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(Markets, Infrastructures, Payment Systems)

Exploring fintech innovation facilitation at central banks:
the case of Milano Hub

by Matteo Amoroso, Andrea Azzola, Camilla Bignotti and Lorenza Masoero



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EXPLORING FINTECH INNOVATION FACILITATION AT CENTRAL BANKS: THE CASE OF MILANO HUB

by Matteo Amoroso*, Andrea Azzola*, Camilla Bignotti* and Lorenza Masoero*

Abstract

Banca d'Italia is among those Central Banks that have set up Innovation Facilitators to dialogue with the fintech ecosystem. Using data from application forms and other complementary *sources*, we conducted an empirical analysis of the human capital involved in the projects submitted in response to the three Calls for Proposals (CfPs) launched by Banca d'Italia's innovation center, Milano Hub. Consistently with the broader Italian landscape, project proposals to Milano Hub involve a greater proportion of experienced individuals than new graduates, a prevalence of backgrounds in economics and STEM subjects, and a substantial gender gap. Linear regression reveals that work experience and STEM education appear to be positively associated with the outcomes of the projects' evaluation in the CfP context. The aim of this study is to initiate a discussion within Banca d'Italia on how to improve, when necessary, fintech facilitation policies and operational models. These findings are also intended, more broadly, to guide Central Banks in positioning their Innovation Facilitators to attract and boost fintech ventures.

JEL Classification: E58, E61, G28, G29, O31.

Keywords: fintech, Central Banks, innovation hub, professional experience, academic background, gender gap.

Sintesi

La Banca d'Italia figura tra le banche centrali che hanno istituito gli Innovation Facilitator per dialogare con l'ecosistema fintech. Utilizzando i dati raccolti attraverso i moduli di candidatura e altre fonti complementari, abbiamo condotto un'analisi del capitale umano coinvolto nei progetti presentati nelle tre Call for Proposals (CfP) lanciate dal centro di innovazione della Banca d'Italia, Milano Hub. In linea con il più ampio contesto italiano, le proposte progettuali presentate a Milano Hub vedono il coinvolgimento di persone con una significativa esperienza professionale, anziché neolaureati, una prevalenza di profili con formazione economica e STEM, e un sostanziale divario di genere. Le regressioni mostrano che esperienza lavorativa e formazione STEM sembrano positivamente associate agli esiti della valutazione dei progetti nell'ambito delle CfP. Lo studio intende stimolare la discussione interna alla Banca d'Italia su come migliorare, ove necessario, politiche e modelli operativi di facilitazione dell'innovazione fintech. Più in generale, i risultati vogliono orientare le banche centrali nel posizionamento dei propri Innovation Facilitator al fine di attrarre e sostenere le iniziative fintech.

* Banca d'Italia, Payments and Market Infrastructures

CONTENTS

INTRODUCTION	7
1. RESEARCH QUESTIONS AND HYPOTHESES	10
2. DATA	10
3. INSIGHTS FROM MILANO HUB PROJECT SUBMISSIONS	11
3.1. The human capital of fintech projects	11
3.2. Experienced professionals for young firms	15
4. ECONOMETRIC ANALYSIS	18
4.1. Models	18
4.2. Results	22
4.3. Robustness and limitations	28
5. FROM EVIDENCE TO POLICY: DISCUSSION OF RESULTS AND OPERATIONAL IMPLICATIONS	29
5.1. Population attracted by Milano Hub	29
5.2. The assessment of applications: human capital across selected projects	30
5.3. Implications and future directions	31
6. CONCLUSIONS	32
REFERENCES	33
ANNEXES	36
ANNEX 1: DETAILED METHODOLOGICAL ASSUMPTIONS UNDERLYING THE REGRESSION MODELS AND VARIABLES	36
ANNEX 2: CHECKS ON MODEL VARIABLES	38
ANNEX 3: DESCRIPTIVE STATISTICS OF STANDARDIZED FINAL SCORE BY COMBINATION OF BACKGROUND - ALL TYPES OF BACKGROUND	40
ANNEX 4: OUTCOME OF THE REGRESSIONS	41
ANNEX 5: ROBUSTNESS OF THE MODELS	51

Introduction¹

In the last decade, it is evident that innovation has been spreading rapidly, impacting every aspect of society, economy and financial sector, including market infrastructures, payments, market operations and many others (e.g. Panetta, 2018); in particular, it is worth mentioning, in all fields, the recurring wide impact of technology, which is reasonable to consider as the main character in the financial ecosystem as such.

Start-ups and fintech companies play a pivotal role in the ongoing evolution of financial innovation, complementing the efforts of incumbent institutions. By offering products and services that, in several cases, more effectively align with customer preferences and streamline business operations, they are actively reshaping the financial supply chain and reducing the reliance on the complex and often cumbersome procedures characteristic of traditional banking systems (e.g. Thakor, 2020).

In this rapidly evolving context, Central Banks and National Competent Authorities (NCAs) have set up the so called ‘Innovation Facilitators (IFs)’ to engage with the fintech players on their innovative business ideas and offer a safe environment to test these projects. In this interaction, the NCAs stay abreast of emerging innovations in the financial sector, enhancing their role in safeguarding financial stability, consumer protection and market integrity (e.g. ESAs, 2023). Banca d’Italia is part of this group of Authorities: in particular, Milano Hub was established in 2021 as an innovation centre to actively support the safe and sound digital transformation of the financial ecosystem, while monitoring its main actors and its developments. Specifically, by engaging directly with fintech operators in developing innovative projects yet to be marketed, Milano Hub aims at accelerating the development of fintech projects and their safe adoption to enhance the competitiveness of the Italian financial market.²

We intend to conduct an empirical study based on the relevant data collected through the three *Calls for Proposals* (*CfPs*) launched so far by Milano Hub, each focused on a specific topic, respectively Artificial Intelligence, Distributed Ledger Technology, and digital payments. More in detail, the rationale behind this study is two-fold: to identify the key features of the fintech projects attracted by Milano Hub and to investigate to what extent these characteristics are connected to the evaluation of these projects made by Milano Hub so far. The assessment procedure, coupled with its peculiar functioning and setup within the system of IFs offered by Banca d’Italia,³ indeed, makes Milano Hub a unique case in the European landscape that is worth examining. Specifically, the study investigates the human capital involved in the projects, with particular attention to three aspects: i) age, ii) gender, and iii) academic background.

The above-mentioned features have been largely investigated in the literature dedicated to the analysis of the fintech ecosystem, also for the purpose of outlining the relevant interlinks (e.g. Stefanelli *et al.*, 2024). However, former works have typically focused on fintech companies and start-ups and provided only limited insights on fintech facilitation by Central Banks and NCAs.

In particular, the impact, or at least certain collateral effects, that socio-demographic characteristics of natural persons working in fintech firms, or more in general in tech companies, might have on the business activities is the most explored among academics. They have received more attention from former literature than the effects, either combined or not, of new technologies and the business areas/

¹ The opinions expressed in this paper are personal and should not be attributed to Banca d’Italia. We would like to thank Giancarlo Goretti, Adriana Dolores, Giulia De Dominicis, Federico Ferraccioli, Guerino Ardizzi and Michele Lanotte for comments and suggestions.

² For a brief overview of the mandate of Milano Hub and the objectives of the *Call for Proposals*, please refer to the Box ‘Milano Hub and its Call for Proposals in a nutshell’.

³ As of October 2023, there were 41 innovation hubs, with at least one in all 30 EEA countries, and 14 regulatory sandboxes in 12 EEA countries. However, only Banca d’Italia has established three IFs to support innovative projects during the entire life cycle. Furthermore, Milano Hub has a unique approach, since each project is supported by a multidisciplinary team composed of professionals from several Banca d’Italia functions.

services where these technologies have applied as determinants of fintech venture success, which have been little emphasized so far, with some limited exceptions (e.g. Röder *et al.*, 2018).

Also, some empirical evidence even indicates that dynamics in the fintech sector are not so much driven by technology as by the educational and business background of the founders (Brandl and Hornuf, 2020; Zarrouk *et al.*, 2021).

On age and educational background of the persons involved in tech-driven initiatives, the literature is miscellaneous and mixed, but it has typically focused on founders' competences and former experiences, as a driver of firm creation (Azoulay *et al.*, 2020) or business performances in the growth phase (Turki and Rieg, 2023; Colombo and Grilli, 2010).

In general, empirical works show that older aged people can influence the performances of the business activities in which they take part (Zhao *et al.*, 2021), basically thanks to a longer experience in the industry (e.g. Colombo and Grilli, 2005). However, despite the growing number of empirical studies, the literature still provides limited guidance on how directors' age can shape business performances in fintech, for example whether management bodies possessing generally less experienced members fare better or worse than those combining a mix of less seasoned and more seasoned officers (e.g. Katsiampa *et al.*, 2024).

With respect to the academic background, the evidence from the literature suggests that new fintech ventures are more frequently established where the fraction of STEM graduates is higher (Farè *et al.*, 2024), albeit in some specific countries the phenomenon is less outspoken (e.g. Dorfleitner *et al.*, 2017 vs. Brandl and Hornuf, 2020, studying fintech in Germany). To the same purpose, the relation between founding fintech companies and educational background in economics has been tested as well, but the actual role of the latter is more uncertain compared to STEM (Poon *et al.* 2024).

The type of qualification seems to be linked to the women representation in fintech companies. In fact, gender gaps in economic and scientific-technological education and entrepreneurial opportunities as a source of barriers to women entering the fintech sector are broadly discussed among academics (e.g. Fox-Robertson and Wójcik, 2024). A scarce presence of women leaders in this industry is identified as well (Sahay and Cihak, 2018).

Some authors have extended the scope of their analyses beyond founders to examine the effects of the so-called 'diversity gap' in fintech companies. Albeit ascertaining that females are less represented in the fintech ecosystem both as leaders and users, a positive association between corporate returns and the share of women in C-levels has been found (Khera *et al.* 2022; Christiansen *et al.*, 2016).

Also, when examining the board composition in fintech, results highlight that female representation in executive boards and firm performance are related: firms with a higher share of women are positively correlated with higher revenue earned and the funding acquired, especially amongst those firms that were founded in the recent years (e.g. Khera *et al.*, 2024).

Notwithstanding the foregoing, it should be noted that female directors tend to be significantly younger than their male counterparts and this may have an adverse impact on financial performance (Jonson *et al.*, 2020).

Our study draws on the mentioned academic contributions, as well as a wide range of other existing studies and adds the perspective of Central Banks' and NCAs' IFs to the discussion. Firstly, it provides relevant insights for theoretical studies which are investigating the fintech phenomenon and, more in detail, its interaction with the banking ecosystem to assess to what extent financial and banking services are being transformed, evolving and getting more competitive (e.g. Gomber *et al.* 2018; Thakor, 2020). Secondly, it contributes to empirical research that, directly gauging the point of view of market players (e.g. Ernst & Young, 2023; World Economic Forum and CCAF, 2024) or Institutions (e.g. Banca d'Italia,

2024), investigates key drivers and future challenges of fintech for all relevant stakeholders.

The paper is divided into six sections. In Section 1 the research hypotheses are formulated. In Section 2 the considered dataset is described. A descriptive statistical analysis of collected data is conducted in Section 3. Section 4 is dedicated to the econometric analysis, comprising the robustness check and model limitations. In Section 5 results are discussed and potential way forward suggested. In the end, concluding remarks are provided in Section 6, discussing the key contributions of our work and further research proposals.

Box: Milano Hub and its *Call for Proposals* in a nutshell

Milano Hub is the innovation centre established by Banca d'Italia to support the digital evolution of the banking, financial, insurance and payments sectors. It operates in synergy with the Fintech Channel, a point of contact through which operators can dialogue easily and informally with the Authority, and the Regulatory Sandbox, dedicated to the testing in liaison with relevant market Authorities.

Milano Hub engages innovators in a place, physical and virtual, in which Banca d'Italia – while respecting its institutional role – through a series of consulting services, mentorship, and educational components to financial intermediaries, startups, and research centres aims at accelerating the development of projects and at promoting the quality and safety of specific innovations. In line with the strategic objectives of Banca d'Italia, Milano Hub is aimed at stimulating the adoption of innovative solutions and enhancing market competitiveness to support the digital evolution of the Italian financial ecosystem.

To maintain a constant dialogue with market operators, Milano Hub works via its *Call for Proposals*: an invite to all market players to submit innovative projects - not marketed yet - on relevant areas of innovation. To date, Milano Hub has launched three *C/Js*: the first focused on Artificial Intelligence, the second on Distributed Ledger Technologies (DLT), and the third on digital payments. The following categories of players, whether Italian or foreign, have been allowed to participate and apply for one of the following areas of operation according to the category they belong to: A. *Fintech Area*: natural persons, non-bank/non-financial undertakings (e.g. technology solution providers); B. *Innovation Area*: banking, financial and insurance intermediaries; C. *Research & Development Area*: universities, research institutes, sector association, other bodies. The first and the second *C/Js* provided for the possibility of collective participations, i.e., a project could be submitted by a subject (the applicant) in collaboration with other subjects (the participants) for the category which the applicant belonged to. Consequently, in those *C/Js* an operator could be a participant (but not applicant) of a project in a different area compared to the category it belongs to (e.g. a non-financial undertaking as a participant in a project in the *Innovation Area*). Only non-commercialized projects are eligible for submission under the *C/Js*.

The received projects have been evaluated by a panel specifically appointed, composed of representatives from the academia and professionals from Banca d'Italia. The evaluation has been performed based on the project description submitted by the applicant using a template provided by Milano Hub. The assessment has assigned to each project a score, based on different criteria, as disciplined by Milano Hub's *C/Js* rules and provisions. Such criteria are grouped in macro-classes, which have been slightly fine-tuned over time. At the time of the third *C/Js*, they were: i) RELEVANCE to the topic of the call, ii) SUSTAINABILITY to the institutional purposes of Banca d'Italia, iii) VALUE and iv) PRACTICABILITY of the project. The finale score is determined as a weighted average of the four scores per criterion. Following the evaluation process and the resulting ranking, the projects with highest scores were admitted to the Milano Hub's program.

The projects selected received developmental support through:

- technical expertise in banking, finance and insurance and in specific areas, for example IT and regulation (for the latter, exclusively with regard to secondary acts adopted by Banca d'Italia and the primary legislation of which these sources constitute implementation);
- organization of seminars, events, conferences with representatives from the projects, institutions and the academic world.

The support has been provided by multidisciplinary teams composed of professionals from various functions of Banca d'Italia, based on the specific needs of each project proposals. Professionals from IVASS collaborated for projects which involved insurance topics. In the context of Milano Hub, Banca d'Italia does not provide any form of financial assistance or any contribution to the acquisition of goods or services, or support the projects in terms of promotional initiatives or marketing activities.

Further information on Milano Hub and its *C/Js* can be found on the dedicated page of Banca d'Italia website.

1. Research questions and hypotheses

As mentioned, we intend first to identify the key characteristics of the population attracted by Milano Hub through the three C/Ps launched so far. More in detail, we have been driven by the questions listed below, pertaining to the human capital involved in the project applications to the C/Ps:

Q1: What are the demographic and educational features of the human capital involved in the fintech firms participating in the Milano Hub C/Ps, with particular attention to age, gender, and academic background?

Q2: To what extent do gender diversity and the age of individuals within fintech projects vary systematically with the entities' years in business?

The evidence found by answering these questions, resulting from descriptive statistics conducted on the set of project submissions to Milano Hub, have also contributed to establishing the empirical background of our econometric analysis, complementary to theoretical studies.

Therefore, factoring in such empirical background as well as the evidence from former studies described before, as a second step of our research, we aim to determine which specific human capital characteristics, among the projects have shown, so far, an association with the assessment criteria outlined in the Box 'Milano Hub and its Call for Proposals in a nutshell'.

In particular, we first want to investigate if the age of the people involved in the projects is statistically relevant. Therefore, by considering higher scores as a proxy of the extent to which the assessment criteria are fulfilled, the following research hypothesis is formulated:

H1: there is a positive correlation between the age of the people engaged in a project application to Milano Hub and the score assigned to the project in the assessment for the purposes of admission to Milano Hub support.

Furthermore, we intend to examine the relevance of STEM (firstly) and economic background (secondly), in this order of importance. In fact, the development of fintech projects⁴ very likely requires more STEM than economic skills. Therefore, the two following additional research hypotheses are formulated:

H2: there is a positive correlation between the presence of technological-scientific background among the people engaged in a project application to Milano Hub and the score assigned to the project.

H3: there is a positive correlation between the presence of economic background among the people engaged in a project application to Milano Hub and the score assigned to the project, but to a lesser extent than the presence of technological-scientific background.⁵

2. Data

To answer the research questions and test our hypotheses, we have collected data through the application forms submitted for the C/Ps, complemented by external sources. Our scope consists of the projects presented by fintech players applying directly to the *Fintech Area*, plus those involved in collective projects.⁶

⁴ The projects presented to Milano Hub demand pre-marketing development pursuant to the applicable rules.

⁵ No hypothesis regarding gender and score has been formulated, due to a very low number of cases (17) in which the project team from the participants' side also included women.

⁶ See the Box 'Milano Hub and its Call for Proposals in a nutshell'.

In particular, in the application forms details are provided regarding the individuals designated as legal representatives or project contact persons⁷ (age and gender), while information about their academic background has been sourced from public platforms, where available.

Data on the legal entities have been supplemented with details from company registration reports, including board composition and years in business. Given the participation of foreign entities and individuals, there are circumstances where information has not been collected in full.

This has resulted in a dataset of 97 observations (31 relative to the first *C/P*, 50 to the second and 16 to the third), each related to a project proposed by and/or involving, as said, a company in the *Fintech Area*. Each observation contains detailed information on the project itself (relevant *C/P*, business areas of application, underlying technologies,⁸ etc.), participant entities (number of participants, years in business, size of the management body, etc.) and people taking part to the project as contact persons for Milano Hub and/or to the activities of the companies on the whole as legal representatives and/or members of the management body (age, gender, university background). The final scores assigned to the projects in the evaluation phase are reported as well.

3. Insights from Milano Hub project submissions

In this section a descriptive statistical analysis is conducted to investigate the main characteristics of the population attracted by Milano Hub through its *C/Ps*, by focusing on age, demographic and educational features.

3.1. The human capital of fintech projects

This sub-section investigates the key characteristics of human capital of projects received through the *C/Ps*. For the purpose of this analysis, we distinguish between *Legal Representatives*, *Project Contact Persons* and *Management Body Members*.

The *Project Contact Person* is directly responsible for and leading the project's implementation,⁹ and in most cases this figure is guiding the project through reaching the main critical success factors of the subsequent go-to market phase.

Instead, the *Legal Representative* serves, especially in fintech companies, as the formal inside promoter of the initiative and, in this position, has a clear vision of the reason behind the project development and its inclusion in a broader innovation path of the entity.

Management Body Members, meanwhile, engage with the project at a strategic level, aligning it with the global corporate objectives.

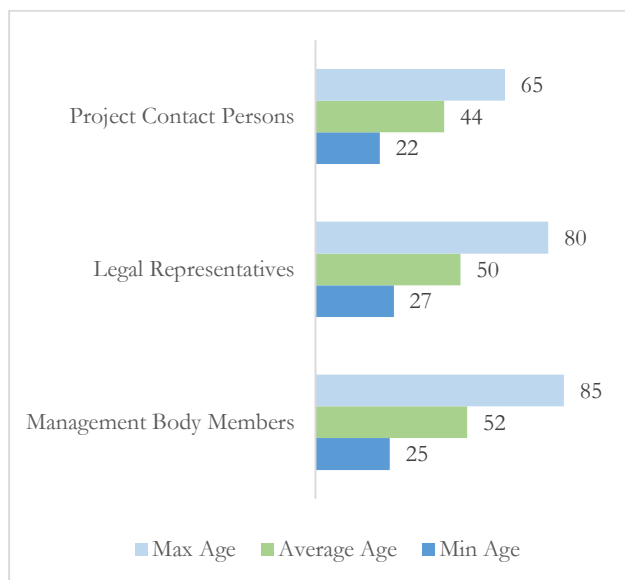
Therefore, the breakdown by these figures provides a more nuanced understanding of the human capital involved in the fintech projects participating in the Milano Hub *C/Ps*.

⁷ According to Milano Hub's rules and provisions, the *Project Contact Person* is an individual indicated in the application form as responsible for the development and the coordination and scientific supervision of the project as well as managing the relationship with Milano Hub during the support phase.

⁸ According to the taxonomy proposed by Lentini *et al.*, 2024.

⁹ Depending on the single participant characteristics, the *Project Contact Persons* could be either the legal representatives or other persons, and their role in the organization may vary.

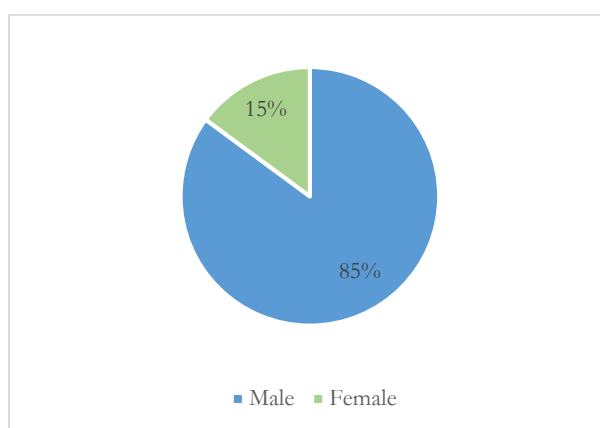
FIGURE 1 - AGE BY ROLES

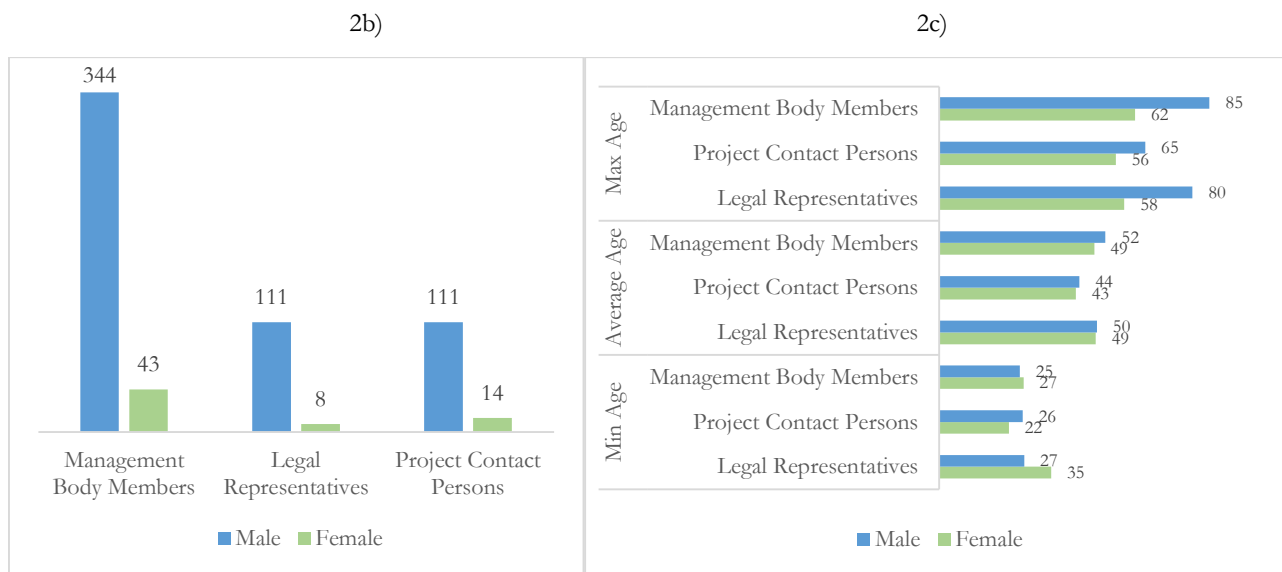


When examining the age of individuals, Figure 1 shows that **the average age across all categories is relatively high, ranging from 44 to 52 years old**. These data indicate that the fintech within the Milano Hub perimeter is predominantly composed of relatively experienced professionals at all levels, from executives to more operational roles, like *Project Contact Persons*. For comparison, the survey conducted by Banca d'Italia (2025), although showing that, at national level, the majority of the staff of non-supervised fintech operators is in the bucket 31-45 years old, reveals that 18% is in the bucket 46-59, singling the need of seasoned professionals, too.

FIGURE 2 - GENDER REPRESENTATION IN DIFFERENT ROLES AND AGE

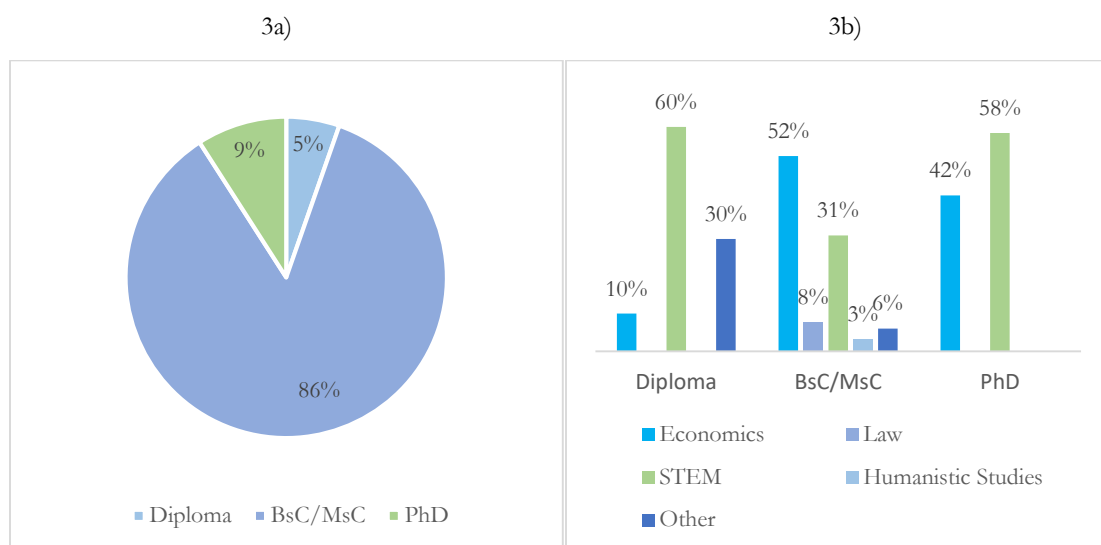
2a)





In terms of gender representation, **Figure 2a reveals a significant disparity, with females making up only 15% of participant individuals.** Therefore, the pool of participants to the *C/Js* seems to replicate the structural imbalance that, more globally, intersects financial, technological, and entrepreneurial gender inequalities (Fox-Robertson and Wójcik, 2024). **This gap is referred to all examined roles:**¹⁰ in fact, there are 344 male *Management Body Members* compared to only 43 females, and more than 100 male *Legal Representatives* and *Project Contact Persons*, while the women in these roles are about one tenth (see Figure 2b). There are also notable differences when examining gender diversity in terms of natural persons' age, with women's ranging lower than men's.¹¹ Even more pronounced differences appear when considering male and female maximum age (see Figure 2c). A similar trend is observed in the survey conducted by Banca d'Italia (2025), reporting 59% of organizations characterized by a strong gender gap, with little, between 1% and 10%, or no female presence. From a broader perspective, a lower representation of women is part of general trend captured by the World Economic Forum and CCAF (2024): the share of female executives is 33% at global level (30% in Europe).

FIGURE 3 - ACADEMIC BACKGROUND OVERVIEW



¹⁰ The three roles are not mutually exclusive.

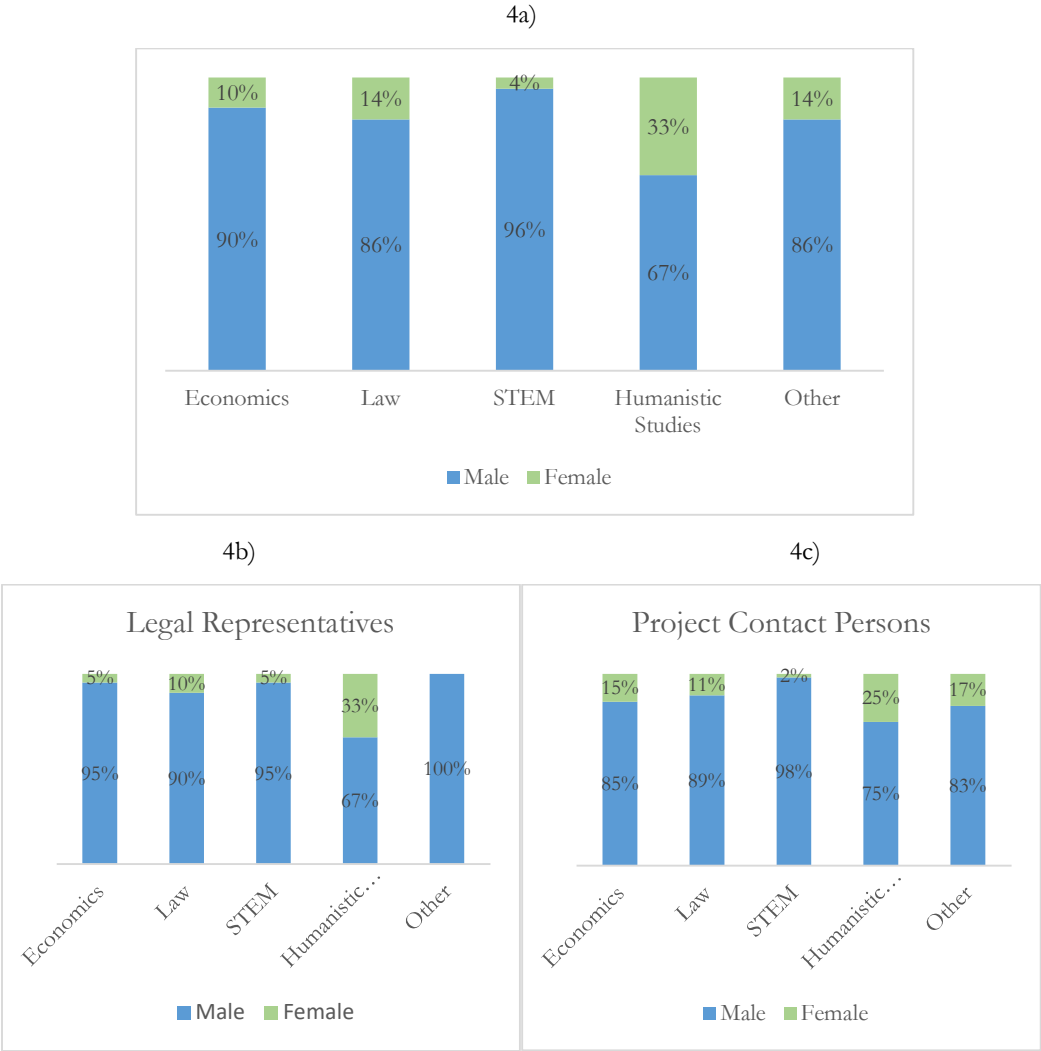
¹¹ Approximately 47 years without distinguishing by role. For men it is approximately 51 years.

Figure 3 offers an overview of the educational background of the participant individuals. The rationale behind the investigation of this feature is crucial to understand what type of skills are linked to starting to develop an innovative project within Milano Hub.¹²

In particular, Figure 3a shows that approximately 86% of the people holds at least a bachelor’s or master’s degree (*BsC/MsC*),¹³ while only the 9% has also a *PhD*.

Focusing on the academic subjects (see Figure 3b), the ***Economics* and *STEM* profiles are prevailing among the *BsC/MsC* and *PhD* qualifications**, whereas *Law* and *Humanistic Studies* show materially lower percentages with null values for the *PhD*. **Our findings on *Economics* and *STEM* as more present in the fintech projects are consistent with the two-fold nature of these initiatives, combining finance and technology**, as also emphasised by Poon *et al.*, 2024. This result is aligned with the survey conducted by Banca d’Italia (2025), where the majority of the fintech workforce interviewed (75%) holds a degree in STEM or economics (respectively, 48% and 29%).

FIGURE 4 - ACADEMIC BACKGROUND OVERVIEW BY GENDER



¹² In light of the remarks made at the beginning of this sub-section, namely the more strategical role of the *Management Body Members* and hence, their smaller operational involvement in the project, figures are referred to the *Project Contact Persons* and the *Legal Representatives*.

¹³ It includes post-graduate master’s programs.

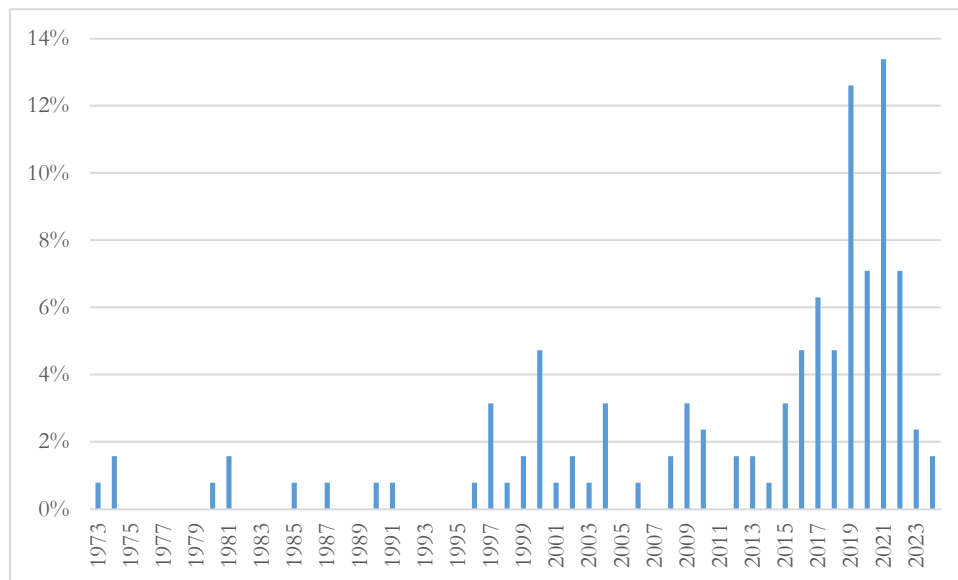
Figure 4a shows the gender gap by academic background, which is clearly affected by the overall gender gap detected in our sample. **That said, it is however worth noting that the share of women among participants with qualifications in *Economics* or *STEM* (respectively, 10% and 4%) is lower than the female participation in the Milano Hub *CfPs* overall (15%).** This gives a picture that is even more extreme than what is generally observed in Italy: in 2023 the percentage of female graduates in STEM disciplines is 16.8%, less than half of male graduates (Istat, 2024), while for economics the shares are more levelled albeit differences still exist (12.0% vs. 17.6%)^{14 15}.

Women appear to be more represented in other academic profiles, like *Humanistic Studies* (33%) and *Law* (14%). In general terms, **women are less represented, not only with respect to the types of academic background intuitively closer to fintech (i.e. *STEM* and *Economics*).** By combining education and role (Figure 4b and Figure 4c), for the *Economics* and *Law* profiles there are fewer females among *Legal Representatives* than *Project Contact Persons*, i.e. a less senior and managerial position. By contrast, it should be noted that men with STEM qualifications are more numerous among *Project Contact Persons* than *Legal Representatives*.

3.2. Experienced professionals for young firms

Based on the relevant interlinks already identified by some authors before (e.g. Khera *et al.*, 2024), this sub-section examines the features of the human capital involved in the Milano Hub *CfPs*, as highlighted above, in combination with the years in business¹⁶ of the legal entities that applied to the *CfPs*. This is, in particular, analysed in relation with the participants' gender and age.

FIGURE 5 - ENTITIES' YEARS IN BUSINESS



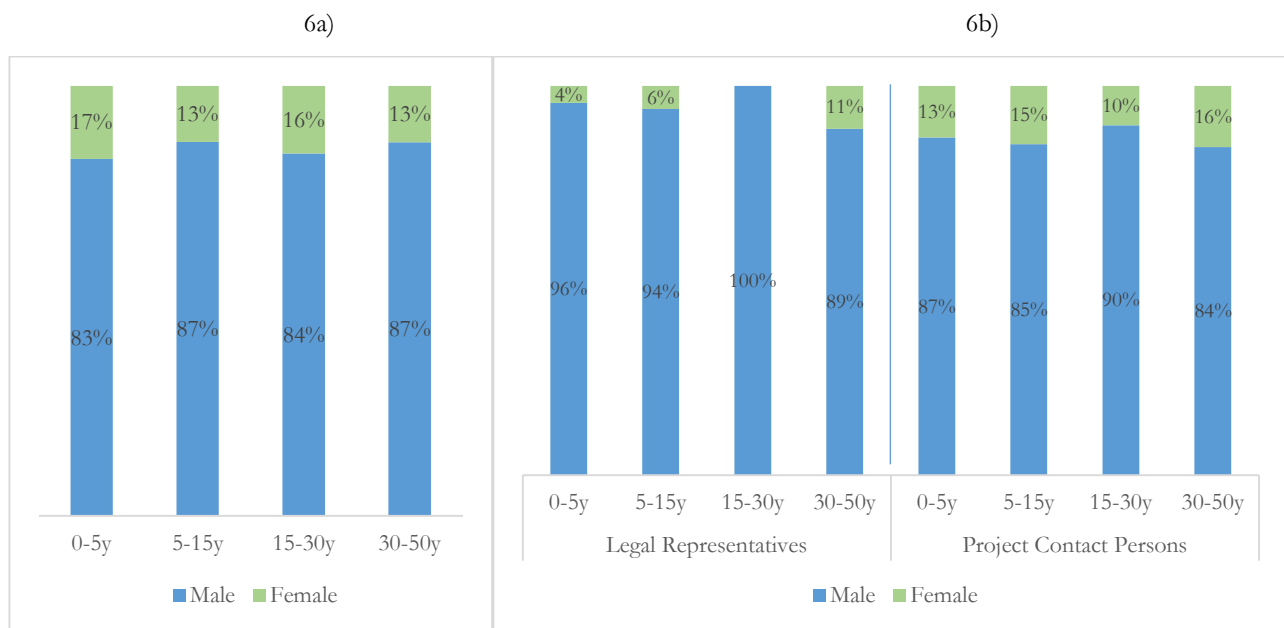
¹⁴ Source: elaboration from AlmaLaurea.

¹⁵ This means that, out of the overall number of graduates in STEM fields, 2/3 are men and 1/3 are women, while for economics the ratios are approx. 60% and 40%.

¹⁶ Firm's years in business has been calculated at the time of the *CfP* the firm participated to.

Figure 5 above shows that the entities participating in Milano Hub C/Ps were mainly established starting from 2015, reaching a peak between 2019 and 2021. This evidence confirms the general trend that is characterising the whole fintech sector in Italy, confirmed by Ernst & Young (2023).¹⁷ This study indeed detects a similar trend for the Italian fintech ecosystem: in particular, over the period 2019-2022 the sector experienced an average Compound Annual Growth Return (CAGR) of over 60% in terms of incorporated companies, signalling an expansive momentum. Also, the spike in fintech founding is also suggested by the fact that in 2022, among the startups interviewed, early-growth were 37% more numerous than in 2020; by contrast, early-stage startups were 25% fewer. **Finally, young firms seem to be more actively involved than more mature ones in presenting new initiatives to Milano Hub.**

FIGURE 6 - ENTITIES' YEARS IN BUSINESS AND GENDER



As this analysis already outlines the consistent gender gap within the Milano Hub's population, Figure 6 explores instead the phenomenon considering the different degrees of maturity of the entities, observing this gap across different stages. In particular, Figure 6a on the left shows the overall percentage of male and female participants¹⁸ by legal entity's maturity stage (cluster of years in business), while Figure 6b on the right displays the breakdown by *Legal Representatives* and *Project Contact Persons*.

Despite the gender gap detected within the whole dataset, from the general overview displayed in Figure 6a, **start-ups (i.e., 0-5y) show a slightly higher share of women than longer-lived undertakings (5-15y, 15-30y and 30-50y).**

However, focusing on the roles of the *Legal Representative* and the *Project Contact Person*, Figure 6b shows that in the longest-lived undertakings the share of female *Legal Representatives* is higher than previous stages (11%). Similarly, regarding the role of the *Project Contact Person*, the gender gap is lower in the 30-50y cluster than the other ones. **The above suggests that greater gender diversity tends to be observed, in the perimeter of project applications to Milano Hub, as for the roles positioned lower in the**

¹⁷ The EY Fintech Waves 2023 study, produced in collaboration with the Fintech District, is derived from a survey based on interviews with over hundred Italian Fintech companies in Italy, from 2016 to 2023.

¹⁸ *Management Body Members* are included in the sample.

organizational hierarchy (*Project Contact Person* usually do not have any legal representative power in the company).

FIGURE 7 - ENTITIES' YEARS IN BUSINESS AND MANAGEMENT BODY MEMBERS' AVERAGE AGE

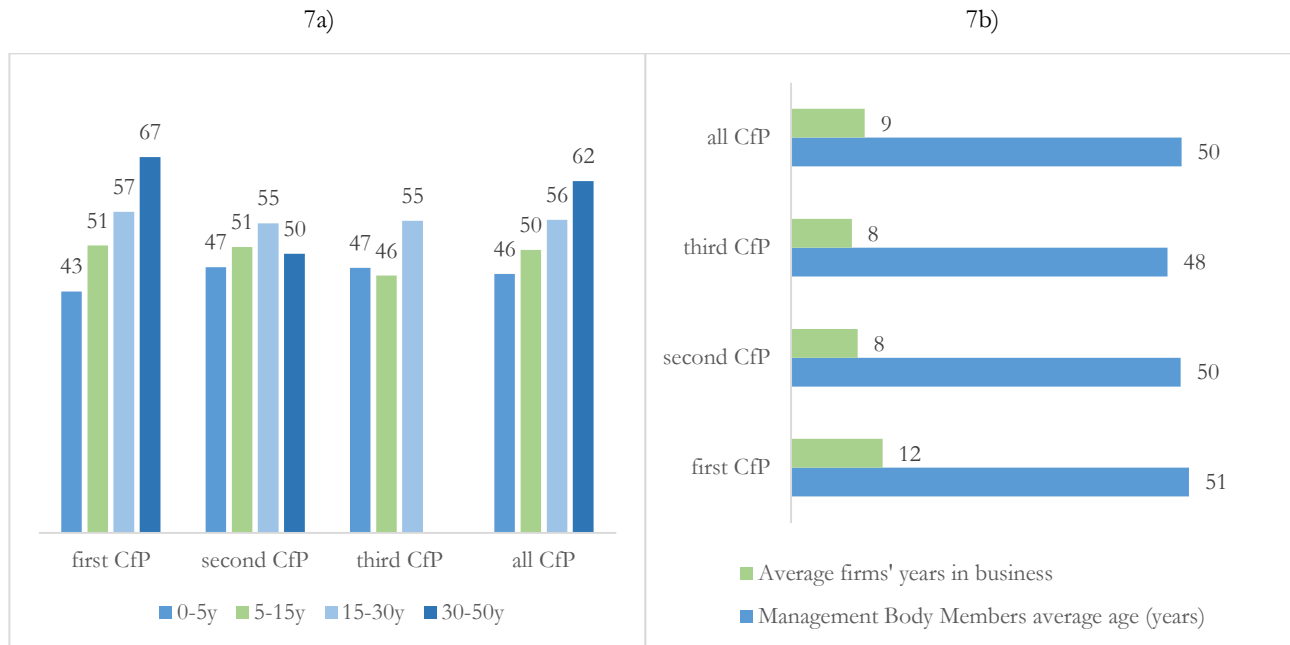


Figure 7a and Figure 7b show that, across the three *CfPs*, a higher average age of the *Management Body Members* is observed in relation to longer years in business.

It should be highlighted that both the people's age and the entities' years in business are decreasing over *CfPs*, with the third one characterised by younger profiles and undertakings (Figure 7b). On average, the years in business of the analysed fintech ventures do not exceed 9 years of activity, while the average age of the *Management Body Members* is around 50 years old. **This result suggests that, in contrast to common belief that fintech initiatives are launched and carried out by young people a 'fintech for experienced people' phenomenon has been detected in the perimeter of the applications to Milano Hub.**

Similar trends have also been captured, although from a different perspective, by Ernst & Young (2025) when considering which relevant factors make investors confident in financing new startups. The study confirms that the previous professional experience of founders positively influences investors' decision to invest in a fintech company (90% of the interviewed investors). Since funding is crucial for start-ups, those led by more seasoned professionals have a better chance of staying in the market.

4. Econometric analysis

4.1. Models

To test our research hypotheses, we have applied a linear regression built on the following baseline model:

$$y_i = a + X_i \beta + \theta_i + \tau_i + \varepsilon_i$$

where y is the final score assigned to the project i , standardized based on the final scores assigned to all projects in the same C/P (Pun_fin_std), X collects the explanatory and control variables (both covariates and dummy), θ and τ are fixed factors proxying the thematic approach for the C/P and ε is the error term.

Table 1 summarizes the list and the description of the variables used, better explained hereinafter.

TABLE 1 - MAIN VARIABLES

Variables	Description
<u>Dependent variable</u>	
Standardized final score (Pun_fin_std) [Pun_fin_std = (Pun_fin - $\mu_{C/P}$) / $\sigma_{C/P}$]	Final score assigned to the project, standardized based on the final scores assigned to all projects in the same C/P , i.e. net of the average of the final scores assigned in the relevant C/P ($\mu_{C/P}$), then divided by the standard deviation of these final scores ($\sigma_{C/P}$)
<u>Explanatory variables</u>	
Average age of the management body members of the applicant entity (Età_media_amm_prop)	Simple average of the age of the members of the management body of the applicant entity at the closure date for applications for the C/P which the project refers to (in case of sole director, it corresponds to the sole director's age)
Years in business of the applicant entity (Anni_di_attività_prop)	Number of years in business of the applicant entity at the closure date for applications for the C/P which the project refers to. It is used as an alternative to Età_media_amm_prop as a proxy of experience in the sector
Existing STEM background in the project (STEM)	Dummy variable indicating existing (if the value is 1) qualifications in STEM fields, with regard to i) the <i>Project Contact Person</i> (or <i>Persons</i> in case of 2 or more participant entities), and ii) for companies in the <i>Fintech Area</i> , the <i>Legal Representative</i> specified in the application (or <i>Representatives</i> in case of 2 or more participant entities)
Existing economic background in the project (Econ)	Dummy variable indicating existing (if the value is 1) qualifications in economics (same specifications as STEM)

Control variables

Existing ‘Artificial Intelligence’ technology in the project (Tech_AI) – only considering its interaction with ‘Time’ (T), see below	Dummy variable indicating the presence (if the value is 1) of Artificial Intelligence among the technologies underlying the project, based on what declared in the application
Existing ‘Distributed Ledger Technology’ in the project (Tech_DLT) – only considering its interaction with ‘Time’ (T), see below	Dummy variable indicating the presence (if the value is 1) of Distributed Ledger Technology among the technologies underlying the project, based on what declared in the application
Time (T) – only considering its interaction with Tech_AI or Tech_DLT, see below	Time frame, in years or fractions of year, between i) the date of Milano Hub’s establishment (Dec-2020), and ii) the closure date for applications for the <i>C/P</i> which the project refers to. It takes only one of the following 3 possible values, in light of 3 <i>C/Ps</i> only: 0.830, 2.082 o 3.581
Product between Tech_AI and T (AIxT)	Variable indicating in which of the time (T) values listed above the AI is present, if it is present. It takes only one of the following 4 possible values: 0, if the AI is not present in the project; 0.830, if the AI is present in a project of the <i>first C/P</i> ; 2.082 or 3.581, accordingly
Product between Tech_DLT and T (DLTxT)	Variable indicating in which of the time (T) values listed above the DLT is present, if it is present (same specifications as AIxT)
Average size of the management body of the participant companies (Dim_media_CdA_part)	Simple average of the number of members of the management body of the participant companies at the closure date for applications for the <i>C/P</i> which the project refers to (in case of no other participants besides the applicant, it corresponds to the number of members of the management body of this latter)
Collective project (Coll)	Dummy variable indicating collaboration in the project between the applicant and one or more other participants. It is used as an alternative to Dim_media_CdA to absorb further effects not absorbed by the latter
Presence of people with PhD among the people engaged in the project (PhD)	Dummy variable indicating existing (if the value is 1) PhD qualifications (same specifications as STEM and Econ)

We have used as explanatory variables (contained in the *X* vector) i) the average age of the management body members of the applicant entity (Età_media_amm_prop) or, as an alternative proxy of experience, the number of years in business of the latter (Anni_di_attività_prop) and, ii) as fixed factors, the dummy

variables STEM and Econ (1 if the relevant background exists in the project, 0 otherwise). Since we are interested in the distinctive contribution of qualifications in STEM fields and economics, these two dummy variables have been included alternatively in the model, this also preventing from possible multicollinearity problems, due to correlations between STEM and Econ,¹⁹ which would make predictions unstable. This results in two macro-models, one having STEM and the other one Econ as a predictor, while Età_media_amm_prop is included in both cases except when replaced by Anni_di_attività_prop (in one case per macro-model).

As control variable we have entered, as covariate, i) the average size of the management body of the participant companies (Dim_media_CdA_part); as fixed factors, ii) the dummy variables for collective projects (Coll) as an alternative to Dim_media_CdA_part to absorb further effects not absorbed by the latter,²⁰ iii) the dummy variable for PhD (PhD), and iv) AIxT and DLTxT,²¹ representing respectively θ_i and τ_i to take the thematic approach for the C/Ps into account. These latter have been modelled also as covariates (i.e., scale variables) in one case per macro-model to consider the mere time effect in the development of the concerned technologies.²²

Logic suggests that some of the control variables could be co-varying with the explanatory ones (e.g. Età_media_amm_prop and Coll) and between each other (e.g. Dim_media_CdA_part and Coll). On the one hand, it would make sense to include all of them simultaneously in the model to isolate the relevant effect on the score. On the other hand, one cannot fail to consider our dataset of 97 observations and the connected potential risk of overfitting. Although according to Hair *et al.* (2010) five observations per regressor could be enough, we have opted for a more prudent ratio of 10:1 to avoid these issues (e.g. Harrell, 2001). Therefore, we have entered no more than four variables per sub-model other than AIxT and DLTxT, that are considered crucial controls and lead to three dummy variables each (four categories, one discarded).

Therefore, we have proceeded as follows:

- a) first, we have entered Età_media_amm_prop and the type of background (STEM or Econ) into the model to test our research hypotheses as described above. Dim_media_CdA_part and PhD have been included as controls, too;
- b) then, Età_media_amm_prop has been replaced by Anni_di_attività_prop as explanatory variable to check if it is a better proxy of experience;
- c) Età_media_amm_prop has been re-entered and Anni_di_attività_prop excluded, while Dim_media_CdA_part have been replaced by Coll to check if it reduces residual variance by absorbing further effects than a pure dimension variable;
- d) Età_media_amm_prop has been excluded again to check if a more parsimonious model with Coll that absorbs also experience effects performs better;
- e) finally, we have come back to our main model – a) – by modelling AIxT and DLTxT as covariates instead of fixed factors.

¹⁹ In light of the fintech nature of the projects, both types of background are largely present in the projects.

²⁰ See Table 5 - Key correlations. In sub-models d), Coll is also substitutive for our explanatory variables – other than the dimension of the entities involved in the project – as the experience in the sector is among the further effects it can absorb (see Annex 1 for more details).

²¹ The software used for running the regression automatically takes the highest value of a categorical variable (transformed into a dummy) as reference for the estimates of the other categories. Therefore, AIxT and DLT have been recoded into AIxT_rec and DLTxT_rec so that the lowest value (0), recoded into a 'fake' 4, is taken as a reference instead of 3.581. In other words, the effects of AIxT and DLTxT must be interpreted as marginal compared to the absence of the concerned technology in the project.

²² Postulating that a technology at T=3.581 is more mature than it is at T=0.830, the identification of AIxT and DLTxT as covariates represents the degree of maturity of the concerned technology at a certain T, which can be assumed as a scale variable, while interaction effects can be assessed only in relation to categorical variables.

All of the above results in 10 sub-models, referred to the two basic macro-models, which are clarified by Table 2 and Table 3 below, while a more comprehensive explanation of the methodological choices made regarding the variables of the models is provided in Annex 1:

TABLE 2 - MACRO-MODEL 1 (STEM AS EXPLANATORY VARIABLE)

	Model 1a	Model 1b	Model 1c	Model 1d	Model 1e
Età_media_amm_prop	X		X		X
Anni_di_attività_prop		X			
STEM	X	X	X	X	X
Dim_media_CdA	X	X			X
Coll			X	X	
AIxT (fixed factor)*	X	X	X	X	
DLTxT (fixed factor)*	X	X	X	X	
AIxT (covariate)					X
DLTxT (covariate)					X
PhD	X	X	X	X	X

* Leading to 4 dummy variables.

TABLE 3 - MACRO-MODEL 2 (ECON AS EXPLANATORY VARIABLE)

	Model 2a	Model 2b	Model 2c	Model 2d	Model 2e
Età_media_amm_prop	X		X		X
Anni_di_attività_prop		X			
Econ	X	X	X	X	X
Dim_media_CdA	X	X			X
Coll			X	X	
AIxT (fixed factor)*	X	X	X	X	
DLTxT (fixed factor)*	X	X	X	X	
AIxT (covariate)					X
DLTxT (covariate)					X
PhD	X	X	X	X	X

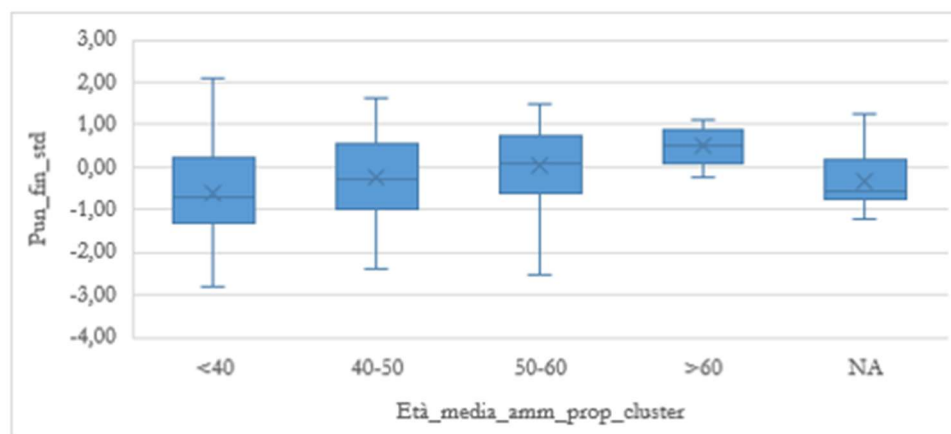
* Leading to 4 dummy variables.

4.2. Results

Descriptive statistics of the standardized final score by i) cluster²³ of age of the members of the applicant's management body and ii) kind of background are consistent with our research hypotheses (see Figure 8 and Table 4, respectively).

In particular, on dimension i), **the average standardized final score** (Pun_fin_std), as well as the quartiles of the distribution of this variable, **increase moving from a 'lower' to a 'higher' cluster of age** (with dispersion having the opposite trend).

FIGURE 8 - STANDARDIZED FINAL SCORE BY CLUSTER OF AGE OF THE MEMBERS OF THE APPLICANT'S



Regarding dimension ii), statistics show that the presence of qualifications in either the economics area or the STEM area leads to a higher average score compared to the same combination of background but without economics or STEM (see Annex 3 for a comprehensive version of Table 4 with all combinations of background types).²⁴

For instance, the average standardized final score for a project having only people with qualifications in the residual class of background ('other', see The human capital of fintech projects) is -1.125; the score rises to -0.743 if qualifications in economics are present, and to 0.200 if also STEM background is in the project.

Table 4, by grouping the combinations of background types, shows that **the contribution to the score by STEM qualifications is much higher compared to qualifications in economics**. In particular, the absence of STEM background leads to a sharper decrease of the score than economic background. Unsurprisingly, the highest mean score corresponds to projects where both Econ and STEM are equal to 1, while the simultaneous absence of both (occurred only in 3 cases, considering the fintech nature of the projects) is heavily penalized.

²³ As Età_media_amm_prop is a continuous variable, clusters of age have been created to make the statistics understandable also visually.

²⁴ With just one exception, involving all background areas except 'other'. However, this is based on a single case only, therefore it could be an outlier related to some other specificities of the concerned project.

TABLE 4 - DESCRIPTIVE STATISTICS OF STANDARDIZED FINAL SCORE BY COMBINATION OF BACKGROUND - ECON AND STEM

Dependent Variable: Pun_fin_std			
	Mean	Std. Deviation	N
Total [Econ=0] & [STEM=0]	-1.473	0.659	3
Total [Econ=0] & [STEM=1]	-0.106	1.158	18
Total [Econ=1] & [STEM=0]	-0.405	0.898	27
Total [Econ=1] & [STEM=1]	0.188	0.772	37
Total [Econ=0]	-0.301	1.193	21
Total [Econ=1]	-0.062	0.872	64
Total [STEM=0]	-0.512	0.927	30
Total [STEM=1]	0.092	0.916	55

In Table 5²⁵ the key correlations with our dependent variable are displayed.²⁶ As expected, all correlations, when significant, are positive, including those related to the explanatory and the control variables of our model, except for Econ (the correlation is not significant).

Consistent with the paradigms of ‘Open Innovation’ (Chesbrough, 2003) and ‘Triple Helix’ (Etzkowitz and Leydesdorff, 1998), **collective projects seem to be linked to higher scores**, in light of a correlation of 0.332, significant at the 0.01 level. The dummy for collective participation (Coll) is also correlated with i) Età_media_amm_prop and ii) Dim_media_CdA_part (respectively, 0.235 and 0.261, both significant at the 0.05 level), suggesting also possible indirect effects of these latter variables on the score via Coll, according to our econometric models. Our interpretation of these correlations is: i) the older the people, the more experience they have in the industry, and hence the wider the network of people in this sector with whom to start a collaboration; ii) the more members a company’s management body has, the wider the network of people with whom the company could start a collaboration.

The average years in business of the entities are correlated as well with Pun_fin_std (0.218, significant at the 0.05 level), Dim_media_CdA_part (0.270, significant at the 0.05 level) and Età_media_amm_prop (0.452, significant at the 0.01 level). On the one hand, **the correlation with the dependent and the other explanatory variable is intuitive if considering years in business as another measure of experience in the sector** (see sub-models 1b) and 2b)), although we have detected that, on average, even young applicant firms are led by seasoned people. In fact, if we assume that a person is expected to get part of a management body when he/she is X years old, after Y years that person is more experienced, and the company is more mature. In other words, we ascribe this correlation to the passage of time. On the other hand, we have interpreted the correlation with Dim_media_CdA_part as follows: the more

²⁵ Anni_di_attività_media_part is the average years in business of all undertakings participating in a project.

²⁶ The correlations between the dependent variable and variables that are a function of others already contained in Table 5 have not been reported. Pun_fin_std is indeed correlated also with:

- the number of participant entities in the ‘Innovation’ area (0.229, significant at the 0.05 level), a function of the dummy variable Coll_fin_inn – indicating a collaboration between Fintech and Innovation – which is in turn a function of the dummy variable Coll, included in Table 5 and indicating a collaboration more in general;
- the size of the management body of the applicant (0.226, significant at the 0.05 level), a function of Dim_media_CdA_part;
- the number of people involved in the project, as *Project Contact Person*, *Legal Representative* and/or *Management Body Member* (0.291, significant at the 0.01 level), a function of the variables under i) and ii) above;
- the average age of a) the *Legal Representatives* and, more in general, b) the *Management Body Members* of the participant entities (0.212 and 0.278, respectively, both significant at the 0.05 level), a function of Età_media_amm_prop.

years in business, the more likely it is that the firm has grown and the greater the need to implement a robust governance structure.

Finally, it should be noted that both STEM and PhD are strongly correlated with the score (respectively, 0.309 and 0.306, both significant at the 0.01 level) and each other (0.250, significant at the 0.05 level).

TABLE 5 - KEY CORRELATIONS²⁷

		Pun_fin_std	Coll	Anni_di_attività_media_part	Dim_media_CdA_part	Età_media_amm_prop	STEM	PhD
Pun_fin_std	Pearson	1	0.332**	0.218*	0.316**	0.278*	0.309**	0.306**
	Correlation							
	Sig. (2-tailed)		0.001	0.039	0.003	0.013	0.004	0.004
	N	93	93	90	86	79	86	86
Coll	Pearson	0.332**	1	0.203	0.261*	0.235*	0.208	0.332**
	Correlation							
	Sig. (2-tailed)	0.001		0.051	0.014	0.035	0.051	0.001
	N	93	97	93	88	81	89	89
Anni_di_attività_media_part	Pearson	0.218*	0.203	1	0.270*	0.452**	0.159	0.021
	Correlation							
	Sig. (2-tailed)	0.039	0.051		0.011	0.000	0.145	0.847
	N	90	93	93	87	80	86	86
Dim_media_CdA_part	Pearson	0.316**	0.261*	0.270*	1	0.161	0.087	0.123
	Correlation							
	Sig. (2-tailed)	0.003	0.014	0.011		0.151	0.435	0.270
	N	86	88	87	88	81	82	82
Età_media_amm_prop	Pearson	0.278*	0.235*	0.452**	0.161	1	0.224	0.157
	Correlation							
	Sig. (2-tailed)	0.013	0.035	0.000	0.151		0.053	0.177
	N	79	81	80	81	81	75	75
STEM	Pearson	0.309**	0.208	0.159	0.087	0.224	1	0.250*
	Correlation							
	Sig. (2-tailed)	0.004	0.051	0.145	0.435	0.053		0.019
	N	86	89	86	82	75	89	88
PhD	Pearson	0.306**	0.332**	0.021	0.123	0.157	0.250*	1
	Correlation							
	Sig. (2-tailed)	0.004	0.001	0.847	0.270	0.177	0.019	
	N	86	89	86	82	75	88	89

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

²⁷ When a dummy variable is involved, the point-biserial correlation, a special case of the Pearson correlation, is displayed.

Table 6 and Table 7 above display the results of the linear regression for macro-model 1 and macro-model 2. A comprehensive outcome of the regression, including full parameter estimates, broken down by sub-models, is reported in Annex 4.

TABLE 6 - LINEAR REGRESSION OUTCOME - MACRO-MODEL 1

	Model 1a	Model 1b	Model 1c	Model 1d	Model 1e
Età_media_amm_prop	0.020*		0.017		0.026**
Anni_di_attività_prop		0.005			
[STEM=1]	0.553***	0.546***	0.561***	0.516***	0.432*
AIxT (fixed factor)	Significant***	Significant***	Significant***	Significant***	
[AIxT=0.83]	1.165***	1.167***	1.144***	0.841***	
[AIxT=2.08]	-0.383	-0.460	-0.384	-0.524**	
[AIxT=3.58]	0.620	0.598	0.659	0.319	
DLTxT (fixed factor)	Significant***	Significant***	Significant***	Significant***	
[DLTxT=0.83]	-0.546	-0.554	-0.596	-0.808*	
[DLTxT=2.08]	1.114***	1.203***	1.107***	1.403***	
[DLTxT=3.58]	0.294	0.357	0.330	0.060	
AIxT (covariate)					0.002
DLTxT (covariate)					0.113
[PhD=1]	0.493*	0.599**	0.501*	0.450*	0.573*
Dim_media_CdA_part	0.024	0.015			0.081*
[Coll=1]			0.234	0.158	
R Squared (Adjusted)	0.498 (0.416)	0.464 (0.377)	0.503 (0.422)	0.409 (0.338)	0.311 (0.247)

***, ** or *. Significant at the 0.01, 0.05 or 0.10 level.

TABLE 7 - LINEAR REGRESSION OUTCOME - MACRO-MODEL 2

	Model 2a	Model 2b	Model 2c	Model 2d	Model 2e
Età_media_amm_prop	0.026**		0.021*		0.031**
Anni_di_attività_prop		0.010			
[Econ=1]	-0.319	-0.334	-0.389	-0.434*	0.197
AIxT (fixed factor)	Significant***	Significant***	Significant***	Significant***	
[AIxT=0.83]	1.249***	1.264***	1.265***	0.972***	
[AIxT=2.08]	-0.240	-0.347	-0.256	-0.411	
[AIxT=3.58]	0.802	0.741	0.905*	0.568	
DLTxT (fixed factor)	Significant***	Significant***	Significant***	Significant***	
[DLTxT=0.83]	-0.492	-0.475	-0.595	-0.836*	
[DLTxT=2.08]	1.169***	1.317***	1.199***	1.134***	
[DLTxT=3.58]	0.050	0.160	0.075	-0.231	
AIxT (covariate)					0.031
DLTxT (covariate)					0.129
[PhD=1]	0.585**	0.712**	0.610**	0.550**	0.673**
Dim_media_CdA_part	0.050	0.037			0.091**
[Coll=1]			0.373	0.342	
R Squared (Adjusted)	0.450 (0.359)	0.415 (0.321)	0.456 (0.367)	0.375 (0.299)	0.279 (0.212)

***, ** or *. Significant at the 0.01, 0.05 or 0.10 level.

First of all, on the aggregate model performances, a worse (Adjusted) R Squared is observed moving from macro-model 1 to macro-model 2. It seems to be driven by the **much lower predictive power of the dummy Econ compared to STEM**, consistent with the evidence from descriptive statistics and correlations above.

Moving within macro-models, the Adjusted R Squared of sub-models a), b) and c) stays in the range of 0.400 for macro-model 1, and 0.350 for macro-model 2. On the other hand, a drop in the coefficient is observed for sub-models d), in the range of 0.300, and e), below 0.300.

In this regard, it is worth noting that **the criterion of the ‘RELEVANCE’ of projects to the topic of the relevant *CIP*²⁸ appears as one of the most powerful predictors** (sub-models a), b) c) and d)), as the variables that represent this criterion (AIxT and DLTxT) are always significant on the whole and explain large part of the variability. This control gives robustness to our model and results overall. However, the effect of the single dummified category is different, as logic suggests. In particular,

²⁸ For the *first CIP*, the ‘RELEVANCE’ was not listed among the evaluation criteria, but it was a precondition. However, it is likely that the extent to which projects were pertinent to the topic of the *CIP* was indirectly quantified and embedded in the score.

- the presence of AI in the *first CjP* (dedicated to AI) is associated with a standardized score 0.841-1.265 higher than missing AI, *ceteris paribus*.
- the presence of DLT in the *second CjP* (in accordance with the topic thereof) is connected to a standardized score 1.107-1.403 higher than missing DLT, *ceteris paribus*.

Having either AI or DLT in other *CjPs* is, generally speaking, not significant for the scoring of the project. Also, modelling AIxT and DLTxT as covariates (sub-models e)) does not lead to significant results, this meaning that nothing can be concluded regarding the impact of technology maturity, but the pertinence of the project to the topic of the *CjP* for sure matters when entering technology and time in the model.

Always in general terms, the number of years in business of the applicant and the nature of collective project are not statistically significant as well. The relation between the remaining variables and the score is more model-dependent.

With respect to macro-model 1,

- **both STEM and PhD are positively connected to the score**, with β in the range of 0.432-0.561 for STEM and 0.450-0.599 for PhD. It is always significant, and for STEM highly significant except for sub-model 1e) (still significant, but at the 0.10 level).
- **The β coefficient referred to the age of the management body members is positive** (0.020-0.026) **and statistically significant in sub-models 1a) and 1e)** (P value below 0.10 and 0.05, respectively). The lack of significance for sub-model 1c) seems to be explained by the correlation with Coll (see Table 5): as argued above, (part of) the effect given by the experience in the sector is likely absorbed also by the latter variable, reducing the β coefficient of the explanatory one; as a result, the t-statistic decreases and the P value increases.
- The role of the size of the management body is not outspoken, as it is statistically significant (at the 0.10 level) only in sub-model 1e), i.e. the most parsimonious in terms of number of regressors, but the least fitting overall.

Regarding macro-model 2,

- **no proper conclusion can be drawn on qualifications in economics** as results reveal that its correlation with the score is not significant, except for sub-model 2d), where the coefficient is negative (-0.434, P value < 0.10). It should be noted that, compared to the previous sub-models, this one has a lower number of regressors, that ‘artificially’ inflate its β and the relevant t-statistic in sub-model 2d), and deflate the P value.
- **For PhD similar remarks as those made for macro-model 1** are applicable, with the addition that here β coefficients are higher, in the range of 0.550-0.712. In our opinion, this is due to absence of correlation between PhD and Econ²⁹ to a similar extent as between PhD and STEM.
- Similarly, **the evidence for the age and the number of management body members is close to macro-model 1**. The key difference lies in the higher significance level of the β coefficients in macro-model 2 compared to the corresponding sub-models of macro-model 1. In particular, the age is always significant (β in the range of 0.021-0.031).

In light of all of the above, our research hypotheses H1 and H2 seem to be verified, although in a weaker way for the former than for the latter, while nothing can be concluded with regard H3.

²⁹ Pearson correlation of 0.71, not statistically significant.

4.3. Robustness and limitations

While affirming the correlational and associative nature of the statistical analysis conducted, which is not suitable for supporting causal inference, we have nevertheless deemed it important to carry out some robustness checks on the models.

The analysis of standardized residuals of regressions indicates an overall satisfactory level of robustness of model 1a) (see Annex 5): the assumptions of linearity, group-wise homoscedasticity and normality of the error terms appear to be fulfilled. The same also applies to models 1c), 2a), and 2d) (see Annex 5). In particular, 1a) and 2a) contain the explanatory variables used to test all our research hypotheses, so conclusions in this regard can be drawn with reasonable confidence. Conversely, the assumptions do not appear to be satisfied for the other models considered, consequently nothing can be inferred in relation to the latter. As a further robustness check, a stepwise regression has been run, identifying a set of regressors that closely mirrors the theoretically grounded specifications in model 1a), providing additional support for the model choices.

Despite the robustness checks performed, we acknowledge that some limitations remain. In our view, these are mainly related to the number of observations in our sample, as it is based on only three *C/P*s launched so far.

The small size of the sample, in fact, does not allow the inclusion of all co-varying variables in the model to estimate their distinct effects, as this could lead to overfitting issues. To the same extent, additional control variables (beyond those already considered, to isolate the effects of other factors) can be hardly included in the model, this resulting in potential presence of omitted variables (e.g. a dummy representing prior interactions with Banca d'Italia to indicate a certain familiarity with its institutional functions³⁰ or, the project assessment process has been paper-based so far, a control variable proxying the experience in preparing documents and project submissions in a context of public competition to isolate the effects of business experience embedded in the applicants' age).

Moving to more specific limitations related to the model variables, in particular to the dependent one, although the scores assigned to projects are based on clearly defined evaluation criteria, we must take into account the presence, albeit residual, of inherently subjective components in the assessment process, ultimately reflected in the scores, and the fact that panelists changed from one *C/P* to another. Therefore, minor variations of scores between the three *C/P*s and potential non-independence within *C/P* cannot be ruled out *a priori*. On the first point, the standardization of scores within *C/P* ensures a satisfactory level of homogeneity, comparability, and consistency across the different editions: a one-way ANOVA has been conducted to compare scores between *C/P*s, not showing any statistically significant differences (see Annex 2). As for the potential non-independence of the error terms within the same *C/P*, the fact that the scores assigned to single panelists are then added together to form a single score for the project is a safeguard in favor of independence (thus, possible personal preferences are mitigated by construction of scores). At the same time, we acknowledge that using cluster-robust standard errors at the level of each *C/P* would have been conceptually more appropriate. However, given the very low number of available clusters, this approach would affect the reliability of statistical inference.

Finally, our last remark pertains to the potential presence of multicollinearity among covarying regressors. While efforts were made, in the specification of the sub-models, to mitigate this issue as far as possible,

³⁰ Anyway, this information has only started to be collected in a structured way and, hence, partially available from the second *C/P* onwards. Introducing this dummy variable would result in missing values concentrated in the first *C/P*.

only more comprehensive multicollinearity diagnostic, that are missing in this paper, could conclusively rule out such a concern.

5. From evidence to policy: discussion of results and operational implications

Focusing on applicants' human capital, our analysis reveals some recurring patterns primarily on the population attracted and secondly in the assessment of fintech projects made for the admission to Milano Hub, so far.

This paper does not intend to be a guide for future applications to Milano Hub's *C/P*. On the contrary, the collected evidence serves as a starting point to stimulate comprehensive reflections on the innovation attracted and supported at present in comparison with the initial expectations. Thus, few recalibrations of Milano Hub's operational model can be suggested. In this section results from the descriptive statistical and econometric analyses are discussed and consequently some potential venues to refine the functioning of the *C/Ps* are proposed.

5.1. Population attracted by Milano Hub

The descriptive statistical analysis has provided an evidence-based assessment of the population which have presented a project proposal to Milano Hub and unveiled three recurring patterns. Namely, the considerable presence of experienced people in the fintech projects, the prominence of economic and STEM background among the professionals therein involved, and a substantial gender gap. **The same types of patterns have been identified by other studies conducted at national level; however, the population attracted by Milano Hub shows some specificities in terms of the relevant magnitude,** by acknowledging that the metrics used in said works and in this paper are not 100% overlapping.

Firstly, the research uncovers a notable '*fintech for experienced people*' phenomenon, whereby the average age of individuals engaged in projects ranges from 44 to 52 years – depending on the role covered – in a context where **the Italian average seems to be a bit lower** (see Sub-section 3.1). **In our opinion, this discrepancy is due to the composition of our sample.** In fact, we have had a view by project, therefore **we have considered only the roles surrounding the project, from the decision to launch it (i.e. management body members') to its implementation (i.e. *Project Contact Person*), and not all the profiles present in the organization overall.** For the same reason, we have extended our analysis to all the participants in case of a collective project,³¹ including more structured organizations like supervised entities, universities and sector associations, that could be characterized by more seasoned directors than fintech. Furthermore, considering applicant players averaging less than nine years of operational history, with management body members of approximately 50 years old on average, this finding suggests that even the relatively young fintech ventures applying to Milano Hub are run by seasoned professionals, contrary to the common belief that new fintech initiatives are carried out by young people.

Secondly, about the academic background of applicants, the study has revealed a relevant concentration of qualifications in economics and STEM disciplines, consistently with the dual nature of fintech, which integrates finance and technology. However, looking at the population attracted by Milano Hub (Figure

³¹ Provided that at least of one of the participants is in the *Fintech Area*, as specified in the foregoing.

3), **the share of graduates in economics and STEM appears to be, respectively, higher and lower than the workforce in the Italian fintech sector.** Albeit potentially counterintuitive to the outcome of the econometric analysis, highlighting the importance of STEM, once again this is connected to the composition of our sample, i.e. a mix between technicians in charge of the execution the projects and more senior managers steering them at a higher level. **It is indeed likely that the latter have more economic than technical background compared to the rest of workers in fintech organizations.**

Thirdly, the analysis emphasised a significant gender gap in the population attracted through the *CjPs*, as female representatives count for only 15% of all individuals involved, reflecting a significant imbalance across all examined roles. However, it should be noted that **such disparity seems to be less marked than the Italian average emerging from the survey of Banca d'Italia (2025)**, according to which female representation is between 1% and 10% for 60% of organizations. Although a direct link between qualifications in economics/STEM and share of women in fintech has not been tested in our work, **all of the above provides a consistent picture:** a sample containing information on management body members connects to higher share of graduates in economics and, hence, lower gender gap than the detected average in Italy. This interpretation could be a topic to explore in future research.

5.2. The assessment of applications: human capital across selected projects

The regressions have revealed a statically significant correlation between the age of the management body members and the final score, confirming our hypothesis H1. This evidence may imply that the work experience can be seen as a valuable characteristic, among other factors, indirectly considered in assessing the project value. In fact, beyond reflecting the quality of innovation itself, the value considers system-wide benefits of the project, which could be the result of cooperation between players (e.g. Azzola *et al.*, 2010). However, while collective participation shows a positive pairwise correlation with both age and scores, its effect is not statistically significant in the regression models. The analysis suggests that projects presented by more experienced players tend to fulfil the assessment criteria, while this is not connected to possible system-wide effects resulting from greater opportunities of collaborating.

In light of the above, the presence of more senior professionals could be partially referred to the institutional purposes of Banca d'Italia. Our interpretation fits into the former literature stating that expert boards and teams with longer work experience, compared to younger officers, have higher risk aversion (e.g. Johnson *et al.*, 2013) and this could allow soundly navigating the complexity of constantly evolving and highly regulated sectors. Thus, by engaging with fintech ventures, Milano Hub helps firms better understand the regulatory framework relevant to the development of their projects and support in setting up appropriate governance structures to effectively mitigate risks. These objectives are part of Milano Hub's mission and are therefore reflected in both the assessment process and the final score.

The presence of STEM education has emerged in the projects with a higher average score, confirming our hypothesis H2. The same cannot be concluded as for the qualifications in the economics area and hypothesis H3, which must be rejected. Moreover, adding PhD to STEM, i.e. a technical background (STEM) at an advanced level (PhD), has been accompanied by even higher scores.

This finding may be related to the circumstance that **the fintech projects presented to Milano Hub must be in a pre-commercialization stage and, consequently, the development carried out during the support period is mainly focused on the technological aspects, rather than on the business strategy.**

Finally, while a significant gender gap emerged from the descriptive statistical analysis, the econometric investigation could not explore this topic, due to the low number of projects with female representatives. Considering also the somewhat contradictory evidence from previous literature regarding the relationship between the share of women and corporate performance, especially when interacting with other factors such as the age of individuals and the maturity of the company, this seems worthy of future research with a larger dataset. It will be discussed in the conclusion section dedicated to the key contribution and developments of our work.

5.3. Implications and future directions

By combining results of both the descriptive statistical and econometric analyses, **this study suggests that the type of population so far attracted by the innovation centre of Banca d'Italia has been partially shaped by the broader Italian fintech ecosystem in which it develops.** No major bias has indeed been identified compared to the latter in terms of socio-demographic and educational features of the applicants. The few minor discrepancies flagged are, in our view, attributable to the indicators used to capture the relevant characteristics, as discussed in the previous sections.

At the same time, the econometric analysis has revealed that the human capital features of fintech may have some associations with the selection criteria, **which are ultimately connected to the institutional tasks, the rules and the operational procedures of Milano Hub as innovation facilitator of Banca d'Italia.** For instance, embedding financial stability objectives in fintech facilitation is related to maintaining also a certain supervisory perspective which, according to our results, is related to engaging with more experienced professionals. To the same extent, the admission limited to non-commercialized projects to avoid jeopardizing market competition necessarily implies fintech projects in an earlier stage of development, where STEM competences are crucial.

Although no distortions have been detected so far, in a longer-term this cannot prevent from the creation of disincentives for certain segments of the population to participate in the *C/Ps* in the future. **Therefore, the collected evidence stimulates a self-assessment on the design and functioning of the *C/Ps*, as well as other possible initiatives of Milano Hub.** This is aimed at elucidating the aspects that require further improvement in the current operational model to attract a more diverse population, in terms of gender, age, and academic background, and more generally at identifying concrete actions to enhance the overall capacity of Milano Hub to engage with the entire ecosystem.

Several actions can be implemented to better calibrate the present operational model of Milano Hub. For example, more flexibility on the phase of development and the assessment of the practicability of the project may be considered in order to embrace a wider range of levels of maturity of the initiatives, potentially starting from the technical/business idea or concept. Remarkably, these considerations must take into account the different approaches adopted across Europe in defining the mandate of innovation hubs at the national level. In particular, potential synergies with the scope of other IFs should be considered. For example, within the Italian ecosystem, the role of the regulatory sandbox is especially relevant, particularly in light of the ongoing discussions regarding amendments to its framework.³²

Finally, it is worth mentioning that *C/Ps* represent just one of the options for Milano Hub, and more generally, for innovation hubs to operate. Ad hoc initiatives dedicated to supporting diversity and

³² The consultation phase has already been concluded; further information can be found at the following link:
https://www.dt.mef.gov.it/it/dipartimento/consultazioni_pubbliche/consultazioni_in_corso/consultazione_fintech/index.html

inclusion in fintech entrepreneurship or targeted collaborations with universities to foster fintech projects and new start-ups led by students are part of the above discussions as well.

These suggestions, first of all, serve as a baseline for recalibrating the Milano hub functioning structure. At the same time, from a broader perspective, our work offers practical guidance for Central Banks that have established, or are considering establishing, their innovation hubs. **The insights derived from our analysis can inform strategic decisions regarding the operational models best suited to position these hubs to effectively engage with and support fintech initiatives, in alignment with their institutional objectives.**

6. Conclusions

The present study shed a light on a partially unexplored key characteristics of fintech projects attracted by institutional innovation facilitators: the human capital. Age and academic background are among the factors associated with the admission to Milano Hub, that reflect goals, rules and procedures typical of a Central Bank. Nevertheless, the attracted population is partially conditioned by the characteristics of the broader fintech ecosystem in which unfolds.

Against this backdrop, our findings not only highlight specific features of the pool of applicants to Milano Hub to date but also inform the broader questions regarding the role of institutional innovation hubs in the fintech sector and the implications of their operational models. Our contribution is, therefore, two-fold. On the one hand, this paper complements and enriches the current literature on fintech key characteristics and evolution over time, by adding the public-oriented and system-wide perspective typical of Central Banks and Authorities. On the other hand, it offers insights into how institutions can effectively position their innovation hubs – such as Milano Hub – to attract and nurture fintech initiatives, consistently with their strategic objectives like financial stability.

Even though our analysis has some limitations, our contribution to advance the understanding of the setup of the Central Bank innovation facilitators for supporting safe and sound innovation can be transposed into further contexts. In fact, despite our study has focused on the *C/Js* launched by Milano Hub, further investigations can extend the analysis to comparable initiatives, for example the *Sandbox Program* recently introduced by the Central Bank of Ireland or the *Innovation Compass* established by the Swedish financial authority (i.e. Finansinspektionen).

By widening the scope of analysis to other realities and thus increasing the size of the dataset, it becomes also possible to consider further factors that could not be duly analyzed in this paper. For example, the interlinks between socio-demographic features of people and characteristics of firms can be further explored, advancing former studies. More in detail, it may be investigated, from the perspective of the IFs, considering also their national specificities, if there is an association between the longevity of fintech firms or projects, the diversity gap among the people involved therein, and their academic and professional experience. Specifically on the gender gap, a key point has been left open in our work regarding possible links between the assessment criteria and female underrepresentation in the fintech projects. Future research efforts should, in our opinion, address the relation that seems to emerge from the sample of project applications to Milano Hub between female presence and STEM background: future analysis can unveil whether differences in academic background can indirectly affect the gender gap or if the contribution of women is playing a role per-se.

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Annexes

Annex 1: detailed methodological assumptions underlying the regression models and variables

Dependent variable

The dependent variable is the final score assigned to each project in our sample. It has been standardized as described in Table 1 to avoid biases in the assessment of projects between *C/Ps*. We have opted for the standardized final score, instead of a dummy variable indicating the admission (if equal to 1) to Milano Hub's support, since there is a cap on the number of admitted projects which is defined *ex ante* by the relevant *C/P* rules. In light of that, we deem that the final score best represents the extent to which the project fits the assessment criteria set by Milano Hub, regardless of the number of seats available in each *C/P* and, therefore, the number of projects actually admitted. As the assessment underlying the scores might not be independent between *C/Ps*, we have conducted a one-way ANOVA to compare scores across the three *C/Ps* (i.e. 1, 2 or 3, modelled as a categorical variable); no statistically significant differences have been found (see Annex 2).

Explanatory variables

The average age of the management body members of the applicant entity has been selected to test hypothesis H1. In our view, it is better to reflect the overall experience within the organization that may contribute to the success of the project than considering the *Project Contact Person(-s)* and/or the *Legal Representative(-s)* only, who are the figures most involved in the Milano Hub fintech projects, as argued above. We have referred to the applicant only, and not to all participant entities, under the assumption that the former is the project creator and, hence, fully aware of the business and industry needs the project intends to satisfy. Moreover, there are potential (and actual, according to the evidence in Table 5) significant correlations between the mentioned variable and the number of years in business of the entity. Therefore, this latter has been selected as well, as a proxy of whole experience alternatively to the age of the management body members, to further verify our assumption.

As for hypotheses H2 and H3, dummy variables for the presence of STEM and economic background in the project have been preferred, for instance, to the number of people with qualifications in such areas because the latter is also an indicator of the size of the team. It has been firstly considered with respect to the *Project Contact Person* (and not to all the examined roles) as the support offered by Milano Hub is focused on the development of the project, in which this figure is the main protagonist. Limited to the companies in the *Fintech Area*, the background of the relevant *Legal Representative* has been considered as well, in addition to the *Project Contact Person*, as based on our experience these players are in most cases small organizations and have a more flexible distribution of tasks, where also the CEO is often directly involved in innovative projects.

Control variables

A simplified form of interaction³³ between AI (Tech_AI) and DLT (Tech_DLT), on the one hand, and time (T), on the other hand, proxied by AIxT and DLTxT has been included, first of all, to control for

³³ To limit model overfitting issues due to a high number of dummy variables resulting from a full interaction between AI (Tech_AI)/DLT (Tech_DLT) and T.

the RELEVANCE criterion, i.e. the pertinence of the projects with the topic of relevant *C/P*, that is embedded in the final score: as said, it was AI for the first *C/P*, DLT for the second and digital payments for the third. However, the interaction between time and a variable depicting the business area of payments among those of application for the project (this information being contained in our dataset) has been discarded due to positive or negative correlations with the technologies and, ultimately, to possible multi-collinearity problems. Actually, the results show significant correlations with both AI (negative) and DLT (positive) (see Annex 2).

As mentioned, the product between the technologies considered and time can be regarded as an indicator of the degree of maturity of the technologies themselves. For this reason, in sub-models e), AIxT and DLTxT have been entered as covariates, to check the distinctive contribution, if any, of the degree of AI and DLT maturity to the final score.

Concerning the background of the people engaged in the project, in addition to including the nature of their qualifications (STEM or economics) as explanatory variable, we have decided to control also the level of knowledge, namely via presence of people with PhD (dummy variable PhD). The same remarks, as those made for STEM and Econ in relation to entering a dummy rather than the number of people with PhD, are applicable.

Also, the average size of the management body of the participant companies has been introduced among controls as a proxy³⁴ of the extent to which the project team is structured in terms of available resources (staff, competences, funds, assets, etc.), under the assumption that the larger the size of the management body, the bigger the company and therefore the stock of resources available. To this purpose, conversely to what done for the explanatory variable *Età_media_amm_prop*, we have considered all participants and, hence, all resources available for the development of the project during the support period offered by Milano Hub. It should also be noted that the stock of available resources is one of the 'VALUE' sub-criteria to assess the projects and contributing to the final score. The size of the management body has been preferred to other proxies of dimension like the turnover, as compared to the latter it is more stable over time, especially for start-ups.

Given that the size of a company is connected to the extension of its network of contacts and, hence, to the likelihood of starting collaborations, a dummy flagging the project as collective or not is part of our controls as well, alternatively to the size of the management body described above. However, this dummy could absorb further effects other than entities' dimensions. For example, it could be correlated to their experience, or the experience of their directors/staff, in the sector (the longer the experience, the wider the network built over time). Therefore, in sub-models d), while including the dummy for collaboration, our explanatory variables have been excluded, to check if the former could absorb also the effects related to the business experience.

Finally, it is worth mentioning that the geographical area (in our case, where the applicant is established), which is commonly used as control variable in regression models, has not been included due to inter-dependencies with some of the selected predictors, in particular the dummy PhD: the outcome of the test of independence for categorical variables are reported in Annex 2.

³⁴ Being specific information lacking in our data sources.

Annex 2: checks on model variables

ANOVA to assess differences in scores across the three C/Ps

ANOVA

Dependent Variable: Pun_fin_std

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	3.161 ^a	2	1.580	1.689	0.191
Intercept	4.819	1	4.819	5.150	0.026
CFP	3.161	2	1.580	1.689	0.191
Error	84.217	90	0.936		
Total	89.958	93			
Corrected Total	87.378	92			

a. R Squared = 0.036 (Adjusted R Squared = 0.015)

Correlations between AI, DLT and payment business area

Correlations

		Tech_AI	Tech_DLT	Sett_pag
Tech_AI	Pearson Correlation	1	-0.371**	-0.394**
	Sig. (2-tailed)		0.000	0.000
	N	96	96	96
Tech_DLT	Pearson Correlation	-0.371**	1	0.226*
	Sig. (2-tailed)	0.000		0.027
	N	96	96	96
Sett_pag	Pearson Correlation	-0.394**	0.226*	1
	Sig. (2-tailed)	0.000	0.027	
	N	96	96	96

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

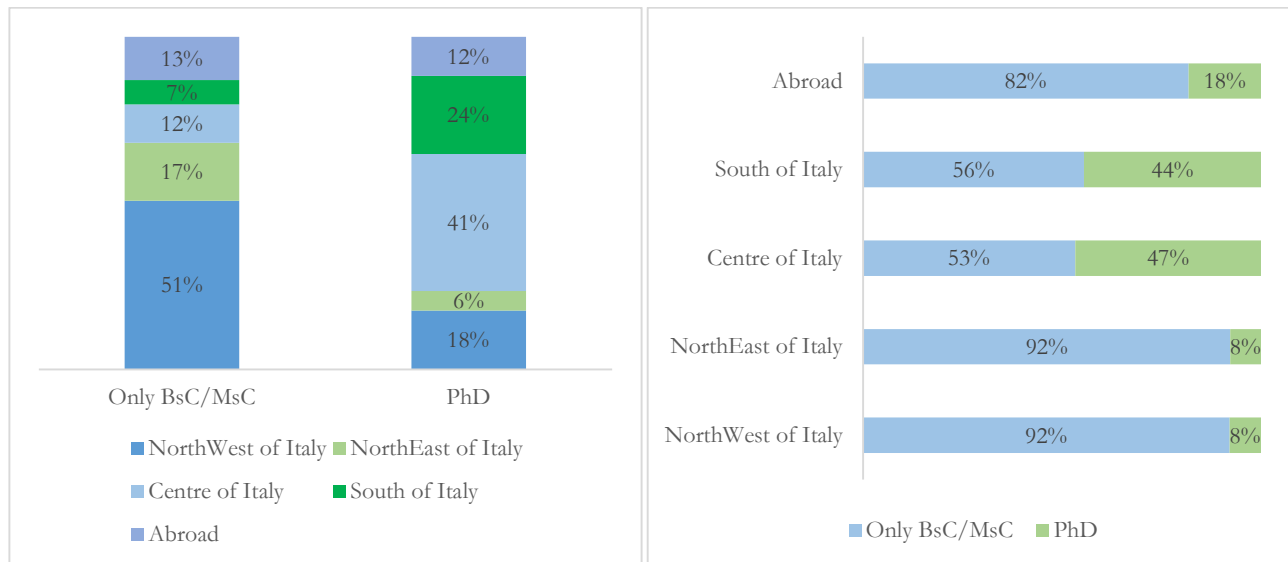
Test of independence - geographical area

In the statistical analysis conducted, a dependency relationship has been found, in particular, between two variables: the level of educational qualifications³⁵ of the *Legal Representatives* and the *Project Contact Persons*, and the location of the corresponding applicant entity.³⁶

To confirm this hypothesis, one statistical test of independence, suitable for cases where at least one expected frequency is less than 5, has been performed, the Fisher's exact test. The (null) hypothesis of independence between the two variables can be rejected, with a p-value lower than 1% (equal to 4‰). Therefore, there is a significant dependency relationship between the two variables, which can also be observed in the following charts.

Further empirical and analytical insights are needed to better understand the nature and determinants of the relationship observed between the two variables but lie outside the scope of this paper.

EDUCATIONAL QUALIFICATIONS AND LOCATION OF THE PROPOSING COMPANY



³⁵ Two categories: 'Only BsC/MsC' and 'PhD'.

³⁶ NorthEast, NorthWest, Centre, South of Italy and Abroad.

Annex 3: descriptive statistics of standardized final score by combination of background
- all types of background

Dependent Variable: Pun_fin_std							
Econ	Giur	STEM	Uman	Altro	Mean	Std. Deviation	N
0	0	0	0	1	-1.125	0.375	2
0	0	1	0	0	-0.204	1.254	14
0	0	1	1	0	0.370	.	1
0	1	0	0	0	-2.170	.	1
0	1	1	0	0	-0.190	0.891	2
0	1	1	1	0	0.970	.	1
1	0	0	0	0	-0.248	0.979	18
1	0	0	0	1	-0.743	0.956	3
1	0	0	1	0	-0.957	0.749	3
1	0	1	0	0	0.033	0.634	21
1	0	1	0	1	0.200	0.961	5
1	0	1	1	0	0.700	.	1
1	1	0	0	0	-0.420	0.127	2
1	1	0	1	0	-0.520	.	1
1	1	1	0	0	0.584	0.893	7
1	1	1	0	1	0.745	1.025	2
1	1	1	1	0	-1.000	.	1
Total [Econ=0] & [STEM=0]					-1.473	0.659	3
Total [Econ=0] & [STEM=1]					-0.106	1.158	18
Total [Econ=1] & [STEM=0]					-0.405	0.898	27
Total [Econ=1] & [STEM=1]					0.188	0.772	37
Total [Econ=0]					-0.301	1.193	21
Total [Econ=1]					-0.062	0.872	64
Total [STEM=0]					-0.512	0.927	30
Total [STEM=1]					0.092	0.916	55

Annex 4: outcome of the regressions

Model 1a

ANOVA

Dependent Variable: Pun_fin_std

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	35.483 ^a	10	3.548	6.056	0.000
Intercept	2.830	1	2.830	4.831	0.032
AIxT_recd	10.780	3	3.593	6.133	0.001
DLTxT_recd	12.675	3	4.225	7.211	0.000
STEM	4.473	1	4.473	7.635	0.008
PhD	2.084	1	2.084	3.558	0.064
Età_media_amm_prop	2.016	1	2.016	3.440	0.068
Dim_media_CdA_part	0.228	1	0.228	0.389	0.535
Error	35.740	61	0.586		
Total	71.859	72			
Corrected Total	71.222	71			

a. R Squared = 0.498 (Adjusted R Squared = 0.416)

Parameter Estimates

Dependent Variable: Pun_fin_std

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-1.299	0.657	-1.976	0.053	-2.613	0.016
[AIxT_recd=0.83]	1.165	0.296	3.937	0.000	0.573	1.756
[AIxT_recd=2.08]	-0.383	0.278	-1.377	0.174	-0.939	0.173
[AIxT_recd=3.58]	0.620	0.491	1.263	0.211	-0.361	1.600
[AIxT_recd=4.00]	0 ^a	.	.	.	.	.
[DLTxT_recd=0.83]	-0.546	0.473	-1.155	0.253	-1.493	0.400
[DLTxT_recd=2.08]	1.114	0.258	4.311	0.000	0.597	1.630
[DLTxT_recd=3.58]	0.294	0.439	0.669	0.506	-0.584	1.172
[DLTxT_recd=4.00]	0 ^a	.	.	.	.	.
[STEM=0]	-0.553	0.200	-2.763	0.008	-0.953	-0.153
[STEM=1]	0 ^a	.	.	.	.	.
[PhD=0]	-0.493	0.262	-1.886	0.064	-1.016	0.030
[PhD=1]	0 ^a	.	.	.	.	.
Età_media_amm_prop	0.020	0.011	1.855	0.068	-0.002	0.041
Dim_media_CdA_part	0.024	0.039	0.624	0.535	-0.054	0.102

a. This parameter is set to zero because it is redundant.

Model 1b

ANOVA

Dependent Variable: Pun_fin_std

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	32.523 ^a	10	3.252	5.356	0.000
Intercept	0.818	1	0.818	1.347	0.250
AIxT_recd	11.453	3	3.818	6.288	0.001
DLTxT_recd	15.137	3	5.046	8.310	0.000
STEM	4.500	1	4.500	7.411	0.008
PhD	3.142	1	3.142	5.175	0.026
Anni_di_attività_prop	0.146	1	0.146	0.241	0.626
Dim_media_CdA_part	0.090	1	0.090	0.149	0.701
Error	37.644	62	0.607		
Total	70.650	73			
Corrected Total	70.166	72			

a. R Squared = 0.464 (Adjusted R Squared = 0.377)

Parameter Estimates

Dependent Variable: Pun_fin_std

Parameter	B	Std. Error	T	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-0.291	0.350	-0.832	0.408	-0.991	0.408
[AIxT_recd=0.83]	1.167	0.301	3.877	0.000	0.566	1.769
[AIxT_recd=2.08]	-0.460	0.280	-1.644	0.105	-1.020	0.099
[AIxT_recd=3.58]	0.598	0.504	1.186	0.240	-0.410	1.606
[AIxT_recd=4.00]	0 ^a					
[DLTxT_recd=0.83]	-0.554	0.487	-1.137	0.260	-1.527	0.419
[DLTxT_recd=2.08]	1.203	0.258	4.664	0.000	0.687	1.718
[DLTxT_recd=3.58]	0.357	0.454	0.787	0.434	-0.550	1.265
[DLTxT_recd=4.00]	0 ^a					
[STEM=0]	-0.546	0.200	-2.722	0.008	-0.946	-0.145
[STEM=1]	0 ^a					
[PhD=0]	-0.599	0.263	-2.275	0.026	-1.125	-0.073
[PhD=1]	0 ^a					
Anni_di_attività_prop	0.005	0.009	0.490	0.626	-0.014	0.024
Dim_media_CdA_part	0.015	0.039	0.386	0.701	-0.064	0.094

a. This parameter is set to zero because it is redundant.

Model 1c

ANOVA

Dependent Variable: Pun_fin_std

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	35.849 ^a	10	3.585	6.182	0.000
Intercept	1.551	1	1.551	2.674	0.107
AIxT_recd	10.873	3	3.624	6.250	0.001
DLTxD_recd	13.356	3	4.452	7.678	0.000
STEM	4.806	1	4.806	8.288	0.005
PhD	2.186	1	2.186	3.770	0.057
Coll	0.594	1	0.594	1.025	0.315
Età_media_amm_prop	1.332	1	1.332	2.296	0.135
Error	35.373	61	0.580		
Total	71.859	72			
Corrected Total	71.222	71			

a. R Squared = 0.503 (Adjusted R Squared = 0.422)

Parameter Estimates

Dependent Variable: Pun_fin_std

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-0.870	0.701	-1.240	0.220	-2.272	0.533
[AIxT_recd=0.83]	1.144	0.294	3.897	0.000	0.557	1.731
[AIxT_recd=2.08]	-0.384	0.272	-1.409	0.164	-0.928	0.161
[AIxT_recd=3.58]	0.659	0.487	1.354	0.181	-0.314	1.633
[AIxT_recd=4.00]	0 ^a	.	.	.	.	.
[DLTxD_recd=0.83]	-0.596	0.467	-1.277	0.206	-1.530	0.337
[DLTxD_recd=2.08]	1.107	0.253	4.377	0.000	0.601	1.613
[DLTxD_recd=3.58]	0.330	0.436	0.758	0.451	-0.541	1.202
[DLTxD_recd=4.00]	0 ^a	.	.	.	.	.
[STEM=0]	-0.561	0.195	-2.879	0.005	-0.951	-0.171
[STEM=1]	0 ^a	.	.	.	.	.
[PhD=0]	-0.501	0.258	-1.942	0.057	-1.016	0.015
[PhD=1]	0 ^a	.	.	.	.	.
[Coll=0]	-0.234	0.231	-1.012	0.315	-0.696	0.228
[Coll=1]	0 ^a	.	.	.	.	.
Età_media_amm_prop	0.017	0.011	1.515	0.135	-0.005	0.039

a. This parameter is set to zero because it is redundant.

Model 1d

ANOVA

Dependent Variable: Pun_fin_std

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	31.585 ^a	9	3.509	5.762	0.000
Intercept	3.032	1	3.032	4.977	0.029
AIxT_recd	8.327	3	2.776	4.557	0.005
DLTxT_recd	15.667	3	5.222	8.573	0.000
STEM	4.575	1	4.575	7.511	0.008
PhD	2.152	1	2.152	3.533	0.064
Coll	0.335	1	0.335	0.550	0.461
Error	45.684	75	0.609		
Total	78.512	85			
Corrected Total	77.269	84			

a. R Squared = 0.409 (Adjusted R Squared = 0.338)

Parameter Estimates

Dependent Variable: Pun_fin_std

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-0.097	0.315	-0.307	0.759	-0.724	0.531
[AIxT_recd=0.83]	0.841	0.279	3.013	0.004	0.285	1.397
[AIxT_recd=2.08]	-0.524	0.264	-1.988	0.050	-1.050	0.001
[AIxT_recd=3.58]	0.319	0.456	0.699	0.487	-0.590	1.228
[AIxT_recd=4.00]	0 ^a	.	.	.	.	.
[DLTxT_recd=0.83]	-0.808	0.419	-1.929	0.057	-1.643	0.026
[DLTxT_recd=2.08]	1.043	0.242	4.303	0.000	0.560	1.526
[DLTxT_recd=3.58]	0.060	0.419	0.142	0.887	-0.775	0.894
[DLTxT_recd=4.00]	0 ^a	.	.	.	.	.
[STEM=0]	-0.516	0.188	-2.741	0.008	-0.891	-0.141
[STEM=1]	0 ^a	.	.	.	.	.
[PhD=0]	-0.450	0.239	-1.880	0.064	-0.927	0.027
[PhD=1]	0 ^a	.	.	.	.	.
[Coll=0]	-0.158	0.213	-0.741	0.461	-0.583	0.267
[Coll=1]	0 ^a	.	.	.	.	.

a. This parameter is set to zero because it is redundant.

Model 1e

ANOVA

Dependent Variable: Pun_fin_std

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	22.134 ^a	6	3.689	4.885	0.000
Intercept	4.939	1	4.939	6.540	0.013
STEM	2.817	1	2.817	3.730	0.058
PhD	2.892	1	2.892	3.830	0.055
AIxT	0.000	1	0.000	0.000	0.983
DLTxT	1.103	1	1.103	1.461	0.231
Età_media_amm_prop	3.663	1	3.663	4.850	0.031
Dim_media_CdA_part	2.812	1	2.812	3.724	0.058
Error	49.088	65	0.755		
Total	71.859	72			
Corrected Total	71.222	71			

a. R Squared = 0.311 (Adjusted R Squared = 0.247)

Parameter Estimates

Dependent Variable: Pun_fin_std

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-1.130	0.716	-1.578	0.119	-2.561	0.300
[STEM=0]	-0.432	0.224	-1.931	0.058	-0.879	0.015
[STEM=1]	0 ^a	.	.	.	.	.
[PhD=0]	-0.573	0.293	-1.957	0.055	-1.157	0.012
[PhD=1]	0 ^a	.	.	.	.	.
AIxT	0.002	0.110	0.021	0.983	-0.218	0.222
DLTxT	0.113	0.094	1.209	0.231	-0.074	0.301
Età_media_amm_prop	0.026	0.012	2.202	0.031	0.002	0.050
Dim_media_CdA_part	0.081	0.042	1.930	0.058	-0.003	0.164

a. This parameter is set to zero because it is redundant.

Model 2a

ANOVA

Dependent Variable: Pun_fin_std

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	32.018 ^a	10	3.202	4.982	0.000
Intercept	4.014	1	4.014	6.246	0.015
AIxT_recd	10.146	3	3.382	5.262	0.003
DLT _x T_recd	12.498	3	4.166	6.482	0.001
Econ	1.008	1	1.008	1.569	0.215
PhD	2.998	1	2.998	4.664	0.035
Età_media_amm_prop	3.651	1	3.651	5.681	0.020
Dim_media_CdA_part	1.003	1	1.003	1.561	0.216
Error	39.205	61	0.643		
Total	71.859	72			
Corrected Total	71.222	71			

a. R Squared = 0.450 (Adjusted R Squared = 0.359)

Parameter Estimates

Dependent Variable: Pun_fin_std

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-1.980	0.678	-2.921	0.005	-3.336	-0.625
[AIxT_recd=0.83]	1.249	0.331	3.779	0.000	0.588	1.910
[AIxT_recd=2.08]	-0.240	0.286	-0.841	0.404	-0.811	0.331
[AIxT_recd=3.58]	0.802	0.521	1.540	0.129	-0.239	1.844
[AIxT_recd=4.00]	0 ^a	.	.	.	.	.
[DLT _x T_recd=0.83]	-0.492	0.495	-0.994	0.324	-1.483	0.498
[DLT _x T_recd=2.08]	1.169	0.282	4.149	0.000	0.606	1.732
[DLT _x T_recd=3.58]	0.050	0.484	0.104	0.917	-0.918	1.019
[DLT _x T_recd=4.00]	0 ^a	.	.	.	.	.
[Econ=0]	0.319	0.255	1.252	0.215	-0.191	0.829
[Econ=1]	0 ^a	.	.	.	.	.
[PhD=0]	-0.585	0.271	-2.160	0.035	-1.127	-0.043
[PhD=1]	0 ^a	.	.	.	.	.
Età_media_amm_prop	0.026	0.011	2.384	0.020	0.004	0.048
Dim_media_CdA_part	0.050	0.040	1.249	0.216	-0.030	0.130

a. This parameter is set to zero because it is redundant.

Model 2b

ANOVA

Dependent Variable: Pun_fin_std

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	29.119 ^a	10	2.912	4.398	0.000
Intercept	0.525	1	0.525	0.793	0.377
AIxT_recd	10.929	3	3.643	5.503	0.002
DLTxT_recd	15.895	3	5.298	8.003	0.000
Econ	1.096	1	1.096	1.656	0.203
PhD	4.591	1	4.591	6.934	0.011
Anni_di_attività_prop	0.739	1	0.739	1.116	0.295
Dim_media_CdA_part	0.557	1	0.557	0.842	0.362
Error	41.048	62	0.662		
Total	70.650	73			
Corrected Total	70.166	72			

a. R Squared = 0.415 (Adjusted R Squared = 0.321)

Parameter Estimates

Dependent Variable: Pun_fin_std

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-0.705	0.391	-1.804	0.076	-1.485	0.076
[AIxT_recd=0.83]	1.264	0.336	3.762	0.000	0.592	1.935
[AIxT_recd=2.08]	-0.347	0.289	-1.201	0.234	-0.924	0.230
[AIxT_recd=3.58]	0.741	0.533	1.391	0.169	-0.324	1.807
[AIxT_recd=4.00]	0 ^a					
[DLTxT_recd=0.83]	-0.475	0.507	-0.937	0.352	-1.489	0.539
[DLTxT_recd=2.08]	1.317	0.282	4.677	0.000	0.754	1.880
[DLTxT_recd=3.58]	0.160	0.497	0.321	0.749	-0.833	1.152
[DLTxT_recd=4.00]	0 ^a					
[Econ=0]	0.334	0.260	1.287	0.203	-0.185	0.854
[Econ=1]	0 ^a					
[PhD=0]	-0.712	0.270	-2.633	0.011	-1.252	-0.171
[PhD=1]	0 ^a					
Anni_di_attività_prop	0.010	0.010	1.057	0.295	-0.009	0.030
Dim_media_CdA_part	0.037	0.040	0.917	0.362	-0.044	0.118

a. This parameter is set to zero because it is redundant.

Model 2c

ANOVA

Dependent Variable: Pun_fin_std

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	32.480 ^a	10	3.248	5.114	0.000
Intercept	1.538	1	1.538	2.422	0.125
AIxT_recd	11.061	3	3.687	5.805	0.001
DLTxT_recd	14.198	3	4.733	7.452	0.000
Econ	1.437	1	1.437	2.263	0.138
PhD	3.344	1	3.344	5.265	0.025
Coll	1.466	1	1.466	2.308	0.134
Età_media_amm_prop	2.168	1	2.168	3.414	0.070
Error	38.742	61	0.635		
Total	71.859	72			
Corrected Total	71.222	71			

a. R Squared = 0.456 (Adjusted R Squared = 0.367)

Parameter Estimates

Dependent Variable: Pun_fin_std

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-1.303	0.729	-1.788	0.079	-2.761	0.154
[AIxT_recd=.83]	1.265	0.326	3.888	0.000	0.615	1.916
[AIxT_recd=2.08]	-0.256	0.281	-0.912	0.366	-0.818	0.306
[AIxT_recd=3.58]	0.905	0.517	1.750	0.085	-0.129	1.939
[AIxT_recd=4.00]	0 ^a	.	.	.	.	.
[DLTxT_recd=.83]	-0.595	0.490	-1.216	0.229	-1.575	0.384
[DLTxT_recd=2.08]	1.199	0.275	4.365	0.000	0.650	1.748
[DLTxT_recd=3.58]	0.075	0.480	0.157	0.876	-0.886	1.036
[DLTxT_recd=4.00]	0 ^a	.	.	.	.	.
[Econ=0]	0.389	0.258	1.504	0.138	-0.128	0.906
[Econ=1]	0 ^a	.	.	.	.	.
[PhD=0]	-0.610	0.266	-2.295	0.025	-1.141	-0.078
[PhD=1]	0 ^a	.	.	.	.	.
[Coll=0]	-0.373	0.245	-1.519	0.134	-0.863	0.118
[Coll=1]	0 ^a	.	.	.	.	.
Età_media_amm_prop	0.021	0.011	1.848	0.070	-0.002	0.044

a. This parameter is set to zero because it is redundant.

Model 2d

ANOVA

Dependent Variable: Pun_fin_std

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	28.939 ^a	9	3.215	4.990	0.000
Intercept	0.691	1	0.691	1.072	0.304
AIxT_recd	8.597	3	2.866	4.447	0.006
DLTxT_recd	16.715	3	5.572	8.646	0.000
Econ	1.929	1	1.929	2.994	0.088
PhD	3.332	1	3.332	5.171	0.026
Coll	1.558	1	1.558	2.418	0.124
Error	48.330	75	0.644		
Total	78.512	85			
Corrected Total	77.269	84			

a. R Squared = 0.375 (Adjusted R Squared = 0.299)

Parameter Estimates

Dependent Variable: Pun_fin_std

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-0.263	0.341	-.773	0.442	-0.942	0.415
[AIxT_recd=.83]	0.972	0.306	3.181	0.002	0.363	1.581
[AIxT_recd=2.08]	-0.411	0.268	-1.534	0.129	-0.945	0.123
[AIxT_recd=3.58]	0.568	0.474	1.199	0.234	-0.376	1.512
[AIxT_recd=4.00]	0 ^a	.	.	.	.	.
[DLTxT_recd=.83]	-0.836	0.432	-1.936	0.057	-1.696	0.024
[DLTxT_recd=2.08]	1.134	0.259	4.373	0.000	0.617	1.650
[DLTxT_recd=3.58]	-0.231	0.459	-.503	0.617	-1.144	0.683
[DLTxT_recd=4.00]	0 ^a	.	.	.	.	.
[Econ=0]	0.434	0.251	1.730	0.088	-0.066	0.934
[Econ=1]	0 ^a	.	.	.	.	.
[PhD=0]	-0.550	0.242	-2.274	0.026	-1.031	-0.068
[PhD=1]	0 ^a	.	.	.	.	.
[Coll=0]	-0.342	0.220	-1.555	0.124	-0.780	0.096
[Coll=1]	0 ^a	.	.	.	.	.

a. This parameter is set to zero because it is redundant.

Model 2e

ANOVA

Dependent Variable: Pun_fin_std

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	19.840 ^a	6	3.307	4.183	0.001
Intercept	6.733	1	6.733	8.517	0.005
Econ	0.523	1	0.523	0.661	0.419
PhD	4.099	1	4.099	5.185	0.026
AIxT	0.063	1	0.063	0.079	0.779
DLTxT	1.392	1	1.392	1.760	0.189
Età_media_amm_prop	5.076	1	5.076	6.422	0.014
Dim_media_CdA_part	3.647	1	3.647	4.613	0.035
Error	51.382	65	0.790		
Total	71.859	72			
Corrected Total	71.222	71			

a. R Squared = 0.279 (Adjusted R Squared = 0.212)

Parameter Estimates

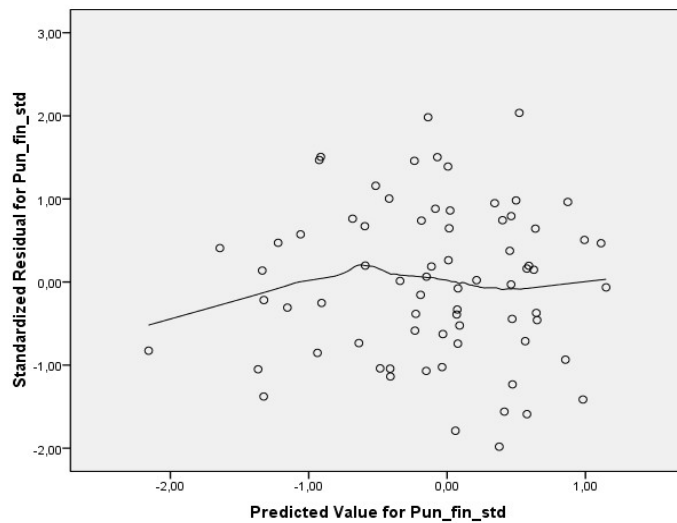
Dependent Variable: Pun_fin_std

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	-1.439	0.710	-2.027	0.047	-2.858	-0.021
[Econ=0]	-0.197	0.243	-0.813	0.419	-0.682	0.287
[Econ=1]	0 ^a	.	.	.	.	.
[PhD=0]	-0.673	0.296	-2.277	0.026	-1.264	-0.083
[PhD=1]	0 ^a	.	.	.	.	.
AIxT	0.031	0.111	0.282	0.779	-0.191	0.254
DLTxT	0.129	0.097	1.327	0.189	-0.065	0.323
Età_media_amm_prop	0.031	0.012	2.534	0.014	0.006	0.055
Dim_media_CdA_part	0.091	0.042	2.148	0.035	0.006	0.176

a. This parameter is set to zero because it is redundant.

Annex 5: robustness of the models

Model 1a



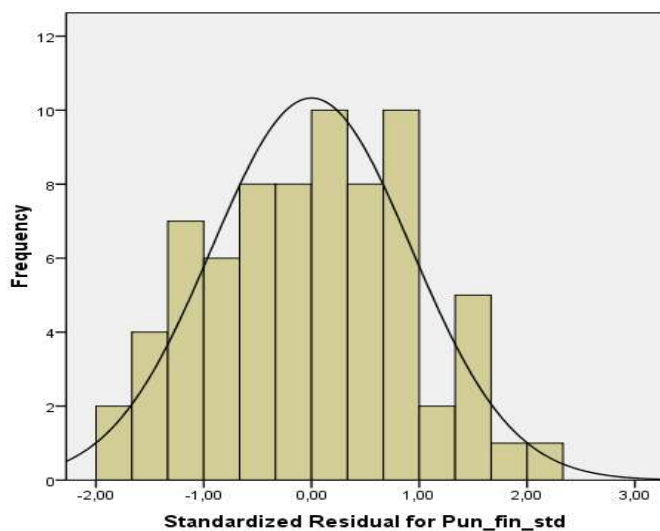
Levene's Test of Equality of Error Variances^a

Dependent Variable: Pun_fin_std

F	df1	df2	Sig.
0.762	23	55	0.760

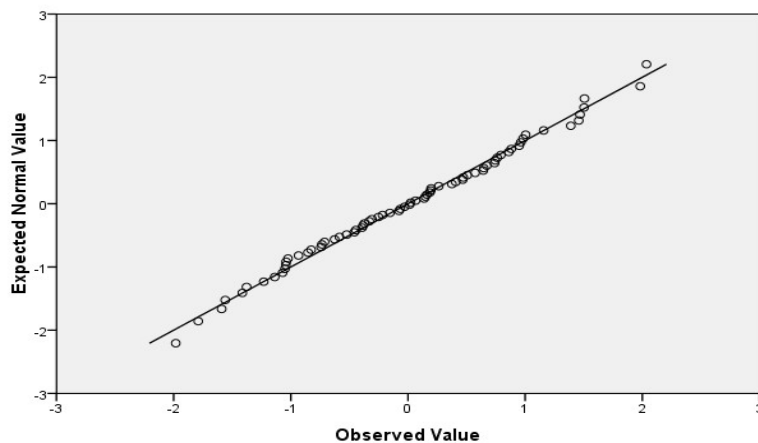
Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + AIxT_recd + DLTxT_recd + STEM + PhD + Età_media_amm_part + Dim_media_CdA_part

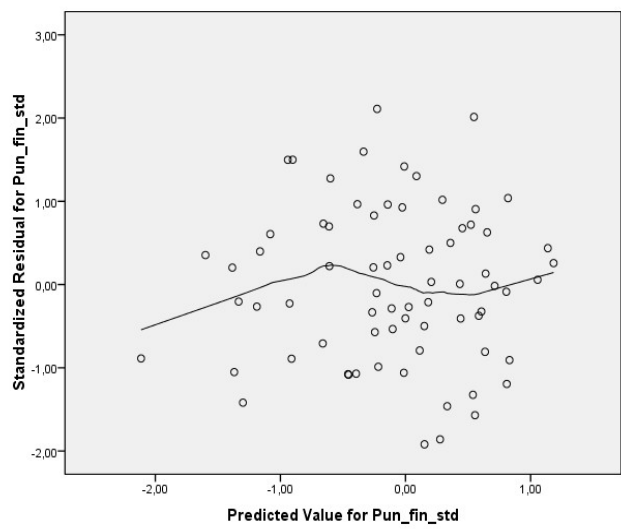


Mean =6,18E-16
Std. Dev. =0,927
N =72

Normal Q-Q Plot of Standardized Residual for Pun_fin_std



Model 1c



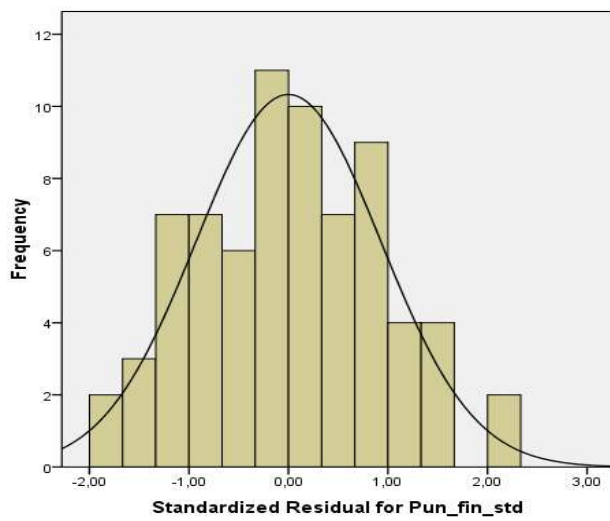
Levene's Test of Equality of Error Variances^a

Dependent Variable: Pun_fin_std

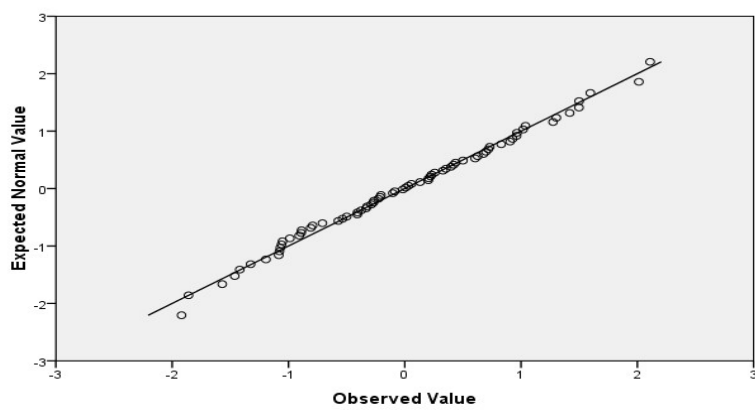
F	df1	df2	Sig.
0.771	30	41	0.769

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

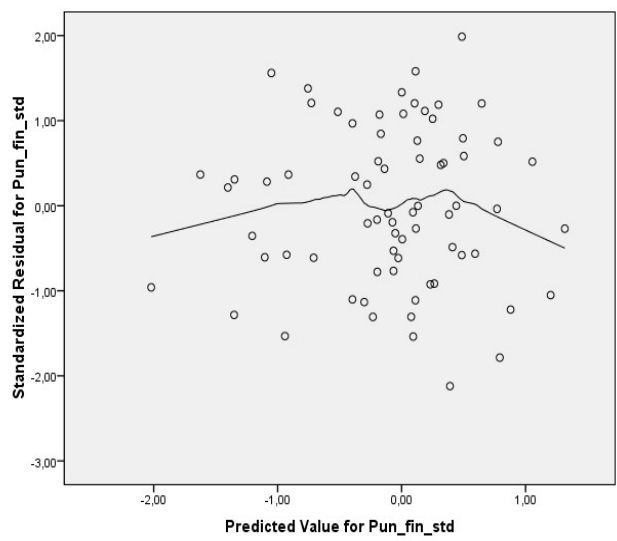
a. Design: Intercept + AIxT_recd + DLTxT_recd + STEM + PhD + Coll + Età_media_amm_prop



Normal Q-Q Plot of Standardized Residual for Pun_fin_std



Model 2a



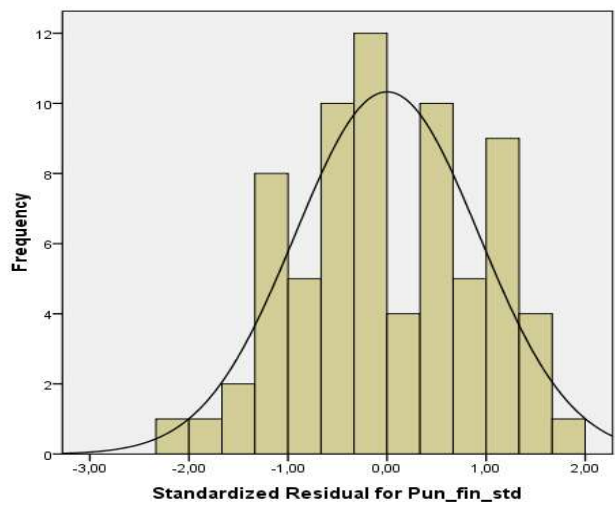
Levene's Test of Equality of Error Variances^a

Dependent Variable: Pun_fin_std

F	df1	df2	Sig.
1.595	20	51	0.091

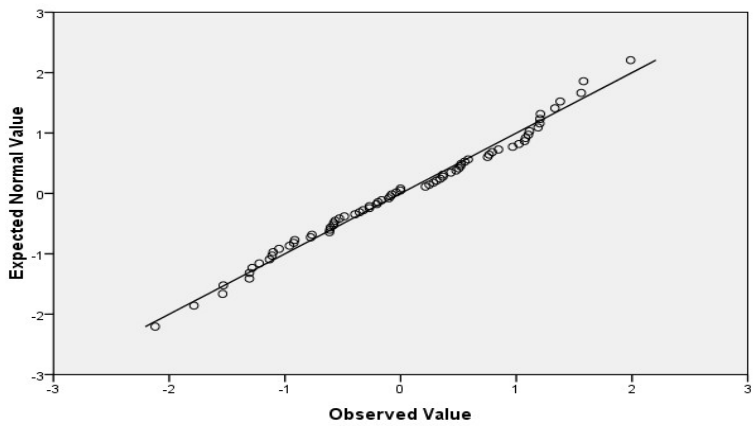
Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + AIxT_recd + DLTxT_recd +
Econ + PhD + Età_media_amm_prop +
Dim_media_CdA_part

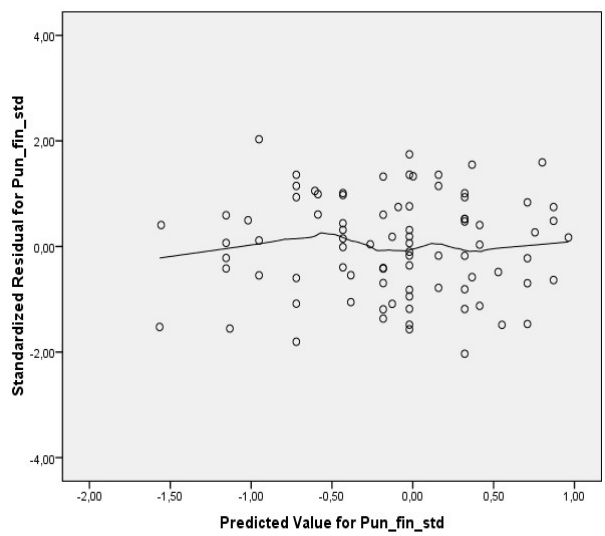


Mean =7,08E-16
Std. Dev. =0,927
N =72

Normal Q-Q Plot of Standardized Residual for Pun_fin_std



Model 2d



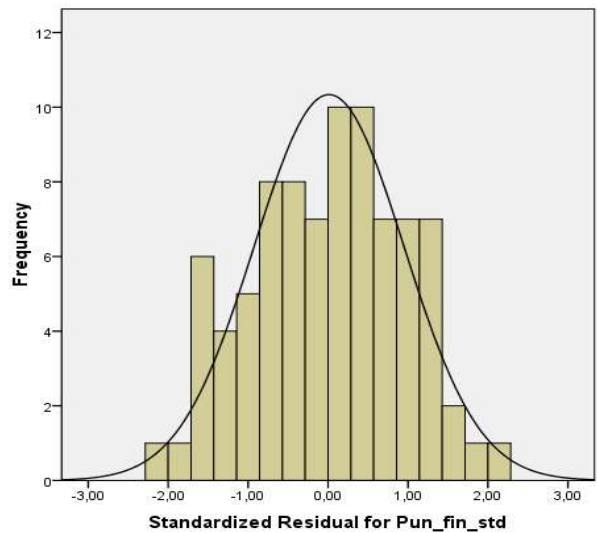
Levene's Test of Equality of Error Variances^a

Dependent Variable: Pun_fin_std

F	df1	df2	Sig.
0.986	27	57	0.501

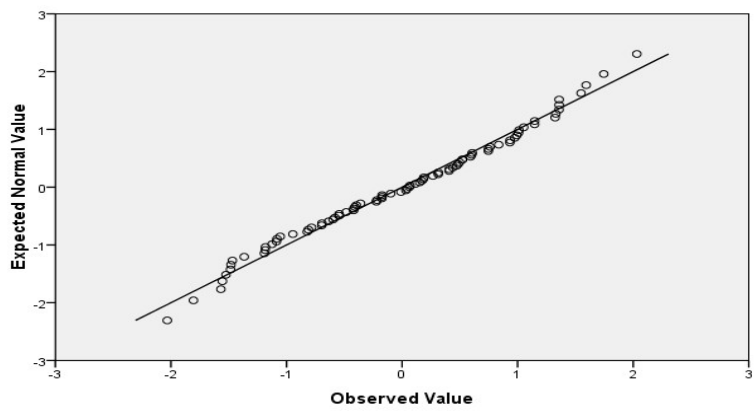
Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + AIXT_recd + DLTxT_recd + Econ + PhD + Coll



Mean = -3.47E-18
Std. Dev. = 0.945
N = 85

Normal Q-Q Plot of Standardized Residual for Pun_fin_std



Stepwise regression output

Selection method: OLS p-value stepwise; entry $p \leq 0.05$; removal $p \geq 0.10$. Constant included in all models. AIxT and DLTxT treated as categorical predictors

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.347 ^a	0.120	0.109	0.925
2	0.429 ^b	0.184	0.163	0.897
3	0.443 ^c	0.196	0.164	0.896
4	0.484 ^d	0.235	0.193	0.881
5	0.572 ^e	0.327	0.261	0.843
6	0.674 ^f	0.454	0.374	0.776
7	0.673 ^g	0.453	0.382	0.771

a. Predictors: (Constant), Età_media_amm_part

b. Predictors: (Constant), Età_media_amm_part, PhD

c. Predictors: (Constant), Età_media_amm_part, PhD, Num_pers³⁷

d. Predictors: (Constant), Età_media_amm_part, PhD, Num_pers, STEM

e. Predictors: (Constant), Età_media_amm_part, PhD, Num_pers, STEM, DLT*T

f. Predictors: (Constant), Età_media_amm_part, PhD, Num_pers, STEM, DLTxT, AIxT

g. Predictors: (Constant), Età_media_amm_part, PhD, STEM, DLTxT, AIxT

³⁷ Num_pers is the number of people involved in the project overall, as either *Project Contact Person* or *Legal Representative* or *Management Body Member*.

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2.049	0.627		-3.267	0.002
	Età_media_amm_part	0.040	0.013	0.359	3.196	0.002
2	(Constant)	-2.045	0.601		-3.402	0.001
	Età_media_amm_part	0.038	0.012	0.335	3.099	0.003
	PhD	0.763	0.286	0.288	2.668	0.010
3	(Constant)	-1.850	0.594		-3.116	0.003
	Età_media_amm_part	0.030	0.012	0.269	2.442	0.017
	PhD	0.679	0.282	0.257	2.410	0.019
	Num_pers	0.031	0.015	0.235	2.114	0.038
4	(Constant)	-1.882	0.584		-3.225	0.002
	Età_media_amm_part	0.026	0.012	0.236	2.160	0.034
	PhD	0.587	0.282	0.222	2.085	0.041
	Num_pers	0.027	0.014	0.207	1.878	0.065
	STEM	0.406	0.221	0.200	1.837	0.071
5	(Constant)	-1.838	0.579		-3.175	0.002
	Età_media_amm_part	0.022	0.012	0.197	1.806	0.076
	PhD	0.671	0.281	0.253	2.387	0.020
	Num_pers	0.023	0.014	0.177	1.627	0.109
	STEM	0.395	0.217	0.195	1.822	0.073
	[DLT×T=0.83]	-0.402	0.516	-0.081	-0.778	0.440
	[DLT×T=2.08]	0.419	0.220	0.211	1.906	0.061
	[DLT×T=3.58]	-0.086	0.456	-0.020	-0.189	0.851
6	(Constant)	-2.227	0.543		-4.097	0.000
	Età_media_amm_part	0.018	0.011	0.164	1.675	0.099
	PhD	0.534	0.254	0.202	2.100	0.040
	Num_pers	0.011	0.013	0.085	0.851	0.398
	STEM	0.505	0.198	0.249	2.550	0.013
	[DLT×T=0.83]	-0.563	0.463	-0.114	-1.215	0.229
	[DLT×T=2.08]	1.129	0.255	0.569	4.426	0.000
	[DLT×T=3.58]	0.302	0.432	0.070	0.700	0.487
	[AI×T=0.83]	1.135	0.288	0.478	3.945	0.000
	[AI×T=2.08]	-0.411	0.273	-0.150	-1.507	0.137
	[AI×T=3.58]	0.637	0.483	0.129	1.319	0.192
7	(Constant)	-2.292	0.537		-4.269	0.000
	Età_media_amm_part	0.020	0.011	0.180	1.875	0.066
	PhD	0.553	0.253	0.209	2.187	0.033
	STEM	0.534	0.194	0.263	2.743	0.008
	[DLT×T=0.83]	-0.562	0.462	-0.114	-1.216	0.229
	[DLT×T=2.08]	1.176	0.249	0.592	4.728	0.000
	[DLT×T=3.58]	0.305	0.431	0.071	0.708	0.482
	[AI×T=0.83]	1.167	0.285	0.491	4.100	0.000
	[AI×T=2.08]	-0.459	0.266	-0.167	-1.724	0.090
	[AI×T=3.58]	0.647	0.482	0.131	1.343	0.184

a. Dependent Variable: Pun_fin_std

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