Dependent Variable:	$\text{ESGInnovationScore}_{t}$
BFR_{t-1}	-0.0003
	(0.0007)
WFR_{t-1}	0.0028
	(0.0018)
EMS_{t-1}	-0.0017
	(0.0088)

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Table 2.11: FE-OLS Results of Hypothesis 2b (continued)

Dependent Variable:	$\text{ESGInnovationScore}_t$
$\text{FemaleMajorityWorkforce}_{t-1}$	-0.0139
	(0.0335)
$\text{EMS}_{t-1} \times \text{FemaleMajorityWorkforce}_{t-1}$	0.0537^{**}
	(0.0248)
$\text{ExecutiveMembersGenderDiversityPercent}_{t-1}$	-0.0010
	(0.0007)
$\text{TotalAssets\_log}_{t-1}$	0.0031
	(0.0252)
$\text{CapitalExpenditures\_log}_{t-1}$	0.1294^{*}
	(0.0662)
CashRatio_{t-1}	0.0213
	(0.0140)
$\text{ReturnOnEquity}_{t-1}$	-0.0011
	(0.0115)
$\text{DebtEquityRatio}_{t-1}$	-0.0013
	(0.0011)
$\text{CeoBoardMember}_{t-1}$	-0.0228
	(0.0263)
$\text{CsrSustainabilityCommittee}_{t-1}$	0.0540
	(0.0456)
$\text{SustainabilityCompensationIncentives}_{t-1}$	0.0090
	(0.0126)
$\text{IndependentBoardMembers}_{t-1}$	-0.0008
	(0.0009)
BoardSize_{t-1}	-0.0004

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Table 2.11: FE-OLS Results of Hypothesis 2b (continued)

Dependent Variable:	$\text{ESGInnovationScore}_t$
	(0.0009)
$\text{AverageBoardTenure}_{t-1}$	-0.0056
	(0.0043)
$\text{BoardAgeDiversity}_{t-1}$	-0.0030
	(0.0034)
Firm FE	Yes
Industry FE	Yes
Year FE	Yes
Observations	3,220
R^2	0.8606
Within R^2	0.0311

Standard errors clustered at the firm (ticker) level are reported in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

2.7 Supplementary Sub-Sample Analysis

The subsample analyses reported in Tables 2.12 and 2.13 help clarify the managerial interpretation of the moderating role of workforce gender composition. In many industries, the gender distribution of employees is shaped by the nature of the firm's activities. For example, firms operating in a service industry (i.e., firms operating in industries with two-digit SIC codes between 70 and 89; e.g., Microsoft as discussed in Section 2.1) often employ a larger share of women, whereas manufacturing firms (i.e., firms operating in industries with two-digit SIC codes between 20 and 39) tend to be more male-dominated. As a result, workforce gender composition may not always be easily altered by managerial choice. In our framework, however, workforce gender composition is not the primary lever of interest. Instead, it represents an organizational context that influences the effectiveness of another governance decision—namely, increasing BFR.

The results suggest that the impact of BFR on environmental innovation depends partly on this organizational context. In the service-sector subsample, where female-majority workforces are more prevalent, the interaction between BFR and the female-majority workforce indicator is positive and statistically significant. This indicates that when women constitute a large share of employees, increases in BFR are more strongly associated with higher levels of environmental innovation. In contrast, the same interaction term is smaller and statistically insignificant in the manufacturing subsample, where female-majority workforces are comparatively rare. Taken together, these patterns imply that the relationship between BFR and environmental innovation is not uniform across sectors, but varies systematically with the gender composition of the workforce.

Importantly, these findings do not imply that firms should attempt to change the gender composition of their workforce in order to improve environmental innovation. Rather, the results highlight how the effectiveness of a governance decision—adfding female directors to the board and thereby increasing BFR—depends on the characteristics of the existing workforce. Firms operating in industries where women represent a substantial share of employees may benefit more from increasing BFR, as the alignment between board composition and workforce composition appears to strengthen the translation of governance diversity into environmentally innovative outcomes. In this sense, workforce gender composition functions as a boundary condition that helps managers identify when increasing BFR is most likely to yield the greatest environmental innovation benefits.

Table 2.12: FE-OLS Results of Hypothesis 1 (Manufacturing Sector Subsample)

Dependent Variable:	$\text{ESGInnovationScore}_t$
BFR_{t-1}	0.0002
	(0.0011)
WFR_{t-1}	0.0036
	(0.0022)
$\text{FemaleMajorityWorkforce}_{t-1}$	−0.0568
	(0.0795)
$\text{BFR}_{t-1} \times \text{FemaleMajorityWorkforce}_{t-1}$	0.0032
	(0.0026)
$\text{ExecutiveMembersGenderDiversityPercent}_{t-1}$	−0.0011
	(0.0009)
$\text{TotalAssets\_log}_{t-1}$	0.0054
	(0.0325)
$\text{CapitalExpenditures\_log}_{t-1}$	0.2599^{***}
	(0.1003)
CashRatio_{t-1}	0.0028
	(0.0119)
$\text{ReturnOnEquity}_{t-1}$	−0.0066
	(0.0173)
$\text{DebtEquityRatio}_{t-1}$	−0.0016
	(0.0012)
$\text{CeoBoardMember}_{t-1}$	−0.0075
	(0.0218)
$\text{CsrSustainabilityCommittee}_{t-1}$	0.1734^{**}
	(0.0767)

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Table 2.12: FE-OLS Results of Hypothesis 1 (Manufacturing Sector Subsample) (continued)

Dependent Variable:	$\text{ESGInnovationScore}_t$
$\text{SustainabilityCompensationIncentives}_{t-1}$	0.0081
	(0.0186)
$\text{IndependentBoardMembers}_{t-1}$	−0.0012
	(0.0013)
BoardSize_{t-1}	0.0001
	(0.0008)
$\text{AverageBoardTenure}_{t-1}$	−0.0084
	(0.0062)
$\text{BoardAgeDiversity}_{t-1}$	0.0023
	(0.0049)
Firm FE	Yes
Industry FE	Yes
Year FE	Yes
Observations	1,655
R^2	0.8512
Within R^2	0.0705

Standard errors clustered at the firm (ticker) level are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The manufacturing subsample includes firms with two-digit SIC codes between 20 and 39.

Table 2.13: FE-OLS Results of Hypothesis 1 (Service Sector Subsample)

Dependent Variable:	$\text{ESGInnovationScore}_t$
BFR_{t-1}	-0.0009
	(0.0012)
WFR_{t-1}	0.0056
	(0.0039)
$\text{FemaleMajorityWorkforce}_{t-1}$	-0.1843^{**}
	(0.0906)
$\text{BFR}_{t-1}\times$ $\text{FemaleMajorityWorkforce}_{t-1}$	0.0061^{***}
	(0.0022)
$\text{ExecutiveMembersGenderDiversityPercent}_{t-1}$	-0.0004
	(0.0005)
$\text{TotalAssets\_log}_{t-1}$	-0.0138
	(0.0420)
$\text{CapitalExpenditures\_log}_{t-1}$	0.0493
	(0.0619)
CashRatio_{t-1}	0.0293
	(0.0252)
$\text{ReturnOnEquity}_{t-1}$	0.0254
	(0.0212)
$\text{DebtEquityRatio}_{t-1}$	0.0002
	(0.0027)
$\text{CeoBoardMember}_{t-1}$	-0.1402
	(0.1262)
$\text{CsrSustainabilityCommittee}_{t-1}$	-0.0524
	(0.0324)
$\text{SustainabilityCompensationIncentives}_{t-1}$	0.0069

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Table 2.13: FE-OLS Results of Hypothesis 1 (Service Sector Subsample) (continued)

Dependent Variable:	$\text{ESGInnovationScore}_t$
	(0.0161)
$\text{IndependentBoardMembers}_{t-1}$	-0.0037^{**}
	(0.0015)
BoardSize_{t-1}	-0.0083
	(0.0052)
$\text{AverageBoardTenure}_{t-1}$	-0.0098
	(0.0068)
$\text{BoardAgeDiversity}_{t-1}$	-0.0265^{***}
	(0.0076)
Firm FE	Yes
Industry FE	Yes
Year FE	Yes
Observations	460
R^2	0.9282
Within R^2	0.1941

Standard errors clustered at the firm (ticker) level are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The service sector subsample includes firms with two-digit SIC codes between 70 and 89.

2.8 Discussion

Operations scholars studying diversity, equity, and inclusion continue to debate whether and when gender representation across organizational layers—from frontline roles to corporate governance—produces substantive changes in the operating systems that underlie sustainable competitive advantage. Prior research provides mixed evidence. On the one hand, gender representation has been linked to concrete operational outcomes, such as faster product recalls that mitigate consumer safety risks (Wowak et al., 2021) and improved service quality when demographic alignment between employees and customers reduces discriminatory frictions (Son et al., 2024). On the other hand, a substantial literature cautions that firms may respond to external pressure by expanding boards rather than reallocating decision rights, thereby increasing symbolic diversity without altering how work is organized or executed (Knippen et al., 2019). Evidence from employee reactions similarly suggests that representation alone does not guarantee operational improvement and may even provoke resistance when it is decoupled from changes in operational practices (Brenner et al., 2023).

Our study advances this debate by demonstrating that BFR translates into environmental innovation only when it is embedded in a specific operational context—namely, a female-majority workforce—and operates through an operational capability: the adoption of environmental management systems (EMS). Our results show that numerical representation becomes operationally consequential when it enables boards to influence the environmental management practices that shape employees' engagement in sustainability-oriented initiatives. Specifically, in female-majority workforces, greater BFR increases the likelihood that firms adopt EMS, which in turn enhances environmental innovation. This pattern highlights that governance diversity matters for environmental innovation because it influences the organizational systems that enable employees to generate and implement environmentally beneficial ideas.

By focusing on EMS adoption, we identify a mechanism that is firmly rooted in operations management. Environmental management systems represent administrative environmental innovations that institutionalize environmental monitoring, target setting, and performance review within operational routines (Melnyk et al., 2003;

Bellamy et al., 2020). These systems create the organizational infrastructure through which environmental initiatives are coordinated and improved. However, environmental management practices do not automatically translate into innovation outcomes. Rather, their effectiveness depends on employee engagement in environmental activities and initiatives. Prior research shows that organizational environmental practices influence employee perceptions that the firm values environmental behaviors, which increases employees' commitment to environmental initiatives and encourages them to propose and implement environmentally innovative practices (Cantor et al., 2012). Our findings therefore shed light on the microfoundations of environmental innovation: governance diversity shapes innovation outcomes when it leads firms to adopt operational systems that motivate employees to engage in sustainability-oriented problem solving.

Our results also refine the symbolic-versus-substantive distinction that runs through the diversity literature. Board gender diversity can remain symbolic when it does not translate into changes in organizational practices. However, when governance diversity influences operational systems—such as the adoption of EMS—it can generate substantive changes in how firms monitor environmental performance and encourage employee participation in sustainability initiatives. Importantly, our results show that this process is contingent on workforce composition. In female-majority workforces, greater BFR appears to amplify employee engagement in environmental management practices, thereby strengthening the link between EMS adoption and environmental innovation. In contrast, when women constitute a minority of the workforce, increases in BFR do not generate comparable innovation outcomes. In this sense, the effectiveness of governance diversity depends not only on representation itself but also on whether the workforce context enables employees to respond to governance signals.

The study contributes to the growing literature on inclusive operations by extending identity-congruence arguments to the level of corporate governance while grounding the mechanism in environmental management practices. Prior research shows that productivity gains from workforce diversity are realized when operational structures accommodate heterogeneous employee motivations and constraints (Narayanan and Terris, 2020; Zhang et al., 2023). Our results extend this insight by showing that board-level gender diversity can shape such operational structures—specifically through the adoption of environmental management systems—when women comprise a large share of the workforce. Moreover, whereas much sustainability research emphasizes external legitimacy or regulatory pressure as drivers of environmental initiatives (Kalkanci et al., 2019), we document an inward-facing channel: governance composition reshapes internal environmental management systems that enable employee-driven environmental innovation.

The managerial implications are correspondingly operational. Rather than treating board diversity as a stand-alone governance reform, firms should view board composition as part of a broader system that includes workforce demographics and operational practices. Workforce gender composition is often determined by industry characteristics and may not be easily altered by managerial decision. Our findings therefore suggest a more actionable implication: the effectiveness of increasing BFR depends partly on how well board composition aligns with the demographic structure of the existing workforce. In firms where women constitute a substantial share of employees, appointing additional female directors may enhance environmental innovation by strengthening the adoption and effectiveness of environmental management systems. In contrast, in male-dominated industries, increasing BFR alone may yield more limited environmental innovation gains unless accompanied by complementary changes in organizational practices.

More broadly, our findings position environmental management systems as a central operational lever through which governance diversity can shape sustainability outcomes.

While EMS adoption is often discussed in the context of stakeholder pressure and external legitimacy (Sarkis et al., 2010; Jacobs et al., 2010), our results highlight its internal operational role as a mechanism that mobilizes employee engagement in environmental initiatives. By linking board-level diversity to the adoption and effectiveness of EMS, this study underscores how governance structures can influence sustainability outcomes by reshaping the operational systems that guide employees' everyday work.

2.9 Limitations and Future Research

Like any empirical study, our analysis has several limitations that suggest opportunities for future research. First, our measure of workforce gender composition reflects the demographic structure of the firm at a given point in time, but it does not capture finer-grained organizational dynamics such as the distribution of women across hierarchical levels or functional roles. In practice, the influence of governance signals may depend not only on whether women constitute a numerical majority in the workforce but also on where they are located within the firm's operational structure. For example, female representation concentrated in administrative roles may generate different innovation dynamics than representation within engineering or production functions. Future research could extend our framework by examining how gender composition across occupational categories or organizational levels conditions the relationship between governance diversity and environmental innovation.

Second, although we identify environmental management systems (EMS) as an operational mechanism linking BFR to environmental innovation, our empirical design cannot directly observe the internal behavioral processes through which employees respond to environmental management practices. Prior research suggests that environmental management practices influence innovation outcomes by shaping employee perceptions of organizational support for environmental behaviors and motivating employees to engage in environmentally oriented initiatives (Cantor et al., 2012). However, our firm-level data do not allow us to directly observe these behavioral micro-foundations. Future research could address this limitation by combining survey-based measures of employee environmental engagement with archival operational data to more directly test the employee-level mechanisms through which governance structures influence environmental innovation.

Third, our analysis focuses on public U.S. firms, which operate in a particular institutional environment characterized by relatively developed corporate governance structures and strong sustainability reporting pressures. The relationship between board gender diversity, environmental management systems, and environmental innovation may differ in institutional contexts where corporate governance norms, labor market structures, or environmental regulatory regimes vary. Cross-country studies could therefore help identify how institutional environments shape the governance–operations relationship documented in this study.

Fourth, while our study conceptualizes workforce gender composition as an important contextual condition, we do not claim that firms can easily manipulate this factor in the short run. Workforce demographics are often shaped by industry characteristics, occupational requirements, and labor market conditions that evolve slowly over time. Nevertheless, future research could examine whether firms can influence the effectiveness of governance diversity through other operational interventions that complement existing workforce structures, such as changes in work design, training programs, or organizational communication practices that encourage employee participation in sustainability initiatives.

Finally, our study focuses on environmental innovation as a key sustainability outcome, but governance diversity may also influence other operational outcomes related to sustainability, such as supply chain environmental performance, process efficiency, or climate-risk management. Future research could extend our framework to examine whether similar governance–workforce alignment mechanisms operate in these domains. Exploring how governance diversity interacts with operational capabilities across different sustainability outcomes would further deepen our understanding of how firms translate governance priorities into tangible operational improvements.

Taken together, these limitations point to a broader research agenda at the intersection of corporate governance, workforce composition, and operational capability development. By examining how governance structures interact with internal organizational contexts to shape operational outcomes, future research can continue to advance a more people-centric understanding of how firms build sustainable operational advantages.

Chapter 3

Female Leadership, Sustainable Executive Compensation, and Responsible Supplier Governance

3.1 Introduction

Responsible supplier governance has become a central governance challenge for firms operating in globally dispersed and interdependent supply networks. Firms are increasingly held accountable not only for their own conduct but also for the environmental and social practices of their suppliers. In response, many firms formalize supplier governance through structured monitoring systems, audit procedures, corrective action protocols, and termination provisions embedded in Supplier Codes of Conduct. Together, these mechanisms constitute an operational governance architecture that separates ongoing monitoring from downstream escalation mechanisms addressing supplier misconduct. Although such architectures are formally documented, their implementation—particularly the design of monitoring systems and escalation provisions—depends on how supply-chain leaders allocate resources, interpret compliance signals, and define thresholds for supplier noncompliance.

Prior research demonstrates both the economic value and managerial complexity of responsible supplier governance. Consumers reward firms that invest in supplier monitoring efforts (Duan et al., 2021), yet governance responses to supplier misconduct often involve trade-offs between short-term operational efficiency and longer-term sustainability objectives (Wu and Pagell, 2011). Importantly, supplier monitoring systems and escalation mechanisms require judgment under conditions of uncertainty and incomplete information, suggesting that governance outcomes depend not only on formal policies but also on how authority is exercised within the supply-chain function (Griffis et al., 2014). These insights point to leadership at the apex of the supply-chain organization as a critical determinant of how supplier governance architectures are structured and implemented.

Drawing on prior supply chain management research, we argue that when the Chief Supply Chain Officer (CSCO) is positioned within a firm's senior executive structure, the role is associated with expanded decision rights over inter-organizational supply-chain processes (Wagner and Kemmerling, 2014). Elevating the CSCO to the upper echelon integrates supplier governance into firm-level strategic deliberation and reallocates authority over monitoring system design, risk assessment protocols, and escalation provisions addressing supplier noncompliance. Consistent with upper echelons theory (Hambrick and Mason, 1984), executive characteristics are most likely to shape organizational outcomes when leaders possess discretion over strategic choices. In the context of supply-chain partnership governance—where monitoring calibration and the design of escalation mechanisms involve managerial judgment rather than automatic rule enforcement—the CSCO exercises such discretion. Accordingly, we examine whether variation in CSCO characteristics influences how firms structure supplier monitoring systems and formalize termination provisions within their supplier governance frameworks. We focus specifically on gender as a source of systematic variation in how discretion is exercised within operational control systems.

Using panel data on S&P 1500 firms from 2010 to 2023, we document three primary findings. First, female CSCO presence is associated with the adoption a supplier monitoring system, reflecting a stronger formalization of oversight over suppliers' environmental and social practices. Second, firms that disclose having an institutionalized supplier monitoring system are also more likely to disclose termination provisions for noncompliant supply-chain partners, consistent with a governance pathway from monitoring architecture to formal escalation mechanisms. Third, the association between female CSCO presence and termination provisions is conditional on incentive alignment: when sustainability objectives are embedded in executive compensation, female supply-chain leadership is more strongly associated with the formal incorporation of termination provisions. We further show that female CEO presence increases the likelihood of appointing a female CSCO and that female leadership of compensation committees is associated with the adoption of sustainability-linked executive compensation. Together, these findings illuminate how supply-chain leadership selection and incentive design shape how supplier governance systems are architected and activated under board oversight.

Our study contributes to supply chain and operations management by illuminating how leadership operates within supply-chain governance systems. Prior research has examined how leadership characteristics affect internal operational outcomes such as product recalls and workplace safety (Wowak et al., 2015, 2021; Son et al., 2025). We extend this literature to the governance of external supply-chain partnerships by demonstrating how the authority structure of the supply-chain function shapes monitoring architectures and escalation provisions across firm boundaries. In addition, we contribute to research on CSCO appointments by identifying CEO gender as a determinant of female CSCO selection (Roh et al., 2016). More broadly, we contribute to the emerging supply chain and operations management–organizational behavior interface by integrating agency theory with operations governance. Specifically, we show that sustainability-linked executive compensation strengthens the formal incorporation of termination provisions within supplier governance architectures.

The remainder of this paper is organized as follows. Section 3.2 develops empirically testable hypotheses regarding (1) the impact of female CSCO presence on responsible supplier governance, (2) corporate leadership determinants of female CSCO appointment, and (3) board compensation committee leadership, sustainable executive compensation, and responsible supplier governance based on a review of relevant literature in SCOM and organizational behavior. Section 3.3, Section 3.4, and Section 3.5 empirically examine the hypotheses in these three areas, respectively. Section 3.6 discusses the managerial implications of the paper's findings, and Section 3.7 concludes with limitations and directions for future research.

3.2 Literature Review and Hypotheses Development

3.2.1 Impact of Female CSCO on Responsible supplier governance

Responsible supplier governance is operationalized through formal Supplier Codes of Conduct that define a governance architecture separating supplier oversight from escalation mechanisms addressing noncompliance. These codes specify structured due diligence procedures—such as supplier self-assessments, third-party audits, risk evaluations, grievance mechanisms, and corrective action plans—that generate and verify compliance information prior to any escalation response. For example, Hershey's Supplier Code describes monitoring through its Responsible Sourcing and Human Rights Due Diligence Programs and specifies that termination may occur only if non-compliance is not remedied within defined timeframes[1]. PZ Cussons similarly

[1] 2023 Hershey's Supplier Code of Conduct

distinguishes between corrective action and potential "termination of a supplier's relationship" in cases of violation[2]. NEC outlines a multi-stage supplier risk assessment system involving self-assessments, third-party audits, and corrective guidance prior to escalation[3], and IWCO conditions suspension or termination on audit-based verification of non-compliance[4]. These governance documents clarify the organizational placement of supplier oversight: responsibility for implementing Supplier Codes of Conduct typically resides within procurement and responsible sourcing functions that ultimately report to the CSCO, positioning the CSCO at the apex of supplier governance oversight.

Although supplier governance architectures formally specify monitoring and escalation procedures, their adoption and implementation entail managerial discretion. Firms vary in whether they institutionalize formal supplier monitoring systems and in how these systems are integrated into procurement and risk-management processes. When the CSCO occupies a position within the senior executive structure, this discretion becomes strategically consequential. Prior operations research shows that elevating the CSCO to the senior executive structure reallocates decision rights over inter-organizational processes, enabling supply-chain leaders to shape sourcing policies, allocate monitoring resources, and coordinate cross-functional responses to supplier risk (Wagner and Kemmerling, 2014).

Upper echelons theory suggests that executive characteristics shape how discretion is exercised within such governance systems (Hambrick and Mason, 1984). In organizational domains involving regulatory exposure and stakeholder scrutiny, leaders influence how governance systems are structured and which control mechanisms are prioritized. Prior research shows that leadership characteristics affect operational governance outcomes in areas such as product safety, risk management, and compli-

[2] 2022 PZ Cusson's Supplier Code of Conduct
[3] 2023 NEC Global's Supply Chain Transparency Report
[4] IWCO's Supplier Code of Conduct

ance oversight (Wowak et al., 2021; Son et al., 2025). These findings suggest that CSCO attributes may shape whether firms formalize supplier monitoring systems and establish escalation provisions addressing supplier misconduct.

In the context of responsible supplier governance, governance-system design may also be influenced by the evaluation environments facing female leaders. Research shows that women in leadership positions often operate under heightened scrutiny and may face stronger reputational penalties when governance failures occur (Saeed and Riaz, 2023). Anticipating such scrutiny, female CSCOs may have stronger incentives to ensure that supplier governance systems generate clear and defensible documentation of suppliers' social, environmental, and ethical compliance. One way to institutionalize such oversight is through the formal adoption of supplier monitoring systems that structure how compliance information is generated, verified, and documented.

Taken together, these arguments suggest that female CSCO presence may reshape the governance architecture of supply-chain partnerships. By influencing whether supplier monitoring systems are formally implemented, female CSCOs strengthen the informational foundation upon which escalation provisions addressing supplier noncompliance are defined. The institutionalization of monitoring systems reduces ambiguity surrounding supplier misconduct and increases the likelihood that firms incorporate termination provisions addressing persistent violations within their supplier governance frameworks. Formally,

Hypothesis 1. Female CSCO presence is associated with the adoption of supplier monitoring systems, which in turn increases the likelihood that firms incorporate termination provisions addressing supplier non-compliance within their supplier governance frameworks.

3.2.2 Corporate Leadership Determinants of Female CSCO Appointment

CSCO appointments are typically framed as CEO-led senior leadership selection decisions, with appointment announcements frequently specifying that the CSCO will report directly to the CEO. For example, Levi Strauss & Co.'s announcement explicitly states that its CSCO reports to the President and CEO and is part of the firm's executive leadership structure,[5] while PVH Corp.'s announcement similarly positions the CSCO as a senior executive within the CEO-led operating structure.[6] Together, such media coverage supports the view that CEOs play a primary role in appointing CSCOs and defining the authority of the position within the firm's upper echelon.

Building on the CEO's central role in configuring the senior executive structure, upper echelons theory suggests that CSCO appointments reflect the CEO's strategic priorities, governance orientation, and preferences for coordination at the senior level. Because the CSCO role is cross-functional and involves substantial discretion over supplier oversight, compliance, and risk management, CEOs are likely to appoint executives they perceive as aligned with their own leadership priorities and organizational objectives. In this context, CEO characteristics can systematically shape senior executive selection decisions.

Female CEOs may be more likely to appoint female CSCOs through mechanisms related to executive search and selection processes. Research on executive labor markets suggests that senior leadership appointments are often influenced by professional networks and referral channels, which can affect the composition of candidate pools and the visibility of qualified candidates (Fernandez-Mateo and Fernandez, 2016). Female CEOs may therefore be more likely to identify and consider female supply-

[5] Levi Strauss & Co. Appoints Chris Callieri as Chief Supply Chain Officer
[6] PVH Corp. Names Chief Supply Chain Officer and Global Head of Operations

chain executives through professional networks or search processes that differ from those traditionally relied upon in senior executive recruitment. In addition, shared demographic characteristics between senior leaders can facilitate trust, communication, and coordination within top management teams, making CEOs more likely to select executives they perceive as compatible collaborators in strategic decision making. These selection and matching dynamics suggest that CEO gender may systematically influence the likelihood that firms appoint female CSCOs. Formally,

Hypothesis 2. Firms led by a female CEO are more likely to appoint a female CSCO than firms led by a male CEO.

3.2.3 Board Compensation Committee Leadership, Sustainable Executive Compensation, and Responsible Supplier Governance

While individual orientations of a CSCO may shape how discretion is exercised within supply-chain governance, the translation of that discretion into observable governance architecture depends critically on the firm's formal control and incentive systems. Agency theory posits that managers allocate attention and effort toward objectives explicitly embedded in performance evaluation and compensation contracts (Jensen and Meckling, 1976). When particular outcomes are incorporated into incentive schemes, they cease to be aspirational commitments and instead become operational criteria that influence resource allocation, monitoring rigor, and the formal escalation mechanisms governing supplier noncompliance.

Empirical evidence supports the behavioral consequences of embedding nonfinancial objectives into incentive systems. Banker et al. (2000) show that incorporating nonfinancial performance measures into executive compensation increases managerial effort along those targeted dimensions without diminishing financial performance. Rather than crowding out financial objectives, nonfinancial metrics legitimize investments in activities that may involve short-term trade-offs but contribute to longer-term value creation. Incentive systems therefore recalibrate how managers evaluate trade-offs between cost efficiency and broader organizational goals.

Within the governance architecture of supply-chain partnerships, sustainability-linked executive compensation alters the institutional environment surrounding supplier governance decisions. Escalating supplier violations through termination provisions can entail short-term operational disruption, switching costs, and internal resistance from cost-focused functions. Even when monitoring systems identify and document violations, escalation mechanisms may remain underutilized if enforcement conflicts with dominant financial incentives. By embedding sustainability performance into executive compensation, firms reduce this internal resistance and align managerial evaluation with the formal enforcement of supplier standards. In doing so, they transform termination provisions from discretionary governance tools into incentive-consistent responses to verified noncompliance.

Under such conditions, the influence of a female CSCO on supplier governance architecture is more likely to materialize. When sustainability performance is formally evaluated and rewarded, the strengthening of supplier monitoring systems and escalation provisions becomes institutionally supported rather than individually driven. Incentive alignment therefore amplifies the association between female CSCO presence and the formal incorporation of termination provisions addressing persistent supplier noncompliance. Formally,

Hypothesis 3a. The association between female CSCO presence and the incorporation of termination provisions addressing supplier noncompliance is more positive when sustainability performance is explicitly embedded in executive compensation.

Prior research shows that executive compensation design is shaped primarily at the compensation committee level rather than by the board as a whole (Daily et al., 1998).

Building on this insight, research on compensation committee processes highlights that influence within the committee is not evenly distributed across members. Drawing on extensive interviews with U.S. public company compensation committee members, Hermanson et al. (2012) document that the compensation committee chair plays a central role in shaping how compensation decisions are framed, discussed, and ultimately resolved. In particular, the chair is heavily involved in agenda setting, coordinating information flows from management and compensation consultants, and guiding deliberations toward particular performance dimensions and evaluation criteria. As a result, the chair's judgments and priorities can exert disproportionate influence over which performance measures are viewed as legitimate and salient in executive compensation design.

Differences in evaluation environments may shape how female leaders exercise this agenda-setting authority. Research on gender and leadership evaluation suggests that female executives and directors often operate under heightened scrutiny from stakeholders and may face stronger reputational penalties when organizational outcomes are perceived as inconsistent with widely valued governance norms (Rosette and Livingston, 2012; Saeed and Riaz, 2023). In the context of executive compensation design, this heightened accountability may create stronger incentives for female compensation committee chairs to structure executive pay in ways that are transparent and defensible to external stakeholders. Sustainability performance metrics represent one such governance mechanism, as they signal a firm's commitment to responsible business practices and provide observable benchmarks for evaluating executives' attention to environmental and social risks. Incorporating such metrics can therefore help demonstrate that executive incentives are aligned with widely recognized ESG expectations. Consequently, compared with male compensation committee chairs, female chairs may be more likely to prioritize the inclusion of sustainability metrics as legitimate dimensions of executive performance, increasing the likelihood that sustainability targets are embedded in executive compensation contracts. Formally

Hypothesis 3b. Firms whose board-level compensation committees are chaired by a female director are more likely to explicitly incorporate sustainability performance into executive compensation.

All the hypotheses are summarized in the conceptual model in Figure 3·1.

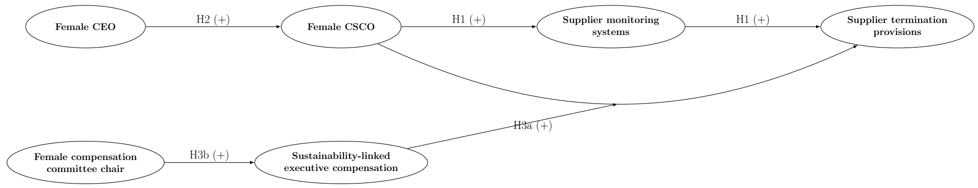

Figure 3·1: Conceptual Model

3.3 Impact of Female CSCO on Responsible Supplier Governance

3.3.1 Methods

Sample

The empirical analysis uses a firm-year panel of S&P 1500–indexed firms from 2010 to 2023. To align with Hypothesis 1's focus on how supply-chain leadership shapes responsible supplier governance architecture, the sample is limited to firms that appointed a CSCO at least once in that window. This allows a within-firm comparison of supply-chain governance in years with a female CSCO versus years with a male CSCO or no CSCO.

An executive is classified as a CSCO if the reported title is "Chief Supply Chain Officer" or "CSCO," or if the title combines senior rank (e.g. Chief, Corporate, or Executive Vice President) with "Supply Chain." Titles that refer only to subfunctions (e.g. procurement, logistics, sourcing, distribution) are excluded unless "Supply Chain" is also stated, so that the measure targets senior executives-level, enterprise-wide supply-chain leadership (Roh et al., 2016). This rule is applied consistently across all data sources.

Executive titles and gender are drawn first from the Execucomp database, which reports Named Executive Officers (NEOs) from 10-K and Proxy Statements. Many firms do not list the CSCO among NEOs, however, so an Execucomp-only approach yields many false negatives. CSCO identification is therefore supplemented with semantic-based extraction from SEC 10-K filings and Proxy Statements (DEF 14A), applying the same title-based rule. Table 3.1 summarizes the resulting identification gains.

Table 3.1: CSCO and female CSCO identification: Execucomp only vs. Execucomp plus 10-K and Proxy Statements

Identification basis	CSCO present (firm-years)	Female CSCO present (firm-years)
Execucomp only	267	26
Execucomp + 10-K + Proxy Statements	1,084	161
Increment from 10-K and Proxy Statements	+817	+135

After requiring non-missing values for the dependent variables, key explanatory variables, and controls, the final sample comprises 3,570 firm-year observations covering 255 S&P 1500 firms in 46 two-digit SIC industries.

The mediation pathway implied by Hypothesis 1 is tested in three steps following the procedure outlined in Baron and Kenny (1986). First, the total effect of female CSCO presence on partnership termination is estimated (path c). Second, the effect of female CSCO presence on supplier monitoring is estimated (path a). Third, both the mediator and female CSCO presence enter the termination equation jointly, yielding the direct effect (path c') and the mediator-to-outcome effect (path b). Mediation is supported when paths a and b are positive and significant and the direct effect c' is attenuated relative to the total effect c.

All three equations are estimated as linear probability models (LPMs) with firm, two-digit SIC industry, and year fixed effects and standard errors clustered at the firm level. Because the quantities of interest are average marginal effects of binary regressors on binary outcomes, the LPM provides consistent estimates under heteroskedasticity-robust inference (Angrist and Pischke, 2009). The LPM also avoids the well-known incidental-parameters problem that arises in nonlinear fixed-effects models with many firm dummies (Neyman and Scott, 1948; Greene, 2004), and it preserves the additive separability required for the Baron–Kenny decomposition, which does not hold in logit models due to scale non-comparability across equations (Mood, 2010).

Measures

Dependent variable. The primary dependent variable captures the formal escalation provisions within firms' responsible supplier governance architecture and is retrieved from the Refinitiv ESG database. `ESGSupplierTerminationProvision` is an indicator equal to one if a firm discloses that it maintains termination provisions allowing the firm to disengage from suppliers that fail to meet environmental or social standards, and zero otherwise (Griffis et al., 2014; Gull et al., 2023). This measure therefore reflects the presence of formal termination clauses embedded in firms' Supplier Codes of Conduct and represents the downstream escalation mechanism within the supplier governance architecture described in the theory section.

Mediator. Consistent with Hypothesis 1's process-based logic, we measure the monitoring component of the governance architecture using `SupplierMonitoringSystem`, also obtained from Refinitiv ESG. This indicator equals one if a firm discloses the existence of supplier monitoring systems—such as oversight procedures, auditing mechanisms, or evaluation processes—designed to assess suppliers' environmental or social performance, and zero otherwise (Duan et al., 2021). Conceptually, this variable captures the information-generating component of supplier governance systems, including due diligence procedures, risk assessments, and corrective action monitoring that precede any escalation response to supplier noncompliance.

Explanatory variable. `FemaleCSCOPresent` is an indicator equal to one in firm-years in which a female Chief Supply Chain Officer is an appointed senior executive, and zero otherwise. This variable is constructed using Execucomp data as described in the data section. In line with our theoretical framing, this measure captures variation in leadership characteristics within the supply-chain governance function.

Controls. The control variables closely follow Roh et al. (2016) and Gull et al. (2023) and account for senior executives' characteristics, corporate governance, firm strategy, and financial characteristics that may influence supply-chain governance decisions. senior executive controls include `NumSeniorExecutiveOfficers`, measured as the number of executive officers reported in Execucomp; `AvgSeniorExecutiveOfficerTenure`, measured as the mean number of years executives have served in their current positions; and `COOPresent`, an indicator equal to one if a chief operating officer other than the CEO is present. Governance controls include `BoardSize`, `CEOBoardMemberDuality`, `CSRSustainabilityCommitteePresent`, `SustainabilityCompensationIncentives`, and `NumFemaleDirectors`. Firm strategy and financial controls include Diversification, Internationalization, Leverage, `FirmSize` (Total Revenue), ROA, Tobin's Q, CASH, `AcquisitionDummy`, `R&DIntensity`, and `CapitalIntensity`. The definitions of Diversification, Internationalization, and Leverage follow Roh et al. (2016). The remaining financial and governance controls follow Gull et al. (2023) and are constructed using Compustat and Refinitiv data.

Instrumental variables. To address potential endogeneity in `FemaleCSCOPresent` and `NumFemaleDirectors` (Wowak et al., 2021), we construct two corresponding instruments. The first instrument, `HQTotalFemaleCSCO` measures the local supply of female CSCOs appointed by other firms headquartered in the same U.S. state-year, excluding the focal firm. The second instrument, `HQAvgNumFemaleDirectors`, captures the average number of female directors appointed by other firms headquartered in the same state-year, again excluding the focal firm. Both instruments exploit regional labor market and peer-environment variation while avoiding mechanical correlation with the focal firm's own leadership decisions.

The detailed definitions of all variables are summarized in Table 3.10. To conserve space, major summary statistics corresponding to the baseline regression variables are reported in Table B.1, and pairwise correlations are reported in Table B.4 in the Online Appendix.

3.3.2 Results

Table 3.2 provides evidence consistent with a monitoring-mediated governance pathway. In Step 1, the presence of a female CSCO is positively associated with the presence of termination provisions addressing supply-chain partners that violate environmental or social standards. This result suggests that firms led by female supply-chain executives are more likely to formalize escalation mechanisms for addressing supplier noncompliance.

Step 2 examines whether female CSCO leadership is associated with changes in upstream supplier oversight. The results indicate that the presence of a female CSCO is positively and significantly associated with the adoption of a formal supplier monitoring system. This finding suggests that leadership changes at the supply-chain executive level are associated with more institutionalized monitoring architectures that increase firms' oversight of suppliers' environmental and social performance.

Step 3 introduces supplier monitoring into the outcome regression. Consistent with the proposed mechanism, supplier monitoring systems are positively and significantly associated with the presence of termination provisions addressing supplier noncompliance. At the same time, the coefficient on female CSCO presence becomes smaller in magnitude, indicating attenuation of the direct association. This pattern is consistent with a partial mediation mechanism, whereby leadership influences the formal governance architecture of supplier partnerships through changes in monitoring systems.

To formally assess the mediated pathway, we conduct a Sobel mediation test using the estimated a and b paths. The indirect effect equals $a \times b = 0.0959$, and the Sobel test indicates that this indirect pathway is statistically significant ($z \approx 2.01$, $p < 0.05$). This result provides additional statistical support for the interpretation that supplier monitoring systems serve as a transmission channel linking female CSCO leadership to the formal incorporation of termination provisions within supplier governance architectures.

Taken together, these findings suggest that female CSCOs reshape the firm's supplier governance architecture not primarily by directly increasing termination actions, but by strengthening the monitoring systems that generate the informational and procedural foundation upon which escalation provisions addressing supplier noncompliance are formalized.

As a robustness check, we further address potential endogeneity using a fixed-effects two-stage least squares (FE-2SLS) specification that instruments both `FemaleCSCOPresent` and `NumFemaleDirectors` simultaneously. The instruments exploit variation in the broader governance environment surrounding the focal firm. Specifically, `FemaleCSCOPresent` is instrumented using the leave-one-out number of female CSCOs among firms headquartered in the same U.S. state (`HQTotalFemaleCSCOsLOO`), while `NumFemaleDirectors` is instrumented using the leave-one-out average number of female directors among other firms headquartered in the same state (`HQAvgNumFemaleDirectorsLOO`). Both instruments are constructed using a leave-the-focal-firm-out approach so that the focal firm's own executives or directors are excluded from the calculation of the instrument values. This design ensures that the instruments are not mechanically correlated with the endogenous regressors through the firm's own governance choices.

However, because `HQTotalFemaleCSCOsLOO` is constructed from the state–year supply of female supply-chain leadership talent, exclusion restriction could be questioned if the instrument is correlated with broader state-level institutional environments, such as ESG norms, political climate, regulatory enforcement intensity, or disclosure culture, that also influence firms' supplier governance architectures. To mitigate this concern, we adopt a more demanding fixed-effects structure that includes firm fixed effects and industry-by-year fixed effects. Firm fixed effects absorb all time-invariant firm characteristics, including persistent regional governance cultures and unobserved managerial preferences, while industry-by-year fixed effects control for time-varying shocks that affect firms within the same industry in a given year, such as changes in ESG standards, regulatory scrutiny, or industry-wide supplier governance practices. This specification therefore limits identification to variation in state–year leadership talent supply after accounting for firm-specific and industry–year confounds. Nevertheless, because the instruments are defined at the state level, we interpret the IV estimates as a robustness check rather than as the primary source of identification.

Instrument relevance is supported by comparing the Cragg–Donald Wald F-statistic against the Stock–Yogo critical value for maximal 2SLS size distortion. Specifically, for the case of two endogenous regressors and two instruments, the Stock–Yogo critical value corresponding to a 10% maximal size distortion is 7.03. Because the Cragg–Donald statistic equals 17.5, which exceeds this threshold, weak instruments are unlikely to be a concern at the 10% size-distortion level.

Turning to the second-stage estimates, the FE-2SLS results reported in Table 3.3 remain consistent with the baseline findings. Taken together, the consistency of the results across the baseline fixed-effects model and the instrumental-variable specification provides additional support for Hypothesis 1.

3.4 Corporate Leadership Determinants of Female CSCO Appointment

3.4.1 Methods

Sample

To test Hypothesis 2, which predicts that firms led by a female CEO are more likely to appoint a female CSCO than firms led by a male CEO, we construct a matched firm-year sample using a coarsened exact matching (CEM) procedure, following the approach implemented by (Roh et al., 2016). The use of CEM is motivated by the relative infrequency of female CSCO appointments and the resulting imbalance between firm-years with and without such appointments, which can bias conventional regression estimates if not properly addressed.

The observation window for this analysis spans 2010–2023, and the population consists of S&P 1500 firms observed at the firm-year level. The treatment universe comprises S&P 1500 firm-year observations in which a female CSCO appointment occurs, while the control universe consists of S&P 1500 firm-year observations without a CSCO appointment. The dependent variable, `FemaleCSCOPresent`, is coded at the firm-year level and equals one in years in which a firm appoints a female CSCO, and zero otherwise.

We implement CEM by first exactly matching firm-year observations on two-digit

SIC industry codes and fiscal year. Exact matching on industry is essential because industry is a categorical variable and because the prevalence and organizational importance of supply-chain leadership roles vary substantially across industries. Exact matching on year is likewise critical, as the institutional environment surrounding executive appointments and gender representation can change meaningfully over time. After matching on industry and year, we further coarsen firm size into total-revenue-based quartiles and retain only those control observations that fall into the same size quartile as a treatment observation. This sequential matching procedure ensures that treated and control firm-years are comparable in terms of industry context, temporal environment, and organizational scale, consistent with prior CSCO research.

Applying this procedure yields a matched sample consisting of 60 firm-year observations with female CSCO appointments and 93 matched control firm-year observations, distributed across 55 matched strata. We estimate conditional logistic regression models that condition on these matched strata, so that the likelihood of appointing a female CSCO is identified solely from within-stratum variation. The effects of the matching variables themselves are differenced out of the conditional likelihood, and identification relies on comparisons among otherwise highly similar firm-year observations.

Measures

Dependent variable. The dependent variable is `FemaleCSCOPresent`, an indicator equal to one in firm-years in which a firm appoints a female CSCO, and zero otherwise. This variable is computed based on the Execucomp database.

Explanatory variable. The key explanatory variable is `FemaleCEO`, an indicator equal to one if the firm's CEO is female in the focal firm-year, and zero otherwise. This variable is computed based on the Execucomp database. This variable is computed based on the Execucomp database.

Controls. Following Roh et al. (2016), we include a comprehensive set of control variables capturing senior executive structure, board composition, and firm characteristics that may independently influence the likelihood of appointing a CSCO and could confound the relationship between CEO gender and female CSCO appointment.

We control for `BoardSize` to account for variation in board structure and governance capacity over senior executive officers, as larger boards may exert different monitoring or advisory influences over senior executive appointments. `NumFemaleDirectors` is included to capture overall board gender composition, which may independently affect firms' openness to appointing female executives at the senior executive level.

Several controls capture attributes of the senior executive officers. `NumSeniorExecutiveOfficers` is included because a larger senior executive structure is mechanically more likely to include specialized functional executives, such as CSCOs. `AvgSeniorExecutiveOfficerTenure` measures the mean tenure of senior executive officers and captures the extent to which the executive team is entrenched; more tenured teams may be more resistant to structural changes such as introducing or altering functional leadership roles. `COOPresent` is included because the presence of a chief operating officer may substitute for, overlap with, or otherwise affect the perceived need for a CSCO, given the COO's cross-functional operational responsibilities.

We further control for firm characteristics that prior research has shown to be associated with CSCO appointment decisions. `FirmSize` (Total Revenue) accounts for organizational scale, as larger firms are more likely to formalize supply-chain leadership roles. `AcquisitionDummy` captures acquisition activity in the focal year, which can disrupt existing organizational structures and alter the need for centralized supply-chain coordination. ROA controls for firm performance, recognizing that firms' executive appointment decisions may be influenced by financial outcomes. Leverage is included to capture capital-structure pressures that can heighten the importance of operational efficiency and coordination. Diversification measures product-market complexity, reflecting the greater supply chain integration and coordination demands faced by diversified firms, which have been shown to increase the likelihood of CSCO appointments. Internationalization is included as a control variable because prior work shows that firms with greater international exposure face higher integration and coordination demands, which can increase the salience of supply-chain leadership roles.

The detailed definition of each variable mentioned above is summarized in Table 3.10. To conserve space, major summary statistics corresponding to the variables in the baseline regression are reported in Table B.2 and pairwise correlations in Table B.5 in the Online Appendix.

3.4.2 Results

Hypothesis 2 predicts that firms led by a female CEO are more likely to appoint a female CSCO than firms led by a male CEO. The baseline conditional logit estimates reported in Table 3.4 provide evidence consistent with this prediction. Using a matched sample constructed via coarsened exact matching on industry, year, and total-revenue quartiles, the conditional logit model exploits only within-stratum variation to compare otherwise similar firm-year observations. The coefficient on `FemaleCEO` is positive and statistically significant, indicating that, within comparable firm contexts and controlling for observable firm characteristics, board composition, and other top-management attributes, firms are more likely to appoint a female CSCO when the CEO is female.

Because the matched design relies on relatively small strata and a limited number of with-stratum appointment events, the conditional logit estimates may be subject to finite-sample instability. In particular, coefficient estimates in stratified logit models can be sensitive to sparse within-stratum variation or small changes in sample construction. To address this concern, we conduct two complementary robustness checks that alter the composition of the matched sample and the definition of the comparison group.

First, we enlarge the control pool to include firm-year observations in which the CSCO position is held by a male executive, in addition to observations in which no CSCO is present. This specification increases the number of available comparison observations while maintaining the matched-stratum structure. As reported in Table 3.5, the coefficient on `FemaleCEO` remains positive and statistically significant. This result indicates that the baseline finding is not driven by the exclusion of male-CSCO observations from the control group.

Second, we relax the matching procedure by requiring exact matching only on industry and year, thereby expanding the number of matched observations and adopting a more permissive matching scheme (Roh et al., 2016). The estimates reported in Table 3.6 again yield a positive and statistically significant coefficient on `FemaleCEO`. The larger matched sample improves statistical precision while preserving the qualitative pattern observed in the baseline specification.

Taken together, the baseline estimates and both robustness checks point to a consistent pattern. Across alternative matched samples and different definitions of the control pool, firms led by female CEOs exhibit a higher likelihood of appointing female CSCOs. Although the matched conditional logit framework necessarily relies on limited within-stratum variation, the stability of the results across these alternative specifications suggests that the observed relationship is not driven by sample-construction artifacts or small-sample instability.

3.5 Board Compensation Committee Leadership, Sustainable Executive Compensation, and Responsible Supplier Governance

3.5.1 Methods

Sample

To examine Hypothesis 3a, we extend the baseline mediation specification used to test Hypothesis 1 by incorporating an interaction term between `FemaleCSCOPresent` and `SustainabilityCompensationIncentives`. This moderated specification evaluates whether the association between female CSCO presence and noncompliant supply-chain partnership termination varies across executive compensation regimes. In line with the theoretical framework, this model tests whether sustainability-linked executive compensation strengthens the activation of termination provisions following documented supplier noncompliance.

We estimate firm-level fixed-effects OLS model that include the interaction term, thereby leveraging within-firm variation over time. This design isolates changes in termination provisions' incorporation in Supplier Code of Conduct associated with female CSCO appointments under differing incentive structures while controlling for time-invariant firm characteristics and common industry- and year-level shocks. Because the moderation operates at the enforcement stage of the governance architecture, `SupplierMonitoringSystem` is retained in the specification to account for the upstream monitoring mechanism identified in Hypothesis 1.

The estimation sample for Hypothesis 3a is identical to that used for Hypothesis 1.

Summary statistics and pairwise correlations for variables included in the moderation specification are reported in Table B.1 and Table B.4 in the Online Appendix.

To empirically examine Hypothesis 3b, we construct a matched firm-year sample using a coarsened exact matching (CEM) procedure and estimate exact conditional logistic regression models. The analysis is conducted over the 2010–2023 period and focuses on S&P 1500 firm-year observations. The treatment universe consists of firm-years in which `SustainabilityCompensationIncentives` equals one, indicating that the firm explicitly incorporates sustainability performance into executive compensation, while the control universe consists of firm-years in which `SustainabilityCompensationIncentives` equals zero.

We implement CEM by exactly matching firm-year observations on two-digit SIC industry and calendar year, and then further coarsening firm size into total-revenue-based quartiles. Exact matching on industry is essential because compensation design practices and board governance norms vary systematically across industries, while exact matching on year accounts for sharp temporal shifts in ESG-related compensation practices and disclosure standards. Matching on revenue-based size quartiles further ensures comparability in organizational scale, which is known to shape the adoption of formal executive incentive schemes (Al-Shaer and Zaman, 2017). After matching, the final sample comprises 1940 treated firm-year observations and 2066 matched control firm-year observations, distributed across 525 matched strata.

Following matching, we estimate exact conditional logistic regression models that condition on the matched strata. This approach differences out all effects of the matching variables by construction and identifies the effect of `CompCommitteeFemaleChair` on `SustainabilityCompensationIncentives` using only within-stratum variation among otherwise comparable firm-year observations. Board-level variables, including compensation committee composition and leadership, are constructed from the Institutional Shareholder Services (ISS) Director Data, while CEO- and senior executive-level characteristics are sourced from Execucomp. Together, this matched-sample design isolates the association between female leadership of the compensation committee and the adoption of sustainability-linked executive compensation within comparable institutional, temporal, and organizational contexts.

Measures

Dependent variable. The dependent variable for Hypothesis 3b is `SustainabilityCompensationIncentive`, an indicator variable equal to one in firm-years in which the firm's senior executives' remunerations are tied to the firm's ESG performance, and zero otherwise. `SustainabilityCompensationIncentive` is directly retrieved from the Refinitiv ESG database.

Explanatory variable. The key explanatory variable for Hypothesis 3b is `CompCommitteeFemaleChair`, an indicator variable equal to one for firm-years in which the firm's board-level compensation committee is chaired by a female director, and zero otherwise. This variable is computed based on the ISS Director Data.

Controls. For Hypothesis 3b, to quantify the specific impact of a female compensation committee chair on the incorporation of ESG metrics into executive pay, it is critical to control for a comprehensive set of governance, demographic, and firm-level determinants to isolate the chair's effect. At the governance level, the model includes `HasCompCommittee` and `CSRSustainabilityCommitteePresent`, as the presence of specialized board-level committees reinforces monitoring and facilitates the integration of sustainability-related performance measures into executive compensation (Abdelmotaal and Abdel-Kader, 2016; Al-Shaer and Zaman, 2017). Similarly, `BoardSize`, `NumIndependentDirectors`, and `AvgOutsideBoards` are included because a high degree of board independence and advisory expertise promotes the consideration of diverse stakeholder interests within managerial contracts (Schiehll and Bellavance, 2009; Al-Shaer and Zaman, 2017). To account for the balance of power between directors and CEO, `AvgBoardTenure` and `PreCEODirectors` control for the board's ability to exert oversight without being dominated by the CEO's influence (Hong et al., 2016). To ensure the female chair's effect is not merely a reflection of broader diversity, the model accounts for `FemaleDirectors`, `AvgBoardAge`, `BoardAgeDiversity` (Std), as cognitive and demographic variety on the board is associated with superior corporate social performance (Byron and Post, 2016). Furthermore, executive characteristics such as `FemaleCEO` and `CEOAge` are vital controls, as CEO's personal traits, including gender and age-related risk preferences, influence the acceptance of non-financial metrics in pay (Wang et al., 2018; Adhikari et al., 2015). Finally, firm-specific controls for `ESGScore`, `FirmSize` (Total Revenue), and ROA account for the firm's baseline sustainability profile, size, and economic capacity to implement complex sustainability-linked incentives (Maas, 2018; Riahi-Belkaoui, 1992; Rekker et al., 2014).

The detailed definitions of all variables are summarized in Table 3.10. To conserve space, major summary statistics corresponding to the baseline regression variables are reported in Table B.3, and pairwise correlations are reported in Table B.6 in the Online Appendix.

3.5.2 Results

Hypothesis 3a posits that the association between female CSCO presence and the incorporation of termination provisions addressing supplier noncompliance is stronger when sustainability objectives are explicitly embedded in executive compensation. The results in Table 3.7 provide support for this conditional prediction. Specifically, the interaction between *FemaleCSCOPresent* and *SustainabilityCompensationIncentives* is positive and statistically significant. This pattern indicates that sustainability-linked incentives strengthen the governance channel through which female supply-chain leadership translates monitoring systems into the formal incorporation of termination provisions within supplier governance architectures.

Hypothesis 3b predicts that firms whose board-level compensation committees are chaired by a female director are more likely to explicitly incorporate sustainability performance into executive compensation. The baseline conditional logit results reported in Table 3.8 provide empirical support for this prediction. After exactly matching firms on industry, year, and total-revenue-based quartiles and conditioning on matched strata, the coefficient on Comp Committee Female Chair is positive and statistically significant. This result indicates that, holding constant board structure, executive characteristics, firm fundamentals, and ESG performance, firms are significantly more likely to adopt sustainability-linked compensation when the compensation committee is chaired by a woman. Importantly, this effect is identified net of the overall presence of female directors and CEO gender, suggesting that gender representation matters most when women occupy positions of decision authority over incentive design rather than simply holding board seats.

The support for Hypothesis 3b remains robust when the matching procedure is relaxed to require exact matching only on industry and year, thereby expanding the sample and increasing statistical power. As shown in Table 3.9, the coefficient on Comp Committee Female Chair remains positive and statistically significant, with a similar magnitude to the baseline specification. The persistence of this effect under a more permissive matching scheme indicates that the baseline result is not driven by restrictive matching on firm size or limited support in narrowly defined strata. Instead, across both tightly matched and more broadly matched samples, firms with female-chaired compensation committees are consistently more likely to embed sustainability criteria into executive pay. Taken together, these findings provide robust empirical support for Hypothesis 3b and reinforce the interpretation that female compensation committee leadership plays a critical role in translating sustainability priorities into binding executive incentive structures.

Table 3.2: FE-OLS Results: Mediation Model

	Step 1 Outcome Variable (c)	Step 2 Mediator (a)	Step 3 Outcome Variable (b, c')
`FemaleCSCOPresent`	0.5776***	0.3653***	0.4817***
	(0.0599)	(0.0721)	(0.0665)
`SupplierMonitoringSystem`			0.2625**
			(0.1199)
`NumSeniorExecutiveOfficers`	0.0002	0.0024	−0.0005
	(0.0023)	(0.0021)	(0.0022)
`AvgSeniorExecutiveOfficerTenure`	−0.0016	0.0018	−0.0021
	(0.0022)	(0.0015)	(0.0021)
`COOPresent`	−0.0016	0.0102	−0.0042
	(0.0172)	(0.0075)	(0.0171)
`SustainabilityCompensationIncentives`	−0.6641***	−0.0081	−0.6620***
	(0.0420)	(0.0071)	(0.0421)

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Table 3.2: FE-OLS Results: Mediation Model (continued)

	Step 1 Outcome Variable (c)	Step 2 Mediator (a)	Step 3 Outcome Variable (b, c')
Diversification	0.0552	0.0057	0.0537
	(0.0369)	(0.0186)	(0.0379)
`FirmSize` (Total Revenue)	$2.22 \times 10^{-6\,*}$	-9.55×10^{-7}	$2.47 \times 10^{-6\,**}$
	(1.32×10^{-6})	(1.16×10^{-6})	(1.13×10^{-6})
`AcquisitionDummy`	0.0148	0.0089	0.0125
	(0.0216)	(0.0114)	(0.0213)
Leverage	−0.0472	−0.0256	−0.0404
	(0.0542)	(0.0243)	(0.0541)
`R&DIntensity`	0.2758	−0.1687	0.3201
	(0.6921)	(0.1975)	(0.6922)
`CapitalIntensity`	−0.0482	−0.0505	−0.0349
	(0.1313)	(0.0406)	(0.1308)
ROA	−0.0134	−0.0130	−0.0100
	(0.0936)	(0.0341)	(0.0935)
CASH	−0.0094	0.0447	−0.0212
	(0.1195)	(0.0368)	(0.1207)
`BoardSize`	−0.0033	0.0018	−0.0038
	(0.0050)	(0.0021)	(0.0050)
Tobin's Q	−0.0022	0.0008	−0.0024
	(0.0076)	(0.0029)	(0.0076)
`CEOBoardMemberDuality`	0.0961^{**}	−0.0007	0.0963^{**}
	(0.0417)	(0.0054)	(0.0426)
`CSRSustainabilityCommitteePresent`	−0.0550	−0.0036	−0.0540
	(0.0388)	(0.0144)	(0.0406)

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Table 3.2: FE-OLS Results: Mediation Model (continued)

	Step 1 Outcome Variable (c)	Step 2 Mediator (a)	Step 3 Outcome Variable (b, c')
NumFemaleDirectors	0.0196**	−0.0029	0.0203**
	(0.0094)	(0.0046)	(0.0094)
Firm FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,570	3,570	3,570
R^2	0.88869	0.97152	0.89080
Within R^2	0.63412	0.37102	0.64103

Standard errors clustered at the firm (ticker) level are reported in parentheses.

Internationalization is removed due to collinearity.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Outcome Variable: `ESGSupplierTerminationProvision`.

Mediator: `SupplierMonitoringSystem`.

Step 1 estimates the total effect (c).

Step 2 estimates the effect of `FemaleCSCOPresent` on the mediator (a).

Step 3 includes the mediator to estimate the direct effect (c') and mediator effect (b).

Table 3.3: FE-2SLS Results: ESG Supplier Termination Provision (Endogeneity)

	First Stage FemaleCSCOPresent	First Stage NumFemaleDirectors	Second Stage ESGSupplierTerminationProvision
HQTotalFemaleCSCOsLOO	−0.0211***	−0.0564**	

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Table 3.3: FE-2SLS Results: ESG Supplier Termination Provision (Endogeneity) (continued)

	First Stage	First Stage	Second Stage
	FemaleCSCOPresent	NumFemaleDirectors	ESGSupplierTerminationProvision
	(0.0056)	(0.0249)	
HQAvgNumFemaleDirectorsLOO	-0.0322^{***}	0.1371^{**}	
	(0.0117)	(0.0627)	
FemaleCSCOPresent			0.8325^{***}
			(0.2551)
NumFemaleDirectors			0.0860
			(0.0736)
NumSeniorExecutiveOfficers	0.0120^{***}	0.0254^{**}	-0.0055
	(0.0046)	(0.0124)	(0.0046)
AvgSeniorExecutiveOfficerTenure	0.0052^{*}	0.0068	-0.0064^{**}
	(0.0028)	(0.0124)	(0.0031)
COOPresent	0.0023	-0.0383	-0.0162
	(0.0149)	(0.0767)	(0.0191)
SustainabilityCompensationIncentives	-0.0057	0.0951	-0.6873^{***}
	(0.0147)	(0.0761)	(0.0461)
Diversification	-0.0221	-0.1239	0.0770^{*}
	(0.0379)	(0.1430)	(0.0440)
FirmSize (Total Revenue)	3.14×10^{-6}	4.27×10^{-6}	6.04×10^{-7}
	(2.61×10^{-6})	(5.00×10^{-6})	(2.56×10^{-6})
AcquisitionDummy	0.0268	0.0179	0.0191
	(0.0252)	(0.0767)	(0.0259)

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Table 3.3: FE-2SLS Results: ESG Supplier Termination Provision (Endogeneity) (continued)

	First Stage FemaleCSCOPresent	First Stage NumFemaleDirectors	Second Stage ESGSupplierTerminationProvision
Leverage	−0.0082	0.4759*	0.0082
	(0.0824)	(0.2831)	(0.0913)
R&DIntensity	1.656**	3.742	0.0275
	(0.7238)	(3.694)	(0.8868)
CapitalIntensity	0.0139	1.473**	−0.2406
	(0.1561)	(0.6882)	(0.2217)
ROA	0.0583	−0.1021	0.0224
	(0.0915)	(0.5332)	(0.1238)
CASH	−0.0960	−0.1053	0.0788
	(0.1152)	(0.3940)	(0.1390)
BoardSize	−0.0012	0.3814***	−0.0300
	(0.0019)	(0.0377)	(0.0287)
Tobin's Q	0.0022	0.0813**	−0.0073
	(0.0074)	(0.0353)	(0.0106)
CEOBoardMemberDuality	−0.0369	−0.2906	0.0878
	(0.0338)	(0.2431)	(0.0585)
CSRSustainabilityCommitteePresent	0.0165	0.2195	−0.0656
	(0.0459)	(0.1517)	(0.0534)
Firm FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
Observations	3,458	3,458	3,458

Standard errors clustered at the firm (ticker) level are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Internationalization is removed due to collinearity.

Cragg–Donald statistic = 17.5. The Stock–Yogo critical value for two endogenous regressors and two instruments under a 10% maximal size distortion is 7.03, indicating that weak instruments are unlikely to be a concern.

Table 3.4: Conditional Logit Results: Female CSCO Appointment

Dependent Variable:	FemaleCSCOPresent
BoardSize	0.0689
	(0.1619)
NumFemaleDirectors	−0.0159
	(0.2843)
FemaleCEO	1.9440*
	(1.166)
NumSeniorExecutiveOfficers	0.0547
	(0.1784)
AvgSeniorExecutiveOfficerTenure	0.0363*
	(0.0187)
COOPresent	−0.7411
	(0.5653)
FirmSize (Total Revenue)	-3.53×10^{-6}
	(5.02×10^{-6})
AcquisitionDummy	1.0510
	(0.7237)
ROA	4.8890
	(3.912)
Leverage	−0.3819

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Table 3.4: Conditional Logit Results: Female CSCO Appointment (continued)

Dependent Variable:	`FemaleCSCOPresent`
	(1.288)
Diversification	-1.0320
	(0.8557)
Stratum FE	Yes
Observations	153
Events	60
Concordance	0.714
Likelihood Ratio Test (p-value)	0.03
Score (Logrank) Test (p-value)	0.06

Exact conditional logistic regression with matched stratum fixed effects.

Standard errors are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Internationalization is omitted because it exhibits no within-stratum variation and is not identified under the conditional likelihood (perfect separation within matched strata).

Table 3.5: Conditional Logit Results: Female CSCO Appointment (Enlarged Control Pool)

Dependent Variable:	`FemaleCSCOPresent`
`BoardSize`	0.0589
	(0.0941)
`NumFemaleDirectors`	-0.1952
	(0.1907)
`FemaleCEO`	1.2270^{*}

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Table 3.5: Conditional Logit Results: Female CSCO Appointment (Enlarged Control Pool) (continued)

Dependent Variable:	FemaleCSCOPresent
	(0.6985)
NumSeniorExecutiveOfficers	0.0241
	(0.1501)
AvgSeniorExecutiveOfficerTenure	0.0415**
	(0.0188)
COOPresent	−0.8242
	(0.5389)
FirmSize (Total Revenue)	-1.98×10^{-6}
	(2.01×10^{-6})
AcquisitionDummy	0.3985
	(0.6108)
ROA	2.9590
	(2.6080)
Leverage	0.1170
	(0.6078)
Diversification	−0.9578
	(0.6615)
Stratum FE	Yes
Observations	241
Events	76
Concordance	0.696
Likelihood Ratio Test (p-value)	0.02
Score (Logrank) Test (p-value)	0.03

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Table 3.5: Conditional Logit Results: Female CSCO Appointment (Enlarged Control Pool) (continued)

Dependent Variable:	`FemaleCSCOPresent`

Exact conditional logistic regression with matched stratum fixed effects.

The control pool is enlarged to include both “no CSCO” and “male CSCO” observations.

Standard errors are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Internationalization is omitted because it exhibits no within-stratum variation and is not identified under the conditional likelihood.

Table 3.6: Conditional Logit Results: Female CSCO Appointment (Broader Match)

Dependent Variable:	`FemaleCSCOPresent`
`BoardSize`	-0.0621
	(0.0770)
`NumFemaleDirectors`	0.3207^{**}
	(0.1423)
`FemaleCEO`	1.1410^{***}
	(0.4281)
`NumSeniorExecutiveOfficers`	0.0819
	(0.1305)
`AvgSeniorExecutiveOfficerTenure`	0.0456^{***}
	(0.0117)
`COOPresent`	-0.2536
	(0.3005)
`FirmSize` (Total Revenue)	3.20×10^{-6}
	(1.52×10^{-6})
`AcquisitionDummy`	0.0412

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Table 3.6: Conditional Logit Results: Female CSCO Appointment (Broader Match) (continued)

Dependent Variable:	FemaleCSCOPresent
	(0.4431)
ROA	1.7900
	(1.807)
Leverage	0.0139
	(0.3937)
Diversification	-1.6470^{***}
	(0.5017)
Stratum FE	Yes
Observations	582
Events	111
Concordance	0.712
Likelihood Ratio Test (p-value)	2×10^{-8}
Score (Logrank) Test (p-value)	2×10^{-8}

Exact conditional logistic regression with matched stratum fixed effects.

Exact matching only on industry and year.

Standard errors are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Internationalization is omitted because it exhibits no within-stratum variation and is not identified under the conditional likelihood.

Table 3.7: FE-OLS Results: Moderated–Mediation Model

Dependent Variable:	ESGSupplierTerminationProvision
FemaleCSCOPresent	0.0970*
	(0.0530)
SupplierMonitoringSystem	0.5488***
	(0.1172)
FemaleCSCOPresent × SustainabilityCompensationIncentives	0.7697***
	(0.0853)
NumSeniorExecutiveOfficers	0.0005
	(0.0021)
AvgSeniorExecutiveOfficerTenure	−0.0010
	(0.0019)
COOPresent	−0.0027
	(0.0154)
SustainabilityCompensationIncentives	−0.7006***
	(0.0426)
Diversification	0.0629*
	(0.0328)
FirmSize (Total Revenue)	1.96×10^{-6}*
	(1.05×10^{-6})
AcquisitionDummy	0.0163
	(0.0215)
Leverage	−0.0410
	(0.0544)
R&DIntensity	0.2689
	(0.6851)
CapitalIntensity	−0.0216

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Table 3.7: FE-OLS Results: Moderated–Mediation Model (continued)

Dependent Variable:	ESGSupplierTerminationProvision
	(0.1324)
ROA	−0.0165
	(0.0930)
CASH	0.0109
	(0.1196)
BoardSize	−0.0043
	(0.0046)
Tobin's Q	−0.0001
	(0.0079)
CEOBoardMemberDuality	0.0968**
	(0.0383)
CSRSustainabilityCommitteePresent	−0.0659*
	(0.0362)
NumFemaleDirectors	0.0193**
	(0.0093)
Firm FE	Yes
Industry FE	Yes
Year FE	Yes
Observations	3,570
R^2	0.90799
Within R^2	0.69756

Standard errors clustered at the firm (ticker) level are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.8: Conditional Logit Results: Sustainability Compensation Incentives

Dependent Variable:	SustainabilityCompensationIncentives
NumFemaleDirectorsOnCompCommittee	−0.0136
	(0.0614)
CompCommitteeFemaleChair	0.1987*
	(0.1116)
BoardSize	−0.0555
	(0.0517)
NumIndependentDirectors	0.0199
	(0.0503)
AvgOutsideBoards	−0.1374
	(0.1158)
AvgBoardTenure	−0.0335*
	(0.0158)
PreCEODirectors	0.0260*
	(0.0142)
AvgBoardAge	−0.0271
	(0.0169)
BoardAgeDiversity (Std)	−0.0154
	(0.0230)
FemaleDirectors	−0.1105**
	(0.0505)
FemaleCEO	0.2906*
	(0.1645)
CEOAge	0.0127*
	(0.00718)
CSRSustainabilityCommitteePresent	0.3612

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Table 3.8: Conditional Logit Results: Sustainability Compensation Incentives (continued)

Dependent Variable:	`SustainabilityCompensationIncentives`
	(0.2540)
`ESGScore`	5.0700^{***}
	(0.3757)
`FirmSize` (Total Revenue)	$4.55 \times 10^{-6\,**}$
	(1.39×10^{-6})
ROA	-1.7530^{**}
	(0.5564)
Stratum FE	Yes
Observations	4006
Events	1940
Concordance	0.692
Likelihood Ratio Test (p-value)	$< 2 \times 10^{-16}$
Score (Logrank) Test (p-value)	$< 2 \times 10^{-16}$

Exact conditional logistic regression with matched stratum fixed effects.

Exact matching on industry and year, followed by matching on total revenue-based quartiles.

CEO-level covariates are lagged by one year to mitigate simultaneity concerns.

Standard errors are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

`HasCompCommittee` is omitted because it exhibits no within-stratum variation and is not identified under the conditional likelihood (perfect separation within matched strata).

Table 3.9: Conditional Logit Results: Sustainability Compensation Incentives (Broader Match)

Dependent Variable:	SustainabilityCompensationIncentives
NumFemaleDirectorsOnCompCommittee	−0.0999*
	(0.0522)
CompCommitteeFemaleChair	0.2451**
	(0.0959)
BoardSize	0.0061
	(0.0415)
NumIndependentDirectors	−0.0296
	(0.0417)
AvgOutsideBoards	−0.0050
	(0.0957)
AvgBoardTenure	−0.0192
	(0.0132)
PreCEODirectors	0.0217*
	(0.0118)
AvgBoardAge	−0.0067
	(0.0138)
BoardAgeDiversity (Std)	−0.0009
	(0.0192)
FemaleDirectors	−0.0597
	(0.0433)
FemaleCEO	0.2519*
	(0.1466)
CEOAge	0.0125*
	(0.00619)

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Table 3.9: Conditional Logit Results: Sustainability Compensation Incentives (Broader Match) (continued)

Dependent Variable:	`SustainabilityCompensationIncentives`
`CSRSustainabilityCommitteePresent`	0.2157
	(0.2029)
`ESGScore`	5.0590^{***}
	(0.3010)
`FirmSize` (Total Revenue)	$2.36 \times 10^{-6\,**}$
	(9.11×10^{-7})
ROA	-0.7974^{*}
	(0.4719)
Stratum FE	Yes
Observations	5015
Events	2372
Concordance	0.698
Likelihood Ratio Test (p-value)	$< 2 \times 10^{-16}$
Score (Logrank) Test (p-value)	$< 2 \times 10^{-16}$

Exact conditional logistic regression with matched stratum fixed effects.

Exact matching on industry and year, followed by matching on total revenue-based quartiles.

Standard errors are reported in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

`HasCompCommittee` is omitted because it exhibits no within-stratum variation and is not identified under the conditional likelihood (perfect separation within matched strata).

3.6 Managerial Implications

This study offers several implications for senior executives and boards seeking to strengthen the governance architecture of supply-chain partnerships. First, the findings underscore that responsible supplier governance is not solely a matter of adopting formal policies, but of how supplier monitoring systems and escalation provisions are structured within the firm's governance architecture. Our results indicate that female CSCO presence is associated with the presence of formal supplier monitoring systems, which in turn are linked to a greater likelihood that firms incorporate termination provisions addressing persistent supplier noncompliance. For managers, this highlights the importance of the CSCO role as an institutional actor within the governance architecture of the firm. Elevating the supply-chain function to the level of senior executive officers and carefully considering who exercises authority over the design of supplier monitoring systems and escalation provisions can materially shape how supplier governance mechanisms are institutionalized. Leadership composition in the supply-chain function therefore has implications for how governance systems are structured in practice, not merely for symbolic representation.

Second, the findings emphasize the central role of CEOs in shaping the authority structure of supply-chain governance. Firms led by female CEOs are significantly more likely to appoint female CSCOs, suggesting that CEO selection indirectly influences how supplier governance architectures are configured. Because the CSCO typically holds decision rights over the design of supplier monitoring systems, supplier risk classification processes, and escalation provisions addressing noncompliance, CEO appointment decisions can have downstream implications for how supplier oversight systems are organized. For boards, this implies that leadership succession decisions should be evaluated not only in terms of firm performance and strategic alignment, but also in terms of their implications for cross-functional governance authority, particularly in complex and sustainability-sensitive supply networks.

Third, the findings demonstrate that leadership authority must be complemented by incentive alignment to produce consistent governance outcomes. While female CSCO presence is associated with the adoption of supplier monitoring systems, the incorporation of termination provisions is more likely when sustainability objectives are explicitly embedded in executive compensation. This suggests that governance responses to supplier noncompliance are sensitive to the broader incentive environment. Formal escalation mechanisms such as termination provisions may impose operational costs and generate internal resistance from cost-focused functions. By incorporating sustainability performance into executive compensation, firms legitimize these escalation mechanisms and reduce organizational barriers to formalizing responses to supplier noncompliance. For directors sitting on the compensation committee, this finding implies that sustainability-linked incentives are not merely symbolic commitments but mechanisms that reinforce the governance architecture surrounding supplier oversight.

Finally, the findings highlight the role of board-level authority in shaping incentive design. Firms whose compensation committees are chaired by female directors are more likely to adopt sustainability-linked executive compensation arrangements. This suggests that diversity in positions of board-level authority, rather than diversity in board composition in general, can influence how sustainability priorities are embedded into formal control systems. For boards seeking to strengthen supply-chain governance, attention should therefore be paid not only to overall representation but also to who occupies leadership roles within key committees responsible for designing executive incentives. Allocating authority within board structures can materially influence how sustainability objectives are incorporated into supplier governance architectures.

Taken together, these implications suggest that strengthening responsible supplier governance requires coordinated alignment across leadership selection, authority allocation, monitoring system design, and incentive structures. Firms seeking to improve supplier governance should view these elements as interconnected components of a broader governance architecture rather than as isolated policy levers.

3.7 Limitations and Future Research

Our study has several limitations that suggest directions for future research. First, our measures of responsible supplier governance rely on disclosure-based indicators derived from firms' publicly reported governance policies. Specifically, the variables capture whether firms disclose the presence of supplier monitoring systems and termination provisions within their Supplier Codes of Conduct. While these indicators provide insight into the formal governance architecture through which firms structure supplier oversight, they do not directly observe how consistently such mechanisms are implemented or how frequently they are applied across individual supplier relationships. Future research could complement disclosure-based measures with more granular operational data, such as supplier-level audit outcomes, third-party certification records, or documented remediation and escalation events. Such data would enable researchers to examine how supply-chain leadership influences the implementation and effectiveness of governance systems deeper within supply networks.

Second, although we focus on the role of female CSCOs, female CEOs, and female compensation committee chairs, we do not directly observe the micro-level decision-making processes through which these actors influence governance outcomes. Our theorizing draws on established leadership and governance theories to infer mechanisms, but future research could employ qualitative methods, surveys, or interviews with executives and board members to unpack how leadership values, intra-organizational influence, and committee dynamics shape supply-chain and compensation decisions in practice.

Third, our analysis is conducted within the context of large publicly traded U.S. firms. Governance structures, executive labor markets, and supply-chain configurations may differ in private firms, smaller organizations, or firms operating in non-U.S. institutional environments. Extending this research to other institutional settings would help assess the generalizability of our findings and clarify how national governance regimes, labor market structures, or stakeholder expectations condition the relationship between leadership composition and supply-chain governance.

Finally, our study focuses on gender as a salient dimension of leadership heterogeneity, but other executive and board characteristics may also shape responsible supplier governance according to upper echelons theory. Future research could examine how leadership experience, functional background, cultural background, or intersectional identities interact with incentive structures and board governance to influence sustainability outcomes. In addition, scholars could explore potential complementarities or tensions among different governance mechanisms—for example, how sustainability-linked compensation interacts with external monitoring, regulatory enforcement, or investor pressure to shape firms' supply-chain practices.

Overall, we view these limitations not as constraints on the contribution of this study, but as opportunities for future research to deepen understanding of how leadership, incentives, and governance structures jointly shape responsible supplier governance.

Table 3.10: Variable Definitions and Linkage to Hypotheses

Variable	Hypothesis	Definition
ESGSupplierTerminationProvision	H1, H3a	Binary indicator equal to 1 if the firm discloses that it is prepared to terminate relationships with suppliers that fail to meet environmental or social standards, and 0 otherwise.
SupplierMonitoringSystem	H1	Binary indicator equal to 1 if the firm discloses active monitoring, auditing, or oversight of suppliers' environmental or social performance, and 0 otherwise.
FemaleCSCOPresent	H1, H2, H3a	Binary indicator equal to 1 in firm-years in which a female Chief Supply Chain Officer (CSCO) is present within a firm's senior executive structure, and 0 otherwise.
SustainabilityCompensationIncentives	H1, H3a, H3b	Binary indicator equal to 1 if sustainability or ESG performance metrics are explicitly incorporated into executive compensation in the firm-year, and 0 otherwise.

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Table 3.10: Variable Definitions and Linkage to Hypotheses (continued)

Variable	**Hypothesis**	**Definition**
`HQTotalFemaleCSCOCapable`	H1	State-by-year, leave-the-focal-firm-out measure capturing the local supply of female CSCO-capable executives in the firm's headquarter state.
`HQAvgNumFemaleDirectors`	H1	State-by-year, leave-the-focal-firm-out average number of female directors appointed by other firms headquartered in the same state-year as the focal firm.
`NumSeniorExecutiveOfficers`	H1, H2, H3a	Number of senior executive officers in the firm-year.
`AvgSeniorExecutiveOfficerTenure`	H1, H2, H3a	Mean number of years senior executive officers have served in their current executive positions.
`COOPresent`	H1, H2, H3a	Binary indicator equal to 1 if a chief operating officer is within a firm's senior executive structure, and 0 otherwise.
Diversification	H1, H2, H3a	Product-market diversification measured as a reverse-coded Herfindahl–Hirschman Index of segment revenues across business segments.
Internationalization	H1, H2, H3a	Ratio of international revenues to total firm revenues.

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Table 3.10: Variable Definitions and Linkage to Hypotheses (continued)

Variable	Hypothesis	Definition
`FirmSize` (Total Revenue)	H1, H2, H3a, H3b	Firm size measured as total revenues in the fiscal year.
`AcquisitionDummy`	H1, H2, H3a	Binary indicator equal to 1 if the firm reports acquisition-related activity in the fiscal year, and 0 otherwise.
Leverage	H1, H2, H3a	Long-term debt divided by total assets.
`R&DIntensity`	H1, H3a	Research and development expenditures divided by total sales.
`CapitalIntensity`	H1, H3a	Total assets divided by total sales.
ROA	H1, H2, H3a, H3b	Return on assets, measured as earnings divided by total assets.
CASH	H1, H3a	Cash and short-term investments divided by total assets.
`BoardSize`	H1, H2, H3a, H3b	Total number of directors serving on the board in the firm-year.

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Table 3.10: Variable Definitions and Linkage to Hypotheses (continued)

Variable	Hypothesis	Definition
Tobin's Q	H1, H3a	Ratio of market capitalization to the book value of shareholders' equity.
`CEOBoardMemberDuality`	H1, H3a	Binary indicator equal to 1 if the CEO simultaneously holds a board leadership position, and 0 otherwise.
`CSRSustainabilityCommitteePresent`	H1, H2, H3a, H3b	Binary indicator equal to 1 if the firm has a board-level CSR or sustainability committee in the firm-year, and 0 otherwise.
`NumFemaleDirectors`	H1, H2, H3a, H3b	Number of female directors serving on the board in the firm-year.
`FemaleCEO`	H2	Binary indicator equal to 1 if the firm's CEO is female in the firm-year, and 0 otherwise.
`NumFemaleDirectorsOnCompCommittee`	H3b	Number of female directors serving on the board-level compensation committee in the firm-year.
`CompCommitteeFemaleChair`	H3b	Binary indicator equal to 1 if the compensation committee is chaired by a female director in the firm-year, and 0 otherwise.

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Table 3.10: Variable Definitions and Linkage to Hypotheses (continued)

Variable	**Hypothesis**	**Definition**
`NumIndependentDirectors`	H3b	Number of independent (non-executive) directors serving on the board in the firm-year.
`AvgOutsideBoards`	H3b	Average number of outside public board seats held by directors in the firm-year.
`AvgBoardTenure`	H3b	Average tenure (in years) of directors serving on the board in the firm-year.
`PreCEODirectors`	H3b	Number of directors appointed to the board prior to the appointment of the current CEO.
`AvgBoardAge`	H3b	Average age of directors serving on the board in the firm-year.
`BoardAgeDiversity` (Std)	H3b	Standard deviation of director ages on the board in the firm-year.
`FemaleCEO`	H3b	The female CEO indicator.
`CEOAge`	H3b	CEO age.
`ESGScore`	H3b	Composite environmental, social, and governance (ESG) performance score in the firm-year.

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Table 3.10: Variable Definitions and Linkage to Hypotheses (continued)

Variable	Hypothesis	Definition

Chapter 4

Risk and Management of Talent Drain

4.1 Introduction

Employee turnover is economically costly. U.S. employers spend spend six to nine months of a departing employee's salary on finding and training replacement alone, an estimated $18,000 per typical employee.[1] With 51 million voluntary exits in 2022, the national aggregate reaches roughly $900 billion.[2] Beyond the direct replacement costs, empkoyee turnover also imposes significant indirect costs on firm performance. For example, assembly-line worker turnover drives product failure rates in manufacturing (Moon et al., 2022). On the revenue front, employee turnover is associated with lower one-quarter-ahead return on assets and sales growth (Li et al., 2022). Because turnover adversely affects both cost and revenue performance, it constitutes a material risk to shareholder value for investors and a pressing operational challenge for managers.

Despite this material risk, the SEC does not mandate prescriptive disclosure of employee turnover.[3] Even if firms voluntarily disclose quit rates, investors are limited to ad-hoc, backward-looking analyses of large-scale turnover episodes that have already occurred. Social media content can play a crucial information intermediary role between firms and investors with unmatched immediacy and accessibility (Aral

[1] Society for Human Resource Management: Essential Elements of Employee Retention
[2] Work Institute: 2023 Retention Report
[3] https://www.law.cornell.edu/cfr/text/17/229.101

et al., 2013). Crowd-sourced employee reviews on platforms such as Glassdoor can fill this information gap by offering ex-ante signals of workforce conditions before a large-scale exodus materializes. There is evidence that investors are already drawing on this source: analysts at Bank of America Merrill Lynch routinely incorporate Glassdoor ratings into equity research, and alternative-data vendors such as Thinknum and Eagle Alpha supply real-time Glassdoor sentiment dashboards to institutional clients.[4][5] However it remains empirically unclear whether investors systematically incorporate employee-generated social media reviews to anticipate and price talent drain risk, instead of reacting after turnover events materialize. Thus, our first research question is:

1. Do investors draw on Glassdoor employee reviews to anticipate and price the risk of impending talent drain before it actually occurs?

The same operational consequences that concern investors also underscore the need for firms to diagnose and predict talent drain before it materializes. Industry practice is already embracing data-driven approaches to talent management (Kokkodis and Ipeirotis, 2023): a 2024 BCG survey reports that 70% of organizations experimenting with AI or generative AI do so within HR.[6] However, existing literature on employee turnover literature primarily emphasizes causal inference related to internal control mechanisms, with limited emphasis on prediction (Aldatmaz et al., 2018; Van der Stede et al., 2020; Emadi and Staats, 2020; Liang et al., 2024). A notable exception is Ke et al. (2025), who demonstrate that structured internal employee data from a large Chinese bank can effectively forecast quits. Compared with internal data, crowd-sourced employee reviews offer three distinctive advantages. First, their rich

[4] Glassdoor: How Investors Use Glassdoor
[5] Eagle Alpha: Employment Data
[6] Boston Consulting Group: How AI Is Changing Recruitment

textual content can be exploited to reveal operational pain points driving talent drain. Second, because the reviews are authored anonymously and hosted outside the firm, they are insulated from the "data contamination" that arises when workers tailor their digital traces to please evaluators. Third, as an external data source, employee reviews can be used to predict both turnover and talent inflow, since many job seekers read reviews before applying.[7] As such, our second research question is:

2. Can the operational themes extracted from Glassdoor reviews reliably signal and help firms predict future talent drain events?

To answer the first research question, we exploit the staggered arrival of the first Glassdoor employee review of S&P 500 firms (i.e., Glassdoor coverage initiation) as treatment events and match each treated firm to comparable S&P 1000 controls. Using a stacked difference-in-differences framework (Wing et al., 2024), we examine the causal effect of Glassdoor coverage initiation on firms' subsequent idiosyncratic risk and exposure to talent drain risk. This quasi-experimental setup follows (Dube and Zhu, 2021), who use the same Glassdoor coverage initiation to show firms improve their workplace practices after being featured on the platform. To measure firm-level talent drain risk exposure, we use end-of-month external outflow as a concrete and objective measure of employee turnover to split S&P 1500 firms' stocks into high- and low-employee-turnover portfolio on a monthly basis. We construct a novel daily talent drain factor as the excess return differential between the two portfolios, a procedure that is comparable to how other conventional factors are constructed (Fama and French, 1993). Using the daily talent drain factor, we estimate firm-level talent drain risk exposure as the daily beta loadings (i.e., talent drain beta) via a rolling-window approach. Stacked DiD results on both idiosyncratic risk and talent

[7] Glassdoor: The Essential Employer Branding Statistics you Need to Know

drain beta consistently show evidence of investor reaction and re-adjusted talent drain risk assessment in response to a firm's Glassdoor coverage initiation. More specifically, we find that only sentiment-neutral inaugural reviews (overall rating of three on Glassdoor's one-to-five scale) trigger a spike in both idiosyncratic risk and talent drain beta. This pattern is consistent with investors' asymmetric attention to newly available information with the most ambiguity (Illeditsch, 2011; Williams, 2015): a neutral first review signals that employee-generated information is now publicly available without resolving whether the firm is good or bad employer, increasing perceived uncertainty about the firm's human capital stability.

We answer the second research question in two stages. We first apply the multinomial inverse regression framework in (Taddy, 2013) to estimate word-level talent drain loadings separately for the pros, cons, and advice sections of Glassdoor employee reviews. With the aid of word embedding, dimensionality reduction, and clustering techniques, we group the words most strongly associated with future talent drain events into interpretable operational themes. These themes help firms diagnose which HR dimensions attract and retain talent and which drive talent away. We then construct text-based talent drain indices from the word-level loadings and use a gradient-boosted classification framework (Hastie et al., 2009) to predict two types of future talent drain events: reduced talent attractiveness and increased talent attrition. The text-based indices provide significant incremental out-of-sample predictive power beyond traditional talent drain signals, ranking among the top predictors in both prediction models. Our results also suggest that different review sections matter for different outcomes: the pros and cons section are most informative for predicting reduced talent attractiveness, while the advice section is most informative for predicting increased talent attrition.

Together, our findings establish the complete information value chain of employee-generated social media content for talent drain risk. From the investor perspective, we show that Glassdoor coverage initiation triggers heightened investor perception of talent drain risk. From the firm perspective, the textual content of these reviews enables firms to diagnose operational drivers of talent drain and pre-empt future talent drain events. Collectively, our analyses show that Glassdoor reviews are both financially material to investors and operationally actionable for firms.

These findings carry direct managerial implications. First, because only sentiment-neutral first reviews trigger heightened investor risk perception, HR leaders should prioritize engaging with ambiguous reviews and addressing them constructively, as such engagement has been to alter organizational image and can limit unnecessary valuation pressure (Yu et al., 2025; Chung et al., 2020). Second, our prediction framework equips firms with data-driven capabilities to preempt future talent drain events using externally available data, complementing internal turnover prediction approaches such as (Ke et al., 2025). More importantly, because the predictive and diagnostic components share the same underlying estimation, the framework provides not only an early warning but also an interpretable explanation of which operational dimensions are driving the risk, giving firms a concrete basis for targeted HR interventions.

The remainder of the paper is organized as follows. Section 4.2 reviews the related literature. Section Section 4.3 presents the causal analysis of Glassdoor coverage initiation on investor perception of talent drain risk. Section 4.4 develops the text-based diagnostic and prediction framework. Section 4.5 discusses limitations and future research directions. A concise description of Glassdoor as the primary setting and data source for our study is relegated to Section C.2.1.5 of the E-Companion.

4.2 Literature Review

IS and marketing research has established that social media generates significant information value for both investors and firms (Aral et al., 2013). Employee turnover carries material economic consequences for shareholder value (Moon et al., 2022; Li et al., 2022), yet the SEC does not mandate prescriptive disclosure of employee turnover. Crowd-sourced employee reviews on platforms such as Glassdoor have the potential to fill this information gap: they are rich in textual content, externally hosted, and anonymous, offering accounts of workplace conditions that bear on a firm's ability to attract and retain talent. Our study connects to two streams of literature: (1) social media and capital markets, and (2) social media and firm strategy. We connect these two streams in the context of corporate human capital by demonstrating the complete information value chain of employee-generated social media content for talent drain risk: Glassdoor coverage initiation triggers heightened investor risk perception, and incorporating the textual content of reviews enables firms to predict future talent drain events.

On social media and capital markets, literature has shown social media metrics have significant predictive power for a firm's financial performance measured by cash flow, excess stock return, idiosyncratic risk, and return on assets (Luo, 2009; Tirunillai and Tellis, 2012; Luo et al., 2013). This body of work focuses predominantly on consumer user-generated content (UGC) such as product reviews and blog posts. Shifting focus from consumer to employee-generated content, Green et al. (2019) and Huang et al. (2020) show that employee opinions on Glassdoor predict stock returns and future operating performance, respectively. However, both studies document predictive associations with general financial outcomes rather than isolating specific risk dimensions or establishing causality. In contrast, we exploit Glassdoor coverage initiation as a quasi-experimental shock to investor information sets, a design that parallels (Dube and Zhu, 2021) and He et al. (2024), who use analogous coverage initiation events to study workplace practices and corporate innovation, respectively. Drawing on information ambiguity theory (Illeditsch, 2011; Williams, 2015), we show that only sentiment-neutral first reviews trigger a spike in idiosyncratic risk and talent drain beta, a pattern that differs from (Tirunillai and Tellis, 2012), who find that negative consumer UGC drives idiosyncratic risk. This suggests that employee-generated content affects investor risk perception through ambiguity rather than directional sentiment. Collectively, our evidence shows that employee opinion matters to investors' talent drain risk assessment, and that employee-oriented platforms such as Glassdoor facilitate the transmission of such information from firms to capital markets.

On social media and firm strategy, prior work has shown the value of social media for firms primarily in the marketing function, including increasing product and service sales (Goh et al., 2013; Chen et al., 2015; Chung et al., 2020) and to secure venture capital funding in the case of startups Aggarwal et al. (2012); Wang et al. (2024). In a health-care setting, Miller and Tucker (2013) find that hospitals' active social media management generates more content from employees than from clients, suggesting that the role of social media in firms extends beyond the marketing function to employee-facing applications such as talent management. Yet existing work on employee turnover prediction relies primarily on structured internal data. Ke et al. (2025) show that internal employee records can effectively forecast individual quits, but such data cannot capture talent attraction and may be contaminated when employees tailor their digital traces to please evaluators. Sainju et al. (2021) apply structural topic modeling to Indeed.com reviews of Fortune 50 firms to uncover latent drivers of employee satisfaction and turnover, but their contribution remains primarily descriptive. In contrast, we move beyond thematic identification to build an explainable machine learning framework using externally available Glassdoor reviews to (1) diagnose the operational drivers of talent attraction and retention, and (2) predict future talent drain events beyond what traditional financial and operational controls alone can achieve. Our analysis demonstrates the value of employee-generated social media content for firms' human capital management.

4.3 Glassdoor Employee Reviews and Investor Perception of Future Talent Drain Risk

To answer the first research question, we assess the causal effect of a firm's Glassdoor coverage initiation on investor perception of future talent drain risk. We operationalize such risk perception via idiosyncratic risk (Luo, 2009; Tirunillai and Tellis, 2012; Luo et al., 2013; Wang et al., 2021), the standard deviation of the portion of a firm's excess return unexplained by standard market factors in the Fama-French three factor model (Fama and French, 1993), and the beta on a novel talent drain factor. Albuquerque et al. (2019) and Chen et al. (2025) similarly use the market beta, a factor beta, as their dependent variables.

4.3.1 Talent Drain Factor

The talent drain factor computes the excess return differential between two portfolios of the stocks of firms experiencing "high" employee turnover and "low" employee turnover. We measure voluntary employee turnover by monthly external outflow drawn from the Workforce Dynamics database of the Revelio Labs (Revelio Labs, 2025).

Revelio Labs is a labour-market analytics firm that collects résumé histories and online professional-profile updates, reconciles them with regulatory filings, and maps each job spell to a unified occupation and employer ID. Its Workforce Dynamics database aggregates these records into firm-month metrics, including external inflow, external outflow, and net flow, covering essentially all publicly traded U.S. companies from 2008 onward. External outflow is calculated as the count of employees who depart for a different employer during month t, scaled by the average number of employees during the same month and weighted to account for the bias due to where the raw numbers were sourced from, as well as time scaling, making it an ideal measure for voluntary employee turnover.

Our universe consists of the stocks of all S&P 1500 firms. On the last trading day of each month, firms are ranked by external outflow and median-split into a high-turnover portfolio H and a low-turnover portfolio L. Both portfolios are equally weighted and held for the following month, and the sorting is repeated monthly. The daily talent-drain factor is

$$TD_t = \bar{r}_{H,t} - \bar{r}_{L,t}, \qquad \bar{r}_{H,t} = \frac{1}{N_H}\sum_{i \in H}(r_{i,t} - r_{f,t}), \qquad \bar{r}_{L,t} = \frac{1}{N_L}\sum_{i \in L}(r_{i,t} - r_{f,t}),$$

where $r_{i,t}$ is the raw return of stock i on day t and $r_{f,t}$ is the one-month Treasury-bill rate. Adding TD_t to the Fama-French three factor model produces

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{\mathrm{MKT},i} MKT_t + \beta_{\mathrm{SMB},i} SMB_t + \beta_{\mathrm{HML},i} HML_t + \beta_{\mathrm{TD},i} TD_t + \varepsilon_{i,t},$$

which we estimate by OLS in a 90-trading day rolling window (minimum 45 observations); $\beta_{\mathrm{TD},i}$ is the talent-drain beta, and the remaining betas capture exposures to the market, size, and value factors. The daily factor returns for the three factor model are downloaded from French (2025a).

To assess the validity of our proposed talent drain factor, we adopt a two-step approach. First, we conduct the squared Sharpe ratio test proposed by (Barillas and Shanken, 2018). Adding the talent drain factor to the Fama-French three-factor model (base model) lifts the annualized tangency Sharpe ratio from 0.698 to 1.095, and the Barillas-Shanken Wald statistic of 1444.78 (one degree of freedom) decisively rejects the null that the talent drain factor is spanned by the existing factors. Second, to examine whether exposure to talent drain risk is priced in the cross section, we regress each stock's average daily excess return on its pre-estimated factor betas (Fama and MacBeth, 1973). According to Table 4.1, the slope on the talent drain beta is positive and highly significant ($0.0003, t = 3.23$), indicating that investors demand compensation for exposure to talent drain risk. Collectively, the Sharpe ratio enlargement demonstrates that the talent drain factor adds information orthogonal to the standard factors, while the cross-sectional regression shows that this information is priced. Together, these findings support the use of the tlanet-drain factor in our subsequent analyses.

Table 4.1: Cross-sectional regression of average excess returns on factor betas

	Average excess return
	(1)
Intercept	-0.0020^{***}
	(0.000)
β_{MKT}	0.0322
	(0.029)
β_{SMB}	-0.0539^{***}
	(0.018)
β_{HML}	-0.0018
	(0.016)
β_{TD}	0.0003^{***}
	(0.000)
R^2	0.008
Adjusted R^2	0.006
F-statistic	3.16

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Table 4.1: Cross-sectional regression of average excess returns on factor betas (continued)

	Average excess return
	(1)
p-value (F)	0.013
Observations	1,489

Notes: The table reports a Fama–MacBeth style cross-sectional regression of average daily excess returns (2008–2020) on factor betas. Standard errors are shown in parentheses. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

4.3.2 Sample Construction

We obtain all Glassdoor employee reviews for S&P 1500 firms between January 25, 2008 and September 2024, scraped from Glassdoor. The raw dataset comprises 4,907,893 reviews covering 1,386 unique firms, of which 481 are S&P 500 constituents and 905 belong to the S&P 1000 (S&P MidCap 400 and the S&P SmallCap 600). We merge the review data with Compustat North America by ticker and fiscal year to obtain firm-level accounting variables, and with Refinitiv's annual ESG WorkforceScore to capture workforce quality ratings. Restricting the sample to firms with non-zero WorkforceScore values yields 1,287,091 reviews across 1,231 firms with valid financial and ESG data.

A firm is classified as treated if it is a constituent of the S&P 500 at any point during the sample period; its event (treatment) date is the calendar day on which its first-ever Glassdoor review is posted. The initial screen yields 438 treated firms corresponding to 236 distinct event dates. The control universe consists of 797 S&P 1000 firms with non-missing ESG data. For each treated firm, we require a control candidate to (1) share the treated firm's two-digit SIC code, (2) lie in the same WorkforceScore quintile in the fiscal year preceding the event, and (3) have its first

Glassdoor review posted at least 40 days after but no more than two years after the treated firm's event date (firms that never receive a Glassdoor review during this window remain eligible). After matching, the final estimation sample comprises 237 treated firms and 264 control firms. Because each treated firm may match to multiple controls, this produces 600 treated-control pairs.

The matching procedure assigns each unique treated firm-event date combination a cohort identifier; all matched controls inherit this identifier, so there is one treated firm per cohort. For every treated-control pair, we build an event-time panel covering 61 calendar days (-30 to +30) around the event date. Because a given control firm can match to multiple treated firms, it may appear in more than one cohort. We retain these duplicates and cluster standard errors at the firm level. We construct two separate analysis panels by merging this event-time panel with (1) daily idiosyncratic risk, computed from the Fama-French three-factor model using a 90-day rolling window

For every treated–control pair we build an event-time panel covering 61 calendar days (-30 to +30) around the treatment date. This yields 73,200 firm-date observations. Because a given control firm can match to multiple treated firms, it may appear more than once on the same calendar day under different cohort identifiers; we retain these duplicates and cluster standard errors at the firm level.

We construct two separate analysis panels. The first merges the event-time panel with daily idiosyncratic risk, computed from the Fama-French three-factor model using a 90-day rolling window. The second merges with daily talent drain beta values constructed in Section 4.3.1. Both merges are performed in a forward-looking manner with a tolerance of 3 calendar days to account for holidays and non-trading days. After filtering observations with missing data, overall, the idiosyncratic risk panel contains 53,514 firm-date observations spanning 415 unique firms (206 treated and 209 controls). The talent drain beta panel contains 55,484 firm-date observations spanning 408 unique firms (203 treated and 205 control firms).

We enrich both panels with three sets of control variables. The first set consists of firm-year accounting and governance controls from Compustat, lagged by one year relative to the event date: return on assets (ROA), leverage, firm size (Size), cash holdings (Cash), R&D intensity (R&D), advertising intensity (Advertising), capital expenditures (CapEX), earnings variability (EarVar), book-to-market (BTM), the Hadlock-Pierce financial constraints index (Hadlock and Pierce, 2010) (SA_Index), log labor intensity (log_labor_Intensity), and variables capturing executive stock variables capturing executive stock options (EXEOPT), employee ownership (EMPSTK), institutional ownership (InstOwn), and managerial ownership (ManOwn). The second set adds the composite ESG score (ESGScore) from Refinitiv, also measured annually and lagged by one year. In addition, to account for the daily setup and investor reaction to corporate media coverage, our third set include two firm-date-level media controls from RavenPack: news count (log_news_count), defined as the natural logarithm of one plus the number of news articles with relevance ≥ 75 mentioning the firm on a given day, and sentiment score (sentiment_score), the average composite sentiment of those articles. Our resulting panels combine idiosyncratic risk and talent drain beta measures with financial, governance, ESG, and media characteristics, and are used in all regression specifications. Variable definitions and summary statistics corresponding to the idiosyncratic risk and talent drain beta panels are summarized in Table C.1 and Table C.2 of the E-Companion, respectively.

4.3.3 Methodology

Let $Treated$ denote the group of treated firms in the idiosyncratic risk/talent drain beta panel. $y_{i,t}$ denotes firm i's idiosyncratic risk/talent drain beta on day t.

$$\begin{aligned} y_{i,t} = & \alpha_0 + \alpha_1 \mathbf{1}[i \in Treated] \\ & + \sum_{h=t_{c_i}-e}^{t_{c_i}+e} \Big[\beta_h \big(\mathbf{1}[i \in Treated] \times \mathbf{1}[t - t_{c_i} = h] \big) \\ & \qquad + \delta_h \mathbf{1}[t - t_{c_i} = h] \Big] \\ & + Controls_{i,y_t - 1} + MediaCoverage_{i,t} + \eta_{c_i} + \epsilon_{i,t} \end{aligned} \tag{4.1}$$

t_{c_i} denotes the date of Glassdoor coverage initiation corresponding to the cohort containing firm i. $e = 30$, which is the event window. $Controls$ include ROA, Leverage, Size, R&D, Advertising, CapEX, Cash, EarVar, EXEPOT, ManOwn, EMPSTK, InstOwn, ESGScore, BTM, SA_Index, and log_labor_Intensity computed at a yearly level. $y_t - 1$ denotes the year preceding date t. $MediaCoverage$ denotes the vector of daily news volume and average sentiment. η_{c_i} denote the cohort-specific fixed effects and $\mathbf{1}[t - t_{c_i} = h]$ the event time dummies. SEs are clustered at the firm level. β_h, the estimand of interest, represents the average treatment effect on the treated (ATT) h day after t_{c_i}. β_{-1} is normalized to 0 for ease of interpretation.

With this event-study setup, pre-trends assumption are supported by the 90% confidence bands of all pre-treatment ATTs crossing the y-axis.

4.3.4 Analysis

The stacked DiD event study for the full sample (Figure 4·1) shows an instantaneous jump in idiosyncratic risk the day after a firm's Glassdoor coverage initiation. To examine whether the sentiment of the first review drives this effect, we partition the sample by the rating of the inaugural review: firms whose first review has a rating of 3 on Glassdoor's 1–5 scale constitutes the sentiment-neutral subsample, and all others (rating $\neq 3$) constitute the sentiment-loaded subsample.[8] The sentiment-neutral sample (Figure 4·2) shows a contemporaneous yet more pronounced idiosyncratic risk jump than the full sample, but the sentiment-loaded sample (Figure 4·3) displays no comparable jump. In Panel (a) of Table 4.2, we report the exact ATT estimates for the sentiment-neutral sample and confirm the visual evidence in Figure 4·2. Collectively, investors increase the idiosyncratic risk premium only when the first review is neither good nor bad.

We find a similar pattern for the talent drain beta. The aggregate event study (Figure 4·4) masks a pronounced jump in the neutral subsample: Figure 4·5 shows a steady build-up beginning around $T = 5$, and Panel (b) in Table 4.2 reports that the coefficients for $T = 6$ through $T = 9$ are positive and significant, while earlier and later windows are muted. The sentiment-loaded subsample (Figure 4·6) again exhibits no comparable movement. The evidence indicates that when the inaugural Glassdoor review is ambiguous, investors re-price the firm as more exposed to employee-turnover risk, whereas unequivocally positive or negative reviews leave perceived talent drain risk exposure unchanged.

Taken together, the twin spikes in idiosyncratic risk and in the talent drain beta factor concentrate entirely in the sentiment-neutral subsample. The effect is absent for both positive and negative first review samples, indicating that directional sentiment does not drive the repricing. This pattern is instead consistent with information ambiguity theory (Illeditsch, 2011; Williams, 2015): a neutral first review signals that employee-generated information about the firm is now publicly available, without revealing whether the firm is a good or bad employer. Investors face a new

[8] Glassdoor: Understanding the 5-Point Rating Scale

information channel whose directional implications are ambiguous, and they respond by increasing the risk premium they assign to the firm. A clearly positive or negative first review resolves this ambiguity immediately, so perceived uncertainty does not increase. For neutral first reviews, however, the ambiguity persists, as investors know the information channel exists but cannot assess its directional implications. This heightened uncertainty about internal human-capital stability is consequently capitalized into both total-risk and factor-risk dimensions of the firm's return.

For robustness, we construct the talent drain factor and its associated beta based on the Fama-French five factor model (Fama and French, 2015) and re-run the DiD analysis using the constructed talent drain beta. Results in Section C.1.3.1 of the E-Companion corroborate the main finding that only sentiment-neutral first reviews trigger a spike in investors' talent drain risk perception.

To further improve the comparability between the treated and control firms, we conduct propensity score matching (PSM) following the procedure in Dube and Zhu (2021). For each Glassdoor coverage initiation year t, the treated group consists of S&P 500 firms that received their first Glassdoor reviews sometime in year t, and the control group consists of S&P 1000 firms that received their first Glassdoor review no earlier than year year $t+1$. We fit a separate logit model for each coverage initiation year on the year-specific treated and control groups as a function of Size, ROA, BTM, Leverage, SA_Index, R&D, log_labor_Intensity, and WorkforceScore values in year $t-1$. Each treated firm is then matched to the same-industry control firm with the closest propensity score, with replacement. Table C.5 shows that the propensity score matched treated and control firms are comparable on the matching covariates for the vast majority of years. Figures C.6 through C.8 and Table C.6 show that our main finding that sentiment-neutral first reviews trigger a spike in idiosyncratic risk continue to hold in the propensity score matched sample, and Figures C.9 through

C.11 and Table C.7 show the same for the talent drain beta.

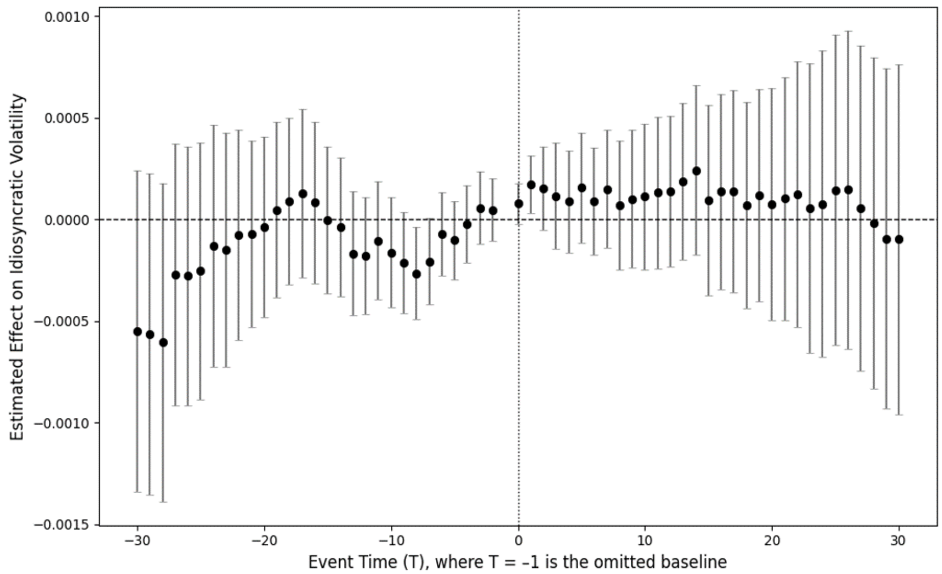

Figure 4·1: Stacked DiD on ivol: Full Sample

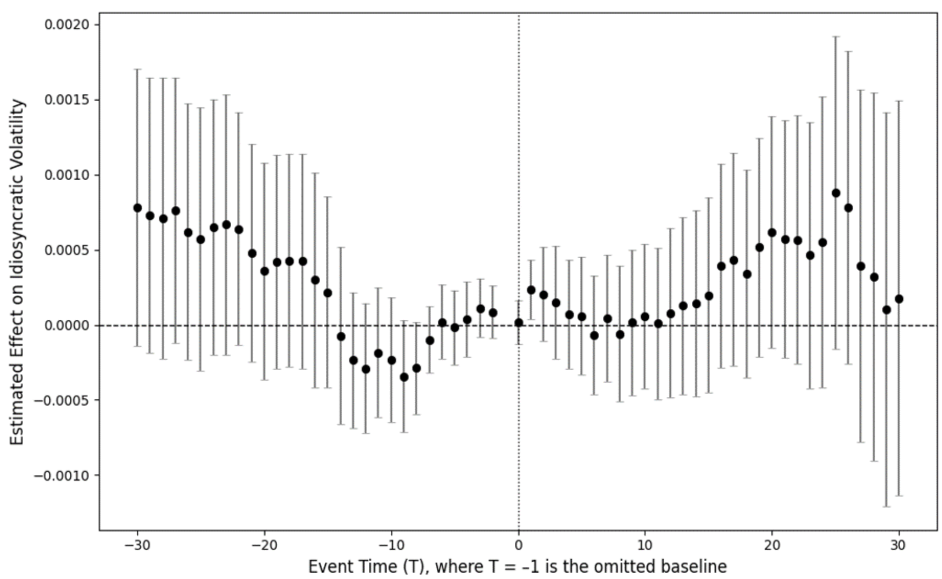

Figure 4·2: Stacked DiD on ivol: Neutral Sample

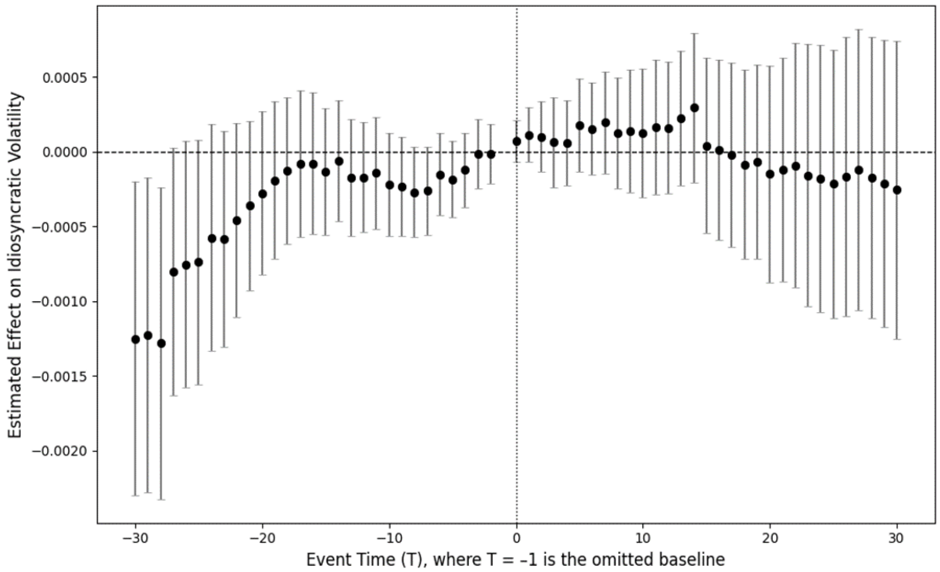

Figure 4·3: Stacked DiD on ivol: Sentiment-Loaded Sample

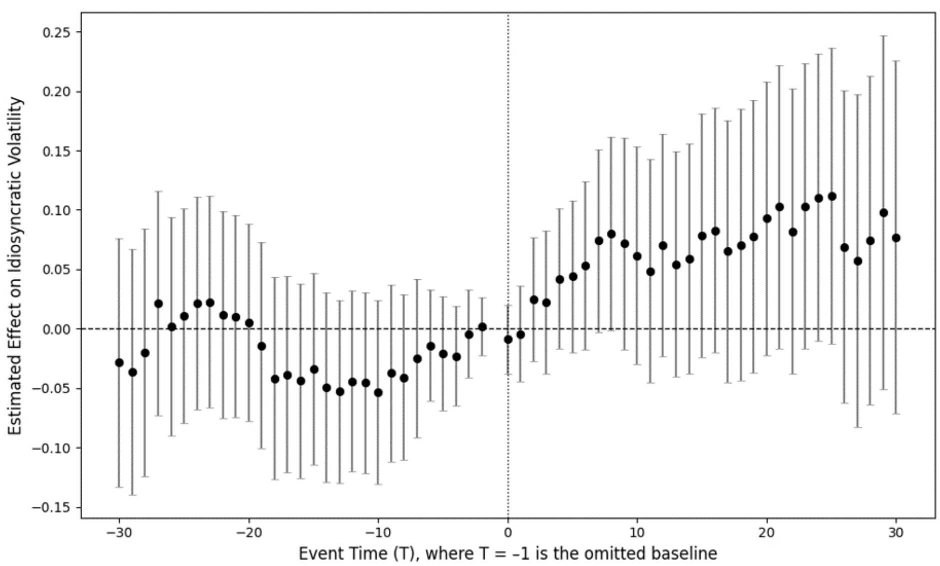

Figure 4·4: Stacked DiD on Talent Drain Beta: Full Sample

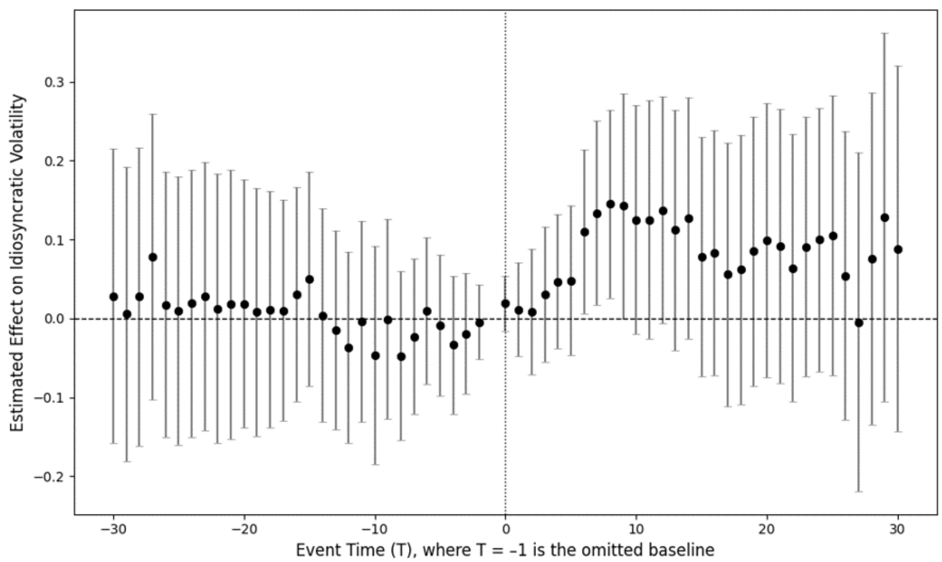

Figure 4·5: Stacked DiD on Talent Drain Beta: Neutral Sample

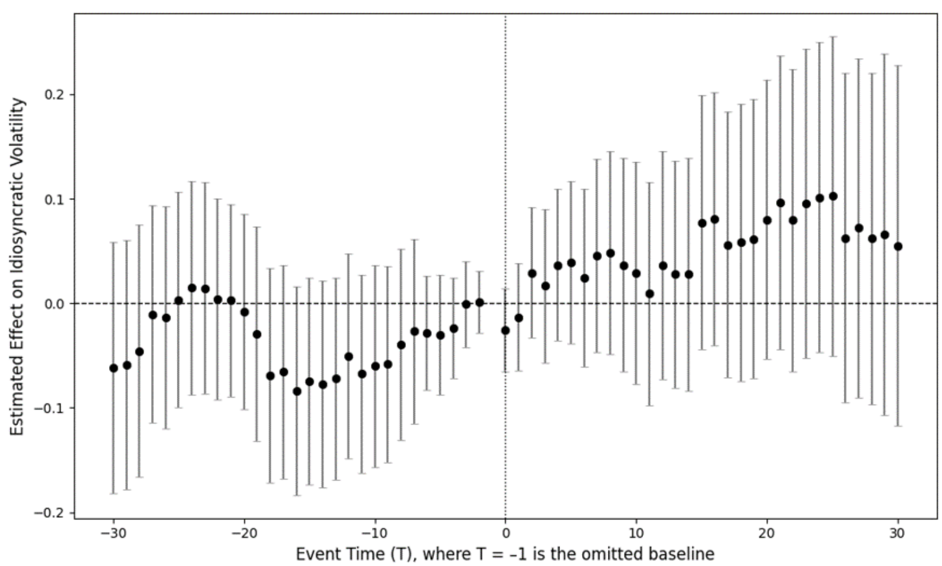

Figure 4·6: Stacked DiD on Talent Drain Beta: Sentiment-Loaded Sample

(a) Stacked DiD on ivol Regression Results

Table 4.2: Stacked DiD Regression Results: Neutral Sample

	Coef.	z	p-value
Treated × $T = -10$	−0.0002	−0.9210	0.3570
Treated × $T = -9$	−0.0003	−1.5160	0.1300
Treated × $T = -8$	−0.0003	−1.5470	0.1220
Treated × $T = -7$	−0.0001	−0.7470	0.4550
Treated × $T = -6$	0.0000	0.1290	0.8970
Treated × $T = -5$	0.0000	−0.1140	0.9090
Treated × $T = -4$	0.0000	0.2440	0.8070
Treated × $T = -3$	0.0001	0.9360	0.3490
Treated × $T = -2$	0.0001	0.8090	0.4190
Treated × $T = 0$	0.0000	0.1600	0.8730
Treated × $T = 1$	0.0002	1.9750	0.0480
Treated × $T = 2$	0.0002	1.0760	0.2820
Treated × $T = 3$	0.0001	0.6370	0.5240
Treated × $T = 4$	0.0001	0.3170	0.7510
Treated × $T = 5$	0.0001	0.2460	0.8060
Treated × $T = 6$	−0.0001	−0.2880	0.7730
Treated × $T = 7$	0.0000	0.1660	0.8680
Treated × $T = 8$	−0.0001	−0.2170	0.8280
Treated × $T = 9$	0.0000	0.0490	0.9610
Treated × $T = 10$	0.0001	0.1850	0.8530
Treated	0.0036	2.1660	0.0300
Intercept	0.0617	6.1950	0.0000
Controls		Yes	
Event time dummies		Yes	
Cohort fixed effects		Yes	
R^2		0.709	
Adj. R^2		0.706	
F–stat		3.84×10^7	
Obs.		17,444	

Notes: Robust SEs clustered at firm level. Yellow shading marks post-treatment ATTs significant at 10%. Period $T = -1$ is omitted.

(b) Stacked DiD on Talent Drain Beta Regression Results

Stacked DiD on Talent Drain Beta Regression Results (neutral sample)

	Coef.	z	p-value
Treated × $T = -10$	−0.0469	−0.5560	0.5790
Treated × $T = -9$	−0.0013	−0.0170	0.9870
Treated × $T = -8$	−0.0476	−0.7330	0.4640
Treated × $T = -7$	−0.0229	−0.3810	0.7030
Treated × $T = -6$	0.0096	0.1700	0.8650
Treated × $T = -5$	−0.0087	−0.1600	0.8730
Treated × $T = -4$	−0.0338	−0.6340	0.5260
Treated × $T = -3$	−0.0197	−0.4240	0.6720
Treated × $T = -2$	−0.0047	−0.1650	0.8690
Treated × $T = 0$	0.0188	0.8890	0.3740
Treated × $T = 1$	0.0108	0.3000	0.7640
Treated × $T = 2$	0.0083	0.1720	0.8640
Treated × $T = 3$	0.0304	0.5800	0.5620
Treated × $T = 4$	0.0468	0.9000	0.3680
Treated × $T = 5$	0.0479	0.8290	0.4070
Treated × $T = 6$	0.1097	1.7280	0.0840
Treated × $T = 7$	0.1336	1.8810	0.0600
Treated × $T = 8$	0.1449	1.9970	0.0460
Treated × $T = 9$	0.1428	1.6480	0.0990
Treated × $T = 10$	0.1251	1.4220	0.1550
Treated	−0.3159	−1.6630	0.0960
Intercept	−3.7879	−2.4450	0.0140
Controls		Yes	
Event time dummies		Yes	
Cohort fixed effects		Yes	
R^2		0.527	
Adj. R^2		0.522	
F–stat		5.53×10^5	
Obs.		17,677	

Notes: Robust SEs clustered at firm level. Yellow shading marks post-treatment ATTs significant at 10%. Period $T = -1$ is omitted.

4.4 Extracting Talent Drain Signals from Glassdoor Employee Reviews

The preceding section establishes the first half of the information value chain: Glassdoor coverage initiation leads investors to reprice talent drain risk, confirming that employee-generated content is financially material to capital markets. In this section, we turn to the second half, examining whether firms themselves can mine Glassdoor reviews to pinpoint operational areas most predictive of future talent drain risk and, ultimately, to forecast talent drain events.

4.4.1 Data Sources

Our empirical analyses draw on a panel of publicly listed U.S. firms from 2010–2017 that integrates nine complementary data sources.

Workforce dynamics. We source monthly employee inflow, outflow, and compensation figures from Revelio Labs' Workforce Dynamics and Individual Positions products, allowing us to track talent movements and average pay.

Employee voice. We collect Glassdoor reviews, which supply rich, crowd-sourced ratings and free-text content that proxy for the valence and intensity of workforce sentiment.

External information environment. We obtain firm-specific news volume and tone from RavenPack. We also capture regulatory exposure via Good Jobs First's Violation Tracker.

Financial fundamentals and corporate governance. We append annual accounting ratios from Compustat Fundamentals; executive incentives from Compustat-ExecuComp; employee share ownership from Form 5500 filings; institutional ownership from LSEG 13F holdings; and overall sustainability performance from Refinitiv ESG scores.

Together these sources provide a unified view of firms' talent flows, employee perceptions, stakeholder scrutiny, and financial condition. A detailed data sources description is provided in Section C.2.1 of the E-Companion.

4.4.2 Future Talent Drain Events

Using data from the Workforce Dynamics database provided by Revelio Labs (Revelio Labs, 2025), we construct two binary outcome variables. The first indicates whether a firm's annual external inflow of talent next year is smaller than that this year (external_inflow_reduction), as a proxy for reduction in a firm's attractiveness as a potential employer. The second indicates whether a firm's annual external outflow of talent next year is greater than that this year, as a proxy for increased talent attrition.

4.4.3 Controls

Corporate Misconduct, Media Coverage, and ESG Performance

Corporate misconduct fundamentally undermines the employer-employee relationship, eroding trust and morale and prompting valuable talent to seek opportunities elsewhere. Such misconduct affect both talent retention and attraction: firms with strong corporate social responsibility (CSR) records experience markedly lower employee turnover (Carnahan et al., 2017), while corporate social irresponsibility (CSI) significantly impedes a firm's ability to attract propsective talent (Darby et al., 2025).

Episodes of financial misreporting and other corporate wrongdoing have similarly been linked to spikes in employee attrition and erosion of employee trust in management (Gao and Jia, 2021). By incorporating quantitative measures of a firm's legal violations and penalties (especially those related to workforce practices), the model captures a critical dimension of organizational culture and risk that overlooked by traditional financial or operational predictors. Therefore, we control for the natural log of one plus the total number of corporate violations (log_violation_count), their associated monetary penalties (log_total_penalty) and their worforce-specific counterparts (log_workforce_violation_count and log_total_workforce_penalty) associated with a firm in a given year from Violation Tracker (Good Jobs First, 2025). For similar reasons, as CSR enhances talent retention while CSI deters prospective talent, we control for the composite ESG score computed by Refinitive (LSEG ESG, 2025).

Relatedly, the press is a major source for disseminating information on corporate misconduct. Thus, we control for press coverage of a firm in a given year using the natural log of one plus the number of news articles written about the firm (log_news_count). Following the cutoff in RavenPack (RavenPack, 2020), we deem only articles with a relevance score of at least 75 to be of direct relevance to a sampled firm. We also control for the average composite sentiment score of all articles of direct relevance to the firm (sentiment_score).

Accounting & Corporate Governance Characteristics

In constructing our predictive model, we include a comprehensive set of firm-level financial and accounting characteristics to capture organizational conditions known to influence employee retention. We control for profitability (ROA) because financial performance and retention are linked in a self-reinforcing cycle: poor performance triggers an exodus of talent, which in turn undermines future profitability (Li et al., 2022). We include leverage (long-term debt/asset) and cash ratio as gauges of financial risk and slack that affect employees' sense of job security. Firms often adopt conservative debt policies specifically to mitigate workers' layoff concerns (Agrawal and Matsa, 2013), while ample liquidity provides a buffer that enable firms to sustain investment in their workforce during downturns and reduce voluntary turnover. We further control for firm size (log assets), R&D and advertising expenditures as proxies for intangible asset intensity and growth orientation, capital expenditures (CapEX) to account for expansion and modernization efforts that may influence retention.

We also incorporate variables capturing compensation and governance, which theory and evidence link to employee retention. We include average employee annual salary because salary increases directly lower the likelihood of voluntary turnover (Emadi and Staats, 2020). We control for executive stock option grants (EXEOPT) and managerial equity ownership (ManOwn) because they affect managerial decision-making and firm culture: misaligned, short-term focused executive incentives can lead to cost-cutting or unethical practices that undermine employee trust and prompt turnover (Gao and Jia, 2021), while strong managerial ownership aligns leadership with long-term firm value, fostering a more secure environment for employees (Emadi and Staats, 2020). We also account for broad-based employee ownership (EMPSTK), as employee options create "golden handcuff" incentives that temporarily suppress departures (Aldatmaz et al., 2018). Finally, we control for institutional ownership (InstOwn) because concentrated or short-term-oriented institutional investors can pressure management for efficiency gains that often involve layoffs or restructuring, indirectly elevating turnover rates (Falato et al., 2025).

Glassdoor Review Metadata

We include three Glassdoor review metadata variables: the natural log of the number of reviews (log_review_count), average rating (rating), and natural log of total number of words in the reviews (log_total_review_words), because these features capture critical dimensions of employee sentiment and engagement that foreshadow turnover events. The average rating provides a summary measure of job satisfaction, a well-established predictor of employee retention (low satisfaction is strongly associated with higher quit rates (Carnahan et al., 2017)). Abrupt surges in the number of reviews and review length can indicate heightened employee unrest or turnover intention, as departing or disgruntled staff are often motivated to voice grievances publicly before exiting (Hirschman, 1970).

4.4.4 Sample Construction

We begin with the 206 treated firms from the idiosyncratic risk study and construct a firm-year panel spanning 2010-2017.[9] We retrieve every RavenPack news story that names one of those firms in the headline or first paragraph (relevance score ≥ 75) and record the press coverage controls for each firm and year. We then draw enforcement actions from Violation Tracker and compute the violation measures for each firm and year. Using Revelio Labs' Workforce Dynamics data, we sum monthly external inflow and outflow across regions and months to create annua totals; year-over-year changes identify whether inflow falls or outflow rises. Three tickers are not recognized by Revelio, leaving 200 firms. We also merge the Glassdoor review metadata, as well as the accounting, governance, and ESG controls from their respective sources. The resulting panel covers 200 firms and 1,549 firm-year observations. Variable definition

[9] The sample stops in 2017 to match the coverage of the Violation Tracker file kindly shared by Dennis W. Campbell and Ruidi Shang.

and descriptive statistics are in Section C.2.2 of the E-Companion.

4.4.5 Methodology

Our methodology proceeds in four steps. First, we preprocess the text of Glassdoor reviews to extract a clean vocabulary of lemmas (Section 4.4.5). Second, for each review section and outcome variable, we use multinomial inverse regression to estimate how strongly each lemma is associated with a future talent drain event (Section 4.4.5). Third, we cluster the most predictive lemmas into interpretable HR themes using word embeddings, enabling firms to diagnose what attracts and retains talent and what drives it away (Section 4.4.5). Fourth, we aggregate the lemma-level loadings into firm-year text-based scores and use them alongside traditional controls to predict future talent drain events via gradient boosting (Section 4.4.5).

Review Preprocessing

Each Glassdoor review contains three free-text sections (pros, cons, and advice), which we preprocess separately as a given lemma may carry different predictive content depending on the section in which it appears. First, we lemmatize each section using the English pipeline by spaCY[10],transforming each word into its canonical form. We then remove punctuation and special characters, non-English lemmas and misspellings via NLTK's Words Corpus[11], and common stopwords via NLTK's Stopwords Corpus (Porter, 2001)[12]. Finally, following Campbell and Shang (2022), we remove lemmas that either appear in more than 50% of the reviews or fewer than five reviews as lemmas that are too common or too rare are uninformative for assessing talent drain risk. This yields 12,019 unique lemmas.

[10] en_core_web_sm
[11] Words corpus
[12] Stopwords Corpus

Multinomial Inverse Regression

We use the multinomial inverse regression framework developed in Taddy (2013) to identify lemmas most associated with a future inflow reduction and outflow increase event for the pros, cons, and advice sections, respectively. Specifically,

$$\mathbb{E}[W_{jit}|\mathbf{x}_{it}, v_{it+1}] = e^{\alpha_j + \beta_j^T \mathbf{x}_{it} + \phi_j v_{it+1} + u_{it}}, \tag{4.2}$$

where W_{jit} denotes the count of lemma j in the pros/cons/advice section of all reviews posted on firm i in year t. $\mathbf{x}_{it}$ is the vector of controls for firm i in year t defined in Section 4.4.3 along with firm and year indicators. v_{it+1} is an indicator for a future talent drain event: either a reduction in external inflow or an increase in external outflow in year $t+1$ relative to year t. The main parameter of interest is ϕ_j (loading), which quantifies how strongly a specific lemma appearing in the pros/cons/advice section foreshadows a next-year reduction in external inflow or spike in external outflow.

For each outcome variable-review section combination, we use the distributed approach proposed in Taddy (2015) to fit a separate Poisson regression for each of 12,019 lemmas independently and simultaneously. To guard against over-fitting in this high-dimensional setting, we regularize regressions using the gamma lasso path of one-step estimators (POSE) (Taddy, 2017). This approach applies large penalties to small noise loadings while relaxing the penalty on strong signals, combining sparsity with bias reduction to yield more reliable lemma-level coefficients. Penalty selection is guided by corrected information criteria (AICc) (Hurvich and Tsai, 1989), which balances model fit against complexity to select the optimal penalty strength. The combination of sparsity, bias reduction, and principled penalty selection ensures that the estimated loadings are robust to noise and stable across distributed regressions, enhancing the reliability of the constructed text-based talent drain indices. This yields 72,114 separate regressions (3 review sections × 2 outcome variables × 12,019 unique lemmas). To isolate this step from the downstream future talent drain event prediction task, we estimate all loadings on firm-year observations from 2010 to 2013 and reserve 2014 to 2017 for prediction.

Word Embedding and Talent Drain Operations Topic Modeling

The preceding step estimates a loading for each lemma-section-outcome combination. While these loadings identify which individual words predict talent drain, interpreting thousands of separate word-level signals is impractical. Therefore, we cluster the most predictive lemmas into interpretable HR themes, which helps us answer two managerially relevant questions: (1) what HR themes help firms attract new and retain existing talent, and (2) what HR themes drive talent away. For the first question, we train a skip-gram embedding model (Mikolov et al., 2013) on the pros section of all reviews posted on our sampled firms from 2010 to 2017, transforming lemmas into 300-dimensional vectors such that semantically similar lemmas are closer together. We then feed all lemmas with a negative pros loading into the trained model to obtain their embeddings, as a negative loading indicates that the word appears more frequently in the pros reviews of firms that successfully attract and retain talent. We dimension-reduce the embeddings to two dimensions using UMAP (McInnes et al., 2018), and cluster them into disparate themes using HDBSCAN (McInnes et al., 2017). We answer the second question in a similar fashion, training on the cons section and feeding lemmas with a positive cons loading, as these words appear more frequently in the cons reviews of firms that subsequently experience talent drain. We present the top five talent-retaining HR themes ranked by the cluster's average absolute lemma loading in Figure C.12, and the top five talent-draining HR themes in FIgure C.13.

Predicting Future Talent Drain Events

For each section-outcome combination, we follow Campbell and Shang (2022) and aggregate the loadings as follows:

$$\text{text-based score} = \sum_{j=1}^{12019} \hat{\phi}_j \frac{W_{jit}}{\sum W_{it}}, \tag{4.3}$$

where $\hat{\phi}_j$ is the estimate of ϕ_j, and $\sum W_{it}$ is the total count of all lemmas in all reviews posted on firm i in year t. We hereinafter refer to the six text-based scores as pros_text_score_inflow, cons_text_score_inflow, advice_text_score_inflow, pros_text_score_outflow, cons_text_score_outflow, and advice_text_score_outflow, respectively.

With the six text-based scores, we perform two prediction tasks, one targeting one-year-ahead external inflow reduction and one one-year-ahead external outflow increase. For each task, we use the three text-based scores corresponding to that outcome (e.g., pros_text_score_inflow, cons_text_score_inflow, advice_text_score_inflow for external inflow reduction), along with the full set of controls defined in Section 4.4.3 and industry and year indicators as predictors to estimate a gradient-boosted binary classifier (Hastie et al., 2009). Ensemble learning methods such as gradient boosting are well-suited to this setting due to their ability to capture nonlinear interactions among predictors (Bao et al., 2020; Gu et al., 2020; Campbell and Shang, 2022; Guenther et al., 2023; Starica and Marton, 2025). Consistent with (Campbell and Shang, 2022), we set the learning rate to 0.01, n_estimators to 10,000. max_depth to 5, and subsample to 0.5. We split the 2014-2017 firm-year observations into a training set (2014-2016) and test set (2017). This train-test splitting scheme mirrors how a firm might deploy a talent drain prediction algorithm in practice. The comprehensive control structure ensures that any predictive gains from the text-based scores reflect the incremental value of Glassdoor review content beyond what firm-level fundamentals already capture.

For each future talent drain event, we define the no-score model as the model that excludes the text-based scores as predictors, and the full model as the model that includes them. We fit both models on the training set and evaluate their respective performance on the out-of-sample test set using both accuracy and the area under the receiver operating characteristic curve (AUC). We conduct a McNemar test (Dietterich, 1998) to evaluate whether the full model's out-of-sample accuracy is significantly higher than the no-score model's, and a non-parametric DeLong test (DeLong et al., 1988) on the difference in out-of-sample AUC.

4.4.6 Analysis

Pros Section: Thematic Map

Figure C.12 visualizes the top five HR themes that help firms attract future talents or retain current talents. We discuss them in detail below.

Fair Rewards & Empowering growth This theme portrays an employment deal that balances two psychologically powerful signals: credible monetary fairness and tangible personal development. On the compensation side, employees emphasize that pay rises in step with living-cost pressure. For example, one employee comments "Continuous increments in the salary according to inflation. Good compensation & benefits." Such comments signal that workers see proof the firm recognizes external economic reality and adjusts accordingly, transforming pay from a potential irritant into a stabilizing anchor. On the development side, employees underline opportunities to expand professional capital. They value a culture where they can contribute ideas, tackle challenging problems, and accumulate portable expertise, with one contributor recalling that management "valued my input—projects reflected ideas straight from the ground level." When employees see both fair rewards and meaningful growth, the incentive to seek opportunities elsewhere diminishes.

Flexible Work Schedule This theme links talent retention to the freedom employees have over when and how long they work. Flexibility operates at multiple levels, from daily scheduling and shift structure to holiday leave and career experimentation. One contributor notes that "Shift work allows for three or four days off in a row—work-life balance actually happens here," while another highlights that the company grants "extra leave for Christmas and Thanksgiving holidays, on top of the generous annual allotment." Beyond scheduling, flexibility extends to career experimentation. One employee comment recounts that the firm "let you keep your benefits when you try shiny new experiences," signaling management's willingness to endorse lateral moves rather than penalize them. This perception of control over one's schedule forms a protective buffer against future talent drain.

Career-Building Programs & Benefit Schemes This theme underline a two-pronged value proposition: structured pathways that help employees grow into larger roles and benefit packages that reinforce long-term financial security. On the career development side, one employee credits a formal entry track, noting "Very good apprentice and graduate scheme ensures new talent is given every opportunity to contribute," while another highlights a domain-specific pipeline: "Clear path to leasing and property-management career—good pay, strong bonuses, top-notch training." These remarks suggest that upward mobility is not reserved for a select few but embedded in the operating model. On the benefits side, benefit schemes reinforce the growth promise by anchoring employees' financial future. One reviewer cites a broad safety net: "Best reasons: great people and strong benefits across banking, mortgage, loans, credit cards, etc." Together, the structured career pathways and durable benefit schemes give employees both a pathway to mastery and economic scaffolding to make that journey worthwhile, powerfully discouraging voluntary exit.

Supportive & Learning-Friendly Culture This theme conveys a workplace where collegial goodwill and ongoing learning are daily realities, not slogans. One contributor captures the tone succinctly: "Good work-life balance, freedom, forgiving culture, minimal politics; they even encourage job rotation and extra training." The reference to forgiveness and structured rotation signals psychological safety—employees can experiment, err, and still advance. Trust lowers social barriers, making knowledge-sharing natural. Another reviewer enthuses that there are "so many creative people you can bounce an idea off; constant exciting projects and announcements," indicating that curiosity is rewarded rather than restrained. Support also takes tangible form: technology upgrades remove friction, and leadership's long-term outlook reinforces employees' confidence in the firm's future.

Close-Knit Workforce & Interpersonal Rapport This theme draws a picture of a workplace where day-to-day interactions breed strong social glue. Friendship surfaces not as a perk but as a defining feature: "the benefits are good and the friendship among co-workers is good," writes one reviewer, reinforcing the link between interpersonal warmth and perceived organizational generosity. Even high-pressure learning curves are reframed through camaraderie; an engineer observes that onboarding can feel like "drinking from a fire hose, but there are zero barriers to information flow." When colleagues trust one another, freely trade know-how, and celebrate collective craftsmanship, the workplace becomes more than a job; it turns into a community. Such interpersonal rapport forms an intangible yet robust barrier against future talent drain.

Cons Section: Thematic Map

Figure C.13 visualizes the top five HR themes that reduce a firm's talent attractiveness or push current talents away. We discuss them one by one below.

Goal-Capacity Gap Under this theme, reviewers share a skepticism that corporate targets can be realized with available resources. One contributor laments "Very high sales goals which are not always reachable; leadership blames front-line staff when the numbers slip." Timelines also feel out of touch with reality: "Project management is poor—resource gaps are never factored into deliverable dates we promised clients." Together these voices reveal a gap between ambition and practical capacity that drains energy and encourages voluntary exit.

Legacy Elitism Culture This theme describes a workplace governed by a privileged inner circle operating atop outdated systems. One comment notes that "If you're not the elite designer, you're a disposable set of hands," while another complains that IT remains "primitive—data-management methods are sloppy . . . total time-waster." Administrative overhead compounds frustration: "Like any large company there is the requisite red tape and politics; getting approvals can take weeks." The combination of elitism, antiquated tools, and bureaucracy signals organizational stasis that pushes talent away.

Pay & Promotion Bias This theme centers on perceived unfairness in pay and advancement. A reviewer points out that "Performance appraise was never transparent," echoing a colleague who observes "Full of favoritism, partiality and politics." Pay policies also draw criticism; one employee urges leadership to "revisit the pay structure to stay competitive," suggesting misalignment between contribution and reward. The impression that opportunity is rationed through partiality rather than merit weakens commitment and heightens turnover risk.

Fragmented Leadership & Resource Thinness This theme highlights strategic drift and under-investment. A reviewer observes that leadership "regionally changes every one to two years—new boss, new priorities, no continuity," and another states management seems "intentionally ignorant of the resulting churn" created by low pay hiring practices. Strategic clarity is questioned: "Within business lines we're strategically confused; cliques set direction and it changes every quarter." Thin budgets amplify the strain, as one employee remarks that vertical growth is "slim—easy to stay invisible in such a big place." Such fragmentation erodes confidence in the firm's future, exacerbating attrition.

Workplace Decay & Safety Neglect This theme captures subpar physical conditions and safety lapses. One reviewer warns that headquarters sits in a "very, very dangerous" area, while another reports a persistent "moldy smell" that never went away. Employees also experience outdated or defective equipment: "Horrible computer systems make you wrestle with problems instead of focusing on your actual job." When day-to-day work occurs amid decay and hazard, loyalty falters and exits accelerate.

Predicting Future Talent Drain Events

We fit and test the no-score and full models for both external_inflow_reduction and external_outflow_increase, and report the out-of-sample predictive performance in

Table 4.4. For external_inflow_reduction, incorporating the three proposed text-based scores (i.e., pros_text_score_inflow, cons_text_score_inflow, and advice_text_score_inflow) boosts both accuracy (from 0.719 to 0.769) and AUC (from 0.534 to 0.594), demonstrating the incremental out-of-sample predictive power of the text of Glassdoor reviews in forecasting a firm's reduced talent attractiveness. Correspondingly, a McNemar test gives a p-value of 0.0309, suggesting that the difference in accuracy is significant at 5%; a DeLong test results in a p-value of 0.0866, an indication that the difference in AUC is significant at 10%.

For external_outflow_reduction, incorporating the three text-based scores (i.e., pros_text_score_outflow, cons_text_score_outflow, advice_text_score_outflow) similarly improves out-of-sample accuracy (from 0.623 to 0.653) and AUC (from 0.525 to 0.576). The DeLong test confirms that the AUC improvement is significant at 5% (p-value = 0.0354). However, a McNemar test on the difference in accuracy yields a p-value of 0.3075, indicating that the difference is not statistically significant.

To decompose the relative contribution of each predictor, we compute the mean absolute SHapley Additive exPlanations (SHAP) values (Lundberg and Lee, 2017; Ragodos et al., 2024) on the training sample for both models, reported in Figure 4·7 and 4·8. In the inflow reduction model (Figure 4·7), the calendar year exerts the strongest marginal effect (year, 2.21), followed by pros-section-based score (pros_text_score_inflow, 1.68) and capital expenditure intensity (CapEX, 1.50). Cons-section-based score also ranks among the top contributors. Media coverage (log_news_count), overall Glassdoor rating (rating), managerial ownership (ManOwn), review sentiment (sentiment_score), and institutional ownership (InstOwn) cluster in the 0.94-1.50 range, while the remaining controls are collectively material (8.98) but individually immaterial.

In the outflow increase model (Figure 4·8), contemporaneous sentiment score dominates (sentiment_score, 2.22), followed by profitability (ROA, 1.56), advice-section-based score (advice_text_score_outflow, 1.39) and temporal trend (year, 1.34). Rating, managerial ownership (ManOwn), capital expenditure intensity (CapEX), ESG performance (ESGScore), and institutional ownership (InstOwn) each contributing roughly one SHAP unit, while the residual feature set jointly sums to 10.48.

Two findings stand out. First, the SHAP analysis reveals that the text-based scores rank among the most important predictors in both models. In particular, pros-section-based score ranks ahead of every other financial variable in the inflow model, and advice-section-based score ranks third in the outflow model. Combined with the significant out-of-sample prediction improvements, these results indicate that the textual content of Glassdoor reviews carries incremental predictive information about talent drain risk beyond what firm-level fundamentals capture. Second, different review sections dominate for different outcomes. In particular, the pros section is the most informative for predicting reduced talent attractiveness, while the advice section is most informative for predicting increased talent attrition. This mapping is intuitive: prospective employees assess whether a firm is worth joining by reading what current employees praise, while the advice section reveals internal frustrations from employees evaluating whether to stay. For inflow prediction, cons-section-based score also contributes meaningfully, suggesting that a firm's internal problems become externally visible through negative reviews and deter prospective talent as well. It is important to note that because the text-based scores are constructed from the same MNIR loadings that generate the diagnostic themes in Sections 4.4.6 and 4.4.6, our framework provides not only an early warning of future talent drain but also an explanation of which operational dimensions are driving it.

Table 4.4: Out-of-Sample Prediction Performance

	Accuracy		AUC	
Outcome	No scores	Full	No scores	Full
external_inflow_reduction	0.719	0.769	0.534	0.594
external_outflow_increase	0.623	0.653	0.525	0.576

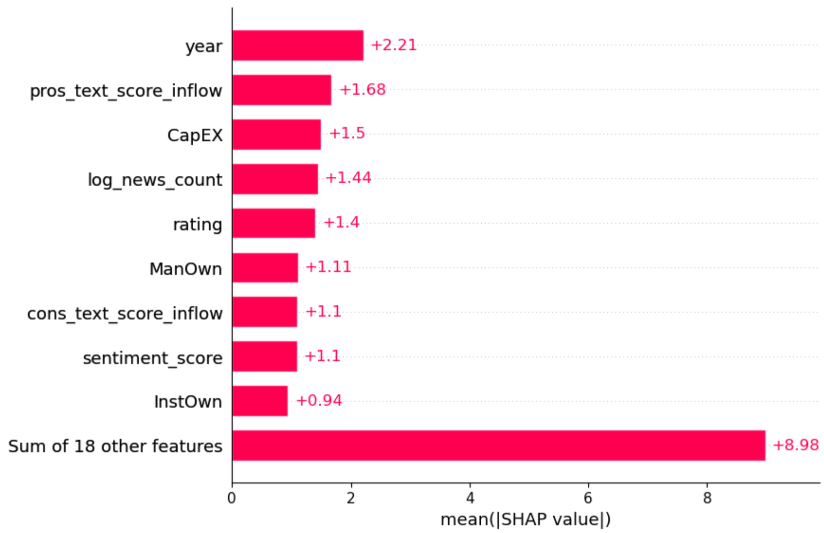

Figure 4·7: Mean absolute SHAP values for features predicting a future external inflow reduction (higher bars indicate greater average contribution to the model's output).

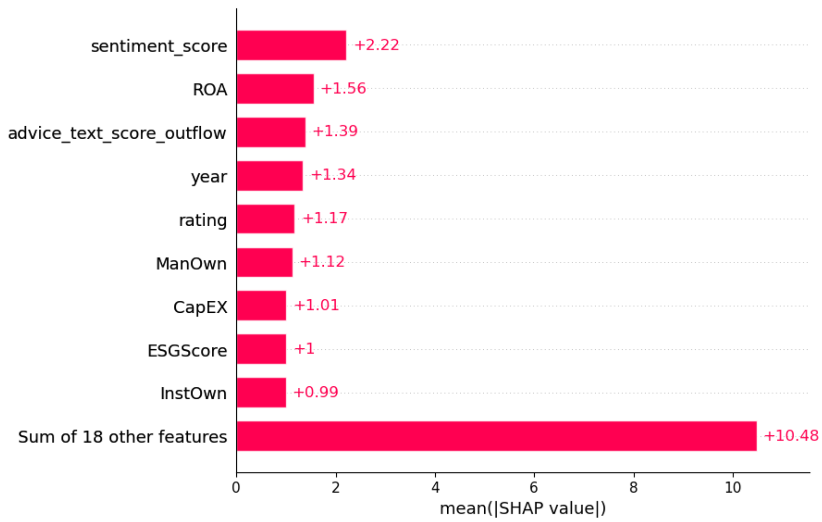

Figure 4·8: Mean absolute SHAP values for features predicting a future external outflow increase (higher bars indicate greater average contribution to the model's output).

4.5 Limitations and Future Research

Our findings have several practical implications. The diagnostic themes extracted from Glassdoor review text offer firms an immediate audit tool: the talent-retaining themes (e.g., fair rewards, flexible scheduling, career-building programs) identify operational areas to maintain, while the talent-draining themes (e.g., goal-capacity gaps, pay and promotion bias, fragmented leadership) pinpoint areas requiring intervention. The prediction framework can be deployed at multiple levels of the workforce. For example, at the executive level, where individual departures carry significant profitability consequences (Messersmith et al., 2014), it can serve as an early warning system for senior leadership attrition. At the rank-and-file level, where turnover can degrade operational performance such as product failure rates (Moon et al., 2022), it can help firms anticipate and mitigate disruptions. For investor relations, our findings that sentiment-neutral first reviews trigger heightened risk perception suggests that HR leaders should prioritize engaging with ambiguous reviews constructively, as such engagement can alter organizational image and limit unnecessary valuation pressure (Yu et al., 2025; Chung et al., 2020). Although we focus on Glassdoor, the underlying framework can be generalized to other platforms with structured employee review sections, such as Indeed or Blind.

Although this study yields new insights into how Glassdoor reviews can foreshadow firm-level talent dynamics, several avenues remain for future research. The multinomial inverse regression framework that we use to link review text to future talent drain events is based on word frequencies and thus overlooks the talent drain-related information that is hidden in the semantics of the pros, cons, and advice sections; we encourage future methodological research into developing semantics-aware data mining tools capable of discovering textual entities most associated with managerial target variables (Lee et al., 2025). In addition, future work could unify our aggregate-level prediction framework with individual-level turnover predictors (Ke et al., 2025), thereby illuminating how micro motives aggregate into the macro patterns of talent drain. Relatedly, we encourage researchers to extend our static talent drain prediction framework into a dynamic version that supports online learning, enabling the model to continuously relearn the relationship between talent drain events and word usage in Glassdoor employee reviews as new data arrive. Finally, while we show that investors adjust their talent drain risk perception promptly in response to newly available employee-generated reviews on Glassdoor, future work can examine whether firms' responses to their inaugural Glassdoor reviews can help temper investors' talent drain risk assessment (Chung et al., 2020).

Chapter 5

Conclusion

This dissertation examines how leadership structure, workforce composition, and employee-generated information jointly shape important operational outcomes. Across three essays, I study environmental innovation, supplier governance, and talent-drain risk in settings where firms face increasing pressure to align performance with sustainability and human-capital resilience. The central message is that operational outcomes are not determined by formal policies alone. They depend on whether governance choices are supported by organizational context, incentive design, and credible information signals.

Chapter 2 shows that board female representation is associated with stronger environmental innovation, but the effect is conditional rather than universal. The relationship is most pronounced when women represent a majority of the workforce and is mediated by environmental management system (EMS) adoption. In other words, governance diversity at the board level appears to be translated into innovation through operational systems and employee engagement channels. This finding helps explain why prior evidence on board diversity and sustainability outcomes is often mixed: the same governance input can produce different operational outputs depending on internal workforce conditions.

Chapter 3 shifts from environmental innovation to responsible supplier governance. The evidence indicates that female chief supply chain officer (CSCO) presence is associated with stronger supplier monitoring architectures and, through that channel, greater use of termination provisions for non-compliant suppliers. The chapter also shows that female CEO presence and female leadership on compensation committees are associated with a higher likelihood of appointing female CSCOs, and that sustainability-linked executive compensation strengthens the female CSCO-governance relationship. Together, these results highlight that governance outcomes in supply networks depend on both who holds authority and how incentive systems reinforce that authority.

Chapter 4 focuses on talent-drain risk and investor response to new employee-information channels. Using Glassdoor coverage initiation as a quasi-experimental shock, the chapter documents that investors increase required risk premia when the first employee signal is sentiment-neutral, with corresponding increases in idiosyncratic risk and talent-drain factor exposure. Positive or negative first signals do not produce the same repricing pattern, consistent with ambiguity rather than directional sentiment driving the response. The chapter further demonstrates that text-derived human-resource themes from employee reviews improve out-of-sample prediction of future inflow reduction and outflow increase. This evidence suggests that employee voice contains operationally relevant information that markets and managers can use to monitor workforce fragility earlier.

Taken together, the three essays contribute to operations management in four ways. First, they provide evidence that organizational demography and leadership composition are economically meaningful operational levers, not merely symbolic governance attributes. Second, they identify mechanisms through which governance affects outcomes, especially EMS adoption and supplier-monitoring formalization. Third, they show that incentive alignment is a critical amplifier: governance intent translates into outcomes more reliably when compensation structures reward the targeted behavior. Fourth, they demonstrate that external employee-generated information can materially affect both market pricing and internal risk diagnostics.

The dissertation also offers practical guidance. For boards and top management teams, diversity initiatives should be paired with implementation systems and workforce-aware design rather than treated as stand-alone targets. For supply chain leaders, responsible supplier governance requires coordinated choices across role design, monitoring infrastructure, and escalation rules, supported by incentive contracts. For investor-relations and human-resources functions, employee-review platforms should be treated as strategic early-warning systems that can inform both communication strategy and retention policy before turnover pressures become visible in lagged accounting outcomes.

Several limitations point to promising future research. First, while the empirical designs address major endogeneity concerns, they remain observational and context-specific; replication across countries and private firms would strengthen external validity. Second, the governance channels studied here likely interact with other organizational features such as unionization, labor-market tightness, and technological change; richer institutional heterogeneity is a natural next step. Third, future work can extend the measurement frontier by combining employee text, internal HR process data, and operational performance metrics in real time to evaluate intervention effectiveness. Finally, causal experiments on how firms respond to ambiguity in employee-generated signals would deepen understanding of when market learning and managerial learning converge or diverge.

Overall, this dissertation argues that sustainable and resilient operations are fundamentally socio-technical: they emerge from the interaction of governance architecture, incentives, workforce composition, and information environments. By connecting these elements across environmental innovation, supplier governance, and talent-drain risk, the three essays provide a coherent foundation for research and practice at the intersection of operations strategy, organizational design, and human capital.

Appendix A

Appendix for Chapter 2

A.1 Select Data Points Comprising Refinitiv's Environmental Pillar

Table A.1 lists the nature and number of data points comprising each dimension of Refinitiv's environmental pillar, as well as select exemplary data points.

Table A.1: Refinitiv's environmental data points summary table.

Sustainability Pillar	**Dimension**	**Sampling of Data Points**	**No. Data Points**
Environmental	**Emissions**	Direct scope-1 CO2 and CO2 equivalent emissions in tonnes; Indirect scope-3 CO2 and CO2 equivalent emissions; Total amount of ozone depleting substances emitted in tonnes; Ratio of waste recycled/reused to total waste produced; Self-reported environmental fines; Whether a firm reports on activities to reduce its operations' impacts on the native ecosystems and species; Whether a firm reports on initiatives to reduce, substitute, or phase out PM10; Whether a firm reports on initiatives to reduce, substitute, or phase out volatile organic compounds.	180
	Innovation	Percentage of green products or services; Research and development (R&D) expenditures for products and services focused on improving environmental impact; A firm's total energy distributed or produced from renewable energy sources divided by the total energy distributed or produced; Whether a firm reports on specific eco-designed products; Whether a firm reports on at least one product line or service that is designed to have positive effects on the environment; Whether a firm reports on noise-reducing products; Whether a firm is a signatory of the Equator Principles (commitment to manage environmental issues in project financing); Whether a firm claims to evaluate projects based on environmental or biodiversity risks; Does a firm report or show initiatives to produce or promote organic food or other products?	36
	Resource Use	Water usage in cubic meters; Energy usage in gigajoules; Whether a firm has a policy to improve its water efficiency; Whether a firm has a policy to improve its energy efficiency; Whether a firm has a policy to improve its use of sustainable packaging; Whether a firm has a policy to include its supply chain in its efforts to lessen the firm's overall environmental impact; Whether a firm sets targets/objectives to be achieved on water efficiency; Whether a firm sets targets/objectives to be achieved on energy efficiency; Whether a firm claims to use environmental criteria to source or eliminate materials.	40

A.2 Illustration of How a firm's Sustainability Performance is Computed

For illustration, let's consider the following simplifying example: in the water and related utilities industry group, there are four firms ABC, DEF, GHI, and JKL. The goal is to compute the environmental pillar score of ABC. To do so, we carry out the illustration by following the steps below:

A.2.1 Compute Environmental Dimension Scores

We will assume that numeric data point $TotalCO2andEquivalents$[1] and boolean data point $PolicyEmissions$ (whether a firm has an emissions reduction policy in a given fiscal year)[2] are the two data points denominating the Emissions dimension score. Further, we will assume that numeric data point $R\&DExpenditure$[3] and boolean data point $ProductImpactMinimization$ (whether a firm practices take-back procedures and recycling programs to reduce the potential risks entering the environment?)[4] are the two data points denominating the Innovation dimension score, and numeric data point $TotalRenewableEnergy$ (total primary renewable energy purchased and produced in gigajoules)[5] and boolean data point $ResourceReductionPolicy$ (whether a firm has a policy for reducing the use of natural resources or to lessen the environmental impact of its supply chain)[6] are the two data points denominating the Resource Use dimension score. In fiscal year 2023, ABC, DEF, GHI, JKL have the following raw

[1]This is a data point of negative polarity whereby the lower the value, the better.

[2]The associated preference order is: yes > no = null. Moreover, the values corresponding to yes, no, and null are 1, 0, 0 respectively.

[3]This is a data point of positive polarity whereby the higher the value, the better.

[4]The associated preference order is: yes > no = null. Moreover, the values corresponding to yes, no, and null are 1, 0, 0 respectively.

[5]This is a data point of positive polarity whereby the higher the value, the better.

[6]The associated preference order is : yes > no = null. Moreover, the values corresponding to yes, no, and null are 1, 0, 0 respectively.

values for the aforementioned numeric and boolean data points:

Table A.2: Illustrative firm scores on *TotalCO2andEquivalents*, *PolicyEmissions*, *R&DExpenditure*, *ProductImpactMinimization*, *TotalRenewableEnergy*, and *ResourceReductionPolicy* in fiscal year 2023.

Firm	TotalCO2andEquivalents	PolicyEmissions	R&DExpenditure	ProductImpactMinimization	TotalRenewableEnergy	ResourceReductionPolicy
ABC	0.000005	Yes	$1,200,000	Yes	15,000 MWh	Yes
DEF	0.000123	No	$850,000	No	10,000 MWh	No
GHI	0.000182	Null	$920,000	Yes	20,000 MWh	Null
JKL	0.000250	Yes	$1,500,000	No	18,000 MWh	Yes

To take into account how other industry peers perform on a data point when evaluating a focal firm's performance on the data point, the Refinitiv ESG database uses the percentile scoring methodology illustrated as follows:

$$\text{score} = \frac{N_{\text{worse}} + \frac{1}{2}N_{\text{same}}}{N_{\text{total}}},$$

where N_{worse} is the number of firms with a worse value, N_{same} is the number of firms with the same value (including the focal firm), and N_{total} is the number of firms with a value. Then, the percentile scores of ABC, DEF, GHI, and JKL on $TotalCO2andEquivalents$ are $(3 + (1/2))/4 = 0.875$, $(2 + (1/2))/4 = 0.625$, $(1 + (1/2))/4 = 0.375$, and $(0 + (1/2))/4 = 0.125$. The percentile scores of ABC, DEF, GHI, and JKL on $PolicyEmissions$ are $(2+(2/2))/4 = 0.75$, $(0+(2/2))/4 = 0.25$, $(0+(2/2)/4) = 0.25$, and $(2 + (2/2))/4 = 0.75$. Summing up the data point-level percentile scores for each firm, we have the following firm-level percentile score for ABC, DEF, GHI, and JKL: $0.875 + 0.75 = 1.625$, $0.625 + 0.25 = 0.875$, and $0.375 + 0.25 = 0.625$, and $0.125 + 0.75 = 0.875$. Here, the Refinitiv ESG database would apply percentile scoring again on the three firm-level percentile scores to get the emission dimension scores for ABC, DEF, GHI, and JKL. They are: $(3 + (1/2))/4 = 0.875$ for ABC, $(1 + (2/2))/4 = 0.5$ for DEF, $(0 + (1/2))/4 = 0.125$ for GHI, and $(1 + (2/2))/4 = 0.5$ for JKL.

Next, for the environmental innovation dimension, the percentile scores for $R\&DExpenditure$ are: $(2 + 1/2)/4 = 0.625$ for ABC, $(0 + 1/2)/4 = 0.125$ for DEF, $(1 + 1/2)/4 = 0.375$ for GHI, and $(3 + 1/2)/4 = 0.875$ for JKL. The percentile scores for $ProductImpactMinimization$ are: $(2+2/2)/4 = 0.75$ for ABC, $(0+2/2)/4 = 0.25$ for DEF, $(2 + 2/2)/4 = 0.75$ for GHI, and $(0 + 2/2)/4 = 0.25$ for JKL. Summing up the data point-level percentile scores for each firm, we have the following firm-level percentile scores: $0.625 + 0.75 = 1.375$ for ABC, $0.125 + 0.25 = 0.375$ for DEF, $0.375 + 0.75 = 1.125$ for GHI, and $0.875 + 0.25 = 1.125$ for JKL. Applying the percentile scoring again on the firm-level scores, we get: $(3 + 1/2)/4 = 0.875$ for ABC, $(0 + 1/2)/4 = 0.125$ for DEF, $(1 + 1/2)/4 = 0.375$ for GHI, and $(1 + 1/2)/4 = 0.375$ for JKL.

Finally, for the resource use dimension, the percentile scores for $TotalRenewableEnergy$ are: $(1 + 1/2)/4 = 0.375$ for ABC, $(0 + 1/2)/4 = 0.125$ for DEF, $(3 + 1/2)/4 = 0.875$ for GHI, and $(2 + 1/2)/4 = 0.625$ for JKL. The percentile scores for $ResourceReductionPolicy$ are: $(2 + 2/2)/4 = 0.75$ for ABC, $(0 + 1/2)/4 = 0.125$ for DEF, $(0 + 1/2)/4 = 0.125$ for GHI, and $(2 + 2/2)/4 = 0.75$ for JKL. Summing up the data point-level percentile scores for each firm, we have the following firm-level percentile scores: $0.375 + 0.75 = 1.125$ for ABC, $0.125 + 0.125 = 0.25$ for DEF, $0.875 + 0.125 = 1.0$ for GHI, and $0.625 + 0.75 = 1.375$ for JKL. Applying the percentile scoring again on the firm-level scores, we get: $(2 + 1/2)/4 = 0.625$ for ABC, $(0 + 1/2)/4 = 0.125$ for DEF, $(1 + 1/2)/4 = 0.375$ for GHI, and $(3 + 1/2)/4 = 0.875$ for JKL. Tabulating the afore-calculated environmental dimension scores gives rise to the following table:

Table A.3: Illustrative firm environmental dimension scores in fiscal year 2023.

Firm	Dimension	Dimension Score
ABC	emissions	0.875
DEF	emissions	0.5
GHI	emissions	0.125
JKL	emissions	0.5
ABC	environmental innovation	0.875
DEF	environmental innovation	0.125
GHI	environmental innovation	0.375
JKL	environmental innovation	0.375
ABC	resource use	0.625
DEF	resource use	0.125
GHI	resource use	0.375
JKL	resource use	0.875

A.2.2 Compute Environmental Dimension Weights

Let's start by assuming the following magnitude weights for the hypothesized firms in the water & related utilities industry group. Note that magnitude weights are decile ranks. More specifically, for an industry and a dimension, the higher the magnitude weight/decile rank, the more relevant the dimension is to the industry compared with the other industries in Refinitiv's industry universe.

Table A.4: The magnitude weights of the water and related utilities industry group.

Industry group	Environmental			Social				Governance		
	Emission	Innovation	Resource use	Human rights	Product resp.	Workforce	Community	Management	Shareholders	CSR strategy
Water & Related Utilities	9	8	9	3	2	8	5	10	3	2

Based on Table A.4, the sum of all magnitude weights is $9+8+9+3+2+8+5+10+3+2=59$. The dimension weights are obtained by dividing water & related utilities industry's magnitude weights by the sum of all magnitude weights to make the notion comparable across different dimensions. The dimension weights are as follows:

Table A.5: The dimension weights of the water and related utilities industry group.

Industry group	Environmental			Social				Governance		
	Emission	Innovation	Resource use	Human rights	Product resp.	Workforce	Community	Management	Shareholders	CSR strategy
Water & Related Utilities	$9/59 = 0.153$	$8/59 = 0.136$	$9/59 = 0.153$	$3/59 = 0.051$	$2/59 = 0.034$	$8/59 = 0.136$	$5/59 = 0.085$	$10/59 = 0.169$	$3/59 = 0.051$	$2/59 = 0.034$

For each pillar, a new dimension weight is derived by dividing each original dimension weight by the sum of the original dimension weights corresponding to all the dimensions constituting the pillar. Specifically, the sums of all the dimension weights for the environmental pillar, the social pillar, and the governance pillar are $0.153 + 0.136 + 0.153 = 0.442$, $0.0508 + 0.0339 + 0.136 + 0.0847 = 0.3054$, and $0.169 + 0.0508 + 0.0339 = 0.2537$. As such, the new dimension weights for the water and related utilities industry group are:

Table A.6: The new dimension weights of the water and related utilities industry group.

Industry group	Environmental			Social				Governance		
	Emission	Innovation	Resource use	Human rights	Product resp.	Workforce	Community	Management	Shareholders	CSR strategy
Water & Related Utilities	$\frac{0.153}{0.442} = 0.346$	$\frac{0.136}{0.442} = 0.308$	$\frac{0.153}{0.442} = 0.346$	$\frac{0.051}{0.305} = 0.166$	$\frac{0.034}{0.305} = 0.111$	$\frac{0.136}{0.305} = 0.445$	$\frac{0.085}{0.305} = 0.277$	$\frac{0.169}{0.254} = 0.666$	$\frac{0.051}{0.254} = 0.200$	$\frac{0.034}{0.254} = 0.134$

A.2.3 Compute Environmental Sustainability Performance

Based on the environmental dimension scores and corresponding weights, ABC's environmental pillar score in fiscal year 2023 is $0.875 \times 0.346 + 0.875 \times 0.308 + 0.625 \times 0.346 = 0.7885$.

Appendix B

Appendix for Chapter 3

B.1 Summary Statistics and Univariate Correlation Analysis

Table B.1: Summary Statistics for Baseline Regression Variables (H1, H3a)

	Count	Mean	SD	Skewness	Min	Q25	Median	Q75	Max
`SupplierMonitoringSystem`	3570	0.53	0.50	-0.13	0	0	1	1	1
`ESGSupplierTerminationProvision`	3570	0.37	0.48	0.55	0	0	0	1	1
`FemaleCSCOPresent`	3570	0.05	0.21	4.38	0	0	0	0	1
`NumSeniorExecutiveOfficers`	3570	5.12	1.91	-1.42	0	5	5	6	13
`AvgSeniorExecutiveOfficerTenure`	3570	15.16	7.84	1.69	0.32	13.83	13.83	13.83	46.00
`COOPresent`	3570	0.20	0.40	1.49	0	0	0	0	1
`SustainabilityCompensationIncentives`	3570	0.23	0.42	1.32	0	0	0	0	1
`Diversification`	3570	0.32	0.29	0.13	0	0	0.36	0.59	0.93
`Internationalization`	3570	0	0	NA	0	0	0	0	0
`FirmSize` (Total Revenue)	3570	12485.80	37908.63	10.00	36.16	2543.14	4390.40	8219.80	608481.00
`AcquisitionDummy`	3570	0.08	0.27	3.13	0	0	0	0	1
`Leverage`	3570	0.33	0.25	6.06	0	0.22	0.32	0.40	3.89
`R&DIntensity`	3570	0.02	0.02	4.17	0	0.01	0.01	0.01	0.28
`CapitalIntensity`	3570	0.26	0.19	1.36	0.00	0.14	0.21	0.33	0.91
`ROA`	3570	0.06	0.06	-1.28	-0.49	0.04	0.06	0.08	0.40
`CASH`	3570	0.10	0.10	2.25	0	0.04	0.07	0.12	0.63
`BoardSize`	3570	10.11	2.41	13.85	4	9	10	11	98
Tobin's Q	3570	1.52	1.36	5.13	0.07	0.88	1.19	1.67	27.69
`CEOBoardMember`	3570	0.99	0.07	-13.59	0	1	1	1	1
`CSRSustainabilityCommittee`	3570	0.96	0.19	-4.93	0	1	1	1	1
`NumFemaleDirectors`	3570	2.29	1.37	7.96	0	2	2	3	43

Note: Skewness is undefined for Internationalization because it equals zero for all firm-year observations; it is therefore reported as NA.

Table B.2: Summary Statistics for Baseline Regression Variables (H2)

	Count	Mean	SD	Skewness	Min	Q25	Median	Q75	Max
FemaleCSCOPresent	153	0.39	0.49	0.44	0	0	0	1	1
BoardSize	153	10.52	1.89	0.32	6	9	10	12	15
NumFemaleDirectors	153	2.86	1.22	0.43	0	2	3	3	6
FemaleCEO	153	0.07	0.26	3.28	0	0	0	0	1
NumSeniorExecutiveOfficers	153	5.77	1.11	-0.00	2	5	6	6	9
AvgSeniorExecutiveOfficerTenure	153	19.97	10.90	1.08	1.98	13.83	13.83	23.75	46.00
COOPresent	153	0.17	0.38	1.74	0	0	0	0	1
FirmSize (Total Revenue)	153	19092.88	46541.14	7.97	52.60	2622.86	6868.62	12682.00	511729.00
AcquisitionDummy	153	0.08	0.28	2.95	0	0	0	0	1
ROA	153	0.06	0.07	-1.20	-0.32	0.03	0.06	0.10	0.35
Internationalization	153	0	0	NA	0	0	0	0	0
Leverage	153	0.30	0.18	0.81	0	0.19	0.31	0.41	0.98
Diversification	153	0.30	0.30	0.26	0	0	0.24	0.62	0.82

Note: Skewness is undefined for Internationalization because it is always equal to 0 for all firm-year observations; it is thus marked with NA.

Table B.3: Summary Statistics for Compensation Committee Analysis (H3b)

	Count	Mean	SD	Skewness	Min	Q25	Median	Q75	Max
`SustainabilityCompensationIncentives`	4006	0.484	0.5	0.06	0	0	0	1	1
`HasCompCommittee`	4006	1	0	NA	1	1	1	1	1
`FemaleCountCompCommittee`	4006	1.009	0.835	0.56	0	0	1	2	5
`CompCommitteeFemaleChair`	4006	0.233	0.423	1.26	0	0	0	0	1
`BoardSize`	4006	10.71	2.119	0.69	4	9	11	12	30
`IndependentDirectors`	4006	8.98	2.094	0.4	3	8	9	10	24
`AvgOutsideBoards`	4006	0.967	0.428	0.34	0	0.667	1	1.25	4.778
`AvgBoardTenure`	4006	8.13	3.22	1.12	0.5	6	7.833	9.727	30.17
`PreCEODirectors`	4006	4.164	3.255	0.5	0	1	4	6	23
`AvgBoardAge`	4006	62.46	3.056	-0.18	49	60.5	62.67	64.45	74.43
`BoardAgeDiversity` (Std)	4006	7.068	2.077	0.74	1.787	5.601	6.81	8.328	17.55
`FemaleDirectors`	4006	2.672	1.224	0.61	0	2	3	3	9
`FemaleCEO`	4006	0.069	0.254	3.39	0	0	0	0	1
`CEOAge`	4006	65.23	7.172	0.17	38	60	65	70	98
`CSRSustainabilityCommitteePresent`	4006	0.967	0.18	-5.19	0	1	1	1	1
`ESGScore`	4006	0.607	0.155	-0.4	0.115	0.5	0.626	0.723	0.952
`FirmSize` (Total Revenue)	4006	20688.49	43059.76	6.39	61.29	3021.92	7598.50	19015.45	608481
`ROA`	4006	0.128	0.093	1.63	−0.586	0.069	0.118	0.171	1.481

Note: Skewness is undefined for HasCompCommittee because it is always equal to 1 for all firm-year observations; it is thus marked with NA.

Table B.4: Correlation Matrix for Baseline Regression Variables (H1, H3a)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 SupplierMonitoringSystem																				
2 ESGSupplierTerminationProvision	0.55***																			
3 FemaleCSCOPresent	0.20***	0.27***																		
4 NumSeniorExecutiveOfficers	0.25***	0.14***	0.06***																	
5 AvgSeniorExecutiveOfficerTenure	0.18***	0.11***	0.15***	0.12***																
6 COOPresent	0.14***	0.07***	0.01	0.16***	0.02															
7 SustainabilityCompensationIncentives	0.31***	-0.33***	0.06***	0.15***	0.08***	0.06***														
8 Diversification	0.08***	0.01	-0.03*	0.12***	0.01	0.04*	0.06***													
9 Internationalization	NA	NA	NA	NA	NA	NA	NA	NA												
10 FirmSize (Total Revenue)	0.18***	0.02	0.17***	0.06***	0.15***	-0.01	0.21***	-0.06***	NA											
11 AcquisitionDummy	0.08***	0.07***	-0.02	0.04*	-0.01	0.00	0.04*	0.11***	NA	-0.03*										
12 Leverage	0.02	0.08***	0.04*	-0.06***	-0.02	0.00	0.00	-0.06***	NA	-0.02	-0.02									
13 R&DIntensity	0.15***	0.07***	-0.02	0.09***	-0.03	-0.03	0.00	0.07***	NA	-0.07***	0.10***	-0.10***								
14 CapitalIntensity	0.13***	0.01	0.06***	0.12***	0.08***	0.10***	0.23***	-0.16***	NA	0.18***	-0.12***	0.12***	-0.26***							
15 ROA	0.00	0.07***	0.05**	0.01	0.05**	0.00	-0.05**	-0.07***	NA	0.02	-0.12***	0.11***	-0.02	0.03						
16 CASH	0.07***	0.09***	-0.02	0.04*	0.06***	-0.02	-0.07***	-0.03*	NA	-0.07***	-0.02	-0.12***	0.39***	-0.27***	0.10***					
17 BoardSize	0.17***	0.03*	0.05**	0.06***	0.14***	0.05**	0.14***	0.05**	NA	0.23***	-0.06***	0.01	-0.13***	0.15***	0.02	-0.13***				
18 Tobin's Q	0.01	0.08***	0.02	-0.03*	0.07***	-0.04*	-0.08***	-0.13***	NA	-0.07***	-0.08***	0.16***	0.12***	-0.08***	0.39***	0.34***	-0.04*			
19 CEOBoardMember	-0.01	0.00	0.02	-0.05**	0.01	0.00	-0.01	-0.01	NA	-0.01	0.01	-0.02	0.01	-0.03	0.02	0.01	0.03*	0.03		
20 CSRSustainabilityCommittee	-0.08***	-0.13***	0.04*	-0.04*	0.04**	-0.01	0.03	-0.02	NA	0.00	-0.03	0.03	-0.03	0.04*	-0.04*	0.01	-0.04*	-0.02	0.01	
21 NumFemaleDirectors	0.19***	0.09***	0.09***	0.12***	0.18***	0.03	0.19***	0.03	NA	0.18***	-0.06***	0.08***	-0.04*	0.14***	0.06***	-0.05**	0.67***	0.02	0.03	0.05**

Notes: All non-integer results are recorded with two decimal places. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Internationalization exhibits zero variance in the sample; correlations involving this variable are therefore undefined and reported as NA.

Table B.5: Correlation Matrix for Baseline Regression Variables (H2)

	1	2	3	4	5	6	7	8	9	10	11	12	13
1 `FemaleCSCOPresent`													
2 `BoardSize`	0.11												
3 `NumFemaleDirectors`	0.16*	0.61***											
4 `FemaleCEO`	0.24**	-0.04	0.22**										
5 `NumSeniorExecutiveOfficers`	0.01	0.06	0.06	0.01									
6 `AvgSeniorExecutiveOfficerTenure`	0.14	0.13	0.07	-0.09	-0.05								
7 `COOPresent`	-0.15	-0.16*	-0.13	-0.13	0.06	-0.06							
8 `FirmSize` (Total Revenue)	0.03	0.31***	0.14	-0.07	-0.06	0.30***	-0.04						
9 `AcquisitionDummy`	0.04	0.02	-0.06	-0.08	0.02	-0.07	-0.01	-0.06					
10 `ROA`	0.18*	0.05	0.15	0.16*	0.06	0.06	0.09	0.05	-0.16				
11 `Internationalization`	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA			
12 `Leverage`	-0.07	0.08	0.09	0.07	0.05	-0.12	0.06	-0.06	0.11	-0.06	NA		
13 `Diversification`	-0.16*	0.23**	0.07	-0.12	0.19*	0.05	-0.12	0.02	0.06	-0.18*	NA	0.02	

Notes: All non-integer results are reported with two decimal places. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Internationalization exhibits zero variance in the sample; correlations involving this variable are undefined and reported as NA.

Table B.6: Correlation Matrix for Baseline Regression Variables (H3b)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 SustainabilityCompensationIncentives																		
2 HasCompCommittee	NA																	
3 FemaleCountCompCommittee	0.02	NA																
4 CompCommitteeFemaleChair	0.02	NA	0.49***															
5 BoardSize	0.06***	NA	0.08***	-0.04**														
6 NumIndependentDirectors	0.09***	NA	0.12***	-0.03*	0.88***													
7 AvgOutsideBoards	0.07***	NA	0.04*	-0.02	0.10***	0.18***												
8 AvgBoardTenure	-0.07***	NA	-0.08***	-0.06***	0.03	-0.13***	-0.19***											
9 PreCEODirectors	0.06***	NA	-0.01	-0.02	0.30***	0.24***	0.02	0.07***										
10 AvgBoardAge	0.02	NA	-0.07***	-0.09***	0.06***	0.06***	0.01	0.36***	0.04*									
11 AgeDiversity (Std)	-0.09***	NA	0.00	0.01	0.03*	-0.14***	-0.19***	0.14***	0.02	-0.15***								
12 FemaleDirectors	0.09***	NA	0.42***	0.23***	0.45***	0.46***	0.09***	-0.11***	0.10***	-0.12***	-0.02							
13 FemaleCEO	0.05**	NA	0.05**	0.07***	0.03	0.06***	0.04**	-0.11***	0.03	-0.02	-0.06***	0.22***						
14 CEOAge	0.03	NA	-0.08***	-0.13***	0.13***	0.08***	0.10***	0.24***	-0.04*	0.36***	-0.15***	-0.11***	-0.05**					
15 CSRSustainabilityCommittee	0.06***	NA	0.04**	0.07***	0.02	0.03	0.01	-0.05**	0.03*	0.00	0.00	0.08***	0.00	-0.07***				
16 ESGScore	0.23***	NA	0.13***	0.04**	0.25***	0.34***	0.30***	-0.12***	0.08***	0.01	-0.16***	0.34***	0.08***	-0.05**	0.16***			
17 FirmSize (Total Revenue)	0.07***	NA	0.06***	0.05***	0.21***	0.16***	0.18***	-0.02	0.06***	-0.02	-0.01	0.18***	0.04*	0.02	0.04**	0.30***		
18 ROA	-0.05**	NA	0.01	0.01	-0.14***	-0.14***	0.10***	0.08***	-0.01	-0.06***	0.05**	-0.07***	-0.02	0.00	0.00	0.08***	0.00	

Notes: All non-integer correlations are reported with two decimal places. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. HasCompCommittee exhibits no within-sample variation; correlations involving this variable are undefined and reported as NA.

Appendix C

Appendix for Chapter 4

C.1 Glassdoor Employee Reviews and Investor Perception of Future Talent Drain Risk

C.1.1 Idiosyncratic Risk Analysis

C.1.1.1 Variable Definitions and Summary Statistics

Table C.1: Descriptive Statistics

	Definition	Mean	Std Dev	25th pctl	Median	75th pctl	Skewness
Fundamentals							
Annual							
ROA	Net income/total assets	0.110	0.115	0.053	0.113	0.171	-0.584
Leverage	Long-term debt/total assets	0.200	0.182	0.054	0.151	0.283	1.160
Size	Natural log of total assets	8.023	1.839	6.707	7.877	9.216	0.445
R&D	R&D expenditure	0.043	0.066	0.000	0.014	0.059	2.143
Advertising	Advertising expenditure	0.009	0.024	0.000	0.000	0.006	4.149
CapEX	Capital expenditure/total assets	0.037	0.042	0.011	0.024	0.048	2.265
Cash	Cash ratio, calculated as cash and cash equivalents/(total assets − cash and cash equivalents)	0.170	0.187	0.035	0.089	0.234	1.477
EarVar	Standard deviation of income before extraordinary items per share using a five-year rolling window	89.556	133.010	8.667	25.477	103.098	1.776
LogLaborIntensity	$\log\big(1+\text{Employees/Assets }(\$m)\big)$	1.084	0.724	0.442	1.057	1.598	0.424
SAIndex	Hadlock–Pierce financial constraints index	-3.829	0.592	-4.503	-3.717	-3.377	0.085

Table C.1 – continued from previous page

	Definition	Mean	Std Dev	25th pctl	Median	75th pctl	Skewness
ExecuComp							
EXEOPT	Executive stock options granted during the year	0.237	0.216	0.050	0.194	0.337	1.066
ManOwn	Percentage of common shares held by top executives	0.226	0.364	0.000	0.019	0.303	1.385
Fundamentals Annual, Form 5500							
EMPSTK	Employee stock ownership as a percentage of total shares outstanding	0.009	0.020	0.000	0.000	0.009	3.835
LSEG 13F filings							
InstOwn	Percentage of common shares held by institutional investors	0.634	0.305	0.540	0.740	0.859	-1.081
Refinitiv							

Table C.1 – continued from previous page

	Definition	Mean	Std Dev	25th pctl	Median	75th pctl	Skewness
ESGScore	ESG overall score, capturing firm-level environmental, social, and governance performance	0.342	0.154	0.230	0.314	0.436	0.856
RavenPack							
LogNewsCount	Natural log of (1+the number of relevant news articles on a firm on a given day)	0.607	0.981	0.000	0.000	1.099	2.026
SentimentScore	Average sentiment score of relevant news articles on a firm on a given day	0.006	0.039	0.000	0.000	0.012	-1.675
CRSP							
BTM	Book-to-market ratio	0.556	0.480	0.256	0.425	0.657	2.780
ivol	Idiosyncratic volatility from WRDS Beta Suite using daily Fama-French 3-factor model	0.022	0.011	0.014	0.019	0.026	1.838

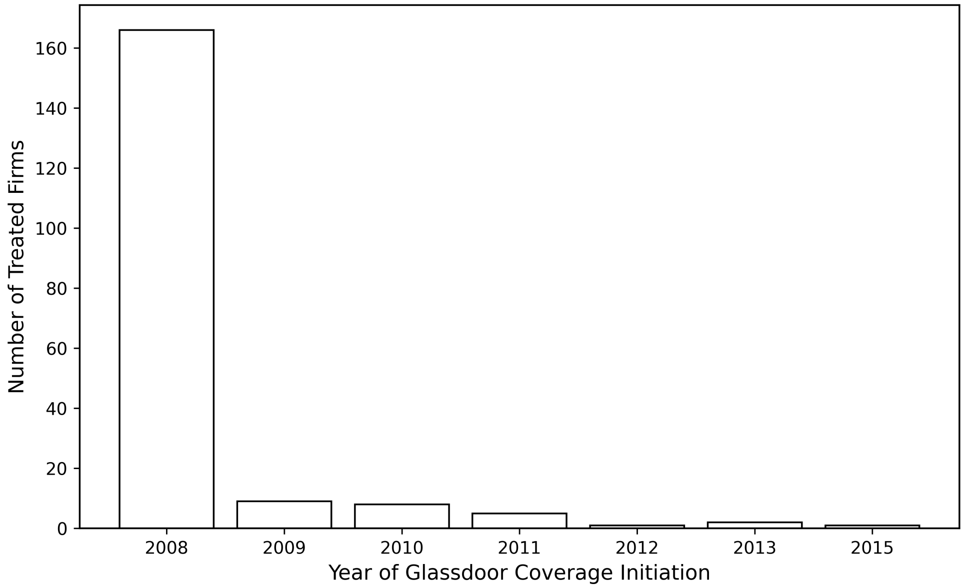

Figure C.1: Distribution of Glassdoor coverage initiation years for treated firms in the Idiosyncratic Risk sample

C.1.2 Talent Drain Beta Analysis

C.1.2.1 Variable Definitions and Summary Statistics

Table C.2: Descriptive Statistics

	Definition	Mean	Std Dev	25th pctl	Median	75th pctl	Skewness
Fundamentals							
Annual							
ROA	Net income/total assets	0.108	0.113	0.050	0.111	0.170	-0.617
Leverage	Long-term debt/total assets	0.219	0.190	0.063	0.172	0.331	0.996
Size	Natural log of total assets	7.981	1.808	6.742	7.837	9.115	0.486
R&D	R&D expenditure	0.037	0.064	0.000	0.005	0.050	2.431
Advertising	Advertising expenditure	0.008	0.024	0.000	0.000	0.003	4.378
CapEX	Capital expenditure/total assets	0.038	0.043	0.009	0.024	0.052	2.116
Cash	Cash ratio, calculated as cash and cash equivalents/(total assets − cash and cash equivalents)	0.155	0.183	0.031	0.079	0.190	1.695
EarVar	Standard deviation of income before extraordinary items per share using a five-year rolling window	77.378	120.317	8.667	23.708	74.776	2.057
LogLaborIntensity	$\log\big(1 + \text{Employees/Assets } (\$m)\big)$	1.051	0.733	0.378	1.029	1.597	0.425
SAIndex	Hadlock–Pierce financial constraints index	-3.833	0.599	-4.517	-3.717	-3.369	0.069

Table C.2 – continued from previous page

	Definition	Mean	Std Dev	25th pctl	Median	75th pctl	Skewness
ExecuComp							
EXEOPT	Executive stock options granted during the year	0.222	0.205	0.041	0.192	0.333	1.082
ManOwn	Percentage of common shares held by top executives	0.255	0.379	0.000	0.023	0.446	1.186
Fundamentals Annual, Form 5500							
EMPSTK	Employee stock ownership as a percentage of total shares outstanding	0.009	0.020	0.000	0.000	0.009	3.662
LSEG 13F filings							
InstOwn	Percentage of common shares held by institutional investors	0.622	0.316	0.483	0.737	0.860	-0.966
Refinitiv							

Table C.2 – continued from previous page

	Definition	Mean	Std Dev	25th pctl	Median	75th pctl	Skewness
ESGScore	ESG overall score, capturing firm-level environmental, social, and governance performance	0.327	0.145	0.219	0.309	0.407	0.769
RavenPack							
LogNewsCount	Natural log of (1+the number of relevant news articles on a firm on a given day)	0.494	0.851	0.000	0.000	0.693	1.964
SentimentScore	Average sentiment score of relevant news articles on a firm on a given day	0.005	0.038	0.000	0.000	0.007	-0.831
CRSP							
BTM	Book-to-market ratio	0.564	0.485	0.269	0.426	0.687	2.748
Talent drain beta	Firm's exposure to the novel talent drain factor	0.091	1.544	-0.817	0.082	0.910	0.172

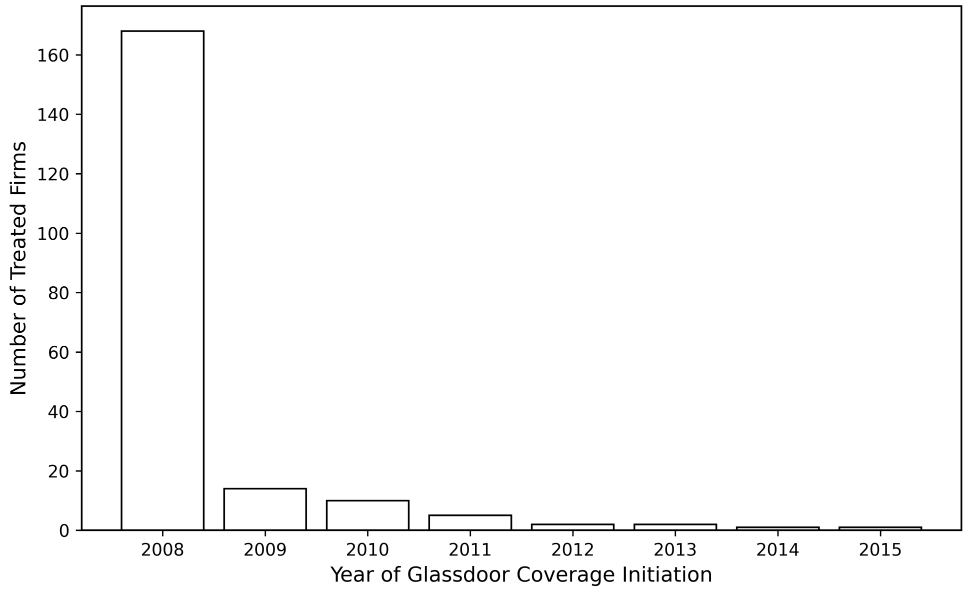

Figure C.2: Distribution of Glassdoor coverage initiation years for treated firms in the talent drain Beta sample

C.1.3 Robustness Check

C.1.3.1 Talent Drain Beta Based on Fama-French Five Factor Model

The finding that Glassdoor coverage initiation triggers a spike in talent drain beta is robust to the underlying asset pricing model chosen for talent drain beta construction. We demonstrate robustness via constructing the talent drain beta based on the Fama-French five factor model (Fama and French, 2015) and re-running the talent drain beta analysis.

Compared to the three factor model, the five factor model additionally includes two factors that account for the relations between a firm's operating profitability (profitability factor or, equivalently, robust-minus-weak (RMW) factor) and investment intensity (investment factor or, equivalently, conservative-minus-aggressive (CMA) factor) and expected return.[1] We download the daily returns for the five factors from

[1] Refer to Fama and French (2015) for a detailed description of factor definitions and construction

French (2025b). The daily talent drain factor is constructed the same way as in the main text. We compute the daily talent drain beta via an OLS estimation of the following equation via a rolling window of 90 trading days (45 minimum days).

$$\begin{aligned} r_{i,t} - r_{f,t} = &\alpha_i + \beta_{\text{MKT},i} MKT_t + \beta_{\text{SMB},i} SMB_t \\ &+ \beta_{\text{HML},i} HML_t + \beta_{\text{RMW},i} RMW_t \\ &+ \beta_{\text{CMA},i} CMA_t + \beta_{\text{TD},i} TD_t + \varepsilon_{i,t}. \end{aligned}$$

The squared Sharpe ratio test shows the non-redundancy of the talent drain factor. Specifically, adding the talent drain factor to the base set of the MKT, SMB, HML, RMW, and CMA factors boosts the annualized tangency Sharpe ratio from 0.969 to 1.343, implying $\Delta SR^2 = SR^2_{aug} - SR^2_{base} = 1.343^2 - 0.969^2 = 0.865$. The Barillas-Shanken χ^2 test gives rise to a test statistic of 1347.69, decisively rejecting the null that the talent drain factor is spanned by the existing factors.

Fama-MacBeth cross-sectional regression results, summarized in Table C.3, confirm that the talent drain factor is priced. Collectively, the squared Shapley ratio analysis and the Fama-MacBeth cross-sectional analysis demonstrate the validity of the talent drain factor and its associated beta constructed based on the Fama-French five factor model.

underlying the five factor model.

Table C.3: Cross-sectional regression of average excess returns on factor betas

	Average excess return
	(1)
Intercept	-0.0025^{***}
	(0.000)
β_{MKT}	0.0624
	(0.031)
β_{SMB}	-0.0351^{***}
	(0.017)
β_{HML}	0.0008
	(0.016)
β_{RMW}	0.0093
	(0.015)
β_{CMA}	0.0591^{***}
	(0.015)
β_{TD}	0.0003^{***}
	(0.000)
R^2	0.02
Adjusted R^2	0.016
F-statistic	5.023
p-value (F)	0.0000415
Observations	1489

Notes: The table reports a Fama–MacBeth style cross-sectional regression of average daily excess returns (2008–2020) on factor betas. Standard errors are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Using the talent drain beta constructed based on the Fama-French five factor model as the dependent variable, Figures C.3, C.4, C.5 and Table C.4 corroborate the main finding that only sentiment-neutral first reviews trigger a spike in investors' talent drain risk exposure.

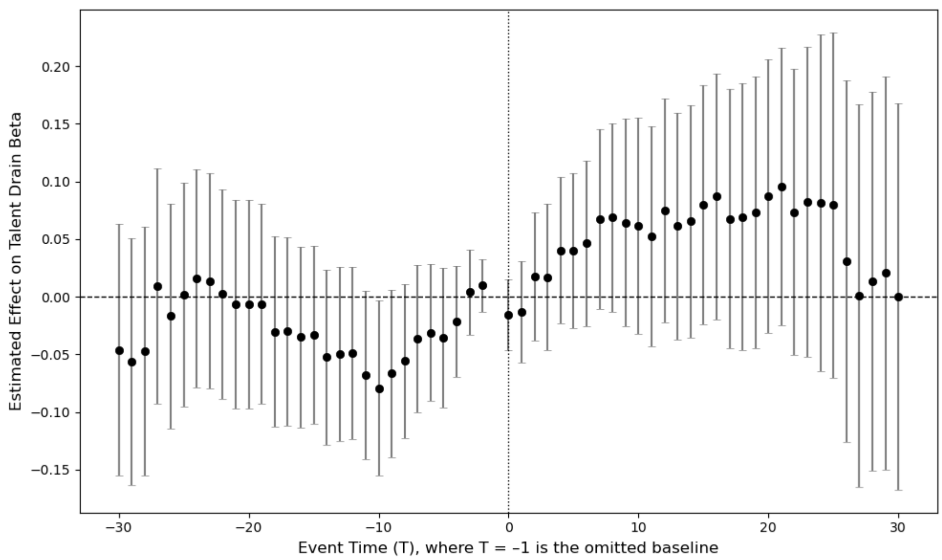

Figure C.3: Stacked DiD on Talent Drain Beta: Full Sample

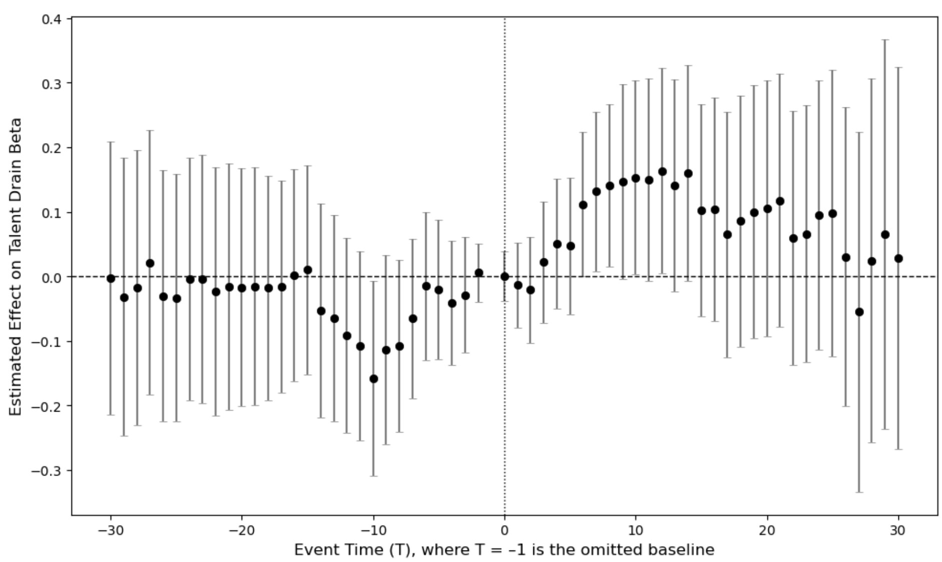

Figure C.4: Stacked DiD on Talent Drain Beta: Neutral Sample

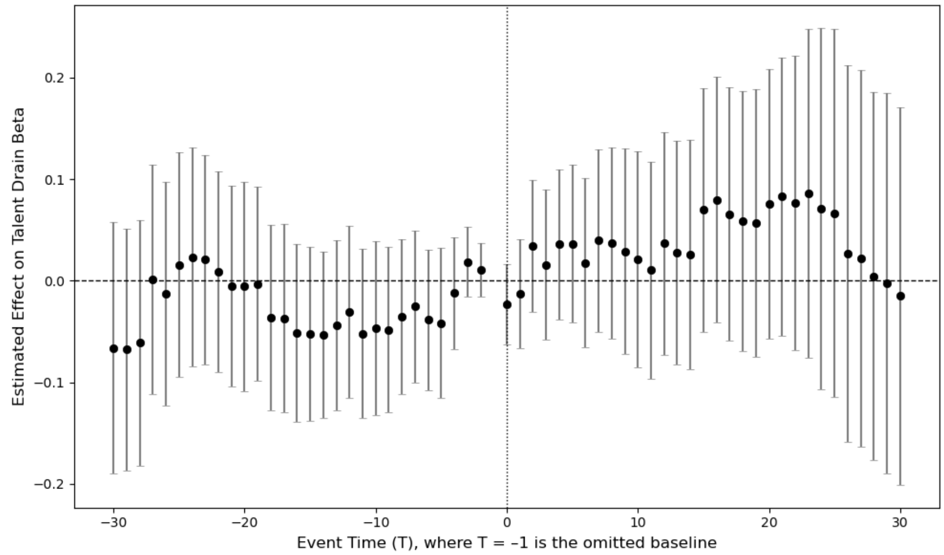

Figure C.5: Stacked DiD on Talent Drain Beta: Sentiment-Loaded Sample

Table C.4: Stacked DiD on Talent Drain Beta Regression Results: Neutral Sample

	Coef.	z	p-value
Treated × $T = -10$	−0.1577	−1.719	0.086
Treated × $T = -9$	−0.1135	−1.276	0.202
Treated × $T = -8$	−0.1076	−1.327	0.185
Treated × $T = -7$	−0.0650	−0.865	0.387
Treated × $T = -6$	−0.0150	−0.215	0.830
Treated × $T = -5$	−0.0204	−0.313	0.754
Treated × $T = -4$	−0.0411	−0.704	0.481
Treated × $T = -3$	−0.0286	−0.523	0.601
Treated × $T = -2$	0.0058	0.211	0.833
Treated × $T = 0$	0.0002	0.007	0.995
Treated × $T = 1$	−0.0136	−0.345	0.730
Treated × $T = 2$	−0.0210	−0.420	0.674
Treated × $T = 3$	0.0219	0.382	0.702
Treated × $T = 4$	0.0507	0.834	0.404
Treated × $T = 5$	0.0473	0.738	0.461
Treated × $T = 6$	0.1117	1.651	0.099
Treated × $T = 7$	0.1311	1.738	0.082
Treated × $T = 8$	0.1409	1.838	0.066
Treated × $T = 9$	0.1468	1.602	0.109
Treated × $T = 10$	0.1527	1.675	0.094
Controls		Yes	
Event time dummies		Yes	
Cohort fixed effects		Yes	
R^2		0.503	
Adjusted R^2		0.497	
F-statistic		135500	
Observations		16835	

Notes: Robust standard errors clustered at the firm level. Yellow shading marks post-treatment average treatment effects on the treated (ATTs) significant at the 10% level. Period $T = -1$ is the omitted reference category.

C.1.3.2 Propensity Score Matching Analysis

Table C.5: Balance Test by Glassdoor Coverage Initiation Year

Year	Covariate	N_treat_bef	N_ctrl_bef	SMD_bef	N_treat_aft	N_ctrl_aft	SMD_aft
	Size			1.524***			0.097
	ROA			0.455***			0.021
	BTM			−0.153**			0.058
2008	Leverage	301	509	−0.202***	301	99	−0.037
	SAIndex			−0.991***			−0.072
	R&D			−0.120*			0.057
	LogLaborIntensity			0.093			-0.188
	WorkforceScore			1.031***			0.070
	Size			0.759***			0.207
	ROA			0.319*			-0.117
	BTM			-0.234			-0.045
2009	Leverage	28	290	0.135	28	23	-0.254
	SAIndex			−0.378*			-0.252
	R&D			-0.002			0.232
	LogLaborIntensity			0.329			0.117

Table C.5 – continued from previous page

Year	Covariate	N_treat_bef	N_ctrl_bef	SMD_bef	N_treat_aft	N_ctrl_aft	SMD_aft
	WorkforceScore			0.463**			0.022
	Size			0.684***			0.048
	ROA			0.279			-0.219
	BTM			−0.467***			-0.082
2010	Leverage	21	174	0.106	21	20	-0.064
	SAIndex			−0.601**			-0.056
	R&D			-0.222			0.180
	LogLaborIntensity			0.058			-0.338
	WorkforceScore			0.465*			0.109
	Size			0.956***			0.142
	ROA			0.038			-0.311
	BTM			0.096			0.131
2011	Leverage	14	131	0.145	14	14	-0.135
	SAIndex			−0.581*			-0.230
	R&D			−0.390*			0.499
	LogLaborIntensity			0.361			0.117
	WorkforceScore			-0.198			-0.630

Table C.5 – continued from previous page

Year	Covariate	N_treat_bef	N_ctrl_bef	SMD_bef	N_treat_aft	N_ctrl_aft	SMD_aft
	Size			0.765			0.839
	ROA			-0.233			0.473
	BTM			0.488			0.063
2012	Leverage	8	62	-0.279	8	7	-0.068
	SAIndex			-0.603			-0.401
	R&D			0.043			-0.319
	LogLaborIntensity			-0.209			0.332
	WorkforceScore			0.603			0.502
	Size			0.965*			0.803
	ROA			0.721*			0.164
	BTM			-0.340			0.308
2013	Leverage	6	51	-0.042	6	5	0.075
	SAIndex			-0.313			-0.028
	R&D			-0.031			-0.135
	LogLaborIntensity			-0.625			-0.362
	WorkforceScore			0.193			-0.261
	Size			1.420**			0.989

Table C.5 – continued from previous page

Year	Covariate	N_treat_bef	N_ctrl_bef	SMD_bef	N_treat_aft	N_ctrl_aft	SMD_aft
	ROA			0.427			0.681
	BTM			0.442			0.828
2014	Leverage	4	47	-0.160	4	4	-0.716
	SAIndex			-0.582			-0.984
	R&D			0.477			0.650
	LogLaborIntensity			0.564			0.556
	WorkforceScore			0.793			0.726
	Size			1.705***			1.422***
	ROA			1.109***			1.122**
	BTM			-0.182			0.027
2015	Leverage	10	56	-0.351	10	8	-0.571
	SAIndex			−0.654*			-0.444
	R&D			−0.564***			-0.579
	LogLaborIntensity			0.376			-0.034
	WorkforceScore			0.597			0.580
	Size			1.738**			1.115
	ROA			0.462			-0.004

Table C.5 – continued from previous page

Year	Covariate	N_treat_bef	N_ctrl_bef	SMD_bef	N_treat_aft	N_ctrl_aft	SMD_aft
	BTM			-0.226			0.174
2016	Leverage	4	25	0.153	4	4	-0.886
	SAIndex			-0.660			0.025
	R&D			-0.381			0.001
	LogLaborIntensity			-0.056			-0.800
	WorkforceScore			0.701			0.971
	Size			1.621*			2.016
	ROA			-0.818			-1.135
	BTM			0.388			0.237
2017	Leverage	2	6	0.030	2	2	1.463
	SAIndex			0.202			0.041
	R&D			-0.296			0.966
	LogLaborIntensity			0.081			0.550
	WorkforceScore			−1.928**			-3.110
	Size			1.175			0.836
	ROA			0.428			0.385
	BTM			0.423			0.375

Table C.5 – continued from previous page

Year	Covariate	N_treat_bef	N_ctrl_bef	SMD_bef	N_treat_aft	N_ctrl_aft	SMD_aft
2018	Leverage	3	5	-0.929	3	3	-0.756
	SAIndex			-0.340			0.129
	R&D			0.893			0.832
	LogLaborIntensity			-0.000			-0.599
	WorkforceScore			0.078			-0.251
	Size			2.142**			2.025*
	ROA			1.818***			0.901
	BTM			0.867			1.086
2019	Leverage	3	13	-0.230	3	3	-0.164
	SAIndex			-1.282			-0.769
	R&D			−0.975**			-0.810
	LogLaborIntensity			0.042			-0.178
	WorkforceScore			0.117			0.801
	Size			2.804*			1.886
	ROA			0.449			1.300
	BTM			1.350			0.422
2020	Leverage	2	4	0.909	2	2	1.386

Table C.5 – continued from previous page

Year	Covariate	N_treat_bef	N_ctrl_bef	SMD_bef	N_treat_aft	N_ctrl_aft	SMD_aft
	SAIndex			-0.687			-0.640
	R&D			-1.348			-0.633
	LogLaborIntensity			0.207			0.842
	WorkforceScore			1.035			4.538

Notes: This table reports standardized mean differences (SMD) for matching covariates before and after propensity score-based nearest neighbor matching with replacement by Glassdoor coverage initiation year. Stars denote significance levels from t-tests of differences in means: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

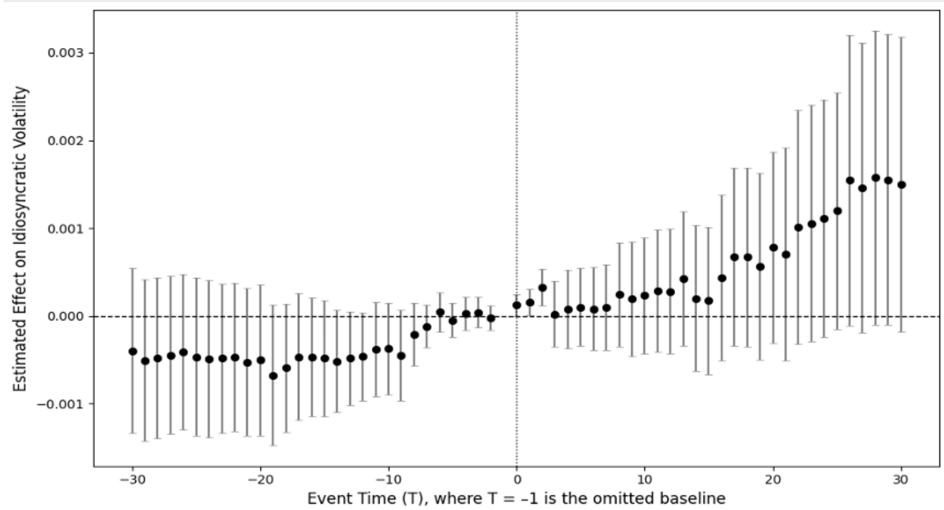

Figure C.6: Stacked DiD (with PSM) on ivol: Full Sample

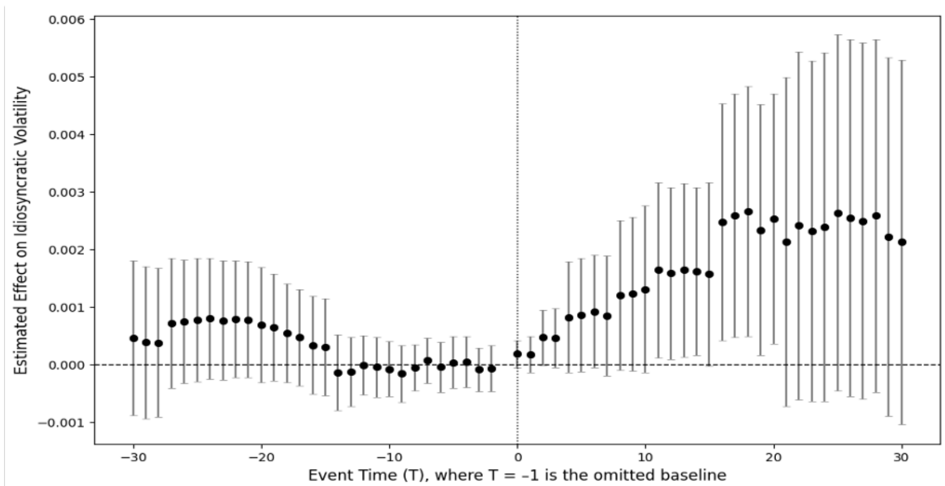

Figure C.7: Stacked DiD (with PSM) on ivol: Neutral Sample

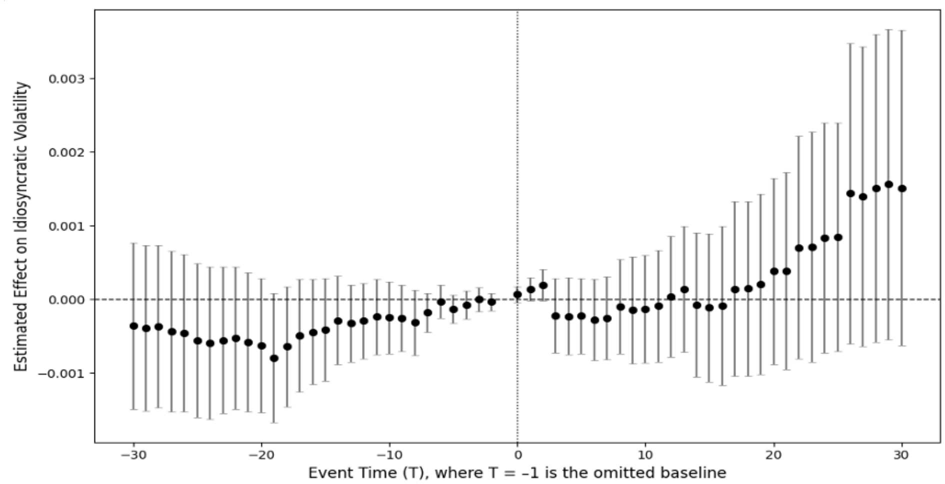

Figure C.8: Stacked DiD (with PSM) on ivol: Sentiment-Loaded Sample

Table C.6: Stacked DiD (with PSM) on ivol Regression Results: Neutral Sample

	Coef.	z	p-value
Treated × $T = -10$	-0.0001	-0.2550	0.7980
Treated × $T = -9$	-0.0002	-0.5240	0.6000
Treated × $T = -8$	-0.0001	-0.2180	0.8270
Treated × $T = -7$	0.0001	0.3140	0.7530
Treated × $T = -6$	-0.0000	-0.1580	0.8750
Treated × $T = -5$	0.0000	0.1400	0.8880
Treated × $T = -4$	0.0001	0.1910	0.8490
Treated × $T = -3$	-0.0001	-0.3750	0.7080
Treated × $T = -2$	-0.0001	-0.2660	0.7900
Treated × $T = 11$	0.0016	1.7740	0.0760
Treated × $T = 12$	0.0016	1.7520	0.0800
Treated × $T = 13$	0.0016	1.7920	0.0730
Treated × $T = 14$	0.0016	1.8310	0.0670
Treated × $T = 15$	0.0016	1.6260	0.1040
Treated × $T = 16$	0.0025	1.9820	0.0470
Treated × $T = 17$	0.0026	2.0170	0.0440
Treated × $T = 18$	0.0027	2.0130	0.0440
Treated × $T = 19$	0.0023	1.7690	0.0770
Treated × $T = 20$	0.0025	1.9220	0.0550
Treated × $T = 21$	0.0021	1.2250	0.2210
Treated × $T = 22$	0.0024	1.3170	0.1880
Treated × $T = 23$	0.0023	1.2920	0.1960
Treated × $T = 24$	0.0024	1.3000	0.1940
Treated × $T = 25$	0.0026	1.4010	0.1610
Treated × $T = 26$	0.0025	1.3520	0.1760
Treated × $T = 27$	0.0025	1.3270	0.1850
Treated × $T = 28$	0.0026	1.3870	0.1650
Treated × $T = 29$	0.0022	1.1730	0.2410
Treated × $T = 30$	0.0021	1.1050	0.2690
Controls		Yes	
Event time dummies		Yes	
Cohort fixed effects		Yes	
R^2		0.978	
Adjusted R^2		0.976	
F–statistic		2,497	
Observations		1,725	

Notes: Robust standard errors clustered at the firm level. Yellow shading marks post-treatment ATTs significant at the 10% level. Period $T = -1$ is the omitted reference category.

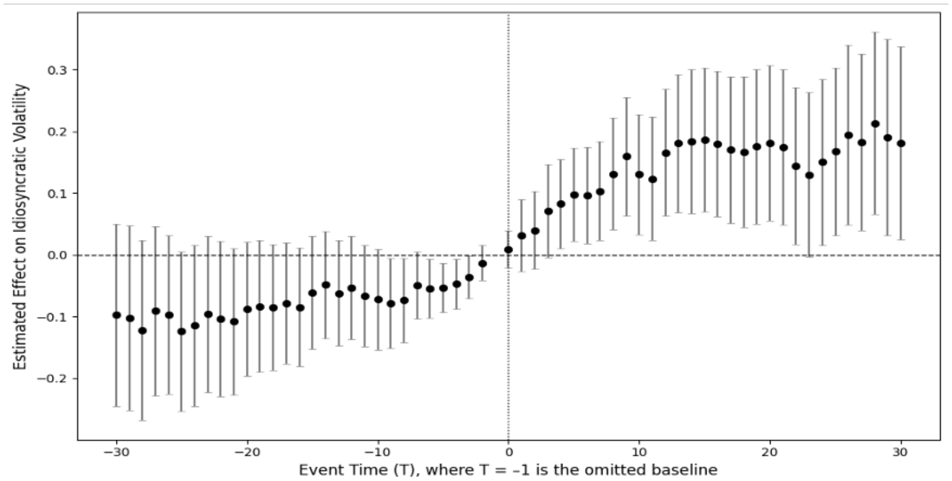

Figure C.9: Stacked DiD (with PSM) on Talent Drain Beta: Full Sample

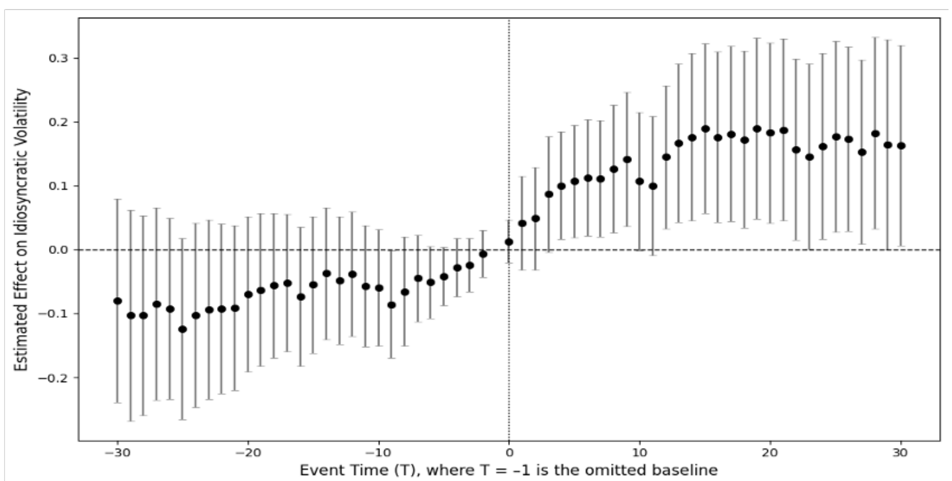

Figure C.10: Stacked DiD (with PSM) on Talent Drain Beta: Neutral Sample

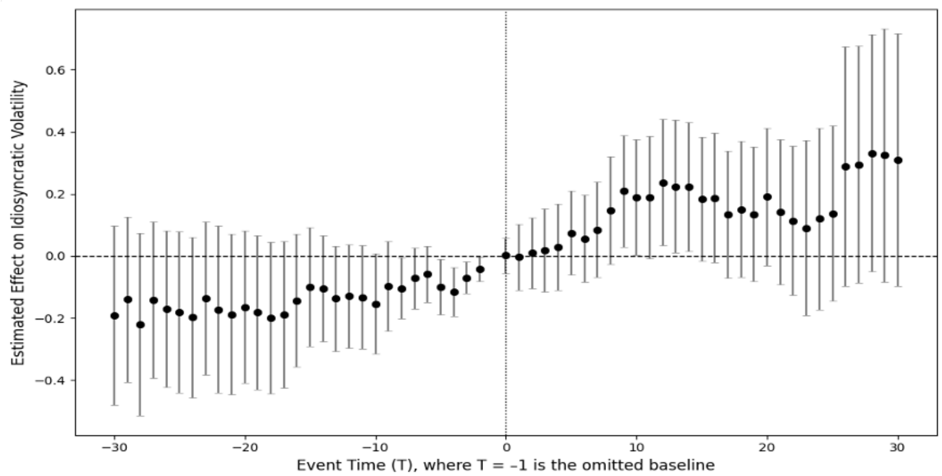

Figure C.11: Stacked DiD (with PSM) on Talent Drain Beta: Sentiment-Loaded Sample

Table C.7: Stacked DiD (with PSM) on Talent Drain Beta Regression Results: Neutral Sample

	Coef.	z	p-value
Treated × $T = -10$	−0.0597	−1.0770	0.2810
Treated × $T = -9$	−0.0861	−1.6830	0.0920
Treated × $T = -8$	−0.0655	−1.2650	0.2060
Treated × $T = -7$	−0.0448	−1.0910	0.2750
Treated × $T = -6$	−0.0514	−1.5020	0.1330
Treated × $T = -5$	−0.0415	−1.5000	0.1340
Treated × $T = -4$	−0.0277	−0.9990	0.3180
Treated × $T = -3$	−0.0246	−0.9720	0.3310
Treated × $T = -2$	−0.0064	−0.2880	0.7730
Treated × $T = 4$	0.1001	1.9550	0.0510
Treated × $T = 5$	0.1071	2.0010	0.0450
Treated × $T = 6$	0.1120	2.0260	0.0430
Treated × $T = 7$	0.1107	1.9960	0.0460
Treated × $T = 8$	0.1261	2.0860	0.0370
Treated × $T = 9$	0.1417	2.2250	0.0260
Treated × $T = 10$	0.1067	1.6290	0.1030
Treated × $T = 11$	0.0999	1.5080	0.1310
Treated × $T = 12$	0.1449	2.1340	0.0330
Treated × $T = 13$	0.1664	2.2110	0.0270
Treated × $T = 14$	0.1757	2.2080	0.0270
Treated × $T = 15$	0.1890	2.3430	0.0190
Treated × $T = 16$	0.1761	2.1770	0.0300
Treated × $T = 17$	0.1811	2.1650	0.0300
Treated × $T = 18$	0.1724	2.0410	0.0410
Treated × $T = 19$	0.1896	2.2030	0.0280
Treated × $T = 20$	0.1826	2.1270	0.0330
Treated × $T = 21$	0.1874	2.1720	0.0300
Treated × $T = 22$	0.1565	1.8120	0.0700
Treated × $T = 23$	0.1455	1.6510	0.0990
Treated × $T = 24$	0.1619	1.8300	0.0670
Treated × $T = 25$	0.1767	1.9530	0.0510
Treated × $T = 26$	0.1726	1.9720	0.0490
Treated × $T = 27$	0.1532	1.7480	0.0800
Treated × $T = 28$	0.1825	2.0000	0.0460
Treated × $T = 29$	0.1640	1.6440	0.1000
Treated × $T = 30$	0.1630	1.7110	0.0870
Controls		Yes	
Event time dummies		Yes	
Cohort fixed effects		Yes	
R^2		0.750	
Adjusted R^2		0.745	
F–statistic		2.04×10^9	
Observations		15,422	

Notes: Robust standard errors clustered at the firm level. Yellow shading marks post-treatment average treatment effects on the treated (ATTs) significant at the 10% level. Period $T = -1$ is the omitted reference category.

C.2 Talent Drain-Related Operations Topic Modeling and Text-Based Predictors

C.2.1 Data Sources

C.2.1.1 Workforce Dynamics Revelio Labs

Revelio Labs is a labour-market analytics firm that collects résumé histories and online professional-profile updates, reconciles them with regulatory filings, and maps each job spell to a unified occupation and employer ID. Its Workforce Dynamics database aggregates those micro records into firm-month metrics—external inflow, external outflow, and net flow—covering essentially all publicly traded U.S. companies from 2008 onward and a large share of global large-caps. We source monthly external inflow and external outflow from the Workforce Dynamics database to construct external inflow reduction and external outflow increase, the two binary outcome variables that we focus on in this part of the analysis.

C.2.1.2 Individual Positions Revelio Labs

The Individual Positions database of Revelio Labs contains data on an employee's position, geographical location, seniority, employment status, and annual salary. The database retrieves updated information from online professional profiles once every end-of-month. We source each employee's annual salary and compute the average annual salary of each sampled firm's workforce.

C.2.1.3 RavenPack

We obtain press–coverage controls from RavenPack Analytics, a real-time news–analytics platform that converts more than 22,000 traditional and web sources into entity–tagged records with millisecond latency (RavenPack, 2020). Each record carries a relevance score from 0 to 100 that measures how central the firm is to the story; values above 75 typically indicate appearance in the headline or first paragraph. This field allows us to exclude tangential mentions and focus on genuinely firm-specific articles, a critical advantage over raw text scrapes. From the filtered feed we construct two firm-year controls: news count, the number of highly relevant stories for a firm, and sentiment score, the mean composite sentiment score across those stories.

C.2.1.4 Violation Tracker

Violation Tracker, maintained by the non-profit Good Jobs First(Good Jobs First, 2025), is the largest public database of U.S. federal, state, and local enforcement actions against corporations, covering more than 500 agencies and dating back to 2000. Each case record is tagged with a primary offense type (e.g., "Employment-Related", "Wage & Hour", "Labor Standards", "Workplace Safety & Health"), allowing us to isolate violations that directly affect the workforce rather than the environment or product markets. Leveraging that taxonomy, we aggregate the raw cases to the firm–year level and construct four control variables: (i) violation count, the total number of enforcement actions a firm receives in a calendar year; (ii) total penalty, the sum of all monetary sanctions; (iii) workforce-violation count, the number of cases whose primary offense falls in the workforce-related categories; and (iv) total workforce penalty, the corresponding dollar sum of those cases.

C.2.1.5 Glassdoor

Glassdoor, launched in 2007, is the largest crowd-sourced platform on which employees rate and discuss their employers, thereby reducing information asymmetry between job-seekers and firms. Each post combines a one-to-five overall rating with free-text "pros," "cons," and, optionally, "advice to management," plus six sub-ratings that map onto common workplace dimensions. Reviews must be submitted through a validated account and pass Glassdoor's automated and human fraud-detection screens; each member can contribute at most one review per firm per year, enhancing authenticity.

The data serve two purposes in this study. First, we treat the text of the pros, cons, and advice sections as an information source to identify operations topics most predictive of future talent drain events. Second, we build firm-year control variables—review count, average overall rating, and total review words—that proxy for the intensity and valence of employee voice. Prior business research demonstrates both the behavioural relevance of Glassdoor sentiment (Green et al., 2019; Huang et al., 2020) and the validity of text-mined constructs in empirical settings (Mejia et al., 2019, 2021), making the platform an ideal source for our analysis.

C.2.1.6 Fundamentals Annual

Compustat North America, provided through S&P Global and distributed on WRDS, is a firm-level fundamentals database that standardises more than 900 annual financial statement items for every U.S. and Canadian public company since 1950, covering both active and inactive firms. We rely on the Fundamentals Annual file (Compustat-Capital IQ, 2025) to build eight control ratios: return on assets (ROA); leverage (long-term debt/total assets); firm size (natural log of total assets); R&D intensity; advertising intensity; capital expenditure ratio; cash ratio; and earnings volatility, computed as the rolling five-year standard deviation of income before extraordinary items per share.

C.2.1.7 ExecuComp

Compustat-Execucomp (Compustat-Execucomp, 2025) supplies firm-officer-level compensation and ownership data drawn directly from each company's annual proxy statement (DEF 14A), covering the S&P 1500 back to 1992 and up to nine named executives per firm-year. The database's panel structure and dedicated option tables—PlanBasedAwards for newly granted awards and OutstandingAwards for options still in force—allow us to extract the value of executive stock-option holdings, while the summary table AnnComp reports each officer's share count and percentage ownership. Aggregating these records, we construct two firm-year governance controls: the Black-Scholes value of outstanding executive options and total managerial ownership as a percentage of shares outstanding.

C.2.1.8 Form 5500

Form 5500 (Employee Benefits Security Administration, 2025) is the annual disclosure report that U.S. employee-benefit plans must file with the Department of Labor and the Internal Revenue Service under the Employee Retirement Income Security Act (ERISA). Among its schedules, Section H ("Financial Information") and Section I ("Financial Information—Small Plan") list the number and fair value of employer securities held by each plan, including shares allocated to Employee Stock Ownership Plans (ESOPs). We extract the share counts for all ESOPs sponsored by a given firm, sum them at the fiscal-year end, and scale by the firm's total shares outstanding from Compustat Fundamentals Annual. The resulting ratio serves as a firm-year control for the proportion of equity committed to employee ownership.

C.2.1.9 LSEG 13F Filings

The LSEG Mutual Fund and Investment Company Common Stock Holdings database (LSEG, 2025) compiles every quarter-end equity position reported by U.S. mutual funds (Form N-30D) and by 13F institutions such as banks, insurers, pensions, and independent advisers, with history back to 1980. Each holding is security-level and tagged with fund or manager identifiers, report date, and share count, which allows aggregation to the company level. We sum the shares held by all 13F managers in a firm at fiscal year-end and divide by total shares outstanding to obtain our institutional-ownership measure.

C.2.1.10 Refinitiv

Refinitiv's ESG database (LSEG ESG, 2025) offers one of the broadest corporate-sustainability datasets available, tracking more than 11000 companies worldwide—over 80% of global market capitalisation—with history back to 2002. For each firm it captures more than 500 environmental, social and governance metrics, refreshes the underlying disclosures weekly, and rolls 186 key indicators into a transparent, percentile-rank overall ESG score that ranges from 0 to 100. The score is industry- and country-adjusted through a materiality matrix and can be further discounted for recent controversies to produce an ESG-combined (ESGC) rating. In this study we extract the overall ESG score as a firm-year control variable, using it to proxy for the level of ESG performance that investors and employees observe.

C.2.2 Variable Definitions and Summary Statistics

Table C.8: Descriptive Statistics

	Definition	Mean	Std Dev	25th pctl	Median	75th pctl	Skewness
RavenPack							
LogNewsCount	Natural log of (1+the number of relevant news articles on a firm in a given year)	6.63	0.78	6.15	6.48	6.90	1.56
SentimentScore	Average sentiment score of relevant news articles on a firm in a given year	0.01	0.02	0.00	0.01	0.03	0.04
Violation Tracker							
LogViolationCount	Natural log of (1+the number of corporate violations a firm commits in a given year)	0.27	0.56	0.00	0.00	0.00	2.27
LogTotalPenalty	Natural log of (1+total penalty amount associated with a firm's corporate violations in a given year)	2.83	5.44	0.00	0.00	0.00	1.63

Table C.8 – continued from previous page

	Definition	Mean	Std Dev	25th pctl	Median	75th pctl	Skewness
LogWorkforceViolationCount	Natural log of (1+the number of workforce-related corporate violations a firm commits in a given year)	0.16	0.42	0.00	0.00	0.00	2.86
LogTotalWorkforcePenalty	Natural log of (1+total penalty amount associated with a firm's workforce-related corporate violations in a given year)	1.64	3.86	0.00	0.00	0.00	2.01
Glassdoor							
LogReviewCount	Natural log of the number of reviews a firm receives in a given year	4.02	1.59	2.89	4.08	5.20	-0.02
Rating	Average overall rating of a firm's reviews in a given year	3.33	0.53	3.04	3.38	3.69	-0.69
LogTotalReviewWords	Natural log of the total number of words in the reviews	8.12	1.68	7.09	8.29	9.36	-0.46

Table C.8 – continued from previous page

	Definition	Mean	Std Dev	25th pctl	Median	75th pctl	Skewness
Fundamentals							
Annual							
ROA	Net income/total assets	0.13	0.09	0.08	0.13	0.18	0.29
Leverage	Long-term debt/total assets	0.24	0.17	0.11	0.20	0.32	1.23
Size	Natural log of total assets	9.46	1.54	8.39	9.41	10.38	0.32
R&D	R&D expenditure	0.03	0.05	0.00	0.01	0.05	2.62
Advertising	Advertising expenditure	0.01	0.02	0.00	0.00	0.01	4.00
CapEX	Capital expenditure/total assets	0.03	0.04	0.01	0.02	0.04	2.14
Cash	Cash ratio, calculated as cash and cash equivalents/(total assets − cash and cash equivalents)	0.15	0.15	0.04	0.10	0.21	1.59
EarVar	Standard deviation of income before extraordinary items per share using a five-year rolling window	227.75	162.68	71.07	194.31	435.31	0.17
ExecuComp							

Table C.8 – continued from previous page

	Definition	Mean	Std Dev	25th pctl	Median	75th pctl	Skewness
EXEOPT	Executive stock options granted during the year	0.16	0.18	0.00	0.13	0.26	1.43
ManOwn	Percentage of common shares held by top executives	0.48	0.33	0.20	0.41	0.77	0.38
Fundamentals Annual, Form 5500							
EMPSTK	Employee stock ownership as a percentage of total shares outstanding	0.01	0.02	0.00	0.00	0.01	4.30
LSEG 13F filings							
InstOwn	Percentage of common shares held by institutional investors	0.72	0.28	0.67	0.81	0.89	-1.70
Refinitiv							

Table C.8 – continued from previous page

	Definition	Mean	Std Dev	25th pctl	Median	75th pctl	Skewness
ESGScore	ESG overall score, capturing firm-level environmental, social, and governance performance	0.49	0.19	0.34	0.48	0.65	0.12
Individual Positions (Revelio Labs)							
Salary	Average salary of an employee in the workforce	75124.06	17983.57	63269.38	74246.60	84218.92	0.99
Workforce Dynamics (Revelio Labs)							
ExternalInflowReduction	Binary variable = 1 if a firm's total external inflow of talent is lower next year than this year	0.30	0.46	0.00	0.00	1.00	0.87
ExternalOutflowIncrease	Binary variable = 1 if a firm's total external outflow of talent is greater next year than this year	0.74	0.44	0.00	1.00	1.00	-1.08

Table C.8 – continued from previous page

Definition	Mean	Std Dev	25th pctl	Median	75th pctl	Skewness

C.2.3 Top Talent Attraction/Retention and Talent Attrition Human Resource Themes

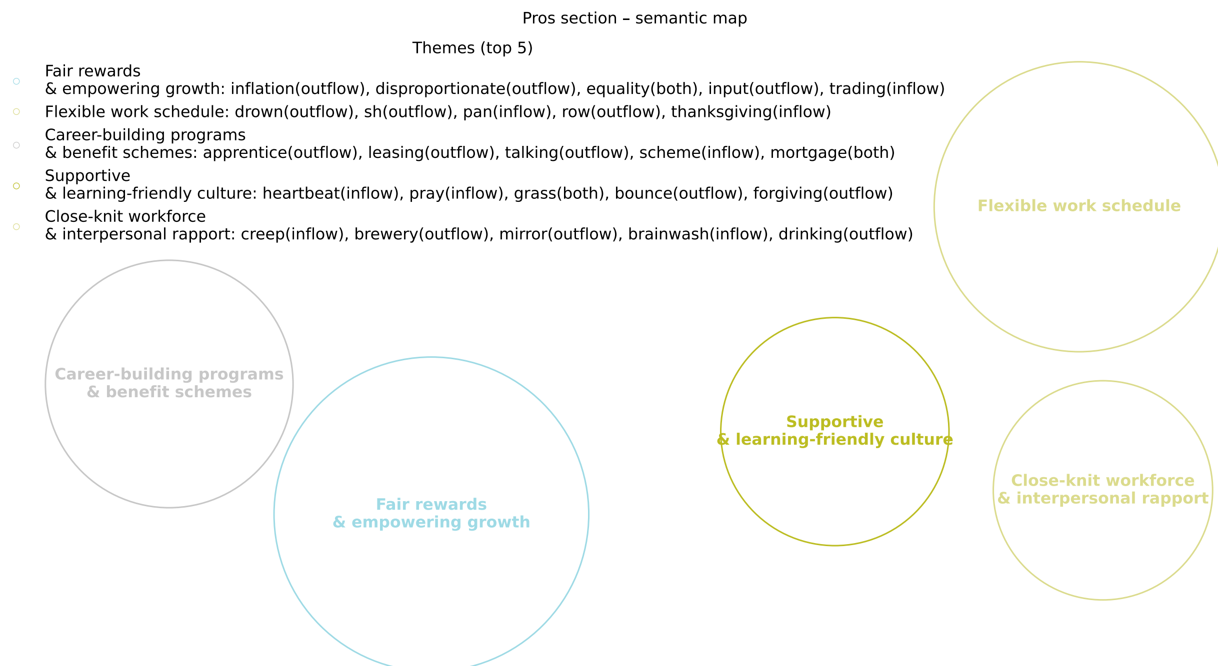

Figure C.12: Semantic map for the pros sections (2010–2017).
Bubble size $\propto$ average absolute lemma loading.
Legend shows the top five representative lemmas for each theme.

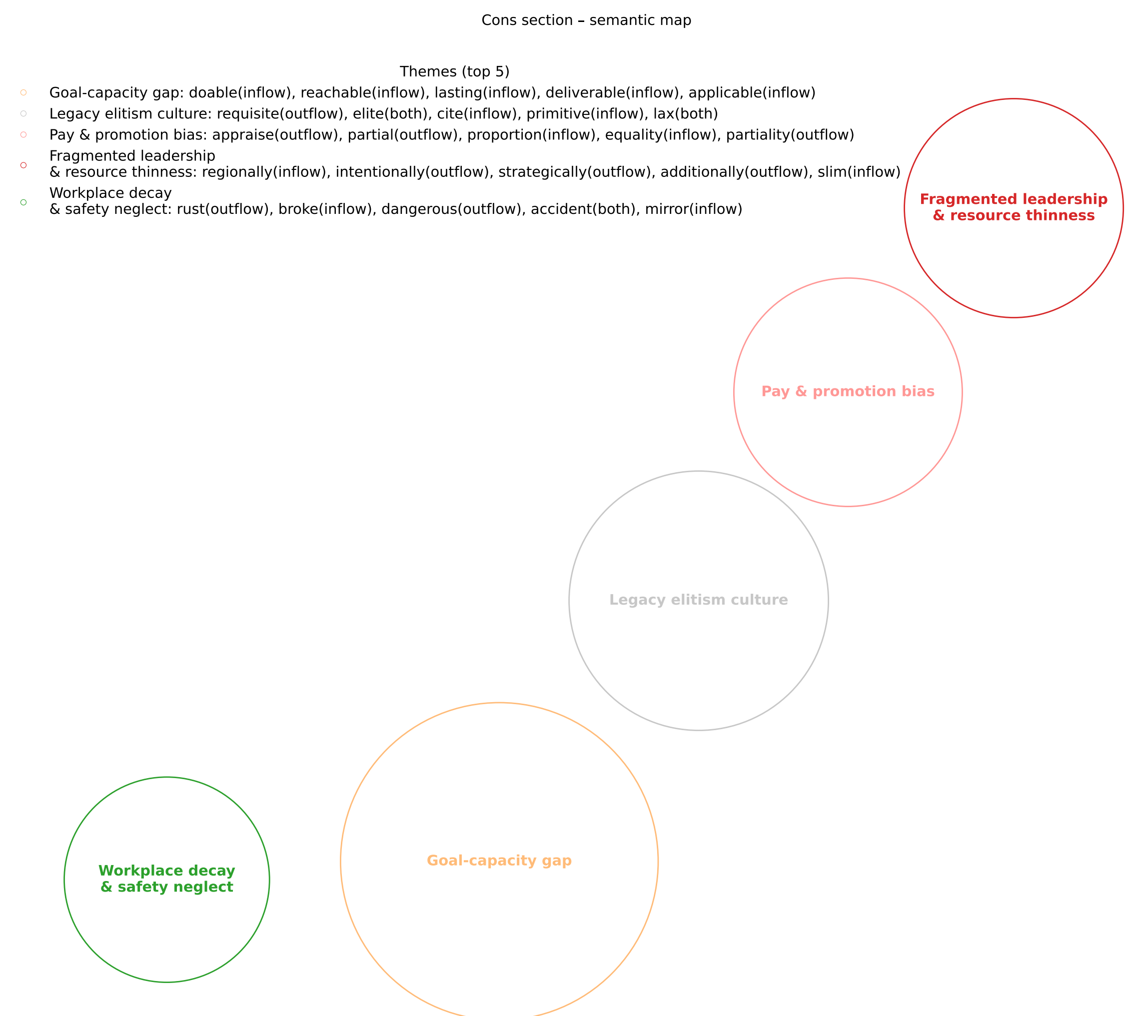

Figure C.13: Semantic map for the cons sections (2010–2017).
Bubble size $\propto$ average absolute lemma loading.
Legend shows the top five representative lemmas for each theme.

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Curriculum Vitae

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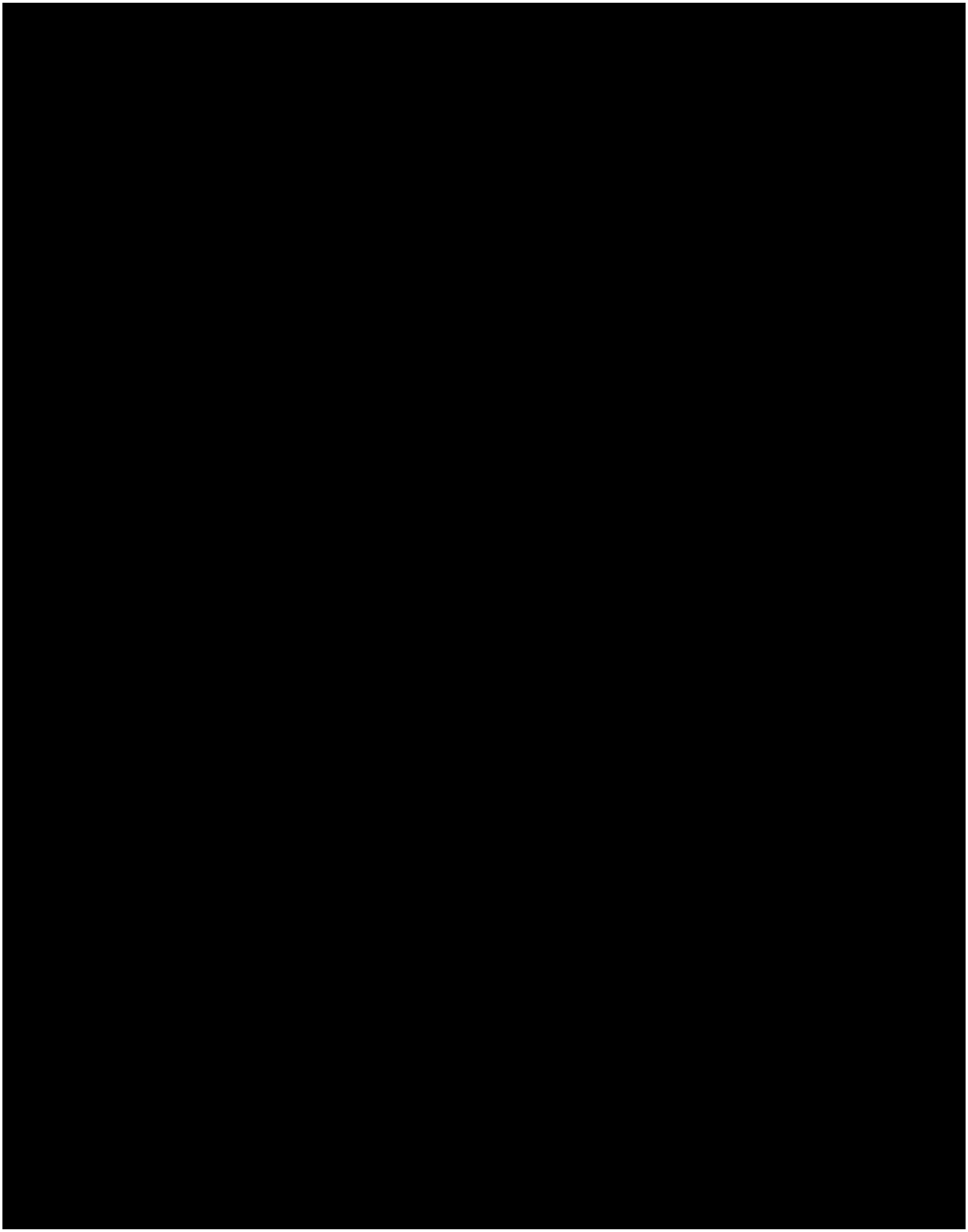

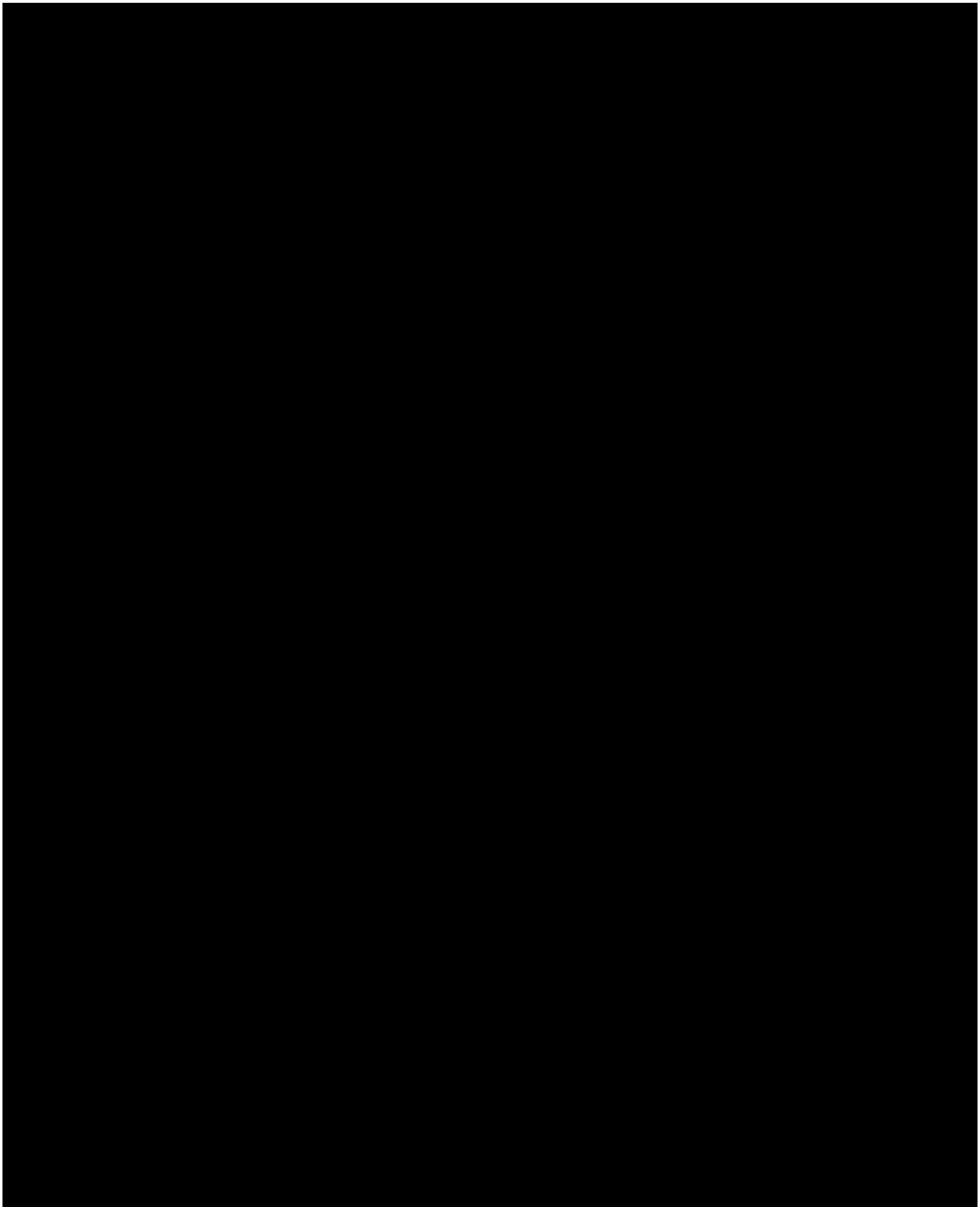

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