The Effects of Startup Accelerator Programs on Innovation and Entrepreneurship *

Bruna Alvarez† Daniel Da Mata‡ Lucas Mation§

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Abstract

This paper investigates the impact of a startup accelerator program in Brazil focused on innovative projects to identify and support the most promising entrepreneurs. Using an integrated worker-firm-owner dataset and an instrumental variable approach based on the assignment of projects to evaluators, we find that the accelerator increases the likelihood of patent applications by 5% while decreasing the probability of entrepreneurship by 10%. These effects are primarily driven by individuals with tertiary education, who are also more likely to secure managerial positions. This suggests that accelerators foster innovation and redirect those less suited for entrepreneurship toward more suitable career paths.

Keywords: Accelerators, startups, innovation, patents, entrepreneurship, value of information, information provision, feedback, management .
JEL Codes: G24, L26, M13, 031

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†Sao Paulo School of Economics - FGV, e-mail: bruna.alvarez@fgv.br.
‡Sao Paulo School of Economics - FGV, e-mail: daniel.damata@fgv.br.
§IPEA, e-mail: lucas.mation@ipea.gov.br.

1 Introduction

Governments worldwide implement policies to stimulate innovative entrepreneurship to foster economic growth.[1] However, evidence suggests that most entrepreneurs fail to generate the major innovations necessary for economic advancement (Haltiwanger et al., 2013; Guzman and Stern, 2020). Even among startups, the growth effects are primarily concentrated in a small fraction of highly successful firms (Kerr et al., 2014). Therefore, the impact of innovative entrepreneurship on economic growth also depends on the "quality" of new firms (Schoar, 2010; Hurst and Pugsley, 2011; Guzman and Stern, 2020). Consequently, effective policies must accurately identify and support high-quality firms, a task that is often challenging.

This study investigates how the InovAtiva program — an accelerator initiative in Brazil designed to foster innovative entrepreneurship — affects patents, firm creation, and labor market outcomes. Administered in collaboration with the Brazilian government and private sector entities, the program targets innovative projects at various stages of development, providing training, mentorship, and networking opportunities without financial support. Accelerator programs focus on innovative projects — even before startup consolidation — as a mechanism to identify and support the most promising entrepreneurs. By providing feedback, accelerators inform aspiring entrepreneurs about the feasibility of their ideas and prompt underperforming firms to close down faster (Yu, 2019). They can also help participants make more informed strategic choices, influencing their entrepreneurial paths and redirecting those less suited for entrepreneurship towards more suitable career trajectories.

To investigate the impact of accelerators on innovative entrepreneurship and labor market spillovers, we use four Brazilian administrative datasets. By linking (i) RAIS, which provides detailed labor market information, (ii) the publicly accessible CNPJ dataset, which contains business registration details, (iii) the INPI dataset on patent applications and grants, and (iv) the InovAtiva administrative dataset, we contribute by providing new empirical facts to the literature on the effects of accelerators on innovation, entrepreneurship, and career trajectories.

To evaluate the program, we exploit the "as if" random assignment of projects to evaluators with varying leniency, in a instrumental variable framework. To rank projects,

[1]Countries with higher research and development spending typically are richer (Jones, 2015). For example, in 2022, the United States invested an estimated $885.6 billion in R&D, with the business sector being the largest contributor (National Science Board, 2024b). Additionally, the U.S. supports small firms through the Small Business Innovation Research (SBIR) program, which aims to increase their participation in federally funded R&D (National Science Board, 2024a).

a panel of three evaluators rates each submission, from which the average score is considered. The 300 top-ranked projects are assigned to the program. To address potential endogeneity from unobserved characteristics, we use the assignment of projects to evaluators and the leave-one-out estimate of evaluators' aggregate leniency as an instrumental variable (IV). Our compliers are individuals whose projects would have received a different outcome if evaluated by different evaluators.

We find that the accelerator program increases the likelihood of patent applications by more than 5%, an effect that persists for three years after treatment. This result is driven by individuals with entrepreneurial and labor market experience and those with high educational attainment. Conversely, entrepreneurial activity appears to be negatively affected among individuals with viable labor market options, such as those employed before participating in the program and those with higher human capital. In particular, there is an overall negative impact of 15% on entrepreneurial propensity almost five years after treatment. The feedback from the accelerator primarily impacts participants with no prior entrepreneurial experience and those with significant outside options, such as individuals who were employed before the program and those with high human capital. These differential effects accentuate the importance of considering heterogeneous impacts when evaluating entrepreneurship training programs. Regarding labor market spillovers, we find a short-term negative impact on the probability of employment by 10%. However, participants, especially those with higher education, are more likely to secure managerial positions, indicating a shift towards stable and high-level employment.

Taken together, our findings indicate that the accelerator program creates a "survival of the fittest" dynamic, benefiting individuals who are more prone to innovation due to their higher human capital and entrepreneurial experience. The program not only increases innovation by boosting patent applications, but also reshapes career trajectories by reducing the likelihood of starting new businesses and enhancing prospects for managerial employment. The intensive training and feedback mechanisms prompt participants to reassess the viability of their ventures, leading to more efficient resource allocation and better career choices. Consequently, participants with viable labor market options, particularly those with higher education and prior employment, are redirected towards stable employment paths, securing managerial positions. These findings emphasize the critical role of non-financial support, such as information and mentorship, in fostering innovation and guiding career decisions.

At a broader level, our study contributes to the extensive body of literature that explores the determinants of innovation and evaluates policies designed to foster it. This literature investigates various factors that may positively or negatively influence innovation, such as legal frameworks (Brown et al., 2013), financial markets (Hsu et al. (2014), He and Tian (2013), Cornaggia et al. (n.d.)), product market competition (Aghion et al., 2005), and institutional ownership (Aghion et al., 2013). Additionally, this branch examines a range of policies that can stimulate innovation.[2] These include tax incentives for research and development (Lucking et al. (2019), Akcigit et al. (2021)), government research grants (Azoulay et al. (2018), Howell (2017)), strategies to augment the supply of human capital dedicated to innovative efforts (Toivanen and Väänänen (2016), Bernstein et al. (2023)), intellectual property regulations (Sampat and Williams (2019), Boldrin and Levine (2013)), and policies that promote market competition (Aghion et al. (2018), Atkin et al. (2017)). We contribute to this literature by analyzing the impact of an early-stage policy intervention: an accelerator program, focused specifically at the project level of innovation. Despite the widespread popularity of accelerators, empirical evidence regarding their effectiveness remains ambiguous. In our study, we explore an initiative that offers mentoring and networking opportunities without financial support, establishing it as a cost-effective strategy to promote innovation. This approach allows us to isolate the effects of non-financial support on innovation outcomes, thereby enhancing the ongoing debate about the efficacy of accelerators in fostering innovative activities.

This paper also contributes to the expanding literature on business accelerators (Cohen et al. (2019), Winston Smith and Hannigan (2015), Fehder (2017), Hallen et al. (2020), Yu (2019), Gonzalez-Uribe (2017), González-Uribe (2021)). Our contributions are threefold. First, we add by examining new outcomes, specifically innovation as measured by patent filings, and assessing potential spillover effects in labor market dynamics. Therefore, our analysis not only considers the impact of accelerators on firm creation but also focuses on their effects on innovative entrepreneurship and the generation of new ideas. Second, the availability of detailed data at the owner, worker, and firm levels provides an opportunity to identify heterogeneous effects. Third, since selection bias is inherent in accelerator programs that tend to select the most promising participants, we build on papers using the judges' leniency instrument (e.g., González-Uribe (2021)) and contribute by studying longer-term effects that have not been previously captured in the literature.

This paper is organized as follows. Section 2 provides an overview of the InovAtiva Brasil program, including its structure and objectives. Section 3 describes the data. Section 4 outlines the empirical strategy employed to identify the program's impact. Section 5 presents the results, focusing on the effects of the program on entrepreneurship and labor market outcomes. Section 6 discusses the findings and their implications for policies. Finally, 7 concludes.

[2]For a more detailed discussion on these topics and additional literature, see Bloom et al. (2019).

2 The InovAtiva Program

InovAtiva Brasil is an accelerator program designed to foster innovation and support new entrepreneurs throughout Brazil. Administered through a partnership between the Brazilian government and private sector entities, the program targets startups and innovative projects by offering comprehensive training, mentorship, and networking opportunities to expedite business development and market entry. The program is biannual, free of charge, and open to innovative solutions from all sectors at various stages of development.

Eligible participants are those developing innovative solutions in products, processes, or services, and possessing scalable business models targeting significant market opportunities. The program is divided into two phases: an initial phase where up to 200 projects or startups engage in mentoring and training activities, and a final phase where up to 100 startups receive specialized mentoring and capacity-building, culminating in presentations to investors.

The admission process is highly competitive, involving a rigorous evaluation of business proposals by a panel of judges who rate each project. Participants are ranked according to average scores, with selections made from the top ranked participants until all spots are filled.

Participants receive training on various aspects of business operations, including financial management, marketing strategies, and legal compliance, along with mentorship from seasoned entrepreneurs and industry experts. This comprehensive support helps participants connect with investors and potential business partners, significantly enhancing their prospects for successful business launches and expansion. Unlike traditional business plan competitions that primarily offer financial awards based on written proposals, the accelerator program provides hands-on training and continuous mentorship. Compared to other types of accelerators that may focus more narrowly on specific sectors or stages of business development and provide financial support, this program adopts a holistic approach that addresses diverse sectors and stages of entrepreneurial projects.

3 Data and Summary Statistics

3.1 Data

RAIS. This study utilizes data from the "Relação Anual de Informações Sociais" (RAIS), a comprehensive matched employee-employer dataset maintained by Brazil's Ministry of Labor. RAIS encompasses detailed records for each formally employed individual at every plant throughout Brazil. This extensive coverage results from a statutory requirement mandating all Brazilian establishments to annually report employee data to RAIS. Our analysis employs annual data spanning from 2010 to 2021. In examining labor market dynamics, we develop measures both at the extensive and intensive margins. At the extensive margin, we introduce an employment indicator, which is assigned a value of one if an individual is formally employed for at least one month in each semester, and zero otherwise. Additionally, we define a variable to identify individuals who have commenced a new job within the study period. At the intensive margin, we quantify the duration of formal employment by calculating the total number of months each individual is employed within the formal sector annually. Furthermore, we aggregate and analyze data on average earnings and occupational categories on a semester basis. At the firm level, we construct a variable reflecting the total number of employees per firm involved with each participant. It is important to note that the RAIS dataset is limited to individuals within the formal labor sector and includes socio-economic characteristics specific to this group.

CNPJ public dataset This analysis incorporates data from the publicly accessible CNPJ registry (National Register of Legal Entities), which is administered by Brazil's Internal Revenue Service. The CNPJ dataset provides detailed establishment-level data, including the date of establishment, sector of economic activity, and ownership details, among other relevant attributes. For the period from 2012 to 2022, we extracted records of all establishments, specifically identifying those owned by participants of the InovAtiva program. Additionally, our selection includes microenterprises that qualify as formal self-employment entities, operating under the legal status of individual microentrepreneurs. To assess entrepreneurial activity, we constructed an entrepreneurship dummy variable. This indicator is assigned a value of one for individuals owning an establishment and maintaining ownership for at least one month in each semester reviewed, and a value of zero otherwise. We also collated data concerning the sectoral distribution of these firms.

INPI - Patents dataset The INPI (Instituto Nacional da Propriedade Industrial) dataset comprises detailed records of patent applications and grants in Brazil. It includes information on patent types, application dates, inventors, and assignees, as well as the legal status and classification of each patent. We use the INPI dataset to track patent applications for all individuals.

InovAtiva - Administrative database The InovAtiva administrative dataset comprises three interrelated databases, focusing on "approved participants," "entrepreneurs," and "evaluations." The first database contains records on approved participants, delineating their advancement through training stages and whether they completed the entire program. The entrepreneurs database captures personal details of the entrepreneurs, such as their CPF (Individual Registry), name, and location. Additionally, the evaluations database provides informations into the assessment process, detailing the evaluators assigned to each participant, the scores awarded, and the evaluators' recommendations concerning the acceptance of participants into the program. We integrate this dataset with the RAIS and CNPJ databases by the Individual Registry.

3.2 Summary statistics

Table 1 presents summary statistics for the 5,123 projects included in the study. The data indicate that 78.3% of participants are male, and 64.7% have tertiary education. The median age is 32 years, with 46.6% of individuals being above this median. In terms of racial composition, 74.4% identify as White, while 15.1% identify as Black or Brown. Additionally, 17.6% of participants were involved in the technology sector before treatment, and 20.5% held managerial positions prior to joining the program.

Table 1: Summary Statistics

Variable	All Mean
# of projects	5,123
Gender	0.783
Education Level	0.647
Age	0.466
White	0.744
Black/Brown	0.151
Technology Sector	0.176
Managerial Position	0.205
Observations	5123

Notes: The variables included in the table represent different characteristics of all individuals. Gender represents the proportion of individuals who are male. Education Level represents the proportion of individuals with tertiary education. Age represents the proportion of individuals with age above the median (32 years). White represents the proportion of individuals who identify as White. Black/Brown represents the proportion of individuals who identify as Black or Brown. Technology Sector represents the proportion of individuals involved in the technology sector before treatment. Managerial Position represents the proportion of individuals in managerial positions before treatment.

4 Empirical Strategy

Project selection may depend on unobserved characteristics and choices that affect both selection into the program and subsequent outcomes. To solve this endogeneity problem, we leverage the assignment of projects to evaluators in a judge IV design. We then estimate the following two-stage least squares model:

$$Y_{ict} = \gamma_{ct} + \alpha_i + \sum_{\tau \neq 0} \beta_\tau D_{ic} \mathbf{1}\{t - s = \tau\} + X_i + u_{it} \tag{1}$$

Where the first-stage is

$$D_{ic}\mathbf{1}\{t - s = \tau\} = \gamma_{ct} + \alpha_i + \psi_{ct}\hat{D}_{ic} + \nu_{it}$$

and the least squares regression is run separetly for each outcome. Here D_{ic} is an indicator for whether individual i in group c was treated, Y_{ict} if the observed outcome, γ_{ct} is the group-semester fixed effects, α_i is the individual fixed-effect, and X_i is a set of controls for individual characteristics, s is the semester where treatment started, and $\hat{D}_{ic}$ is our aggregate leniency measure. If the IV assumptions are satisfied, this analysis will recover a positive weighted effect of InovAtiva participation among compliers, where compliers are defined as individuals' projects that would have received a different assignment outcome had their project been assigned to different judges.

We measure judges' leniency using the mean attribution rate for their assignments. Specifically, we calculate the leniency of the judges to which individual i's project is assigned, $\hat{D}_{ic}$, as the *leave-one-out mean attribution rate (omitting i) for judges j(i) in the cohort (c)*. Let $Q_j(ic)$ be a dummy variable indicating the judge j assigned to individual i's project in group c. We first obtain the leave-one-out estimate of aggregate leniency of judges by running the following regression (Equation 2) and saving the predict values as $\hat{D}_{ic}$. This $\hat{D}_{ic}$ represents the leave-one-out estimate of aggregate leniency of judges j assigned to individual i's project in group c.

$$D_{ic} = \sum_{j \in \mathcal{J}(c)} \mu_j Q_j(ic) + u_{ic} \tag{2}$$

Two conditions for judge leniency to be a valid instrument and be interpretable as a positively weighted average of local treatment effects on compliers are relevance and exogeneity. As shown in Table 2, the F-test joint estimates for each $D_{ic}(\tau)$ are strongly significant, indicating the relevance of our instrument. Additionally, Table 3 demonstrates the the leniency approach addresses most of the imbalance present in the data. While gender remains significant at the 10% level, it becomes insignificant after applying Benjamini and Hochberg (1995) to solve the problem of multiple hypotheses testing. Nevertheless, we include gender as a control variable in the regressions.

Table 2: First Stage

Dependent Var.:	F-test (1st stage)
D_{ic-3}	16.960
D_{ic-2}	16.960
D_{ic-1}	16.960
D_{ic0}	16.960
D_{ic1}	16.960
D_{ic2}	16.960
D_{ic3}	17.942
D_{ic4}	18.754
D_{ic5}	19.478
D_{ic6}	19.857
D_{ic7}	19.411
D_{ic8}	20.806
D_{ic9}	20.806
D_{ic10}	20.806
D_{ic11}	16.611
Fixed-Effects:	
Group and time (ct)	Yes
Individual (i)	Yes
F-test P-value	$< 2.2\text{e-}16$

S.E.: Clustered by Individual. Results from Equation 4.

Table 3: Testing Balance

Variable	Treatment Mean	Control Mean	Diff p-value	Leniency p-value
Gender	0.805	0.773	0.0098***	0.0637*
Education Level	0.719	0.614	0.0007***	0.2536
Age	0.527	0.437	0.0043***	0.5945
White	0.763	0.735	0.0046***	0.8444
Black/Brown	0.133	0.159	0.0085***	0.6835
Technology Sector	0.197	0.166	0.0170**	0.4702
Managerial Position	0.242	0.188	0.0014***	0.6306
Observations	1580	3453	5123	5123

Notes: The variables included in the table represent different characteristics of the individuals in the treatment (2nd column) and control groups (3rd column). The 4th column (Diff p-value) shows the p-value of the difference in means between the treatment and control groups, and the last column (Leniency p-value) provides the p-value by applying our leniency IV methodology. Gender represents the proportion of individuals who are male. Education Level represents the proportion of individuals with a high level of education. Age represents the proportion of individuals with age above the median (32 years). White represents the proportion of individuals who identify as White. Black/Brown represents the proportion of individuals who identify as Black or Brown. Technology Sector represents the proportion of individuals involved in the technology sector before treatment. Managerial Position represents the proportion of individuals in managerial positions before treatment. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.

5 Results

The acceleration program aimed to foster innovation and support new entrepreneurs through training, mentorship, and network connections. To evaluate its effectiveness, we examine the long-term effects on patent applications and startup creation. Our analysis includes the entire sample and disaggregates the results by human capital levels[3], prior entrepreneurial experience[4], and employment status before entering the program[5]. This heterogeneity analysis is crucial to understanding the program's differential impacts, as these outcomes likely vary across these dimensions due to differences in access to opportunities, outside options, and risk-taking capacities.

5.1 Impacts on Innovation

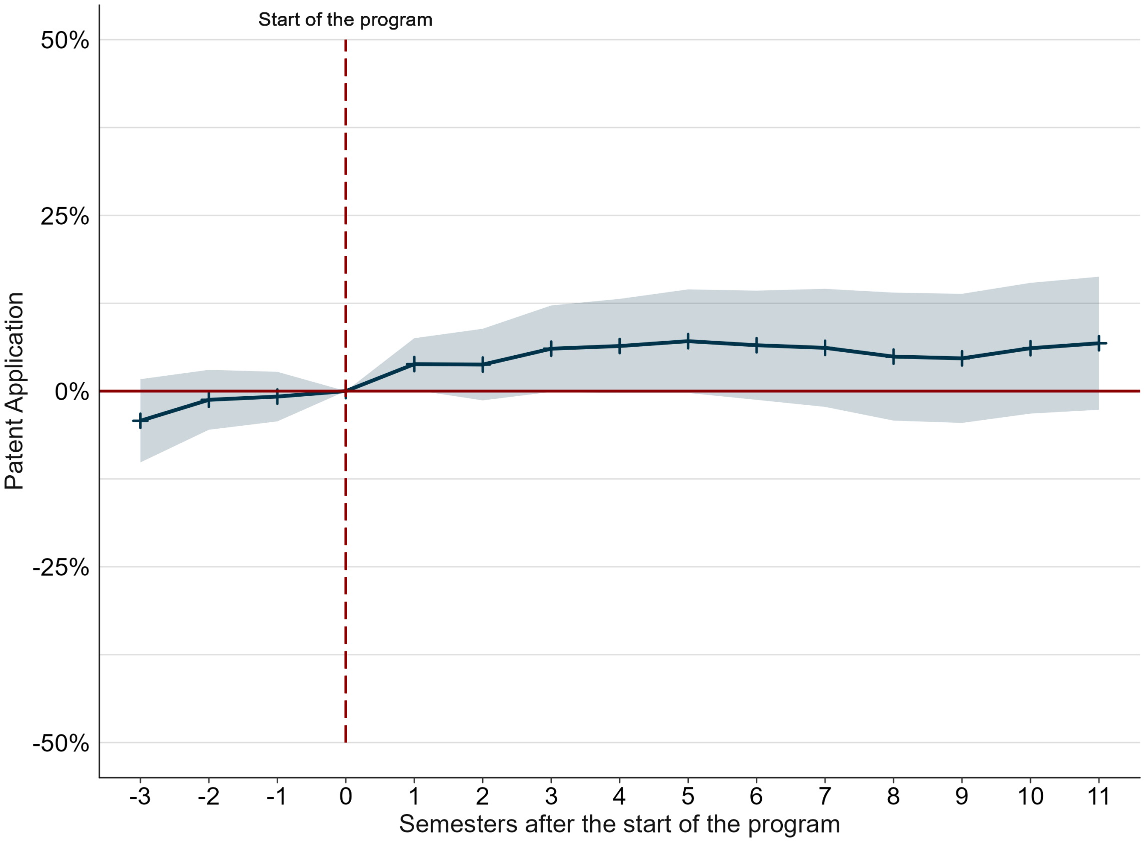
Figure 1 depicts the impact of the program on participants' initiative to innovate by applying for new patents. First, consider the impact on the entire sample. The effects are positive and statistically significant. Accelerated participants applied for patents at a higher rate than the control group, increasing from 3.84 percent in the first semester to 7 percent two years and a half after program participation. We further analyze the program's influence on patent applications across three subgroups, delineated by prior entrepreneurial experience, employment status before treatment, and educational background.

[3]"College Graduate" refers to individuals who had completed a college degree before treatment. "Not College Graduate" refers to individuals who had not completed a college degree before treatment

[4]"Entrepreneurial Experienced" refers to individuals who owned a firm five years prior to treatment; "Non-experienced" refers to individuals who did not own a firm five years prior to treatment

[5]"Employed One Year Before Treatment" refers to individuals who were working one year prior to treatment. "Not Employed One Year Before Treatment" refers to individuals who were not working one year prior to treatment

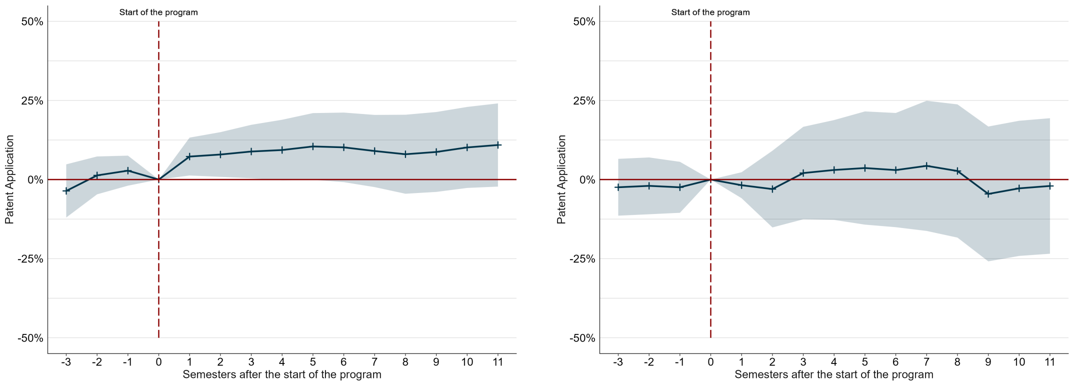
Figure 1: Patent Application



Note: Outcome variable: Patent assignment. This figure shows the probability of participants applying for patents after joining the InovAtiva program.

Entrepreneurial experience. Figure 2 illustrates the differential impacts on subgroups based on their prior entrepreneurial experience. Individuals with prior entrepreneurial experience may have existing skills and knowledge, established networks, higher risk tolerance, and greater efficiency in executing business ideas. These attributes can contribute to a higher baseline of innovation, enabling experienced entrepreneurs to benefit more from the program's resources. Our results show that the propensity to apply for patents is significantly higher among individuals with prior entrepreneurial activities, increasing from 7.26 percent in the first semester to 10.17 percent three years after program participation. In contrast, there is no significant impact on individuals without prior entrepreneurial experience.

Figure 2: Experience x Non-experience

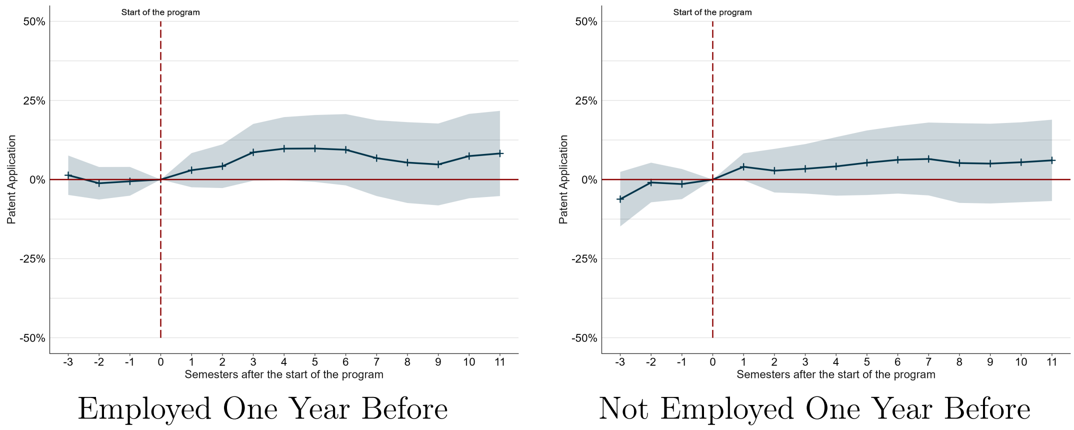


Experienced | Non-experienced

Note: This figure compares patent application rates between individuals with prior entrepreneurial experience and those without such experience. Sample definitions: Experienced refers to individuals who owned a firm five years prior to treatment; Non-experienced refers to individuals who did not own a firm five years prior to treatment.

Employee Experience Figure 3 presents subgroup effects based on employment status one year before treatment. Employment status one year before can represent job security, income stability, transferable skills, professional networks, and the opportunity cost of leaving a stable job to pursue entrepreneurship. Individuals employed prior to participation exhibit sustained patent application activity into the second year post-training (8.59 percent to 9.81 percent three semesters later), whereas those unemployed show this propensity only in the first semester following training. This difference suggests that employed individuals might leverage their job-related skills, networks, and stability to persist in innovative activities, whereas unemployed individuals may face greater financial pressure and uncertainty, limiting their ability to sustain such activities over a longer period.

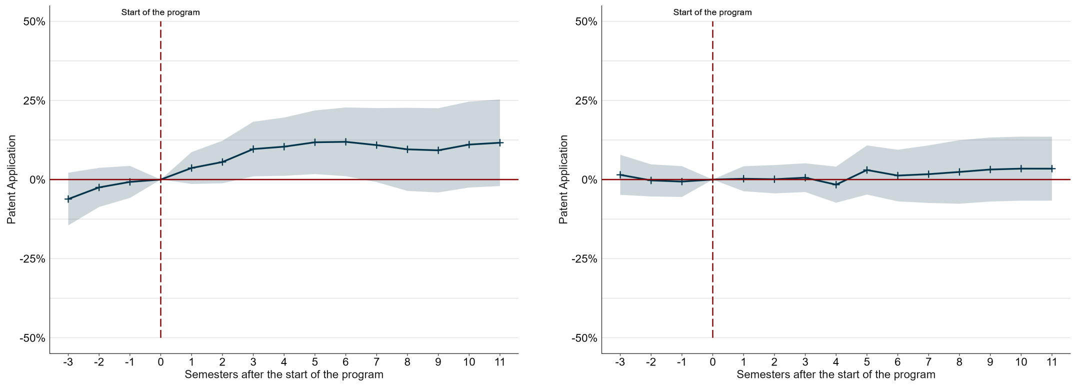
Figure 3: Employee experience



Note: This figure illustrates the patent application rates among individuals employed one year before treatment and those not employed in the same period. Sample definitions: Employed One Year Before Treatment refers to individuals who were working one year prior to treatment. Not Employed One Year Before Treatment refers to individuals who were not working one year prior to treatment.

Educational Background. Figure 4 compares the patent application rates between college graduates and non-graduates. A higher human capital can represent advanced knowledge and skills, enhanced problem-solving abilities, better access to resources, credibility, and networks. Additionally, college graduates face higher opportunity costs when pursuing entrepreneurship due to potentially lucrative job offers in the traditional labor market. These factors can contribute to a higher capacity for innovation. The findings indicate a pronounced positive effect on those with higher educational attainment, with patent application rates increasing from 4.39 percent in the second year to 5.96 percent five semesters later. In contrast, we find no significant impact for non-graduated individuals.

Figure 4: College graduate x Not college graduate



College graduate Not college graduate

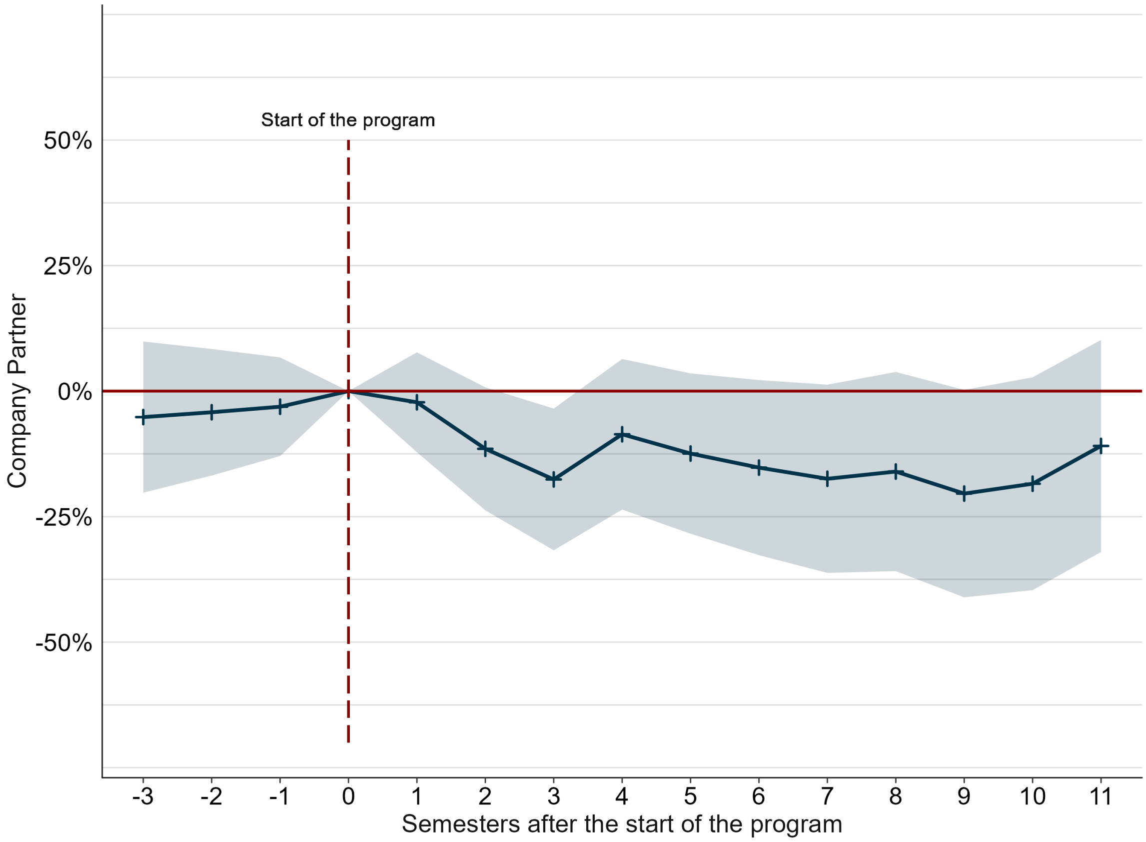
Note: Outcome variable: Patent assignment. This figure shows the probability of participants applying for patents after joining the InovAtiva program. Sample definitions:: "College Graduate" refers to individuals who had completed a college degree before treatment. "Not College Graduate" refers to individuals who had not completed a college degree before treatment.

In summary, the InovAtiva program significantly boosts the likelihood of patent applications among participants, with pronounced positive effects observed in subgroups characterized by prior entrepreneurial experience, prior employment, and higher educational attainment. These findings emphasize the program's role in fostering innovation, particularly among individuals with existing skills, networks, and higher human capital, while the effects are less pronounced or non-existent for those without such backgrounds. This section has demonstrated the program's efficacy in enhancing innovative capacities. Next, we explore how these effects translate into entrepreneurial outcomes.

5.2 Impact on Entrepreneurship

Figure 5 illustrates the effect of the InovAtiva program on the probability of an individual becoming a partner in a company, considering the entire sample. One year after treatment, there is a 17.4 percent decrease in the probability of an individual becoming a partner, and this effect persists in subsequent years, averaging a 15 percent decrease. Since InovAtiva selects participants based on their projects, the program provides valuable feedback for entrepreneurs. Participants receive comprehensive training and have individual contact with entrepreneurship specialists, enabling them to obtain rapid feedback on the viability of their business ideas. These findings suggest that participants may be reevaluating their entrepreneurial ventures after receiving important information from the program.

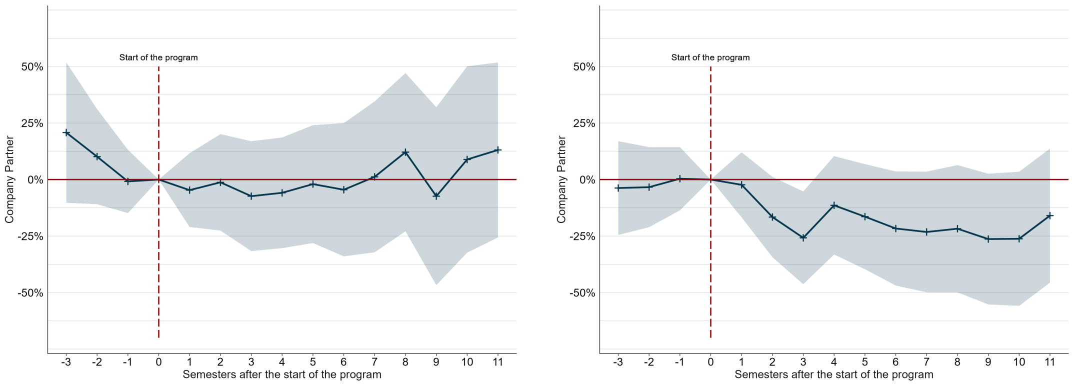
Figure 5: Entrepreneurship



Note: Outcome variable: Company partner. This figure shows the probability of participants becoming partners in a company after joining the InovAtiva program. Sample definitions: Experienced refers to individuals who owned a firm five years prior to treatment; Non-experienced refers to individuals who did not own a firm five years prior to treatment.

Entrepreneurial Experience. Given that information is crucial in the decision to start a business, it is important to examine the heterogeneity among those who already had experience in owning a company. Our findings reveal no significant difference between subgroups with recent entrepreneurial experience. However, we observe significant effects among individuals with more than five years of experience. Figure 6 indicates no significant impact on individuals who had owned a business five years before the program's inception. In contrast, individuals without five years prior entrepreneurial experience (Figure 6) are significantly less likely to start a business after receiving InovAtiva training, with the likelihood of becoming a company partner decreasing from 16 percent in the second semester to 26.2 percent five years later. This suggests that the training and feedback provided by InovAtiva help inexperienced individuals make more informed decisions about the feasibility of their business ideas.

Figure 6: Experience x Non-experience



Experienced more than 5 years — Non-experienced more than 5 years

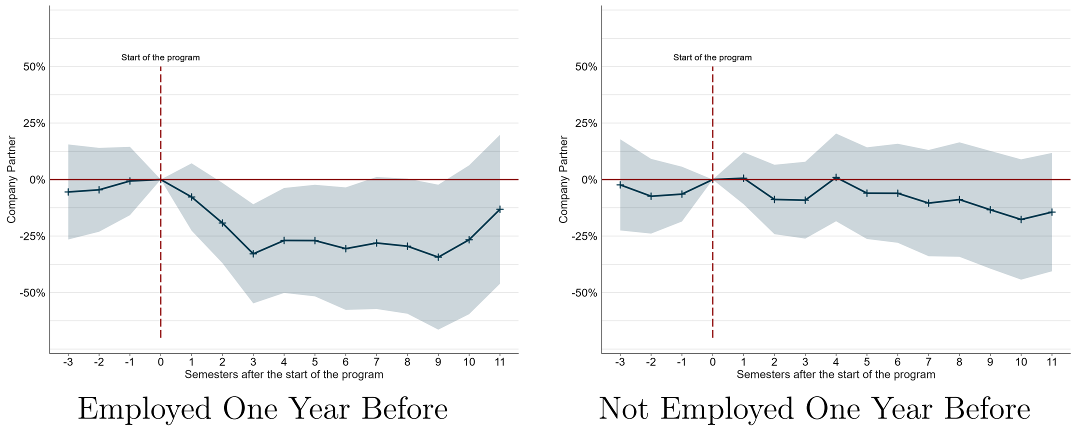
Note: Outcome variable: Company partner. This figure compares the probability of starting a business between individuals with prior entrepreneurial experience and those without. Sample definitions:: Experienced refers to individuals who owned a firm five years prior to treatment. Non-experienced refers to individuals who did not own a firm five years prior to treatment.

Employee Experience. In this analysis, we examine the effect of previous employment status on the likelihood of participants starting a business after participating in the InovAtiva program. Specifically, we investigate those employed one year before treatment (Employed One Year Before Treatment). The results reveal significant differences in entrepreneurial outcomes based on the employment history. Our analysis indicates a significant decrease of 28 percent on average in the probability of starting a business post-treatment for the group that already had a job before treatment.

This suggests that those with work experience might reassess the viability of entrepreneurial ventures more critically. The specialized feedback and training provided by the InovAtiva program likely reinforce this reassessment, leading them to favor more secure employment options over the uncertainties of starting new businesses. These individuals might prioritize stability and leverage the skills acquired from the program to enhance their prospects within the labor market rather than engaging in new business ventures.

Conversely, for the groups categorized as Not Employed One Year Before Treatment, there are no statistically significant changes in the probability of starting a business post-treatment. The absence of significant impact for this group suggests that the lack of recent employment does not materially alter their entrepreneurial inclination. These individuals may either lack the experience to effectively leverage the program's resources for business creation or may not perceive substantial changes in their opportunity cost post-treatment.

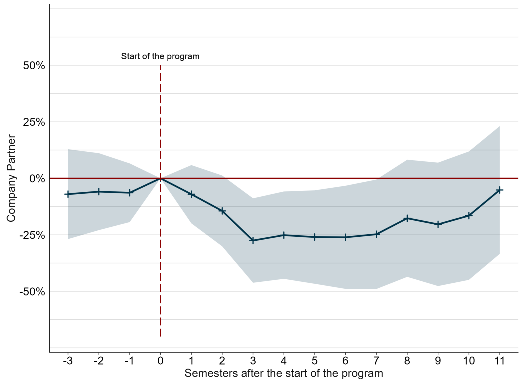
Figure 7: Employee experience



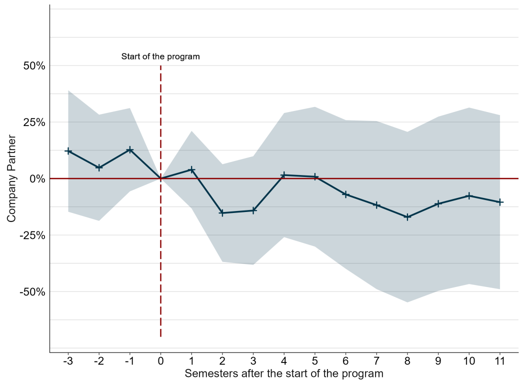
Note: This figure examines the impact of previous employment status on the likelihood of starting a business after the InovAtiva program. Sample definitions: Employed One Year Before Treatment refers to individuals who were working one year prior to treatment. Not Employed One Year Before Treatment refers to individuals who were not working one year prior to treatment.

Educational Background. Having examined the roles of prior experience and employment status on entrepreneurship, we now turn to the differences in human capital levels, specifically comparing college graduates and non-college graduates before treatment. As shown in Figure 8, highly educated individuals exhibit a significant decrease in the probability of starting a business, with an average reduction of 22 percent five years after program participation. These individuals have more alternative options in the labor market and may possess prior knowledge that aids in their decision-making process regarding entrepreneurship. With greater access to alternative opportunities and pre-existing knowledge, they are likely better equipped to critically assess their business prospects and opt for more secure career paths.

Figure 8: College graduate x Not college graduate



College graduate



Not college graduate

Note: This figure shows the probability of starting a business between college graduates and non-graduates. Sample definitions: "College Graduate" refers to individuals who had completed a college degree before treatment. "Not College Graduate" refers to individuals who had not completed a college degree before treatment.

Overall, the InovAtiva program significantly reduces the likelihood of participants becoming partners in a company, particularly among those without prior entrepreneurial experience, those employed before the program, and highly educated individuals. These findings suggest that the program's training and feedback help participants make more informed decisions about their business ventures, leading many to opt for more secure career paths rather than pursuing entrepreneurship. Consequently, in the next section, we examine the program's effect on the labor market.

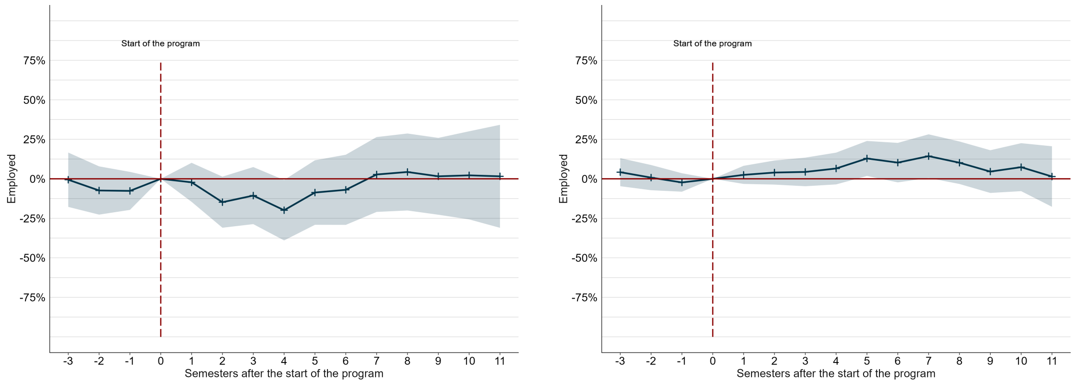
5.3 Labor market

In this section, we examine the trends in the labor market following participation in the InovAtiva program. Figure 9 demonstrates a decline in the probability of employment by 14.7 percent and 19.87 percent one and two years post-treatment, respectively. However, there is no significant effect in subsequent years, suggesting a temporary dislocation rather than a prolonged impact on employment probabilities.

Furthermore, when focusing on employment in managerial roles (Figure 9), we observe an increase in the likelihood of securing such positions. Two years post-treatment, the probability of being employed as a manager is 12.87 percent, increasing to 14.34 percent one and a half years later. This suggests that while initial job losses may occur as participants leave previous positions, they effectively leverage their enhanced skills to ascend to higher-level roles within the labor market.

On the next analysis, we look at the effects on individuals with different educational background, in order to compare the different effects between groups with different outside options and possible opportunities on the labor market.

Figure 9: Employment

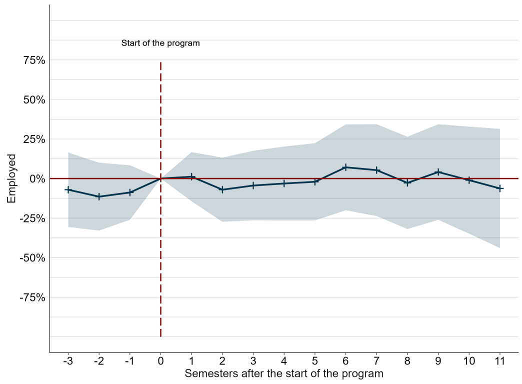


Employed | Employed as Manager

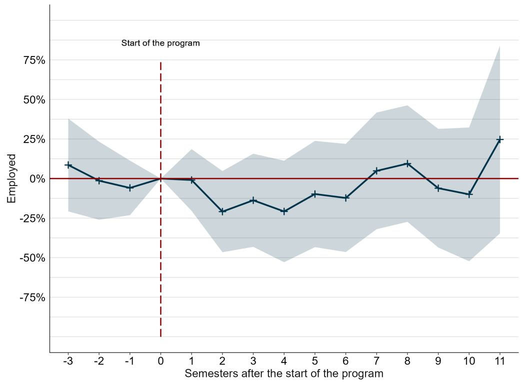
Note: This figure illustrates the changes in the probability of being employed and securing managerial positions among participants of the InovAtiva program.

Educational Background. An analysis of employment outcomes relative to different educational attainment groups reveals no significant overall changes in employment status. However, individuals with higher education levels exhibit a 14.02 percent increase in the likelihood of obtaining managerial position four semesters after completing the training, and this positive effect remains for two years, averaging an 18.3 percent increase, as illustrated in Figure 10). These findings shows the effects of the InovAtiva program on labor market transitions, accentuating the capacity of participants to extend the skills acquired into career advancements, particularly in managerial roles. This analysis also suggests a stratification of benefits, with more educated participants more likely to leverage opportunities for upward mobility.

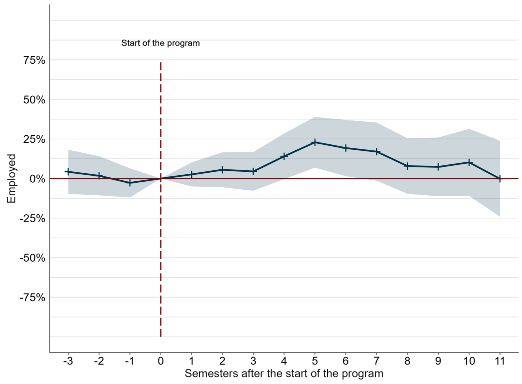
Figure 10: Employed - College graduate x Not college graduate



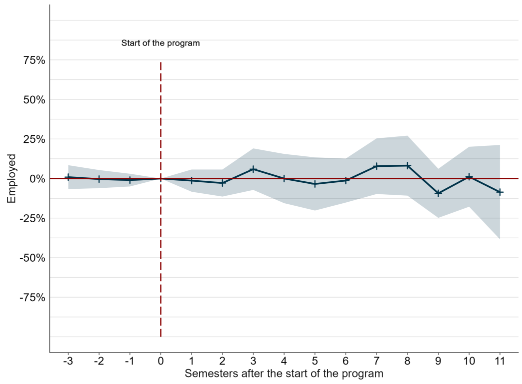
College graduate



Not college graduate



College graduate - Manager



Not college graduate - Manager

Note: This figure shows the likelihood of participants being employed and securing managerial positions after the InovAtiva program between college graduates and non-graduates.

6 Discussion

This study evaluates the impact of startup accelerator programs on innovation, entrepreneurial activities, and labor market outcomes. Our findings show that participation in the program increases the likelihood of patent applications by over 5% for three years post-treatment. On the other hand, the probability of becoming a company partner decreases by more than 15%, particularly for individuals with higher human capital and prior employment. In the labor market, participants experience a short-term drop in employment probability but an increased likelihood of securing managerial positions, particularly among those with higher education. These results suggest that the accelerator program's feedback and training foster a "survival of the fittest" dynamic, supporting individuals with higher innovation potential and entrepreneurial experience.

Our findings align with Yu (2019), who found that accelerator feedback leads to more efficient investment outcomes, prompting underperforming companies to close down earlier and more often while raising less money compared to non-accelerator companies. In our study, we show that this feedback can be crucial even at the project level before substantial investments are made. This early-stage feedback likely leads to more efficient investment and career decisions, reducing entrepreneurial activities among those with viable labor market options. Intensive training and feedback from accelerators prompt participants to reassess the viability of their ventures, leading to a more efficient allocation of resources and better career choices, redirecting those less suited for entrepreneurship towards stable employment paths.

These findings are in line with González-Uribe (2021), who showed that accelerators help identify high-potential entrepreneurs by easing constraints on firm capabilities and unlocking the potential of innovative entrepreneurs but do not turn subpar ideas into high-growth firms. Our results confirm that startup accelerators program can significantly increases the likelihood of patent applications among participants with higher human capital and entrepreneurial experience, emphasizing their role in enhancing the capabilities of already promising individuals rather than transforming less viable ideas into successful ventures.

By demonstrating that non-financial support can significantly impact entrepreneurial and innovation outcomes, this study supports the idea that information and mentorship are critical components of successful entrepreneurship programs. This finding echoes McKenzie (2017), who found that business plan competitions with mentorship components led to higher firm entry and survival rates. Furthermore, Bloom et al. (2012) showed that providing free consulting on management practices significantly improves productivity and leads to the expansion of production plants. They also pointed out that information barriers were the main reason preventing firms from adopting profitable practices before the consultation.

Our results also reveal a spillover effect of startup accelerator programs at the project level by providing management knowledge to participants. We find that the program's training and feedback mechanisms enhance participants' managerial employment prospects, providing them with skills and knowledge. This enables to pursue more stable and higher-level employment opportunities instead of entrepreneurial risk-taking.

Startup accelerator programs can boost innovation among high-potential individuals while guiding others toward more secure employment paths. By providing feedback and mentorship, these programs help participants make informed career choices, ultimately fostering a more efficient and dynamic entrepreneurial ecosystem. The impact of startup accelerator program on innovation, entrepreneurship, and labor market outcomes shows their capacity to select and nurture high-potential entrepreneurs. By providing targeted training and feedback, the program reshapes participants' career paths, aligning with the broader literature on the benefits and limitations of accelerator programs.

7 Conclusion

This study evaluates the impact of the InovAtiva program on innovation, entrepreneurial activities, and labor market outcomes. Participation in the program increases the likelihood of patent applications while also altering participants career by reducing the likelihood of starting new businesses and enhancing prospects for managerial employment.

The program significantly boosts innovation, as evidenced by an increase in patent applications by over 5% for three years post-treatment. This positive effect is primarily driven by individuals with higher human capital and entrepreneurial experience, demonstrating the program's effectiveness in fostering innovative activities among the most capable participants.

Conversely, we find an decrease in entrepreneurial activities, particularly among individuals without prior business experience and those with viable labor market options, especially those with higher education and prior employment. This suggests that the program's intensive training and feedback mechanisms prompt participants to reassess the viability of their entrepreneurial ventures, ultimately opting for more secure career paths. The role of education is equally important; highly educated participants tend to leverage the skills and knowledge gained from the program to secure managerial positions, reflecting a strategic shift towards stable employment rather than entrepreneurial risk-taking.

Overall, the InovAtiva program, through targeted training and feedback, influences innovation while simultaneously reducing entrepreneurship and boosting managerial employment. This demonstrates its ability to identify and support the most promising and innovative entrepreneurs effectively.

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A Coefficients Tables

A.1 Innovation

	All	College Degree		Entrepreneurial Experience		Prior Employment	
		Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	0.0595*	0.0980**	0.0186	0.0898*	0.0031	0.0650	0.0420
	(0.0325)	(0.0447)	(0.0312)	(0.0461)	(0.0705)	(0.0452)	(0.0418)
pvalue	0.06721	0.02839	0.55257	0.05165	0.96538	0.15068	0.31471
Observations	51,991	32,852	13,232	28,196	11,565	22,982	29,009
Group-year and id F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered (id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.2 Entrepreneurship

	All	College Degree		Entrepreneurial Experience		Prior Employment		Experience > 5 years	
		Yes	No	Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	-0.1145*	-0.1739*	-0.0580	-0.0384	-0.0644	-0.2146**	-0.0759	-0.1771*	-0.0079
	(0.0692)	(0.0893)	(0.1304)	(0.0735)	(0.1032)	(0.1047)	(0.0842)	(0.0995)	(0.1210)
pvalue	0.09777	0.05144	0.65640	0.60137	0.53248	0.04056	0.36749	0.07527	0.94779
Observations	51,991	32,852	13,232	28,196	11,565	22,982	29,009	33,389	6,372
Group-year and id F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered (id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.3 Labor market

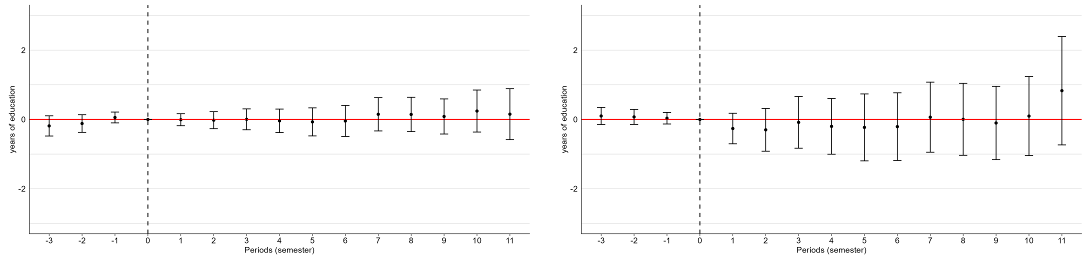
	Employed			Employed as manager		
	All	College Degree		All	College Degree	
		Yes	No		Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.0620	-0.0007	-0.1019	0.0719*	0.1103*	-0.0031
	(0.0819)	(0.1013)	(0.1276)	(0.0414)	(0.0578)	(0.0536)
pvalue	0.44912	0.99443	0.42499	0.08265	0.05630	0.95327
Observations	46,559	29,091	11,934	46,559	29,091	11,934
Group-year and id F.E	Yes	Yes	Yes	Yes	Yes	Yes

Clustered (id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

B Further Analysis

B.1 Years of education

Figure 11: Years of education



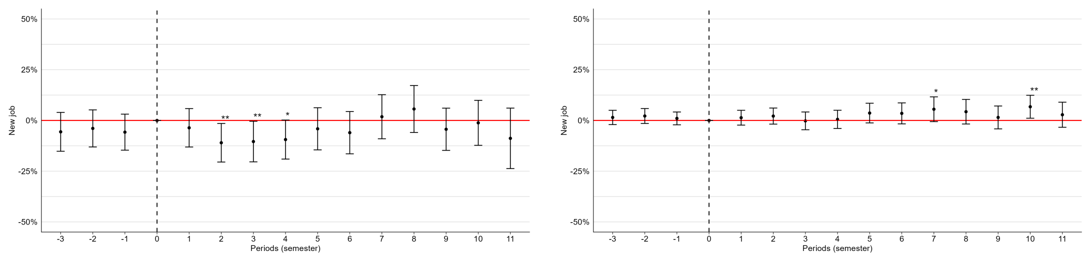
All   Not college graduate

Note:

B.2 New Job Acquisition

Additionally, we investigate whether participants are benefiting from securing new jobs post-treatment. According to Figure 12, in the first two years after treatment, participants have a 10% lower probability of obtaining new jobs compared to non-treated individuals. However, after three years, participants tend to secure new managerial positions, indicating a positive impact of the program on career advancement (Figure 12).

Figure 12: New job

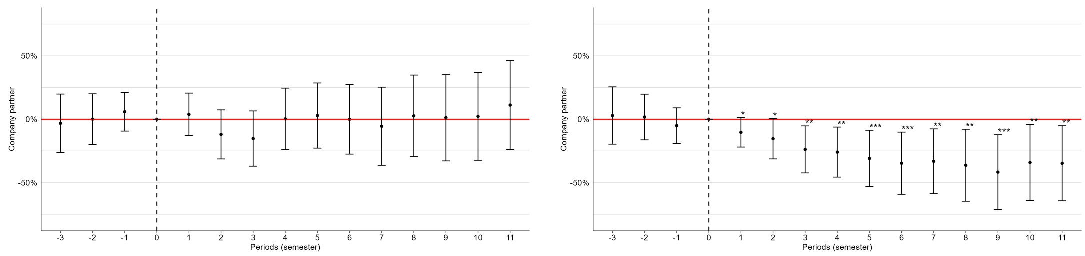


New job   New job as Manager

Note:

B.3 Age

Figure 13: Age



Younger Older

Note: Sample definitions:: Younger refers to individuals whose age before treatment was below the median age of 32. Older refers to individuals whose age before treatment was 32 or older.