Gender Gap and Channels

An Empirical Study on Angel and Venture Capital Financing for Swedish Startups

YANJUN WANG

ZIJIN ZHU

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Abstract:

This paper investigates the gender disparity and its channels in Angel Investor and Venture Capital (AI-VC) entrepreneurial financing amount within the context of Swedish entrepreneurial market. We constructed a unique dataset of 597 AI-VC financing deals secured by enterprises founded between January 1st, 2018 and December 31st, 2023, including comprehensive data of 891 entrepreneurs' educational and professional backgrounds. Our empirical analysis reveals that female entrepreneurs receive less AI-VC investment compared to their male counterparts when controlling enterprise size, company age, deal stage, founder's university degree, and the business industry. We use interaction terms to examine the channel effects through which gender exerts its impact on deal size. The results substantiate that innovation and relevant industry experience act as negative channels for female entrepreneurs to impact AI-VC capital amount. Additionally, MBA background and the availability of financial information demonstrate the marginally significant negative channel.

Keywords:

Gender gap; Entrepreneurial finance; Channel effect; Venture capital; Angel investor

Authors:

Yanjun Wang (42407)
Zijin Zhu (42373)

Tutor:

Anastasia Girshina, Assistant Professor, Department of Finance

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1. Introduction

In recent years, in the process of pursuing development, economies have realized SMEs' roles as key driving forces for economic growth (Deakins and Freel, 1998; Hu, 2010), and among them, entrepreneurship is acknowledged as the protagonist in providing competitiveness and vitality (Thurik and Wennekers, 2004). Currently as an important source of financing for new ideas and technologies (Howell and Nanda, 2019), Angel Investors and Venture Capitals (AI-VCs) represent a pivotal force in the entrepreneurial ecosystem by providing multi-faceted positive support, driving not only the genesis and growth of innovative startups but also promote the prosperity of the global economy.

The worldwide expansion of the AI-VCs industry has provided increased equity financing opportunities for growing entrepreneurial firms. AI-VC capitalists contribute to innovation, job creation, industrial renewal and economic growth, not only through their financial investments, but also through the managerial expertise and deal making leverage they provide to their portfolio companies (Mason, 1999). Concurrently, however, the increased sophistication of limited partners, venture capital firm investment specialization, and growing investment fund size has intensified competition among venture capital firms and, consequently in turn, raised the bar for entrepreneurs seeking equity capital.

On the other hand, the intersection of gender, AI-VC investment, and entrepreneurship forms a critical area of study within the broader fields of business and economics. Whereas research has shown that female entrepreneurs are less likely than males to acquire VCs (Tinkler et al., 2015; Gupta et al., 2008). For instance, an extensive study of high-tech entrepreneurs in 2001 reveals that only 5% of VC investments went to female-owned high-tech firms (Brush et al., 2001), and it is to be the same case in Sweden even in 20201. Despite the increasing participation of females in entrepreneurship, significant disparities remain in access to entrepreneurial financing resources such as angel investors and early-stage VCs, which are crucial for the development and sustainability of startup firms (Brush et al., 2004). Some of the most prominent explanations focus on the effects of human and social capital (Robb, 2009), in which the scarcity of female entrepreneurs reflects the shortage of females with high education and entrepreneurial experience (Greene et al., 2003; Menzies et al., 2004), or the absence of females in strategic entrepreneurial networks (Brush et al., 2004; Mitchell, 2011).

AI-VCs are not only financial resources but also vital components that can influence the success and scale of vibrant startups. In this case, leveraging the role that AI-VCs play in the economy to support the female entrepreneurships would remarkably promote the development of gender equality. Considerable attention has been paid to female's lower likelihood and lower amount of fundraising from early-stage entrepreneurial financing capitalists. Existing research in this area with a particular focus on Sweden market where entrepreneurship and gender equality are highly valued is limited, to our knowledge, no current research has delved into gender's interplay with various aspect including companies, founders, especially their professional background, to examine the gender gap in the sphere of AI-VC funding in Swedish market. Hence, this paper seeks to illuminate the multifaceted relationship between early-stage entrepreneurial investment and female entrepreneurship, particularly focusing on the AI-VC funding disparities, and identify the channels of gaps.

In this paper, a dataset has been constructed to include 579 AI-VC investments secured by Swedish companies founded between 2018 to 2024, composing of 67 deals received by female founding teams and 530 deals received by male founding teams. What makes this dataset unique is that we manually collect 891 founders' educational and professional background such that deal-specific, company-specific, and founder-specific characteristics can be effectively controlled and explored their channel effect for gender.

First, this paper finds that, in Sweden, female does receive less AI-VC investment amount when controlling various deal, company, and founder characteristics and accounting for industry fixed effects.

Further, we use interaction terms to explore the channel effect of various variables for gender to impact investment amount. The aspects we look at are external financial information availability and patenting activity at the company level, MBA degree, prior entrepreneurial experience, and relevant industry experience at the founder level.

We find that patenting activity and prior relevant industry experience work as channels for female entrepreneurs to decrease investment amount from AI-VCs, and the channel effect stays significant at 5% level after adding industry fixed effects, indicating that this finding is relatively robust. This finding suggests that female entrepreneurs' dedication on innovation and their relevant industry experience may be less valuable or undervalued due to systematic bias, resulting in the negative channel effect of patenting and prior industry experience for female to impact early-stage financing deal size.

External financial information availability and MBA background display a marginal significant negative channel effect, and after adding fixed effects, some of the significances disappear, implying that they are potential channels for female to decrease deal size. Moreover, prior entrepreneurial experience does not display any significance but holds a slight positive value to imply a potential positive effect for female entrepreneurs to increase investment amount.

In the remainder of this paper, we start by reviewing relevant existing literature, and derive our research hypotheses based on current studies. Subsequently we move to explain the collection and measurement of our dataset. Building on that, we constructed empirical models and explained the methodology used. Thereafter, we provide descriptive findings based on the dataset. Ultimately, we present and discuss the empirical results and draw our conclusions.

2. Literature Review

2.1. Entrepreneurship and Economic Development

Entrepreneurship is considered to be one of the most enduring force driving the economic development of a country or region by boosting employment, promoting innovations, generating positive impact from small to large cities and further increasing social welfares and dynamics (Acs et al., 2008; Audretsch et al., 2015; Kuratko, 2011; Toma et al., 2014; Szabo and Herman, 2012). Historically large corporations have created the majority of jobs while the trend reversed, and small-sized firms created more innovations than their large firm counterparts, especially during the doc-com bubble (Lerner, 1994; Birch, 1990; Scherer, 1991).

From theoretic perspective, Schumpeterian emphasizes the role of entrepreneurs in facilitating innovation through new products, new processes, and new business models to gain competitive advantages, and integrates the entrepreneurial spirit into the continuous business development, yet other scholars such as Kirznerian argue that entrepreneurs contribute to the economic resource allocation by identifying market imbalances and exploring new opportunities (Roininen and Ylinenpää, 2009; Mehmood et al., 2019).

Indeed, despite the complexity of the factors involved, many empirical studies have demonstrated a positive correlation between entrepreneurship and local economic growth (Acs and Szerb, 2007; Audretsch and Keilbach, 2004; Van Stel et al., 2005). Other studies have also confirmed that the influence of entrepreneurship to the economies depends on contextual factors such as macroeconomic and political-regime stability, local social and humanistic environment, financial market efficiency, regulation and taxation, financing channels and constraints (Ayyagari et al., 2008; Hausmann et al., 2005).

2.2. Entrepreneurial Finance

Entrepreneurial finance is a subsegment of corporate finance. Conventionally speaking, corporate finance lay emphasizes mature, public listed companies while entrepreneurial finance generally applies to young, private firms. Apparently, entrepreneurial finance plays a positive role in enhancing the business performance and promoting growth and development of startups (Fraser et al., 2015), however, one of the most important issues that startups are facing is their capability to obtain capital.

Similar to traditional corporate finance, entrepreneurial finance incorporates diverse financing approaches from debt to crowdfunding or government grants (Cosh et al., 2009). Notwithstanding, for early-stage startups, debt financing is not their primary choice, as they are in demand of large amounts of cash flow while ordinarily not yet profitable enough to argue for favorable loan terms. Moreover, startups typically lack necessary tangible assets and intangible assets to realize their value creation potential (Cumming, 2008). On the contrary, in addition to entrepreneurs' personal savings or financial support from families or friends, they incline to seek equity investment, which not only bridge the capital gaps, but also potentially bring in substantial resources such as knowledge, human capital and advanced management experience. Angel investors and venture capitals are the most common equity investors in this context (Denis, 2004). Angel investors refer to high net worth individuals who provide risk capital to small, private firms, with the aim of boosting the enterprise for return or altruistic reasons, i.e., willingness and interests (Prowse, 1998). Venture capital (VC), a form of institutional financing, usually targets at early stage developed startups or emerging companies with high potential of returns in the future (Gompers and Lerner, 2004).

Formerly, different types of capital providers were treated separately in accordance with their capital sources and investment forms. A large proportion of entrepreneurial finance investors, for instance VCs and private equities, exit through strategic sales or initial public offerings (IPOs) to realize their returns over the years (Cumming, 2008). Nevertheless, recently there appears to be a trend of collaboration among equity investors, with providers sharing information and jointly investing in the target company (Wright, 2015). Efficiency is increasing in the current capital market.

2.3. Early-Stage Entrepreneurial Finance and the Economy

It is widely acknowledged that angel investors and venture capital (AI-VCs) are key components in the entrepreneurial ecosystem, and they have a significant impact on the growth, development, and success of startups. AI-VCs typically use equity instruments in exchange for certain ownership stakes in the company, actively engaging in business management and strategic decisions.

Numerous studies have explored the role of AI-VCs in supporting the growth of startups (Bonini and Capizzi, 2019; Vanacker et al., 2013), and particularly, many scholars highlight the influence of AI-VCs on innovations (Szabo and Herman, 2012; Chemmanur and Fulghieri, 2014). For example, previous research has demonstrated that angel financing assist enterprises in competing effectively, thereby achieving higher levels of innovation (Kerr et al., 2014; Collewaert and Sapienza, 2016). Lerner (2000) argues that VC is more effective in promoting the commercialization of innovations, suggesting a unique role in bringing technologies to market. Gompers and Lerner (2001) further support this view by emphasizing that venture capitalists add value to the investee companies through various methods, including providing more accesses to networking, managerial or technical support, and strategic guidance, rather than just funding. Furthermore, a study carried out by Popov (2014) substantiates that an increase in the supply of VCs is positively correlated with the size of the firm. Scholars' findings have underscored the empirical fact that AI-VC-backed startups are inclined to generate higher sales, grow and scale up faster, and employ more talents than those counterparts without AI-VCs' support.

By facilitating access to resources, enhancing firms' innovative and creative capabilities, and actively engaging in business operation, AI-VCs significantly influence the trajectory of startups.

Furthermore, AI-VCs also make significant contributions to the broader economy, especially in the aspect of creating job opportunities and promoting economic vitality (Hochberg et al., 2007). By studying regional data, research carried out by Samila and Sorenson (2011) indicates that an increase in venture capital activity is associated with higher employment and total revenue of startups, and beyond that, VCs stimulate the creation of more firms than it funds. Going a step further, the study researched by Mollick (2012) suggests that by cultivating entrepreneurial clusters, VCs have exerted their positive influence on not only regional innovation systems, but also the overall enhancement of the economic performance.

Consequently, based on the above research, whether it is angel investment or venture capital, these financing activities have produced considerable positive impacts not only at the corporate level, but further at the social and macroeconomic level.

2.4. Factors Affecting Capital Raising for Entrepreneurs

Firmly admitted, capital is an indispensable element for entrepreneurial success, which enables startups to carry out normal operational activities, foster innovation, and accelerate potential expansion. A variety of factors influence entrepreneurs' abilities to secure funding for their enterprises, ranging from internal individual characteristics and company operation conditions to external markets and investor dynamics.

First of all, the entrepreneur's intrinsic personality and qualities are important in facilitating access to capitals. Milosevic (2018) substantiates that a strong social network not only boosts to raise large capital from the market, but also enhances the entrepreneur's credibility among financial institutions. Studies (Stuart et al., 1999) further demonstrate that the stronger and more prestigious the entrepreneur's networks, the greater their chances of securing funds, particularly from reputable investors. Hsu (2007) further provides empirical evidence proving that prior entrepreneurial experience, particularly success in the financial field, increases the likelihood of fundraising through direct contracts. However, scholars (Verheul and Thurik, 2001) also found that gender exerts its influence on recruitment of start-up capital for entrepreneurs in different ways.

Second, the characteristics of the enterprise itself significantly affect the capability of the founding team to raise capital. One of the most considerable factors that are prioritized by investors is innovativeness. According to Schumpeter (1942), innovation leads to fluctuations in the capital market. Innovation, namely the processes with creative disruption, fuels the revolution of the economic structure and the role of new capital is to facilitate these innovative activities to prompt economic transformation. Enterprises with high levels of innovation, peculiarly those disrupting the existing market, would attract more investment (Schumpeter, 1942; Lerner, 2000; Gompers and Lerner, 2001). Scalability is another consideration, as the potential for rapid scalability makes startups more attractive to investors who seek high returns, value appreciation, liquidity and future exiting approaches (Kerr and Nanda, 2009). Investors would also take the feasibility of the business concept and the corresponding business model into account. In fact, Mason and Stark (2004) have found that bankers emphasize the companies' financial states, while VCs and business angels stress both market condition and the investee firms' 'investor fit'. Further it states that accompanied by a robust business model, which includes clear revenue streams and a detailed market analysis to raise capital, it is easier for the company to raise capital.

Third, the external market environment also determines the enterprises' capital raising activities. Economic climate, social humanity environment, industry reformation, and the competitive dynamics affect the capitalists' willingness and capacity to invest, and in turn, further influencing entrepreneurs' financing behavior. Gompers and Lerner (2001) note that venture capital funding cycles are highly sensitive to economic fluctuations. In the venture capital investment cycle, as expected, when public market signals become more favorable, VCs with the most industry experience increase their investments the most (Gompers et al., 2008). Besides, sector-specific trends, such as the renovation of technology, the application of artificial intelligence or clean energy, could drive the investment direction, which indirectly affect the complexity of fundraising for entrepreneurs.

In addition, investors themselves bring up a set of criteria that influence their decisions to fund startups. For example, younger, less proven startups might attract more risk-tolerant angel investors, whereas those aging, mature firms might be more appealing to conservative VCs or private equities who are seeking relatively lower risk but higher possibility of strategic existing (Cumming, 2008). Many investors also operate their investments following certain strategies such as theme investors who make investment under a specific topic that navigates their funding decisions. Other investors may focus on particular industries, technologies, or stages of business development that it takes time and resources to direct entrepreneurs to the appropriate capital providers.

In general, entrepreneurial financing is influenced by a multifaceted set of factors that encompass the characteristics of both the entrepreneurs and the enterprises, the prevailing market conditions, and specific investor preferences. These factors interact in complex ways to shape the entrepreneurial financing landscape.

2.5. Factors Affecting the Amount of Early-stage Entrepreneurial Financing

As an indispensable impetus in the finance world, angel investors and venture capitals (AI-VCs) provide active capital support to many emerging stars. However, the amount of capital that entrepreneurs can raise for their business at the early stage from AI-VCs varies greatly due to multifaceted factors.

One of the influencing factors that AI-VCs emphasize is the characteristics of the founding team. AI-VCs often evaluate the background, experience, and cohesion of the founding team as primary indicators of a startup's potential success partially because the founding team sets the tone for the startup and a good team implies a high possibility of sound future cooperation (Prowse, 1998). For example, in the research conducted by Shepherd (1999), he notes that VCs place a high value on the team's industry experience and management skills. Hsu (2007) stressed in his research that the educational background of the founders, particularly their attainment from prestigious institutions, can significantly influence the amount of capital raised for their business, as it is often associated with a strong network and a sound credibility in the business community.

The attractiveness of the industry sector and the business model is another profound consideration for AI-VCs. Given that early-stage investors, with active engagement intention, target at businesses that can rapidly scale and achieve market dominance (Kaplan and Strömberg, 2004), startups in high-growth sectors such as technology, biotechnology, and clean energy tend to attract larger amount of capital, not to mention the high potential return and liquidity that facilitate the process of fundraising (Gompers and Lerner, 2001).

Furthermore, external market conditions significantly impact the amount of capital that AI-VCs could provide to entrepreneurs as well. AI-VC funding activities are largely influenced by the economic climate (Gompers and Lerner, 2004; Ning et al., 2015). Besides, hot market topics, liquidity in financial markets, and investor sentiment can dictate the overall availability of capital from AI-VCs. In their study, Jeng and Weels (2000) demonstrate that venture capital cycles are closely correlated with macroeconomic indicators such as GDP growth and capital market performance. Apparently, during economic downturns, the total amount of capital available for new investments typically declines, affecting how much startups can raise， and vice versa, when the economy recovers, the availability of venture capitals increases, and subsequentially the amount of capital that enterprises could raise may increase accordingly.

In addition, investors also attach the point on the development stage of the firms. Early-stage companies might find it challenging to raise large amounts of capital due to the high perceived risks, limited operational history and inaccurate performance forecast (Gompers and Lerner, 1996). In contrast, late-stage companies usually have established stable cash flows, committed customer bases, and proven history of business models and profitability. The relatively mature firms are often capable of raising larger amounts of capital considering their risk profile is lower and the fundings are generally used for scaling operations and expansion.

Overall, the amount of capital that entrepreneurs can secure from VCs is subject to a myriad of factors, each exerting its own influence on the fundraising process. The interplay of these multifaceted factors underlies the complexity of venture capital fundraising activities, with entrepreneurs navigating a dynamic landscape influenced by team dynamics, enterprise development, industry attractiveness, market conditions, and venture capitalists' criteria and preferences in their quest for capital to fuel growth and innovation.

2.6. Gender Gap in Entrepreneurship

Despite the growing participation of females in business, entrepreneurship remains as a male-dominated activity even in the twenty-first century (Alsos et al., 2006). Whether the gender gap exists in entrepreneurship is a top concern of scholars, policymakers and the general public. In 2015, the United Nations proposed the 17 sustainable development goals aiming for the long-term development, of which one of the priorities is inequality and poverty (Halkos and Gkampoura, 2021; Hepp et al., 2019). The Secretary General António Guterres argues that gender equality is far behind making progress in the past years (Ver Steeg, 2022).

Many studies have explored the multiple factors that contribute to this gap, including access to resources, business performance, and the broader socio-economic barriers that disproportionately affect female entrepreneurs (Verheul and Thurik, 2001; Laguía et al. 2022; Tinkler et al., 2015). A primary focus of the research on entrepreneurial gender gap is the differences in access to key business resources, particularly financial resources. Verheul and Thurik (2001) have found that though there are no significant deviations in the type of fundings, females receive smaller amount of investment compared to male entrepreneurs. The empirical finding is further corroborated by Coleman's study (2000), which highlights the point that female entrepreneurs generally have lower levels of startup capital compared to their male counterparts and face more difficulties in raising capitals from VCs. Another study conducted by Muravyev et al. (2009) argue that it is less likely for female entrepreneurs to receive fundings from formal financial institutions while they attribute this phenomenon to females' perceived risk aversion.

In any case, it must be acknowledged that there are widespread stereotypes about the performance of businesses founded by female entrepreneurs (Brush, 2006). Though the empirical research reflects the fact that female-led enterprises tend to underperform relative to male-led ones in terms of revenue and growth metrics (Fairlie and Robb, 2009). Whereas scholars argue that this disparity, at the gender level, is largely attributable to differences in industry distribution, enterprise size, and initial startup capital.

Additionally, the gender disparities also lie in working hours, preferences and the expectations of the business, these factors further enlarging the business performance gaps. In contrast, Du Rietz and Henrekson (2000) argue that after controlling for these factors, the performance gap significantly narrows, indicating that the underlying entrepreneurial competence is roughly similar across genders.

The entrepreneurship gender gap is also affected by the broader socio-economic barriers. Research by Brush et al. (2009) highlights the role of societal norms and gender roles in shaping the entrepreneurial intentions and opportunities for females, noting that the cultural expectations about gender roles often impede females from pursuing entrepreneurships, especially in regions or industries where male dominance is pronounced. Marlow and Patton (2005) discussed the impact of work-life balance challenges in their study, arguing that female entrepreneurs bear a disproportionate burden of family responsibilities, partly arising from the social stereotype of females' gender roles in the family, which largely limit females' capability in running their business.

Many studies have demonstrated that while significant gender disparities exist in entrepreneurship, they are mostly influenced by differential access to resources, performance perceptions, and socio-economic barriers. Efforts to close the gender gap are vital not only for achieving gender equality but also for enhancing overall economic growth. At present, continued research and targeted policy interventions are necessary to realize the full potential of female entrepreneurs in the global economy.

2.7. Entrepreneurship and Gender Gap in Sweden

Sweden is renowned as a global leader in entrepreneurship. Since the end of the last century, Sweden has been influenced by a strong entrepreneurial spirit that its entrepreneurial culture is supported by extensive research and large investments in R&D and the close links between academic institutions and commercialization (Lundqvist and Williams Middleton, 2010). In reality, according to a report by the European Commission, Sweden ranks high in innovation outputs, including patent applications and high-tech exports, thanks to governmental policies and capitalists' praise that complementarily encourage and advocate innovation and entrepreneurship[2]. This positive mechanism is also reflected in the strong collaboration between higher educational institutions and industry. In the study, Jacob et al. (2003) notes that Swedish universities are key players in regional innovation systems, significantly contributing to the entrepreneurial ecosystem.

In the meanwhile, Sweden profoundly commits to gender equality. According to the World Economic Forum's Global Gender Gap Report 2023[3], Sweden consistently ranks at the top countries for gender equality globally, those who have closed at least 80% of gender gap. Swedish emphasis on gender parity is supported politically and socially. For example, policies such as Act on Violence Against Women and parental leave, as well as initiatives to increase the representation of females in leadership positions within both the public and private sectors are steps to promote gender equality (Dahlerup and Leyenaar, 2013).

However, although Sweden ranks among the top countries in the world for both entrepreneurship and gender equality, gender gap still exists. Economies can have a remarkable entrepreneurial environment regardless of income levels. In contrast, in line with Global Entrepreneur Monitor (GEM) 2023/2024 Global Report[4], a country with a high-income level does not guarantee an excellent entrepreneurial environment. Sweden has witnessed the overall assessment of the quality of entrepreneurial environment falling to the "less than sufficient" category after the pandemic. In fact, only a tiny proportion of venture capital (1%) went to female co-founded companies in 2020 in Sweden[1]. A survey conducted among female entrepreneurs reveals that the majority argues the lack of capital being the main difficulty in entrepreneurship and the early-stage revenue is unable to support the business projects (Wang et al., 2022).

2.8. Contribution to Previous Research

Existing studies have proved the important role that AI-VCs play in the business world, and there are gender disparities in entrepreneurships. Scholars have conducted numerous studies showing that there is a persistent gender gap in AI-VC financing activities for entrepreneurs. However, most of the research are focusing on the ownership of AI-VC investments in female-leading businesses (Greene et al. 2001). We believe that gender gaps in AI-VC entrepreneurial financing not only reflect broader issues of gender inequality, but also highlight significant inefficiencies in capital markets that potentially overlook or undervalue businesses led by females. Females are active participants in the global economy, and the increasing of their engagement largely promotes the development of the economy and the society.

This paper contributes to the current studies in three ways. First, we used a unique dataset including both company and entrepreneur aspects information to understand the gender gap status in terms of startups early-stage equity funding of Sweden, one of the leading countries in gender equality and has a vibrant entrepreneurship ecosystem. Second, unlike existing studies that focus on absolute investment amount but neglect the investee's features, we explore whether there are gender disparities in terms of the absolute amount of capital raised from AI-VCs after controlling various company- and founder-characteristics as well as industry fixed effect. Third, we leverage interacting methods to identify the underlying channels that gender plays a role in differences in funding amount. With this paper, we aim to increase the understanding of gender gap and its channel in early-stage entrepreneurial equity financing in Swedish market.

3. Hypotheses Development

According to the research, the rate of entrepreneurial activity in females, indeed, is lower than the rate in males across most countries worldwide for both early-stage entrepreneurial activity and established business ownership (Elam et al., 2019). Similar pattern is further substantiated that in Swedish market, the Total early-stage Entrepreneurial Activity (TEA) by females is 7.4%, 4 % lower than TEA by males[4]. As stated above, a large number of studies have found that the gender disparities persist in diverse financial activities (Brush, 2006), and it becomes particularly apparent in the early stages of their business that male entrepreneurs typically raise higher levels of fundings than their female counterparts do (Kanze et al., 2018). Studies have substantiated that females are at great disadvantage in launching new ventures (Canning et al., 2012; Guzman et al., 2019). Meanwhile, the underlying mechanisms of funding gap and the transmission of gender therein remain controversial. Hence, we raise our primary concern that in terms of early-stage entrepreneurial financing, whether in Sweden the amount of capital, which is, namely the deal size, raised from AI-VCs is influenced by the gender of the founding team through various channels.

Does gender of the founding team have a significant effect on the deal size?

In the first part of this thesis, we aim to test the basic assertion of gender disparity in early-stage entrepreneurial financing amount. We want to investigate that whether female founders, resulting from various systematic differences or biases, receive less fundings than their male counterparts. Building on that, in the detailed hypotheses section, we examine the channels through which gender exerts its effect.

Deal size depends on a variety of company-specific factors (Diaconu, 2012). For example, Cumming (2008) suggests that VCs have the intendency to place more capital on more mature enterprises considering the availability of history performance and risk profiles. Cassar (2009) found that a new venture showcases higher intention of financial reporting if it tends to obtain external funding from financial institutions. At the same time, information asymmetry in equity financing of new ventures could be reduced through financial reporting (Pattanapanyasat, 2021). However, these company-level influencing factors show certain disparities at the gender level as well (Brush et al., 2001). Female-leading enterprises are frequently described as under-performing (Marlow and McAdam, 2013). Gottschalk and Niefert (2013) have found that the financial performance of female founding enterprises is worse on various indicators. A study in Norway further confirmed that, compared with male entrepreneurs, female entrepreneurs' lower level of early-stage entrepreneurial financial capital is related to their lower business growth (Alsos, 2006). Based on the research, financial information is closely associated with deal size for entrepreneurs. Hence, to examine whether gender affects deal size through the availability of financial information, we construct the hypothesis that:

Hypothesis 1: The availability of financial information works as channels through which gender impacts the deal size.

Secondly, innovation is another factor that venture investors value for investment decisions. Maas et al. (2020) find that company's innovation attracts VCs' attention worldwide and VCs' impact over technological innovation is positive and significant with an effect that is more considerable than conventional R&D. Engel and Keilbach (2007) provide empirical evidence in their research, confirming that in the selection process, VCs show significant preference towards enterprises with high innovativeness, and they tend to focus on the commercialization of existing innovations. In terms of innovativeness, patents are usually the indicator for AI-VCs to evaluate a startup. Existing studies have found that patents are a signal for innovative companies to apply for external financing (Beneito et al., 2023), and that the growth and investment amount of new start-ups are positively correlated with patents (Guzman et al., 2019; Mann and Sager, 2007). Whereas disparities against females' patenting activities persist.

Traditionally, the fields with more innovation have long been dominated by males. Nevertheless, with the increasing participation of females in the labor market, many sectors have gradually switched to be led by females[6]. Such interruption has changed the current social and economic landscape, contributing to the creation of new ways of innovation (Belghiti-Mahut et al., 2016). Whereas Alsos et al., (2013) argue that females are treated less- or non-innovative and thus they are marginalized in this field. Another manifestation of this issue is that females' capacities in innovation are misunderstood or far undervalued. That is, if female-led enterprises show a lower level of patenting activities, or their patents are undervalued by investors, the reason why female entrepreneurs may introduce less AI-VC fundings. To investigate whether the patenting works as a channel through which gender influences the deal size for entrepreneurs, we structure the second hypothesis that:

Hypothesis 2: The existence of patenting activities works as channels through which gender impacts the deal size.

As stated above, aside from the company-specific characteristics of startups, founding team specific characteristics would affect the deal size as well. Capital providers usually assess the founding team as a prerequisite for future cooperation (Prowse, 1998). However, that evaluation process is usually a challenging task for AI-VCs because, though they have excellent competence to score an enterprise's measurable outputs by Key Performance Indicators (KPIs) or external forces such as market forecasts, behavioral and personality traits are usually hard to quantify (Dubini, 1989). Furthermore, capital providers themselves may have gender preferences when investing. For instance, nowadays many female angel investors are exclusively investing in companies that founded by females (Oranburg and Geiger, 2019).

In order to explore in detail the extent of the impact that the founding team's gender has over the deal size through founders' personal background, we mainly focus on their previous professional experiences.

Regarding the professional experience, we would like to examine whether founders' prior experience is a channel for gender to exert its influence on deal size, i.e., to raise more capital for future business activities. We take three factors into consideration, namely MBA degree, prior industry experience, and prior entrepreneurial experience.

We categorized MBA degree as professional experience because MBA programs focus on developing students' management skills. Though Nagendra et al. (2014) argue that MBA is not necessary for entrepreneurs, several studies have highlighted the role of MBA programs in advocating entrepreneurial activities. Kuratko and Morris (2018) emphasize that MBA programs equip students with a comprehensive understanding of business operations, which is critical in the early stage of enterprise development. From an individual perspective, a considerable number of people pursuing MBA degrees have the intention to learn how to manage businesses more efficiently and effectively, and expand their network (Awaysheh and Bonfiglio, 2017). Additionally, a study focusing on gender and MBA shows that people's competence development is not gender neutral in MBA programs (Lämsä and Savela, 2014). They exemplify with a case that a female team could challenge or even transform the dominance of masculinity in management. In fact, scholars suggest that female MBA students have greater entrepreneurial self-efficacy than male MBA students (Wilson et al., 2007). There are more social factors, such as entrepreneurial intentions among MBA students (Amofah, et al., 2020), that are not captured. Considering the complex intersected relationship among gender, MBA, and entrepreneurship financing, we propose the following hypothesis:

Hypothesis 3: The MBA degree of the founding team works as a channel through which gender impacts deal size.

We then lay our attention on the founder's prior entrepreneurial experience. Many studies have suggested that prior experience is an important factor affecting personal entrepreneurial learning, thereby transmitting to the success of startups (Politis, 2008; Staniewski, 2016). The prevailing opinion is that successful entrepreneurs acquire and develop specific business knowledge through their previous career experiences, which in turn facilitates their engagement in the entrepreneurial business from identifying and exploring new opportunities (Colombatto and Melnik, 2007; Politis, 2005). Moreover, entrepreneurial self-efficacy positively affects the entrepreneurs entrepreneurial intention and action (Tsai et al., 2016), and this self-efficacy differs at the gender level (Mueller and Conway Dato-on, 2013; Nowiński et al., 2019). The relationship among gender, entrepreneurial experience and deal size is complex after incorporating psychological factors into consideration. However, we are more interested in whether prior entrepreneurial experience is one of the channels through which gender affects deal size.

Other scholars also provide a framework to understand female entrepreneurship that could be relevant to previous experience (Brush et al., 2019). Subsequently our hypothesis is that:

Hypothesis 4: The prior entrepreneurial experience of the founding team works as a channel through which gender impacts deal size.

Similar to prior entrepreneurial experience, prior industry experience is regarded as one of the determinants of startup success for an entrepreneur as well. A substantial body of research has established the positive correlation between prior industry experience and entrepreneurial success. Politis (2005) argues that industry experience enhances business management skills and market understanding, which are critical for navigating competitive environments. Similarly, Ucbasaran et al. (2009) find that entrepreneurs with deep industry knowledge are better equipped to exploit business opportunities and avoid potential pitfalls, thereby increasing their ventures' survival rates. Additionally, Ardichvili et al. (2003) suggest that the familiarity with industry trends enables entrepreneurs to recognize market gaps and emerging trends more readily than newcomers, thereby achieving entrepreneurial success. However, gender gaps persist in terms of prior industry experience. In previous research, scholars observed that females' previous working experience was typically questioned or neglected (Malmström et al., 2017). Our concern stems from this point to examine whether prior industry experience plays the role as a channel, through which gender influences the deal size. Hence, we propose the hypothesis:

Hypothesis 5: The prior industry experience of the founding team works as a channel through which gender impacts deal size.

In this paper, we investigate the gender disparities in AI-VCs deal size for entrepreneurs. Based on the above six hypotheses, we would like to test which are the channels that gender exerts its impact on early-stage entrepreneurial financing amount.

4. Data and Methodology

4.1. Data Sources and Measurement

The selection process primarily relies on PitchBook for deal and company information, and on LinkedIn for entrepreneur information. PitchBook is widely recognized in the financial industry for providing comprehensive, up-to-date, and verified information on private capital markets. In order to focus on Swedish market, we screened only startups headquartered in Sweden, founded between January 1st, 2018, and December 31st, 2023, which we consider a reasonable time period most recent and relevant while preserving relatively adequate number of transactions.

With a focus on venture capital investments, sources such as angel (as individual venture investor), seed, early-stage VC, and late-stage VC (as institutional venture investors) are included. We include individual angel investors in our research because, though traditionally angels provide capital to enterprises at earlier stages to obtain financial and nonfinancial returns while VCs are usually funding at late stages (Ibrahim, 2008), it is becoming more common to find VCs and angels co-invest (Harrison and Mason, 2000) with a converging investment form due to the increasing competitiveness in the market (Hsu et al., 2014). Accelerator or incubator support is excluded because they tend to have particular non-financially driven considerations such as fostering innovation, supporting regional economy, and cultivating certain industries etc. according to Aernoudt (2004). To acquire the most current data, we obtained deal information available up to March 2024. Consequently, the latest deal completion date within our dataset is February 15, 2024.

In addition, among all the deals we collected, some of the startups have raised funds from AI-VCs on multiple occasions over the past six years. In this paper, we treat each deal as a discrete deal, that is, the approach rests on the premise that different AI-VC funding events for the same enterprise are independent of each other, and there is no substantial interdependence with other deals. We consider this a more plausible empirical approach, because around 60% startups in our dataset secured only one deal with disclosed investment amount, and thus our dataset could not be treated as panel data.

After the screening process, we further collect data on the selected deal in the following three aspects: i) deal-specific data such as transaction date, deal size and deal stage etc. ii) company-specific data such as financial information, founded year, and industry category etc. iii) entrepreneurs' information, such as gender, educational background, professional experience in industry and previous entrepreneurship. The following sections 4.1, 4.2, and 4.3 provide a detailed explanation and elaboration of the data collection and processing.

4.1.1. Deal-specific Data

Deal size

Deal size is our dependent variable, and its information is retrieved from PitchBook. The currency measurement was US Dollars (USD). Although most transactions were conducted in Swedish Krona (SEK) and Euros (EUR) as described in deal synopsis, we decided to maintain the original deal size data downloaded from PitchBook in USD instead of converting them to SEK or EUR, because the exchange rates vary over periods, and PitchBook's data updates are timely. We assume that the transaction amounts in USD recorded by PitchBook are based on real-time exchange rates, making deals more reliable and comparable than conducting our own conversions.

Necessary steps have been taken to prepare the size data for empirical analysis. Firstly, winsorized method is implemented to avoid the effect of extreme values, for example, H2 Green Steel received an early-stage VC financing amounting to 5.21 billion USD, a number substantially higher than the average deal size of 14.63 thousand USD in the dataset. The percentile for winsorizing is 1st and 99th, which means that values below the 1st percentile are set to the 1st percentile, and those above 99th percentile are set to the 99th percentile value. This method reduces the influence of outliers in the dataset.

Furthermore, a natural log transformation was applied to normalize the distribution of deal sizes. Since the initial unit of measurement was in million USD, to avoid issues with taking logarithms of values less than 1 (which would result in undefined or negative values), deal sizes were converted to thousand USD. This adjustment ensures that all transformed values are positive and meaningful for statistical analysis, enhancing the interpretability of the regression models.

Deal stage

Information on the deal stage is downloaded from PitchBook. As mentioned above, angel investments are included. Thus, there are four types of deal stage in our dataset in total, which are Angel (individual), seed round, early-stage VC, and late-stage VC. In general, AI-VCs seek startups developing at an early stage with an intention of value appreciation in the future, however, large fundings usually engage in late stage of enterprise fundraising. Research has found that venture capitalists have different preference towards investment stages of a firm (Carter and Van Auken, 1994). While AI-VCs who prefer to invest in the early stage of an enterprise care more about the liquidity and exit strategies, others place a greater amount of investment in the investee’s late stages in necessity of financing growth. According to the empirical research, male and female entrepreneurs may experience varying degrees of success in raising capital at different stages of the deal process (Brush, 2019). As our dependent variable is the deal size and our main topic of interest is gender, the deal stage dummies are included as control variables.

4.1.2. Company-specific Data

Company age when deal happened

To effectively control variations among different deals, especially for multiple deals of the same companies, we use the company age at the transaction time as control variable.

Accordingly, we calculate the age based on enterprise founding time and the deal date.

To get the enterprise's founding time, we check the timeline section of each company's profile page on PitchBook. The exact month or date of incorporation is not disclosed; therefore, we have recorded the year founded for each company. Specific deal date information is sourced from PitchBook, including detailed year, month, and day data, thus the format is in the standard international date format of 'YYYY-MM-DD'. Deals with undisclosed deal date (age is not calculable) are excluded from our dataset.

Consequently, the company age when the transaction happens is calculated based on deal year from deal date minus founding year. For example, a deal that took place on March 28, 2023, involving a startup founded in 2022, is recorded with an age of 1 year at deal time. The company age variable in our dataset is called Age.

Employee number and company size

Employee numbers are sourced from the "Employee Count Timeline" section of each company's profile on PitchBook. In case the employee counts on the exact date of the transaction is not directly available, the nearest available data point is used as an approximation. Nevertheless, of all the 597 deals in the dataset, only 387 deals have employee number information. Thus, size category dummies are created to classify the companies at the time of the deal in order to preserve data. Specifically, the company sizes at each specific deal are divided into small, medium, and large based on the 1/3 and 2/3 quantiles of the distribution of employee numbers. Deals lacking employee number data are categorized as 'missing'. As existing studies have found that the company's size is correlated with the VC investment amount (Popov, 2014) and has correlation with gender (Fischer et al., 1993), we take the four size dummies as control variables.

Financial information

Financial information was collected from the "Financial" section of each company profile on PitchBook. Initially, data on revenue, net income, assets, equity, and debt for each company in the deal year were collected, turning out only 229, 212, 199, 198, 198 data points for each respectively. Such a high missing percentage is likely to introduce bias in analyzing, as the absence of the financial information could be systematically related to the nature and maturity of the companies. With that being said, according to Cassar (2009), financial reporting of start-ups is positively related with external funding, company scale, competition intensity, high-tech etc. As a result, a dummy called Has_Financial has been created to indicate whether there is financial information externally available at the deal year.

Patent information

Patent information was retrieved from the “Patents” section of each company profile on PitchBook. Patent information is important in evaluating the enterprise’ innovation level and high-tech features, which indirectly transmits the impacts on capital raising. The relation has been proven by various research, for example, Conti et al. (2013) have found that patents work as signals by informing investors the company’s invention of quality in start-ups’ fundraising through empirical analysis using a dataset of Israel new ventures. Of 597 deals in our dataset, only 119 deals have corresponding patent information available at the deal time. The sparsity suggests that using a binary variable allows for inclusion of all companies, and this method also aligns with the signal theory. Therefore, a dummy called Has_Patent_Info is created to indicate whether the company has patenting activities at the deal time. A value of 1 means the company has applied for patent (pending status), has patent available (published status), or used to have patents (expired status). A value of 0 represents the company did not engage in any patent filing activities.

Primary industry sector

Two methods are used to classify industry sectors. First is using the “Primary Industry Sector” classification downloaded directly from PitchBook. There are seven sectors:

- Business Products and Services (B2B)
- Consumer Products and Services (B2C)
- Energy
- Financial Services
- Healthcare
- Information Technology
- Materials and Resources

While this classification is immediate and endorsed by PitchBook. The limitation is obvious that the categories B2B and B2C are too broad and may not capture enough differences between companies within these two categories for us to examine and control.

Consequently, another classification method is adopted that we employed Global Industry Classification Standard (GICS) to allocate sectors to each company based on information from various fields on PitchBook, including "Company Description", "Verticals", "All Industries", "Primary Industry Code", "Primary Industry Group". GICS is a widely recognized industry framework developed by MSCI and S&P Dow Jones Indices, and it offers a more specific classification of sectors for us to effectively control for. The sectors by GICS are as follows:

- Energy
- Materials
- Industrials
- Consumer Discretionary
- Consumer Staples
- Health Care
- Financials
- Information Technology
- Communication Services
- Utilities
- Real Estate

The limitation of this method is also obvious since we focus on start-ups universe where authoritative classification is not available. When assigning sectors manually, subjective judgement is unavoidable, especially when business crosses over industries.

In applying industry fixed effects, both classifications are used as a cross-check and a complementary approach.

4.1.3. Founder-specific Data

Founder list is screened on PitchBook by identifying founder or co-founder in positions. After the screening process, the following aspects of founders' background are collected either from PitchBook/LinkedIn or founders' personal websites/company websites.

Gender

Gender information is directly sourced from PitchBook. It is common for businesses to have multiple founders. Since gender gap is our topic of interest, including start-ups with mixed gender founders will complicate the interpretation of any channel effect observed. Additionally, when exploring the impact of other background variables that will be explained below, attributing effects to gender becomes problematic in mixed-gender founder companies, for example, it is difficult to determine to what extent do investors value the entrepreneur experience of female founders compared to that of male founders.

Therefore, we followed the approach of Lins et al. (2016) and Johnsen et al. (2005), that is selecting only enterprises with founders of single gender. With this approach, we get a sample of 597 deals of 375 start-ups, composed of 67 deals of all-female teams and 530 deals of all-male teams. Consequently, a dummy called Female_Team is created.

Higher Education

The educational background of the founders is mainly collected from their LinkedIn profile. While some of the education profiles are missing on LinkedIn, the information is collected from the corresponding personal websites or company websites.

In the academic world, there are many theoretical studies on the linkage between entrepreneurship and education. One of the dominant theories is the human capital theory (Unger et al., 2011; Martin et al., 2013), which argues that human capital is critical in identifying entrepreneurial opportunities, accessing financial resources, accumulating new knowledge and creating advantages for new firms (Marvel, 2016). Other theories that have been widely used to link education to entrepreneurial choices and outcomes include signaling theory (Connelly et al., 2011; Backes-Gellner and Werner, 2007), outsider assistance theory (Chrisman and McMullan, 2004) and knowledge spillover theory (Audretsch et al., 2005).

Across the 597 deals in the dataset, we have a total of 891 founders. We collect founders' educational background based on whether they have a university degree. We did not include MBA in the educational background classification but as a separate variable because studies have found that MBA (including EMBA) students have a higher entrepreneurial profile than students in other studying programs do (Rosado-Cubero, 2021; Rosado-Cubero, 2022).

We focus on founders' higher education background, which is the university degree, as the benchmark. Hence, we create the variable called Has_Uni to indicate that at least one of the founders in the team has a university degree and it is included as a control variable.

MBA Background

Same as education background, the MBA information is collected from founders' LinkedIn profiles, personal websites or company websites. As stated above, studies have found that MBA and EMBA degrees have positive effect over entrepreneurships. In this research, we define the control group as one in which no one in the founding team holds an MBA or EMBA degree. We would like to explore whether MBA/EMBA background will work as a channel for gender to have significant influence on the amount of capital founders raised from AI-VCs. Notably, in our dataset, none of the founder has the EMBA degree. Thus, we create the corresponding variable as Has_MBA.

Industry experience

We define the industry experience as whether, prior to founding the current enterprise, the founders had working experience exactly in the same industry in which the startup operates. The information of industry experience is collected from founders' LinkedIn profiles or the companies' websites. Out of completeness consideration, we also reviewed relative news or interviews that founders demonstrated what inspired them to start their business.

Considering the situation that a company may have more than one founder, we define the variable as Has_Ind_Exp, where 0 represents no prior industry experience and 1 means that the founders has prior relevant industry experience. With this variable, we would like to study whether the prior industry experience will work as a channel for gender of the founding team to have a significant effect on the amount of capital raised from AI-VCs.

Entrepreneurial experience

Similar to industry experience variable, we define entrepreneurial experience as whether, prior to founding this new firm, the founders have previous entrepreneurial experiences. Same as above, the information is gathered from LinkedIn, companies' websites, and other reference sources such as interviews or articles.

Using the same data processing procedure as for industry experience, we use the Has_Entre_Exp variable, where 1 indicates that at least one of the founders has prior entrepreneurial experiences, and 0 otherwise. We then seek to investigate the channel effect of prior entrepreneurial experience for gender to impact significantly VC financing.

Table 1. Variable Description

Variable	*Description*
Dependent variable	
Deal_Size	Natural logarithm of deal size in thousand USD
Independent variables	
Female_Team	Dummy variable with 1 for female team, 0 for male team
Has_Financial	Dummy variable with 1 for the company has externally available financial information, 0 for otherwise
Has_Patent_Info	Dummy variable with 1 for the company has patenting activity, 0 for otherwise
Has_MBA	Dummy variable with 1 for at least one of the founders has MBA degree, 0 for otherwise
Has_Ind_Exp	Dummy variable with 1 for at least one of the founders has prior relevant industry experience, 0 for otherwise
Has_Entre_Exp	Dummy variable with 1 for least one of the founders has prior entrepreneurial experience, 0 for otherwise
Control variables	
Deal_Stage Dummies	Four dummy variables indicating the deal stage of the specific deal, including angel, seed, early-stage VC, and late-stage VC
Size_Category Dummies	Four dummy variables indicating the size of the company based on employee number, including small, medium, big, and missing size
Age	The company's age at the transaction time
Has_Uni	Dummy variable with 1 for at least one of the founders has university degree, 0 for otherwise

Table 1 provides an overview of the variables. While Female_Team is our main topic of interest, Has_Financial, Has_Patent_Info, Has_MBA, Has_Ind_Exp, and Has_Entre_Exp are channel variables with which we will explore the channels through which gender place an impact on investment amount.

4.2. Methodology

To test our research question and hypotheses described in Chapter 3, the following regressions are designed based on our datasets.

4.2.1. Regression for Evaluating Gender Gap

Starting with our main topic of interest, which is:

Whether the gender of the founder team has a significant effect on the deal size.

Controlling company-specific variables, deal-specific variable, and founders' background variable, we isolate the impact of gender on investment amount. Model 1 is developed as follows:

$$Deal\_Size_i = \beta_0 + \beta_1 Female\_Team_{\,i} + X\beta + \varepsilon_i$$

Where:

- $Deal\_Size$ denotes the investment amount
- $Female\_Team$ is a dummy variable reflecting the gender of the founder team (1 for female, 0 for male)
- X is a vector of control variables, including Age, Size_Category from company aspect, Deal_Stage from deal aspect, Has_Uni from founders' personal aspect
- i denotes the $i\ th$ deal
- β_0 is the intercept
- β_1 is the coefficient for team's gender, representing the difference in deal size between female team and male team
- β is a vector of coefficients for all the control variables
- ε is the error term

If β_1 is significantly negative, evidence is provided that female founders receive lower investment amount than male founders, condition on company age, size, deal stage, and founder's university degree.

4.2.2. Regressions for Evaluating Channel Effect

In this section, we aim to explore whether gender influences investment amounts through various channels. As discussed in Chapter 3, we focus on the channel effect of external availability of financial data and patenting activity at the company aspect, MBA degree, entrepreneurial experience, and relevant industry experience at the founder aspect. We followed the approach of Yu et al. (2019), Morchio and Moser (2019), and Kaplan et al.

(2009), that is interacting these variables with our main explanatory variable of interest gender to investigate the channel effect through which gender plays a role.

Consequently, the models to test channel effect is built as:

$$Deal\_Size_i = \beta_0 + \beta_1 Gender_i + \beta_2 Gender_i * Channel\,Variable_i + \beta_3 Channel\,Variable_i + X\beta + \varepsilon_i$$

Where:

- $Deal\_Size$, β_0, $Female\_Team$, β_1, X, i, and β are the same as in the previous model
- $Channel\,Variable_i$ varies according to the specific channel studied in each of our models, including Has_Financial, Has_Patent_Info at firm level, Has_MBA, Has_Ind_Exp, and Has_Entre_Exp at founders level
- β_2 is the coefficient for the interaction term
- β_3 is the coefficient for the channel variable
- ε is the error term

The interaction term is our variable of interest in the channel section. By replacing channel variable with Has_Financial, Has_Patent_Info, Has_MBA, Has_Ind_Exp, and Has_Entre_Exp, we get Model 2 to Model 6 with which we can test Hypothesis 1 to Hypothesis 5.

If β_2 is statistically significant, evidence is provided that the specific variable in this model does work as channel for gender to impact deal size.

4.2.3. Robustness Check

In addition to the basic regression for each model, we include industry fixed effect to control unobserved, industry-invariant characteristics of deals, thus more robust tests could be carried out to examine the hypotheses. As mentioned above, two industry classification methods are used, namely PitchBook classification and GICS, and thus for each model, we use two different industry fixed effects separately, which will provide cross validation. Consequently, for each model to test each hypothesis, we run one regression without industry fixed effect, one regression with GICS industry fixed effect, and one regression with PitchBook industry fixed effect. By doing so, we expect to obtain robust results.

5. Descriptive Findings

Based on the above data collection, screening and data processing, we eventually constructed a dataset with a total of 597 valid deals. Before we proceed to the empirical analysis, in this section we provide a detailed overview of our dataset to better understand the current gender dynamics within the Swedish entrepreneurial market.

5.1. Team Composition and Entrepreneurs Summary

Entrepreneurial Team Composition and Gender Distribution

Table 2. Enterprise Summary, by Gender of the Founding Team and by Year

Enterprise Founded Year	*Male Team Obs.*	*Mixed-Gender Team Obs.*	*Female Team Obs.*	*Male Team Ratio*	*Mixed Team Ratio*	*Female Team Ratio*
2018	80	26	9	69.57%	22.61%	7.83%
2019	84	28	12	67.74%	22.58%	9.68%
2020	74	31	8	65.49%	27.43%	7.08%
2021	56	22	8	65.12%	25.58%	9.30%
2022	29	10	2	70.73%	24.39%	4.88%
2023	11	2	2	73.33%	13.33%	13.33%
Total	334	119	41	-	-	-
Average	-	-	-	68.66%	22.65%	8.68%

First, Table 2 displays the summary of enterprises founded between 2018.1.1 and 2023.12.31, who successfully completed AI-VC deals during the period of 2018.1.1 and 2024.2.15. Considering that we screened for enterprises founded between 2018 and 2023, and startups in the early stages of development typically takes one to two years from their founding time to compete an AI-VC deal, it is reasonable to have few observations after 2022 in our dataset. Although our empirical study uses a dataset comprising only single-gender teams, Table 2 encompasses all transactions with available deal size information during this period, thereby also including mixed-gender teams to better illustrate trends.

As can be seen from the table, obviously, among the enterprises who have completed AI-VC deals, the number of enterprises founded entirely by females is much lower than the number of enterprises founded entirely by males. From 2018 to 2023, the number of all-female-founded businesses accounts for approximately 8.68% of the total sample. Mixed-gender teams with at least one female founder account for about 23% of the total founding teams, and the proportion seems to stay stable within the 6-year horizon. The current situation indicates that when it comes to entrepreneurship and AI-VC backed deals, in Sweden, the entrepreneurial ecosystem is heavily dominated by males while by contrast, females are struggling to stand out. Given that deals happened in 2022 and 2023 are limited in our dataset and bias may lie behind, judging from the deals from 2018 to 2021, there might be a slight increasing trend of female entrepreneurs' engagement in AI-VC backed deals in Sweden.

Table 3. Entrepreneur Summary, by Gender and by Year

Enterprise Founded Year	*Male Obs.*	*Female Obs.*	*Male Ratio*	*Female Ratio*
2018	201	13	22.56%	1.46%
2019	194	19	21.77%	2.13%
2020	184	17	20.65%	1.91%
2021	140	17	15.71%	1.91%
2022	77	3	8.64%	0.34%
2023	24	2	2.69%	0.22%
Total	820	71	92.03%	7.97%

In this paper, we focus on all-male founding enterprises and all-female founding enterprises. Of all the valid 597 deal samples we collected, a total of 334 all-male founding enterprises and 41 all-female founding enterprises received investments from AI-VCs during the last 6 years, representing 820 male entrepreneurs and 71 female entrepreneurs.

The patten is similar when looking at the total number of female entrepreneurs and male entrepreneurs in single-gender teams. Among these 395 companies, male founders far outnumber female founders, with female entrepreneurs accounting for only 7.97% of the total sample size. Moreover, in current environment where the general public is dedicated to promoting gender equality and female entrepreneurship, all-female entrepreneurial teams do not seem to have a clear growth trend.

Table 4. Average Number of Founders per Enterprise Summary, by Gender and by Year

Enterprise Founded Year	*Average Number of Male Founders per Enterprise*	*Average Number of Female Founders per Enterprise*
2018	2.51	1.44
2019	2.31	1.58
2020	2.49	2.13
2021	2.50	2.13
2022	2.66	1.50
2023	2.18	1.00
Total	2.46	1.73

Further, seeing in Table 4, the average number of male founders per enterprise is consistently higher than that of female founders across all years, and among all-male teams, the average appears relatively stable over the years, indicating a generally consistent formation pattern. However, the female team size fluctuates over the years, it in rises to 2.13 in 2020 and 2021 and falls to 1.5 and 1.0 in 2022 and 2023. This could suggest varying trends in how female founders team up over different years, or possibly changing market conditions or opportunities that affect female-founded enterprises differently from male-founded ones. However, given that there are only two female firms founded in 2022 and 2023, respectively, in our dataset, we cannot make any conclusions on this basis. Overall, male entrepreneurs typically collaborate in larger groups compared with female entrepreneurs.

Entrepreneur Education Background and Gender Distribution

Table 5. Entrepreneur Education Background Overview, by Gender

Education Background	*Male Obs.*	*Female Obs.*	*Male Ratio*	*Female Ratio*
With University Degree	671	62	81.83%	87.32%
Without University Degree	149	9	18.17%	12.68%
Total	820	71	100.00%	100.00%

With regards to entrepreneurs' academic experience, we attach the importance on their higher education. Capital providers treat higher education as a symbol of quality when determining the validity of a potential entrepreneur as an investment proposition (Bates, 1991; Åstebro and Bernhardt, 2003; Carter et al., 2003; Xu, 1998). Many scholars argue that entrepreneurs who possess higher education are more exposed to financial resources and accesses (Vos et al., 2007). However, existing research has demonstrated the impact that sociodemographic factors, i.e., age and education, have on entrepreneurial financing and related gender gaps (Langowitz and Minniti, 2007). When it comes to the intersection of gender and education, many scholars have made great contributions in this field (Dickson et al., 2008). Research suggests that education is more important to females than males in the current labor market (Loury, 1997). Cowling and Taylor (2001) argue that in developed countries, female entrepreneurs are generally more educated than males do. The argument is in accordance with the situation in Sweden, as in Table 5, the proportion of female entrepreneurs possessing university degree is higher than that of male entrepreneurs (87.32% vs 81.83%). Overall, there are not many differences at the higher education level between females and males. It is worth noting that, considering entrepreneurs' education backgrounds are manually collected mainly from LinkedIn, there is a possibility that the statistic results may be slightly biased as some of the entrepreneurs do not post their educational experience on social media.

5.2.Company and Financing Summary

Enterprise Size and Gender Distribution

Table 6. Enterprise Size Overview, by Gender

Enterprise Size	*Male*				*Female*			
	Deal Count		*Deal Size(k)*		*Deal Count*		*Deal Size(k)*	
	Obs.	*Ratio*	*Mean*	*Range*	*Obs.*	Ratio	*Mean*	*Range*
Small	118	22.26%	1,070	10~17,150	15	22.39%	720	110~5,000
Medium	111	20.94%	2,545	60~36,750	18	26.87%	13,961	300~220,960
Big	120	22.64%	75,983	140~5,210,000	5	7.46%	1,844	860~3,040
Missing	181	34.15%	3,951	10~254,230	29	43.28%	603	100~1,660
Total	530	100.00%	-	-	67	100.00%	-	-

As stated above, we regard each deal as independent. Of all the 597 deals in our dataset, only 387 deals have available employee number information. After dividing the deals into four categories by company size, it appears that among new enterprises founded during the studied period, the proportion of large enterprises is higher among all-male founding teams that that among all-female founding teams (23% vs. 7%), while all-female founding teams are running slightly more medium-sized enterprises (27% to 21%). When it comes to small enterprises, the percentage of all-male startups is roughly the same as the that of all-female startups (22%). In addition, with the exception of medium-sized enterprises, in general, all-male founding enterprises raise higher amount of AI-VC capital per deal than that of all-female founding enterprises, accompanied with wider range.

The overview of the company size indicates either that the business size is relatively smaller for female entrepreneurs, or that all-female founding enterprises scale more slowly than that of all-male founding enterprises. On the other hand, it may also be the possibility that all-female enterprises are less exposed to AI-VCs out of their preferences. Gender disparities may lie behind and be transmitted to differences in the deal sizes.

Company Age and Gender Distribution

Table 7. Company Age Breakdown, by Gender

Company Age	*Male Team Deal Obs.*	*Female Team Deal Obs.*	*Male Team Deal Ratio*	*Female Team Deal Ratio*
0	78	15	14.72%	22.39%
1	149	13	28.11%	19.40%
2	120	21	22.64%	31.34%
3	114	11	21.51%	16.42%
4	48	4	9.06%	5.97%
5	20	3	3.77%	4.48%
6	1	0	0.19%	0.00%
Total	530	67	100%	100%

Table 7 displays the deal breakdown by company ages. The results are not surprising, because it suggests that the majority of startups received AI-VC funding within the first three years since their founding. And the gender difference by company age is not obvious.

Financing Frequency and Gender Distribution

Table 8. Financing Frequency Summary, by Gender

Financing Frequency	*Male Team Enterprise Obs.*	*Female Team Enterprise Obs.*	*Male Team Enterprise Ratio*	*Female Team Enterprise Ratio*
1	200	24	59.88%	58.54%
2	89	12	26.65%	29.27%
3	32	2	9.58%	4.88%
4	11	2	3.29%	4.88%
5	0	1	0.00%	2.44%
6	2	0	0.60%	0.00%
Total	334	41	100%	100%

Given that the total 597 deals collected only involved 375 companies, it is apparent that part of them have had multiple rounds of financing in the past six years. After screening, we counted the number of financing rounds, and judging from the average frequency, most companies have completed one or two financings. This result is expected considering the essential of early-stage entrepreneurial investments. It is rare the situation that angel investors or VCs are making frequent investments during a short period. When making investment decisions, capitalists tend to invest in companies with future potential and high return as most of the startups may not survive – 20% of startups fail in their first year and 65% of them fail in the next ten years[5]. Therefore, frequent valuations in a short period of time are less likely, and considering factors such as valuation costs, the strategy to lower valuation costs and maintain high precision is common.

Investment Stage and Gender Distribution

Table 9. Investment Stage Overview, by Gender

Investment Stage	*Male*				*Female*			
	Deal Count		*Deal Size(k)*		*Deal Count*		*Deal Size(k)*	
	Obs.	*Ratio*	*Mean*	*Range*	*Obs.*	Ratio	*Mean*	*Range*
Angel	44	8.3%	1,065	80~9,790	14	20.90%	548	100~2,070
Seed Round	212	40.00%	2,568	20~181,630	30	44.78%	945	110~5,000
Early-Stage VC	255	48.11%	36,063	10~5,210,000	22	32.84%	11,352	230~220,960
Late-Stage VC	19	3.58%	23,928	190~205,000	1	1.49%	3,040	3,040~3,040
Total	530	100%	-	-	67	100%	-	-

Even though we concentrate only on entrepreneurs' early-stage financing activities from AI-VCs, the sample still shows some disparities in terms of funding stages. Of the current total 597 deals, a significant proportion of all-female-founding entrepreneurs received capitals from angel individuals, which making up 21% of the total funding stages in the samples, compared with 8% of that for all-male-founding teams, even though female entrepreneurs receive relatively less amount from angel investors per deal. However, within the six-year horizon, the majority of male teams received their funding at the seed round and VC early stage, accounting for 40% and 48% of the total all-male-founding team deals respectively. For female entrepreneurs, though approximately 45% teams are funding their businesses at seed rounds, whereas only 33% of the female teams receiving capitals at the early VC stage. The relatively underdeveloped fundraising activities for females is further reflected at the late VC stage that only 1% of the female teams (1 out of 67 deals) successfully completed their fundraising at this stage while for male teams the proportion is slightly higher at 4% (19 out of 530). Additionally, when looking at financing activities at all the stages, it is apparent that deal sizes for all-male founding teams are higher than those for all-female teams.

Although studies have shown that in terms of capital sources, female entrepreneurs are more inclined to seek funding from family, friends and angel investors in the early stages to support their business development (Constantinidis et al., 2006; Chaganti et al., 1996). The result may reflect the gender differences in risk appetite and financial resource preferences, but it may also be caused by other factors, for example, the real difficulty for female entrepreneurs to seek fundings from VCs.

Industry Distribution

Figure 1. GICS Industry Distribution

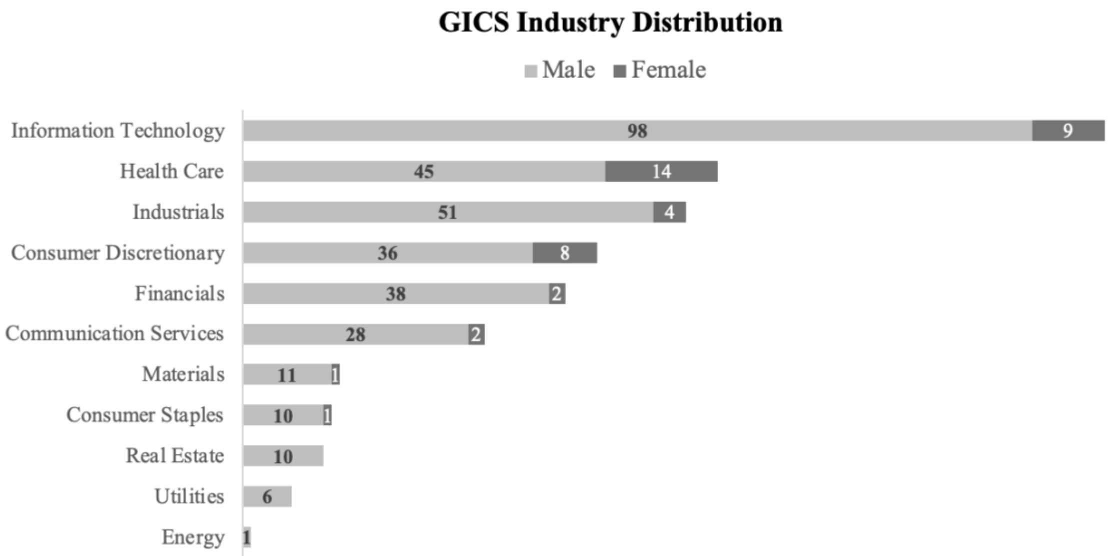
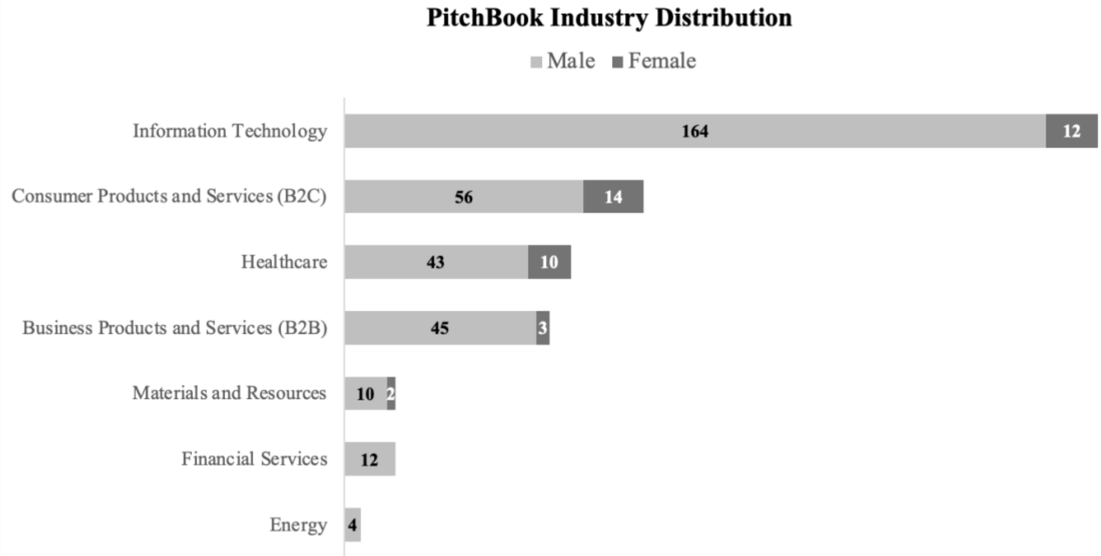


Figure 2. PitchBook Industry Distribution



Even though PitchBook and GICS use different methods for industry classification, the two charts still show similar characteristics. The industry distribution in the sample seems to be rather concentrated. Specifically, whether it is an all-male founding team or an all-female founding team, the largest number of startups focus on the information technology industry, followed by the health care industry. Considering that these industries are more light-asset industries and accommodating more innovations and cutting-edge technologies, the concentration of the business industries is expected. On the other hand, few companies operate in the energy or materials sectors, probably due to the need of the large amount of initial capital required to start up and the limited accesses to resources, which in turn leads to the difficulty of raising large amount of capital in the early stages of a business. On the contrary, it is also possible that companies engaged in these asset-heavy industries are more inclined to choose funding sources such as bank loans, bonds or government grants instead of AI-VCs. Given that AI-VCs are mostly expecting to realize returns within a certain time period, they also have their investment preferences when selecting investee companies.

As far as gender is our main concern for this research, the differences are not obvious regarding industries.

6. Empirical Analysis and Results

6.1. Preliminary Statistical Analysis

Before plugging the transformed dataset into regressions, in this section, some preliminary analyses are performed to ensure the validity of the regression analysis. We start with an overview of the dataset, later t-test on descriptive statistics of different gender team is performed to compare whether the mean of variables is significantly different for female and male. To ensure the statistical rationality of incorporating industry fixed effects, ANOVA test is applied. Then correlation analysis is presented along with multicollinearity test to validate later regressions. Finally, heteroskedasticity test is conducted to understand the necessity of robust methods.

6.1.1. Descriptive Statistics

Table 10. Descriptive Statistics

Variables	*Obs.*	*Mean*	*Median*	*S.D.*	*Min*	*Max*	*Skew*
Dependent Variable							
Deal_Size	597	6.97	6.87	1.60	3.43	12.23	0.69
Independent Variables							
Female_Team	597	0.11	0	0.32	0	1	2.46
Has_Financial	597	0.40	0	0.49	0	1	0.39
Has_Patent_Info	597	0.20	0	0.40	0	1	1.51
Has_MBA	597	0.10	0	0.30	0	1	2.63
Has_Ind_Exp	597	0.31	0	0.46	0	1	0.81
Has_Entre_Exp	597	0.66	1	0.48	0	1	-0.66
Control Variables							
Angel_Stage_Dummy	597	0.10	0	0.30	0	1	2.73
Seed_Stage_Dummy	597	0.41	0	0.49	0	1	0.39
Early_Stage_VC_Dummy	597	0.46	0	0.50	0	1	0.14
Late_Stage_VC_Dummy	597	0.03	0	0.18	0	1	5.20
Small_Size_Dummy	597	0.22	0	0.42	0	1	1.34
Medium_Size_Dummy	597	0.22	0	0.41	0	1	1.38
Big_Size_Dummy	597	0.21	0	0.41	0	1	1.43
Missing_Size_Dummy	597	0.35	0	0.48	0	1	0.62
Age	597	1.92	2	1.35	0	6	0.39
Has_Uni	597	0.52	1	0.50	0	1	-0.08

Table 10 presents an overview of our dataset where the deal size has been transformed by winsorizing and natural log. As can be seen, the dataset includes 597 observations. The average natural log deal size in thousand USD is 6.97, with a median very close at 6.87, which, combined with a skewness of 0,69, suggests a fairly symmetrical distribution around the center.

6.1.2. Gender-based T-test

The descriptive statistics in Table 11 presents a gender-based t-test to compare the mean of variables between female-founding enterprises and male-founding enterprises.

Table 11. T-test Result

Variables	*Female Team*			*Male Team*			*t-value*	*p-value*
	Obs.	*Mean*	*S.D.*	*Obs.*	*Mean*	*S.D.*		
Dependent variable								
Deal_Size	67	6.51	1.21	530	7.03	1.63	-2.531	0.012**
Independent variables								
Age	67	1.78	1.37	530	1.94	1.35	-0.945	0.345
Has_Financial	67	0.34	0.48	530	0.41	0.49	-1.069	0.286
Has_Patent_Info	67	0.04	0.21	530	0.22	0.41	-3.387	0.001***
Has_MBA	67	0.06	0.24	530	0.11	0.31	-1.218	0.224
Has_Ind_Exp	67	0.40	0.49	530	0.30	0.46	1.682	0.093*
Has_Entre_Exp	67	0.52	0.50	530	0.67	0.47	-2.464	0.014**
Control Variables								
Angel_Stage_Dummy	67	0.21	0.41	530	0.08	0.28	3.304	0.001***
Seed_Stage_Dummy	67	0.45	0.50	530	0.40	0.49	0.749	0.454
Early_Stage_VC_Dummy	67	0.33	0.47	530	0.48	0.50	-2.370	0.018**
Late_Stage_VC_Dummy	67	0.01	0.12	530	0.04	0.19	-0.896	0.371
Small_Size_Dummy	67	0.22	0.42	530	0.22	0.42	0.023	0.982
Medium_Size_Dummy	67	0.27	0.45	530	0.21	0.41	1.109	0.268
Big_Size_Dummy	67	0.07	0.26	530	0.23	0.42	-2.893	0.004***
Missing_Size_Dummy	67	0.43	0.50	530	0.34	0.47	1.475	0.141
Age	67	1.78	1.37	530	1.94	1.35	-0.945	0.345
Has_Uni	67	0.45	0.50	530	0.53	0.50	-1.243	0.214

*Note: *p<0.1; **p<0.05; ***p<0.01*

The mean deal size of female team is 6.51 with a standard deviation of 1.21, whereas the mean deal size for male is 7,03 with a slightly larger standard deviation of 1,63, implying that female teams receive a lower AI-VC investment than male teams at a 5% significance level, and male team has a broader spread of deal sizes.

At the company and deal side, male teams tend to have higher possibility of participating in patenting activity than female teams, which are statistically significant at the 1% level. At the same time, fewer female teams have a big company size (among our dataset), which could potentially explain that there are more angel stage deals and less early-stage VC secured by female teams than male teams.

With regard the founders' background, female teams show a higher ratio of having relevant industry experience at 10% significant level, while male teams show a higher ratio of having prior entrepreneurial experience at 5% significant level.

This table suggests several size and deal stage factors significantly differ between female and male teams, thus, incorporating these variables as controls allows us to isolate the effect of gender. At the same time, patenting activity, prior industry experience, and prior entrepreneurial experience differ by gender significantly, indicating potential areas where channel effect for gender might exist.

6.1.3. Industry Variance Test

Before industry fixed effects are added into our regressions, ANOVA test is conducted across industries. This test aims to detect any significant differences in average deal size that could be due to industries.

The results are shown in Appendix 1. With p values lower than 0,01 for GICS_Industry and PicthBook_Industry, the result indicates significant difference existing in deal size across industries, suggesting that industry variations play an unneglectable role in AI-VC investments secured by startups. This finding justifies the inclusion of industry fixed effects in the regressions.

6.1.4. Correlation and Multicollinearity Test

Considering there are both continuous and binary variables in the dataset, the Spearman correlation method is applied instead of the most common Pearson method which assumes linear relationship among variables. Appendix 2 displays the correlation coefficients matrix between variables. The results show that deal size has a slight correlation with team gender, which is in line with our t-test finding. University degree, MBA background, and prior entrepreneurial experience have a moderately positive correlation with deal size. There are stronger correlations of deal size with company sizes dummies, with smaller startups receiving less AI-VC fundings, while larger enterprises receiving more fundings. It is worth noting that the missing category dummy shows a negative relationship with deal size at a similar extent as the small size dummy, this might indicate that the employee numbers show a systematical missing pattern - smaller startups might tend to not disclose employee numbers. Variables like Age and Has_Fanancial also show a moderate positive correlation with deal size, implying that older companies with externally available financial information are related to larger deal sizes. Lastly, the pattern of correlation between deal stages and deal size is in line with expectations.

Further, multicollinearity test is applied to all models together with industry to ensure the validity of regressions. Appendix 3 shows the Generalized Variance Inflation Factor (GVIF) result. Typically, a GIVF above 5 or 10 indicates a problematic level of multicollinearity. All GIVF values except for industry are close to 1, and the highest level of GVIF is for the interaction term between Female_Team and Has_Entre_Exp at approximately 2.43, which is far below the threshold. With the low level of multicollinearity, there is more confidence in the reliability of the coefficient estimates. Thus, multicollinearity is not a significant concern in our regressions.

6.1.5. Heteroskedasticity Test and Robust Method

Finally, Breusch-Pagan (BP) test is applied to detect heteroskedasticity in the basic Model 1, as heteroskedasticity leads to invalid estimates and unreliable hypothesis testing. Appendix 4 displays the BP test result, which shows a p-value lower than 0.001, thus, there is heteroskedasticity in the basic model. Consequently, the white robust method is used throughout all the regressions.

6.2. Empirical Results and Discussion

This section displays and illustrates results of empirical regressions, as well as their implications for predefined hypotheses.

Table 12. Model 1 - Results for Gender Gap

	Deal_Size		
Variables	*(1)*	*(2)*	*(3)*
Female_Team	-0.181	-0.243*	-0.242*
	(0.140)	(0.143)	(0.137)
Constant	5.710***		
	(0.185)		
Controls	YES	YES	YES
GICS Industry FE	NO	YES	NO
PitchBook Industry FE	NO	NO	YES
Observations	597	597	594
R Sqaure	0.294	0.327	0.334
Adjusted R Sqaure	0.283	0.305	0.317

*Note: The table reports the impact of gender on log deal size, and with GICS and PitchBook industry fixed effect respectively. Variables of Company Age, Company Size, Deal Stage and Entrepreneur's University Degree are controlled in the regression. Full table please refer to Appendix 5. The numbers in brackets are standard error and they are heteroscedasticity robust. Significance levels are denoted as follows: *p<0.1; **p<0.05; ***p<0.01.*

We start by examining the gender impact on deal size. As mentioned above, the control variables include company size and company age at the transaction time, deal stage of the specific deal, and university degree held by at least one founder in the team.

Column 1 displays the result of the basic model without any fixed effect, the coefficient of gender is not statistically significant. However, after adding industry fixed effect, as shown in column 2 with GICS industry fixed effect, and column 3 with PitchBook industry fixed effect, the coefficient of gender becomes significant at 10% level, meaning that female team is associated with approximately 24% less investment amount compared to male team once variations across industries are accounted for.

The result suggests that within the context of this dataset in Swedish market, the impact of the founding team's gender on deal size becomes significant after controlling various company, deal, founder variables as well as industry fixed effect. With a significance level of 10%, our result suggests a potential gender gap in the amount of early-stage equity financing secured by female team than male team. This finding aligns with existing studies with focuses on other regions that found women uses less venture capital funding than men with a dataset from Germany market by Lins et al. (2016), and that found a notable disparity in venture capital allocation to women-led ventures in the US by Patricia et al. (2001). Despite the leading gender-equal status of Sweden, the presence of a gender gap in investment amount might still persist in the Swedish AI-VC investment landscape. Possible explanation could be that female teams use higher proportion of debt or internal financing in their capital structure, thereby their financing exposures to AI-VC capital being relatively smaller. This is consist with the existing study that in France female entrepreneurs is less likely to use external equity financing (Hebert, 2023). Moreover, as a complementary, studies find that female and male founders showcase different preference to internal and external sources of capital (Greene, 2003). If this is the case in Sweden, female founders might use a higher proportion of personal savings or fundings from other resources to support their business, which is reflected in the smaller amounts of AI-VC investment they receive.

Furthermore, the impact of intersectionality of various factors with gender on funding is still unknown, in the following part of this paper, the channel effect of various variables for gender to play a role will be examined.

Table 13. Model 2 - Results for Financial Information Availability Channel

	Deal_Size		
Variables	*(1)*	*(2)*	*(3)*
Female_Team	0.011	-0.090	-0.084
	(0.194)	(0.197)	(0.184)
Female_Team:Has_Financial	-0.529**	-0.416	-0.442*
	(0.255)	(0.256)	(0.244)
Has_Financial	0.365***	0.405***	0.409***
	(0.127)	(0.123)	(0.122)
Constant	5.631***		
	(0.184)		
Controls	YES	YES	YES
GICS Industry FE	NO	YES	NO
PitchBook Industry FE	NO	NO	YES
Observations	597	597	594
R Square	0.304	0.339	0.346
Adjusted R Square	0.291	0.315	0.327

*Note: The table reports the channel impact of financial information availability for gender on log deal size, and with GICS and PitchBook industry fixed effect respectively. Variables of Company Age, Company Size, Deal Stage and Entrepreneur's University Degree are controlled in the regression. Full table please refer to Appendix 5. The numbers in brackets are standard error and they are heteroscedasticity robust. Significance levels are denoted as follows: *p<0.1; **p<0.05; ***p<0.01.*

We then switch to examine the channel effect of company-specific features. Models 2 include the financial information availability variable and its interaction with gender to examine its channel effect. Column 1 displays the model without industry fixed effect, and column 2 and 3 display the model with GICS industry fixed effect and PitchBook industry fixed effect in column 3, respectively.

The coefficient of female team becomes insignificant in three columns, suggesting that external availability of financial information is the potential channel for gender. The significant positive coefficients of Has_Financial indicate that providing financial data publicly generally improves an enterprise's ability to secure fundings for the business.

The interaction term between gender and financial information in column 1 is significant at 5% level, while in the PitchBook fixed effect model, it is significant at 10%. However, in GICS fixed effect model, the interaction term is not significant, thus, no definite conclusion can be drawn for Hypothesis 1. With that being said, the negative sign of interaction terms does imply that the availability of financial information works as a channel for female to reduce AI-VC investment amount. For example, in column 1, all else being equal, a female team with external available financial information receives 48.2% less investment.

The variance could be attributed to gender bias as well as be due to distinct financial performance. As discussed above, female-founding enterprises have a significant lower ratio of having large employee size in our dataset, which could possibly result in lower operating and revenue scale. Several studies also found that female-led companies tend to have lower level of profit, total assets, growth rate than male-led ones (Fairlie et al., 2009; Rosa et al., 1996), But on the other hand, female-founding and male-founding firms perform equally well in terms of risk-adjusted performance such as Sharpe Ratio (Robb et al., 2012). Thus, one possible explanation for the potential gender gap we found in the financial information availibity channel could be risk-seeking venture capital investors care more about the former metrics than risk-adjusted metrics. To delve deeper into the reason, adequate financial data is needed, due to the high missing percentage of financial data in our dataset, we are currently limited in drawing conclusions and digging up roots.

Table 14. Model 3 - Results for Patenting Channel

	Deal_Size		
Variables	*(1)*	*(2)*	*(3)*
Female_Team	-0.099	-0.166	-0.148
	(0.147)	(0.149)	(0.146)
Female_Team:Has_Patent_Info	-0.947***	-0.806**	-0.835**
	(0.366)	(0.408)	(0.404)
Has_Patent_Info	0.268*	0.218	0.313*
	(0.157)	(0.158)	(0.189)
Constant	5.693***		
	(0.185)		
Controls	YES	YES	YES
GICS Industry FE	NO	YES	NO
PitchBook Industry FE	NO	NO	YES
Observations	597	597	594
R Square	0.299	0.330	0.339
Adjusted R Square	0.286	0.306	0.319

*Note: The table reports the channel impact of patenting for gender on log deal size, and with GICS and PitchBook industry fixed effect respectively. Variables of Company Age, Company Size, Deal Stage and Entrepreneur's University Degree are controlled in the regression. Full table please refer to Appendix 5. The numbers in brackets are standard error and they are heteroscedasticity robust. Significance levels are denoted as follows: *p<0.1; **p<0.05; ***p<0.01.*

Moving to patenting activity, we add the patenting activity dummy and have it interacted with gender. Similar to financial aspect, the significance of Female_Team disappears, suggesting patenting is also the potential channel.

The interaction term between gender and patenting is significantly negative at 1% level in column 1 without fixed effect, and in the fixed effect columns, significance slightly decrease but still at 5% level. Considering that the significantly positive coefficient of Has_Patent_Info alone indicates a positive effect of patent activity on fundings for males, the negative coefficient of interaction term with a much higher number in absolute value indicates that the positive effect reverses, and engaging in patent activity is correlated with lower deal amount for female teams. Thus, the channel effect of patenting is significant in our dataset.

Accordingly, Hypothesis 2 is supported, that the channel effect of startup's patenting activity for female to decrease deal size is obvious in our datasets focusing on Swedish market.

The negative effect of patenting activity on female team is surprising. While current studies found female-led team with higher innovation display less increase in use of venture capital than male-led teams (Lins et al. 2016), our finding suggests that engaging in patenting activity potentially secures less fundings than without patenting for female teams. This suggests that possibly capitalists in the deals of our datasets might show a high tendency of discrimination over females' innovativeness and patenting behavior due to lack of scrutiny of gender-bias, and thus undervalue females' patents (Beneito et al., 2023). Alternatively, the disparity could be due to different patent qualities, hence further studies of taking patent citations data to control patent quality is worth conducting.

Table 15. Model 4 - Results for MBA Degree Channel

	Deal_Size		
Variables	*(1)*	*(2)*	*(3)*
Female_Team	-0.121	-0.175	-0.189
	(0.147)	(0.148)	(0.143)
Female_Team:Has_MBA	-0.713*	-0.788**	-0.612
	(0.367)	(0.377)	(0.397)
Has_MBA	0.560***	0.520***	0.458**
	(0.196)	(0.200)	(0.206)
Constant	5.664***		
	(0.186)		
Controls	YES	YES	YES
GICS Industry FE	NO	YES	NO
PitchBook Industry FE	NO	NO	YES
Observations	597	597	594
R Square	0.304	0.336	0.340
Adjusted R Square	0.291	0.312	0.321

*Note: The table reports the channel impact of MBA degree for gender on log deal size, and with GICS and PitchBook industry fixed effect respectively. Variables of Company Age, Company Size, Deal Stage and Entrepreneur's University Degree are controlled in the regression. Full table please refer to Appendix 5. The numbers in brackets are standard error and they are heteroscedasticity robust. Significance levels are denoted as follows: *p<0.1; **p<0.05; ***p<0.01.*

We then shift our focus to founders' personal professional background, starting with the MBA degree channel.

The MBA variable has a strong positive correlation with deal amount at a 1% or 5% significance level. This is in expectation and a possible explanation is that in MBA through relevant courses and networking help founders understand how venture capital works, including technicals behind financial instruments, and investment rounds etc., such knowledge serve to reduce information asymmetry (Glücksman, 2020).

The same pattern happens that the gender variable becomes insignificant, implying the channel effect of MBA. Looking at the interaction term, it is negative at 10% level in column 1 (without fixed effect), and at 5% level in column 2 (with GICS fixed effect), and it is insignificant in column 2 (with PitchBook industry fixed effect).

The partially significant interaction between MBA and gender suggests with a negative sign that MBA might work as a channel for female team to decrease deal size. This finding aligns with previous research among MBA students, where Wang et al. (2020) find that female entrepreneurs receive much less external financing due to their less social capital, i.e., network and social trust, despite females' willingness to explore opportunities.

Considering the inconsistent significance, no absolute evidence is found to support Hypothesis 3 and we cannot draw definite conclusion on the possible negative channel effect of MBA for gender to impact deal amount in the Swedish market. With that being said, we believe that whether there exists a channel effect of MBA degree on entrepreneurial financing for females is a research topic worthy of further exploration.

Table 16. Model 5 - Results for Prior Entrepreneurial Experience Channel

	Deal_Size		
Variables	*(1)*	*(2)*	*(3)*
Female_Team	-0.317*	-0.294	-0.251
	(0.176)	(0.180)	(0.182)
Female_Team:Has_Entre_Exp	0.270	0.119	0.040
	(0.287)	(0.290)	(0.272)
Has_Entre_Exp	0.046	0.092	0.117
	(0.134)	(0.127)	(0.127)
Constant	5.682***		
	(0.202)		
Controls	YES	YES	YES
GICS Industry FE	NO	YES	NO
PitchBook Industry FE	NO	NO	YES
Observations	597	597	594
R Square	0.295	0.328	0.335
Adjusted R Square	0.282	0.304	0.316

*Note: The table reports the channel impact of prior entrepreneurial experience for gender on log deal size, and with GICS and PitchBook industry fixed effect respectively. Variables of Company Age, Company Size, Deal Stage and Entrepreneur's University Degree are controlled in the regression. Full table please refer to Appendix 5. The numbers in brackets are standard error and they are heteroscedasticity robust. Significance levels are denoted as follows: *p<0.1; **p<0.05; ***p<0.01.*

The second aspect of founders' professional background that we are interested in is founders' prior entrepreneurial experience. In Table 16, we add the interaction term between entrepreneurial experience and gender to examine its channel effect.

After adding the interaction term between gender and prior entrepreneurial experience, the standalone coefficient of female team decreases from insignificant -0.181 in Model 1 (without fixed effect) to -0.317 at 10% significant level, suggesting that the negative impact of female team increases when isolating the entrepreneurial experience effect.

Looking at the interaction term, the positive sign (statistically insignificant) suggest that prior entrepreneurial experience might work as a slightly positive channel for female to impact investment amount. Research suggests that prior entrepreneurial experience plays an important role in enhancing entrepreneurs' entrepreneurial self-efficacy in the form of enactive mastery (Zhao et al., 2005; Chowdhury et al., 2019) and further for female entrepreneurs, feminine characteristics have positive effect on entrepreneurial self-efficacy in early business searching and planning stages (Li et al., 2020). Generally speaking, the results suggest a potentially empowering effect of entrepreneurial background for female founders when it comes to securing deals, or that such prior experience can be regarded as a proof of female entrepreneurs for their ability to VCs.

Nonetheless, the positive channel effect of entrepreneurial experience is not sufficient to eliminate the negative effect of female variable alone, especially when we control for PicthBook industry fixed effects, the value of the interaction term becomes very minor at 0.04. More importantly, since all the interaction terms in three columns are insignificant in our existing dataset, there is no evidence to support a positive channel effect of prior entrepreneurial experience for female, thus Hypothesis 4 is rejected.

Table 17. Model 6 - Results for Industry Experience Channel

	Deal_Size		
Variables	*(1)*	*(2)*	*(3)*
Female_Team	0.003	-0.018	-0.046
	(0.183)	(0.188)	(0.172)
Female_Team: Has_Ind_Exp	-0.599**	-0.676**	-0.609**
	(0.278)	(0.275)	(0.264)
Has_Ind_Exp	0.419***	0.395***	0.376***
	(0.140)	(0.137)	(0.134)
Constant	5.597***		
	(0.186)		
Controls	YES	YES	YES
GICS Industry FE	NO	YES	NO
PitchBook Industry FE	NO	NO	YES
Observations	597	597	594
R Square	0.307	0.339	0.344
Adjusted R Square	0.294	0.315	0.325

*Note: The table reports the channel impact of prior industry experience for gender on log deal size, and with GICS and PitchBook industry fixed effect respectively. Variables of Company Age, Company Size, Deal Stage and Entrepreneur's University Degree are controlled in the regression. Full table please refer to Appendix 5. The numbers in brackets are standard error and they are heteroscedasticity robust. Significance levels are denoted as follows: *p<0.1; **p<0.05; ***p<0.01.*

The last channel we would like to examine is founders' relevant prior industry experience of the founders. In Table 17, we include the interaction term between industry experience and gender.

In Model 1, the female founding team is negatively associated with the deal size at a 10% significant level. After introducing the interaction term, the value of the coefficient of female becomes very minor and statistically insignificant in all three columns in Table 17. This suggests that the potential negative effect of gender alone might be captured by the channel effect of industry experience.

Further looking at the interaction term, we found that without any industry fixed effect, a negative channel effect of industry experience is indicated by a 5% level significant coefficient of -0.599. After controlling industry fixed effect with two methods, the interaction term is still significant to 5% level, and the negative channel effect increases slightly. The consistent negative interaction term across all three columns provides strong evidence for Hypothesis 5, that prior industry experience does serve as a channel through which female decreases deal size.

This finding is surprising, as existing research confirms that females with prior industry experience increase the productivity of their firms (Grekou, 2023), and female and male entrepreneurial success are statistically equal after controlling for factors including prior industry experience, risk preferences, and working hours etc. (Artz, 2017). Combining these studies, one possible explanation of the channel effect of industry experience for female is that the expertise, knowledge, and network female accumulate through prior industry experience have less value than those of males. However, it is also possible that that prior industry experiences of female entrepreneurs are potentially undervalued by angel and VC investors, and that investors hold unconscious biases that lead them to question female entrepreneurs' ability to translate industry knowledge into successful business strategies. And the less value or the systematic undervaluation serve as the channel through which the gender gap manifest, resulting in lower early-stage equity funding amount for female-led startups.

6.3. Limitation

This paper has some limitations due to the constraints of the dataset.

First, there may be endogeneity problems due to omitted variables. This research did not attach the point on the business models, and we have no exact information regarding the content or quality of the business plans. It is more likely that venture capital institutions are willing to invest more money because the company itself has a very good business plan and model, and the success of the business model has been verified (Mason and Stark, 2004). In addition, we do not include information on the investor side due to limited capacity, while the amount of investment is correlated with the capital owned by the investor. Also, the AI-VC industry is highly male-dominated, and existing research has found that the gender of investors also matters (Ewens and Townsend, 2020; Snellman and Solal, 2023). What's more, the amount of capital raised from AI-VCs also varies upon many other factors such as the management's networking, their risk appetite or share-dilution etc. (Kaplan and Strömberg, 2004).

Second, as we mentioned in the result discussion, we can only draw conclusion on gender gap in the absolute amount of AI-VC investment, channel effect of having patenting activity, and channel effect of having relevant industry experience. In terms whether they are due to the different performance or preference of men and women or due to prejudice is not certain, thus, our study only suggests potential areas where prejudice exists. In terms of the amount gap, startups often raise funds through other channels like private funding, loans or crowdfunding, and using surveys to get these alternative sources information and controlling for them allow further investigation into gender bias. As for patenting, if the quality of the patent can be controlled, there could also be better understanding of its channel effects. With regard to industry experience, possible research could incorporate the entrepreneur's previous position, network, and company information.

Finally, in the dataset used in this study, entrepreneurs' prior industry experience and the GICS industry classification were obtained by manual judgment, thus there exists subjectivity to some extent.

7. Conclusion

This paper uses a dataset composed of 597 deals secured by enterprises founded between 2018.1.1 and 2023.12.31 to investigate the gender gap and its channel mechanism in investment amount in early-stage entrepreneurial equity financing, namely angel investments and venture capitals, within the context of the Swedish market. We find that despite Sweden's strong commitment to gender equality, there is still gender-based disparities in AI-VC capital allocation after adjusting for deal stage, enterprise size, company age, and founders' university degree characteristics, as well as taking into consideration the industry fixed effects.

Furthermore, this paper identifies patenting activity and founders' prior industry experience as significant negative channels through which female entrepreneurs influence the AI-VC backed investment amount for their businesses. One possible explanation is that the innovation and industry experience of female entrepreneurs might hold less value compared to those of their male counterparts. Alternatively, females' dedication to innovation and industry expertise may be systematically undervalued by the market. Overall, the consistent and robust negative channel effects of patenting and industry experience highlight the potential areas where gender bias exists for female entrepreneurs.

Additionally, the negative channel effects of the externally available financial information and MBA background are found to be marginally significant, suggesting that they may be channels through which gender exerts its influence on fund raising. In addition to potential bias, female-founding enterprises may not perform as well financially as those of males, or their financial excellence may not be generally valued by investors. In terms of MBA background, females may have accumulated less social capital (e.g., interpersonal network) than males with MBA experience.

Finally, we find that prior entrepreneurial experience might act as a positive channel for females to obtain slightly more AI-VC capital, although no significance at all.

As an important equity financing resources, angel investors and venture capitals provide entrepreneurs with much financial support, enabling enterprises to grow, innovate and expand in the early stages of business development, thereby promoting the development of the regional economy. The intersection between gender and equity financing has been a focal point of academic research. This paper contributes to the existing literature by identifying the gender gap in investment amount in Sweden and analyzing the channel effects through which gender impact the size of deals at the early stage of the business. By providing evidence on the gender gap and its channels, we highlight the potential areas where bias might exist for future studies to further examine. Our findings also sugget relevant stakeholders, including entrepreneurs, angel and venture capitalists, and policymakers reassess the gender gap in the entrepreneurial ecosystem and the potential bias reflected by patenting and industry experience.

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9. Appendix

Appendix 1a. ANOVA Test for GICS Industry

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
GICS_Industry	10	70.9	7.092	2.869	0.00167***
Residuals	586	1448.3	2.472		

*Note: *p<0.1; **p<0.05; ***p<0.01*

Appendix 1b. ANOVA Test for PitchBook Industry

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
PitchBook_Industry	6	89.7	14.948	6.154	2.84e-06***
Residuals	587	1425.7	2.429		

*Note: *p<0.1; **p<0.05; ***p<0.01*

Appendix 2. Spearman Correlation Matrix

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	*Deal_Size*	1																
2	*Female_Team*	-0.12	1															
3	*Has_Bachelor*	0.12	-0.05	1														
4	*Has_MBA*	0.14	-0.05	0.10	1													
5	*Has_Ind_Exp*	0.09	0.07	0.03	0.05	1												
6	*Has_Entre_Exp*	0.13	-0.10	0.17	0.14	0.13	1											
7	*Small_Size_Dummy*	-0.28	0.00	-0.06	-0.02	0.02	-0.10	1										
8	*Medium_Size_Dummy*	0.09	0.05	0.06	-0.03	-0.06	0.01	-0.28	1									
9	*Big_Size_Dummy*	0.46	-0.12	0.05	0.10	0.13	0.16	-0.28	-0.27	1								
10	*Missing_Size_Dummy*	-0.22	0.06	-0.04	-0.04	-0.07	-0.06	-0.39	-0.39	-0.38	1							
11	*Age*	0.26	-0.04	-0.03	-0.01	-0.01	-0.06	-0.18	0.17	0.30	-0.24	1						
12	*Has_Financial*	0.24	-0.04	0.09	0.04	0.00	0.03	-0.16	0.03	0.25	-0.10	0.29	1					
13	*Had_Patent_Info*	0.12	-0.14	-0.09	0.16	-0.01	0.00	-0.08	-0.04	0.09	0.02	0.16	0.06	1				
14	*Angel_Stage_Dummy*	-0.15	0.13	0.01	0.00	0.01	-0.01	0.07	-0.02	-0.13	0.07	-0.04	0.03	-0.15	1			
15	*Seed_Stage_Dummy*	-0.10	0.03	-0.05	-0.04	0.00	-0.03	0.12	0.06	-0.11	-0.06	-0.21	-0.12	-0.10	-0.27	1		
16	*Early_Stage_VC_Dummy*	0.13	-0.10	0.04	0.05	0.00	0.01	-0.13	-0.02	0.11	0.04	0.13	0.07	0.14	-0.31	-0.77	1	
17	*Late_Stage_VC_Dummy*	0.15	-0.04	0.01	-0.03	-0.03	0.08	-0.10	-0.05	0.22	-0.06	0.27	0.09	0.14	-0.06	-0.15	-0.17	1

Appendix 3a. Multicollinearity Test with PitchBook Industry

	Model 1		*Model 2*		*Model 3*		*Model 4*		*Model 5*		*Model 6*	
	GVIF	*Df*	*GVIF*	*Df*	*GVIF*	*Df*	*GVIF*	*Df*	*GVIF*	*Df*	*GVIF*	*Df*
Female_Team	1.07	1	1.60	1	1.15	1	1.13	1	2.35	1	1.70	1
Age	1.42	1	1.49	1	1.42	1	1.42	1	1.44	1	1.42	1
Size_Category	1.43	3	1.49	3	1.44	3	1.45	3	1.47	3	1.47	3
Deal_Stage	1.40	3	1.42	3	1.44	3	1.43	3	1.41	3	1.42	3
Has_Uni	1.03	1	1.04	1	1.04	1	1.07	1	1.08	1	1.04	1
PitchBook_Industry	1.26	6	1.30	6	1.59	6	1.35	6	1.33	6	1.28	6
Has_Financial			1.33	1								
Female_Team:Has_Financial			1.68	1								
Has_Patent_Info					1.42	1						
Female_Team:Has_Patent_Info					1.09	1						
Has_MBA							1.16	1				
Female_Team:Has_MBA							1.22	1				
Has_Entre_Exp									1.27	1		
Female_Team:Has_Entre_Exp									2.43	1		
Has_Ind_Exp											1.21	1
Female_Team:Has_Ind_Exp											1.86	1

Note: This table displays multicollinearity test with PitchBook industry

Appendix 3b. Multicollinearity Test with GICS Industry

	Model 1		*Model 2*		*Model 3*		*Model 4*		*Model 5*		*Model 6*	
	GVIF	*Df*	*GVIF*	*Df*	*GVIF*	*Df*	*GVIF*	*Df*	*GVIF*	*Df*	*GVIF*	*Df*
Female_Team	1.09	1	1.66	1	1.17	1	1.15	1	2.38	1	1.75	1
Age	1.40	1	1.46	1	1.42	1	1.40	1	1.43	1	1.41	1
Size_Category	1.40	3	1.47	3	1.42	3	1.42	3	1.45	3	1.44	3
Deal_Stage	1.38	3	1.40	3	1.43	3	1.41	3	1.39	3	1.40	3
Has_Uni	1.06	1	1.07	1	1.07	1	1.08	1	1.09	1	1.06	1
GICS_Industry	1.27	10	1.35	10	1.34	10	1.33	10	1.37	10	1.32	10
Has_Financial			1.32	1								
Female_Team:Has_Financial			1.74	1								
Has_Patent_Info					1.19	1						
Female_Team:Has_Patent_Info					1.10	1						
Has_MBA							1.14	1				
Female_Team:Has_MBA							1.19	1				
Has_Entre_Exp									1.31	1		
Female_Team:Has_Entre_Exp									2.38	1		
Has_Ind_Exp											1.22	1
Female_Team:Has_Ind_Exp											1.89	1

Note: This table displays multicollinearity test with GICS industry

Appendix 4. Heteroskedasticity test

studentized Breusch-Pagan test		
Data: Model 1		
BP = 31.383	df = 9	p-value = 0.0002544

Appendix 5a. Full Table of Regression Results for Model 1 to Model 3 without Industry Fixed Effect

	Deal_Size		
Variables	*(1)*	*(2)*	*(3)*
Female_Team	-0.181	0.011	-0.099
	(0.140)	(0.194)	(0.147)
Female_Team:Has_Financial		-0.529**	
		(0.255)	
Female_Team:Has_Patent_Info			-0.947***
			(0.366)
Has_Financial		0.365***	
		(0.127)	
Has_Patent_Info			0.268*
			(0.157)
Age	0.060	0.035	0.051
	(0.046)	(0.047)	(0.046)
Size_Medium	0.860***	0.822***	0.859***
	(0.144)	(0.145)	(0.144)
Size_Big	2.012***	1.906***	2.006***
	(0.183)	(0.187)	(0.181)
Size_Missing	0.296**	0.259*	0.292**
	(0.143)	(0.144)	(0.144)
Stage_Early Stage VC	0.483***	0.509***	0.445***
	(0.148)	(0.146)	(0.152)
Stage_Late Stage VC	0.696*	0.738*	0.610
	(0.398)	(0.395)	(0.382)
Stage_Seed Round	0.162	0.214	0.136
	(0.140)	(0.139)	(0.142)
Has_Uni	0.280**	0.250**	0.298***
	(0.111)	(0.108)	(0.113)
Constant	5.710***	5.631***	5.693***
	(0.185)	(0.184)	(0.185)
GICS Industry FE	NO	NO	NO
PitchBook Industry FE	NO	NO	NO
Observations	597	597	597
R Sqaure	0.294	0.304	0.299
Adjusted R Sqaure	0.283	0.291	0.286
Residual Std. Error	1.352	1.344	1.349
	(df = 587)	(df = 585)	(df = 585)

*Note: The table reports the impact of gender on log deal size, and with GICS and PitchBook industry fixed effect respectively. Variables of Company Age, Company Size, Deal Stage and Entrepreneur's University Degree are controlled in the regression. The sample consists of completed AI-VC deals in Sweden in the period from 2018.01.01 to 2024.02.15. The numbers in brackets are standard error and they are heteroscedasticity robust. Significance levels are denoted as follows: *p<0.1; **p<0.05; ***p<0.01.*

Appendix 5b. Full Table of Regression Results for Model 4 to Model 6 without Industry Fixed Effect

	Deal_Size		
Variables	*(4)*	*(5)*	*(6)*
Female_Team	-0.121	-0.317*	0.003
	(0.147)	(0.176)	(0.183)
Female_Team:Has_MBA	-0.713*		
	(0.367)		
Female_Team:Has_Entre_Exp		0.270	
		(0.287)	
Female_Team:Has_Ind_Exp			-0.599**
			(0.278)
Has_MBA	0.560***		
	(0.196)		
Has_Entre_Exp		0.046	
		(0.134)	
Has_Ind_Exp			0.419***
			(0.140)
Age	0.062	0.066	0.067
	(0.046)	(0.047)	(0.045)
Size_Medium	0.869***	0.845***	0.874***
	(0.144)	(0.146)	(0.145)
Size_Big	1.979***	1.988***	1.950***
	(0.184)	(0.188)	(0.178)
Size_Missing	0.305**	0.285**	0.315**
	(0.142)	(0.144)	(0.143)
Stage_Early Stage VC	0.478***	0.479***	0.457***
	(0.150)	(0.150)	(0.150)
Stage_Late Stage VC	0.781*	0.668*	0.707*
	(0.403)	(0.401)	(0.391)
Stage_Seed Round	0.174	0.157	0.149
	(0.143)	(0.142)	(0.143)
Has_Uni	0.238**	0.281**	0.266**
	(0.112)	(0.113)	(0.110)
Constant	5.664***	5.682***	5.597***
	(0.186)	(0.202)	(0.186)
GICS Industry FE	NO	NO	NO
PitchBook Industry FE	NO	NO	NO
Observations	597	597	597
R Sqaure	0.304	0.295	0.307
Adjusted R Sqaure	0.291	0.282	0.294
Residual Std. Error	1.344	1.353	1.342
	(df = 585)	(df = 585)	(df = 585)

*Note: The table reports the impact of gender on log deal size, and with GICS and PitchBook industry fixed effect respectively. Variables of Company Age, Company Size, Deal Stage and Entrepreneur's University Degree are controlled in the regression. The sample consists of completed AI-VC deals in Sweden in the period from 2018.01.01 to 2024.02.15. The numbers in brackets are standard error and they are heteroscedasticity robust. Significance levels are denoted as follows: *p<0.1; **p<0.05; ***p<0.01.*

Appendix 5c. Full Table of Regression Results for Model 1 to Model 3 with GICS Industry Fixed Effect

	Deal_Size		
Variables	*(1)*	*(2)*	*(3)*
Female_Team	-0.243*	-0.090	-0.166
	(0.143)	(0.197)	(0.149)
Female_Team:Has_Financial		-0.416	
		(0.256)	
Female_Team:Has_Patent_Info			-0.806**
			(0.408)
Has_Financial		0.405***	
		(0.123)	
Has_Patent_Info			0.218
			(0.158)
Age	0.065	0.036	0.057
	(0.046)	(0.047)	(0.047)
Size_Medium	0.891***	0.854***	0.893***
	(0.144)	(0.145)	(0.144)
Size_Big	2.022***	1.907***	2.017***
	(0.179)	(0.181)	(0.178)
Size_Missing	0.306**	0.270*	0.306**
	(0.143)	(0.145)	(0.145)
Stage_Early Stage VC	0.380***	0.408***	0.354**
	(0.146)	(0.145)	(0.150)
Stage_Late Stage VC	0.539	0.598	0.478
	(0.399)	(0.396)	(0.387)
Stage_Seed Round	0.107	0.158	0.088
	(0.141)	(0.141)	(0.143)
Has_Uni	0.267**	0.235**	0.281**
	(0.112)	(0.110)	(0.114)
GICS Industry FE	YES	YES	YES
PitchBook Industry FE	NO	NO	NO
Observations	597	597	597
R Sqaure	0.327	0.339	0.330
Adjusted R Sqaure	0.305	0.315	0.306
Residual Std. Error	1.331	1.322	1.330
	(df = 577)	(df = 575)	(df = 575)

*Note: The table reports the impact of gender on log deal size, and with GICS and PitchBook industry fixed effect respectively. Variables of Company Age, Company Size, Deal Stage and Entrepreneur's University Degree are controlled in the regression. The sample consists of completed AI-VC deals in Sweden in the period from 2018.01.01 to 2024.02.15. The numbers in brackets are standard error and they are heteroscedasticity robust. Significance levels are denoted as follows: *p<0.1; **p<0.05; ***p<0.01.*

Appendix 5d. Full Table of Regression Results for Model 4 to Model 6 with GICS Industry Fixed Effect

	Deal_Size		
Variables	*(4)*	*(5)*	*(6)*
Female_Team	-0.175	-0.294	-0.018
	(0.148)	(0.180)	(0.188)
Female_Team:Has_MBA	-0.788**		
	(0.377)		
Female_Team:Has_Entre_Exp		0.119	
		(0.290)	
Female_Team:Has_Ind_Exp			-0.676**
			(0.275)
Has_MBA	0.520***		
	(0.200)		
Has_Entre_Exp		0.092	
		(0.127)	
Has_Ind_Exp			0.395***
			(0.137)
Age	0.065	0.071	0.072
	(0.046)	(0.047)	(0.045)
Size_Medium	0.904***	0.878***	0.901***
	(0.145)	(0.145)	(0.145)
Size_Big	1.994***	1.994***	1.966***
	(0.181)	(0.185)	(0.176)
Size_Missing	0.318**	0.297**	0.320**
	(0.143)	(0.145)	(0.144)
Stage_Early Stage VC	0.377**	0.382**	0.355**
	(0.148)	(0.148)	(0.150)
Stage_Late Stage VC	0.636	0.520	0.548
	(0.403)	(0.399)	(0.394)
Stage_Seed Round	0.115	0.107	0.090
	(0.143)	(0.143)	(0.146)
Has_Uni	0.230**	0.260**	0.255**
	(0.112)	(0.115)	(0.111)
GICS Industry FE	YES	YES	YES
PitchBook Industry FE	NO	NO	NO
Observations	597	597	597
R Sqaure	0.336	0.328	0.339
Adjusted R Sqaure	0.312	0.304	0.315
Residual Std. Error	1.325 (df = 575)	1.332 (df = 575)	1.322 (df = 575)

*Note: The table reports the impact of gender on log deal size, and with GICS and PitchBook industry fixed effect respectively. Variables of Company Age, Company Size, Deal Stage and Entrepreneur's University Degree are controlled in the regression. The sample consists of completed AI-VC deals in Sweden in the period from 2018.01.01 to 2024.02.15. The numbers in brackets are standard error and they are heteroscedasticity robust. Significance levels are denoted as follows: *p<0.1; **p<0.05; ***p<0.01.*

Appendix 5e. Full Table of Regression Results for Model 1 to Model 3 with PitchBook Industry Fixed Effect

	Deal_Size		
Variables	*(1)*	*(2)*	*(3)*
Female_Team	-0.242*	-0.084	-0.148
	(0.137)	(0.184)	(0.146)
Female_Team:Has_Financial		-0.442*	
		(0.244)	
Female_Team:Has_Patent_Info			-0.835**
			(0.404)
Has_Financial		0.409***	
		(0.122)	
Has_Patent_Info			0.313*
			(0.189)
Age	0.025	-0.006	0.020
	(0.046)	(0.047)	(0.046)
Size_Medium	0.842***	0.804***	0.829***
	(0.145)	(0.147)	(0.146)
Size_Big	2.026***	1.912***	1.996***
	(0.183)	(0.185)	(0.181)
Size_Missing	0.248*	0.210	0.244*
	(0.143)	(0.146)	(0.144)
Stage_Early Stage VC	0.396***	0.418***	0.377**
	(0.152)	(0.150)	(0.151)
Stage_Late Stage VC	0.774*	0.830**	0.690*
	(0.403)	(0.399)	(0.388)
Stage_Seed Round	0.162	0.213	0.149
	(0.143)	(0.142)	(0.144)
Has_Uni	0.315***	0.282***	0.333***
	(0.108)	(0.105)	(0.111)
GICS Industry FE	NO	NO	NO
PitchBook Industry FE	YES	YES	YES
Observations	594	594	594
R Sqaure	0.334	0.346	0.339
Adjusted R Sqaure	0.317	0.327	0.319
Residual Std. Error	1.321	1.312	1.319
	(df = 378)	(df = 376)	(df = 376)

*Note: The table reports the impact of gender on log deal size, and with GICS and PitchBook industry fixed effect respectively. Variables of Company Age, Company Size, Deal Stage and Entrepreneur's University Degree are controlled in the regression. The sample consists of completed AI-VC deals in Sweden in the period from 2018.01.01 to 2024.02.15. The numbers in brackets are standard error and they are heteroscedasticity robust. Significance levels are denoted as follows: *p<0.1; **p<0.05; ***p<0.01*

Appendix 5f. Full Table of Regression Results for Model 4 to Model 6 with PitchBook Industry Fixed Effect

	Deal_Size		
Variables	*(4)*	*(5)*	*(6)*
Female_Team	-0.189	-0.251	-0.046
	(0.143)	(0.182)	(0.172)
Female_Team:Has_MBA	-0.612		
	(0.397)		
Female_Team:Has_Entre_Exp		0.040	
		(0.272)	
Female_Team:Has_Ind_Exp			-0.609**
			(0.264)
Has_MBA	0.458**		
	(0.206)		
Has_Entre_Exp		0.117	
		(0.127)	
Has_Ind_Exp			0.376***
			(0.134)
Age	0.030	0.031	0.032
	(0.046)	(0.047)	(0.045)
Size_Medium	0.847***	0.827***	0.856***
	(0.146)	(0.147)	(0.145)
Size_Big	1.995***	1.997***	1.968***
	(0.183)	(0.187)	(0.178)
Size_Missing	0.258*	0.240*	0.264*
	(0.143)	(0.145)	(0.144)
Stage_Early Stage VC	0.413***	0.398**	0.367**
	(0.153)	(0.154)	(0.154)
Stage_Late Stage VC	0.854**	0.749*	0.776*
	(0.408)	(0.404)	(0.397)
Stage_Seed Round	0.184	0.166	0.145
	(0.145)	(0.145)	(0.146)
Has_Uni	0.276**	0.301***	0.302***
	(0.110)	(0.113)	(0.108)
GICS Industry FE	NO	NO	NO
PitchBook Industry FE	YES	YES	YES
Observations	594	594	594
R Sqaure	0.340	0.335	0.344
Adjusted R Sqaure	0.321	0.316	0.325
Residual Std. Error	1.317	1.323	1.313
	(df = 376)	(df = 376)	(df = 376)

*Note: The table reports the impact of gender on log deal size, and with GICS and PitchBook industry fixed effect respectively. Variables of Company Age, Company Size, Deal Stage and Entrepreneur's University Degree are controlled in the regression. The sample consists of completed AI-VC deals in Sweden in the period from 2018.01.01 to 2024.02.15. The numbers in brackets are standard error and they are heteroscedasticity robust. Significance levels are denoted as follows: *p<0.1; **p<0.05; ***p<0.01*