ESSAYS ON WOMEN'S ENTREPRENEURSHIP: MARGINALIZED BY SOCIETY AND YET READY TO CHALLENGE ITS NORMS

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AARON POHLMANN

aus Flensburg

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Zusammenfassung

In den vergangenen Jahren lässt sich ein signifikant steigendes Interesse von Forschenden am Unternehmertum von Frauen beobachten. Dabei betonen manche das Potenzial, traditionelle Geschlechternormen infrage zu stellen und Gleichstellung der Geschlechter zu fördern. Andere konzentrieren sich auf die besonderen Herausforderungen, mit denen Gründerinnen konfrontiert sind. Aufbauend auf diesen Werken untersucht die vorliegende Dissertation einerseits, wie das Unternehmertum von Frauen durch gesellschaftliche Erwartungen, Stereotypen und Machtstrukturen geprägt ist. Andererseits wird analysiert, ob die Zunahme von Gründerinnen mit einem positiven gesellschaftlichen Wandel verbunden ist. Die Dissertation besteht aus einem Einführungskapitel (Kapitel 1), drei Aufsätzen (Kapitel 2–4) und einem Schlusskapitel (Kapitel 5). Kapitel 2 zeigt, dass unerfahrene Gründerinnen von auf Frauen beschränkten Programmen profitieren, während sich für erfahrenere Entrepreneurinnen besonders Kohorten mit männlicher Mehrheit auszahlen. Ebenso profitieren männliche Gründer mit mehr Erfahrung von geschlechtergemischten Kohorten. Im zweiten Aufsatz (Kapitel 3) wird aufgezeigt, dass Frauen eher Start-ups in Bereichen gründen, die mit einer geringeren Benachteiligung gegenüber Männern verbunden sind. Im Allgemeinen erhalten von Frauen gegründete Unternehmen weniger Investments als von Männern gegründete Firmen. Diese Ungleichheit ist zwar bei sozialen und bildungsbezogenen Unternehmen weniger ausgeprägt, dafür aber bei Unternehmen, die umweltfreundliche Ziele verfolgen, umso stärker. Das dritte Papier (Kapitel 4) zeigt, dass Frauen, die Geschäftsideen identifizieren und verfolgen, einen positiven Effekt auf die Vertretung von Frauen in Unternehmensvorständen hat. Dieser positive Effekt nimmt in Bereichen ab, in denen Frauen strukturell bessergestellt sind (d. h. in Ländern mit einem hohen Grad an politischer und wirtschaftlicher Vertretung von Frauen, in denen das Gesetz Männer nicht gegenüber Frauen bevorzugt). In Regionen, in denen Frauen sich gesellschaftlich besser positionieren, (d.h. in Ländern, in denen Frauen dazu neigen, Entscheidungen über ihre Gesundheit und Arbeitsbedingungen zu treffen, die sie benachteiligen), wird der Effekt jedoch stärker. Diese Ergebnisse sind für Forscher, Gründer, Investoren und Manager von Accelerator- oder Inkubationsprogrammen bedeutend und tragen zur bestehenden Literatur zu sozialen Aspekten des Unternehmertums von Frauen bei.

Summary

In recent years, the interest of researchers in women's entrepreneurship increased significantly. Some researchers posit that women's entrepreneurship has the potential to challenge traditional gender norms and foster gender equity. Others emphasize the unique challenges that women business owners face. In this vein, this dissertation examines how women's entrepreneurship is shaped by and shapes the societal expectations, stereotypes, and power structures surrounding it. The dissertation comprises an introductory chapter (Chapter 1), three papers (Chapters 2-4), and a concluding chapter (Chapter 5). The initial paper (Chapter 2) demonstrates that inexperienced women founders benefit particularly from women-only cohorts, whereas experienced women gain more from men-dominated ones. Similarly, men founders with more experience benefit from gender-diverse cohorts. The second paper (Chapter 3) finds that women are likelier to establish startups with a business focus connected to a lower gender-related funding gap. In general, women-founded startups receive comparatively less funding per round. However, this disparity is less pronounced among social and educational ventures but particularly strong among those pursuing pro-environmental objectives. The third paper (Chapter 4) reveals that an increase in women's participation in opportunity-based entrepreneurship has a positive, time-lagged effect on women's representation on corporate boards. This positive effect decreases in structurally empowered environments (i.e., countries with high levels of women's political and economic representation, where the law does not favor men over women). In contrast, it becomes more pronounced in socially empowered regions (i.e., countries where women tend to make decisions about their health and working conditions that disadvantage them). These findings have important implications for researchers and practitioners (i.e., founders, investors, and managers of entrepreneurial support organizations) and contribute to the existing literature on women's entrepreneurship and society.

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1. Introduction to this Dissertation

The existing body of literature indicates that women's[1] entrepreneurship can serve as a catalyst for women's empowerment[2] (Atarah, Finotto, Nolan, & Van Stel, 2023), challenge traditional gender norms, and foster gender equity (Hasan Emon & Nisa Nipa, 2024). However, despite these promising potentials, research demonstrates that women business owners are confronted with unique challenges, and it is imperative that policymakers allocate more resources to empower them (Feng, Ahmad, & Zheng, 2023). These gender-specific challenges faced by women include restricted access to formal financial resources, entrepreneurial training, and increased barriers to networking and mentorship (e.g., Brush, Edelman, Manolova, & Welter, 2019). Existing research argues that these issues are often related to gender biases and societal norms that reinforce traditional gender role expectations (Hasan Emon & Nisa Nipa, 2024).

Thus, it appears that women's entrepreneurship exerts an influence on and is itself influenced by the prevailing gender stereotypes. Moreover, the extent to which those stereotypes adversely impact women entrepreneurs increases when entrepreneurship is linked to stereotypically male attributes (Gupta, Goktan, & Gunay, 2014). As a consequence, they are particularly important in male-dominated fields (Martiarena, 2022) such as high-growth entrepreneurship (Gupta, Wieland, & Turban, 2019).

Entrepreneurship in these fields is typically oriented towards pursuing promising market opportunities, a phenomenon commonly referred to as "opportunity entrepreneurship" in academic literature. This concept is fundamentally distinct from "necessity entrepreneurship", which is frequently driven by a lack of viable alternatives and often serves as a means of survival (Solesvik, Iakovleva, & Trifilova, 2019). It is noteworthy that opportunity entrepreneurship is predominantly male-dominated, whereas necessity entrepreneurship is more prevalent among women (Elam et al., 2022; Jafari-Sadeghi, 2020). Consequently, a considerable number of authors have recently concentrated their attention on developing strategies designed to facilitate the empowerment of women entrepreneurs operating within men-dominated sectors (Vershinina, Rodgers, Tarba, Khan, & Stokes, 2020).

In this context, a significant challenge is the disconnect between women founders and the high-growth venture community (Greene, Brush, Hart, & Saparito, 2001; Neumeyer, Santos, Caetano, &

[1] Following others, the terms women and men refer to gender in this dissertation, which is associated with social or cultural aspects (e.g., gender bias) rather than biological factors (Muehlenhard & Peterson, 2011).

[2] Empowerment can be defined as a multi-dimensional social process that enables women to gain control over their own lives. It is a process that enables women to exercise power in their own lives, their communities, and their society by taking action on issues they deem important (Page & Czuba, 1999).

Kalbfleisch, 2019). This creates a lack of contacts and networks that could provide access to investment opportunities, which are often referred to as social capital (Shao & Sun, 2021). The concept of social networks and social capital is frequently addressed in the literature on entrepreneurial ecosystems (Pittz, White, & Zoller, 2021), which are defined as "entrepreneurial actors, entrepreneurial organizations, institutions, and entrepreneurial processes which (…) connect, mediate and govern the performance within the local entrepreneurial environment" (Mason & Brown, 2013). Within such ecosystems, entrepreneurial support organizations (i.e., business accelerators and business incubators) are often considered crucial in reducing existing gender inequalities (Avnimelech & Rechter, 2023), particularly because they play a vital role in the formation of relationships (Goswami, Mitchell, & Bhagavatula, 2018).

Nevertheless, these support organizations are often gendered (Brush et al., 2019; Marlow & McAdam, 2015). For example, stereotypical gendered expectations in high-technology venturing reproduce masculine norms of entrepreneurial behavior (Marlow & McAdam, 2012; Ozkazanc-Pan & Clark Muntean, 2018). In response to this challenge, policymakers and managers of entrepreneurial support programs have recently focused on stimulating and supporting women's entrepreneurship through women-only support networks. These networks are designed to facilitate the building of networks and the provision of role models and resources (Harrison, Leitch, & McAdam, 2020).

However, this strategy may result in a situation where participants in such programs are unable to access sufficient economic and social capital to become successful entrepreneurs, which could unintendedly foster isolation and underrepresentation in the entrepreneurial ecosystem (McAdam, Harrison, & Leitch, 2019). Thus, it appears that entrepreneurial support organizations that focus exclusively on women may not always adequately address the social capital-related challenges women entrepreneurs face. Instead, cross-gender collaboration may be more beneficial for women entrepreneurs, as they can increase their social capital (Godwin, Stevens, & Brenner, 2006).

As previously stated, a deficiency in social capital is associated with a reduction in the number of contacts and networks, which in turn limits access to investment opportunities. Nonetheless, a substantial body of research on women in entrepreneurship and funding attraction also identifies a multitude of additional factors contributing to the gender-related funding gap. For instance, male investors show minor interest in women entrepreneurs than in their male counterparts (Ewens & Townsend, 2017) and generally prefer to invest in firms from male-dominated industries (Brush, Carter, Gatewood, Greene, & Hart, 2008; Ozkazanc-Pan & Clark Muntean, 2018).

Furthermore, women entrepreneurs often show lower levels of entrepreneurial self-efficacy, which can be defined as believing in one's capability to perform tasks and roles aimed at entrepreneurial outcomes (Dempsey & Jennings, 2014). Self-efficacy increases with the experience of founders and positively impacts a firm's performance and growth (Baum & Locke, 2004).

In essence, extant research demonstrates the existence of a gender-related funding gap, which is influenced by a confluence of factors, including existing power structures (e.g., men entrepreneurs are better connected within entrepreneurial ecosystems), normative systems (e.g., gender stereotypes), and psychological factors (e.g., entrepreneurial self-efficacy). Conversely, the literature also indicates that women's entrepreneurship can alter these antecedents to the funding gap. This thesis aims to examine the role of these factors as both a driver and a consequence of women's entrepreneurship. To this end, the three essays presented in Chapters 2-4 focus on different aspects to disentangle the complex interrelationships between these factors. The following section summarizes these essays and culminates in Figure 1.1, which provides an overview of this dissertation's conceptual framework.

The first essay – presented in Chapter 2 – contributes to the aforementioned literature by addressing how the gender composition of acceleration cohorts affects the post-accelerator funding prospects of entrepreneurs. The article is titled *"Building Inclusive Ecosystems: Why the Gender Composition of Accelerators Matters for Startup Funding"* and is a joint work with Theresa Veer. The theoretical foundation of this paper is situated within the domains of social capital theory and entrepreneurial self-efficacy literature. As illustrated in Figure 1.1 in the blue box, we examined the impact of varying gender compositions within business accelerators on the likelihood of men and women founders receiving investments following the accelerator program. Additionally, we examined the influence of the founder's entrepreneurial experience on this relationship. To this end, we gathered a dataset of 1,588 observations based on Crunchbase data and proprietary data from a corporate venture capitalist's acceleration program, which is present in ten European and Latin American countries. Due to the binary nature of the dependent variable and the hierarchical data structure (i.e., entrepreneurs are nested in accelerators), the empirical analysis is based on hierarchical logit modeling.

The article offers three principal insights. Firstly, inexperienced women founders can benefit from participating in cohorts composed primarily of women. Secondly, experienced women can benefit from participating in men-dominated cohorts. Thirdly, male founders with extensive experience take advantage of cohorts that include a greater proportion of women. These results contribute to the existing literature on the design of accelerator programs and the importance of cohort member selection (Cohen, Fehder, Hochberg, & Murray, 2019) and add to the literature on gendered entrepreneurial ecosystems and support systems (Brush et al., 2019). Moreover, our findings extend the existing body of literature on critical perspectives on accelerators as neutral support providers (Ozkazanc-Pan & Clark Muntean, 2018). More specifically, male-dominated cohorts appear to have a beneficial impact on the post-accelerator funding of experienced female founders. Yet, they also contribute to the emergence of a more masculinized discourse and culture within the acceleration cohorts. Accelerators may, therefore, prefer to rely on their external networks and contacts to stimulate women's social capital. Meanwhile, gender-balanced cohorts help to reduce women's marginalization and undervaluation, which ultimately increases their self-efficacy in the long term.

In addition to these findings, existing literature suggests that undervaluation can also have its origin in expectations of how persons of a specific gender should behave (Cowden, Creek, & Maurer, 2021). The related concept of gender role expectations is deeply embedded in role congruity theory. The theory suggests that gender differences in social behavior are a consequence of the societal division of labor between genders (Eagly & Steffen, 1984) and has its roots in social role theory (Eagly, 1987). Furthermore, role congruity theory posits that people hold stereotypical expectations for individuals occupying a particular social position or belonging to certain social categories.

As a result, when an individual assumes multiple social roles concurrently, conflicts and evaluation biases between these roles can emerge (Del Carmen Triana, Song, Um, & Huang, 2024; Eagly & Karau, 2002). This places women entrepreneurs in a challenging position because, in numerous cultures, entrepreneurship is strongly associated with masculine characteristics, such as ambition and self-confidence (e.g., Gupta, Batra, & Gupta, 2022). At the same time, stereotypical feminine attributes include kindness and sensibility (e.g., Hancock, Pérez-Quintana, & Hormiga, 2014). Consequently, individuals tend to attribute the capacity to successfully start, lead, and manage businesses to men rather than women (Gupta et al., 2014; Laguía, García-Ael, Wach, & Moriano, 2019).

Moreover, this unfavorable perception of women entrepreneurs has a detrimental impact on the material consequences of role incongruity perceptions in organizational contexts (Del Carmen Triana et al., 2024). For example, the observable role incongruity of women occupying the role of CEO has been found to have a negative impact on investor assessment of women-led mature corporations (Bigelow, Lundmark, McLean Parks, & Wuebker, 2014). Similarly, women-founded startups are less likely to be selected for acceleration programs (Yang, Kher, & Newbert, 2020) or to receive funding (Anglin, Kincaid, Short, & Allen, 2022; Eddleston, Ladge, Mitteness, & Balachandra, 2016). In this context, it is notable that a recently published literature review on role congruity theory encourages researchers to consider the conceptualization of social roles outside of studies on leadership and to examine how interactional roles influence the effects that gender role congruity has in these fields (Del Carmen Triana et al., 2024).

Although women are not traditionally associated with entrepreneurship, they are often perceived as more concerned with sustainability (Brough, Wilkie, Ma, Isaac, & Gal, 2016). Consequently, a female entrepreneur who establishes a venture with a business focus on sustainability would be perceived as more aligned with conventional gender roles than women who pursue business opportunities with less sustainable outcomes.

In this context, research is increasingly distinguishing between social and environmental aspects of sustainability (George, Merrill, & Schillebeeckx, 2021; Kamaludin, 2023). This distinction is in accordance with the 17 Sustainable Development Goals, which recognize that sustainable development occurs when poverty and gender inequality decline and health and education improve while combating climate change and the destruction of oceans and forests (United Nations, 2024).

These considerations serve as the impetus for the essay presented in Chapter 3, which is graphically summarized in the red box in Figure 1.1. The single-authored paper is titled *"Beyond the Norms: Unveiling Gendered Patterns in Sustainable Entrepreneurship Funding"*. Theoretically situated within the framework of gender role theory, the paper addresses two research questions: (1) "Do high-growth-oriented startups with higher proportions of women founders focus more on social, educational, or pro-environmental objectives?" and (2) "Do high-growth-oriented startups with higher proportions of women founders receive more funding per investment round if their startups have social, educational, or pro-environmental objectives?".

To shed light on these questions, I leveraged data from Crunchbase and the United Nations Sustainable Development Goals Indicator Database. In addition to the extracted variables, I conducted an exploratory factor analysis, which yielded the identification of three factor variables describing a startup's social, educational, or environmental orientation. The resulting dataset comprised 115,660 observations from 163 countries collected between 1992 and 2022.

The results of the empirical analysis, which employed fixed-effects ordinary least squares regression, indicate that the proportion of women in a team is positively correlated with a firm's social and educational focus but negatively correlated with a firm's pro-environmental focus. Moreover, the results demonstrate that women-founded startups receive less funding per round than men-founded startups. This result is consistent for all the models and thus independent of the startup's business focus. However, the gender-related funding gap becomes smaller among startups with a social or educational orientation and is aggravated if the respective startups have a pro-environmental focus.

A post-hoc longitudinal analysis indicates that the aggravation of the gender funding gap in pro-environmental entrepreneurship can be attributed, at least partially, to the fact that women-founded startups consistently receive smaller funding rounds over time. Furthermore, the analysis highlights that the heavily male-dominated tech industry serves to amplify the funding gap for women-led social tech companies.

The article adds to the existing body of literature on gender role congruity (Anglin et al., 2022; Cowden et al., 2021) by suggesting that investors reward some traditionally female-typed business orientations (i.e., social or educational business focus) but penalize women-founded pro-environmental startups in terms of the investments these startups attract. Moreover, the empirical results contribute to existing research on the gender-related funding gap in entrepreneurship (Guzman & Kacperczyk, 2019) by showing that a startup's increased share of women founders negatively impacts the investments the company attracts. Additionally, the study provides insights into how the startup's business orientation moderates this effect.

Finally, as the overall results indicate that women are more likely to start businesses with a business focus that is related to a lower gender funding gap, my results can encourage future research to analyze if women do not naturally focus on industries that signal a lower growth potential to investors (Guzman & Kacperczyk, 2019) but choose industries in which men- and women-founded startups do differ less regarding the funding they attract.

The practical implications of this research indicate that an exclusive reliance on all-women programs that provide relatively small investments may impede women entrepreneurs with a focus on cost-intensive industries (e.g., pro-environmental tech startups) from attracting competitive financial investments. Instead of adapting support uniquely to women entrepreneurs, it should consequentially also consider the needs of the specific industries (Bullough, Hechavarría, Brush & Edelman, 2019).

Although Chapter 3 primarily demonstrates how investors punish perceived gender role incongruity, existing research raises an important question: "Can role incongruity lead to positive results?" (Del Carmen Triana et al., 2024). Based on the assumption that women's entrepreneurship itself is an example of gender role-incongruent behavior (Gupta et al., 2014; Laguía et al., 2019), the aforementioned literature would suggest that the answer to this question is affirmative. This is because women's entrepreneurship has the potential to facilitate women's emancipation (e.g., Atarah, Finotto, Nolan, & Van Stel, 2023) and challenge traditional gender norms (Hasan Emon & Nisa Nipa, 2024).

The following example demonstrates these dynamics. On the one hand, men in power positions tend to support women who think and act like men (Adams & Funk, 2012). Conversely, male investors or managers are more likely to support women who aspire to achieve positions of authority if they had personal encounters with successful female entrepreneurs or have heard about them (Duehr & Bono, 2006).

Another important aspect is that women tend to regard the successful establishment and management of businesses by other women as a source of inspiration, thereby becoming aware of alternative occupational opportunities (Van Der Zwan, Verheul, & Thurik, 2012). Consequently, women's entrepreneurship has the potential to challenge traditional gender norms and role expectations. As individuals tend to feel the urgency to act in accordance with how they are socially perceived by others (Del Carmen Triana et al., 2024; Eagly, 1987), women's behavior will probably adapt to these changes in society.

These considerations provide the theoretical foundation for Chapter 4 (illustrated in the purple box in Figure 1.1). The single-authored essay is titled "*Cracking the Glass Ceiling: Exploring the Link Between Women Entrepreneurship and the Corporate Glass Ceiling*". This paper examines the hypothesis that an increase in women's participation in opportunity-based entrepreneurship may weaken the corporate glass ceiling. It also considers the impact of local conditions that either empower or disempower women on this relationship.

In order to shed light on these relationships, an exploratory factor analysis was conducted based on World Bank data, which revealed two factors: Women's structural empowerment is contingent upon a country's legal framework and the structural representation of women. In contrast, the notion of women's societal empowerment pertains to the extent to which women make decisions that are disadvantageous to them and align with the internalized hierarchical societal norms.

After merging these factors with further data leveraged from the Global Entrepreneurship Monitor, the World Bank, and the OECD, four datasets, including between 173 and 182 observations, emerged. The study employs time-and-country fixed-effect panel regression, taking into account varying time lags, and provides empirical evidence for a positive effect of a country's share of opportunity-based women entrepreneurs on women's representation in corporate boards. Furthermore, a negative moderation effect indicates that the positive impact of women opportunity entrepreneurs on women's board representation is diminished in structurally highly empowered environments but increased in societally empowered regions.

The paper offers valuable insights that contribute to the existing body of literature on women's entrepreneurship. Firstly, it introduces women's representation in opportunity entrepreneurship as an antecedent of an increased share of women in corporate boards. In doing so, it adds to existing research positing that an increased share of women in the labor market or management positions leads to similar effects (Grosvold, Rayton, & Brammer, 2015). Secondly, this article's results support previous research findings indicating that the positive impact of gender diversity on corporate boards is significantly influenced by institutional features (Lewellyn & Muller-Kahle, 2020). The practical implications of the generated insights include the proposition that entrepreneurial education and entrepreneurial support programs (i.e., networking events, incubation programs, acceleration programs) for women represent effective tools for increasing the rates of female opportunity entrepreneurship, which can result in more gender-balanced corporate boards. This recommendation receives support from research suggesting that targeted programs can facilitate the visibility of underrepresented groups (Hernandez, Nunn, & Warnecke, 2012).

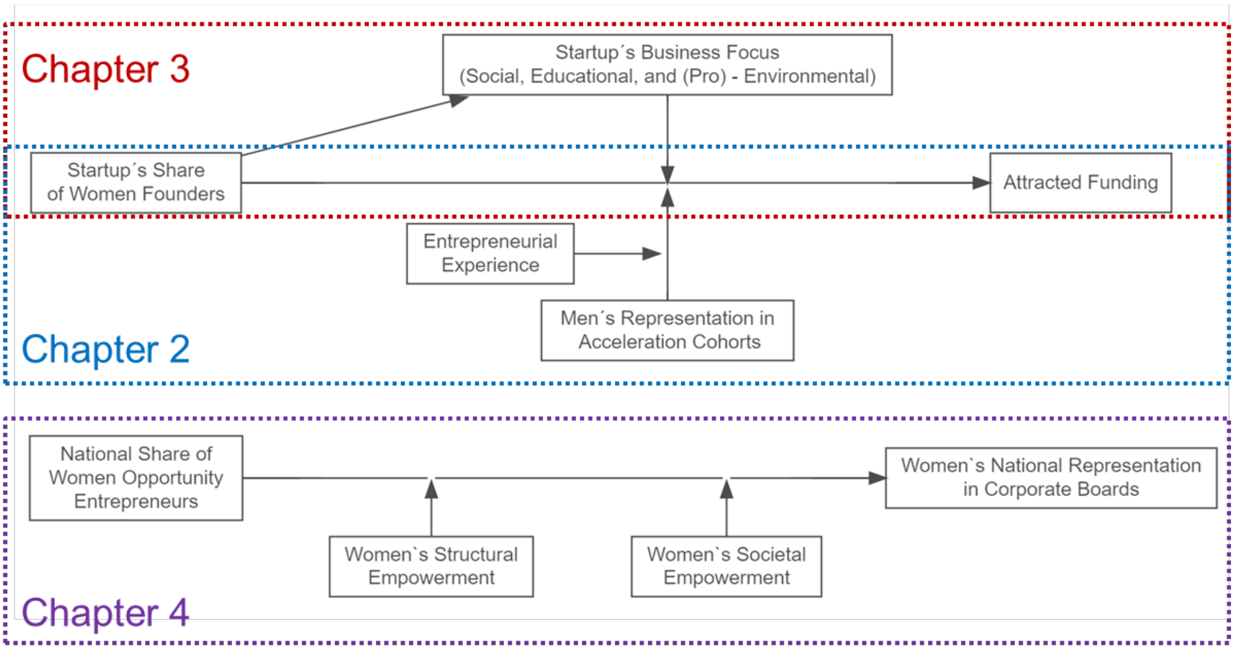

Figure 1.1 - The Conceptual Framework of the Thesis and its Chapters

Figure 1.1 presents a graphical representation of the conceptual framework of the thesis and the three essays presented in Chapters 2 to 4. It should be noted that Chapter 4 differs substantially from Chapters 2 and 3 in terms of its unit of analysis and integrates an economic perspective into the field, while the other articles focus on the startup level. Each of these articles provides unique insights into the intricate relationship between women's entrepreneurship and society. They suggest that women's entrepreneurship remains marginalized and is significantly influenced by gender role expectations. However, as a small rock can trigger an avalanche, women's entrepreneurship has the potential to bring about a profound transformation in gender stereotypes that can extend beyond the entrepreneurial realm.

Overall, this dissertation intends to extend the body of literature on women's entrepreneurship in two ways. Firstly, Chapters 2 and 3 provide empirical evidence of how women's entrepreneurship is affected by the societal expectations, stereotypes, and power structures surrounding it. Secondly, Chapter 4 focuses on the potential of women's entrepreneurship to disrupt these structures and beliefs. In doing so, this thesis contributes to a better understanding of women's entrepreneurship in today's society and is a valuable addition to the existing literature. The results of the three empirical studies presented in Chapters 2 to 4 are potentially relevant to policymakers, managers of entrepreneurial support organizations, and society at large. This dissertation will conclude by presenting conclusions drawn from this doctoral dissertation in Chapter 5.

2. Building Inclusive Ecosystems – Why the Gender Composition of Accelerators Matters for Startup Funding

Aaron Pohlmann & Theresa Veer

ABOUT THIS CHAPTER:

A slightly modified version of Chapter 2 will be published soon as a chapter within the volume "Gendering Entrepreneurial Ecosystems – Leveling the Field" of the book series "Routledge Studies in Entrepreneurship". The contributions of the authors are as follows: Aaron Pohlmann had the initial idea for the study, and conducted the data collection, management, and analysis. He was also the main person responsible for writing and editing the manuscript. Theresa Veer supervised the entire research project, gave feedback, and also edited and revised the drafts.

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Abstract

This chapter examines how the gender composition of startup accelerator cohorts influences women entrepreneurs' funding outcomes. Theoretically rooted in social capital theory and entrepreneurial self-efficacy literature, we use hierarchical logit-modelling and find a positive moderation effect of an acceleration cohort's share of men entrepreneurs on women entrepreneurs' post-accelerator funding prospects. However, the optimal gender composition of cohorts varies depending on previous founding experience. Our results reveal unique benefits for inexperienced women founders who participate in women-only cohorts. In contrast, experienced women entrepreneurs profit most from male-dominated cohorts. Similarly, experienced male founders can benefit from female representation in the cohort. These findings contribute to the discourse on accelerator program design by introducing pre-accelerator founding experience and gender as crucial factors for selecting entrepreneurs for acceleration. Further, they underpin accelerators' vital role in promoting inclusive ecosystems by showing how these variables impact women entrepreneurs' funding prospects.

2.1. INTRODUCTION

Business accelerators – fixed-term, cohort-based educational and mentorship programs for startups, which culminate in a graduation event (Cohen, Fehder, Hochberg, & Murray, 2019) – are pivotal for the startup infrastructure and the development of entrepreneurial ecosystems (Bliemel, Flores, Klerk, & Miles, 2019). Their importance genuinely derives from their mission to support groups of entrepreneurs (from now on referred to as cohorts) with their entrepreneurial endeavors. Accelerators impact an entrepreneurial ecosystem's resource reallocation (Avnimelech & Rechter, 2023). In this role, they create opportunities for entrepreneurial actors to connect and interact, which is essential to a thriving ecosystem (Daymond, Knight, Rumyantseva, & Maguire, 2023). Concurrently, acceleration programs are critical contributors to entrepreneurial ecosystems (Cao & Shi, 2021). These ecosystems are defined as "entrepreneurial actors, entrepreneurial organizations, institutions, and entrepreneurial processes which (…) connect, mediate and govern the performance within the local entrepreneurial environment" (Mason & Brown, 2013: 5).

Notably, research comparing accelerator participants to non-participants suggests that accelerators increase the chances of receiving funding for women more than men (Dams, Sarria-Allende, Cornejo, Pasquini, & Robiolo, 2022). Hence, accelerators can be a means to decrease the gender gap in venture capital. Yet, entrepreneurship remains gender-biased (Ding, Ohyama, & Agarwal, 2021), and post-accelerator equity investments are predominantly directed toward all-male teams (Lall, Chen, & Roberts, 2020). Nevertheless, acceleration programs can benefit women. A possible reason behind this observation is that women are often excluded from male-dominated networks providing access to financial resources (Greene, Brush, Hart, & Saparito, 2001). Contacts and networks embedding access to investment opportunities (referred to as social capital in the following) are, therefore, often especially fruitful for women founders. One hallmark characteristic of accelerators is their cohort-based structure. As entrepreneurs enter and exit the programs in groups, they have opportunities to build relationships with other founders (Cohen, 2013). These new contacts connect individuals to networks outside their circles, providing otherwise unavailable resources (Granovetter, 1973). For instance, women can benefit from contacts with men entrepreneurs, who face fewer difficulties entering male-dominated networks that provide access to financial capital.

Similar to research suggesting that mixed-gender teams help women entrepreneurs increase their social capital (Godwin, Stevens, & Brenner, 2006), we analyze the following research question: *"How does the gender composition of acceleration cohorts affect entrepreneurs' post-accelerator funding prospects?".*

Following others, we use the terms women and men to refer to gender, which is associated with social or cultural aspects (e.g., gender bias) rather than biological factors (Muehlenhard & Peterson, 2011). Furthermore, individuals who self-identify as men or women are treated as such.

The empirical analysis leads to three main findings regarding the relationship between gender and post-acceleration funding prospects. First, inexperienced women benefit from participating in women-dominated cohorts. Second, experienced women benefit from participating in men-dominated cohorts. Third, experienced male founders benefit from an enhanced representation of women in the cohort. These insights contribute to the discourse on accelerator program design by introducing entrepreneurial experience and gender as crucial factors in selecting entrepreneurs for acceleration.

2.2. Theoretical Background

Accelerators are crucial to startup infrastructure and entrepreneurial ecosystem development because they provide resources like co-working spaces and networking opportunities to cohorts of entrepreneurs (Ratten, 2020). As intermediaries, they connect disparate actors and networks, spurring investment activities and knowledge sharing among founders (Goswami, Mitchell, & Bhagavatula, 2018).

2.2.1. Social Capital

Entrepreneurship is embedded in network relationships, directing resource flows to those who are better connected (Hoang & Antoncic, 2003). However, social capital research indicates that entrepreneurial success requires more than just an extensive network of contacts. Instead, successful entrepreneurs adapt their social networks to changing resource needs (Maurer & Ebers, 2006).

Social capital literature distinguishes between cognitive, relational, and structural components of social capital. First, the cognitive dimension facilitates a mutual understanding of common goals and norms among parties. Second, the relational dimension describes how actors develop personal relationships with each other (Uzzi, 1996). Finally, the structural dimension describes the overall pattern of connections between individuals embedded in social networks (Nahapiet & Ghoshal, 1998). Both cognitive and relational elements of social capital facilitate network building with similar actors (Nahapiet & Ghoshal, 1998). Nevertheless, relying exclusively on these ties leads to entrepreneurs lacking resources and information from outside their circles. Therefore, over time, founders rely more on the structural dimension (Hite, 2005), considered most important for startups aspiring for growth and funding (Jonsson & Lindbergh, 2013). Depending on the cohort composition, accelerators can emphasize cognitive/relational aspects of social capital (i.e., focus on identity as female entrepreneurs) or the structural dimension (i.e., focus on cross-gender/cross-industry relationship building).

2.2.2. Benefitting from each Other's Social Capital

Research shows that men and women entrepreneurs are similar in connectivity within already existing circles. However, women are often disconnected from the high-growth venture community (Neumeyer, Santos, Caetano, & Kalbfleisch, 2019) and, therefore, struggle to leverage the structural dimension of social capital in this industry.

The existing literature provides two main reasons for this observation. First, male-oriented cultural norms dominate these venture communities, and most experienced entrepreneurs are men who support male norms (Marlow & McAdam, 2013). Second, research mentions the gender bias of investors (Malmström, Johansson, & Wincent, 2017) and their lack of interest in female-dominated industries (Brush, Carter, Gatewood, Greene, & Hart, 2008). Concurrently, women face more obstacles in finding intermediaries to access the relevant funding-related networks (Neumeyer et al., 2019). In this line, we hypothesize:

Hypothesis 1*: Women, compared to men entrepreneurs, are less likely to receive funding after participating in an acceleration program.*

Within cohorts, founders can interact, collaborate, and bond. As men entrepreneurs have easier access to networks leveraging relevant social capital (Neumeyer et al., 2019), women benefit from bonding with them during the programme. Further research on startup teams suggests that a mixed-gender composition in startup teams helps women increase their social capital (Godwin et al., 2006). Additionally, accelerators focused on women entrepreneurs suffer from a lower legitimacy among investors because entrepreneurship is still perceived as a male domain (Laguía, García-Ael, Wach, & Moriano, 2019). Consequently, women would benefit most from men-dominated cohorts.

On average, women represent only 22% of acceleration cohorts (Brush, Edelman, Manolova, & Welter, 2019) potentially because women founders are not commonly invited to consider accelerator opportunities (Ozkazanc-Pan & Clark Muntean, 2018). Underlying reasons for that are unspoken norms of masculinity that dominate the entrepreneurial realm and often ascribe lower potential to women entrepreneurs, rooted in a status of inferiority relative to men entrepreneurs (Marlow & McAdam, 2013). Thus, women are less likely to be identified as growth-oriented entrepreneurs (Brush et al., 2019).

Therefore, we argue that acceleration programs particularly impact women entrepreneurs' post-accelerator chances of receiving venture capital (Dams et al., 2022). Given that men entrepreneurs have easier access to finances, all-men cohorts will likely show the densest funding-related network. Conversely, women's contacts also open doors to less male-dominated market sectors (e.g., lifestyle ventures) (Neumeyer et al., 2019). Thus, cross-gender collaboration can also enhance the performance of men-founded startups. However, regarding post-accelerator funding, it is likely that men entrepreneurs benefit from other men's social capital. In this line, we hypothesize:

Hypothesis 2*: The higher share of men in an accelerator cohort…*

a. … increases women entrepreneurs' post-accelerator funding prospects.
b. … increases men entrepreneurs' post-accelerator funding prospects.

2.2.3. Founding Experience: Crucial for Women, Less for Men

Existing literature suggests that the effectiveness of accelerators depends on individual design choices, including the cohorts' size and composition (Cohen et al., 2019). However, further research suggests that these effects vary with the entrepreneur's previous founding experience. For example, it increases the performance-inducing effect of social capital (Assenova & Amit, 2022). A possible mechanism behind these findings is that experienced founders are more likely to have access to critical resources and information through their networks (Shen, Wang, Hua, & Zhang, 2021). Being fully mediated by self-efficacy, this positively influences firm performance and growth (Baum & Locke, 2004). Self-efficacy is defined as an individual's belief in their capability to perform tasks and roles aimed at entrepreneurial outcomes (Chen, Greene, & Crick, 1998).

Noteworthy to our context, the most researched individual-level antecedent of entrepreneurial self-efficacy is gender (Newman, Obschonka, Schwarz, Cohen, & Nielsen, 2019). Notably, women entrepreneurs show lower levels of self-efficacy (Dempsey & Jennings, 2014). Thus, we expect inexperienced women founders to be less able to take advantage of increased social capital than inexperienced men entrepreneurs (Debrulle, Maes, & Sels, 2014). Nevertheless, founders with more start-up experience are likelier to experience success stories and learn from failed ventures. As this impacts self-efficacy (Chen et al., 1998), higher experience should stimulate the ability to use available social capital. Consequently, inexperienced women entrepreneurs might profit from increased female representation, as seeing women role models enhances their self-efficacy (Bechthold & Rosendahl Huber, 2018). However, the more experienced the founder, the better she can use the structural social capital available. Therefore, we predict:

Hypothesis 3*: Pre-accelerator entrepreneurial experience positively moderates the influence of male representation on women entrepreneurs' future funding prospects such that less experienced founders benefit less from male representation and more from female representation in the acceleration cohort.*

2.3. Dataset and Methodology

2.3.1. Data Generation

We test our hypotheses using a dataset consisting of Crunchbase data and proprietary data from a corporate venture capitalist's acceleration program present in ten countries in Europe and Latin America. In the first step, we detected accelerators based on available company descriptions. Additionally, we determined startups that received investments from these accelerators simultaneously. We also derived information on the startup's industries, age, and investment received. Finally, we identified the founders and their (self-reported) gender, as well as the number of startups they had founded before attending the acceleration program. In the second step, we created an indicator for the cohorts' completeness. To this end, we divided the number of startups with known founders by the total amount of startups in the respective cohort. Afterward, we calculated the share of men founders in each cohort by dividing the number of entrepreneurs identifying as men by the total number of (known) founders.

Lastly, we excluded outliers and inconsistent observations. Here, we consulted accelerator websites and excluded observations from hybrid or online programs, as our theoretical background applies best to settings where founders are physically in the same place during the program (1,237 out of 2,995 observations excluded). Additionally, we only considered observations from ventures younger than 15 years (21 additional observations excluded). There are two main reasons for this decision. Firstly, research often refers to startups only as young firms (Schuh, Studerus, & Hämmerle, 2022). Over time, these firms become established organizations that are increasingly rigid. Therefore, older firms are less attractive to investors (Lahr & Mina, 2016). Secondly, most high-growth startups exit the market after less than 20 years (Pisoni & Onetti, 2018). Therefore, observing startups older than 15 years participating in acceleration programs may be misreported or unlikely to succeed. One additional observation was excluded because the founder had founded 17 startups before the program, while the second most experienced founder had started four entrepreneurial projects before. We excluded 24 observations because founders did not report their gender.

Finally, we only included cohorts with at least five startups that provided information on at least 25% of the startups (93 additional observations excluded). This ensures that each considered cohort contains at least two different founding teams, a prerequisite for interaction within the accelerator.

2.3.2. THE FINAL DATASET

Our dataset features 1,588 observations from 256 cohorts, graduating from 70 accelerators, and located in 32 countries (for an overview, consult Table 2.1). Entrepreneurs' gender is self-reported, and Crunchbase accepts a broad range of non-binary genders. However, our analyses focus on persons identifying as men or women because only five observations were available for other genders (<0.1% of the initial dataset). Typically for high-growth entrepreneurship, the dataset includes roughly 4.5 times more men than women.

Variable Name	*Description*	*N*	*Mean*	*SD*	*Min*	*Max*
			Cohort			
Size	Size of accelerator-cohort (# startups)	1588	10.80	8.33	5.00	46.00
% Men	Cohort's percentage of men entrepreneurs	1588	78.52	19.67	0.00	100.00
Completeness	Within the cohort: degree to which information on founders could be derived.	1588	0.68	0.22	0.25	1.00
Completeness (Weights)	To assign lower weights to incomplete cohorts, we normalized *Completeness* between 0 and 1	1588	0.58	0.29	0.00	1.00
Country Code	Country of acceleration program	1588	Categorical variable representing thirty-two countries. Largest three country representations: USA (n=700), Canada (n=159), UK (n=117)			
Accelerator ID	Unique identifier of the acceleration program	1588	Categorical variable representing 70 accelerators.			
			Startup			
Age	Startup's age (years)	1588	2.05	2.16	0.00	14.97
Post-Accelerator Funding	Post-accelerator funding attracted by startup (1 = funded / 0 = not funded)	1588	0.52	0.50	0.00	1.00
Industry: Consumer Goods	Industry dummy variable (Consumer goods)	1588	0.13	0.34	0.00	1.00
Industry: Manufacturing	Industry dummy variable (Manufacturing)	1588	0.16	0.37	0.00	1.00
Industry: Technology	Industry dummy variable (Technology)	1588	0.19	0.39	0.00	1.00
Industry: Sports	Industry dummy variable (Sports)	1588	0.11	0.32	0.00	1.00
Industry: Service	Industry dummy variable (Service)	1588	0.30	0.46	0.00	1.00
			Founder			
Gender	Founder’s gender (1 = female, 0 = male)	1588	0.19	0.39	0.00	1.00
Gender (reverse)	Founder’s gender (0 = female, 1 = male)	1588	0.81	0.39	0.00	1.00
Founding Experience	Total number of startups founded before accelerator	1588	1.13	0.47	0.00	4.00

Table 2.1- Dataset Descriptives

2.3.3. METHODOLOGY

Due to the hierarchical data structure (entrepreneurs are nested in accelerators) and the binary nature of the dependent variable (1 = funded, 0 = not funded), our analysis relies on hierarchical logit modeling. Random effects account for the variability between accelerators and countries, which is not explained by the model's fixed effects. This acknowledges that a startup's behavior may differ not only based on observable factors like gender and industry but also due to unobservable factors associated with the specific accelerator and country.

The fixed effects included as control variables refer to aspects that vary among different cohorts of a single accelerator. For example, the dummy variables in the model indicate whether the startup founded by a specific founder is active in the consumer goods, manufacturing, technology, sports, or service sectors. We also control the startup's age and the cohort size (i.e., the number of startups per cohort). Doing so, we take insights from previous research into account that suggest that these variables affect the performance-inducing effects of program design (Cohen et al., 2019). Because the degree to which we could retrieve information on each cohort's startups and their founders vastly differs, we weigh the regressions on each cohort's normalized degree of data completeness. Therefore, the lowest positive weight is assigned to cohorts marginally more complete than 25%. Thus, more complete cohorts impact the regression coefficients more strongly than incomplete ones.

We tested H1, considering linear relationships between gender, male representation in the cohort, and previous entrepreneurial experience. Then, we orthogonally transformed the moderating variable representing the share of men in the acceleration cohort. The model includes a linear and a quadratic transformation of the variable to test H2 and H3. The respective models included interaction effects between the linear and quadratic terms of male representation, the respective founders' gender (H2a, H2b, and H3), and the entrepreneurs' previous founding experience (H3). Finally, we calculated the model's variance inflation factors to account for potential multicollinearity issues, which consistently score below two. For further details on correlations between the different variables, please refer to Table 2.2.

	Post-Accelerator Funding	Gender	Industry: Consumer Goods	Industry: Manufacturing	Industry: Technology	Industry: Sports	Industry: Service	Startup Age	Cohort Size	Cohort Completeness	Cohort: % Men	Founding Experience
Post-Accelerator Funding	**1.000**											
Gender	-0.074**	**1.000**										
Industry: Consumer Goods	0.040	0.030	**1.000**									
Industry: Manufacturing	-0.025	0.121***	-0.128***	**1.000**								
Industry: Technology	0.048	-0.022	0.048	-0.049	**1.000**							
Industry: Sports	0.037	-0.008	-0.076**	0.065**	-0.074**	**1.000**						
Industry: Service	-0.023	0.009	-0.006	-0.144***	-0.087***	-0.156***	**1.000**					
Startup Age	-0.218***	0.025	-0.090***	0.005	-0.067**	0.098	-0.043	**1.000**				
Cohort Size	-0.075***	0.044	-0.001	0.029	0.030	0.065	-0.010	0.035	**1.000**			
Cohort Completeness	0.012	0.009	-0.090***	0.112***	-0.098***	0.037	0.068***	0.038	-0.104***	**1.000**		
Cohort: % Men	0.085***	-0.447***	0.020	-0.168***	0.039	-0.066**	0.019	-0.100***	-0.117***	-0.006	**1.000**	
Founding Experience	-0.018	-0.050	-0.004	-0.042	-0.024	0.021	-0.024	0.080	-0.010	0.065**	0.023	**1.000**

Table 2.2 - Correlation Table

• $p<0.1$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$

2.4. RESULTS

Tables 2.3 and 2.4 summarize the regression models' results concerning the relationships suggested in H1, H2, and H3. The tables show supportive results for H1 (ß = 0.54, p = 0.01), which predicted a negative effect of being a woman (as opposed to a man) entrepreneur on the likelihood of post-accelerator funding attraction.

Models 2-3 explore the boundary conditions to the main effect of male representation in acceleration cohorts. Model 2 suggests a non-linear moderation most pronounced for high and low shares of men in the cohort (ß = 2.78×10^{10}, p = 0.08). Model 3 tests whether the founder's experience additionally moderates this relationship but does not provide significant results. Models 4-6 focus on the same relationships but use an inversed gender variable. By doing so, Model 4 shows that men are more likely to attract post-accelerator funding (ß = 1.50, p = 0.10). Surprisingly, Model 5 suggests that this effect disappears as the share of men in a cohort increases (ß = 0.00, p = 0.10). Finally, Model 6 indicates that the entrepreneurs' founding experience does not significantly moderate this relation.

However, we cannot draw conclusions based on these coefficients. This is because the interaction effect in logit models does not equal the marginal effect of the interaction term, which might even be of the opposite sign. Therefore, we must calculate the marginal effects (Ai & Norton, 2003).

Dependent variable:

Post-accelerator funding attracted by the participating startup (Y/N)

	Model 1		*Model 2*		*Model 3*	
Predictors	*Odds Ratios*	*p*	*Odds Ratios*	*p*	*Odds Ratios*	*p*
Gender (1 = female, 0 = male)	0.54**	**0.010**	1.033•	**0.919**	0.264	0.344
Startup Age	0.82***	**<0.001**	0.832***	**<0.001**	0.831***	**<0.001**
Cohort Size	0.98*	**0.022**	0.980*	**0.035**	0.981*	**0.044**
Cohort: % Men [1st degree]			1.024 x 10^{7}*	**0.040**	1.051 x 10^{25}*	**0.027**
Cohort: % Men [2nd degree]			0.000•	**0.088**	0.000	0.101
Gender ×Cohort: % Men [1st degree]			2.889 x 10^{7}	0.184	0.000•	**0.070**
Gender × Cohort: % Men [2nd degree]			2.475 x 10^{10}•	**0.079**	1.200 x 10^{12}	0.596
Founding Experience					1.354	0.272
Gender × Founding Experience					3.509	0.337
Gender × Cohort: % Men [1st degree] × Founding Experience					3.530 x 10^{46}*	**0.032**
Gender × Cohort: % Men [2nd degree] × Founding Experience					0.021	0.935
Industry Dummy Variables	YES		YES		YES	
Observations	1588		1588		1588	
Marginal R^2/Conditional R^2	0.079/0.087		0.123/0.123		0.140/0.140	

Table 2.3 - Regression Table H2a & H3 • p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Dependent variable:

Post-accelerator funding attracted by the participating startup (Y/N)

	Model 4		*Model 5*		*Model 6*	
Predictors	*Odds Ratios*	*p*	*Odds Ratios*	*p*	*Odds Ratios*	*p*
Gender (reversed) (1 = female, 0 = male)	$1.500^{\bullet}$	**0.100**	0.801	0.502	3.08	0.458
Startup Age	0.802	**<0.001**	0.815***	**<0.001**	0.814	**<0.001**
Cohort Size	0.983	0.122	0.985	0.165	0.986	0.205
Cohort: % Men [1^{st} degree]			2.967×10^{14}**	**0.001**	0.000	0.412
Cohort: % Men [2^{nd} degree]			2.165×10^{4}	0.349	0.000	0.687
Gender (reversed) × Cohort: % Men [1^{st} degree]			0.000	0.136	$1.785 \times 10^{43*}$	**0.050**
Gender (reversed) × Cohort: % Men [2^{nd} degree]			$0.000^{\bullet}$	**0.100**	0.000	0.598
Founding Experience					4.629	0.250
Gender (reversed) × Founding Experience					0.288	0.373
Gender (reversed) × Cohort: % Men [1^{st} degree] × Founding Experience					0.000*	**0.019**
Gender (reversed) × Cohort: % Men [2^{nd} degree] × Founding Experience					1.889×10^{4}	0.861
Industry Dummy Variables	YES		YES		YES	
Observations	1588		1588		1588	
Marginal R^2/Conditional R^2	0.08/0.09		0.109/0.144		0.129/0.165	

Table 2.4 - Regression Table H2b & H3 $^{\bullet}$ p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Table 2.5 summarizes the marginal effects regarding women's post-accelerator funding prospects and how male cohort representation impacts them (H1 and H2a). The first column captures the negative impact of being a woman entrepreneur on the odds of attracting post-accelerator funding (ß = - 0.14, p = 0.01) in support of H1. In line with H2a, Model 2 suggests that higher shares of male participants in a cohort are related to a lower post-accelerator funding gap between men and women (ß = 0.28, p = 0.05). Further, cohorts nearly exclusively composed of women (ß = - 0.28, p = 0.03) have the lowest odds of attracting post-acceleration funding. Table 2.6 summarizes the marginal effects regarding men's post-accelerator funding prospects and how male cohort representation impacts them (H2b). Model 4 shows a direct, positive effect of being a man on the likelihood of post-accelerator funding (ß = 0.13, p = 0.06). In line with H2b, Model 5 shows that this effect becomes stronger if the share of men founders in the accelerator increases (ß = 0.35, p = 0.08). However, the coefficients diminish if the cohort is nearly only composed of men (ß= - 0.19, p = 0.09).

H2a: Women entrepreneurs' post-accelerator funding prospects[3]				
Male Share in Cohort (Moderator)	**Model 1:** Founder Gender (direct effect of being a *woman*)	p.value (Model 1)	**Model 2:** Founder Gender x Male Representation [2nd degree]	p.value (Model 2)
	-0.14**	0.012		
0%-5%			0.11	0.51
5%-50%			0.20•	0.06
50%-95%			0.30*	0.02
95%-100%			0.19•	0.10
0%-100%			**0.73*****	**0.00**

Table 2.5 - Marginal Effects H2a • p<0.1 * p<0.05 ** p<0.01 *** p<0.001

H2b: Men entrepreneurs' post-accelerator funding prospects[4]				
Male Share in Cohort (Moderator)	**Model 4:** Founder Gender (direct effect of being a *man*)	p.value (Model 4)	**Model 5:** Founder Gender x Male Representation [2nd degree]	p.value (Model 5)
	0.13•	0.057		
0%-5%			-0.08	0.727
5%-50%			0.29•	0.095
50%-95%			0.28***	<0.001
95%-100%			-0.19•	0.097
0%-100%			**0.35•**	**0.082**

Table 2.6 - Marginal Effects H2b • p<0.1 * p<0.05 ** p<0.01 *** p<0.001

[3] Models 1-2 describe how male representation affects women (Founder Gender = 1) compared to men (Founder Gender = 0) founders.
[4] Models 4-5 describe how male representation affects men (Founder Gender = 0) compared to women (Founder Gender = 1) founders.

Figure 2.1 visualizes the differences in marginal effects between male and female entrepreneurs, which have implications for the optimal gender composition of the cohort. The graph indicates a tipping point for male founders at a cohort composition of 80% men and 20% women. For female entrepreneurs, the optimal composition is within male-dominated cohorts.

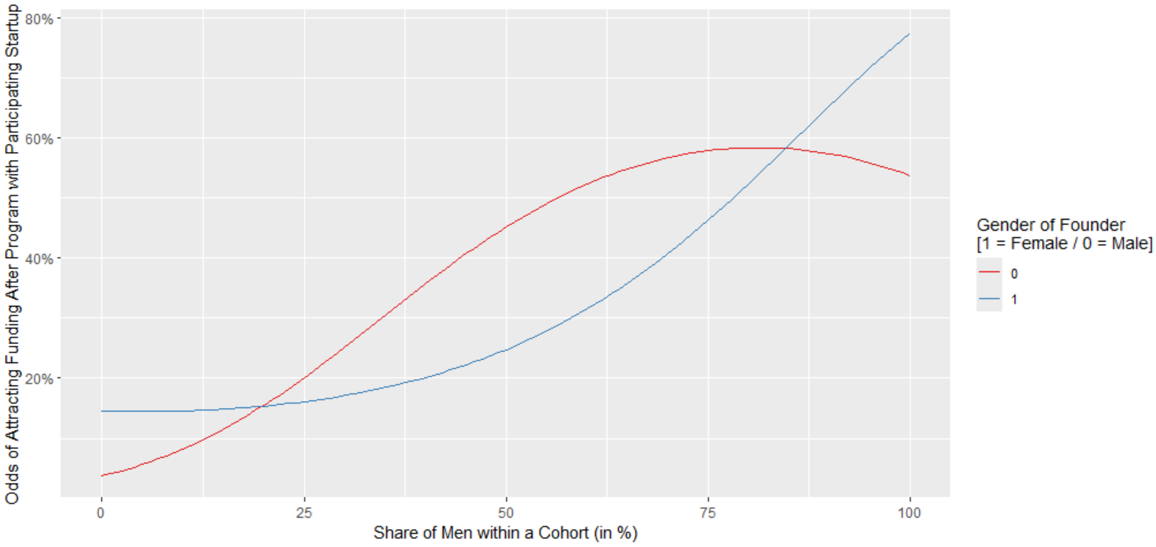

Figure 2.1 - Male Representation and the Funding Gap

Table 2.7 summarizes the marginal effects of Model 4, providing support for H3 (ß = 0.71, p = 0.00). It shows that having more pre-accelerator experience enhances the positive impact of the proportion of male participants on women's post-accelerator funding prospects. Table 2.8 summarizes Model 6, which suggests that pre-accelerator founding experience only impacts men's likelihood to attract post-accelerator funding in male-dominated cohorts (ß = 0.09, p = 0.03).

H3: Women entrepreneurs' post-accelerator funding prospects and pre-accelerator founding experience[5]				
Male Share in Cohort (Moderator)	**Comparison of (in)experienced founders** Founder Gender x Male Representation [2nd degree] x		**Model 3:** Founder Gender x Male Representation [2nd degree] x Pre-Accelerator Founding Experience	p.value (Model 3**)**
	Experience = 0	**Experience = 1**		
0%-5%	0.01 (0.961)	0.01 (0.972)	0.17	0.35
5%-50%	0.09 (0.225)	0.08 (0.372)	0.27***	<0.001
50%-95%	0.22• (0.065)	0.55*** (<0.001)	0.38**	0.01
95%-100%	0.17 (0.162)	0.36*** (<0.001)	0.09	0.57
0%-100%	**0.58***** (<0.001)	**0.85***** <0.001	**0.71*****	**<0.001**

Table 2.7 - Marginal Effects H3 • p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Additional Analysis: Men entrepreneurs' post-accelerator funding prospects and pre-accelerator founding experience[6]				
Male Share in Cohort (Moderator)	**Comparison of (in)experienced founders** Founder Gender x Male Representation [2nd degree] x		**Model 6:** Founder Gender x Male Representation [2nd degree] x Pre-Accelerator Founding Experience	p.value (Model 6**)**
	Experience = 0	**Experience = 1**		
0%-5%	-0.00 (1.00)	0.48 (0.503)	-0.30	0.827
5%-50%	0.30 (0.124)	0.33 (0.539)	0.03	0.979
50%-95%	0.29 (<0.001)	0.16 (0.202)	0.38	0.862
95%-100%	-0.16 (0.162)	0.36 (0.520)	0.09*	0.029
0%-100%	**0.36 (0.105)**	**0.29 (0.631)**	**0.18**	**0.898**

Table 2.8 - Marginal Effects Additional Analysis • p<0.1 * p<0.05 ** p<0.01 *** p<0.001

[5] Model 3 describes how male representation affects women (Founder Gender = 1) compared to men (Founder Gender = 0) founders.
[6] Model 6 describes how male representation affects men (Founder Gender = 0) compared to women (Founder Gender = 1) founders.

For easier interpretation, we plotted the results regarding H3 in Figure 2.2. On the right-hand side, it becomes evident that inexperienced women entrepreneurs benefit the most from gender-mixed cohorts, with a female majority of 70 percent. However, with increasing experience, they tend to benefit more from a higher proportion of males in the group. Hence, a male-dominated gender composition becomes most beneficial to them. On the left, Figure 2.2 shows that highly experienced male entrepreneurs benefit less from male-dominated cohorts than less experienced ones.

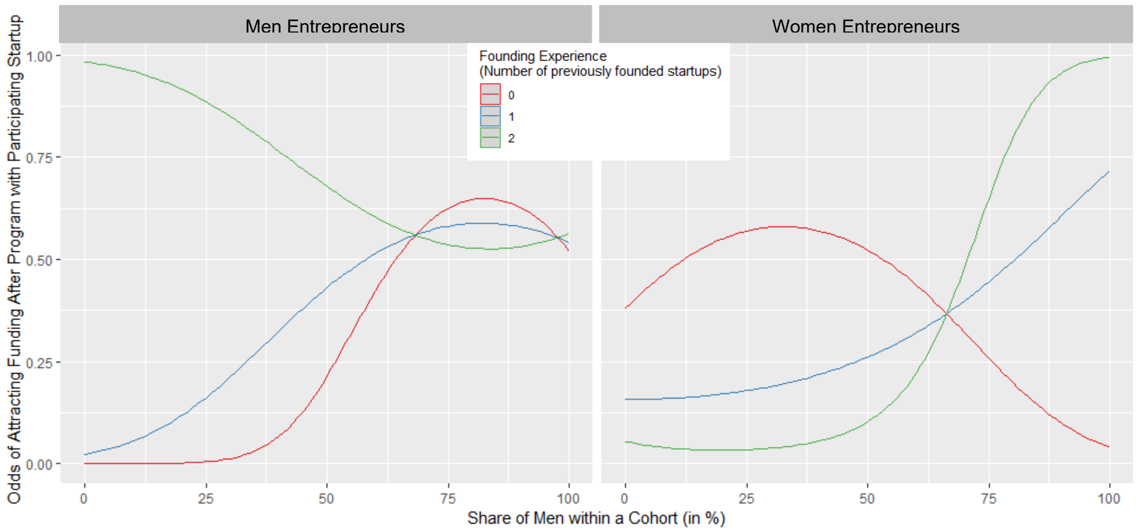

Figure 2.2 - Male Representation, Entrepreneurial Experience, and the Funding Gap

2.5. DISCUSSION

This research indicates that the gender composition of acceleration cohorts impacts the post-accelerator attraction of funding for both men and women. However, the ideal cohort gender composition depends on the founders' previous founding experience. Therefore, three main results emerge: (1) Experienced women founders benefit more from heavily male-dominated cohorts (2) For inexperienced women's startups, participation in cohorts with a female majority is an attractive option (3) Men entrepreneurs with little to no experience benefit most from cohorts composed of 80% men and 20% women, while those with more experience increase their chances of funding after the program through increased female representation in the cohort.

These results contribute to the literature on accelerator program design and the importance of cohort member selection (Cohen et al., 2019). They enhance our comprehension of accelerator cohort composition and introduce pre-accelerator experience as a crucial variable for participant selection. More specifically, they contribute to the literature on gendered entrepreneurial ecosystems and support systems (Brush et al., 2019). Our empirical evidence supports previous research endorsing accelerators as an appropriate means of supporting women's entrepreneurship (Avnimelech &

Rechter, 2023) and reducing the gender funding gap. Furthermore, the findings add to the existing literature on the distribution of social capital in entrepreneurial ecosystems (Neumeyer et al., 2019) by showing that acceleration cohorts offer a platform for founders to interact and decrease socially constructed barriers, facilitating women's access to social capital embedded in male networks. However, our results also extend the existing body of literature on critical perspectives on accelerators as neutral support providers (Ozkazanc-Pan & Clark Muntean, 2018). They suggest that gender-unbalanced acceleration programs might benefit women founders in the short run, but neither men-only nor women-only cohorts are likely to alter the existing power relations and gender dynamics within the entrepreneurial landscape. Instead, male-dominated cohorts restrict the number of women who can benefit from the program, while women-dominated cohorts limit interactions between women and men founders.

Nevertheless, women-dominated cohorts can provide a safe space for those seeking to escape from being "othered" by dominant masculine norms (MacNeil et al., 2023). This may be particularly beneficial for inexperienced women entrepreneurs who can benefit from self-efficacy-enhancing role model effects (Neumeyer, 2022) within such cohorts. However, managers need to be aware that a less masculinized discourse and culture can reduce women's marginalization and underestimation. Such an approach can boost less experienced women's self-efficacy, regardless of the presence of other women (MacNeil, Schoonmaker, & McAdam, 2022). Conversely, while male-dominated cohorts appear to positively impact experienced women founders' post-accelerator funding, they also contribute to a more masculinized discourse and culture of accelerators. Therefore, accelerators may prefer to rely on their external networks and contacts to stimulate women's social capital. Meanwhile, gender-balanced cohorts help to reduce women's marginalization and undervaluation and ultimately increase their self-efficacy in the long term.

Despite our results' theoretical and managerial contributions, our research has certain limitations. Firstly, a selection effect may affect our data and analysis, where women-founded startups accepted for male-dominated cohorts have higher potential than those participating in more gender-balanced acceleration programs. Secondly, our theoretical argumentation relies on self-efficacy and social capital theory. Yet, we lack direct measures of self-efficacy and social capital. Therefore, this presents opportunities for future research. Observational studies and interviews could shed light on the evolution of self-efficacy during acceleration programs. More precise measurements of social capital could be embedded in social network studies (e.g., using LinkedIn data).

2.6. Conclusion

This study puts forth significant insights for both academia and practice. Beyond existing work focusing on accelerators and female entrepreneurship, it establishes the potential of well-structured accelerator programs in mitigating gender-related disparities in social capital. Moreover, it contributes to the discourse on acceleration cohorts' design by underpinning the importance of the founder's experience and gender regarding the cohorts' composition. Due to the crucial position of entrepreneurial support organizations in developing entrepreneurial ecosystems, our findings underscore the vital role of accelerators in shaping inclusive ecosystems. Our research indicates that the gender composition of accelerator cohorts affects both men and women entrepreneurs' post-accelerator funding prospects. The optimal gender composition for women entrepreneurs further depends on the respective founders' entrepreneurial experience. Unexperienced women-founded startups stand to gain from predominantly female cohorts. In the discussion section, we emphasize that a gender-unbalanced cohort design perpetuates gender inequality. In the long run, a gender-balanced composition of acceleration cohorts might be the better option, alongside the use of external networks to stimulate women's social capital.

2.7. References Chapter 2

Ai, C., & Norton, E. 2003. Interaction terms in logit and probit models. Economics Letters, 80(1): 123–129.

Assenova, V., & Amit, R. 2022. Poised for Growth: Cohorts' Knowledge and its Effects on Post-Acceleration Startup Growth. Strategic Management Journal, 45(6): 1029-1060.

Avnimelech, G., & Rechter, E. 2023. How and why accelerators enhance female entrepreneurship. Research Policy, 52(2): 104669.

Baum, J., & Locke, E. 2004. The relationship of entrepreneurial traits, skill, and motivation to subsequent venture growth. The Journal of applied psychology, 89(4): 587–598.

Bechthold, L., & Rosendahl Huber, L. 2018. Yes, I can! – A Field Experiment on Female Role Model Effects in Entrepreneurship. Academy of Management Proceedings, 2018(1): 1-6.

Bliemel, M., Flores, R., Klerk, S. de, & Miles, M. 2019. Accelerators as start-up infrastructure for entrepreneurial clusters. Entrepreneurship & Regional Development, 31(1-2): 133–149.

Brush, C., Carter, N., Gatewood, E. , Greene, P., & Hart, M. 2008. The Diana Project: Women Business Owners and Equity Capital: The Myths Dispelled. Babson College Center for entrepreneurship Research Paper, 2009(11): 1-24.

Brush, C., Edelman, L. F., Manolova, T., & Welter, F. 2019. A gendered look at entrepreneurship ecosystems. Small Business Economics, 53(2): 393–408.

Cao, Z., & Shi, X. 2021. A systematic literature review of entrepreneurial ecosystems in advanced and emerging economies. Small Business Economics, 57(1): 75–110.

Chen, C., Greene, P., & Crick, A. 1998. Does entrepreneurial self-efficacy distinguish entrepreneurs from managers? Journal of Business Venturing, 13(4): 295–316.

Cohen, S. 2013. What Do Accelerators Do? Insights from Incubators and Angels. Innovations: Technology, Governance, Globalization, 8(3-4): 19–25.

Cohen, S., Fehder, D., Hochberg, Y., & Murray, F. 2019. The design of startup accelerators. Research Policy, 48(7): 1781–1797.

Dams, C., Sarria-Allende, V., Cornejo, M., Pasquini, R., & Robiolo, G. 2022. Impact of Accelerators, as Education & Training Programs, on Female Entrepreneurs. Entrepreneurship Research Journal, 12(3): 329–362.

Daymond, J., Knight, E., Rumyantseva, M., & Maguire, S. 2023. Managing ecosystem emergence and evolution: Strategies for ecosystem architects. Strategic Management Journal, 44(4): 1–27.

Debrulle, J., Maes, J., & Sels, L. 2014. Start-up absorptive capacity: Does the owner's human and social capital matter? International Small Business Journal: Researching Entrepreneurship, 32(7): 777–801.

Dempsey, D., & Jennings, J. 2014. Gender and entrepreneurial self-efficacy: a learning perspective. International Journal of Gender and Entrepreneurship, 6(1): 28–49.

Ding, W., Ohyama, A., & Agarwal, R. 2021. Trends in gender pay gaps of scientists and engineers in academia and industry. Nature biotechnology, 39(8): 1019–1024.

Godwin, L., Stevens, C., & Brenner, N. 2006. Forced to Play by the Rules? Theorizing how Mixed–Sex Founding Teams Benefit Women Entrepreneurs in Male–Dominated Contexts. Entrepreneurship Theory and Practice, 30(5): 623–642.

Goswami, K., Mitchell, J., & Bhagavatula, S. 2018. Accelerator expertise: Understanding the intermediary role of accelerators in the development of the Bangalore entrepreneurial ecosystem. Strategic Entrepreneurship Journal, 12(1): 117–150.

Granovetter, M. 1973. The Strength of Weak Ties. American Journal of Sociology, 78(6): 1360–1380.

Greene, P., Brush, C., Hart, M. , & Saparito, P. 2001. Patterns of venture capital funding: Is gender a factor? Venture Capital, 3(1): 63–83.

Hite, J. 2005. Evolutionary Processes and Paths of Relationally Embedded Network Ties in Emerging Entrepreneurial Firms. Entrepreneurship Theory and Practice, 29(1): 113–144.

Hoang, H., & Antoncic, B. 2003. Network-based research in entrepreneurship. Journal of Business Venturing, 18(2): 165–187.

Jonsson, S., & Lindbergh, J. 2013. The Development of Social Capital and Financing of Entrepreneurial Firms: From Financial Bootstrapping to Bank Funding. Entrepreneurship Theory and Practice, 37(4): 661–686.

Lahr, H., & Mina, A. 2016. Venture capital investments and the technological performance of portfolio firms. Research Policy, 45(1): 303–318.

Lall, S., Chen, L., & Roberts, P. 2020. Are we accelerating equity investment into impact-oriented ventures? World Development, 131: 1–12.

MacNeil, H., Schoonmaker, M., & McAdam, M. 2022. Accelerating alienation: gender and self-efficacy in the accelerator context. International Journal of Entrepreneurial Behavior & Research, 28(8): 2083–2102.

Malmström, M., Johansson, J., & Wincent, J. 2017. Gender Stereotypes and Venture Support Decisions: How Governmental Venture Capitalists Socially Construct Entrepreneurs' Potential. Entrepreneurship Theory and Practice, 41(5): 833–860.

Marlow, S., & McAdam, M. 2013. Gender and entrepreneurship. International Journal of Entrepreneurial Behavior & Research, 19(1): 114–124.

Mason, C., & Brown, R. 2013. Creating good public policy to support high-growth firms. Small Business Economics, 40(2): 211–225.

Maurer, I., & Ebers, M. 2006. Dynamics of Social Capital and Their Performance Implications: Lessons from Biotechnology Start-ups. Administrative Science Quarterly, 51(2): 262–292.

Muehlenhard, C., & Peterson, Z. 2011. Distinguishing Between Sex and Gender: History, Current Conceptualizations, and Implications. Sex Roles, 64(11-12): 791–803.

Nahapiet, J., & Ghoshal, S. 1998. Social Capital, Intellectual Capital, and the Organizational Advantage. Academy of Management Review, 23(2): 242–266.

Neumeyer, X. 2022. Inclusive High-Growth Entrepreneurial Ecosystems: Fostering Female Entrepreneurs' Participation in Incubator and Accelerator Programs. IEEE Transactions on Engineering Management, 69(4): 1728–1737.

Neumeyer, X., Santos, S. C., Caetano, A., & Kalbfleisch, P. 2019. Entrepreneurship ecosystems and women entrepreneurs: a social capital and network approach. Small Business Economics, 53(2): 475–489.

Newman, A., Obschonka, M., Schwarz, S., Cohen, M., & Nielsen, I. 2019. Entrepreneurial self-efficacy: A systematic review of the literature on its theoretical foundations, measurement, antecedents, and outcomes, and an agenda for future research. Journal of Vocational Behavior, 110: 403–419.

Ozkazanc-Pan, B., & Clark Muntean, S. 2018. Networking towards (in)equality: Women entrepreneurs in technology. Gender, Work & Organization, 25(4): 379–400.

Pisoni, A., & Onetti, A. 2018. When startups exit: comparing strategies in Europe and the USA. Journal of Business Strategy, 39(3): 26–33.

Ratten, V. 2020. Entrepreneurial Ecosystems: The Role of Accelerators. In V. Ratten (Ed.), Entrepreneurship as Empowerment: Knowledge Spillovers and Entrepreneurial Ecosystems, Emerald Publishing Limited, Leeds: 11-22.

Schuh, G., Studerus, B., & Hämmerle, C. 2022. Development of a Life Cycle Model for Deep Tech Startups. Journal of Production Systems and Logistics, 2(5): 1-17.

Shen, Y., Wang, Q., Hua, D., & Zhang, Z. 2021. Entrepreneurial Learning, Self-Efficacy, and Firm Performance: Exploring Moderating Effect of Entrepreneurial Orientation. Frontiers in psychology, 12: 731628.

Uzzi, B. 1996. The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect. American Sociological Review, 61(4): 674–698.

3. Beyond the Norms: Unveiling Gendered Patterns in Sustainable Entrepreneurship Funding

Aaron Pohlmann

ABOUT THIS CHAPTER:

Chapter 3 presents a modified version of the working paper "Female Entrepreneurship and Sustainable Development", which I presented at the DRUID Academy in January 2024. As this is a single-authored essay, I assume the sole responsibility for the data collection, preparation, and analysis, as well as for interpreting the results and preparing the manuscript.

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Abstract

This study investigates if women-founded startups focus more on social, educational, or pro-environmental businesses than men-founded ones and if such a choice impacts the firm's funding prospects as suggested by institutional theory and gender role theory. Based on fixed-effects ordinary least squares regression, the results indicate that women-founded startups are more likely to initiate social- and educational startups but less likely to found environmental ones. Further, the paper provides empirical evidence of a gender-related funding gap regarding startups' attracted funding per round. This gap decreases among socially- and educationally-oriented startups but increases among pro-environmentally focused ones. However, post-hoc panel analysis shows that a social and environmental focus increases the likelihood of attracting funding compared to the average women-founded startup. The article contributes to the body of literature on gender role congruity and startup funding. It also entails important implications for policymakers and managers of entrepreneurial support organizations: Smaller funding rounds are important for women-founded startups that do not require large investments for growth. Nevertheless, others might not acquire enough financial capital to be competitive and need less all-women- and more gender-balanced, industry-focused support.

Beyond the Norms: Unveiling Gendered Patterns in Sustainable Entrepreneurship Funding

3.1. INTRODUCTION

In the complex entrepreneurship landscape, gender dynamics and societal expectations create a silent code that influences the success of startups[7] - especially those led by women[8]. For example, investors reward persons conforming to societal expectations of how a person of a specific gender should behave (e.g., Cowden, Creek, & Maurer, 2021). For instance, stereotypical "male" traits overlap with those ascribed to successful high-growth entrepreneurs, including being bold, calculative, risk-taking, and aggressive. Contrarily, "feminine" attributes include being kind, caring, and sensitive (Hancock, Pérez-Quintana, & Hormiga, 2014; Laguía, García-Ael, Wach, & Moriano, 2019).

Research finds that these societal attitudes and gender patterns are influential forces shaping female underrepresentation in economic sectors. For instance, women high-growth entrepreneurs are less likely to obtain external capital from investors than men (Gatewood, Carter, Brush, Greene, & Hart, 2003; Guzman & Kacperczyk, 2019). Further, women tend to focus on business activities that align with existing gender role stereotypes. For example, women entrepreneurs are more likely to start pro-environmentally oriented ventures (Hechavarría, 2016; Liu, Anser, & Zaman, 2021) and are more aware of their venture's social impact (Spiegler & Halberstadt, 2018). Overall, women are nearly twice as likely as men to start businesses focusing on health, education, and social matters (Elam et al., 2022). At this point, it would be possible to argue that women are naturally more inclined to start businesses with a pro-environmental, educational, or social orientation. However, existing literature paints a different picture: In particular, gender role theory proposes that the degree to which an individual of a given gender conforms to gender expectations [hereafter referred to as gender role congruity] plays a vital role in a women-founded firm`s success (Strawser, Hechavarría, & Passerini, 2021). Thus, individuals who conform to gender expectations tend to benefit from stakeholders (Eagly & Carli, 2003; Eagly & Karau, 2002). Consequently, women are more likely to be successful if they align their businesses with existing gender role expectations.

Further, founders often group up and build founding teams (Chowdhury, 2005). Similar to individual persons, gender role stereotypes affect these groups of founders. For example, research suggests that founding teams with increased female representation are more likely to pursue social motives in new ventures (Chandler, Short, Hasan, & Fan, 2022) and tend to attract less funding than all-male teams (Färber & Klein, 2021). This raises the impression that social pressures push women

[7] In this paper, the term startup describes a high-growth-oriented entrepreneurial project of a founder or a founding team.

[8] This paper refers to gender as opposed to sex (Helgeson, 2020). Gender is associated with social or cultural aspects (e.g., gender bias) rather than biological factors (Muehlenhard and Peterson, 2011). Furthermore, individuals who self-identify as men or women are treated as such.

founders and mixed entrepreneurial teams into pursuing pro-environmental and socially oriented business activities. Consistent with these considerations, women-founded businesses [referring to sole women founders and mixed founding teams] seem more likely to succeed if they align with existing gender role expectations. To disentangle the driving forces behind the interplay of gender, the attraction of funding, and a startup's business orientation, this research therefore analyzes the following questions:

1. *Do high-growth-oriented startups with higher proportions of women founders focus more on social, educational, or pro-environmental objectives?*
2. *Do high-growth-oriented startups with higher proportions of women founders receive more funding per investment round if their startups have social, educational, or pro-environmental objectives?*

Drawing on institutional theory (Zucker, 1987) and gender role theory (Diekman & Eagly, 2013; Powell, 2019), three hypotheses emerge: First, the proportion of women in a startup's founding team positively affects the startup's social orientation (H1A), the startup's educational orientation (H1B), and the startup's environmental orientation (H1C). Second, new ventures with more women on the founding team receive less funding per round (H2). Finally, the negative impact of having a higher proportion of women in the founding team on attracting funding is reduced for socially (H3A), educationally (H3B), or pro-environmentally (H3C) oriented startups.

The dataset for this study includes 115,660 observations from 163 different countries collected from 1992 to 2022. It combines information from the United Nations Sustainable Development Goals Indicator Database with Crunchbase data, which provides information on entrepreneurs, founding teams, and startup characteristics. To complete the data collection, I calculated semantic similarities by comparing startup descriptions from Crunchbase to each of the 17 United Nations Sustainable Development Goals using a pre-trained Word2Vec model. This resulted in the identification of 17 semantic proximity indicators. Each of these indicators represents a different aspect of sustainable development, which makes them likely to be interrelated. To identify the underlying factors explaining these correlations among the indicators, I conducted an exploratory factor analysis that yielded three factors. The first factor loads strongly on reducing poverty and inequality indicators and describes the startup's social orientation. The second factor is most strongly related to indicators related to education and measures a firm's educational orientation. The third and final factor loads strongly on indicators related to sustainable consumption and resource use and describes the startup's environmental orientation.

I utilized these variables as dependent variables to test H1 and as moderating variables to test H3, relying on fixed-effects ordinary least squares regression. As H2 only requires the share of female founders as the independent variable and attracted funding per investment round as the dependent variable, I did not have to consider the factors for its statistical analysis.

This paper's results support H1A, H1B, and H2, as well as H3A and H3B. At the same time, the proportion of women in a team negatively correlates with a firm's focus on sustainable consumption and resource use (environmental focus), which is precisely the opposite of the hypothesized relationship in H1C. Contrary to H3C, the expected funding per round is lowest for women-dominated teams with a pro-environmental focus. Yet, post-hoc analysis suggests that these firms are more likely to attract funding than the average women-founded startup.

Existing research further suggests that men often tend to focus on technological solutions to sustainability issues (Bloodhart & Swim, 2020; Brody, Demetriades, & Esplen, 2008). Based on this consideration, I conducted an additional moderation analysis to determine whether the results differ between startups with and without a technological business orientation. This is theoretically motivated by literature suggesting that women face unique challenges in the male-dominated technology sector (Gupta, Wieland, & Turban, 2019; OECD, 2023). However, the analysis did not provide significant results that would facilitate a better understanding of the unexpected results from H1C and H3C. Thus, further research is needed to understand these relationships.

Still, this paper's empirical evidence indicates differences in sustainability orientation between women and men entrepreneurs, which investors further reinforce and contribute significantly to the existing body of literature. Firstly, the study contributes to the existing body of literature on gender and sustainable entrepreneurship (e.g., Dickel & Eckardt, 2021) by providing empirical evidence that women and men-founded impact sustainable development in different ways. It also suggests that women-founded startups are not necessarily more pro-environmentally oriented than male-founded ones. While women's consumer behavior may be more environmentally conscious in general (e.g., Blocker & Eckberg, 1997; Khan, Du Jianguo, Ali, Saleem, & Usman, 2019; Vicente-Molina, Fernández-Sainz, & Izagirre-Olaizola, 2018; Zelezny, Chua, & Aldrich, 2000), the results of this study suggest that men-founded startups focus to a greater extent on ecological sustainability than women-founded ones. Secondly, the results regarding H3A and H3B demonstrate that investors reward founding teams if they align their behaviors with the gender role expectations imposed on their members. This extends the body of literature on gender role congruity (e.g., Anglin, Courtney, & Allison, 2022; Butticè, Croce, & Ughetto, 2023; e.g. Cowden et al., 2021).

However, the study also highlights that the gender funding gap persists even within the realm of social and education startups. Thus, male-founded businesses are still better funded than female-founded ones, even in stereotypically "female" domains. These findings have practical implications for policymakers and entrepreneurial support organizations, suggesting women founders focusing on pro-environmental entrepreneurship may require targeted support (e.g., networking events to find investors) due to unique challenges in attracting funding.

3.2. THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

As mentioned in the introduction, a society's gender role system may prescribe behaviors that are stereotypically male or female (Eagly, 1987; Marlow & Carter, 2004). According to institutional theory, it, therefore, shapes social thought and actions (Baughn, Chua, & Neupert, 2006; Covaleski & Dirsmith, 1988). This impact occurs primarily because members of society internalize the normative system and act in accordance with the value standard (Parsons, 1951).

3.2.1. GENDER STEREOTYPES

Existing literature suggests that gender stereotypes implicitly impact society's expectations regarding the qualities, priorities, and needs of individual men and women (Ellemers, 2018) and are particularly important in male-dominated fields (Martiarena, 2022) such as high-growth entrepreneurship (Gupta et al., 2019). These stereotypes are widely shared generalizations about how men and women should behave (Hentschel, Heilman, & Peus, 2019). One driver behind this observation is the distribution of men and women in social roles at home and work (Koenig & Eagly, 2014). For example, women are more likely to occupy domestic, caretaking roles. In contrast, men are often responsible for financially supporting their families (Eagly & Wood, 2012). In the workplace, women tend to hold people-oriented, service occupations rather than things-oriented, competitive occupations traditionally occupied by men (Lippa, Preston, & Penner, 2014).

One of the most prominent examples of gender stereotypes is related to the "agency-communion paradigm" (Koenig, Eagly, Mitchell, & Ristikari, 2011: 617). The term "agency" represents traits such as competence, instrumentality, and independence, whereas "communion" captures nurturance, warmth, and concern for others (Kite, Deaux, & Haines, 2008). Stereotypically, people assume that women are more communal and men more agentic (e.g., Abele, 2003). This stereotypical perception persists even though people nowadays perceive women and men as equally competent and intelligent (ibid). While this indicates that stereotypes are changing over time, it also shows that this process is a slow and gradual one (Eagly & Koenig, 2021).

3.2.2. Gender Role Congruity in Entrepreneurship

Exploring the role that gender stereotypes play in business, gender role theory introduces the concept of gender role congruity (Eagly & Karau, 2002). It describes the degree to which someone of a given gender aligns with the societal expectations of how a person of their gender should behave. Further, those who show role-congruent behavior tend to benefit from stakeholders (Eagly & Karau, 2002; Joshi, Son, & Roh, 2015). Gender role theory initially explored how the inconsistency between women and leadership roles leads to prejudicial evaluations against women leaders while underlining preference for men (Eagly & Karau, 2002). Quickly after its publication, a large body of research on leadership supported the basic notion of the theory (e.g., Muller-Kahle & Schiehll, 2013; Mulvaney, O'Neill, Cleveland, & Crouter, 2007). In this line, early empirical work on gender role congruity suggests that women candidates for leadership positions in gender-role incongruent industries (e.g., car manufacturing) suffer from prejudices from the decision-makers during the selection process (Garcia-Retamero & López-Zafra, 2006).

Existing literature further elaborates on these insights and suggests that career choices, including entrepreneurial ones, are generally shaped by what society deems desirable and correct for one's gender (Achtenhagen & Welter, 2011). It is, therefore, no surprise that the model has become substantial to entrepreneurship research. At the heart of this literature stream lies the notion that the entrepreneurial role is often described as bold, aggressive, calculative, risk-taking, and aggressive - attributes stereotypically associated with men (Laguía et al., 2019). Conversely, attributes perceived as feminine include being kind or sensitive (Hancock et al., 2014; Laguía et al., 2019). As a consequence, women with a masculine or androgynous orientation are more likely to develop entrepreneurial careers (Liñán, Jaén, & Martín, 2022).

Finally, recent research focuses increasingly on the relationship between the gender of founders and the funding they attract. For example, they show that women founders receive more funding when they start social ventures (Anglin et al., 2022) and demonstrate feminine characteristics such as agreeableness and humility (Cowden et al., 2021). The combination of these conditions with the perception of entrepreneurship as a male domain presents a complex situation for women entrepreneurs. They must navigate the challenge of behaving in a manner perceived as masculine enough to be accepted as entrepreneurs while simultaneously demonstrating characteristics perceived as feminine to increase their chances of securing funding. This matters particularly because less funding is linked to lower firm growth (Alsos, Isaksen, & Ljunggren, 2006).

3.2.3. HORIZONTAL SEGREGATION IN ENTREPRENEURSHIP

Entrepreneurship is heavily male-typed, particularly in high-growth sectors such as the digital and technology industry (Gupta et al., 2019; Laguía et al., 2019). Because women are often not taken seriously outside of traditionally female-typed niches (Bates, 2002), it is unsurprising that women are underrepresented (OECD, 2023) in these domains.

Furthermore, women who start a business are nearly twice as likely as men to start businesses in health, education, and social services and less than half as likely to start a business in agriculture, forestry, and mining (Elam et al., 2022). This phenomenon where women cluster in occupations different from their male counterparts is referred to as horizontal labor market segregation in literature and is often associated with lower income, skills, and status levels for women than for men (Guzman & Kacperczyk, 2019; Marlow, 2002).

3.2.4. ENTREPRENEURIAL TEAMS AND GENDER

It is well known that founders often group up and build founding teams (Chowdhury, 2005; Forbes, Borchert, Zellmer–Bruhn, & Sapienza, 2006), particularly in high-growth entrepreneurship (Gundry & Welsch, 2001). Notably, team-founded startups are often more successful than single-founded ones in the high-tech sector (Lechler, 2001), which is most likely related to the notion that entrepreneurial teams possess more extensive networks than solo founders that can provide faster access to resources (Witt, 2004). Nevertheless, research suggests that gender-related team composition affects these teams similarly to how it influences individual founders. In line with the presented gender stereotypes above, research indicates that all-female management teams tend to be less aggressive and more engaged in social sustainability initiatives than other team compositions (Apesteguia, Azmat, & Iriberri, 2012). A particularly well-suited tool to promote social sustainability is to improve sustainability-related education (Sharma & Monteiro, 2016). Further, research suggests that companies with more women at the top of the organization are more likely to promote high levels of eco-innovation by successfully implementing corporate social responsibility strategies (Issa & Bensalem, 2022). Finally, male attributes, such as being more risk-seeking, typically characterize entrepreneurial teams with an enhanced level of male presence (Bogan, Just, & Dev, 2013).

However, the gender composition of entrepreneurial teams is not only linked to stereotypical scopes of business but also to differences regarding the attracted funding. More precisely, mixed teams attract more funding than all-female teams (Cicchiello, Kazemikhasragh, & Monferrà, 2022; Vogel, Puhan, Shehu, Kliger, & Beese, 2014) and ventures founded by all-female teams or only one woman have lower chances of survival (e.g., Box & Larsson Segerlind, 2018). Therefore, research suggests that female entrepreneurs should strategically choose to form teams with a mixed-sex composition to increase their chances of attracting funding (Cicchiello et al., 2022; Godwin, Stevens, & Brenner, 2006).

3.2.5. Hypothesis Development

As described above, women's entrepreneurial activity often agglomerates in industry sectors, which are stereotypically considered more female than others. For example, they are nearly twice as likely as men to start businesses with a business focus on health, education, and social matters (Elam et al., 2022) and tend to internalize communal goals to a stronger extent than men do (Diekman & Eagly, 2013). In this line, existing literature states that women entrepreneurs (Spiegler & Halberstadt, 2018), and all-women founding teams in general (Apesteguia et al., 2012), focus more on the social impact of their businesses, and consider social entrepreneurial intentions more desirable than teams composed of more men (Dickel & Eckardt, 2021). Entrepreneurial teams composed of more women are, additionally, positively associated with pursuing social motives in new ventures (Chandler et al., 2022).

Literature on social entrepreneurship pronounces women's stronger inclination to tackle issues related to socio-economic development and poverty alleviation (Kimbu & Ngoasong, 2016; Rosca, Agarwal, & Brem, 2020) in this context. A social entrepreneur can be defined as "(…) a mission-driven individual who uses a set of entrepreneurial behaviors to deliver a social value to the less privileged, all through an entrepreneurially oriented entity that is financially independent, self-sufficient, or sustainable" (Abu-Saifan, 2012: 25). Since this definition is relatively vague, I will refrain from using the term "social entrepreneurship". Instead, I will refer to a startup's social orientation as its tendency to tackle poverty and inequality-related societal problems. Further, stereotypes are particularly important in fields where the number of women entrepreneurs is low (Martiarena, 2022). As high-growth entrepreneurship is heavily male-typed (Gupta et al., 2019; Laguía et al., 2019), I expect to add to the existing literature by showing that high-growth-focused startups with higher shares of women founders show an increased focus on social matters. Doing so, I hypothesize:

Hypothesis 1A: *An increasing share of women in the founding team or being a women solo founder of a high-growth-oriented startup positively influences the startup's social orientation (its focus on poverty and inequality reduction).*

As mentioned before, women are expected to be more communal (Koenig et al., 2011) and more concerned for others than men (Kite et al., 2008). Consequently, acting in line with these expectations leads to an enhanced motivation to solve issues of social nature. Thus, they are more likely to establish businesses in the education sector (Austin, Stevenson, & Wei–Skillern, 2006; Elam et al., 2022). Additionally, borrowing from the literature on the shortage of male teachers (McGrath, Moosa, van Bergen, & Bhana, 2020; See, Munthe, Ross, Hitt, & El Soufi, 2022), it becomes evident that men seem less likely to engage in education-related activities. Therefore, I argue that women entrepreneurs (Spiegler & Halberstadt, 2018) and women-founded firms in general (Apesteguia et al., 2012) focus not only on the social impact of their businesses (Dickel & Eckardt, 2021) but also tend to prioritize educational entrepreneurship in particular. This leads to the following hypothesis:

Hypothesis 1B: *An increasing share of women in the founding team or being a women solo founder of a high-growth-oriented startup positively influences the startup's educational orientation (its focus on education).*

In addition to these two expectations, research suggests that women show an enhanced disposition to engage in environmentally friendly behaviors (Blocker & Eckberg, 1997; Khan et al., 2019; Vicente-Molina et al., 2018; Zelezny et al., 2000). Further, women are more likely to start pro-environmentally oriented businesses than men (Hechavarría, 2016) and are more aware of climate change events and their consequences (Akinbami, Olawoye, Adesina, & Nelson, 2019).One possible reason for these observations is suggested by empirical evidence suggesting that "being green" is perceived as a female attribute, and men feel that engaging in green activities threatens their masculinity (Brough, Wilkie, Ma, Isaac, & Gal, 2016). Finally, the presence of women in power positions within organizations is associated with greater engagement in social and environmental projects (Bannò, Filippi, & Trento, 2023), and women's participation on boards of directors has a positive impact on voluntary carbon disclosure and its quality (Caby, Coron, & Ziane, 2024).

Considering this existing literature and the tendency of women to engage more in communal behaviors than men (Koenig & Eagly, 2014), I argue that a higher share of women in a high-growth-oriented startup's founder team positively affects a pro-environmental business focus. Therefore, the last part of this first set of hypotheses reads as follows:

Hypothesis 1C: *An increasing share of women in the founding team of a high-growth-oriented startup positively influences the environmental orientation (its focus on sustainable consumption and use of resources).*

As described before, high-growth entrepreneurship is a heavily male-typed field (Gupta et al., 2019; Laguía et al., 2019). As a result, there is an implicit perception that women's high-growth entrepreneurship is less legitimate than men's entrepreneurship, which is likely to negatively influence both women's intention to expand their businesses and the willingness of potential investors to invest in a women-led startup (Achtenhagen & Welter, 2011; Edelman, Donnelly, Manolova, & Brush, 2018).

Even if women engage in the male-typed field of high-growth entrepreneurship (Schmidt, 2002), they are likely to suffer from restricted access to financial resources (e.g., Gicheva & Link, 2015; Guzman & Kacperczyk, 2019). Thus, it is no surprise that only ten percent of all venture-backed startups are female-founded (Guzman & Kacperczyk, 2019). This matters particularly because the lack of access to financial resources limits female-owned startup's growth and survival (Alsos et al., 2006; Feng, Ahmad, & Zheng, 2022). These dynamics impact both solo founders and mixed teams. More concretely, research suggests that mixed teams are more likely to attract financial resources than all-female teams through crowdfunding (Cicchiello et al., 2022) and venture capital attraction (Vogel et al., 2014). Additionally, even if only one woman is present on the founding team, firms receive significantly lower company evaluation by angel investors than all-male firms (Poczter & Shapsis, 2018). Based on this existing empirical evidence, I argue that a high-growth-oriented startup's total funding attracted (including investments of angel investors, firms, (corporate) venture capitalists, crowdfunding, and grants) decreases as the share of women founders increases. Thus, I hypothesize:

Hypothesis 2: *High-growth-oriented startups with a higher proportion of women founders attract less total funding than those with a higher proportion of men founders.*

A potential mechanism for the hypothesized relationship in H2 often mentioned by the existing body of literature is that women entrepreneurs concentrate on industries that are unattractive to investors (e.g., Aernoudt & San José, 2020). However, this argument does not consider that the existing societal structures reward might set incentives that guide them towards these industries.

Yet, these considerations are necessary to understand how the gender-related funding gap in entrepreneurship affects different industries. In particular, research suggests that investors reward role-congruent behaviors by higher investments (e.g., Cowden et al., 2021). Thus, women-owned firms in industries considered feminine are more likely to achieve high growth than women-owned firms in "non-feminine" market sectors (Yacus, Esposito, & Yang, 2019).

While this mechanism at least partially drives the gender funding gap in the male-dominated domain of high-growth entrepreneurship, it is also likely to affect the disparity regarding the attracted funding within the industries previously outlined as feminine ones (socially-oriented, education-oriented, and pro-environmentally-oriented entrepreneurship). Thus, women entrepreneurs living in an environment where traditional gender stereotypes (e.g., domestic duties are primarily women's responsibility) prevail tend to be more involved in pro-environmental entrepreneurial activities than their male counterparts (Hechavarría, 2016; Liu et al., 2021) because it can be expected that the society in general, and investors in particular, reward this behavior (Uzuegbunam, Pathak, Taylor-Bianco, & Ofem, 2021). This tendency is not only observable in countries characterized by traditional gender stereotypes but also in countries with more relaxed role stereotypes (Harms & Groen, 2017).

Finally, an enhanced founding team's percentage of women improves the chances of success during and after the crowdfunding campaign in entrepreneurship focused on environmental, social, and economic issues (Bento, Gianfrate, & Thoni, 2019). Consequently, the impact of women in the entrepreneurial team on the startup's funding prospects is not continuous across industries. Instead, I expect that engaging in social, educational, or environmental entrepreneurship helps women attract more funding. In this line, the third set of hypotheses emerges.

Hypothesis 3: *The negative effect of a higher proportion of women founders on attracting funding decreases for...*

a) … startups with a social orientation.
b) … startups with an educational orientation.
c) … startups with a pro-environmental orientation.

3.3. Methods

3.3.1. Data Sources

To test H1-H3, I created a unique dataset relying on two primary data sources:

The United Nations Sustainable Development Goals Indicator Database describes the 17 Sustainable Development Goals (summarized in Table 3.1) adopted by all 193 United Nations member states in 2015, as well as the indicators used to measure a country's progress towards them. They are part of the 2030 Agenda for Sustainable Development, which intends to be a guideline for peace and prosperity for people and the planet, now and into the future (United Nations, 2024). Recently, the Database was subject to several articles in management and entrepreneurship research (e.g., Dhahri, Slimani, & Omri, 2021; Kiefner, Mohr, & Schumacher, 2022). In this research, I will use the text describing each of the 17 sustainable development goals to determine how similar or dissimilar it is to startup descriptions from Crunchbase.

Crunchbase was created in 2007 and is a popular data platform tracking technology-based startup companies and their founders. To date, it is one of the primary databases used in entrepreneurship research and is particularly well-suited for research on innovative firms that receive external financing (Dalle, Besten, & Menoni, 2023). The platform provides a variety of subsets containing information regarding different topics. For this paper, I use four of those data samples: The first one contains general organizational attributes (name, founding date, country of location, target industries, organizational role (Investor / School / Firm), contact information, number of funding rounds raised, total sum of investment received). The second one provides a self-reported description of each company listed in this first dataset. The third one describes the characteristics of people listed on Crunchbase (i.e., name, location, gender). Finally, the fourth subset provides information on the work histories of people listed on the platform (i.e., start date, end date, job title).

The United Nations Sustainable Development Goals	
Goal 1	End poverty in all its forms everywhere.
Goal 2	End hunger, achieve food security and improved nutrition, and promote sustainable agriculture.
Goal 3	Ensure healthy lives and promote well-being for all at all ages.
Goal 4	Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all.
Goal 5	Achieve gender equality and empower all women and girls.
Goal 6	Ensure availability and sustainable management of water and sanitation for all.
Goal 7	Ensure access to affordable, reliable, sustainable, and modern energy for all.
Goal 8	Promote sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all.
Goal 9	Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation.
Goal 10	Reduce inequality within and among countries.
Goal 11	Make cities and human settlements inclusive, safe, resilient, and sustainable.
Goal 12	Ensure sustainable consumption and production patterns.
Goal 13	Take urgent action to combat climate change and its impacts.
Goal 14	Conserve and sustainably use the oceans, seas, and marine resources for sustainable development.
Goal 15	Protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification and halt and reverse land degradation, and halt biodiversity loss.
Goal 16	Promote peaceful and inclusive societies for sustainable development, provide access to justice for all, and build effective, accountable, and inclusive institutions at all levels.
Goal 17	Strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development.

Table 3.1 - The United Nations Sustainable Development Goals

3.3.2. Data Generation

For this paper, data on startups, their founding teams, the funding they attracted, and control variables for the statistical models can be derived directly from Crunchbase.

In the first step, I used data on an organization's primary activity to only include entrepreneurial organizations. The indicator also revealed firms that invest in other companies even though it is not their principal field of business. The newly generated variable, *Investment Activities Dummy*, captures this information. Additionally, the data provides information on a firm's country of location, social media profiles, and target industries.

The original target industry classification system allows an unlimited number of category labels. To consolidate this information, I re-categorized these classifications and converted them into 14 dummy variables (indicating a focus on service, agriculture/farming, sales/marketing, consumer products, education, food/beverage, government/military, healthcare, manufacturing, media/entertainment, technology, real estate, science/engineering, and sports) in the second step. As more than one dummy variable per observation can equal 1, this approach acknowledges that firms can operate in multiple industries.

Thirdly, I used information on existing Facebook, LinkedIn, and Twitter profiles to measure a firm's social media platform usage. This insight matters because research shows that social media usage can significantly benefit start-ups throughout their life cycle (e.g., Mujahid & Mubarik, 2021; Pitafi, Kanwal, Ali, Khan, & Waqas Ameen, 2018). Finally, I identified the founders of the startups included in the dataset by matching firm-related data with the work history of people listed on Crunchbase. Doing so also revealed central variables such as the founding team size, the maximum number of startups founded by a single team member (*Maximal Entrepreneurial Experience*), and the largest number of jobs held by one founder (*Maximal Work Experience*) before the startup's inception.

As diversity measures such as ethnic diversity influence business activities (e.g., Brixy, Brunow, & D'Ambrosio, 2020), I created a variable indicating the *Share of Foreign Founders* in the founding team by comparing the firm's location with the founder's country of origin. I further included the Share of *Non-Binary Founders* per startup to consider non-binary individuals in this study, who are likely to be affected by gender role stereotypes as well (e.g., Hansen & Żółtak, 2022). However, this variable is not at the center of this research, and the most essential variable in this dataset is the proportion of women founders per entrepreneurial team. Noteworthy to the context, the entrepreneur's gender is self-reported, and Crunchbase accepts a wide range of non-binary genders.

The dependent variable in Models 2 and 3 is the average amount of funding attracted per funding round (*Attracted Funding per Round*). I will use other funding-related indicators provided by Crunchbase (e.g., the number of rounds raised, the total amount raised, and the average amount raised per round) as dependent variables in the post-hoc analysis. Further, analyzing the degree to which the startup's business focus aligns with sustainability's social, educational, and environmental dimensions requires the additional use of the United Nations Sustainable Development Goals Indicator Database. To do so, I use the brief texts describing each firm provided by Crunchbase and compare them to each of the 17 Sustainable Development Goals (see Table 3.1) by calculating the respective semantic similarities based on a specific natural language processing algorithm called "word embedding". Specifically, I used a pre-trained Word2Vec model that captures information about each word's meaning and context. In Word2Vec, unique vectors of numbers represent each word. Thus, it converts each word describing the company and the sustainability goal into a numerical vector.

The general context of each text is found by calculating the semantic centroids of both the company description and the sustainability goals. These centroids represent the geometric center of the vectors describing each word. Further, they semantically and topically characterize text documents and thus can act as their very compact representation in automatic text processing tasks (Unger & Kubek, 2019).

Finally, calculating the values of each text's centroid is necessary to compute the cosine similarity between the firm's description and the United Nations Sustainable Development Goal. The cosine similarity describes the cosine of the angle between two vectors. The cosine similarity ranges from -1 to 1. The maximum of 1 indicates that the two vectors are identical, 0 suggests they are unrelated, and -1 means that they are opposites. Generally, a lower value indicates increased dissimilarity in the context of this study. The firm descriptions contain many repeated words (e.g., mission, objective, business), so the cosine similarities are likely generally high. To pronounce the differences between the calculated cosine similarities more strongly, I normalized the values between 0 and 1 so that one indicates that the two vectors are identical and 0 represents the lowest cosine similarity observed. Table 3.2 illustrates this entire procedure, making the complex process more accessible.

Word Representations and Centroids							
Description Firm A: "(…) cheap solar power (…)"				**Description Firm B:** "(…) oil and gas producer (…)"			
Cheap	$X_{1,1} = 0.09$	(…)	$X_{1,100} = 0.17$	*Oil*	$X_{4,1} = -0.05$	(…)	$X_{4,100} = 0.15$
Solar	$X_{2,1} = -0.16$	(…)	$X_{2,100} = 0.63$	*Gas*	$X_{5,1} = 0.10$	(…)	$X_{5,100} = 0.55$
Power	$X_{3,1} = 0.11$	(…)	$X_{3,100} = 0.94$	*Producer*	$X_{6,1} = -0.58$	(…)	$X_{6,100} = 0.10$
Centroid* A:	$\mathbf{C^A{}_1 = 0.00}$	**(…)**	$\mathbf{C^A{}_{100} = 0.33}$	**Centroid* B:**	$\mathbf{C^B{}_1 = -0.24}$	**(…)**	$\mathbf{C^B{}_{100} = 0.25}$

*equals the geometric center of the vectors describing each word.

UNSDG Goal 13: "Take urgent action to combat climate change and its impacts."
Centroid Goal:** $\mathbf{C^{UN13}{}_1 = 0.07}$ **(…)** $\mathbf{C^{UN13}{}_{100} = 0.11}$

**calculated based on Word Representations following the same structure shown exemplarily for the firm's company descriptions.

Cosine Similarities

The cosine similarity measures the similarity of two non-zero vectors defined in an inner product space. It is the cosine of the angle between the vectors; that is, it is the scalar product of the vectors divided by the product of their lengths.

$$\text{cosine similarity} = S_c(A, B) = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \cdot \sqrt{\sum_{i=1}^{n} B_i^2}}$$

Therefore, cosine similarity is calculated for the centroids of the firm descriptions and the United Nations Sustainable Development Goals:

Firm A: $S_c\left(C^A, C^{UN13}\right) = 0.69$ **Firm B:** $S_c\left(C^B, C^{UN13}\right) = 0.60$

The (unstandardized) cosine similarity indicates that the description of firm A is semantically more similar to the UN Sustainable Development Goal 13.

Table 3.2 - Word Representations and Cosine Similarities

This procedure resulted in seventeen columns describing the alignment of startup descriptions with each of the seventeen sustainability goals. Because these indicators are likely interrelated, it is difficult to choose some and assume they are more critical to this research than others. Therefore, I conducted an exploratory factor analysis to identify underlying factors explaining correlations between the indicators. As shown in Table 3.3, three factors emerge.

The first factor loads most strongly on the indicators describing poverty reduction [Goal 1] (0.89) and ensuring healthy lives [Goal 3] (0.80). In addition, it loads strongly on the indicator related to Goal 5 - "Achieve gender equality and empower all women and girls" (0.75). Based on these loadings, the factor is named *Factor: Inequality*. The Cronbach's alpha for this factor is also close to one (0.97), confirming internal consistency. This variable will proxy a startup's social orientation in further empirical analysis.

The second factor loads moderately on most indicators. However, it is strongly related to Goal 4 - "Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all" (0.71). Therefore, I labeled this factor as *Factor: Education*. The Cronbach's alpha for this factor is 0.97, which confirms its internal consistency. This variable will proxy a startup's educational orientation in further empirical analysis.

The third and final factor loads highly on indicators related to the availability of water [Goal 6] (0.88), energy [Goal 7] (0.82), sustainable use of terrestrial [Goal 15] (0.81), and marine resources [Goal 14] (0.87). Finally, it strongly loads on indicator 12 - "Ensure sustainable consumption and production patterns" (0.87). Thus, I labeled it *Factor: Consumption.* The Cronbach's alpha for this factor is very high (0.99), confirming its internal consistency. This variable will proxy a startup's environmental orientation in further empirical analysis.

Overview of Factor Loadings: Three Dimensions of Sustainability

Comment: 5 strongest loadings are underlined **Indicator**		**Factor 1:** Factor: Inequality	**Factor 2** Factor: Education	**Factor 3:** Factor: Consumption
Goal 1	End poverty in all its forms everywhere	<u>0.89</u>	0.10	0.29
Goal 2	End hunger, achieve food security and improved nutrition, and promote sustainable agriculture	0.44	0.40	0.76
Goal 3	Ensure healthy lives and promote well-being for all at all ages	<u>0.80</u>	0.37	0.30
Goal 4	Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all	0.46	<u>0.71</u>	0.50
Goal 5	Achieve gender equality and empower all women and girls	<u>0.76</u>	<u>0.54</u>	0.15
Goal 6	Ensure availability and sustainable management of water and sanitation for all	0.15	0.28	<u>0.88</u>
Goal 7	Ensure access to affordable, reliable, sustainable, and modern energy for all	0.33	0.37	<u>0.82</u>
Goal 8	Promote sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all	0.55	<u>0.59</u>	0.55
Goal 9	Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation	0.35	<u>0.54</u>	0.71
Goal 10	Reduce inequality within and among countries	<u>0.70</u>	0.29	0.56
Goal 11	Make cities and human settlements inclusive, safe, resilient, and sustainable	0.52	0.36	0.67
Goal 12	Ensure sustainable consumption and production patterns	0.36	0.15	<u>0.87</u>
Goal 13	Take urgent action to combat climate change and its impacts	<u>0.66</u>	0.26	0.59
Goal 14	Conserve and sustainably use the oceans, seas, and marine resources for sustainable development	0.32	0.27	<u>0.88</u>
Goal 15	Protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss	0.53	0.15	<u>0.81</u>
Goal 16	Promote peaceful and inclusive societies for sustainable development, provide access to justice for all, and build effective, accountable, and inclusive institutions at all levels	0.54	<u>0.59</u>	0.57
Goal 17	Strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development	0.23	<u>0.54</u>	0.75
SS loadings		4.99	3.00	7.47
Proportion Var		0.29	0.17	0.44
Cumulative Var		0.29	0.46	0.91
Cronbach's. α		0.97	0.97	0.99
ω_t (total omega)		0.99	0.99	0.99

Table 3.3 - Overview of Loadings (Factor Analysis)

3.3.3. Sample Description

The generated dataset included 301,077 observations. However, after filtering for firms founded between 1992 and 2022, 279,136 observations remained. Further, I deleted 9,443 observations with unknown startup locations and 154,031 observations that did not provide information on the *Attracted Funding per Round*. At this point, the total data sample included 115,662 observations.

To reduce the effect of outliers on the results, I winsorized *Attracted Funding per Round*. This means that I capped the values at the 5th and 95th percentile. Before winsorizing, the smallest value lies at 0 USD per investment round and the largest at 100,000,000,000 USD per investment round. The median was 1,208,000 USD per investment round, and the Mean was 11,070,000. After the transformation, the minimum is 30,000 USD, and the maximum is 34,000,000 USD per investment round. The median is 1,207,898 USD, and the Mean is 5,126,054 USD per investment round.

Forty-nine percent of the observations are from startups based in the United States of America. The remaining 51 percent come from Great Britain (N = 8,872), India (N = 5,279), China (N = 5,157), Canada (N = 4,150), France (N = 3,235), Germany (N = 2,501), Israel (N = 2,034), Australia (N = 1,752) as well as 152 other countries. On average, these startups existed 8.66 years before they closed, went public, or were bought. Further, they received funding at an average age of 4.12 years.

The startup teams have an average size of 1.79 founders (min = 1.00, max = 38.00). The person who held the most jobs in the team had 0.80 jobs on average (min = 0.00, max = 63.00), and the most experienced founder of the team founded 0.26 startups before the one included in the dataset. The founding teams primarily consist of a male majority with an average of 0.11 women (min = 0.00, max = 1.00) and 0.00 (min = 0.00, max = 1.00) non-binary founders per team. At the same time, 0.11 percent (min = 0.00, max = 1.00) of the average founding team are foreigners.

As this data set provides cross-sectional data, I ran additional analyses based on a longitudinal dataset where I controlled for the startup's age when receiving funding to test the robustness of my results.

3.3.4. VARIABLE DESCRIPTION

INDEPENDENT VARIABLE

I will use the *Share of Women Founders* as the only independent variable from this rich data set. The variable describes the proportion of women in the founding teams, and the dataset includes all-men (min = 0.00), all-women (max = 1.00), and mixed teams. Nevertheless, women are in the minority, representing only 11% of the founders per team (mean = 0.11). Additionally, the median and even the 75% quantile are 0.00, indicating that a vast majority of the teams do not have women in their funding team.

DEPENDENT VARIABLES

This paper draws on four different dependent variables to test the hypotheses. First, *Factor: Inequality* describes the degree to which firms focus on poverty and inequality. The values are normalized so that the highest engagement equals a value of 1, and a value of 0 represents the lowest engagement. On average, firm descriptions are slightly inclined to focus on inequality-related business missions (mean = 0.62). The standard deviation equals 0.11. Secondly, *Factor: Education* describes the degree to which firms concentrate on education. The normalized variable ranges from 0 to 1. The mean lies at 0.59, and most values are expected to lie between 0.49 and 0.69 (standard deviation = 0.10). Thus, this scope of business seems slightly less popular than a focus on inequality. Third, *Factor: Consumption* describes the degree to which firms focus on consumption and sustainable resource use. The normalized variable ranges from 0 to 1. The mean is 0.68, and most values are expected to lie between 0.59 and 0.77 (standard deviation = 0.09). Finally*, Attracted Funding per Round* describes the funding that firms attract per investment round. The minimum is 30,000 USD, and the maximum is 34,000,000 USD. The average *Attracted Funding per Round* is 5,126,054 USD. The relatively high standard deviation of 8,777,972 suggests considerable variability in the funding attracted per investment round among startups.

To test Hypothesis 3, the above-described variables *Factor: Inequality* (H3A), *Factor: Education* (H3B), and *Factor: Consumption* (H3C) will be used additionally as moderation variables. *Attracted Funding per Round* is the dependent, and the Share of Women Founders is the independent variable.

CONTROL VARIABLES

The models will further include the proportion of founders on the founding team who identify as non-binary *(Share of Non-Binary Founders)*, the proportion of foreign founders *(Share of Foreign Founders)*, the number of social media accounts used by the startup *(Number of Social Media Accounts)*, the number of startups founded by the founder with the most entrepreneurial experience *(Maximal Founding Experience)*, the number of jobs held by the founder with the most work experience *(Maximal Work Experience)*, and team size *(Founding Team Size)* as control variables.

In addition, the statistical analysis will include dummy variables indicating whether the firm invests in other firms and the target industry of the startup (services, agriculture/farming, sales/marketing, consumer goods, education, food and beverage, government/military, healthcare, manufacturing, technology, real estate, science/engineering, sports, tourism) as control variables. Finally, the models include fixed effects for the startup's founding year *(started_on)* and the country of its location *(country_code)*, and standard errors are clustered on the same variables to control for possible correlations between observations from a given year or country. For a more detailed overview of the dataset and the control variables, please consult Table 3.4.

Variable Name	Description	N	Mean	SD	Min	Max
Main Variables						
Share of Women Founders	Share of women per startup team	115,662	0.11	0.27	0.00	1.00
Attracted Funding per Round	Funding attracted per investment round (in Tsd, per startup)	115,662	5,126.05	8,777.97	30.00	34,000.00
Factor: Inequality	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to reducing poverty and inequality	115,662	0.62	0.11	0.02	0.97
Factor: Education	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to education	115,662	0.58	0.10	0.00	0.98
Factor: Consumption	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to consumption and sustainable use of resources	115,662	0.68	0.09	0.02	1.00
Control Variables						
Share of Non-Binary Founders	Share of non-binary persons per startup team	115,662	0.00	0.06	0.00	1.00
Share of Foreign Founders	Share of foreigners per startup team	115,662	0.11	0.28	0.00	1.00
Founding Team Size	Number of founders per team	115,662	1.79	1.00	1.00	38.00
Maximal Work Experience	Number of jobs of the generally most experienced team member	115,662	0.80	1.83	0.00	63.00
Maximal Founding Experience	Number of startups founded by the entrepreneurially most experienced team member	115,662	0.26	0.74	0.00	31.00
Number of Social Media Accounts	Number of social media accounts used by startup	115,662	2.07	1.04	0.00	3.00
Investment Activities Dummy	Own investment activities of the startup (Y/N)	115,662	0.02	0.14	0.00	1.00
Industry Dummy: Services	Target industry indicator: Services (Y/N)	115,662	0.27	0.44	0.00	1.00
Industry Dummy: Agriculture and Farming	Target industry indicator: Agriculture & Farming (Y/N)	115,662	0.02	0.13	0.00	1.00
Industry Dummy: Sales and Marketing	Target industry indicator: Sales & Marketing (Y/N)	115,662	0.06	0.24	0.00	1.00
Industry Dummy: Consumer Goods	Target industry indicator: Consumer goods (Y/N)	115,662	0.16	0.37	0.00	1.00
Industry Dummy: Education	Target industry indicator: Education (Y/N)	115,662	0.06	0.25	0.00	1.00
Industry Dummy: Food and Beverages	Target industry indicator: Foods & Beverages (Y/N)	115,662	0.05	0.22	0.00	1.00
Industry Dummy: Government and Military	Target industry indicator: Government & Military (Y/N)	115,662	0.05	0.22	0.00	1.00
Industry Dummy: Healthcare	Target industry indicator: Healthcare (Y/N)	115,662	0.01	0.09	0.00	1.00
Industry Dummy: Manufacturing	Target industry indicator: Manufacturing (Y/N)	115,662	0.18	0.38	0.00	1.00
Industry Dummy: Technology	Target industry indicator: Technology (Y/N)	115,662	0.18	0.39	0.00	1.00
Industry Dummy: Real Estate	Target industry indicator: Real estate (Y/N)	115,662	0.05	0.21	0.00	1.00
Industry Dummy: Science & Engineering	Target industry indicator: Science & Engineering (Y/N)	115,662	0.04	0.20	0.00	1.00
Industry Dummy: Sports	Target industry indicator: Sports (Y/N)	115,662	0.16	0.36	0.00	1.00
Industry Dummy: Tourism	Target industry indicator: Tourism (Y/N)	115,662	0.03	0.18	0.00	1.00
Fixed Effects						
started_on	The founding date of the startup	115,662	2013.00	5.64	1992.00	2022.00
country_code	Country location of the startup	115,662	7.45	2.35	1.00	9.00

Table 3.4 - Descriptive Statistics of the Dataset

	Variable Names	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Founding Team Size	1.00													
2	Startup: Funding Founds Attracted (Number)	0.17***	1.00												
3	Startup: Total Funding Attracted (USD)	0.04***	0.17***	1.00											
4	Industry Focus: Service	0.02***	-0.01	0.00	1.00										
5	Industry Focus: Agriculture and Service	-0.00	0.02***	-0.01	-0.03***	1.00									
6	Industry Focus: Sales and Marketing	-0.05***	0.03***	0.02***	-0.09***	0.02***	1.00								
7	Industry Focus: Consumer Goods	0.03***	-0.00	-0.00	-0.01**	-0.04***	-0.05***	1.00							
8	Industry Focus: Education	-0.01**	-0.01***	-0.00	-0.00	-0.01***	0.06***	0.10***	1.00						
9	Industry Focus: Food and Beverage	0.00	-0.02***	-0.01***	0.02***	-0.03***	-0.05***	-0.06***	-0.04***	1.00					
10	Industry Focus: Government and Military	-0.01***	-0.01***	-0.00	-0.01***	0.10***	0.01**	0.01***	0.03***	-0.05***	1.00				
11	Industry Focus: Healthcare	0.00	0.01*	-0.00	0.01***	-0.01	0.01**	-0.02***	-0.01***	-0.00	-0.02***	1.00			
12	Industry Focus: Manufacturing	-0.03***	0.09***	0.00	-0.14***	-0.03***	-0.01**	-0.16***	-0.04***	-0.06***	-0.03***	-0.02***	1.00		
13	Industry Focus: Technology	0.04***	0.01*	-0.01***	-0.07***	-0.04***	-0.04***	0.05***	-0.03***	0.01***	-0.07***	-0.00	-0.13***	1.00	
14	Industry Focus: Real Estate	0.03***	0.05***	0.00	0.03***	-0.02***	-0.03***	0.01**	-0.03***	-0.02***	-0.04***	0.03***	-0.08***	-0.02***	1.00
15	Industry Focus: Science and Engineering	0.01**	0.00	-0.00	0.00	-0.01***	0.00	0.04***	0.02***	-0.04***	-0.04***	0.01**	-0.08***	-0.04***	-0.01
16	Industry Focus: Sports	-0.04***	0.11***	0.03***	-0.17***	0.06***	0.22***	-0.15***	-0.04***	-0.09***	-0.03***	-0.00	0.28***	-0.13***	-0.06***
17	Industry Focus: Tourism	-0.00	-0.02***	-0.01**	-0.05***	-0.02***	-0.02***	-0.01***	-0.00	0.00	0.00	-0.01**	0.10***	0.01***	-0.03***
18	Startup: Social Media Accounts (Number)	0.16***	0.19***	0.03***	0.09***	-0.01**	-0.07***	0.08***	0.03***	0.05***	0.02***	0.02***	-0.11***	0.06***	0.06***
19	Startup: Investment activities (Y/N)	0.04***	0.14***	0.15***	0.04***	-0.01***	-0.01*	0.01*	-0.00	-0.01*	-0.01***	0.00	-0.02***	-0.01*	0.01***
20	Founding Team: Maximal Work Experience (Number of Jobs)	0.23***	0.10***	0.03***	0.02***	-0.02***	-0.05***	0.03***	-0.01***	-0.01***	-0.03***	-0.00	-0.01***	0.04***	0.04***
21	Founding Team: Maximal Founding Experience (Number of Startups Founded)	0.21***	0.08***	0.03***	0.02***	-0.02***	-0.04***	0.03***	-0.01***	-0.01***	-0.02***	-0.00	-0.02***	0.03***	0.02***
22	Founding Team: Women Founders (%)	-0.01***	-0.02***	-0.02***	0.03***	0.00	-0.02***	0.01*	0.11***	0.05***	0.05***	0.00	0.07***	-0.01**	-0.03***
23	Founding Team: Non-Binary Founders (%)	-0.04***	-0.02***	-0.00	-0.00	-0.00	0.00	-0.00	0.00	0.00	-0.00	-0.00	0.00	-0.00	-0.01*
24	Founding Team: Foreign Founders (%)	0.05***	-0.01***	-0.00	0.01***	-0.01***	-0.03***	0.02***	-0.01**	-0.00	-0.03***	-0.01***	-0.05***	0.03***	0.02***
25	Factor: Consumption & Use of Resources	-0.00	0.13***	0.02***	-0.04***	0.18***	0.16***	-0.06***	-0.09***	-0.13***	-0.00	0.03***	0.01***	-0.12***	0.07***
26	Factor: Inequality	0.08***	0.04***	-0.01*	0.08***	-0.00	-0.13***	0.03***	0.01***	0.08***	-0.02***	0.02***	0.03***	0.07***	0.00
27	Factor: Education	0.02***	-0.03***	-0.01	0.21***	-0.11***	-0.19***	0.04***	-0.06***	0.26***	-0.16***	0.02***	-0.01***	0.04***	0.03***
28	Startup: Attracted Funding per Round	0.05***	0.24***	0.23***	0.00	-0.02***	0.02***	-0.04***	-0.02***	-0.05***	-0.03***	-0.01**	0.07***	-0.05***	0.03***

Table 3.5 - Correlation Table (continues on next page)

* p<0.05 ** p<0.01 *** p<0.001

	Variable Names	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1	Founding Team Size														
2	Startup: Funding Founds Attracted (Number)														
3	Startup: Total Funding Attracted (USD)														
4	Industry Focus: Service														
5	Industry Focus: Agriculture and Service														
6	Industry Focus: Sales and Marketing														
7	Industry Focus: Consumer Goods														
8	Industry Focus: Education														
9	Industry Focus: Food and Beverage														
10	Industry Focus: Government and Military														
11	Industry Focus: Healthcare														
12	Industry Focus: Manufacturing														
13	Industry Focus: Technology														
14	Industry Focus: Real Estate														
15	Industry Focus: Science and Engineering	1.00													
16	Industry Focus: Sports	-0.03***	1.00												
17	Industry Focus: Tourism	-0.03***	-0.06***	1.00											
18	Startup: Social Media Accounts (Number)	0.03***	-0.15***	0.04***	1.00										
19	Startup: Investment activities (Y/N)	0.00	-0.01**	-0.01***	0.05***	1.00									
20	Founding Team: Maximal Work Experience (Number of Jobs)	0.00	-0.03***	-0.00	0.09***	0.04***	1.00								
21	Founding Team: Maximal Founding Experience (Number of Startups Founded)	0.00	-0.03***	-0.00	0.08***	0.04***	0.71***	1.00							
22	Founding Team: Women Founders (%)	-0.01***	-0.01*	0.01*	0.04***	-0.03***	-0.03***	-0.04***	1.00						
23	Founding Team: Non-Binary Founders (%)	-0.01*	-0.00	-0.00	-0.07***	0.00	-0.02***	-0.02***	-0.02***	1.00					
24	Founding Team: Foreign Founders (%)	-0.02***	-0.04***	-0.01**	0.03***	0.01	0.02***	0.04***	-0.03***	-0.02***	1.00				
25	Factor: Consumption & Use of Resources	0.07***	0.05***	0.29***	-0.11***	-0.03***	0.02***	-0.01**	-0.02***	-0.07***	-0.00	-0.01***			
26	Factor: Inequality	0.00	-0.02***	-0.12***	0.05***	0.18***	-0.00	0.05***	0.04***	0.07***	-0.03***	0.03***	-0.01***		
27	Factor: Education	0.03***	0.02***	-0.28***	0.05***	0.12***	0.04***	0.03***	0.02***	0.04***	0.00	0.01	-0.05***	0.05***	
28	Startup: Attracted Funding per Round	0.03***	0.00	0.13***	-0.04***	0.01*	0.23***	0.10***	0.08***	-0.08***	0.01***	-0.01*	0.12***	-0.06***	0.00

Table 3.5 - Correlation Table

* p<0.05 ** p<0.01 *** p<0.001

3.3.5. The Analytical Approach

In this study, the unit of analysis is the entrepreneurial team. The primary dependent variables are *Attracted Funding per Round, Factor: Inequality, Factor: Education,* and *Factor: Consumption.* As all of them are continuous and the hypotheses suggest linear relationships, I used ordinary least squares regression models to test them. All models include country- and time-fixed effects to control for unobserved heterogeneity at the country and year levels. More specifically, the fixed effects account for a country's unobserved characteristics (e.g., political systems, language spoken, etc.) as well as time-specific unobserved changes (e.g., global crisis, cultural shifts, etc.) that might affect a startup's business orientation and funding prospects. Finally, I clustered the standard errors on the same variables to consider possible correlations among observations from specific regions and years in the models.

Before running the models, variance inflation factors were calculated. They were all less than 2, indicating no multicollinearity problems (Brunsveld, Page, & Hair, 2019). Additionally, no problematic correlations were observed in the correlation table (see Table 3.5). I also analyzed the data using different model specifications for robustness, which I discuss in the section on supplemental analysis and robustness checks.

3.4. Results

Models 1-3 test H1A, H1B, and H1C. Model 1 considers *Factor: Inequality* as the dependent variable, Model 2 tests H1B by regressing on *Factor: Education,* and Model 3 uses *Factor: Consumption* as the outcome variable. In doing so, the models analyze if the dataset reflects gender role congruent behaviors as outlined in the theoretical part of this paper.

The empirical results from Model 1 support H1A (ß = 0.02, p = 0.00), suggesting that a one percent increase in *Share of Women Founders* increases *Factor: Inequality* by 2 percent. Further, Model 2 backs Hypothesis H1B (ß = 0.01, p = 0.00) and indicates that a one percent increase of women in the founding team is related to a one percent increase in *Factor: Education*. H1C did not receive support. Instead, Model 3 suggests a negative relationship between *Share of Women Founders* and *Factor: Consumption* (ß = - 0.2, p = 0.00). This means that an increase of one percent in the founding team's female representation correlates with a two percent decrease in a firm's involvement in business models related to sustainable consumption and use of resources. Conversely, a one percent increase in the share of women founding team members is linked to a firm description that is one percent more aligned with education-related sustainable development goals and two percent more aligned with inequality-related sustainable development goals. Models 1-3 are summarized in Table 3.6.

Model 4 (summarized in Table 3.7) tests H2 to provide empirical evidence for a gender-related funding gap in this paper's data sample and serves as a baseline model for Models 5-7. In line with the theoretical predictions, the model shows that startups with a higher *Share of Women Founders* are characterized by less *Attracted Funding per Round* (ß = - 0.57, p = 0.00). As I used the natural logarithm of *Attracted Funding per Round* for this model, the percentual change of *Attracted Funding per Round* must be calculated by $ß_{H2,\%}$ = (exp(- 0.57) - 1) x 100 % = - 43.45 %. Doing so indicates that all-women founding teams, compared to all-men founding teams, receive 43.45 percent less funding per round. For a change in *Share of Women Founders* of one percent, the *Attracted Funding per Round* decreases by 0.57 percent [calculation: $ß_{H2,\%}$ = (exp(- 0.57 x 0.01) - 1) x 100 % = - 0.57] which is equivalent to the correlation coefficient. In the following, I will interpret the correlation coefficient as the degree to which *Attracted Funding per Round* changes if the *Share of Women Founders* increases by one percent.

Finally, Models 5-7 (summarized in Table 3.8) analyze whether this relationship increases or decreases when startups focus more/less on social issues (H3A), educational issues (H3B), or environmental issues (H3C). Therefore, they include a moderation term between the share of women founders and the respective factor (H3A: *Factor: Inequality*, H3B: *Factor: Education*, H3C: *Factor: Consumption*).

Model 5 supports H3A. Even though the coefficient of the interaction *Share of Women Founders x Factor: Inequality is* still negative (ß = - 0.39, p = 0.02), it is greater than the direct baseline value from Model 4. This indicates a negative moderation effect of *Factor: Inequality* on the relation between *Share of Women Founders* and *Attracted Funding per Round. In this case, a* one-percent increase in the *Share of Women Founders* is related to a decrease in the *Attracted Funding per Round* by 0.39 percent. Notably, the direct effect of *the Share of Women Founders on Attracted Funding Per Round* remains negative. However, it decreases in size (ß = - 0.31, p = 0.01) after including *Factor: Inequality* and the interaction term *Share of Women Founders x Factor: Inequality* in the model. *Factor: Inequality* has a direct negative effect on the *Attracted Funding per Round (ß = - 0.76, p = 0.00).*

Model 6 supports H3B. The borderline significant interaction term *Share of Women Founders x Factor: Education* has a negative impact on *Attracted Funding per Round* (ß = - 0.36, p = 0.06), which is weaker than the direct effect of *Share of Women Founders* on the *Attracted Funding per Round* in Model 4, which points towards another negative moderation effect. In this context*, a* one-percent increase in the number of women in the founding team is related to a decrease in the *Attracted Funding per Round* by 0.36 percent. Further, all-women-founded startups receive 30.23 percent less funding per round than all-men-founded firms [calculation: $ß_{H3B,\%}$ = (exp(- 0.36) - 1) x 100 % = 30.23].

Notably, the direct effect of *the Share of Women Founders on Attracted Funding Per Round* remains significant and negative. Nevertheless, the effect (ß = - 0.36, p = 0.00) is smaller than in Model 4 after including *Factor:* Education and the interaction term *Share of Women Founders x Factor: Education* in the model. The direct effect of *Factor: Education* on *Attracted Funding per Round* is positive (ß = 0.58,p =0.08).

Model 7 does not provide empirical evidence for H3C. Instead, the negative relationship between the *Share of Women Founders* and *the Attracted Funding per Round* (ß = - 1.08, p = 0.00) increases for greater values of *Factor: Consumption*, which suggests a positive moderation effect. Here*, a* one-percent increase in the *Share of Women Founders* is related to a decrease in *Attracted Funding per* R*ound by 1.04 percent.* Further, all-men founding teams receive 66.04 percent more funding than all-women founding teams [calculation: $ß_{H3C,\%}$ = (exp(- 1.08) - 1) x 100 % = 66.04]. The direct effect of *Factor: Consumption* on *Attracted Funding per Round* is positive (ß = 2.26, p = 0.00). Finally, the R^2 of Model 7 (R^2 = 0.22) improved slightly compared to Model 4 (R^2 = 0.21).

		Model 1 (H1A)	Model 2 (H1B)	Model 3 (H1C)
	Dependent Variable:	Factor: Inequality	Factor: Education	Factor: Consumption
Founding Team	Share of Women Founders	0.02 ***	0.01 ***	-0.02 ***
		(<0.001)	(<0.001)	(<0.001)
	Share of Non-Binary Founders	-0.02 ***	0.00	-0.00
		(<0.001)	(0.78)	(0.47)
	Share of Foreign Founders	0.01 **	-0.00	-0.00
		(0.00)	(0.19)	(0.50)
	Maximal Work Experience	0.00 *	0.00 ***	0.00 **
		(0.02)	(<0.001)	(0.00)
	Maximal Founding Experience	0.00	-0.00	-0.00 ***
		(0.76)	(0.41)	(<0.001)
	Team Size	0.00 ***	-0.00 **	0.00 **
		(<0.001)	(0.01)	(0.00)
Startup	Number of Social Media Accounts	0.01 ***	0.01 ***	0.00 **
		(<0.001)	(<0.001)	(0.01)
	Own Investment Activities	0.00	0.01 ***	0.01
		(0.77)	(<0.001)	(0.14)
	Industry Dummy Variables	YES	YES	YES
	R^2 (within)	0.06	0.22	0.16
	R^2	0.09	0.22	0.18

Table 3.6 - Regression Table H1 * p<0.05 ** p<0.01 *** p<0.001

		Model 4 (H2)
	Dependent Variable	Log (Attracted Funding per Round)
Founding Team	Share of Women Founders	-0.57 ***
		(<0.001)
	Share of Non-Binary Founders	-0.07
		(0.20)
	Share of Foreign Founders	-0.08
		(0.17)
	Maximal Work Experience	0.10 ***
		(<0.001)
	Maximal Founding Experience	0.06 **
		(0.01)
	Team Size	0.13 ***
		(<0.001)
Startup	Number of Social Media Accounts	0.19 ***
		(<0.001)
	Own Investment Activities	1.40 ***
		(<0.001)
	Industry Dummy Variables	YES
	R^2 (within)	0.08
	R^2	0.21

Table 3.7 - Regression Table H2 * p<0.05 ** p<0.01 *** p<0.001

		Model 5 (H3A)	Model 6 (H3B)	Model 7(H3C)
	Dependent Variable	Log (Attracted Funding per Round)		
Founding Team	Share of Women Founders	-0.31 ***	-0.36	0.18
		(<0.001)	(0.08)	(0.33)
	Share of Non-Binary Founders	-0.09	-0.07	-0.06
		(0.11)	(0.19)	(0.27)
	Share of Foreign Founders	-0.08	-0.08	-0.08
		(0.18)	(0.17)	(0.18)
Startup	Number of Social Media Accounts	0.20 ***	0.19 ***	0.19 ***
		(<0.001)	(0.00)	(<0.001)
	Own Investment Activities	1.40 ***	1.39 ***	1.39 ***
		(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality	-0.76 ***	-	-
		(<0.001)	-	-
	Share of Women Founders x Factor: Inequality	-0.39 *	-	-
		(0.02)	-	-
	Factor: Education		0.58 ***	-
			(<0.001)	-
	Share of Women Founders x Factor: Education		-0.36 *	-
			(0.06)	-
	Factor: Consumption			2.26
				(<0.001)
	Share of Women Founders x Factor: Consumption			-1.08 ***
				(<0.001)
Additional Controls	Industry Dummy Variables	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES
	Maximal Work Experience	YES	YES	YES
	Team Size	YES	YES	YES
	R^2 (within)	0.08	0.08	0.09
	R^2	0.21	0.21	0.22

Table 3.8 - Regression Table H3 * $p<0.05$ ** $p<0.01$ *** $p<0.001$

3.5. Supplemental Analysis and Robustness Checks

3.5.1. Educational Background of Founding Team

The primary analysis already took some team characteristics (team, number of startups founded by most experienced founder, number of jobs held by most experienced jobholder). However, it is possible that educational team characteristics also impact a startup team's decision to engage in social, educational, or pro-environmental entrepreneurship. For example, founders whose university education prepared them to become teachers might be more likely to start a company focused on educational matters.

Therefore, I used Crunchbase data on the founders' education to extract information on university titles (Bachelor, Master, Doctor) and study fields (Agriculture, Architecture/Real Estate, Business, Economics, Teaching, Engineering, Health, IT, Languages/Culture, Law, Media, Medicine, Music/Fashion/Arts, Psychology, Public Services, Religion/Philosophy, Sciences, Social Sciences, Sports, Tourism /Gastronomy). Doing so, I assigned a bachelor's degree a value of 1, a master's title a value of 2, and a doctor's title a value of 3. The variable *Average Educational Degree* expresses the mean of these values per founding team. Secondly, nineteen dummy variables (corresponding to the study fields mentioned above) indicate whether at least one founding team member studied with a focus on the respective field. Consecutively, I added these 20 newly created variables to the models as control variables. As education-related information was unavailable for some startups in the initial sample, these models run based on 64,190 observations (Table A3.1 in the appendix summarizes more details on the dataset).

Models 8-10 (summarized in Table A3.2 in the appendix) show that this variation of the Models regarding H1 does not affect the main effect coefficients describing the effect of *Share of Women Founders* on the startup's inclination towards socially oriented entrepreneurship (ß = 0.02, p = 0.00), educational entrepreneurship (ß = 0.01, p = 0.00), and pro-environmental entrepreneurship (ß = - 0.02, p = 0.00). Including the education-related variables led to a slightly improved R^2 for Model 9 (R^2 = 0.23) and Model 10 (R^2 = 0.19) compared to Models 2-3.

Further, Models 11-14 (see Table A3.3 in the appendix) summarize the results regarding *the Attracted Funding per Round* of women-founded startups. Model 11 supports the idea that women receive less funding per round than men, whereby the coefficient (ß = - 0.64, p = 0.00) is even more negative than in Model 4 (ß = - 0.35, ß = 0.00). Model 12 does not provide significant results for the interaction term. However, the negative direct effect of *Share of Women Founders* on *Attracted Funding Per Round* becomes weaker (ß = - 0.45, p = 0.01) compared to Model 11. The direct effect of *Factor: Inequality* on *Attracted Funding per Round* is negative (ß = - 0.59, p = 0.00), and the one of *Average Educational Degree* is positive (ß = 0.17, p = 0.00).

Further, Model 13 suggests, contrary to the main analysis (Model 6), that education-focused, women-founded startups have even worse funding prospects than the average women-founded startup (ß = - 0.71, p = 0.00). Additionally, borderline significant results show that *Share of Women Founders'* direct negative effect on *Attracted Funding Per Round* is less pronounced (ß = - 0.21, p = 0.06) than in Model 11. *Factor: Education* directly and negatively affects *Attracted Funding per Round* (ß = - 0.71, p = 0.00). Contrarily, the *Average Educational Degree* impacts the dependent variable positively (ß = 0.17, p = 0.00). Finally, Model 14 supports the notion of particularly poor funding prospects for environmental-focused, women-founded startups (ß = - 1.17, p = 0.00). In this model, the direct effect of *Share of Women Founders* on *Attracted Funding Per Round* becomes statistically insignificant (ß = 0.17, p = 0.47). The direct effects of *Factor: Consumption* (ß = 2.60, p =0.00) and *Average Educational Degree* (ß = 0.15, p =0.00) on *Attracted Funding per Round* are positive. In all four cases (Models 11-14), the R^2 increased after including the education-related variables in the models.

3.5.2. THE ROLE OF TECHNOLOGICAL ORIENTATION

The main results presented above (Models 1-7) do not entirely support the a priori expectations. First, I expected startups with a higher share of women entrepreneurs to focus more on environmental matters (H1C). Second, I hypothesized that startups with a higher percentage of women founders would receive more funding per round when they have a business orientation on sustainable consumption (H3C). Nevertheless, the empirical results indicate the exact opposite. A possible reason for this observation might be that the three factor variables *(Factor: Education, Factor: Inequality, and Factor: Consumption)* only capture a startup's sustainability-related business orientation. However, the variable does not distinguish between technological and non-technological approaches. This matters because existing research suggests that women are more likely to focus on non-technology-related business solutions to sustainability-related issues than men (Bloodhart & Swim, 2020; Brody et al., 2008).

I created a new variable called Dummy: Tech/Engineering Approach to test this possibility. This differs from the self-reported variable *Industry Dummy: Technology,* which only indicates if the startup targets the Technology sector. Nevertheless, it is likely that some startups do not focus on the technology market but still rely on technological approaches. Therefore, I created a dummy variable called *Dummy: Tech/Engineering Approach.* This new indicator *equals* one if (1) a company's description includes the terms "tech*" or "engineer*" or (2) if *Industry Dummy: Technology* equals 1. The created variable has a mean of 0.45, and the standard deviation equals 0.50 (summarized in Table A3.4 in the appendix). In the respective analysis, I eliminated *Industry Focus: Technology* and *Industry Focus: Science and Engineering* from the models to avoid multicollinearity problems.

Models 15-17 (summarized in Table A3.5 in the appendix) analyze whether *Dummy: Tech/Engineering Approach* moderates the relationship between S*hare of Women Founders* and *Factor: Inequality* (Model 15), *Factor: Education* (Model 16)*,* and *Factor: Consumption* (Model 17). They indeed reveal statistically significant moderation effects in line with the literature mentioned above, suggesting that the positive impact of increased shares of women in startup teams on businesses focusing on inequality (ß = - 0.01, p = 0.01) and education (ß = 0.00, p = 0.00) decreases if the respective firms are technology oriented. Nevertheless, Model 17 does not provide support for moderation. Further, the direct effects of S*hare of Women Founders* on the factor variables remain positive in Model 15 (ß = 0.02, p = 0.00) and Model 16 (ß = 0.01, p = 0.00) and negative in Model 17 (ß = - 0.01, p = 0.00). Compared to Models 1-3, the R^2 improved in the case of Model 16 (R^2 = 0.23) and Model 17 (R^2 = 0.18).

Models 18-21 are summarized in Table A3.6 in the appendix. Model 18 shows that the direct effect of *Share of Women Founders* on *Attracted Funding per Round* after controlling for *Dummy: Tech/Engineering Approach and Share of Women Founders x Dummy: Tech/Engineering Approach* does not change compared to Model 4 (ß = - 0.57, p = 0.00). *Dummy: Tech/Engineering* Approach positively impacts *Attracted Funding per Round* (ß = 0.21, p = 0.00). Models 19-21 test a double moderation of *Dummy: Tech/Engineering Approach* and the respective factor variables on the relationship between the *Share of Women Founders.* However, the models do not provide significant results for such a relationship. The coefficients from Model 19 show that *Factor: Inequality* (ß = - 1.03, p = 0.00), *Share of Women Founders* (ß = - 0.41, p = 0.00), and Dummy: Tech/Engineering Approach (ß = - 0.25, p 0.00) negatively correlate with the *Attracted Funding per Round.* Model 20 suggests that the *Share of Women* is less negatively related to *Attracted Funding per Round* if the entrepreneurs focus on educational businesses (ß = - 0.38, p = 0.02). The model further indicates a direct, positive effect of *Factor: Education* (ß = 0.30, p = 0.03) and a direct negative effect of the *Share of Women Founders* (ß = - 0.35, p = 0.00) on the dependent variable. Finally, Model 21 indicates a direct, positive effect of *Factor: Consumption* (ß = 2.14, p = 0.00), as well as a significant interaction between *Share of Women Founders* and *Factor: Consumption* (ß = - 1.31, p = 0.00). This indicates a positive moderation of *Factor Consumption* that increases the funding gap for pro-environmentally oriented startups compared to the main model (Model 7). Notably, the R^2 does not improve for Models 18-21 compared to Models 4-7.

3.5.3. Longitudinal Data

The main analysis relies on a cross-sectional dataset, including one observation per startup and averaged data between 1992 and 2022. Further, I applied fixed effects on the startup's founding year and country of location. However, attracting funding during some years was likely particularly difficult (e.g., 2020-2022 due to the COVID-19 pandemic).

Based on these considerations, I used Crunchbase data on investment rounds to derive data on each startup-year combination where investments took place. The new panel data set covers 209,813 observations. For a more detailed overview, please consult Table A3.7 in the appendix. Regarding the first hypothesis set (Women's tendency to focus on inequality, education, or the environment), this model is not suited because the decision regarding the business focus is taken only once in the year of the startup's foundation. Thus, only one observation per startup is necessary. However, for H2 and H3, this approach allows the inclusion of the respective investment period as an additional fixed effect. Additionally, I controlled for the startup age. Given the assumption that startups are most attractive to investors after some first successes and less if they become more consolidated (e.g., Bertoni et al., 2015), I controlled for a quadratic transformation of the *Startup Age* variable.

Details on Models 22-25 are summarized in Table A3.8 in the appendix. Model 22 provides additional support for H2, providing evidence for a gender-related funding gap (ß = - 0.51, p = 0.00). Model 23 underpins the previous results from Model 6 and indicates that female-founded businesses focusing on inequality-related business matters are less affected by this funding gap (ß = - 0.45, p = 0.00). The direct effects of *Share of Women Founders* on *Attracted Funding per Round* (ß = - 0.22, p = 0.01) and *Factor: Inequality* (ß = - 0.30, p = 0.00) remained negative and significant. Further, borderline significant results from Model 24 suggest that women founders focusing on education are slightly better off than the average women entrepreneur in terms of *Attracted Funding per Round* (ß = - 0.50, p = 0.06). The model further shows a positive effect *of Factor: Education* on the *Attracted Funding per Round* (ß = 0.59, p = 0.00). Finally, Model 25 contradicts the results from Model 7. It suggests that pro-environmentally oriented startups are even less affected by the gender funding gap than socially- or educationally-oriented ones (ß = - 0.43, p = 0.05). The direct effect of *Share of Women Founders* on *Attracted Funding per Round* becomes insignificant in this model. At the same time, *Factor: Consumption* itself positively affects the dependent variable (ß = 1.17, p = 0.00).

Models 26-29 (summarized in Table A3.9 in the appendix) suggest that a technological orientation does not significantly affect most of these results. More concretely, Model 26 suggests a direct, adverse effect of *the Share of Women Founders on Attracted Funding per Round (ß = - 0.53, p = 0.00) and does not show signs of* a moderating effect of *Dummy: Tech/Engineering Approach* on this relation. Hereby, *Dummy: Tech/Engineering Approach* affects the dependent variable positively (ß = 0.09, p = 0.00). The results from Model 27 are slightly different.

More precisely, the interaction term *Share of Women Founders x Dummy: Tech/Engineering Approach* becomes significant (ß = 0.40, p = 0.00). The direct effects of *Share of Women Founders* (ß = - 0.38, p = 0.00), *Dummy: Tech/Engineering Approach* (ß = - 0.29, p = 0.00), and *Factor: Education* (ß = - 0.55, p = 0.00) are all negative. Finally, Share of *Women Founders x Factor: Inequality x Dummy: Tech/Engineering Approach* shows a negative coefficient (ß = - 0.56, p = 0.00). To better understand this double-interaction term, I plotted it in Figure 3.1. The graph provides three main insights into this complex relationship. First, startups with a technological focus generally attract more funding per round. Second, ventures founded by women-dominated founding teams are less affected by the funding gap if they demonstrate lower levels of social business orientation. Finally, men-dominated founding teams with a technological business scope can benefit from socially oriented entrepreneurship regarding the *Attracted Funding per Round.*

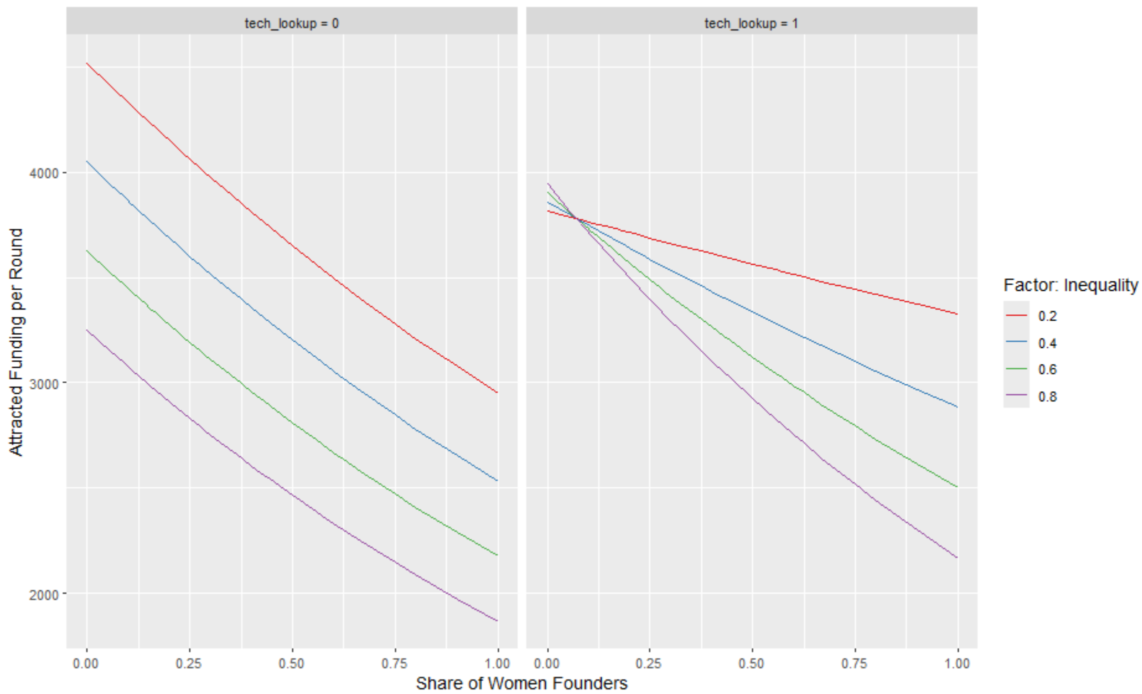

Figure 3.1 - Model 27: The Interaction of Share of Women Founders, Factor: Inequality, Dummy: Tech/Engineering Approach, and Attracted Funding per Round (Panel Data)

Model 28 does not provide significant results in terms of any moderating effects of *Dummy: Tech/Engineering*. However, it has a direct negative impact on the dependent variable (ß = - 0.32, p = 0.00). *Share of Women Founders* shows a similar coefficient (ß = -0.30, p = 0.01). *Factor: Education* has a borderline significant, positive effect on the *Attracted Funding per Round* (ß = 0.29, p = 0.09). Finally, the interaction term *Share of Women Founders x Factor: Education* is significant and negative (ß = 0.39, p = 0.01). Model 29 shows a negative coefficient for *Share of Women Founders x Factor: Consumption* (ß = - 0.70, p = 0.00). Further, both *Dummy: Tech/Engineering Approach* (ß = 0.39, p = 0.00) and *Factor: Consumption* (ß = 1.31, p = 0.00) affect the outcome variable positively. The R^2 of the models did not improve compared to Models 22-25.

So far, I have applied fixed effects on the startup's founding year, the country of location, and each investment period (1992 to 2022). However, this does not take into account that unobserved time-related differences can vary between different countries (e.g., countries took different means during the COVID-19 pandemic). Therefore, I added a model where I interacted the country- and time-related fixed effects with each other, additionally to the direct country and time-fixed effects. As before, these models are designed to test Hypotheses 2 and 3. The corresponding Models 30-33 are summarized in Table A3.10 in the appendix. In accordance with Model 4, Model 30 suggests that women receive less funding per round than men (ß = - 0.50, p = 0.00). Model 31 indicates that this effect is lower if women-founded startups focus on inequality-related business concepts (ß = - 0.47, ß = 0.00). *Factor: Inequality* impacts the dependent variable negatively (ß = - 0.28, p = 0.00). At the same time, the coefficient describing the relationship between the *Share of Women Founders* and *Attracted Funding Per Round* decreases (ß = - 0.20, p = 0.03). Model 32 shows similar findings concerning *Factor: Education*. The model's borderline significant results suggest that women-founded startups are slightly less affected by the gender funding gap than the average woman entrepreneur (ß = - 0.49, p = 0.07). However, *Factor: Education* has a direct, positive impact on the outcome variable (ß = 0.59, p = 0.00). Lastly, Model 33 suggests that women-founded businesses attract the most funding compared to men-founded startups if they engage in pro-environmental entrepreneurship (ß = - 0.46, p = 0.03). Hereby, *Factor: Consumption*, measuring the involvement in pro-environmental entrepreneurship, has a strong, positive influence on the dependent variable (ß = 1.15, p = 0.00). The R^2 increased slightly compared to Models 22-25 and strongly compared to Models 5-7.

Unlike fixed effect models, random effect models are appropriate when the dataset's unobserved heterogeneity is not correlated with the independent variables. This means that country- and time-fixed effect models consider a correlation between unobservable variables (i.e., all time-invariant characteristics of countries, all common trends across years) and the independent variables. On the other hand, random effect models assume that the country-specific and time-specific effects are assumed to be random samples from a larger population. Hence, they control for unobserved heterogeneity instead of unobservable correlations within a group. To this end, random effect models remove the constant, unobserved heterogeneity from the longitudinal data through differencing (Wooldridge, 2010).

In the context of my panel dataset, other unobservable influences likely shape each country-founding year combination. For example, governmental and entrepreneurial actors reacted differently to COVID-19 during the year 2020 in Germany than in Spain, and the situation was different for startups founded in 2018 in both countries. Therefore, I added a random effect on each country-founding year combination. This includes the assumption that the variable *started_on* is nested in *country_code in the model.* Additionally, I control for fixed effects of the respective investment period. This way, global events that might affect the general investment sizes are still taken into account. As the model includes both random and fixed effects, it is not a pure random effect model but a mixed effect model.

Models 34-36 underpin findings regarding H2, H3A, and H3B (Models 4-6). However, Model 37 contradicts the findings regarding H3C, actually supporting the hypothesis. Model 34 shows that the *Share of Women Founders* correlates negatively with the *Attracted Funding per Round* (ß = - 0.51, p = 0.00). Model 35 suggests that this effect decreases among women-founded, socially oriented startups (ß = - 0.47, p = 0.00). Additionally, the Model shows that both *Share of Women Founders (ß = - 0.21, p = 0.02)* and *Factor: Inequality (ß = - 0.26, p = 0.00)* are negatively correlated to the *Attracted Funding per Round*. Model 36 shows a similar result regarding the moderation effect, as Factor: Education also seems to negatively moderate the relationship between *Share of Women Founders* and *Attracted Funding per Round* (ß = - 0.47, p = 0.00). The *Share of Women Founders* has a direct negative (ß = - 0.21, p = 0.02), and *Factor: Education* has a direct positive (ß = 0.59, p = 0.00) effect on the dependent variable.

As in the other models based on longitudinal data, Model 37 contradicts the findings from Model 4 in the main analysis, which was based on cross-sectional data. More specifically, the model suggests that the interaction term *Share of Women Founders x Factor: Consumption* has a negative, linear relationship with *Attracted Funding per Round* (ß = - 0.49, p = 0.00) but that this effect is smaller than the direct effect of *Share of Women Founders* on the dependent variable from Model 34. Thus, the model suggests a negative, instead of a positive, moderation on the negative relationship between the *Share of Women Founders* and *the Attracted Funding per Round*. The marginal R^2 describes the proportion of variance explained by fixed effects alone, while the conditional R^2 describes the total variance explained by both fixed and random effects. As the conditional R^2 is higher than in previous models (R^2 = 0.48 for Models 34-37), it seems that it is the best model in terms of variance explained. Models 34-37 are summarized in Table A3.11 in the appendix.

3.5.4. Alternative Dependent Variables

To better understand the gender-related funding gap in entrepreneurship and the effect that an inequality-educational—or environmental-focused business focus has on this relationship, I ran additional models with the following alternative yet similar dependent variables: First, the *Total Funding Attracted*. Second, *the Number of Funding Rounds Attracted*. Finally, I analyzed the effects on the *Likelihood of Attracting Funding*.

Total Funding Attracted

Models 38-45 (see details in Table A3.13 in the appendix) show the analysis results based on the cross-sectional dataset (summarized in Table 3.4 and Table A3.4 in the appendix). The results of Model 38 suggest that women entrepreneurs attract less total funding than men (ß = - 0.68, p = 0.00). Model 39 shows borderline significant results indicating that women-founded startups engaging in socially-focused entrepreneurship are less disadvantaged (ß = - 0.42, p = 0.07). The direct effects of *Share of Women Founders* (ß = - 0.40, p = 0.01) and *Factor: Inequality* (ß = - 0.68, p = 0.00) on *Total Funding Attracted* are negative. According to Model 40, an educational focus also decreases the negative effect (ß = - 0.42, p = 0.05). Further, the direct effect of the *Share of Women Founders* on *Total Funding Attracted* is negative (ß = - 0.40, p = 0.01). On the other hand, *Factor: Education* affects the dependent variable positively (ß = 0.42, p = 0.00). Finally, the worst funding prospects arise for women entrepreneurs who focus on environmental entrepreneurship (ß = - 1.13, p = 0.00), as shown by Model 41. In this model, the direct effect of the *Share of Women Founders* on *Total Funding Attracted* remains negative (ß = - 0.43, p = 0.0). *Factor: Consumption* correlates strongly and positively with the dependent variable (ß = 3.11, p = 0.00).

Models 42-45 analyze if a technological business orientation affects the relation between the *Share of Women Founders* and *Total Funding Attracted.* Model 42 does not provide evidence for any moderating effect of *Dummy: Tech/Engineering Approach.* The effect of the *Share of Women Founders* on the *Total Funding Attracted* does not change compared to Model 38 (ß = - 0.68, p = 0.00). *Dummy: Tech/Engineering Approach* positively affects the dependent variable (ß = 0.30, p = 0.00). In Model 43, the *Share of Women Founders* is negatively (ß = - 0.52, p = 0.01), and *Dummy: Tech/Engineering Approach* is positively linked (ß = 0.30, p = 0.00) to the *Total Funding Attracted*. However, the model does not provide evidence for a moderation of *Dummy: Tech/Engineering Approach.* In Model 44, Share of *Women Founders x Factor: Education* is negatively linked to the dependent variable (ß = - 0.46, p = 0.02) even after including *Dummy: Tech/Engineering Approach* and *Share of Women Founders x Factor: Education x Dummy: Tech/Engineering Approach* into the model. Additionally, the *Share of Women Founders* correlates negatively with the *Total Funding Attracted* (ß = - 0.52, p = 0.01).

Model 45 shows a strong positive impact of *Factor: Consumption* on *Total Funding Attracted* (ß = 2.94, p = 0.00). Further, the model indicates that women-founded companies involved in pro-environmental entrepreneurship have relatively bad funding prospects (ß = - 1.49, p = 0.00). Finally, the model suggests a positive relationship between the interaction term *Share of Women Founders x Factor: Consumption x Dummy: Tech/Engineering Approach* and the *Total Funding Attracted* (ß = 0.85, p = 0.06). However, as illustrated in Figure 3.2, this does not imply that women-founded tech startups are generally better off than men-founded ones. Instead, all-women-founded tech startups attract the least funding. Comparing technologically oriented firms to others also reveals that a technological focus is related to higher funding attracted for both men- and women-dominated teams for high- and medium values of *Factor: Consumption*. However, Women-founded startups with very low values of *Factor: Consumption* and non-technological business approach seem to attract more money than all-men-founded startups. Including *Dummy: Tech/Engineering Approach* does not enhance the R^2 of the models.

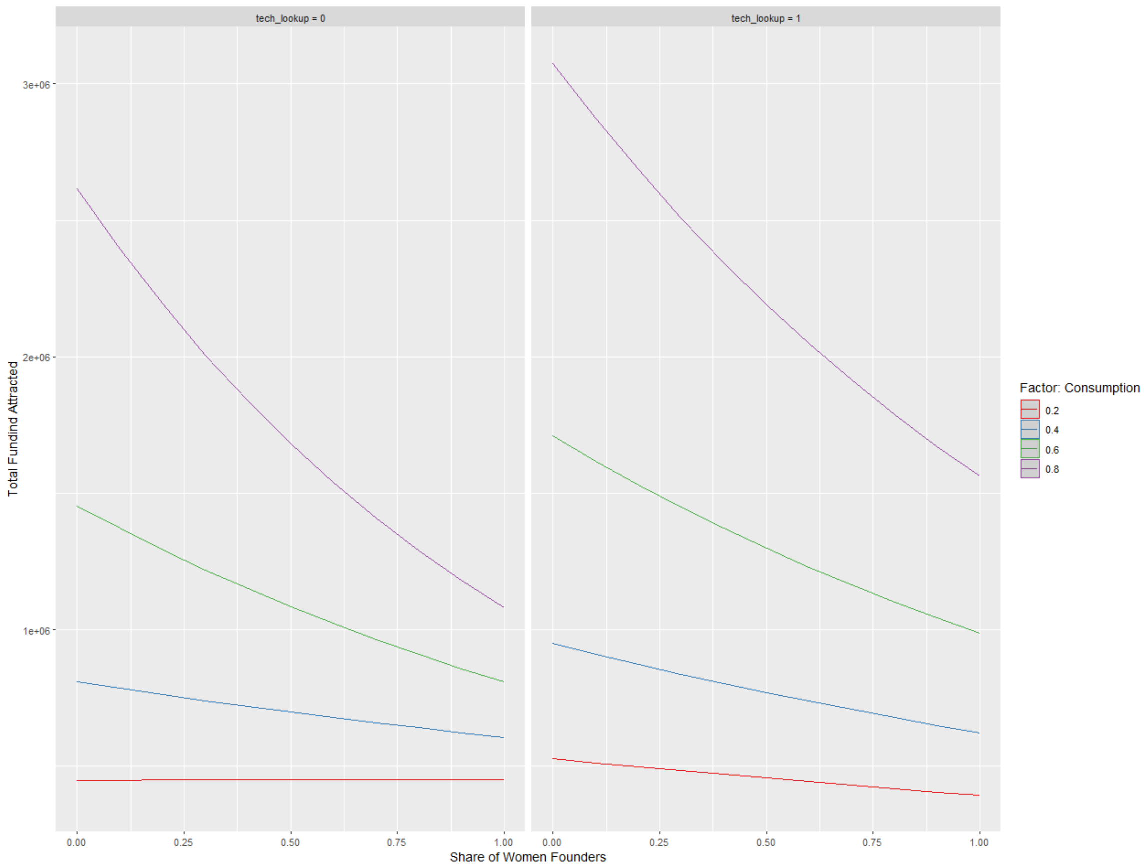

Figure 3.2 - Model 45: The Interaction of Share of Women Founders, Factor: Consumption, Dummy: Tech/Engineering Approach, and Total Funding Attracted (Cross-Sectional Data)

Models 46-49 (Summarized in Table A3.13 in the appendix) additionally control for educational-related variables. The corresponding dataset is summarized in Table A3.2. This way, the R^2 of the models increases compared to Models 38-41. Model 46 provides further evidence for the existence of a gender-related funding gap (ß = - 0.75, p = 0.00). The newly introduced *Average Educational Degree* positively influences the dependent variable (ß = 0.24, p = 0.00). Model 47 shows that *Share of Women Founders* (ß = - 0.56, p = 0.01) and *Factor: Inequality* (ß = - 0.58, p = 0.00) impact the *Total Funding Attracted negatively*, and *Average Educational Degree* influences the dependent variable (ß = 0.24, p = 0.00) positively. Model 48 shows the same coefficients for *Average Educational Degree*. Further, *Factor: Education* positively correlates with the dependent variable (ß = 0.65, p = 0.00). Finally, *Share of Women Founders x Factor: Education* (ß = - 0.88, p = 0.00) suggests that women-founded educational startups receive less total funding than the average women entrepreneur. *Factor: Consumption* has a strong positive effect on the dependent variable (ß = 3.66, p 0.00). Similarly to Model 48, Model 49 suggests that pro-environmentally oriented, women-founded startups receive significantly less funding than the average women entrepreneur (ß = - 1.29, p = 0.01).

Further, Models 50-57 are summarized in Table A3.14 in the appendix. They are based on the longitudinal panel dataset (summarized in Table A3.7) and consider fixed effects on the startup's founding year, its country of location, and the respective investment periods. The results of Model 50 reconfirm the existence of a gender-related funding gap (ß = - 0.52, p = 0.00). Model 51 shows a negative moderation effect of an inequality-related business focus (ß = - 0.44, p = 0.00). *Factor: Inequality* (ß = - 0.29, p = 0.00) and *Share of Women Founders* (ß = - 0.23, p = 0.01) have a direct, negative effect on the total funding attracted. Model 52 provides borderline significant evidence for a negative moderation effect of an education-related business focus (ß = - 0.48, p = 0.06) on the relationship between the *Share of Women Founders* and the *Total Funding Attracted*. In this model, *Factor: Education* directly and positively impacts the dependent variable (ß = 0.54, p = 0.00). Model 53 also provides borderline significant results suggesting that women-founded startups with a pro-environmental focus are less affected by the gender-related funding gap than the average women entrepreneur (ß = - 0.38, p = 0.07). *Factor: Consumption* has a direct, positive effect on the *Total Funding Attracted* (ß = 1.20, p = 0.00). The *Share of Women Founders* shows a borderline significant coefficient (ß = - 0.25, p = 0.09).

Models 54-57 additionally consider a potential moderation effect of *Dummy: Tech/Engineering Orientation* on the relation between *the Share of Women Founders* and *Total Funding Attracted*. After controlling for the interaction term *Share of Women Founders x Dummy: Tech/Engineering Orientation* (ß = 0.06, p = 0.09) and a direct effect of *Dummy: Tech/Engineering orientation (ß = 0.09, p = 0.00),* Model 54 still shows a negative correlation between the *Share of Women Founders* and *Total Funding Attracted* (ß = - 0.54, p = 0.00). Model 55 supports this notion (ß = - 0.38, p = 0.00). Further, the direct effects of *Factor: Inequality* on *Total Funding Attract* (ß = - 0.55, p = 0.00), *Dummy: Tech/Engineering Orientation (ß = - 0.29, p = 0.00), and Factor: Inequality (ß = - 0.55, p = 0.00)* are negative. Finally, the model shows a negative coefficient describing the effects of the interaction term *Share of Women*

Founders x Factor: Inequality x Dummy: Tech/Engineering Approach (ß = - 0.48, p = 0.01). To facilitate the understanding of this result, I plotted this relationship in Figure 3.3. The graph reveals four main insights. First, all-men-founded startups are better funded than women-founded ones with similar firm characteristics. Second, the more inequality-focused the startups are, the less funding they attract, independent of the gender composition of their founding team if they do not have a technological business approach. Third, a decreasing slope indicates that the gender funding gap becomes smaller among tech startups with a low focus on inequality. Finally, while non-technological startups receive the highest amount of funding - independently of the gender composition of the founding team - if they do not focus on environmental entrepreneurship, the gender composition matters for tech startups. All-men teams attract the highest investments if they concentrate on pro-environmental businesses, while all-women teams attract the lowest funding if they do so.

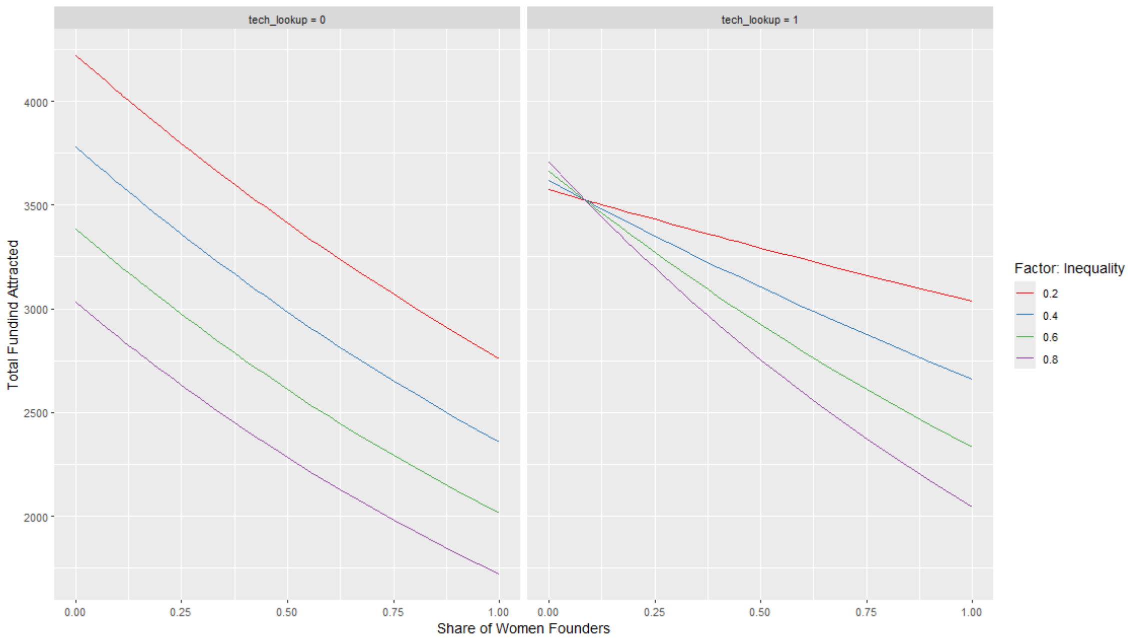

Figure 3.3 - Model 55: The Interaction of Share of Women Founders, Factor: Inequality, Dummy: Tech/Engineering Approach, and Total Funding Attracted (Panel Data)

Model 56 does not return significant results regarding the role of *Dummy: Tech/Engineering Orientation*. However, the interaction *term Share of Women Founders x Factor: Education* is significant and negative (ß = - 0.36, p = 0.02). *Share of Women Founders* (ß = - 0.33, p = 0.00) and *Dummy: Tech/Engineering Orientation* (ß = - 0.31, p = 0.00) are negatively related to the dependent variable. Similarly, Model 57 shows a negative coefficient describing the effect of the interaction *term Share of Women Founders x Factor: Consumption* on *Total Funding Attracted* (ß = - 0.67, p = 0.01). Also, *Factor: Consumption* and *Dummy: Tech/Engineering Orientation* (ß = 0.37, p = 0.00) are positively related to the dependent variable (ß = 1.35, p = 0.00). Finally, *Dummy: Tech/Engineering Orientation* in the regression models only increases the R^2 of Models 54-57 to a very limited extent, compared to Models 50-53.

Models 58-61 are summarized in Table A3.15 in the appendix. They are based on the panel dataset and consider fixed effects on the startup's founding year, its country of location, each country-founding-year combination, and the respective investment periods. Model 58's results underpin previous results suggesting a gender-related funding gap (ß = - 0.51, p = 0.00). Further, this effect becomes weaker among startups focusing on reducing inequality (ß = - 0.46, p = 0.00) in Model 59. The direct effect of the *Share of Women Founders* on *Total Funding Attracted* is negative (ß = - 0.21, p = 0.00) and the direct effect of *Factor: Inequality* on *Total Funding Attracted* is negative (ß = - 0.28, p = 0.00). Model 60 further shows that the gender-related funding gap also diminishes among startups focused on educational entrepreneurship (ß = - 0.47, 0.08). In this model, the direct effect of *Factor: Education* on *Total Funding Attracted* is positive (ß = 0.54, p = 0.00). Model 61 suggests that the gender-related funding gap is less pronounced among startups focused on environmentally oriented business models (Model 61: ß = - 0.40, p = 0.05). It further shows that *Factor: Consumption* positively affects the dependent variable (ß = 1.19, p = 0.00).

Models 62-65 are based on the panel dataset and consider fixed effects on the respective investment periods. Additionally, they take random effects on each combination of countries and founding years into account. They are summarized in Table A3.16 in the appendix. The results of Model 62 support previous results suggesting that startups with a higher share of women founders receive less total funding (ß = - 0.52, p = 0.00). Model 63 shows this effect weakens among startups focusing on inequality reduction (ß = - 0.48, p = 0.00). The direct effects of *Share of Women Founders* (ß = - 0.21, p = 0.02). and *Factor: Inequality* (ß = - 0.27, p = 0.00) on *Total Funding Attracted* are negative. Similarly, Model 64 indicates that education-oriented firms are less affected by the gender-related funding gap than the average startup (ß = - 0.47, p = 0.00). Further, the coefficient describing the direct effect of *Share of Women Founders* on *Total Funding Attracted* shows a negative sign (ß = - 0.25, p = 0.00), while the one describing *Factor: Education's* effect shows a positive one (ß = 0.55, p = 0.00). Finally, Model 65 shows that startups with a higher share of women founders and a focus on pro-environmental entrepreneurship attract the highest total funding of the analyzed groups (ß = - 0.45, p = 0.00). The R^2 of these models is higher than in previous models (R^2 = 0.48).

NUMBER OF FUNDING ROUNDS ATTRACTED

Models 66-73 are based on the cross-sectional dataset and summarized in Table A3.17 in the appendix. The results of Model 66 suggest that startups founded by teams including more women attract fewer funding rounds (ß = - 0.16, p = 0.00). Model 67 indicates a positive relationship between *Factor: Inequality* and the *Number of Funding Rounds Attracted* (ß = 0.32, p = 0.01). Further, inequality-oriented women-founded startups experience a higher gender discrepancy regarding the *Number of Funding Rounds Attracted* (ß = - 0.28, p = 0.03). On the other hand, Model 68 shows that women-founded startups can benefit from a focus on education (ß = - 0.15, p = 0.01). Further, *Factor: Education* is negatively linked to the *Number of Funding Rounds Attracted* (ß = - 0.57, p = 0.00). Model 69 suggests that *Factor: Consumption* positively impacts the dependent variable (ß = 2.09, p = 0.00).

Models 70-73 consider a potential moderation effect of a startup's technological/engineering-related orientation on the relation between the *Share of Women Founders* and *the Number of Funding Rounds Attracted*. Model 70 does not suggest any significant moderation effects. However, the direct effect *of Share of Women Founders on Funding Rounds Attracted* remains negative and highly significant (ß = - 0.17, p = 0.00), while the effect of *Dummy: Tech/Engineering Approach* is positive (ß = 0.28, p = 0.00). Model 71 suggests that *Factor: Inequality* has a positive impact on the startups' *Number of Funding Rounds Attracted* (ß = 0.18, p = 0.04). Further, the interaction term *Share of Women Founders x Factor:* Inequality shows a negative coefficient (ß = - 0.39, p = 0.02). Model 72 shows that *Factor: Education* (ß = - 0.45, p = 0.00) and *Share of Women Founders (ß = - 0.14, p = 0.08)* relate negatively to the dependent variable, while *Dummy: Tech/Engineering Approach* has a positive direct effect on it (ß = 0.64, p = 0.00). Model 73 suggests that *Dummy: Tech/Engineering Approach* (ß = - 0.32, p = 0.00) has a negative, and *Factor: Consumption* (ß = 1.60, p = 0.00) has a positive direct effect on *the Number of Funding Rounds Attracted*. Further, the interaction term *Share of Women Founders x Factor: Consumption* is negative (ß = - 0.40, p = 0.06). Finally, the coefficient describing the relation between *Share of Women Founders x Factor: Consumption x Dummy: Tech/Engineering Approach* and the *independent variable is positive* (ß = 0.87, p = 0.01). To facilitate the interpretation of this coefficient, I plotted it in Figure 3.4.

The plot reveals three main findings. First, if startups apply a technological business approach, differences among those with different levels of *Factor: Consumption* become more pronounced. Second, a pro-environmental focus leads to the highest number of funding rounds attracted, independently of the founding team's gender composition. Finally, the gender-related difference in the *Number of Funding Rounds Attracted* becomes less pronounced for pro-environmental tech startups. However, the R^2 of these models is not higher than in Models 66-69.

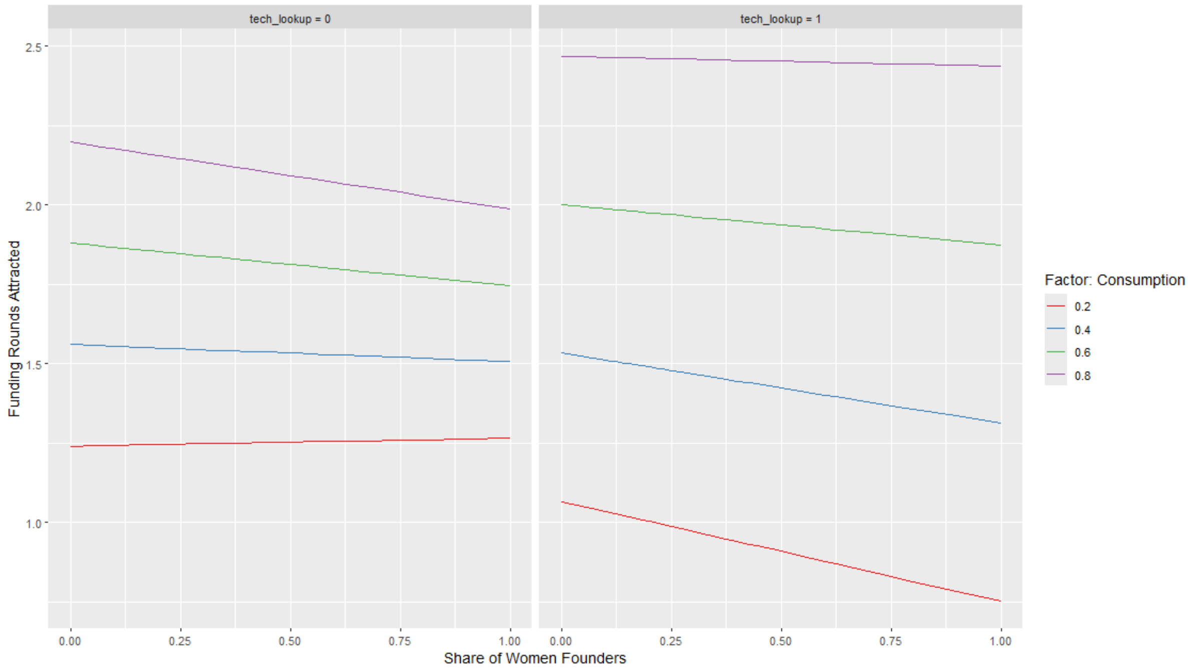

Figure 3.4 - Model 73: The Interaction of Share of Women Founders, Factor: Consumption, Dummy: Tech/Engineering Approach, and Number of Funding Rounds Attracted (Cross-Sectional Data)

Models 74-77 (Table A3.18 in the appendix) summarize how controlling for education-related variables affects the results from Models 70-73. The underlying cross-sectional dataset is summarized in Table A3.2 in the appendix. Model 74 suggests a direct negative effect of the *Share of Women Founders* on the *Number of Funding Rounds Attracted* (ß = - 0.20, p = 0.00). The direct effect of the *Average Educational Degree* on the *Number of Funding Rounds Attracted* is positive (ß = 0.19, p = 0.00). Model 75 shows the same effect size regarding the relationship between *Average Educational Degree* and the dependent variable but does not provide further significant results. Model 76 also does so. Additionally, *Factor: Education* is negatively related to the *Number of Funding Rounds Attracted* (ß = - 0.51, p = 0.00). Lastly, the model suggests that women-founded startups receive even fewer funding rounds when engaging in educational entrepreneurship (ß = - 0.30, p = 0.01). Finally, Model 77 shows that *Factor: Consumption* positively affects the dependent variable (ß = 2.65, p = 0.00). The effect of *Average Educational Degree* is positive (ß = 0.16, p = 0.00). The R^2 for these models is slightly higher than in previous models (Model 74-76: R^2 = 0.17, Model 77: R^2 = 0.18).

Models 78-85 rely on the longitudinal panel dataset (summarized in Table A3.7) and consider fixed effects on the startup's founding year, its country of location, and the respective investment periods. They are summarized in Table A3.19 in the appendix. Model 78 suggests that women-founded startups receive fewer funding rounds (ß = - 0.01, p = 0.00). Model 79 does not provide any significant results. Model 80 shows a direct, negative effect of *Share of Women Founders* (ß = - 0.03, p = 0.04) and *Factor: Education* (ß = - 0.08, p = 0.00) on the dependent variable. Model 81 indicates that women-founded startups with a strong focus on environmentally oriented business models receive more investment rounds than their male counterparts (ß = 0.08, p = 0.05). The direct effect of the *Share of Women Founders* on the *Number of Funding Rounds Attracted* remains negative in this model (ß= - 0.06, p = 0.02). *Factor: Consumption*, on the other hand, relates positively to the dependent variable (ß = 0.06, p = 0.00).

Models 82-85 analyze whether a technological business approach affects these relationships. After controlling for *Dummy: Tech/Engineering Approach* and *Share of Women Founders x Dummy: Tech/Engineering Approach*, Model 82 suggests a negative effect of the *Share of Women Founders* on the *Number of Funding Rounds Attracted* (ß = - 0.01, p = 0.00). Further, *Dummy: Tech/Engineering Approach positively impacts* the dependent variable (ß = 0.01, p = 0.00). Model 83 borderline significant results suggest a positive correlation between *Share of Women Founders x Factor: Inequality x Dummy: Tech/Engineering Approach* on the *Number of Funding Rounds Attracted* (ß = 0.13, p = 0.08). To facilitate the interpretation of this coefficient, I plotted the relation in Figure A3.1 in the appendix. The plot reveals that women-founded startups with a technological approach benefit from a strong focus on socially-oriented entrepreneurship, even attracting more funding rounds than all-men-founded companies. On the other hand, if *Dummy: Tech/Engineering Approach* equals zero, women-founded startups benefit more from a lower focus on social matters.

Model 84 suggests a negative effect of *Share of Women Founders* (ß = - 0.06, p = 0.00) and *Factor: Education* (ß = - 0.09, p = 0.00) on the *Number of Funding Rounds Attracted.* Further, the model suggests that *Dummy: Tech/Engineering Approach* turns the signs of the relationship between the *Share of Women Founders* and the *Number of Funding Rounds Attracted* around so that the sign switches from a negative to a positive one (ß = 0.10, p = 0.00). *Factor: Education* similarly affects the main relation (ß = 0.08, p = 0.01). Finally, *Share of Women Founders x Factor: Education x Dummy: Tech/Engineering Approach* correlates negatively to the dependent variable (ß = - 0.14, p = 0.01). This relationship is plotted in Figure A3.2 in the appendix, which suggests that women-founded startups with an educational orientation are better off without a technological business approach. On the other hand, women-founded tech startups benefit more from a lower educational focus.

Finally, Model 85 suggests a positive effect of Factor: Consumption (ß = 0.05, p = 0.01) on the dependent variable but does not show signs of further moderation. Unfortunately, the R^2 for Models 78-86 is extremely low (R^2 = 0.01).

Due to the low variance explained (R^2 = 0.03) by the Models analyzing the effect of the *Share of Women Founders* on the *Number of Funding Rounds Attracted,* I will only briefly summarize Models 86-93. The models (summarized in Table A3.20 in the appendix) consider fixed effects on the startup's founding year, its country of location, each country-founding-year combination, and the respective investment periods. The models suggest that women-founded startups receive fewer funding rounds (ß = - 0.01, p = 0.00). Further, this effect becomes even more pronounced among education-oriented startups (ß = - 0.08, p = 0.00). However, for pro-environmentally oriented startups, the sign of the effect changes (ß = 0.06, p = 0.00). Models 90-93 (Table A3.21 in the appendix) are based on the panel dataset and consider fixed effects on the respective investment periods as well as random effects on each combination of countries and founding years. The models show that women attract fewer funding rounds (ß = - 0.01, p = 0.00). For pro-environmentally oriented startups, the sign of the effect changes (ß = 0.09, p = 0.01).

LIKELIHOOD TO ATTRACT FUNDING

Finally, I analyzed the probabilities of men and women to attract funding. To do so, I also included non-funded startups in the dataset. Additionally, I included the dummy variable *Dummy: Funding Attracted.* In the cross-sectional dataset, the variable equals one if the startup received funding through its business activity and zero if it never received funding. In the panel dataset, *Dummy: Funding Attracted* equals one if the startup received funding in the respective period between 1992 and 2022 and zero if it does not. The descriptive statistics of this dataset are summarized in Table A3.22 in the appendix.

As *Dummy: Funding Attracted* is a binary variable, I applied logit-link binomial regression instead of ordinary least squares regression and calculated the marginal effects for each model. I must also calculate marginal effects because the interaction effect in logit models does not equal the marginal effect of the interaction term, which might even be of the opposite sign (Ai & Norton, 2003). To do so, I considered team compositions with a minority (25%) and a majority (75%) of women founders, as well as the extremes (1 / 0) of the respective factor variable.

Model 94 suggests that women-founded startups are less likely to receive funding than male-founded ones (ß = - 0.03, p = 0.00). However, according to Model 95, inequality-focused, women-founded firms are even more likely to attract funding than men-founded ones (ß = 0.20, p = 0.00). Further, Model 96 shows that educationally oriented startups with a higher share of women founders are most unlikely to receive funding (ß = - 0.42, p = 0.00). Finally, Model 97 suggests that women-founded, environmentally-oriented startups are likelier to attract funding than male-founded ones (ß = 0.24, p = 0.00). Models 94-97 are summarized in Table A3.24 in the appendix.

Model 98 shows the general likelihood of attracting funding increases for women-founded, tech-oriented startups (ß = 0.02, p = 0.00). Further, Models 99-101 analyze whether *Dummy: Tech/Engineering Approach* also impacts the interaction terms *Share of Women Founders x Factor: Inequality* (Model 99), *Share of Women Founders x Factor: Education* (Model 100), and *Share of Women Founders x Factor: Consumption* (Model 101). Model 99 shows a positive effect of the double interaction term *Share of Women Founders x Factor: Inequality x Dummy: Tech/Engineering Approach* on *Dummy: Funding Attracted* (ß = 0.25, p = 0.00). To facilitate the interpretation of this coefficient, I plotted the relation in Figure 3.5. The plot shows that the likelihood of receiving funding is equally gender skewed for tech- and non-tech startups. However, socially oriented tech startups (i.e., those scoring higher in *Factor: Inequality*) are much more likely to receive funding than the average young business.

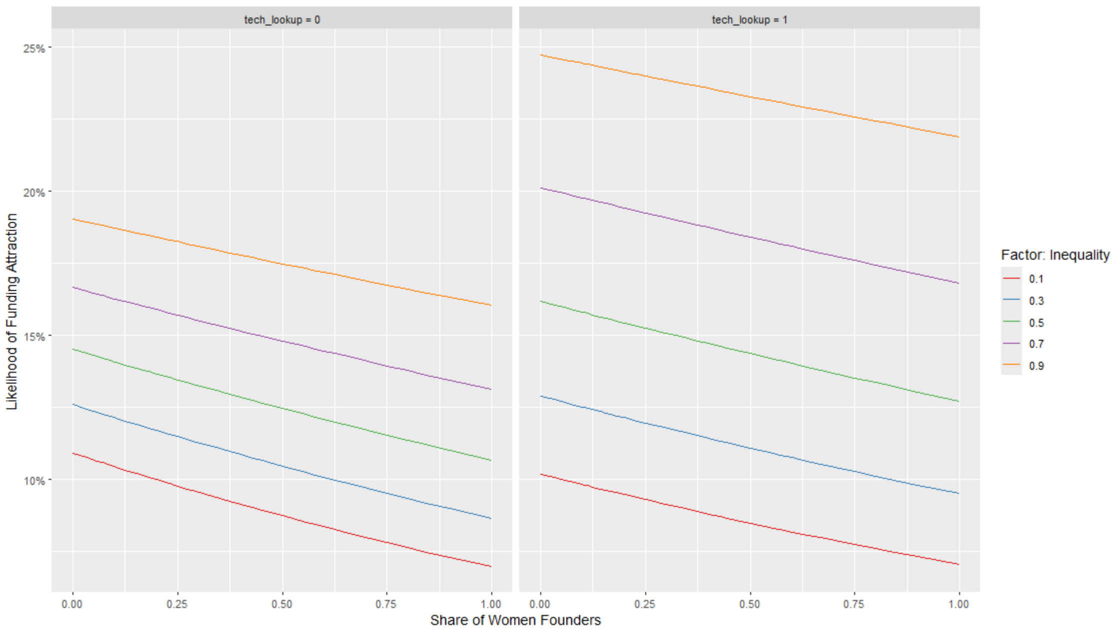

Figure 3.5 - Model 99: The interaction of Share of Women Founders, Factor: Inequality, Dummy: Tech/Engineering Approach, and the Likelihood of Funding Attraction (Cross-Sectional Data)

On the other hand, Model 100 shows a negative coefficient related to the effect of the double interaction term *Share of Women Founders x Factor: Education x Dummy: Tech/Engineering Approach* on the dependent variable (ß = - 0.40, p = 0.00). I plotted the relationship in Figure 3.6. The graph illustrates that startups focusing less on educational matters are more likely to attract funding. Further, in most cases, women-founded startups are less likely to receive financing. However, it is surprising that women-founded tech startups with a low educational business orientation seem to attract more funding than men-founded ones.

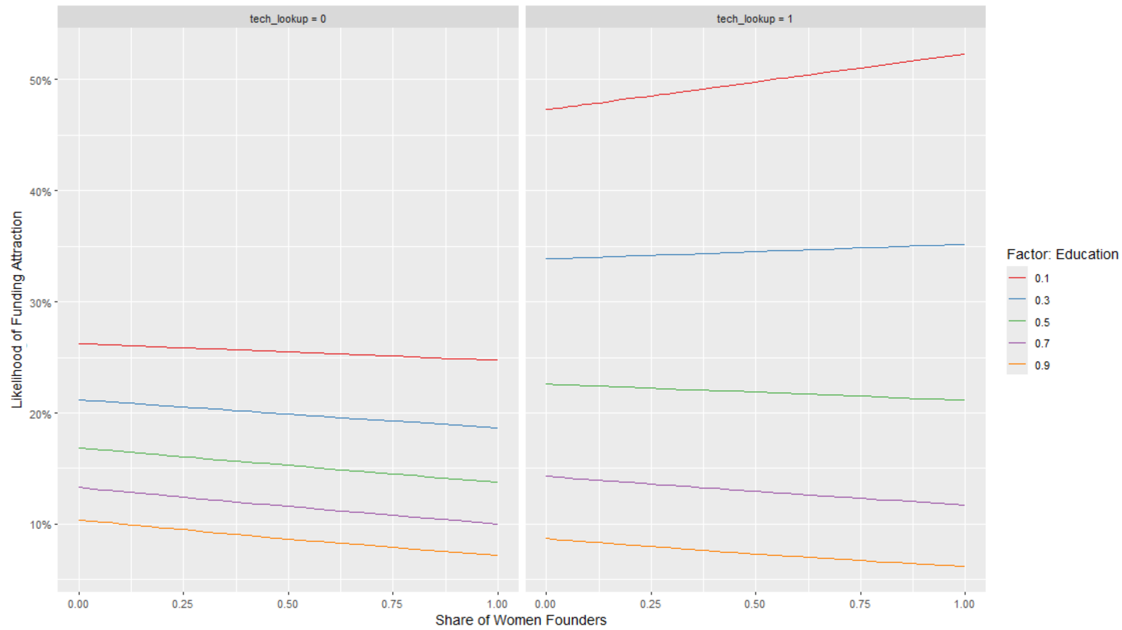

Figure 3.6 - Model 100: The interaction of Share of Women Founders, Factor: Education, Dummy: Tech/Engineering Approach, and the Likelihood of Funding Attraction (Cross-Sectional Data)

Like Model 99, Model 101 shows that the coefficient describing the relation between the double interaction term *Share of Women Founders x Factor: Consumption x Dummy: Tech/Engineering Approach* and *Dummy: Funding Attracted is positive* (ß = 0.24, 0.00). I plotted this relation in 3.7, which suggests that tech startups are more likely to receive funding. However, both tech- and non-tech startups are equally confronted with the gender gap. The marginal effects of Models 98-101 are summarized in Table A3.24 in the appendix. The regression table in Table A3.25 shows the regression coefficients behind Models 94–101.

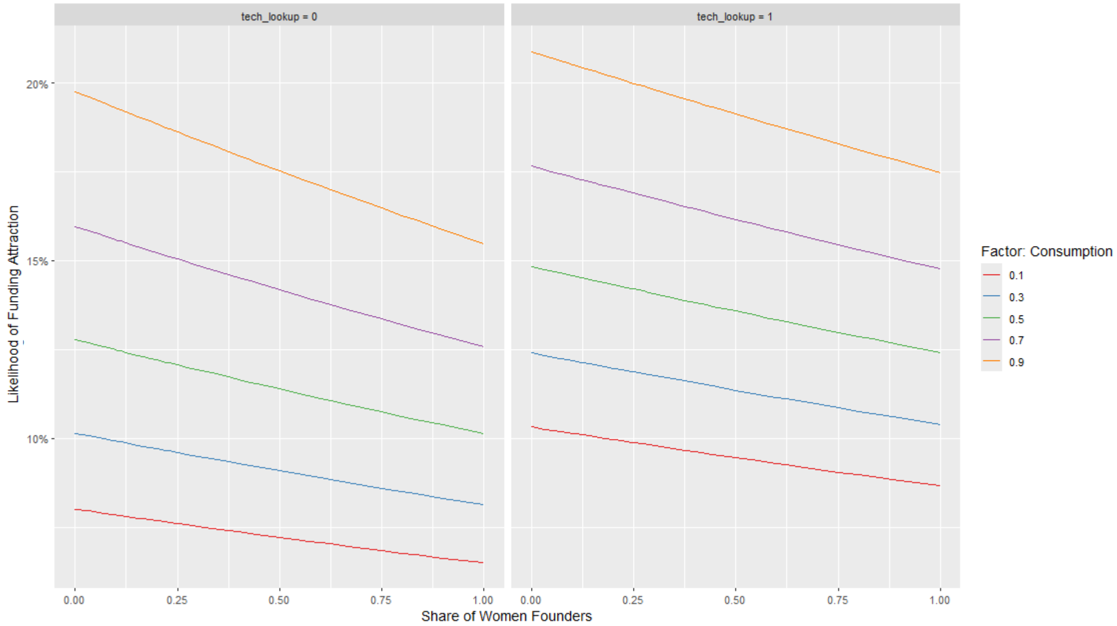

Figure 3.7 - Model 101: The interaction of Share of Women Founders, Factor: Consumption, Dummy: Tech/Engineering Approach, and the Likelihood of Funding Attraction (Cross-Sectional Data)

Models 102-105 (Table A3.28 in the appendix) are based on the cross-sectional data set but take educational aspects (study subject and academic degree) into account. The dataset behind these models is summarized in Table A3.26 in the appendix. Model 102 shows that including these factors leads to a negative effect from *Share of Women Founders* on the dependent variable (ß = - 0.03, p = 0.00). Model 103 suggests an even better funding prospect for women-founded firms with a business focus on inequality reduction (ß = 0.34, p = 0.00). Further, Model 104 suggests that the negative effect among women-founded, educationally focused startups becomes even more negative (ß = - 0.44, p = 0.00). Finally, women-founded startups with a pro-environmental business focus seem to be disadvantaged in terms of their likelihood to attract funding according to Model 105 (ß = 0.22, p = 0.00). The respective regression tables are summarized in Table A3.27 in the appendix.

Table A3.29 shows the characteristics of the panel dataset that includes funded and unfunded startups. Based on this data, I ran Models 106-113 (summarized in Tables A30-A32 in the appendix). They consider fixed effects on the startup's founding year, its country of location, and the investment periods. Model 106 suggests that women in founding teams decrease the startup's likelihood of attracting funding (ß = - 0.01, p = 0.00). Further, Model 107 does not provide significant results. On the other hand side, Model 108 suggests that women-founded startups with educational business missions have a particularly low likelihood of attracting funding (ß = - 0.12, p = 0.00). According to Model 109, women-founded startups with business models related to environmental entrepreneurship encounter the highest likelihood of attracting funding (ß = 0.11, p = 0.00). Models 110-113 analyze the influence of *Dummy: Tech/Engineering Approach* on women-founded startups' *Likelihood of Funding Attraction*.

Model 110 suggests that technologically oriented businesses with an increased share of women founders are likelier to attract funding than the average women-founded startup (ß = 0.01, p = 0.00).

Model 111 shows a positive effect of the double interaction term *Share of Women Founders x Factor: Inequality x Dummy: Tech/Engineering Approach* on *Dummy: Funding Attracted* (ß = 0.02, p = 0.04). To facilitate the interpretation of this coefficient, I plotted the relation in Figure 3.8. The plot shows that men-founded tech startups are likelier to attract funding than women-founded tech startups. Further, a social entrepreneurial focus increases the funding prospects independent of the founding teams' gender composition, but men-dominated teams seem to benefit slightly more from this effect. For non-tech-related companies, the gender funding gap increases as the focus on social matters increases. However, women-founded startups with a very low social business orientation are likelier to attract funding than men-founded teams with the same business focus.

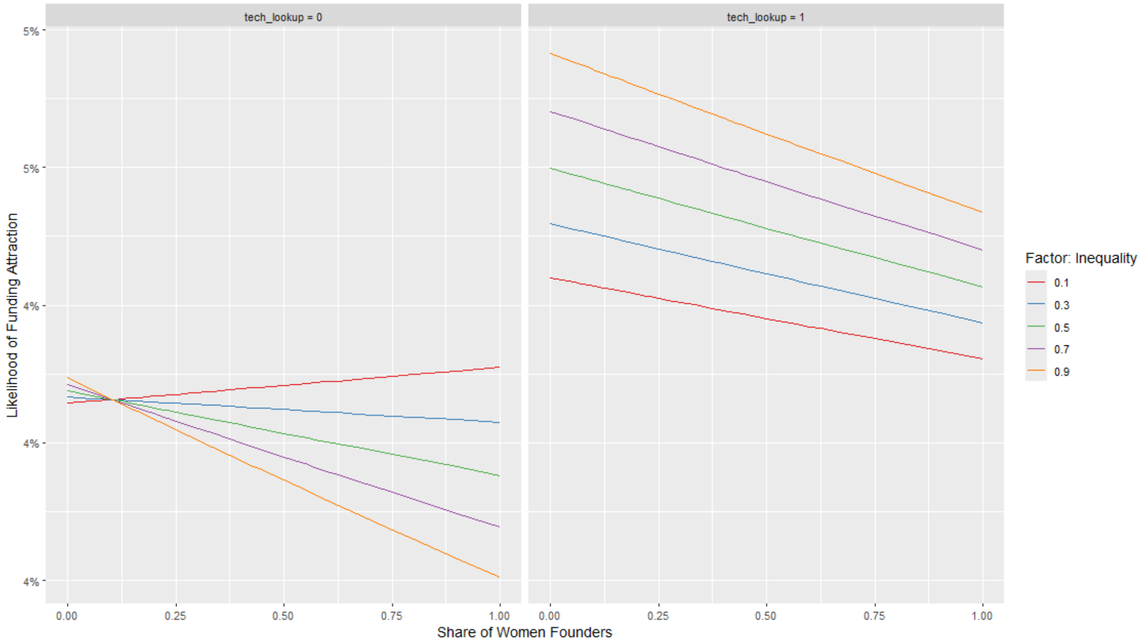

Figure 3.8 - Model 111: The interaction of Share of Women Founders, Factor: Inequality, Dummy: Tech/Engineering Approach, and the Likelihood of Funding Attraction (Panel Data)

On the other hand, Model 112 shows a positive effect of the double interaction term *Share of Women Founders x Factor: Education x Dummy: Tech/Engineering Approach* on the dependent variable (ß = - 0.003, p = 0.00). I plotted the relationship in Figure 3.9. The graph suggests that women-founded tech startups suffer less from the gender funding gap if they have a strong educational business focus. In this case, their chances of funding attraction are even higher than men-founded tech startups focusing on education to an equal extent.

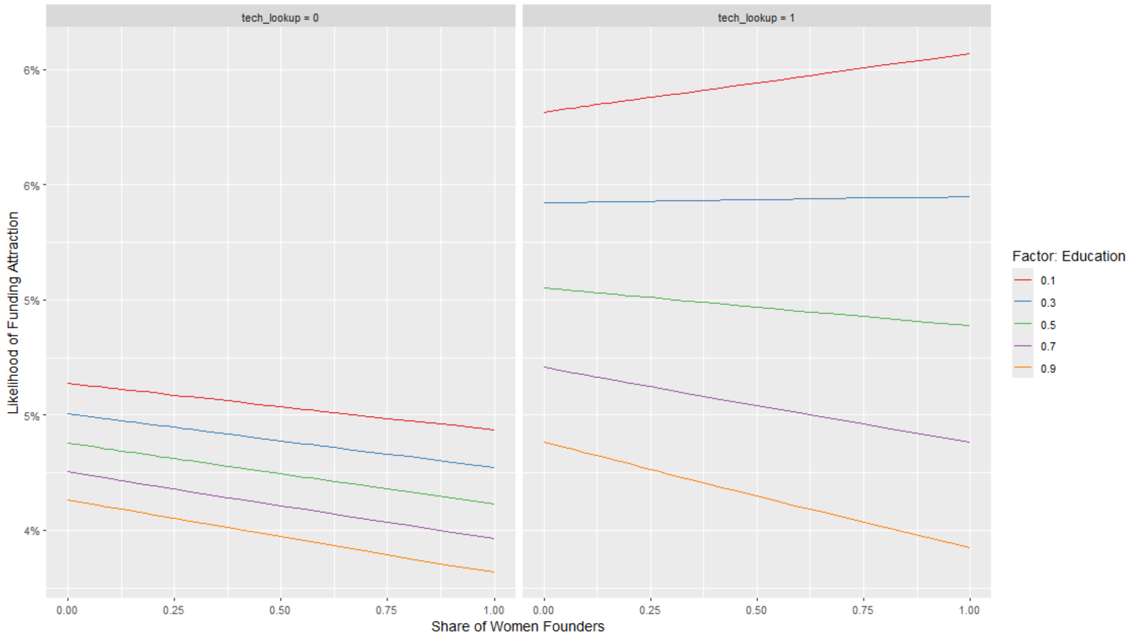

Figure 3.9 - Model 112: The interaction of Share of Women Founders, Factor: Education, Dummy: Tech/Engineering Approach, and Number of Funding Rounds Attracted (Panel Data)

Finally, Model 113 shows that the coefficient describing the relation between the double interaction term *Share of Women Founders x Factor: Consumption x Dummy: Tech/Engineering Approach* and *Dummy: Funding Attracted is positive* (ß = 0.20, p = 0.00). I plotted this relation in Figure 3.10, which suggests that women-founded tech startups suffer less from the gender funding gap if they focus strongly on a pro-environmental business approach. For non-tech-related companies, the gender funding gap increases as the focus on environmental matters increases. However, women-founded startups with a very low environmental business orientation are likelier to attract funding than men-founded teams with the same business focus.

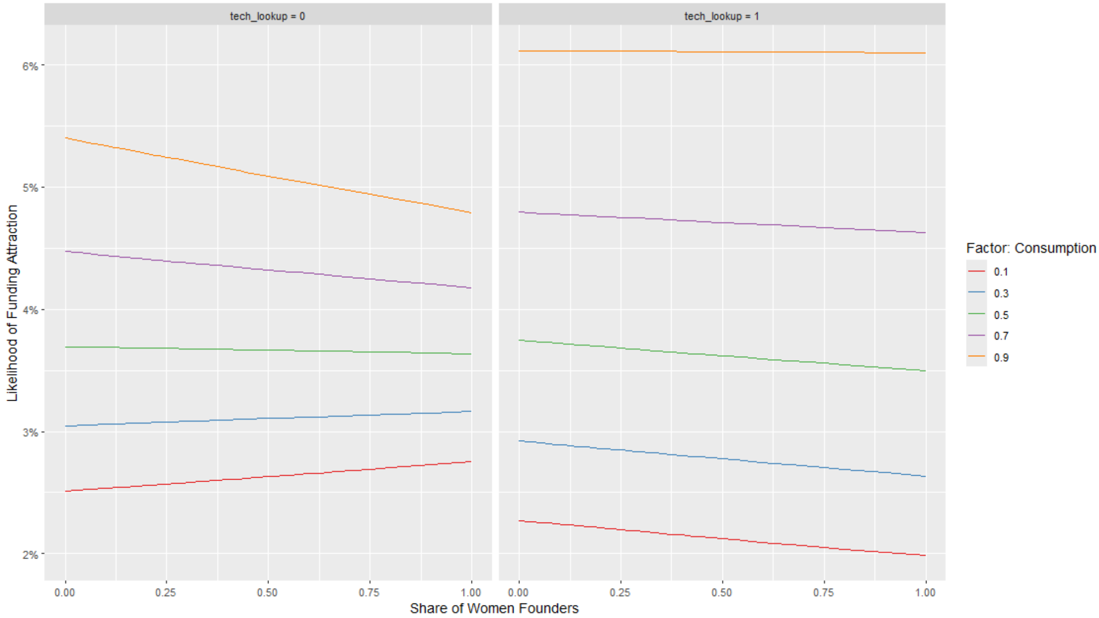

Figure 3.10 - Model 113: The interaction of Share of Women Founders, Factor: Consumption, Dummy: Tech/Engineering Approach, and Number of Funding Rounds Attracted (Panel Data)

Models 114-117 (summarized in Tables A33-A34 in the appendix) additionally consider a fixed effect on each combination of the startup's founding year and its country of location. Model 114 suggests a positive impact of a higher share of women in the startup team on the likelihood of attracting funding (ß = - 0.01, p = 0.00). Further, Model 115 does not provide significant results. However, if the startups focus on educational business missions, Model 116 suggests that the negative effect from Model 114 becomes even more negative (ß = - 0.05, p = 0.00). Finally, more women in the startup team increase the likelihood of attracting funding for pro-environmental businesses (ß = 0.19, p = 0.00).

The last four Models (Models 118-121) consider both fixed (investment period) and random effects (combination of founding year and country location). The results of Model 118 suggest that a higher share of women in the startup team correlates negatively with the likelihood of attracting funding (ß = - 0.01, p = 0.00). Model 119 suggests that this effect becomes insignificant if the startups focus on reducing inequality (ß = - 0.00, p = 0.48). Nevertheless, comparing all-women to all-men-founded startups, borderline significant results suggest that the effect decreased (Model 118: ß = - 0.012, p = 0.00, Model 119: ß = -0.008, p = 0.08). However, if the startups focus on educational business missions, the negative effect from Model 120 becomes even more negative (ß = - 0.04, p = 0.00). Finally, in Model 121, an increased share of women in the startup team leads to a higher likelihood of attracting funding if the business focuses on environmental matters (ß = 0.18, p = 0.00). These models are summarized in Tables A35-A36 in the appendix.

3.6. Summary of the Results

3.6.1. Gender-Related Differences Regarding the Scope of Business (Hypothesis 1)

H1A–H1C suggested that the share of women within a startup's founding team positively correlates with a startup's social (H1A), educational (H1B), and environmental (H1C) orientation. The analysis supported H1A and H1B but surprisingly found a negative relationship between women's representation in the startup team and an environmental business orientation. Post-hoc analysis shows that the effect sizes related to H1A and H1B decrease if a firm has a technological business orientation. Furthermore, the direct, negative effect of women's representation in the startup teams on an environmental business orientation decreases when controlling for terms related to a firm's technological business orientation (i.e., technological business orientation and the interaction term between the share of female founders and the firm's technological business orientation). All findings regarding H1A-H1C are robust and unaffected by introducing additional control variables related to the team members' education to the statistical models.

3.6.2. The Effect of the Gender Team Composition on the Attracted Funding per Round (Hypothesis 2)

H2 suggested a negative relationship between a startup's percentage of women founders and the funding per round attracted by these companies. This hypothesis received support, and the findings are robust to different model specifications (e.g., considering a potential moderation influence of a technological, social, educational, or environmental startup orientation and additional education-related control variables). The use of longitudinal data in place of cross-sectional data allowed for the consideration of different fixed and random effects, as well as controlling for the company's age at the time of investment attraction. A post-hoc analysis was conducted to assess the impact of these factors on the results related to H2. However, this did not result in any changes.

3.6.3. The Moderating Effect of the Business Orientation on the Gender Funding Gap (Hypothesis 3)

H3A-C hypothesized that the gender-related funding gap in terms of the *Attracted Funding per Round* decreases if the startups have businesses focusing on social (H3A), educational (H3B), or environmental matters (H3C). The findings support H3A and were reproduced through models based on longitudinal data considering different compositions of fixed and random effects. However, longitudinal moderation analysis suggests that there are notable differences between tech- and non-tech businesses: While the gender funding gap remains relatively stable for non-tech companies, it increases with an inequality orientation in the case of tech startups.

H3B also receives support through my analysis. As for H3A, I showed the effect for cross-sectional and longitudinal data, considering different compositions of fixed and random effects. However, the results do not differ significantly for tech- and non-tech businesses. The addition of education-related control variables to the main models based on cross-sectional data yielded unexpected results. These suggest that women-founded, educationally-oriented startups receive even less funding per round than the average women-founded firm. A possible explanation for these unexpected findings is that introducing 20 additional variables to the model can lead to collinearity-related issues during the moderation analysis. These issues might inflate the coefficients' sizes. Finally, H3C did not receive support from the main models that were based on cross-sectional data. Instead, they suggested that the gender-related funding gap in terms of the attracted funding per round increases for pro-environmental startups. However, post-hoc analysis based on a panel dataset controlling for the startup's age at the time of the investment provides results that support the initial hypothesis. This points toward the importance of considering that investments can vary according to the respective year, across countries, and depending on the startup's age.

3.6.4. Alternative Dependent Variables

Total Funding Attracted

Different models consistently indicate a gender-related funding gap regarding total funding attracted. Models based on the cross-sectional dataset suggest that this discrepancy is smaller among socially oriented startups but larger for educationally and pro-environmentally oriented startups. This funding gap impacts both tech and non-tech startups. However, pro-environmental startups attract more funding if they are tech-oriented. Rerunning the analysis relying on the longitudinal dataset paints a slightly different picture. More precisely, it provides further evidence for the existence of a gender-related funding gap but suggests that a startup's social, educational, and pro-environmental orientation negatively moderates this effect. In the case of socially oriented entrepreneurship, the results of the panel regressions also vary between technological and non-technological startups. While the gender funding gap remains relatively stable for non-tech businesses, it increases with a firm's social orientation in the case of tech startups.

Number of Funding Rounds Attracted

The cross-sectional data analysis indicates that a higher proportion of women founders is associated with fewer funding rounds attracted. This effect is more pronounced among socially oriented startups but less evident in those focused on education or the environment. Among environmentally oriented startups, the effect differs between tech- and non-tech-focused startups. Discrepancies are more significant among startups with a low or moderate focus on pro-environmental business models. However, women-founded tech startups with a strong pro-environmental focus are less disadvantaged if they choose a tech-related approach. Introducing the additional education-related variables to the models leads to results that reconfirm the existence of a general funding gap but suggest that educational business orientation leads to fewer funding rounds attracted by women-founded firms. Unfortunately, the longitudinal models only explain a very small part of the data's variance.

Likelihood to Attract Funding

The percentage of women founders negatively correlates with the probability of securing funding. This relationship is weaker for startups with a social or pro-environmental focus and stronger for those in the education sector. Social and pro-environmental startups are even more likely to attract funding than those founded by men. These findings hold across different models based on cross-sectional and longitudinal data. Unexpectedly, the findings of the models based on cross-sectional data that incorporate education-related control variables suggest that women-founded startups are more likely to secure funding than men-founded ones. This seems to affect particularly inequality- and consumption-focused women-founded startups, while educationally oriented ones remain to be less likely to receive financing. Lastly, women-founded tech startups are more likely to attract funding than non-tech-oriented ones. The cross-sectional models indicate that women-founded startups are exposed to a less gender-skewed funding distribution for both technology and non-technology startups if they do not focus on environmental or educational issues. Noteworthy, an increased environmental focus is related to better funding prospects.

Taking into account the potential influence of country and year on these relationships, the longitudinal models indicate that non-tech, women-founded startups are more likely than men-founded ones to attract funding if they do not pursue environmentally or socially oriented businesses. However, this behavior is associated with reduced funding prospects. Firms with a pro-environmental and tech-oriented focus have a high probability of securing funding, which is largely independent of the gender composition of their founding team. Additionally, a strong emphasis on education coupled with a technology-centric business strategy is associated with a greater likelihood of obtaining funding, particularly in the case of women-led startups. Conversely, women-led firms that are not socially oriented tend to face fewer challenges in securing financing, although this also results in a relatively low probability of success.

3.7. Discussion

Based on the literature on gender role stereotypes, gender stereotypes, and entrepreneurial teams, I hypothesized that (H1) An increasing share of women in the founding team of a high-growth oriented high-growth focused startup will positively influence a startup's social (H1A), educational (H1B), and environmental (H1C) orientation. An increasing share of women in the founding team is associated with lower investments per round (H2). Further, I expected that focusing on social (H3A), educational (H3B), or environmental matters (H3C) reduces the negative effect that the share of women founders has on the funding attracted per investment round.

I measured a startup's business orientation using three factors, which emerged from exploratory factor analysis on seventeen items describing the semantic similarity between the Crunchbase-provided description of the startup and each of the United Nations Sustainable Development Goals. The first factor proxies a startup's social orientation, loading strongly on United Nations Sustainable Development Goals related to social inequality and poverty alleviation. The second factor variable proxies a company's educational orientation and loads strongly on United Nations Sustainable Development Goals related to education. Finally, the third factor variable proxies the environmental orientation and strongly loads on United Nations Sustainable Development Goals related to the sustainable consumption and use of resources.

This paper's empirical analysis relies on ordinary least squares regression and supports H1A, H1B, H2, H3A, and H3B. Opposite to H1C, women-founded startups are less likely than men-founded ones to pursue entrepreneurial ventures related to sustainable resource endowment and consumption. Lastly, contradicting H3C, the gender gap in terms of the attracted funding per round increases when the business pursues ideas related to sustainable resource use. In the post-hoc analysis, I analyzed whether these relationships differ between tech- and non-tech startups and used alternative dependent variables to better understand the relationships described in H2 and H3. Finally, I compared these results to models based on cross-sectional data that considered education-related control variables and models based on longitudinal data that considered different combinations of fixed- and random effects. An extensive overview of the results is provided above in Chapter 3.6.

3.7.1. Theoretical Contributions

First, the results regarding the first hypothesis contribute to the literature on gender, entrepreneurship, and sustainability (e.g., Dickel & Eckardt, 2021; Hechavarria, Bullough, Brush, & Edelman, 2019; Liu et al., 2021). They support previous research suggesting that men and women have different approaches to promoting sustainability. For example, existing literature suggests that men often focus on technological solutions to sustainability issues (Brody et al., 2008). This paper's results add to this literature by showing that gender-mixed founding teams are more likely to found social or educational startups than all-male teams. Nevertheless, teams with an increased proportion of male founders are more likely to establish pro-environmental startups that address sustainable consumption and the sustainable utilization of existing resources. A technological business approach negatively moderates the effect of an increased share of women in the startup on a social or educational business orientation. However, it does not affect how increased gender diversity among the firm's founders impacts the decision to engage in pro-environmental entrepreneurship.

Second, my results confirming the second hypothesis add to the literature on the funding gap in entrepreneurship (e.g., Guzman & Kacperczyk, 2019). The findings indicate that not only are women who establish businesses on their own less likely to receive funding than their male counterparts, but also that founding teams comprising a higher proportion of women are similarly less likely to secure funding. Subsequent post-hoc analysis indicates that these adverse effects extend to the overall level of financing attracted and the number of funding rounds attracted. However, women entrepreneurs are even more likely to attract funding than men. The incorporation of these supplementary variables provides further support for the existing literature, which posits discrepancies between the gender gaps regarding funding amount and funding success (Geiger, 2020). Current research posits that the gender funding gap is influenced by the selection of women into industries that are perceived as having a lower growth potential by investors (Guzman & Kacperczyk, 2019). Although this argument posits that women's business orientations are the source of the gender funding gap, it does not clarify why this phenomenon occurs. One potential explanation is that these are the sectors where the disparity in funding for men- and women-founded startups is least pronounced.

Testing the third set of hypotheses led to another main contribution of this paper, as the results add to the body of literature on gender role congruity (e.g., Anglin et al., 2022; Butticè et al., 2023; Cowden et al., 2021). More concretely, the results suggest that focusing on traditionally female-typed business activities (i.e., social or educational focus) decreases the gender-related funding gap, suggesting that investors reward gender role-congruent behavior. However, comparing the funding firms attract during their existence, pro-environmental women-founded businesses receive even less average funding per round than the average women-founded startup. Digging deeper into these relationships, post-hoc analysis further suggests that these businesses receive more funding rounds but a lower total sum of funding attracted. These observations may also elucidate why longitudinal models indicate that pro-environmental women-founded businesses receive, in fact, greater funding per round than the average women-founded startup.

More precisely, comparing pro-environmental and average women-founded businesses, the longitudinal fixed effect models might outweigh the relative underfunding in some years by the consistency of funding across more years. In terms of gender role congruity, it seems that investors tend to reward women-founded startups that engage in environmentally-oriented ventures, particularly in terms of the number of investment rounds they provide. Conversely, they appear to penalize these startups in terms of the size of these investments. Finally, the post-hoc analysis also suggests that the combination of organizational characteristics influences the size of the gender funding gap. For example, it decreases generally among socially oriented ventures. However, if those businesses are tech startups, focusing on social matters even increases the gender-related funding gap. A possible driver of this observation could be that the tech industry is heavily male typed. Thus, women-founded tech startups might be perceived as heavily role-incongruent despite their social business orientation.

3.7.2. Practical Contributions

This paper also has important implications for policymakers and entrepreneurial support organizations that want to empower women-founded startups:

Female-founded startups struggling to attract funding may need tailored support. In this context, connecting women-founded startups with investors and other critical entrepreneurial players might be an apt approach. Therefore, entrepreneurial support organizations, such as business accelerators or incubators, play a crucial role in creating an embedded financial support network for these startups (van Rijnsoever, 2022). Entrepreneurial support organizations, such as business accelerators, frequently implement all-women programs that are designed for women but not specifically tailored to specific industries. (Bullough, Hechavarría, Brush & Edelman, 2019). While this might help women-founded startups that do not require large investments for growth, others might not acquire enough financial capital to be competitive. For example, the regression results suggest that pro-environmentally oriented startups generally attract higher funding than socially- or educationally-oriented ones. Thus, women-founded startups in this field would require higher financial investments to be competitive. However, if women-focused support programs offer insufficient capital, women might prefer to found less cost-intensive businesses.

Similarly, women-founded technology startups with an emphasis on inequality or educational issues may necessitate a greater level of financial capital, which these programs are unable to provide. Consequently, they may opt to pursue non-technology-related solutions. Instead of exclusively female-focused entrepreneurial support programs, a more promising approach to motivating and supporting pro-environmental, women-founded startups would be implementing gender-balanced programs that accept a selection of startups with similar business focuses and adapt the provided funding to the industry-specific needs. Yet, creating an environment where women founders are not excluded or underestimated is essential. Otherwise, they might still prefer all-women programs to escape being "othered" by dominant masculine norms (e.g., MacNeil, Schoonmaker, & McAdam, 2022).

3.7.3. LIMITATIONS AND FURTHER RESEARCH

Despite this paper's theoretical and managerial implications, it has certain limitations: First, Crunchbase data is self-reported and prone to misinformation and response biases. This could be problematic despite the extensive data-cleaning process and the exclusion of ambiguous observations. For example, misleading wording (e.g., greenwashing) can affect centroids and cosine distances. Therefore, some startup descriptions may appear very similar to specific United Nations Sustainable Development Goals, even though they are not. To mitigate this problem, I calculated the relevant factor variables based on all seventeen United Nations Sustainable Development Goals. Thus, the misleading wording would have to affect several of them to influence this paper's results severely. Further, information on the startup's target industries, the number of funding rounds, and the total funding attracted could be missing or be wrong. However, because of the ample sample size and the extensive post-hoc analysis, I do not expect these factors to significantly bias this paper's empirical results.

Secondly, existing research suggests that variables not considered in this article might impact the analyzed relationships. For example, women-founded startups often have lower growth intentions than male-founded ones (e.g., Bardasi, Sabarwal, & Terrell, 2011). As this can be crucial when attracting funding, future research could integrate more founding team characteristics and measurement of their growth intentions into their empirical analysis. Even though I could not consider this in my analysis, it is likely that firms voluntarily reporting data to Crunchbase have relatively high growth intentions. Another factor that could affect my results is that the similarity of venture capitalists and startups impacts the timing and the risk-taking related to investments (e.g., Fu, Qi & An, 2024). Furthermore, receiving early investments can signal high performance of startups to investors and thus positively impact the willingness of other investors to attract (e.g., Guzman & Kacperczyk, 2019). Therefore, future longitudinal studies might benefit from including measurements of the similarity between investors and startups (e.g., industry fit) and the previous investments startups attracted.

Nonetheless, considering too many variables in the statistical analysis can lead to multicollinearity issues and inflated coefficients. It is likely that this problem also affected the post-hoc models considering education-related control variables. To be able to include these variables in the analysis, it would, therefore, be essential to identify more complex relationships. For example, it would be possible to argue that societal gender role expectations push women into university careers that are less attractive to investors (e.g., Charlesworth & Banaji, 2022). In this case, the educational choices would explain at least a part of the gender funding gap. The analytical approach in this case would be to conduct a mediation analysis to explain how much of the main effect is explained by women's educational choices.

3.7.4. CONCLUSION

Based on gender role theory (Diekman & Eagly, 2013; Powell, 2019), I hypothesized that (1) An increasing share of women in the founding team of a high-growth-oriented startup positively influences a startup's social, educational, and environmental orientation, (2) An increasing share of women in the founding team is related to lower investments per round, and (3) Focusing on social, educational, or environmental matters reduces the negative effect that the share of women in the founding team has on the funding attracted per investment round.

I tested these hypotheses based on ordinary least squares regression and conducted a series of post-hoc regression models to better understand the results. The empirical evidence suggests (1) that startups with higher proportions of women founders focus more on social-, and educational-, but not necessarily on pro-environmental objectives, (2) that startups with higher proportions of women founders generally receive lower investments per round than all-men teams, and (3) that focusing on social, educational, or environmental matters reduces this adverse effect, but a pro-environmental focus does not. A post-hoc analysis was conducted, which further suggests that women-founded startups attract fewer funding rounds than men-founded ones. However, this effect diminishes among socially, educationally, and pro-environmentally oriented firms.

The study's contributes to the body of literature on gender and sustainability (e.g., Dickel & Eckardt, 2021), the gender funding gap in entrepreneurship (e.g., Guzman & Kacperczyk, 2019) and gender role congruity (e.g., Eagly & Karau, 2002). Practical implications for policymakers and entrepreneurial support organizations include the possibility of reducing the funding gap through the implementation of women-focused support programs on the one hand and industry-specific gender-balanced support programs on the other. Startups founded by women in industries that require higher levels of investment might particularly benefit from the latter.

In conclusion, this study has shed light on the complex relationship between societal expectations, gender dynamics, and the funding landscape in women's entrepreneurship. Unfortunately, the entrepreneurial gender funding gap persists, even within female-typed industries. However, the results suggest that investors are less likely to neglect these startups than the average women-founded startup.

3.8. References Chapter 3

Abele, A. E. 2003. The dynamics of masculine-agentic and feminine-communal traits: findings from a prospective study. Journal of Personality and Social Psychology, 85(4): 768–776.

Abu-Saifan, S. 2012. Social Entrepreneurship: Definition and Boundaries. Technology Innovation Management Review, 2(1): 22-27

Achtenhagen, L., & Welter, F. 2011. 'Surfing on the ironing board' – the representation of women's entrepreneurship in German newspapers. Entrepreneurship & Regional Development, 23(9-10): 763–786.

Aernoudt, R., & San José, A. de. 2020. A gender financing gap: fake news or evidence? Venture Capital, 22(2): 127–134.

Ai, C., & Norton, E. C. 2003. Interaction terms in logit and probit models. Economics Letters, 80(1): 123–129.

Akinbami, C. A. O., Olawoye, J. E., Adesina, F. A., & Nelson, V. 2019. Exploring potential climate-related entrepreneurship opportunities and challenges for rural Nigerian women. Journal of Global Entrepreneurship Research, 9(19): 1-28.

Alsos, G. A., Isaksen, E. J., & Ljunggren, E. 2006. New Venture Financing and Subsequent Business Growth in Men– and Women–Led Businesses. Entrepreneurship Theory and Practice, 30(5): 667–686.

Anglin, A. H., Courtney, C., & Allison, T. H. 2022. Venturing for Others, Subject to Role Expectations? A Role Congruity Theory Approach to Social Venture Crowd Funding. Entrepreneurship Theory and Practice, 46(2): 421–448.

Apesteguia, J., Azmat, G., & Iriberri, N. 2012. The Impact of Gender Composition on Team Performance and Decision Making: Evidence from the Field. Management Science, 58(1): 78–93.

Austin, J., Stevenson, H., & Wei–Skillern, J. 2006. Social and Commercial Entrepreneurship: Same, Different, or Both? Entrepreneurship Theory and Practice, 30(1): 1–22.

Bannò, M., Filippi, E., & Trento, S. 2023. Women in top echelon positions and their effects on sustainability: a review, synthesis and future research agenda. Journal of Management and Governance, 27(1): 181–251.

Bardasi, E., Sabarwal, S., & Terrell, K. 2011. How do female entrepreneurs perform? Evidence from three developing regions. Small Business Economics, 37(4): 417–441.

Bates, T. 2002. Restricted access to markets characterizes women-owned businesses. Journal of Business Venturing, 17(4): 313–324.

Baughn, C. C., Chua, B.-L., & Neupert, K. E. 2006. The Normative Context for Women's Participation in Entrepreneurship: A Multicountry Study. Entrepreneurship Theory and Practice, 30(5): 687–708.

Bento, N., Gianfrate, G., & Thoni, M. H. 2019. Crowdfunding for sustainability ventures. Journal of Cleaner Production, 237: 117751.

Bertoni, F., Colombo, M, & Quas, A. 2015. The patterns of venture capital investment in Europe. Small Business Economics, 45 (3): 543-560.

Blocker, T. J., & Eckberg, D. L. 1997. Gender and Environmentalism: Results from the 1993 General Social Survey. Social Science Quarterly, 78(4): 841–858.

Bloodhart, B., & Swim, J. K. 2020. Sustainability and Consumption: What's Gender Got to Do with It? Journal of Social Issues, 76(1): 101–113.

Bogan, V. L., Just, D. R., & Dev, C. S. 2013. Team gender diversity and investment decision-making behavior. Review of Behavioural Finance, 5(2): 134–152.

Bollough, A., Hechavarría, D., Brush, C., & Edelman, L. 2019. "Introduction: Programs, Policies, and Practices: Fostering High-Growth Women's Entrepreneurship." In High-Growth Women's Entrepreneurship, 12. Edward Elgar Publishing.

Box, M., & Larsson Segerlind, T. 2018. Entrepreneurial Teams, Gender, and New Venture Survival: Contexts and Institutions. SAGE Open, 8(2): 1-17.

Brixy, U., Brunow, S., & D'Ambrosio, A. 2020. The unlikely encounter: Is ethnic diversity in start-ups associated with innovation? Research Policy, 49(4): 103950.

Brody, A., Demetriades, J., & Esplen E. 2008. Gender and climate change: Mapping the linkages: A scoping study on knowledge and gaps. Brighton. Retrieved from http://www.adequations.org/IMG/pdf/GenderAndClimateChange.pdf. Downloaded on January 2, 2024.

Brough, A. R., Wilkie, J. E. B., Ma, J., Isaac, M. S., & Gal, D. 2016. Is Eco-Friendly Unmanly? The Green-Feminine Stereotype and Its Effect on Sustainable Consumption. Journal of Consumer Research, 43(4): 567–582.

Brunsveld, N., Page, M., & Hair, J. F., JR. 2019. Essentials of Business Research Methods. Routledge.

Butticè, V., Croce, A., & Ughetto, E. 2023. Gender Diversity, Role Congruity and the Success of VC Investments. Entrepreneurship Theory and Practice, 47(5): 1660–1698.

Caby, J., Coron, C., & Ziane, Y. 2024. How does gender diversity in top management teams affect carbon disclosure and its quality: Evidence from the technological industry. Technological Forecasting and Social Change, 199: 123077.

Chandler, J. A., Short, J. C., Hasan, M. K., & Fan, G. 2022. Founding team characteristics and the pursuit of social motives: A role theory perspective. Journal of Business Venturing Insights, 17: e00289.

Charlesworth, T. & Banaji, M. 2022. Patterns of Implicit and Explicit Attitudes: IV. Change and Stability From 2007 to 2020. Psychological Science, 33(9): 1347-1371.

Chowdhury, S. 2005. Demographic diversity for building an effective entrepreneurial team: is it important? Journal of Business Venturing, 20(6): 727–746.

Cicchiello, A. F., Kazemikhasragh, A., & Monferrà, S. 2022. Gender differences in new venture financing: evidence from equity crowdfunding in Latin America. International Journal of Emerging Markets, 17(5): 1175–1197.

Covaleski, M. A., & Dirsmith, M. W. 1988. An Institutional Perspective on the Rise, Social Transformation, and Fall of a University Budget Category. Administrative Science Quarterly, 33(4): 562.

Cowden, B. J., Creek, S. A., & Maurer, J. D. 2021. Gender role congruity and crowdfunding success. Journal of Small Business Management, 59(sup1): 134-152.

Dalle, J.-M., Besten, M. den, & Menoni, C. 2023. Using Crunchbase for economic and managerial research.

Dhahri, S., Slimani, S., & Omri, A. 2021. Behavioral entrepreneurship for achieving the sustainable development goals. Technological Forecasting and Social Change, 165: 120561.

Dickel, P., & Eckardt, G. 2021. Who wants to be a social entrepreneur? The role of gender and sustainability orientation. Journal of Small Business Management, 59(1): 196–218.

Diekman, A. B., & Eagly, A. H. 2013. Of men, women, and motivation: A role congruity account. In J. Y. Shah & W. L. Gardner (Eds.), Handbook of Motivation Science: 434–437. New York: Guilford Publications.

Eagly, A. H. 1987. Sex differences in social behavior: A social-role interpretation. Hillsdale, New Jersey, London: Lawrence Erlbaum Associates Publishers.

Eagly, A. H., & Carli, L. L. 2003. The female leadership advantage: An evaluation of the evidence. The Leadership Quarterly, 14(6): 807–834.

Eagly, A. H., & Karau, S. J. 2002. Role congruity theory of prejudice toward female leaders. Psychological review, 109(3): 573–598.

Eagly, A. H., & Koenig, A. M. 2021. The Vicious Cycle Linking Stereotypes and Social Roles. Current Directions in Psychological Science, 30(4): 343–350.

Eagly, A. H., & Wood, W. 2012. Social Role Theory. In P. van Lange, A. Kruglanski & E. Higgins (Eds.), Handbook of Theories of Social Psychology: 458–476. 1 Oliver's Yard, 55 City Road, London EC1Y 1SP United Kingdom: SAGE Publications Ltd.

Edelman, L. F., Donnelly, R., Manolova, T., & Brush, C. G. 2018. Gender stereotypes in the angel investment process. International Journal of Gender and Entrepreneurship, 10(2): 134–157.

Elam, A., Baumer, B., Schott, T., Samsami, M., Dwivedi, A., Baldegger, R., Guerrero, M., Boutaleb, F., & Hughes, K. 2022. Global Entrepreneurship Monitor 2021/22 Women's Entrepreneurship Report: From Crisis to Opportunity, London.

Ellemers, N. 2018. Gender Stereotypes. Annual review of psychology, 69: 275–298.

Färber, M., & Klein, A. 2021. Are Investors Biased Against Women? Analyzing How Gender Affects Startup Funding in Europe.

Feng, J., Ahmad, Z., & Zheng, W. 2022. Factors influencing women's entrepreneurial success: A multi-analytical approach. Frontiers in psychology, 13: 1099760.

Forbes, D. P., Borchert, P. S., Zellmer–Bruhn, M. E., & Sapienza, H. J. 2006. Entrepreneurial Team Formation: An Exploration of New Member Addition. Entrepreneurship Theory and Practice, 30(2): 225–248.

Fu, H., Qi, H., & An, Y. 2024. When do venture capital and startups team up? Matching matters. Pacific-Basin Finance Journal, 85(1): 1-25

Garcia-Retamero, R., & López-Zafra, E. 2006. Prejudice against Women in Male-congenial Environments: Perceptions of Gender Role Congruity in Leadership. Sex Roles, 55(1-2): 51–61.

Gatewood E. J., Carter N. M., Brush C. G., Greene P. G., & Hart M. M. (Eds.). 2003. Women entrepreneurs, their ventures, and the venture capital industry: An annotated bibliography. Stockholm: Entrepreneurship and Small Business Research Institute (ESBRI).

Geiger, M. 2020. A meta-analysis of the gender gap(s) in venture funding: Funder- and entrepreneur-driven perspectives. Journal of Business Venturing Insights, 13(1): 1-22.

Gicheva, D., & Link, A. N. 2015. The gender gap in federal and private support for entrepreneurship. Small Business Economics, 45(4): 729–733.

Godwin, L. N., Stevens, C. E., & Brenner, N. L. 2006. Forced to Play by the Rules? Theorizing how Mixed–Sex Founding Teams Benefit Women Entrepreneurs in Male–Dominated Contexts. Entrepreneurship Theory and Practice, 30(5): 623–642.

Gundry, L. K., & Welsch, H. P. 2001. The ambitious entrepreneur. Journal of Business Venturing, 16(5): 453–470.

Gupta, V. K., Wieland, A. M., & Turban, D. B. 2019. Gender Characterizations in Entrepreneurship: A Multi-Level Investigation of Sex-Role Stereotypes about High-Growth, Commercial, and Social Entrepreneurs. Journal of Small Business Management, 57(1): 131–153.

Guzman, J., & Kacperczyk, A. 2019. Gender gap in entrepreneurship. Research Policy, 48(7): 1666–1680.

Hancock, C., Pérez-Quintana, A., & Hormiga, E. 2014. Stereotypical Notions of the Entrepreneur: An Analysis from a Perspective of Gender. Journal of Promotion Management, 20(1): 82–94.

Hansen, K., & Żółtak, K. 2022. Social Perception of Non-Binary Individuals. Archives of sexual behavior, 51(4): 2027–2035.

Harms, R., & Groen, A. 2017. Loosen up? Cultural tightness and national entrepreneurial activity. Technological Forecasting and Social Change, 121: 196–204.

Hechavarria, D., Bullough, A., Brush, C., & Edelman, L. 2019. High-Growth Women's Entrepreneurship: Fueling Social and Economic Development. Journal of Small Business Management, 57(1): 5–13.

Hechavarría, D. M. 2016. Mother nature's son? International Journal of Gender and Entrepreneurship, 8(2): 137–172.

Helgeson, V. S. 2020. Psychology of Gender. Routledge.

Hentschel, T., Heilman, M. E., & Peus, C. V. 2019. The Multiple Dimensions of Gender Stereotypes: A Current Look at Men's and Women's Characterizations of Others and Themselves. Frontiers in psychology, 10(11): 1-19

Issa, A & Bensalem, N. 2022. Are gender-diverse boards eco-innovative? The mediating role of corporate social responsibility strategy. Corporate Social Responsibility and Environmental Management, 30(2): 742-754

Joshi, A., Son, J., & Roh, H. 2015. When Can Women Close the Gap? A Meta-Analytic Test of Sex Differences in Performance and Rewards. Academy of Management Journal, 58(5): 1516–1545.

Khan, M. A. S., Du Jianguo, Ali, M., Saleem, S., & Usman, M. 2019. Interrelations Between Ethical Leadership, Green Psychological Climate, and Organizational Environmental Citizenship Behavior: A Moderated Mediation Model. Frontiers in psychology, 1081): 1–18.

Kiefner, V., Mohr, A., & Schumacher, C. 2022. Female executives and multinationals' support of the UN's sustainable development goals. Journal of World Business, 57(3): 101304.

Kimbu, A. N., & Ngoasong, M. Z. 2016. Women as vectors of social entrepreneurship. Annals of Tourism Research, 60: 63–79.

Kite, M., Deaux, K., & Haines, E. L. 2008. Gender stereotypes. In F. L. Denmark, M. A. Paludi & L. L. Adler (Eds.), Psychology of women: A handbook of issues and theories: 205–236 (2nd ed.). Westport (Conn.): Praeger.

Koenig, A. M., & Eagly, A. H. 2014. Evidence for the social role theory of stereotype content: observations of groups' roles shape stereotypes. Journal of Personality and Social Psychology, 107(3): 371–392.

Koenig, A. M., Eagly, A. H., Mitchell, A. A., & Ristikari, T. 2011. Are leader stereotypes masculine? A meta-analysis of three research paradigms. Psychological bulletin, 137(4): 616–642.

Laguía, A., García-Ael, C., Wach, D., & Moriano, J. A. 2019. "Think entrepreneur - think male": a task and relationship scale to measure gender stereotypes in entrepreneurship. The International Entrepreneurship and Management Journal, 15(3): 749–772.

Lechler, T. 2001. A Determinant of Entrepreneurial Team Venture Success. Small Business Economics, 16(4): 263-278.

Liñán, F., Jaén, I., & Martín, D. 2022. Does entrepreneurship fit her? Women entrepreneurs, gender-role orientation, and entrepreneurial culture. Small Business Economics, 58(2): 1051–1071.

Lippa, R. A., Preston, K., & Penner, J. 2014. Women's representation in 60 occupations from 1972 to 2010: more women in high-status jobs, few women in things-oriented jobs. PloS one, 9(5): e95960.

Liu, Y., Anser, M. K., & Zaman, K. 2021. Ecofeminism and Natural Resource Management: Justice Delayed, Justice Denied. Sustainability, 13(13): 7319.

Marlow, S. 2002. Women and Self-Employment. The International Journal of Entrepreneurship and Innovation, 3(2): 83–91.

Marlow, S., & Carter, S. 2004. Accounting for change: professional status, gender disadvantage and self-employment. Women in Management Review, 19(1): 5–17.

Martiarena, A. 2022. How gender stereotypes shape venture growth expectations. Small Business Economics, 58(2): 1015–1034.

McGrath, K. F., Moosa, S., van Bergen, P., & Bhana, D. 2020. The Plight of the Male Teacher: An Interdisciplinary and Multileveled Theoretical Framework for Researching a Shortage of Male Teachers. The Journal of Men's Studies, 28(2): 149–164.

McNeil, H., Schoonmaker, M., & ;McAdam, M. 2022. Accelerating alienation: gender and self-efficacy in the accelerator context. International Journal of Entrepreneurial Behavior & Research, 28(8): 2083-2102.

Muehlenhard, C. L., & Peterson, Z. D. 2011. Distinguishing Between Sex and Gender: History, Current Conceptualizations, and Implications. Sex Roles, 64(11-12): 791–803.

Mujahid, M. S., & Mubarik, M. S. 2021. The Bright Side of Social Media: Social Media Platforms Adoption and Start-Up Sustainability. Frontiers in psychology, 12: 661649.

Muller-Kahle, M. I., & Schiehll, E. 2013. Gaining the ultimate power edge: Women in the dual role of CEO and Chair. The Leadership Quarterly, 24(5): 666–679.

Mulvaney, R. H., O'Neill, J. W., Cleveland, J. N., & Crouter, A. C. 2007. A model of work-family dynamics of hotel managers. Annals of Tourism Research, 34(1): 66–87.

OECD. 2023. The Missing Entrepreneurs 2023. OECD.

Parsons, T. 1951. Social System (Routledge sociology classics). Routledge.

Pitafi, A. H., Kanwal, S., Ali, A., Khan, A. N., & Waqas Ameen, M. 2018. Moderating roles of IT competency and work cooperation on employee work performance in an ESM environment. Technology in Society, 55: 199–208.

Poczter, S., & Shapsis, M. 2018. Gender disparity in angel financing. Small Business Economics, 51(1): 31–55.

Powell, G. N. 2019. Women and men in management (5th ed.). Thousand Oaks, California: Sage Publications, Inc.

Rosca, E., Agarwal, N., & Brem, A. 2020. Women entrepreneurs as agents of change: A comparative analysis of social entrepreneurship processes in emerging markets. Technological Forecasting and Social Change, 157: 120067.

Schmidt, D. 2002. Im Schatten der "großen Männer": Zur unterbelichteten Rolle der Unternehmerinnen in der deutschen Wirtschaftsgeschichte des 19. und 20. Jahrhunderts'. In F. Maier & A. Fiedler (Eds.), Gender Matters: Feministische Analysen zur Wirtschafts- und Sozialpolitik: 211–231. Berlin: Edition Sigma.

See, B. H., Munthe, E., Ross, S. A., Hitt, L., & El Soufi, N. 2022. Who becomes a teacher and why? Review of Education, 10(3): 1-40

Sharma, R & Monteiro, S. 2016. Creating Social Change: The Ultimate Goal of Education for Sustainability. International Journal of Social Science and Humanity, 6 (1): 72:76

Spiegler, A. B., & Halberstadt, J. 2018. SHEstainability: how relationship networks influence the idea generation in opportunity recognition process by female social entrepreneurs. International Journal of Entrepreneurial Venturing, 10(2): 202235.

Strawser, J. A., Hechavarría, D. M., & Passerini, K. 2021. Gender and entrepreneurship: Research frameworks, barriers and opportunities for women entrepreneurship worldwide. Journal of Small Business Management, 59(sup1): 1-15.

Unger, H., & Kubek, M. 2019. On Evolving Text Centroids. In H. Unger, S. Sodsee & P. Meesad (Eds.), Recent Advances in Information and Communication Technology 2018: 75–82. Cham: Springer International Publishing.

United Nations. 2024. History of the Social Development Goals. Retrieved from https://sdgs.un.org/goals. Downloaded on January 25, 2024.

Uzuegbunam, I., Pathak, S., Taylor-Bianco, A., & Ofem, B. 2021. How cultural tightness interacts with gender in founding teams: Insights from the commercialization of social ventures. Journal of Business Venturing, 36(4): 106127.

van Rijnsoever, F. J. 2022. Intermediaries for the greater good: How entrepreneurial support organizations can embed constrained sustainable development startups in entrepreneurial ecosystems. Research Policy, 51(2): 104438.

Vicente-Molina, M. A., Fernández-Sainz, A., & Izagirre-Olaizola, J. 2018. Does gender make a difference in pro-environmental behavior? The case of the Basque Country University students. Journal of Cleaner Production, 176: 89–98.

Vogel, R., Puhan, T. X., Shehu, E., Kliger, D., & Beese, H. 2014. Funding decisions and entrepreneurial team diversity: A field study. Journal of Economic Behavior & Organization, 107: 595–613.

Witt, P. 2004. Entrepreneurs' networks and the success of start-ups. Entrepreneurship & Regional Development, 16(5): 391–412.

Woolridge, J. 2010. Econometric analysis of cross section and panel data (2nd ed.). Cambridge, Mass.: MIT Press.

Yacus, A. M., Esposito, S. E., & Yang, Y. 2019. The Influence of Funding Approaches, Growth Expectations, and Industry Gender Distribution on High-Growth Women Entrepreneurs. Journal of Small Business Management, 57(1): 59–80.

Zelezny, L. C., Chua, P.-P., & Aldrich, C. 2000. New Ways of Thinking about Environmentalism: Elaborating on Gender Differences in Environmentalism. Journal of Social Issues, 56(3): 443–457.

Zucker, L. G. 1987. Institutional Theories of Organization. Annual Review of Sociology, 13(1): 443–464.

3.9. APPENDIX

3.9.2 TABLES

Variable Name	Description	N	Mean	SD	Min	Max
Main variables						
Share of Women Founders	Share of women per startup team	64,190	0.12	0.27	0.00	1.00
Number of Funding Rounds Attracted	Total number of funding rounds attracted by a startup	64,190	3.08	2.51	1.00	41.00
Total Funding Attracted	Total Sum of all funding rounds attracted by a startup (in Tsd, per startup)	64,190	50,061.22	553,384.01	<0.01	100,000,000.00
Attracted Funding per Round	Funding attracted per investment round (in Tsd, per startup)	64,190	5,641.27	9,196.58	30.00	34,000.00
Dummy: Technological Orientation	Business approach: company description refers to technological or engineering approach (Y / N)	64,190	0.46	0.50	0.00	1.00
Factor: Inequality	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to reducing poverty and inequality.	64,190	0.63	0.10	0.08	0.97
Factor: Education	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to education.	64,190	0.58	0.10	0.00	0.97
Factor: Consumption	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to consumption and sustainable use of resources.	64,190	0.68	0.09	0.03	1.00
Control variables						
Share of Non-Binary Founders	Share of non-binary persons per startup team	64,190	0.00	0.03	0.00	1.00
Share of Foreign Founders	Share of foreigners per startup team	64,190	0.12	0.28	0.00	1.00
Founding Team Size	Number of founders per team	64,190	2.18	1.21	1.00	38.00
Maximal Work Experience	Number of jobs of the generally most experienced team member	64,190	1.41	2.42	0.00	63.00
Maximal Founding Experience	Number of startups founded by the entrepreneurially most experienced team member	64,190	0.44	0.98	0.00	31.00
Number of Social Media Accounts	Number of social media accounts used by startup	64,190	2.24	0.97	0.00	3.00
Investment Activities Dummy	Own investment activities of the startup (Y/N)	64,190	0.03	0.16	0.00	1.00
Average Degree	The mean level of education of a startup team (Bachelor = 1, Master = 2, PhD = 3)	64,190	1.74	0.64	1.00	3.00
Education Dummy: Agriculture	Dummy Indicator: A team member studied an agriculture-related career (Y/N)	64,190	0.00	0.03	0.00	1.00
Education Dummy: Architecture	Dummy Indicator: A team member studied an architecture-related career (Y/N)	64,190	0.00	0.04	0.00	1.00
Education Dummy: Business	Dummy Indicator: A team member studied a business-related career (Y/N)	64,190	0.29	0.45	0.00	1.00
Education Dummy: Economics	Dummy Indicator: A team member studied an economics-related career (Y/N)	64,190	0.07	0.26	0.00	1.00
Education Dummy: Education	Dummy Indicator: A team member studied an education-related career (Y/N)	64,190	0.00	0.06	0.00	1.00
Education Dummy: Engineering	Dummy Indicator: A team member studied an engineering-related career (Y/N)	64,190	0.35	0.48	0.00	1.00
Education Dummy: Health	Dummy Indicator: A team member studied a health-related career (Y/N)	64,190	0.00	0.05	0.00	1.00
Education Dummy: IT	Dummy Indicator: A team member studied an IT-related career (Y/N)	64,190	0.22	0.41	0.00	1.00
Education Dummy: Languages	Dummy Indicator: A team member studied a language-related career (Y/N)	64,190	0.01	0.09	0.00	1.00
Education Dummy: Law	Dummy Indicator: A team member studied a law-related career (Y/N)	64,190	0.02	0.15	0.00	1.00

Table A3.1- Descriptive statistics: Cross-Sectional Dataset (Only Funded Startups, Education-Related Variables)
(continues on next page)

Education Dummy: Media	Dummy Indicator: A team member studied a media-related career (Y/N)	64,190	0.00	0.04	0.00	1.00
Education Dummy: Medicine	Dummy Indicator: A team member studied a medicine-related career (Y/N)	64,190	0.02	0.15	0.00	1.00
Education Dummy: Arts	Dummy Indicator: A team member studied an arts-related career (Y/N)	64,190	0.02	0.13	0.00	1.00
Education Dummy: Psychology	Dummy Indicator: A team member studied a psychology-related career (Y/N)	64,190	0.01	0.11	0.00	1.00
Education Dummy: Public Services	Dummy Indicator: A team member studied with a focus on public service (Y/N)	64,190	0.00	0.02	0.00	1.00
Education Dummy: Religion & Philosophy	Dummy Indicator: A team member studied a religion- or philosophy-related career (Y/N)	64,190	0.01	0.09	0.00	1.00
Education Dummy: Sciences	Dummy Indicator: A team member studied a science-related career (Y/N)	64,190	0.13	0.34	0.00	1.00
Education Dummy: Social Sciences	Dummy Indicator: A team member studied a social-science-related career (Y/N)	64,190	0.02	0.13	0.00	1.00
Education Dummy: Sports	Dummy Indicator: A team member studied a sports-related career (Y/N)	64,190	0.00	0.03	0.00	1.00
Education Dummy: Tourism	Dummy Indicator: A team member studied a tourism-related career (Y/N)	64,190	0.00	0.02	0.00	1.00
Industry Dummy: Services	Target industry indicator: Services (Y/N)	64,190	0.28	0.45	0.00	1.00
Industry Dummy: Agriculture and Farming	Target industry indicator: Agriculture & Farming (Y/N)	64,190	0.02	0.13	0.00	1.00
Industry Dummy: Sales and Marketing	Target industry indicator: Sales & Marketing (Y/N)	64,190	0.05	0.22	0.00	1.00
Industry Dummy: Consumer Goods	Target industry indicator: Consumer goods (Y/N)	64,190	0.17	0.38	0.00	1.00
Industry Dummy: Education	Target industry indicator: Education (Y/N)	64,190	0.06	0.24	0.00	1.00
Industry Dummy: Food and Beverages	Target industry indicator: Foods & Beverages (Y/N)	64,190	0.05	0.23	0.00	1.00
Industry Dummy: Government and Military	Target industry indicator: Government & Military (Y/N)	64,190	0.04	0.20	0.00	1.00
Industry Dummy: Healthcare	Target industry indicator: Healthcare (Y/N)	64,190	0.01	0.10	0.00	1.00
Industry Dummy: Manufacturing	Target industry indicator: Manufacturing (Y/N)	64,190	0.18	0.38	0.00	1.00
Industry Dummy: Technology	Target industry indicator: Technology (Y/N)	64,190	0.19	0.39	0.00	1.00
Industry Dummy: Real Estate	Target industry indicator: Real estate (Y/N)	64,190	0.06	0.23	0.00	1.00
Industry Dummy: Science & Engineering	Target industry indicator: Science & Engineering (Y/N)	64,190	0.04	0.20	0.00	1.00
Industry Dummy: Sports	Target industry indicator: Sports (Y/N)	64,190	0.15	0.36	0.00	1.00
Industry Dummy: Tourism	Target industry indicator: Tourism (Y/N)	64,190	0.03	0.18	0.00	1.00
		Fixed effects				
started_on	The founding date of the startup	64,190	2012.96	5.31	1992.00	2022.00
country_code	Country location of the startup	64,190	101.86	46.40	1.00	144.00

Table A3.1 - Descriptive Statistics: Cross-Sectional Dataset (Only Funded Startups, Education-Related Variables)

		Model 8	Model 9	Model 10
	Dependent Variable:	Factor: Inequality	Factor: Education	Factor: Consumption
Founding Team	Share of Women Founders	0.02 ***	0.01 ***	-0.02 ***
		(<0.001)	(<0.001)	(<0.001)
	Share of Non-Binary Founders	-0.04 *	-0.01	-0.04 ***
		(0.01)	(0.72)	(<0.001)
	Share of Foreign Founders	0.01 **	-0.00	-0.00
		(0.01)	(0.15)	(0.54)
	Maximal Work Experience	0.00	0.00 ***	0.00
		(0.72)	(<0.001)	(0.22)
	Maximal Founding Experience	0.00	-0.00	-0.00 **
		(0.73)	(1.93)	(0.01)
	Team Size	0.00 ***	-0.00	0.00 *
		(<0.001)	(0.39)	(0.03)
	Average Educational Degree	-0.01 ***	-0.00 **	0.01 ***
		(<0.001)	(0.01)	(<0.001)
Startup	Number of Social Media Accounts	0.01 ***	0.01 ***	0.01 **
		(<0.001)	(<0.001)	(0.00)
	Own Investment Activities	-0.00	0.01 ***	0.01
		(0.43)	(<0.001)	(0.05)
	Education Dummy Variables	YES	YES	YES
	Industry Dummy Variables	YES	YES	YES
	R^2 (within)	0.06	0.22	0.17
	R^2	0.09	0.23	0.19

Table A3.2 - Founding Tendencies: Cross-Sectional Data (Education-Related Controls) * p<0.05 ** p<0.01 *** p<0.001

		Model 11	Model 12	Model 13	Model 14
	Dependent Variable	Log (Attracted Funding per Round)			
Founding Team	Share of Women Founders	-0.64 ***	-0.45 **	-0.21	0.17 *
		(<0.001)	(0.01)	(0.06)	(0.47)
	Share of Non-Binary Founders	-0.37	-0.39	-0.36	-0.26
		(0.30)	(0.27)	(0.30)	(0.47)
	Share of Foreign Founders	-0.12	-0.12	-0.12	-0.12
		(0.08)	(0.10)	(0.09)	(0.10)
Startup	Number of Social Media Accounts	0.25 ***	0.26 ***	0.25***	0.24 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	1.37 ***	1.37 ***	1.36 ***	1.36 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Average Educational Degree	0.17 ***	0.17 ***	0.17 ***	0.15 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality		-0.59 ***	-	-
			(<0.001)	-	-
	Share of Women Founders x Factor: Inequality		0.27	-	-
			(0.28)	-	-
	Factor: Education			0.71 ***	-
				(<0.001)	-
	Share of Women Founders x Factor: Education			-0.71 ***	-
				(<0.001)	-
	Factor: Consumption				2.60 ***
					(<0.001)
	Share of Women Founders x Factor: Consumption				-1.17 **
					(0.00)
	Industry Dummy Variables	YES	YES	YES	YES
	Education Dummy Variables	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal Work Experience	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES
	R^2 (within)	0.12	0.12	0.12	0.13
	R^2	0.24	0.24	0.24	0.25

Table A3.3 – Funding per Round: Cross-Sectional Data (Education-Related Controls) * p<0.05 ** p<0.01 *** p<0.001

Variable Name	Description	N	Mean	SD	Min	Max
Main variables						
Number of funding rounds attracted	Total number of funding rounds attracted by a startup	115,662	2.67	2.20	1.00	41.00
Total funding attracted	Total Sum of all funding rounds attracted by a startup (in Tsd, per startup)	115,662	36,284.38	411,864.96	<0.1	100,000,000.00
Dummy: Tech/Engineering Approach	Business approach: company description refers to technological or engineering approach (Y / N)	115,662	0.45	0.50	0.00	1.00

Table A3.4 - Descriptive statistics: Cross-Sectional Dataset: New Variables for Robustness Check

	Dependent Variable:	**Model 15** Factor: Inequality	**Model 16** Factor: Education	**Model 17** Factor: Consumption
Founding Team	Share of Women Founders	0.02 ***	0.01 ***	-0.01 ***
		(<0.001)	(<0.001)	(<0.001)
	Share of Non-Binary Founders	-0.03 ***	0.00	-0.01
		(0.00)	(0.58)	(0.42)
	Share of Foreign Founders	0.01 **	-0.00	-0.00
		(0.00)	(0.20)	(0.63)
	Maximal Work Experience	0.00 *	0.00 ***	0.00 **
		(0.02)	(<0.001)	(0.01)
	Maximal Founding Experience	0.00	-0.00	-0.00 ***
		(0.76)	(0.44)	(<0.001)
	Team Size	0.00 ***	0.00 **	0.00 **
		(<0.001)	(0.00)	(0.00)
Startup	Number of Social Media Accounts	0.01 ***	0.01 ***	0.00 **
		(<0.001)	(<0.001)	(0.01)
	Own Investment Activities	0.00	0.01 ***	0.00
		(0.77)	(0.00)	(0.20)
Tech Orientation	Dummy: Tech/Engineering Approach	0.00	0.02 ***	0.05 ***
		(0.40)	(<0.001)	(<0.001)
	Share of Women Founders x Dummy: Tech/Engineering Approach	-0.01 *	0.00 ***	0.00
		(0.01)	(0.00)	(0.77)
	Industry Dummy Variables	YES	YES	YES
	R^2 (within)	0.06	0.22	0.21
	R^2	0.09	0.23	0.23

Table A3.5 - Founding Tendencies: Cross-Sectional Data (Moderation of Technological Orientation) * p<0.05 ** p<0.01 *** p<0.001

	Model 18	Model 19	Model 20	Model 21
Dependent Variable:		Log (Attracted Funding per Round)		
Share of Women Founders	-0.57 ***	-0.41 ***	0.35 **	0.29
	(<0.001)	(<0.001)	(0.00)	(0.18)
Dummy: Tech/Engineering Approach	0.21 ***	-0.25 ***	-0.11	0.17
	(<0.001)	(<0.001)	(0.13)	(0.21)
Share of Women Founders x Dummy: Tech/Engineering Approach	0.03	0.22	-0.13	-0.31
	(0.40)	(0.35)	(0.55)	(0.18)
Factor: Inequality		-1.03 ***	-	-
		(<0.001)	-	-
Share of Women Founders x Factor: Inequality		-0.21	-	-
		(0.18)	-	-
Share of Women Founders x Factor: Inequality x Dummy: Tech/Engineering Approach		-0.34	-	-
		(0.34)	-	-
Factor: Education			0.30 *	-
			(0.03)	-
Share of Women Founders x Factor: Education			-0.38 *	-
			(0.02)	-
Share of Women Founders x Factor: Education x Dummy: Tech/Engineering Approach			0.26	-
			(0.26)	-
Factor: Consumption				2.14 ***
				(<0.001)
Share of Women Founders x Factor: Consumption				-1.31 ***
				(<0.001)
Share of Women Founders x Factor: Consumption x Dummy: Tech/Engineering Approach				0.57
				(0.13)
Share of Non-Binary founders	YES	YES	YES	YES
Share of Foreign Founders	YES	YES	YES	YES
Industry Dummy Variables	YES	YES	YES	YES
Maximal Founding Experience	YES	YES	YES	YES
Maximal Work Experience	YES	YES	YES	YES
Number of Social Media Accounts	YES	YES	YES	YES
Own Investment Activities	YES	YES	YES	YES
Team Size	YES	YES	YES	YES
Factor: Inequality x Dummy: Tech/Engineering Approach	NO	YES	NO	NO
Factor: Education x Dummy: Tech/Engineering Approach	NO	NO	YES	NO
Factor: Consumption x Dummy: Tech/Engineering Approach	NO	NO	NO	YES
R^2 (within)	0.08	0.09	0.08	0.09
R^2	0.21	0.21	0.21	0.22

Factors and Interaction Terms

Table A3.6 - Funding per Round: Cross-Sectional Data (Moderation of Technological Orientation) * p<0.05 ** p<0.01 *** p<0.001

Variable Name	Description	N	Mean	SD	Min	Max
			Main variables			
Share of Women Founders	Share of women per startup team	209,813	0.10	0.26	0.00	1.00
Number of funding rounds attracted	Total number of funding rounds attracted by a startup	209,813	1.13	0.41	1.00	17.00
Total funding attracted	Total Sum of all funding rounds attracted by a startup (in Tsd, per startup)	209,813	17,572.29	253,570.19	<0.01	100,000,000.00
Attracted Funding per Round	Funding attracted per investment round (in Tsd, per startup)	209,813	15,029.94	242,741.11	<0.01	100,000,000.00
Dummy: Tech/Engineering Orientation	Business approach: company description refers to technological or engineering approach (1 = Yes)	209,813	0.48	0.50	0.00	1.00
Factor: Inequality	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to reducing poverty and inequality.	209,813	0.62	0.10	0.02	0.97
Factor: Education	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to education.	209,813	0.58	0.10	0.00	0.98
Factor: Consumption	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to consumption and sustainable use of resources.	209,813	0.68	0.09	0.02	1.00
			Control variables			
Share of Non-Binary Founders	Share of non-binary persons per startup team	209,813	0.00	0.06	0.00	1.00
Share of Foreign Founders	Share of foreigners per startup team	209,813	0.10	0.27	0.00	1.00
Founding Team Size	Number of founders per team	209,813	1.88	1.08	1.00	38.00
Maximal Work Experience	Number of jobs of the generally most experienced team member	209,813	0.92	1.94	0.00	63.00
Maximal Founding Experience	Number of startups founded by the entrepreneurially most experienced team member	209,813	0.29	0.78	0.00	31.00
Number of Social Media Accounts	Number of social media accounts used by startup	209,813	2.18	1.01	0.00	3.00
Startup Age	Age of startup in the respective period	209,813	4.06	4.15	0.00	30.00
Investment Activities Dummy	Own investment activities of the startup (Y/N)	209,813	0.03	0.18	0.00	1.00
Industry Dummy: Services	Target industry indicator: Services (Y/N)	209,813	0.26	0.44	0.00	1.00
Industry Dummy: Agriculture and Farming	Target industry indicator: Agriculture & Farming (Y/N)	209,813	0.02	0.14	0.00	1.00
Industry Dummy: Sales and Marketing	Target industry indicator: Sales & Marketing (Y/N)	209,813	0.07	0.25	0.00	1.00

Table A3.7- Descriptive Statistics: Panel Data (Only Funded Startups) (continues on next page)

Industry Dummy: Consumer Goods	Target industry indicator: Consumer goods (Y/N)	209,813	0.16	0.37	0.00	1.00
Industry Dummy: Education	Target industry indicator: Education (Y/N)	209,813	0.06	0.24	0.00	1.00
Industry Dummy: Food and Beverages	Target industry indicator: Foods & Beverages (Y/N)	209,813	0.05	0.21	0.00	1.00
Industry Dummy: Government and Military	Target industry indicator: Government & Military (Y/N)	209,813	0.05	0.21	0.00	1.00
Industry Dummy: Healthcare	Target industry indicator: Healthcare (Y/N)	209,813	0.01	0.09	0.00	1.00
Industry Dummy: Manufacturing	Target industry indicator: Manufacturing (Y/N)	209,813	0.20	0.40	0.00	1.00
Industry Dummy: Technology	Target industry indicator: Technology (Y/N)	209,813	0.18	0.39	0.00	1.00
Industry Dummy: Real Estate	Target industry indicator: Real estate (Y/N)	209,813	0.06	0.23	0.00	1.00
Industry Dummy: Science & Engineering	Target industry indicator: Science & Engineering (Y/N)	209,813	0.04	0.20	0.00	1.00
Industry Dummy: Sports	Target industry indicator: Sports (Y/N)	209,813	0.19	0.39	0.00	1.00
Industry Dummy: Tourism	Target industry indicator: Tourism (Y/N)	209,813	0.03	0.17	0.00	1.00
Fixed effects						
started_on	The founding date of the startup	209,813	2014.24	4.87	1901.00	2022.00
announced_on	Year in which investment in a startup took place	209,813	2016.13	4.47	1992	2022
*country_code**	Country location of the startup	209,813	111.31	54.23	1.00	162.00

Table A3.7 - Descriptive Statistics: Panel Data (Only Funded Startups)

		Model 22	Model 23	Model 24	Model 25
	Dependent Variable	Log (Attracted Funding per Round)			
Founding Team	Share of Women Founders	-0.51 ***	-0.22 *	-0.21	0.09
		(<0.001)	(0.02)	(0.26)	(0.51)
	Share of Non-Binary Founders	-0.15	-0.16	-0.16	-0.16
		(0.20)	(0.18)	(0.19)	(0.21)
	Share of Foreign Founders	-0.11	-0.11	-0.11 *	-0.11 *
		(0.05)	(0.05)	(0.05)	(0.05)
Startup	Number of Social Media Accounts	0.14 ***	0.14 ***	0.13 ***	0.14 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	1.30 ***	1.29 ***	1.28 ***	1.32 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality		-0.30 ***	-	-
			(<0.001)	-	-
	Share of Women Founders x Factor: Inequality		-0.45 **	-	-
			(0.00)	-	-
	Factor: Education			0.59 **	-
				(0.00)	-
	Share of Women Founders x Factor: Education			-0.50	-
				(0.06)	-
	Factor: Consumption				1.17 ***
					(<0.001)
	Share of Women Founders x Factor: Consumption				-0.43 *
					(0.05)
Additional Controls	Industry Dummy Variables	YES	YES	YES	YES
	Firm Age [linear term]	YES	YES	YES	YES
	Firm Age [squared term]	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal Work Experience	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES
	R^2 (within)	0.11	0.11	0.11	0.12
	R^2	0.31	0.31	0.31	0.31

Table A3.8 - Attracted Funding per Round: Panel Data * p<0.05 ** p<0.01 *** p<0.001

	Model 26	Model 27	Model 28	Model 29
Dependent Variable:	Log (Attracted Funding per Round)			
Share of Women Founders	-0.53 ***	-0.38 ***	-0.30 *	-0.06
	(<0.001)	(<0.001)	(0.01)	(0.71)
Factors and Interaction Terms				
Dummy: Tech/Engineering Approach	0.09 ***	-0.29 **	-0.32 ***	0.36 **
	(<0.001)	(0.00)	(<0.001)	(0.00)
Share of Women Founders x Dummy: Tech/Engineering Approach	0.06	0.40 ***	0.14	-0.26
	(0.18)	(<0.001)	(0.52)	(0.32)
Factor: Inequality		-0.55 ***	-	-
		(<0.001)	-	-
Share of Women Founders x Factor: Inequality		-0.21	-	-
		(0.19)	-	-
Share of Women Founders x Factor: Inequality x Dummy: Tech/Engineering Approach		-0.56 **	-	-
		(0.00)	-	-
Factor: Education			0.29	-
			(0.09)	-
Share of Women Founders x Factor: Education			-0.39 *	-
			(0.01)	-
Share of Women Founders x Factor: Education x Dummy: Tech/Engineering Approach			-0.16	-
			(0.71)	-
Factor: Consumption				1.31 ***
				(<0.001)
Share of Women Founders x Factor: Consumption				-0.70 **
				(0.00)
Share of women founders x Factor: Consumption x Dummy: Tech/Engineering Approach				0.48
				(0.27)
Share of Non-Binary Founders	YES	YES	YES	YES
Firm Age [linear term]	YES	YES	YES	YES
Firm Age [squared term]	YES	YES	YES	YES
Share of Foreign Founders	YES	YES	YES	YES
Industry Dummy Variables	YES	YES	YES	YES
Maximal Founding Experience	YES	YES	YES	YES
Maximal Work Experience	YES	YES	YES	YES
Number of Social Media Accounts	YES	YES	YES	YES
Own Investment Activities	YES	YES	YES	YES
Team Size	YES	YES	YES	YES
Factor: Inequality x Dummy: Tech/Engineering Approach	NO	YES	NO	NO
Factor: Education x Dummy: Tech/Engineering Approach	NO	NO	YES	NO
Factor: Consumption x Dummy: Tech/Engineering Approach	NO	NO	NO	YES
R^2 (within)	0.11	0.11	0.11	0.12
R^2	0.35	0.35	0.35	0.35

Table A3.9 - Funding per Round: Panel Data (Moderation of Technological Orientation) * $p<0.05$ ** $p<0.01$ *** $p<0.001$

		Model 30	Model 31	Model 32	Model 33
	Dependent Variable	Log (Attracted Funding per Round)			
Founding Team	Share of Women Founders	-0.50 ***	-0.20 *	-0.22	-0.19
		(<0.001)	(0.03)	(0.26)	(0.21)
	Share of Non-Binary Founders	-0.17	-0.18	-0.18	-0.16
		(0.21)	(0.18)	(0.20)	(0.25)
	Share of Foreign Founders	-0.00 *	-0.00 *	-0.00 *	-0.00 *
		(0.97)	(0.96)	(0.96)	(1.00)
Startup	Number of Social Media Accounts	0.13 ***	0.14 ***	0.13 ***	0.13 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	1.35 ***	1.35 ***	1.34 ***	1.35 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality		-0.28 ***	-	-
			(<0.001)	-	-
	Share of Women Founders x Factor: Inequality		-0.47 **	-	-
			(0.00)	-	-
	Factor: Education			0.59 **	-
				(0.00)	-
	Share of Women Founders x Factor: Education			-0.49	-
				(0.07)	-
	Factor: Consumption				1.15 ***
					(<0.001)
	Share of Women Founders x Factor: Consumption				-0.46 *
					(0.03)
Additional Controls	Industry Dummy Variables	YES	YES	YES	YES
	Firm Age [linear term]	YES	YES	YES	YES
	Firm Age [squared term]	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal Work Experience	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES
	R^2 (within)	0.11	0.11	0.12	0.12
	R^2	0.36	0.36	0.36	0.36

Table A3.10 - Funding per Round: Panel Data (Interacted Fixed Effects) * p<0.05 ** p<0.01 *** p<0.001

		Model 34	Model 35	Model 36	Model 37
	Dependent Variable	Log (Attracted Funding per Round)			
Founding Team	Share of Women Founders	-0.51 ***	-0.21 *	-0.23 *	-0.17
		(<0.001)	(0.02)	(0.01)	(0.10)
	Share of Non-Binary Founders	-0.19 **	-0.19 **	-0.19 **	-0.18 **
		(0.01)	(0.00)	(0.00)	(0.01)
	Share of Foreign Founders	0.01	-0.01***	0.01	-0.00
		(0.71)	(0.63)	(0.65)	(0.84)
Startup	Number of Social Media Accounts	0.14 ***	0.14 ***	0.13 ***	0.13 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	1.35 ***	1.35 ***	1.34 ***	1.35 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality		-0.26 ***	-	-
			(<0.001)	-	-
	Share of Women Founders x Factor: Inequality		-0.47 ***	-	-
			(<0.001)	-	-
	Factor: Education			0.59 ***	-
				(<0.001)	-
	Share of Women Founders x Factor: Education			-0.47 ***	-
				(<0.001)	-
	Factor: Consumption				1.17 ***
					(<0.001)
	Share of Women Founders x Factor: Consumption				-0.49 **
					(0.00)
Additional Controls	Industry Dummy Variables	YES	YES	YES	YES
	Firm Age [linear term]	YES	YES	YES	YES
	Firm Age [squared term]	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal General Work Experience	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES
	R^2 (within)	0.21	0.21	0.21	0.22
	R^2 (conditional)	0.48	0.48	0.48	0.48

Table A3.11 - Funding per Round: Panel Data (Random Effects) * p<0.05 ** p<0.01 *** p<0.001

		Model 38	Model 39	Model 40	Model 41	Model 42	Model 43	Model 44	Model 45
	Dependent Variable:	*Log (Total Funding Attracted)*							
	Share of women founders	-0.68 ***	-0.40 **	-0.43 **	0.11 *	-0.68 ***	-0.52	-0.41	0.31
		(<0.001)	(0.01)	(0.00)	(0.67)	(<0.001)	(0.01)	(0.00)	(0.31)
Moderation Analysis: Factor Variables	Factor: Inequality		-0.68 ***	-	-	-	-0.71 ***	-	-
			(<0.001)	-	-	-	(<0.001)	-	-
	Share of Women Founders x Factor: Inequality		-0.42	-	-	-	-0.37	-	-
			(0.07)	-	-	-	(0.13)	-	-
	Factor: Education			0.42 **	-	-	-	0.08	-
				(0.00)	-	-	-	(0.41)	-
	Share of Women Founders x Factor: Education			-0.42 *	-	-	-	-0.44 *	-
				(0.05)	-	-	-	(0.04)	-
	Factor: Consumption				3.11 ***	-	-	-	2.39 ***
					(<0.001)	-	-	-	(<0.001)
	Share of Women Founders x Factor: Consumption				-1.13 **	-	-	-	-1.42 **
					(0.01)	-	-	-	(0.00)
Double Moderation Analysis: Factor Variables and Technological Orientation	Dummy: Tech/Engineering Approach					0.30 ***	-0.28 ***	0.09	0.16
						(<0.001)	(<0.001)	(0.18)	(0.30)
	Share of Women Founders x Dummy: Tech/Engineering Approach					-0.05	0.26	-0.11	-0.47
						(0.24)	(0.42)	(0.71)	(0.10)
	Share of Women Founders x Factor: Inequality x Dummy: Tech/Engineering Approach						-0.37	-	-
							(0.45)	-	-
	Share of Women Founders x Factor: Education x Dummy: Tech/Engineering Approach							0.26	-
								(0.60)	-
	Share of Women Founders x Factor: Consumption x Dummy: Tech/Engineering Approach								0.85
									(0.06)
	Share of Non-Binary Founders	YES	YES	YES	YES	YES	YES	YES	YES
	Share of Foreign Founders	YES	YES	YES	YES	YES	YES	YES	YES
	Industry Dummy variables	YES	YES	YES	YES	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES	YES	YES	YES	YES
	Maximal Work Experience	YES	YES	YES	YES	YES	YES	YES	YES
	Number of Social Media Accounts	YES	YES	YES	YES	YES	YES	YES	YES
	Own Investment Activities	YES	YES	YES	YES	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES	YES	YES	YES	YES
	Factor: Inequality x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	YES	NO	NO
	Factor: Education x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	NO	YES	NO
	Factor: Consumption x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	NO	NO	YES
	R^2 (within)	0.11	0.11	0.11	0.13	0.12	0.12	0.12	0.13
	R^2	0.22	0.22	0.22	0.23	0.22	0.22	0.22	0.23

Table A3.12 - Total Funding Attracted: Cross-Sectional Data * p<0.05 ** p<0.01 *** p<0.001

		Model 46	Model 47	Model 48	Model 49
	Dependent Variable	Log (Total Funding Attracted)			
Founding Team	Share of Women Founders	-0.75 ***	-0.56 **	-0.22	0.15
		(<0.001)	(0.01)	(0.08)	(0.62)
	Share of Non-Binary Founders	-0.38	-0.41	-0.38	-0.24
		(0.36)	(0.33)	(0.37)	(0.59)
	Share of Foreign Founders	-0.18 *	-0.18 *	-0.18 *	-0.18 *
		(0.01)	(0.01)	(0.03)	(0.02)
	Average Educational Degree	0.24 ***	0.24 ***	0.24 ***	0.21 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Startup	Number of Social Media Accounts	0.45 ***	0.45 ***	0.44 ***	0.43 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	2.20 ***	2.19 ***	2.19 ***	2.17 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality		-0.58 ***	-	-
			(<0.001)	-	-
	Share of Women Founders x Factor: Inequality		-0.29	-	-
			(0.36)	-	-
	Factor: Education			0.65 **	-
				(<0.001)	-
	Share of Women Founders x Factor: Education			-0.88 ***	-
				(<0.001)	-
	Factor: Consumption				3.66 ***
					(<0.001)
	Share of Women Founders x Factor: Consumption				-1.29 **
					(0.01)
Additional Controls	Industry Dummy Variables	YES	YES	YES	YES
	Education Dummy Variables	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal Work Experience	YES	YES	YES	YES
	Team size	YES	YES	YES	YES
	R^2 (within)	0.16	0.16	0.16	0.17
	R^2	0.26	0.26	0.26	0.27

Table A3.13 - Total Funding Attracted: Cross-Sectional Data (Education-Related Controls) * p<0.05 ** p<0.01 *** p<0.001

	Model 50	Model 51	Model 52	Model 53	Model 54	Model 55	Model 56	Model 57
Dependent Variable:	*Log (Total Funding Attracted)*							
Share of Women Founders	-0.52 ***	-0.23 **	-0.13	-0.25	-0.54 ***	-0.38 ***	-0.33 **	-0.09
	(<0.001)	(0.01)	(0.13)	(0.09)	(<0.001)	(<0.001)	(0.05)	(0.57)
Moderation Analysis: Factor Variables								
Factor: Inequality		-0.29 ***	-	-	-	-0.55 ***	-	-
		(<0.001)	-	-	-	(<0.001)	-	-
Share of Women Founders x Factor: Inequality		-0.44 **	-	-	-	-0.24	-	-
		(0.01)	-	-	-	(0.12)	-	-
Factor: Education			-0.54 **	-	-	-	0.23	-
			(0.00)	-	-	-	(0.17)	-
Share of Women Founders x Factor: Education			-0.48	-	-	-	-0.36 *	-
			(0.06)	-	-	-	(0.02)	-
Factor: Consumption				1.20 ***	-	-	-	1.35 ***
				(<0.001)	-	-	-	(<0.001)
Share of Women Founders x Factor: Consumption				-0.38	-	-	-	-0.67 **
				(0.07)	-	-	-	(0.01)
Double Moderation Analysis: Factor Variables and Technological Orientation								
Dummy: Tech/Engineering Orientation					0.09 ***	-0.29 **	-0.31 ***	0.37 **
					(<0.001)	(0.00)	(<0.001)	(0.00)
Share of Women Founders x Dummy: Tech/Engineering Orientation					0.06	0.36 ***	0.19	-0.28
					(0.09)	(<0.001)	(0.39)	(0.30)
Share of Women Founders x Factor: Inequality x Dummy: Tech/Engineering Orientation						-0.48 **	-	-
						(0.01)	-	-
Share of Women Founders x Factor: Education x Dummy: Tech/Engineering Orientation							-0.22	-
							(0.58)	-
Share of Women Founders x Factor: Consumption x Dummy: Tech/Engineering Orientation								0.52
								(0.25)
Share of Non-Binary Founders	YES	YES	YES	YES	YES	YES	YES	YES
Share of Foreign Founders	YES	YES	YES	YES	YES	YES	YES	YES
Industry Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES
Maximal Founding Experience	YES	YES	YES	YES	YES	YES	YES	YES
Maximal Work Experience	YES	YES	YES	YES	YES	YES	YES	YES
Number of Social Media Accounts	YES	YES	YES	YES	YES	YES	YES	YES
Own Investment Activities	YES	YES	YES	YES	YES	YES	YES	YES
Team Size	YES	YES	YES	YES	YES	YES	YES	YES
Factor: Inequality x Dummy: Tech/Engineering Orientation	NO	NO	NO	NO	NO	YES	NO	NO
Factor: Education x Dummy: Tech/Engineering Orientation	NO	NO	NO	NO	NO	NO	YES	NO
Factor: Consumption x Dummy: Tech/Engineering Orientation	NO	NO	NO	NO	NO	NO	NO	YES
R^2 (within)	0.11	0.11	0.11	0.12	0.11	0.11	0.11	0.12
R^2	0.34	0.34	0.34	0.35	0.34	0.34	0.34	0.35

Table A3.14 - Total Funding Attracted: Panel Data

* p<0.05 ** p<0.01 *** p<0.001

		Model 58	Model 59	Model 60	Model 61
	Dependent Variable	Log (Total Funding Attracted)			
Founding Team	Share of Women Founders	-0.51 ***	-0.21 *	-0.23	-0.23
		(<0.001)	(0.02)	(0.14)	(0.11)
	Share of Non-Binary Founders	-0.17	-0.18	-0.18	-0.17
		(0.20)	(0.18)	(0.20)	(0.24)
	Share of Foreign Founders	0.01	0.01	0.01	0.00 *
		(0.93)	(0.91)	(0.92)	(0.95)
Startup	Number of Social Media Accounts	0.14 ***	0.15 ***	0.14 ***	0.14 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	1.38 ***	1.38 ***	1.37 ***	1.38 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality		-0.28 ***	-	-
			(<0.001)	-	-
	Share of Women Founders x Factor: Inequality		-0.46 **	-	-
			(0.00)	-	-
	Factor: Education			0.54 **	-
				(0.00)	-
	Share of Women Founders x Factor: Education			-0.47	-
				(0.08)	-
	Factor: Consumption				1.19 ***
					(<0.001)
	Share of Women Founders x Factor: Consumption				-0.40 **
					(0.05)
Additional Controls	Industry Dummy Variables	YES	YES	YES	YES
	Firm Age [linear term]	YES	YES	YES	YES
	Firm Age [squared term]	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal Work Experience	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES
	R^2 (within)	0.11	0.11	0.11	0.12
	R^2	0.36	0.36	0.36	0.36

Table A3.15 - Total Funding Attracted: Panel Data (Interacted Fixed Effects) * p<0.05 ** p<0.01 *** p<0.001

		Model 62	Model 63	Model 64	Model 65
	Dependent Variable	Log (Total Funding Attracted)			
Founding Team	Share of Women Founders	-0.52 ***	-0.21 *	-0.25 **	-0.20
		(<0.001)	(0.02)	(0.00)	(006)
	Share of Non-Binary Founders	-0.19 **	-0.20 **	-0.20 *	-0.18 **
		(0.00)	(0.00)	(0.00)	(0.01)
	Share of Foreign Founders	0.01	0.01	0.01	0.01
		(0.52)	(0.46)	(0.48)	(0.64)
Startup	Number of Social Media Accounts	0.15 ***	0.15 ***	0.14 ***	0.14 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	1.39 ***	1.39 ***	1.38 ***	1.339***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality		-0.27 ***	-	-
			(<0.001)	-	-
	Share of Women Founders x Factor: Inequality		-0.48 **	-	-
			(0.01)	-	-
	Factor: Education			0.55 ***	-
				(<0.001)	-
	Share of Women Founders x Factor: Education			-0.47 **	-
				(0.00)	-
	Factor: Consumption				1.23 ***
					(<0.001)
	Share of Women Founders x Factor: Consumption				-0.45 **
					(0.00)
Additional Controls	Industry Dummy Variables	YES	YES	YES	YES
	Firm Age [linear term]	YES	YES	YES	YES
	Firm Age [squared term]	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal Work Experience	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES
	R^2 (marginal)	0.22	0.22	0.22	0.22
	R^2	0.48	0.48	0.48	0.48

Table A3.16 - Total Funding Attracted: Panel Data (Random Effects) * p<0.05 ** p<0.01 *** p<0.001

	Model 66	Model 67	Model 68	Model 69	Model 70	Model 71	Model 72	Model 73
Dependent Variable:	Number of Funding Rounds Attracted							
Share of Women Founders	-0.16 ***	0.01	-0.07	-0.06	-0.17 ***	0.08	-0.14	0.10
	(<0.001)	(0.84)	(0.30)	(0.64)	(<0.001)	(0.43)	(0.08)	(0.45)
Moderation Analysis: Factor Variables								
Factor: Inequality		0.32 **	-	-	-	0.18 *	-	-
		(0.01)	-	-	-	(0.04)	-	-
Share of Women Founders x Factor: Inequality		-0.28 *	-	-	-	-0.39	-	-
		(0.03)	-	-	-	(0.02)	-	-
Factor: Education			-0.57 ***	-	-	-	-0.45 ***	-
			(<0.001)	-	-	-	(<0.001)	-
Share of Women Founders x Factor: Education			-0.15 **	-	-	-	-0.04	-
			(0.01)	-	-	-	(0.72)	-
Factor: Consumption				2.09 ***	-	-	-	1.60 ***
				(<0.001)	-	-	-	(<0.001)
Share of Women Founders x Factor: Consumption				-0.10	-	-	-	-0.40
				(0.62)	-	-	-	(0.06)
Double Moderation Analysis: Factor Variables and Technological Orientation								
Dummy: Tech/Engineering Approach					0.28 ***	0.08	0.64 ***	-0.32 ***
					(<0.001)	(0.54)	(<0.001)	(<0.001)
Share of Women Founders x Dummy: Tech/Engineering Approach					0.04	-0.22	0.28	-0.51 *
					(0.18)	(0.41)	(0.10)	(0.02)
Share of Women Founders x Factor: Inequality x Dummy: Tech/Engineering Approach						0.39	-	-
						(0.33)	-	-
Share of Women Founders x Factor: Education x Dummy: Tech/Engineering Approach							-0.38	-
							(0.17)	-
Share of Women Founders x Factor: Consumption x Dummy: Tech/Engineering Approach								0.87 **
								(0.01)
Share of Non-Binary Founders	YES	YES	YES	YES	YES	YES	YES	YES
Share of Foreign Founders	YES	YES	YES	YES	YES	YES	YES	YES
Industry Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES
Maximal Founding Experience	YES	YES	YES	YES	YES	YES	YES	YES
Maximal Work Experience	YES	YES	YES	YES	YES	YES	YES	YES
Number of Social Media Accounts	YES	YES	YES	YES	YES	YES	YES	YES
Own Investment Activities	YES	YES	YES	YES	YES	YES	YES	YES
Team Size	YES	YES	YES	YES	YES	YES	YES	YES
Factor: Inequality x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	YES	NO	NO
Factor: Education x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	NO	YES	NO
Factor: Consumption x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	NO	NO	YES
R^2 (within)	0.10	0.10	0.10	0.10	0.10	0.10	0.11	0.11
R^2	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14

Table A3.17 - Number of Funding Rounds: Cross-Sectional Data * p<0.05 ** p<0.01 *** p<0.001

		Model 74	Model 75	Model 76	Model 77
	Dependent Variable	Number of Funding Rounds Attracted			
Founding Team	Share of Women Founders	-0.20 ***	-0.02	-0.04	0.06
		(<0.001)	(0.91)	(0.07)	(0.78)
	Share of Non-Binary Founders	-0.21	-0.20	-0.09	2.82 ***
		(0.51)	(0..52)	(0.08)	(<0.001)
	Share of Foreign Founders	-0.18 ***	-0.18 ***	-0.18 **	-0.17 **
		(<0.001)	(<0.001)	(0.00)	(0.00)
	Average Educational Degree	0.19 ***	0.19 ***	0.19 ***	0.176***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Startup	Number of Social Media Accounts	0.54 ***	0.54 ***	0.55 ***	0.53 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	2.17 ***	2.17 ***	2.18 ***	2.15 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality		0.17	-	-
			(0.22)	-	-
	Share of Women Founders x Factor: Inequality		-0.30	-	-
			(0.18)	-	-
	Factor: Education			-0.51 ***	-
				(<0.001)	-
	Share of Women Founders x Factor: Education			-0.30 **	-
				(0.01)	-
	Factor: Consumption				2.65 ***
					(<0.001)
	Share of Women Founders x Factor: Consumption				-0.19
					(0.41)
Additional Controls	Industry Dummy Variables	YES	YES	YES	YES
	Education Dummy Variables	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal Work Experience	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES
	R^2 (within)	0.12	0.12	0.12	0.13
	R^2	0.17	0.17	0.17	0.18

* p<0.05 ** p<0.01 *** p<0.001

Table A3.18 - Number of Funding Rounds: Cross-Sectional Data (Education-Related Controls)

	Model 78	Model 79	Model 80	Model 81	Model 82	Model 83	Model 84	Model 85
Dependent Variable:	*Number of Funding Rounds Attracted*							
Share of Women Founders	-0.01 ***	-0.02	-0.03 *	-0.09 ***	-0.03 ***	-0.03	-0.06 ***	-0.06 **
	(0.00)	(0.48)	(0.02)	(<0.001)	(<0.001)	(0.16)	(<0.001)	(0.00)
Moderation Analysis: Factor Variables								
Factor: Inequality		0.00	-	-	-	-0.00	-	-
		(0.85)	-	-	-	(0.69)	-	-
Share of Women Founders x Factor: Inequality		0.01	-	-	-	-0.04	-	-
		(0.83)	-	-	-	(0.32)	-	-
Factor: Education			-0.08 ***	-	-	-	-0.09 ***	-
			(<0.001)	-	-	-	(<0.001)	-
Share of Women Founders x Factor: Education			0.03	-	-	-	0.08 **	-
			(0.18)	-	-	-	(0.01)	-
Factor: Consumption				0.06 **	-	-	-	0.05 *
				(0.00)	-	-	-	(0.01)
Share of Women Founders x Factor: Consumption				0.08 *	-	-	-	0.04 *
				(0.05)	-	-	-	(0.43)
Double Moderation Analysis: Factor Variables and Technological Orientation								
Dummy: Tech/Engineering Approach					0.01 ***	0.00	0.01	0.02
					(<0.001)	(0.79)	(0.59)	(0.17)
Share of Women Founders x Dummy: Tech/Engineering Approach					0.01 **	-0.07	0.10 ***	-0.05
					(0.18)	(0.17)	(<0.001)	(0.22)
Share of Women Founders x Factor: Inequality x Dummy: Tech/Engineering Approach						0.13	-	-
						(0.08)	-	-
Share of Women Founders x Factor: Education x Dummy: Tech/Engineering Approach							-0.14 **	-
							(0.01)	-
Share of Women Founders x Factor: Consumption x Dummy: Tech/Engineering Approach								0.09
								(0.13)
Share of Non-Binary Founders	YES	YES	YES	YES	YES	YES	YES	YES
Share of Foreign Founders	YES	YES	YES	YES	YES	YES	YES	YES
Industry Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm Age [linear term]	YES	YES	YES	YES	YES	YES	YES	YES
Firm Age [squared term]	YES	YES	YES	YES	YES	YES	YES	YES
Maximal Founding Experience	YES	YES	YES	YES	YES	YES	YES	YES
Maximal Work Experience	YES	YES	YES	YES	YES	YES	YES	YES
Number of Social Media Accounts	YES	YES	YES	YES	YES	YES	YES	YES
Own Investment Activities	YES	YES	YES	YES	YES	YES	YES	YES
Team Size	YES	YES	YES	YES	YES	YES	YES	YES
Factor: Inequality x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	YES	NO	NO
Factor: Education x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	NO	YES	NO
Factor: Consumption x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	NO	NO	YES
R^2 (within)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table A3.19 - Number of Funding Rounds: Panel Data * $p<0.05$ ** $p<0.01$ *** $p<0.001$

		Model 86	Model 87	Model 88	Model 89
	Dependent Variable	Number of Funding Rounds Attracted			
Founding Team	Share of Women Founders	-0.01 *	-0.02	-0.03 *	-0.06 *
		(0.03)	(0.37)	(0.04)	(0.02)
	Share of Non-Binary Founders	-0.00	-0.00	-0.00	-0.00
		(0.72)	(0.72)	(0.77)	(0.76)
	Share of Foreign Founders	0.01	0.01	0.01	0.01
		(0.09)	(0.09)	(0.09)	(0.09)
Startup	Number of Social Media Accounts	0.02 ***	0.02 ***	0.02 ***	0.02 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	0.06 *	0.06 *	0.06 *	0.06 *
		(0.04)	(0.04)	(0.04)	(0.04)
Factors and Interaction Terms	Factor: Inequality		0.00	-	-
			(0.82)	-	-
	Share of Women Founders x Factor: Inequality		0.01	-	-
			(0.70)	-	-
	Factor: Education			-0.08 ***	-
				(<0.001)	-
	Share of Women Founders x Factor: Education			0.03	-
				(0.17)	-
	Factor: Consumption				0.06 **
					(0.00)
	Share of Women Founders x Factor: Consumption				0.08 *
					(0.05)
Additional Controls	Industry Dummy Variables	YES	YES	YES	YES
	Firm Age [linear term]	YES	YES	YES	YES
	Firm Age [squared term]	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal General Work Experience	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES
	R^2 (within)	0.01	0.01	0.01	0.01
	R^2	0.02	0.02	0.03	0.02

* p<0.05 ** p<0.01 *** p<0.001

Table A3.20 - Number of Funding Rounds: Panel Data (Interacted Fixed Effects)

		Model 90	Model 91	Model 92	Model 93
	Dependent Variable	Number of Funding Rounds Attracted			
Founding Team	Share of Women Founders	-0.01 **	-0.01	-0.03	-0.07 **
		(0.00)	(0.49)	(0.18)	(0.00))
	Share of Non-Binary Founders	-0.01	-0.01	-0.01	-0.01
		(0.59(	(0.59)	(0.62)	(0.61)
	Share of Foreign Founders	0.01 *	0.01 *	0.01 *	0.01 *
		(0.03)	(0.03)	(0.04)	(0.04)
Startup	Number of Social Media Accounts	0.02 ***	0.02 ***	0.02 ***	0.02 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	0.06 ***	0.06 ***	0.07 ***	0.06 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality		0.00	-	-
			(0.60)	-	-
	Share of Women Founders x Factor: Inequality		0.01	-	-
			(0.83)	-	-
	Factor: Education			-0.08 ***	-
				(<0.001)	-
	Share of Women Founders x Factor: Education			0.03	-
				(0.39)	-
	Factor: Consumption				0.06 *
					(0.01)
	Share of Women Founders x Factor: Consumption				0.09 **
					(0.01)
Additional Controls	Industry Dummy Variables	YES	YES	YES	YES
	Firm Age [linear term]	YES	YES	YES	YES
	Firm Age [squared term]	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal General Work Experience	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES
	R^2 (marginal)	0.01	0.01	0.02	0.01
	R^2	0.03	0.03	0.03	0.03

* p<0.05 ** p<0.01 *** p<0.001 .

Table A3.21 - Number of Funding Rounds: Panel Data (Random Effects)

Variable Name	Description	N	Mean	SD	Min	Max
Main Variables						
Share of Women Founders	Share of women per startup team	269,693	0.12	0.30	0.00	1.00
Dummy: Funding Attracted	Dummy variable describing whether the startup received funding or not (1 = Funded)	269,693	0.43	0.49	0.00	1.00
Dummy: Tech/Engineering Approach	Business approach: company description refers to technological or engineering approach (1 = Yes)	269,693	0.43	0.50	0.00	1.00
Factor: Inequality	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to reducing poverty and inequality.	269,693	0.61	0.11	0.00	1.00
Factor: Education	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to education.	269,693	0.60	0.10	0.00	1.00
Factor: Consumption	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to consumption and sustainable use of resources.	269,693	0.66	0.10	0.00	1.00
Control Variables						
Share of Non-Binary Founders	Share of non-binary persons per startup team	269,693	0.00	0.05	0.00	1.00
Share of Foreign Founders	Share of foreigners per startup team	269,693	0.10	0.28	0.00	1.00
Founding Team Size	Number of founders per team	269,693	1.56	0.87	1.00	38.00
Maximal Work Experience	Number of jobs of the generally most experienced team member	269,693	0.64	1.59	0.00	63.00
Maximal Founding Experience	Number of startups founded by the entrepreneurially most experienced team member	269,693	0.22	0.66	0.00	31.00
Number of Social Media Accounts	Number of social media accounts used by startup	269,693	2.08	1.01	0.00	3.00
Investment Activities Dummy	Own investment activities of the startup (Y/N)	269,693	0.02	0.13	0.00	1.00
Industry Dummy: Services	Target industry indicator: Services (Y/N)	269,693	0.30	0.46	0.00	1.00
Industry Dummy: Agriculture and Farming	Target industry indicator: Agriculture & Farming (Y/N)	269,693	0.01	0.11	0.00	1.00
Industry Dummy: Sales and Marketing	Target industry indicator: Sales & Marketing (Y/N)	269,693	0.05	0.23	0.00	1.00
Industry Dummy: Consumer Goods	Target industry indicator: Consumer goods (Y/N)	269,693	0.19	0.39	0.00	1.00
Industry Dummy: Education	Target industry indicator: Education (Y/N)	269,693	0.06	0.24	0.00	1.00
Industry Dummy: Food and Beverages	Target industry indicator: Foods & Beverages (Y/N)	269,693	0.06	0.24	0.00	1.00
Industry Dummy: Government and Military	Target industry indicator: Government & Military (Y/N)	269,693	0.04	0.20	0.00	1.00
Industry Dummy: Healthcare	Target industry indicator: Healthcare (Y/N)	269,693	0.01	0.09	0.00	1.00
Industry Dummy: Manufacturing	Target industry indicator: Manufacturing (Y/N)	269,693	0.13	0.34	0.00	1.00
Industry Dummy: Technology	Target industry indicator: Technology (Y/N)	269,693	0.19	0.39	0.00	1.00
Industry Dummy: Real Estate	Target industry indicator: Real estate (Y/N)	269,693	0.04	0.19	0.00	1.00
Industry Dummy: Science & Engineering	Target industry indicator: Science & Engineering (Y/N)	269,693	0.05	0.22	0.00	1.00
Industry Dummy: Sports	Target industry indicator: Sports (Y/N)	269,693	0.11	0.31	0.00	1.00
Industry Dummy: Tourism	Target industry indicator: Tourism (Y/N)	269,693	0.03	0.17	0.00	1.00
Fixed Effects						
started_on	The founding date of the startup	269,693	2011.98	6.35	1992.00	2022.00
*country_code**	Country location of the startup	269,693	121.50	60.74	1.00	184.00

Table A3.22 - Descriptive Statistics: Cross-Sectional Dataset (Funded and Non-Funded Startups)

		Model 94	Model 95	Model 96	Model 97	Model 98	Model 99	Model 100	Model 101
	Dependent Variable:	Investment Received (Y/N)							
	Share of Women Founders	-0.28 ***	-0.47 **	-0.02	-0.23 ***	-0.29 ***	0.53 ***	-0.04	-0.22 **
		(<0.001)	(0.01)	(0.56)	(<0.001)	(<0.001)	(<0.001)	(0.72)	(0.00)
Moderation Analysis: Factor Variables	Factor: Inequality		1.00 ***	-	-	-	0.82 ***	-	-
			(<0.001)	-	-	-	(<0.001)	-	-
	Share of Women Founders x Factor: Inequality		0.30	-	-	-	0.35	-	-
			(0.22)	-	-	-	(0.08)	-	-
	Factor: Education			-1.80 ***	-	-	-	-1.40 ***	-
				(<0.001)	-	-	-	(<0.001)	-
	Share of Women Founders x Factor: Education			-0.37 **	-	-	-	-0.40 **	-
				(0.00)	-	-	-	(0.00)	-
	Factor: Consumption				-1.34 ***	-	-	-	1.30 ***
					(<0.001)	-	-	-	(<0.001)
	Share of Women Founders x Factor: Consumption				-0.03	-	-		-0.09
					(0.75)	-	-		(0.27)
Double Moderation Analysis: Factor Variables and Technological Orientation	Technological orientation					0.19 ***	-0.13	1.06 ***	0.30 *
						(<0.001)	(0.12)	(<0.001)	(0.02)
	Share of Women Founders x Dummy: Tech/Engineering Approach					0.07	0.09	0.31	0.03
						(0.06)	(0.60)	(0.08)	(0.70)
	Share of Women Founders x Factor: Inequality x Dummy: Tech/Engineering Approach						-0.05	-	-
							(0.87)	-	-
	Share of Women Founders x Factor: Education x Dummy: Tech/Engineering Approach							-0.31	-
								(0.35)	-
	Share of Women Founders x Factor: Consumption x Dummy: Tech/Engineering Approach								0.05
									(0.57)
	Share of Non-Binary Founders	YES	YES	YES	YES	YES	YES	YES	YES
	Share of Foreign Founders	YES	YES	YES	YES	YES	YES	YES	YES
	Industry Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES
	Firm Age [linear term]	YES	YES	YES	YES	YES	YES	YES	YES
	Firm Age [squared term]	YES	YES	YES	YES	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES	YES	YES	YES	YES
	Maximal Work Experience	YES	YES	YES	YES	YES	YES	YES	YES
	Number of Social Media Accounts	YES	YES	YES	YES	YES	YES	YES	YES
	Own Investment Activities	YES	YES	YES	YES	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES	YES	YES	YES	YES
	Factor: Inequality x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	YES	NO	NO
	Factor: Education x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	NO	YES	NO
	Factor: Consumption x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	NO	NO	YES
	R^2 (adjusted)	0.11	0.11	0.11	0.11	0.11	0.11	0.12	0.11
	R^2	0.11	0.11	0.12	0.11	0.11	0.11	0.12	0.11

* p<0.05 ** p<0.01 *** p<0.001 .

Table A3.23 - Likelihood of Funding Attraction: Cross-Sectional Data (Moderation of Technological Orientation)

Share of Women in Startup Team	Model 94: Share of Women in Startup Team	Model 95: Share of Women in Startup Team X Factor: Inequality	Model 96: Share of Women in Startup Team X Factor: Education	Model 97: Share of Women in Startup Team X Factor: Consumption
25%-75%	**-0.03 *****	**0.20 *****	**-0.42 *****	**0.24 *****
	(<0.001)	**(<0.001)**	**(<0.001)**	**(<0.001)**
0%-100%	-0.06 ***	0.17 ***	-0.44 ***	0.21 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Comment:	*Marginal Effects are calculated based on a change from 0 to 1 of the respective factor variable*			

Table A3.24 – Likelihood of Funding Attraction: Marginal Effects, Cross-Sectional Data * p<0.05 ** p<0.01 *** p<0.001

Share of Women in Startup Team	Model 98: Share of Women in Startup Team X Dummy: Tech	Model 99: Share of Women in Startup Team X Factor: Inequality X Dummy: Tech	Model 100: Share of Women in Startup Team X Factor: Education X Dummy: Tech	Model 101: Share of Women in Startup Team X Factor: Consumption X Dummy: Tech
25%-75%	**0.02 *****	**0.25 *****	**-0.40 *****	**0.24 *****
	(<0.001)	**(<0.001)**	**(<0.001)**	**(<0.001)**
0%-100%	-0.01 ***	0.22 ***	-0.41 ***	0.22 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Comment:	*Marginal Effects are calculated based on a change from 0 to 1 of the respective factor variable and Dummy: Tech*			

* p<0.05 ** p<0.01 *** p<0.001

Table A3.25 - Likelihood of Funding Attraction: Marginal Effects, Cross-Sectional Data (Moderation of Technological Orientation)

Variable Name	Description	N	Mean	SD	Min	Max
			Main Variables			
Share of Women Founders	Share of women per startup team	129,905	0.13	0.29	0.00	1.00
Dummy: Funding Attracted	Dummy variable describing whether the startup received funding or not (1 = Funded)	129,905	0.49	0.50	0.00	1.00
Dummy: Tech/Engineering Approach	Business approach: company description refers to technological or engineering approach (1 = Yes)	129,905	0.44	0.50	0.00	1.00
Factor: Inequality	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to reducing poverty and inequality.	129,905	0.61	0.11	0.00	1.00
Factor: Education	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to education.	129,905	0.60	0.10	0.00	1.00
Factor: Consumption	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to consumption and sustainable use of resources.	129,905	0.67	0.09	0.00	1.00
			Control Variables			
Share of Non-Binary Founders	Share of non-binary persons per startup team	129,905	0.00	0.03	0.00	1.00
Share of Foreign Founders	Share of foreigners per startup team	129,905	0.12	0.29	0.00	1.00
Founding Team Size	Number of founders per team	129,905	1.88	1.10	1.00	38.00
Maximal Work Experience	Number of jobs of the generally most experienced team member	129,905	1.17	2.15	0.00	63.00
Maximal Founding Experience	Number of startups founded by the entrepreneurially most experienced team member	129,905	0.37	0.86	0.00	31.00
Number of Social Media Accounts	Number of social media accounts used by startup	129,905	2.17	0.97	0.00	3.00
Investment Activities Dummy	Own investment activities of the startup (Y/N)	129,905	0.02	0.14	0.00	1.00
Average Degree	The mean level of education of a startup team (Bachelor = 1, Master = 2, PhD = 3)	129,905	1.69	0.64	0.00	1.00
Education Dummy: Agriculture	Dummy Indicator: A team member studied an agriculture-related career (Y/N)	129,905	0.00	0.03	0.00	1.00
Education Dummy: Architecture	Dummy Indicator: A team member studied an architecture-related career (Y/N)	129,905	0.00	0.04	0.00	1.00
Education Dummy: Business	Dummy Indicator: A team member studied a business-related career (Y/N)	129,905	0.30	0.46	0.00	1.00
Education Dummy: Economics	Dummy Indicator: A team member studied an economics-related career (Y/N)	129,905	0.07	0.25	0.00	1.00
Education Dummy: Education	Dummy Indicator: A team member studied an education-related career (Y/N)	129,905	0.00	0.07	0.00	1.00
Education Dummy: Engineering	Dummy Indicator: A team member studied an engineering-related career (Y/N)	129,905	0.34	0.47	0.00	1.00
Education Dummy: Health	Dummy Indicator: A team member studied a health-related career (Y/N)	129,905	0.00	0.05	0.00	1.00
Education Dummy: IT	Dummy Indicator: A team member studied an IT-related career (Y/N)	129,905	0.21	0.41	0.00	1.00
Education Dummy: Languages	Dummy Indicator: A team member studied a language-related career (Y/N)	129,905	0.01	0.09	0.00	1.00
Education Dummy: Law	Dummy Indicator: A team member studied a law-related career (Y/N)	129,905	0.02	0.15	0.00	1.00
Education Dummy: Media	Dummy Indicator: A team member studied a media-related career (Y/N)	129,905	0.00	0.04	0.00	1.00

Table A3.26 - Descriptive statistics: Cross-Sectional Data (Non- Funded Startups, Education-Related Variables)
(continues on next page)

Education Dummy: Medicine	Dummy Indicator: A team member studied a medicine-related career (Y/N)	129,905	0.02	0.14	0.00	1.00
Education Dummy: Arts	Dummy Indicator: A team member studied an arts-related career (Y/N)	129,905	0.02	0.14	0.00	1.00
Education Dummy: Psychology	Dummy Indicator: A team member studied a psychology-related career (Y/N)	129,905	0.01	0.11	0.00	1.00
Education Dummy: Public Services	Dummy Indicator: A team member studied with a focus on public service (Y/N)	129,905	0.00	0.02	0.00	1.00
Education Dummy: Religion & Philosophy	Dummy Indicator: A team member studied a religion- or philosophy-related career (Y/N)	129,905	0.01	0.09	0.00	1.00
Education Dummy: Sciences	Dummy Indicator: A team member studied a science-related career (Y/N)	129,905	0.11	0.32	0.00	1.00
Education Dummy: Social Sciences	Dummy Indicator: A team member studied a social-science-related career (Y/N)	129,905	0.02	0.14	0.00	1.00
Education Dummy: Sports	Dummy Indicator: A team member studied a sports-related career (Y/N)	129,905	0.00	0.03	0.00	1.00
Educataion Dummy: Tourism	Dummy Indicator: A team member studied a tourism-related career (Y/N)	129,905	0.00	0.02	0.00	1.00
Industry Dummy: Services	Target industry indicator: Services (Y/N)	129,905	0.31	0.46	0.00	1.00
Industry Dummy: Agriculture and Farming	Target industry indicator: Agriculture & Farming (Y/N)	129,905	0.01	0.11	0.00	1.00
Industry Dummy: Sales and Marketing	Target industry indicator: Sales & Marketing (Y/N)	129,905	0.05	0.21	0.00	1.00
Industry Dummy: Consumer Goods	Target industry indicator: Consumer goods (Y/N)	129,905	0.19	0.39	0.00	1.00
Industry Dummy: Education	Target industry indicator: Education (Y/N)	129,905	0.06	0.24	0.00	1.00
Industry Dummy: Food and Beverages	Target industry indicator: Foods & Beverages (Y/N)	129,905	0.06	0.24	0.00	1.00
Industry Dummy: Government and Military	Target industry indicator: Government & Military (Y/N)	129,905	0.04	0.19	0.00	1.00
Industry Dummy: Healthcare	Target industry indicator: Healthcare (Y/N)	129,905	0.01	0.10	0.00	1.00
Industry Dummy: Manufacturing	Target industry indicator: Manufacturing (Y/N)	129,905	0.15	0.36	0.00	1.00
Industry Dummy: Technology	Target industry indicator: Technology (Y/N)	129,905	0.20	0.40	0.00	1.00
Industry Dummy: Real Estate	Target industry indicator: Real estate (Y/N)	129,905	0.04	0.20	0.00	1.00
Industry Dummy: Science & Engineering	Target industry indicator: Science & Engineering (Y/N)	129,905	0.05	0.22	0.00	1.00
Industry Dummy: Sports	Target industry indicator: Sports (Y/N)	129,905	0.11	0.31	0.00	1.00
Industry Dummy: Tourism	Target industry indicator: Tourism (Y/N)	129,905	0.03	0.17	0.00	1.00
		Fixed Effects				
started_on	The founding date of the startup	129,905	2012.41	6.00	1992.00	2022.00
country_code	Country location of the startup	129,905	117.32	54.79	1.00	167.00

Table A3.26 - Descriptive statistics: Cross-Sectional Data (Non-Funded Startups, Education-Related Variables)

		Model 102	Model 103	Model 104	Model 105
	Dependent Variable	Investment received (Y/N)			
Founding Team	Share of Women Founders	0.86 **	0.53 ***	1.28 *	1.13
		(0.00)	(<0.001)	(0.04)	(0.20)
	Share of Non-Binary Founders	1.35	1.35	1.33 *	1.63 **
		(0.07)	(0.06)	(0.03)	(0.00)
	Share of Foreign Founders	0.98	0.97	0.97	0.98
		(0.48)	(0.33)	(0.23)	(0.73)
Startup	Number of Social Media Accounts	1.14 ***	1.13 ***	1.16 ***	1.14 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	1.63 ***	1.62 ***	1.67 ***	1.60 **
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality		4.13 ***	-	-
			(<0.001)	-	-
	Share of Women Founders x Factor: Inequality		2.12 ***	-	-
			(<0.001)	-	-
	Factor: Education			0.16 ***	-
				(<0.001)	-
	Share of Women Founders x Factor: Education			0.55 **	-
				(0.00)	-
	Factor: Consumption				3.55 ***
					(<0.001)
	Share of Women Founders x Factor: Consumption				0.72 **
					(0.00)
Additional Controls	Industry Dummy Variables	YES	YES	YES	YES
	Firm Age [linear term]	YES	YES	YES	YES
	Firm Age [squared term]	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal General Work Experience	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES
	R^2 (adjusted)	0.11	0.11	0.11	0.11
	R^2	0.11	0.11	0.11	0.11

* p<0.05 ** p<0.01 *** p<0.001

Table A3.27 - Likelihood of Funding Attraction: Cross-Sectional Data (Considering Education-Related Controls)

Share of Women in Startup Team	**Model 102: Share of Women in Startup Team**	**Model 103: Share of Women in Startup Team X Factor: Inequality**	**Model 104: Share of Women in Startup Team X Factor: Education**	**Model 105: Share of Women in Startup Team X Factor: Consumption**
25%-75%	**-0.02 *****	**0.34 *****	**-0.44 *****	**0.22 ****
	(<0.001)	**(<0.001)**	**(<0.001)**	**(0.00)**
0%-100%	-0.03 ***	0.32 ***	-0.44 ***	0.22 **
	(<0.001)	(<0.001)	(<0.001)	(0.00)
Comment:	*Marginal Effects are calculated based on a change from 0 to 1 of the respective factor variable*			

* p<0.05 ** p<0.01 *** p<0.001 .

Table A3.28 - Likelihood of Funding Attraction: Marginal Effects, Cross-Sectional Data (Education-Related Controls

Variable Name	Description	N	Mean	SD	Min	Max
Main Variables						
Share of Women Founders	Share of women per startup team	1,054,182	0.10	0.26	0	1
Dummy: Funding Attracted	Dummy variable describing whether the startup received funding or not.	1,054,182	0.27	0.45	0	1
Dummy: Tech/Engineering Approach	Business approach: company description refers to technological or engineering approach (Y/N).	1,054,182	0.46	0.50	0	1
Factor: Inequality	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to reducing poverty and inequality.	1,054,182	0.63	0.11	0	1
Factor: Education	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to education.	1,054,182	0.59	0.10	0	1
Factor: Consumption	Factor describing the degree to which the startup's focus on United Nations Sustainable Development Goals related to consumption and sustainable use of resources.	1,054,182	0.67	0.10	0	1
Control Variables						
Share of Non-Binary founders	Share of non-binary persons per startup team	1,054,182	0.00	0.06	0	1
Share of Foreign Founders	Share of foreigners per startup team	1,054,182	0.11	0.28	0	1
Founding Team Size	Number of founders per team	1,054,182	1.76	1.01	1	38
Maximal Work Experience	Number of jobs of the generally most experienced team member	1,054,182	0.77	1.83	0	63
Maximal Founding Experience	Number of startups founded by the entrepreneurially most experienced team member	1,054,182	0.24	0.75	0	31
Number of Social Media Accounts	Number of social media accounts used by startup	1,054,182	2.05	1.07	0	3
Firm age	Age of startup in the respective period	1,054,182	4.57	4.14	0	30
Investment Activities Dummy	Own investment activities of the startup (Y/N)	1,054,182	0.03	0.17	0	1
Industry Dummy: Services	Target industry indicator: Services (Y/N)	1,054,182	0.26	0.44	0	1
Industry Dummy: Agriculture and Farming	Target industry indicator: Agriculture & Farming (Y/N)	1,054,182	0.01	0.12	0	1
Industry Dummy: Sales and Marketing	Target industry indicator: Sales & Marketing (Y/N)	1,054,182	0.06	0.24	0	1
Industry Dummy: Consumer Goods	Target industry indicator: Consumer goods (Y/N)	1,054,182	0.17	0.38	0	1
Industry Dummy: Education	Target industry indicator: Education (Y/N)	1,054,182	0.06	0.24	0	1
Industry Dummy: Food and Beverages	Target industry indicator: Foods & Beverages (Y/N)	1,054,182	0.05	0.22	0	1
Industry Dummy: Government and Military	Target industry indicator: Government & Military (Y/N)	1,054,182	0.04	0.20	0	1

Table A3.29 - Descriptive Statistics: Panel Data (Non-Funded Startups) (continues on next page)

Industry Dummy: Healthcare	Target industry indicator: Healthcare (Y/N)	1,054,182	0.01	0.09	0	1
Industry Dummy: Manufacturing	Target industry indicator: Manufacturing (Y/N)	1,054,182	0.17	0.37	0	1
Industry Dummy: Technology	Target industry indicator: Technology (Y/N)	1,054,182	0.19	0.39	0	1
Industry Dummy: Real Estate	Target industry indicator: Real estate (Y/N)	1,054,182	0.06	0.23	0	1
Industry Dummy: Science & Engineering	Target industry indicator: Science & Engineering (Y/N)	1,054,182	0.04	0.19	0	1
Industry Dummy: Sports	Target industry indicator: Sports (Y/N)	1,054,182	0.15	0.36	0	1
Industry Dummy: Tourism	Target industry indicator: Tourism (Y/N)	1,054,182	0.03	0.17	0	1
Fixed Effects						
started_on	The founding date of the startup	1,054,182	2012.86	5.08	1992	2022
announced_on	Year in which investment in a startup took place	1,054,182	2017.43	4.14	1992	2022
country_code	Country location of the startup	1,054,182	113.03	55.27	1	166

Table A3.29 - Descriptive Statistics: Panel Data (Funded and Non-Funded Startups)

	Model 106	Model 107	Model 108	Model 109	Model 110	Model 111	Model 112	Model 113
Dependent Variable:	Investment received (Y/N)							
Share of Women Founders	0.10 ***	0.02	-0.03	0.08	-0.09 ***	0.05	-0.06	0.20
	(<0.001)	(0.60)	(0.39)	(0.38)	(<0.001)	(0.56)	(0.07)	(0.08)
Moderation Analysis: Factor Variables								
Factor: Inequality		0.09	-	-	-	0.02	-	-
		(0.31)	-	-	-	(0.78)	-	-
Share of Women Founders x Factor: Inequality		-0.18 ***	-	-	-	-0.23 *	-	-
		(<0.001)	-	-	-	(0.03)	-	-
Factor: Education			-0.25 ***	-	-	-	-0.20 ***	-
			(<0.001)	-	-	-	(<0.001)	-
Share of Women Founders x Factor: Education			-0.11 ***	-	-	-	-0.06	-
			(<0.001)	-	-	-	(0.42)	-
Factor: Consumption				1.63 ***	-	-	-	1.35 ***
				(0.00)	-	-	-	(<0.001)
Share of Women Founders x Factor: Consumption				-0.23 *	-	-	-	-0.43 **
				(0.05)	-	-	-	(0.00)
Double Moderation Analysis: Factor Variables and Technological Orientation								
Dummy: Tech/Engineering Approach					0.17 ***	0.07	0.36 ***	-0.19 ***
					(<0.001)	(0.25)	(<0.001)	(<0.001)
Share of Women Founders x Dummy: Tech/Engineering Approach					0.01	-0.10	0.13	-0.38 *
					(0.79)	(0.54)	(0.22)	(0.01)
Share of Women Founders x Factor: Inequality x Dummy: Tech/Engineering Approach						0.16	-	-
						(0.50)	-	-
Share of Women Founders x Factor: Education x Dummy: Tech/Engineering Approach							-0.19	-
							(0.33)	-
Share of Women Founders x Factor: Consumption x Dummy: Tech/Engineering Approach								0.61 **
								(0.00)
Share of Non-Binary Founders	YES	YES	YES	YES	YES	YES	YES	YES
Share of Foreign Founders	YES	YES	YES	YES	YES	YES	YES	YES
Industry Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm Age [linear term]	YES	YES	YES	YES	YES	YES	YES	YES
Firm Age [squared term]	YES	YES	YES	YES	YES	YES	YES	YES
Maximal Founding Experience	YES	YES	YES	YES	YES	YES	YES	YES
Maximal Work Experience	YES	YES	YES	YES	YES	YES	YES	YES
Number of Social Media Accounts	YES	YES	YES	YES	YES	YES	YES	YES
Own Investment Activities	YES	YES	YES	YES	YES	YES	YES	YES
Team Size	YES	YES	YES	YES	YES	YES	YES	YES
Factor: Inequality x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	YES	NO	NO
Factor: Education x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	NO	YES	NO
Factor: Consumption x Dummy: Tech/Engineering Approach	NO	NO	NO	NO	NO	NO	NO	YES
R^2 (adjusted)	0.29	0.29	0.29	0.30	0.29	0.29	0.29	0.30
R^2	0.29	0.29	0.29	0.30	0.29	0.29	0.29	0.30

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table A3.30 - Likelihood of Funding Attraction: Panel Data (Moderation of Technological Orientation)

Share of Women in Startup Team	Model 106: Share of Women in Startup Team	Model 107: Share of Women in Startup Team X Factor: Inequality	Model 108: Share of Women in Startup Team X Factor: Education	Model 109: Share of Women in Startup Team X Factor: Consumption
25%-75%	**-0.01 *****	**-0.00**	**-0.05 *****	**0.18 *****
	(<0.001)	**(0.70)**	**(<0.001)**	**(<0.001)**
0%-100%	-0.01 ***	-0.01	-0.05 ***	0.18 ***
	(<0.001)	(0.39)	(<0.001)	(<0.001)
Comment:	*Marginal Effects are calculated based on a change from 0 to 1 of the respective factor variable*			

* p<0.05 ** p<0.01 *** p<0.001

Table A3.31 - Likelihood of Funding Attraction: Marginal Effects, Panel Data

Share of Women in Startup Team	Model 110: Share of Women in Startup Team X Dummy: Tech	Model 111: Share of Women in Startup Team X Factor: Inequality X Dummy: Tech	Model 112: Share of Women in Startup Team X Factor: Education X Dummy: Tech	Model 113: Share of Women in Startup Team X Factor: Consumption X Dummy: Tech
25%-75%	**-0.01 *****	**0.02 *****	**-0.03 *****	**0.20 *****
	(<0.001)	**(0.04)**	**(<0.001)**	**(<0.001)**
0%-100%	-0.01 ***	0.02 ***	-0.04 ***	0.20 ***
	(<0.001)	(0.04)	(<0.001)	(<0.001)
Comment:	*Marginal Effects are calculated based on a change from 0 to 1 of the respective factor variable and Dummy: Tech*			

* p<0.05 ** p<0.01 *** p<0.001

Table A3.32 - Likelihood of Funding Attraction: Marginal Effects, Panel Data (Moderation of Technological Orientation)

		Model 114	Model 115	Model 116	Model 117
	Dependent variable	Investment received (Y/N)			
Founding Team	Share of Women Founders	0.91 ***	1.02	0.97	1.10
		(<0.001)	(0.58)	(0.38)	(0.32)
	Share of Non-Binary Founders	0.97	0.97	0.97	0.97
		(0.60)	(0.63)	(0.61)	(0.63)
	Share of Foreign Founders	0.92 *	0.92 *	0.92 *	0.92 *
		(0.01)	(0.01)	(0.01)	(0.01)
Startup	Number of Social Media Accounts	1.33 ***	1.33 ***	1.33 ***	1.32 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	1.63 **	1.63 **	1.64 **	1.61 **
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality		1.10	-	-
			(0.31)	-	-
	Share of Women Founders x Factor: Inequality		0.83 ***	-	-
			(<0.001)	-	-
	Factor: Education			0.78 ***	-
				(<0.001)	-
	Share of Women Founders x Factor: Education			0.90 ***	-
				(<0.001)	-
	Factor: Consumption				5.22 ***
					(<0.001)
	Share of Women Founders x Factor: Consumption				0.75 *
					(0.04)
Additional Controls	Industry Dummy Variables	YES	YES	YES	YES
	Firm Age [linear term]	YES	YES	YES	YES
	Firm Age [squared term]	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal General Work Experience	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES
	R^2 (adjusted)	0.30	0.30	0.30	0.30
	R^2	0.30	0.30	0.30	0.30

* p<0.05 ** p<0.01 *** p<0.001

Table A3.33 - Likelihood of Funding Attraction: Panel Data (Interacted Fixed Effects)

Share of Women in Startup Team	Model 114: Share of Women in Startup Team	Model 115: Share of Women in Startup Team X Factor: Inequality	Model 116: Share of Women in Startup Team X Factor: Education	Model 117: Share of Women in Startup Team X Factor: Consumption
25%-75%	**-0.01**	**-0.00**	**-0.05**	**0.18**
	(<0.001)	**(0.71)**	**(<0.001)**	**(<0.001)**
0%-100%	-0.01	0.01	-0.05	0.18
	(<0.001)	(0.41)	(<0.001)	(<0.001)
Comment:		*Marginal Effects are calculated based on a change from 0 to 1 of the respective factor variable*		

* p<0.05 ** p<0.01 *** p<0.001

Table A3.34 - Likelihood of Funding Attraction: Marginal Effects, Panel Data (Interacted Fixed Effects)

		Model 118	Model 119	Model 120	Model 121
	Dependent variable	Investment received (Y/N)			
Founding Team	Share of Women Founders	0.92 ***	1.03	0.97	1.10
		(<0.001)	(0.67)	(0.59)	(0.17)
	Share of Non-Binary Founders	0.96	0.96	0.96	0.97
		(0.41)	(0.43)	(0.41)	(0.56)
	Share of Foreign Founders	0.93 ***	0.93 ***	0.93 ***	0.93 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Startup	Number of Social Media Accounts	1.30 ***	1.32 ***	1.33 ***	1.31 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Own Investment Activities	1.63 ***	1.64 ***	1.65 ***	1.62 ***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)
Factors and Interaction Terms	Factor: Inequality		1.10 ***	-	-
			(<0.001)	-	-
	Share of Women Founders x Factor: Inequality		0.83 *	-	-
			(0.04)	-	-
	Factor: Education			0.79 ***	-
				(<0.001)	-
	Share of Women Founders x Factor: Education			0.90	-
				(0.27)	-
	Factor: Consumption				5.10 ***
					(<0.001)
	Share of Women Founders x Factor: Consumption				0.79 *
					(0.02)
Additional Controls	Industry Dummy Variables	YES	YES	YES	YES
	Firm Age [linear term]	YES	YES	YES	YES
	Firm Age [squared term]	YES	YES	YES	YES
	Maximal Founding Experience	YES	YES	YES	YES
	Maximal General Work Experience	YES	YES	YES	YES
	Team Size	YES	YES	YES	YES
	R^2 (marginal)	0.54	0.47	0.47	0.48
	R^2	0.60	0.53	0.53	0.53

* p<0.05 ** p<0.01 *** p<0.001

Table A3.35 - Likelihood of Funding Attraction: Panel Data (Random Effects)

Share of Women in Startup Team	Model 118: Share of Women in Startup Team	Model 119: Share of Women in Startup Team X Factor: Inequality	Model 120: Share of Women in Startup Team X Factor: Education	Model 121: Share of Women in Startup Team X Factor: Consumption
25%-75%	**-0.01 *****	**-0.00 *****	**-0.04 *****	**0.18 *****
	(<0.001)	**(<0.001)**	**(<0.001)**	**(<0.001)**
0%-100%	-0.01 ***	-0.01	-0.05 ***	0.18 ***
	(<0.001)	(0.08)	(<0.001)	(<0.001)
Comment:	*Marginal Effects are calculated based on a change from 0 to 1 of the respective factor variable and Dummy: Tech*			

* p<0.05 ** p<0.01 *** p<0.001

Table A3.36 - Likelihood of Funding Attraction, Marginal Effects, Panel Data (Random Effects)

3.9.3 GRAPHS

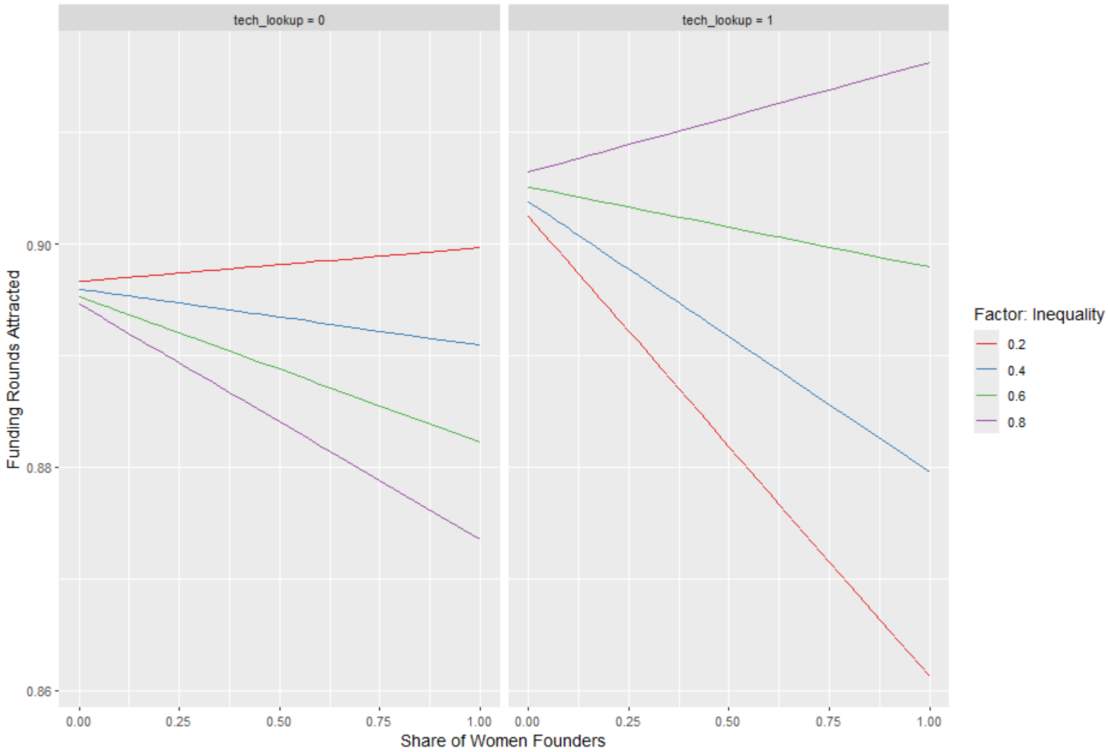

Figure A3.1 – Model 83: The Interaction of Share of Women Founders, Factor: Inequality, Dummy: Tech/Engineering Approach, and Number of Funding Rounds Attracted (Panel Data)

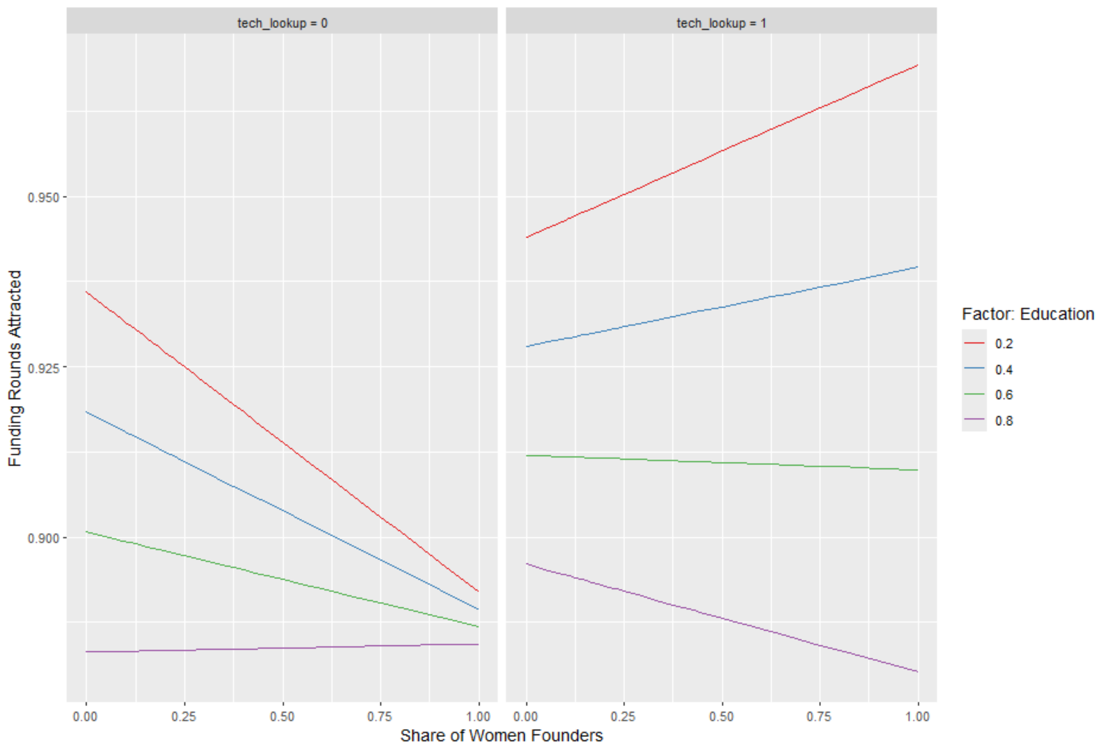

Figure A3.2 – Model 84: The Interaction of Share of Women Founders, Factor: Education, Dummy: Tech/Engineering Approach, and Number of Funding Rounds Attracted (Panel Data)

4. Cracking the Glass Ceiling: Exploring the Link Between Women Entrepreneurship and the Corporate Glass Ceiling

Aaron Pohlmann

ABOUT THIS CHAPTER:

This chapter presents a revised version of the working paper "Female Entrepreneurship - A Catalyst for Social Change?", which I presented in July 2023 at the Diana International Research Conference in Boston and the DRUID conference in Lisbon. Moreover, the research was presented in September 2023 at the TIE conference in Frankfurt and the G-Forum in Darmstadt. I am the sole author of this chapter and thus assume the full responsibility for the data collection, preparation, and analysis, as well as for the interpretation of the results and the writing of the manuscript.

Acknowledgments: First, I want to thank Theresa Veer for her willingness to go the extra mile to help me with my research and present the working paper at the G-Forum in Darmstadt. Second, I would like to express my gratitude to the attendees of the various conferences who provided invaluable feedback and insights that have been pivotal in advancing my research.

Abstract

This chapter examines the relationship between women's entrepreneurship and the corporate glass ceiling, proposing that increased female involvement in opportunity-based entrepreneurship may potentially diminish this barrier. Moreover, it is postulated that this beneficial effect is moderated negatively in contexts where structural empowerment is present but enhanced in regions where societal empowerment is observed. The data from the Global Entrepreneurship Monitor, the World Bank, and the OECD were combined into four datasets, considering the varying time lags between three and six years. A time-and-country fixed-effect panel regression provided empirical evidence for the initial hypotheses. The findings contribute to the existing body of literature by identifying women's representation in opportunity entrepreneurship as a precursor to higher representation in corporate boards and highlighting the influence of institutional features on gender diversity in corporate boards. The results suggest that entrepreneurial education and support programs for women might effectively increase female opportunity entrepreneurship, which would, in turn, lead to more gender-balanced corporate boards.

4.1. Introduction

Even in a world of constant change, some things remain unchanged. For example, women[9] are still underrepresented in boardrooms (e.g., Lewellyn & Muller-Kahle, 2020) and in entrepreneurship (Elam, Hughes, & Samsami, 2023). However, in line with institutional theory (Zucker, 1987), social representation theory (Moscovici, 1972), and gender role theory (Eagly & Karau, 2002), I argue and empirically show that increasing the representation of women among entrepreneurs is not just a win for gender equality but also a catalyst that propels more women into top management and board positions, transforming the leadership landscape. The focus lies on women who identify and pursue business opportunities to increase their independence or income [in the following referred to as "opportunity-based entrepreneurs" following Global Entrepreneurship Monitor (2023)].

Doing so, this study explores the impact of women's opportunity entrepreneurship on breaking the corporate glass ceiling. More concretely, it seeks to find an answer to the following question: *"Does increasing participation of women in opportunity-based entrepreneurship mitigate the corporate glass ceiling?".*

Relying on institutional theory (Zucker, 1987), social representation theory (Moscovici, 1972), and gender role theory (Eagly & Karau, 2002), this paper posits that women engaging in opportunity-based entrepreneurship represent a deviation from traditional gender norms. By doing so, they inspire other women and increase the legitimacy of businesswomen by interacting with influential men. Thus, an increasing share of women opportunity entrepreneurs is expected to enhance the prospects of women reaching top managerial positions (H1). Moreover, this research analyzes how the degree to which women are empowered affects this relationship. Societal empowerment captures women's decisions regarding health-threatening pregnancies and vulnerable employment and thus represents how they internalized their status as the inferior group. Structural empowerment, on the other hand, describes the legal position of women in society and the gender equity of parliaments and labor markets.

In line with social dominance theory (Sidanius & Pratto, 1999), I argue that low levels of structural empowerment are likely to be related to higher levels of prejudice and discrimination (Kteily, Sidanius, & Leven, 2011). Where low levels of structural empowerment prevail, women entrepreneurs are expected to be particularly stigmatized. Consequently, women negatively affected by social pressures will likely benefit more from role models that inspire them within such settings. Thus, I hypothesize that the positive effect of opportunity-based women entrepreneurship on breaking the corporate glass ceiling is particularly powerful in an environment shaped by lower levels of structural empowerment

[9] This paper refers to gender as opposed to sex (Helgeson, 2020). Hereby, Gender is associated with social or cultural aspects (e.g., gender bias) rather than biological factors (Muehlenhard and Peterson, 2011). Furthermore, individuals who self-identify as men or women are treated as such.

(H2A). On the other hand, I argue that women who strongly internalize stereotypes are less likely to change their behaviors and accept their empowered societal position. Thus, I hypothesize that the positive effect of women's opportunity entrepreneurship on a reduction of the corporate glass ceiling is particularly pronounced in regions characterized by high levels of societal empowerment (H2B)

The empirical analysis employs time-and-country fixed-effect panel regressions with time lags of three, four, five, and six years. The underlying datasets rely on Global Entrepreneurship Monitor, World Bank data, and OECD data and cover between 173 and 182 observations from the years between 2004 and 2018. The findings support the hypothesized relationships, indicating a positive correlation between opportunity-based women's entrepreneurship and subsequent female representation in corporate boards. Additionally, a negative moderation effect suggests that the positive impact of women opportunity entrepreneurs on women's board representation diminishes in structurally highly empowered environments but increases in societally empowered regions.

This research contributes to the literature on institutional change by demonstrating that women deviating from existing institutional norms can influence broader normative institutions. It also sheds light on the corporate glass ceiling and enriches the literature on women entrepreneurship by integrating an economic perspective. The study highlights the value of women's entrepreneurship in promoting social progress and gender equality, revealing complex relationships influenced by institutional theory. It also suggests that higher proportions of women entrepreneurs can challenge existing gender stereotypes, potentially reducing male dominance in positions of power. While acknowledging limitations, such as the lack of empirical evidence on the mechanisms driving the observed effects, the paper highlights the importance of entrepreneurial education and support programs for women, particularly in developing countries. Finally, it offers policy implications and avenues for future research.

4.2. Theoretical Background

4.2.1. Institutional Perspective on Social Change

Institutional theory distinguishes between three main drivers of institutional change - functional, political, and social sources (Oliver, 1997), whereby the latter includes aspects such as an increasing representation of women in the male-dominated entrepreneurial field. When social sources lead to institutional change, theorization and legitimation by existing or new actors occurs. First, theorization involves identifying shortcomings in existing norms and practices and justifying new ones based on moral or pragmatic grounds. As this process spreads among organizations in a particular domain, new norms and practices gain legitimacy and become institutionalized (Greenwood, Hinings, & Suddaby, 2002). As a consequence, an increasing share of women in opportunity entrepreneurship can help people identify shortcomings in existing beliefs about gender role expectations, which justifies updating them. Such social norms are institutionalized over time and, therefore, seem natural and are frequently not recognized as discriminatory (Blanchard & Warnecke, 2010). Hence, institutional rigidity caused by institutional habits and routines can make it challenging to develop more inclusive systems (Tool, 1998). One of the ideas deeply embedded in institutional habit is the "Think business - think male" paradigm.

4.2.2. Think Entrepreneur - Think Male.

Research shows that men and women entrepreneurs differ in their willingness to become entrepreneurs (Verheul, Thurik, Grilo, & van der Zwan, 2012) and the attraction of external capital (Brush, Carter, Gatewood, Greene, & Hart, 2006). However, it is crucial to note that women entrepreneurs do not perform worse than their male counterparts (Bardasi, Sabarwal, & Terrell, 2011).

According to social role theory (Eagly & Karau, 2002), gender-related differences in attitudes and behaviors are socially constructed through social learning, societal power relations, and status structures. Therefore, the theory suggests that these differences are not innate but rather a result of societal influences (Eagly & Steffen, 1984). Noteworthy to our context, gender role expectations have been historically influenced, with men traditionally providing financial support for their families and occupying positions of power, prestige, and authority (Blocker & Eckberg, 1997; Samuelson & Zeckhauser, 1988). As a consequence, people tend to ascribe the ability to successfully found, lead, and manage businesses to men instead of women (Gupta, Turban, Wasti, & Sikdar, 2009; Laguía, García-Ael, Wach, & Moriano, 2019). Based on these considerations, the "think entrepreneur – think male" paradigm suggests that entrepreneurship is strongly associated with masculine characteristics, such as ambition and self-confidence. Contrarily, kindness and sensibility traditionally describe feminine attributes (Hancock, Pérez-Quintana, & Hormiga, 2014; Laguía et al., 2019). This perspective extends the "think manager - think male" literature, which suggests that the traits and attitudes of successful managers are rather masculine than feminine attributes (Schein, 1973). As a result, people's perceptions of women leaders often distinguish between their masculine and feminine traits (Koenig, Eagly, Mitchell, & Ristikari, 2011).

In the management context, research suggests that men in power positions prefer to promote women who think and act like men (Adams & Funk, 2012). These dynamics might explain the severe underrepresentation of women at the top management level of organizations to some extent (Cotter, Hermsen, Ovadia, & Vanneman, 2001). At the same time, women's representation in middle management grows much faster than the occurrence of female CEOs (Oakley, 2000) and the share of women in corporate boards (Smith & Parrotta, 2018). Research often refers to these barriers for women at the top of organizations as the "corporate glass ceiling" (Cotter et al., 2001).

4.2.3. WOMEN ENTREPRENEURS: UPDATING EXISTING GENDER ROLE STEREOTYPES.

As mentioned above, women entrepreneurs and businesswomen represent deviations from traditional gender role expectations. However, research also claims that history represents one of the main antecedents of existing gender role stereotypes. Thus, in line with social representation theory (Moscovici, 1972), I argue that the increasing involvement of women in entrepreneurship impacts people's future beliefs regarding gender roles.

A possible reason for the expected relationship is provided by research: men in power positions (e.g., investors or managers) who have personal encounters with successful female entrepreneurs or hear about them will be more likely to support women who want to achieve power positions themselves (Duehr & Bono, 2006). At this moment, it is essential to mention that opportunity entrepreneurs are likely to interact with men in power positions (e.g., investors, managers, CEOs) throughout their entrepreneurial experience. Therefore, they impact existing role stereotypes to a greater extent than women engaging in entrepreneurship out of necessity or seeking to maintain their income.

Witnessing an enhanced level of women's entrepreneurial activity affects not only men's beliefs but also women themselves via two distinct mechanisms. First, observing role models makes other women aware of alternative occupational opportunities (van der Zwan, Verheul, & Thurik, 2012). Secondly, successful women entrepreneurs can serve as mentors to other female founders. As mentor gender has a powerful impact on female entrepreneurs' performance (Germann, Anderson, Chintagunta, & Vilcassim, 2023), this positively affects their businesses' chances of survival. Consequently, successful entrepreneurs are more likely to become CEOs of their firms at some point. This entrepreneurial journey helps to create relevant business contacts and meet other CEOs and board members, which increases their likelihood of being perceived as qualified to join a firm's board (Burke, 1997a,b). In this line, I argue that higher shares of women's national, opportunity-based entrepreneurship positively affect the nomination of women for board positions. Therefore, I predict:

Hypothesis 1: *A higher national share of opportunity-based women entrepreneurs in t0 positively impacts the share of women in corporate boards in t1.*

4.2.4. FEMALE ENTREPRENEURSHIP, THE GLASS CEILING, AND WOMEN'S EMPOWERMENT.

Research suggests that the representation of women at the top of organizations positively relates to women's economic and political empowerment. Economic empowerment describes women's opportunities to enhance their financial resources in a given institutional context, while political empowerment describes women's opportunities to be involved in political affairs and public life (Haugh & Talwar, 2016; Lewellyn & Muller-Kahle, 2020). Another dimension of empowerment is social empowerment, which is a consequence of increasing a group's status in the community (Haugh &

Talwar, 2016). In this study, I apply a slightly different concept of empowerment and distinguish between structural and societal empowerment.

First, *structural empowerment* describes women's representation in politics and the labor market. Additionally, the concept captures whether the law prohibits gender discrimination in employment or credit institutions. Thus, structural empowerment is similar to political empowerment but also considers economy-related aspects such as women's labor market representation and access to credits. Concurrently, low levels of structural empowerment imply that men are the high-status group that dominates politics and economics while being legally privileged. Secondly, societal empowerment describes how women's decisions reflect an internalization of this lower-status position. Low levels are related to women accepting working under vulnerable conditions (e.g., being self-employed without employees or unpaid family workers) to a greater extent than men. Another example of low levels is a high number of women entering pregnancy despite being undernourished or not receiving adequate prenatal care, which leads to a higher prevalence of diseases among pregnant women (Kabeer, 1999). Consequently, low levels of women's structural empowerment describe systems where men have disproportionate social and political power and easier access to things of positive social value and, therefore, characterize male-dominated countries (Pratto, Sidanius, & Levin, 2006). Within such environments, higher levels of prejudice and discrimination prevail (e.g., Kteily et al., 2011). Thus, societies characterized by higher levels of women's structural empowerment will likely be shaped by an enhanced female representation in entrepreneurship and society. Therefore, it is likely that women entrepreneurs can spur social change to a more substantial degree within structurally less empowered environments.

On the other side, low levels of women's societal empowerment characterize countries where women profoundly internalize their lower-status position. Doing so leads to women trusting their skills stereotypically perceived as feminine more than those perceived as male ones (Angus, 2020) and reduces status-related behavior of leader self-development (Hogue, Knapp, Peck, & Weems-Landigham, 2023). Therefore, such behaviors reinforce gender differences through self-fulfilling prophecies (Word, Zanna, & Cooper, 1974). In an extreme case, women might even be against empowering policies because they are reluctant to change due to the strong internalization of their lower status position. Thus, it is likely that regions with low levels of social empowerment are less likely to benefit from the positive effect of an increasing national share of opportunity-based women entrepreneurs on the share of women on corporate boards. Based on these considerations, I predict:

Hypothesis 2: *The positive effect of an increasing national share of opportunity-based women entrepreneurs in t0 on the share of women in corporate boards in t1 becomes (H2A) weaker as women's structural and (H2B) stronger as societal empowerment increases.*

4.3. METHODOLOGY

4.3.1. DATA SOURCES

The Global Entrepreneurship Monitor

The Global Entrepreneurship Monitor is the world's largest entrepreneurship research organization. The organization collects data on perceptions of entrepreneurship, social capital, intellectual capital, and demographic data and recently has become a popular dataset for empiric work in the fields of entrepreneurship and management (e.g., Arafat, Saleem, Dviwedi, & Khan, 2018; Khefacha, Romdhane, & Salem, 2024). The data is collected from telephone interviews and questionnaires and covers at least 2,000 participants per country from 1999 to 2016 and is available on the website (Global Entrepreneurship Monitor, 2023). For this paper, I extracted three important variables from this dataset: (1) *Share of Women Opportunity Entrepreneurs* describes the "Percentage of those females involved in TEA who (i) claim to be driven by opportunity as opposed to finding no other option for work; and (ii) who indicate the main driver for being involved in this opportunity is being independent or increasing their income, rather than just maintaining it". (2) *Perceived Entrepreneurial Environments* reflects the degree to which the interviewees perceive that their environment provides good entrepreneurial conditions. (3) *Perceived Entrepreneurially Skills* shows the degree to which contestants felt entrepreneurially skilled.

World Bank Data

The World Bank Open Data database provides a sheer endless list of economic, political, and social development indicators. Therefore, it is no surprise that the data portal is one of the most well-known data sources across disciplines. Some of the most used variables are development indicators such as countries' Gross Domestic Product (e.g., Ordeñana, Vera-Gilces, Zambrano-Vera, & Jiménez; 2024), often in combination with Global Entrepreneurship Monitor Data (e.g., Brownell, Hechvarria, Roo, & Kickul, 2024). From this data source, I use *Share of Women in Middle Management*, and a variety of women-related indicators for factor analysis (e.g., *Share of Employed Women in Vulnerable Employment, Proportions of Seats held by Women in National Parliaments*).

OECD Data

The Organization for Economic Co-operation and Development (OECD) provides indicators similar to those the World Bank offers. It covers 297 indicators describing the economic, political, and social global development. As the other data sources, it is frequently used in combination with the Global Entrepreneurship Monitor Database in entrepreneurship research (e.g., Solomon, Bendickson, Marvel, McDowell, & Mahto, 2021). For this paper, I use six variables from this dataset: (1) *Share Women Board Directors* describes the percentage of Women on boards of the largest publicly listed companies (2) *Wage Growth* shows the real wage growth of average gross annual wages per full-time employee (3)

Employment Protection describes the strictness of regulation on dismissals and the use of temporary contracts. (4) *Social Expenditure* describes public spending on Social Expenditure as a percentage of the Gross Domestic Product (5) *Share Women Inventors* provides information on the percentage of women in the total number of national inventors (6) *Replacement Rate* describes the ratio of net household income after the first month of unemployment compared to the household's income before the job loss.

4.3.2. DATA GENERATION

Factor Analysis: Structural and Societal Empowerment

I applied an explorative factor analysis to examine the underlying structure of World Bank Indicators and find factors representing different dimensions of women's empowerment. The results are summarized in Table 4.1.

To identify these factor variables, I first extracted 68 indicators from the World Bank database whose description included the words "female", "gender", or "women". Unfortunately, the emerging dataset averaged 63 percent missing values. To tackle the problem, I identified the completeness of each indicator-country combination for the years between 2003 and 2018. For those indicators that provided values for at least 75 percent during those years, I imputed missing data points based on cubic spline interpolation. I did not impute values that were followed by another missing value. Such an imputation method considers a limited number of data points surrounding the missing values and thus takes into account local effects, in addition to the global trend, for interpolation. Further, the method has been recently used in entrepreneurship research (Hincapié, 2020). Nevertheless, this only slightly lowered the sparsity of the dataset, leading to an average of 60 percent missing values per column. Due to this restriction, I excluded the columns that were less than 75 percent complete. Sixteen variables remained in the data set after this step. These variables could be used as items in the analysis of variance. However, some of these variables correlated strongly with each other (e.g., labor force participation and unemployment rate). Sticking only with one of these correlated variables led to a final selection of 9 items. Based on these indicators, I conducted an exploratory factor analysis. The Chi-Square Test of Model Fit suggested that five latent variables fit the data well ($p = 0.07$). However, only the first two factors show a considerable relationship (i.e., loadings > 0.3) with more than one item.

As illustrated in Table 4.1, the first factor loads strongly negatively on the prevalence of anemia among pregnant women (ß = - 0,98) and female vulnerable employment (ß = - 0.85). As both items are related to decisions (i.e., the decision to work under bad conditions or to carry a child even though this puts one's health in danger) based on internalized societal norms, I labeled this factor variable *Women's Societal Empowerment*. The second factor variable loads positively on laws that prohibit gender discrimination in employment (ß = 0.58) and credit institutions (ß = 0.41), the ratio of female to male labor force participation rate (ß = 0.54), the proportion of seats held by women in national parliaments (ß = 0.46), and negatively on the ratio of female to male youth unemployment rate (ß = - 0.46). Because these aspects are related to a country's legal basis and the structural representation of women, I termed this factor *Structural Empowerment*.

Interestingly, some items load positively on *Structural Employment* but negatively on *Societal Employment* (women in vulnerable employment, ratio of female to male labor force participation) or vice versa (ratio of female to male youth unemployment rate). In each of those cases, one of the factors is weakly related to undesirable outcomes, while the other factor variable strongly relates to positive ones. However, I quickly want to address why these effects can occur.

First, *Structural Empowerment* is inherently linked to an enhanced representation of women in the labor market and decreased women's unemployment. However, *Societal Empowerment* is most likely related to a lower likelihood of women marrying young (Asaolu, Okafor, Ehiri, Dreifuss, & Ehiri, 2017; Jensen, 2012). This results in fewer women reporting as unemployed because they take care of the household and are not actively looking for a job (Choi & Valladares-Esteban, 2016). Secondly, *Structural Empowerment* is closely linked to economic development (Duflo, 2012). In many developed countries (i.e., particularly in the Western world), young people often take time off after graduation from school before becoming students or jobholders (Greffrath & Roux, 2012). Additionally, students are vulnerable to exploitation by employees seeking (almost) free labor (Gregory, 1998). As an alternative, young students might also be likely to accept unpaid work for friends or family members and start small businesses to gain money or experience. As women's empowerment leads to more female students (Afridi, 2010), it might also increase women's participation in vulnerable employment. Finally, *Structural Empowerment* in the absence of *Societal Empowerment* is likely to catalyze such effects because women have the same rights as men but do not exercise them because they internalized patriarchal values.

There are some challenges to assessing the internal validity of the two factor variables. Most commonly, Cronbach's Alpha would be used for this task. However, the measurement might not be the right choice in this study for three main reasons. First, it requires equal variance and thus the same scale of the scale's items. Second, it assumes equal factor loadings. Finally, it works best for large scales with many items. Therefore, I also report Omega Total, which is less affected by the number of items on the scale, the item's loadings, or their variance (Dunn, Baguley, & Brunsden, 2014).

For the first factor labeled (*Women's) Societal Empowerment,* Cronbach's Alpha ($\alpha = 0.70$) and Omega Total ($\omega_t = 0.81$) suggest a good reliability of the scale. For (*Women's) Structural Empowerment,* Cronbach's Alpha only points to moderated reliability ($\alpha = 0.62$), while Omega Total indicates good reliability ($\omega_t = 0.70$). However, as Omega Total is the better indicator for internal validity in this case, the scale can be considered of acceptable reliability.

Item	**Factor 1: (Women's) Societal Empowerment**	**Factor 2: (Women's) Structural Empowerment**
Prevalence of anemia among pregnant women (%)	-0.98	-0.15
Proportion of seats held by women in national parliaments (%)	0.25	0.46
Ratio of female to male labor force participation rate (%) (modeled ILO estimate)	-0.11	0.54
Ratio of female to male youth unemployment rate (% ages 15-24) (modeled ILO estimate)	0.10	-0.46
Start-up procedures to register a business, female (number)	-0.13	-0.11
Time required to start a business, female (days)	-	-
The law prohibits discrimination in employment based on gender (1=yes; 0=no)	0.14	0.41
The law prohibits discrimination in access to credit based on gender (1=yes; 0=no)	0.33	0.57
Vulnerable employment, female (% of female employment)	-0.85	0.15
SS loadings	1.91	1.26
Proportion Var	0.21	0.14
Cumulative Var	0.21	0.35
α	**0.70**	**0.62**
ω_t (total omega)	**0.81**	**0.70**

Table 4.1 - Factor Loadings

4.3.3. THE DATASETS

Because I do not expect an increase of women opportunity entrepreneurs to create immediate change but with a time lag, I built four different datasets with a three-year, four-year, five-year, and six-year time lag of the dependent variable, respectively. As before, I imputed missing points based on cubic spline interpolation for country-variable combinations that were at least 75 percent complete. I made an exception for the variable Public Social Expenditure because values were provided every second year and only changed to a minimal extent from one observation to another. Therefore, I decided to impute single missing values if the dataset was at least 50 percent complete. I did not impute values followed by another missing value for any variable.

Doing so resulted in four different datasets labeled *Dataset A-D*, each including observations from 25 countries. *Dataset A* represents the Data based on a three-year time lag. It includes 173 observations from 2007 to 2018 (2010-2021 for the dependent variable). *Dataset B* considers a four-year time lag between the independent and the dependent variable. It includes 184 observations between 2006 and 2018 (2009-2022 for the dependent variable). *Dataset C* takes a five-year time lag into account and consists of 189 observations collected between 2005 and 2017 (2010-2022 for the dependent variable). Finally, Dataset D includes 182 observations between 2004 and 2016 (2010-2022 for the dependent variable) and considers a six-year time lag. I summarized the characteristics of the datasets and their variables in Table 4.2.

4.3.4. VARIABLE DESCRIPTION

Dependent Variable

The dependent variable is taken from the OECD Database and describes the share of women on boards of the largest publicly listed companies. The variable is provided for 47 countries and regions from 2010 to 2022. Before imputation and merging, the minimum of the provided values was 2.10 %, and the maximum was 48.10 %. The mean was 21.28 %. After imputation and merging with the other variables, the values only change slightly. For a time lag of three years *(Dataset A)*, the mean is 24.3 %; for a time lag of four years *(Dataset B)*, it is 25.7 %. Further, for a five-year time lag (*Dataset C*), the mean of the dependent variable is 26.4 %, and for the last dataset, considering a six-year time lag *(Dataset D)*, it is 27.3 %. More details on all the variables are summarized in Table 4.2.

Independent Variable

The Global Entrepreneurship Monitor provides the independent variable *Share of Women Opportunity Entrepreneurs*. It describes the share of women entrepreneurs that engage in opportunity entrepreneurship. The variable is available for 111 countries between 2000 and 2018. Before imputation and merging, the smallest value was 0.13 %, and the largest was 35.46 %. The mean was 6.24 %. After merging and imputation, the mean values of the datasets differed vastly due to the different countries and periods included in the smaller datasets, which also influenced the smallest and largest observations. More precisely, the raw data provided 1,003 data points, and the smaller datasets consistently under 200 observations. Thus, for a time lag of three years *(Dataset A)*, a mean value of 3.90 % results. The mean of the data considering a four-year time lag *(Dataset B)* is 3.84 %. For a five-year time lag *(Dataset C),* a mean value of 3.73 % can be observed. Finally, the mean for the six-year time-lagged dataset *(Dataset D) is 3.56 %.*

Control Variables

Share of Women in Middle Management: The original data from the World Bank Database, which covered 133 countries from 2003 to 2018 and included 1,070 observations, had a mean of 29.98 %, a minimal value of 1.19 %, and a maximal value of 74.19 %. Fortunately, the mean value remained relatively constant over the smaller subsamples even after merging and imputing missing values. Based on a three-year time lag (*Dataset A*), the dataset showed a mean of 29.43 %. A four-year time lag *(Dataset B)* leads to an average of 29.36 %. For a five-year time lag (*Dataset C*), the mean is 29.28 %, and for a six-year time lag *(Dataset D)*, it is 29.05 %. I included the variable in the model because women in these positions represent a potential pool of candidates for top management and board positions. For more details, please consult Table 4.2.

Share of Women Inventors: This OECD-provided indicator describes the share of women inventors among the total amount of inventors and was provided originally for 40 different countries between 2003 and 2019. Ranging from a minimum of 4.39 % to a maximum of 29.48 %, the 631 observations averaged 12.94 %. In *Dataset A*, this mean increased slightly to 12.97 % and then decreased to 12.01 % in Dataset B. This trend continued, as the variable averages 12.00 % in *Dataset C*. Finally, *Dataset D* shows a mean of 11.87 %. I included this control variable to take an alternative reason that could lead to a change of gender stereotypes (i.e., women might be perceived as more innovative if more inventors are women.

Public Social Expenditure: This variable is provided by the OECD Database and describes the public social expenditure as a percentage of the Gross Domestic Product. Before merging and imputing missing values, it included 259 observations from 36 countries collected between 2003 and 2018, ranging from 6.65 % to 31.4 %, with a mean of 20.25 %. The smaller datasets consistently showed larger means ($Mean_{Dataset\ A}$= 23.32 %, $Mean_{Dataset\ B}$= 23.20 %, $Mean_{Dataset\ C}$= 23.12 %, $Mean_{Dataset\ D}$= 23.16 %). One of the reasons for this observation is that the values increased heavily after 2006, and the smaller data samples include mainly countries with higher scores. I control for this indicator to account for the infrastructure, education, healthcare, and, thus, proxy the economic development of a region.

Strictness of Employment Protection: The indicator is an index describing the strictness of regulations on dismissals and the use of temporary contracts. I originally retrieved 628 observations from the OECD Database, which were collected from 2003 to 2018 in 73 countries. The minimum was 0.09, the maximum 4.58, and the mean 2.16. The smaller datasets show nearly the same means after merging and imputing missing values. More precisely, the variable has a mean of 2.19 in *Dataset A* and averages 2.20 in *Dataset B.* In *Dataset C,* the average value is 2.19, and in *Dataset D* it is again 2.20. I included this control variable because it is an important indicator of economic and workplace stability.

Replacement Rate: The replacement rate measures the percentage of a worker's pre-unemployment income that is replaced by unemployment benefits (one month after becoming unemployed). The OECD-based variable covers 527 observations from 33 countries during the years 2003 to 2018. The smallest value was 27.00 % and the largest one was 87.00 %. The mean of the full data was 57.69 %. After merging with the other variables and imputing missing values, the mean of *Dataset A* is 60.05 %. For *Dataset B,* the mean is 59.98 %. In the case of *Dataset C*, the average value is 59.59 %, and the variable averages 59,55 % in *Dataset D*. I included the variable because it influences the economic stability a job provides. Further, lower replacement rates are likely to be related to fewer people only engaging in entrepreneurship to survive.

Wage Growth: The OECD database provides this variable, which describes a country's annual wage growth. Values are available for 617 observations collected between 2003 and 2018 in 38 different countries. The minimum is -15.40 %, the maximum is 23.30 %, and the average is 1.47 %. However, the means of the time-lagged datasets suggest that the country-year combinations with the highest wage growths were excluded during the merging process ($Mean_{Dataset\ A}$ = 0.42 %, $Mean_{Dataset\ B}$ = 0.49 %, $Mean_{Dataset\ C}$ = 0.53 %, $Mean_{Dataset\ D}$ = 0.57 %). Controlling for the annual wage growth allows to proxy the standard of living in statistical models.

Perceived Founding Skills: This variable is taken from the Global Entrepreneurship Monitor database. It includes 873 observations from 111 countries covering the years 2003 to 2018 and describes the share of persons within a country who think they have the knowledge, skills, and experience required to start a new business. It ranges from 0.11 % to 89.48 % and averages 49.77 %. The data merging process led to the exclusion of some of the country-year combinations with the highest scores. Therefore, the average values dropped down to 41.70 % (*Dataset A*), 41.57 % (*Dataset B*), 41.55 % (*Dataset C*), and 41.44 %(*Dataset D*). Including the variable as a control variable allows me to control for the higher inclination of people with more confidence in their entrepreneurial skills to start businesses.

Perceived Entrepreneurial Environment: Also provided by the Global Entrepreneurship Monitor database, this indicator describes the share of people who expect good opportunities for starting a business in their area. The raw data was available for 831 observations from 112 countries covering the time between 2003 and 2018, and ranged from 2.85 % to 85.54 %. The mean of this full dataset was 41.06 %. Losing some of the observations with the highest scores during the merging process, the time-lagged datasets showed slightly lower means ($Mean_{Dataset\ A}$ = 36.66 %, $Mean_{Dataset\ B}$ = 36.57 %, $Mean_{Dataset\ C}$ = 36.39 %, $Mean_{Dataset\ D}$ = 35.91 %).

Moderator Variables

Structural Empowerment: The self-created factor variable describing a country's legal basis and the structural representation of women was initially available for 2,566 observations from 173 countries from 2003 to 2018. The values ranged from 0 to 1, and the mean was 0.77. For each of the time-lagged datasets, I normalized the variable again between 0 and 1 to facilitate the interpretation of the results and reduce potential multicollinearity issues. After doing so, it seems that the distribution of the values within the smaller data sets is very similar to the one of all the available values. This becomes evident when comparing the statistical means ($Mean_{Dataset\ A}$ = 0.72, $Mean_{Dataset\ B}$ = 0.79, $Mean_{Dataset\ C}$ = 0.78, $Mean_{Dataset\ D}$ = 0.77) and other descriptive statistics summarized in Table 4.2.

Societal Empowerment: The second self-created factor variable describing the degree to which women internalized existing gender stereotypes also provided 2,566 observations gathered in 173 countries between 2003 and 2018. The values ranged from 0 to 1, with an average of 0.69. As before, I re-normalized the variable after merging it into each of the time-lagged datasets. The respective means for those datasets are as follows: $Mean_{Dataset\ A}$ = 0.49, $Mean_{Dataset\ B}$ = 0.50, $Mean_{Dataset\ C}$ = 0.51, $Mean_{Dataset\ D}$ = 0.52. This suggests that countries or years shaped by low levels of Societal Empowerment are stronger represented in the datasets A-D than in the total amount of observations provided by the Global Entrepreneurship Monitor.

More details on the Datasets and the respective variables are summarized in Table 4.2.

Variable Name and Description	*Time Lag (years)*	*N*	*Mean*	*SD*	*Min*	*Max*
iso3c	3	173	13.03	6.74	1.00	25.00
iso3c code of the respective country	4	184	12.90	6.71	1.00	25.00
	5	189	12.65	6.73	1.00	25.00
	6	182	12.39	6.70	1.00	25.00
year	3	173	2012.80	3.19	2007.00	2018.00
respective year	4	184	2012.39	3.49	2006.00	2018.00
	5	189	2011.64	3.65	2005.00	2017.00
	6	182	2010.75	3.64	2004.00	2016.00
Share Women Board Directors	3	173	24.26	10.29	3.50	48.10
share of women on boards of the largest publicly listed national companies	4	184	25.67	10.28	4.50	48.10
	5	189	26.37	10.27	4.50	48.10
	6	182	27.34	9.94	4.50	45.30
Share Women Opportunity Entrepreneurs	3	173	3.90	1.91	1.13	10.60
share of women opportunity entrepreneurs among women entrepreneurs	4	184	3.84	1.89	0.83	10.60
	5	189	3.73	1.87	0.66	10.60
	6	182	3.56	1.72	0.66	9.12
Societal Empowerment	3	173	0.49	0.20	0.00	1.00
describing the degree to which women internalized existing gender stereotypes	4	184	0.50	0.19	0.00	1.00
	5	189	0.51	0.19	0.00	1.00
	6	182	0.52	0.17	0.00	1.00

Variable Name and Description	*Time Lag (years)*	*N*	*Mean*	*SD*	*Min*	*Max*
Structural Empowerment	3	173	0.72	0.17	0.00	1.00
factor describing the women's legal status and the structural representation of women	4	184	0.79	0.13	0.00	1.00
	5	189	0.78	0.14	0.00	1.00
	6	182	0.77	0.14	0.00	1.00
Share Women Middle Management	3	173	29.43	5.93	10.85	41.89
share of women in middle management	4	184	29.36	5.91	10.85	41.89
	5	189	29.28	6.04	10.85	42.76
	6	182	29.05	5.88	10.85	42.76
Share Women Inventors	3	173	12.07	4.23	5.35	27.73
share of women inventors among the total amount of inventors	4	184	12.01	4.20	5.35	27.73
	5	189	12.00	4.19	4.78	27.73
	6	182	11.87	4.20	4.78	27.73
Public Social Expenditure	3	173	23.32	3.96	13.36	31.48
public social expenditure as a percentage of the GDP	4	184	23.20	3.96	13.36	31.48
	5	189	23.12	3.88	13.36	31.48
	6	182	23.16	3.73	13.36	31.48
Wage Growth	3	173	0.42	2.25	-15.40	6.30
a country's annual wage growth	4	184	0.48	2.23	-15.40	6.30
	5	189	0.53	2.23	-15.40	6.30
	6	182	0.57	2.29	-15.40	6.30

Table 4.2 - Descriptive Statistics (continues on next page)

Variable Name and Description	*Time Lag (years)*	*N*	*Mean*	*SD*	*Min*	*Max*
Replacement Rate worker's pre-unemployment income that is replaced by unemployment benefits (%)	3	173	60.05	12.57	28.00	86.00
	4	184	59.98	12.35	28.00	86.00
	5	189	59.59	12.34	28.00	86.00
	6	182	59.55	11.97	28.00	86.00
Employment Protection index describing the strictness of regulations on dismissals and the use of temporary contracts	3	173	2.19	0.73	0.09	4.13
	4	184	2.20	0.73	0.09	4.13
	5	189	2.19	0.73	0.09	4.13
	6	182	2.21	0.72	0.09	4.13
Perceived Founding Skills share of persons who think they have the knowledge, skills, and experience to start a new business	3	173	41.70	7.84	10.77	55.74
	4	184	41.57	7.71	10.77	55.74
	5	189	41.55	7.60	10.77	55.74
	6	182	41.44	7.29	12.23	55.74
Perceived Entrepreneurial Environment share of people who expect good opportunities for starting a business	3	173	36.66	14.28	7.27	70.59
	4	184	36.57	14.33	7.27	70.59
	5	189	36.39	14.32	7.27	70.59
	6	182	35.91	13.81	7.27	70.59

Table 4.2 - Descriptive Statistics

		1	2	3	4	5	6	7	8	9	10	11	12
1	*Share Women Board Directors*	1											
2	*Wage Growth*	0.11	1										
3	*Employment Protection*	0.02	0.01	1									
4	*Social Expenditure*	0.26***	-0.09	0.00	1								
5	*Share Women Inventors*	-0.18*	-0.13	0.09	0.07	1							
6	*Replacement Rate*	0.05	0.15	0.54***	-0.05	-0.07	1						
7	*Share Women Middle Management*	0.35***	0.00	-0.33***	0.13	0.16*	-0.35***	1					
8	*Share Women Opportunity Entrepreneurs*	0.04	0.02	-0.27***	-0.29***	0.02	-0.18*	0.25***	1				
9	*Perceived Founding Skills*	-0.18*	-0.10	-0.13	-0.21**	0.22**	-0.31***	0.36***	0.52***	1			
10	*Perceived Entrepreneurial Conditions*	0.42***	0.21**	-0.22**	-0.16*	-0.33***	0.07	0.20*	0.48***	0.07	1		
11	*Societal Empowerment*	0.22**	-0.03	-0.37***	0.48***	-0.19*	-0.13	0.26***	0.07	0.00	0.35***	1	
12	*Structural Empowerment*	0.36***	0.02	0.11	0.35***	0.13	0.13	0.22**	0.03	0.14	0.31***	0.42***	1

Table 4.3 - Correlation Table (Three-Year Time Lag)

• p<0.1 * p<0.05 ** p<0.01 *** p<0.001

		1	2	3	4	5	6	7	8	9	10	11	12
1	*Share Women Board Directors*	1											
2	*Wage Growth*	0.00	1										
3	*Employment Protection*	-0.00	0.01	1									
4	*Social Expenditure*	0.27***	-0.12	-0.02	1								
5	*Share Women Inventors*	-0.15*	-0.14	0.06	0.07	1							
6	*Replacement Rate*	0.04	0.12	0.53***	-0.03	-0.07	1						
7	*Share Women Middle Management*	0.35***	0.02	-0.32***	0.14	0.15*	-0.35***	1					
8	*Share Women Opportunity Entrepreneurs*	0.07	0.01	-0.27***	-0.28***	0.04	-0.17*	0.24***	1				
9	*Perceived Founding Skills*	-0.16*	-0.10	-0.13	-0.20**	0.23**	-0.32***	0.34***	0.52***	1			
10	*Perceived Entrepreneurial Conditions*	0.39***	0.20**	-0.23**	-0.17*	-0.31***	0.07	0.17*	0.48***	0.07	1		
11	*Societal Empowerment*	0.22**	-0.03	-0.37***	0.48***	-0.18*	-0.12	0.26***	0.05	-0.00	0.32***	1	
12	*Structural Empowerment*	0.39***	-0.04	0.03	0.37***	0.13	0.14	0.20**	0.06	0.14	0.30***	0.38***	1

Table 4.4 - Correlation Table (Four-Year Time Lag)

• p<0.1 * p<0.05 ** p<0.01 *** p<0.001

		1	2	3	4	5	6	7	8	9	10	11	12
1	*Share Women Board Directors*	1											
2	*Wage Growth*	-0.01	1										
3	*Employment Protection*	-0.02	0.01	1									
4	*Social Expenditure*	0.29***	-0.13	-0.02	1								
5	*Share Women Inventors*	-0.10	-0.14	0.07	0.06	1							
6	*Replacement Rate*	0.04	0.10	0.52***	-0.01	-0.05	1						
7	*Share Women Middle Management*	0.36***	0.03	-0.33***	0.13	0.14	-0.34***	1					
8	*Share Women Opportunity Entrepreneurs*	0.10	0.03	-0.29***	-0.27***	0.07	-0.21**	0.25***	1				
9	*Perceived Founding Skills*	-0.15*	-0.10	-0.15*	-0.20**	0.23**	-0.34***	0.33***	0.49***	1			
10	*Perceived Entrepreneurial Conditions*	0.34***	0.22**	-0.28***	-0.19**	-0.27***	0.03	0.19**	0.45***	0.07	1		
11	*Societal Empowerment*	0.22**	-0.02	-0.37***	0.47***	-0.20**	-0.13	0.27***	0.04	0.03	0.32***	1	
12	*Structural Empowerment*	*0.42****	*-0.05*	*0.02*	*0.36****	*0.13*	*0.12*	*0.21***	*0.09*	*0.15**	*0.28****	*0.33****	*1*

Table 4.5 - Correlation Table (Five-Year Time Lag)

• p<0.1 * p<0.05 ** p<0.01 *** p<0.001

		1	2	3	4	5	6	7	8	9	10	11	12
1	*Share Women Board Directors*	1											
2	*Wage Growth*	-0.00	1										
3	*Employment Protection*	-0.01	0.00	1									
4	*Social Expenditure*	0.30***	-0.12	-0.02	1								
5	*Share Women Inventors*	-0.09	-0.15*	0.07	0.06	1							
6	*Replacement Rate*	0.07	0.07	0.53***	0.00	0.01	1						
7	*Share Women Middle Management*	0.42***	0.01	-0.34***	0.15	0.11	-0.31***	1					
8	*Share Women Opportunity Entrepreneurs*	0.15*	-0.00	-0.29***	-0.23**	0.06	-0.22**	0.25***	1				
9	*Perceived Founding Skills*	-0.15*	-0.12	-0.18*	-0.19**	0.22**	-0.36***	0.28***	0.50***	1			
10	*Perceived Entrepreneurial Conditions*	0.31***	0.23**	-0.29***	-0.21**	-0.27***	0.03	0.17*	0.38***	0.00	1		
11	*Societal Empowerment*	0.20**	0.02	-0.40***	0.45***	-0.21**	-0.17*	0.30***	0.06	0.02	0.30***	1	
12	*Structural Empowerment*	0.45***	-0.05	-0.02	0.38***	0.11	0.14	0.23**	0.12	0.10	0.25***	0.29***	1

Table 4.6 - Correlation Table (Six-Year Time Lag)

• p<0.1 * p<0.05 ** p<0.01 *** p<0.001

4.4. Empirical Analysis

Before running the actual statistical analysis, I analyzed the variance inflation factors. Scoring consistently lower than 10 (Neter, Wasserman, & Kutner, 1989), the results showed no potential multicollinearity issues. Tables 4.3-4.6 summarize additional information on correlations between the control variables.

Afterward, I built three sets of Models. Models 1-4 test H1, Models 5-8 test H2A, and Models 9-12 test H2B. The regression models within each set rely on identical variables and assumptions but use different time lags varying between 3 and 6 years and are based on ordinary least-squared regression.

To test H1, I use the *Share Women Opportunity Entrepreneurs* as the independent variable and the *Share Women Board Directors* as the dependent variable. The models further control for *Wage Growth, Employment Protection, Social Expenditure, Share Women Inventors, Replacement Rate, Share Women Middle Management, Perceived Founding Skills,* and *Perceived Entrepreneurial Conditions* (Details on these variables are gathered above in paragraph 4.3. and Table 4.2). Finally, I consider fixed effects on the country and the year level. I consider a time lag of three years for Model 1 and four years to six years for Models 2 to 4, respectively.

The second set of Models (Models 5-8) tests H2A (Model 5: three-year time lag; Model 6: four-year time lag, Model 7: five-year time lag; Model 8: six-year time lag). The only difference to Models 1-4 is the consideration of an interaction term between *Share Women Opportunity Entrepreneurs* and *Societal Empowerment*. Similarly, the last set of Models (Models 9-12) tests H2B. Like Models 5-8, they only differ regarding the time lag between a change in the independent variable and an observable effect of the dependent one. Instead of *Societal Empowerment*, this set of Models considers *Structural Empowerment*.

Finally, I clustered the standard errors on the country and the year level to control for possible correlations between observations from a specific year or country. As the Breusch-Godfrey Test (Breusch, 1978) suggests serial correlation ($p < 0.001$) and the Pesaran Cross-Sectional Dependence Test (Pesaran, 2015) suggests spatial dependence ($p = 0.04$), I use Driscoll-Kraay standard errors (Driscoll & Kraay, 1998) to return robust standard errors.

In addition to the regression models, I tested for Granger causality (Granger, 1969). The significant results indicate that changes in *Share Women Opportunity Entrepreneurs* have predictive power for future changes in *Share Women Board Directors* for a time lag of three, four, five, and six years ($p = 0.01$). Furthermore, considering a four- five- and six-year time lag, *Share Women Board Directors* may also predict future changes in *Share Women Opportunity Entrepreneurs* ($p = 0.04$).

4.5. RESULTS

The coefficients describing the direct relationship between *Share Women Opportunity Entrepreneurs* and *Share Women Board Directors* are consistently positive. However, the effect is only statistically (borderline) significant in Model 4, which considers a time lag of 6 years (ß = 0.57, p = 0.08). This implies limited support for H1 and suggests that a one-percent increase in *Share Women Opportunity Entrepreneurs* leads to a 0.57 percent increase in *Share Women Board Directors*. These results are summarized in Table 4.7.

	Model 1 (time lag = 3)	**Model 2 (time lag = 4)**	**Model 3 (time lag = 5)**	**Model 4 (time lag = 6)**
Share Women Opportunity Entrepreneurs	0.28	0.25	0.23	**0.57 ˙**
	(0.50)	(0.43)	(0.43)	**(0.08)**
Share Women Middle Management	-0.10	-0.12	0.06	0.08
	(0.38)	(0.15)	(0.25)	(0.14)
Share Women Inventors	0.06	0.17	0.21	-0.01
	(0.86)	(0.49)	(0.25)	(0.98)
Wage Growth	0.28	0.08	0.15	0.14
	(0.09)	(0.71)	(0.44)	(0.36)
Perceived Founding Skills	-0.16	-0.23	-0.12	0.01
	(0.10)	(0.07)	(0.35)	(0.97)
Perceived Entrepreneurial Conditions	**-0.11 ***	-0.05	-0.03	-0.07
	(0.01)	(0.38)	(0.50)	(0.32)
Strictness Employment Protection	-1.47	-1.77	-2.45	**-4.93 ****
	(0.49)	(0.33)	(0.21)	**(0.01)**
SocialExpenditure	-0.66 *	**-0.69 ˙**	**-0.64 ***	**-0.73 ***
	(0.01)	**(0.05)**	**(0.05)**	**(0.02)**
Replacement Rate	0.13	-0.13	-0.19	-0.09
	(0.34)	(0.46)	(0.14)	(0.49)
R^2 (within)	**0.13**	**0.13**	**0.13**	**0.14**

Table 4.7 - Regression Table H1

˙ p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Table 4.8 summarizes the results regarding H2A. While the coefficients of the interaction term *Share Women Opportunity Entrepreneurs x Societal Empowerment* are larger than the direct effects suggested in Models 1-4, only Models 5 (ß = 2.25, p = 0.03) and 6 (ß = 2.10, p = 0.08) provide (borderline) significant results. This suggests that Societal Empowerment impacts not only the strength but also the speed of the effect of *Share Women Opportunity Entrepreneurs* on *Share Women Board Directors.* Thus, H2A receives partial support. Furthermore, the R^2 of Models 5-8 is consistently larger than the R^2 of Models 1-4, suggesting that including the interaction term in the regression models increases the regression's explanatory power.

	Model 5	**Model 6**	**Model 7**	**Model 8**
	(time lag = 3)	**(time lag = 4)**	**(time lag = 5)**	**(time lag = 6)**
Share Women Opportunity Entrepreneurs	-0.68	-0.68	-0.86	0.12
	(0.26)	(0.23)	(0.18)	(0.90)
Societal Empowerment	-38.09	-32.26	-33.57	**-39.28 •**
	(0.18)	(0.22)	(0.19)	**(0.06)**
Share Women Middle Management	-0.08	-0.09	0.09	0.10
	(0.33)	(0.15)	(0.17)	(0.19)
Share Women Inventors	0.19	0.24	0.23	-0.04
	(0.56)	(0.36)	(0.24)	0.92)
Wage Growth	**0.28 •**	0.09	0.14	0.11
	(0.09)	(0.70)	(0.47)	(0.43)
Perceived Founding Skills	**-0.15 •**	**-0.23 •**	-0.11	-0.03
	(0.07)	**(0.09)**	(0.40)	(0.84)
Perceived Entrepreneurial Conditions	**-0.10 ****	-0.04	-0.03	-0.04
	(0.01)	(0.41)	(0.59)	(0.52)
Strictness Employment Protection	-1.52	-1.56	-2.18	**-4.62 •**
	(0.50)	(0.43)	(0.29)	**(0.06)**
SocialExpenditure	**-0.60 ****	**-0.63 •**	**-0.61 •**	**-0.73***
	(0.01)	**(0.05)**	**(0.05)**	**(0.01)***
Replacement Rate	0.19	-0.09	-0.16	-0.07
	(0.20)	(0.61)	(0.24)	(0.65)
Share Women Opportunity Entrepreneurs	**2.25 ***	**2.10 •**	2.39	1.05
x *Societal Empowerment*	**(0.03)**	**(0.08)**	(0.11)	(0.53)
R^2 (within)	**0.17**	**0.16**	**0.16**	**0.18**

Table 4.8 - Regression Table H2A • p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Regarding the final hypothesis, H2B, Models 9-12 provide interesting insights and support H2B. First, the coefficients describing the effect of the interaction term *Share Women Opportunity Entrepreneurs x Structural Empowerment* on the dependent variable are consistently negative across all the different models. In particular, Model 10 (ß = - 0.46, p = 0.06), Model 11 (ß = - 8.83, 0.03), Model 12 (ß = - 10.49, p = 0.00) suggest that the negative effect increases in size and statistical significance over time. Additionally, the effect of *Share Women Opportunity Entrepreneurs* increases in its size over time and is consistently higher than in Models 1-4 ($ß_{\text{Model 10}}$ = 5.30, $p_{\text{Model 10}}$ = 0.06; $ß_{\text{Model 11}}$ = 7.11, $p_{\text{Model 11}}$ = 0.03; $ß_{\text{Model 12}}$ = 8.83, $p_{\text{Model 12}}$ = 0.00). The R^2 of the respective models indicates that including the interaction term and *Structural Empowerment* in the regression models improves the model's quality.

	Model 9 (time lag = 3)	**Model 10** (time lag = 4)	**Model 11** (time lag = 5)	**Model 12** (time lag = 6)
Share Women Opportunity Entrepreneurs	1.94	**5.30**	**7.11 ***	**8.83 *****
	(0.18)	**(0.06)**	**(0.03)**	**(<0.001)**
Structural Empowerment	-0.17	4.46	17.25	**33.25 ****
	(0.99)	(0.66)	(0.24)	**(0.00)**
Share Women Middle Management	-0.10	-0.12	0.09	0.07
	(0.42)	(0.18)	(0.10)	(0.36)
Share Women Inventors	0.06	0.29	**0.44**	0.30
	(0.84)	(0.34)	**(0.08)**	(0.24)
Wage Growth	0.29	0.11	0.16	0.14
	(0.12)	(0.64)	(0.34)	(0.29)
Perceived Founding Skills	-0.15	**-0.16**	-0.02	0.05
	(0.13)	**(0.09)**	(0.84)	(0.67)
Perceived Entrepreneurial Conditions	**-0.12 ***	-0.09	-0.05	-0.06
	(0.01)	(0.10)	(0.26)	(0.29)
Strictness Employment Protection	-1.49	-2.35	-2.78	**-4.92 ****
	(0.49)	(0.20)	(0.12)	**(0.00)**
SocialExpenditure	**-0.64 ***	-0.67	-0.50	-0.45
	(0.02)	(0.06)	(0.16)	(0.15)
Replacement Rate	0.16	-0.02	-0.13	-0.11
	(0.26)	(0.92)	(0.25)	(0.32)
Share Women Opportunity Entrepreneurs	-2.30	**-6.46**	**-8.83 ***	**-10.49 *****
x *Structural Empowerment*	(0.18)	**(0.06)**	**(0.03)**	**(<0.001)**
R^2 (within)	**0.14**	**0.20**	**0.20**	**0.24**

Table 4.9 - Regression Table H2B ˙ p<0.1 * p<0.05 ** p<0.01 *** p<0.001

To further facilitate a better understanding of the effect's size and speed, I plotted the results in Figure 4.1. On the left side, I plotted the results of the direct effect of *Share Women Opportunity Entrepreneurs* on *Share Women Board Directors.* This first graph captures that the coefficients are consistently positive across the different model compositions. As the results are only significant for a time lag of six years, indicating that the effect becomes salient relatively slowly, these results weakly support H1.

The coefficients regarding H2A are summarized in the middle of Figure 4.1 and describe the effect of *Share Women Opportunity Entrepreneurs x Societal Empowerment* on *Share Women Board Directors.* Unfortunately, there are no significant results for data with a six-year time lag, so I cannot directly compare the coefficient sizes of the interaction terms to the direct effect because only the two models with a time lag of 3 and 4 years provided significant results. This indicates that this effect becomes statistically salient after a shorter period of time than the direct effect from H1. Further, the graph shows that the interaction term's impact on the dependent variable is consistently positive and greater than the direct effects plotted on the left-hand side. Therefore, the statistical analysis provides limited support to H2A.

Finally, the graph on the right-hand side of Figure 4.1 describes the coefficients related to the effect of *Share Women Opportunity Entrepreneurs x Structural Empowerment* on *Share Women Board Directors.* The values are consistently negative and, therefore, much lower than the direct effects of *Share Women Opportunity Entrepreneurs* on *Share Women Board Directors.* The effects are significant for a four, five, and six-year time lag. Comparing the coefficient from Model 12 ($ß = -10.49$, $p = 0.00$) describing the interaction term's impact on the dependent variable to the direct effect from Model 4 ($ß = 0.57$, $p = 0.08$) suggests a negative moderation effect which supports H2B.

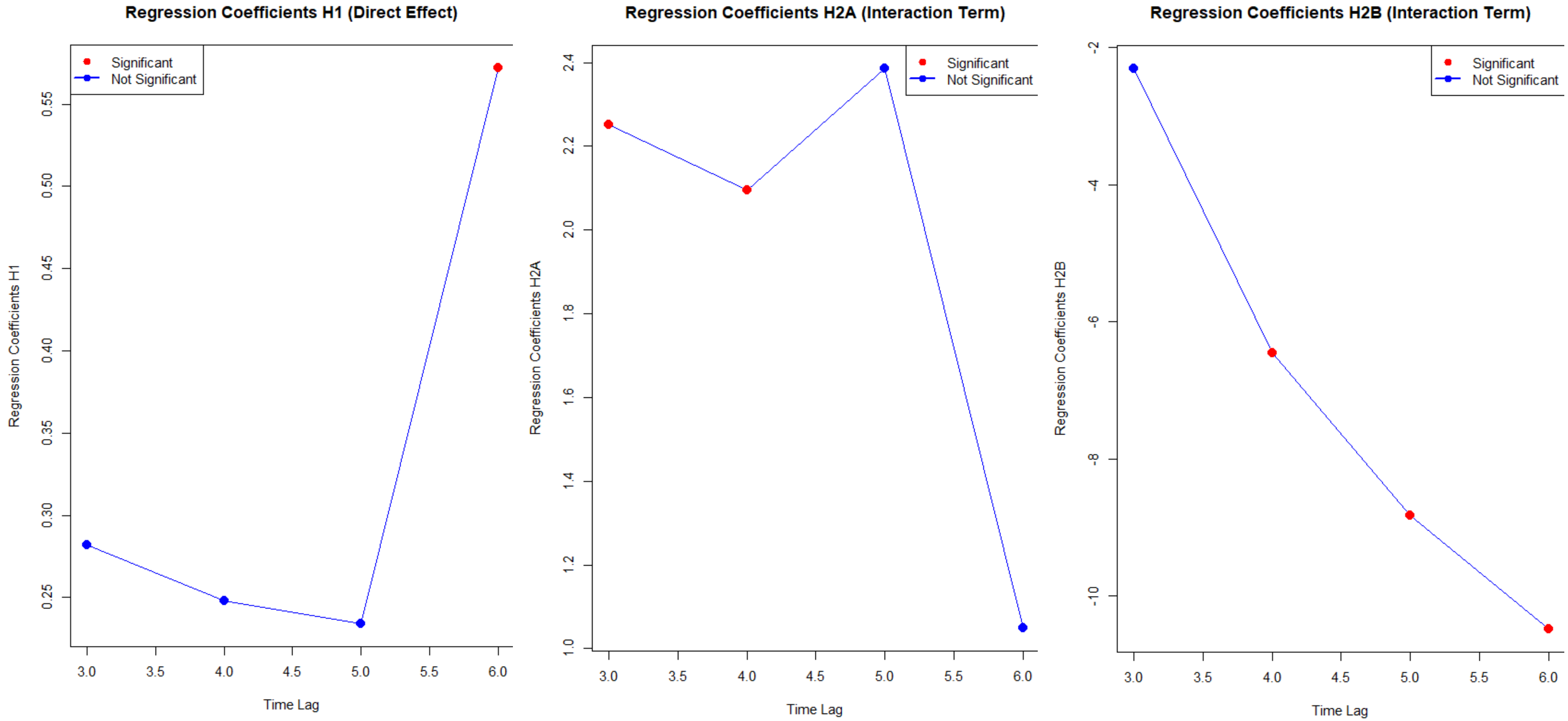

Figure 4.1 - The Relationship of Women's Opportunity Entrepreneurship and the Share of Women in Boards over Time

4.6. POST-HOC ANALYSIS

4.6.1. MEDIATION ANALYSIS

There is an ongoing conversation on how women's entrepreneurship empowers women. For example, some authors argue that it helps women overcome the gender gap, promotes social inclusion, and combats poverty and discrimination (Cardella, Hernández-Sánchez, & Sánchez-Garcia, 2020; Datta & Gailey, 2012). In this line of thought, it can be argued that *Share Women Opportunity Entrepreneurs* might only have a limited direct effect on *Share Women Board Directors*. Instead, the self-generated empowerment indicators (*Structural Empowerment and Societal Empowerment*) might mediate this effect and thus explain the effect. I conducted a mediation analysis for each time lag and empowerment-related factor variable to test these considerations.

The results summarized in Table 4.10 suggest that *Structural Empowerment* does not mediate the relationship proposed in H1. However, Table 4.11 shows that *Societal Empowerment* mediates the relationship between *Share Women Opportunity Entrepreneurs* and *Share Women Board Directors* when a three-, four-, or five-year time lag is taken into account. The sign of the significant mediation effect is consistently negative, implying that the mediator variable negatively impacts the relationship between the independent variable and the dependent one. This mechanism is also referred to as suppression in the literature (Hsu, Mitchell, & Cao, 2024). This implies that the presence of the mediator in the regression model would actually increase either the direct effect's size or its statistical significance. For a six-year time lag, this effect disappears in the analysis.

	Estimate (3-year lag)	**p-value (3-year lag)**	**Estimate (4-year lag)**	**p-value (4-year lag)**	**Estimate (5-year lag)**	**p-value (5-year lag)**	**Estimate (6-year lag)**	**p-value (6-year lag)**
ACME	-0.00	0.91	0.04	0.55	0.06	0.33	-0.06	0.30
ADE	0.29	0.42	0.20	0.58	0.15	0.65	**0.63 •**	**0.08**
Total Effect	0.28	0.45	0.24	0.51	0.21	0.12	0.57	0.12
Prop. Mediated	0.00	0.98	0.07	0.70	0.08	0.65	-0.08	0.37

Table 4.10 - Mediation Analysis Structural Empowerment • p<0.1 * p<0.05 ** p<0.01 *** p<0.001

	Estimate (3-year lag)	**p-value (3-year lag)**	**Estimate (4-year lag)**	**p-value (4-year lag)**	**Estimate (5-year lag)**	**p-value (5-year lag)**	**Estimate (6-year lag)**	**p-value (6-year lag)**
ACME	**-0.17 ***	**0.04**	**-0.13 •**	**0.07**	**-0.12 •**	**0.06**	-0.11	0.17
ADE	0.46	0.19	0.36	0.28	0.34	0.35	**0.68 ***	**0.04**
Total Effect	0.29	0.42	0.23	0.48	**0.22**	**0.09**	**0.57 •**	**0.09**
Prop. Mediated	-0.28	0.45	-0.23	0.51	-0.17	0.58	-0.16	0.26

Table 4.11 - Mediation Analysis Societal Empowerment • p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Because of the mediation analysis results, I reran the Models regarding H1. As expected, the coefficients of the direct effect of *Share Women Opportunity Entrepreneurs* on *Share Women Board Directors* increased, and the p-values dropped. Still, only the analysis based on a six-year time lag leads to a significant result (ß = 0.68, p = 0.06).

	Model 13 (time lag = 3)	**Model 14 (time lag = 4)**	**Model 15 (time lag = 5)**	**Model 16 (time lag = 6)**
Share Women Opportunity Entrepreneurs	0.45	0.38	0.35	**0.68**
	(0.34)	(0.30)	(0.30)	**(0.06)**
Societal Empowerment	-34.35	-28.86	-29.71	-37.27
	(0.20)	(0.25)	(0.22)	(0.08)
Share Women Middle Management	-0.08	-0.09	0.09	0.10
	(0.38)	(0.16)	(0.17)	(0.18)
Share Women Inventors	0.18	0.23	0.22	-0.03
	(0.60)	(0.41)	(0.27)	(0.94)
Wage Growth	**0.27**	0.09	0.13	0.10
	(0.08)	(0.70)	(0.47)	(0.44)
Perceived Founding Skills	**-0.18**	**-0.25**	-0.14	-0.03
	(0.08)	**(0.07)**	(0.31)	(0.81)
Perceived Entrepreneurial Conditions	-0.10	-0.04	-0.02	-0.03
	(0.01)	(0.46)	(0.72)	(0.55)
Strictness Employment Protection	-1.33	-1.39	-1.97	**-4.41**
	(0.54)	(0.47)	(0.34)	**(0.05)**
Social Expenditure	**-0.63**	**-0.66**	**-0.64**	**-0.73**
	(0.01)	**(0.04)**	**(0.04)**	**(0.02)**
Replacement Rate	0.19	-0.09	-0.17	-0.07
	(0.22)	(0.61)	(0.23)	(0.64)
R (within)	**0.16**	**0.15**	**0.15**	**0.18**

Table 4.12 - Post-Hoc Regression H1 (Controlling for Societal Empowerment) • $p<0.1$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$

4.7. ALTERNATIVE MODERATION MEASUREMENTS

Although *Societal Empowerment* captures to some extent the degree to which women act on existing gender stereotypes, none of the analyses conducted so far can measure these stereotypes explicitly. Therefore, I use data from the Implicit Association Test (Greenwald et al.,1998) to capture the existence of gender stereotypes. Among other things, the Implicit Association Test measures the implicit association of "career" or "family" with being "female" or "male". On the other hand, explicit stereotypes are measured on a 7-point Likert-type scale that assesses the degree to which an attribute is perceived as "female" or "male by the respondents. Millions of people have already taken the IAT, and it has received increasing attention in academia (e.g., Charlesworth, Navon, Rabinocich, Lofaro, & Kurdi, 2023). Fortunately, Charlesworth, and Banaji (2021) even published their code and empirical analysis with R. Therefore, I could rely on their data cleaning process.

I used the provided measurements of stereotypes to analyze whether the effect of Share Women Opportunity Entrepreneurs on Share Women Board Directors becomes stronger if gender stereotypes prevail to a greater extent within the country. As argued above, women engaging in opportunity entrepreneurship will likely act against existing gender role stereotypes. However, the less pronounced these stereotypes are in a society, the less impact women's representation in opportunity entrepreneurship has on women's representation on corporate boards.

The models for this analysis are nearly identical to the ones used in the main analysis. However, I included Societal Empowerment and Structural Empowerment as control variables to control for the moderation and mediation effects they have on the main relationship. Further, I used Explicit Stereotypes and Implicit Stereotypes as potential moderators. Finally, I calculated the variance inflation factors for the models, which were consistently lower than ten and thus did not indicate multicollinearity problems (Neter et al., 1989).

Previous results showed that *Societal Empowerment* impacted the relationship between Share Women Opportunity Entrepreneurs and Share Women Board Directors when a lower time lag was taken into account. As I argued that Societal Empowerment is related to the internalization of Stereotypes, it is reasonable to assume that the strength of the existing stereotypes also affects the effects of the independent on the dependent variable, particularly for lower time lags. Therefore, I extended the analysis and took only a two-year time lag into account. The relevant datasets are summarized in Table 4.13.

Variable Name and Description	*Time Lag (years)*	*N*	*Mean*	*SD*	*Min*	*Max*
iso3c	2	126	9.82	5.03	1.00	19.00
iso3c code of the respective country	3	140	9.80	5.07	1.00	19.00
	4	149	9.74	5.03	1.00	19.00
	5	145	9.70	5.09	1.00	19.00
	6	134	9.59	5.12	1.00	19.00
year	2	126	2012.95	2.96	2008.00	2018.00
respective year	3	140	2012.53	3.20	2007.00	2018.00
	4	149	2012.13	3.47	2006.00	2018.00
	5	145	2011.88	3.30	2006.00	2017.00
	6	134	2011.40	3.04	2006.00	2016.00
Share Women Board Directors	2	126	23.92	10.17	4.50	45.30
share of women on boards of the largest publicly listed national companies	3	140	25.13	10.39	4.50	48.10
	4	149	26.61	10.33	4.50	48.10
	5	145	28.15	9.81	5.90	48.10
	6	134	29.62	9.03	8.40	45.30
Share Women Opportunity Entrepreneurs	2	126	3.66	1.81	1.13	9.38
share of women opportunity entrepreneurs among women entrepreneurs	3	140	3.63	1.82	1.13	9.38
	4	149	3.58	1.81	0.83	9.38
	5	145	3.60	1.83	0.83	9.38
	6	134	3.54	1.75	0.83	9.12

Variable Name and Description	*Time Lag (years)*	*N*	*Mean*	*SD*	*Min*	*Max*
Implicit Stereotypes	2	126	0.53	0.11	0.22	0.84
measures the implicit association of “career” or “family” with being “female” or “male”	3	140	0.54	0.10	0.22	0.84
	4	149	0.54	0.11	0.22	0.95
	5	145	0.54	0.11	0.22	0.95
	6	134	0.55	0.11	0.22	0.95
Explicit Stereotypes	2	126	0.49	0.13	0.18	0.81
measures the explicit association of “career” or “family” with being “female” or “male”	3	140	0.49	0.13	0.18	0.81
	4	149	0.50	0.13	0.18	0.81
	5	145	0.50	0.13	0.18	0.81
	6	134	0.49	0.12	0.18	0.81
Share Women Middle Management	2	126	30.29	5.48	11.39	40.70
share of women in middle management	3	140	30.08	5.73	10.85	40.70
	4	149	29.99	5.75	10.85	40.70
	5	145	29.94	5.78	10.85	40.70
	6	134	29.98	5.66	10.85	40.70
Share Women Inventors	2	126	12.72	4.50	5.35	27.73
share of women inventors among the total amount of inventors	3	140	12.55	4.43	5.35	27.73
	4	149	12.50	4.39	5.35	27.73
	5	145	12.56	4.36	5.62	27.73
	6	134	12.49	4.38	5.62	27.73

Table 4.13 - Descriptive Statistics Post-Hoc: Stereotypes (continues on next page)

Variable Name and Description	Time Lag (years)	N	Mean	SD	Min	Max
Public Social Expenditure public social expenditure as a percentage of the GDP	2	126	24.28	3.40	14.60	31.48
	3	140	24.08	3.47	14.60	31.48
	4	149	23.93	3.51	14.60	31.48
	5	145	23.91	3.44	14.60	31.48
	6	134	23.93	3.35	14.60	31.48
Wage Growth a country's annual wage growth	2	126	0.17	2.42	-15.40	6.30
	3	140	0.25	2.35	-15.40	6.30
	4	149	0.32	2.33	-15.40	6.30
	5	145	0.34	2.37	-15.40	6.30
	6	134	0.34	2.45	-15.40	6.30
Replacement Rate worker's pre-unemployment income that is replaced by unemployment benefits (%)	2	126	57.10	12.04	28.00	75.00
	3	140	57.35	11.74	28.00	75.00
	4	149	57.42	11.53	28.00	75.00
	5	145	57.27	11.91	28.00	75.00
	6	134	57.46	11.77	28.00	75.00
Employment Protection index describing the strictness of regulations on dismissals and the use of temporary contracts	2	126	2.08	0.71	0.09	4.13
	3	140	2.07	0.71	0.09	4.13
	4	149	2.07	0.70	0.09	4.13
	5	145	2.06	0.71	0.09	4.13
	6	134	2.08	0.70	0.09	4.13

Variable Name and Description	Time Lag (years)	N	Mean	SD	Min	Max
Perceived Founding Skills share of persons who think they have the knowledge, skills, and experience to start a new business	2	126	40.97	7.93	10.77	55.71
	3	140	40.91	8.20	10.77	55.74
	4	149	40.85	8.06	10.77	55.74
	5	145	40.88	8.07	10.77	55.74
	6	134	41.03	7.82	12.23	55.74
Perceived Entrepreneurial Environment share of people who expect good opportunities for starting a business	2	126	35.70	14.08	7.27	68.93
	3	140	35.98	14.30	7.27	70.59
	4	149	35.91	14.41	7.27	70.59
	5	145	35.91	14.57	7.27	70.59
	6	134	35.72	14.38	7.27	70.59
Societal Empowerment describing the degree to which women internalized existing gender stereotypes	2	126	0.54	0.15	0.07	1.00
	3	140	0.53	0.16	0.06	1.00
	4	149	0.53	0.15	0.06	1.00
	5	145	0.54	0.15	0.06	1.00
	6	134	0.55	0.15	0.06	1.00
Structural Empowerment factor describing the women's legal status and the structural representation of women	2	126	0.74	0.15	0.00	1.00
	3	140	0.72	0.16	0.00	1.00
	4	149	0.79	0.12	0.28	1.00
	5	145	0.79	0.12	0.28	1.00
	6	134	0.79	0.11	0.28	1.00

Table 4.13 - Descriptive Statistics Post-Hoc: Stereotypes

<u>Results Regarding the Role of the Explicit Stereotypes Indicator</u>

Table 4.14 summarizes Models 17-21 that represent the baseline effects with varying time lags. As in the main models, the analysis based on the six-year lagged dataset led to (borderline) significant results (ß = 0.96, p = 0.09). A similar effect can also be observed in the dataset considering a four-year time lag (ß = 0.93, p = 0.02). These results underpin the results of the main analysis and show that the datasets used for these models are still large enough to reproduce the main results of this paper.

Models 22-26 (summarized in Table 4.15) examine how the prevalence of *Explicit Stereotypes* affects the results from Models 17-21. However, only Model 22, considering a two-year time lag, provides significant results (ß = 5.12, p = 0.04). Even though there was no significant corresponding direct effect for a two-year time lag in Model 17, this value is much higher than all observed direct effects in Models 1-4 and 17-21. Therefore, it is reasonable to argue that *Explicit Stereotypes* positively moderate the relationship between *Share Women Opportunity Entrepreneurs* and *Share Women Board Directors* when considering a time lag of two years. Noteworthy, *Explicit Stereotypes* have a direct, negative impact on the dependent variable (ß = - 21.85, P = 0.03), and the direct effect of *Share Women Opportunity Entrepreneurs* on *Share Women Board Directors* becomes negative after controlling for *Explicit Stereotypes* and *Share Women Opportunity Entrepreneurs × Explicit Stereotypes* (ß = -2.20, p = 0.03).

<u>Results Regarding the Role of the Implicit Stereotypes Indicator</u>

Finally, Table 4.16 summarizes Models 27-31 that intend to shed light on the role of Implicit Stereotypes in the relationship between *Share Women Opportunity Entrepreneurs* and *Share Women Board Directors*. However, these models did not provide any significant results. Therefore, the analysis provides evidence that the relationship suggested in Hypothesis 1 becomes stronger at places where stereotypes are openly expressed. However, there is no statistical evidence for the assumption that implicit stereotypes affect the relationship similarly.

	Model 17 (time lag = 2)	Model 18 (time lag = 3)	Model 19 (time lag = 4)	Model 20 (time lag = 5)	Model 21 (time lag = 6)
Share Women Opportunity Entrepreneurs	0.25	0.82	**0.93 ***	0.58	**0.96 •**
	(0.51)	(0.21)	**(0.02)**	(0.19)	**(0.09)**
Societal Empowerment	-20.96	-41.17	**-54.03 •**	**-41.76 •**	-49.75
	(0.47)	(0.15)	**(0.03)**	**(0.09)**	(0.12)
Structural Empowerment	5.77	-9.95	-8.09	-8.47	-0.62
	(0.72)	(0.36)	(0.27)	(0.37)	(0.94)
Share Women Middle Management	-0.19	-0.07	-0.07	0.08	0.08
	(0.36)	(0.50)	(0.49)	(0.38)	(0.44)
Share Women Inventors	-0.67	-0.15	0.40	**0.78****	0.59
	(0.12)	(0.70)	(0.25)	**(0.00)**	(0.12)
Wage Growth	**0.39 •**	0.27	-0.10	-0.02	0.02
	(0.06)	(0.16)	(0.61)	(0.91)	(0.89)
Perceived Founding Skills	0.00	-0.11	-0.17	-0.13	-0.08
	(0.98)	(0.21)	(0.08)	(0.29)	(0.47)
Perceived Entrepreneurial Environment	**-0.10 ***	**-0.15 ****	**-0.12 ***	**-0.12 ****	-0.05
	(0.02)	**(0.00)**	**(0.02)**	**(0.01)**	(0.10)
Employment Protection	-4.28	-3.00	-3.18	-1.67	**-4.29 ***
	(0.11)	(0.23)	(0.13)	(0.36)	**(0.04)**
Social Expenditure	**-0.43 ****	**-0.76 ****	**-0.96 ****	**-0.89 ****	**-0.85 ****
	(0.01)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**
Replacement Rate	0.13	0.27	0.20	0.12	0.08
	(0.44)	(0.12)	(0.12)	(0.20)	(0.32)
R^2 (within)	**0.18**	**0.19**	**0.27**	**0.25**	**0.34**

Table 4.14 - Regression Table Baseline Explicit Stereotypes • p<0.1 * p<0.05 ** p<0.01 *** p<0.001

	Model 22 (time lag = 2)	Model 23 (time lag = 3)	Model 24 (time lag = 4)	Model 25 (time lag = 5)	Model 26 (time lag = 6)
Share Women Opportunity Entrepreneurs	**-2.20 ***	-0.79	0.14	0.11	0.21
	(0.03)	(0.46)	(0.90)	(0.91)	(0.84)
Societal Empowerment	-14.90	-40.92	**-53.24 ***	**-41.54 •**	-49.00
	(0.58)	(0.17)	**(0.03)**	**(0.07)**	(0.11)
Structural Empowerment	6.56	-11.54	-11.01	-10.65	-1.90
	(0.67)	(0.32(	(0.17)	(0.25)	(0.78)
Share Women Middle Management	-0.20	-0.10	-0.09	0.07	0.08
	(0.34)	(0.38)	(0.44)	(0.44)	(0.46)
Share Women Inventors	-0.67	-0.11	0.41	**0.76 ****	0.66
	(0.14)	(0.78)	(0.22)	**(0.00)**	(0.16)
Wage Growth	**0.38 •**	0.27	-0.08	-0.01	0.02
	(0.07)	(0.18)	(0.67)	(0.95)	(0.88)
Perceived Founding Skills	0.04	-0.10	**-0.17 •**	-0.13	-0.08
	(0.74)	(0.27)	**(0.09)**	(0.26)	(0.44)
Perceived Entrepreneurial Environment	-0.10	-0.16	-0.13	-0.13	-0.06
	(0.01)	(0.00)	(0.02)	(0.01)	(0.05)
Employment Protection	**-4.64 •**	-3.46	-3.56	-2.10	-4.30 •
	(0.08)	(0.20)	(0.11)	(0.28)	**(0.06)**
Social Expenditure	-0.41	-0.74	-0.94	-0.87	-0.85
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
Replacement Rate	0.09	0.30	**0.25 •**	**0.17 •**	**0.11 •**
	(0.60)	(0.13)	**(0.09)**	**(0.07)**	**(0.09)**
Explicit Stereotypes	**-21.85 ***	-7.58	1.81	4.48	-0.03
	(0.03)	(0.23)	(0.82)	(0.53)	(1.00)
Share Women Opportunity Entrepreneurs	**5.12 ***	3.13	1.56	1.00	1.56
× Explicit Stereotypes	**(0.04)**	(0.16)	(0.50)	(0.66)	(0.48)
R^2 (within)	**0.24**	**0.21**	**0.29**	**0.27**	**0.36**

Table 4.15 - Regression Table Moderation Explicit • p<0.1 * p<0.05 ** p<0.01 *** p<0.001

	Model 27 (time lag = 2)	**Model 28** (time lag = 3)	**Model 29** (time lag = 4)	**Model 30** (time lag = 5)	**Model 31** (time lag = 6)
Share Women Opportunity Entrepreneurs	-1.73	-1.33	-0.94	-1.17	0.40
	(0.34)	(0.41)	(0.49)	(0.27)	(0.60)
Societal Empowerment	-6.21	-9.65	**-15.19 •**	-14.98	-7.97
	(0.70)	(0.46)	**(0.09)**	(0.11)	(0.28)
Structural Empowerment	-24.54	-42.89	**-54.85 ***	**-42.32 •**	-50.00
	(0.42)	(0.17)	**(0.03)**	**(0.08)**	(0.11)
Share Women Middle Management	3.93	-9.93	-8.28	-8.72	0.14
	(0.79)	(0.34)	(0.29)	(0.39)	(0.99)
Share Women Inventors	-0.22	-0.09	-0.03	**0.13 •**	0.13
	(0.22)	(0.44)	(0.78)	**(0.09)**	(0.17)
Wage Growth	-0.59	-0.07	0.44	**0.79 ***	0.58
	(0.16)	(0.85)	(0.18)	**(0.00)**	(0.14)
Perceived Founding Skills	**0.40 •**	0.27	-0.11	-0.04	0.01
	(0.06)	(0.19)	(0.58)	(0.82)	(0.96)
Perceived Entrepreneurial Environment	**-0.01 •**	-0.12	-0.16	-0.11	-0.07
	(0.93)	(0.22)	(0.12)	(0.32)	(0.53)
Employment Protection	**-0.10 ***	**-0.15 ****	**-0.13 ***	**-0.13 ****	-0.05
	(0.03)	**(0.01)**	**(0.01)**	**(0.00)**	(0.07)
Social Expenditure	-3.34	-2.21	-3.10	-1.77	**-4.65 ***
	(0.24)	(0.37)	(0.11)	(0.26)	**(0.02)**
Replacement Rate	**-0.45 ***	**-0.78 ****	**-1.04 ****	**-0.94 ****	**-0.89 *****
	(0.03)	**(0.00)**	**(0.00)**	**(0.00)**	**(<0.001)**
Implicit Stereotypes	0.14	0.28	0.21	0.13	0.09
	(0.45)	(0.16)	(0.12)	(0.12)	(0.18)
Share Women Opportunity Entrepreneurs	3.76	3.99	3.47	3.27	1.06
× Implicit Stereotypes	(0.35)	(0.28)	(0.22)	(0.17)	(0.49)
R^2 (within)	**0.21**	**0.21**	**0.29**	**0.28**	**0.36**

Table 4.16 - Regression Table Moderation Implicit Stereotypes • p<0.1 * p<0.05 ** p<0.01 *** p<0.001

4.8. DISCUSSION

Based on institutional theory and social representation theory, I argued that the increasing share of women in opportunity-based entrepreneurship challenges existing gender norms and legitimizes new beliefs about women's capabilities in business. I hypothesized that, as a consequence, firms are more likely to hire women in board positions (H1). I further expected that this effect is particularly pronounced in regions with low Structural Empowerment (H2A), where the impact of successful women entrepreneurs can break down barriers to a stronger extent than in areas where women are well-represented in economics as well as in politics and are legally empowered. Finally, in societies with high societal empowerment, women do not internalize lower-status positions, making them more likely to pursue and succeed in leadership roles. Therefore, I hypothesized that the positive impact of women entrepreneurs on women's board representation is stronger within such societies (H2B). I tested these hypotheses using ordinary least-squared panel regression. Based on the assumption that changing existing gender norms takes some time, I ran those regression models with a three-, four--, five--, and six-year time lag.

H1 received support, but the (borderline) significant results suggest that the effect becomes only statistically significant after six years. H2 also received support. Statistically significant results for a three- and four-year time lag indicate that a higher share of women opportunity entrepreneurs leads to faster change in organizational boards in a socially empowered environment. Finally, H3 is also empirically supported. Statistically significant results for a four-, five-, and six-year time lag suggest a negative moderation effect in line with the hypothesis. Post-hoc analysis reveals additional mediation effects of Societal Empowerment on the relationship between *Share Women Opportunity Entrepreneurs* and *Share Women Board Directors* for a three-, four-, and five-year time lag. This effect is negative, indicating suppression (reducing the apparent strength of the direct effect). However, rerunning the models related to H1 controlling for *Societal Empowerment* did not affect the results. Finally, I showed for two-year- time-lagged data that the direct effect of Share Women Opportunity Entrepreneurs on Share Women Board Directors is moderated by the existence of Explicit Stereotypes.

The main contribution of this paper is to the literature on women's empowerment and the corporate glass ceiling. Building on existing research that analyzed the effect of women's empowerment on gender diversity on corporate boards (e.g., Lewellyn & Muller-Kahle, 2020), I show - In line with existing literature (Ojediran & Anderson, 2020; Sharma, 2022). - that women's representation in opportunity entrepreneurship has similar effects and promotes gender equity in corporate boards. Therefore, this paper extends the list of antecedents of a higher representation of women in organizational boards, which already includes aspects such as women's representation in the labor market and management positions (Grosvold, Rayton, & Brammer, 2015).

However, research also suggests that such positive effects of gender diversity on corporate boards are heavily affected by institutional features (Lewellyn & Muller-Kahle, 2020). I add to this stream of literature by showing that societal and structural empowerment, as well as the prevalence of explicit gender stereotypes, change the effect's size. By further showing that these moderation effects differ in direction, this paper shows that women's empowerment is not a homogenous concept. Instead, it is a complex concept embedding various interrelated factors.

In this line, the results suggest that indicators of *Societal Empowerment* (i.e., lower share of women in vulnerable employment conditions) increase and accelerate the effect of women's representation in opportunity entrepreneurship on gender equity at the top of organizations, while indicators related to Structural Empowerment (i.e., increased proportion of seats held by women in national parliaments) are linked to a decrease of such effects. This underpins literature suggesting that "part of what enables women to step away from the expectations that limit them comes from seeing themselves and their options in a different light" (Cornwall, 2016, p. 353).

In a broader sense, this article contributes to the female entrepreneurship literature in two ways: First, it integrates an economic perspective into the field, which predominantly takes an individual or an organizational perspective. Secondly, it highlights the value of female entrepreneurship in terms of social progress and gender equity. Further, this paper provides new insights into the complex relationship between women-founded startups and their social environment. More concretely, women's opportunity entrepreneurship has the potential to decrease the corporate glass ceiling. Moreover, this effect is particularly strong in regions where men dominate politics and the economy, suggesting that promoting women's opportunity entrepreneurship is an excellent tool for initiating a change regarding existing gender hierarchies. Doing so, this paper contributes to a broader literature stream embedded in the social dominance theory (e.g.,Pratto, Sidanius, & Levin, 2006). Similarly, this paper contributes to the literature on gender stereotypes (e.g., Eagly & Steffen, 1984) by showing that the prevalence of explicit stereotypes is likely to correlate with a stronger transformative potential of female opportunity entrepreneurship.

Finally, I show that the corporate glass ceiling is strongly affected by increasing rates of women entrepreneurs within countries characterized by lower structural empowerment levels. First, this adds to the literature on institutional settings shaping women's entrepreneurial experiences (e.g., Bui, Kuan, & Chu, 2018). Second, this adds to the literature on the importance of women's entrepreneurship for social change in developing countries (e.g., Aparicio, Audretsch, Noguera, & Urbano, 2022) by suggesting that those countries can particularly benefit from women's entrepreneurship in terms of higher gender equity at the top of organizations.

Besides the theoretical contributions, this paper has important policy implications, especially in developing countries. In particular, entrepreneurial education and entrepreneurial support programs for women might lead to increasing rates of female opportunity entrepreneurship, which then positively affects gender equity in corporate boards. This recommendation receives support from research suggesting that targeted programs can help underrepresented groups become more visible (Hernandez, Nunn, & Warnecke, 2012).

Despite this paper's theoretical and practical implications, it has limitations. First, the data does not allow us to measure the mechanisms that cause this paper's main effect. This limitation does not affect the main message that a relationship exists between women's entrepreneurial and board representation. Still, it leaves an empirical hole regarding the mechanisms that drive it. For example, I argued that role model effects and changes in gender role expectations and attitudes explain my observations. Yet, I cannot provide empirical evidence for these statements. However, this provides an excellent opportunity for future research.

Second, the factor analysis considers only a few items which can cause problems. In particular, the factor describing women's Societal Empowerment loads very weakly on most of the items except the prevalence of anemia among pregnant women and women's vulnerable employment. Therefore, it might be ambitious to argue that the factor variable represents the degree to which women internalize existing stereotypes. Therefore, future research might be necessary to show how women's decisions are shaped by existing stereotypes and how these decisions influence the occurrence of women's empowerment.

This research's third but most important limitation is that the time-lagged samples only include a limited number of observations. In some cases, this leads to a limited generalizability of my results. For example, the data samples represent mostly countries with little opportunity-based entrepreneurial activity of women. While this limits the generalizability of this research, the small sample sizes are also likely to be partly responsible for the low number of statistically significant results. Unfortunately, I did not have access to larger and more complete datasets. However, I am positive that future research reproducing this research based on more ample datasets could underpin my findings by providing more generalizable results.

Finally, future research can build on the insight that the percentage of women on corporate boards has predictive power for future changes in the share of women opportunity entrepreneurs. For example, it could analyze whether gender quotas in corporate boards affect a country's number of women opportunity entrepreneurs.

4.9. CONCLUSION

In conclusion, this study provides valuable insights into the transformative potential of women's entrepreneurship as a tool to weaken the corporate glass ceiling. By providing empirical evidence of the positive relationship between women's participation in opportunity-based entrepreneurship and subsequent female representation in corporate boards, the research underscores the positive impact of women deviating from traditional gender norms. It also shows that the positive effects of women's entrepreneurship on female representation in corporate boards diminish in highly structurally empowered environments but become more pronounced in socially empowered societies. This nuanced understanding significantly contributes to the literature on institutional change and women's entrepreneurship, highlighting the complex interplay between societal norms, levels of empowerment, and the transformative potential of women in business. In a world where gender stereotypes persist, the study suggests promoting women's increased participation in entrepreneurship, particularly in less empowered environments, might be an essential strategy for breaking down barriers and promoting gender equality in business leadership. This conclusion underscores the importance of targeted policies and programs to support entrepreneurship, particularly in developing countries, to harness the full potential of women's entrepreneurship to reshape societal expectations and challenge prevailing norms.

4.10. REFERENCES CHAPTER 4

Adams, R., & Funk, P. 2012. Beyond the Glass Ceiling: Does Gender Matter? Management Science, 58(2): 219–235.

Afridi, F. 2010. Women's empowerment and the goal of parity between the sexes in schooling in India. Population Studies, 64(2): 131-145.

Angus, C. 2020. Gender Stereotype and Its Consequences on Female Managers. Journal of Scientific Research 6(1): 6-12.

Arafat, M., Saleem, I., Dwivedi, A., & Khan, A. 2020. Determinants of agricultural entrepreneurship: a GEM data based study. International Entrepreneurship and Management Journal, 16(1): 345-370.

Asaolu, I; Okafor, C; Ehiri, J; Dreifuss, H; & Ehiri, J. 2017. Association between Measures of Women's Empowerment and Use of Modern Contraceptives: An Analysis of Nigeria's Demographic and Health Surveys. Frontiers in Public Health, 4(2016): 1-7.

Bardasi, E., Sabarwal, S., & Terrell, K. 2011. How do female entrepreneurs perform? Evidence from three developing regions. Small Business Economics, 37(4): 417–441.

Blanchard, A., & Warnecke, T. 2010. Shaping economic practices in China's post-command economy period: the interaction of politics, economics, and institutional constraints. International Journal of Pluralism and Economics Education, 1(4): 290-302.

Blocker, T., & Eckberg, D. 1997. Gender and Environmentalism: Results from the 1993 General Social Survey. Social Science Quarterly, 78(4): 841–858.

Breusch, T. 1978. Testing for autocorrelation in dynamic linear models. Australian Economic Papers, 17(31): 334-55.

Brownell, K; Hechavarria, D; Robb, C; & Kickul, J.2024. Culture and social entrepreneurship: the role of value-practice misalignment. Small Business Economics, 2024: 1-25.

Burke, R. 1997a. Women directors: Selection, acceptance and benefits of board membership. Corporate Governance: An International Review, 5(3): 118-125

Burke, R. 1997b. Women on corporate boards of directors: A needed resource. Journal of Business Ethics, 16(9): 909-915.

Cardella, G., Hernández-Sánchez, B., & Sánchez-García, J. C. 2020. Women entrepreneurship: A systematic review to outline the boundaries of scientific literature. Frontiers in psychology, 11(1557): 1-18

Charlesworth , T; & Banaji, M. 2022. Patterns of Implicit and Explicit Stereotypes III: Long-Term Change in Gender Stereotypes. Social Psychological and Personality Science, 13(1): 14-26.

Charlesworth, T; Navon, M; Rabinovich, Y; Lofaro, N; & Kurdi, B. 2023. The project implicit international dataset: Measuring implicit and explicit social group attitudes and stereotypes across 34 countries (2009–2019). Behavior Research Method, 55(2023): 1413-1440.

Choi, S; & Valladares-Esteban. 2017. Choi, S., & Valladares-Esteban, A. (2017). The marriage unemployment gap. The B.E. Journal of Macroeconomics, 18(1): 1-14.

Cotter, D., Hermsen, J. M., Ovadia, S., & Vanneman, R. 2001. The Glass Ceiling Effect. Social Forces, 80(2): 655–681.

Cornwall, A. 2016. WOMEN'S EMPOWERMENT: WHAT WORKS?. Journal of International Development, 28(1): 342-359.

Datta, P., & Gailey, R. 2012. Empowering women through social entrepreneurship: Case study of a women's cooperative in India. Entrepreneurship theory and Practice, 36(3): 569-587.

Driscoll, J., & Kraay, A. 1998. Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. Review of Economics and Statistics, 80(4): 549–560.

Duehr, E., & Bono, J. 2006. Men, Women, and Managers: Are stereotypes finally changing? Personnel Psychology, 59(4): 815–846.

Duflo, E. 2012. Women Empowerment and Economic Development. Journal of Economic Literature, 50(4): 1051-1079.

Dunn, T., Baguley, T., & Brunsden, V. 2014. From alpha to omega: a practical solution to the pervasive problem of internal consistency estimation. British journal of psychology (London, England 1953), 105(3): 399–412.

Eagly, A., & Karau, S. 2002. Role congruity theory of prejudice toward female leaders. Psychological review, 109(3): 573–598.

Eagly, A., & Steffen, V. 1984. Gender stereotypes stem from the distribution of women and men into social roles. Journal of Personality and Social Psychology, 46(4): 735–754.

Elam, A., Hughes, K., & Samsami, M. 2023. Global Entrepreneurship Monitor 2022/23 Women's Entrepreneurship Report: Challenging Bias and Stereotypes.

Germann, F., Anderson, S. J., Chintagunta, P. K., & Vilcassim, N. 2023. Frontiers: Breaking the Glass Ceiling: Empowering Female Entrepreneurs Through Female Mentors. Marketing Science, 43(2): 244-253.

Global Entrepreneurship Monitor. 2023. GEM Knowledge Base. Retrieved from http://gem-consortium.ns-client.xyz/about/wiki. Downloaded on September 14, 2023.

Granger, C. 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society, 37(3):* 424-438.

Greenwald, A., McGhee, D., & Schwartz, J. 1998. Measuring individual differences in implicit cognition: the implicit association test. Journal of personality and social psychology, 74(6): 1464-1480.

Greenwood, R., Hinings, C., & Suddaby, R. 2002. THEORIZING CHANGE: THE ROLE OF PROFESSIONAL ASSOCIATIONS IN THE TRANSFORMATION OF INSTITUTIONALIZED FIELDS. Academy of Management Journal, 45(1): 58–80.

Greffrath, G; & Roux, C. 2012. The effect of a gap year with selected adventure-related activities on certain personal competence-related factors on school graduates: recreation and tourism, African Journal for Physical, Health Education, Recreation and Dance, 18(1): 460-473.

Gregory, D. 1998. The Problematic Employment Dynamics of Student Internships. Notre Dame Journal of Law, Ethics & Public Policy, 12(1): 227-264.

Grosvold, J; Rayton, B; & Brammer, S. 2015. Women on Corporate Boards: A Comparative Institutional Analysis. Business & Society, 55(8): 1157-1196.

Gupta, V., Turban, D., Wasti, S., & Sikdar, A. 2009. The Role of Gender Stereotypes in Perceptions of Entrepreneurs and Intentions to Become an Entrepreneur. Entrepreneurship Theory and Practice, 33(2): 397–417.

Hancock, C., Pérez-Quintana, A., & Hormiga, E. 2014. Stereotypical Notions of the Entrepreneur: An Analysis from a Perspective of Gender. Journal of Promotion Management, 20(1): 82–94.

Haugh, H. M., & Talwar, A. 2016. Linking Social Entrepreneurship and Social Change: The Mediating Role of Empowerment. Journal of Business Ethics, 133(4): 643–658.

Hincapié, A. 2020. ENTREPRENEURSHIP OVER THE LIFECYCLE: WHERE ARE THE YOUNG ENTREPRENEURS?. International Economic Review, 61(2): 617-681.

Hogue, M., Knapp, D, Peck, J., & Weems-Landingham. 2022. The status of internalized prejudice in leader self-development. Management Decision, 61(4): 944-958.

Hsu, D., Mitchell, J., & Cao, X. 2024. Examining psychological mediators in entrepreneurship: Experimental designs, remedies, and recommendations. Entrepreneurship Theory and Practice, 48(1): 418-445.

Jensen, R. 2012. Do Labor Market Opportunities Affect Young Women's Work and Family Decisions? Experimental Evidence from India. The Quarterly Journal of Economics, 127(2): 753-792.

Kabeer, N. 1999. Resources, agency, achievements: Reflections on the measurement of women's empowerment. Development and change, 30(3): 435-464.

Khefacha, I; Romdhane, R; & Haj Salem, H. 2024. Unveiling the relationship between entrepreneurial aspirations and prosperity: An international panel study using GEM data, International Entrepreneurship and Management Journal, 20(1): 421-449.

Kteily, N., Sidanius, & J., Levin, S. 2011. Social dominance orientation: Cause or mere effect? Evidence for SDO as a causal predictor of prejudice and discrimination against ethnic and racial outgroups. Journal of Experimental Social Psychology, 47(2011): 208-214.

Koenig, A., Eagly, A., Mitchell, A., & Ristikari, T. 2011. Are leader stereotypes masculine? A meta-analysis of three research paradigms. Psychological bulletin, 137(4): 616–642.

Laguía, A., García-Ael, C., Wach, D., & Moriano, J. A. 2019. “Think entrepreneur - think male”: a task and relationship scale to measure gender stereotypes in entrepreneurship. The International Entrepreneurship and Management Journal, 15(3): 749–772.

Lewellyn, K., & Muller-Kahle, M. 2020. The Corporate Board Glass Ceiling: The Role of Empowerment and Culture in Shaping Board Gender Diversity. Journal of Business Ethics, 165(2): 329–346.

Moscovici, S. (1972). Theory and society in social psychology. In J. Israel & H. Tajfel (Eds.), The context of social psychology: A critical assessment: 17–68. London: Academic Press.

Neter,.J; Wasserman, W; & Kutner, M. 1989. Applied Linear Regression Models.

Oakley, J. G. 2000. Oakley, J.G. Gender-based Barriers to Senior Management Positions: Understanding the Scarcity of Female CEOs. Journal of Business Ethics, 27(4): 321–334.

Oliver, C. 1997. Sustainable competitive advantage: combining institutional and resource-based views. Strategic Management Journal, 18(9): 697–713.

Ordeñana, X; Vera-Gilces, P; Zambrano-Vera; & Jiménez, A. 2024. The effect of high-growth and innovative entrepreneurship on economic growth. Journal of Business Research, 171(2024): 114243

Pesaran, M. 2015. Testing weak cross-sectional dependence in large panels. Econometric reviews, 34(6-10): 1089-1117.

Pratto, F., Sidanius, J., & Levin, S. 2006. Social dominance theory and the dynamics of intergroup relations: Taking stock and looking forward. European Review of Social Psychology, 17(1): 271–320.

Samuelson, W., & Zeckhauser, R. 1988. Status quo bias in decision making. Journal of Risk and Uncertainty, 1(1): 7–59.

Schein, V. 1973. The relationship between sex role stereotypes and requisite management characteristics. The Journal of applied psychology, 57(2): 95–100.

Sharma, L. 2022. Assessing the “entrepreneurship as emancipation” perspective among women in STEM. Management Decision, 60(6): 1585-1605.

Sidanius, J. & Pratto, F. 1999. Social Dominance: An intergroup theory of social hierarchy and oppression. Cambridge University Press

Smith, N., & Parrotta, P. 2018. Why so few women on boards of directors? Empirical evidence from Danish companies in 1998–2010. Journal of Business Ethics, 147(1): 445-467.

Solomon, S; Bendickson, S; Marvel, M; McDowell, W; & Mahto, R. 2021. Agency theory and entrepreneurship: A cross-country analysis. Journal of Business Research, 122(2021): 466-476

Tool, M. 1998. Founding Institutional Econs. New York, Los Angeles: Routledge; Sony Electronics Distributor.

van der Zwan, P., Verheul, I., & Thurik, A. R. 2012. The entrepreneurial ladder, gender, and regional development. Small Business Economics, 39(3): 627–643.

Verheul, I., Thurik, R., Grilo, I., & van der Zwan, P. 2012. Explaining preferences and actual involvement in self-employment: Gender and the entrepreneurial personality. Journal of Economic Psychology, 33(2): 325–341.

Word, C; Zanna, M; & Cooper, J. 1974. The nonverbal mediation of self-fulfilling prophecies in interracial interaction. Journal of Experimental Social Psychology, 10(2): 109-120.

Zucker, L. 1987. Institutional Theories of Organization. Annual Review of Sociology, 13(1): 443–464.

5. Conclusions of this Dissertation

In recent years, there has been a growing interest in women's entrepreneurship among researchers worldwide, in both emerging economies (e.g., Ahmetaj, Kruja, & Hysa, 2023; Barkema, Bindl, & Tanveer, 2024) and the world's most developed countries[10] (e.g., Avnimelech & Rechter, 2023; Henry, Coleman, Orser, & Foss, 2022). In this context, some research particularly pronounces its potential to challenge traditional gender norms and foster gender equity (Hasan Emon & Nisa Nipa, 2024), while other authors emphasize the unique challenges that women business owners have to face (Feng et al., 2023).

In accordance with these considerations, the objective of this thesis has been to contribute to the existing literature by providing empirical evidence of the manner in which women's entrepreneurship is influenced by and influences the societal expectations, stereotypes, and power structures surrounding it. To address this matter, Chapters 2, 3, and 4 address it in different ways, with each chapter providing unique and relevant insights on the topic. Their individual findings are of particular value to entrepreneurial support organizations, policymakers, and the larger society. The following section will briefly summarize the primary findings presented in each chapter and conclude with a remark on their contribution to the broader research field.

Chapter 2 delves into the gender dynamics within startup accelerators, emphasizing the importance of cohort composition for post-accelerator funding success. The study reveals that inexperienced women founders benefit from women-only cohorts, while experienced women gain more from male-dominated environments. Similarly, experienced male founders also benefit from gender-diverse cohorts. These findings highlight the nuanced role of gender and experience in accelerator program outcomes, suggesting that tailored cohort designs can foster more inclusive and effective entrepreneurial ecosystems.

Chapter 3 examines the extent to which women entrepreneurs adhere to prevailing gender role stereotypes and how this impacts their funding prospects. The findings indicate that women are more likely to establish startups with a focus on social and educational initiatives and less likely to pursue pro-environmentally oriented ventures. Furthermore, a gender-related funding disparity persists, with female-founded startups receiving comparatively less funding per investment round. However, this disparity is less pronounced among social and educational ventures but increases among pro-environmental ventures. These findings underscore the need for targeted support that considers gender and the specific needs of different industry sectors.

[10] As the world's most developed countries, I consider the 25 countries scoring highest in terms of the Human Development Index (Conceição, 2024).

Chapter 4 investigates the potential of women's entrepreneurship to disrupt the corporate glass ceiling. The study reveals that an increase in women's participation in opportunity-based entrepreneurship has a positive, time-lagged effect on women's representation on corporate boards. Furthermore, this effect is moderated by the level of structural and societal empowerment within a country. More specifically, the positive effect decreases in structurally empowered environments (i.e., countries with high levels of women's political and economic representation, where the law does not favor men over women), whereas it increases in socially empowered regions (i.e., countries where women tend to make decisions about their health and working conditions that disadvantage them). These findings contribute to the understanding of how local conditions influence the advancement of women in corporate leadership and suggest that entrepreneurial education and support programs can be effective tools to promote gender-balanced boards in the long run.

All in all, this thesis investigates the interplay between women's entrepreneurship and societal norms and expectations from a variety of different perspectives. Chapters 2 and 3 demonstrate that the field of entrepreneurship is gendered, with men continuing to enjoy a greater degree of privilege than women. However, both articles also identify factors that influence the strength of this relationship. To be more precise, Chapter 2 suggests that women are more likely to attract post-acceleration financing if they participate in acceleration programs with a majority of male participants. Moreover, Chapter 3 demonstrates that women-led enterprises that engage in business activities typically associated with women (e.g., social or education-oriented businesses) receive greater funding than the average female entrepreneur, yet still less than their male counterparts. These insights suggest that women entrepreneurs are most successful when they align their actions with societal norms and expectations that favor men. However, such behavior perpetuates—and potentially even exacerbates—a hierarchical order in which women are the disadvantaged party.

Therefore, both essays entail an important implication for managers of entrepreneurial support organizations. Women entrepreneurs still often need support if they want to establish their businesses in male-dominated industries. However, it is essential to recognize that women entrepreneurs are not a homogeneous group and that their needs vary considerably with respect to what is required for them to succeed. For instance, the level of experience that founders possess (Chapter 2) and the cost intensity of their startups (Chapter 3) should be taken into account when designing support initiatives. Finally, Chapter 4 shows that women's entrepreneurship can lead to broader changes in society. This not only underpins the value of women entrepreneurs for society but also complements Chapters 2 and 3 by suggesting that role-incongruent behaviors (i.e., engaging in high-growth entrepreneurship) can lead to social change in the long run, even though they are often punished by society in the short run.

In conclusion, this dissertation examined how social forces shape - and are shaped - by women entrepreneurs. The thesis entails important implications for researchers and practitioners (i.e., founders, investors, and managers of entrepreneurial support organizations). Lastly, the United Nations has identified "achieving gender equality and empowering all women and girls" as an essential component of a nation's sustainable development (United Nations, 2024) and I am confident that this dissertation makes a small but valuable contribution to this objective.

6. References

Adams, R. B., & Funk, P. 2012. Beyond the Glass Ceiling: Does Gender Matter? Management Science, 58(2): 219–235.

Ahmetaj, B., Kruja, A. D., & Hysa, E. 2023. Women Entrepreneurship: Challenges and Perspectives of an Emerging Economy. Administrative Sciences, 13(4): 111.

Anglin, A. H., Kincaid, P. A., Short, J. C., & Allen, D. G. 2022. Role Theory Perspectives: Past, Present, and Future Applications of Role Theories in Management Research. Journal of Management, 48(6): 1469–1502.

Atarah, B. A., Finotto, V., Nolan, E., & Van Stel, A. 2023. Entrepreneurship as emancipation: A process framework for female entrepreneurs in resource-constrained environments. Journal of Small Business and Enterprise Development, 30(4): 734–758.

Avnimelech, G., & Rechter, E. 2023. How and why accelerators enhance female entrepreneurship. Research Policy, 52(2): 104669.

Barkema, H. G., Bindl, U. K., & Tanveer, L. 2024. How Entrepreneurs Achieve Purpose Beyond Profit: The Case of Women Entrepreneurs in Nigeria. Organization Science, 35(3): 1042–1071.

Baum, J., & Locke, E. A. 2004. The Relationship of Entrepreneurial Traits, Skill, and Motivation to Subsequent Venture Growth. Journal of Applied Psychology, 89(4): 587–598.

Bigelow, L., Lundmark, L., McLean Parks, J., & Wuebker, R. 2014. Skirting the Issues: Experimental Evidence of Gender Bias in IPO Prospectus Evaluations. Journal of Management, 40(6): 1732–1759.

Brough, A. R., Wilkie, J. E. B., Ma, J., Isaac, M. S., & Gal, D. 2016. Is Eco-Friendly Unmanly? The Green-Feminine Stereotype and Its Effect on Sustainable Consumption. Journal of Consumer Research, 43(4): 567–582.

Brush, C., Carter, N., Gatewood, E., Greene, P., & Hart, M. 2008. The Diana Project: Women Business Owners and Equity Capital: The Myths Dispelled. SSRN Electronic Journal.

Brush, C., Edelman, L., Manolova, T., & Welter, F. 2019. A gendered look at entrepreneurship ecosystems. Small Business Economics, 53(2): 393–408.

Cohen, S., Fehder, D. C., Hochberg, Y. V., & Murray, F. 2019. The design of startup accelerators. Research Policy, 48(7): 1781–1797.

Conceição, P. 2024. Human Development Report 2023/2024. Lanham: Bernan Press.

Cowden, B. J., Creek, S. A., & Maurer, J. D. 2021. Gender role congruity and crowdfunding success. Journal of Small Business Management, 59(sup1): 134–152.

Del Carmen Triana, M., Song, R., Um, C. T., & Huang, L. 2024. Stereotypical Perception in Management: A Review and Expansion of Role Congruity Theory. Journal of Management, 50(1): 188–215.

Dempsey, D., & Jennings, J. 2014. Gender and entrepreneurial self-efficacy: A learning perspective. International Journal of Gender and Entrepreneurship, 6(1): 28–49.

Duehr, E. E., & Bono, J. E. 2006. MEN, WOMEN, AND MANAGERS: ARE STEREOTYPES FINALLY CHANGING? Personnel Psychology, 59(4): 815–846.

Eagly, A. H. 1987. Sex Differences in Social Behavior: A Social-role interpretation (1st ed.). Psychology Press.

Eagly, A. H., & Karau, S. J. 2002. Role congruity theory of prejudice toward female leaders. Psychological Review, 109(3): 573–598.

Eagly, A. H., & Steffen, V. J. 1984. Gender stereotypes stem from the distribution of women and men into social roles. Journal of Personality and Social Psychology, 46(4): 735–754.

Eddleston, K. A., Ladge, J. J., Mitteness, C., & Balachandra, L. 2016. Do you See what I See? Signaling Effects of Gender and Firm Characteristics on Financing Entrepreneurial Ventures. Entrepreneurship Theory and Practice, 40(3): 489–514.

Elam, A., Baumer, B., Schott, T., Samsami, M., Dwivedi, A., et al. 2022. GEM 2021/22 Women's Entrepreneurship Report: From Crisis to Opportunity.

Ewens, M., & Townsend, R. R. 2020. Are early stage investors biased against women?. Journal of Financial Economics, 135(3): 653-677.

Feng, J., Ahmad, Z., & Zheng, W. 2023. Factors influencing women's entrepreneurial success: A multi-analytical approach. Frontiers in Psychology, 13: 1099760.

George, G., Merrill, R. K., & Schillebeeckx, S. J. D. 2021. Digital Sustainability and Entrepreneurship: How Digital Innovations Are Helping Tackle Climate Change and Sustainable Development. Entrepreneurship Theory and Practice, 45(5): 999–1027.

Godwin, L. N., Stevens, C. E., & Brenner, N. L. 2006. Forced to Play by the Rules? Theorizing how Mixed–Sex Founding Teams Benefit Women Entrepreneurs in Male–Dominated Contexts. Entrepreneurship Theory and Practice, 30(5): 623–642.

Goswami, K., Mitchell, J. R., & Bhagavatula, S. 2018. Accelerator expertise: Understanding the intermediary role of accelerators in the development of the Bangalore entrepreneurial ecosystem. Strategic Entrepreneurship Journal, 12(1): 117–150.

Greene, P. G., Brush, C. G., Hart, M. M., & Saparito, P. 2001. Patterns of venture capital funding: Is gender a factor? Venture Capital, 3(1): 63–83.

Gupta, A., Batra, S., & Gupta, V. K. 2022. Gender, culture, and implicit theories about entrepreneurs: A cross-national investigation. Small Business Economics, 58(2): 1073–1089.

Gupta, V., Goktan, A., & Gunay, G. 2014. Gender differences in evaluation of new business opportunity: A stereotype threat perspective. Journal of Business Venturing, 29(2): 273–288.

Gupta, V.., Wieland, A., & Turban, D. B. 2019. Gender Characterizations in Entrepreneurship: A Multi-Level Investigation of Sex-Role Stereotypes about High-Growth, Commercial, and Social Entrepreneurs: Journal of Small Business Management. Journal of Small Business Management, 57(1): 131–153.

Guzman, J., & Kacperczyk, A. (Olenka). 2019. Gender gap in entrepreneurship. Research Policy, 48(7): 1666–1680.

Hancock, C., Pérez-Quintana, A., & Hormiga, E. 2014. Stereotypical Notions of the Entrepreneur: An Analysis from a Perspective of Gender. Journal of Promotion Management, 20(1): 82–94.

Harrison, R. T., Leitch, C. M., & McAdam, M. 2020. Woman's entrepreneurship as a gendered niche: The implications for regional development policy. Journal of Economic Geography, 20(4): 1041–1067.

Hasan Emon, M., & Nisa Nipa, M. 2024. Exploring the Gender Dimension in Entrepreneurship Development: A Systematic Literature Review in the Context of Bangladesh. Westcliff International Journal of Applied Research, 8(1): 34–49.

Henry, C., Coleman, S., Orser, B., & Foss, L. 2022. Women's Entrepreneurship Policy and Access to Financial Capital in Different Countries: An Institutional Perspective. Entrepreneurship Research Journal, 12(3): 227–262.

Hernandez, L., Nunn, N., & Warnecke, T. 2012. Female entrepreneurship in China: Opportunity- or necessity-based? International Journal of Entrepreneurship and Small Business, 15(4): 411.

Jafari-Sadeghi, V. 2020. The motivational factors of business venturing: Opportunity versus necessity? A gendered perspective on European countries. Journal of Business Research, 113: 279–289.

Kamaludin, M. F. 2023. Social sustainability within social entrepreneurship. Technological Forecasting and Social Change, 192: 122541.

Laguía, A., García-Ael, C., Wach, D., & Moriano, J. A. 2019. "Think entrepreneur - think male": A task and relationship scale to measure gender stereotypes in entrepreneurship. International Entrepreneurship and Management Journal, 15(3): 749–772.

Lewellyn, K. B., & Muller-Kahle, M. I. 2020. The Corporate Board Glass Ceiling: The Role of Empowerment and Culture in Shaping Board Gender Diversity. Journal of Business Ethics, 165(2): 329–346.

Marlow, S., & McAdam, M. 2012. Analyzing the Influence of Gender upon High–Technology Venturing within the Context of Business Incubation. Entrepreneurship Theory and Practice, 36(4): 655–676.

Marlow, S., & McAdam, M. 2015. Incubation or Induction? Gendered Identity Work in the Context of Technology Business Incubation. Entrepreneurship Theory and Practice, 39(4): 791–816.

Martiarena, A. 2022. How gender stereotypes shape venture growth expectations. Small Business Economics, 58(2): 1015–1034.

Mason, C., & Brown, R. 2013. Creating good public policy to support high-growth firms. Small Business Economics, 40(2): 211–225.

McAdam, M., Harrison, R. T., & Leitch, C. M. 2019. Stories from the field: Womens networking as gender capital in entrepreneurial ecosystems. Small Business Economics, 53(2): 459–474.

Muehlenhard, C. L., & Peterson, Z. D. 2011. Distinguishing Between Sex and Gender: History, Current Conceptualizations, and Implications. Sex Roles, 64(11–12): 791–803.

Neumeyer, X., Santos, S. C., Caetano, A., & Kalbfleisch, P. 2019. Entrepreneurship ecosystems and women entrepreneurs: A social capital and network approach. Small Business Economics, 53(2): 475–489.

Ozkazanc-Pan, B., & Clark Muntean, S. 2018. Networking towards (in)equality: Women entrepreneurs in technology. Gender, Work & Organization, 25(4): 379–400.

Page, N., & Czuba, C. 1999. Empowerment: What is it. Journal of Extension, 37(5): 1–5.

Pittz, T. G., White, R., & Zoller, T. 2021. Entrepreneurial ecosystems and social network centrality: The power of regional dealmakers. Small Business Economics, 56(4): 1273–1286.

Shao, Y., & Sun, L. 2021. Entrepreneurs' social capital and venture capital financing. Journal of Business Research, 136: 499–512.

Solesvik, M., Iakovleva, T., & Trifilova, A. 2019. Motivation of female entrepreneurs: A cross-national study. Journal of Small Business and Enterprise Development, 26(5): 684–705.

United Nations. 2024. History of the Social Development Goals. Retrieved from https://sdgs.un.org/goals. Downloaded on January 25, 2024.

Van Der Zwan, P., Verheul, I., & Thurik, A. R. 2012. The entrepreneurial ladder, gender, and regional development. Small Business Economics, 39(3): 627–643.

Vershinina, N., Rodgers, P., Tarba, S., Khan, Z., & Stokes, P. 2020. Gaining legitimacy through proactive stakeholder management: The experiences of high-tech women entrepreneurs in Russia. Journal of Business Research, 119: 111–121.

Yang, S., Kher, R., & Newbert, S. L. 2020. What signals matter for social startups? It depends: The influence of gender role congruity on social impact accelerator selection decisions. Journal of Business Venturing, 35(2): 105932.