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Innovative Startups in Italy – a gender analysis

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"The degree of emancipation of women is the natural measure of general emancipation."

Jean Baptiste Joseph Fourier

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To my father, who always fought against injustices, for having instilled in me his values and determination.
You are both my inspiration.
Thanks to my brother, for giving me helpful suggestions, I love you.
Thanks to my grandma Berit, for her constant love and support.
Thanks to Franco and Nella, though you are no longer here, you remain in my heart.

I dedicate this thesis to all my female friends and colleagues who, even for just a moment, have felt judged, inadequate, or not up to the task because women.

Abstract

Innovative startups have been attracting increasing attention from the media as well as private and public entities for several years now, with many organizations choosing to invest in young entrepreneurs as a channel for new employment opportunities and economic growth. Startups gained popularity in Italy well before legislative initiatives in this area were introduced in 2012, through various events, discussion groups, competitions, and calls for proposals.

Despite the increased attention from public debate, the academic research conducted so far has been limited when it comes to examining the representation of women in this context. This gap in knowledge and understanding inspired me to investigate the Italian startup ecosystem, with a particular focus on the gender variable.

By analysing two datasets, I aim to shed light on the gender composition within Italian startups. The findings from this analysis have revealed a significant disparity between women and men in Italian startups. This alarming difference raises questions about the underlying factors that contribute to this disparity and the potential barriers that female entrepreneurs face.

By conducting a more in-depth exploration of the gender proportions within the startup ecosystem, I hope I will highlight the areas where interventions are needed to foster a more inclusive and equitable environment for women in entrepreneurship. Addressing these challenges is crucial not only for promoting gender equality but also for harnessing the potential that women entrepreneurs bring to the table.

This research seeks to contribute to the literature concerning gender dynamics within Italian startups and serves as a basis for future initiatives aimed at creating a more diverse and inclusive entrepreneurial landscape.

Table of content

1. Introduction

In the past decade, an increasing number of jurisdictions worldwide have adopted quotas mandating the representation of women on corporate boards and set forth disclosure requirements on the matter. Nevertheless, disparities in participation, resource accessibility, and outcomes persistently characterize the entrepreneurial ecosystems in disfavour of women in contrast to their male counterparts. Besides compliance obligations, many companies actively pursue greater diversity as a strategic choice, as gender diversity has been demonstrated to be correlated with both enhanced profitability and value creation (Hunt et al., 2015). Many companies recognize that diverse perspectives lead to a broader understanding of the consumers' needs thus the creation of inclusive products and services which ultimately lead to higher profits. The absence of women on corporate boards, especially in innovative environments such as tech companies and startups, has important consequences. Several striking examples are given by Emily Chang in "Brotopia" when discussing the Silicon Valley case. The author pinpoints that the lack of female participation in tech companies has for years led to the creation of products designed for only 50 percent of the population. Prominent examples include violent and sexist video games that a generation of children has become addicted to or virtual (one-time only females) assistants. As late as 2016, if you were to tell Siri, Google Now, or other assistants "I'm having a heart attack", you'd immediately get valuable information about what to do next. If instead, you were to say, "I'm being kidnapped," or "I'm being abused by my husband," the female voice would say "I don't understand what that is". In short, women's participation in product design and workforce in general is of uttermost importance.

The objective of this thesis is to shed light on gender disparities within Italian startups, particularly concerning innovative startups. This research proposes itself as a basis for future studies and hopes to highlight the importance of new research in the field.

This thesis starts with the explanation of the databases used and the variables retained. It continues with the exploration of the broader context of Italian Innovative Startups, from the legal requirements needed to the numbers and sectors that characterize the Italian startup ecosystem.

In the subsequent chapter, attention is directed towards gender inequalities within this domain. Issues on the matter are highlighted with the use of graphs and tables computed with Python 3.9. Data visualization is used to underline the relationship between gender and other variables of the dataset.

2 Preliminaries

In this section the description of the data sources used is provided. The following two databases, “AIDA” and “Registro Imprese”, are the ones used to retrieve data for the analysis.

2.1 Registro Imprese

Registro Imprese is a centralized database managed by the Italian Chambers of Commerce (Camere di Commercio). It serves as the official repository for information related to businesses operating in Italy. Registro Imprese provides data on various aspects of businesses, including their production of the year, the capital class, youth prevalence and other relevant details. According to the database, there are 12542 innovative startups registered in Italy from 2014 to 2023.
To access data from this database I downloaded the xlsx file from the Innovative startups section of the Registro Imprese website and uploaded the file on Jupyter Notebook. Then the xlsx file was transformed into a data frame using Pandas specific module.
This database is used to analyse the Italian startup ecosystem, focusing on different variables and relations, excluding statistics which include gender analysis. I decided to exclude gender statistics from this dataset for the reasoning which follows. This database includes a column named “Female Prevalence” which do not count the number of females per startup but propose a range of percentage over total employees: [0 - 50%, 51 - 66%, 67 - 99%, 100%]. Indeed, the given column of the database “Number of employees” of the database was not to give a finite number but again the following range: [0-4, 5-9, 10-19, 20-49, 40-249, at least 250]. Because the scope of my analysis was to be as accurate as possible, I preferred to use the database AIDA (see description below) to analyse the gender composition of the startups.

2.2 AIDA

AIDA, developed by Bureau van Dijk S.p.A., serves as a comprehensive database and analytical tool focusing on Italian companies, providing detailed financial insights including balance sheets, profit and loss statements, and cash flow statements.
By applying three specific filters - the title of innovative startup, a minimum of one employee, and a commencement date of operation post 2014 - I identified 3169 active Innovative Startups in Italy from 2014 to 2023.

The use of AIDA is essential to analyse the gender composition of the startups under study. In fact, while Registro Imprese contains a larger number of startups, it is not possible to extrapolate the exact number of females in the company. To visualize the data, the csv file was downloaded and then converted in a Pandas data frame in Jupyter notebook.
The column of objective is 'Gender' which contains as many 'm' as males and as many 'f' as females. An algorithm is performed to obtain the number of females and the number of males for startup; this number is then stored in two new columns of the database: 'Number of Females' and 'Number of Males'. These two columns are then added to obtain a third column: 'Number of employees.'

2.3 Cross_Match database for gender analysis

By cross matching AIDA and Registro Imprese on the name of the startups, a third database was obtained. The database, given the name Cross_match, is used to obtain a data visualization on the gender composition of the startups. To address missing data, I implemented the following procedures:

- Rows lacking gender and the name of the startup were excluded.
- Missing values for Return on Assets (ROA) and Return on Equity (ROE) were imputed using the K-Nearest Neighbours (KNN) algorithm with a parameter setting of 5 neighbours.
- Missing values from other columns have been transformed in the string 'Not available'.

"Cross_match" dataset has the following variables:

Name: The name or title of the company or organization under consideration. This variable serves as a unique identifier for each entity in the dataset.

ATECO Code 2007: The ATECO Code 2007 is assigned to the company based on its primary economic activity. This code classifies businesses into specific industry categories for standardization and analysis purposes.

"A": "AGRICULTURE, FORESTRY, AND FISHING",
"B": "EXTRACTION OF MINERALS FROM QUARRIES AND MINES",

"C": "MANUFACTURING ACTIVITIES",
"D": "SUPPLY OF ELECTRICITY, GAS, STEAM, AND AIR CONDITIONING",
"E": "WATER SUPPLY; SEWERAGE, WASTE MANAGEMENT, AND REMEDIATION ACTIVITIES",
"F": "CONSTRUCTION",
"G": "WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES",
"H": "TRANSPORTATION AND STORAGE",
"I": "ACCOMMODATION AND FOOD SERVICE ACTIVITIES",
"J": "INFORMATION AND COMMUNICATION SERVICES",
"L": "REAL ESTATE ACTIVITIES",
"M": "PROFESSIONAL, SCIENTIFIC, AND TECHNICAL ACTIVITIES",
"N": "RENTAL AND TRAVEL AGENCY ACTIVITIES; BUSINESS SUPPORT SERVICES",
"O": "PUBLIC ADMINISTRATION AND DEFENSE; MANDATORY SOCIAL SECURITY",
"P": "EDUCATION",
"Q": "HEALTH AND SOCIAL WORK ACTIVITIES (NON-RESIDENTIAL)",
"R": "ARTS, ENTERTAINMENT, RECREATION, AND OTHER SERVICES",
"S": "OTHER SERVICE ACTIVITIES",
"T": "ACTIVITIES OF HOUSEHOLDS AS EMPLOYERS OF DOMESTIC PERSONNEL",
"U": "EXTRATERRITORIAL ORGANIZATIONS AND BODIES"

Number of Females: Number of female employees per startup**.**

Number of Males: Number of male employees per startup.

Number of Employees: Number of employees per startup. Computed by adding ‘Number of Females’ to ‘Number of Males’.

Return on Equity (ROE): A financial metric representing the profitability of the company relative to its shareholders' equity. It indicates the company's ability to generate profits from the funds invested by its shareholders.

Return on Assets (ROA): A financial metric indicating the company's profitability relative to its total assets. It measures the efficiency of the company in utilizing its assets to generate profits.

Status: Takes values ‘Active’ or ‘Inactive’.

Year of Establishment: The year in which the company was established or founded.

Region: The geographical region or location associated with the company's legal address or operational base.

Production class of the last year.

Value of production	Class of production
0 - 100.000 €	A
100.001 - 500.000 €	B
500.001 - 1.000.000 €	C
1.000.001 - 2.000.000 €	D
2.000.001 - 5.000.000 €	E
5.000.001 - 10.000.000 €	F
10.000.001 - 50.000.000 €	G
More than 50.000.000 €	H
Not available	

Capital class of the last year.

Value of capital	Class of capital
1 €	1
From 1 to 5mila €	2
From 5 to 10mila €	3
From 10 to 50mila €	4
From 50 to 100mila €	5
From 100 to 250mila €	6

From 250 to 500mila €	7
From 500 to 1mln €	8
From 1 to 2,5mln €	9
Not available	

High technological value enterprise in the energy field.

An enterprise is considered to have high technological value in the energy field if it develops and exclusively markets innovative products or services with high technological value in the energy sector. Enterprises classified with the ATECO code "72.1 - RESEARCH AND EXPERIMENTAL DEVELOPMENT IN THE FIELD OF NATURAL SCIENCES AND ENGINEERING" that do not operate in the energy sector are considered excluded.

Requirements:

- 1st requirement for innovativeness :15% of the higher between costs and total production values concern research and development activities.
- 2nd requirement for innovativeness: A team composed of 2/3 of personnel holding a master's degree or 1/3 of doctoral students, PhD holders, or graduates with 3 years of certified research experience.
- 3rd requirement for innovativeness: Enterprise holding or licensee of industrial property rights, or holder of registered software.

Youth prevalence.

Value of prevalence	Description
None	[% of social capital + % of Administrators] / 2 ≤ 50%
Majority	[% of social capital + % of Administrators] / 2 > 50% and <= 66%
Strong	[% of social capital + % of Administrators] / 2 > 66% and <100%

Exclusive	[% of social capital + % of Administrators] / 2 = 100%
Not available	

Female participation: To understand and visualize the distribution of female participation in the dataset, I categorized the female participation in each startup with a function labelling a startup into one of five categories: 'not available', 'Exclusive Presence', 'Dominant Presence', 'Strong Presence', 'Balanced Presence', or 'Low Presence' based on the percentage of women inside it. These categories help us to clearly define and label the level of female participation based on specific thresholds.

The count of startups for category are displayed in **Table 1.**

```python
def categorize_female_participation(female_percentage):

    if pd.isna(female_percentage):
        return 'not available'

    elif female_percentage == 100:
        return 'Exclusive Presence'

    elif female_percentage >= 66 and female_percentage < 100:
        return 'Dominant Presence'

    elif female_percentage >= 50 and female_percentage < 66:
        return 'Strong Presence'

    elif female_percentage == 50:
        return 'Balanced Presence'

    else:
        return 'Low Presence'
```

Figure 1- Python function to define the class 'female participation'.

	female participation	count
0	Low Presence	2663
1	Exclusive Presence	331
2	Strong Presence	130
3	Dominant Presence	45

Table 1 – Startups count by female participation class.

3. Startups

Startups usually come into existence because an entrepreneur identifies an opportunity for a product and/or business model that the market is willing to pay for. Regardless of the product or service a startup offers, securing adequate funding is a fundamental aspect to ensure progress and growth. Such financial backing equips a startup with resources crucial for research, purchasing working capital, marketing services, and paying initial operational and living expenses (Parker, 2009). The process of acquiring funding is often challenging and competitive, especially for tech startups. It requires a solid business plan, an innovative product or service, a capable team, and the potential for high growth. According to Parker (2009), to fulfil their financial needs, startups collect financial resources in the form of personal equity (self-finance) or raise funds from external sources such as Business Angels, Venture Capitalists, Banks, Grant governments, Initial Public Offering (IPO) or strategic investors.

3.1 Italian Innovative Startups

In 2012 the Italian government engaged in the creation of an all-encompassing legislation intended to promote the establishment and the growth of new innovative firms with a high technological value. Such endeavour has culminated with the introduction of the Decree-Law 179/20121 on "Further urgent measures for Italy's economic growth", also known as "Decreto Crescita 2.0" ("Growth Decree 2.0"), converted into Law 221/2012.

The aim of the decree was the creation of a legal framework that could stimulate the development of innovative startups along their life cycle, including subsidies to start the company, a specific labour code that allowed employees to take an equity stake in the company, and fiscal incentives that should help innovative firms to access external finance.

To be classified as an innovative startup, a firm must be less than four years old, incorporated in Italy, have less than 5 million sales, not yet paid out dividends, and have an innovative activity as its core business. The term innovative is intended as a high R&D expenditure (at least 15% of sales), or a set of highly qualified workers (at least one-third with a Ph.D. or two-thirds with a master's) or owning patents or registered software.

3.1.1 Year of establishment

In 2023, 12542 startups were registered as innovative startups at the Chamber of Commerce in Italy. **Figure 2** illustrates the evolution in the number of startups in Italy over time, presenting an interesting picture of growth dynamics. Although the year reporting highest growth is 2021 (i.e. 2862 start-ups), the highest growth rates are concentrated in the period between 2014-2019. Because of the relatively low number of startups in the years preceding 2017, the growth rate results impressively high. The low number of startups characterizing this period may be due to the introduction of the Decree-Law 179/20121 in 2012, since it could have taken some time for entrepreneurs to react to the related incentives and leverage the law by creating new start-ups. As we move across the timescale, however, we notice that despite the growth in the number of startups, the rate at which new enterprises enter the scene begins to decrease, as depicted by **Figure 3.**
Even so, it's important to note that the histogram does not show a decline at any point but demonstrates a positive trend throughout. This signifies that despite the reduced rate of growth, the overall number of startups in Italy continues to grow.
The significant increase in the number of newly born startups starting from 2019, consistently exceeding 1,500 new startups per year, could be attributed to the impact of the COVID-19 pandemic. The unprecedented circumstances of the lockdown may have catalysed entrepreneurial activity, driving individuals to explore new business opportunities, particularly in digital and technology sectors.

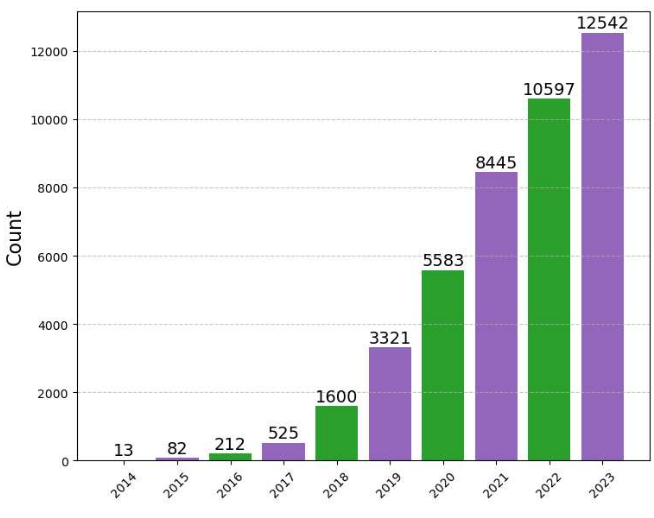

Figure 2 – Number of startups per year

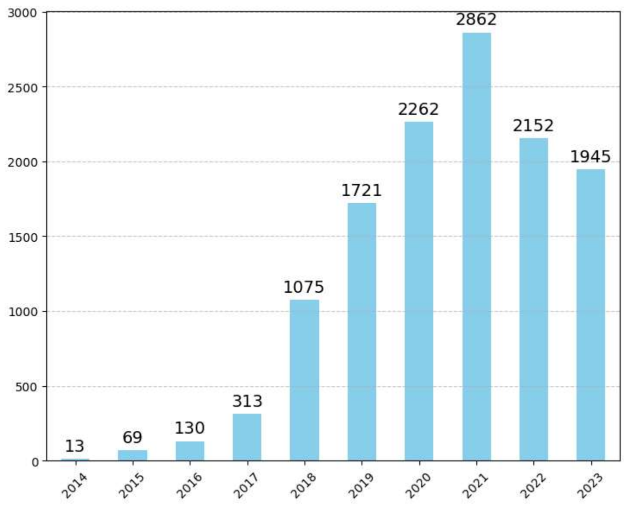

Figure 3 – Number of newly born startups per year

3.1.2 Geographical distribution

In absolute terms, Lombardy is the region with the largest number of innovative start-ups: 3465 (26.6% of the total amount of Italian start-ups). Followed by Lazio with 1555 start-ups (12.4 %), Campania 1433 (11.4 %), Emilia Romagna 867 (6.9%) and Piemonte 699 (5.6 %). At the bottom of the list there are Basilicata (115), Molise (84) and Valle D'Aosta (17).

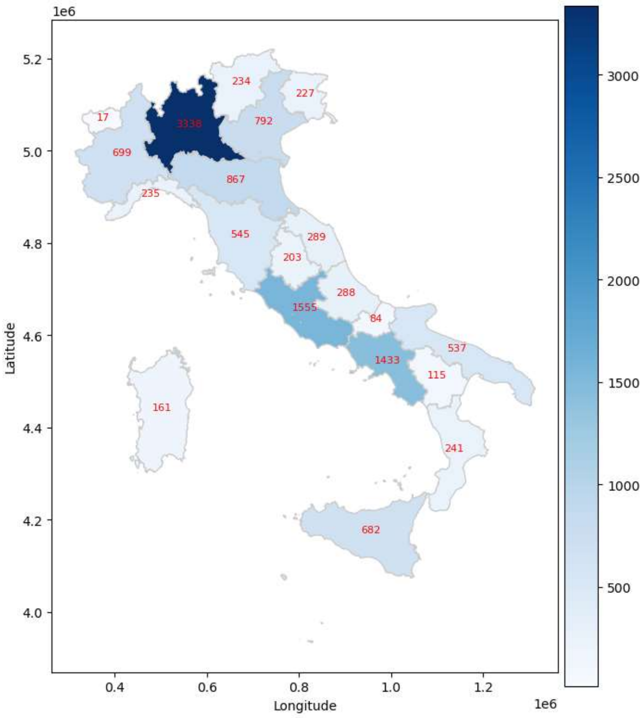

Figure 4 – Number of startups by region

DEN_REG	Percentage Region Count	startups_count
Lombardia	26.6	3338
Lazio	12.4	1555
Campania	11.4	1433
Emilia-Romagna	6.9	867
Veneto	6.3	792
Piemonte	5.6	699
Sicilia	5.4	682
Toscana	4.3	545
Puglia	4.3	537
Marche	2.3	289
Abruzzo	2.3	288
Calabria	1.9	241
Liguria	1.9	235
Trentino-Alto Adige	1.9	234
Friuli-Venezia Giulia	1.8	227
Umbria	1.6	203
Sardegna	1.3	161
Basilicata	0.9	115
Molise	0.7	84
Valle d'Aosta	0.1	17

Table 2 – Percentage and number of startups by region

The role of incubators is of particular importance when analysing the reasons behind a higher number of startups in certain region. Incubators and accelerators provide support and training on entrepreneurial skills through workshops, mentorships, and ongoing support, but also by opening a network of investors, customers, potential partners and more. Innovation funding and incubators at universities often provide young students and researchers with the support to develop a business idea from scratch. Milan houses multiple renowned universities and research centres like Politecnico di Milano and Bocconi University, fostering a continuous flow of talent and ideas. Research centres include Talent Garden Milano, Impact Hub Milano, and PoliHub.
The city of Rome ranks as Italy's second most bustling startup hub. The city boasts over twenty universities, including La Sapienza and Luiss, which have actively supported startups and young entrepreneurs.
Moreover, events also play a vital role in connecting the dots between knowledge, skills, and

networking. By uniting key personalities from startups and related fields, these events make way for strong and lasting business connections.

3.1.3 ATECO Code 2007

An essential aspect of the sample analysis deals with the sector in which the sampled startups operate. Utilizing the ATECO code 2007, a comprehensive classification system employed to standardize economic and industrial activity definitions in Italy, each company is categorized into specific sectors. This code comprises four digits and encompasses various general categories, each denoted by an alphabetical letter. I have condensed the code to its first digit, facilitating the identification of primary sectors for each company and built a bar plot (**Figure 5**).

The major categories with more than 20 startups have been selected for analysis. Remarkably, Information and communication services (J) emerge as the dominant category, housing 6565 startups, 52.6% of our dataset. ICT is followed by Professional, scientific, and technical activities (M) with 2955 startups and Manufacturing (C) with 1664 startups. The other categories encompass less that 400 startups each. At the lower end of our analysis, 21 companies engage in water supply, sewerage, waste management, and remediation activities (E).

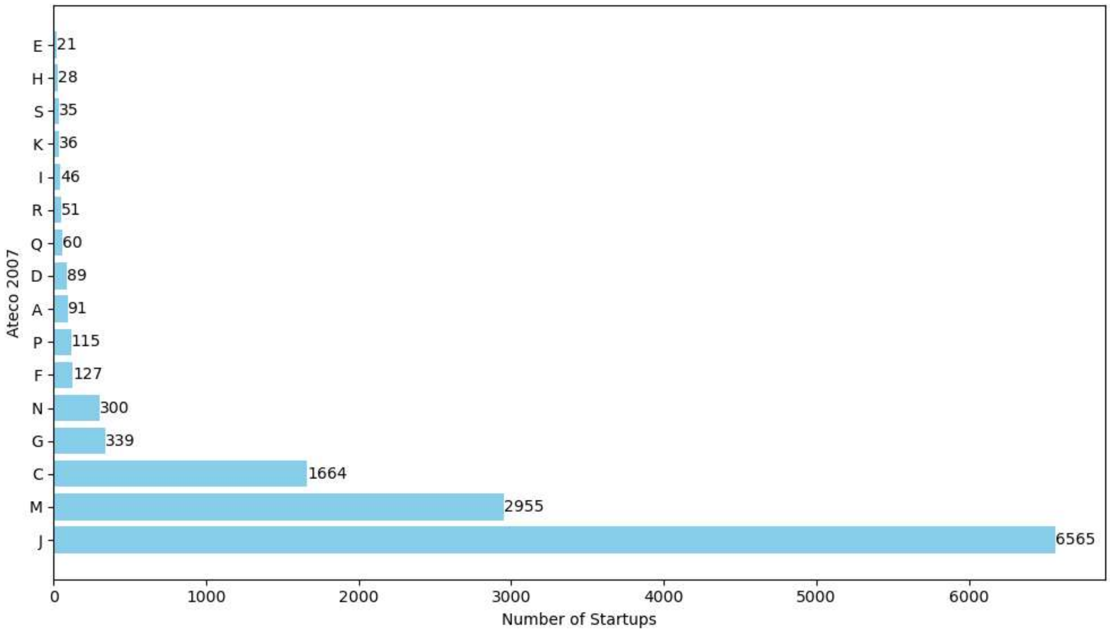

Figure 5 - Number of startups divided by type of activity (only categories with more than 20 startups)

The prevalence of startups in Information and Communication Technology (ICT) can be attributed to several factors. Firstly, the rapid advancement of technology has facilitated the born of innovative solutions and platforms, lowering barriers to entry for entrepreneurs. Secondly, the demand for digital services, ranging from software development to data analytics, has grown, representing a big opportunity for tech startups. Additionally, the relatively low initial investment required for tech-based ventures, along with the potential for scalability, attracts ambitious individuals and investors alike.

3.1.4 Startup Size

Regarding the size of the start-ups within the sample, firms show a low number of employees, and this is coherent with the nature of small and new enterprises. Specifically, the range of employees go from 0 to 26, with an average of 2.26 and a median of 1. Interestingly enough, the 75th percentile is 3 employees, which suggests us that the startup having 26 employees is an outlier and out of ordinary case.

Usually, the only employee is the director who also is the founder or has the full ownership of the firm. One of the dilemmas faced before founding a startup is deciding whether to seek collaborators to develop the project or to proceed individually. There are various motivations that lead a founder to lean towards one direction or the other: forming a team increases the skills and resources available and allows for sharing entrepreneurial risks, but on the other hand, it also involves the division of profits and potential disputes when making decisions. Although investors tend to favour startups founded by two or more people, it has been shown that enterprises with a single founder are more enduring and profitable (Greenberg and Mollick 2018).

```
count    3169.000000
mean        2.247081
std         2.015058
min         1.000000
25%         1.000000
50%         1.000000
75%         3.000000
max        26.000000
Name: Number of employees, dtype: float64
```

3.1.5 Class of capital

Investigating the social capital that investors contribute to a startup yields significant knowledge about the extent of their willingness to take risks and serves as an indicator of the project's level of ambition and risk. Without capital, entrepreneurs may find themselves unable to launch their idea or have difficulty sustaining growth. This capital can be used to pay for rent, utilities, equipment, marketing materials, labour, and other expenses related to the launch of a business.
For readability purposes, I state again the following legend:

Value of capital	Class of capital
1 €	1
From 1 to 5 k €	2
From 5 to 10 k €	3
From 10 to 50 k €	4
From 50 to 100 k €	5
From 100 to 250 k €	6
From 250 to 500 k €	7
From 500 to 1mln €	8
From 1 to 2,5mln €	9
Not available	

According to **Table 3**, the highest number of startups (5162) have capital class 3 (value from 5 k to 10 k €), for a total of 41.15 % of the dataset. It follows capital class 4 (from 10 k to 50 k €) and capital class 2 (from 1 € to 5 k €).

Capital class of the last year	Capital Count	Percentage
1	134	1.068
2	1988	15.851
3	5162	41.158
4	3180	25.355
5	743	5.924
6	671	5.350
7	333	2.655
8	156	1.244
9	112	0.893
not available	63	0.502

Table 3 – Percentage and count of capital classes associated with Innovative Startups

From **Figure 6** we can see how the capital class follows a bell shape, increasing from capital class 1 to capital class 3 and then slowly reaching 9. We don't have information on 63 startups (capital class 'not available').

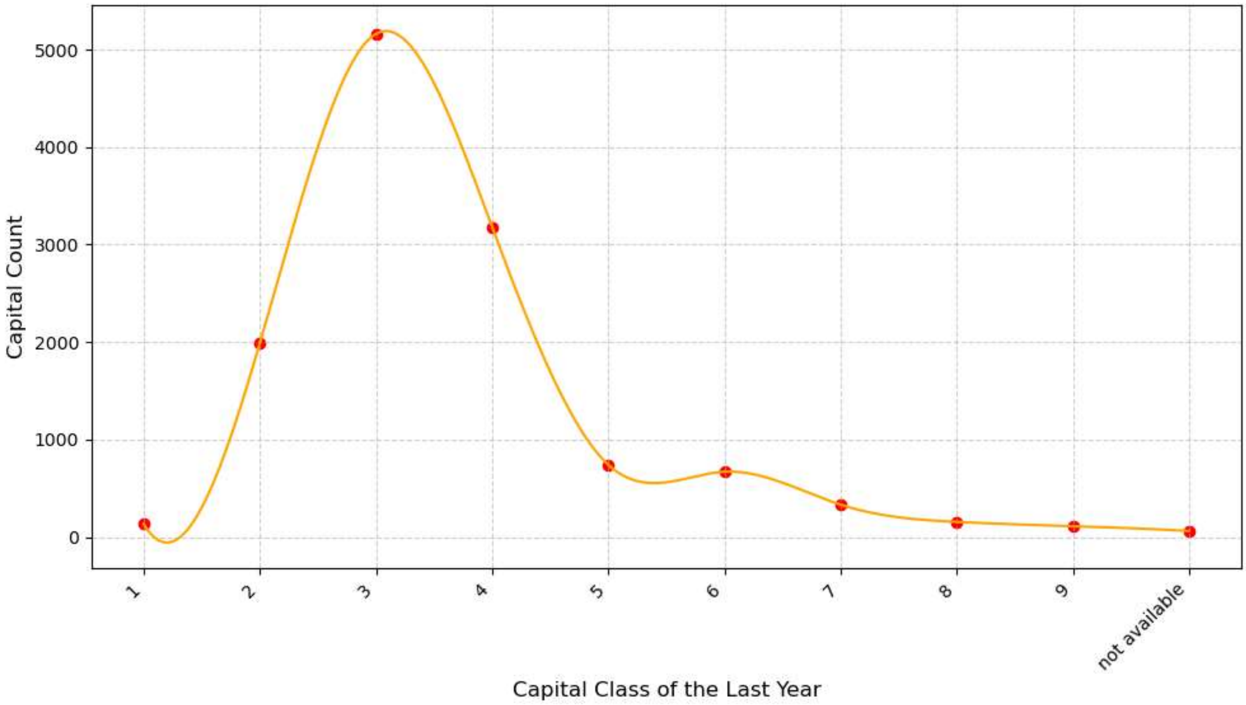

Figure 6 – Visualization of the count of startups by capital class

The heatmap in **Figure 7** help us understand the relation between the class of capital and the sector in which a startup operates. Darker regions correspond to higher counts while lighter regions to smaller counts. The heatmap shows that among startups with capital class 3, the majority are in the information and communication industry (2651). Only few startups have more than 5mln in capital and those who have, are operating in ICT (J) (44), professional, scientific, and technical activities (M) (31) and manufacturing activities (C) (21). It is reasonable to assume that this sector need a big initial investment in capital. A total of 1988 startups have capital class 2 (from 1 € to 5 k €), with the majority (1076) concentrated again in the ICT sector.

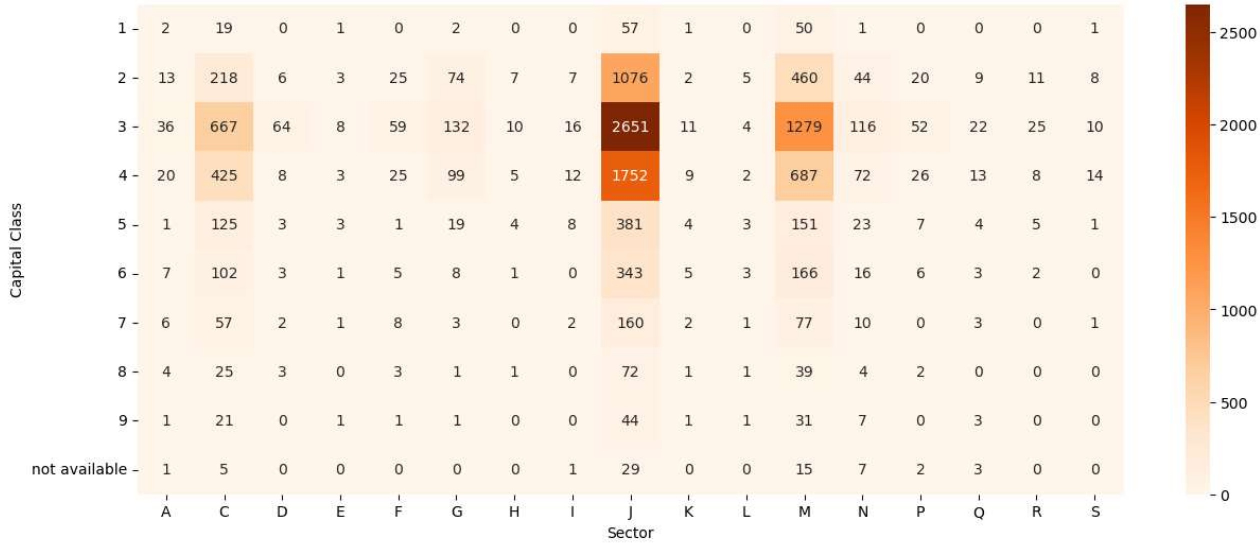

Figure 7 – Heatmap with sectors on the x – axis and capital classes on the y- axis

3.1.6 Class of production

The value of production represents the value of goods or services produced by a company within its main activity. For readability purposes, I state again the following legend:

Value of production	Class of production
0 - 100.000 €	A
100.001 - 500.000 €	B
500.001 - 1.000.000 €	C
1.000.001 - 2.000.000 €	D
2.000.001 - 5.000.000 €	E
5.000.001 - 10.000.000 €	F
10.000.001 - 50.000.000 €	G
More than 50.000.000 €	H
Not available	

Table 4 displays the number and percentages of startups based on the production class to which they belong. It shows that 42.6% of startups count a production class between 0 and 100k € (class A). 18.59% of startups have a production class B (from 100.001 to 500.000 €). While the other classes of production comprehend less than 8% of the sample.

Production class of the last year	Production Count	Percentage
A	5347	42.633
B	2332	18.594
C	516	4.114
D	282	2.248
E	128	1.021
F	18	0.144
G	4	0.032
not available	3915	31.215

Table 4 – Percentage and count of production classes associated with startups.

From **Figure 8** is clear the decreasing trend of the production classes. It is reasonable to assume that this finding is a sign of early-stage development. In fact, these startups may still be in their early stage or working towards generating revenue, resulting in lower production classes. Nevertheless, it is not possible to provide a certain conclusion due to the high amount of unavailable data (31.2%).

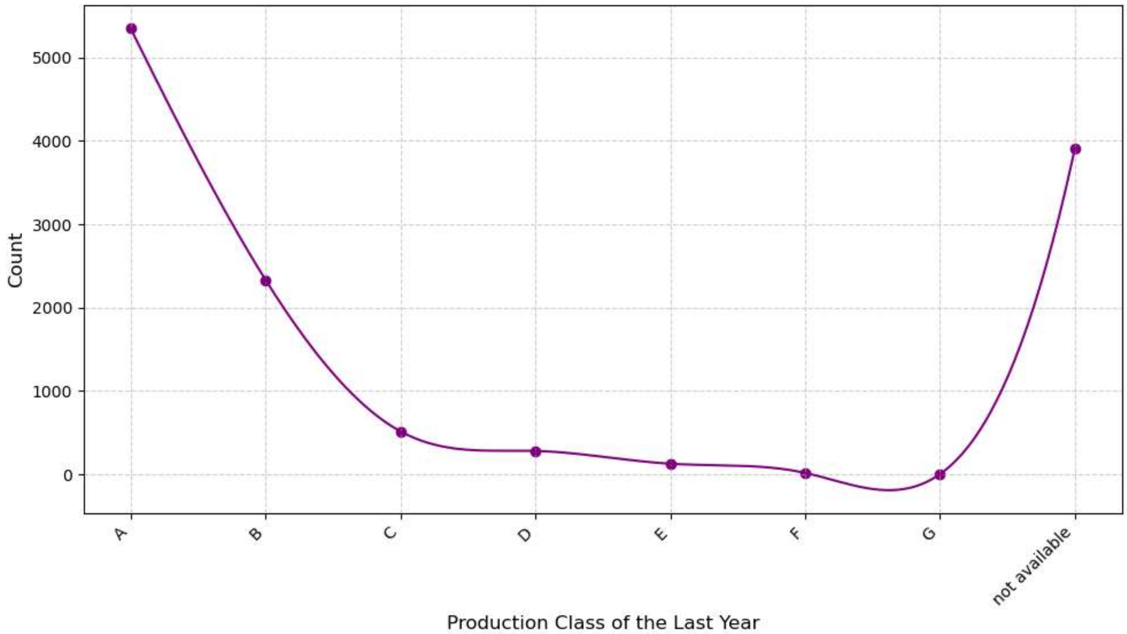

Figure 8 –Visualization of the count of startups by production class

The heatmap in **Figure 9** help us understand the relation between the class of production and the sector in which startups operate. Darker regions correspond to higher counts while lighter regions to smaller counts. The heatmap shows that among startups with capital class A (between 0 and 100k €) , the majority are in the information and communication industry (2781). Only few startups have more than 10 million and less than 50 million € in production and those who have, are operating in ICT (J) (2), supply of electricity, gas, steam, and air conditioning (D) (1) and manufacturing activities (C) (1). No startups reach more than 50 million € in production (production class H).

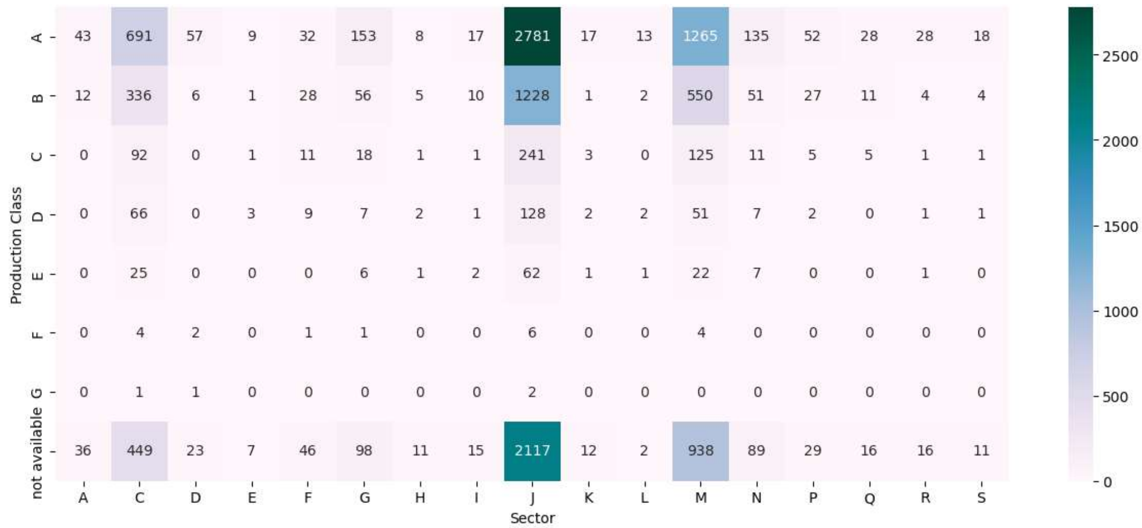

Figure 9 – Heatmap with sectors on the x – axis and capital classes on the y- axis

To analyse the relation between the production class and capital class variables, I created a contingency table (**Figure 10**).

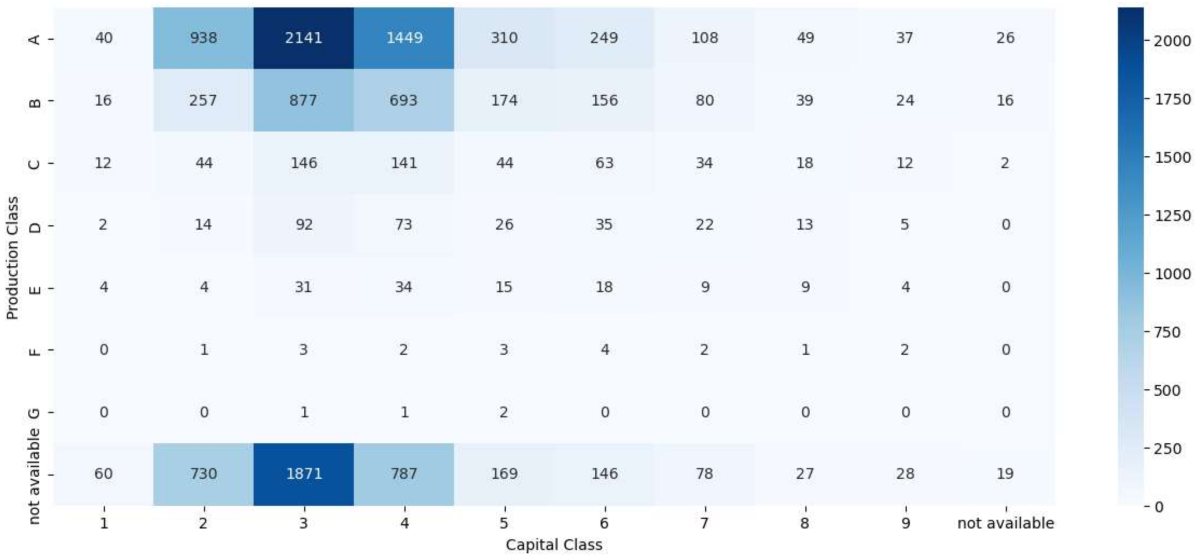

Figure 10 - Heatmap with capital classes on the x – axis and production classes on the y- axis

A clear observation from the heatmap is the dominance of startups in the lower production class, specifically those with a production value between "0 - 100,000 €". This category holds a substantial concentration of startups with a capital "from 5k € to 10k €" (2141) and "from 10k € to 50k €" capital classes. It suggests that while startups are in their early stages of production, they still manage to secure a quite significant capital. This may indicate that investors are willing to take risks on nascent ventures that show potential, even if their current production levels are low.

Among the startups which received from 1 to 2,5mln € in capital (production class 9), none was able to achieve more than 10 million and less than 50 million €, 2 were able to achieve from 5 Mln to 10 Mln € in production, 4 achieved from 2 Mln to 5 Mln € in production while 37 startups remained on the lowest class of production (A). Even with the lowest class of capital, 34 startups succeeded in having a production class above or equal to 100.000 €, these startups might have been auto financed or with low costs.
No startup which received the lowest class of capital was able to achieve the maximum production class, highlighting the already mentioned importance of financing for the success of a venture.
The "Not available" category indicates missing or undisclosed data, startups in this category either do not disclose their production values or have not yet clearly defined them.

4. Gender diversity in Startups

The glass ceiling phenomenon is a well-acknowledged phenomenon that outlines the difficulties faced by talented women when advancing their careers into senior executive roles. The glass ceiling not only inhibits women from reaching their full potential but also restrains organizations from exploiting the rich benefits of gender diversity in leadership. Outside the corporate setting, a second glass ceiling exists for women entrepreneurs. This second glass ceiling is a gender bias that obstructs women-owned small firms from accessing the financial capital required to start new firms and fuel the growth of existing firms (OECD/European Commission, 2021). When they do receive financials, they typically receive less funding than men (Coleman & Kariv, 2014; Kremel & Yazdanfar, 2015), smaller loans (Bardasi, Sabarwal, and Terrell, 2011), pay higher interest rates and need to provide more collaterals (Lassébie et al., 2019; Thebaud and Sharkey, 2016). Notably, the recent Global Entrepreneurship Monitor (GEM) Global Women’s Report highlights significant disparities in startup rates between men and women across 74 economies, with only a mere five economies demonstrating gender parity (GEM Global Report, 2016/2017).
Dautzenberg points out that “founding a technology-based firm is commonly regarded as a male domain” (Kirsti Dautzenberg, 2012), an argument based on the low proportion of women among technology-based startup founders, on the conceptualization of entrepreneurial traits as stereotypically male and reinforced by gender differences in entrepreneurial motivations (J. McGrath Cohoon et al. 2010) and the lack of inclusion of women in the technology sectors (Smith, V. 2015). Thus, women founders of startups face double gender barriers (Sperber & Linder, 2023)

as they struggle simultaneously with two typically male professional contexts: technology and entrepreneurship.
Official data by the Startup Heatmap Europe shows that in Europe, 15.5% of founders or co-founders of startups are women. Indeed, according to data, women receive 38% less funding than their male counterparts when starting up under the same conditions (Startup Heatmap Europe, 2020). While the presence of a significant gender-based funding gap in entrepreneurship is widely acknowledged, there is still disagreement regarding the mechanisms driving this gap. Investor-centric explanations propose that the process of capital allocation disproportionately favours male entrepreneurs due to uncertainties inherent in investors' decision-making (Alsos & Ljunggren, 2017; Kanze et al., 2018). Although very interesting, explanations concerning this phenomenon won't be objective of the analysis. In the following chapters, the Italian Innovative startup ecosystem is analysed from a gender perspective.

4.1 The Italian Case

While there has been a notable increase in the number of women entering the Italian workforce in recent years, a concerning trend in gender disparity persists. The World Economic Forum's (WEF) Global Gender Gap Report 2023, which annually assesses the state of gender inequality worldwide, places Italy in the 79th position out of 146 countries analysed. This represents a drop of 16 positions compared to the 2022 findings and a significant gap compared to numerous other Eurozone countries. A deeper analysis reveals a more alarming scenario, as Italy ranks 104th in the specific category of "economic participation and opportunity," with a score of 0.5976, far from the ideal value of 1 denoting parity.

As represented by **Figure 11**, women employees participating in innovative startups account for 15.4 % of the total employees of our dataset.

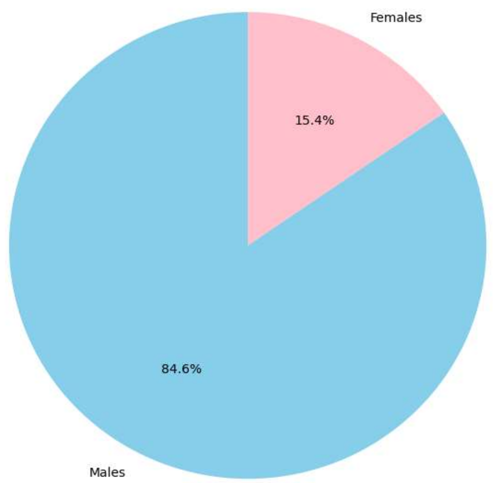

Figure 11 – Gender diversity in the dataset cross_match

4.1.1 Year of establishment

Over the past three years, innovative startups have seen an increase in the number of employees. As of December 2023, there were 1094 female employees (+49% compared to 2020 and a whopping +122% compared to 2019). **Figure 15** depicts the trend.

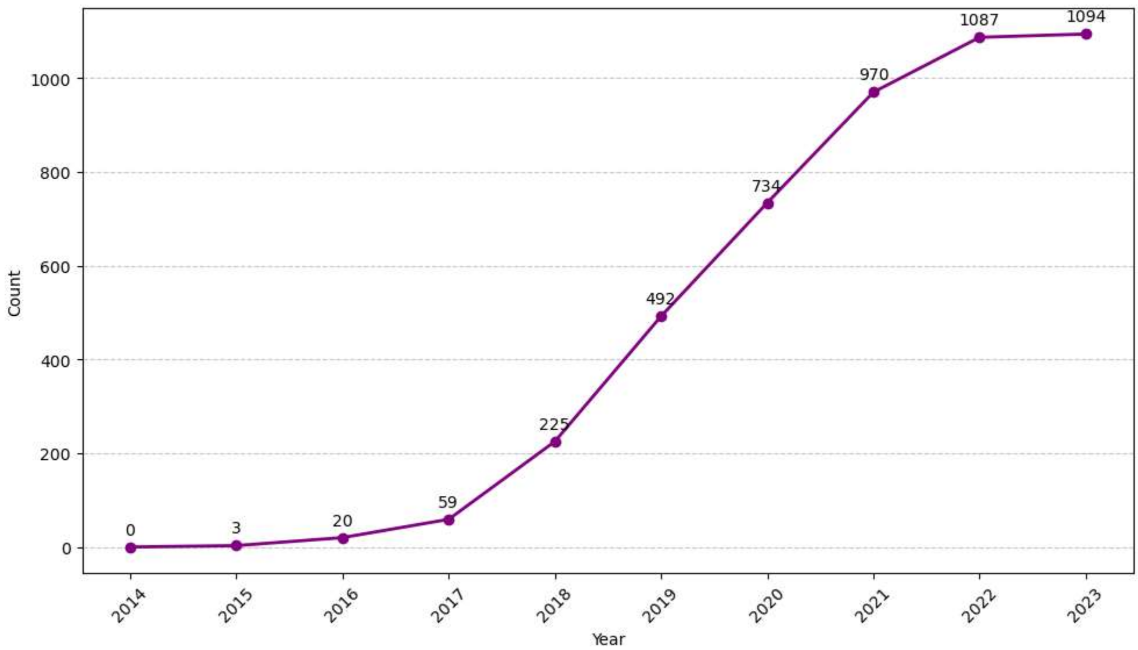

Figure 15 – Count of females in startups by year

Moreover, I calculated the average percentage of women employed for startup for each year from 2014 to 2023 and created the bar plot in **Figure 16**. The two highest average values are recorded in the years 2016 (23.38%) and 2019 (18.25%).

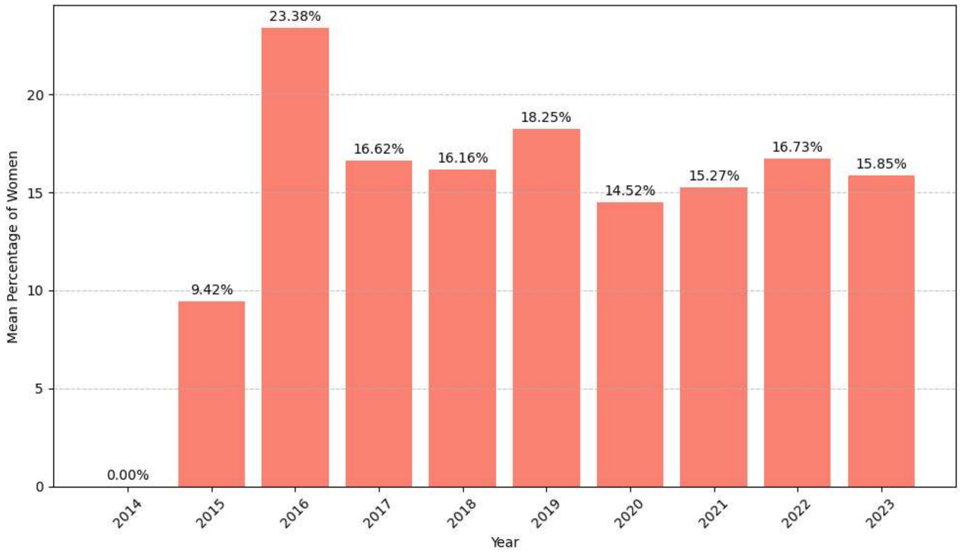

Figure 16 – Mean percentage of women on total employees in Italian innovative startups by year

It is interesting to note that despite the steady increase in number of innovative startups (see **Figure 1**), the percentage of female has not grown linearly, showing a decrease of almost 8 points percentage from the peak in 2016 to 2023; what we expected was a progressive increase in the presence of women within startups, also due to the numerous incentives in favour of female entrepreneurship.

4.1.2 Geographical distribution

To analyse the geographic distribution of female representation in startups, I have constructed two prominent figures for analysis. On the left, **Figure 12** showcases a geographic plot of Italy, with each region shaded to reflect the mean percentage of females associated with startups in that respective area. Warmer hues indicate a higher percentage, while cooler ones represent a lower percentage. Conversely, the **Figure 13** exhibits regions shaded based on the count of females affiliated with startups. Warmer shades in this figure denote a larger count, while cooler shades signify a lower count. It is particularly noteworthy to consider two exceptional cases within these figures, namely Molise and Lombardy. Molise stands out as the darkest region in the first map, indicating the highest average percentage of female employees among all employees in innovative startups. However, it is amongst the regions with the lowest count of female individuals operating within startups. This indicates that in Molise, there are less women in total contributing to the startup ecosystem but at the same time is more likely to find a women employed in one of the startups of the region. However, this conclusion is highly influenced by the low number of startups (and consequently employees) characterizing the region does should not be taken as definitive.

On the other hand, Lombardia emerges as the darkest region in the second map, signifying the highest count of females operating in startups across Italy. Despite this, the average percentage of females per startup remains relatively low in this region. That is to say that while the number of women engaged in startups follow the high trend of number of startups in the territory, it is more likely for a single startup, to have a very low percentage of female employees.

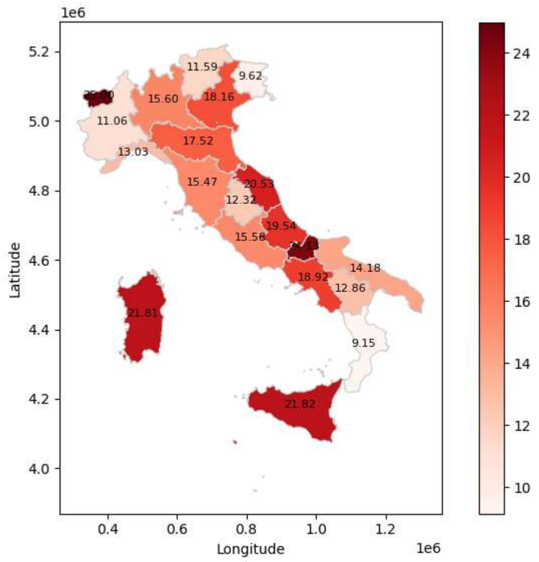

Figure 12 – Mean percentage of females for startup by region.

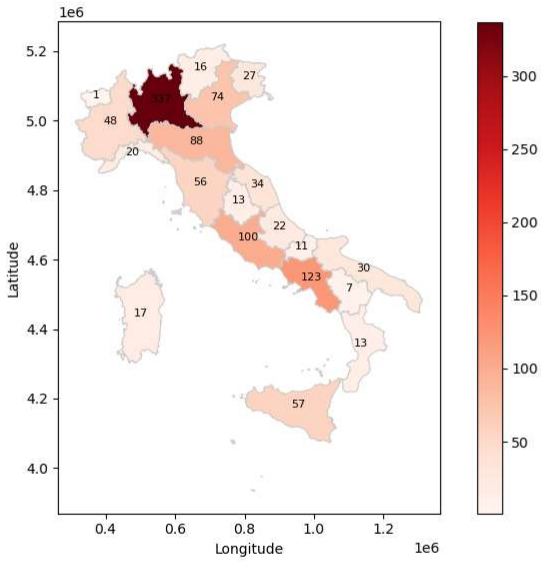

Figure 13 – Count of female employees by region.

DEN_REG	Percentage on Total Females	Females Count	Males Count
Lombardia	30.8	337	1944
Campania	11.2	123	532
Lazio	9.1	100	568
Emilia-Romagna	8.0	88	471
Veneto	6.8	74	400
Sicilia	5.2	57	223
Toscana	5.1	56	332
Piemonte	4.4	48	415
Marche	3.1	34	117
Puglia	2.7	30	185
Friuli-Venezia Giulia	2.5	27	173
Abruzzo	2.0	22	92
Liguria	1.8	20	135
Sardegna	1.6	17	59
Trentino-Alto Adige	1.5	16	128
Umbria	1.2	13	84
Calabria	1.2	13	77
Molise	1.0	11	35
Basilicata	0.6	7	49
Valle d'Aosta	0.1	1	8

Table 5 – Percentage and number of females and males associated with innovative startups by region.

4.1.3 Startups composition

Specifically, startups in which the number of females is higher than the number of males make up 11.9 % of the total number of startups, those in which the number of females is equal to the number of man are 3.9%, those with strong man's participation instead are 84.2 %.

Category	Count	Percentage
More Women	369	11.9
Equal Gender	122	3.9
More Men	2614	84.2

Figure 14 exhibits the percentage of innovative startups in which the number of females is higher than the number of males among startups of the region. "Women-dominant" innovative startups are predominantly located in the northwestern part of the peninsula, with 25% in Valle d'Aosta). Molise (20.0%) ranks second, being the top region in Southern Italy. The ranking include Sicilia (17.8%), Marche (17.8%), Abruzzo (16.7%), Sardegna (17.5%), Veneto (15.6%), Campania (15.5%), Lazio (12.4%), Emilia-Romagna (12.1%), Toscana (11.2%), Lombardia (10.4%) and Umbria (9.8 %).

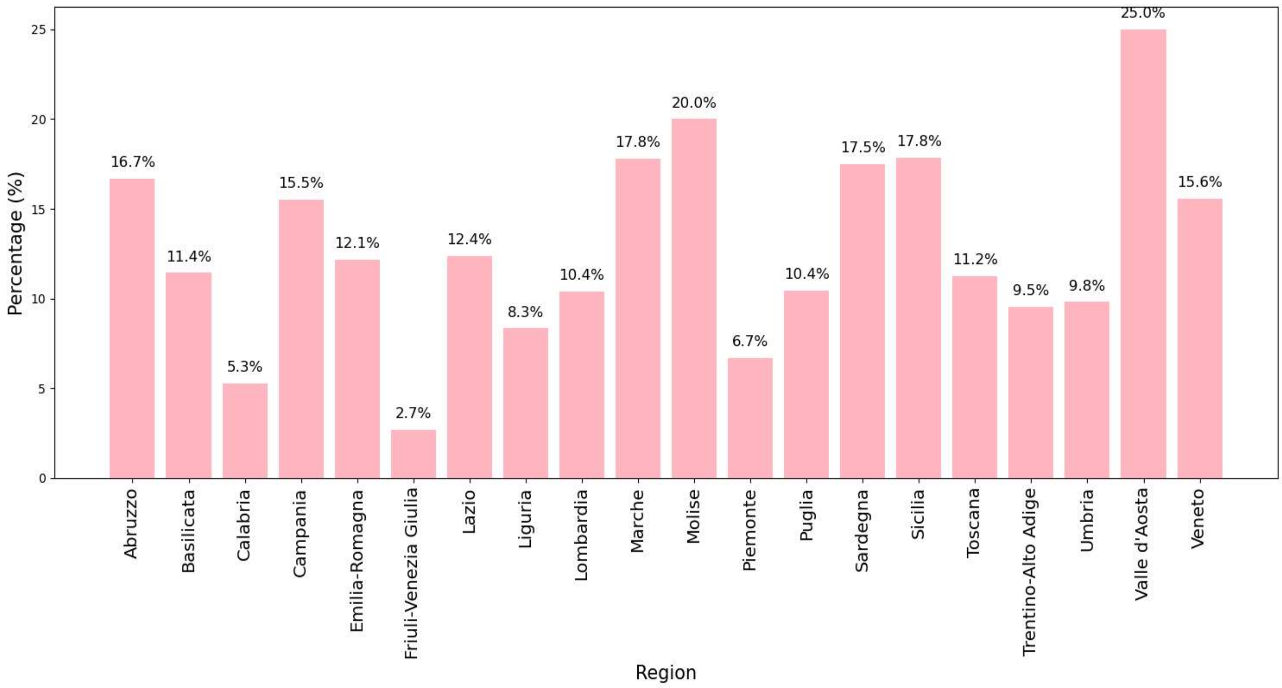

Figure 14 - Percentage of startups with more females than males by region

Lombardia despite being the region with the highest number of females employed in startups, only ranks 12th in the ranking for % of startups with more female than male. We can therefore deduct that the highest part of the women startupper in the region are engaged in male dominant teams.

4.1.4 ATECO Classification

To investigate the relationship between ATECO codes and the count of women within startups, I created a table (Table number) grouping startups by their category and calculating the number male and female working in each category. What we expected and what has been confirmed is the different distribution of women in various areas of work. The category with the highest prevalence of women is "Information and Communication services" (J) (492) followed by "Professional, Scientific and Technical Activities" (M) (281). With respect to the percentage of women over the total number of employees per activity we see a relatively high participation in the 'Health and Social Work Activities' (Q) (31.03%) and in 'Supply of electricity, gas, steam, and air conditioning' (D) (30.0%). We could also claim a high participation in 'Other Activities' but the total number of employees is so low as not to be a focus of interest. Noteworthy is, as aforementioned, the number of women participating in the ICT sector which is the highest among the others. Nevertheless, if we take the percentage of women on total employees in the sector, we find out that it is a male prevailed field, with on average about 13 women every 100 men.

activity	Number of Females	Number of Males	Percentage Women
A	6	26	18.75
C	157	892	14.97
D	6	14	30.00
E	1	9	10.00
F	7	59	10.61
G	41	156	20.81
H	6	39	13.33
I	7	24	22.58
J	492	3301	12.97
K	8	32	20.00
L	1	15	6.25
M	281	1212	18.82
N	44	136	24.44
P	13	54	19.40
Q	18	40	31.03
R	3	15	16.67
S	3	3	50.00

Table 5 – Number of females, number of males and percentage of females divided by type of activity.

Women have not always been underrepresented in the ICT sector. In numerous countries, the proportion of women working in IT was considerably higher during the 1970s and 1980s. This was largely due to the nature of the jobs at the time, which were predominantly low-status and clerical.

However, in the 1990s, with the emergence of personal-computers and the development of the world wide web, the nature of ICT jobs changed. Roles that required low skills, such as data entry and basic analysis, were progressively outsourced to other countries or automated and due to the new high status associated with the field, more men entered and advanced in it.
Gendered representations also changed from the gender-neutral image of the IT technician, to the popular figures of the ‘geek’ or ‘hacker’ closely associated with masculinity (Segal, 1993).

Figure 17 and **Figure 18** present a detailed visualization of ICT startup distribution and female participation in the field across different regions in Italy. **Figure 17** illustrates the number of ICT startups across various Italian regions. Lombardy, in northern Italy, emerges as the clear leader with 499 ICT startups, a number significantly higher than other regions. This high concentration confirms Lombardy as a hub for technological innovation and business activities.
Lazio also demonstrates a substantial presence in the ICT sector with 200 startups. Other regions with relatively high ICT startup activities include Campania (176 startups), Emilia-Romagna (105 startups), and Veneto (86 startups).

Figure 18 focuses on the percentage of ICT startups with a female participation over or equal to 50%. Valle d'Aosta and Molise stand out with the highest percentages (33.3%), indicating a strong female participation in ICT startups within this region. Sardinia follows with 24.1%, Friuli-Venezia Giulia with 21.1% and Basilicata with 15.7%.
Conversely, regions like Calabria (6.2%) and Emilia Romagna (7.6%) have lower percentages of ICT startups with significant female participation. Interestingly, Lombardy, despite having the highest number of ICT startups, shows a relatively modest female participation rate at 12.4%. This discrepancy suggests that having a large number of startups does not necessarily imply higher female involvement. The variation in female participation across regions points to different success levels of local initiatives and cultural factors promoting gender diversity in the tech sector. High female participation in regions with fewer total ICT startups, such as Sardinia, may suggest that focused local efforts can make significant strides in promoting gender inclusivity.

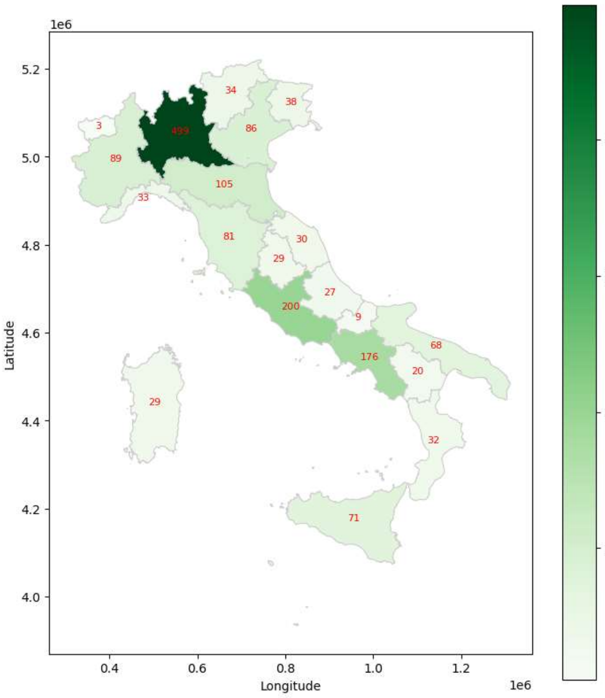

Figure 17 – Number of startups in the ICT domain by region.

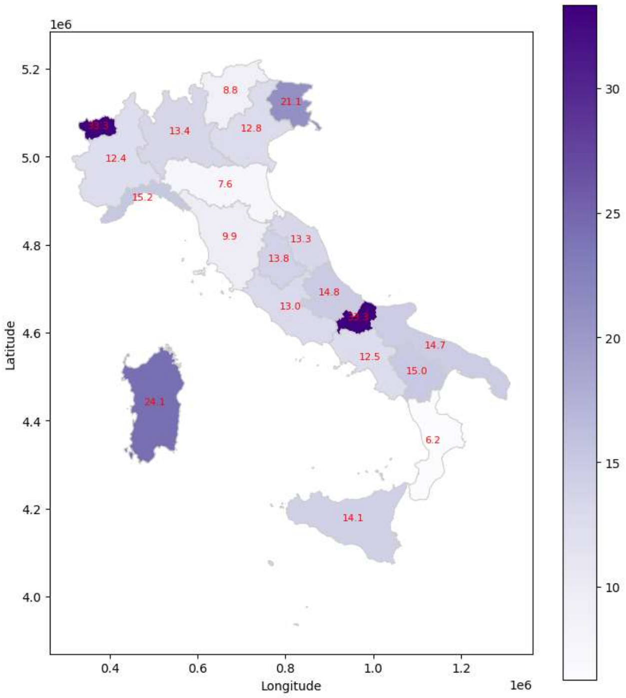

Figure 18 – Number of startups in ICT with females >=50%.

Figure 19 displays the number of ICT employees across various regions. Lombardy emerges as the predominant region with the highest concentration of ICT employees (1375).
Other regions with notable ICT employment include Lazio (394 employees), Campania (295 employees), and Piemonte (250 employees). Conversely, regions such as Molise (11 employees), Basilicata (33 employees), and Valle d'Aosta (7 employees) have less employees in Innovative ICT

startups. **Figure 20** details the percentage of female employees within the ICT sector by region. Molise stands out with the highest female participation rate at 27.3%, indicating a significant presence of women in the ICT workforce. Marche also shows a high female participation rate at 20.3%, followed by Sardinia at 18%. These figures suggest that certain regions are making substantial strides in promoting gender diversity within the ICT sector.
On the other hand, regions such as Veneto (8.9%) and Toscana (9.1%) exhibit lower percentages of female ICT employees. Lombardy, despite having the highest number of ICT employees overall, shows a female participation rate of 14.3%. This indicates that a high total number of employees does not necessarily correlate with higher female representation. Further research would be necessary to explore the factors contributing to high female participation in certain regions.

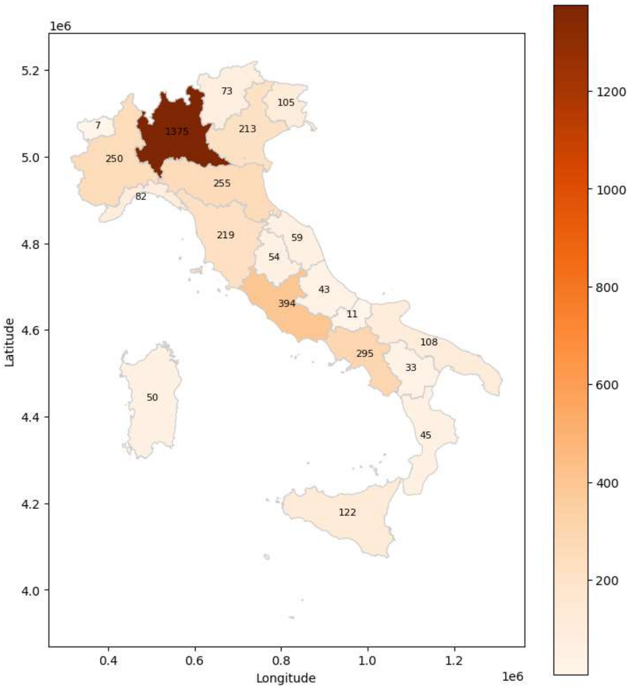

Figure 19 - Number of employees in the ICT domain by region.

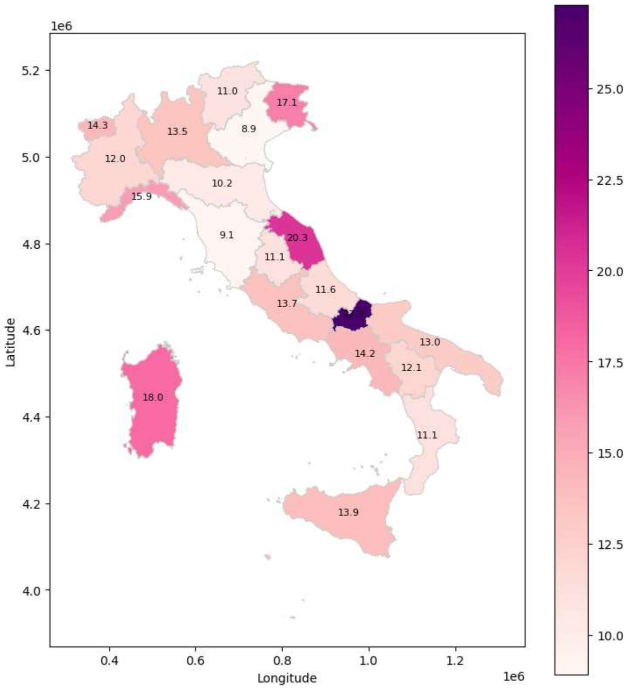

Figure 20 – Percentage of females in ICT by region.

4.1.5 Startup Size

To understand whether the size of the startup was to change according to the gender composition, I created two databases. The first one is obtained by filtering 'cross_match' based on the condition 'percentage of women >= 50%', the second one is obtained by filtering 'cross_match' based on the condition 'percentage of women < 50%'.

The results in **Figure 21** summarizes the statistics of the column 'Number of employees' for both databases. On the left the statistics for the database with a higher or equal percentage of women, on the right the statistics for the database with a lower than 50% of female employees.
We observe that in general startups with half or more females are smaller, with a mean of 1.78 employee per startup and a 75th percentile of 2 employees compared to a mean of 2.33 employees and a 75th percentile of 3 from the statistics on the right. Interestingly, the maximum number of employees (26) is reached in a startup belonging to the first database.

```
count    506.000000
mean       1.784585
std        1.669481
min        1.000000
25%        1.000000
50%        1.000000
75%        2.000000
max       26.000000
Name: Number of employees, dtype: float64
```

```
count    2663.000000
mean        2.334961
std         2.062802
min         1.000000
25%         1.000000
50%         1.000000
75%         3.000000
max        15.000000
Name: Number of employees, dtype: float64
```

Figure 21 – On the right: statistics on number of employees for startups with female percentage >=50%. On the left: statistics on number of employees for startups with female percentage <50%.

4.1.6 Blau Index

In the analysis of gender diversity within startups, I employed the Blau's Index to quantify gender diversity. The Blau's Index is a well-established metric in diversity studies, it captures the probability that two individuals randomly selected from a population belong to different categories, in this case male and female.
Blau's Index is computed using the formula:

$$Blau's\ Index = 1 - \sum p_i^2$$

where p_i represents the proportion of individuals in the i-th category (male or female).
The resulting Blau's Index ranges from 0 to 0.5 where a value of 0 indicates a uniformity (either all males or all females) while a value of 0.5 indicates an equal number of males and females, thus maximum gender diversity. Upon computing Blau's Index for our sample of 3,169 startups, we observed the following descriptive statistics:

```
count    3169.000000
mean        0.065119
std         0.154098
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         0.500000
Name: blau_index, dtype: float64
```

Table 6 – Blau Index statistics.

These numbers reveal several key insights: the mean of 0.0651 indicates a low level of gender diversity across the sample. The minimum, 25th percentile, and median values are all zeroes, suggesting that at least half of the startups have uniform composition (from our previous findings we can say that the uniformity concerns teams of only males much more frequently than only females). The maximum value of 0.5000 shows that there are instances of startups with perfectly balanced gender representation. The predominance of low Blau's Index values in the dataset highlights the significant gender imbalance within startup bodies.

4.1.7 Requirements

Most startups (56.15%) of total employees, fall into the 1st requirement for innovativeness, meaning that 15% of the higher between costs and total production values concern research and development activities.

The 56.15% is composed as follow: 8.38% of total employees follow requirement 1 and are women, while 47.7% of total employees follow requirement 1 and are men.

Only 3.90% of total employees are woman and follow the 2nd requirement for innovativeness, i.e. a team composed of 2/3 of personnel holding a master's degree or 1/3 of doctoral students, PhD holders, or graduates with 3 years of certified research experience, for a total of 21.62% summing females and males for the 2^{nd} requirement.

The 3^{rd} requirement, which counts enterprises with holding or licensee of industrial property rights, or holders of registered software, counts the lowest percentage of both total employees per requirement and female on total employees, with 20.57% and 2.78% respectively.

Figure 22 – Percentages of females and males on total employees by requirement

4.1.8 ROA

The first performance indicator analysed is ROA (Return On Assets). This indicator is used to assess how efficiently a company uses its assets to generate profit. ROA measures the income generated by a company in relation to the total value of its assets.
A high ROA indicates that the company can generate more profit with the same assets or fewer resources. Companies strive to maximize ROA because it indicates a greater ability to generate profits from their investments.
However, ROA has some limitations, such as not considering differences in companies' debt levels, which could affect the assessment of their efficiency, and it may be influenced by accounting choices and variations in asset value.

The Return on Assets (ROA) is calculated as

$$ROA = \frac{Net\ Income}{Total\ Assets}$$

For clarity, I display again the number of startups for each category of female participation:

	female participation	count
0	Low Presence	2663
1	Exclusive Presence	331
2	Strong Presence	130
3	Dominant Presence	45

From the results obtained in **Figure 23**, it is evident that for each class of female participation, the average ROA is negative. This negative result should not surprise us since the average ROA for all startups is -8.962. There are several reasons why the average ROA is so low. Among them the fact that entering a new market or industry usually involves substantial costs, such as market research, regulatory compliance, and establishing a brand. These initial costs can outweigh early revenues.
It is interesting to notice that startups with a low presence of female have a % of ROA below average (-9.269%). When the presence increases to 'Strong' the ROA increases as well to -8.369%. When the presence becomes 'Dominant' (from 66 to 99% presence) there is a high drop in the ROA, resulting in a -12.664%. This result may be influenced by the low number of startups (45) in this category. Interestingly, when the presence of women is 'Exclusive' (100% of females in the startup) the average ROA increases to its highest level (-6.226%). It would be interesting to analyse the 'Exclusive Presence' category in detail, but this analysis won't be part of this work, I leave it for future research.

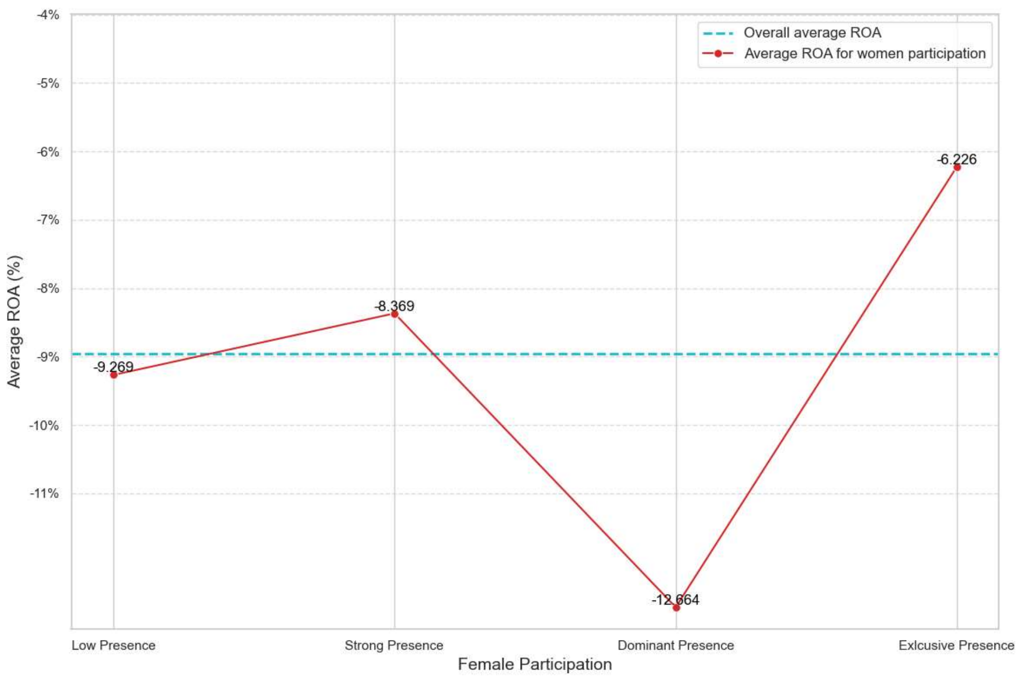

Figure 23 – Average ROA by female participation vs overall average ROA

4.1.9 ROE

The second performance indicator analysed is represented by the ROE (Return On Equity). It represents another important financial performance indicator used to evaluate the profitability and efficiency of a company in relation to its shareholders' investments or equity. Essentially, ROE measures how much profit a company generates relative to its shareholders' equity. ROE is calculated as

$$ROE = \frac{Net\ Income}{Equity}$$

where Equity is the difference between total assets and total liabilities of the company.
A high ROE indicates that the company is obtaining a significant return on shareholders' investment. ROE can be influenced by accounting choices and variations in asset values thus very high ROE values may be due to a significant level of financial leverage (i.e., the use of debt), which can increase risk.
As was done previously for the analysis of the ROA values, also for the ROE, its average values for each class of participation of are analysed. Below is the **Figure 24** with the results. Specifically, the lowest ROE level (-13.217 %) is reached in startups where women are in dominant presence. Conversely, the highest ROE (-4.210) is found in the class where the female participation is exclusive. These results are analogous to the ROA results obtained.

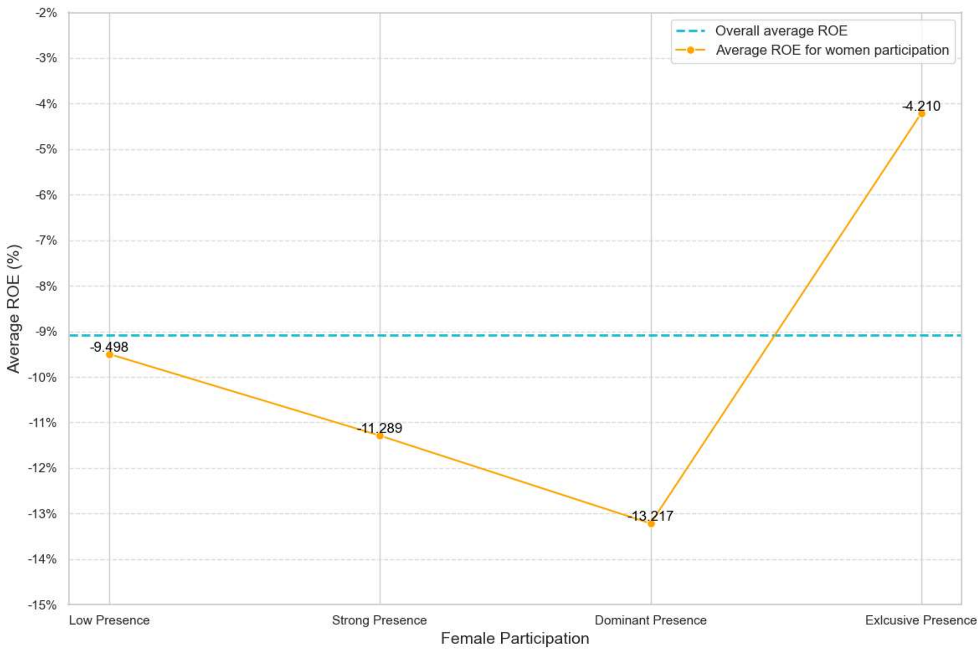

Figure 24 – Average ROE by female participation vs overall ROE

4.1.10 Class of capital

In Italy, there are startups for each class of capital. However, we observe that there is a big disparity in the capital allocation by female participation. For readability purposes, I state again the following legend:

Value of capital	Class of capital
1 €	1
From 1 to 5 k €	2
From 5 to 10 k €	3
From 10 to 50 k €	4
From 50 to 100 k €	5
From 100 to 250 k €	6
From 250 to 500 k €	7
From 500 to 1mln €	8
From 1 to 2,5mln €	9
Not available	

From **Table 7** we observe that only 10 startups where women participation is higher than ‘low presence’ share capital ranging from 1 to 2.5 million €. Of this 10, 5 have strong presence of women and 5 are exclusively women startups. With reference to mode, the most common social capital class is Class 3, with a share capital of 5000.01 to 10000 €. For Italian startups overall, the least common class is Class 9, which hosts 45 startups. Among these, 35 have low female presence, 5 strong presence, 0 dominant presence and 5 exclusive presences. The trend of the share capital classes, both for women and for Italian startups overall, is almost a “bell curve”: It gradually increases until reaching its peak in Class 3, and then slowly decreases until the minimum is reached, in Class 9.

	Low Presence	Strong Presence	Dominant Presence	Exclusive Presence
1	26	1	0	1
2	243	15	3	49
3	865	30	15	147
4	802	48	14	79
5	232	11	4	17
6	247	16	3	23
7	129	4	1	7
8	72	0	3	3
9	35	5	0	5
not available	12	0	2	0

Table 7 – Gender distribution by capital class

4.1.11 Class of production

For readability purposes, I state again the following legend:

Value of production	Class of production
0 - 100.000 €	A
100.001 - 500.000 €	B
500.001 - 1.000.000 €	C
1.000.001 - 2.000.000 €	D
2.000.001 - 5.000.000 €	E
5.000.001 - 10.000.000 €	F
10.000.001 - 50.000.000 €	G
More than 50.000.000 €	H
Not available	

Table 8 displays the number of startups which fall in each category of female participation (Low, strong, Dominant, Exclusive). From the table it's possible to observe that on a total of 4 startups, only one where female participation is higher than 'low presence', achieved a production ranging from 10 million to 50 million €. While only 3 out of 15, with a female participation higher than 'lower' produced a value from 5 million to 10 million €.

The most common production class is Class B (production from 100.001 to 500.000 €), in this class we find the highest count of startups for each female participation label. The trend of production classes, both for women and for Italian startups overall, increases until it reaches its peak in Class B, then slowly decreases until the minimum number of startups in Class G.

	Low Presence	Strong Presence	Dominant Presence	Exclusive Presence
A	825	33	11	141
B	1160	56	24	127
C	336	20	4	30
D	198	8	4	17
E	88	8	1	7
F	12	2	0	1
G	3	1	0	0
not available	41	2	1	8

Table 8 – Gender distribution by production class

5 Conclusions

Ever since I was a child, I was told that I had endless possibilities, all avenues open for me to do what I wanted and become who I wanted. I believed it and I still believe it, but I know that the road won't be as linear as promised. Even though Italy has made efforts to promote the participation of women in the entrepreneurial scene, rooted sexist attitudes still prevent them from reaching the highest roles in companies as easily as men. This issue is of great importance when considering startups, which are for their nature source of innovation and development. Because of the close link between education and entrepreneurship, it is interesting o have a look to the Italian scenario to see whether there is a difference between the two genders.

According to the ISTAT report of 2022, among the people from 25 to 64 years old, 23.5% of females have a college degree, versus 17.1% of males. Yet, surprisingly enough, women's employment rate (in the class from 20 to 64 years old) remains lower than men's (57.3% versus 78%) (ISTAT, 2022). Moreover, the employment rate among females' universities graduates is 18,4 points higher than female high school graduated (versus only 5,1 points among men).

Even though females appear to be more educated than men, big disparity occur in fields crucial for innovation and economic growth, such as science, technology, engineering, and mathematics (STEM). The fact that there are fewer female graduates in scientific-technological disciplines than men (16.6% versus 34.5%), may reasonably have affected the number of females in the startup ecosystem. In fact, within the startup landscape, where technological advancements drive progress, STEM fields play a crucial role. In fact, it is with no surprise that most of the startups, as demonstrated by this thesis, concern the ICT sector, which evolve around STEM subjects.

Why less women than men decide to pursue a career in startups can be source of research. Among the reasons it may be that females tend to regard themselves less capable of leading such domains and in males amplifying this stereotype.

Being a student in STEM subjects, I had the chance to witness some of the stereotypes related to my field, among those the one portraying women as more interpersonally oriented but less capable than men in terms of practical skills and initiative. I have personally observed this several times over, but it should be said that it occurred without males (and females as well) deliberately wishing to offend, it was like this was the norm. Thus, it seems obvious that any change must start from education, by fostering an environment where children learn about the value of equality and feel free to follow their passion despite their gender.

This low representation of women in startups highlights existing gender biases and systemic disadvantages in social structures, making visible the male dominance that exists at the intersection of STEM and entrepreneurship.

In conclusion, the gender composition of the Italian startup scene reflects broader societal challenges and systemic biases that hinder the full participation of women in entrepreneurship, particularly in startups. By recognizing these barriers, it will be possible to address them through targeted interventions and policies.

6 Limitations

There are several limitations in the present research. First, the conclusions should probably not be cut in stone due to the limited availability of data. By sampling from two public institutions (Registro imprese and AIDA), I obtained a total of 3169 startups which is about a fourth of the original dataset. Second, although the process for coding did not exhibit errors, the numbers of the findings need to be interpreted with caution since are the result of data cleaning.

Moreover, the type of activity conducted by the startups have been limited in classification to the broader field. It would be interesting to dive deep into the ATECO codes to create more precise statistics.

Despite limitations, the current results provide a foundation for investigating women in Italian startups, an area that have been relatively unexplored in existing studies. I think this work could create an important avenue for future investigation. An example could be analysing the reasons behind such disparities by conducting surveys to founders of startups and graduates from university.

7 References

Alsos, G.A. and Ljunggren, E. (2017), "The role of gender in entrepreneur–investor relationships: a signalling theory approach", Entrepreneurship: Theory and Practice, Vol. 41 No. 4, pp. 567-590, doi: 10.1111/etp.12226.

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

Coleman, S. & Kariv, D. (2014). Deconstructing' entrepreneurial self-efficacy: A gendered perspective on the impact of ESE and community entrepreneurial culture on the financial strategies and performance of new firms. Venture Capital, 16(2), 157–181
(PDF) Gender Stereotypes and Venture Support Decisions: How Governmental Venture Capitalists

Gender Stereotypes and Venture Support Decisions: How Governmental Venture Capitalists Socially Construct Entrepreneurs' Potential. Available from: https://www.researchgate.net/publication/313222599_Gender_Stereotypes_and_Venture_Support_Decisions_How_Governmental_Venture_Capitalists_Socially_Construct_Entrepreneurs'_Potential [accessed April 22 2024].

Global Entrepreneurship Monitor. (2016/2017). GEM Global Women's Report.
Parker, S. (2009). The economics of entrepreneurship. New York: Cambridge University Press

Greenberg, Jason and Mollick, Ethan R., Sole Survivors: Solo Ventures Versus Founding Teams (January 23, 2018). Available at SSRN: https://ssrn.com/abstract=3107898 or http://dx.doi.org/10.2139/ssrn.3107898.

Hunt, D. V., Layton, D., & Prince, S. (2015, January 1). Why diversity matters. McKinsey & Company. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/why-diversity-matters

ISTAT. (2022). Report livelli di istruzione e ritorni occupazionali [Press release].

J. McGrath Cohoon, Vivek Wadhwa, and Lesa Mitchell. 2010. The Anatomy of an Entrepreneur: Are Successful Women Entrepreneurs Different from Men?. Ewing Marion Kauffman Foundation, Kansas City, MO, USA. https://dx.doi.org/10.2139/ssrn.1604653

Kanze, D., Huang, L., Conley, M. and Higgins, E.T. (2018), “We ask men to win and women not to lose: closing the gender gap in startup funding”, Academy of Management Journal, Vol. 61 No. 2, pp. 586-614, doi: 10.1016/j.jfma.2016.06.004.

Kirsti Dautzenberg. 2012. Gender differences of business owners in technology-based firms. International Journal of Gender and Entrepreneurship 4, 1 (Mar. 2012), 79–98. https://dx.doi.org/10.1108/17566261211202990

Kremel, A., & Yazdanfar, D. (2015). Business advisory services and risk among start-ups and young companies: A gender perspective. International Journal of Gender and Entrepreneurship.

Lassébie, J. et al. (2019), “Levelling the playing field : Dissecting the gender gap in the funding of start-ups”, OECD Science Technology and Industry Policy Paper, No. 73, OECD Publishing, Paris, https://doi.org/10.1787/23074957.

OECD/European Commission (2021), The Missing Entrepreneurs 2021: Policies for Inclusive Entrepreneurship and Self-Employment, OECD Publishing, Paris, https://doi.org/10.1787/71b7a9bb-en.

Segal, L. (1993), Slow motion — Changing masculinities, changing men, Rutgers University Press, New Brunswick

Smith, V. (2015). Women In Tech : Addressing the Root Causes of Attrition.

Socially Construct Entrepreneurs’ Potential. Available from: https://www.researchgate.net/publication/313222599_Gender_Stereotypes_and_Venture_Support_Decisions_How_Governmental_Venture_Capitalists_Socially_Construct_Entrepreneurs'_Potential [accessed May 1 2024].

Startup Heatmap Europe. (2020, November 4). Report on women entrepreneurs in Europe. https://startupsandplaces. com/startup-heatmap-europe-report-on-womenentrepreneurs-in-europe/

Thebaud, S. and A. Sharkey (2016), “Unequal Hard Times: The Influence of the Great Recession on Gender Bias in Entrepreneurial Financing”, Sociological Science, Vol. 3, pp. 1-31, https://doi.org/10.15195/v3.a1.