



Vigilada Mineducación

SCALING NEW VENTURES WITH PUBLIC FUNDING: ASSESSING A
BUSINESS ACCELERATION PROGRAM IN A DEVELOPING COUNTRY

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Tesis para optar al grado de Magíster en Economía Aplicada

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Scaling new ventures with public funding: Assessing a business acceleration program in a developing country

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Abstract: A debate on whether new ventures should be supported or not with public funding is alive. Taking a position in this discussion requires rigorous assessments of implemented programs. However, a few efforts mostly focused on regional cases in developed countries exists. By filling up this gap, our paper seeks to measure the effects of a regional acceleration program from Medellín, Colombia. We take support from capabilities theory, which sets the basis to suggest different firm characteristics that help with the identification of an appropriate impact evaluation modeling through propensity score match, using a sample of 60 (treatment) and 16,994 (control) firms. Our matching results indicate that treated firms had a higher revenue on average than control firms, confirming a positive impact on growth measures. However, such financial growth is mostly observed in service firms as compared to other economic sectors. These findings tip the balance in favor of the literature suggesting supportive programs for high-growth firms as opposed to everyday entrepreneurship. Further evaluations, with a longer time span, and using more outcome variables, are suggested in the context of similar public funded programs in developing countries.

Keywords: Entrepreneurship; impact evaluation; public funds; acceleration programs; developing countries

JEL Classification: L26; D04; E6; R58

1. Introduction

Entrepreneurship policy is a matter of concern for governmental policies due to the importance of entrepreneurial activity for creating economic growth, employment opportunities, and total factor productivity (Cho & Honorati, 2014; Urbano & Aparicio, 2016). According to Audretsch et al. (2020), these policy initiatives for incentivizing entrepreneurship often means programs, schemes or plans implemented with the aim of supporting the establishment or development of

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entrepreneurial activity, with special focus on mitigating any or several constraints faced by the entrepreneurs in the initial stages of the venture creation.

Some literature suggests that the support should be equal to all kinds of entrepreneurial initiatives as inclusive programs (e.g., acceleration) would help regions in one way or another (Welter et al., 2017). However, when it comes to public funding, a debate on whether some ventures should be supported as compared to others is still open (Acs et al., 2016). For example, although entrepreneurial activity is desirable in an economy, entrepreneurship policy is sometimes related to undesired outcomes. Encouraging the creation of average start-ups can result in low productivity firms that creates few jobs and little wealth (Shane, 2009). This brings different challenges when implementing a policy. On the one hand, policymakers should focus on detecting and fostering high growth and innovative startups with high survival rates (Colombelli et al., 2016), which are prone to generate creative destruction (Clarysse et al., 2015). On the other hand, this process of selecting high-growth startups is difficult to carry out, based mainly on two reasons. First, there is a well-known scarcity of these kinds of companies in developing economies as compared to developed countries (Eslava et al., 2019; Puente et al., 2019). Second, even under optimal conditions, government is probably not in the capacity of deciding over variables than even venture capital professionals find difficult to predict (Coad et al., 2014; Kantis et al., 2020).

Under this scenario, is both/either the government and/or any other organization able to effectively select high-growth startups and accompany them to alleviate their constraints for growth? In this context, the public-private partnership takes place to better identify and publicly support firms with high-growth potential. As part of an entrepreneurship ecosystem (Wurth et al., 2021), the public-private partnership enables private business accelerators manage public funding to “pick the winners” and develop an important role in entrepreneurship policy. These accelerators focus on stimulating start-up activity in their focal region, selecting high-growth

firms, and alleviating their constraints for growth using different strategies, such as working space, money, mentoring, and/or guidance (Clarysse et al., 2015).

Given its growing popularity, importance, and the (public) budget devoted to support entrepreneurship policies, it becomes relevant to measure the effects of accelerator programs on the ventures that get accepted to these programs. However, there is a gap in this literature as only a few studies evaluating the impact of business accelerators exists (González-Uribe & Reyes, 2020; Hallen et al., 2020). To some extent, this limitation is explained because each program has different settings depending on geography and the ability to provide high quality guidance to startup companies (Bone et al., 2017; Fairlie, 2021; Kantis et al., 2021). These specific settings can either positively or negatively impact the results on a regional level. From a taxpayer point of view, it is relevant to know whether to fund an acceleration program—intended to allocate entrepreneurial resources efficiently, alleviate constraints for growth, and build firm capabilities—entails a good use of public money or not.

Despite the efforts so far, an important shortcoming is observed when fewer studies on impact evaluation devote attention to supportive programs in developing countries (Kantis et al., 2020; Srhoj et al., 2021), which is needed for promoting discussion around the topic, as well as achieving better public policy design. Being aware of the limitations in the existing literature, this research aims to answer the following question: Does a public funded accelerator program really help new ventures grow?

Hence, this paper seeks to measure the effects of a local acceleration program from Medellín, Colombia. The acceleration program is operated by Créame, which is a private, nonprofit institution founded in 1996 in Medellín by several public and private partners that were seeking an effective way to promote entrepreneurial activity in a city devastated by violence, poverty, and social exclusion. The program operates as a traditional accelerator with a sponsorship scheme provided by the Mayor's Office of Medellín, and is focused solely on

high-impact ventures, which are selected in each acceleration cohort using a highly selective approach that results in a score above or below the cutoff to enroll in the program considering several variables, such as business sector, sales, company age, and technological processes used for companies' operation. The program is 24 weeks long and has different modules, with a special focus on financial training and assessment.

To answer our research question, we take support from (firm) capabilities theory (Sutton, 2012). Thanks to this framework, we empirically analyze a sample of 60 (treatment) and 16,994 (control) ventures, which comes from the Créame's database, as well as the Chamber of Commerce of Medellín. Using propensity score matching, we find that the acceleration program has helped the treated firms to achieve financial growth as compared to ventures with similar characteristics but out of the program.

Based on our findings, we provide three contributions to literature. First, we acknowledge prior efforts in empirically evaluating entrepreneurship supportive programs (for a thorough review, see Dvouletý et al., 2020). However, entrepreneurship research still needs evidence on the real benefits (or losses) stemmed from initiatives funded with public budget. Our study sheds some light on that direction. Second, entrepreneurship policies have opened a debate amongst scholars, in which the selection criteria have been reduced to characteristics such as innovation, technology-based, that ultimately become high-growth entrepreneurship (cf. Shane, 2009), versus everyday entrepreneurship (cf. Welter et al., 2017). We suggest that picking “winners” or “losers” before the treatment would necessarily lead positive results. Finally, we contribute to policymakers by emphasizing the selection criteria in a region such as Medellín, which is part of a developing country. This entails a discussion about the quality of policy design, including implementation and assessment with clear information for impact evaluation.

After this introduction, the paper continues as follows. Section 2 focuses on the case of Medellín, which motivates the use of (firm) capabilities as the main theory that frames our literature analysis. Section 3 explains the methodological approach, including data and empirical strategy. Section 4 offers and explains the main findings, whereas Section 5 is devoted to the conclusions, contributions, limitations, and future research lines.

2. Background, framework, and literature review

2.1. Medellín as an entrepreneurial region in Colombia

Consistent with Baumol (1990), Medellín has shown different entrepreneurial dynamics. On the one hand, there has existed a long tradition of productive entrepreneurship in the region thanks to the creation and expansion of firms in industries such as food, concrete, insurance, banking, and public services (Álvarez Morales, 2005; Mejía, 2011). On the other hand, destructive entrepreneurs such as Pablo Escobar and other drug dealers, as well as military groups and guerrillas also emerged. As a result, Medellín suffered destruction of capital at the firm level, and poverty, violence, and inequality at the societal level. After fighting against drug dealers and guerrillas, Medellín was able to rebuild the city and achieve social inclusion.

Entrepreneurship and innovation have been key in such a process. Since the mid of the 2000s, Medellín has been well known in the Latin American spectrum for making public-private partnerships and investments to foster innovation and high-impact entrepreneurship, taking advantage of its dynamic ecosystem (Alcaldía de Medellín & Créame Incubadora de Empresas, 2018). Just in 2018, Medellín was the city with the highest research and development (R&D) budget in Colombia, measured as a percentage of GDP (Observatorio Colombiano de Ciencia y Tecnología, 2020).

Part of the policies applied in the city have been focused on tackling issues such as informality, unemployment, territorial competitiveness, and productive development.

Responding to the interesting ecosystem development throughout the 21st century, a complete economic development public policy was implemented in 2017, having a special core on solving the problem of high company mortality rate, and low innovative companies birth rate (García & Jaramillo, 2018). This policy was focused on grouping and coordinating some key ecosystem private actors that were initially functioning distant to each other, such as the Chamber of Commerce.

Thanks to this and previous dynamics, different private and public organizations have jointed the ecosystem. For example, programs such as “Parque E”, the first university incubator in the city, was born from an alliance between Mayor’s Office of Medellín and University of Antioquia, the most important public university in the region. Other relevant entrepreneurship programs in the city include “Cedezo” (with a special focus on everyday entrepreneurship), “Seed Capital” (public grant for high-impact entrepreneurship), and the accelerator program, funded by the Mayor’s Office and executed by Créame (Alcaldía de Medellín & Créame Incubadora de Empresas, 2018).

In general, the city has shown positive numbers in terms of entrepreneurial activity as it is one of the Colombian cities with the highest level of entrepreneurship (Gómez et al., 2011). Despite all these initiatives, the city has not conducted estimations that account for the net benefits or loses coming from (accelerator) programs as part of public policy.

It is important, then, to evaluate the first and only business acceleration program that is offered publicly with the sponsorship of the Mayor’s Office. It is also crucial to discover the role the acceleration program has played in last years, both in the city’s ecosystem and the companies that went through the program. Although the same environment surrounds these companies, there exist firm characteristics and capabilities that create heterogeneity, making difficult the selection of those ventures that can benefit from acceleration programs. This is

precisely one of the major issues when it comes to entrepreneurship policies as public funds might be wasted (Acs et al., 2016).

2.2. Theoretical framework

To see the effect of public funded programs on ventures growth, this research takes support from capabilities theory (Sutton, 2012), which considers firm capabilities as a set of elements of know-how or working practices of the group of individuals inside the company. Firm capabilities are relevant to partially explain productivity differences among firms (Syverson, 2011). Accordingly, firm capabilities constitute resources that could be misallocated, hence reducing intra-firm productivity and total factor productivity (Hopenhayn, 2014; Hsieh & Klenow, 2009).

As Butler et al. (2016) stated, the misallocation of entrepreneurial resources (i.e., when the entrepreneurial talent is not being fully exploited into firms) and economic resources in general, could account for most productivity differences across countries (Eslava et al., 2019). One of the main consequences of this misallocation of resources is the creation of firms with low productivity that do not account for a majority of job creation or aggregate wealth production.

This misallocation of entrepreneurial capacity is deeply related to occupational decisions faced by entrepreneurs: subsistence entrepreneurship (or self-employment) exists as a direct alternative to wage employment with fixed salaries, particularly in developing economies (Cho et al., 2016; Shane, 2009). In developed countries, where wages and wealth are higher on average, the opportunity costs of starting a company are higher (Cho & Honorati, 2014). This occupational decision is also constrained by several variables that must be taken into consideration, such as the lack of managerial skills that can reduce expected profits and survival probability of any new venture (Bloom et al., 2011; Mano et al., 2012).

For entrepreneurship policy design and accelerator programs focused on high-growth ventures, it is fundamental to create highly selective processes to pick the companies that have the most potential of economic impact (productivity, employment, and economic growth) (Autio & Rannikko, 2016). After completing this stage, the main challenge remaining is to make efforts to alleviate their constraints for building firm capabilities (González-Uribe & Reyes, 2020). A literature analysis can help us understand the mechanisms behind the relationship between supportive programs and firm capabilities for growth.

2.3. Literature review

There is a growing literature which aims at exploring the possible outcomes of using public resources to encourage new venture creation, firm growth, and its desirable results. In this sense, several authors have stated that fostering entrepreneurial activity is not a great usage of taxpayer's money, unless the public policy is focused on high-growth and high-impact ventures with a huge potential of job creation (Åstebro, 2017; Shane, 2009). Different authors emphasize the role of public policy in solving a clearly identified market failure related to constraints and firm capabilities (Acs et al., 2016; Åstebro, 2017; Lerner, 2012; McKenzie & Woodruff, 2014; Shane, 2009).

Business accelerators are now an important figure worldwide focusing on alleviating firms' constraints for growth, providing services through a highly selective, cohort-based program of limited duration (Clarysse et al., 2015; Shankar & Shepherd, 2019). The first accelerator program can be traced back to 2005 with the origin of Y Combinator, which was focused on digital startups and was funded mainly by venture capitalists based in San Francisco (Bone et al., 2017). Since the inception of the first accelerator program 15 years ago, numerous similar programs have appeared worldwide, also being established and financed by a variety of organizations.

Despite the differences between programs and settings specific to countries or sectors, there are four main mechanisms by which accelerators support entrepreneurship and innovation (Crişan et al., 2021). Namely, i) the validation of ideas and products, ii) the provision of product development, iii) support to increase market access and growth, and iv) support for innovation. Crişan et al. (2021) conclude that acceleration platforms have a key role in developing entrepreneurial climate and are perceived as vehicles that could revitalize industries and regions.

According to Clarysse et al. (2015), there are three accelerator archetypes based on their strategic focus. First, the investor-led accelerator, for companies seeking to maximize venture capital investment attractiveness. Second, the matchmaker accelerator, set up by corporates interested in providing services to stakeholders. And third, the ecosystem accelerator, with government agencies as the main stakeholder and the objective to stimulate startup activity in certain ecosystem. Moreover, this ecosystem accelerator archetype is the one in which is possible to find the conjunction between accelerator programs and entrepreneurship policy.

Given the importance of a well-justified entrepreneurship policy, there is also limited but growing body of literature evaluating and measuring the effects of singular entrepreneurship programs all around the world. Although there are important results to consider, studies are highly dependent on local specific patterns, both related to firms' dynamics and ecosystem dynamics (Kantis et al., 2021; Venâncio & Jorge, 2021). For example, regarding public grants for SMEs, Dvouletý et al. (2020) found positive effects of grants on firm survival, employment, and tangible assets, as well as mixed results about labor productivity and total factor productivity.

In the impact evaluation literature specifically focused on entrepreneurship policy, it is possible to find that the most common used outcome variables in the empirical models are profits and/or revenue, number of employers, and survival (Dvouletý et al. 2020; Kantis et al.,

2021). However, Audretsch et al. (2020) found that the results of these (and other) variables are highly skewed, and only a small group of outlier firms are driving the contributions in most evaluated policies.

It is relevant for public policy interventions to clearly identify the ventures that are moving the impact needle, using highly selective mechanisms to exclude the firms with less probabilities of success (Autio & Rannikko, 2016). One of these mechanisms to find high-impact, high-growth ventures is the propensity for process and product innovation of a given firm (Colombelli et al., 2016).

In the high-impact entrepreneurship policy scenario, there are two impact evaluation studies that show positive results over employment and firm survival, but mixed or inconclusive results over sales and revenue (Butler et al., 2016; Giraud et al., 2019). Nonetheless, McKenzie (2017) found positive results over employment, survival probability, sales, and profitability using similar settings that included business training and government grants.

Regarding more specific public policy interventions focused solely on business training, it is possible to identify different results. Bruhn et al. (2013) found positive effects on return-on-assets, total factor productivity, and employment in SMEs. For business training in survival entrepreneurship settings, de Mel et al. (2014) found significant impacts over profitability. Lastly, for business training focused on social entrepreneurship, Åstebro & Hoos (2021) found positive significant effects on entrepreneurial activities up to three years after the intervention.

For impact evaluations of business accelerator programs, it is possible to identify positive effects on capital raised and firm survival (Gonzalez-Uribe & Leatherbee, 2017; (Hallen et al., 2020; Venâncio & Jorge, 2021), employment and valuation (Gonzalez-Uribe & Leatherbee, 2017), and revenue (Autio & Rannikko, 2016; González-Uribe & Reyes, 2020). The evaluations by Gonzalez-Uribe et al. (2017; 2020) provide a relevant benchmark for our

research, given the similar settings both in terms of geographical context (i.e., developing country) and business accelerator archetype context (i.e., ecosystem accelerators).

Also, there are some studies that have used matching methods to evaluate different entrepreneurship programs executed with public funds. Due to the variety of programs, each study focused on particular outcome variables, being sales or revenue the one that was common to all matching studies. Regarding sales, three of these studies found positive effects of the program (Autio & Rannikko, 2016; Fairlie, 2021; Nyikos et al., 2020; Oh et al., 2009). The remaining studies found either negative or non-significant effects of the program ((Dvouletý et al., 2018; Efobi & Orkoh, 2018; Norrman & Bager-Sjögren, 2011). For a summary of the literature on impact evaluation of public entrepreneurship programs, see Table 1.

Table 1. Impact evaluations of entrepreneurship programs.

Author(s)	Title	Type of Program	Country	Evaluation Method	D. variable (Outcome)	Were expected results achieved? (Program Impact)
1. González-Uribe & Reyes (2020)	Identifying and Boosting "Gazelles": Evidence from Business Accelerators	Business Accelerator (Public)	Colombia	Instrumental variables	Revenue	Yes
2. Gonzalez-Uribe & Leatherbee (2017)	The Effects of Business Accelerators on Venture Performance: Evidence from Start-Up Chile	Business Accelerator (Public)	Chile	Regression discontinuity design (RDD)	Performance proxies (Capital raised, valuation, sales, # employees, survival).	Yes
3. McKenzie (2017)	Identifying and Spurring High-Growth Entrepreneurship: Experimental Evidence from a Business Plan Competition	Business Training Course (Public)	Nigeria	Randomized experiment	Survival; # Employees; Sales; Profits; Firm+10Workers; Firm+25Workers	Yes
4. Hallen, Cohen, & Bingham (2020)	Do accelerators work? If so, how?	Business Accelerator (Private)	USA	Logit; quasi-Regression discontinuity	Survival; Capital raised; Web traffic (proxy of traction)	Yes (Survival) No (Traction)

				design (RDD) ³		
5. Butler, Galassi, & Ruffo (2016)	Public funding for startups in Argentina: an impact evaluation	Grants (Public)	Argentina	Regression discontinuity design (RDD)	Survival; Revenue; Employment	Yes (Survival) No (Revenue) Yes (Employment)
6. Autio & Rannikko (2015)	Retaining winners: Can policy boost high-growth entrepreneurship?	Business Accelerator (Public)	Finland	Propensity score matching; Difference in differences	SalesGrowth: (log difference of sales between the year before and three subsequent years after the program).	Yes
7. de Mel, McKenzie, & Woodruff (2014)	Business training and female enterprise start-up, growth, and dynamics: Experimental evidence from Sri Lanka	Business Training Course (Public)	Sri Lanka	Randomized experiment.	Monthly profits; Monthly sales; Capital stock	Yes ⁴
8. Bruhn, Karlan, & Schoar (2013)	The Impact of Consulting Services on Small and Medium Enterprises: Evidence from a Randomized Trial in Mexico	Subsidized consulting services (Public)	México	Randomized experiment.	Profits; Return-on-assets; Productivity residual; Employment	No (Profits) Yes (ROA) Yes (TFP) Yes (Employment)
9. Åstebro & Hoos (2021)	Impact measurement based on repeated randomized control trials: The case of a training program to encourage social entrepreneurship	Business training (Public)	France	Randomized experiment.	Entrepreneurial activity; New venture creation	Yes
10. Nkiyos, Béres, Laposa, & Zavecs (2020)	Do financial instruments or grants have a bigger effect on SMEs' access to finance? Evidence from Hungary	Grants (non-refundable) & financial instruments (refundable) ⁵ (Public)	Hungary	Propensity score matching; DiD	Employment; Sales; Productivity	Yes (Employment) Yes (Sales) No (Productivity)
11. Oh, Lee, Heshmati, & Choi (2009)	Evaluation of credit guarantee policy using propensity score matching	Credit guarantee (Public)	South Korea	Propensity score matching	Sales; Employment; Wage; Survival; TFP	Yes (Sales, Employment, Wage, Survival) No (TFP)

³ Due to the ventures not being classified with a specific score, the authors were able to use a method stylistically similar, but not the same, as the RDD approach.

⁴ Business training was found useful only for second group: women entrepreneurs that were interested in starting a business and were not already the owners of one.

⁵ Financial instruments in this context refer to repayable tools such as loans, guarantees, equity and venture capital.

12. Norrman & Bager-Sjögren (2011)	Entrepreneurship policy to support new innovative ventures: Is it effective?	Business Accelerator & Grant (Public)	Sweden	Matching pair analysis	Sales; Assets; Employment	No
13. Efobi & Orkoh (2018)	Analysis of the impacts of entrepreneurship training on growth performance of firms: Quasi-experimental evidence from Nigeria	Business Training Course (Public)	Nigeria	Propensity score matching; DiD	Sales; Innovation; Employment	No (Sales) Yes (Innovation, Employment)
14. Dvouletý (2017)	Effects of Soft Loans and Credit Guarantees on Performance of Supported Firms: Evidence from the Czech Public Programme START	Soft loans & credit guarantees (Public)	Czech Republic	Propensity score matching	Sales; Return on Assets (ROA); Return on Equity (ROE);	No (Either negative effect or not statistically significant effect).
15. Dvouletý, Longo, Blažková, Lukeš, & Andera (2018)	Are publicly funded Czech incubators effective? The comparison of performance of supported and non-supported firms	Business incubation (Public)	Czech Republic	Propensity score matching	Sales; Asset turnover; Personnel costs; Total assets	No (Either negative effect or not statistically significant effect).
16. Smith & Hannigan (2015)	Swinging for the fences: How do top accelerators impact the trajectories of new ventures	Business accelerator (Private)	USA	Probit; Coarsened Exact matching (CEM).	TimeToExit; TimeToQuit; TimeforVCRound	Yes ⁶
17. Fairlie (2021)	Evaluating entrepreneurship training: How important are field experiments for estimating impacts?	Business training (Public)	USA	Nearest-neighbor matching; Propensity-score matching	Business ownership; Monthly sales; Employment	Yes
18. Venâncio, A. & Jorge (2022)	The role of accelerator programs on the capital structure of start-ups	Business accelerator (Private)	World	Propensity-score matching	External Equity To Capital Ratio	Yes

Finally, on a regional perspective, it is important to point out that entrepreneurial activity in Colombia depends on survival entrepreneurship. According to Bosma et al. (2020), 90% of

⁶ New ventures that went through a top accelerator were found to reach exit or first venture capital round faster than those who did not went through those accelerators.

the total early-stage entrepreneurial activity (TEA) in Colombia is from people looking for a living, instead of exploiting a market opportunity with high-growth potential. This fact alone reinforces our initial question about the capacity of any organization, managing public funds, to pick high-impact entrepreneurs efficiently and help them grow. Although the fraction of the TEA that belongs to innovate entrepreneurship is low, Aparicio, Urbano, and Gómez (2016) found that this type of entrepreneurship could contribute to a sustainable economic growth for Colombia, when projected until 2032, and even reach a growth peak of 6.7%.

To reach that peak of economic activity, government decisions, such as stop promoting the indiscriminate creation of low productive firms, should be considered (Consejo Privado de Competitividad, 2020). Any high-impact entrepreneurship program in Colombia, whether regional or national, should have a design in which the evaluation of results is prioritized, so evaluators can determine the effectiveness of the executed public policy (Consejo Privado de Competitividad, 2020). This is precisely one of the largest gaps in Colombian entrepreneurship studies. There is only one previous well-known impact evaluation of a business accelerator in Cali, Colombia, led by González-Uribe and Reyes (2020), highlighting the need of conducting impact evaluation of entrepreneurship policy. Responding to this call, as well as the divergent results of entrepreneurship supportive programs' evaluation, we ask whether the acceleration initiative implemented in Medellin has been helpful in terms of firm growth or not. The next section explains the methodology we utilized for impact evaluation.

3. Methodology

3.1. A main method to assess the acceleration program

For this research, the matching methodology was adopted to measure the effects of the acceleration program. According to Rosenbaum and Rubin (1983), the right measure of a program's effect relies on the construction of a proper counterfactual (i.e., the results in the

treatment group in absence of the program). Therefore, it is not possible to estimate the impact of the acceleration program just comparing the group of supported firms and the group of non-supported firms, since their previous characteristics were already different.

Thus, an appropriate impact measure of a program in a non-experimental setting would be to compare the performances of two firms with the same previous characteristics, assuming one of them went through the acceleration program and the other did not. The problem relies on finding a comparison group (i.e., control group) that holds these similar characteristics.

Hence, this research uses matching techniques (Rosenbaum & Rubin, 1983), which facilitate the construction of a control group by matching similar firms based on the propensity score of firms not supported by the program. Matching techniques estimate a maximum likelihood model of the conditional probability of participating in the acceleration program (usually a logit or probit regression to ensure fitted values stay between 0 and 1), and then the technique uses these propensity score values to make comparisons between treated and non-treated firms (Cunningham, 2021).

Matching methods requires fulfillment of two assumptions. First, the conditional independence assumption (CIA). It means that conditioned on the observable characteristics (e.g., X variables) of possible participant firms, the decision for participation in the acceleration program should be independent of the outcome measure (Oh et al., 2009). In other words, conditional on X , the assignment of firms to the treatment is as good as random (Cunningham, 2021). This assumption is written as follows:

$$(Y_1, Y_0) \perp D \mid X \tag{1}$$

where \perp means independence, Y_1 is the outcome of the accelerated firm and Y_0 denotes the outcome of non-accelerated firm. D is an indicator variable denoting participation in the acceleration program. X is the set of variables being used for conditioning.

The second assumption is the common support assumption. It is written as follows:

$$0 < \Pr(D = 1 | X) < 1 \quad (2)$$

which means that for any given probability, there must be firms in both the treatment group and the control group. It requires that for each value of X , there is a positive probability of being both treated and untreated. According to Rosenbaum and Rubin (1983), if these assumptions can be satisfied, it is theoretically possible to obtain an unbiased estimation of the effect of a program.

Propensity score, in the context of this research, is the probability of firms to participate in the acceleration program conditional on the observable characteristics of those firms. This can be expressed mathematically as:

$$\text{Propensity score} = p(X) = \Pr(D = 1 | X) \quad (3)$$

Given propensity score equation (3), and assuming equations (1) and (2), all biases due to observable variables can be removed by conditioning on the propensity score (Rosenbaum & Rubin, 1983). That is, D and X are independent of one another conditioning on the propensity score, which can be represented through the following equation:

$$(Y_1, Y_0) \perp D | p(X) \quad (4)$$

Based on (4), the policy effect can be defined for a population of units denoted by i , as the average effect of treatment on the treated (ATT):

$$ATT = E_{p(X_i)} \{E(Y_{1i} | D_i = 1, p(X_i)) - E(Y_{0i} | D_i = 0, p(X_i)) | D_i = 1\} \quad (5)$$

The ATT is the difference in average results of the firms supported and not supported by the acceleration program, where the group of not supported firms was previously formed matching units based on the propensity score.

3.2. Data and empirical approach

The first step for this research consisted of contacting Créame's acceleration program and gather information from the 77 companies accelerated from 2018 to 2020. The acceleration program operates since 2012, but the information of cohorts before 2018 is incomplete or difficult to access. Being selected in the program depends on different factors analyzed by a committee of internal and external judges with experience in entrepreneurship, company building, and consultancy. Variables considered for evaluation have changed slightly since 2012, but the focus remains on the following ones: sector, founding team experience, previous sales and sales growth, company age, business model, and company's use of technology.

The data for pre-treatment period was obtained by Créame's inscription databases. Post-treatment information was obtained from a survey that must be filled by the entrepreneurs annually for following up on the acceleration program descriptive results. With this survey, it was possible to gather information from three cohorts of the acceleration program and their results in the outcome variables (number of employees and revenue) for the year 2021. From the 77 companies that were part of the program in those three cohorts, and it was possible to obtain information from 60 of them using the survey. It was not possible to gather information for the remaining companies in a timely manner for this research. During the whole research process, the names of the companies remained confidential.

For building a solid control group, we had access to the official "Registro Único Empresarial", a company registry containing all the information of companies in territories that make part of the jurisdiction managed by Chamber of Commerce of Medellin. Since all the treated companies were located in Medellin, the database for control group consisted in 70,000 companies registered in Medellin until 2018 with their baseline characteristics and their 2021 revenue as an outcome variable. We proceed to exclude companies that were not from services, manufacturing, or commerce, since those were the sectors found in the treatment group. Also,

we excluded large companies from the group, leaving only micro, small, and medium-sized enterprises.

To ensure that the outcome variable was similar in characteristics between both treatment and control groups, we also excluded companies in control group which had zero revenue for post-treatment period. Lastly, some specific International Standard Industrial Classification (ISIC) codes were also excluded from the control group sample because were not present in treatment group. After these exclusions, the remaining control group before starting the matching process had 16,994 observations.

Based on the available information for control group, the only outcome variable possible to measure in this research was revenue. According to Autio and Rannikko (2016) and Dvouletý et al. (2018), this remains to be a key performance indicator to determine the impact of a determined entrepreneurship program. Employment or other financial variables that are also useful to determine the impact of the program were not possible to measure due to not having the required post-treatment period information for the control group.

Also, the controls for the model are number of employees, company's age in years, founder/CEO gender, legal form, company size, and sector. Founder/CEO gender was built using the name of the legal representative of each company and using a special algorithm called Genderize.io to determine the gender based on the name. Prior literature on impact evaluation of entrepreneurship programs has used gender dummies due to the differences between female-led ventures and otherwise (Butler et al., 2016; Gonzalez-Uribe & Leatherbee, 2017; González-Uribe & Reyes, 2020; McKenzie, 2017). The rest of controls have been relevant for other impact evaluations using matching techniques in entrepreneurship policy (Autio & Rannikko, 2016; Dvouletý, 2017; Dvouletý & Blažková, 2019). The list of variables is presented in Table 2.

Table 2. Variables and definitions.

Definition	Variable
<i>Treated variable</i>	
Accelerated	Dummy variable equal to 1 indicating whether the company was part of the acceleration program; 0 otherwise.
<i>Control (matching) variables</i>	
Employees	Variable refers to the number of employees before treatment period (2018).
Company's age	Variable refers to the years of existence of the company since its original registration.
Founder/CEO gender	Variable refers to a dummy equal to 1 if startup had a female CEO. This variable was created estimating legal representatives' genre based on their names using a special algorithm called genderized.io.
Manufacturing	Variable refers to a dummy equal to 1 indicating if company belongs to any of the International Standard Industrial Classification (ISIC) codes referring to industrial or manufacturing activities; 0 otherwise.
Commerce	Variable refers to a dummy equal to 1 indicating if company belongs to any of the International Standard Industrial Classification (ISIC) codes referring to commercial activities; 0 otherwise.
Services	Variable refers to a dummy equal to 1 indicating if company belongs to any of the International Standard Industrial Classification (ISIC) codes referring to professional and technical services, or information, technology, and communication services; 0 otherwise.
Micro	Variable refers to a dummy equal to 1 indicating if company is a micro business according to international classification (1-9 employees); 0 otherwise.
Small	Variable refers to a dummy equal to 1 indicating if company is a micro business according to international classification (10-49 employees); 0 otherwise.
Legal form	Variable refers to a dummy equal to 1 indicating if company holds a joint-stock legal structure or otherwise; 0 otherwise.
<i>Outcome Variable</i>	
Ln Revenue	Variable refers to the natural logarithm of post-treatment period revenue.

4. Findings

4.1 Descriptive results

Table 3 reports the summary statistics of each variable, both for control and treatment groups. For the outcome variable (Ln Revenue), it was found that the difference in mean between treatment and control groups before matching is 0.926. The interval of values for the control group is wider and has a higher standard deviation than the treatment group. Regarding continuous control variables (i.e., employees, company's age), the standard deviation for control group is again higher than the treatment group, but still the average values remain close to each other. Treated companies have more employees and are younger, on average, when compared to control group.

Table 3. Descriptive statistics for controls and outcome variable across both treatment and control groups.

Variable	Group	N	Mean	SD	Min	Max
Ln Revenue (Outcome)	Control	16994	19.505	2.255	0.693	25.017
	Treatment	60	20.431	0.926	18.325	22.810
Employees	Control	16994	13.006	45.224	0	3000
	Treatment	60	15.033	15.527	1	94
Company's age	Control	16994	9.183	8.954	0	65.600
	Treatment	60	6.218	4.116	0.700	15.300
Founder/CEO gender	Control	16869	0.279	0.449	0	1
	Treatment	60	0.433	0.500	0	1
Manufacturing	Control	16994	0.277	0.448	0	1
	Treatment	60	0.200	0.403	0	1
Legal form	Control	16994	0.888	0.315	0	1
	Treatment	60	0.817	0.390	0	1
Micro	Control	16994	0.738	0.440	0	1
	Treatment	60	0.433	0.500	0	1
Small	Control	16994	0.209	0.406	0	1
	Treatment	60	0.517	0.504	0	1
Commerce	Control	16994	0.311	0.463	0	1
	Treatment	60	0.133	0.343	0	1
Services	Control	16994	0.236	0.424	0	1
	Treatment	60	0.533	0.503	0	1

For discrete control variables (i.e., founder/CEO gender, manufacturing, commerce, services, micro, small, legal form), standard deviations of treatment group are in most cases

higher than control group. On average, there are more treated companies that are run by female CEOs than the control group sample. Also, manufacturing, and commerce are sector categories more present in the control group, as compared to the treatment group. In contrast, there are more treated firms involved in services activities (professional and scientific services, and information, communication, and technology services) in comparison to the control group. The strong presence of services sector in treated companies is expected given the initial evaluation criteria for entering the program.

Heterogeneity between control and treatment groups can be found in this initial comparison in different variables. The matching process, then, is necessary to diminish the potential bias found in this initial comparison, and to calculate an accurate average treatment effect on the treated (Cunningham, 2021).

4.2. Propensity score estimation

As it was presented before, the propensity score mechanism (Rosenbaum & Rubin, 1983) has been used in non-experimental settings in different knowledge areas. The first step in the estimation is to calculate the propensity score of participation in the acceleration program. This is accomplished using a logistic regression model with the treatment variable (Accelerated) as the dependent variable. The result of this logistic regression is then used to match the control group and the treatment group using different mechanisms (kernel matching, nearest neighbor matching) and, after this matching, the result of the ATT will be available as a difference between both groups in the outcome variable.

Results of the estimation are shown in Table 4. For the logistics regression and posterior matching, we used a nested approach resulting in three different models with different covariates. Model 1 only takes into consideration the main internal characteristics of the firm (employees, company's age, founder/CEO gender, legal form). We include another set of variables in model 2, which involves micro and small-sized firms. Finally, model 3 considers

all the previous variables plus economic sector (i.e., manufacturing, commerce, and services). With this strategy, we guarantee that including control variables model by model, results remain similar and robust. Despite employees, which changes in direction and significance, the rest of variables hold across models.

Table 4. Robust logistic regression used for the estimation of propensity score

Variables	Model 1	Model 2	Model 3
Employees	0.001*** (0.000)	-0.007 (0.006)	-0.004 (0.006)
Company's Age	-0.115*** (0.039)	-0.142*** (0.039)	-0.139*** (0.037)
Founder/CEO gender	0.635** (0.261)	0.700*** (0.262)	0.613** (0.262)
Legal form	-1.664*** (0.556)	-1.711*** (0.507)	-1.631*** (0.467)
Micro		-1.820* (1.009)	-1.947* (0.999)
Small		0.0533 (0.882)	0.136 (0.888)
Manufacturing			-0.065 (0.456)
Commerce			-0.404 (0.501)
Services			1.376*** (0.397)
Constant	-3.614*** (0.688)	-2.207** (1.095)	-2.679** (1.080)
Observations	16,929	16,929	16,929

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. Dependent variable: dummy = 1 if company was treated.

Regarding the results of the propensity score, it can be found that some variables are not statistically significant to the estimation. However, according to previous literature of matching techniques (Angrist & Pischke, 2008; Caliendo & Kopeinig, 2005; Cunningham, 2021) and the most common used covariates found in impact evaluations of entrepreneurship programs and their empirical findings (Autio & Rannikko, 2016; Dvouletý, 2017; Dvouletý et al., 2019; Efobi

& Orkoh, 2018), we decided to include them to have a more precise estimation of the propensity score.

The propensity score estimation shows that company's age, founder/CEO gender, company sector, company size, and legal structure are statistically significant to determine the probability of participation into treatment. Regarding sectors, it was found that companies focused on services (i.e., information, communication, and technology, as well as professional, technical, and scientific services) are more likely to be accelerated than other sectors. Also, companies with women founder/CEO are more likely to be treated than their counterpart with men founder/CEO.

The common support region remaining after propensity score estimation shows that, using Model 3 covariates, there is a positive probability of being treated up to 31.4% for both accelerated and non-accelerated firms. However, most of the probability distribution is concentrated on the left tale, indicating overall a low probability of treatment for both treated and control firms. Common support was also calculated using Model 2 and Model 1 covariates, resulting in maximum probability values of 15.1% and 7.8%, respectively. This means, it is possible to find a wider common support region with Model 3, being the estimation that better fits the first assumption of matching techniques, as seen in previous section.

As in Caliendo and Kopeinig (2005), given the low probability of being treated and the concentration on the left side of the distribution, a trimming method for the common support region was applied, limiting the matching algorithm to the region above 0.15% probability of being accelerated. This trimming caused different observations of both treatment and control groups, in each one of the three models, to be excluded for matching process. For a detailed common support graphic of each model after the trimming procedure was applied, see Figure A1 in Appendix.

4.3. Main results

The next step then is to execute the matching with different mechanisms already having calculated the propensity score for each model. This estimation is based on the outcome variable revenue, which is expressed in the natural logarithm form to reduce variance.

According to Oh et al. (2009), to get an accurate calculation of ATT, in theory, one should match accelerated and non-accelerated firms precisely in the base of the propensity score. However, it is not possible to match precisely in the propensity score in practice, so it is fundamental to use alternative matching techniques. For this study, kernel matching and nearest neighbor matching were used and compared for robustness check. The estimations show the average difference between treatment group (accelerated startups) and control group (non-accelerated startups). It is important to bear in mind that the calculated impacts are local for the treatment group and cannot be expanded to a broader sample of startups. Results, using previously explained nested approach, are shown in Table 5.

Table 5. Estimated average treatment effect on the treated after matching.

Outcome Variable	Matching criterion	Model 1	Model 2	Model 3
Ln Revenue	Nearest Neighbor (5)	0.563***	0.327*	0.054
		(0.177)	(0.192)	(0.186)
		[3.180]	[1.710]	[0.290]
Ln Revenue	Nearest Neighbor (10)	0.915***	0.573***	0.397**
		(0.156)	(0.177)	(0.170)
		[5.860]	[3.250]	[2.340]
Ln Revenue	Kernel	1.145***	1.113***	0.812***
		(0.122)	(0.143)	(0.139)
		[9.410]	[7.810]	[5.830]
Observations		14,069	11,330	7,835

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard error in parentheses; t-stat in square brackets.

Overall, we find a positive difference between treated and control group across matching techniques and models used. For models 1 and 2, we see a statistically significant difference between treated and controls in every matching criterion used. Although this is positive, it is important to remember the narrower common support found with these two models.

Regarding Model 3, when using nearest neighbor matching with 10 nearest neighbors, a statistically significant difference at 5% level between treatment and control groups is found on the outcome variable. The significance of this difference increases at 1% level when using kernel matching technique. However, when using five nearest neighbors, the difference is smaller and not significant at any level. The number of observations analyzed and matched were 7,835 due to the common support region trimming done in the previous section.

It is worth noting that in kernel matching every treated subject is matched with a weighted average of all control subjects. This means less variance in the estimation but also an increased bias compared to a matching algorithm done with a smaller group of control subjects. Hence, the common support assumption is especially important when using kernel matching, to ensure all the treatment and control subjects have a positive probability of participation into treatment (Caliendo & Kopeinig, 2005).

As an alternative, using nearest neighbor matching implies the opposite problem (i.e., less biased estimation but more variance), because every treated subject is matched with a specific number of closest neighbors from control group (Cunningham, 2021). This also means an extra decision to make regarding the number of nearest neighbors for the estimation. In this case, since the available treatment group is quite small compared to the available control group sample, the probability to find just one near neighbor to match remains small; hence, as in Oh et al. (2009), we decided to proceed with the matching algorithm using five and 10 nearest neighbors, being the latter more appropriate than the former.

Overall, based on the estimates for Model 3, using nearest neighbor matching with 10 nearest neighbors and using kernel matching, accelerated firms on average have higher revenue three years after treatment than non-accelerated firms. The direction of this impact remains the same, although not statistically significant, when discretionally using five nearest neighbors with nearest neighbor matching algorithm.

As an additional robustness check, we changed the variables representing firms' size as the classification varies according to Colombian criteria (*Decreto 1074 de 2015 Sector Comercio, Industria y Turismo*, 2015). In Colombia, this classification is not made based on number of employees, but instead annual operational revenue and sector. Revenue limits for micro, small, and medium enterprises can go up to US\$440,000; US\$4,174,000; and US\$20,920,000, respectively, depending on sector⁷ (Bancoldex, 2021). Table A1 in Appendix shows the logit estimation following the previously mentioned nested approach, showing that, although size variables are not statistically significant, they follow similar direction and magnitudes, which indicate that our model remains solid when this regulation takes place. Table A2 in Appendix confirms that the ATT is also positive for treated companies. With these results, we are confident that our modeling approach was appropriate and reliable to conduct an analysis.

5. Discussion and conclusions

Motivated by the lack of studies assessing the impact of supportive entrepreneurship programs (particularly acceleration), which is more evident when considering developing countries, we measured the effects of a regional acceleration program from Medellin, Colombia. Using capabilities theory (Sutton, 2012) that framed our literature review, we explored previous works suggesting different characteristics that have been utilized when assessing the impact of supportive entrepreneurship programs on outcome variables such as revenues. Thanks to both logit regressions and propensity score matching, we identified that company age, founder/CEO gender, company size, and sector, were important variables to match treated and non-treated firms. The average treatment effects technique revealed that the Créame's acceleration program

⁷ Using the average exchange rate of 2021 (3,780 COP/USD).

sponsored by Mayor's Office of Medellin was successful in increasing the revenue of treated ventures.

Regarding company age, we found that there is a higher probability of being treated when the firm is younger, which is consistent with other impact evaluation studies, mainly Dvouletý (2017), González-Uribe and Leatherbee (2017), and Hallen et al. (2020). This result might exemplify the focus given on new ventures as part of the business policy and ecosystem dynamics.

As per founder/CEO gender, our results indicated that being a woman CEO positively influences the probability of treatment. This means, among other aspects, that the acceleration program is giving special attention to tackle gender disparities issues in entrepreneurship. This is important given recent literature showing entrepreneurial decisions by women are closely linked to social mobility issues (Aparicio et al., 2022).

Also, sector is determinant for participation into treatment. This is consistent with the majority of impact evaluations done for entrepreneurship programs, were services companies (specifically information and technology services) are the ones both being chosen and getting the best outcomes from those programs (Bone et al., 2017; Yu, 2019).

Thanks to these findings, this non-experimental impact evaluation is filling an existing gap in the literature. We offered new evidence about impact evaluation in a developing country, which was useful to bring insights into the discussion about entrepreneurship policies (Acs et al., 2016; Shane, 2009; Welter et al., 2017) and suggestions for policymakers when considering public funds to support entrepreneurship and new venture growth.

5.1. Contributions to literature about impact evaluation in entrepreneurship

Acceleration programs are expanding worldwide precisely because, on the one hand, analyzing firm-level effects, they focus on building firm capabilities and alleviating constraints for growth faced by entrepreneurs in young ventures (Clarysse et al., 2015). As the literature

review showed, there are several programs (both public and private-led) achieving this goal. To measure the effectiveness of a determined program, it was necessary to evaluate outcome variables that could demonstrate company growth, such as revenue, assets, profitability, or employment (Autio & Rannikko, 2016).

It can be said, then, that the Créame's local acceleration program was effectively alleviating constraints for growth and building firm capabilities of young ventures, when analyzed in light of the compared revenue three years after the program. Although this conclusion is positive, further variables should be considered for a thorough and more precise result of the impact. Also, given that the program is trying to select mostly technology-based companies, and some of these companies are not focused on growing revenue metrics in the initial years of operation due to technology and product development, the whole selection of revenue as a performance indicator could be debatable (Dvouletý et al., 2018).

On the other hand, regarding ecosystem or city-level effects, some accelerators and other publicly funded entrepreneurship programs also focus on allocating entrepreneurial resources in an efficient way. That means, for instance, to promote the allocation of top entrepreneurial talent in high-impact, high-growth ventures, and to disincentivize the creation of survival ventures created by low-skilled entrepreneurs (Shane, 2009).

Given the kinds of companies selected for the program and the ATT results found in this research, we could say that the program is efficiently allocating entrepreneurial resources and “picking winners” —i.e., selecting entrepreneurs with potential to become gazelles and unicorns— (Autio & Rannikko, 2016). However, for a thorough analysis on this specific allocation problem, further productivity variables and spillover information should be measured (Butler et al., 2016; Eslava et al., 2019).

5.2. Contributions to the debate about entrepreneurship policy

Despite the results and whether the program is efficiently picking winners or not, it remains important to frame this public policy approach using the current trends in entrepreneurship literature. There is a group of scholars —mainly Åstebro (2017), Acs et al. (2016), Autio & Rannikko (2016), Cho & Honorati (2014), and Shane (2009)— arguing in favor of entrepreneurship policy focused on picking winners and promoting the creation of opportunity ventures —that is, ventures created by highly talented entrepreneurs exploiting huge market opportunities—. The reason is that these firms are the ones interested in innovation and end up pushing the needle of different macroeconomic variables such as employment, productivity, and economic growth. Also, these scholars generally agree that encouraging the creation of subsistence entrepreneurship —that is, companies that would not be created if a decent job opportunity was on the table for the founders— is, overall, bad for the economy, due to possible negative effects on formality, employment, productivity, and company size in the long-term.

However, there is another group of scholars —mainly Aparicio et al. (2022), Arshed et al. (2014), Puente et al. (2019), Welter et al. (2017)— arguing for a more thorough approach to entrepreneurship study that avoids classic dichotomies (opportunity vs. necessity). This group of authors considers necessary to give a right place to the bulk of ventures that does not fit the Silicon Valley rubric of being venture capital backed, innovative, technology-based, and with high-growth rates. Overall, these gazelles and unicorns only account to 1% of the firms, and much less in developing economies.

Furthermore, the obsession with Silicon-Valley-type entrepreneurship could harm entrepreneurial ecosystems, because it was born thanks to a series of intricate and almost irreplicable chain of decisions that accumulated for more than 50 years (Audretsch, 2019) and, to date, there is no other country with a similar dynamic (Nicholas, 2019). Instead of trying to

replicate these settings—which, according to Audretsch (2019), fostering Silicon-Valley-type entrepreneurship is positive, but not enough—developing countries could be more focused on creating their own ecosystem versions, after deeply understanding their economic activities, human capital potential, and institutional arrangements. Pahnke and Welter (2019) is a good example of this possibility.

5.3. Public policy implications for a region in a developing country

In the local context of developing countries, it is important to address these previous perspectives. Although Colombia and Latin America are in a positive venture-backed entrepreneurship trend, with record-hitting venture capital rounds quarter by quarter since 2020 (Stanford, 2022) and innovative entrepreneurship will gradually become more relevant for economic growth in Colombia (Aparicio, Urbano, & Audretsch, 2016), most of the firms will not receive funding from venture capital deals and will face two possible outcomes: either the founders get pass through the Death Valley and start growing steadily and constantly with bootstrapping strategies, or they end up closing their business.

It is proven that, despite all the efforts worldwide to have the best criteria for picking winner ventures, there are still several problems and a lot of randomness involved. For instance, a majority of venture capital funds in the US, decade by decade since 1970, cannot outperform public markets (Nicholas, 2019). It is relevant, then, that local business accelerators in developing countries—fundamentally ecosystem accelerators as defined in Clarysse et al. (2015)—can have precise criteria for selecting the entrepreneurs that will enter different cohorts, but without getting obsessed by the dichotomic categories for classifying those participant firms. As mentioned before, whether the company will become a unicorn in the next five years or not, there is evidence enough to state that a good acceleration program will still alleviate constraints for growth and build firm capabilities (González-Uribe & Reyes, 2020).

Regarding other design and policy recommendations, it is fundamental to narrow down participants into treatment to more specific economic activities, as well as maintaining a given participation criteria for at least three years. Furthermore, the technology-based categorization will be useful only if there is a clear step-by-step for judges to avoid subjective selection (Gonzalez-Uribe & Leatherbee, 2017). Also, the way information is gathered in the periods pre-treatment and post-treatment is key to ensure more robust impact evaluations can be done in the future (Consejo Privado de Competitividad, 2020), even with a different mechanism such as regression discontinuity design (RDD) that exploits mean differences in outcome variables between accelerated and non-accelerated firms close to the cutoff line. Lastly, for future research, would be key to get access to more financial data from the startups' balance sheets or profit & loss statements (Dvouletý et al., 2018).

5.4. Limitations and future research avenues

Despite filling an important gap, we acknowledged limitations of the study. First, the effects caused by COVID-19 pandemic in different sectors of the economy were huge and difficult to ignore, and the results could be distorted for measuring the outcome variable precisely in a year of economic recovery. In that sense, it is advisable to use an average of 2-3 years in the outcome variables (Dvouletý et al., 2018). Second, the bulk of treated startups are too heterogeneous between them, due to already mentioned changes in the program focus and eligibility criteria. This complicated an accurate comparison with a control group and, overall, lowers the probability of being treated when calculating the propensity score (Caliendo & Kopeinig, 2005). Third, for assessing multilevel effects of the acceleration program on the ecosystem, it would be necessary to expand the time span between pre-treatment and post-treatment period.

Lastly, the treatment group was smaller than expected due to not having access to previous years of information. This increases the heterogeneity problem and lowers the

statistical power of the results (Cunningham, 2021). However, there are some impact evaluations found in the literature with small sample sizes, especially when the sample is made of companies and not of individual economic agents. For instance, Bloom et al. (2011) use 14 treatment plants and 14 control plants. Mano et al. (2014) used 47 participants for a business training program evaluation. Also, for the proposed matching method, good estimation of the ATT relies on the construction of an accurate control group that can suffice both common support and conditional independence assumptions (Cunningham, 2021).

5.5. Conclusion

In this study, we focused on the relationship between a local business acceleration program sponsored with public funds, and firm-performance (measured through revenue) in the region of Medellin, Colombia, which have been under-researched by entrepreneurship scholars. We used firm-level information obtained from both the program operational team and through surveys, to then compared it with a database of non-accelerated firms located in the same region. Contrasted to the control group, accelerated firms show significantly better revenue using nearest neighbor matching with 10 nearest neighbors, and using kernel matching. Although more outcome variables need measure, this exploratory research shows that the acceleration program is efficiently alleviating constraints for growth and building firm capabilities. Further measures with an extended time span, and focus on multi-level effects, are needed to address the problem of efficient entrepreneurial resources allocation. On a broader public policy view, we suggest that the program should not obsess with picking winners, but instead keep improving its design to assess more accurately common growth pains faced by new ventures.

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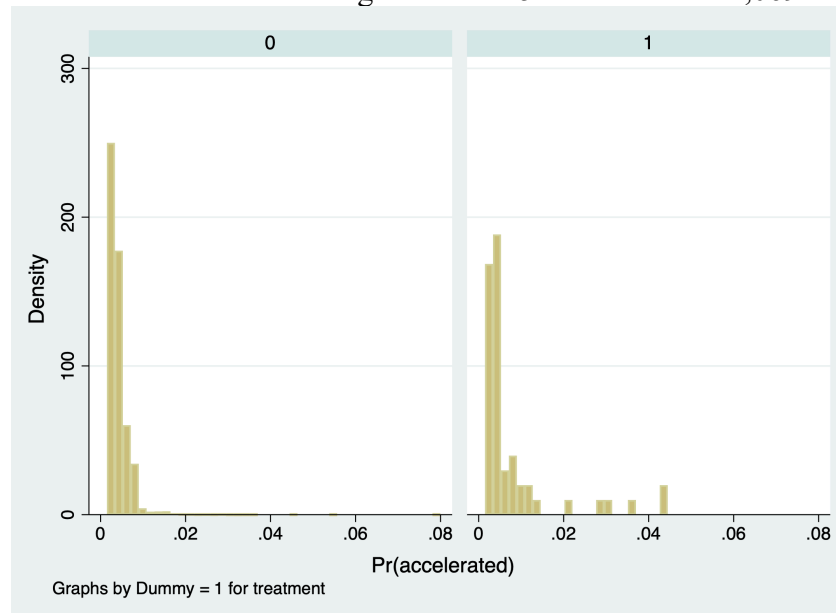
Appendix.

Figure A1. Common support region for three different models with probability values above 0.15%

A) Model 1

Maximum probability: 7.8%

Observations after trimming: treatment 54 and control 14,069

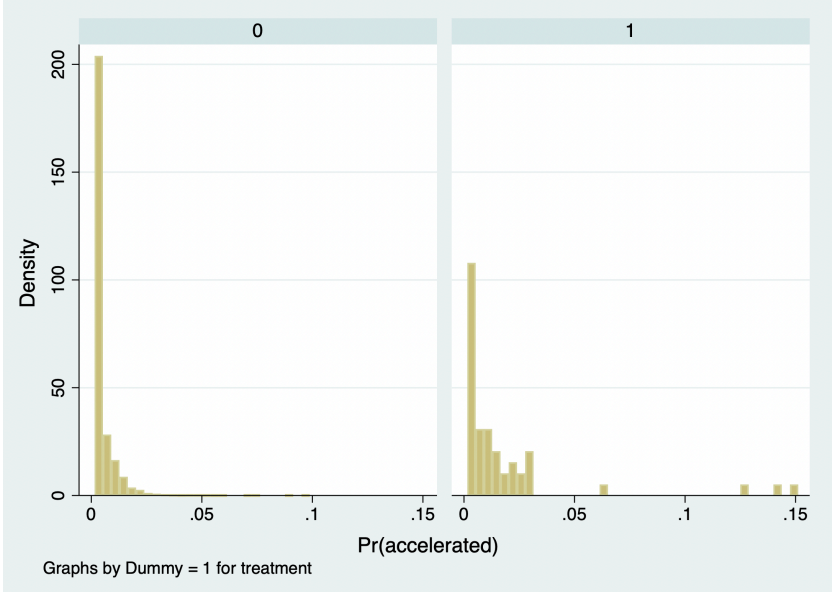


Source: Own elaboration.

B) Model 2

Maximum probability: 15.1%

Observations after trimming: treatment 52 and control 11,278

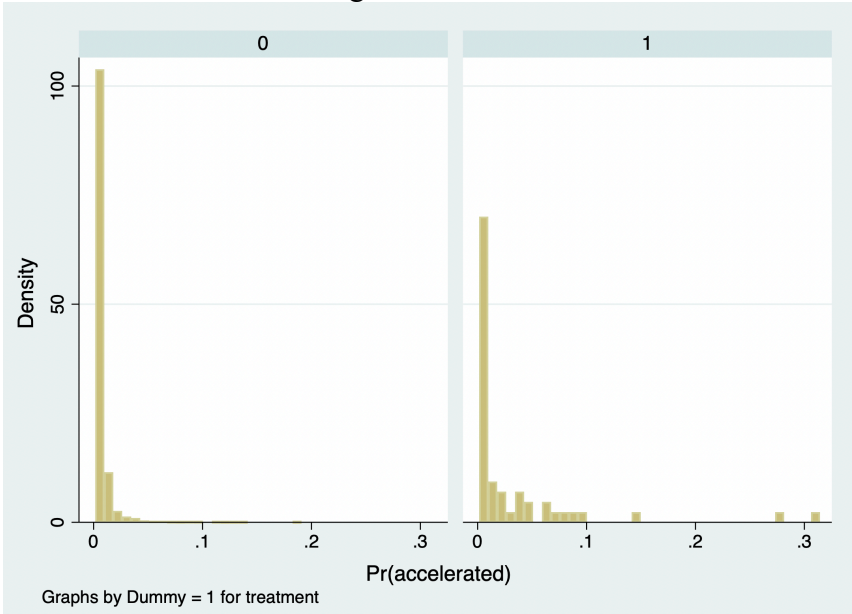


Source: Own elaboration.

C) Model 3

Maximum probability: 31.4%

Observations after trimming: treatment 52 and control 7,783



Source: Own elaboration.

Table A1. Robust logistic regression used for the estimation of propensity score with local size parameter (L_p) variables

Variables	Model 1	Model 2	Model 3
Employees	0.001*** (0.000)	0.001** (0.000)	0.001*** (0.000)

Company's Age	-0.115*** (0.039)	-0.120*** (0.039)	-0.117*** (0.038)
Founder/CEO gender	0.635** (0.261)	0.646*** (0.261)	0.597** (0.262)
Legal form	-1.664*** (0.556)	-1.668*** (0.545)	-1.618*** (0.522)
Micro (Lp)		-0.040 (0.788)	-0.275 (0.782)
Small (Lp)		0.304 (0.807)	0.346 (0.782)
Manufacturing			-0.024 (0.458)
Commerce			-0.532 (0.506)
Services			1.132*** (0.407)
Constant	-3.614*** (0.688)	-3.621*** (1.014)	-3.822** (0.990)
Observations	16,929	16,929	16,929

Table A2. Estimated average treatment effect on the treated after matching using local size parameter variables

Outcome Variable	Matching criterion	Model 1	Model 2	Model 3
Ln Revenue	Nearest Neighbor (5)	0.563*** (0.177) [3.180]	0.500*** (0.175) [2.860]	1.321*** (0.217) [6.080]
Ln Revenue	Nearest Neighbor (10)	0.915*** (0.156) [5.860]	0.653*** (0.155) [4.210]	1.261*** (0.183) [6.880]
Ln Revenue	Kernel	1.145*** (0.122) [9.410]	1.114*** (0.122) [9.160]	1.112*** (0.127) [8.840]
Observations		14,123	14,125	11,531

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard error in parentheses; t -stat in square brackets.