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It Depends Where You Play: Industry Context and the Female Funding Penalty

A Quantitative Study Examining How Industry Category Moderates the Relationship Between Founder Gender Composition and Equity Funding Outcomes

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Abstract

Despite growing awareness of gender disparities in entrepreneurial finance, little is known about how the funding penalty varies across specific industry contexts. Drawing on gender role congruity theory, this study examines whether industry category moderates the relationship between founder gender composition and equity funding outcomes. Using an OLS regression model on 41,711 startups from the United States and Europe between 2016 and 2026, we find a negative and statistically significant gender funding gap, indicating that female-only and mixed-gender founding teams are associated with lower equity funding than comparable male-only teams. The gap varies significantly across industries for female-only teams but no equivalent industry moderation is found for mixed-gender teams. Theoretically, the study contributes by providing evidence from a combined United States and European sample that gendered funding penalties are associated with industry context differently across founding team compositions: the female-only penalty appears industry-contingent, while no equivalent industry-contingent pattern is found for mixed-gender teams. By mapping the gap across six specific industry categories, the study moves beyond the binary sector classifications commonly used in prior work. Managerially, awareness of where and how the penalty operates across specific sectors is a necessary step toward more informed and equitable investment decisions.

Keywords*: Gender Funding Gap, Venture Capital, Industry, Equity Financing, Role Congruity Theory, Gender Composition, Signaling Theory*

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1. Introduction

Entrepreneurship plays an important role in economic development by supporting the creation of jobs, productivity growth, and the commercialization of high-quality innovations (van Praag & Versloot, 2007). Despite a strong global emphasis on gender equality, both empirical studies and a systematic review show that entrepreneurial opportunities and outcomes remain unevenly distributed across genders (Brush et al., 2018; Hebert, 2025; Koziol et al., 2025). Women represent a growing share of startup founders, approximately 30% globally, yet they secure only 10−15% of venture capital and other equity funding (Hebert, 2025). This inequality is not a recent phenomenon. Women-led ventures received less than 4% of US venture capital on average per year between 1981 and 1999 (Greene et al., 2001). Brush et al. (2018) found that this share had nearly tripled to around 15% by 2013, but all-male founding teams remained four times more likely to receive financing than teams with even one woman. More recent evidence confirms that the gap persists, with female entrepreneurs on average 22% less likely than their male peers to be financed by equity and venture capital (Hebert, 2025). That women now found nearly a third of all startups and still receive a fraction of the capital available to their male counterparts reflects a systematic misallocation of resources (Hebert, 2025).

Team composition is one dimension along which these disparities operate. Research demonstrates that all-male teams are more likely to receive funding (Brush et al., 2018; Hebert, 2025), while Koziol et al. (2025), in their systematic literature review, note that some investors may favor gender-diverse teams. A further structural feature of the entrepreneurial landscape is industry segregation by gender. Female entrepreneurs tend to cluster in retail, consumer, and service industries, while male entrepreneurs are overrepresented in technology, manufacturing, and other capital-intensive sectors (Yacus et al., 2019). This matters because industry context is associated with both growth potential and access to external funding. As Hebert (2025) and Kanze et al. (2020) demonstrate, the equity gender gap is widest in male-dominated sectors.

This study focuses on equity financing rather than debt, as the two operate under fundamentally different evaluation logics and debt financing is often less accessible to early-stage ventures. Banks rely on standardized, rule-based metrics such as credit scores, collateral, and repayment capacity, whereas equity investors seek ventures capable of generating large returns and depend heavily on qualitative judgments about the founders themselves, their backgrounds, competence, and perceived ability to execute (Hebert, 2025; Winton & Yerramilli, 2008).

Subjective evaluation becomes especially important at early stages, where pronounced information asymmetry means investors must form judgments under considerable uncertainty, often in the absence of audited financials or revenue (Alsos & Ljunggren, 2017). This difference in evaluation logic matters because it opens the door to bias: while banks assess male and female entrepreneurs on broadly comparable objective terms, equity investors do not (Hebert, 2025; Winton & Yerramilli, 2008).

Despite a growing literature on gender and entrepreneurial finance, important limitations remain. Existing studies are geographically fragmented. Hebert (2025) studies French startups exclusively, Kanze et al. (2020) focus on US ventures, and the systematic review by Koziol et al. (2025) documents a similarly narrow landscape. The United States and Europe together account for a substantial share of global venture capital activity. In 2024, US-based startups attracted $209 billion in venture capital and European startups $62.4 billion, together representing roughly three-quarters of the $368 billion invested globally (KPMG, 2025). Prior research also remains limited in terms of industry specificity, as existing studies often rely on broad binary male- versus female-dominated classifications, and in terms of team composition, as mixed-gender teams are less often treated as a distinct category. To address these limitations, the purpose of this study is to examine whether founder gender composition is associated with equity financing outcomes and whether this relationship varies systematically across industry categories.

Accordingly, the following research question is addressed: *Is the gender composition of founding teams associated with equity financing outcomes, and does this association vary systematically across industry categories?*

2. Literature Review

2.1 Gender Disparities in Equity Financing

The gender funding gap is one of the most persistent structural inequalities in entrepreneurial finance, and prior research has established that female entrepreneurs face greater challenges in accessing startup capital than their male counterparts (Brush et al., 2019; Greene et al., 2001; Hebert, 2025).

Even after controlling for a comprehensive set of founder and firm characteristics, including education, experience, growth motivations, and initial capital, only 42% of this gap can be explained (Hebert, 2025). This means that more than half of the funding disadvantage remains even when female and male entrepreneurs are comparable on observable characteristics, which points to something beyond firm quality driving the funding gap (Ewens & Townsend, 2020; Hebert, 2025). The scale of the disadvantage is further illustrated by Koziol et al. (2025), whose systematic literature review shows that prior studies generally find a male advantage over female entrepreneurs in both the likelihood of obtaining funding and the total amount raised from venture capitalists and business angels.

Equity financing encompasses several distinct funding mechanisms, including venture capital, angel investment, and equity crowdfunding, among others. These differ in stage focus, typical investment size, investor profile, and degree of post-investment involvement, but share the common feature of exchanging capital for a share of company ownership (Drover et al., 2017). The mechanisms discussed below reflect those represented in this study's dataset, spanning from early-stage angel and seed rounds to growth-stage venture capital and equity crowdfunding as an alternative funding pathway. Angel investors are individuals who invest their own capital in early-stage ventures, often during the seed phase, before stable financing exists (Deias & Magrini, 2023). They contribute with expertise and mentorship alongside financing and are increasingly organized through angel groups and online platforms (Drover et al., 2017). Venture capital, the most widely recognized form of equity financing, is provided by firms that raise money from limited partners and selectively invest in high-potential companies, typically taking an active governance role (Drover et al., 2017; Winton & Yerramilli, 2008). Series A and B rounds are considered earlier-stage financing for ventures in their development stage, while Series C and beyond represent later-stage growth rounds typically designed for established ventures scaling their operations (Deias & Magrini, 2023). Equity crowdfunding, a more recent addition, disperses ownership across a large number of investors who each contribute relatively small amounts (Drover et al., 2017). While venture capital captures the largest share of aggregate dollars, seed and angel investments account for the majority of US funding deals by volume (Kanze et al., 2018).

The structural characteristics of early-stage ventures make debt financing largely inaccessible, which is why equity financing is the primary external funding mechanism for high-growth startups. Most startups lack the stable cash flows and repayment histories that banks require, and their assets are often intangible, such as human capital or untested business models, which further limits their creditworthiness (Hebert, 2025). Rather than borrowing, capital is raised by selling an ownership stake to investors who accept the downside risk in exchange for a share of the upside (Drover et al., 2017). Access to equity financing can therefore make the difference between success and failure for growth-oriented ventures, including those led by women (Drover et al., 2017; Hebert, 2025). Furthermore, Geiger’s (2020) meta-analysis shows that the relationship between gender and funding differs meaningfully depending on whether the funding context is traditional equity or crowdfunding and whether the outcome measured is funding likelihood or funding amount. Across the studies included in Geiger’s (2020) meta-analysis, women are generally disadvantaged in traditional equity contexts on both dimensions. In crowdfunding, however, the picture is more nuanced, with female entrepreneurs being equally or more likely to successfully reach their funding goal. Nevertheless, they still tend to raise lower total amounts than their male counterparts, as documented in Geiger's (2020) meta-analysis and by Geiger & Oranburg (2018).

In male-dominated industries, the concentration of bias does not simply reduce the number of women who receive funding; it also distorts the quality threshold at which they receive it. Female-founded startups that do obtain venture capital backing in these sectors are 17% more likely to survive after three years and achieve 50% higher revenue growth than their male counterparts (Hebert, 2025). This pattern suggests that investors apply a disproportionately high standard to female founders (Hebert, 2025), resulting in a selection effect where only the most exceptional female-led ventures receive funding, while comparable male-led ventures are funded at a lower quality threshold.

2.2 The Mechanisms Associated with the Funding Gap

This section examines some of the underlying mechanisms that drive the gender funding gap. Geiger’s (2020) meta-analysis notes that the gap is shaped by both supply-side factors, relating to investor behavior, and demand-side factors, relating to entrepreneur behavior and context.

From an investor perspective, the founding team and entrepreneur become especially important in the evaluation of early-stage ventures, where measurable performance indicators are often limited or absent (Geiger, 2020; Hebert, 2025; Winton & Yerramilli, 2008). Koziol et al. (2025) note in their systematic review that gender is one easily observable characteristic, and that investors often rely on it as a shortcut to predict a venture's potential and guide their investment decisions. They summarize this reliance on gender as stemming from two broad sources: first, real differences between female and male entrepreneurs in characteristics such as industry preference, risk-taking behavior, and leadership styles; and second, stereotypes and biased beliefs that alter how investors perceive these characteristics (Koziol et al., 2025).

The gap can further be explained through the theory of homophily, which is the tendency of individuals to associate with others based on shared characteristics (Geiger, 2020; Greenberg & Mollick, 2017). In the meta-analysis, Geiger (2020) discusses three distinct mechanisms of homophily that help explain the funding gap. First, induced homophily suggests that female entrepreneurs face greater difficulty obtaining funding because they are underrepresented in traditional funding networks. Second, interpersonal homophily suggests that a male investor may be more comfortable funding a male entrepreneur because the investor identifies more strongly with the entrepreneur. Third, activist choice homophily, in contrast, suggests that female investors are more likely to support female entrepreneurs out of a desire to help others facing similar barriers (Geiger, 2020; Greenberg & Mollick, 2017). This suggests that female entrepreneurs are disadvantaged in traditional equity markets due to the structural underrepresentation of female investors. Historically, more than 90% of the entrepreneurial and venture capital labor pool has been male (Calder-Wang & Gompers, 2021). Conversely, the meta-analysis further suggests that in non-traditional contexts such as equity crowdfunding, the gender gap is less pronounced, which can be explained by the greater female representation among funders in those contexts (Geiger, 2020).

The bias against female entrepreneurs also manifests in the pitch and evaluation process. Kanze et al. (2018) observed that venture capitalists ask male entrepreneurs promotion-oriented questions focused on growth and potential, while female entrepreneurs are asked primarily prevention-oriented questions focused on risk and safety. The difference in framing was associated with funding outcomes, as entrepreneurs who received promotion-based questions raised seven times more funding than those asked prevention-based questions, suggesting that differential treatment is associated with substantial differences in funding outcomes (Kanze et al., 2018). Furthermore, consistent with this, Brooks et al. (2014) show that investors prefer entrepreneurial pitches presented by male entrepreneurs compared to identical pitches presented by female entrepreneurs, despite the content being the same. These findings support that investor evaluations are not solely based on venture quality but also influenced by gender biases and perceptions (Brooks et al., 2014).

Beyond investor behavior, Geiger’s (2020) meta-analysis also highlights demand-side explanations for the gap. Entrepreneurship itself is widely perceived as a stereotypically masculine endeavor, meaning female entrepreneurs enter an environment constructed around male norms and practices, which can influence both how they are evaluated and how they evaluate their own chances of success (Jennings & Brush, 2013). Furthermore, investors tend to evaluate entrepreneurs based on masculine characteristics, leading to similar qualifications being interpreted differently across genders (Alsos & Ljunggren, 2017). Gender socialization further shapes how entrepreneurs behave and what they pursue, as synthesized by Geiger (2020) across the gender funding gap literature. Drawing on this meta-analysis, individuals are found to internalize gender-linked norms that can lead to a self-stereotyping process, whereby female entrepreneurs self-select into industries and smaller venture sizes consistent with gender stereotypical expectations (Geiger, 2020; Yacus et al., 2019). This in turn is associated with reduced external financing sought by female entrepreneurs, reinforcing the general funding gap from the demand side, as further documented in Geiger's (2020) meta-analysis.

Taken together, supply- and demand-side mechanisms, along with stereotypes and biased beliefs, help partly explain why the gender funding gap persists even among observably comparable entrepreneurs. Critically, however, these mechanisms do not operate uniformly. As Koziol et al. (2025) note in their systematic literature review, prior research has shown that they depend on contextual factors, which is the focus of the following section.

3. Theoretical Framework and Hypothesis Development

3.1 Theoretical Overview

This study integrates three theoretical perspectives. The foundation is gender role congruity theory (Eagly & Karau, 2002), which proposes that prejudice arises when perceivers detect an incongruity between the attributes associated with a social group and those believed to be required for success in a given role. Applied to gender, women are ascribed communal attributes such as sympathy and helpfulness, while men are portrayed as achievement-oriented with agentic traits such as assertiveness and confidence (Heilman, 2001).

In addition, Bordalo et al. (2016) show that decision makers overweight the most representative attributes of a group when forming judgments. Because the historically successful founder is predominantly male, the male entrepreneur may function as the implicit prototype, distorting evaluations independently of actual venture quality.

Signaling theory provides a third lens by explaining how gender bias enters the investor evaluation process. Under conditions of information asymmetry, investors cannot directly assess venture quality and instead rely on observable founder characteristics as proxies (Alsos & Ljunggren, 2017). Gender shapes both the signals entrepreneurs can produce and how investors interpret them. Together, these three perspectives explain how gendered role expectations, stereotype-based judgments, and signal interpretation may shape investor evaluations, respectively.

3.2 Research Gap and Study Contribution

While prior research has established gender disparities in entrepreneurial financing, several important limitations remain. First, both Hebert (2025) and Kanze et al. (2020) examined how industry context shapes the gender funding gap. However, they operationalize industry context as a binary, male-dominated versus female-dominated, based on the share of female founders or employees in a sector. This framing assumes the penalty varies with female representation, leaving it unclear how the funding penalty varies across specific named industry categories. Second, prior research rarely examines mixed-gender founding teams separately from all-male and all-female teams, meaning the moderation effect has rarely been systematically tested across all three team compositions. Third, much of the empirical evidence in this area is drawn from single-country contexts, as illustrated by studies such as Hebert (2025) and Kanze et al. (2020). Koziol et al. (2025), in their systematic literature review, similarly point to the fragmented nature of the existing evidence base, limiting understanding of whether similar patterns are observed across broader regional contexts. This study addresses all three gaps by mapping the gender funding penalty across six specific industry categories and across three team compositions, drawing on startups from both the United States and Europe.

3.3 Team Gender Composition and Equity Funding

Having established the theoretical foundations of role congruity, stereotype representativeness, and signaling theory, this section applies these perspectives to founding-team gender composition. Because the entrepreneurial role is stereotypically portrayed as masculine, founding and leading a venture is associated with agentic qualities such as assertiveness, confidence, and achievement orientation that are more commonly ascribed to men (Heilman, 2001; Jennings & Brush, 2013; Malmström et al., 2017; Yacus et al., 2019). Female entrepreneurs are perceived as incongruent with these expectations, producing two reinforcing forms of prejudice: they are seen as less suited for the entrepreneurial role, and when they do behave agentically, that behavior is judged more harshly than identical behavior displayed by men (Eagly & Karau, 2002; Malmström et al., 2017). This suggests that equity investors do not evaluate venture potential in isolation from the founders presenting it; founder gender composition shapes how investors perceive entrepreneurial fit, competence, and legitimacy.

This cognitive process is further explained by stereotype representativeness (Bordalo et al., 2016). Applied to entrepreneurship, this suggests that the male founder will function as the representative type against which all entrepreneurs are implicitly assessed, which may place female founders at a disadvantage (Hebert, 2025; Jennings & Brush, 2013). Signaling theory further helps explain why these biases may be reflected in funding outcomes. Under conditions of information asymmetry, investors rely on observable signals to assess venture potential, but gender shapes both how signals are produced and how they are interpreted (Alsos & Ljunggren, 2017). Gendered career paths and unequal access to human, social, and financial capital may shape the signals female founders are able to send credibly, while the same signal carries different weight depending on the gender of the sender. This suggests female founders face a higher burden of proof, having to signal their legitimacy more strongly to receive equivalent evaluation (Alsos & Ljunggren, 2017). Taken together, role incongruity, stereotype-based evaluation, and biased signal interpretation suggest that female founders face systematic disadvantage relative to male founders, both in initial perceptions of their suitability and in investor evaluation during the funding process. While prior studies have documented this disadvantage, this study examines it in a combined United States and European sample, treating mixed-gender teams as a distinct group, to assess whether these patterns generalize across institutional environments and team types.

Following this, we hypothesize:

H1: *Female-only founding teams receive significantly less equity funding than male-only founding teams.*

Role congruity theory predicts that mixed-gender teams occupy an intermediate position between all-male and all-female teams. While the presence of male founders provides partial congruity with the male prototype of entrepreneurship, female participation still introduces some degree of incongruity into investor evaluations (Eagly & Karau, 2002).

Following this, we hypothesize:

H2: *Mixed-gender founding teams receive significantly less equity funding than male-only founding teams.*

3.4 Industry Context as a Moderator

The mechanisms outlined do not operate with equal strength across all industries (Hebert, 2025; Kanze et al., 2020). While role congruity theory suggests a general penalty for female entrepreneurs, it also predicts that this penalty is not constant. The penalty is amplified in contexts where the incongruity between female gender and role expectations is greatest and reduced where the two align more naturally (Eagly & Karau, 2002; Johansson et al., 2021). Industry context can be understood as a moderating factor because different industries carry different gender stereotypes, which may be associated with investors' perception of founder fit (Hebert, 2025). Drawing on Bordalo et al. (2016), industry context can be understood as shaping the representative entrepreneurial prototype, as sectors where dominant industry associations align closely with male attributes, the perceived incongruity facing female founders is amplified. This suggests that industries such as Tech, Finance and Business Services, and Industrial, Energy and Transportation, which are associated with masculine attributes such as technical expertise and analytical rigor (Yacus et al., 2019), are likely to produce larger penalties for female founders, while industries such as Consumer and Retail, where industry associations may be more communal and congruent with female founders (Yacus et al., 2019), are expected to produce smaller penalties.

Signaling theory reinforces this prediction. In industries built on intangible assets or complex business models, information asymmetry is high, leaving investors with limited objective criteria for evaluation (Alsos & Ljunggren, 2017). Under these conditions, observable founder characteristics, including gender, can become more influential as proxies for quality, potentially amplifying the biases described above. Alsos and Ljunggren (2017) illustrate this dynamic concretely, showing that venture capitalists placed greater value on a male entrepreneur's experience in a male-dominated industry than on a female entrepreneur's directly relevant experience. Female founders in such contexts may therefore face a compounded disadvantage: the industries where investors struggle most to evaluate ventures objectively are the same industries where gender incongruity is most pronounced, meaning both sources of bias peak simultaneously. While prior studies have tested whether industry context is associated with variation in the penalty using binary male- versus female-dominated classifications, this study estimates the gap across six specific named industry categories, to assess whether the penalty varies across distinct sectors and team compositions.

Therefore, we hypothesize the following:

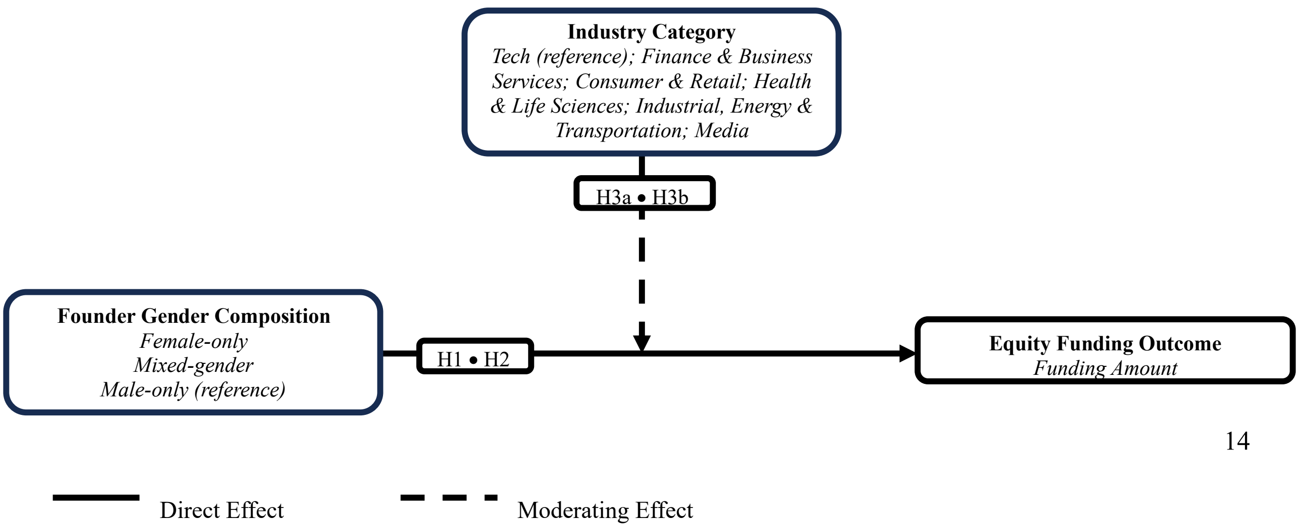
H3a: *The funding gap between female-only and male-only founding teams varies significantly across specific industry categories*.

This logic extends to mixed-gender teams. While the presence of male founders partially offsets the congruity gap, female participation still introduces a degree of incongruity that all-male teams do not face. In industries with a strongly masculine founder profile, even partial female representation may trigger the same evaluative penalties, as investors anchor to the dominant male prototype. Following the same reasoning, the penalty for mixed-gender teams is expected to be larger in industries with strongly masculine associations and high information asymmetry, such as Tech and Finance and Business Services, and smaller in industries where the incongruity between female participation and industry expectations is less pronounced.

Therefore, we hypothesize the following:

H3b: *The funding gap between mixed-gender and male-only founding teams varies significantly across specific industry categories*.

Figure 1: Conceptual Framework



4. Methodology

4.1 Data

This study is based on the Crunchbase Funding Database, a comprehensive dataset mapping global funding deals, including both equity and debt financing (Crunchbase, 2026). The dataset includes information such as headquarters location, company founding year, total equity funding amount, number of funding rounds, number of employees, type of funding, and founder names. We restricted the dataset to equity funding observations within the last ten years (2016–2026), motivated by the aim of capturing current equity financing dynamics. Furthermore, we limited the sample to companies with a maximum of 100 employees to exclude large corporations and mature enterprises. After these initial restrictions, the sample consisted of 123,849 observations. Although the dataset spans 2016 to 2026, each company contributes a single observation reflecting its cumulative equity funding, making this a cross-sectional snapshot rather than a panel.

4.1.1 Data Cleaning

To ensure the quality of the dataset, observations with missing values in the key variables of interest, including headquarters location, founder names, industry group, total equity funding, and number of funding rounds, were removed. Observations with zero values in total equity funding were also dropped at this stage. The dataset was further filtered to include only equity-based financing types, specifically Seed, Pre-Seed, Series A through I, Angel, and Equity Crowdfunding. This ensured that the sample reflected equity financing for ventures, excluding fundamentally different funding mechanisms such as Post-IPO Equity and Initial Coin Offerings (Drover et al., 2017). We subsequently restricted the dataset to companies headquartered in the United States or Europe.

Since funding amounts were reported in multiple currencies across the dataset, all monetary values for total equity funding were converted to EUR using a 10-year average between 2016 and 2026 based on daily exchange rates obtained from the European Central Bank, ensuring comparability across observations (European Central Bank, 2026). Two additional variables, company age and funding period, were constructed using the founding year. Industry classifications were consolidated from the multiple descriptive tags provided in the dataset's industry group column into six broad categories: Tech; Health and Life Sciences; Finance and

Business Services; Consumer and Retail; Industrial, Energy and Transportation; and Media (Table 3). Each company was assigned a category using a predefined set of prioritization rules.

To address the absence of gender classification in the original dataset, a gender inference approach was implemented using a Python-based gender prediction package, which was applied to founder names. To ensure clear categorization, companies were subsequently classified based on the gender composition of the founding teams. Firms with exclusively female founders were labeled as female-only, those with exclusively male founders as male-only, and firms with both male and female founders were categorized as mixed-gender. After cleaning and transforming the dataset, the final sample consisted of 41,711 observations. Claude and ChatGPT were used to assist with Python coding for data cleaning, variable construction, and regression analysis. All outputs were critically reviewed and verified by the authors.

4.1.2 Summary Statistics

Table 1: Summary Statistics

Variable		**Count**
Number of observations		41,711
Female-only teams		3,520
Mixed-gender teams		5,839
Male-only teams		32,352
US-based companies		26,481
Europe-based companies[1]		15,230
Total funding in € millions (Mean)		11.28
Total funding in € millions (SD)		38.67
Total funding in € millions (Median)		2.67
Company age (Mean)		9.36
Number of founders (Mean)		2.02
Number of funding rounds (Mean)		2.81
Industry	**% of Sample**	**Count**
Tech	61.5%	25,690
Finance & Business Services	10.4%	4,345
Health & Life Sciences	10.1%	4,236
Consumer & Retail	8.9%	3,733
Media	4.5%	1,858
Industrial, Energy & Transportation	4.4%	1,849

[1] Albania, Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Gibraltar, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Macedonia, Malta, Norway, Poland, Portugal, Romania, Serbia, Slovakia (Slovak Republic), Slovenia, Spain, Sweden, Switzerland, The Netherlands, Turkey, Ukraine, United Kingdom

Industry	% F	% M	% Mix
Tech	7.1%	79.4%	13.6%
Finance & Business Services	7.9%	78.6%	13.6%
Health & Life Sciences	10.4%	72.6%	17.1%
Consumer & Retail	18.9%	65.4%	15.7%
Media	6.8%	79.6%	13.5%
Industrial, Energy & Transportation	5.0%	84.5%	10.6%

Note: Authors' own calculations based on Crunchbase (2026)

Table 1 provides a summary of the key statistics for the dataset used in this study, where Total Funding Amount is presented in millions of EUR. It also presents the distribution of observations across the six industry sectors and the gender composition of founding teams within each sector.

Table 2: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Log funding share	1.000								
(2) Female-only	-.084	1.000							
(3) Mixed-gender	-.017	-.122	1.000						
(4) Funding period	.155	-.010	-.007	1.000					
(5) Company age	.100	-.023	-.038	.545	1.000				
(6) Number of founders	.127	-.180	.314	-.041	-.083	1.000			
(7) Average employees	.469	-.087	-.034	.163	.199	.078	1.000		
(8) US-based	.078	.037	.004	-.001	-.012	-.032	-.058	1.000	
(9) Number of funding rounds	.379	-.022	.039	.198	.208	.144	.220	.015	1.000

Note: Authors' own calculations based on Crunchbase (2026)

Table 2 presents the correlation matrix for the main variables included in the regression analysis. Overall, the correlations between the explanatory variables are relatively low to moderate, suggesting that multicollinearity is unlikely to be a major concern. The highest correlation among the explanatory variables is between funding period and company age ($r = 0.545$), which remains below the common threshold of 0.70. The dependent variable, log funding share within industry, is most strongly correlated with average employees ($r = 0.469$) and number of funding rounds ($r = 0.379$), suggesting that larger firms and firms with more financing rounds tend to receive higher relative funding. In contrast, the correlations between gender composition and funding outcomes are weak. Female-only teams are negatively correlated with funding outcomes ($r = -0.084$), while mixed-gender teams show a very small negative correlation ($r = -0.017$), suggesting that gender composition captures a dimension of funding outcomes that is distinct from firm size and financing history.

4.1.3 Data Limitations

While considerable efforts were made to ensure a high level of data quality and consistency, several limitations should be acknowledged.

First, the dataset exhibits an imbalance across observations, particularly with respect to geographic representation. A larger proportion of the data points in the dataset originate from the United States, while regions in Europe are comparatively underrepresented. This uneven distribution may limit the extent to which results can be generalized across different contexts. In addition, the dataset consisted of multiple currencies, and monetary values were converted to euros using a 10-year average exchange rate, reflecting the timespan of the dataset. While this approach ensures consistency across the data, it may introduce some measurement imprecision, as it does not account for year-specific fluctuations in exchange rates.

Second, the classification of founder gender relies on a Python-based gender inference tool. Although this approach enables gender classification at scale and is commonly applied in empirical research, it introduces potential measurement errors. Names are not always unambiguous indicators of gender and may vary across cultures and regions, increasing the likelihood of misclassification. In addition, the method imposes a binary gender framework and is therefore unable to capture non-binary identities. Gender-neutral names and incomplete names further contribute to potential inaccuracies in the classification. However, in our study, all unclassified names were dropped from the dataset.

Third, the original dataset obtained from Crunchbase did not provide standardized industry categories but instead relied on keyword-based tags that described main firm activities. Consequently, broader industry groupings were constructed manually, and firms were assigned to their final industry classifications using a rule-based hierarchy approach. While this method ensured a systematic and consistent classification, it remained dependent on the chosen classification rules. As a result, the final industry categorization was shaped by these methodological decisions, which may have affected the empirical results. However, several tests and exploratory analyses were conducted prior to establishing the classification approach to ensure that the resulting industry assignments were reasonable and well aligned with firm activities.

Finally, as the dataset obtained from Crunchbase is observational in nature, this study may be subject to selection bias, as funding decisions may be influenced by factors not captured in the data, such as founder experience and network connections.

4.2 Variables

4.2.1 Dependent Variable

Log Funding Share within Industry is constructed in two steps. First, each firm's total equity funding in EUR is divided by the average total equity funding of all companies within the same industry group and multiplied by 100, yielding a within-industry funding share. This step adjusts for structural differences in funding levels across industries, which is important as industries differ substantially in their funding requirements and failing to account for this would risk conflating industry-level funding differences with gender-based differences. Second, this share is log-transformed to address the right skew in equity funding distributions, where a small number of firms raise disproportionately large amounts, reducing the influence of outliers on the regression estimates.

We acknowledge a key limitation of this variable: because the data are a cross-sectional snapshot, it captures cumulative funding up to the point of data collection rather than funding from a specific round or year. This means that older companies have had more time to accumulate funding, which is why company age and funding period are included as control variables to partially address this concern.

4.2.2 Independent Variable

Gender Composition serves as the independent variable in this study. All firms in the dataset were categorized into three groups based on the gender composition of the founders: male-only, female-only, or mixed-gender teams. Since gender information was not available in the dataset, founder gender was inferred using a gender prediction package in Python based on founders' first names. While this approach may introduce some degree of measurement error, it provides a consistent and systematic method for classifying founder gender across the dataset. In the regression, dummy coding was applied. Male-only served as the reference category, and two dummy variables were created, female-only and mixed-gender. This specification makes it possible to estimate differences in funding outcomes relative to male-only founding teams and to identify whether female-only or mixed-gender teams are associated with systematically different funding outcomes.

4.2.3 Moderating Variable

Industry Classification serves as the moderating variable in this study, capturing whether the relationship between gender composition and funding outcomes varies across industries. In the original dataset, the industry group column consisted of multiple keyword-based tags describing the sectors in which each company operated, with firms often associated with several tags simultaneously. To ensure comparability across firms and align with the objectives of this study, we systematically mapped these tags to six broad categories using the Crunchbase industry glossary as a reference (Crunchbase, 2024). The final classification scheme consisted of the following categories: Tech; Health and Life Sciences; Finance and Business Services; Consumer and Retail; Industrial, Energy and Transportation; and Media (Table 3).

Table 3: Industry Classification and Keywords

Main industry	**Keywords**
Tech	Software, Information Technology, Data and Analytics, Internet Services, Apps, Mobile, Platforms, Privacy and Security, Messaging and Telecommunications, Navigation and Mapping, Hardware, Science and Engineering, Artificial Intelligence (AI)
Health & Life Sciences	Healthcare, Biotechnology
Finance & Business Services	Financial Services, Payments, Lending and Investments, Blockchain and Cryptocurrency, Professional Services, Administrative Services
Consumer & Retail	Commerce and Shopping, Consumer Goods, Food and Beverage, Clothing and Apparel, Consumer Electronics
Industrial, Energy & Transportation	Manufacturing, Energy, Natural Resources, Agriculture and Farming, Transportation
Media	Media and Entertainment, Content and Publishing, Video, Music and Audio, Advertising, Sales and Marketing

Note: Industry categories constructed by the authors based on Crunchbase (2026)

Each company was assigned to one category using a predefined set of classification rules. First, a dominant category rule was applied, assigning each company to the industry category represented by the majority of its associated tags, reflecting their core business activity.

Second, a fallback hierarchy was applied. Under this rule, companies were assigned based on a predefined prioritization order: Tech; Finance and Business Services; Consumer and Retail; Health and Life Sciences; Industrial, Energy and Transportation; and Media. This hierarchy was developed through iterative testing and sampling to maximize classification accuracy, with more distinctly defined and mutually exclusive categories assigned higher priority. Nevertheless, we acknowledge that the classification outcomes depend on the rules applied, and that alternative classification rules may yield different category assignments. While these six categories enable systematic comparison across industries, they remain relatively broad and likely capture substantial heterogeneity within each group, meaning that firm-level variation within categories is not accounted for.

Industry was modeled as a categorical variable using dummy coding across the six industries, with Tech serving as the reference category. Rather than including industry solely as a control, the model directly incorporates interaction terms between gender composition and industry category, allowing the gender funding gap to vary across sectors. This specification enables a direct test of whether industry moderates the relationship between founding team gender composition and equity financing outcomes, without assuming that the gender penalty is constant across industries.

4.2.4 Control Variables

Number of Funding Rounds refers to the total number of funding rounds in which a company has participated. The control variable is included since firms with more funding rounds have had more opportunities to raise capital.

Table 4: Funding Stage Classification

Group	Includes	Count
Early Stage	Angel, Pre-Seed, Seed	22,639
Venture Stage	Venture, Series A, Series B	16,500
Growth Stage	Series C, D, E, F, G, H, I, Private Equity	1,463
Alternative Funding	Equity Crowdfunding	1,109

Note: Authors' own calculations based on Crunchbase (2026)

Last Funding Type denotes the type of the most recent funding round. It is categorized into Early Stage, Venture Stage, Growth Stage, and Alternative Funding based on Crunchbase's funding-type definitions (Crunchbase, 2025). The categorization is presented in Table 4. Funding stage is treated as a categorical variable using dummy-variable coding, with Early Stage serving as the reference category. The variable is included to account for differences in companies' funding stages as later-stage funding rounds are typically associated with larger investment amounts.

Location serves as a dummy variable indicating whether the company is headquartered in the United States or in Europe (1 = United States, 0 = Europe). It is included as a control variable to account for differences in market conditions across different geographical contexts.

Company Age is calculated as the difference between 2026 and the year when the company was founded, capturing how long the company has been in operation.

Funding Period is defined as the year of the most recent funding round minus the founding year, reflecting the time span over which the company actively received investment. Unlike company age, which captures the total lifespan of the company, the funding period specifically measures the duration of the company's fundraising activity, which may independently influence total funding outcomes.

Average Number of Employees is a control variable that captures firm size in terms of the workforce and number of employees. The original dataset reported employee counts in ranges: 1–10, 11–50, and 51–100. Each range category was converted into a representative midpoint to create an approximate proxy for firm size, as it influences a company's capacity to raise funding.

4.3 Empirical Method

We used Ordinary Least Squares (OLS) regression to examine whether industry moderates the gender funding gap in equity financing. The main empirical specification was an interaction model including founder gender composition, industry categories, gender × industry interaction terms, and control variables. From this model, we first estimated the overall gender funding gap by calculating weighted average gender gaps across industries. Second, we tested whether this gap varied significantly across industry groups using interaction terms and joint F-tests. Third, we conducted exploratory pairwise comparisons across all industry combinations to identify which industry pairs appear to differ in the size of the funding gap.

4.3.1 OLS Regression Model

The main empirical specification was an interaction model that estimated the overall gender funding gap and tested whether it varied across industries. The model took the following form:

$$\text{Log Funding Share Within Industry}_i = \beta_0 + \beta_1\text{Female}_i + \beta_2\text{Mixed}_i + \beta_3\text{Industry}_i + \beta_4(\text{Female}_i \times \text{Industry}_i) + \beta_5(\text{Mixed}_i \times \text{Industry}_i) + \beta_6\text{Controls}_i + \varepsilon_i$$

where the dependent variable is the natural logarithm of each company's total equity funding expressed as a percentage of its industry average. The dependent variable was constructed as:

$$\text{Log Funding Share Within Industry}_i = \ln\left[\left(\left(\text{Total Funding}_i / \text{Industry Average Funding}_j\right) \times 100\right) + 1\right]$$

β_1 captures the female-only funding gap in the reference industry, Tech, while β_2 captures the mixed-gender funding gap in Tech. The interaction coefficients β_4 and β_5 capture whether the female-only and mixed-gender gaps are significantly larger or smaller in each non-Tech industry relative to Tech. Tech was chosen as the reference category as it constitutes 61.5% of the sample (Table 1). The choice of reference category does not affect the substance of the results, only the interpretation of the coefficients changes.

Female_i and Mixed_i are indicator variables equal to one if the founding team consists entirely of female founders or a mix of male and female founders respectively, with male-only teams serving as the reference category. Control variables included company age, funding period, number of founders, average employees, funding stage, US-based, and number of funding rounds.

The overall gender funding gap was estimated from this model as a weighted average of the industry-specific gender gaps, using each industry's share of the sample as weights. This approach recovers a single summary estimate of the average penalty faced by female-only and mixed-gender teams across the full sample, while accounting for the fact that the gap may differ by industry. Industry moderation was then assessed using a joint F-test on all five Female × Industry interaction terms, testing the null hypothesis that the female-only funding gap is identical across all industries. Rejecting this null hypothesis provides evidence that industry context moderates the funding gap for female-only teams. A separate joint F-test was conducted for the Mixed × Industry interaction terms to examine whether the same pattern holds for mixed-gender founding teams.

4.3.2 Pairwise Industry Comparisons

To obtain a more granular picture of where the gender funding gap differs most across sectors, we conducted exploratory pairwise comparisons across all industry combinations using linear hypothesis tests on the interaction coefficients from the interaction model. For pairs involving Tech, the test examined whether the relevant interaction coefficient differed significantly from zero. For pairs not involving Tech, the test examined whether two interaction coefficients differed significantly from each other. These comparisons were exploratory in nature and were not tied to a pre-specified hypothesis. It should be noted that conducting multiple comparisons increases the risk of Type I error, and the results were therefore interpreted with appropriate caution.

4.3.3 Standard Errors and Inference

The models were estimated with heteroscedasticity-robust standard errors using the HC3 correction, as venture funding data exhibits substantial heteroscedasticity given the large range of company sizes and funding stages in the sample. Rather than assuming constant error variance across all observations, HC3 accounts for unequal variance and provides more reliable statistical inference. Individual coefficient significance was assessed at the 1%, 5%, and 10% levels, with the 5% level serving as the conventional threshold for statistical significance.

5. Results

5.1 Model Fit

Table 5: Sequential Model Results

	Model 0 Controls only	Model 1 + Gender	Model 2 + Industry FE	Model 3 + Interactions
Female-only		−0.1604***	−0.1822***	−0.2123***
Mixed-gender		−0.1360***	−0.1300***	−0.1374***
Female-only × Finance & Business Services				−0.0459
Female-only × Consumer & Retail				+0.1434*
Female-only × Health & Life Sciences				−0.0096
Female-only × Industrial, Energy & Trans.				+0.0670
Female-only × Media				+0.2131*
Mixed × Finance & Business Services				+0.0743
Mixed × Consumer & Retail				+0.0059
Mixed × Health & Life Sciences				−0.0009

Mixed × Industrial, Energy & Trans.				−0.0452
Mixed × Media				+0.0407
Controls	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes
Gender × Industry interactions	No	No	No	Yes
N	41,711	41,711	41,711	41,711
R^2	0.489	0.490	0.501	0.502
Adj. R^2	0.488	0.490	0.501	0.501
AIC	132,309	132,205	131,267	131,273
BIC	132,395	132,309	131,414	131,506
HC3 Robust SE	Yes	Yes	Yes	Yes

** p<0.05, ** p<0.01, *** p<0.001. Controls include funding period, company age, number of founders, average employees, funding stage, US-based, and number of funding rounds. Reference categories: Male-only (gender), Tech (industry), Early stage (funding stage). Note: Authors' own calculations based on Crunchbase (2026)*

Table 5 reports the sequential model results across four specifications, illustrating the incremental contribution of each set of variables. Models 0 through 3 add gender composition, industry fixed effects, and gender × industry interactions stepwise, allowing the stability of the gender coefficients to be assessed as controls are added. The gender coefficients for both female-only and mixed-gender teams remain negative and statistically significant across Models 1, 2, and 3, suggesting that the funding penalty is not an artifact of omitted industry-level differences. In terms of model fit, adding gender composition (Model 0 to Model 1) produced only a marginal increase in R^2, which was expected given that a single categorical variable cannot be expected to explain much of the overall variation in funding outcomes. Adding industry fixed effects in Model 2 produced the largest, though still modest, improvement in R^2, consistent with industry being one of several relevant factors associated with funding outcomes. The marginal increase in AIC and BIC from Model 2 to Model 3 may reflect the cost of adding ten interaction parameters against a modest improvement in model fit, with BIC penalizing the added complexity more heavily given its stronger penalty for additional parameters. The interaction model was nonetheless retained as it was theoretically motivated by the research question.

5.2 The Gender Funding Gap: Establishing the Baseline and the Industry Moderation

Table 6: OLS Interaction Model

	Weighted gap	z-statistic	P-value
Female-only weighted average gender gap	−0.1928	−8.45	<0.001
Mixed-gender weighted average gender gap	−0.1294	−7.49	<0.001
Variable	**Coef.**	**Robust SE**	**P-value**
Gender in Tech (ref: Male-only)			
Female-only	−0.2123	0.031	<0.001
Mixed-gender	−0.1374	0.022	<0.001
Female-only × Industry interactions (ref: Tech)			
× Finance & Business Services	−0.0459	0.073	0.529
× Consumer & Retail	+0.1434	0.057	0.012
× Health & Life Sciences	−0.0096	0.066	0.884
× Industrial, Energy & Transportation	+0.0670	0.124	0.588
× Media	+0.2131	0.104	0.040
Mixed-gender × Industry interactions (ref: Tech)			
× Finance & Business Services	+0.0743	0.055	0.175
× Consumer & Retail	+0.0059	0.056	0.917
× Health & Life Sciences	−0.0009	0.052	0.986
× Industrial, Energy & Transportation	−0.0452	0.091	0.618
× Media	+0.0407	0.081	0.617
Controls			
Funding period	+0.0134	0.002	<0.001
Company age	−0.0517	0.002	<0.001
Number of founders	+0.0934	0.006	<0.001
Average employees	+0.0199	0.000	<0.001
Funding stage (Stage 2)	+1.5411	0.015	<0.001
Funding stage (Stage 3)	+2.4665	0.042	<0.001
Funding stage (Stage 4)	+0.0868	0.035	0.013
US-based	+0.2517	0.012	<0.001
Number of funding rounds	+0.1495	0.003	<0.001
N			41,711
R^2			0.502
Adj. R^2			0.501
H3a Joint F-test female-only			$F = 2.35$, $p = 0.039$
H3b Joint F-test mixed-gender			$F = 0.49$, $p = 0.785$
HC3 Robust SE			Yes
Industry FE			Yes

Note: Authors' own calculations based on Crunchbase (2026)

To test H1 and H2, the average gender funding gap was estimated across all six industries. The results indicate a significant funding disadvantage for both female-only and mixed-gender teams across the combined sample of ventures from the United States and Europe. Female-only teams raised approximately 17.5% less than comparable male-only teams (weighted gap = −0.1928, $p < 0.001$), and mixed-gender teams raised approximately 12.1% less (weighted gap = −0.1294, $p < 0.001$), with percentage figures derived using the transformation $(e^\beta - 1) \times 100$ to account for the log-transformed dependent variable. Among the control variables, funding stage showed the strongest effects, with venture-stage rounds ($\beta = +1.541$, $p < 0.001$) and growth-stage rounds ($\beta = +2.467$, $p < 0.001$) associated with larger total funding than early-stage rounds. US-based firms raised more than European firms ($\beta = +0.252$, $p < 0.001$). Additional funding rounds, larger founding teams, and higher employee counts were all positively associated with funding. Company age carried a small negative coefficient ($\beta = -0.052$, $p < 0.001$).

These results support H1 and H2. The weighted average gap confirmed that the funding disadvantage was statistically significant on average across all industries. The same holds for mixed-gender teams, whose penalty was smaller but also statistically significant. H1 and H2 are therefore supported.

Table 7: Per-Industry Gender Funding Gaps

Industry	F-only gap	P-value	Mixed gap	P-value
Tech	−0.2123	<0.001	−0.1374	<0.001
Finance & Business Services	−0.2582	<0.001	−0.0632	0.213
Consumer & Retail	−0.0689	0.154	−0.1316	0.012
Health & Life Sciences	−0.2219	<0.001	−0.1383	0.004
Industrial, Energy & Transportation	−0.1453	0.225	−0.1826	0.039
Media	+0.0008	0.994	−0.0967	0.219

Note: Authors' own calculations based on Crunchbase (2026)

Interaction terms between gender composition and industry were included to test H3a and H3b. Since the interaction coefficients only showed differences relative to Tech, the total funding penalty for each industry was calculated by combining the baseline coefficient with the relevant interaction term, giving a direct estimate of the female funding gap in each sector (Table 7). The penalty was largest and statistically significant in Finance and Business Services (−0.2582, $p<0.001$), Health and Life Sciences (−0.2219, $p < 0.001$), and Tech (−0.2123, $p < 0.001$). The penalty was not statistically significant in Consumer and Retail (−0.0689, $p = 0.154$), Industrial, Energy and Transportation (−0.1453, $p = 0.225$), and Media (+0.0008, $p = 0.994$). For mixed-gender teams, the penalty was statistically significant in Tech (−0.1374, $p < 0.001$), Consumer and Retail (−0.1316, $p = 0.012$), Health and Life Sciences (−0.1383, $p = 0.004$), and Industrial, Energy and Transportation (−0.1826, $p = 0.039$).

The joint F-test on the five female-only interaction terms was significant ($F = 2.35$, $p = 0.039$), indicating that the funding penalty faced by female-only founding teams varied systematically across industry categories. H3a was therefore supported. For mixed-gender teams, the joint F-test was not significant ($F = 0.49$, $p = 0.785$), meaning that the industry-level differences did not amount to systematic industry moderation for mixed-gender teams. H3b was therefore not supported.

5.3 Exploratory Extension: Pairwise Industry Comparisons

Table 8: Pairwise Industry Comparisons

Pair	F-statistic	P-value
Female-only teams		
Tech vs Consumer & Retail	6.29	0.012
Tech vs Media	4.23	0.040
Finance vs Consumer & Retail	5.35	0.021
Finance vs Media	4.73	0.030
Consumer & Retail vs Health & Life Sciences	4.07	0.044
Health & Life Sciences vs Media	3.75	0.053
Mixed-gender teams		
No significant pairwise differences at the 5% level	—	—

Note: Authors' own calculations based on Crunchbase (2026)

From the additional exploratory pairwise comparisons, five pairs reached statistical significance at the 5% level for female-only teams. The female penalty differed significantly between Tech and Consumer and Retail ($F = 6.29$, $p = 0.012$), and between Tech and Media ($F = 4.23$, $p = 0.040$). It also differed significantly between Finance and Business Services and Consumer and Retail ($F = 5.35$, $p = 0.021$), and between Finance and Business Services and Media ($F = 4.73$, $p = 0.030$). The difference between Consumer and Retail and Health and Life Sciences ($F = 4.07$, $p = 0.044$) reached significance at the 5% level, while the difference between Health and Life Sciences and Media was only marginally significant at the 10% level ($F = 3.75$, $p = 0.053$). The remaining pairs were not statistically significant.

5.4 Robustness Checks

Table 9: Robustness Checks

Specification	N	H1: Female-only	H2: Mixed	H3a: F-test female-only	H3b: F-test mixed
Main model					
Baseline	41,711	−0.1928 p<0.001	−0.1294 p<0.001	F=2.35, p=0.039	F=0.49, p=0.785
Robustness checks					
Check 1: Raw log funding	41,711	−0.2336 p<0.001	−0.1421 p<0.001	F=2.51, p=0.028	F=0.37, p=0.867
Check 2: Core VC sample	39,138	−0.1991 p<0.001	−0.1299 p<0.001	F=2.76, p=0.017	F=0.43, p=0.830
Check 3: Winsorized	41,711	−0.1929 p<0.001	−0.1275 p<0.001	F=2.43, p=0.033	F=0.50, p=0.780
Check 4: Continuous gender measure	41,711	−0.2100 p<0.001	—	F=2.19, p=0.053	—
HC3 Robust SE	Yes				

Note: Authors' own calculations based on Crunchbase (2026)

Four robustness checks were conducted to assess the sensitivity of the main findings. As a first robustness check, the main dependent variable was replaced with the natural logarithm of raw total funding in EUR, removing the industry normalization step to test whether the gender funding gap existed in absolute rather than relative terms. H1 remained supported with the female-only penalty being significant (−0.2336, $p < 0.001$), and H2 remained supported with the mixed-gender penalty also being significant (−0.1421, $p < 0.001$). H3a remained supported ($F = 2.51$, $p = 0.028$) and H3b remained not supported ($F = 0.37$, $p = 0.867$), suggesting that the findings were not an artifact of the industry normalization procedure.

As a second robustness check, the sample was restricted to Early and Venture Stage funding rounds, reducing the sample from 41,711 to 39,138 observations. All four hypotheses produced consistent results: H1 (−0.1991, $p < 0.001$) and H2 (−0.1299, $p < 0.001$) remained supported, H3a remained supported ($F = 2.76$, $p = 0.017$), and H3b remained not supported ($F = 0.43$, $p = 0.830$), suggesting that the results were not driven by the inclusion of crowdfunding or late-stage private equity rounds.

As a third robustness check, total funding amounts were winsorized at the 1st and 99th percentiles. Results were again consistent: H1 (−0.1929, $p < 0.001$) and H2 (−0.1275, $p < 0.001$) remained supported, H3a remained supported ($F = 2.43$, $p = 0.033$), and H3b remained not supported ($F = 0.50$, $p = 0.780$), suggesting that the findings reflected a systematic pattern rather than the influence of a small number of outliers.

As a fourth robustness check, the categorical gender composition variable was replaced with a continuous measure of female founder share, calculated as the number of female founders divided by the total number of classified founders. This specification tested whether the results were sensitive to treating gender composition as discrete categories rather than as a continuous team-level measure. Results were broadly consistent with the main findings: the association between female founder share and funding was negative and statistically significant (−0.2100, $p < 0.001$), indicating that a higher share of female founders was associated with lower funding. The joint industry-moderation test was marginally significant ($F = 2.19$, $p = 0.053$), suggesting a similar but slightly weaker pattern of industry variation than in the categorical specification. The categorical operationalization used in the main model is nevertheless preferred because it allows female-only and mixed-gender teams to be estimated separately. This distinction is theoretically important, as mixed-gender teams may not simply represent an intermediate point between male-only and female-only teams, and the main results indicate that female-only and mixed-gender teams follow different patterns of disadvantage.

Across all four robustness checks, the core findings remained broadly consistent, suggesting that the results were robust to alternative dependent variable constructions, sample restrictions, outlier treatment, and the continuous operationalization of founder gender composition.

6. Discussion

This study set out to examine whether the gender composition of founding teams is associated with equity financing outcomes and whether this relationship varies across industry categories in the United States and Europe.

Table 10: Summary of Hypothesis Testing

Hypothesis		**Result**
H1	Female-only founding teams receive significantly less equity funding than male-only founding teams.	Supported ($p < 0.001$)
H2	Mixed-gender founding teams receive significantly less equity funding than male-only founding teams.	Supported ($p < 0.001$)
H3a	The gender funding gap between female-only and male-only founding teams varies significantly across specific industry categories.	Supported ($p = 0.039$)

H3b	The gender funding gap between mixed-gender and male-only founding teams varies significantly across specific industry categories.	Not supported ($p = 0.785$)

Our results support H1 and H2, indicating that female-only and mixed-gender founding teams are associated with significantly lower funding than male-only teams. These findings are consistent with prior evidence documenting a persistent equity gender gap (Brush et al., 2018; Kanze et al., 2020; Hebert, 2025) and extend it to a combined sample covering both the United States and Europe.

One explanation discussed in Koziol et al.'s (2025) systematic literature review is that women may raise less capital partly because they cluster in industries that require less funding. Our findings challenge this interpretation. Because our regression compares female-only, mixed-gender, and male-only teams within the same industry, the penalty we estimate is unlikely to be explained solely by women operating in lower-capital sectors. The gap persists even after industry is held constant, and it persists most strongly in Finance and Business Services, Health and Life Sciences, and Tech (Table 7), sectors not characterized by low capital intensity. This aligns with Kanze et al. (2020), who also reject the view that the gender funding gap can be explained by women starting businesses in less capital-intensive industries.

H3a was supported, indicating that the funding penalty for female-only teams varied significantly across industry categories. However, a closer examination of the pattern reveals that this variation cannot be fully captured by the binary classifications used in previous research, which divides industries into male- and female-dominated categories when comparing the funding gap.

Examining this variation more closely through the exploratory pairwise comparisons across all industry combinations revealed that the variation was concentrated in a small set of industry pairs, rather than spread evenly across the six categories. While the female-only penalty in Consumer and Retail and Media was not statistically significant on its own (Table 7), the pairwise comparisons show that these industries differed from several higher-penalty sectors (Table 8). Only Consumer and Retail and Media show a female penalty that is significantly smaller than in Tech, and the remaining sectors are statistically indistinguishable from the Tech baseline, even though they differ from one another in their female founder shares (Table 1). The female penalty therefore does not appear to scale with the demographic composition of an industry. Instead, it operates as a baseline across most sectors and softens only in two specific cases. This is consistent with the broader claim that entrepreneurship itself is portrayed as a stereotypically masculine endeavor (Jennings & Brush, 2013), suggesting that the male prototype of the entrepreneur remains salient across industries regardless of their internal demographic composition.

Our findings extend prior research that has established the existence of an industry-moderated gap (Hebert, 2025; Kanze et al., 2020) by showing that this moderation is not a linear function of female industry representation. Consumer and Retail had the highest female founder share in the sample (Table 1), and its female penalty was significantly smaller than in Tech ($p = 0.012$). This is consistent with the prediction that a higher female founder share reduces perceived incongruity between founder gender and industry context, extending the logic of Hebert (2025) and Kanze et al. (2020) to a combined sample of United States and European ventures. Media, however, did not align with the demographic framing. Its female founder share was almost identical to Tech's (Table 1), yet the pairwise comparison revealed a significantly smaller penalty relative to Tech ($p = 0.040$), a difference that cannot be attributed to differences in female industry representation. Under the binary framing used in prior research (Hebert, 2025; Kanze et al., 2020), Media should pattern with Tech and Finance and Business Services, but it does not.

This can be interpreted as an elaboration rather than a rejection of role congruity theory. The theory's core mechanism, perceived alignment between gender and the attributes required for success in a role, holds. However, the role expectations that matter appear to be inferred from the activity an industry performs, not only from its demographic composition. Bordalo et al. (2016) suggest that stereotypes are context-dependent and shift based on the reference group, which implies that the relevant entrepreneurial prototype is not fixed but shaped by the associations investors hold about what a given industry does. One possible interpretation is that work in Media, including content, advertising, and communication, may be associated with more communal attributes, which Heilman (2001) identifies as core elements of the female stereotype, even though founders raising equity financing in this sector remain predominantly male. This suggests that female founders in Media may have been perceived as congruent with the nature of the work, even when incongruent with its demographic composition, which could help explain why the penalty was smaller.

Signaling theory helps explain how role incongruity may translate into funding outcomes more broadly. In sectors where the entrepreneurial prototype is strongly masculine, female founders must send stronger signals to overcome the gender bias embedded in how investors decode founder characteristics (Alsos & Ljunggren, 2017). Our results further suggest that industry-level business model complexity may amplify this dynamic. In sectors such as Finance and Business Services, Health and Life Sciences, and Tech, where ventures are often built around intangible assets and complex business models, investors could face greater difficulty evaluating quality objectively. Under these conditions, investors may rely more heavily on founder signals, potentially intensifying the signaling burden that female founders already face due to gender incongruity. Unlike female-only teams, mixed-gender teams did not show significant variation in their funding penalty across industries, pointing to a different mechanism at work.

Mixed-gender teams faced a significant overall penalty of 12.1%, but this penalty did not vary significantly across industries (Table 6), meaning H3b was not supported. One possible explanation is that the presence of at least one male co-founder may anchor investor evaluation to the male entrepreneurial prototype regardless of industry context (Bordalo et al., 2016), absorbing the industry-specific variation that emerges for female-only teams. This is consistent with role congruity theory's prediction that male co-founders provide partial congruity with the entrepreneurial prototype (Eagly & Karau, 2002) and is further reflected in the per-industry estimates, which show a smaller average penalty for mixed-gender teams than for female-only teams (Table 7).

Taken together, the findings suggest that industry context is associated with the female funding penalty in ways that go beyond demographic composition. The Media result points to activity-based industry associations as a previously overlooked dimension of role congruity, while the concentration of the penalty in complex industries such as Finance and Business Services, Health and Life Sciences, and Tech suggests that information asymmetry further amplifies the disadvantage.

6.1 Theoretical Contributions

The findings of this study contribute to the existing literature on gender and equity financing in several ways. First, this study extends prior single-country evidence by examining whether the industry-moderated gender funding gap is observable in a combined sample of ventures from the United States and Europe (Hebert, 2025; Kanze et al., 2020). By examining 41,711 ventures across both the United States and Europe, the analysis confirms that female-only teams face a significant funding penalty across industries, suggesting that the patterns documented in prior single-country studies reflect a broader structural phenomenon rather than a context-specific one.

Second, the findings allow us to elaborate on the application of gender role congruity theory by suggesting that industry gender stereotypes may be better captured by the nature of the work performed than by the demographic composition of those performing it. Prior research has classified industries by their female founder share to explain variation in the funding gap (Hebert, 2025; Kanze et al., 2020), but the Media result demonstrates that this classification is incomplete: an industry with a low female founder share can still produce a smaller penalty (Table 8).

Third, this study contributes to the literature by mapping the gender funding penalty across six specific, named industry categories, Tech, Finance and Business Services, Health and Life Sciences, Consumer and Retail, Industrial, Energy and Transportation, and Media, rather than relying on the binary male- versus female-dominated classifications (Hebert, 2025; Kanze et al., 2020). This approach reveals variation that broad classifications overlook. By naming these industries explicitly and estimating sector-specific gaps, the study provides a more actionable map of where the funding gap is most pronounced.

Fourth, the study contributes to the literature on the gender funding gap by treating mixed-gender teams as a distinct category alongside female-only and male-only teams. The results show that female-only and mixed-gender teams face different patterns of disadvantage, suggesting that the two cannot be assumed to operate under the same dynamics. Future research would benefit from maintaining this distinction rather than collapsing team compositions into binary gender categories.

6.2 Managerial Implications

The findings of this study carry implications that extend beyond the individual entrepreneur. Limited access to capital is associated with lower survival rates even among high-potential ventures (Hebert, 2025). Our results indicate that female-led teams in our sample are associated with lower levels of equity funding. This pattern may reflect not only a disadvantage for the individual founders involved, but also a potential misallocation of resources within the entrepreneurial ecosystem, with possible implications for innovation, firm growth, and job creation. This is supported by Hebert (2025), who argues that gender-biased financing practices are associated with reduced access to capital for female-led ventures and missed profitable opportunities, particularly in male-dominated sectors.

For investors, one implication is awareness. Kanze et al. (2020) argue that bias against female founders can lead investors to overlook strong ventures and back weaker ones, which hurts portfolio performance. Our findings build on this by suggesting where the estimated funding penalties are most pronounced. The female penalty is not uniform across the market; it is large in Finance and Business Services, Health and Life Sciences, and Tech. Investors active in these industries should therefore be especially aware that comparable female-led ventures in their portfolios may be undercapitalized relative to their potential. Investors should also be cautious of the assumption that the gap simply reflects women operating in less capital-intensive industries, as our results show the penalty persists even when men and women are compared in the same sector. Beyond general awareness, the industry-level estimates produced by this study offer investors a more concrete reference point. Rather than relying on the assumption that bias operates uniformly, investors in Finance and Business Services, Health and Life Sciences, and Tech can treat these sectors as higher-risk environments for gender-biased evaluation and consider introducing more structured and criteria-based assessment processes in these contexts.

For female entrepreneurs, the implication is not that they should self-select into industries congruent with their gender. Rather, we suggest that the implication is informational. Female founders may benefit from understanding that the gap is not uniform. Female founders entering Finance and Business Services, Health and Life Sciences, or Tech could face a steeper signaling burden and should be prepared to provide stronger objective evidence of venture quality to counteract the evaluative disadvantage documented in these sectors. Equally important, our findings suggest that female founders cannot rely only on the gender composition of an industry as a potential guide to where the funding gap is likely to be most pronounced. This means that choosing an industry with more women is not a reliable strategy for avoiding bias, since the gap is potentially associated with industry characteristics that go beyond demographic composition.

Taken together, these implications point to the importance of spreading awareness rather than offering a single solution to the gender funding gap. Greater awareness of where and how the gap operates is a necessary first step toward more informed decisions across the entrepreneurial ecosystem.

6.3 Limitations and Future Research

Like any study, this one has its limitations which should be acknowledged. First, our analysis identifies associations rather than causal relationships. Because the study is based on observational data, the estimated funding gaps should be interpreted as associations between founder gender composition, industry category, and funding outcomes, rather than as causal effects. We document evidence of industry-moderated funding gaps for female-only teams, but our study cannot rule out that selection effects also play a role. Hebert (2025) addresses a similar concern using exit-performance data and finds that selection by investors reinforces the funding gap, but our dataset does not allow for an equivalent post-funding analysis. Future research linking funding data to outcomes such as firm survival, exits, or revenue growth would help clarify whether the smaller penalty in these sectors reflects reduced bias or the entry of stronger ventures into specific markets.

Second, the dataset imposed two related limitations. The six industry categories were manually created and are relatively broad, each likely capturing substantial within-category heterogeneity that the current analysis cannot unpack, and access to more granular industry data would help build a more complete picture of how the penalty operates. Additionally, smaller industries such as Media and Industrial, Energy and Transportation contain relatively few observations (Table 1), and because female founders are systematically underrepresented across all sectors, the female-led subsamples within these categories become even smaller, reducing the precision of industry-specific estimates.

Third, our analysis does not account for inflation. Our dataset captures total funding amounts and the overall period during which funding was received rather than year-specific funding rounds; therefore, we were unable to deflate the funding values to a common base year. Future research with access to round-level funding data, including the date of each round, would allow for inflation adjustments and more precise estimates of funding gaps over time.

Fourth, a further limitation concerns the demand side of the funding process. The dataset did not include information on the amount of funding requested. If female founders systematically request less funding than male founders, the observed gap may partly reflect differences in demand. Future research with access to funding request data would allow a cleaner separation of supply- and demand-side explanations.

Finally, while the findings document where the gender funding gap is most and least pronounced, the dataset does not allow us to identify the mechanisms behind these patterns. We can show that Consumer and Retail and Media exhibit smaller penalties than Tech and Finance and Business Services, and that these differences are not fully explained by female founder representation, suggesting that the binary male-dominated versus female-dominated classification widely used in prior research (Hebert, 2025; Kanze et al., 2020) does not capture everything that matters. Future research could build on the patterns documented here by shifting the analytical focus from who is in an industry to what the industry is associated with.

7. Conclusion

The gender funding gap does not appear to be uniform; our study shows that it is a context-dependent phenomenon associated with the industry in which a venture operates. Using a large combined sample of ventures from the United States and Europe, this study finds that female-only teams are associated with significantly lower funding than male-only teams, and that the magnitude of this gap varies by industry in ways that broad binary male- versus female-dominated industry classifications fail to capture. Mixed-gender teams are also associated with lower funding, but unlike female-only teams, this gap does not vary significantly across industries. This suggests that female-only teams experience a more industry-contingent disadvantage, while mixed-gender teams face a broader and more general funding penalty. Addressing the gap therefore may require moving beyond averages and binary classifications. For founders and investors, knowing where and how the penalty operates is a necessary first step toward more equitable capital allocation.

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9. Appendix

AI Disclosure

Throughout the work on this thesis, we used two AI tools, ChatGPT and Claude. These tools were used to support the research process and improve the quality of the work. ChatGPT was primarily used for idea assessment and critique, as well as for Python coding. It was used as a discussion partner for evaluating arguments and the methodological choices underlying the study. Claude was primarily used to assist with Python coding for data cleaning, variable construction, and regression analysis, as well as providing feedback on the overall structure of the thesis. Claude also helped with table construction. Throughout the project, both tools were also used to provide feedback on written text, including clarity, coherence, and academic tone.

We also acknowledge the risks associated with using AI in the thesis process. AI tools may generate inaccurate references, misrepresent article content, or misunderstand the meaning of academic sources. Therefore, we read and verified all articles ourselves and ensured that all references and interpretations were accurate. While AI was useful for improving grammar, flow, and academic phrasing, its language could sometimes be generic and unclear. Nevertheless, no AI-generated text was included without thorough critical review and modification.