

## **Assessing the Economic Value of Female Leadership in Top Management Teams Through an Instrumental Variable Framework and Industry-Level Analysis**

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### **ABSTRACT**

*This study examines whether female representation in top management teams (TMTs) causally affects firm performance using a shift–share instrumental variable approach. The dataset combines Compustat and ExecuComp panel data for 1,589 U.S. public firms from 1997 to 2023. Results show that a one percentage-point increase in female TMT representation raises net income by about \$18.85 million, or roughly \$377 million for a one-woman swap in a five-member executive team. However, when analyzed by sector, female leadership is less effective in the primary sector for internal performance (net income decreases by about \$67 million per 1 pp) and in the quaternary sector for external performance (Tobin’s Q decreases by 0.071 per 1 pp). These results suggest that female leadership faces barriers in capital-intensive industries, where structural and technical demands limit their impact on internal performance. Additionally, in knowledge-based sectors, external market valuations tend to fall under female-led management, reflecting investor and public bias in assessing leadership effectiveness and thus company success. The study contributes to strategic management and human resource management research by providing causal evidence of the economic value of gender diversity. Female representation should be prioritized in executive teams, yet its impact remains shaped by industry and environmental contexts rather than being uniform across all firms.*

**Keywords:** Top Management Team Gender Diversity, Female Leadership Representation, Shift-Share Instrumental Variable, Industry-Level Analysis, Panel Data Modeling, Firm Performance Evaluation

### **1. Introduction**

Across various industries and regions, gender diversity in leadership has become both a corporate social responsibility and an economic priority. Governments and corporations are implementing

measures to increase representation, including Nordic quota laws and DEI initiatives in the United States. Gender diversity has been a prevalent issue that the public now views gender balance as an indicator of sound governance and long-term firm value. Yet despite this momentum, women remain underrepresented in executive decision-making roles, constrained by structural barriers such as the glass ceiling. As diversity initiatives continue to expand, the question has shifted from whether inclusion is fair to whether it is effective: does greater female representation and more diverse compositions of top management teams (TMTs) enhance firm performance?

Current strategic management literature offers no definitive answer. Some studies link gender-diverse leadership teams to higher profitability and innovation, while others find weak, inconsistent, or even negative relationships. The lack of consensus in the literature is a significant gap because these findings influence real policies and investor expectations that shape corporate behavior. Strategic management, therefore, requires greater contributions for clearer, causal evidence.

This research study examines whether greater female representation in top management teams (TMT) improves firm performance and its heterogeneous effects across industries. By applying a shift-share instrumental variable approach to address endogeneity, this study aims to identify causal links between gender diversity and both internal (return on assets) and market-based (Tobin's Q) outcomes. Ultimately, this research seeks to inform policy and literature in strategic management by understanding the extent to which women contribute to firm success through their executive leadership.

## **2. Theoretical Background**

### **2.1 Gender Diversity**

Classic organizational theories posit that TMT composition shapes firm strategy and outcomes according to the upper echelons theory (Hambrick & Mason, 1984). According to the cognitive resource perspective, heterogeneous teams have a broader range of cognitive resources, leading to better decision quality (Pletzer et al., 2024). Diverse members contribute different knowledge, experiences, and problem-solving approaches, which expand the team's information processing capabilities (Williams & O'Reilly, 1998). This decision-making perspective suggests that incorporating underrepresented groups, such as women, stimulates bigger consideration for non-obvious alternatives and more thorough analysis. For example, increasing the number of female executives broadens the range of perspectives available to recognize strategic opportunities and willingness to adapt to change (Wiersema & Bantel, 1992). A sense-making view further argues that diverse groups of decision-makers and managers with varied thinking will perceive complex

business environments differently and thus make more thoughtful and complete decisions for the company (Daft & Weick, 1984). Cognitive resource acquisition and enhanced decision-making processes give evidence that gender-diverse TMTs improve adaptability, innovation, and problem-solving, resulting in better financial outcomes for firms.

While there are several benefits of TMT diversity, seminal organizational theories also acknowledge potential costs. The upper echelons framework also originally notes that diversity can have both positive and negative effects on team decision-making depending on the context. One perspective of theory favors homogeneity, where similarity among team members promotes cohesion, communication, and faster consensus. Utilizing social identity theory (Tajfel & Turner, 1979) and the similarity-attraction paradigm (Byrne, 1971) suggests that people more easily cooperate with those who share their demographic or cultural characteristics. In a gender-homogeneous TMT, members may experience fewer interpersonal conflicts and better social integration, leading to more cohesive strategy decisions. Furthered by the social categorization theory (Tajfel & Turner, 1979), visible TMT diversity can trigger subgroup splits, like potentially crossing gender lines, which impedes collaboration and knowledge sharing across the whole team. Research confirms that when such fault lines emerge, TMT functioning and decision quality can suffer (Lau & Murnighan, 1998; van Knippenberg et al., 2011). Early strategic organizational research documents that diverse teams have the benefit of more ideas but face the liability of slower, less harmonious decision processes.

## **2.2 Female Leadership**

We highlight not only the importance of gender diversity but also the particularly unique value of female executives in TMTs. Drawing on the cognitive resource perspective, women often possess distinct human and social capital that complements their male counterparts. Adding women to TMTs increases the team's change orientation and decreases its risk-taking propensity, aligning with the view that women in leadership supply unique knowledge, skills, and insights not already present (Post et al., 2022). The gender differences theory also proposes that females approach leadership differently, in a more participative and less autocratic way, which can be beneficial in various business scenarios (Lu 2024). Furthermore, women in leadership often prioritize ethics, fairness, and long-term stakeholder interests, which are qualities that can enhance a firm's ethical climate and social responsibility initiatives (Kirsch 2018). Women also tend to use more effective leadership styles, like being transformational and supportive, while men more often rely on less effective passive styles (Eagly et al., 2003). Within the organization, female executives are more likely to mentor and empower other women, helping to cultivate talent and reduce barriers at lower levels (Kanter, 1977).

Conversely, theories like role congruity and social role theories propose the opposite effects of

female-gendered leadership in TMTs. The role congruity theory calls upon the perceived misfit (incongruity) between the female gender role traditionally seen as nurturing and submissive, and the leader role seen as assertive and authoritative (Eagly & Karau, 2002). Due to this misalignment, company workers and investors might view women as less suitable for leadership compared to men. Additionally, a study found a negative relationship between the proportion of women executives and firm profitability in a developing market context (Darmadi 2013). Such outcomes could stem from tokenism, a lone female executive unable to influence a male-dominated team, or backlash and stereotypes that hinder female-led initiatives (Kanter 1977).

### **2.3 Industry Analysis**

Researchers increasingly highlight that context matters when studying the impacts of female leadership, like the industry in which a firm operates. Sectors vary in innovation, risk, regulation, competition, gender norms, and capital intensity. These factors shape which industries enhance or disregard gender diversity in top management teams.

Industries can be categorized in several ways, including NAICS (North American Industry Classification System), GICS (Global Industry Classification Standard), the 3 Sector Model (and the extended 4 Sector Model), or a functional clustering approach based on observed characteristics. In this research study, we classify industries based on their 2-digit NAICS codes, and for a more holistic analysis, an extended 4-sector model approach (Kenton, 2025).

#### **2.3.1 2-Digit NAICS**

This study classifies industries based on their 2-digit NAICS codes, which cluster firms into industry groups; for instance, "31" for manufacturing and "62" for healthcare (U.S. Census). Below, five industries of interest out of seventeen in our data are described and how the structural demands of these industries may favor or hinder female versus male leadership.

**Information Technology.** The information technology industry belongs in the quaternary sector and is characterized by rapid innovation, disruption, and knowledge work. Female executives in top management teams (TMTs) can leverage diverse perspectives and inclusive climates to drive idea generation and adaptive strategies. For example, research finds that female TMT representation can boost innovation, especially when innovation is central to a firm's strategy (Dezso & Ross, 2012). Still, technology is notoriously male-dominated, and women leaders may face cultural resistance or pressure to conform to more aggressive or agentic styles. In practice, some women in software leadership adapt by shifting between more relational to more task-driven styles based on context (Nguyen-Duc et al., 2017). Thus, women may bring unique value, but structural and cultural barriers can limit their effectiveness in tech.

**Healthcare.** Also in the quaternary sector, health care combines regulation, public scrutiny, and knowledge-intensive operations. Here, female leaders' strengths in stakeholder coordination, ethics, communication, and compliance orientation can be valuable. In a regulated environment, women's propensity for risk moderation and compliance helps avoid regulatory missteps (Adams & Funk, 2012). That said, parts of healthcare, especially research-intensive or clinical specialties, still favor male prestige norms, requiring women to navigate professional hierarchies carefully. But compared to tech, healthcare generally offers more normative support for women in leadership roles.

**Utilities.** Utilities manage critical infrastructure with heavy regulation and capital demands. Female leadership may be advantageous here because women often adopt more cautious financial strategies (Huang & Kisgen, 2013) and lower-risk profiles (Faccio et al., 2016). Because utilities demand compliance and social legitimacy, women's strengths in stakeholder trust and governance may be especially prized (Perryman, Fernando, & Tripathy, 2016). But utility management is deeply technical and historically male-dominated, making it harder for women to gain credibility and external support from the public and investors.

**Manufacturing.** Manufacturing involves scale, efficiency, capital investment, and process innovation. Women leaders may benefit from bringing diverse analytical frames to incremental improvements and process optimization. However, women's caution in financial decisions might trade off against boldness in expansion or adoption of new technologies (Faccio et al., 2016). Moreover, cultural resistance in factory and engineering environments may force women to adapt to masculine norms to lead effectively or create an unsupportive environment for female leadership.

**Education.** Education is a knowledge service industry that operates in a mission-driven, stakeholder-rich environment. Innovations here tend to be slower, but relational leadership is crucial. Female leaders' strengths, like inclusive communication and consensus-building, are well aligned with the demands of governance and stakeholder management (Lu 2024). Also, societal norms often support women's roles in educational settings, which can reduce legitimacy challenges. Because education is less about high-risk bets and more about maintaining sustainable institutions, women may be especially well-suited to lead in this domain.

### **2.3.2 The 4 Sector Model**

The four-sector model builds on the classic three-sector approach by adding a dedicated "knowledge and information" sector, also known as the quaternary sector. In this model, the primary sector includes industries that extract or deliver raw resources, such as agriculture, oil and gas, and utilities (because utilities often manage natural resources like water and electricity).

The secondary sector is made up of industries that take raw inputs and turn them into goods, like manufacturing and construction. The tertiary sector encompasses general services that are not explicitly knowledge-driven, such as retail trade, wholesale, transportation, administrative services, and other service businesses. And lastly, the quaternary sector involves services centered on knowledge, information, and innovation, including information technology, health care, education, professional services, real estate, and entertainment.

Each sector has different structural demands. The primary and secondary sectors are often capital-intensive, with heavy investment in infrastructure and machinery. They usually face higher regulatory burdens and asset risk. The tertiary sector emphasizes operations and human capital with comparatively lower barriers than the first two sectors. The quaternary sector places high importance on innovation, knowledge generation, intellectual capital, and the firm's adaptability to change. Because sectors differ in these dimensions—innovation, capital intensity, regulation, risk exposure, competition, and normative culture—they create spaces for different types of successful leaders. A leadership style that thrives in a knowledge-intensive, fast-paced sector may not perform as well in a highly regulated environment.

## **2.5 Econometric Approaches and Limitations in Research**

Many empirical studies report positive, negative, or null relationships between TMT gender diversity and firm performance, highlighting the empirical ambiguity in this field. Sieweke et al. (2023) notes that earlier work shows mixed findings, and in their own IV estimates find that TMT gender diversity improves profitability, liquidity, and growth, while showing no significant effect on market-based performance. Some studies support positive effects, such as Dezsó & Ross (2012), who argue female representation enhances firm performance in innovation-driven firms. Others report null effects, for instance Post & Byron (2015), or show negative associations in certain contexts, as in Darmadi (2013). Additional evidence comes from Wagdi & Fathi (2024), who find a insignificant effect of gender diversity in emerging market firms; Laible (2013), who documents a slight negative association in German firms; and Bue et al. (2024), where female-led firms in services exhibit lower productivity on average. Some comprehensive reviews and meta-analyses, such as Borges et al. (2025) and Lu (2024), highlight that while there is a modest average positive effect, the relationship is highly contingent on context, which emphasizes the necessity of more rigorous econometric approaches for causal interpretations and industry-specific analyses.

Much of the empirical literature on gender diversity in TMTs relies on panel data models, specifically fixed-effect regressions. The fixed effects (FE) estimator is widely used because it differences out unobserved, constant firm traits, reducing omitted variable bias (Bell & Jones, 2015). Yet, FE models have notable limitations: they consume degrees of freedom, reduce

external validity, and cannot address endogeneity stemming from time-varying unobservables or reverse causality (Hill, 2020). For example, unobserved shocks in a firm's environment may simultaneously influence women's promotion to a TMT and firm performance, invalidating causal interpretation (Millimet, 2023).

To address endogeneity concerns, many studies adopt instrumental variables (IV). Some board-gender studies use external instruments (e.g., quotas, spillovers, industry-level shifts) to isolate exogenous variation (Dang, 2023). The recent Sieweke et al. (2023) work on TMT gender diversity introduced a shift-share IV design that exploits industry-level shifts in female representation interacted with preexisting firm composition to generate exogenous variation. This technique helps overcome simultaneity and omitted variable bias, making the causal interpretation more robust. Nonetheless, IV methods critically depend on the validity of the instrument: if the instrument is weak or correlated with the error term, it introduces new bias (weak instrument bias) or inconsistency.

## **2.6 Unique Contribution**

This study presents two key contributions to the growing literature on gender diversity in TMTs and firm performance. First, it uses an instrumental variable (IV) approach with a shift-share instrument, which combines industry-level changes in female representation with firm-specific exposure to identify causal effects. So far, only one other study, Sieweke et al. (2023), has applied this method to analyze TMT gender diversity, making this approach both rigorous and relatively uncommon. Second, and more importantly, this study introduces an industry-level analysis of female leadership effectiveness. Since prior research shows that the impact of gender diversity depends heavily on industry context, including factors such as innovation intensity, regulation, competition, capital intensity, and gender norms, this context helps analyze where female leadership is most and least effective. By comparing results across industries, the study provides a clearer understanding of how context shapes the value of gender-diverse leadership and offers more practical insights for both policy and the field of strategic management.

## **3. Methods and Results**

### **3.1 Data**

#### **3.1.1 Data Description**

This research study constructs a panel dataset by merging firm-level financial information from the CompuStat North America database with executive person-level data from the ExecuComp database. Both data sources were accessed through the Wharton Research Data Services (WRDS) platform. The sample spans from 1997 to 2023, covering the S&P 1,500, a stock index

that includes the S&P 500 (large-sized firms), the S&P 400 (medium-sized firms), and the S&P 600 (small-sized firms). Using the S&P 1500, as opposed to an S&P 500, incorporates different market caps, giving a varied sample and results that are more representative of U.S. public firms.

Although the S&P 1500 index consists of approximately 1,500 firms at any given time, the ExecuComp database covers a broader range of publicly traded firms. ExecuComp tracks roughly 2,500 firms per year, including former S&P 1,500 members if they are still publicly trading, as well as some client requests. This wider coverage allows for a more extensive dataset and explains why the final sample includes more unique firms than the index size (1500) suggests.

In the panel data, the cross-sectional unit is the firm, and the time unit is the year. A firm-year observational unit was obtained by averaging the executive-level ExecuComp data to the firm level and aggregating it with the corresponding firm-level annual financial data. The datasets were merged using a unique firm identifier, resulting in a panel with firms beginning in 1997 but can exit the sample over time. To ensure data quality and consistency, the sample excludes all firms with missing or incomplete executive gender information. Observations with missing financial values are dropped during the time of running the regressions, as dropped values are dependent upon the dependent variable being tested. The final analytical sample consists of 1,589 unique firms, a period of 27 years, and a total of 22,609 firm-year observations, covering a broad range of industries, grouped by the 2-digit NAICS codes and by the 4 sectors.

**Table 1: Descriptive Statistics and Correlations**  
**Panel A. Summary Statistics**

Variables	Mean	SD
(1) Percent Female	7.59	12.08
(2) Shift-share IV	7.07	19.47
(3) Base Female Share 1996	3.20	8.08
(4) Industry Shift 3y	2.24	0.97
(5) Net Income	362.27	1841.67
(6) Tobin's Q	2.03	2.09
(7) Total Assets	8052.20	25876.63
(8) Total Assets (log) <sup>a</sup>	7.53	1.70
(9) Market Value	12429.22	43480.96
(10) Closing Price (adj.)	88.76	2115.23
(11) High Price (adj.)	108.73	2507.58
(12) Low Price (adj.)	65.91	1630.10

**Panel B. Correlations (Variables 1–12)**

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Percent Female											
(2) Shift–share IV	0.26										
(3) Base Female Share 3y Firm	0.31	0.91									
(4) Industry Shift 3y	0.16	0.15	-0.01								
(5) Net Income	0.02	-0.03	-0.04	0.07							
(6) Tobin’s Q	0.00	0.02	0.03	-0.05	-0.03						
(7) Total Assets	0.01	-0.05	-0.07	0.11	0.56	-0.04					
(8) Total Assets (log)	0.04	-0.06	-0.12	0.22	0.34	-0.11	0.65				
(9) Market Value	0.04	-0.04	-0.05	0.10	0.69	0.12	0.65	0.45			
(10) Closing Price (adj.)	-0.01	-0.01	-0.01	0.00	0.07	-0.00	0.07	0.14	0.01		
(11) High Price (adj.)	-0.01	-0.01	-0.01	0.00	0.07	0.01	0.07	0.16	0.07	0.94	
(12) Low Price (adj.)	-0.01	-0.01	-0.01	0.00	0.07	-0.01	0.07	0.14	0.06	0.99	0.94

Notes: Mean and standard deviation (SD) are reported in Panel A. Panel B reports Pearson correlation coefficients among variables (1)–(12). Lower triangle shown; upper triangle and diagonal entries (1.00) omitted.

<sup>a</sup> Log-transformed. Net Income, Market Value, and Total Assets are measured in millions of U.S. dollars.

Table 1 lists the means, standard deviations, and correlations of all relevant variables. The variables will be further explained in sections 4.2 Variable Construction and 4.4 Instrumental Variable Strategy.

### 3.2 Variable Construction

#### 3.2.1 Key Independent Variable

Our key independent variable is the gender composition of the top management team (TMT), captured by the percentage of female executives within a given company in a specific year. This measure is constructed by dividing the number of women in the TMT by the total number of executives and multiplying by 100, which allows us to scale representation relative to team size. This approach is consistent with prior studies such as Perryman et al., 2016 and Sieweke et al., 2023. Data on TMT composition is collected from the ExecuComp database, which gathers annual proxy statements (DEF14A) filed with the SEC, allowing us to identify the top five to nine executive officers for each firm.

#### 3.2.2 Key Dependent Variables

We employ two complementary measures, computed from the CompuStat database, to evaluate how female leadership in TMTs affects firm financial performance: an internal metric, Return on Assets (ROA), and an external metric, Tobin’s Q. Both ROA and Tobin’s Q reflect operational efficiency and market perception, respectively.

Return on Assets (ROA), which measures how well a company uses its assets to generate earnings, is frequently used in the literature to assess internal operational performance. Internal

success measurements like ROA represent realized performance, emphasizing firm productivity and profitability (Zhang 2020). However, to mitigate the well-documented issues in management research using ratio-based dependent variables, such as the loss of statistical power and fluctuation of estimates, we follow the recommendation of Certo et al. (2020). We split ROA into its components, so we use net income as the dependent variable while controlling for firm size using total assets (Certo et al., 2020; Sieweke et al., 2023). This approach maintains the statistical significance and interpretive power of ROA, while avoiding the downsides of ratio-based models. Profitability can be framed as a mediator between internal efficiency and overall financial performance, supporting the decision of ROA as a good internal financial-based outcome as well (Rima, 2024). Signal theory also notes that operational efficiency sends strong internal signals about a firm's capacity to manage resources and generate profits, which are traits best captured through direct measures like return on assets (Rima, 2024). Following recommendations of Certo et al. (2020) and Sieweke et al. (2023), all ROA models will use net income as its dependent variable and log total assets as a control variable.

As our second dependent variable, we use Tobin's Q to capture external market perceptions of firm value. Tobin's Q is a forward-looking ratio of market value to the replacement value of a firm's assets. This represents how investors perceive the firm's value to grow in the future. Tobin's Q distinguishes between market expectations and the actual internal return of ROA by directly measuring the market's assessment of a company's long-term value (Zhang 2020). Other studies, such as Perryman et al. 2016, also utilize Tobin's Q as their primary measure of firm performance when studying gender diversity in TMTs. The study further highlights that Tobin's Q is particularly sensitive to intangible assets and aligns with investor sentiment. Because Tobin's Q is based on market capitalization, it reflects external shareholder perceptions and can serve as an indicator of how diversity in TMTs can shape stock prices and investor expectations. All Tobin's Q models will use the Tobin's Q ratio as its dependent variable and log total assets as a control variable.

Using metrics to assess both internal efficiencies and external valuations is a dual approach consistent with recent literature (Zhang, 2020; Sieweke et al., 2023; Perryman et al., 2016), emphasizing the importance of capturing both intrinsic and extrinsic extents of firm performance.

### **3.2.3 Key Control Variables**

In all regression model specifications, we include the natural logarithm of total assets, widely regarded as the best proxy for firm size (Dalbor et al., 2004). Company size is a firm- and time-varying factor that significantly influences financial performance, including net income and Tobin's Q, due to efficient operations and stable reputation. It also correlates with the

independent variable, percent female, because larger firms tend to have more structured HR systems and formalized promotion pipelines, as well as stronger board-level diversity compliance, which increase female representation in executive teams. Thus, firm size, as measured by the natural log of total assets, must be accounted for in all models. We use the log transformation to reduce right-skewness and account for diminishing marginal effects.

### 3.3 OLS and Fixed Effects Regressions

#### 3.3.1 Pooled OLS Model

As a base for our analysis, we first estimate a pooled ordinary-least-squares (OLS) model that treats the panel as one large cross-section.

For both dependent variables, our pooled OLS regression equations are

$$net\ income = \beta_0 + \beta_1\text{percent female} + \beta_2\log(\text{assets}) + \varepsilon \tag{1}$$

$$tobin's\ q = \beta_0 + \beta_1\text{percent female} + \beta_2\log(\text{assets}) + \varepsilon \tag{2}$$

Standard errors are clustered at the firm level to mitigate heteroskedasticity and serial correlation within firms. This specification provides a benchmark that shows the raw association between female leadership in TMTs and company financial outcomes before more advanced specifications.

**Table 2: OLS Model: Firm Performance on TMT Gender Diversity**

	<b>Model 1</b> <i>Net Income</i>	<b>Model 2</b> <i>Tobin's Q</i>
Percent Female	1.6774* (0.0793)	0.0006994 (0.5450)
Log Assets	366.6903*** (0.0)	-0.1406*** (0.0)
Intercept	-2411.2422*** (0.0)	3.0819*** (0.0)
Observations	22,586	22,367
R <sup>2</sup>	0.1142	0.0129

Signif. codes: 0.01 \*\*\* 0.05 \*\* 0.1 \*

Notes: Heteroskedasticity-robust standard errors clustered at the firm level. P-values in parentheses.

In the first model, the estimated effect of a one percentage-point increase in percent female on net income (1.6774;  $p = 0.08$ ) and Tobin's Q (0.0007;  $p = 0.55$ ) is statistically insignificant and essentially zero to the 5% level. Both coefficients on log assets are very statistically significant, and their signs (directionality of coefficients) align with expectations, because as a firm's assets increase, they grow bigger and earn a higher net income but also reach their maturity stage with a declining tobin's Q. The intercepts in both regressions represent the outcomes when the explanatory variables equal zero but carry little stand alone economic meaning. Across 22,586 observations for net income and 22,367 for tobin's Q, the  $R^2$  values are about 0.12 and 0.013, respectively. These OLS results show that there is no statistically significant effect of female leadership on internal and external firm performance.

The pooled OLS model has significant limitations because it doesn't account for the panel structure of the data, so within-firm changes over time and cross-firm differences are vulnerable to omitted-variable bias. Time-invariant traits such as corporate culture and strategy, which cannot be explicitly observed as a variable, cannot be controlled for through an OLS model. Similarly, firm-invariant traits such as the effects of macroeconomic shocks will be omitted as well. Although firm-level clustered standard errors can protect from intra-firm serial correlation, they do nothing to correct for bias in the coefficient itself. Consequently, while the pooled OLS specification can serve as a base model for our analyses, it does little to determine a causal effect between TMT gender diversity and company financial performance. These shortcomings motivate a two-way fixed-effects model, where we explicitly absorb firm and time differences.

### 3.3.2 Fixed Effects Model

To account for the data's panel structure and reduce omitted variable bias, we estimate models with firm fixed effects and time fixed effects. Firm fixed effects remove all time-invariant traits that differ among companies, like culture, baseline risk, and strategy, that cannot be explicitly controlled for (Angrist, 2010). Time fixed effects then soak up shocks that hit companies collectively each year, like government regulations and universal trends.

The fixed effects models for both net income and tobin's Q are shown below.

$$\text{net income} = \beta_0 \text{ percent female} + \beta_1 \log(\text{assets}) + \alpha_i + \lambda_t + \varepsilon_{it} \quad (3)$$

$$\text{tobin's q} = \beta_0 \text{ percent female} + \beta_1 \log(\text{assets}) + \alpha_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where  $\alpha_i$  is firm fixed effects to account for firm-variant traits and  $\lambda_t$  is time fixed effects to control for time-variant shocks. Standard errors are clustered at the firm level.

**Table 3: Fixed Effects Model: Firm Performance on TMT Gender Diversity**

	<b>Model 1</b> <i>Net Income</i>	<b>Model 2</b> <i>Tobin's Q</i>
Percent Female	2.65069 (0.2540)	-0.001902 (0.3213)
Log Assets	250.0116** (0.0114)	-0.6495*** (0.0)
Observations	22,588	22,369
R <sup>2</sup>	0.4400	0.3528

*Signif. codes:* 0.01 \*\*\* 0.05 \*\* 0.1 \*

*Fixed Effects:* Firm and Year

*Notes:* Heteroskedasticity-robust standard errors clustered at the firm level. P-values in parentheses.

As shown in Table 3, across the fixed effects model specifications, the coefficients on percent female for net income (2.6507;  $p = 0.25$ ) and tobin's Q (-0.0019;  $p = 0.32$ ) are statistically insignificant, suggesting that we have inconclusive evidence to suggest that greater gender diversity in top executive groups causes firms to perform better. Though interestingly, the positive coefficient on percent female in Model 1 can suggest that greater female representation leads to better internal success. However, the small negative coefficient in Model 2 can suggest the opposite for outward-facing metrics related to firm market performance. The control of log assets follows relatively the same trends as it did in the Pooled OLS model and is statistically significant to the 5% level.

Though fixed effects can control for a lot of the omitted variable bias, they can't control all of it, particularly the time-varying omitted variables that are heterogeneous to firms. To draw causal rather than correlational results, we have to address these concerns using a more rigorous econometric strategy: an instrumental variable regression approach.

### 3.4 Instrumental Variable Strategy

#### 3.4.1 Addressing Endogeneity Concerns

Numerous sources of endogeneity, as previously stated, make it difficult to estimate the causal relationship between TMT gender diversity and firm performance. One instance is omitted variable bias, which occurs when unobserved firm characteristics, like long-term strategy, corporate culture, or governance style, affect both the firm's financial performance and TMT gender diversity (Sieweke et al., 2023). Reverse causality is also a significant problem, where higher firm performance may attract more female executives or enable governance reforms that increase female representation, which is the opposite of the relationship being tested (Antonakis

et al., 2010). More generally, endogeneity occurs whenever the key independent variable is correlated with the error term in the regression equation, whether due to omitted variables, simultaneity, or non-random selection into the treatment (Wooldridge, 2010). In this research context, these issues threaten the internal validity or the cause-and-effect relationship in the OLS and fixed effects estimates.

Instrumental variables (IV) estimation techniques offer a solution by isolating the component of variation in the endogenous independent variable that is uncorrelated with the error term through an instrument. A valid instrument must satisfy two conditions. Firstly, relevance requires that the instrument strongly predict the endogenous regressor (Staiger & Stock, 1997). Secondly, exogeneity, also known as the exclusion restriction, requires that the instrument influence the dependent variable only through its effect on the endogenous regressor (Angrist & Krueger, 2001). Under these two conditions, the IV regression provides causal estimates by exploiting only the exogenous variation in the regressor on the explanatory variable induced by the instrument (Wooldridge, 2010). While relevance can be tested empirically via the weak instruments test and the first-stage F-statistic, the exogeneity principle is inherently untestable and must be justified through research design and theory (Staiger & Stock, 1997; Morgan & Winship, 2015). We introduce our instrumental variable and justify its relevance and exogeneity to determine a causal relationship between TMT gender diversity and firm financial performance.

### 3.4.2 Shift Share Instruments

We address endogeneity using a specific type of instrumental variable called the shift-share (Bartik) instrument, which creates plausibly exogenous variation by interacting a unit's predetermined exposure ("share") with aggregate shocks ("shift") that vary across groups and over time (Bartik, 1991; Goldsmith-Pinkham, Sorkin, and Swift, 2020). Following the shift-share methodology by Sieweke et al. (2023), the shift-share instrument for firm  $i$  in industry  $j$  and year  $t$  is as follows,

$$Z_{ijt} = \underbrace{\text{BaseFemaleShare}_{ij,1996}^{(3y)}}_{\text{share}} \times \underbrace{\Delta \text{IndustryFemaleShare}_{j,t}^{(3y)}}_{\text{shift}} \quad (5)$$

where  $\text{BaseFemaleShare}^{(3y)}_{ij,1996}$  is firm  $i$ 's three-year averaged baseline TMT female share in industry  $j$  measured in 1996, and  $\Delta \text{IndustryFemaleShare}^{(3y)}_{j,t}$  represents the three-year smoothed change in industry-level female representation between year  $t$  and the base year 1996. This interaction produces firm-specific exposure to industry-wide diversity shocks.

The share part shows how much female leadership a firm already had, and the shift shows how gender diversity in its industry changed over time. Firms that started with more women leaders are

expected to change more as their industries diversify executive teams, while firms with few or no women see little change. This setup helps create outside variation in firm gender diversity that comes from industry trends, not from the firm itself (Bartik, 1991; Goldsmith-Pinkham et al., 2020).

In order to validate the use of our shift-share instrument, we need to test the plausibility of the two identifying assumptions: the relevance and exclusion principles. We support the relevance of our shift-share instrument both empirically and theoretically. Empirically, the first-stage F-statistic is 724.7 with a p-value of approximately 0, far exceeding the threshold of 10, which indicates a very strong instrument (Staiger & Stock, 1997). Strategic management and organizational behavior theory also supports the instrument's relevance. From a conceptual standpoint, the instrument is relevant if industry-wide changes in TMT gender diversity and/or a firm's baseline exposure to female leadership influence the firm's gender composition for a certain year. Institutional isomorphism suggests that firms imitate industry standards to maintain legitimacy, so as particular industries diversify their top management teams, firms within that industry will face pressure to follow suit (DiMaggio & Powell, 1983). Role congruity theory from social psychology also argues that greater industry-level female representation reduces the perceived incongruity between women and leadership, making firm-level change in diversity more likely (Eagly & Karau, 2002). Finally, baseline exposure matters because firms with a stronger history of gender-diverse leadership are more likely to have inclusive organizational cultures and establishments that increase their responsiveness to industry-wide diversity trends. Together, these empirical and theoretical justifications explain why our shift-share instrument satisfies the relevance condition.

The second identifying assumption is the exclusion or exogeneity restriction, which requires that the instrument influence firm performance only through its effect on TMT gender diversity and not through any alternative channel. While the relevance condition can be tested empirically, exclusion cannot be formally verified and instead must be defended on theoretical grounds (Morgan & Winship, 2015). An advantage of the shift-share instrument is that only one component, either the shift or share, needs to be plausibly exogenous to the regression's error term. Similar to Sieweke et al., 2023, we use a 1996 base year to create temporal distance from the beginning of our analysis period (1997) to strengthen the share component of the instrument's exogeneity. Additionally, we don't believe that TMT gender diversity in the industry over time will affect firm-level financial performance through outside environmental factors. Broader industry changes are unlikely to align with idiosyncratic firm performance (Autor et al., 2013; Sieweke et al., 2023). Taken together, the plausible exogeneity of the shift and share components supports the validity of the exclusion restriction.

### 3.4.3 Shift Share Regression Equation and Results

We estimate a fixed-effects shift-share instrumental variables (IV) model to identify the causal effect of TMT gender diversity on firm performance. Our IV regression, also known as a two-stage OLS regression, has the following first-stage and second-stage regression equations

$$\text{PercentFemale}_{it} = \pi_0 Z_{it} + \pi_1 \log(\text{Assets}_{it}) + \alpha_i + \lambda_t + u_{it} \tag{6}$$

$$\text{NetIncome}_{it} = \beta_0 \widehat{\text{PercentFemale}}_{it} + \beta_1 \log(\text{Assets}_{it}) + \alpha_i + \lambda_t + \varepsilon_{it} \tag{7}$$

$$\text{TobinQ}_{it} = \gamma_0 \widehat{\text{PercentFemale}}_{it} + \gamma_2 \log(\text{Assets}_{it}) + \alpha_i + \lambda_t + v_{it} \tag{8}$$

where  $\alpha_i$  are firm fixed effects,  $\lambda_t$  are year fixed effects, and errors are clustered by 2-digit NAICS industry. Wild bootstrap  $p$ -values are reported to account for the small number of clusters.

**Table 4: Shift-Share IV Regression Model: Firm Performance on TMT Gender Diversity**

	Model 1 <i>Net Income</i>	Model 2 <i>Tobin's Q</i>
Percent Female (instrumented)	18.8462** (0.0063)	0.003629 (0.8343)
Log Assets	257.0945*** (0.0023)	-0.647166*** (0.0002)
Observations	22,588	22,369
$R^2$	0.4401	0.3528

Signif. codes: 0.01 \*\*\* 0.05 \*\* 0.1 \*

Fixed effects: firm and year. SEs: clustered by 2-digit NAICS industry.

Bootstrapped  $p$ -values shown are in parentheses.

In Table 4, the IV estimates indicate that a one percentage-point increase in TMT female representation raises net income by about \$18.85 million ( $p = 0.0063$ ). For a typical company that has an average of 5 executives in its TMT, a change from one male to one female executive raises percent female by 20 pp and predicts a raised net income of approximately \$377 million. The effect is economically large and statistically significant, suggesting that gender-diverse TMTs causally improve internal profitability. For Tobin's Q, the coefficient of 0.0036 ( $p = 0.834$ ) indicates that a 1 pp increase in female representation on the TMT is associated with a 0.0036 increase in Q (roughly 0.18% of the mean Q of 2.03 from Table 1). For a firm with \$10 billion

in assets, this corresponds to about \$18 million higher market valuation. However, the coefficient is economically small and statistically insignificant, so we do not have enough evidence to prove a relationship between TMT female share and external firm performance. Like previous regression models, the log(assets) as our firm size control variable is highly statistically significant.

The improvement in R<sup>2</sup> is visible with values of 0.4401 and 0.3528 in both models, respectively, suggesting that the inclusion of the instrumental variable explains a larger proportion of the variation in firm performance after accounting for firm and year fixed effects. Standard errors are clustered at the 2-digit NAICS industry description level to account for shocks across firms within industries. This approach also follows econometric guidance that clustering should align with the level of identifying variation. In this case, it is at the industry level due to the IV’s shift component (Cameron & Miller, 2015). Because the number of clusters is below 50, we report wild bootstrap p-values to avoid the issue of few clusters (Cameron & Miller, 2015).

### 3.5 Industry Level Analysis

#### 3.5.1 The Importance of Industry Level Analysis

Looking at firm performance in the aggregate can hide the heterogeneous effects of TMT gender diversity that play out across industries. An industry-level analysis can shine light on areas where female representation in top management has the most pronounced effects on firm performance and where it has little or a negative impact.

Distinguishing between internal measures of performance and external market valuations, in terms of an industry- level analysis, is equally as important. Such analysis allows us to see whether female representation influences these dimensions differently. In some cases, internal metrics can reveal gains in productivity and profitability, while market perceptions remain unchanged. However, in others, investors may reward diversity even when internal indicators might show failing signs. Exploring the nuances between what happens within firms versus how the market interprets them ensures a complete analysis.

#### 3.5.2 Summary Statistics by Industry

**Table 5: Descriptive Statistics by Industry**

Industry	No. of Obs.	Mean Percent Female	Shift-share IV	Industry Shift (3y)	Base Female Share (1996)
Administrative Waste Services	470	8.83	11.92	5.97	3.82
Agriculture	45	0.76	0.00	0.00	0.00
Conglomerates	178	3.22	0.00	0.00	0.00
Construction	294	5.24	2.75	1.67	2.66

Educational Services	102	18.04	26.43	12.11	8.47
Entertainment	121	8.44	9.42	6.88	3.79
Health Care	422	7.67	5.40	3.55	3.44
Information	1930	8.11	6.50	4.21	4.04
Manufacturing	10999	6.17	4.98	2.91	2.34
Mining, Oil & Gas	1118	4.91	6.55	3.48	2.37
Other Services	135	3.07	4.69	2.15	1.45
Professional Services	850	7.32	9.21	5.03	3.26
Real Estate	167	11.13	11.78	6.77	5.53
Retail Trade	1778	14.58	15.87	9.55	7.71
Transportation Warehousing	897	5.88	5.97	3.41	1.99
Utilities	1582	10.88	9.86	6.23	3.48
Wholesale Trade	891	7.65	5.03	3.12	3.64

Industry	Mean Net Income	Mean Tobin's Q	Mean Total Assets	Mean Log Assets	Mean Market Value
Administrative Waste Services	95.78	2.19	3120.75	7.07	4599.19
Agriculture	10.36	1.83	1540.22	7.28	1076.89
Conglomerates	2689.79	1.62	32674.81	8.00	73052.94
Construction	135.15	1.35	6854.32	7.74	3431.40
Educational Services	106.83	2.77	1983.46	6.73	3119.30
Entertainment	34.22	1.64	1024.67	6.50	2004.36
Health Care	266.55	1.79	4567.12	7.58	7825.17
Information	590.79	2.66	15341.27	7.63	24353.49
Manufacturing	401.98	2.15	10852.11	7.32	12772.04
Mining, Oil & Gas	229.63	1.57	17942.68	8.08	11406.38
Other Services	68.46	1.66	2156.47	7.29	3034.75
Professional Services	64.84	2.32	1879.56	6.76	4155.37
Real Estate	79.40	1.50	2469.12	7.78	2605.08
Retail Trade	400.94	1.96	8951.38	7.61	15439.54
Transportation Warehousing	266.94	1.64	11752.89	8.14	9388.06
Utilities	266.89	1.23	8674.32	8.84	8361.15
Wholesale Trade	118.23	1.70	5511.49	7.36	4382.67

Notes: "Number of Observations" refers to firm-year observations. Net Income, Market Value, and Total Assets (both raw and log) are reported in millions of U.S. dollars. Finance & Insurance, Food & Accommodation, and Public Administration industries are omitted from dataset due to different regulation policies or few observations (< 30).

### 3.5.3 Industry Level Analysis

To capture the industry-wide effects and assess how it compares with outcomes from other industries, we employ instrumental variables that incorporate interaction terms. The first stage predicts percent female using the shift-share instrument. The fitted values from this stage are then predict the performance variables (net income or Tobin's Q) in the second stage, where the industry interaction terms are included.

It is important to note that clustering can be done at either the firm or industry level, but each approach will adjust standard errors differently. Because the key variation is at the industry level, that is the more appropriate specification (Cameron & Miller, 2015). Since the number of industries in our sample is fewer than 50, conventional cluster-robust errors can be biased, so we use wild bootstrapping to obtain more accurate estimates. The bootstrapped industry-level errors are larger and therefore more conservative, which reduces statistical significance compared to firm-level clustering. Even though this makes the results appear less significant, the industry-level bootstrap version is methodologically superior and the correct one to rely on. Nonetheless, we

report results of both types of clustering.

Table 6: Firm Analysis by Industry Coefficients Summary: Industry Level Clustering

	Model 1 Net Income	Model 2 Tobin's Q
Agriculture	-22.77 (0.49)	-0.05 (0.49)
Mining, Oil, and Gas	-121.99 (0.17)	0.01 (0.48)
Utilities	-22.38 (0.41)	0.04 (0.46)
Construction	-26.42 (0.47)	0.01 (0.61)
Manufacturing	2.33 (0.87)	0.03 (0.23)
Wholesale Trade	-38.58 (0.24)	0.00 (0.99)
Retail Trade	12.68 (0.43)	-0.42 (0.32)
Transportation Warehousing	-2.17 (0.81)	0.02 (0.49)
Information	85.26 (0.49)	-0.11 (0.34)
Real Estate	-5.28 (0.68)	-0.02 (0.56)
Professional Services	-14.51 (0.47)	0.01 (0.57)
Administrative Waste Services	-16.31 (0.48)	-0.01 (0.51)
Educational Services	-24.29 (0.50)	-0.30 (0.89)
Health Care	19.04 (0.48)	-0.01 (0.59)
Entertainment	-12.88 (0.50)	-0.03 (0.48)
Other Services	-5.10 (0.68)	-0.06 (0.83)
Conglomerates	206.33 (0.53)	-0.18 (0.85)

Signif. codes: 0.01 \*\*\* 0.05 \*\* 0.1 \*  
Notes: Heteroskedasticity-robust SEs clustered at the industry level. Bootstrapped p-values in parentheses.

Table 7: Firm Analysis by Industry Coefficients Summary: Firm Level Clustering

	Model 1 Net Income	Model 2 Tobin's Q
Agriculture	-22.77 (0.20)	-0.05 (0.40)
Mining, Oil, and Gas	-121.99*** (0.00)	0.01*** (0.00)
Utilities	-22.38* (0.09)	0.04*** (0.00)
Construction	-26.42* (0.08)	0.01 (0.69)
Manufacturing	2.33 (0.88)	0.03* (0.08)
Wholesale Trade	-38.58*** (0.00)	0.00 (0.99)
Retail Trade	12.68 (0.46)	-0.42** (0.04)
Transportation Warehousing	-2.17 (0.91)	0.02 (0.33)
Information	85.26** (0.03)	-0.11** (0.02)
Real Estate	-5.28 (0.65)	-0.02 (0.33)
Professional Services	-14.51 (0.17)	0.01 (0.80)
Administrative Waste Services	-16.31 (0.29)	-0.01 (0.88)
Educational Services	-24.29 (0.29)	-0.30* (0.89)
Health Care	19.04 (0.48)	-0.01 (0.77)
Entertainment	-12.88 (0.50)	-0.03 (0.70)
Other Services	-5.10 (0.70)	-0.06** (0.01)
Conglomerates	206.33 (0.67)	-0.18** (0.03)

Signif. codes: 0.01 \*\*\* 0.05 \*\* 0.1 \*  
Notes: Heteroskedasticity-robust SEs clustered at the firm level. P-values in parentheses.

Both tables report identical coefficients for each interaction term, but they have different standard errors. Table 6, which clusters standard errors at the industry level, produces results that are largely statistically insignificant. By contrast, Table 7, which applies firm-level clustering, produces statistically significant results for certain industries. Since industry-level clustering is our standard in this paper, we cannot claim statistical significance for any of the coefficients. However, analyzing the signs and magnitudes of firm-level clustered coefficients can still give meaningful insights.

According to Table 6, the manufacturing, retail trade, information, health care, and conglomerates industries have positive coefficients in Model 1 (Net Income). Among these positive coefficients, information is the only industry whose coefficient is statistically significant ( $p < 0.05$ ). In information, the slope is +85.26 (millions USD per 1 pp), meaning an increase in \$85 million per 1 pp increase in percent female and about \$1.71 billion for a 20 pp increase,

which is an additional female in a 5 person executive team, in net income per year. Female leadership in agriculture, mining oil & gas, utilities, construction, wholesale trade, transportation warehousing, real estate, professional services, administrative waste services, educational services, entertainment, industries of other services are negatively associated with net income. Among these industries, mining oil & gas and wholesale trade are statistically significant to the 1% level ( $p < 0.01$ ) and utilities and construction are statistically significant to the 10% level ( $p < 0.1$ ). These industries are often male-dominated, require manual labor and raw materials, and stigmatize female representation. For mining, oil & gas, the firm-clustered coefficient is -121.997 ( $p = 0.0$ ), so a 20 pp increase in TMT female share is associated with about a \$2.44 billion decrease per year. As for wholesale trade, the coefficient is -38.5779 ( $p = 0.0$ ), implying roughly -\$771.6 million per period for a +20 pp change.

In Model 2 where Tobin's Q is the dependent variable, TMT female representation in the mining oil & gas, utilities, construction, manufacturing, wholesale trade, transportation warehousing, and professional services industries have positive associations with Tobin's Q. Particularly, mining oil & gas and utilities are statistically significant to the 1% level ( $p < 0.01$ ) and manufacturing is statistically significant to the 10% level ( $p < 0.1$ ). In the mining oil & gas industry, a 1 pp increase in TMT female share corresponds to an increase of about 0.0133 points ( $p = 0.0$ ) of Tobin's

Q. Thus, a 20 pp increase would be an increase of 0.276 points of Tobin's Q. This is a modest positive change in valuation, meaning market value rises relative to replacement cost. A 1 pp increase in TMT female share in the utilities industry relates to a 0.0396-point ( $p = 0.0$ ) increase in Tobin's Q. Thus, a 20 pp increase would have a positive 0.792-point impact on Tobin's Q. That is a large positive change in valuation, indicating a meaningfully higher market value relative to the replacement cost. In the industries that produce a negative coefficient, like agriculture, retail trade, information, real estate, administrative waste services, educational services, health care, entertainment, other services, and conglomerates, few are statistically significant. Retail trade, information, other services, and conglomerates are significant to the 5% level ( $p < 0.05$ ), and educational services is significant to the 10% level ( $p < 0.1$ ). For these industries, swapping for one woman in a five-person TMT, which raises the female share by 20 pp, contributes to a very large drop in Tobin's Q, suggesting that the market value of firms in these industries is lower relative to the cost of replacing their asset base. However, these results are from models whose standard errors are clustered by firm instead of industry, which is the standard of our paper. Thus, with these findings, no causal relationship of performance on TMT percent female can be established, but important insights from the magnitude and sign of coefficients from firm-clustered models can be extracted.

**Table 8: Four Sector Industry Analysis Summary: Industry Level Clustering**

	<b>Model 1</b> <i>Net Income</i>	<b>Model 2</b> <i>Tobin's Q</i>
Primary Sector	-67.0225* (0.0730)	0.030271 (0.2595)
Secondary Sector	0.745362 (0.9598)	0.029385 (0.2348)
Tertiary Sector	-8.13947 (0.5963)	-0.018108 (0.4967)
Quaternary Sector	50.06382 (0.2497)	-0.070607** (0.0157)

*Signif. codes:* 0.01 \*\*\* 0.05 \*\* 0.1 \*

*Notes:* Heteroskedasticity-robust standard errors clustered at the industry level. Bootstrapped p-values in parentheses.

Now, we take a look at Table 8 for our four-sector industry model and a broader analysis of the impact of TMT female leadership. This model clusters standard errors by industry, which aligns with this paper’s standards. Generally, disregarding statistical significance, female leadership shows positive effects on net income (internal performance) with information-based and knowledge-based industries like the quaternary sector. All other sectors exhibit either negative or close-to-zero impacts. As for the external performance metric Tobin’s Q, raw material, manufacturing, and manufacturing-adjacent industries in the primary and secondary sectors contain positive effects due to female TMT leadership, while the opposite is true for the tertiary and quaternary, service-based sectors.

The impacts of female TMT leadership on net income in the primary sector and on Tobin’s Q ratio in the quaternary sector are statistically significant at the 10% level ( $p < 0.1$ ) and 5% level ( $p < 0.05$ ), respectively. For Model 1 (Net Income), the primary sector coefficient is -67.0225 ( $p = 0.073$ ), which implies that each 1 percentage point higher female share in the TMT is associated with about \$67.0 million lower net income per year; a one-person change in a five-member TMT (20 pp) corresponds to about a \$1.34 billion loss. For Tobin’s Q, the coefficient of -0.0706 ( $p = 0.0157$ ) indicates that a 1 pp increase in female representation on top management teams in the quaternary sector is associated with a 0.0706-point decline in Q (about 3.5 % of the mean Q). For an average firm with \$10 billion in assets, this corresponds to an estimated \$350 million decrease in market valuation, an economically moderate but statistically significant effect.

#### 4. Conclusion

This study examined whether female representation in top management teams causally

influences firm performance by applying a shift–share instrumental variable approach, which isolates exogenous variation in gender diversity. Prior work has often been limited by endogeneity, where unobserved firm culture, selection effects, and reverse causality bias persist. The shift–share instrument, which interacts firms’ baseline exposure to female leadership with industry-wide changes in diversity, overcomes these concerns. Because the instrument varies at the industry–year level, standard errors are clustered by industry, making the estimates causal and consistent with econometric work. Unlike prior correlational studies, this study provides a causal estimate of how women in leadership affect both internal and external firm outcomes through net income and Tobin’s Q values.

The results show that a 1 pp in female TMT representation raises net income by about \$18.85 million ( $p = 0.0063$ ). For a five-member TMT, replacing one male with one female executive (a 20 pp increase) predicts roughly a \$377 million increase in annual profitability. This supports the upper echelons theory (Hambrick & Mason, 1984) and the cognitive resource perspective (Williams & O’Reilly, 1998), which argue that diverse teams process information more effectively and make higher-quality decisions. However, the coefficient on Tobin’s Q (0.0036,  $p = 0.834$ ) is statistically insignificant, showing that markets do not yet translate internal improvements into higher valuations, consistent with role congruity theory (Eagly & Karau, 2002), where investors and the general public may undervalue female leadership due to gendered expectations of authority.

At the industry level, firm-clustered regressions indicate that women’s leadership was most positively associated with internal performance in the information sector (+\$85.26 million per 1 pp; +\$1.71 billion per 20 pp), while negative effects appeared in capital-intensive industries such as mining, oil, and gas (–\$122 million per 1 pp; –\$2.44 billion per 20 pp). For Tobin’s Q, positive associations emerged in primary and secondary sectors, particularly mining, utilities, and manufacturing, yet negative effects appeared in tertiary and quaternary sectors like retail and information. This duality is notable. In innovation-driven or service sectors, women improve internal profitability but face weaker market valuations, suggesting investors undervalue their success. In contrast, in traditional, male-dominated sectors, women have limited internal influence, but their presence signals progressive governance that markets reward. These relationships mirror social identity and role-congruity theories, showing that gendered norms alter how both employees and investors interpret female leadership.

The four-sector model reinforces these patterns. Women’s leadership significantly decreases internal performance in the primary sector (–\$67 million per 1 pp; –\$1.34 billion per 20 pp) and external performance in the quaternary sector (–0.071 Tobin’s Q per 1 pp; \$350M loss in a \$10B-asset company for +20 pp). Though opposite signs appear, albeit insignificantly, for external performance in primary sectors and internal performance in quaternary sectors. These

findings suggest that women's impact is highly contextual: it depends on the industry's structure, gender norms, and how investors perceive risk. Overall, this study provides some causal evidence that female executives strengthen firms internally but remain undervalued externally. Female leadership drives measurable economic value, yet its recognition varies with cultural and sectoral context. Gender-diverse leadership will only reach its full potential when investors and industries change to completely match perception with performance.

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