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RODRIGO LIBANEZ MELAN

BEYOND CMOS INCENTIVES: HOW GENDER AND SIGNALING SHAPE THE FIRM MARKET CAPITALIZATION

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BEYOND CMOS INCENTIVES: HOW GENDER AND SIGNALING SHAPE THE FIRM MARKET CAPITALIZATION

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RESUMO

Este estudo examina como os incentivos de compensação de salário do *Chief Marketing Officer* (CMO) influenciam a capitalização de mercado das empresas e como sinais de gênero moldam essa relação. Com base na Teoria da Sinalização, argumenta-se que os incentivos de compensação não apenas alinham interesses entre gestores e acionistas, mas também sinalizam qualidade gerencial ao mercado. Utilizando dados em painel das empresas de capital aberto nos Estados Unidos, testa-se uma relação moderada pelo gênero do CMO e do *Chief Financial Officer* (CFO). A amostra final é composta por 2.596 observações empresa-ano no período de 2010 a 2024. Os resultados indicam que os incentivos de compensação do CMO impactam positivamente a capitalização de mercado, com retornos marginais decrescentes, sugerindo saturação dos sinais. Ademais, o efeito positivo é amplificado quando a CMO é mulher, evidenciando o papel do gênero como sinal complementar. Entretanto, esse efeito é reduzido quando CMO e CFO são do gênero feminino, indicando que a interação entre sinais pode gerar ambiguidade e reativar estereótipos de gênero. Os achados contribuem para a literatura *Role Congruity Theory* ao integrar mecanismos de sinalização com interpretações baseadas em gênero e ao demonstrar como múltiplos sinais influenciam conjuntamente o valor das empresas.

Palavras-Chave: CMO; incentivos em ações; Teoria da Sinalização; Teoria da Agência; gênero; capitalização de mercado; alta gestão.

ABSTRACT

This study examines how Chief Marketing Officer (CMO) equity incentives influence firm market capitalization and how gender signals shape this relationship. Building on Signaling Theory, we argue that equity incentives not only align managerial and shareholder interests but also signal managerial quality to the market. Using panel data from U.S. publicly traded firms, we test a moderated relationship involving CMO gender and Chief Financial Officer (CFO) gender. The final sample comprises 2,596 firm-year observations over the 2010–2024 period. The results show that CMO equity incentives positively affect market capitalization, with diminishing marginal returns, indicating signal saturation. Furthermore, the positive effect of incentives is amplified when the CMO is female, supporting the role of gender as a complementary signal. However, this effect is attenuated when both the CMO and CFO are female, suggesting that signal interactions may introduce ambiguity and reactivate gender stereotypes. These findings extend the Role Congruity Theory by integrating signaling mechanisms with gender-based interpretations and by demonstrating how multiple signals jointly influence firm valuation.

Keywords: CMO; equity incentives; Signaling Theory; Agency Theory; gender; market capitalization; top management team.

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1. Introduction

Despite CMOs' central role in generating customer-based assets and driving long-term revenue growth, research examining incentives has predominantly focused on top executives (Bansal et al., 2016; Nath & Bharadwaj, 2020). Within the limited body of research on this topic, CMO equity incentives are primarily evaluated through the lens of Agency Theory (e.g., Fabrizi, 2014; Kim et al., 2016). This represents a restricted perspective for comprehending the broader informational role these incentives may play, particularly concerning the underlying attributes of the recipients. Furthermore, the interplay between incentives and other variables has only been explored by Kim et al. (2016), underscoring the necessity to identify and analyze factors that may moderate the effects of CMO equity incentives.

Firms address the misalignment between ownership and control that creates conflicts of interest between managers and shareholders by granting equity incentives—such as stocks and options—which tie managerial wealth to shareholder value and, in turn, improve firm outcomes (Jensen & Meckling, 1979; You et al., 2020), including market capitalization. Because marketing investments are uncertain, long-term, and difficult to evaluate financially (Barwise et al., 1989; Srivastava et al., 1998), investors face substantial information asymmetry regarding CMO ability. In this context, equity incentives not only align managerial and shareholder interests but also act as signals of managerial quality, which are incorporated into firm market capitalization (Connelly et al., 2011; Fama, 1970; Spence, 1973).

By reducing this information asymmetry, these incentives mitigate the historical difficulties CMOs face in justifying their investments. This is because the mere alignment of interests promoted by incentives (Jensen & Meckling, 1979) is not sufficient for investors to trust those responsible for marketing assets; it also requires the CMO's capability to leverage these assets to generate value. Objective costs, such as those tied to the loss of personal wealth, alongside reputational costs, such as a damaged image in the labor market, discourage low-quality CMOs from accepting equity incentives (Connelly et al., 2011, 2025; Ross, 1977), thereby establishing them as credible signals of the executive's capability. Despite the importance of incentives in corporate governance studies grounded in the Agency Theory perspective, they prove to be central to the marketing field when viewed through the lens of Signaling Theory, as they enable CMOs to garner shareholder trust.

Prior research largely assumes a positive, linear, and monotonic (unidirectional) relationship between executive equity incentives and firm value (e.g., Fabrizi, 2014; Kim et al., 2016). This implies that identical increases in incentives result in equal increases in market capitalization. Rooted primarily in Agency Theory, this perspective suggests that higher levels of incentives consistently lead to stronger alignment and, consequently, better firm performance. However, the assumption of linearity is theoretically restrictive and potentially misleading. Signaling Theory suggests that the effectiveness of a signal depends not only on its presence but also on its intensity and interpretation (Connelly et al., 2011, 2025). At lower levels, equity incentives may enhance alignment and provide credible information about managerial quality. Yet, beyond an optimal threshold, additional incentives may generate diminishing informational value, introduce ambiguity regarding managerial motives, or even signal entrenchment and excessive risk alignment (Holmström, 1999; McConnell & Servaes, 1990; Morck et al., 1988). As a result, the relationship between CMO equity incentives and firm market capitalization is likely curvilinear, characterized by increasing benefits at lower levels and diminishing—or even negative—returns at higher levels. Despite its theoretical relevance, this non-linear pattern remains largely unexplored in the CMO and marketing literature, representing a critical gap in understanding how incentives translate into firm value.

Beyond incentive structures, the characteristics of the CMO play a critical role in shaping strategic outcomes. Upper Echelons Theory posits that organizational outcomes reflect the values, experiences, and cognitive bases of top executives (Hambrick & Mason, 1984). The CMO role has evolved into a strategic position responsible for customer relationship management, brand equity development, and the orchestration of market-based assets that drive long-term firm performance (Ruyter & Wetzels, 2000; Srivastava et al., 1999). As such, CMOs are not only implementers of marketing strategy but also key decision-makers whose attributes influence how resources are allocated and how signals are conveyed to external stakeholders, including investors.

One important yet underexplored characteristic is the gender of the CMO. Drawing on Upper Echelons Theory and gender-based perspectives, female executives tend to adopt more cautious, consistent, and stakeholder-oriented approaches (Bear et al., 2010; Faccio et al., 2016; B. Francis et al., 2015; B. B. Francis et al., 2014), which can enhance perceptions of credibility and authenticity. Moreover, while Role Congruity Theory proposes that women possess traits socially perceived as incongruent with leadership roles, it further suggests that a reduced need for masculine attributes in such positions can diminish this bias (Eagly & Karau, 2002). This seems to be the case for female CMOs, considering their recently growing representation in marketing leadership relative to other members of the Top Management Team (TMT) (Spencer

Stuart, 2025). Despite growing interest in executive gender, prior research has largely overlooked how CMO gender interacts with incentive structures.

At the same time, the interpretation of signals depends on the broader top management team (TMT) context, given that accounting for other TMT members can yield more compelling explanations about the firm (Hambrick, 2007) and, consequently, about how it is viewed and perceived. Chief Financial Officers (CFOs) play a central strategic role in financial oversight, capital allocation, and communication with capital markets (Agrawal et al., 2013; Zorn, 2004), directly influencing investor perceptions and firm valuation. Research shows that CFO characteristics shape financial policies, risk-taking, and investment decisions, making the CFO a key actor in determining how marketing initiatives are funded and evaluated (B. B. Francis et al., 2014; Huang & Kisgen, 2013). From a signaling perspective, multiple executive attributes interact to shape how external stakeholders interpret firm actions (Connelly et al., 2025). In this regard, the presence of a female CFO introduces an additional layer of interpretation. While female executives are often associated with prudence and risk aversion (B. Francis et al., 2015; Varma et al., 2023), the combination of a female CMO and a female CFO may introduce ambiguity rather than clarity, potentially reinforcing stereotypes of excessive caution or limited strategic aggressiveness (Eagly & Karau, 2002; Heilman, 2012). Despite this potential interaction, prior literature has largely neglected how gender combinations within the TMT jointly shape the effectiveness of incentive signals, representing a third important gap.

To address these three gaps, this study integrates Signaling Theory and Role Congruity Theory to examine how CMO equity incentives influence firm market capitalization. We specifically focus on market capitalization as our dependent variable because it is a forward-looking metric that directly captures investor expectations, making it the ideal proxy to assess how the market interprets the signals sent by executive compensation and gender dynamics. Our findings contribute to the literature by (1) challenging the prevailing assumption of linearity in executive compensation research, (2) advancing understanding of how executive gender shapes the effectiveness of incentive signals, and (3) demonstrating how multiple signals within the TMT interact to influence investor perceptions and firm valuation. These insights offer important implications for theory and practice, particularly in designing compensation structures and understanding the strategic role of marketing leadership in capital markets.

1.1. Research Question

How do equity incentive signals and the gender of the Chief Marketing Officer (CMO) interact to influence firm market capitalization, and how does the gender of the Chief Financial Officer (CFO) moderate this relationship?

1.2. Main Goal

- The research goal is to examine the impact of CMO equity incentives on market capitalization, specifically investigating how gender-based signals from both the CMO and CFO enhance or attenuate the effectiveness of these incentives as indicators of firm quality.

1.2.1. Secondary Goals

- Analyze the direct relationship between CMO equity incentives and market capitalization to determine if higher levels of incentives lead to diminishing marginal returns in firm value.
- Investigate the moderating role of CMO gender, testing whether a female CMO signal strengthens the positive relationship between equity incentives and market capitalization due to perceived attribute convergence.
- Examine whether a female CFO weakens the positive market signal generated by a female CMO's equity incentives.
- Evaluate the robustness of these signals against alternative executive pairings (CEO and COO) and different financial metrics (Tobin's Q vs. Market Capitalization) to isolate the specific impact of the CFO-CMO gender dyad.

1.3. Rationale and Scope of the Study

The literature examining CMO equity incentives is scarce (see Table 1), particularly regarding the boundary conditions that affect their impact on firm market capitalization. Existing studies have relied on Agency Theory to explain how CMO incentives promote firm value (e.g., Fabrizi, 2014; Kim et al., 2016), leaving gaps regarding their informational role from the perspective of Signaling Theory. Equity incentives signal high CMO quality (Connelly et al., 2011, 2025) but are subject to saturation when conveying this signal (Holmström, 1999). Beyond failing to evaluate this effect, prior research has not explored other boundary conditions—a necessary endeavor given the interaction among multiple signals, cognitive processes, investor sentiment, and biases to which equity incentives are subject (Connelly et al., 2025). One such condition is associated with a female CMO, which affects these incentives by indicating a high potential for value creation due to the convergence between her more empathetic and communal socially viewed attributes (Eagly & Karau, 2002; Heilman, 2012) and the demands of the role, which are centered on building and maintaining meaningful relationships (Ruyter & Wetzels, 2000; Srivastava et al., 1999). Conversely, a female CFO may signal ambiguity and difficulties for the CMO in securing resources, stemming from more conservative financial management (B. B. Francis et al., 2014; Huang & Kisgen, 2013) combined with a CMO whose gender is socially perceived as less agentic, as posited by Role Congruity Theory (Eagly & Karau, 2002; Heilman, 2012). Therefore, this study presents an innovative approach to CMO equity incentives by addressing boundary conditions governing their effects on market capitalization that fall outside the scope of Agency Theory, such as gender. Furthermore, by examining CMO and CFO gender, this study shifts the analytical focus "beyond" the boundaries of the firm. Rather than restricting the analysis to internal moderators, as in Kim et al. (2016), it enables the evaluation of the impact of incentive signals based on information readily available to the market.

Table 1

Scope of Studies on CMO Equity Incentives

Author	Antecedent	Consequent	Moderator	Moderator Description	Context and Findings
Fabrizi (2014)	*Equity incentives*	Tobin's Q	No	-	Firms listed in the Compustat database, with observations between the years 2000 and 2009. CMO equity incentives are linked to positive shareholder value.
	Marketing intensity	*Equity incentives*	No		
Kim et al. (2016)	*Equity incentives*	Market capitalization	Yes	CMO strategic, operational, and financial discretion	Firms with a CMO in the ExecuComp database. Period between the years 1993 and 2009. CMO equity incentives are linked to positive shareholder value and are positively moderated by their discretion.

Author	Antecedent	Consequent	Moderator	Moderator Description	Context and Findings
Bansal et al. (2016)	Deviations in the expected value of equity incentives	Return on assets, abnormal returns, and annual stock returns	No	-	Period between 1992 and 2013 for firms in databases containing executive data, such as ExecuComp. Deviations in the expected value of CMO equity incentives negatively impact firm performance.
	Advertising and research and development (R&D) intensity	*Equity incentives*	No	-	CMOs in firms with higher advertising and R&D intensity receive larger equity incentive packages.
Artz e Mizik (2023)	*Equity incentives*	Myopic marketing	No	-	Firms listed in the Compustat, Center for Research in Security Prices (CRSP), ExecuComp, and Thomson Reuters Insider Filing Data Feed (IFDF) databases. Period between the years 1993 and 2014. CMO equity incentives are antecedents of myopic marketing.
This study	*Equity incentives*	Market capitalization	Yes	CMO and CFO gender	Firms with a CMO in the ExecuComp database. Period between the years 2010 and 2024.

Specifically regarding Signaling Theory, this study addresses a facet seldom explored in extant literature: the utilization of multiple signals, extending beyond analyses limited to a single signaler and receiver (Connelly et al., 2025). We employ a combination of three signals—CMO equity incentives, CMO gender, and CFO gender—alongside two types of signalers: Chief Marketing Officers (CMOs) and Chief Financial Officers (CFOs). This richer approach aligns with the inherent complexity of signaling environments (Connelly et al., 2025), providing more precise explanations regarding the effects of CMO equity incentives on firm value. Furthermore, this study advances the rigor with which Signaling Theory is applied, addressing the common lack of adequate description regarding the theory's core components: the unobserved construct, signal honesty (its relationship to the construct), and its associated costs (Connelly et al., 2025). This study addresses these elements as follows (see the theoretical and empirical framework subsection for further details):

- Core components: CMO equity incentives and the gender of both the CMO and CFO as signals; CMOs and CFOs as signalers; and shareholders (the market) as receivers.

- Construct: CMO quality inferred from equity incentives; congruence with role attributes for female CMOs; and potential conflicts and ambiguity in resource management for female CFOs in combination with female CMOs. These are socially evaluated constructs within the market.
- Signal honesty: Equity incentives are associated with perceived CMO quality due to the reduction of information asymmetry, based on signal fit and the costs of accepting such incentives. Female CMOs possess attributes—socially perceived—that align with the role requirements. Finally, female CFOs tend to be more conservative, signaling additional hurdles for CMOs in resource acquisition and management ambiguity (a more conservative CFO combined with a CMO incentivized to generate value from marketing expenditures).
- Costs: For CMO equity incentives, these relate to potential losses in reputation and personal wealth. This is particularly relevant for female CMOs, who are subject to greater scrutiny. For female CFOs, the costs of accepting the position are also associated with the reputational loss resulting from poor performance. However, CFO quality holds a substantially different meaning than CMO quality, as it entails responsibility for control, oversight, efficiency, and resource allocation, which may trigger the aforementioned conflicts.

Concerning Role Congruity Theory, this research contributes by specifying and examining one of its established boundary conditions—that is, the effects of the level of gender attributes associated with the evaluated leadership position on the social perception of incongruity (Eagly & Karau, 2002).

Furthermore, this study presents methodological and practical contributions that justify its relevance. The deployment of multiple tests and analyses demonstrating the diminishing marginal returns of equity incentives, alongside the methodological approach to small sample sizes for female dyads, establishes methodological avenues that can be replicated or adapted in future studies. In practical terms, establishing that the relationship between CMO equity incentives and market capitalization is diminishing marginal returns addresses a critical strategic gap for Boards of Directors, Compensation Committees, and investors. If the prevailing assumption is linear, firms may continuously increase CMO equity under the false premise that it will proportionally drive market value. However, demonstrating a saturation point changes the strategic management of these firms by shifting the focus from maximizing to optimizing executive compensation. For corporate governance, this means that allocating additional equity may become an inefficient use of corporate resources, risking unnecessary shareholder dilution. Consequently, optimizing these incentive packages allows firms to redirect resources toward other value-creating initiatives, such as marketing investments or R&D. This optimization significantly impacts market capitalization because investors—acting as signal receivers—calibrate their valuations not just on the presence of incentives, but on their efficiency. Furthermore, the gender moderations indicate that firms can leverage the value promoted by equity incentives through a female CMO, while they must remain mindful of the signals that female CFOs send to investors within a female dyad, tailoring compensation and communication strategies accordingly.

2. Theoretical Background

Drawing on Signaling Theory, this study conceptualizes CMO equity incentives as signals of managerial quality, extending beyond their traditional role of aligning interests with shareholders. Drawing on Role Congruity Theory, we examine how gender signals from the CMO and CFO shape the interpretation of these incentives as boundary conditions. This shift from the prevailing Agency Theory perspective—which dominates the marketing-finance interface—is theoretically innovative because it addresses the profound information asymmetry inherent to marketing investments. By repositioning equity packages as costly signals rather than mere alignment mechanisms, this study explains how CMOs successfully communicate unobservable managerial quality and value-creation potential to capital markets.

2.1. Signaling Theory

To address the divergent interests of agents and principals, Agency Theory proposes that incentives can mitigate conflicts arising from their relationship. This theoretical lens focuses primarily on the alignment of interests (Jensen & Meckling, 1979). However, Agency Theory does not explain how incentives reduce information asymmetries, particularly regarding the quality of the managers who hold them—a role attributed to Signaling Theory. Prior research has primarily relied on Agency Theory (e.g., Fabrizi, 2014; Kim et al., 2016), which focuses on incentive alignment but does not explain how markets interpret such signals. We therefore use Agency Theory only as complementary background (Appendix A).

Signaling Theory centers on elements that communicate valuable and credible information, such as actions, attributes, and messages; essentially, it focuses on signals (Connelly et al., 2025) and establishes that incentives, especially equity incentives, function as informational vehicles. Signals indicate that a firm employs high-quality executives capable of generating positive future cash flows (Connelly et al., 2011; Ross, 1977). Understanding these associations requires characterizing a core component of the theory: information asymmetry (Morris, 1987). Embedded in the firm's daily operations, managers possess privileged information relevant to investment decisions. In the specific case of CMOs, they tend to understand the value-creation potential of marketing resources better than shareholders. This is because shareholder value stems from customer-driven revenue over time, which creates positive cash flows—potential that shareholders cannot readily observe (Kumar & Shah, 2009).

These efforts align with the fundamental function of marketing: attracting and retaining customers by delivering superior value relative to competitors (Srivastava et al., 1999).

Asymmetry arises from industry-specific characteristics, such as long-term investment returns like brand equity (Crass et al., 2019), and the difficulty of translating these into financial metrics (Srivastava et al., 1998). The existence of information asymmetry alone does not trigger signaling via equity incentives. Signaling Theory suggests that if managers believe in their ability to deliver the results expected by current and potential shareholders, they will signal this through equity incentives under two conditions: (i) shareholders use proxies to evaluate their quality, and (ii) the signaling costs are lower for high-quality managers than for low-quality ones (Connelly et al., 2011; Kirmani & Rao, 2000). Shareholders can directly observe several CMO characteristics to infer quality, ranging from individual attributes (education and experience) to the intersection of the individual and their current role. Equity incentives constitute valuable proxies because they reside at this intersection and express "signal fit"—the correspondence between the signal and the quality being evaluated (Connelly et al., 2011). Because a manager's wealth is linked to that of shareholders when both hold a stake in the firm, a CMO who accepts equity-based compensation signals the ability to activate and leverage this link.

However, signal fit is not sufficient for equity incentives to serve as quality proxies. Low-quality managers might attempt to signal alignment if they faced no sanctions (Spence, 1973). This risk is mitigated by potential penalties and costs, such as a damaged reputation in the labor market and personal wealth loss (Connelly et al., 2011, 2025; Ross, 1977). These consequences are particularly relevant for CMOs, who face higher dismissal rates and shorter average tenures (4.3 years in 2024) compared to other TMT members (Spencer Stuart, 2025). Furthermore, CMOs lead a department that often struggles to justify investments and interacts with diverse stakeholders beyond shareholders (Kumar & Shah, 2009; Srivastava et al., 1998), increasing their exposure to performance-related penalties. Consequently, a CMO with high equity incentives signals to the market an ability to promote sustained growth through the firm's marketing assets. By tying compensation to shareholder wealth, the CMO sends a signal regarding both personal quality and asset quality, reducing shareholder uncertainty. Conversely, if signal fit were low, the resulting penalties would discourage managers from signaling quality through incentives.

Just as equity incentives are subject to non-linearity with firm value—due to misaligned interests, risk aversion, and myopia (Artz & Mizik, 2023; Edmans et al., 2017)—signals are subject to noise. Shareholders may interpret excessive incentive levels negatively, fearing a management team focused on short-term results or poor decision-making due to high personal risk. Moreover, increasing signal intensity can lead to saturation, resulting in diminishing marginal returns. Incentives aim to reduce market uncertainty regarding a CMO's ability to create value (Connelly et al., 2011, 2025; Ross, 1977). Because incentives are proxies, they never reduce uncertainty to zero (Kirmani & Rao, 2000). Incremental additions to equity incentive packages are used to decrease uncertainty and are incorporated into stock prices, which reflect all available information (Fama, 1970). Given constant absolute increases in incentives, ceteris paribus, the reduction in uncertainty regarding CMO quality must necessarily decrease to avoid hitting zero, characterizing diminishing marginal returns (saturation). We build the occurrence of saturation for equity incentives primarily from (Holmström, 1999).

The precision of the quality signal inferred by the market (η) at period $t + 1$ (the inverse of its variance) is mathematically the sum of the initial precision and the precision brought by new information at t (Holmström, 1999)[1]:

$$h_{t+1} = h_1 + t \times h_\varepsilon \qquad 1$$

where h_{t+1} is the precision of the signal η at $t + 1$; h_1 is the initial precision regarding η; t is the current period; and h_ε is the precision of the new information signal. Holmström (1999) uses time as an accumulator of observations to re-evaluate η.

Since equity incentives can serve as a quality signal (Connelly et al., 2011, 2025; Ross, 1977) and are subject to accumulation (ranging from 0% to 100% of total compensation), they can be related to firm performance across different levels. Assuming a rational market and signals with linear costs negatively correlated with a manager's marginal productivity[2] (Spence, 1973), higher-quality managers should receive a larger share of equity incentives. In this perspective, incentives play the role of "time" in Holmström's (1999) model by subsidizing market-estimated precision adjustments for η.

[1] It is assumed that the prior belief and the noise associated with the new information regarding η are normally distributed (Holmström, 1999), a necessary condition for the precisions to be summed algebraically.

[2] In the general formulation of Signaling Theory, Spence (1973) posits that signals are negatively correlated with the marginal productivity of the signaler, utilizing a numerical example in which this relationship is linear. The author suggests, however, that conditions potentially affecting these assumptions—such as the cooperative behavior of signalers and the stochastic nature (randomness) of signaling costs—should be investigated. Given that this study employs a longitudinal panel dataset comprising multiple firms and years, the general approach was adopted for the theoretical articulations developed herein, moderated by gender variables as detailed below. Following rigorous analysis, the results provided support for these conceptions.

From a signaling perspective, the mechanism associated with adjusting the relationship between a signal and the attribute it represents is called feedback (Spence, 1973). Through cycles, the signal is compared against the attributes (manager quality) and results (performance) to which it is linked. The perceived strength of these links is adjusted in each cycle, as is the compensation paid to the sender (Spence, 1973). Executives who demonstrate the ability to increase share value are granted larger equity packages; thus, higher incentive intensity suggests higher CMO quality. Therefore, feedbacks and the accumulation of time in Holmström (1999) exert equivalent effects. Without assuming a specific mathematical form, we can write:

$$h_{t+1} = h_1 + f(I) \times h_\varepsilon \qquad 2$$

where *f(I)* is the signal intensity function for different levels of equity incentives *I*, replacing *t* in Equation 1. Since precision is the inverse of variance (Holmström, 1999), which measures uncertainty regarding, we write:

$$\sigma^2_{t+1} = \frac{1}{h_1 + f(I) \times h_\varepsilon} \qquad 3$$

where σ^2_{t+1} is the variance (uncertainty) regarding η. Thus, the informational gain relative to the baseline precision is:

$$g(I) = \frac{1}{h_1} - \frac{1}{h_1 + f(I) \times h_\varepsilon} \qquad 4$$

where *g(I)* is the information gain regarding η. Calculating the first and second derivatives of Equation 4 yields:

$$g'(I) = \frac{h_\varepsilon \times f'(I)}{(h_1 + f(I) \times h_\varepsilon)^2} \qquad 5$$

$$g''(I) = \frac{h_\varepsilon \times f''(I)}{(h_1 + f(I) \times h_\varepsilon)^2} - 2\frac{(h_\varepsilon \times f'(I))^2}{(h_1 + f(I) \times h_\varepsilon)^3} \qquad 6$$

In Equation 5, the sign depends exclusively on $f'(I)$, which measures the rate of change in signal intensity. Since higher levels of equity incentives are expected to associate with higher value generation, implying $f'(I) > 0$, informational gains are always positive.

The second derivative in Equation 6 will be negative, implying diminishing marginal returns. The second term in Equation 6 is always positive because the numerator is squared. Its magnitude depends on $f(I)$, which is positive since precision must increase as the estimate approaches the real value of η (Holmström, 1999). For the first term of Equation 6, the sign is determined by $f''(I)$. If $f''(I) \leq 0$, then $g''(I) < 0$, confirming diminishing marginal returns. A scenario where $f''(I) > 0$ would imply that signal intensity increases more than proportionally with incentive levels (e.g., a move from 80% to 90% equity having a greater impact than 10% to 20%), which is implausible under rational market conditions with constant manager quality and linear signal costs. Therefore, $f''(I)$ will not exceed zero; hence, $g''(I) < 0$, yielding diminishing marginal returns. Holmström (1999) reiterates this saturation effect: accumulated data provides high informational gains initially and lower gains later.

If a CMO is risk-averse, prone to marketing myopia, or has variable quality, these diminishing returns may accelerate. As more compensation is tied to equity, the potential impact of unsuccessful marketing expenditures on the manager's wealth increases, leading to "conservative" management that may reduce firm value. In this scenario, the market "discounts" the CMO's risk aversion and perceived quality η, leading to earlier precision saturation. Similarly, if the quality of the CMO is variable, it introduces stochastic noise, implying:

$$\sigma_{t+1}^{2} = \frac{1}{h_1 + f(I) \times h_\varepsilon} + \frac{1}{h_\delta} \qquad 7$$

where h_δ is the precision of the change in η at $t + 1$. The saturation of η occurs at a lower maximum precision level, meaning it saturates with less expressive equity incentive packages.

Beyond the complexity of incentive signaling, the interaction between multiple signals and the cognitive biases of receivers (Connelly et al., 2025) affects how signaling is interpreted. Gender[3] is a relevant signal in this context (Heilman, 2012). For example, increased board

[3] "In this study, the gender variable was treated as binary (female and male), reflecting the original classification in the database employed (ExecuComp). Although gender was originally conceptualized as an index due to its immutability relative to signals (Spence, 1973), firms can alter the gender composition of their Top Management Teams (TMTs) to signal quality or intent (Connelly et al., 2011) to the market.

diversity has been associated with decreased market value when investors perceive diversity as a commitment prioritized over shareholder value (Solal & Snellman, 2019). Conversely, a meta-analysis suggests that female TMT members associate positively with long-term performance but negatively with short-term metrics (Jeong & Harrison, 2016). Perceptions of gender-role congruity can significantly affect firm value. Thus, female CMOs may send different quality signals than their male counterparts.

Gender stereotypes tend to diminish when manager evaluation is objective and performance is linked to the evaluator's interests (Heilman, 2012). Equity incentives are objective and specific, linking CMO performance to shareholder value creation. In this scenario, the signals of female CMOs may be amplified as stereotypes are reduced. However, when signals are ambiguous, gender stereotypes are more likely to flourish (Heilman, 2012). Equity incentives may be attenuated when they interact with contradictory signals, such as potential friction between the CMO and the CFO. Marketing and finance executives often operate in "different thought worlds" (Ruyter & Wetzels, 2000; Zinkhan & Verbrugge, 2000). Therefore, the signal attached to the CFO's gender can amplify or attenuate the effects of a female CMO's equity incentives by signaling the potential for executive alignment or conflict.

Despite the importance of intersecting gender with market signals, few studies have done so. Among nearly 100 Signaling Theory papers identified by Connelly et al. (2025), only five treated gender as a signal (Table 2), and only two used shareholders as the receivers. These gaps extend beyond Signaling Theory, as gender differences remain under-explored for specific TMT roles like the CMO (Varma et al., 2023).

Table 2

Classification of Research on Gender and Signaling Theory

Authors	Signaler	Signal	Receiver	Findings
Mawdsley et al. (2023)	Buyers of rival services	Increase in buyers' gender diversity	Firm	The firm increases its internal diversity in response to the increased diversity of its competitors' clients.
Windscheid et al. (2016)	Firms	Pro-gender diversity messages and	Prospective employees	Mixed signals (diversity messages vs. board composition) reduce perceived

Authors	Signaler	Signal	Receiver	Findings
		board gender composition		organizational attractiveness.
Hussain et al. (2023)	Gender coalitions	Coalition gender mix	Employees	Mixed-gender coalitions possess higher legitimacy than single-gender coalitions.
Solal & Snellman (2019)	Firms	Appointment of female executives	Shareholders	Increases in board diversity negatively impact the firm's market value.
Reinwald et al. (2023)	Firms	Appointment of female executives	Shareholders	Firms increase female appointments to the Top Management Team (TMT) following periods of poor performance.

Note. Adapted from Connelly et al. (2025).

2.2. Role Congruity Theory

Role Congruity Theory explains how gender influences evaluations of leadership effectiveness (Eagly & Karau, 2002). Leadership roles are traditionally associated with masculine attributes such as assertiveness, control, and independence (Schein, 1973). In contrast, women are socially perceived as more communal—caring, supportive, and relationship-oriented—while men are viewed as more agentic and dominant (Eagly & Karau, 2002; Heilman, 2012). This mismatch creates perceived incongruity between the female gender role and leadership expectations, which can negatively affect women in top management positions (Eagly & Karau, 2002; Heilman, 2012; Triana et al., 2024).

This mismatch produces two forms of bias: 1) lower perceived leadership potential and 2) harsher evaluations of performance for women compared to men (Eagly & Karau, 2002; Heilman, 2012). These biases stem from inconsistencies between descriptive norms (what women are perceived to be) and injunctive norms (what leaders are expected to be) (Triana et al., 2024). Empirical evidence supports these effects. Women remain underrepresented in top roles—holding only 6% of CEO positions in 2019 (Boorstin, 2020; Dooley, 2020) and 11% in

2025 among Fortune 500 firms (Estrada, 2025)—and face stronger scrutiny and higher dismissal likelihood than male counterparts (Gupta et al., 2018, 2020). Even when exhibiting similar behaviors, men are more likely to emerge as leaders (Schlamp et al., 2020).

However, Role Congruity Theory also predicts that these effects vary depending on the alignment between role requirements and gendered attributes (Eagly & Karau, 2002). The CMO role provides a relevant context where such alignment may occur. CMOs focus on attracting and retaining customers, building relationships, and coordinating across functions to deliver value (Moorman & Rust, 1999; Nath & Bharadwaj, 2020; Srivastava et al., 1999). These relational and integrative demands align with traits socially associated with women, such as empathy and concern for others (Dooley, 2020; Eagly & Karau, 2002; Heilman, 2012). Recent trends support this alignment. Women represented 53% of CMOs in Fortune 500 firms in 2024, reflecting substantial growth since 2020 (Spencer Stuart, 2025), while their representation in other TMT roles remains lower (Estrada, 2025). As marketing evolves from an operational to a strategic function centered on relationship building and stakeholder integration (Ruyter & Wetzels, 2000; Srivastava et al., 1999), the alignment between female-associated traits and CMO responsibilities becomes stronger (Table 3). Consequently, this alignment can mitigate bias and enhance the perceived effectiveness of female CMOs, particularly in contexts where relational capabilities drive firm value.

Table 3

Convergence of CMO Role-Specific and Female Attributes Toward Strategic and Relational Marketing Activities

Product Development	Supply Chain Management	Customer Relationship Management
Create products that allow customers to extract maximum value and benefit from their use.	Design, manage, and integrate the firm's supply chain with those of suppliers and customers.	Manage customer relationships to understand their needs and the best ways to satisfy them.
Design and develop solutions that can be customized to create and satisfy customer needs.	Manage and integrate all supply chain elements to facilitate the design, development, production, and delivery of solutions.	Work with each customer individually so that the complete solution is tailored to their specific needs.
Foster continuous and closely-linked relationships, both internal and external to the organization.	Develop relationships with external suppliers for the next generation of supplies.	Develop, foster, and leverage relationships with individual customers and customer groups.

Lead and participate in multiple networks to generate, nurture, and integrate product development.	Lead and participate in multiple supply chain networks to obtain necessary inputs that would otherwise be impossible.	Develop and manage a network of relationships with other actors (such as competitors, distribution channels, end-users, and marketing professionals) to identify, reach, and satisfy customers in ways that would be impossible otherwise.

Note. Adapted from Srivastava et al. (1999).

2.2.1. Female Tension in CMO and CFO Roles

Despite the growing presence of women in marketing leadership, research on the relationship between CMO gender and firm performance remains limited (Varma et al., 2023). Existing evidence suggests that female CMOs tend to make less risky decisions, partly due to fear of failure and heightened scrutiny (Varma et al., 2023). At the same time, female marketing executives with greater discretion are associated with improved firm performance (Oh & Song, 2023), indicating their potential to create value when empowered. However, appointing a female CMO alone does not signal competence to the market. Gender stereotypes persist across contexts (Heilman, 2012), and information asymmetry about managerial ability remains higher for investors than for hiring boards.

Investors do not directly observe CMO selection processes, which increases uncertainty about managerial quality. Under such conditions, gender stereotypes become more influential in shaping evaluations (Heilman, 2012), often leading to negative inferences about women in leadership roles (Eagly & Karau, 2002; Heilman, 2012; Triana et al., 2024). Objective and performance-linked signals, such as equity incentives, can mitigate these biases. Equity incentives tie CMO wealth to shareholder value and provide observable metrics of performance alignment. As argued earlier, they represent high-quality signals due to their strong fit, firm-specific nature, and high cost for low-quality managers (Connelly et al., 2011, 2025; Ross, 1977). For female CMOs, these signaling costs are even higher, reinforcing credibility. CMOs already face high turnover and challenges in justifying marketing investments (Kumar & Shah, 2009; Spencer Stuart, 2025). Women in these roles encounter additional scrutiny and higher dismissal risk (Gupta et al., 2018, 2020), increasing the stakes of accepting equity-based compensation. This dual pressure—role and gender—makes equity incentives particularly credible signals of ability. As a result, such incentives can reduce gender bias and allow relational attributes associated with women to signal greater value creation through customer and stakeholder relationships (Eagly & Karau, 2002; Heilman, 2012; Kumar & Shah, 2009; Srivastava et al., 1999).

CMOs rely on access to firm resources, often controlled by CFOs, to execute value-creating marketing strategies. This dependence creates potential tension, as finance and marketing functions prioritize different objectives (Ruyter & Wetzels, 2000; Zinkhan & Verbrugge, 2000). CFOs emphasize control, efficiency, and financial reporting, shaping resource allocation decisions and firm strategy (Agrawal et al., 2013; Zorn, 2004). Their risk preferences directly affect investments, particularly in marketing, which involves uncertain, long-term returns (Barwise et al., 1989; Srivastava et al., 1998). Evidence shows that female CFOs tend to adopt more conservative financial policies. Firms with female CFOs are less likely to issue debt, grow more slowly, and undertake fewer investments, generating a high tension with female CMOs that are more focused in the long term (Huang & Kisgen, 2013). Female CFOs engage in less aggressive tax strategies (B. B. Francis et al., 2014). These patterns suggest higher risk aversion (B. Francis et al., 2015), which may constrain marketing investments and signal potential limitations on value creation.

We suggest that the combination of a female CMO and a female CFO may introduce ambiguity, reducing the influence of equity incentives on market capitalization. While equity incentives encourage the CMO to pursue long-term value creation through marketing investments (Jensen & Murphy, 1990), a more conservative CFO may signal tighter resource constraints, generating ambiguity. This divergence can create uncertainty about the firm's strategic direction. Because ambiguity increases reliance on stereotypes (Heilman, 2012), investors may discount the positive signal conveyed by CMO equity incentives. Moreover, female CMOs may be perceived as less agentic in competing for resources (Eagly & Karau, 2002; Heilman, 2012), reinforcing concerns about their ability to execute growth strategies. Consequently, the presence of a female CFO may weaken the positive effect of CMO equity incentives on firm value by introducing conflicting signals about risk, resource allocation, and strategic execution.

Finally, it is important to clarify why CFO gender is examined exclusively as a conditional moderator rather than a direct predictor of market capitalization. Theoretically, the CMO role is inherently linked to the generation of customer-based assets—such as brand equity and market-based value—which serve as primary drivers of market capitalization. In contrast, the CFO's mandate is centered on financial oversight, risk mitigation, and resource discipline (Agrawal et al., 2013; Zorn, 2004), which operate as foundational constraints for, rather than direct generators of, market-based value. Consequently, treating CFO gender as an independent predictor would theoretically conflate the signal's source (the CMO) with the strategic environment in which that signal is interpreted (the CFO's financial posture). Therefore, the moderating approach adopted here is the most theoretically consistent method to capture how top management team (TMT) dynamics, specifically the interplay between financial conservatism and marketing-driven growth, jointly shape investor perceptions of firm valuation.

To synthesize the theoretical arguments and empirical evidence discussed, Table 4 contrasts the nature of signals sent to the market and the strategic decision-making profiles of CMOs and CFOs across genders. While male executives are traditionally perceived through the lens of agentic attributes and higher risk tolerance, female executives face different signaling conditions and exhibit distinct empirical behaviors, such as higher financial conservatism for CFOs and relationship-oriented, cautious decision-making for CMOs (Eagly & Karau, 2002; B. Francis et al., 2015; Varma et al., 2023). This synthesis highlights the fundamental tension and ambiguity that arise when integrating these gender-role configurations within the TMT.

Table 4

Empirical Evidence on Gender-Based Signals and Strategic Decision-Making in CMO and CFO Roles

Executive – Gender Role	Nature of the Signal	Empirical Evidence	Key References
CMO – Female	Signals alignment with relational, communal, and stakeholder-oriented role demands. High signaling costs due to elevated scrutiny convey strong managerial quality and credibility	Tends to make less risky, cautious marketing decisions due to fear of failure, but drives improved long-term firm performance when empowered	Srivastava et al. (1999), Eagly & Karau (2002), Heilman (2012), Varma et al. (2023), Oh & Song (2023), and Triana et al. (2024)
CMO – Male	Signals traditional agentic leadership attributes (assertiveness, independence) often uncoupled from the communal needs of modern marketing integration.	Tends to exhibit higher risk-taking behavior in marketing investments compared to female counterparts	

Executive – Gender Role	Nature of the Signal	Empirical Evidence	Key References
CFO – Female	Signals higher financial discipline, prudence, and strict resource control. May introduce ambiguity regarding growth support when paired with long-term marketing initiatives.	Adopts highly conservative financial policies, issues less debt, undertakes fewer investments, and engages in less aggressive tax strategies	B. B. Francis et al. (2014), B. Francis et al. (2015), and Huang & Kisgen (2013)
CFO – Male	Signals standard financial oversight and competence, without the stereotype-driven perceptions of excessive caution or risk aversion	Demonstrates lower risk aversion, higher tolerance for leverage, and generally faster growth/investment adoption relative to female CFOs	

3. Hypotheses

3.1. The Signal of CMO Equity Incentives

We propose that CMO equity incentives predict firm market capitalization, with CMO and CFO gender acting as moderators (Figure 1). Prior research generally assumes a positive and linear relationship between executive equity incentives and firm value, grounded in Agency Theory and supported by evidence that stronger incentive alignment improves firm outcomes (e.g., Fabrizi, 2014; Kim et al., 2016). Extending this logic, we argue that equity incentives function as positive signals to investors, increasing firm value by conveying information about managerial quality.

This signaling role is particularly relevant for CMOs due to the high level of information asymmetry surrounding marketing activities. CMOs possess superior knowledge of their ability to create value through marketing resources, which drive customer-based revenues and long-term cash flows (Kumar & Shah, 2009; Srivastava et al., 1999). Because investors cannot directly observe these capabilities, equity incentives serve as valuable proxies of managerial quality (Connelly et al., 2011, 2025; Ross, 1977). By accepting compensation tied to firm value, CMOs signal confidence in their ability to generate future performance, aligning their wealth with that of shareholders. This creates strong signal fit, as incentives directly link executive actions to firm outcomes. Moreover, signaling operates dynamically: investors update their beliefs about managerial quality based on observed outcomes and adjust firm valuations accordingly (Spence, 1973). Because markets incorporate available information into stock prices (Fama, 1970), higher levels of equity incentives are generally associated with more favorable expectations and higher firm market capitalization.

However, the assumption of a linear relationship is theoretically incomplete. Signaling Theory suggests that the effectiveness of a signal depends not only on its presence but also on its intensity and marginal informational value (Connelly et al., 2011, 2025). At lower levels, increases in equity incentives strengthen alignment and enhance the credibility of the signal, leading to positive market reactions. Yet, as incentive intensity rises, the incremental informational gain diminishes, and the signal may begin to saturate (Holmström, 1999). Beyond an optimal level, excessively high incentives may introduce ambiguity regarding managerial motives, increase concerns about short-termism in marketing decisions (Artz & Mizik, 2023), or amplify perceived risk-related distortions (Dittmann & Maug, 2007). Because uncertainty about managerial quality can never be fully eliminated (Kirmani & Rao, 2000), additional incentives eventually provide limited new information to investors. As a result, the signaling value of CMO equity incentives exhibits diminishing marginal returns, implying that firm market capitalization increases at a decreasing rate as incentives grow. Consistent with market efficiency (Fama, 1970) and feedback-based belief updating (Spence, 1973), this pattern is reflected in stock prices and, consequently, in firm market capitalization. Then,

> H_1: CMO equity incentives are positively associated with firm market capitalization, but at a diminishing rate.

3.2. Moderating Effect of CMO Gender

Executive characteristics shape how strategic decisions are made and how external stakeholders interpret firm actions. Prior research highlights systematic differences between male and female executives, particularly in terms of risk preferences, decision consistency, and stakeholder orientation. Female executives are generally associated with more cautious, consistent, and relational approaches to decision-making, as well as stronger stakeholder orientation and long-term focus (Bear et al., 2010; Faccio et al., 2016; B. Francis et al., 2015; B. B. Francis et al., 2014). In contrast, male executives are more often associated with higher risk-taking and more aggressive strategic behavior. These differences are particularly relevant in the marketing domain, where value creation depends on managing customer relationships, brand equity, and other intangible assets under high uncertainty.

Role Congruity Theory suggests that the effectiveness of these characteristics depends on the alignment between gendered traits and role expectations (Eagly & Karau, 2002; Schein, 1973). The CMO role is inherently relational and stakeholder-oriented, emphasizing customer engagement, cross-functional integration, and long-term value creation (Moorman & Rust, 1999; Nath & Bharadwaj, 2020; Srivastava et al., 1999). These demands align more closely with communal attributes socially associated with women, such as empathy, collaboration, and relationship-building (Heilman, 2012). As a result, female CMOs are more likely to be perceived as fitting the role. This enhanced role fit improves how investors interpret signals about managerial quality.

In a signaling context, this alignment functions as a complementary signal that increases the credibility and clarity of equity incentives. Because investors cannot directly observe managerial ability, they rely on observable cues—such as compensation structures and executive characteristics—to infer quality (Connelly et al., 2011; Spence, 1973). For female

CMOs, equity incentives are likely to be interpreted as more informative signals, as they are consistent with both the demands of the role and the executive's perceived attributes. Moreover, female executives often face greater scrutiny and higher performance expectations (Gupta et al., 2018, 2020), which increases the perceived cost of failure. This higher signaling cost enhances credibility: when female CMOs accept equity-based compensation, investors are more likely to interpret this as a strong commitment to value creation.

Consequently, female CMO gender strengthens the effectiveness of equity incentives as signals of managerial quality, leading to stronger investor responses. This implies that the positive portion of the relationship between CMO equity incentives and firm market capitalization becomes steeper when the CMO is female, reflecting an amplification of the signaling effect relative to male CMOs.

> *H_2:* The positive effect of CMO equity incentives on firm market capitalization is stronger when the CMO is female than when the CMO is male.

3.3. The Ambiguity of CMO and CFO gender

Top management team (TMT) members differ not only in their individual characteristics but also in the functional roles they occupy, which shape how their decisions are interpreted by external stakeholders. In particular, the Chief Marketing Officer (CMO) and Chief Financial Officer (CFO) represent distinct and often contrasting strategic orientations. The CMO is primarily responsible for driving growth through customer relationships, brand equity, and long-term market development, typically operating under high uncertainty and emphasizing future cash flows. In contrast, the CFO focuses on financial discipline, risk management, and capital allocation, prioritizing efficiency, accountability, and the protection of firm resources (Agrawal et al., 2013; Zorn, 2004). These differences create an inherent tension between growth-oriented and control-oriented perspectives within the TMT.

Gender further shapes how these roles are enacted and interpreted. While female CMOs tend to be associated with relational, stakeholder-oriented, and consistent strategic approaches that align with the demands of the marketing function, female CFOs are often associated with greater financial conservatism, including lower leverage, fewer investments, and more cautious resource allocation (B. B. Francis et al., 2014; Huang & Kisgen, 2013). These tendencies are consistent with broader evidence that female executives exhibit more risk-averse and disciplined decision-making patterns. Although such characteristics can enhance credibility in isolation, their interaction across functional roles may generate unintended consequences for how signals are interpreted.

From a Signaling Theory perspective, the effectiveness of a signal depends on its clarity and consistency with other available cues (Connelly et al., 2011, 2025; Spence, 1973). CMO equity incentives signal growth potential and confidence in future value creation, particularly under conditions of high information asymmetry. However, when multiple signals from the TMT convey conflicting implications, their joint interpretation becomes more complex. Specifically, the growth-oriented signal embedded in CMO equity incentives may conflict with the more conservative signal associated with a female CFO's financial posture. This inconsistency can create interpretive ambiguity, reducing the clarity and credibility of the overall signal.

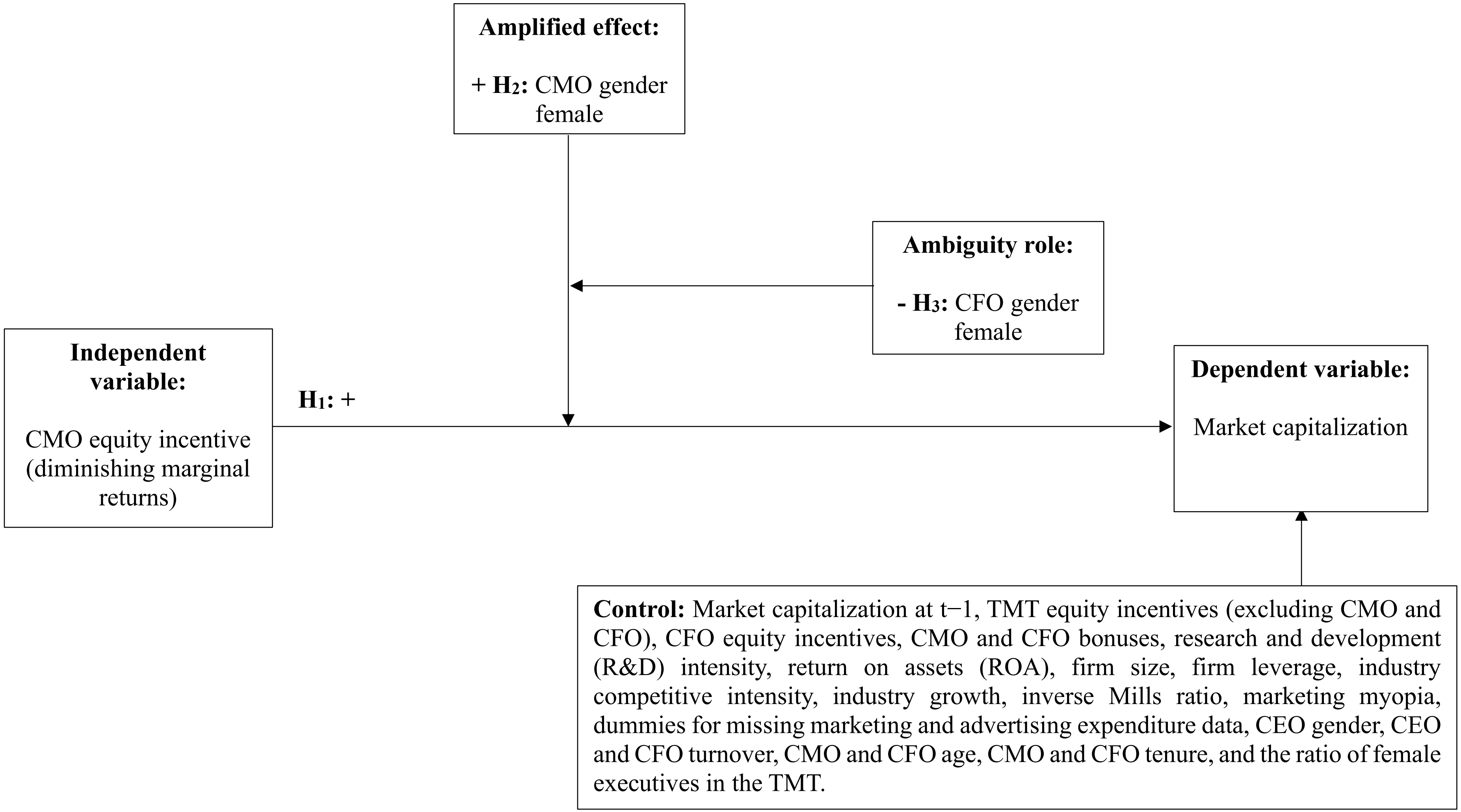
Under such ambiguity, investors are more likely to rely on cognitive shortcuts and stereotypes to resolve uncertainty (Heilman, 2012). In the case of a female CMO paired with a female CFO, overlapping gender-based expectations—such as heightened caution or reduced strategic aggressiveness—may become more salient. Rather than reinforcing signal credibility, the combination of these cues may reactivate bias and lead investors to question the firm's ability to effectively pursue growth-oriented strategies. As a result, the complementary signaling advantage associated with a female CMO (as proposed in H_2) is weakened when a female CFO is also present. This reflects a broader Upper Echelons perspective, whereby firm outcomes depend not only on individual executive characteristics but also on how these characteristics interact within the TMT to shape strategic coherence and external perceptions (Hambrick & Mason, 1984).

Consequently, the joint presence of a female CMO and a female CFO introduces signal conflict and ambiguity, attenuating the positive effect of CMO equity incentives on firm market capitalization. In other words, the amplifying effect of female CMO gender on the incentive–value relationship becomes weaker when the CFO is also female. Then,

> *H_3:* The positive moderating effect of female CMO gender on the relationship between CMO equity incentives and firm market capitalization is weakened when the CFO is female.

Figure 1

Theoretical Model



4. Methodological Procedures

4.1. Data and Sample

This study uses data from Compustat and ExecuComp, both provided by Standard & Poor's. The former contains financial and economic data for publicly traded companies across more than 80 countries, encompassing over 24,000 active and 10,000 inactive firms (Wharton, 2026a). The latter dataset provides data on 2,500 firms, including constituents of the S&P 1500 index, and their top executives. (Wharton, 2026b). We extract firm-level financial variables for publicly traded North American firms from the Compustat database, alongside executive compensation data from ExecuComp, for the period spanning 2010 to 2024. Merging both datasets resulted in 6,331 firm-year observations for 1,267 companies, which were subsequently narrowed down to 2,596 observations for 749 firms in the main regression.

We build the main regression on Kim et al. (2016) and add gender moderators, myopic marketing and additional controls. We identify CMOs using job titles in ExecuComp. Following prior work (Artz & Mizik, 2023; Bansal et al., 2016), we classify executives as CMOs when titles include terms such as marketing, cmo, customer, brand, channel, product, pricing, advertising, sales, merchandise, consumer, and retail.[4] We identified a 21.5% prevalence of observations featuring a CMO. This proportion is consistent with both the dataset utilized and the extant literature examining this executive figure, considering that Bansal et al. (2016), utilizing the same database, reported a prevalence of approximately 25%.

4.2. Measures

4.2.1. Independent Variable: CMOINCENTIVE

We measure CMO equity incentives as the sensitivity of the executive's stock and option holdings to stock price changes (Artz & Mizik, 2023; Core & Guay, 2002). This is a proxy used in previous research (Fabrizi, 2014; Kim et al., 2016). We winsorize the equity incentives variable at 1% and 99% (Bendig et al., 2022) and apply the square root transformation:

[4] In instances where multiple CMOs were identified for a single firm-year, the individual with the highest total compensation was selected (Bansal et al., 2016).

$$\text{CMOINCENTIVE}_{it} = \sqrt{\frac{\text{Onepct}_{it}}{\text{Onepct}_{it} + \text{Salary}_{it} + \text{Bonus}_{it}}} \qquad 8$$

where *Onepct* captures the dollar change in the CMO's equity portfolio for a 1% stock price change, and *Salary* and *Bonus* represent annual compensation.[5]

The square root reflects diminishing marginal returns[6]. Under Agency Theory, risk aversion increases compensation costs and encourages conservative behavior, leading to saturation at high incentive levels (Dittmann & Maug, 2007). Under Signaling Theory, high incentives may signal risk aversion and conservatism, which investors incorporate into stock prices (Connelly et al., 2011; Fama, 1970). Prior evidence also supports diminishing returns (Edmans et al., 2017) and feedback effects on investor beliefs (Spence, 1973). Methodologically, the square root preserves the original [0,1] range and accommodates zero values without transformation bias, unlike logarithms (Wooldridge, 2016). The *Onepct* variable is constructed following the formulation of Kim et al. (2016):

$$\text{Onepct}_{it} = 0{,}01 \times \text{Price}_{it} \times (\text{number of shares and options held by the CMO}_{it}) \qquad 9$$

We do not adjust options using Black-Scholes deltas. This choice improves transparency and aligns with Signaling Theory, as simpler metrics are more observable and interpretable (Connelly et al., 2011). Executives also tend to overestimate option value relative to risk-adjusted measures (Devers et al., 2007; Pepper & Gore, 2015), reinforcing the fit between the signal and investor interpretation.

4.2.2. Dependent variable: Market Capitalization

Market capitalization measure captures long-term value better than accounting metrics because marketing assets generate returns over time (Srinivasan & Hanssens, 2009). Stock prices incorporate available information, including signals from CMO incentives (Connelly et al., 2011, 2025; Fama, 1970; Ross, 1977). We mitigate reverse causality because firms set compensation early in the year and include lagged market capitalization (*t–1*) to capture price

[5] If an executive departed the firm during year t, that year's observation was excluded. This ensures that the effect of equity incentives on market capitalization is not confounded by the presence of different CMOs within the same period (Kim et al., 2016), thereby preventing the introduction of noise into the regressions.

[6] The mathematical formalization utilizing the square-root specification is detailed in Appendix B.

inertia (Kim et al., 2016). We further test reverse causality in additional analyses. Compared to accounting measures (e.g., ROA, Tobin's Q), market capitalization better reflects investor interpretation of signals, avoiding noise from structural and efficiency factors. We measure firm value as market capitalization (Kim et al., 2016):

$$\text{Market cap}_{\text{it}} = \ln(\text{Price}_{\text{it}} \times \text{stock quantity}_{\text{it}}) \qquad 10$$

where *$MarketCap_{it}$* is the market capitalization of firm *i* in year *t*; and *$ln(Price_{it}$ x stock $quantity_{it})$* is the natural logarithm of the product of the closing stock price and the number of outstanding shares of firm *i* in year *t*.

4.2.3. Moderator Variables: CMO and CFO gender

We test the second and third hypotheses by coding CMOGENDER and CFOGENDER as 1 (female) and 0 (male). Using men as the baseline allows us to isolate the signaling effect of female leadership in marketing and its interaction with female CFO. In the main regression, we find that 363 (14%) of the observations correspond to female CMOs and 341 (13.1%) to female CFOs.

4.2.4. Control for Marketing Myopia

We control for marketing myopia (MYOPIC), which increases short-term performance (Mizik, 2010; Mizik & Jacobson, 2007) and may result from equity incentives (Artz & Mizik, 2023). This control isolates the signaling effect from opportunistic spending cuts. For creating marketing myopia proxy, we estimate expected ROA (Equation 11), marketing intensity, and R&D intensity using dynamic models and define myopia when firms simultaneously exhibit positive abnormal ROA and negative abnormal marketing and R&D spending (Mizik, 2010; Morri Garcia et al., 2025). See details in equations 12 and 13. We estimate these models using system GMM (Blundell-Bond) to address persistence and avoid Nickell bias (Nickell, 1981; Wintoki et al., 2012). We limit instrument proliferation by collapsing instruments and using lags t–2 to t–5 (Roodman, 2009).

$$\text{ROA}_{\text{it}} = \alpha_1 \text{ROA}_{\text{i,t}-1} + \mu_{\text{i}} + \omega_{\text{t}} + \varepsilon_{\text{ROA}_{\text{it}}} \qquad 11$$

$$\mathrm{MKT_{it}} = \beta_1 \mathrm{MKT_{i,t-1}} + \mu_i + \omega_t + \varepsilon_{\mathrm{MKT_{it}}} \quad 12$$

$$\mathrm{P\&D_{it}} = \gamma_1 \mathrm{P\&D_{i,t-1}} + \mu_i + \omega_t + \varepsilon_{\mathrm{P\&D_{it}}} \quad 13$$

where ROA_{it}, MKT_{it}, and $P\&D_{it}$ refer, in this order, to return on assets, marketing intensity (a proxy for marketing expenditures), and R&D intensity (a proxy for R&D expenditures) for firm i in year t; μ_i and ω_t represent the unobserved firm and time fixed effects, respectively; and the lagged terms ($t-1$) capture the historical persistence of the series.

4.2.5. Covariates

We address selection bias using a two-stage Heckman (1979) model. The first-stage probit predicts CMO presence using firm characteristics, performance, governance variables, and TMT features (Kim et al., 2016; Nath & Mahajan, 2008). In the second stage, we include the inverse Mills ratio (INVMILLS) in the main regression. We control for executive, firm, and industry factors affecting firm value, including lagged market capitalization, TMT incentives, CMO bonus, R&D intensity, ROA, firm size, industry competition, and growth (Kim et al., 2016). We also include leverage (Jensen, 1986; Jensen & Meckling, 1979), CFO compensation variables, and R&D missingness (Koh & Reeb, 2015). To account for gender selection, we control for CEO and CFO turnover, firm performance, CEO gender, and female representation in the TMT (Cook & Glass, 2014; Matsa & Miller, 2011). We also control for executive tenure and age, given gender differences in career trajectories (Bertrand & Hallock, 2001). Finally, we include firm and year fixed effects to address unobserved heterogeneity and macro shocks. We winsorize continuous variables (except ratios bounded between 0 and 1) and standardize them using z-scores. Table 5 summarizes all variables and measures.

Tabela 5

Operational Definition of Variables

Variable	Description	Type	Calculation	Reference
CMOINCENTIVE	CMO equity incentives	Independent	See Equation 8	Kim et al. (2016)
MARKETCAP	Market capitalization	Dependent	Natural logarithm of the product of the stock price and the number of outstanding shares	Kim et al. (2016)

Variable	Description	Type	Calculation	Reference
CMOGENDER	CMO gender	Moderator	Value of 1 assigned to females and 0 to males, to align with the hypotheses of this study	Signaling Theory (Spence, 1973) and Role Congruity Theory (Eagly & Karau, 2002) as the theoretical basis for its use
CFOGENDER	CFO gender			
MYOPIC	Marketing myopia	Control	Abnormal return on assets and abnormal marketing and R&D intensity	Mizik (2010) and Mizik & Jacobson (2007)
INVMILLS	Inverse Mills ratio	Control	Two-stage Heckman (1979) model	Heckman (1979), Kim et al. (2016), and Nath & Mahajan (2008)
LAGMC	One-period lagged market capitalization (*t – 1*)	Control	-	Kim et al. (2016) and Kumar & Shah (2009)
TMTINCENTIVE	Equity incentives of executives other than the CMO and CFO	Control	Equity incentives (Equation 1) weighted by each executive's total compensation	Kim et al. (2016)
CMOBONUS	CMO bonus	Control	Monetary value of the bonus at the end of the period	Kim et al. (2016)
CFOBONUS	CFO bonus	Control	Monetary value of the bonus at the end of the period	Although Kim et al. (2016) do not adopt it, this study includes it for reasons analogous to CMOBONUS
RDINTENSITY	R&D expenditures intensity	Control	Ratio of research and development expenditures to net sales	Kim et al. (2016)
RADDUM	Missing R&D data dummy	Control	Dummy variable equal to 1 for the presence of R&D data and 0 otherwise	Koh & Reeb (2015)
ROA	Return on assets	Control	Ratio of income before extraordinary items to total assets	Kim et al. (2016)
SIZE	Firm size	Control	Natural logarithm of the number of employees	Kim et al. (2016)
LEVERAGE	Firm leverage	Control	Ratio of total liabilities to total assets	Jensen (1986) and Jensen & Meckling (1979)

Variable	Description	Type	Calculation	Reference
INDCOMP	Industry competitive intensity	Control	Variation in the Herfindahl-Hirschman Index for the firm's two-digit SIC[a]	Kim et al. (2016)
INDGROWTH	Industry growth	Control	Average sales growth for firms in the same two-digit SIC[a]	Kim et al. (2016)
CFOINCENTIVE	CFO equity incentives	Control	See Equation 8	Jiang et al. (2010)
CEOTURNOVER	CEO turnover	Control	Dummy variable equal to 1 for executive change and 0 otherwise	Cook & Glass (2014) and Ryan & Haslam (2005)
CFOTURNOVER	CFO turnover	Control	Dummy variable equal to 1 for executive change and 0 otherwise	Cook & Glass (2014) and Ryan & Haslam (2005)
CEOGENDER	CEO gender	Control	Value of 1 assigned to females and 0 to males	Matsa & Miller (2011) and Rovelli & Mismetti (2025)
TMTGENDER	Proportion of females in the TMT	Control	Ratio of the number of females to the total number of TMT members	Matsa & Miller (2011) and Rovelli & Mismetti (2025)
CMOTENURE	Executive tenure in the firm	Control	Period between the current year and the executive's first observed year in the firm	Bertrand & Hallock (2001) and Varma et al. (2023)
CFOTENURE	Executive tenure in the firm	Control	Period between the current year and the executive's first observed year in the firm	Bertrand & Hallock (2001) and Varma et al. (2023)
CMOAGE	Executive age	Control	-	Bertrand & Hallock (2001) and Varma et al. (2023)
CFOAGE	Executive age	Control	-	Bertrand & Hallock (2001) and Varma et al. (2023)

Note. [a] Industry classification was based on the first two digits of the SIC code (Kim et al., 2016).

4.2.5. Model Estimation

Building on Kim et al. (2016) and incorporating the proposed moderators and controls, we estimate the following longitudinal panel regression model:

$$
\begin{gathered}
\mathrm{MARKETCAP_{it}} = \alpha + \beta_1\mathrm{CMOINCENTIVE_{it}} \\
+ \beta_2\mathrm{CMOGENDER_{it}} + \beta_3\mathrm{CFOGENDER_{it}} \\
+ \beta_4(\mathrm{CMOINCENTIVE_{it}} \times \mathrm{CMOGENDER_{it}}) \\
+ \beta_5(\mathrm{CMOINCENTIVE_{it}} \times \mathrm{CFOGENDER_{it}}) \\
+ \beta_6(\mathrm{CMOGENDER_{it}} \times \mathrm{CFOGENDER_{it}}) \\
+ \beta_7(\mathrm{CMOINCENTIVE_{it}} \times \mathrm{CMOGENDER_{it}} \times \mathrm{CFOGENDER_{it}}) \\
+ \sum_{k=1}^{K} \gamma_k \mathrm{CONTROL_{kit}} + \mu_i + \lambda_t + \varepsilon_{it} \quad {}_{14}
\end{gathered}
$$

where *MARKETCAP*$_{it}$ refers to the natural logarithm of the market capitalization for firm *i* in year *t*; *CMOINCENTIVE*$_{it}$ is the CMO equity incentive for firm *i* in year *t*; *CMOGENDER*$_{it}$ is the CMO gender for firm *i* in year *t*; *CFOGENDER*$_{it}$ is the CFO gender for firm *i* in year *t*; *CONTROL*$_{it}$ represents the control variables used for firm *i* in year *t*; μ_i denotes firm fixed effects; and λ_t denotes year fixed effects. Standard errors are clustered at the firm level to account for serial autocorrelation.

We controlled for market capitalization at t−1, TMT equity incentives (excluding CMO and CFO), CFO equity incentives, CMO and CFO bonuses, research and development (R&D) intensity, return on assets (ROA), firm size, firm leverage, industry competitive intensity, industry growth, inverse Mills ratio, marketing myopia, dummies for missing marketing and advertising expenditure data, CEO gender, CEO and CFO turnover, CMO and CFO age, CMO and CFO tenure, and the ratio of female executives in the TMT.

5. Results

5.1. Correlation Matrix and Descriptive Statistics

Tables 6 and 7 display the descriptive statistics and correlations between variables. The correlation between market capitalization and CMO equity incentive is significant at 1% with a value of r = .46. The moderator CMO gender did not show a significant correlation with market capitalization, while CFO gender presented a value of r = .05 (significant at 1%). These results suggest that no significant multicollinearity exists between the main variables of the regression model.

The statistics in Tables 6 and 7 indicate that the sample employed in this study possesses internal coherence and external validity. The positive correlation between market capitalization and firm size (.63, p-value < .01) consistently indicates that larger firms are more highly capitalized. A similar result was obtained by Kim et al. (2016) (~ .63, p-value < .01). Equity incentives for the CMO, the CFO, and other TMT members (TMTINCENTIVE) are positively and significantly correlated with each other at 1%, demonstrating coherence among compensation packages for the same firms within the same year. Kim et al. (2016) found a positive correlation (p-value < .01) between CMOINCENTIVE and TMTINCENTIVE (the latter including CFO equity incentives). Fabrizi (2014) and Artz and Mizik (2023) verified a positive association (p-value < .01) between CMO and CEO incentives. The average percentage of women in the TMT was 13.4%, which is very close to the 12.58% found by Whitler et al. (2018).

Table 6

Correlation Matrix

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
(1) MARKETCAP	1												
(2) CMOINCENTIVE	.46***	1											
(3) CMOGENDER	.02	-.07***	1										
(4) CFOGENDER	.05***	.02*	.05***	1									
(5) TMTGENDER	.09***	.01	.12***	.56***	1								
(6) CEOGENDER	-.02	-.05***	.10***	.04***	.07***	1							
(7) LAGMC	.96***	.46***	.02	.06***	.11***	-.02	1						
(8) TMTINCENTIVE	.41***	.55***	-.07***	.01	-.02*	-.08***	.38***	1					
(9) CFOINCENTIVE	.41***	.60***	-.06***	-.01	-.05***	-.06***	.38***	.56***	1				
(10) CMOBONUS	.19***	-.07***	.03**	.01	.02	-.01	.16***	-.06***	-.05***	1			
(11) CFOBONUS	.19***	-.03**	.04***	.03**	.03**	.00	.20***	-.07***	-.08***	.69***	1		
(12) CFOTENURE	.12***	-.01	.00	-.04***	-.03**	.01	.10***	.09***	.23***	.01	.00	1	
(13) CMOTENURE	.09***	.15***	.00	.01	.03**	-.01	.07***	.08***	.00	-.04***	.00	.40***	1
(14) CMOAGE	.04***	.04***	-.08***	-.03**	-.05***	.00	.02	-.03**	-.01	.02	.02	.13***	.34***
(15) CFOAGE	.07***	-.01	-.02*	-.07***	-.05***	.00	.05***	.03**	.12***	.04***	.06***	.31***	.10***
(16) CFOTURNOVER	-.01	-.06***	.04***	.05***	.06***	.01	-.01	-.12***	-.23***	.03*	.09***	-.30***	.04***
(17) CEOTURNOVER	-.01	-.06***	.00	.04***	.04***	.03**	-.01	-.17***	-.10***	.01	.02	-.02**	.00
(18) ROA	.36***	.22***	.00	.03**	.03**	.03**	.31***	.26***	.23***	.01	.01	.07***	.04***
(19) SIZE	.63***	.18***	.08***	.08***	.13***	.06***	.65***	.15***	.15***	.13***	.13***	.01	.00
(20) LEVERAGE	.14***	-.03**	.08***	.00	.03**	.04***	.17***	-.15***	-.07***	.09***	.08***	-.01	.02
(21) MYOPIC	.02	.07***	-.02	-.01	-.01	-.02*	.00	.06***	.04***	.01	.00	.02	-.01
(22) RADDUM	-.03**	.10***	-.07***	.04***	.03***	-.02	-.03**	.10***	.11***	-.07***	-.07***	-.03**	-.09***
(23) RDINTENSITY	-.02	.11***	-.10***	-.01	-.04***	-.08***	-.01	.13***	.08***	-.04***	-.05***	-.02	-.04***
(24) INDCOMP	.01	.00	.03**	.03**	.05***	.03**	.03**	.01	-.03**	-.01	-.02	.03*	.04***
(25) INDGROWTH	.00	.02	-.01	-.01	-.03**	-.01	.00	-.01	.02	.06***	.04***	-.01	-.01
(26) INVMILLS	.04**	-.04**	.11***	-.07***	-.07***	-.08***	.05***	-.02	-.01	-.01	.00	.01	-.04**

Variable	14	15	16	17	18	19	20	21	22	23	24	25	26
(1) MARKETCAP													
(2) CMOINCENTIVE													
(3) CMOGENDER													
(4) CFOGENDER													
(5) TMTGENDER													
(6) CEOGENDER													
(7) LAGMC													
(8) TMTINCENTIVE													
(9) CFOINCENTIVE													
(10) CMOBONUS													
(11) CFOBONUS													
(12) CFOTENURE													
(13) CMOTENURE													
(14) CMOAGE	1												
(15) CFOAGE	.17***	1											
(16) CFOTURNOVER	-.02	-.14***	1										
(17) CEOTURNOVER	-.01	-.04***	.14***	1									
(18) ROA	.03**	.02*	-.07***	-.05***	1								
(19) SIZE	.03**	.05***	.03***	.06***	.15***	1							
(20) LEVERAGE	.03**	-.02	.08***	.07***	-.20***	.32***	1						
(21) MYOPIC	-.05***	.02	-.01	-.01	.08***	-.13***	-.11***	1					
(22) RADDUM	-.10***	.00	.01	.02	-.01	-.04***	-.25***	.18***	1				
(23) RDINTENSITY	-.09***	.03***	.01	-.03***	-.19***	-.27***	-.31***	.19***	.47***	1			
(24) INDCOMP	-.02	-.01	-.01	.03**	-.02	.06***	.03**	.00	.02	.00	1		
(25) INDGROWTH	.01	.00	-.02*	.01	.00	-.06***	.00	.05***	-.01	.02	-.04***	1	
(26) INVMILLS	.00	-.04***	.00	.01	-.03**	.05***	.12***	-.03**	-.09***	-.09***	.04***	.04***	1

Note. ***p-value < .01; ** p-value < .05; * p-value < .10.

Table 7

Descriptive Statistics

Variable	N	Mean	Std. Dev.	Minimum	Maximum	N (Dummy = 1)	Percentage[a]
(1) MARKETCAP	6,234	7.859	1.812	-3.382	14.795	-	-
(2) CMOINCENTIVE	5,467	0.282	0.178	0.000	1.000	-	-
(3) CMOGENDER	-	-	-	-	-	798	14.4%
(4) CFOGENDER	-	-	-	-	-	759	12.1%
(5) TMTGENDER	6,331	0.134	0.200	0.000	1.000	-	-
(6) CEOGENDER	-	-	-	-	-	407	6.4%
(7) LAGMC	4,339	7.850	1.781	-3.135	14.659	-	-
(8) TMTINCENTIVE	6,321	0.193	0.102	0.000	0.672	-	-
(9) CFOINCENTIVE	6,187	0.297	0.174	0.000	1.000	-	-
(10) CMOBONUS	5,550	67.198	269.548	0.000	4,652.667	-	-
(11) CFOBONUS	6,274	74.932	303.379	0.000	3,850.429	-	-
(12) CFOTENURE	6,274	3.006	2.827	0.000	14.000	-	-
(13) CMOTENURE	5,550	2.672	2.724	0.000	14.000	-	-
(14) CMOAGE	5,519	52.515	6.555	34.930	69.000	-	-
(15) CFOAGE	6,262	51.825	6.558	35.810	71.000	-	-
(16) CFOTURNOVER	-	-	-	-	-	921	14.7%
(17) CEOTURNOVER	-	-	-	-	-	637	10.1%
(18) ROA	6,325	0.041	0.097	-0.488	0.335	-	-
(19) SIZE	6,304	1.550	1.683	-2.504	6.046	-	-
(20) LEVERAGE	6,294	0.579	0.279	0.084	1.780	-	-
(21) MYOPIC	-	-	-	-	-	517	9.1%
(22) RADDUM	-	-	-	-	-	3,891	61.5%
(23) RDINTENSITY	6,322	0.054	0.090	0.000	0.594	-	-
(24) INDCOMP	5,737	0.004	0.025	-0.110	0.489	-	-
(25) INDGROWTH	5,737	0.199	0.877	-0.979	15.035	-	-
(26) INVMILLS	4,210	1.705	0.805	0.299	6.692	-	-

Note. [a] Percentage of the sample before conducting the regressions.

5.2. CMO Equity Incentives and Market Capitalization

Table 8 displays the results of the longitudinal panel data regressions. For comparison, columns (1) and (3) present models with equity incentive variables (TMTINCENTIVE and CFOINCENTIVE) in linear form, following Kim et al. (2016). Model 2, when compared to its linear incentive equivalent (Model 1), explains more of the variation in market capitalization for the same firm over time (R^2 within of .5997 versus .5855), and its TMTINCENTIVE and CFOINCENTIVE coefficients show better fit (higher t-values). These results hold when Model 4 is paired with its linear incentive equivalent (Model 3), suggesting the existence of saturation for equity incentive signals. Tests for an "inverted U-shaped" relationship are in the next topic and confirm diminishing marginal returns. Building upon this optimal specification, Models 5 through 8 employ a hierarchical approach to test the gender boundary conditions. Model 5 introduces the main gender effects, while Models 6 and 7 isolate the two-way interactions. Finally, Model 8 specifies the full three-way interaction (Hypothesis 3). This stepwise inclusion transparently demonstrates that the signaling coefficients remain robust and stable as complex moderators are progressively added.

The models are robust regarding multicollinearity, with a maximum Variance Inflation Factor (VIF) of 2.97 (Model 8), which is lower than the recommended threshold of 4 (Kabacoff, 2015). Robustness is also expressed in the adequate control of selection bias for firms with a CMO, given that all models present an inverse Mills ratio (INVMILLS) significant at .05. There is explanatory consistency in the results, as Models 2 and 4 through 8—developed in increasing order of complexity—show a progressive increase in R^2 within, rising from .5997 in Model 2 to .6111 in Model 8, alongside a regressive RMSE. Furthermore, the relevance of marketing myopia as a control variable in the regressions is noteworthy, as its positive and significant coefficients (p-value < .01) suggest an increase of market capitalization.

Models 1 and 3 present the equity incentive variables (CMOINCENTIVE, TMTINCENTIVE, and CFOINCENTIVE) in their linear forms, consistent with the specifications of prior studies (e.g., Fabrizi, 2014; Kim et al., 2016). The coefficients for these variables are positive and significant, as expected; however, the equivalent models accounting for diminishing marginal returns (Models 2 and 4, respectively) demonstrate superior specification (yielding a higher within R^2 and a lower RMSE). The results suggest that the diminishing marginal returns of equity incentives provide a more pertinent explanation for how they are priced into firm shares, indicating that informational gains are most pronounced at lower levels of incentive allocation. In this regard, this study demonstrates that the alignment of interests posited by Agency Theory is influenced by additional signals that these incentives convey to the market, thereby challenging the assumption that equity incentives invariably indicate an alignment of interests.

The first hypothesis proposes that the relationship between CMO equity incentive signals and market capitalization is positive, but occurs at a diminishing rate. This result is verified in all models containing CMOINCENTIVE where this variable is expressed as the square root of the incentives, such as Model 8 ($\beta 1 = 0.065$, $p < .01$) (main model). The tests for the non-linear relationship are discussed in detail in the next section. These results indicate that equity incentives signal CMO quality to the market, as posited by Signaling Theory (Connelly et al., 2011, 2025; Ross, 1977), thereby acting as a proxy for this attribute. The mere alignment of interests does not guarantee the potential for shareholder value creation, as the CMO must possess the capability to generate such value given their accessible resources. By holding higher levels of incentives, CMOs indicate a greater potential for value creation, which is consistent with the dynamic feedback mechanism between their quality and the outcomes they produce (Spence, 1973), as well as with the positive monotonic relationship observed in Table 8 between their equity incentives and market capitalization. The diminishing marginal returns observed in the models are also consistent with Signaling Theory, indicating a saturation of informational gains regarding CMO quality, given that equity incentives serve as a proxy (Holmström, 1999). Furthermore, higher levels of incentives signal an increased likelihood of myopic marketing management (Artz & Mizik, 2023) and suboptimal management due to heightened risk aversion (Dittmann & Maug, 2007), leading to diminishing marginal returns as these signals are incorporated into stock prices (Connelly et al., 2011; Fama, 1970).

Confirming the curvilinear main effect proposed in Hypothesis 1, the economic benefit of CMO equity incentives is highly dependent on baseline saturation. Independent of TMT gender configurations, shifting CMO equity incentives from a low baseline (10% to 20%) yields an average estimated increase of 5.97% ($p < .001$) in firm market capitalization. Conversely, the exact same 10-percentage-point increase implemented at a saturated threshold (70% to 80%) yields an attenuated average increase of only 2.59% ($p < .001$). This general sample effect confirms the diminishing marginal utility of signaling mechanisms, demonstrating that the market rewards initial alignments of interest but discounts over-allocation. Furthermore, isolating this effect reveals that CMO equity incentives account for an additional 0.7% of the within-firm variance in market capitalization (the R^2 difference between Models 4 and 2).

The second hypothesis establishes that the positive effect of CMO equity incentives on firm market capitalization is stronger when the CMO is female than when the CMO is male. This is supported by the interaction coefficient between CMOINCENTIVE and CMOGENDER, as seen in Model 8 ($\beta 4 = 0.110$, p-value $< .01$). Role Congruity Theory posits that the prejudice women experience in leadership positions can be mitigated by a lower intensity of masculine attributes required by those roles, an effect our results suggest occurs for CMOs. This is due to a convergence between communal attributes socially perceived as feminine—such as empathy, collaboration, and relationship-building (Heilman, 2012)—and those of the CMO, which are inherently relational and stakeholder-oriented, and aimed at customer engagement, cross-functional integration, and long-term value creation (Moorman & Rust, 1999; Nath & Bharadwaj, 2020; Srivastava et al., 1999). The convergence of attributes signals a higher potential for value creation by female CMOs, and the associated high signaling costs lend credibility to this convergence, thereby yielding a greater positive effect on market capitalization. These higher costs for women stem from the intensified scrutiny and stricter performance evaluations they face in leadership positions (Gupta et al., 2018, 2020).

The third hypothesis proposes that the female CFO gender signal negatively moderates the relationship between a female CMO's equity incentive signals and market capitalization. This hypothesis is supported by the triple interaction coefficient between CMOINCENTIVE, CMOGENDER, and CFOGENDER ($\beta 7 = -0.155$, p-value $< .05$). These results highlight the complexity of the signaling environment, where signals interact with one another (Connelly et al., 2025), and corroborate the Upper Echelons perspective, which posits that the characteristics of TMT members interact to shape strategic coherence and external perceptions (Hambrick & Mason, 1984). The combination of a female CFO and a female CMO signals ambiguity to the market, as the former tends to exhibit greater conservatism in resource management (B. Francis et al., 2015; B. B. Francis et al., 2014; Huang & Kisgen, 2013), while the latter must channel these resources into investments that are traditionally uncertain, long-term, and difficult to evaluate financially (Barwise et al., 1989; Srivastava et al., 1998). This ambiguity triggers the reactivation of gender stereotypes (Heilman, 2012) and suggests that the inherent tension between marketing and finance translates into bias against the female CMO, thereby diminishing the positive effects of her equity incentives on market capitalization. Furthermore, because signal effectiveness depends on clarity and consistency with other available cues (Connelly et al., 2011, 2025; Spence, 1973), this ambiguity inherently weakens the signaling power of the CMO's equity incentives. The effects of a female CFO are particularly relevant for a female CMO because the latter does not benefit from the social presumption of competence in leadership roles, nor from the socially ascribed agentic attributes (Eagly & Karau, 2002; Schein, 1973) required to successfully compete for resources with the CFO.

Although no hypothesis was formulated regarding the relationship between executive gender variables and market capitalization, it is worth noting that all present negative coefficients. This applies to the dummies (CMOGENDER, CFOGENDER, and CEOGENDER) and the proportion of women in the TMT (TMTGENDER). Despite CMOGENDER being the only one significant at a minimum p-value of .05 (Models 5 to 8), these results echo the general premise of Role Congruity Theory that leadership positions are viewed as typically masculine (Eagly & Karau, 2002; Schein, 1973).

Table 8

Relationship between CMO equity incentives, market capitalization, and CMO and CFO gender

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	MC[a,b]	***t-value***	**MC[a]**	***t-value***	**MC[a,b]**	***t-value***	**MC[a]**	***t-value***	**MC[a]**	***t-value***	**MC[a]**	***t-value***	**MC[a]**	***t-value***	**MC[a]**	***t-value***
PREDICTOR: CMOINCENTIVE **(H_1)**	-	-	-	-	0.075***	3.629	0.079***	4.200	0.079***	4.236	0.067***	3.397	0.067***	3.358	0.065***	3.255
CMOGENDER	-	-	-	-	-	-	-	-	-0.105**	-2.450	-0.096**	-2.264	-0.096**	-2.264	-0.106**	-2.359
CFOGENDER	-	-	-	-	-	-	-	-	-0.055	-1.208	-0.057	-1.251	-0.057	-1.200	-0.075	-1.397
CMOINCENTIVE × CMOGENDER **(H_2)**	-	-	-	-	-	-	-	-	-	-	0.091***	2.602	0.091***	2.601	0.110***	2.970
CMOINCENTIVE × CFOGENDER	-	-	-	-	-	-	-	-	-	-	-	-	0.002	0.086	0.020	0.650
CMOGENDER × CFOGENDER	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.090	1.232
CMOINCENTIVE × CMOGENDER × CFOGENDER **(H_3)**	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.155**	-2.264
TMTGENDER	-0.012	-0.769	-0.012	-0.806	-0.012	-0.802	-0.013	-0.851	-0.007	-0.448	-0.008	-0.513	-0.008	-0.514	-0.008	-0.484
CEOGENDER	-0.115*	-1.681	-0.099	-1.386	-0.121*	-1.784	-0.108	-1.518	-0.108	-1.510	-0.109	-1.531	-0.109	-1.520	-0.109	-1.512
LAGMC	0.455***	7.240	0.448***	7.230	0.447***	7.219	0.441***	7.258	0.437***	7.205	0.434***	7.178	0.434***	7.176	0.433***	7.164
TMTINCENTIVE	0.100***	5.826	0.147***	7.218	0.087***	5.236	0.128***	6.521	0.128***	6.516	0.127***	6.469	0.127***	6.400	0.127***	6.384
CFOINCENTIVE	0.109***	4.441	0.117***	5.504	0.088***	3.941	0.097***	4.893	0.096***	4.959	0.098***	5.039	0.098***	5.041	0.101***	5.180
CMOBONUS	0.042	1.642	0.036	1.447	0.049*	1.893	0.046*	1.791	0.042*	1.663	0.042	1.633	0.041	1.629	0.041	1.624
CFOBONUS	0.016	1.044	0.032**	2.420	0.018	1.221	0.029**	2.273	0.031**	2.470	0.032**	2.512	0.032**	2.525	0.033***	2.642
CFOTENURE	-0.029	-1.451	-0.032*	-1.668	-0.021	-1.060	-0.026	-1.346	-0.025	-1.291	-0.025	-1.322	-0.025	-1.311	-0.025	-1.298
CMOTENURE	0.004	0.207	0.005	0.257	-0.005	-0.280	-0.004	-0.235	-0.011	-0.593	-0.009	-0.510	-0.009	-0.511	-0.009	-0.489
CMOAGE	0.015	0.718	0.019	0.870	0.010	0.497	0.012	0.574	0.015	0.684	0.016	0.743	0.016	0.742	0.015	0.705
CFOAGE	0.010	0.605	0.013	0.783	0.007	0.401	0.009	0.581	0.011	0.645	0.009	0.558	0.009	0.552	0.008	0.509
CFOTURNOVER	0.024	0.881	0.041	1.518	0.019	0.692	0.033	1.231	0.037	1.405	0.037	1.409	0.037	1.410	0.038	1.446
CEOTURNOVER	-0.026	-0.873	-0.004	-0.152	-0.025	-0.858	-0.002	-0.060	-0.005	-0.163	-0.008	-0.292	-0.008	-0.300	-0.009	-0.326
ROA	0.183***	8.765	0.170***	8.497	0.178***	8.537	0.165***	8.316	0.166***	8.389	0.164***	8.275	0.164***	8.257	0.164***	8.327
SIZE	0.653***	4.713	0.657***	4.763	0.622***	4.566	0.628***	4.645	0.633***	4.750	0.644***	4.840	0.644***	4.830	0.641***	4.824
LEVERAGE	-0.137***	-2.880	-0.137***	-2.993	-0.148***	-3.103	-0.142***	-3.121	-0.143***	-3.187	-0.139***	-3.149	-0.139***	-3.151	-0.139***	-3.161
MYOPIC	0.121***	3.745	0.125***	3.959	0.117***	3.619	0.122***	3.871	0.120***	3.798	0.121***	3.846	0.121***	3.832	0.119***	3.798
RADDUM	0.104	0.792	0.108	0.792	0.097	0.757	0.092	0.716	0.073	0.575	0.060	0.501	0.060	0.498	0.064	0.542
RDINTENSITY	0.051	0.983	0.051	1.003	0.049	0.938	0.051	1.006	0.051	1.000	0.050	0.968	0.050	0.963	0.048	0.923
INDCOMP	-0.021**	-2.454	-0.022***	-2.606	-0.021**	-2.551	-0.021***	-2.623	-0.021***	-2.587	-0.020**	-2.503	-0.020**	-2.507	-0.019**	-2.482
INDGROWTH	0.024	1.590	0.023	1.601	0.022	1.524	0.021	1.507	0.021	1.590	0.021	1.582	0.021	1.582	0.022	1.642
INVMILLS	0.090***	2.760	0.084**	2.540	0.097***	2.965	0.086***	2.613	0.089***	2.699	0.086***	2.634	0.086***	2.631	0.084**	2.561
INTERCEPT	4.239***	8.536	4.282***	8.726	4.309***	8.828	4.352***	9.089	4.421***	9.217	4.454***	9.335	4.454***	9.333	4.462***	9.371

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,596	2,596	2,596	2,596	2,596	2,596	2,596	2,596
Firms	749	749	749	749	749	749	749	749
F	36.9***	37.7***	34.7***	36.7***	35.9***	40.4***	38.9***	37.0***
RMSE	0.261	0.256	0.258	0.254	0.253	0.253	0.253	0.252
R^2	.5855	.5997	.5922	.6067	.6086	.6102	.6103	.6111
Max VIF	2.68	2.74	2.74	2.77	2.87	2.88	2.91	2.97

Note. ***p-value < .01; ** p-value < .05; * p-value < .10.

Coefficients of continuous variables are z-score standardized.

Standard errors are clustered at the firm level.

RMSE refers to the root mean square error.

R^2 refers to the within variance.

[a] MARKETCAP.

[b] CMOINCENTIVE, TMTINCENTIVE, and CFOINCENTIVE variables are considered in their linear form, as in Kim et al. (2016).

Figure 2 illustrates the relationship between CMO equity incentives and market capitalization, comparing the linear specification with the diminishing marginal returns. Specifically, the diminishing marginal trajectory of market capitalization exhibits a steep initial increase at lower incentive levels, remaining above the linear fit until equity incentives reach approximately 50%. Marginal gains subsequently diminish as the proportion of equity incentives approaches the upper end of the distribution, dropping below the linear projection beyond the 50% threshold. Furthermore, an evaluation of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for both models demonstrates that the diminishing marginal specification provides a superior fit: it yields an AIC of 1,815.434 (compared to 1,825.596 for the linear model) and a BIC of 6,411.028 (compared to 6,421.190 for the linear model). The reductions in both AIC and BIC exceed 10 points, providing very strong statistical evidence of better fit (Burnham & Anderson, 2004; Kass & Raftery, 1995).

Figure 2

Main Effect of CMO Equity Incentives: Linear vs. Diminishing Marginal Returns

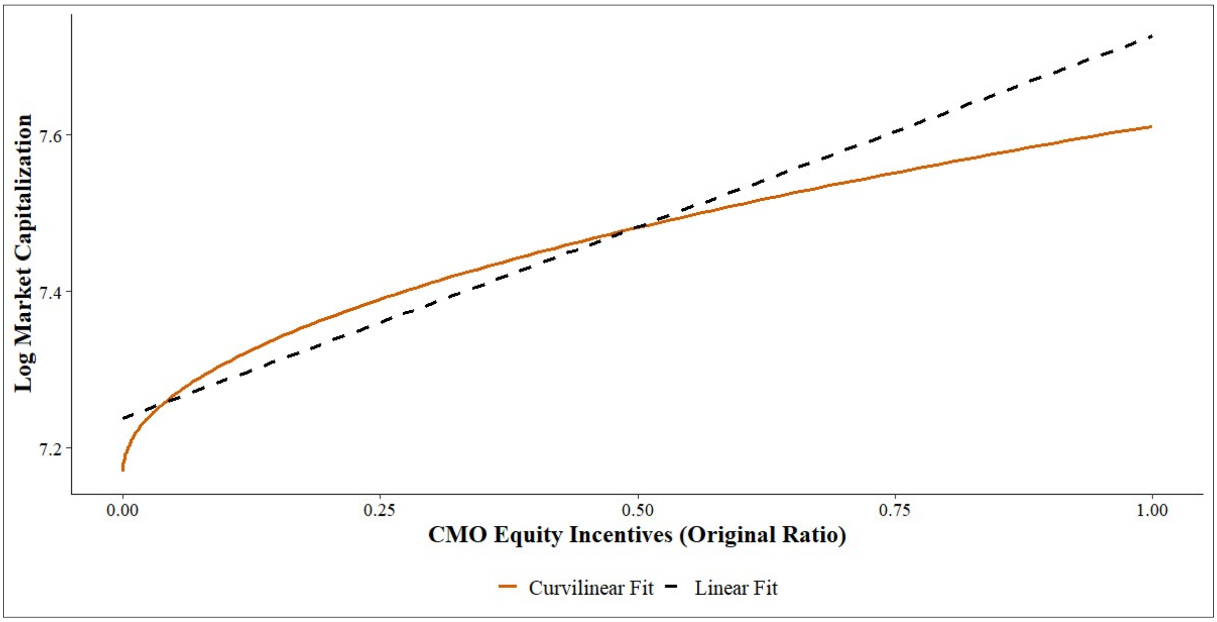


Figure 3 illustrates the moderating effect of female CMO gender, evidenced by a steeper increase in market capitalization for equivalent increments in equity incentives (red line). Beyond a threshold of approximately 25% incentive levels, market capitalization for firms with female CMOs surpasses those with male CMOs.

Figure 3

Moderating Effect of CMO Gender

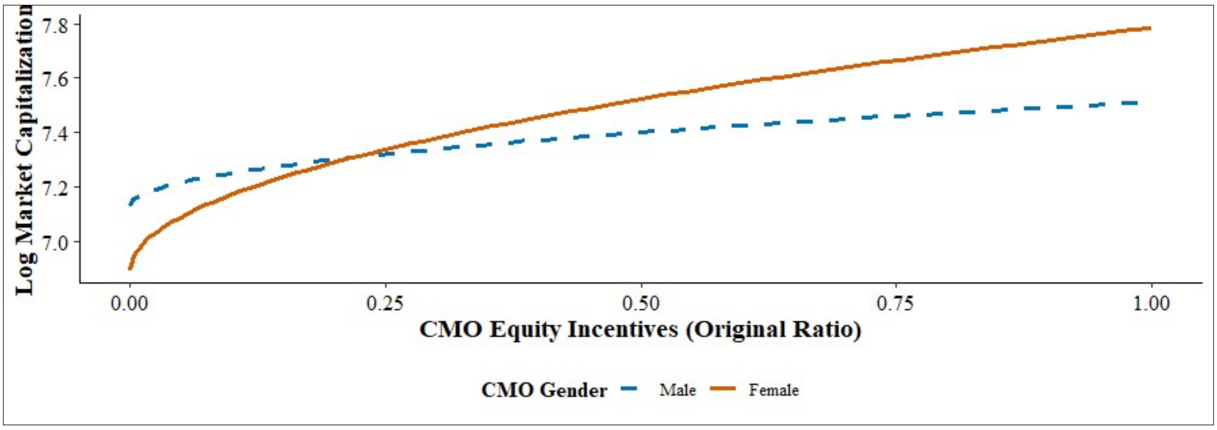


Figure 4 illustrates the absence of a moderating effect of CFO gender on the relationship between CMO equity incentives and firm value, based on Model 7 in Table 8. This null finding is evidenced by the parallel trajectories of the red and blue lines, indicating that the marginal impact of CMO incentives remains invariant regardless of CFO gender. Statistically, this result is expected, given that the moderation coefficient of CFOGENDER on CMOINCENTIVE is 0.002 and non-significant in Model 7. Furthermore, these results reinforce H_3, which posits that the female CFO gender signal negatively moderates the relationship between a female CMO's equity incentive signals and market capitalization. This is because Figure 4 depicts the average effects of CFOGENDER on the equity incentives of CMOs across both genders; consequently, the absence of an effect for male CMOs ultimately overrides that of their female counterparts, due to the predominance of male CMOs in the sample.

Figure 4

Moderating Effect of CFO Gender

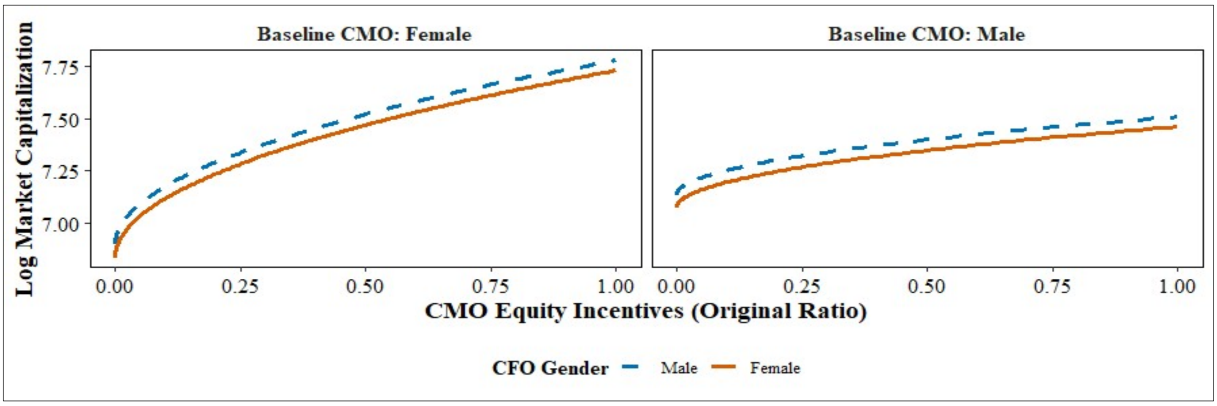
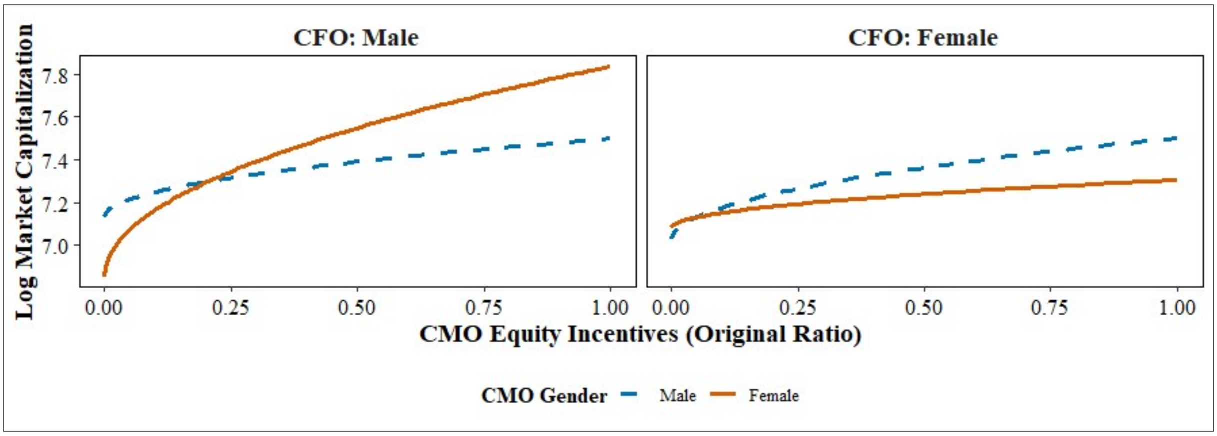


Figure 5 illustrates the results of the three-way interaction between CMO equity incentives, CMO gender, and CFO gender. In the Female CFO facet, the red line depicts the impact of the female financial leadership signal (CFOGENDER = 1) on market capitalization when a woman also occupies the CMO position (H_3). Notably, the slope of the red line becomes nearly horizontal, suggesting a negative moderating effect (or attenuating effect) exerted by the female CFO gender.

Figure 5

Three-Way Interaction (CMO Incentives × CMO Gender × CFO Gender)



To deepen the interpretation of Figure 5, tests of the marginal effects of CMO equity incentives on market capitalization were performed for each gender dyad (Table 9), as proposed by (Hayes, 2022). The results indicate that for male CMOs, the effects are stable and positive, with a coefficient of 0.065 (p-value < .01) when paired with a male CFO and 0.085 (p-value < 0.5) if the CFO is female. For the female CMO, when in the presence of a male CFO, her effect on market capitalization is highly significant (β = 0.175, p-value < .001), while it is indistinguishable from zero if accompanied by a female CFO (β = 0.040, p > .10). The female-female dyad suggests that the CMO's equity incentive signal is lost, ceasing to be relevant for the marketing executive and offering support for H_3.

The marginal effect of 0.175 (p-value < .001) for the female CMO and male CFO dyad demonstrates the strength of this signal to the market. As previously described, a female CMO embodies gender attributes that are socially perceived as congruent with the demands of her role (Heilman, 2012; Moorman & Rust, 1999; Nath & Bharadwaj, 2020; Srivastava et al., 1999), while also facing high costs to signal quality through equity incentives (Gupta et al., 2018, 2020). Regarding the male CFO, his gender implies the possession of critical traits for fostering corporate growth—such as aggressiveness, ambition, and self-confidence (Eagly & Karau, 2002; Heilman, 2012)—and indicates, on average, lower risk aversion compared to female counterparts in the same position (B. Francis et al., 2015). Consequently, this dyad signals that the female CMO can benefit from the male CFO's greater propensity to provide her with necessary resources, rendering this signal consistent and allowing it to be priced into the firm's shares (Connelly et al., 2011; Fama, 1970).

Table 9

Marginal Effects of CMO Equity Incentives on Market Capitalization across CMO-CFO Dyad Combinations

CMO gender	**CFO gender**	**Marginal effect (β)**	**Std. Error**
Female	Male	0.175***	0.036
Female	Female	0.040	0.057
Male	Male	0.065***	0.020
Male	Female	0.085**	0.034

Note. ***p-value < .01; **p-value < .05; *p-value < .10.

We conducted Wald tests for the difference in effects of the female CMO and male CFO dyad (red line of the male CFO facet in Figure 5) compared to the others. The results reinforce the argument for the relevance of convergence between role and gender after the issuance of the equity incentive signal. For the scenario where both roles are occupied by women, the difference is greater, as expected (Δ = 0.135, p-value < .05). Compared to the all-male dyad, there are positive effects (Δ = 0.110, p-value < .01), as well as over the combination of a male CMO with a female CFO (Δ = 0.090, p-value < .05).

The empirical results challenge the prevailing assumption of linearity in executive compensation, revealing that the informational gains from CMO equity incentives are subject to diminishing marginal returns. While Agency Theory traditionally views these incentives as mechanisms for aligning interests, a Signaling Theory perspective offers a more nuanced interpretation. As equity packages grow, the market progressively discounts their value due to signal saturation. From an authorial standpoint, this saturation likely occurs because investors perceive that excessive incentives may induce executive risk aversion or myopic marketing behavior, thereby degrading the signal's efficiency. Consequently, boards must optimize rather than maximize equity allocation, recognizing that the market heavily rewards initial alignments but penalizes over-entrenchment.

Furthermore, the amplified market response to female CMOs establishes gender as a critical boundary condition for signal effectiveness. Grounded in Role Congruity Theory, the marketing function's relational and stakeholder-oriented demands strongly align with the communal attributes socially associated with female executives. In a signaling context, this attribute convergence creates a high signal fit. Moreover, because female leaders historically face greater scrutiny and higher dismissal risks, their acceptance of equity-based compensation represents a highly costly—and thus exceptionally credible—signal of managerial quality. Investors internalize this credibility, pricing the convergence of role expectations and gender attributes directly into higher firm valuation.

Finally, from an Upper Echelons perspective, the interaction between functional roles and executive gender can inadvertently generate signal ambiguity. While a female CMO signals strategic and relational congruence, the presence of a female CFO—often stereotypically associated with strict financial conservatism and risk aversion—introduces conflicting cues regarding long-term resource allocation. This strategic ambiguity reactivates underlying gender stereotypes, leading investors to neutralize the CMO's incentive signal. Ultimately, these findings indicate that the capital market evaluates executive signals not in isolation, but holistically, severely punishing structural ambiguity within the TMT and demonstrating that cognitive biases carry tangible financial costs.

5.3. Robustness Tests

To ensure the robustness of our findings across various specifications, we conducted a series of complementary tests and analyses. First, we examined whether the results remained consistent when accounting for the number of shares outstanding, as share volume can directly influence market capitalization. Second, we investigated whether CFO gender moderated their own equity incentives to determine if the positive moderation observed for female CMOs extends to other TMT roles. Third, we employed Tobin's Q as an alternative dependent variable to assess the stability of our primary results. Subsequently, we verified the robustness of the diminishing marginal returns associated with equity incentives. We then compared our main model—which utilizes the square root of incentives—against alternative functional forms, specifically linear and logarithmic models. As additional robustness checks, we investigated whether CEO and COO gender moderated the link between female CMO equity incentives and market capitalization, while also testing for reverse causality in the primary model. Finally, we utilized simulation and wild bootstrapping to evaluate the robustness of our findings given the reduced sample size of the female dyad.

When utilizing the quantity of shares (STOCKS) as a control in a complementary regression on Model 8, the results evidence that the MARKETCAP gains verified in this model are not due to movements in the number of shares (Table 10). They are consistent with positive market reactions to the signals of CMOINCENTIVE, CMOGENDER, and CFOGENDER, reiterating the strength of the effects confirming the research hypotheses.

Table 10

Longitudinal Panel Data Regression for Independent Variables CMOINCENTIVE, CMOGENDER, and CFOGENDER, Controlling for the Number of Shares (STOCKS)

	MARKETCAP	***t-value***
PREDICTOR: CMOINCENTIVE	0.066***	3.282
CMOGENDER	-0.103**	-2.293
CFOGENDER	-0.077	-1.418
CMOINCENTIVE × CMOGENDER	0.110***	2.973
CMOINCENTIVE × CFOGENDER	0.019	0.638
CMOGENDER × CFOGENDER	0.083	1.129
CMOINCENTIVE × CMOGENDER × CFOGENDER	-0.155**	-2.280
STOCKS	0.052	1.312
TMTGENDER	-0.007	-0.412
CEOGENDER	-0.111	-1.544
LAGMC	0.432***	7.154
TMTINCENTIVE	0.126***	6.362
CFOINCENTIVE	0.101***	5.186
CMOBONUS	0.040	1.586
CFOBONUS	0.032***	2.648
CFOTENURE	-0.026	-1.325
CMOTENURE	-0.008	-0.444
CMOAGE	0.015	0.703
CFOAGE	0.009	0.538
CFOTURNOVER	0.038	1.434
CEOTURNOVER	-0.010	-0.340
ROA	0.165***	8.331
SIZE	0.637***	4.805
LEVERAGE	-0.137***	-3.117
MYOPIC	0.117***	3.733
RADDUM	0.064	0.532
RDINTENSITY	0.047	0.909
INDCOMP	-0.019**	-2.468
INDGROWTH	0.022*	1.661

	MARKETCAP	***t-value***
INVMILLS	0.084**	2.548
Firm fixed effects	Yes	
Year fixed effects	Yes	
Observations	2,596	
Firms	749	
F	35.8***	
R2	.6115	
Max VIF	2.98	

Note. ***p-value < .01; ** p-value < .05; * p-value < .10.
Coefficients of continuous variables are z-score standardized.
Standard errors are clustered at the firm level.
R^2 refers to the within variance.

In the regression of CFO equity incentives (CFOINCENTIVE) against market capitalization moderated by their gender (CFOGENDER), it is verified that CFOGENDER has no statistically relevant effects (Appendix C). This result reinforces the argument that the positive moderation of the female CMO gender signal (H_2) occurs through the combination of the credibility of her equity incentive signal and the convergence of CMO role attributes and feminine attributes.

The use of Tobin's Q as the dependent variable in Model 8 shows an absence of significant statistical importance for the interactions, although CMO equity incentives remain significant (Appendix D). This suggests that gender signals are expressed in metrics more closely linked to market perception and cleared of accounting noise, such as market capitalization.

The relationship between equity incentives and firm value may take the form of an "inverted U" (e.g., McConnell & Servaes, 1990); thus, steps recommended by Haans et al. (2016) were used to evaluate its occurrence. These consisted of (i) testing the slopes of the ends of the quadratic regression and the peak point (Fieller, 1954; Lind & Mehlum, 2010); (ii) evaluating the cubic model; (iii) testing the split sample at the peak point; and (iv) graphical analysis. The results of the regressions for steps (i) and (ii) are set out in Table 11 and Appendix E, respectively.

The coefficient accompanying the quadratic term of CMOINCENTIVE is negative and significant at p-value < .01, initially confirming the "inverted U." The extremes present values with the expected signs for this format, with slopes of 0.185 and -0.149 (both p-value < .01 via Wald test). The peak point corresponds to a CMOINCENTIVE of 3.205 (2.449; 4.503), values contained within the data range (-0.806; 6.434) according to the Fieller (1954) method, corroborating the "inverted U."

However, the cubic term of CMOINCENTIVE (0.007) was significant at p-value < .05, suggesting that the quadratic form of CMOINCENTIVE may not be the most appropriate to explain market capitalization. This result, however, does not reflect a true S-shaped relationship; rather, it is a statistical artifact. The significance of the cubic term in polynomial tests is driven by data sparsity at higher incentive levels. The scarcity of observations at the extreme right tail widens the confidence intervals, making polynomial models highly sensitive to noise and allowing a cubic term to artificially achieve statistical significance within this range.

The split-sample test revealed that the left and right halves are quite disparate regarding data volume. When conducting regressions on each, the first had 2,531 observations and the second only 65, which yields spurious results for the effect of CMOINCENTIVE on market capitalization in the right half. These results suggest diminishing marginal returns, which is reiterated by Figure 6. In this figure, the local smoothing curve (Loess, in blue) indicates more pronounced effects of CMOINCENTIVE on market capitalization at lower incentive levels. Furthermore, the quadratic regression curve (dashed red) deviates from the confidence interval of the local estimate (shaded area), falling below it. This evidences that the quadratic regression (Table 11) is not suitable for the sample used here—a finding consistent with what was proposed in the theoretical and empirical framework: informational gains regarding CMO quality from their equity incentives saturate as their representativeness in total compensation increases.

Table 11

Longitudinal Panel Data Regression for Quadratic CMOINCENTIVE

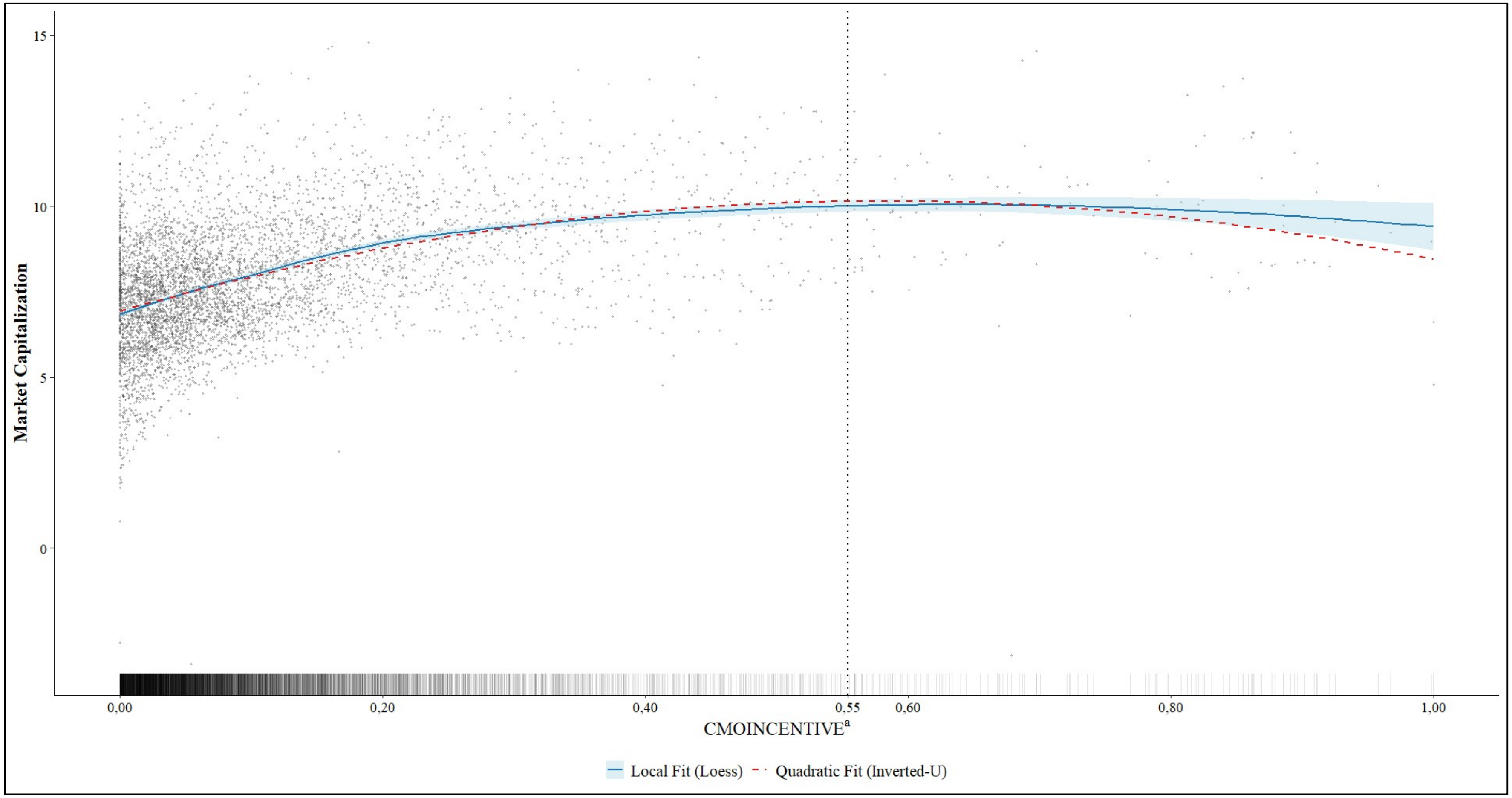
	MARKETCAP	***t-value***
PREDICTOR: $(\text{CMOINCENTIVE})^2$	-0.023***	-4.410
CMOINCENTIVE	0.148***	5.267
CMOGENDER	-0.112**	-2.540
CFOGENDER	-0.072	-1.522
TMTGENDER	-0.007	-0.426
CEOGENDER	-0.129*	-1.885
LAGMC	0.442***	7.189
TMTINCENTIVE	0.083***	5.131
CFOINCENTIVE	0.087***	4.123
CMOBONUS	0.049*	1.909
CFOBONUS	0.018	1.294
CFOTENURE	-0.022	-1.125
CMOTENURE	-0.015	-0.778
CMOAGE	0.009	0.432
CFOAGE	0.009	0.524

CFOTURNOVER	0.021	0.805
CEOTURNOVER	-0.024	-0.825
ROA	0.176***	8.524
SIZE	0.636***	4.786
LEVERAGE	-0.144***	-3.109
MYOPIC	0.115***	3.676
RADDUM	0.069	0.551
RDINTENSITY	0.051	0.975
INDCOMP	-0.020**	-2.488
INDGROWTH	0.022	1.584
INVMILLS	0.092***	2.808
Firm fixed effects	Yes	
Year fixed effects	Yes	
Observations	2,596	
Firms	749	
F	37.2***	
R2	.5988	
Max VIF	2.91	

Note. ***p-value < .01; ** p-value < .05; * p-value < .10.
Coefficients of continuous variables are z-score standardized.
Standard errors are clustered at the firm level.
R^2 refers to the within variance.
CMOINCENTIVE, TMTINCENTIVE, and CFOINCENTIVE variables specified in their linear form, following Kim et al. (2016).

Figure 6

Local and Quadratic Fit Curve for the Effect of CMOINCENTIVE on Market Capitalization



Note. [a] CMO equity incentives in their ratio form (Kim et al., 2016) and unstandardized.
The solid blue line represents the non-parametric local polynomial regression fit (Loess) along with its 95% confidence interval (shaded area). The dashed red line illustrates the parametric quadratic fit (inverted-U). The vertical dotted line indicates the inflection point of the quadratic model.

To evaluate the relevance of the square root for addressing diminishing marginal returns in this work, Models 1, 2, and 3 (Appendix F) were assigned linear, logarithmic, and square root incentives, respectively. The calculation of the logarithm of zero-value equity incentives required adding 1 to the variable (Wooldridge, 2016), although this adaptation compresses the variance of incentives, as noted in the methodological procedures, potentially implying a decrease in explanatory power. The results suggest the square root of incentives is more pertinent, given the higher R^2 within (.6111) and lower RMSE (0.252). Moreover, even with the variance compression of CMOINCENTIVE, TMTINCENTIVE, and CFOINCENTIVE, the research hypotheses remain valid for Model 2 (logarithmic), indicating the robustness of the findings.

The moderations of the female CEO and COO gender signals were tested against the female CMO moderation, with results shown in Appendices G and H. Neither was statistically significant at the 10% level. This adds robustness to the specific effect of the female CFO as a moderator of the relationship between female CMO equity incentives and market capitalization (H_3). To rule out reverse causality, the variation in market capitalization at $t - 1$ was regressed against CMO equity incentives (CMOINCENTIVE) at *t* (Appendix I). The results alleviate concerns regarding reverse causality in the Table 8 models, as variation in MARKETCAP at $t - 1$ is not significantly associated with CMOINCENTIVE at *t*.

Given the low number of observations where both the CMO and CFO are female (Table 12), tests were performed to validate the double moderation in the relationship between CMOINCENTIVE and market capitalization. This is because high-magnitude effects, such as that of the female dyad in Table 8 ($\beta_7 = -0.155$, p-value < .05), can occur more easily by chance with few observations. Based on Abadie et al. (2010), a placebo effect for the moderation of CMO and CFO genders was evaluated. To this end, the genders in the original sample were replaced randomly with values of 1 and 0, and the results were compared with the triple interaction effect in the main regression (Table 8). By undertaking 10,000 Monte Carlo simulations, an empirical p-value of .005 was obtained, meaning there is less than a 1% probability of finding the coefficient of -0.155 by chance. This result provides strong robustness to the female CFO moderation effect. The simulation results are illustrated in Figure 7.

Table 12

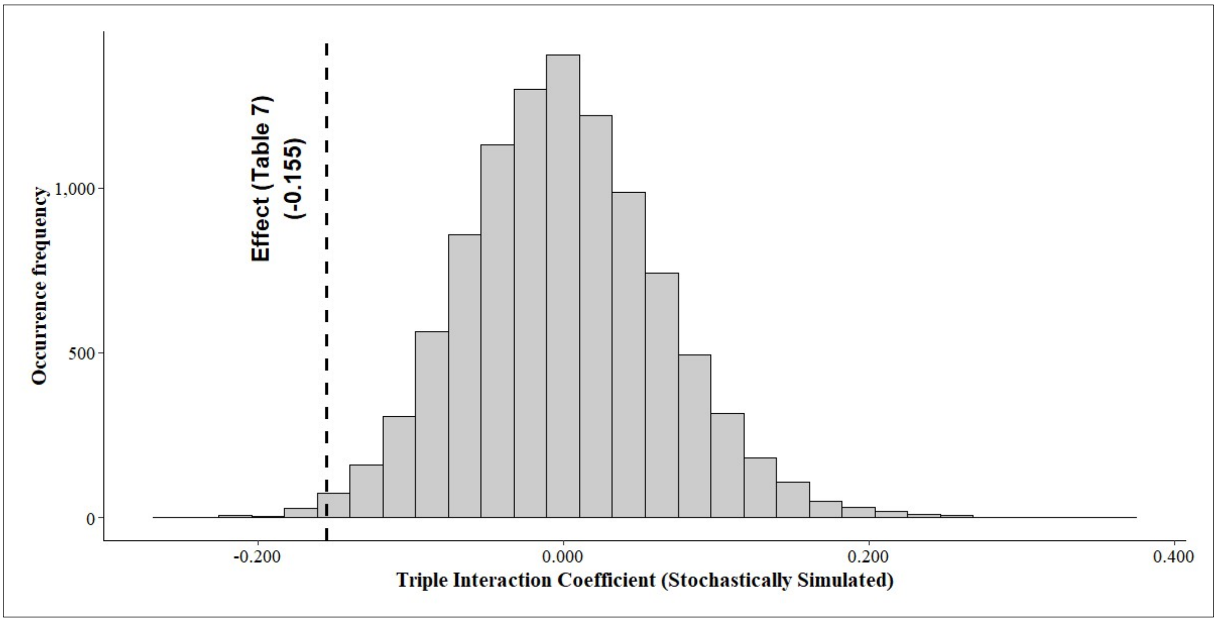
Observations utilized in the main regressions of this study, disaggregated by gender category

CFO gender	CMO gender	
	0	1
0	1,947	308
1	286	55[a]

Note. The values 1 (one) and 0 (zero) denote female and male genders, respectively.
[a] For 33 distinct firms.

Figure 7

Monte Carlo Simulation for the Triple Interaction Coefficient between CMOINCENTIVE, CMOGENDER, and CFOGENDER



Finally, the wild bootstrap method was used to handle the consequence of the low number of firms in the female dyad (only 33) on the standard errors. In regressions using clustered standard errors, small groups can artificially lower p-values, increasing Type I error probability (Cameron et al., 2008). To avoid this, a simulation was performed with the residuals of the original regression randomly multiplied by Webb weights (Webb, 2014). The same weights were applied to each firm to maintain the data structure. The new residuals were added to the value predicted by the original model to obtain the simulated market capitalization. Regressions were then performed (repeated 10,000 times). The empirical p-value was .069, confirming that the female CFO moderation effect survives at the 10% significance level.

6. Conclusion

6.1. Theoretical Implications

This study provides three definitive contributions to the marketing-finance interface by moving beyond the traditional Agency Theory framework. First, it empirically challenges the prevailing assumption of linearity in executive compensation, proving that the informational gains from CMO equity incentives are subject to strict diminishing marginal returns. Second, it establishes executive gender as a critical boundary condition for signal effectiveness, demonstrating that the market applies a premium to female CMOs due to the strong convergence between their socially perceived communal attributes and the relational demands of the marketing role. Third, it extends Role Congruity Theory to the TMT level by revealing that capital markets evaluate executive signals holistically; the data proves that the presence of a female CFO introduces strategic ambiguity that entirely neutralizes the female CMO's signaling advantage.

Prior studies on CMO equity incentives rely primarily on Agency Theory (e.g., Bansal et al., 2016; Fabrizi, 2014; Kim et al., 2016), which posits that incentives align managers' and shareholders' interests (Jensen & Meckling, 1979) and enhance firm outcomes (e.g., Hall & Liebman, 1998; Tosi et al., 2000; You et al., 2020). Our findings support this logic (H_1), showing a positive relationship between CMO equity incentives and market capitalization. However, Agency Theory alone cannot explain how markets interpret these incentives. By incorporating Signaling Theory, we show that equity incentives not only align interests but also signal managerial quality to external audiences. Consistent with Jensen and Murphy (1990), markets require confidence in managerial ability to price long-term value. Thus, CMO incentives function as observable signals that reduce information asymmetry and influence firm valuation.

This study extends the literature by demonstrating that the relationship between CMO incentives and firm value is not linear. While prior work reports a positive association (e.g., Fabrizi, 2014; Kim et al., 2016), our results reveal diminishing marginal returns, consistent with informational saturation. Drawing on Holmström (1999), we argue that incentives can substitute for time in generating information about managerial quality. Through feedback mechanisms central to Signaling Theory (Spence, 1973), markets progressively learn from these signals, which eventually lose incremental informativeness. This evidence refines H_1 by showing that, although supported, its effect weakens at higher incentive levels due to declining informational gains.

By introducing gender as a moderator, we contribute to both Signaling Theory and Role Congruity Theory. We find strong support for H_2: the positive effect of CMO equity incentives on market capitalization becomes stronger when the CMO is female. This result suggests that gender operates as a complementary signal that enhances the credibility and impact of financial incentives. In line with Role Congruity Theory (Eagly & Karau, 2002; Schein, 1973), female leaders face stereotype-based incongruence; however, when combined with strong economic signals (equity incentives), this incongruence can be mitigated or even reversed. Our findings therefore show that multiple signals—financial and social—interact to shape market perceptions, extending prior research that typically examines signals in isolation (Connelly et al., 2025). Our results therefore establish a boundary condition for Role Congruity Theory, suggesting that the general perception of leadership as typically masculine (Eagly & Karau, 2002; Schein, 1973) fades in the presence of credible and objective signals (Heilman, 2012), giving way to the evaluation of attributes that are critical to the specific leadership role.

Finally, we provide novel evidence supporting H_3 by showing that the gender of the CFO negatively moderates the effect observed in H_2. Specifically, when both CMO and CFO are female, the positive signaling effect of CMO incentives weakens. We interpret this result through both signaling ambiguity and gender stereotyping. Given evidence that female executives are perceived as more risk-averse (B. Francis et al., 2015), the presence of a female CFO may introduce conflicting signals regarding resource allocation and strategic risk, particularly at the marketing–finance interface. This ambiguity can reactivate gender stereotypes (Heilman, 2012) and reduce the effectiveness of incentive-based signals. Thus, our results highlight that signal interactions are complex and context-dependent, reinforcing the multidimensional nature of Signaling Theory (Connelly et al., 2025) while extending Role Congruity Theory to executive dyads. By introducing a gender lens to the marketing-finance interface, we demonstrate that stereotyping does not merely penalize individual female managers; it penalizes the organization as a whole. Firms may suffer market devaluation due to the signaling of friction within this critical interface, proving that cognitive biases carry tangible financial costs.

6.2. Managerial Implication

Because marketing has traditionally struggled to justify its investments (Kumar & Shah, 2009; Srivastava et al., 1998), firms rely more heavily on observable signals to assess CMO quality. Our results show that equity incentives serve as an effective mechanism to reduce information asymmetry about marketing executives. By tying compensation to firm value, these incentives provide a credible, market-visible indicator of managerial quality and expected performance. The findings further indicate that female CMOs amplify the market impact of equity incentive signals. When firms grant equity-based compensation to female CMOs, investors infer stronger future performance and incorporate these expectations into stock prices, increasing market capitalization. Higher market capitalization, in turn, improves access to external financing, supports long-term investments in marketing assets such as brand equity, and enhances protection against hostile takeovers. Thus, firms can use incentive design not only to align interests but also to strategically influence market perceptions.

The results also inform TMT diversity decisions. Firms pursuing long-term growth through marketing capabilities benefit more when a female CMO operates alongside a male CFO, as this dyad strengthens positive market expectations. In contrast, the female CMO–female CFO dyad attenuates the signaling effect, reducing the firm's ability to convey value creation prospects. Investors appear to interpret these configurations differently, suggesting that gender composition within the TMT shapes how signals are received and priced. Consequently, governance decisions should consider not only diversity per se but also how different role combinations affect market interpretation. Given that some gender configurations enhance firm value while others weaken it, corporate governance and investor relations functions should actively manage these signaling effects. Because signals interact with cognitive processes, emotions, and biases (Connelly et al., 2025), firms can design communication strategies that reinforce signal consistency and mitigate negative interpretations. In particular, firms should address potential ambiguity associated with female CMO–female CFO dyads, as inconsistent signals may intensify gender stereotypes (Heilman, 2012). Such efforts are also critical for improving access to and retention of women in top leadership positions, given persistent biases before and after appointment (Eagly & Karau, 2002). Without deliberate action, firms risk discouraging highly qualified female executives from pursuing leadership roles, thereby limiting their talent pool and long-term performance potential.

For corporate boards and compensation committees, the empirical results dictate a shift from maximizing to optimizing CMO equity incentives. Because the signaling value of these packages saturates and yields diminishing marginal returns, boards must carefully evaluate the baseline threshold of their executives to prevent over-allocation and the subsequent market discount. Furthermore, the findings provide actionable intelligence for TMT composition: firms seeking to maximize market capitalization through marketing leadership benefit disproportionately from the female CMO and male CFO dyad, which emits the clearest growth signal to investors. Conversely, firms deploying a female-female dyad at the marketing-finance interface must proactively manage investor relations to counter entrenched market biases and clarify resource allocation strategies, as investors currently penalize this configuration with a non-significant market reaction.

6.3. Limitations and Future Research

A primary limitation of these empirical findings is the restricted sample size regarding the specific female CMO-female CFO dyad, which consists of only 33 distinct firms. Although the negative moderation effect survived rigorous robustness checks, including Monte Carlo simulations and wild bootstrapping, the restricted external validity of this specific configuration requires further investigation. As structural barriers to women's advancement in leadership positions decline (Heilman, 2012), these effects may evolve. Future longitudinal studies should track changes in female representation in top management teams and examine how gender-based signals develop and influence market perceptions over time.

This study also faces limitations inherent to quantitative approaches in capturing signaling processes related to gender. While we isolate the effects on market capitalization using rigorous controls, qualitative research could deepen our understanding of how investors interpret these signals. Analyses based on shareholder narratives may uncover additional mechanisms, suggest new control variables, and identify other relevant signals beyond equity incentives. Future research should therefore explore how alternative forms of executive compensation function as signals of managerial quality.

By focusing on gender, this study draws on stereotypes to explain how signals affect firm value. However, other forms of bias—such as those related to ethnicity, nationality, or background—may shape signal interpretation differently. Future research should investigate how multiple identity-based signals interact with financial signals, including equity incentives, and how these interactions affect market valuation. Such work could also examine strategies to mitigate stereotyping and improve access to and retention in top executive roles. Expanding the analysis to include non-binary gender identities would further enrich this research agenda.

Finally, this study examines publicly traded U.S. firms listed in Compustat and ExecuComp and focuses on TMT executives. These contextual constraints may limit external validity. Given the complexity of signaling processes—shaped by interactions among signals, cognitive mechanisms, emotions, and biases (Connelly et al., 2025)—future studies should test the generalizability of our findings across institutional settings, ownership structures, and cultural contexts.

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Appendix A
Agency Theory explaining Equity Incentives and CMO

Agency Theory examines how firms align managers' and owners' interests. It argues that the separation of ownership and control creates principal–agent conflicts that firms mitigate through audits, formal controls, budget constraints, and incentive-based compensation (Jensen & Meckling, 1979). Empirical evidence shows that executive pay is positively associated with firm performance (e.g., Hall & Liebman, 1998; Tosi et al., 2000; You et al., 2020). However, research on CMO incentives remains limited, although existing studies also report a positive association between CMO equity incentives and firm outcomes (e.g., Fabrizi, 2014; Kim et al., 2016). Equity incentives are particularly relevant when CMOs influence firm value because they tie managerial wealth to shareholder wealth. CMOs create value through marketing actions that increase customer lifetime value and generate cash flows (Kumar & Shah, 2009), especially via customer relationship management, which involves identifying needs, designing programs, and building trust and loyalty (Srivastava et al., 1999). Therefore, equity incentives motivate CMOs to undertake value-creating marketing activities.

The relationship between CMO equity incentives and firm value is not necessarily linear. Prior studies suggest inverted U-shaped or mixed patterns, in which performance increases up to a point and then declines (e.g., McConnell & Servaes, 1990; Morck et al., 1988). However, identifying these forms requires rigorous testing, which is often absent (Haans et al., 2016). In many cases, the relationship reflects diminishing marginal returns: additional incentives generate progressively smaller gains. This pattern arises because equity incentives become redundant as governance mechanisms strengthen and dismissal threats increase (Lund & Polsky, 2011), while other forces—such as competition, internal career concerns, takeover threats, and non-monetary rewards—substitute for financial incentives (Jensen & Murphy, 1990). Risk aversion further reinforces this effect. Larger incentive packages increase perceived risk and compensation costs, leading managers to adopt more conservative strategies (Dittmann & Maug, 2007). CMOs may avoid risky but value-creating marketing actions, such as innovation and new product development (Srivastava et al., 1999). In addition, equity incentives can induce marketing myopia, where managers prioritize short-term stock performance over long-term value (Artz & Mizik, 2023; Mizik, 2010; Mizik & Jacobson, 2007). Consequently, although equity incentives align interests (Jensen & Meckling, 1979), their effects weaken or reverse at higher levels. Overall, the literature supports positive effects at low levels of incentives but diminishing or negative effects at higher levels (Edmans et al., 2017), while largely overlooking CMOs and focusing on CEOs and CFOs (Kim et al., 2016; Menz, 2012), indicating the need to examine incentives across the broader TMT (Hambrick, 2007).

Appendix B

Mathematical Formalization of Diminishing Marginal Returns for Information Gains regarding CMO Quality using Square-Root Incentives

Consider Equation 4 in the theoretical and empirical framework subsection, where *f(I)* represents the signal intensity function for distinct levels of equity incentives *I*, and *g(I)* denotes the informational gain regarding η (CMO quality):

$$g(\mathrm{I}) = \frac{1}{h_1} - \frac{1}{h_1 + f(\mathrm{I}) \times h_\varepsilon}$$

Substituting *f(I)* with the square root of the incentives yields:

$$g(\mathrm{I}) = \frac{1}{h_1} - \frac{1}{h_1 + \sqrt{\mathrm{I}} \times h_\varepsilon} \qquad 15$$

Computing the first and second derivatives of Equation 15—by substituting *f(I)* in Equations 5 and 6 with the square root of the incentives—yields:

$$g'(\mathrm{I}) = \frac{h_\varepsilon}{2 \times \sqrt{\mathrm{I}} \times \left(h_1 + \sqrt{\mathrm{I}} \times h_\varepsilon\right)^2} \qquad 16$$

$$g''(\mathrm{I}) = -\frac{h_\varepsilon \times (h_1 + 3 \times h_\varepsilon \times \sqrt{\mathrm{I}})}{4 \times \mathrm{I} \times \sqrt{\mathrm{I}} \times \left(h_1 + \sqrt{\mathrm{I}} \times h_\varepsilon\right)^3} \qquad 17$$

Notably, *g'(I)* and *g''(I)* are strictly positive and negative, respectively. This follows from the fact that *I* is a proportion bounded between 0 and 1, and the precisions (h_1 and h_ε)—defined as inverse variances (Holmström, 1999)—are inherently positive. Consequently, informational gains are monotonically increasing and concave with respect to equity incentives, corroborating the presence of diminishing marginal returns.

Appendix C

Longitudinal Panel Data Regression for Independent Variables CFOINCENTIVE and CFOGENDER

	MARKETCAP	***t-value***
PREDICTOR: CFOINCENTIVE	0.125***	5.972
CFOGENDER	-0.065	-1.040
CFOINCENTIVE × CFOGENDER	-0.032	-0.875
TMTGENDER	0.001	0.075
CEOGENDER	-0.043	-0.610
CMOGENDER	-0.058*	-1.839
LAGMC	0.479***	13.245
TMTINCENTIVE	0.047***	2.891
CMOINCENTIVE	0.047***	2.891
CMOBONUS	0.030	1.270
CFOBONUS	0.020	0.948
CFOTENURE	-0.021	-0.925
CMOTENURE	-0.014	-0.848
CMOAGE	-0.012	-0.705
CFOAGE	-0.014	-0.560
CMOTURNOVER	-0.004	-0.182
CEOTURNOVER	-0.000	-0.002
ROA	0.149***	7.455
SIZE	0.700***	7.810
LEVERAGE	-0.154***	-3.533
MYOPIC	0.105***	3.249
RADDUM	0.091	0.760
RDINTENSITY	0.021	0.425
INDCOMP	-0.017*	-1.805
INDGROWTH	0.003	0.218
INVMILLS	0.086***	3.192
Firm fixed effects	Yes	
Year fixed effects	Yes	
Observations	2,245	
Firms	693	
F	35.7***	
R^2	.6341	
Max VIF	2.33	

Note. ***p-value < .01; ** p-value < .05; * p-value < .10.
Coefficients of continuous variables are z-score standardized.
Standard errors are clustered at the firm level.
R^2 refers to the within variance.
Observations are excluded in the year of a CFO turnover.

Appendix D

Longitudinal Panel Data Regression for Independent Variables CMOINCENTIVE, CMOGENDER, and CFOGENDER with Tobin's Q as the Dependent Variable

	Tobin's Q	***t-value***
PREDICTOR: CMOINCENTIVE	0.110***	2.801
CMOGENDER	-0.084	-1.465
CFOGENDER	-0.021	-0.360
CMOINCENTIVE × CMOGENDER	-0.077	-1.396
CMOINCENTIVE × CFOGENDER	-0.013	-0.256
CMOGENDER × CFOGENDER	0.067	0.652
CMOINCENTIVE × CMOGENDER × CFOGENDER	-0.105	-0.838
TMTGENDER	0.005	0.298
CEOGENDER	-0.068	-0.840
LAG[a]	0.418***	10.463
TMTINCENTIVE	0.146***	4.608
CFOINCENTIVE	0.091***	2.753
CMOBONUS	0.088*	1.843
CFOBONUS	0.020	1.097
CFOTENURE	-0.015	-0.394
CMOTENURE	0.016	0.702
CMOAGE	-0.001	-0.050
CFOAGE	0.009	0.358
CFOTURNOVER	0.056	1.493
CEOTURNOVER	0.011	0.296
ROA	0.129***	4.526
SIZE	-0.156	-1.434
LEVERAGE	0.065	1.600
MYOPIC	0.107**	2.089
RADDUM	0.015	0.213
RDINTENSITY	0.042	0.515
INDCOMP	-0.019**	-2.113
INDGROWTH	0.031	1.524
INVMILLS	0.078**	1.969
Firm fixed effects	Yes	
Year fixed effects	Yes	
Observations	2,348	
Firms	681	
F	14.1***	
R^2	.3681	
Max VIF	4.35	

Note. ***p-value < .01; ** p-value < .05; * p-value < .10.
Coefficients of continuous variables are z-score standardized.
Standard errors are clustered at the firm level.
R^2 refers to the within variance.
[a] One-period lag of the dependent variable.

Appendix E

Longitudinal Panel Data Regression for Cubic CMOINCENTIVE

	MARKETCAP	***t-value***
PREDICTOR: $(\text{CMOINCENTIVE})^3$	0.007**	2.073
$(\text{CMOINCENTIVE})^2$	-0.063***	-3.018
CMOINCENTIVE	0.173***	5.840
CMOGENDER	-0.118***	-2.709
CFOGENDER	-0.067	-1.420
TMTGENDER	-0.006	-0.339
CEOGENDER	-0.128*	1.861
LAGMC	0.441***	7.189
TMTINCENTIVE	0.081***	5.002
CFOINCENTIVE	0.090***	4.219
CMOBONUS	0.049*	1.905
CFOBONUS	0.016	1.137
CFOTENURE	-0.024	-1.237
CMOTENURE	-0.015	-0.809
CMOAGE	0.007	0.324
CFOAGE	0.009	0.554
CFOTURNOVER	0.022	0.845
CEOTURNOVER	-0.021	-0.724
ROA	0.176***	8.559
SIZE	0.638***	4.815
LEVERAGE	-0.141***	-3.071
MYOPIC	0.117***	3.662
RADDUM	0.064	0.510
RDINTENSITY	0.051	0.983
INDCOMP	-0.020**	-2.443
INDGROWTH	0.022	1.572
INVMILLS	0.089***	2.724
Firm fixed effects	Yes	
Year fixed effects	Yes	
Observations	2,596	
Firms	749	
F	34.5***	
R^2	.6003	
Max VIF	2.95	

Note. ***p-value < .01; ** p-value < .05; * p-value < .10.
Coefficients of continuous variables are z-score standardized.
Standard errors are clustered at the firm level.
R^2 refers to the within variance.
CMOINCENTIVE, TMTINCENTIVE, and CFOINCENTIVE variables specified in their linear form, following Kim et al. (2016).

Appendix F

Panel Data Regression for Linear, Square Root, and Logarithmic Models

	(1) MARKETCAP[a]	*t-value*	(2) MARKETCAP[b]	*t-value*	(3) MARKETCAP[c]	*t-value*
PREDICTOR: CMOINCENTIVE	0.064***	3.049	0.070***	3.261	0.065***	3.255
CMOGENDER	-0.098**	-2.198	-0.102**	-2.290	-0.106**	-2.359
CFOGENDER	-0.089	-1.558	-0.088	-1.554	-0.075	-1.397
CMOINCENTIVE × CMOGENDER	0.128***	2.761	0.120***	2.818	0.110***	2.970
CMOINCENTIVE × CFOGENDER	0.008	0.316	0.013	0.459	0.020	0.650
CMOGENDER × CFOGENDER	0.088	1.160	0.088	1.158	0.090	1.232
CMOINCENTIVE × CMOGENDER × CFOGENDER	-0.158**	-2.341	-0.154**	-2.235	-0.155**	-2.264
TMTGENDER	-0.006	-0.345	-0.007	-0.404	-0.008	-0.484
CEOGENDER	-0.130*	-1.867	-0.128*	-1.833	-0.109	-1.512
LAGMC	0.439***	7.121	0.437***	7.120	0.433***	7.164
TMTINCENTIVE	0.086***	5.203	0.088***	5.280	0.127***	6.384
CFOINCENTIVE	0.092***	4.310	0.095***	4.519	0.101***	5.180
CMOBONUS	0.046*	1.751	0.046*	1.775	0.041	1.624
CFOBONUS	0.021	1.529	0.023*	1.706	0.033***	2.642
CFOTENURE	-0.020	-1.037	-0.022	-1.119	-0.025	-1.298
CMOTENURE	-0.010	-0.552	-0.011	-0.594	-0.009	-0.489
CMOAGE	0.014	0.664	0.013	0.623	0.015	0.705
CFOAGE	0.006	0.342	0.006	0.362	0.008	0.509
CFOTURNOVER	0.023	0.864	0.026	0.970	0.038	1.446
CEOTURNOVER	-0.032	-1.091	-0.030	-1.027	-0.009	-0.326
ROA	0.178***	8.560	0.175***	8.480	0.164***	8.327
SIZE	0.638***	4.751	0.637***	4.763	0.641***	4.824
LEVERAGE	-0.147***	-3.182	-0.147***	-3.198	-0.139***	-3.161
MYOPIC	0.114***	3.541	0.115***	3.587	0.119***	3.798
RADDUM	0.075	0.608	0.075	0.614	0.064	0.542
RDINTENSITY	0.049	0.922	0.049	0.917	0.048	0.923
INDCOMP	-0.020**	-2.428	-0.020**	-2.454	-0.019**	-2.482
INDGROWTH	0.024	1.634	0.023	1.642	0.022	1.642
INVMILLS	0.096***	2.927	0.095***	2.892	0.084**	2.561

	MARKETCAP[a]	MARKETCAP[b]	MARKETCAP[c]
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	2,596	2,596	2,596
Firms	749	749	749
F	32.7***	33.7***	37.0***
RMSE	0.257	0.256	0.252
R^2	.5968	.5998	.6111
Max VIF	2.83	2.85	2.97

Note. ***p-value < .01; ** p-value < .05; * p-value < .10.
Coefficients of continuous variables are z-score standardized.
Standard errors are clustered at the firm level.
RMSE refers to the root mean square error.
R^2 refers to the within variance.
[a, b, c] Linear, logarithmic, and square root models for equity incentives, respectively.

Appendix G

Longitudinal Panel Data Regression for the Independent Variables: CMOINCENTIVE, CMOGENDER, and CEOGENDER

	MARKETCAP	***t-value***
PREDICTOR: CMOINCENTIVE	0.049**	2.494
CMOGENDER	-0.111***	-2.617
CEOGENDER	-0.118	-1.143
CMOINCENTIVE × CMOGENDER	0.067*	1.766
CMOINCENTIVE × CEOGENDER	0.041	0.555
CMOGENDER × CEOGENDER	-0.019	-0.179
CMOINCENTIVE × CMOGENDER × CEOGENDER	0.077	0.866
TMTGENDER	-0.022	-1.409
LAGMC	0.423***	6.990
TMTINCENTIVE	0.084***	5.091
CEOINCENTIVE	0.193***	5.910
CMOBONUS	0.027	1.014
CEOBONUS	-0.118	-1.143
CEOTENURE	-0.026	-0.985
CMOTENURE	-0.001	-0.064
CMOAGE	0.013	0.626
CEOAGE	-0.048**	-2.378
CFOTURNOVER	0.019	0.829
CEOTURNOVER	-0.007	-0.206
ROA	0.168***	8.682
SIZE	0.638	4.962
LEVERAGE	-0.132***	-2.980
MYOPIC	0.126***	4.197
RADDUM	0.031	0.217
RDINTENSITY	0.042	0.868
INDCOMP	-0.016*	-1.854
INDGROWTH	0.019	1.441
INVMILLS	0.053*	1.654
Firm fixed effects	Yes	
Year fixed effects	Yes	
Observations	2,598	
Firms	749	
F	39.5***	
R^2	.6149	
Max VIF	3.12	

Note. ***p-value < .01; ** p-value < .05; * p-value < .10.
Coefficients of continuous variables are z-score standardized.
Standard errors are clustered at the firm level.
R^2 refers to the within variance.

Appendix H

Longitudinal Panel Data Regression for the Independent Variables: CMOINCENTIVE, CMOGENDER, and COOGENDER

	MARKETCAP	*t-value*
PREDICTOR: CMOINCENTIVE	0.078***	2.787
CMOGENDER	0.049	0.503
COOGENDER	-0.010	-0.142
CMOINCENTIVE × CMOGENDER	0.136*	1.708
CMOINCENTIVE × COOGENDER	-0.047	-0.734
CMOGENDER × COOGENDER	-0.106	-0.876
CMOINCENTIVE × CMOGENDER × COOGENDER	-0.063	-0.650
TMTGENDER	-0.004	-0.200
CEOGENDER	-0.118	-1.592
LAGMC	0.495***	11.745
TMTINCENTIVE	0.096***	3.942
COOINCENTIVE	0.051**	2.410
CMOBONUS	0.022	0.782
COOBONUS	0.016	0.842
COOTENURE	-0.075***	-3.360
CMOTENURE	0.034	1.161
CMOAGE	0.026	0.849
COOAGE	-0.025	-1.123
CFOTURNOVER	0.032	1.025
CEOTURNOVER	-0.002	-0.044
ROA	0.160***	5.187
SIZE	0.562***	4.706
LEVERAGE	-0.113**	-2.203
MYOPIC	0.143***	2.936
RADDUM	-0.216	-1.343
RDINTENSITY	0.066	0.812
INDCOMP	-0.023	-1.621
INDGROWTH	0.026	0.978
INVMILLS	0.000	0.003
Firm fixed effects	Yes	
Year fixed effects	Yes	
Observations	1,304	
Firms	478	
F	34.2***	
R^2	.6388	
Max VIF	4.26	

Note. ***p-value < .01; ** p-value < .05; * p-value < .10.
Coefficients of continuous variables are z-score standardized.
Standard errors are clustered at the firm level.
R^2 refers to the within variance.

Appendix I

Longitudinal Panel Data Regression: Lagged Variation in MC (t−1) as the Independent Variable and CMOINCENTIVE (t) as the Dependent Variable

	CMOINCENTIVE	***t-value***
PREDICTOR: MARKETCAP[a]	0.049	0.714
CMOGENDER	0.042	0.320
CFOGENDER	0.003	0.034
TMTGENDER	-0.015	-0.459
CEOGENDER	-0.019	-0.140
TMTINCENTIVE	0.232***	5.671
CFOINCENTIVE	0.253***	5.876
CMOBONUS	-0.101***	-2.639
CFOBONUS	0.041	1.262
CFOTENURE	-0.070	-1.527
CMOTENURE	0.102*	1.924
CMOAGE	0.095	1.420
CFOAGE	0.032	0.697
CFOTURNOVER	0.072*	1.751
CEOTURNOVER	-0.052	-1.038
ROA	0.069**	2.194
SIZE	0.529**	2.425
LEVERAGE	-0.016	-0.240
MYOPIC	0.093	1.321
RADDUM	0.316	1.350
RDINTENSITY	0.034	0.337
INDCOMP	-0.011	-0.630
INDGROWTH	0.035*	1.910
INVMILLS	-0.047	-0.694
Firm fixed effects	Yes	
Year fixed effects	Yes	
Observations	2,073	
Firms	618	
F	10.3***	
R^2	.2271	
Max VIF	3.45	

Note. ***p-value < .01; ** p-value < .05; * p-value < .10.
[a] Refers to the variation in market capitalization at t−1.
Coefficients of continuous variables are z-score standardized.
Standard errors are clustered at the firm level.
R^2 refers to the within variance.

Appendix J

R Scripts

J.1. Wrangling

```
library(tidyverse)
library(readxl)
library(fixest)
library(plm)
library(lubridate)
library(conflicted)
library(knitr)

conflict_prefer("lag", "dplyr")
conflict_prefer("filter", "dplyr")
conflict_prefer("year", "lubridate")
conflict_prefer("select", "dplyr")

# Função de Winsorização (Segura para vetores com NAs)
minha_winsorize <- function(x, probs = c(0.01, 0.99)) {
  if(!is.numeric(x) | all(is.na(x))) return(x)
  qs <- quantile(x, probs = probs, na.rm = TRUE)
  x[x < qs[1]] <- qs[1]
  x[x > qs[2]] <- qs[2]
  return(x)
}

#
==========================================================================
===
# 1. CARREGAMENTO COMPUSTAT E EXECUCOMP E HARMONIZAÇÃO DE GVKEY E YEAR
#
==========================================================================
===

# Carregar Dados Brutos
df_compustat_raw <- read_excel("Compustat.xlsx")
df_execucomp_raw <- read_csv("ExecuComp.csv")

# Processar COMPUSTAT
df_compustat_final <- df_compustat_raw %>%
  rename(gvkey = `Global Company Key`, year = `Data Year - Fiscal`) %>%
  mutate(gvkey = as.character(gvkey), year = as.integer(year)) %>%
  dplyr::filter(`Industry Format` == "INDL", !is.na(gvkey), !is.na(year))

# Processar ExecuComp
df_execucomp_final <- df_execucomp_raw %>%
  mutate(year = as.integer(year)) %>%
  dplyr::filter(!is.na(gvkey), !is.na(year))

# Executar o Merge Final (Left Join preserva Compustat financial data)
dados_long  <-  left_join(df_compustat_final,  df_execucomp_final,  by  =
c("gvkey", "year")) %>%
  filter(!is.na(sic))

rm(df_compustat_raw,        df_execucomp_raw,        df_compustat_final,
df_execucomp_final)
data_final <- dados_long

#
==========================================================================
===
# 2. RENOMEAÇÃO E PREPARAÇÃO NUMÉRICA (COM DUMMIES DE CONTROLE)
```

```
#
============================================================================
===

cols_map <- c(
  OIBD = "Operating Income Before Depreciation", SGAE = "Selling, General
and Administrative Expense",
  RAD = "Research and Development Expense", AT = "Assets - Total", LT =
"Liabilities - Total",
  CST = "Common Shares Traded - Annual - Fiscal", CSO = "Common Shares
Outstanding",
  PRC = "Price Close - Annual - Fiscal", PSL = "Preferred Stock - Liquidating
Value",
  CLT = "Current Liabilities - Total", CAT = "Current Assets - Total", LTD
= "Long-Term Debt - Total",
  Sales = "Sales/Turnover (Net)", XAD = "Advertising Expense", COGS = "Cost
of Goods Sold",
  NIL = "Net Income (Loss)", OANCF = "Operating Activities - Net Cash Flow",
EMPL = "Employees",
  IBEI = "Income Before Extraordinary Items", BECCEO = "becameceo", JCOMP =
"joined_co",
  SAL = "salary", BON = "bonus", SHOEP = "shrown_excl_opts", OPTEX =
"opt_unex_exer_num", OPTUNEX = "opt_unex_unexer_num",
  CAT = "Current Assets - Total", CLT = "Current Liabilities - Total", DVPSX_F
= "Dividends per Share - Ex-Date - Fiscal"
)

existing_cols <- names(data_final)
cols_to_rename <- cols_map[cols_map %in% existing_cols]
if(length(cols_to_rename) > 0) data_final <- data_final %>%
rename(!!!cols_to_rename)

data_final <- data_final %>%
  mutate(
    SIC = str_sub(as.character(sic), 1, 2), year = as.integer(year), gvkey
= as.character(gvkey),
    Sales = as.numeric(Sales), AT = as.numeric(AT), LT = as.numeric(LT), IBEI
= as.numeric(IBEI),
    OIBD = as.numeric(OIBD), OANCF = as.numeric(OANCF), EMPL =
as.numeric(EMPL), CSO = as.numeric(CSO),
    PRC = as.numeric(PRC), PSL = as.numeric(PSL), CLT = as.numeric(CLT), CAT
= as.numeric(CAT),
    LTD = as.numeric(LTD), COGS = as.numeric(COGS), CST = as.numeric(CST),
    RAD = as.numeric(RAD), XAD = as.numeric(XAD)
  ) %>%
  mutate(
    RAD_dum = if_else(!is.na(RAD), 1, 0),
    XAD_dum = if_else(!is.na(XAD), 1, 0),
    RAD = replace_na(RAD, 0),
    XAD = replace_na(XAD, 0)
  )

#
============================================================================
===
# 3. IDENTIFICAÇÃO CMO E CEO
#
============================================================================
===

cmo_patt                                                                 <-
"marketing|cmo|customer|brand|channel|product\\b|pricing|advertising|sales|
merchandise|consumer|retail"

data_final <- data_final %>%
  mutate(
    title_l = str_to_lower(titleann),
    IS_CMO = if_else(str_detect(title_l, cmo_patt), 1, 0, missing = 0),
    is_ceo_flag = case_when(
```

```
      as.character(ceoann) %in% c("CEO", "1", "TRUE") ~ TRUE,
      str_detect(title_l, "chief executive") ~ TRUE,
      TRUE ~ FALSE
    )
  )

#
==========================================================================
===
# 4. CÁLCULOS DAS VARIÁVEIS DE DESEMPENHO E CONTROLES FINANCEIROS (FIRM-
LEVEL)
#
==========================================================================
===

firm_base_unique <- data_final %>%
  distinct(gvkey, year, .keep_all = TRUE) %>%
  arrange(gvkey, year) %>%
  group_by(gvkey) %>%
  mutate(
    SIZE = ifelse(EMPL > 0, log(EMPL), NA_real_),
    ROA = ifelse(AT > 0, IBEI / AT, NA_real_),
    Leverage = ifelse(AT > 0, LT / AT, NA_real_),
    MVE = CSO * PRC,
    TobinQ = (MVE + PSL + CLT - CAT + LTD) / AT,
    ln_MC = ifelse(MVE > 0, log(MVE), NA_real_),

    RD_intensity = ifelse(Sales > 0, RAD / Sales, NA_real_),

    year_diff = year - dplyr::lag(year, 1),
    is_consecutive = (year_diff == 1),

    Sales_lag = ifelse(is_consecutive, dplyr::lag(Sales), NA_real_),
    Firm_Growth  =  ifelse(Sales_lag  >  0,  (Sales  -  Sales_lag)/Sales_lag,
NA_real_)
  ) %>%
  ungroup() %>%
  dplyr::select(gvkey, year, SIZE, ROA, Leverage, MVE, TobinQ, ln_MC,
                RD_intensity, Firm_Growth, Sales_lag)

data_final  <-  left_join(data_final,  firm_base_unique,  by  =  c("gvkey",
"year"))
rm(firm_base_unique)

#
==========================================================================
===
# 5. CÁLCULOS DE INDÚSTRIA
#
==========================================================================
===

industry_stats <- data_final %>%
  distinct(gvkey, year, .keep_all = TRUE) %>%
  dplyr::filter(!is.na(SIC)) %>%
  group_by(year, SIC) %>%
  mutate(
    Ind_Total_Sales = sum(Sales, na.rm = TRUE),
    Mkt_Share  =  ifelse(Ind_Total_Sales  >  0,  Sales  /  Ind_Total_Sales,
NA_real_),
    Mkt_Share_Sq = Mkt_Share^2
  ) %>%
  summarise(
    HHI = sum(Mkt_Share_Sq, na.rm = TRUE),
    INDGROWTH = mean(Firm_Growth, na.rm = TRUE),
    .groups = "drop"
  )

industry_stats <- industry_stats %>%
```

```
  arrange(SIC, year) %>%
  group_by(SIC) %>%
  mutate(
    HHI_lag  =  ifelse(year  ==  dplyr::lag(year)  +  1,  dplyr::lag(HHI),
NA_real_),
    IND_COMP_INTENSITY = HHI - HHI_lag
  ) %>%
  ungroup()

data_final <- left_join(data_final, industry_stats, by = c("year", "SIC"))

tabela_industria <- data_final %>%
  distinct(gvkey, .keep_all = TRUE) %>%
  mutate(
    # Garantindo que SIC seja tratado como caractere para o str_sub
    SIC_val = as.character(SIC),
    SIC_2dig = as.numeric(str_sub(SIC_val, 1, 2)),
    Setor = case_when(
      SIC_2dig >= 1 & SIC_2dig <= 9 ~ "Agriculture & Fishing",
      SIC_2dig >= 10 & SIC_2dig <= 14 ~ "Mining",
      SIC_2dig >= 15 & SIC_2dig <= 17 ~ "Construction",
      SIC_2dig >= 20 & SIC_2dig <= 39 ~ "Manufacturing",
      SIC_2dig >= 40 & SIC_2dig <= 49 ~ "Transportation & Utilities",
      SIC_2dig >= 50 & SIC_2dig <= 51 ~ "Wholesale Trade",
      SIC_2dig >= 52 & SIC_2dig <= 59 ~ "Retail Trade",
      SIC_2dig >= 60 & SIC_2dig <= 67 ~ "Finance, Insurance & Real Estate",
      SIC_2dig >= 70 & SIC_2dig <= 89 ~ "Services",
      TRUE ~ "Other/Public Admin"
    )
  ) %>%
  group_by(Setor) %>%
  summarise(Firms = n(), .groups = "drop") %>%
  mutate(Percentage = round((Firms / sum(Firms)) * 100, 2)) %>%
  arrange(desc(Firms))

print(tabela_industria)

rm(industry_stats)

#
===========================================================================
===
# 6. MENSURAÇÃO DA MIOPIA DE MARKETING
# Metodologia: Mizik & Jacobson (2007, 2010) via Resíduos de GMM
#
===========================================================================
===

firm_unique <- data_final %>%
  distinct(gvkey, year, .keep_all = TRUE) %>%
  mutate(ROA_GMM = OIBD / AT, MKT_int = (SGAE - RAD) / AT, RAD_int = RAD /
AT) %>%
  mutate(across(c(ROA_GMM, MKT_int, RAD_int), minha_winsorize)) %>%
  dplyr::filter(!is.na(ROA_GMM), !is.na(MKT_int), !is.na(RAD_int))

p_stats <- pdata.frame(firm_unique, index = c("gvkey", "year"))

try({
  gmm_ROA <- pgmm(ROA_GMM ~ plm::lag(ROA_GMM, 1) | plm::lag(ROA_GMM, 2:5),
data = p_stats, effect = "twoways", model = "onestep", transformation = "ld",
collapse = TRUE)
  gmm_MKT <- pgmm(MKT_int ~ plm::lag(MKT_int, 1) | plm::lag(MKT_int, 2:5),
data = p_stats, effect = "twoways", model = "onestep", transformation = "ld",
collapse = TRUE)
  gmm_RAD <- pgmm(RAD_int ~ plm::lag(RAD_int, 1) | plm::lag(RAD_int, 2:5),
data = p_stats, effect = "twoways", model = "onestep", transformation = "ld",
collapse = TRUE)

  get_level_residuals <- function(gmm_model, data, variable_name) {
```

```
    beta <- coef(gmm_model)[1]
    y <- data[[variable_name]]
    y_lag <- dplyr::lag(data[[variable_name]], 1)
    valid_idx <- !is.na(y) & !is.na(y_lag)
    partial_res <- rep(NA, length(y))
    partial_res[valid_idx] <- y[valid_idx] - (beta * y_lag[valid_idx])
    temp_df <- data.frame(gvkey = index(data)[[1]], partial = partial_res)
%>%
      group_by(gvkey) %>% mutate(alpha_i = mean(partial, na.rm = TRUE),
final_res = partial - alpha_i) %>% ungroup()
    return(temp_df$final_res)
  }

  firm_unique$res_ROA <- get_level_residuals(gmm_ROA, p_stats, "ROA_GMM")
  firm_unique$res_MKT <- get_level_residuals(gmm_MKT, p_stats, "MKT_int")
  firm_unique$res_RAD <- get_level_residuals(gmm_RAD, p_stats, "RAD_int")

  firm_unique <- firm_unique %>% mutate(myopic = if_else(res_ROA > 0 &
res_MKT < 0 & res_RAD < 0, 1, 0))

  cols_to_add <- firm_unique %>% as.data.frame() %>% dplyr::select(gvkey,
year, myopic, res_MKT, res_RAD)
  data_final <- left_join(data_final, cols_to_add, by = c("gvkey", "year"))
}, silent = FALSE)

rm(firm_unique, p_stats)
if(exists("gmm_ROA")) rm(gmm_ROA, gmm_MKT, gmm_RAD, get_level_residuals)

#
===========================================================================
===
# 7. MENSURAÇÃO DOS INCENTIVOS DE EQUITY (DELTA) E INCENTIVOS DOS PARES (TMT)
#
===========================================================================
===

data_final <- data_final %>%
  mutate(across(c(PRC, SHOEP, OPTEX, OPTUNEX, SAL, BON, tdc1), as.numeric))
%>%
  mutate(
    BON = if_else(!is.na(SAL) & is.na(BON), 0, BON),
    SHOEP = if_else(!is.na(SAL) & is.na(SHOEP), 0, SHOEP),
    OPTEX = if_else(!is.na(SAL) & is.na(OPTEX), 0, OPTEX),
    OPTUNEX = if_else(!is.na(SAL) & is.na(OPTUNEX), 0, OPTUNEX),

    onepct = 0.01 * PRC * (SHOEP + OPTEX + OPTUNEX),
    total_comp = onepct + SAL + BON,
    Equity_inc = ifelse(total_comp > 0, onepct / total_comp, NA_real_),

    CMOBONUS = ifelse(IS_CMO == 1, BON, 0),
    CEOBONUS = ifelse(is_ceo_flag, BON, 0)
  )

# 2. TMT Incentive
termos_coo_check    <-    "engineering|operating|procurement|quality|supply
chain|\\bcoo\\b"

tmt_inc <- data_final %>%
  group_by(gvkey, year) %>%
  mutate(
    tot_pay = sum(tdc1, na.rm = TRUE),
    w_eq = ifelse(tot_pay > 0, (tdc1/tot_pay) * Equity_inc, NA_real_),

    # Identificadores booleanos de cargo
    is_cfo_flag = replace_na(as.character(cfoann), "") == "CFO",
    is_coo_flag = case_when(
      is_ceo_flag == TRUE ~ FALSE,
      as.character(cfoann) == "CFO" ~ FALSE,
      str_detect(str_to_lower(titleann), termos_coo_check) ~ TRUE,
```

```
      str_detect(str_to_lower(titleann),           "president")          &
!str_detect(str_to_lower(titleann), "vice president|vp") ~ TRUE,
      TRUE ~ FALSE
    ),
    is_triad = (IS_CMO == 1 | is_ceo_flag == TRUE | is_cfo_flag == TRUE)
  ) %>%
  summarise(
    # Original
    n_non_cmo = sum(IS_CMO == 0, na.rm = TRUE),
    s_w = sum(w_eq[IS_CMO == 0], na.rm = TRUE),
    TMTINCENTIVE = ifelse(n_non_cmo > 0, s_w / n_non_cmo, NA_real_),

    # 2 (Exclui Triade)
    n_rest_tmt = sum(!is_triad, na.rm = TRUE),
    s_w_rest   = sum(w_eq[!is_triad], na.rm = TRUE),
    TMTINCENTIVE_2 = ifelse(n_rest_tmt > 0, s_w_rest / n_rest_tmt, NA_real_),

    # 3 (Modelo Base - Exclui CMO e CFO)
    n_no_cmo_cfo = sum(IS_CMO == 0 & !is_cfo_flag, na.rm = TRUE),
    s_w_no_cmo_cfo = sum(w_eq[IS_CMO == 0 & !is_cfo_flag], na.rm = TRUE),
    TMTINCENTIVE_3 = ifelse(n_no_cmo_cfo > 0, s_w_no_cmo_cfo / n_no_cmo_cfo,
NA_real_),

    # TMT CEO (Exclui CMO e CEO, inclui CFO)
    n_ex_ceo = sum(IS_CMO == 0 & !is_ceo_flag, na.rm = TRUE),
    s_w_ex_ceo = sum(w_eq[IS_CMO == 0 & !is_ceo_flag], na.rm = TRUE),
    TMTINCENTIVE_EX_CEO  =  ifelse(n_ex_ceo  >  0,  s_w_ex_ceo  /  n_ex_ceo,
NA_real_),

    # TMT COO (Exclui CMO e COO, inclui CFO)
    n_ex_coo = sum(IS_CMO == 0 & !is_coo_flag, na.rm = TRUE),
    s_w_ex_coo = sum(w_eq[IS_CMO == 0 & !is_coo_flag], na.rm = TRUE),
    TMTINCENTIVE_EX_COO  =  ifelse(n_ex_coo  >  0,  s_w_ex_coo  /  n_ex_coo,
NA_real_),

    .groups="drop"
  )

data_final <- left_join(data_final, tmt_inc, by = c("gvkey", "year"))
rm(tmt_inc, termos_coo_check)

#
==========================================================================
===
# 8. HECKMAN (PROBIT)
#
==========================================================================
===

real_cmo_flag <- data_final %>%
  dplyr::filter(IS_CMO == 1) %>%
  group_by(gvkey, year) %>%
  arrange(desc(tdc1)) %>%
  slice(1) %>%
  ungroup() %>%
  mutate(is_the_real_cmo = TRUE) %>%
  dplyr::select(gvkey, year, execid, is_the_real_cmo)

data_final <- data_final %>%
  left_join(real_cmo_flag, by = c("gvkey", "year", "execid")) %>%
  mutate(is_the_real_cmo = replace_na(is_the_real_cmo, FALSE))

rm(real_cmo_flag)

# A. TMT MKT EXP
cmo_patt                                                                <-
"marketing|cmo|customer|brand|channel|product\\b|pricing|advertising|sales|
merchandise|consumer|retail"
```

```
tmt_mkt_df <- data_final %>%
  group_by(gvkey, year) %>%
  summarise(
    n_mkt_execs = sum(case_when(
      is_ceo_flag == TRUE ~ 0,
      is_the_real_cmo == TRUE ~ 0,
      str_detect(str_to_lower(titleann), cmo_patt) ~ 1,
      TRUE ~ 0
    ), na.rm = TRUE),
    n_tmt_peers = n_distinct(execid[!is_the_real_cmo & !is_ceo_flag]),
    n_tmt_peers = ifelse(n_tmt_peers < 1, 1, n_tmt_peers),
    TMT_MKT_Experience_Proxy = ifelse(n_mkt_execs > 0, n_mkt_execs /
n_tmt_peers, 0),
    .groups = "drop"
  )
data_final <- data_final %>% left_join(tmt_mkt_df, by = c("gvkey", "year"))
rm(tmt_mkt_df)

# B. COO Presence
termos_menz <- "engineering|operating|procurement|quality|supply
chain|\\bcoo\\b"
coo_df <- data_final %>%
  group_by(gvkey, year) %>%
  summarise(
    COO_presence = max(case_when(
      is_ceo_flag == TRUE ~ 0,
      as.character(cfoann) == "CFO" ~ 0,
      str_detect(str_to_lower(titleann), termos_menz) ~ 1,
      str_detect(str_to_lower(titleann), "president") &
!str_detect(str_to_lower(titleann), "vice president|vp") ~ 1,
      TRUE ~ 0
    ), na.rm = TRUE),
    .groups = "drop"
  )
data_final <- data_final %>% left_join(coo_df, by = c("gvkey", "year"))
rm(coo_df, termos_menz)

# C. Diversification Proxy
termos_coo_check <- "engineering|operating|procurement|quality|supply
chain|\\bcoo\\b"
termos_divisao <- "group|sector|division|unit|subsidiary|region"

div_df <- data_final %>%
  group_by(gvkey, year) %>%
  summarise(
    n_div_execs = sum(case_when(
      is_ceo_flag == TRUE ~ 0,
      as.character(cfoann) == "CFO" ~ 0,
      str_detect(str_to_lower(titleann), termos_coo_check) ~ 0,
      str_detect(str_to_lower(titleann), termos_divisao) ~ 1,
      str_detect(str_to_lower(titleann), "president") &
!str_detect(str_to_lower(titleann), "vice president|vp") ~ 1,
      TRUE ~ 0
    ), na.rm = TRUE),
    total_execs = n_distinct(execid),
    Diversification_Proxy = ifelse(total_execs > 0, n_div_execs /
total_execs, 0),
    .groups = "drop"
  )
data_final <- data_final %>% left_join(div_df %>% dplyr::select(gvkey, year,
Diversification_Proxy), by = c("gvkey", "year"))
rm(div_df, termos_divisao, termos_coo_check)

# Preparação Probit
data_final <- data_final %>%
  arrange(gvkey, year) %>%
  group_by(gvkey) %>%
  mutate(
```

```
    log_SGA  =  ifelse(!is.na(SGAE),  log(abs(as.numeric(SGAE))  +  1),
NA_real_),
    log_XAD = ifelse(!is.na(XAD), log(abs(as.numeric(XAD)) + 1), NA_real_),
    Book_Val = AT - LT,
    MTB  =  ifelse(!is.na(Book_Val)  &  Book_Val  >  0  &  !is.na(MVE),  MVE  /
Book_Val, NA_real_),
    price_lag = dplyr::lag(PRC, 1),
    Stock_Return = ifelse(!is.na(price_lag) & price_lag > 0 & !is.na(PRC),
((PRC + DVPSX_F) - price_lag) / price_lag, NA_real_)
  ) %>%
  ungroup()

vars_to_lag <- c("SIZE", "ROA", "Leverage", "log_SGA", "log_XAD", "XAD_dum",
"MTB", "Stock_Return")
vars_current     <-     c("TMT_MKT_Experience_Proxy",     "COO_presence",
"Diversification_Proxy", "HHI")

probit_data <- data_final %>%
  distinct(gvkey, year, .keep_all = TRUE) %>%
  group_by(year) %>%
  mutate(across(any_of(c(vars_to_lag, vars_current)), minha_winsorize)) %>%
  ungroup() %>%
  group_by(gvkey) %>%
  mutate(
    across(all_of(vars_to_lag), ~ dplyr::lag(., 1), .names = "{.col}_lag"),
    IS_CMO_FIRM = max(IS_CMO, na.rm = TRUE)
  ) %>%
  ungroup() %>%
  mutate(IS_CMO_FIRM = ifelse(is.infinite(IS_CMO_FIRM), 0, IS_CMO_FIRM)) %>%
  dplyr::filter(!is.na(IS_CMO_FIRM)) %>%
  dplyr::filter(!is.na(SIZE_lag), !is.na(ROA_lag), !is.na(log_SGA_lag))

try({
  probit_model <- glm(IS_CMO_FIRM ~
                        SIZE_lag + ROA_lag + Leverage_lag +
                        log_SGA_lag + log_XAD_lag + XAD_dum_lag +
                        MTB_lag + Stock_Return_lag +
                        TMT_MKT_Experience_Proxy + COO_presence +
                        Diversification_Proxy + HHI +
                        factor(year) + factor(SIC),
                      family = binomial(link = "probit"),
                      data = probit_data,
                      na.action = na.exclude)

  pred_link <- predict(probit_model, type = "link")
  probit_data$Inverse_Mill <- dnorm(pred_link) / pnorm(pred_link)

  data_final <- left_join(data_final,
                          probit_data   %>%   dplyr::select(gvkey,   year,
Inverse_Mill),
                          by = c("gvkey", "year"))
}, silent = FALSE)

rm(probit_data, probit_model, pred_link, vars_to_lag, vars_current)
gc()

#
============================================================================
===
# 9. CÁLCULO DE TENURE E VARIÁVEIS DEMOGRÁFICAS
#
============================================================================
===

exec_history <- data_final %>%
  group_by(gvkey, execid) %>%
  mutate(
    First_Year_Observed = min(year, na.rm = TRUE),
    Tenure_Firm_Observed = year - First_Year_Observed
```

```
  ) %>%
  ungroup()

data_final <- data_final %>%
  left_join(exec_history    %>%    dplyr::select(gvkey,    execid,    year,
Tenure_Firm_Observed),
            by = c("gvkey", "execid", "year"))
rm(exec_history)

ceo_info <- data_final %>%
  dplyr::filter(is_ceo_flag) %>%
  distinct(gvkey, year, .keep_all = TRUE) %>%
  mutate(
    date_b = ymd(BECCEO), date_j = ymd(JCOMP),
    yrs_before  =  ifelse(!is.na(date_b)  &  !is.na(date_j),  year(date_b)  -
year(date_j), NA),
    Outsider_CEO = ifelse(!is.na(yrs_before) & yrs_before <= 0, 1, 0)
  ) %>% dplyr::select(gvkey, year, Outsider_CEO)

data_final <- left_join(data_final, ceo_info, by = c("gvkey", "year"))
rm(ceo_info)

tmt_gender_stats <- data_final %>%
  filter(is_ceo_flag == FALSE & IS_CMO == 0) %>%
  group_by(gvkey, year) %>%
  summarise(
    n_female_peers = sum(gender == "FEMALE", na.rm = TRUE),
    n_total_peers = n(),
    .groups = "drop"
  ) %>%
  mutate(
    TMT_Female_Ratio   =   ifelse(n_total_peers   >   0,   n_female_peers   /
n_total_peers, 0)
  ) %>%
  dplyr::select(gvkey, year, TMT_Female_Ratio)

data_final <- data_final %>%
  left_join(tmt_gender_stats, by = c("gvkey", "year")) %>%
  mutate(TMT_Female_Ratio = replace_na(TMT_Female_Ratio, 0))
rm(tmt_gender_stats)

#
======================================================================
===
# 10. CONSOLIDAÇÃO DA DÍADE ESTRATÉGICA E UNIDADE DE ANÁLISE (Firma-Ano)
# Objeto Final: data_firm_3 (Base Principal para Regressões)
#
======================================================================
===

# A. CMO Principal
cmo_attrs <- data_final %>%
  dplyr::filter(IS_CMO == 1) %>%
  group_by(gvkey, year) %>%
  arrange(desc(tdc1)) %>%
  slice(1) %>%
  ungroup() %>%
  arrange(gvkey, year) %>%
  group_by(gvkey) %>%
  mutate(
    prev_cmo_id = dplyr::lag(execid),
    prev_year = dplyr::lag(year),
    is_consecutive = (year - prev_year == 1),
    is_turnover_strict = case_when(
      !is_consecutive ~ FALSE,
      is.na(prev_cmo_id) ~ FALSE,
      execid != prev_cmo_id ~ TRUE,
      TRUE ~ FALSE
    )
```

```
  ) %>%
  ungroup() %>%
  dplyr::filter(is_turnover_strict == FALSE) %>%
  mutate(
    Equity_inc_CMO_final = Equity_inc,
    CMO_Tenure_Abs = Tenure_Firm_Observed,
    CMO_gender_raw = gender,
    CMOBONUS_Final = BON,
    CMO_age = age
  ) %>%
  dplyr::select(gvkey, year, principal_cmo_id = execid,
                Equity_inc_CMO_final,
                CMO_Tenure_Abs, CMO_gender_raw, CMOBONUS_Final,
                CMO_age)

# B. CEO Principal
ceo_attrs <- data_final %>%
  dplyr::filter(is_ceo_flag) %>%
  group_by(gvkey, year) %>%
  arrange(desc(tdc1)) %>%
  slice(1) %>%
  ungroup() %>%
  arrange(gvkey, year) %>%
  group_by(gvkey) %>%
  mutate(
    prev_ceo_id = dplyr::lag(execid),
    prev_year = dplyr::lag(year),
    CEO_Turnover  =  case_when((year  -  prev_year  ==  1)  &  (execid  !=
prev_ceo_id) ~ 1, TRUE ~ 0 )
  ) %>%
  ungroup() %>%
  mutate(
    CEO_Tenure_Abs = Tenure_Firm_Observed,
    CEO_gender_raw = gender,
    CEOBONUS_Final = BON,
    CEO_age = age,
    Equity_inc_CEO_final = Equity_inc
  ) %>%
  dplyr::select(gvkey, year, principal_ceo_id = execid, CEO_Turnover,
                CEO_Tenure_Abs, CEO_gender_raw, CEOBONUS_Final, CEO_age,
                Equity_inc_CEO_final = Equity_inc)

# C. CFO Principal
cfo_attrs <- data_final %>%
  dplyr::filter(cfoann == "CFO") %>%
  group_by(gvkey, year) %>%
  arrange(desc(tdc1)) %>%
  slice(1) %>%
  ungroup() %>%
  arrange(gvkey, year) %>%
  group_by(gvkey) %>%
  mutate(
    prev_cfo_id = dplyr::lag(execid),
    prev_year = dplyr::lag(year),
    CFO_Turnover  =  case_when((year  -  prev_year  ==  1)  &  (execid  !=
prev_cfo_id) ~ 1, TRUE ~ 0 )
  ) %>%
  ungroup() %>%
  mutate(
    CFO_Tenure = Tenure_Firm_Observed,
    CFO_gender_raw = gender,
    CFO_age = age,
    Equity_inc_CFO = Equity_inc,
    CFOBONUS_Final = BON
  ) %>%
  dplyr::select(gvkey, year, principal_cfo_id = execid, CFO_Turnover,
                CFO_Tenure, CFO_gender_raw, CFO_age,
                Equity_inc_CFO, CFOBONUS_Final)
```

```
# D. COO Principal
termos_coo_check    <-    "engineering|operating|procurement|quality|supply
chain|\\bcoo\\b"

coo_attrs <- data_final %>%
  filter(
    is_ceo_flag == FALSE,
    replace_na(as.character(cfoann), "") != "CFO",
    !is.na(titleann),
    str_detect(str_to_lower(titleann), termos_coo_check) |
      (str_detect(str_to_lower(titleann),          "president")          &
!str_detect(str_to_lower(titleann), "vice president|vp"))
  ) %>%
  group_by(gvkey, year) %>%
  arrange(desc(tdc1)) %>%
  slice(1) %>%
  ungroup() %>%
  mutate(
    COO_gender_raw = gender,
    COO_Tenure = Tenure_Firm_Observed,
    COO_age = age,
    COOBONUS = BON,
    sqrt_Equity_COO = sqrt(Equity_inc)
  ) %>%
  dplyr::select(gvkey,  year,  principal_coo_id  =  execid,  COO_gender_raw,
COO_Tenure, COO_age, COOBONUS, sqrt_Equity_COO)

# Merge Final
data_firm_3 <- data_final %>%
  group_by(gvkey, year) %>%
  left_join(cmo_attrs, by = c("gvkey", "year")) %>%
  left_join(ceo_attrs, by = c("gvkey", "year")) %>%
  left_join(cfo_attrs, by = c("gvkey", "year")) %>%
  left_join(coo_attrs, by = c("gvkey", "year")) %>%
  mutate(IS_CMO_Firm_Flag = max(IS_CMO, na.rm = TRUE)) %>%
  distinct(gvkey, year, .keep_all = TRUE) %>%
  ungroup() %>%
  mutate(
    IS_CMO_Firm       =       ifelse(is.infinite(IS_CMO_Firm_Flag)       |
is.na(IS_CMO_Firm_Flag), 0, IS_CMO_Firm_Flag),
    Equity_inc_CMO = Equity_inc_CMO_final,
    Equity_inc_CEO = Equity_inc_CEO_final,

    CMOBONUS = CMOBONUS_Final,
    CEOBONUS = CEOBONUS_Final,
    CFOBONUS = CFOBONUS_Final,

    CMO_gender = ifelse(CMO_gender_raw == "FEMALE", 1, 0),
    CEO_gender = ifelse(CEO_gender_raw == "FEMALE", 1, 0),
    CFO_gender = ifelse(CFO_gender_raw == "FEMALE", 1, 0),
    COO_gender = ifelse(COO_gender_raw == "FEMALE", 1, 0),

    CMO_Tenure = CMO_Tenure_Abs,
    CEO_Tenure = CEO_Tenure_Abs
  ) %>%
  dplyr::select(
    gvkey, year, ln_MC, CSO, TobinQ,
    IS_CMO_Firm, Equity_inc_CMO, CMOBONUS, CMO_Tenure, CMO_gender, CMO_age,
    CEOBONUS, CEO_Tenure, CEO_gender, CEO_age, CEO_Turnover,
    CFOBONUS, CFO_gender, CFO_age, CFO_Tenure, Equity_inc_CFO, CFO_Turnover,
    COO_gender, COOBONUS, sqrt_Equity_COO, COO_age, COO_Tenure,
    TMT_Female_Ratio,
    SIZE, ROA, Leverage, RD_intensity, RAD_dum,
    myopic, res_MKT, res_RAD, Inverse_Mill,
    IND_COMP_INTENSITY, INDGROWTH, TMTINCENTIVE_3,
    Equity_inc_CEO, TMTINCENTIVE_EX_CEO,
    TMTINCENTIVE_EX_COO
  ) %>%
  arrange(gvkey, year)
```

```
#
================================================================================
===
# 10.B - CRIANDO A BASE PARALELA (EXCLUI TURNOVER DO CFO, MANTÉM CMO)
#
================================================================================
===

# 1. Recriar os atributos do CMO SEM FILTRAR o turnover
cmo_attrs_com_turnover <- data_final %>%
  dplyr::filter(IS_CMO == 1) %>%
  group_by(gvkey, year) %>%
  arrange(desc(tdc1)) %>%
  slice(1) %>%
  ungroup() %>%
  arrange(gvkey, year) %>%
  group_by(gvkey) %>%
  mutate(
    prev_cmo_id = dplyr::lag(execid),
    prev_year = dplyr::lag(year),
    CMO_Turnover = case_when(
      (year - prev_year == 1) & (execid != prev_cmo_id) ~ 1,
      TRUE ~ 0
    )
  ) %>%
  ungroup() %>%
  mutate(
    Equity_inc_CMO_final = Equity_inc,
    CMO_Tenure_Abs = Tenure_Firm_Observed,
    CMO_gender_raw = gender,
    CMOBONUS_Final = BON,
    CMO_age = age
  ) %>%
  dplyr::select(gvkey, year, principal_cmo_id = execid,
                Equity_inc_CMO_final,
                CMO_Tenure_Abs, CMO_gender_raw, CMOBONUS_Final,
                CMO_age, CMO_Turnover)

# 2. Merge Final para a Base Paralela
data_firm_com_turnover <- data_final %>%
  group_by(gvkey, year) %>%
  left_join(cmo_attrs_com_turnover, by = c("gvkey", "year")) %>%
  left_join(ceo_attrs, by = c("gvkey", "year")) %>%
  left_join(cfo_attrs, by = c("gvkey", "year")) %>%
  left_join(coo_attrs, by = c("gvkey", "year")) %>%
  mutate(IS_CMO_Firm_Flag = max(IS_CMO, na.rm = TRUE)) %>%
  distinct(gvkey, year, .keep_all = TRUE) %>%
  ungroup() %>%
  mutate(
    IS_CMO_Firm       =       ifelse(is.infinite(IS_CMO_Firm_Flag)       |
is.na(IS_CMO_Firm_Flag), 0, IS_CMO_Firm_Flag),
    Equity_inc_CMO = Equity_inc_CMO_final,
    Equity_inc_CEO = Equity_inc_CEO_final,

    CMOBONUS = CMOBONUS_Final,
    CEOBONUS = CEOBONUS_Final,
    CFOBONUS = CFOBONUS_Final,

    CMO_gender = ifelse(CMO_gender_raw == "FEMALE", 1, 0),
    CEO_gender = ifelse(CEO_gender_raw == "FEMALE", 1, 0),
    CFO_gender = ifelse(CFO_gender_raw == "FEMALE", 1, 0),
    COO_gender = ifelse(COO_gender_raw == "FEMALE", 1, 0),

    CMO_Tenure = CMO_Tenure_Abs,
    CEO_Tenure = CEO_Tenure_Abs
  ) %>%
  dplyr::select(
    gvkey, year, ln_MC, CSO, TobinQ,
```

```
    IS_CMO_Firm, Equity_inc_CMO, CMOBONUS, CMO_Tenure, CMO_gender, CMO_age,
CMO_Turnover,
    CEOBONUS, CEO_Tenure, CEO_gender, CEO_age, CEO_Turnover,
    CFOBONUS, CFO_gender, CFO_age, CFO_Tenure, Equity_inc_CFO, CFO_Turnover,
    COO_gender, COOBONUS, sqrt_Equity_COO, COO_age, COO_Tenure,
    TMT_Female_Ratio,
    SIZE, ROA, Leverage, RD_intensity, RAD_dum,
    myopic, res_MKT, res_RAD, Inverse_Mill,
    IND_COMP_INTENSITY, INDGROWTH, TMTINCENTIVE_3,
    Equity_inc_CEO, TMTINCENTIVE_EX_CEO, TMTINCENTIVE_EX_COO
  ) %>%
  arrange(gvkey, year) %>%
  filter(IS_CMO_Firm >= 1) %>%
  filter(CFO_Turnover == 0) # <--- Excluímos o turnover do CFO.

# 3. Winsorização e Transformações
vars_to_winsorize <- c(
  "CMOBONUS", "COOBONUS", "CMO_Tenure", "COO_Tenure", "CMO_age",
  "CEOBONUS", "CEO_Tenure", "CEO_age",
  "CFOBONUS", "CFO_Tenure", "CFO_age", "COO_age",
  "SIZE", "ROA", "Leverage", "RD_intensity",
  "res_MKT", "res_RAD", "IND_COMP_INTENSITY", "INDGROWTH", "CSO"
)

existing_vars_win      <-      vars_to_winsorize[vars_to_winsorize      %in%
names(data_firm_com_turnover)]

data_firm_com_turnover <- data_firm_com_turnover %>%
  group_by(year) %>%
  mutate(across(all_of(existing_vars_win),  ~  minha_winsorize(.,  probs  =
c(0.01, 0.99)))) %>%
  ungroup() %>%
  mutate(
    sqrt_Equity_CMO = sqrt(Equity_inc_CMO),
    sqrt_Equity_CFO = sqrt(Equity_inc_CFO),
    sqrt_Equity_CEO = sqrt(Equity_inc_CEO),
    sqrt_TMT_Inc    = sqrt(TMTINCENTIVE_3),
    sqrt_TMT_Inc_CEO = sqrt(TMTINCENTIVE_EX_CEO),
    sqrt_TMT_Inc_COO = sqrt(TMTINCENTIVE_EX_COO)
  )

# 4. Padronização final
standardize_vector <- function(x) {
  if(!is.numeric(x) | all(is.na(x))) return(x)
  mean_val <- mean(x, na.rm = TRUE)
  sd_val <- sd(x, na.rm = TRUE)
  if(is.na(sd_val) | sd_val == 0) return(x)
  return((x - mean_val) / sd_val)
}

vars_to_standardize <- c(
  "sqrt_Equity_CMO", "sqrt_Equity_COO", "Equity_inc_CMO",
  "CMOBONUS", "CMO_Tenure", "CMO_age",
  "Equity_inc_CFO", "CEOBONUS", "CEO_Tenure", "CEO_age",
  "CFOBONUS", "CFO_Tenure", "CFO_age",
  "TMTINCENTIVE_3", "TMT_Female_Ratio",
  "SIZE", "ROA", "Leverage", "RD_intensity",
  "Inverse_Mill", "res_MKT", "res_RAD",
  "IND_COMP_INTENSITY", "INDGROWTH",
  "sqrt_Equity_CFO", "sqrt_TMT_Inc",
  "CSO", "TobinQ", "sqrt_Equity_CEO", "sqrt_TMT_Inc_CEO", "sqrt_TMT_Inc_COO"
)

existing_vars_std     <-     vars_to_standardize[vars_to_standardize     %in%
names(data_firm_com_turnover)]

data_firm_com_turnover <- data_firm_com_turnover %>%
  mutate(across(all_of(existing_vars_std), standardize_vector))
```

```
#
================================================================================
===
# WINSORIZAÇÃO, PADRONIZAÇÃO E LIMPEZA
#
================================================================================
===

data_firm_3 <- data_firm_3 %>% filter(IS_CMO_Firm >= 1)

vars_to_winsorize <- c(
  "CMOBONUS", "COOBONUS", "CMO_Tenure", "COO_Tenure", "CMO_age",
  "CEOBONUS", "CEO_Tenure", "CEO_age",
  "CFOBONUS", "CFO_Tenure", "CFO_age", "COO_age",
  "SIZE", "ROA", "Leverage", "RD_intensity",
  "res_MKT", "res_RAD", "IND_COMP_INTENSITY", "INDGROWTH", "CSO"
)

existing_vars_win      <-      vars_to_winsorize[vars_to_winsorize      %in%
names(data_firm_3)]

data_firm_3 <- data_firm_3 %>%
  group_by(year) %>%
  mutate(across(all_of(existing_vars_win),  ~  minha_winsorize(.,  probs  =
c(0.01, 0.99)))) %>%
  ungroup()

base_sem_padronizar <- data_firm_3 %>%
  mutate(
    # Raízes
    sqrt_Equity_CMO = sqrt(Equity_inc_CMO),
    sqrt_Equity_CFO = sqrt(Equity_inc_CFO),
    sqrt_Equity_CEO = sqrt(Equity_inc_CEO),
    sqrt_TMT_Inc    = sqrt(TMTINCENTIVE_3),
    sqrt_TMT_Inc_CEO = sqrt(TMTINCENTIVE_EX_CEO),
    sqrt_TMT_Inc_COO = sqrt(TMTINCENTIVE_EX_COO),

    # Logs (Usando log1p para evitar -Inf em zeros originais)
    log_Equity_inc_CMO = log1p(Equity_inc_CMO),
    log_Equity_inc_CFO = log1p(Equity_inc_CFO),
    log_TMTINCENTIVE_3 = log1p(TMTINCENTIVE_3)
  )

data_firm_3 <- base_sem_padronizar

standardize_vector <- function(x) {
  if(!is.numeric(x) | all(is.na(x))) return(x)
  mean_val <- mean(x, na.rm = TRUE)
  sd_val <- sd(x, na.rm = TRUE)
  if(is.na(sd_val) | sd_val == 0) return(x)
  return((x - mean_val) / sd_val)
}

# Lista atualizada incluindo os logs
vars_to_standardize <- c(
  "sqrt_Equity_CMO",          "sqrt_Equity_COO",          "Equity_inc_CMO",
"log_Equity_inc_CMO",
  "CMOBONUS", "CMO_Tenure", "CMO_age",
  "Equity_inc_CFO",    "log_Equity_inc_CFO",    "CEOBONUS",    "CEO_Tenure",
"CEO_age",
  "CFOBONUS", "CFO_Tenure", "CFO_age",
  "TMTINCENTIVE_3", "log_TMTINCENTIVE_3", "TMT_Female_Ratio",
  "SIZE", "ROA", "Leverage", "RD_intensity",
  "Inverse_Mill", "res_MKT", "res_RAD",
  "IND_COMP_INTENSITY", "INDGROWTH",
  "sqrt_Equity_CFO", "sqrt_TMT_Inc",
  "CSO",      "TobinQ",       "sqrt_Equity_CEO",       "sqrt_TMT_Inc_CEO",
"sqrt_TMT_Inc_COO",
  "COOBONUS", "COO_age", "COO_Tenure"
```

```
)
existing_vars_std    <-    vars_to_standardize[vars_to_standardize    %in%
names(data_firm_3)]

data_firm_3 <- data_firm_3 %>%
  mutate(across(all_of(existing_vars_std), standardize_vector))

rm(existing_vars_std,        existing_vars_win,       vars_to_standardize,
vars_to_winsorize,
   standardize_vector, cmo_patt, cols_map, cols_to_rename, existing_cols)

objetos_para_manter <- c("dados_long", "data_firm_3", "base_sem_padronizar",
"minha_winsorize",
                         "data_firm_com_turnover")
rm(list = setdiff(ls(), objetos_para_manter))
gc()
```

J.2. Descriptive Analysis

```
#
============================================================================
===
# 12. ESTATÍSTICAS DESCRITIVAS E CORRELAÇÃO (Ordem Ajustada)
#
============================================================================
===

# 1. Carregar Pacotes
library(dplyr)
library(Hmisc)

# 2. Engenharia de Variáveis (Criar o Lag Corretamente lidando com Gaps
temporais)
dados_com_lag <- base_sem_padronizar %>%
  arrange(gvkey, year) %>%       # Ordena temporalmente
  group_by(gvkey) %>%            # Agrupa por empresa
  mutate(
    # Verifica se o ano da linha anterior é exatamente 1 ano atrás
    LAG_MC = if_else(year == dplyr::lag(year, n = 1) + 1,
                     dplyr::lag(ln_MC, n = 1),
                     NA_real_)   # Se não for, ou se for o 1º ano, retorna
NA
  ) %>%
  ungroup()

# 3. Definir a Ordem Exata
vars_ordenadas <- c(
  "ln_MC",                # MC
  "sqrt_Equity_CMO",      # CMOINCENTIVE
  "CMO_gender",           # CMOGENDER
  "CFO_gender",           # CFOGENDER
  "TMT_Female_Ratio",     # TMTGENDER
  "CEO_gender",           # CEOGENDER
  "LAG_MC",               # LAGMC
  "sqrt_TMT_Inc",         # TMTINCENTIVE
  "sqrt_Equity_CFO",      # CFOINCENTIVE
  "CMOBONUS",             # CMOBONUS
  "CFOBONUS",             # CFOBONUS
  "CFO_Tenure",           # CFOTENURE
  "CMO_Tenure",           # CMOTENURE
  "CMO_age",              # CMOAGE
  "CFO_age",              # CFOAGE
  "CFO_Turnover",         # CFOTURNOVER
  "CEO_Turnover",         # CEOTURNOVER
  "ROA",                  # ROA
```

```
  "SIZE",                # SIZE
  "Leverage",            # LEVERAGE
  "myopic",              # MYOPIC
  "RAD_dum",             # RADDUM
  "RD_intensity",        # RDINTENSITY
  "IND_COMP_INTENSITY", # INDCOMP
  "INDGROWTH",           # INDGROWTH
  "Inverse_Mill"         # INVMILLS
)

# Nomes para exibição
nomes_finais <- c(
  "MC", "CMOINCENTIVE", "CMOGENDER", "CFOGENDER", "TMTGENDER",
  "CEOGENDER", "LAGMC", "TMTINCENTIVE", "CFOINCENTIVE", "CMOBONUS",
  "CFOBONUS", "CFOTENURE", "CMOTENURE", "CMOAGE", "CFOAGE",
  "CFOTURNOVER", "CEOTURNOVER", "ROA", "SIZE", "LEVERAGE",
  "MYOPIC", "RADDUM", "RDINTENSITY", "INDCOMP", "INDGROWTH",
  "INVMILLS"
)

# 4. Selecionar e Renomear
dados_finais <- dados_com_lag %>%
  select(all_of(vars_ordenadas))

colnames(dados_finais) <- nomes_finais

#
===========================================================================
===
# 5. PARTE A e B: Separar para Descritiva (Contínuas vs Dummies)
#
===========================================================================
===

# Identificando quais colunas são dummies (binárias 0/1) para separar
vars_dummies_names <- c("MYOPIC", "CMOGENDER", "CFOGENDER", "RADDUM",
                        "CEOGENDER", "CEOTURNOVER", "CFOTURNOVER")

# Separa os dados mantendo a ordem relativa
dados_dum  <- dados_finais %>% select(any_of(vars_dummies_names))
dados_cont <- dados_finais %>% select(-any_of(vars_dummies_names))

# --- Descritiva Contínuas ---
desc_cont <- data.frame(
  Variavel = names(dados_cont),
  Media = sapply(dados_cont, mean, na.rm = TRUE),
  SD = sapply(dados_cont, sd, na.rm = TRUE),
  Min = sapply(dados_cont, min, na.rm = TRUE),
  Max = sapply(dados_cont, max, na.rm = TRUE),
  Obs = sapply(dados_cont, function(x) sum(!is.na(x)))
)
desc_cont[, 2:5] <- round(desc_cont[, 2:5], 3)

# --- Descritiva Dummies ---
calc_dummy <- function(x) {
  x_validos <- x[!is.na(x)]
  n_1 <- sum(x_validos == 1)
  n_total <- length(x_validos)
  pct <- if(n_total > 0) (n_1 / n_total) * 100 else 0
  return(c(n_1, pct, n_total))
}

if(ncol(dados_dum) > 0) {
  stats_dum <- t(sapply(dados_dum, calc_dummy))
  desc_dummy <- data.frame(
    Variavel = rownames(stats_dum),
    `Ocorrencias (1)` = stats_dum[, 1],
    `Porcentagem (%)` = round(stats_dum[, 2], 1),
    `Total Obs Validas` = stats_dum[, 3],
```

```
    check.names = FALSE
  )
} else {
  desc_dummy <- data.frame()
}

#
===========================================================================
===
# 6. PARTE C: Matriz de Correlação
#
===========================================================================
===

cor_matrix <- rcorr(as.matrix(dados_finais), type = "pearson")
R <- cor_matrix$r
P <- cor_matrix$P

formatar_cor <- function(r, p) {
  if(is.na(p) | is.na(r)) return("")
  stars <- ""
  if(p < 0.01) stars <- "***"
  else if(p < 0.05) stars <- "**"
  else if(p < 0.10) stars <- "*"
  return(paste0(format(round(r, 2), nsmall=2), stars))
}

matriz_final   <-   matrix("",   nrow   =   ncol(dados_finais),   ncol   =
ncol(dados_finais))
rownames(matriz_final) <- colnames(dados_finais)
colnames(matriz_final) <- 1:ncol(dados_finais)

for(i in 1:nrow(R)) {
  for(j in 1:ncol(R)) {
    if(j < i) {
      matriz_final[i, j] <- formatar_cor(R[i, j], P[i, j])
    } else if (i == j) {
      matriz_final[i, j] <- "1"
    }
  }
}

df_correlacao <- as.data.frame(matriz_final)
df_correlacao <- cbind(Variavel = rownames(df_correlacao), df_correlacao)

#
===========================================================================
===
# Limpeza do Ambiente
#
===========================================================================
===
#  As  tabelas  resultantes  foram  adicionadas  aos  objetos  mantidos  para
visualização no R
objetos_para_manter <- c("dados_long", "data_firm_3", "base_sem_padronizar",
                         "desc_cont",    "desc_dummy",    "df_correlacao",
"dados_finais",
                         "data_firm_com_turnover")
rm(list = setdiff(ls(), objetos_para_manter))
gc()
```

J.3. Main Models

```
#
===========================================================================
===
# 13. MODELOS PRINCIPAIS OLS (feols) E EXTRAÇÃO DE INTERCEPTOS (plm)
```

```
#
================================================================================
===

library(fixest)
library(plm)
library(sandwich)
library(performance)

#
================================================================================
===
# 1. DEFINIÇÃO DOS CONTROLES BASE (Para evitar repetição de código)
#
================================================================================
===
# Controles para feols (com efeitos fixos agrupados no final pelo pipe "|")
ctrl_feols_lin <- "+ l(ln_MC, 1) + TMTINCENTIVE_3 + CMOBONUS + RD_intensity
+ ROA + SIZE + IND_COMP_INTENSITY + INDGROWTH + Inverse_Mill + myopic +
RAD_dum + CEO_gender + CEO_Turnover + CFO_Turnover + CFOBONUS +
Equity_inc_CFO + CFO_age + CFO_Tenure + CMO_Tenure + CMO_age +
TMT_Female_Ratio + Leverage | year + gvkey"

ctrl_feols_sq  <- "+ l(ln_MC, 1) + sqrt_TMT_Inc + CMOBONUS + RD_intensity +
ROA + SIZE + IND_COMP_INTENSITY + INDGROWTH + Inverse_Mill + myopic + RAD_dum
+ CEO_gender + CEO_Turnover + CFO_Turnover + CFOBONUS + sqrt_Equity_CFO +
CFO_age + CFO_Tenure + CMO_Tenure + CMO_age + TMT_Female_Ratio + Leverage |
year + gvkey"

# Controles para plm (Sem o pipe, pois os efeitos fixos vão no argumento
'effect')
ctrl_plm_lin  <-  "+  plm::lag(ln_MC,  1)  +  TMTINCENTIVE_3  +  CMOBONUS  +
RD_intensity + ROA + SIZE + IND_COMP_INTENSITY + INDGROWTH + Inverse_Mill +
myopic + RAD_dum + CEO_gender + CEO_Turnover + CFO_Turnover + CFOBONUS +
Equity_inc_CFO  +  CFO_age  +  CFO_Tenure  +  CMO_Tenure  +  CMO_age  +
TMT_Female_Ratio + Leverage"

ctrl_plm_sq  <- "+ plm::lag(ln_MC, 1) + sqrt_TMT_Inc + CMOBONUS + RD_intensity
+ ROA + SIZE + IND_COMP_INTENSITY + INDGROWTH + Inverse_Mill + myopic +
RAD_dum  +  CEO_gender  +  CEO_Turnover  +  CFO_Turnover  +  CFOBONUS  +
sqrt_Equity_CFO  +  CFO_age  +  CFO_Tenure  +  CMO_Tenure  +  CMO_age  +
TMT_Female_Ratio + Leverage"

#
================================================================================
===
# 2. ESTIMAÇÃO DOS MODELOS ESTRUTURAIS (feols)
#
================================================================================
===
formulas_feols <- list(
  "M1_Linear" = as.formula(paste("ln_MC ~", ctrl_feols_lin)),
  "M2_Raiz"   = as.formula(paste("ln_MC ~", ctrl_feols_sq)),
  "M3"       = as.formula(paste("ln_MC ~ Equity_inc_CMO", ctrl_feols_lin)),
  "M4"       = as.formula(paste("ln_MC ~ sqrt_Equity_CMO", ctrl_feols_sq)),
  "M5"         = as.formula(paste("ln_MC ~ sqrt_Equity_CMO + CMO_gender +
CFO_gender", ctrl_feols_sq)),
  "M6"          =  as.formula(paste("ln_MC  ~  sqrt_Equity_CMO*CMO_gender  +
CFO_gender", ctrl_feols_sq)),
  "M7"          =  as.formula(paste("ln_MC  ~  sqrt_Equity_CMO*CMO_gender  +
sqrt_Equity_CMO*CFO_gender", ctrl_feols_sq)),
  "M8"                                =    as.formula(paste("ln_MC    ~
sqrt_Equity_CMO*CMO_gender*CFO_gender", ctrl_feols_sq))
)

# Estima todos os modelos e guarda em uma lista
modelos_feols <- lapply(formulas_feols, function(f) {
  feols(f, panel.id = ~gvkey + year, cluster = ~gvkey, data = data_firm_3)
})
```

```
# 
=========================================================================
===
# 2.5. IMPRESSÃO DOS SUMÁRIOS E TESTES NO CONSOLE (feols)
# 
=========================================================================
===
cat("\n==================================================================
=\n")
cat("          SUMÁRIO E TESTES DOS MODELOS ESTRUTURAIS (feols)\n")
cat("=================================================================\
n\n")

for (nome in names(modelos_feols)) {
  cat(sprintf(">>> RESULTADOS PARA O MODELO: %s <<<\n", toupper(nome)))

  cat("\n--- Sumário (Coeficientes e Significância) ---\n")
  print(summary(modelos_feols[[nome]]))

  cat("\n--- Teste de Wald (Significância Global) ---\n")
  print(wald(modelos_feols[[nome]]))

  cat("\n--- Teste de Colinearidade (VIF) ---\n")
  # Try/catch para evitar que o loop quebre se algum modelo não puder calcular
VIF perfeito
  tryCatch({
    print(check_collinearity(modelos_feols[[nome]]))
  }, error = function(e) cat("Não foi possível calcular o VIF para este
modelo.\n"))


cat("\n==================================================================
=\n\n")
}

# 
=========================================================================
===
# 3. EXTRAÇÃO DE INTERCEPTOS GLOBAIS (Twoways) COM PLM
# 
=========================================================================
===
# Garantir que a base está formatada como painel formal para o plm
pdata_firm <- pdata.frame(data_firm_3, index = c("gvkey", "year"))

formulas_plm <- list(
  "Modelo 1" = as.formula(paste("ln_MC ~", ctrl_plm_lin)),
  "Modelo 2" = as.formula(paste("ln_MC ~", ctrl_plm_sq)),
  "Modelo 3" = as.formula(paste("ln_MC ~ Equity_inc_CMO", ctrl_plm_lin)),
  "Modelo 4" = as.formula(paste("ln_MC ~ sqrt_Equity_CMO", ctrl_plm_sq)),
  "Modelo 5" = as.formula(paste("ln_MC ~ sqrt_Equity_CMO + CMO_gender +
CFO_gender", ctrl_plm_sq)),
  "Modelo 6" = as.formula(paste("ln_MC ~ sqrt_Equity_CMO*CMO_gender +
CFO_gender", ctrl_plm_sq)),
  "Modelo 7" = as.formula(paste("ln_MC ~ sqrt_Equity_CMO*CMO_gender +
sqrt_Equity_CMO*CFO_gender", ctrl_plm_sq)),
  "Modelo 8" = as.formula(paste("ln_MC ~
sqrt_Equity_CMO*CMO_gender*CFO_gender", ctrl_plm_sq))
)

cat("\n==================================================================
=\n")
cat("          EXTRAÇÃO DE INTERCEPTOS (TWOWAYS) - MODELOS 1 A 8\n")
cat("=================================================================\
n\n")

for (nome_modelo in names(formulas_plm)) {
```

```
  modelo_plm <- plm(formulas_plm[[nome_modelo]],
                    data = pdata_firm,
                    effect = "twoways",
                    model = "within")

  # Extrai estatísticas com clusterização por firma (gvkey)
  estats_int <- within_intercept(modelo_plm,
                                 vcov = function(x) vcovHC(x, type = "HC1",
cluster = "group"))

  intercepto  <- as.numeric(estats_int)
  erro_padrao <- attr(estats_int, "se")
  t_value     <- intercepto / erro_padrao

  gl <- df.residual(modelo_plm)
  p_value <- 2 * pt(q = -abs(t_value), df = gl)

  sig_stars <- ifelse(p_value < 0.001, "***",
                      ifelse(p_value < 0.01, "**",
                             ifelse(p_value < 0.05, "*",
                                    ifelse(p_value < 0.1, ".", ""))))

  cat(sprintf("--- %s ---\n", toupper(nome_modelo)))
  cat(sprintf("Intercepto: %.3f%s\n", intercepto, sig_stars))
  cat(sprintf("Erro-Padrão: (%.3f)\n", erro_padrao))
  cat(sprintf("t-value: %.3f\n", t_value))
  cat("---------------------------\n\n")
}

#
=========================================================================
===
# Limpeza de memória
#
=========================================================================
===
rm(ctrl_feols_lin, ctrl_feols_sq, ctrl_plm_lin, ctrl_plm_sq, formulas_feols,
formulas_plm, nome,
   modelo_plm, estats_int, intercepto, erro_padrao, t_value, gl, p_value,
sig_stars, nome_modelo, pdata_firm)
gc()
```

J.4. Main Graphs

```
#
=========================================================================
===
# 15. GRÁFICOS (STORYTELLING ENXUTO: PRINCIPAL, MODERAÇÃO H2 E TRIPLA H3)
#
=========================================================================
===

library(marginaleffects)
library(ggplot2)
library(scales)
library(dplyr)

#
=========================================================================
===
# 1. PREPARAÇÃO DA BASE E CONTROLES
#
=========================================================================
===
# Criar a coluna de lag fixa para garantir o comportamento correto do
marginaleffects
data_firm_3 <- data_firm_3 %>%
  arrange(gvkey, year) %>%
  group_by(gvkey) %>%
```

```
  mutate(lag_ln_MC_fixo = ifelse(year == dplyr::lag(year, 1) + 1,
                                 dplyr::lag(ln_MC, 1),
                                 NA_real_)) %>%
  ungroup()

# Resgatar média e desvio da base original para reconstruir a curva no eixo
X
mean_sqrt <- mean(base_sem_padronizar$sqrt_Equity_CMO, na.rm = TRUE)
sd_sqrt   <- sd(base_sem_padronizar$sqrt_Equity_CMO, na.rm = TRUE)
mean_eq   <- mean(base_sem_padronizar$Equity_inc_CMO, na.rm = TRUE)
sd_eq     <- sd(base_sem_padronizar$Equity_inc_CMO, na.rm = TRUE)

# Fatores para os gráficos em inglês
data_firm_3$CMO_gender_f <- factor(data_firm_3$CMO_gender, levels = c(0, 1),
labels = c("Male", "Female"))
data_firm_3$CFO_gender_f <- factor(data_firm_3$CFO_gender, levels = c(0, 1),
labels = c("Male", "Female"))

# Paleta de cores científica e colorblind-friendly (padrão de publicação)
paleta_cores <- c("Male" = "#0072B2", "Female" = "#D55E00")

# Controles padronizados com a variável de lag fixa
controles_fixos <- "+ lag_ln_MC_fixo + sqrt_TMT_Inc + CMOBONUS + RD_intensity
+ ROA + SIZE + IND_COMP_INTENSITY + INDGROWTH + Inverse_Mill + myopic +
RAD_dum + CEO_gender + CEO_Turnover + CFO_Turnover + CFOBONUS +
sqrt_Equity_CFO + CFO_age + CFO_Tenure + CMO_Tenure + CMO_age +
TMT_Female_Ratio + Leverage | year + gvkey"

# Reestimação rápida dos modelos para os gráficos
f_m3 <- as.formula(paste("ln_MC ~ Equity_inc_CMO", controles_fixos))
f_m4 <- as.formula(paste("ln_MC ~ sqrt_Equity_CMO", controles_fixos))
f_m6   <-   as.formula(paste("ln_MC   ~   sqrt_Equity_CMO*CMO_gender_f   +
CFO_gender_f", controles_fixos))
f_m7   <-   as.formula(paste("ln_MC   ~   sqrt_Equity_CMO*CMO_gender_f   +
sqrt_Equity_CMO*CFO_gender_f", controles_fixos))
f_m8              <-             as.formula(paste("ln_MC                 ~
sqrt_Equity_CMO*CMO_gender_f*CFO_gender_f", controles_fixos))

m3_plot <- feols(f_m3, cluster = ~gvkey, panel.id = ~gvkey + year, data =
data_firm_3)
m4_plot <- feols(f_m4, cluster = ~gvkey, panel.id = ~gvkey + year, data =
data_firm_3)
m6_plot <- feols(f_m6, cluster = ~gvkey, panel.id = ~gvkey + year, data =
data_firm_3)
m7_plot <- feols(f_m7, cluster = ~gvkey, panel.id = ~gvkey + year, data =
data_firm_3)
m8_plot <- feols(f_m8, cluster = ~gvkey, panel.id = ~gvkey + year, data =
data_firm_3)


#
==========================================================================
===
# GRÁFICO 1: EFEITO PRINCIPAL LINEAR (MODELO 3)
#
==========================================================================
===
pred_linear <- predictions(m3_plot,
                           newdata = datagrid(model = m3_plot,
                                              Equity_inc_CMO             =
seq(min(data_firm_3$Equity_inc_CMO,                          na.rm=TRUE),
max(data_firm_3$Equity_inc_CMO, na.rm=TRUE), length.out=100)),
                           vcov = FALSE) %>%
  mutate(Equity_Raw = (Equity_inc_CMO * sd_eq) + mean_eq,
         Model_Fit = "Linear Fit")

fig_linear <- ggplot(pred_linear, aes(x = Equity_Raw, y = estimate)) +
  geom_line(linewidth = 1.2, color = "black") +
```

```
  scale_y_continuous(labels = label_number(decimal.mark = ".", big.mark =
",")) +
  scale_x_continuous(labels = label_number(decimal.mark = ".", big.mark =
",")) +
  labs(x = "CMO Equity Incentives (Original Ratio)",
       y = "Log Market Capitalization") +
  theme_classic(base_family = "serif", base_size = 14) +
  theme(plot.title = element_text(face = "bold", hjust = 0.5, size = 18),
        axis.title = element_text(face = "bold", size = 18),
        axis.text = element_text(color = "black", size = 14))

print(fig_linear)


#
===========================================================================
===
# FIGURA 2: EFEITO PRINCIPAL CURVILINEAR (MODELO 4)
#
===========================================================================
===
pred_main <- predictions(m4_plot,
                         newdata = datagrid(model = m4_plot,
                                            sqrt_Equity_CMO               =
seq(min(data_firm_3$sqrt_Equity_CMO,                         na.rm=TRUE),
max(data_firm_3$sqrt_Equity_CMO, na.rm=TRUE), length.out=100)),
                         vcov = FALSE) %>%
  mutate(Equity_Raw = ((sqrt_Equity_CMO * sd_sqrt) + mean_sqrt)^2,
         Model_Fit = "Curvilinear Fit")

fig2 <- ggplot(pred_main, aes(x = Equity_Raw, y = estimate)) +
  geom_line(linewidth = 1.2, color = "black") +
  scale_y_continuous(labels = label_number(decimal.mark = ".", big.mark =
",")) +
  scale_x_continuous(labels = label_number(decimal.mark = ".", big.mark =
",")) +
  labs(x = "CMO Equity Incentives (Original Ratio)",
       y = "Log Market Capitalization") +
  theme_classic(base_family = "serif", base_size = 14) +
  theme(plot.title = element_text(face = "bold", hjust = 0.5, size = 18),
        axis.title = element_text(face = "bold", size = 18),
        axis.text = element_text(color = "black", size = 14))

print(fig2)


#
===========================================================================
===
# FIGURA 2 (UNIFICADA): EFEITO PRINCIPAL LINEAR VS CURVILINEAR
#
===========================================================================
===
combined_preds <- bind_rows(
  pred_linear %>% select(Equity_Raw, estimate, Model_Fit),
  pred_main %>% select(Equity_Raw, estimate, Model_Fit)
)

fig2_combined <- ggplot(combined_preds, aes(x = Equity_Raw, y = estimate,
color = Model_Fit, linetype = Model_Fit)) +
  geom_line(linewidth = 1.2) +
  scale_color_manual(values = c("Curvilinear Fit" = "#D55E00", "Linear Fit"
= "black")) +
  scale_linetype_manual(values = c("Curvilinear Fit" = "solid", "Linear Fit"
= "dashed")) +
  scale_y_continuous(labels = label_number(decimal.mark = ".", big.mark =
",")) +
  scale_x_continuous(labels = label_number(decimal.mark = ".", big.mark =
",")) +
```

```
  labs(x = "CMO Equity Incentives (Original Ratio)",
       y = "Log Market Capitalization",
       color = "", linetype = "") +
  theme_classic(base_family = "serif", base_size = 14) +
  theme(plot.title = element_text(face = "bold", hjust = 0.5, size = 18),
        legend.position = "bottom",
        legend.title = element_blank(),
        legend.text = element_text(size = 16),
        axis.title = element_text(face = "bold", size = 18),
        axis.text = element_text(color = "black", size = 14))

print(fig2_combined)


#
=========================================================================
===
# FIGURA 3: MODERAÇÃO DO GÊNERO DO CMO - H2 (MODELO 6)
#
=========================================================================
===
pred_cmo <- predictions(m6_plot,
                        newdata = datagrid(model = m6_plot,
                                           sqrt_Equity_CMO              =
seq(min(data_firm_3$sqrt_Equity_CMO,                       na.rm=TRUE),
max(data_firm_3$sqrt_Equity_CMO, na.rm=TRUE), length.out=100),
                                           CMO_gender_f     =     c("Male",
"Female"),
                                           CFO_gender_f = "Male"),
                        vcov = FALSE) %>%
  mutate(Gender = CMO_gender_f,
         Equity_Raw = ((sqrt_Equity_CMO * sd_sqrt) + mean_sqrt)^2)

fig3 <- ggplot(pred_cmo, aes(x = Equity_Raw, y = estimate, color = Gender,
linetype = Gender)) +
  geom_line(linewidth = 1.2) +
  scale_color_manual(values = paleta_cores) +
  scale_linetype_manual(values = c("Male" = "dashed", "Female" = "solid")) +
  scale_y_continuous(labels = label_number(decimal.mark = ".", big.mark =
",")) +
  scale_x_continuous(labels = label_number(decimal.mark = ".", big.mark =
",")) +
  labs(x = "CMO Equity Incentives (Original Ratio)",
       y = "Log Market Capitalization", color = "CMO Gender", linetype = "CMO
Gender") +
  theme_classic(base_family = "serif", base_size = 14) +
  theme(plot.title = element_text(face = "bold", hjust = 0.5, size = 18),
        legend.position = "bottom",
        legend.title = element_text(face = "bold", size = 16),
        legend.text = element_text(size = 14),
        axis.title = element_text(face = "bold", size = 18),
        axis.text = element_text(color = "black", size = 14))

print(fig3)


#
=========================================================================
===
# FIGURA 4: MODERAÇÃO DO GÊNERO DO CFO - p=ns (MODELO 7 COM DUAS FACETAS)
#
=========================================================================
===
pred_cfo <- predictions(m7_plot,
                        newdata = datagrid(model = m7_plot,
                                           sqrt_Equity_CMO              =
seq(min(data_firm_3$sqrt_Equity_CMO, na.rm=TRUE),

max(data_firm_3$sqrt_Equity_CMO, na.rm=TRUE),
```

```
length.out=100),
                                            CFO_gender_f     =     c("Male",
"Female"),
                                            CMO_gender_f     =     c("Male",
"Female")),
                        vcov = FALSE) %>%
  mutate(Gender = CFO_gender_f,
         Facet_CMO = paste("Baseline CMO:", CMO_gender_f),
         Equity_Raw = ((sqrt_Equity_CMO * sd_sqrt) + mean_sqrt)^2)

fig4 <- ggplot(pred_cfo, aes(x = Equity_Raw, y = estimate, color = Gender,
linetype = Gender)) +
  geom_line(linewidth = 1.2) +
  facet_wrap(~ Facet_CMO) +
  scale_color_manual(values = paleta_cores) +
  scale_linetype_manual(values = c("Male" = "dashed", "Female" = "solid")) +
  scale_y_continuous(labels  =  label_number(decimal.mark  =  ".",  big.mark  =
",")) +
  scale_x_continuous(labels  =  label_number(decimal.mark  =  ".",  big.mark  =
",")) +
  labs(x = "CMO Equity Incentives (Original Ratio)",
       y = "Log Market Capitalization",
       color = "CFO Gender",
       linetype = "CFO Gender") +
  theme_classic(base_family = "serif", base_size = 14) +
  theme(plot.title = element_text(face = "bold", hjust = 0.5, size = 18),
        strip.background = element_blank(),
        strip.text = element_text(face = "bold", size = 16),
        legend.position = "bottom",
        legend.title = element_text(face = "bold", size = 16),
        legend.text = element_text(size = 14),
        axis.title = element_text(face = "bold", size = 18),
        axis.text = element_text(color = "black", size = 14),
        panel.border = element_rect(color = "black", fill = NA, linewidth =
0.5))

print(fig4)


#
===========================================================================
===
# FIGURA 5: MODERAÇÃO TRIPLA - H3 (MODELO 8)
#
===========================================================================
===
pred_3way <- predictions(m8_plot,
                         newdata = datagrid(model = m8_plot,
                                            sqrt_Equity_CMO              =
seq(min(data_firm_3$sqrt_Equity_CMO,                          na.rm=TRUE),
max(data_firm_3$sqrt_Equity_CMO, na.rm=TRUE), length.out=100),
                                            CMO_gender_f     =     c("Male",
"Female"),
                                            CFO_gender_f     =     c("Male",
"Female")),
                         vcov = FALSE) %>%
  mutate(Gender = CMO_gender_f,
         Facet    =    factor(CFO_gender_f,    levels=c("Male",    "Female"),
labels=c("CFO: Male", "CFO: Female")),
         Equity_Raw = ((sqrt_Equity_CMO * sd_sqrt) + mean_sqrt)^2)

fig5 <- ggplot(pred_3way, aes(x = Equity_Raw, y = estimate, color = Gender,
linetype = Gender)) +
  geom_line(linewidth = 1.2) +
  facet_wrap(~ Facet) +
  scale_color_manual(values = paleta_cores) +
  scale_linetype_manual(values = c("Male" = "dashed", "Female" = "solid")) +
```

```
  scale_y_continuous(labels = label_number(decimal.mark = ".", big.mark =
",")) +
  scale_x_continuous(labels = label_number(decimal.mark = ".", big.mark =
",")) +
  labs(x = "CMO Equity Incentives (Original Ratio)",
       y = "Log Market Capitalization", color = "CMO Gender", linetype = "CMO
Gender") +
  theme_classic(base_family = "serif", base_size = 14) +
  theme(plot.title = element_text(face = "bold", hjust = 0.5, size = 18),
        strip.background = element_blank(),
        strip.text = element_text(face = "bold", size = 16),
        legend.position = "bottom",
        legend.title = element_text(face = "bold", size = 16),
        legend.text = element_text(size = 14),
        axis.title = element_text(face = "bold", size = 18),
        axis.text = element_text(color = "black", size = 14),
        panel.border = element_rect(color = "black", fill = NA, linewidth =
0.5))

print(fig5)

AIC(m3_plot, m4_plot)
BIC(m3_plot, m4_plot)


# Limpeza de Memória
rm(m3_plot,  m4_plot,  m6_plot,  m7_plot,  m8_plot,  pred_linear,  pred_main,
combined_preds, pred_cmo, pred_cfo, pred_3way, mean_sqrt, sd_sqrt,
   controles_fixos, f_m3, f_m4, f_m6, f_m7, f_m8, mean_eq, sd_eq)
gc()
```

J.5. Marginal Effects

```
#
===========================================================================
===
# 18. EFEITOS MARGINAIS E TESTES DE WALD DA DÍADE (TABELA 8 DA TESE)
#
===========================================================================
===

library(marginaleffects)
library(fixest)
library(dplyr)

cat("\n=====================================================================
=\n")
cat("        EFEITOS MARGINAIS (slopes) POR COMBINAÇÃO DE GÊNERO (Tabela
8)\n")
cat("====================================================================\
n\n")

# 1. CRIAR A COLUNA DE LAG FIXA (Vacina contra o bug do marginaleffects)
data_firm_3 <- data_firm_3 %>%
  arrange(gvkey, year) %>%
  group_by(gvkey) %>%
  mutate(lag_ln_MC_fixo = ifelse(year == dplyr::lag(year, 1) + 1,
                                 dplyr::lag(ln_MC, 1),
                                 NA_real_)) %>%
  ungroup()

# 2. Reestimando o Modelo 8 de forma EXPLÍCITA e com o Lag Fixo
modelo_8_oficial <- feols(
  ln_MC ~ sqrt_Equity_CMO * CMO_gender * CFO_gender +
    lag_ln_MC_fixo + sqrt_TMT_Inc + CMOBONUS + RD_intensity +
    ROA + SIZE + IND_COMP_INTENSITY + INDGROWTH + Inverse_Mill +
    myopic + RAD_dum + CEO_gender + CEO_Turnover + CFO_Turnover +
    CFOBONUS + sqrt_Equity_CFO + CFO_age + CFO_Tenure + CMO_Tenure +
```

```
    CMO_age + TMT_Female_Ratio + Leverage | year + gvkey,
  panel.id = ~gvkey + year,
  cluster = ~gvkey,
  data = data_firm_3
)

# 3. Calculando os Efeitos Marginais Condicionais (Slopes)
inclinacoes <- slopes(
  modelo_8_oficial,
  variables = "sqrt_Equity_CMO",
  newdata = datagrid(
    model = modelo_8_oficial,
    CMO_gender = c(0, 1),
    CFO_gender = c(0, 1)
  )
)

# Imprime o resultado base (os valores de Estimate e Std. Error baterão com
a Tabela 8)
print(inclinacoes)

cat("\n==============================================================
=\n")
cat("       TESTES DE WALD: DIFERENÇAS ENTRE AS RETAS DA DÍADE\n")
cat("=============================================================\
n\n")

# 4. Testando as diferenças estatísticas entre as combinações
# Verifique a ordem no console (geralmente b1=0/0, b2=1/0, b3=0/1, b4=1/1).
testes_cruzados <- hypotheses(inclinacoes, hypothesis = c(
  "b1 = b2",  # A diferença entre a díade masculina e CMO Mulher/CFO Homem
  "b3 = b4",  # A diferença quando a CFO é Mulher: importa o CMO ser Homem
ou Mulher?
  "b1 = b4"    # A diferença entre os extremos: Díade Masculina x Díade
Feminina
))

print(testes_cruzados)

cat("\n--- Testes de Superioridade da CMO Feminina com Validador Masculino
---\n\n")

testes_superioridade <- hypotheses(inclinacoes, hypothesis = c(
  "b3 = b4",  # vs. Ambos Mulheres: Esperado Delta = 0.135
  "b3 = b1",  # vs. Ambos Homens: Esperado Delta = 0.110
  "b3 = b2"   # vs. CMO Homem / CFO Mulher: Esperado Delta = 0.090
))

print(testes_superioridade)

# Limpeza de Memória do Bloco
rm(modelo_8_oficial, inclinacoes, testes_cruzados, testes_superioridade)
gc()
```

J.6. Robustness

```
model_stocks <- feols(ln_MC ~

                          sqrt_Equity_CMO*CMO_gender*CFO_gender

                        #Controles

                        + CSO

                        + l(ln_MC, 1)
                        + sqrt_TMT_Inc
                        + CMOBONUS
                        + RD_intensity
                        + ROA
```

```
                        + SIZE
                        + IND_COMP_INTENSITY
                        + INDGROWTH

                        + Inverse_Mill

                        #Minhas adições:

                        + myopic
                        + RAD_dum
                        + CEO_gender
                        + CEO_Turnover
                        + CFO_Turnover
                        + CFOBONUS
                        + sqrt_Equity_CFO
                        + CFO_age
                        + CFO_Tenure
                        + CMO_Tenure
                        + CMO_age
                        + TMT_Female_Ratio
                        + Leverage

                        | year + gvkey,
                        panel.id = ~gvkey + year,
                        cluster = ~gvkey,
                        data = data_firm_3)

summary(model_stocks)
check_collinearity(model_stocks)
wald(model_stocks)

model_CFOGENDER <- feols(ln_MC ~

                          sqrt_Equity_CFO*CFO_gender

                        #Controles

                        + TMT_Female_Ratio
                        + CEO_gender
                        + CMO_gender
                        + l(ln_MC, 1)
                        + sqrt_TMT_Inc
                        + sqrt_Equity_CMO
                        + CMOBONUS
                        + CFOBONUS
                        + CFO_Tenure
                        + CMO_Tenure
                        + CMO_age
                        + CFO_age
                        + CMO_Turnover
                        + CEO_Turnover
                        + ROA
                        + SIZE
                        + Leverage
                        + myopic
                        + RAD_dum
                        + RD_intensity
                        + IND_COMP_INTENSITY
                        + INDGROWTH
                        + Inverse_Mill

                        | year + gvkey,
                        panel.id = ~gvkey + year,
                        cluster = ~gvkey,
                        data = data_firm_com_turnover)

summary(model_CFOGENDER)
check_collinearity(model_CFOGENDER)
wald(model_CFOGENDER)
```

```
model_QTOBIN <- feols(TobinQ ~

                        sqrt_Equity_CMO*CMO_gender*CFO_gender

                      #Controles

                      + l(TobinQ, 1)
                      + sqrt_TMT_Inc
                      + CMOBONUS
                      + RD_intensity
                      + ROA
                      + SIZE
                      + IND_COMP_INTENSITY
                      + INDGROWTH

                      + Inverse_Mill

                      #Minhas adições:

                      + myopic
                      + RAD_dum
                      + CEO_gender
                      + CEO_Turnover
                      + CFO_Turnover
                      + CFOBONUS
                      + sqrt_Equity_CFO
                      + CFO_age
                      + CFO_Tenure
                      + CMO_Tenure
                      + CMO_age
                      + TMT_Female_Ratio
                      + Leverage

                      | year + gvkey,
                      panel.id = ~gvkey + year,
                      cluster = ~gvkey,
                      data = data_firm_3)

summary(model_QTOBIN)
check_collinearity(model_QTOBIN)
wald(model_QTOBIN)

#
===========================================================================
===
# 1. MODELO QUADRÁTICO
#
===========================================================================
===

library(car)
library(ggplot2)
library(scales)

# Nota: CMO, TMT e CFO Incentives em forma linear (sem sqrt), conforme a
tese.
modelo_Quad <- feols(ln_MC ~
                      I(Equity_inc_CMO^2) + Equity_inc_CMO +
                      CMO_gender  +  CFO_gender  +  TMT_Female_Ratio  +
CEO_gender +
                      l(ln_MC, 1) + TMTINCENTIVE_3 + Equity_inc_CFO +
                      CMOBONUS + CFOBONUS + CFO_Tenure + CMO_Tenure +
                      CMO_age + CFO_age + CFO_Turnover + CEO_Turnover +
                      ROA + SIZE + Leverage + myopic + RAD_dum +
                      RD_intensity  +  IND_COMP_INTENSITY  +  INDGROWTH  +
Inverse_Mill
                     | year + gvkey,
                     panel.id = ~gvkey + year,
```

```
                    cluster = ~gvkey,
                    data = data_firm_3)

cat("\n--- RESULTADOS: TABELA 10 (QUADRÁTICA) ---\n")
summary(modelo_Quad)
check_collinearity(modelo_Quad)
wald(modelo_Quad)

#
============================================================================
===
# 2. MODELO CÚBICO (Apêndice E)
#
============================================================================
===
modelo_Cubico <- feols(ln_MC ~
                         I(Equity_inc_CMO^3)    +    I(Equity_inc_CMO^2)    +
Equity_inc_CMO +
                         CMO_gender   +   CFO_gender   +   TMT_Female_Ratio   +
CEO_gender +
                         l(ln_MC, 1) + TMTINCENTIVE_3 + Equity_inc_CFO +
                         CMOBONUS + CFOBONUS + CFO_Tenure + CMO_Tenure +
                         CMO_age + CFO_age + CFO_Turnover + CEO_Turnover +
                         ROA + SIZE + Leverage + myopic + RAD_dum +
                         RD_intensity  +  IND_COMP_INTENSITY  +  INDGROWTH  +
Inverse_Mill
                       | year + gvkey,
                       panel.id = ~gvkey + year,
                       cluster = ~gvkey,
                       data = data_firm_3)

cat("\n--- RESULTADOS: APÊNDICE E (CÚBICA) ---\n")
summary(modelo_Cubico)
check_collinearity(modelo_Cubico)
wald(modelo_Cubico)

#
============================================================================
===
# 3. BATERIA DE TESTES: HAANS ET AL. (2016)
#
============================================================================
===
# Extração de coeficientes
b1 <- coef(modelo_Quad)["Equity_inc_CMO"]
b2 <- coef(modelo_Quad)["I(Equity_inc_CMO^2)"]

x_min <- min(data_firm_3$Equity_inc_CMO, na.rm = TRUE)
x_max <- max(data_firm_3$Equity_inc_CMO, na.rm = TRUE)

print(x_min)
print(x_max)

slope_min <- b1 + 2 * b2 * x_min
slope_max <- b1 + 2 * b2 * x_max

print(slope_min)
print(slope_max)

cat("\n--- TESTE 1: INCLINAÇÕES NAS EXTREMIDADES (LHT) ---\n")
query_min <- sprintf("Equity_inc_CMO + %f * I(Equity_inc_CMO^2) = 0", 2 *
x_min)
query_max <- sprintf("Equity_inc_CMO + %f * I(Equity_inc_CMO^2) = 0", 2 *
x_max)

cat("Testando o limite inferior (x_min) - Esperado > 0:\n")
print(linearHypothesis(modelo_Quad, query_min, test = "F"))

cat("\nTestando o limite superior (x_max) - Esperado < 0:\n")
```

```
print(linearHypothesis(modelo_Quad, query_max, test = "F"))

# Cálculo de Fieller
vcov_mat <- vcov(modelo_Quad)
var_b1 <- vcov_mat["Equity_inc_CMO", "Equity_inc_CMO"]
var_b2 <- vcov_mat["I(Equity_inc_CMO^2)", "I(Equity_inc_CMO^2)"]
cov_b1_b2 <- vcov_mat["Equity_inc_CMO", "I(Equity_inc_CMO^2)"]

a <- -b1
b <- 2 * b2
v11 <- var_b1
v22 <- 4 * var_b2
v12 <- -2 * cov_b1_b2
t_val <- 1.96

A_fieller <- (b^2) - (t_val^2 * v22)
B_fieller <- -2 * ((a * b) - (t_val^2 * v12))
C_fieller <- (a^2) - (t_val^2 * v11)
delta <- (B_fieller^2) - (4 * A_fieller * C_fieller)

raiz1 <- (-B_fieller + sqrt(delta)) / (2 * A_fieller)
raiz2 <- (-B_fieller - sqrt(delta)) / (2 * A_fieller)

ci_lower <- min(raiz1, raiz2)
ci_upper <- max(raiz1, raiz2)
inflexao_z <- -b1 / (2 * b2)

cat("\n--- TESTE 2: PONTO DE INFLEXÃO E FIELLER ---\n")
cat(sprintf("Ponto de Inflexão (Z-score): %.3f\n", inflexao_z))
cat(sprintf("Intervalo de Confiança Fieller 95%%: [%.3f ; %.3f]\n", ci_lower,
ci_upper))
cat(sprintf("Range dos Dados (Z-score): [%.3f ; %.3f]\n", x_min, x_max))

#
============================================================================
===
# 4. TESTE DE AMOSTRA DIVIDIDA (SPLIT SAMPLE)
#
============================================================================
===
cat("\n--- TESTE 3: SPLIT SAMPLE (CORRIGIDO PARA USO DE L() DO FIXEST) ---
\n")
if(inflexao_z < x_max & inflexao_z > x_min) {

  # A regressão em data split com l() precisa que a série temporal não quebre.
  # Portanto, criamos o lag ANTES de dividir a base.
  data_split <- data_firm_3 %>%
    group_by(gvkey) %>%
    arrange(year, .by_group = TRUE) %>%
    mutate(lag_ln_MC_split  =  ifelse(year  ==  dplyr::lag(year,  1)  +  1,
dplyr::lag(ln_MC, 1), NA_real_)) %>%
    ungroup()

  sample_low  <- data_split %>% filter(Equity_inc_CMO < inflexao_z)
  sample_high <- data_split %>% filter(Equity_inc_CMO >= inflexao_z)

  formula_split  <-  ln_MC  ~  Equity_inc_CMO  +  CMO_gender  +  CFO_gender  +
TMT_Female_Ratio +
    CEO_gender + lag_ln_MC_split + TMTINCENTIVE_3 + Equity_inc_CFO +
    CMOBONUS + CFOBONUS + CFO_Tenure + CMO_Tenure + CMO_age +
    CFO_age + CFO_Turnover + CEO_Turnover + ROA + SIZE +
    Leverage + myopic + RAD_dum + RD_intensity +
    IND_COMP_INTENSITY + INDGROWTH + Inverse_Mill

  mod_low  <- feols(formula_split, panel.id = ~gvkey + year, cluster = ~gvkey,
data = sample_low)
  mod_high  <-  feols(formula_split,  panel.id  =  ~gvkey  +  year,  cluster  =
~gvkey, data = sample_high)
```

```
  cat(sprintf("N (Amostra Esquerda - Subida): %d\n", nobs(mod_low)))
  cat(sprintf("N (Amostra Direita - Descida): %d\n", nobs(mod_high)))
  cat(sprintf("Coeficiente   Lado   Esquerdo   (Esperado   +):   %.3f\n",
coef(mod_low)["Equity_inc_CMO"]))
  cat(sprintf("Coeficiente   Lado   Direito   (Esperado   -):   %.3f\n",
coef(mod_high)["Equity_inc_CMO"]))
} else {
  cat("Ponto de inflexão fora da amostra. Amostra não dividida.\n")
}

#
=========================================================================
===
# 5. CONSTRUÇÃO DA FIGURA 4 (Valores de Razão/Não-Padronizados no Eixo X)
#
=========================================================================
===

# Resgatar a média e o desvio padrão da base bruta para desfazer a
padronização Z-score
mean_eq <- mean(base_sem_padronizar$Equity_inc_CMO, na.rm = TRUE)
sd_eq   <- sd(base_sem_padronizar$Equity_inc_CMO, na.rm = TRUE)

# Converter o ponto de inflexão de Z-score de volta para a escala de Razão
inflexao_raw <- (inflexao_z * sd_eq) + mean_eq

# Preparar dados para o gráfico
dados_grafico <- data_firm_3 %>%
  filter(!is.na(Equity_inc_CMO) &
           !is.na(ln_MC) &
           is.finite(ln_MC) &
           is.finite(Equity_inc_CMO)) %>%
  mutate(
    # Desfaz a padronização para o Eixo X exibir valores entre ~0.00 e 1.00
    Equity_Raw = (Equity_inc_CMO * sd_eq) + mean_eq
  )

grafico_figura_4 <- ggplot(dados_grafico, aes(x = Equity_Raw, y = ln_MC)) +

  # Scatter plot de fundo (os pontos que compõem a amostra)
  geom_point(alpha = 0.30, color = "gray30", size = 0.8) +

  # A franja/rug na base do eixo X (prova visual da densidade da amostra)
  geom_rug(alpha = 0.1, color = "black", sides = "b") +

  # Curva de Ajuste Local (Loess em Azul com área sombreada)
  geom_smooth(aes(color = "Local Fit (Loess)", linetype = "Local Fit
(Loess)"),
              method = "loess", se = TRUE, linewidth = 1, fill = "lightblue",
alpha = 0.4) +

  # Curva do Ajuste Quadrático (Vermelha tracejada)
  geom_smooth(aes(color = "Quadratic Fit (Inverted-U)", linetype = "Quadratic
Fit (Inverted-U)"),
              method = "lm", formula = y ~ x + I(x^2), linewidth = 1, se =
FALSE) +

  # Linha vertical demonstrando o ponto de inflexão cravado
  geom_vline(xintercept = inflexao_raw, linetype = "dotted", color = "black",
linewidth = 0.8) +

  # Configuração de Cores e Estilos para coincidir exatamente com sua legenda
  scale_color_manual(name = "",
                     values = c("Local Fit (Loess)" = "#1f78b4",
                                "Quadratic Fit (Inverted-U)" = "#e31a1c")) +
  scale_linetype_manual(name = "",
                        values = c("Local Fit (Loess)" = "solid",
                                   "Quadratic Fit (Inverted-U)" = "dashed"))
+
```

```
  # Formatação acadêmica dos eixos (Vírgula para decimais)
  scale_x_continuous(
    breaks = function(x) sort(unique(c(pretty(x), inflexao_raw))),
    labels = function(x) format(round(x, 2), nsmall = 2, decimal.mark = ",")
  ) +
  scale_y_continuous(
    labels = function(y) format(y, decimal.mark = ",")
  ) +

  labs(
    x = expression(CMOINCENTIVE^a),
    y = "Market Capitalization"
  ) +

  # Padrão acadêmico APA da sua tese
  theme_classic(base_family = "serif", base_size = 14) +
  theme(
    # --- MODIFICAÇÃO APENAS AQUI: Tamanhos de fonte adicionados ---
    axis.title = element_text(face = "bold", color = "black", size = 18), #
Tamanho do título dos eixos
    axis.text = element_text(color = "black", size = 14),              #
Tamanho dos números dos eixos
    legend.text = element_text(size = 16),                             #
Tamanho do texto da legenda
    legend.position = "bottom",
    legend.title = element_blank()
  )

# Exibe o gráfico
print(grafico_figura_4)

#
==========================================================================
===
# Limpeza do Ambiente
#
==========================================================================
===
# As tabelas resultantes foram adicionadas aos objetos mantidos para
visualização no R
objetos_para_manter <- c("dados_long", "data_firm_3", "base_sem_padronizar",
                         "desc_cont",    "desc_dummy",    "df_correlacao",
"dados_finais",
                         "data_firm_com_turnover", "modelos_feols")
rm(list = setdiff(ls(), objetos_para_manter))
gc()


#
==========================================================================
===
# 1. MODELOS ALTERNATIVOS
#
==========================================================================
===

modelo_linear <- feols(ln_MC ~

                         Equity_inc_CMO*CMO_gender*CFO_gender

                       #Controles

                       + l(ln_MC, 1)
                       + TMTINCENTIVE_3
                       + CMOBONUS
                       + RD_intensity
                       + ROA
                       + SIZE
```

```
                        + IND_COMP_INTENSITY
                        + INDGROWTH

                        + Inverse_Mill

                        #Minhas adições:

                        + myopic
                        + RAD_dum
                        + CEO_gender
                        + CEO_Turnover
                        + CFO_Turnover
                        + CFOBONUS
                        + Equity_inc_CFO
                        + CFO_age
                        + CFO_Tenure
                        + CMO_Tenure
                        + CMO_age
                        + TMT_Female_Ratio
                        + Leverage

                        | year + gvkey,
                        panel.id = ~gvkey + year,
                        cluster = ~gvkey,
                        data = data_firm_3)

summary(modelo_linear)
check_collinearity(modelo_linear)
wald(modelo_linear)

modelo_log <- feols(ln_MC ~

                       log_Equity_inc_CMO*CMO_gender*CFO_gender

                     #Controles

                     + l(ln_MC, 1)
                     + log_TMTINCENTIVE_3
                     + CMOBONUS
                     + RD_intensity
                     + ROA
                     + SIZE
                     + IND_COMP_INTENSITY
                     + INDGROWTH

                     + Inverse_Mill

                     #Minhas adições:

                     + myopic
                     + RAD_dum
                     + CEO_gender
                     + CEO_Turnover
                     + CFO_Turnover
                     + CFOBONUS
                     + log_Equity_inc_CFO
                     + CFO_age
                     + CFO_Tenure
                     + CMO_Tenure
                     + CMO_age
                     + TMT_Female_Ratio
                     + Leverage

                     | year + gvkey,
                     panel.id = ~gvkey + year,
                     cluster = ~gvkey,
                     data = data_firm_3)

summary(modelo_log)
```

```
check_collinearity(modelo_log)
wald(modelo_log)

modelo_raiz <- feols(ln_MC ~

                       sqrt_Equity_CMO*CMO_gender*CFO_gender

                     #Controles

                     + l(ln_MC, 1)
                     + sqrt_TMT_Inc
                     + CMOBONUS
                     + RD_intensity
                     + ROA
                     + SIZE
                     + IND_COMP_INTENSITY
                     + INDGROWTH

                     + Inverse_Mill

                     #Minhas adições:

                     + myopic
                     + RAD_dum
                     + CEO_gender
                     + CEO_Turnover
                     + CFO_Turnover
                     + CFOBONUS
                     + sqrt_Equity_CFO
                     + CFO_age
                     + CFO_Tenure
                     + CMO_Tenure
                     + CMO_age
                     + TMT_Female_Ratio
                     + Leverage

                     | year + gvkey,
                     panel.id = ~gvkey + year,
                     cluster = ~gvkey,
                     data = data_firm_3)

summary(modelo_raiz)
check_collinearity(modelo_raiz)
wald(modelo_raiz)

#
===========================================================================
===
# MODERAÇÕES COM GÊNERO DE CEO E COO
#
===========================================================================
===

modelo_CEO <- feols(ln_MC ~

                      sqrt_Equity_CMO*CMO_gender*CEO_gender

                    #Controles

                    + l(ln_MC, 1)
                    + sqrt_TMT_Inc_CEO
                    + CMOBONUS
                    + RD_intensity
                    + ROA
                    + SIZE
                    + IND_COMP_INTENSITY
                    + INDGROWTH

                    + Inverse_Mill
```

```
                    #Minhas adições:

                    + myopic
                    + RAD_dum
                    + CEO_Turnover
                    + CFO_Turnover
                    + CEOBONUS
                    + sqrt_Equity_CEO
                    + CEO_age
                    + CEO_Tenure
                    + CMO_Tenure
                    + CMO_age
                    + TMT_Female_Ratio
                    + Leverage

                    | year + gvkey,
                    panel.id = ~gvkey + year,
                    cluster = ~gvkey,
                    data = data_firm_3)

summary(modelo_CEO)
check_collinearity(modelo_CEO)
wald(modelo_CEO)

modelo_COO <- feols(ln_MC ~

                      sqrt_Equity_CMO*CMO_gender*COO_gender

                    #Controles

                    + l(ln_MC, 1)
                    + sqrt_TMT_Inc_COO #<- AQUI
                    + CMOBONUS
                    + RD_intensity
                    + ROA
                    + SIZE
                    + IND_COMP_INTENSITY
                    + INDGROWTH

                    + Inverse_Mill

                    #Minhas adições:

                    + myopic
                    + RAD_dum
                    + CEO_gender
                    + CEO_Turnover
                    + CFO_Turnover
                    + COOBONUS #<- AQUI
                    + sqrt_Equity_COO #<- AQUI
                    + COO_age #<- AQUI
                    + COO_Tenure #<- AQUI
                    + CMO_Tenure
                    + CMO_age
                    + TMT_Female_Ratio
                    + Leverage

                    | year + gvkey,
                    panel.id = ~gvkey + year,
                    cluster = ~gvkey,
                    data = data_firm_3)

summary(modelo_COO)
check_collinearity(modelo_COO)
wald(modelo_COO)
```

```
#
================================================================================
===
# CAUSALIDADE REVERSA
#
================================================================================
===

###________________Causalidade
reversa________________________________________________

# Calculando a variação defasada com proteção contra "buracos" no painel
data_firm_3 <- data_firm_3 %>%
  group_by(gvkey) %>%
  arrange(year, .by_group = TRUE) %>%
  mutate(
    # 1. Calcula o crescimento apenas se a linha anterior for exatamente do
ano passado
    crescimento_MC = if_else(year == dplyr::lag(year, 1) + 1,
                             ln_MC - dplyr::lag(ln_MC, 1),
                             NA_real_),

    # 2. Defasa o crescimento apenas se a linha anterior for exatamente do
ano passado
    lag_crescimento_MC = if_else(year == dplyr::lag(year, 1) + 1,
                                 dplyr::lag(crescimento_MC, 1),
                                 NA_real_)
  ) %>%
  ungroup()

modelo_reverso <- feols(sqrt_Equity_CMO ~

                          lag_crescimento_MC + CMO_gender + CFO_gender

                        #Controles

                        + sqrt_TMT_Inc
                        + CMOBONUS
                        + RD_intensity
                        + ROA
                        + SIZE
                        + IND_COMP_INTENSITY
                        + INDGROWTH

                        + Inverse_Mill

                        #Minhas adições:

                        + myopic
                        + RAD_dum
                        + CEO_gender
                        + CEO_Turnover
                        + CFO_Turnover
                        + CFOBONUS
                        + sqrt_Equity_CFO
                        + CFO_age
                        + CFO_Tenure
                        + CMO_Tenure
                        + CMO_age
                        + TMT_Female_Ratio
                        + Leverage

                        | year + gvkey,
                        panel.id = ~gvkey + year,
                        cluster = ~gvkey,
                        data = data_firm_3)

summary(modelo_reverso)
check_collinearity(modelo_reverso)
```

```
wald(modelo_reverso)

#
===========================================================================
===
# TABELA 11: OBSERVAÇÕES E EMPRESAS ÚNICAS NA DÍADE
#
===========================================================================
===
library(dplyr)
library(knitr)

# 1. Recuperar a amostra EXATA usada no Modelo 8 (M8 dentro da lista)
indices_usados <- unlist(modelos_feols[["M8"]]$obs_selection)
data_used <- data_firm_3[indices_usados, ]

# 2. Gerar Tabela Cruzada de Observações (N)
tabela_obs <- table(CMO = data_used$CMO_gender, CFO = data_used$CFO_gender)

# 3. Descobrir o número exato de empresas únicas na díade feminina (1-1)
n_empresas_fem <- data_used %>%
  filter(CMO_gender == 1 & CFO_gender == 1) %>%
  summarise(Empresas_Unicas = n_distinct(gvkey)) %>%
  pull(Empresas_Unicas)

cat("\n=== TABELA 11: OBSERVAÇÕES UTILIZADAS NA REGRESSÃO ===\n")
cat("Gênero: 0 = Masculino, 1 = Feminino\n\n")
print(tabela_obs)
cat(sprintf("\nNota: Existem exatamente %d empresas únicas compondo as %d
observações da díade CMO Feminino / CFO Feminino.\n",
            n_empresas_fem, tabela_obs["1", "1"]))

#
===========================================================================
===
# EFEITO PLACEBO (MONTE CARLO) - FIGURA 5 (CORRIGIDO PARA MANTER O 'N')
#
===========================================================================
===
library(ggplot2)
library(scales)
library(fixest)
library(dplyr)

# 0. CRIAR A COLUNA DE LAG FIXA NA BASE (Antes de puxar a amostra do modelo)
# Isso impede o feols de recalcular o lag dinamicamente e perder observações
no loop
data_firm_3 <- data_firm_3 %>%
  arrange(gvkey, year) %>%
  group_by(gvkey) %>%
  mutate(
    lag_ln_MC_fixo = ifelse(year == dplyr::lag(year, 1) + 1,
                            dplyr::lag(ln_MC, 1),
                            NA_real_)
  ) %>%
  ungroup()

# 1. Recuperar a amostra EXATA usada no Modelo M8 (agora ela carrega o
lag_fixo)
indices_usados <- unlist(modelos_feols[["M8"]]$obs_selection)
data_used <- data_firm_3[indices_usados, ]

# 2. Extrair o coeficiente real da interação tripla do modelo M8 oficial
coef_real                                                              <-
coef(modelos_feols[["M8"]])["sqrt_Equity_CMO:CMO_gender:CFO_gender"]

# 3. Preparar o loop do Teste Placebo
n_simulacoes <- 10000
coefs_falsos <- numeric(n_simulacoes)
```

```
cat("\nIniciando 10.000 simulações de Monte Carlo (com N blindado)...\n")
set.seed(1) # Garante reprodutibilidade

# CORREÇÃO CRÍTICA: Substituímos 'l(ln_MC, 1)' por 'lag_ln_MC_fixo'
formula_placebo  <-  as.formula("ln_MC  ~  sqrt_Equity_CMO  *  CMO_gender  *
CFO_gender +
                       lag_ln_MC_fixo   +   sqrt_TMT_Inc   +   CMOBONUS   +
RD_intensity +
                       ROA  +  SIZE  +  IND_COMP_INTENSITY  +  INDGROWTH  +
Inverse_Mill +
                       myopic  +  RAD_dum  +  CEO_gender  +  CEO_Turnover  +
CFO_Turnover +
                       CFOBONUS + sqrt_Equity_CFO + CFO_age + CFO_Tenure +
                       CMO_Tenure + CMO_age + TMT_Female_Ratio + Leverage |
                       year + gvkey")

for(i in 1:n_simulacoes) {
  # Aleatorizar os gêneros para destruir a relação causal real
  data_fake <- data_used %>%
    mutate(
      CMO_gender = sample(CMO_gender),
      CFO_gender = sample(CFO_gender)
    )

  # Rodar o modelo placebo (Nota: sem o panel.id, pois o lag já está fixo)
  modelo_fake <- feols(formula_placebo,
                       cluster = ~gvkey,
                       data = data_fake,
                       notes = FALSE)

  # Salvar o coeficiente falso gerado pelo acaso
  coefs_falsos[i]                                                       <-
coef(modelo_fake)["sqrt_Equity_CMO:CMO_gender:CFO_gender"]
}

# 4. Calcular o p-valor empírico
p_valor_placebo <- sum(coefs_falsos <= coef_real) / n_simulacoes
cat(sprintf("P-Valor Empírico (Monte Carlo): %.4f\n", p_valor_placebo))

# 5. Plotar a Figura 5 (Norma APA - Inglês)
dados_grafico <- data.frame(Coeficientes = coefs_falsos)
max_y   <-   max(hist(dados_grafico$Coeficientes,   breaks   =   30,   plot   =
FALSE)$counts)

# Removido o gsub que forçava a vírgula. Agora mantém o ponto decimal do R.
texto_beta <- sprintf("%.3f", coef_real)

figura_5 <- ggplot(dados_grafico, aes(x = Coeficientes)) +
  geom_histogram(bins = 30, fill = "#CCCCCC", color = "black", alpha = 1) +
  geom_vline(xintercept = coef_real, color = "black", linetype = "dashed",
linewidth = 1.2) +

  # Alterado decimal.mark para "." e big.mark para ","
  scale_x_continuous(labels = label_number(accuracy = 0.001, decimal.mark =
".", big.mark = ",")) +
  scale_y_continuous(labels = label_number(accuracy = 1, decimal.mark = ".",
big.mark = ",")) +

  labs(
    x = "Triple Interaction Coefficient (Stochastically Simulated)",
    y = "Occurrence frequency"
  ) +
  theme_classic(base_family = "serif", base_size = 14) +
  theme(
    axis.line = element_line(color = "black", linewidth = 0.5),
    axis.text = element_text(color = "black", size = 14),
    axis.title = element_text(color = "black", size = 16, face = "bold"),
    plot.margin = margin(t = 20, r = 20, b = 20, l = 20)
```

```
  ) +
  annotate("text", x = coef_real, y = max_y * 0.8,
           label = paste0("Effect (Table 8)\n(", texto_beta, ")"),
           color = "black", angle = 90, vjust = -0.5,
           size = 6,
           fontface = "bold")

print(figura_5)

#
==========================================================================
===
# WILD CLUSTER BOOTSTRAP (SOLUÇÃO DEFINITIVA E BLINDADA)
#
==========================================================================
===
library(fwildclusterboot)
library(dqrng)
library(fixest)
library(dplyr)
library(tidyr)

cat("\n=== WILD CLUSTER BOOTSTRAP (PESOS DE WEBB) ===\n")

# 1. CRIAR A COLUNA DE LAG E CONVERTER F.E. PARA FATORES (Evita o bug de
soma)
data_firm_3 <- data_firm_3 %>%
  arrange(gvkey, year) %>%
  group_by(gvkey) %>%
  mutate(
    lag_ln_MC_fixo = ifelse(year == dplyr::lag(year, 1) + 1,
                            dplyr::lag(ln_MC, 1),
                            NA_real_)
  ) %>%
  ungroup() %>%
  mutate(
    gvkey_factor = as.factor(gvkey), # Transforma em fator
    year_factor = as.factor(year)    # Transforma em fator
  )

# 2. DEFINIR APENAS AS COLUNAS QUE O MODELO VAI USAR
colunas_modelo <- c(
  "ln_MC", "sqrt_Equity_CMO", "CMO_gender", "CFO_gender", "lag_ln_MC_fixo",
  "sqrt_TMT_Inc", "CMOBONUS", "RD_intensity", "ROA", "SIZE",
  "IND_COMP_INTENSITY", "INDGROWTH", "Inverse_Mill", "myopic", "RAD_dum",
  "CEO_gender",      "CEO_Turnover",      "CFO_Turnover",      "CFOBONUS",
"sqrt_Equity_CFO",
  "CFO_age",  "CFO_Tenure",  "CMO_Tenure",  "CMO_age",  "TMT_Female_Ratio",
"Leverage",
  "year_factor", "gvkey_factor"
)

# 3. CRIAR A BASE PERFEITA (Exclui NAs antes da regressão)
data_boot_perfeita <- data_firm_3 %>%
  select(all_of(colunas_modelo)) %>%
  drop_na() %>%
  droplevels()

# 4. RODAR O MODELO BASE NA BASE PERFEITA
# Nota: Usamos os "fatores" nos efeitos fixos para o fwildclusterboot não
quebrar
modelo_base_boot <- feols(ln_MC ~
                            sqrt_Equity_CMO * CMO_gender * CFO_gender
                          + lag_ln_MC_fixo
                          + sqrt_TMT_Inc + CMOBONUS + RD_intensity + ROA +
SIZE
                          + IND_COMP_INTENSITY + INDGROWTH + Inverse_Mill
                          + myopic + RAD_dum + CEO_gender + CEO_Turnover +
CFO_Turnover
```

```
                          + CFOBONUS + sqrt_Equity_CFO + CFO_age + CFO_Tenure
                          +  CMO_Tenure  +  CMO_age  +  TMT_Female_Ratio  +
Leverage
                          | year_factor + gvkey_factor,
                          cluster = ~gvkey_factor,
                          data = data_boot_perfeita)

# 5. RODAR O BOOTSTRAP
set.seed(1)
dqset.seed(1)

# Agora os tamanhos das matrizes batem e os tipos de dados são compatíveis
boot_h3_oficial <- boottest(
  modelo_base_boot,
  param = "sqrt_Equity_CMO:CMO_gender:CFO_gender",
  B = 9999,
  clustid = "gvkey_factor",
  type = "webb"
)

# 6. O VEREDITO FINAL
summary(boot_h3_oficial)
```