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Entrepreneurship Education Programs at University

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It is not the critic who counts; not the man who points out how the strong man stumbles, or where the doer of deeds could have done them better. The credit belongs to the man who is actually in the arena, whose face is marred by dust and sweat and blood; who strives valiantly; who errs, who comes short again and again, because there is no effort without error and shortcoming; but who does actually strive to do the deeds; who knows great enthusiasms, the great devotions; who spends himself in a worthy cause; who at the best knows in the end the triumph of high achievement, and who at the worst, if he fails, at least fails while daring greatly, so that his place shall never be with those cold and timid souls who neither know victory nor defeat.

Theodore Roosevelt, April 23rd 1910

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Much of my professional and personal development over the past years is linked to CDTM. Joining as a student in 2016 and then again 2019 as part of the management team has had a profound impact on my life. My desire to understand whether this personal experience was also reflected in the data motivated this dissertation. With the presented results I hope to contribute to the ongoing development of CDTM and its larger community.

Finally, I would like to thank my family and my friends for their love and support throughout this journey. Thank you!

Abstract

Entrepreneurship is a driving force for economic and social wealth. Its importance for society is recognized by regional, national, and international policy makers. In recent years universities have increasingly acknowledged entrepreneurship as part of their mission to contribute to society. However, rigorous research on the impact of entrepreneurship education at university is sparse and existing studies paint an ambivalent picture of the outcomes it produces. It is not clear under which conditions entrepreneurship education can increase entrepreneurial outcomes, such as entrepreneurship rates and startup quality, and whether the generated socioeconomic returns are a net-positive for society if funded with tax-payer money.

This dissertation addresses these questions with four empirical studies. First, we show that applicants (N=495) of entrepreneurship education programs at university are a-priori more “entrepreneurial” along several psychometrical constructs compared to university students who do not apply (N=359).

In our second study, we evaluate the impact of participation in an entrepreneurship education program during university on subsequent entrepreneurial activity by comparing career decisions between program participants (N=478) and the best applicants not accepted to the program (N=544) using a regression discontinuity design. This quasi-experimental analysis allows us to distinguish cause and effect and represents a substantial methodological improvement over past studies. Our results show that program participation has large positive effects on both entrepreneurship rates and startup success.

In our third study, we juxtapose the costs for running the program over a ten-year period with the tax revenue generated from the jobs created by alumni-founded companies (N=155). A comparison to companies founded by the best applicants not accepted to the program (N=142) allows us to control for startup and job creation in the absence of the program. We find that the additional direct tax returns alone far exceed the investments into the program, even with the most conservative assumptions. We estimate that the created socioeconomic returns in Germany in 2022 alone are more than six times the cost of running the program over ten years.

In our final study, we adopt an ecosystem perspective and investigate how successful exit events impact the development of entrepreneurial ecosystems. During data collection for the previous studies, we found anecdotal evidence of how the acquisition of one successful startup spurred a number of business angel investments and newly founded ventures in Munich. Using a panel data set covering 46 European cities over 19 years, we show that this phenomenon is not

the exception and can be observed across ecosystems. In the years following an increase in successful startup exits in an ecosystem, we observe an increase in newly founded startups and business angel investments. While our dataset constrains us from making causal claims, these results indicate that founders and employees are likely to use their resources to pursue renewed entrepreneurial activities after successful exit events, and thus, not only the exited founders, but the ecosystem at large benefits.

In summary, the studies presented in this dissertation provide strong evidence of the positive socioeconomic impact of entrepreneurship, and in particular, entrepreneurship education programs at university. This dissertation shows that entrepreneurship education programs can not only be effective in raising entrepreneurship rates and startup quality among participants, but also that investing in them is economically rational. The generated tax revenue through created jobs as a result of program participation more than cover the total cost of running the program.

These results are highly relevant for research and practice. Our quasi-experimental evaluation addresses the call for rigorous evaluation studies in literature and allows us to make causal claims about the effects it produces. The detailed analyses discussed within the presented studies add to our theoretical understanding of the mechanisms through which entrepreneurship education affects participants. For policy makers our results show that investing in entrepreneurship education programs can be an effective policy intervention to stimulate regional economic job growth from which society at large benefits.

Kurzfassung

Unternehmertum ist eine treibende Kraft für wirtschaftlichen und sozialen Wohlstand. Seine Bedeutung für die Gesellschaft wird von regionalen, nationalen und internationalen politischen Entscheidungsträgern anerkannt. In den letzten Jahren haben Universitäten Unternehmertum zunehmend als Teil ihrer Aufgabe anerkannt, einen Beitrag zur Gesellschaft zu leisten. Es gibt jedoch nur wenige aussagekräftige Studien über die Auswirkungen von Entrepreneurship-Programmen an Hochschulen. Die vorhandenen Studien zeichnen ein nicht eindeutiges Bild von den Ergebnissen. Es ist nicht klar, unter welchen Bedingungen die Entrepreneurship-Ausbildung die unternehmerischen Ergebnisse, wie z. B. die Gründungsraten und die Qualität der Gründungen, steigern kann und ob die sozioökonomischen Erträge für die Gesellschaft positiv sind, wenn sie mit Steuergeldern finanziert werden.

In dieser Dissertation werden diese Fragen anhand von vier empirischen Studien untersucht. Zunächst zeigen wir, dass Bewerber (N=495) von Entrepreneurship-Programmen an Universitäten im Vergleich zu Universitätsstudenten, die sich nicht bewerben (N=359), in mehreren psychometrischen Konstrukten a-priori "unternehmerischer" sind.

In unserer zweiten Studie untersuchen wir die Auswirkungen der Teilnahme an einem Entrepreneurship-Programm während des Studiums auf die spätere unternehmerische Aktivität, indem wir die Karriereentscheidungen von Programmteilnehmern (N=478) und den besten Bewerbern, die nicht in das Programm aufgenommen wurden (N=544), mit Hilfe eines Regressionsdiskontinuitätsdesigns vergleichen. Diese quasi-experimentelle Analyse ermöglicht es, Ursache und Wirkung zu unterscheiden und stellt eine wesentliche methodische Verbesserung gegenüber früheren Studien dar. Unsere Ergebnisse zeigen, dass die Programmteilnahme große positive Auswirkungen sowohl auf die Gründungsrate der Teilnehmer als auch auf den Erfolg von Unternehmensgründungen hat.

In unserer dritten Studie stellen wir die Kosten für die Durchführung des Programms über einen Zeitraum von zehn Jahren den Steuereinnahmen gegenüber, die durch die von Alumni gegründeten Unternehmen (N=155) geschaffenen Arbeitsplätze generiert werden. Ein Vergleich mit Unternehmen, die von den besten Bewerbern gegründet wurden, die nicht in das Programm aufgenommen wurden (N=142), ermöglicht es uns, für die Gründung und Schaffung von Arbeitsplätzen, ohne das Programm zu kontrollieren. Unsere Ergebnisse zeigen, dass die zusätzlichen direkten Steuereinnahmen die Kosten des Programms selbst bei den konservativsten Annahmen weit übersteigen. Wir schätzen, dass die sozioökonomischen Erträge in Deutschland

allein im Jahr 2022 mehr als das Sechsfache der Kosten für die Durchführung des Programms über die vollen zehn Jahre betragen.

In unserer letzten Studie nehmen wir eine Ökosystem-Perspektive ein und untersuchen, wie sich erfolgreiche Exit-Ereignisse auf die Entwicklung von unternehmerischen Ökosystemen auswirken. Während der Datenerhebung für die vorangegangenen Studien fanden wir anekdotische Belege dafür, wie die Übernahme eines erfolgreichen Start-ups eine Reihe von Business-Angel-Investitionen und Neugründungen in München anspornte. Anhand eines Paneldatensatzes, der 46 europäische Städte über einen Zeitraum von 19 Jahren abdeckt, zeigen wir, dass dieses Phänomen kein Einzelfall ist und in allen Ökosystemen beobachtet werden kann. In den Jahren, die auf einen Anstieg der erfolgreichen Exits von Startups in einem Ökosystem folgen, beobachten wir einen Anstieg von Neugründungen und Business-Angel-Investitionen. Auch wenn wir aufgrund unseres Datensatzes keine kausalen Behauptungen aufstellen können, deuten diese Ergebnisse darauf hin, dass Gründer und Angestellte ihre Ressourcen nach einem erfolgreichen Startup Exit wahrscheinlich für neue unternehmerische Aktivitäten nutzen, wovon nicht nur die Gründer, sondern das gesamte Ökosystem profitiert.

Zusammenfassend lässt sich sagen, dass die in dieser Dissertation vorgestellten Studien starke Belege für die positiven sozioökonomischen Auswirkungen des Unternehmertums und insbesondere der Entrepreneurship-Programme an Universitäten liefern. Die Dissertation zeigt, dass Entrepreneurship-Programme nicht nur die Gründungsrate und die Qualität der Gründungen unter den Teilnehmern erhöhen können, sondern auch, dass Investitionen in diese Programme wirtschaftlich sinnvoll sind. Die Steuereinnahmen, die durch die Schaffung von Arbeitsplätzen infolge der Programmteilnahme generiert werden, decken die Gesamtkosten für die Durchführung des Programms mehr als ab.

Diese Ergebnisse sind für Forschung und Praxis von großer Bedeutung. Unsere quasi-experimentelle Evaluierung entspricht der Forderung nach strengen Evaluierungsstudien in der Literatur und ermöglicht es uns, kausale Aussagen über die erzielten Effekte zu machen. Die detaillierten Analysen, die in den vorgestellten Studien erörtert werden, tragen zu unserem theoretischen Verständnis der Mechanismen bei, durch die die Entrepreneurship-Ausbildung die Teilnehmer beeinflusst. Für politische Entscheidungsträger zeigen unsere Ergebnisse, dass Investitionen in universitäre Entrepreneurship-Programme eine wirksame politische Maßnahme sein können, um ein regionales wirtschaftliches Wachstum zu stimulieren, von dem die Gesellschaft als Ganzes profitiert.

Content

1 | Introduction

The Struggle is when you wonder why you started the company in the first place. The Struggle is when people ask you why you don't quit and you don't know the answer. The Struggle is when your employees think you are lying and you think they may be right. The Struggle is when food loses its taste.

Ben Horowitz, 2014, The Hard Thing About Hard Things (p. 60)

1.1 | Background and Research Objectives

Entrepreneurship has been recognized as engine for economic growth and wealth creation. The notion of the entrepreneur as the lone genius once championed by Schumpeter (Schumpeter, 1934) has long been challenged. According to entrepreneurial ecosystem theory, successful entrepreneurship is enabled by the interaction of different elements of the respective entrepreneurial ecosystem (Stam, 2015; Wurth, Stam, & Spigel, 2021). Policy makers may foster entrepreneurship by developing the underlying ecosystem and ecosystem elements.

Universities were shown to be substantial contributors to the economy (Bramwell & Wolfe, 2008; Roessner, Bond, Okubo, & Planting, 2013) and play an equally important role in the development of entrepreneurial ecosystems (Hayter, Nelson, Zayed, & O'Connor, 2018; Prokop, 2021). Through the traditional pillars of research and education, but increasingly also through recognizing entrepreneurial training as part of their third mission to contribute to society (Nicotra, Giudice, & Romano, 2021).

While large parts of existing research examining entrepreneurship in the context of universities has focused on intellectual property, technology transfer, and spin-offs (Dahlstrand, 1997; Di Gregorio & Shane, 2003; Etzkowitz, 2003) the economic impact of entrepreneurship education targeting students has received relatively little attention. Students and graduates are worth looking at as a substantial number of university alumni go on to create businesses (C. E. Eesley & Miller, 2018; Hsu, Roberts, & Eesley, 2007; Lerner & Malmendier, 2013). In fact, the number of companies founded by recently graduated students was shown to be at least an order of magnitude larger than faculty spin-offs while being of comparable quality (Åstebro, Bazzazian, & Braguinsky, 2012).

However, research evaluating the impact of entrepreneurship education for university students by looking at actual post-graduation career choices is still relatively sparse (C. E. Eesley

& Lee, 2021). Despite the introduction of entrepreneurship programs at many universities (Katz, 2003; Volkmann & Audretsch, 2017) and increasing interest from policy makers (European Commission & Directorate-General for Employment Social Affairs and Inclusion, 2021) scholarly research on its impact has developed only slowly (Neck & Corbett, 2018).

There are several limitations recognized in literature. First, existing studies have primarily focused on students' entrepreneurial orientation, not actual post-graduation career behavior and companies they founded (C. E. Eesley & Lee, 2021). Second, the methodological rigor of existing studies has been a point of ongoing critique over the past decade with many published studies not meeting key elements for rigorous evaluation research (Rideout & Gray, 2013; Yi & Duval-Couetil, 2021). Third, pedagogical differences between courses and programs have largely been underreported and ignored (Nabi, Liñán, Fayolle, Krueger, & Walmsley, 2017). It is thus not all that surprising that meta-analyses examining the effect of entrepreneurship education on entrepreneurship-related human capital (Martin, McNally, & Kay, 2013) and entrepreneurial intention (Bae, Qian, Miao, & Fiet, 2014) paint an overall ambivalent picture on its effects.

In recent years, a small stream of research has started to address this gap. Lyons & Zhang (2017) evaluate a non-profit entrepreneurship education program in Canada, targeting undergraduate students. They report a positive effect on entrepreneurship rates and startup quality after program completion. With a large-scale survey of Stanford University alumni, Eesley & Lee (2021) take a broader approach and evaluate the establishment of two entrepreneurship centers using a difference-in-difference approach. They find that their creation, at school level, had little to no effect on founding rates but increased overall startup quality. They also provide initial evidence that the Mayfield Fellowship, an experiential entrepreneurship education program for a small group of students, was effective in also raising founding rates.

These results support the argument that different pedagogical approaches may produce differential outcomes (Nabi et al., 2017). For example, while initiatives targeting a broad population of students may have none or even negative effects on founding rates (C. E. Eesley & Lee, 2021), specific experiential entrepreneurship education programs may succeed in increasing them (C. E. Eesley & Lee, 2021; Lyons & Zhang, 2017). Part of the mechanism leading to this variation in outcomes may be found in hidden alignment and sorting effects (Von Graevenitz, Harhoff, & Weber, 2010), i.e. students learning about their innate fit between entrepreneurship and their own aptitude in relation to it (C. E. Eesley & Lee, 2021).

These studies provide first evidence for the potential positive relationship between small-scale entrepreneurship education programs for university students and entrepreneurial outcomes.

However, their study designs do not provide causal evidence and leave important questions open. First, entrepreneurship programs typically have a limited intake and aim to select the most suited candidates from a pool of applicants. This raises the question whether potential outcomes are actually driven by participation or rather by selection of the right participants. Second, while Eesley & Lee (2021) speculate about two mechanisms influencing outcomes – skill and social network development – we lack empirical evidence on how these influence entrepreneurship education programs at university. Third, so far research has only looked at outcomes of entrepreneurship without accounting for the resources that had to be invested into these programs. Even if entrepreneurship education succeeds in raising entrepreneurship rates and startup quality, it might be an economically irrational investment for public funding, if the overall investment cost outweighs the created socioeconomic benefits.

The overall objective of this dissertation is to address these research gaps and empirically investigate the question: *"How does participation in entrepreneurship education programs at university affect entrepreneurial career outcomes of participants and the quality of their startups?"*.

1.2 | Dissertation Structure

This dissertation presents four studies. The first three focus on the evaluation of an entrepreneurship education program open to university students at the Ludwig Maximilian Universität and the Technical University of Munich. The program is worth looking at, as alumni of the program appear to have created startups of disproportionate quality (Antler in Germany, 2022) relative to the overall number of participants. The final study is an excursus, investigating the impact of successful startup exits on the subsequent development of their entrepreneurial ecosystem. Table 1 provides an overview of the guiding research questions, the used data and methods, and the key findings for each of the studies.

Self-Selection into Entrepreneurship Education and Gender Differences

In the first study. we examine how students applying to the program differ from those who do not apply along several psychometric dimensions frequently used to evaluate entrepreneurship education. The results clearly show that applicants are more "*entrepreneurial"* with regards to personality traits, entrepreneurial intention, and past exposure to entrepreneurship. These findings establish that evaluation studies of entrepreneurship education need to use applicants who were not accepted to the program as control group instead of convenience samples from a general population of students to avoid bias through self-selection.

Table 1: Overview of Dissertation Structure and Included Studies

Guiding Research Questions	Data and Method	Results and Key Findings
Self-Selection into Entrepreneurship Education and Gender Differences		
How do students who apply to entrepreneurship programs at university differ from students who do not apply along relevant psychometric constructs?	N = 854 students of which 495 applied to the entrepreneurship program and 359 who did not. Data collection with surveys measuring several psychometric constructs related to entrepreneurship. Hypothesizes-testing with between groups mean comparison (t-tests) and estimation of probit regression models.	- Students applying to entrepreneurship education programs are more "entrepreneurial" along several psychometric constructs compared to students who do not apply. - Studies evaluating entrepreneurship education need to carefully select control groups to not run at risk of self-selection bias.
Impact of Entrepreneurship Education Programs at University: Quasi-Experimental Evidence		
What impact does participation in entrepreneurship education programs at university have on the entrepreneurial career choices of students and the quality of their startups?	N = 1022 students who applied to the entrepreneurship program and advanced to the final step of the application process between 2011 and 2020. 478 were accepted, 544 were not. Career path data on from LinkedIn. Data on startup success from Crunchbase. Regression discontinuity design using original interview ranks to construct a quasi-experiment. Several secondary analyses (e.g. regression analysis, hazard models, heterogeneity).	- Participation in the entrepreneurship program increased selection into entrepreneurship related careers, entrepreneurship rates, and startup success along different metrics. - The effect on entrepreneurship rates is visible for 10+ years after application. - Several secondary analyses indicate that the effect is driven by social capital rather than increased skills, knowledge, and abilities through education and training.
Entrepreneurship Education, Job Creation, and Generated Tax Revenues		
Are investments into entrepreneurship education programs at university economically rational? (i.e. do the generated returns exceed the cost of running the program?)	N = 297 startup companies of which 155 were founded by program participants and 142 by applicants almost accepted into the program. Funding data from Crunchbase. Employee data from LinkedIn. Data on key assumptions from DeStatis. OLS regression to estimate program effect on startup quality. Model calculation using different assumptions to derive generated socioeconomic benefits through created jobs.	- Under conservative assumptions the generated direct tax returns exceed the cost after 10 years. - Most jobs are generated in geographical proximity to the program location. - We estimate a break-even point at national level between year six and seven. - Public investment into experiential entrepreneurship programs at university can yield high socioeconomic returns.
How do Different Forms of Exits Impact Entrepreneurial Ecosystem Development? Longitudinal Evidence		
Are accounts of founders and employees engaging in renewed entrepreneurship and as business angles after successful exits a common phenomenon?	Panel data set of newly founded ventures, investment rounds, and startup exits covering N = 46 ecosystem from 1999 – 2018. Data collection from Crunchbase. Panel data regression, including several robustness tests – e.g. removal of highly active ecosystems and dynamic panel regressions.	- An increase in successful exits in an ecosystem is followed by an increase in newly founded startups and business angel investments in the subsequent one to two years. - Exits by acquisitions (not IPOs) lead to an increase in business angel investments. - The increase in newly founded ventures is only visible one year after the increase in exits, indicating that employees and founders found shortly after the exit.

Notes: As of submission of this dissertation, the presented studies are under review in the following journals. "Self-Selection into Entrepreneurship Education and Gender Differences" in Academy of Management Education and Learning (AMLE). "Impact of Entrepreneurship Education Programs at University: Quasi-Experimental Evidence" in the Strategic Management Journal (SMJ). "Entrepreneurship Education, Job Creation, and Generated Tax Revenues" in Research Policy (RP). "How do Different Forms of Exits Impact Entrepreneurial Ecosystem Development? Longitudinal Evidence" in the Small Business Economics Journal (SBEJ).

Impact of Entrepreneurship Education Programs at University: Quasi-Experimental Evidence

In the second study, we investigate the career impact of participation in the entrepreneurship program based on actual entrepreneurial activity over a 10-year timeframe using a quasi-experimental design. Building on the findings from the first study, we use the applicants who were only closely not accepted to the program as a control group. Employing a regression discontinuity design allows us to control for active selection by using the rank of applicants in the application process. Our results show that program participation has a positive effect on individuals' selection into careers related to entrepreneurship, their likelihood of founding, and the quality of their startups. Secondary analyses further indicate that the observed effects are likely driven by social capital developed through program participation rather than a mere increase in skills.

Entrepreneurship Education, Job Creation, and Generated Tax Revenues

In the third study, we analyze the economic impact created over the same 10-year timeframe by the startups founded by program participants and estimate the tax revenue generated through the jobs they create. While the results of the previous study provide strong evidence that the program has a positive impact on entrepreneurial outcomes, it is not clear in which relation the generated socioeconomic benefits stand to the cost of running the program. By analyzing the jobs created by alumni founded startups and employing a set of model assumptions, we find that the generated direct income tax revenue in 2022 alone far exceeds the cost for running the program. We further show that the majority of jobs are created in Bavaria in regional proximity to the program.

Excursus: How do Successful Exits Impact the Development of Entrepreneurial Ecosystems?

Finally, in a fourth study, we present an excursus back to the entrepreneurial ecosystem level. During our analysis of the companies founded by alumni of the program, we stumbled across the case of Stylight. The startup was founded by four alumni, Anselm Bauer, Benjamin Günther, Max-Josef Meier and Sebastian Schuon in 2008. After they successfully sold their start-up in 2016, they used their newly acquired capital and knowledge to invest into, and mentor new start-ups – many of which have been founded by program participants from the cohorts we looked at. More than that, they also founded again, creating start-ups that by now raised more than €179m in equity funding.

For one, this example provides anecdotal evidence on how the community of alumni and social network surrounding entrepreneurship programs supports nascent entrepreneurs to start their businesses. Their support also shows how successful startup exits can spur the development of the entrepreneurial ecosystem they are embedded in. When looking into existing literature, we found case studies detailing similar effects.

However, we were curious to understand whether this reinvestment of time and resources into the next generation of founders, and consequently the underlying entrepreneurial ecosystem, could be a more general phenomenon. The existing body of research on exits and their regional impact is characterized by case studies. Using a panel data set of 46 European ecosystems covering 19 years from 1999 to 2018, we investigated the impact of successful startup exits on a broad level and discuss the differences between exits by acquisition and IPOs.

1.3 | Research Methods and Data Sources

All studies presented in this dissertation are of empirical nature. The first three studies evolve around the add-on study program "*Technology Management*" offered by the Center for Digital Technology and Management (CDTM) in Munich, Germany. The fourth study takes a more general perspective by looking at 46 European entrepreneurial ecosystems. In the first study, we collected data by surveying students. The remaining studies use data gathered from online platforms and databases, most prominently LinkedIn and Crunchbase.

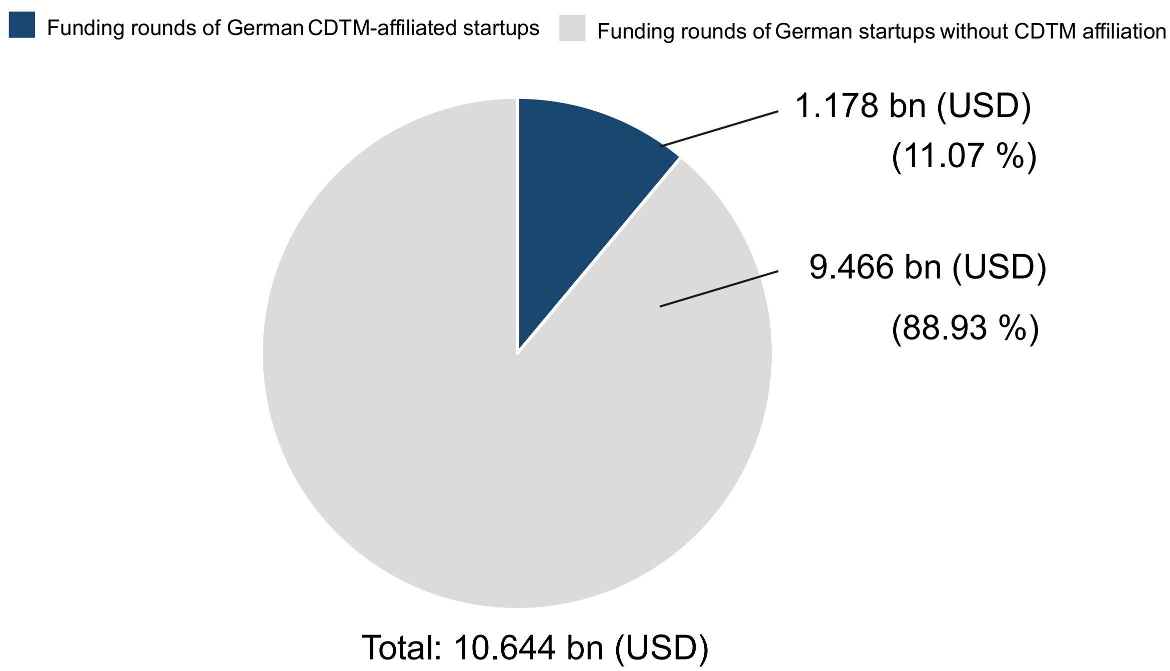
1.3.1 | Empirical Context

Our empirical setting is an add-on entrepreneurship program offered to students enrolled at the Ludwig Maximilian Universität (LMU) or Technical University of Munich (TUM) in Munich, Germany. It is offered by the Center for Digital Technology and Management (CDTM), a joint institution of both universities that is supported by 22 professors from both universities and run by a management team of ten doctoral candidates.

The goal of the program is to "*Connect, Educate, and Empower the Innovators of Tomorrow*" through a combination of coursework, mentorship, access to industry partners and alumni of the program. In doing so, the program adopts a broad framing of entrepreneurship education (Bhatia & Levina, 2020), allowing students to practice entrepreneurial thinking and problem solving and thereby evaluate whether it would be an appropriate career for themselves. Participants do not work on their own business ideas throughout the core modules. Instead, each core module is conducted in collaboration with project partners from industry introducing a real-world problem context. Courses are organized and managed by doctoral candidates. Lecturers and mentors are typically professionals from varying fields – experienced entrepreneurs, venture capitalists, business angels, consultants, academics, and corporate experts. In combination with an active community of alumni this provides participants with an opportunity to develop a network in the regional entrepreneurial ecosystem.

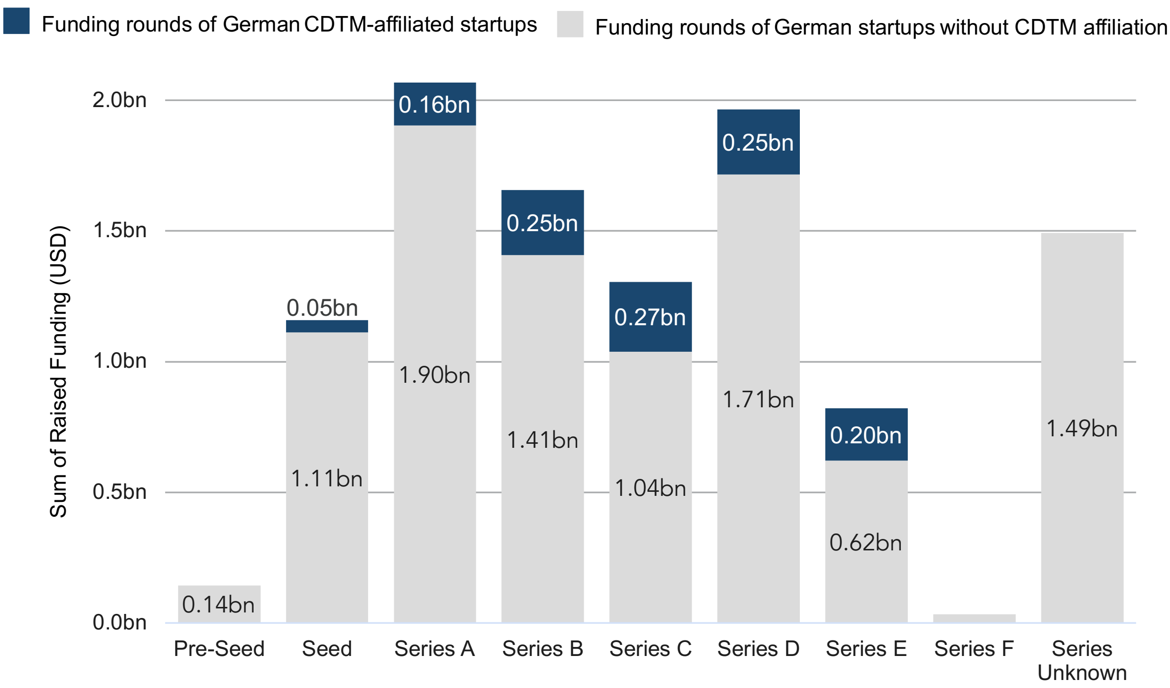
The program is worth looking at because its alumni have founded many successful startups, which have a disproportionately high impact on the German entrepreneurship ecosystem (Antler in Germany, 2022). In 2022, 11.07% percent of the venture capital volume flowing to German startups tracked on Crunchbase went to companies who were co-founded by alumni of CDTM. When looking at later stage funding rounds the share is even higher. This is remarkable, as the program has an annual intake of only 50 students compared to 2.95 million students enrolled in Germany's universities in the winter semester of 2021 (Davies, 2022).

Figure 1 and Figure 2 illustrate the venture capital raised by startups affiliated with the program in relation to the overall venture capital flowing to startups headquartered in Germany in 2022.



Notes: Based on data from Crunchbase. Considering only startups headquarted in Germany. A startup is considered CDTM affiliated, if at least on co-founder studied at CDTM. Considering only pre-seed, seed, Series A – Series J equity funding rounds.

Figure 1: Venture Funding (USD) Raised by CDTM and Non-CDTM Startups in 2022



Share CDTM:	0%	3.96%	7.96%	15.08%	20.54%	12.72%	24.35%	0%	0%

Notes: Based on data from Crunchbase. Considering only startups headquarted in Germany. A startup is considered CDTM affiliated, if at least on co-founder studied at CDTM. Considering only pre-seed, seed, Series A – Series J equity funding rounds.

Figure 2: Venture Funding (USD) Raised by CDTM and Non-CDTM Startups in 2022 by Funding Type

1.3.2 | Program Participant Selection

The program runs twice a year. Each cohort about 25 students are admitted, following a competitive three-step application process. The first step consists of a written online application submitted via a dedicated online platform. Each application is reviewed in a double-blinded process by three to four people associated with the program. From the initial pool of applicants, a set of 60 finalists is selected, who are then invited to in-person interviews.[1] In the context of the studies presented in this dissertation, the selection process is relevant for two reasons.

First, in the study presented in Chapter 2 we utilize the first step of the process, the submission of a written application via a dedicated online platform, to distinguish between students who applied and those who created an account but decided to not submit their application. In doing so, we show that students who self-select into entrepreneurship education programs are a-priori more entrepreneurial along several psychometric constructs (e.g. innovativeness, risk taking propensity, entrepreneurial intention) compared to students who do not apply. Our results empirically confirm concerns that many studies evaluating entrepreneurship education may run at risk of (self-) selection bias (Bae et al., 2014; Liñán,

[1]A detailed description of the application process and participant selection can be found in Chapter 3 (Page 47).

Ceresia, & Bernal, 2018). These results establish that students chosen from a general population are not an adequate control group when evaluation entrepreneurship education programs.

Second, in the studies presented in Chapter 3 and Chapter 4 we use the population of applicants who advanced to the final step of the selection process and were almost admitted to the program as control group. This allows us to avoid bias through self-selection but raises the issue of active selection. Given the limited spots each semester, the selection process of the program aims at identifying the candidates that are most suited to the program. Following the stated program goals, the selection process is not directly aimed at identifying the students most eager to found. Nonetheless, we must assume that candidates ranked higher in the interview process would also be, to some degree, more suited for an entrepreneurial career even without participation in the program. We cope with this concern in two ways: First, following recent examples (Hallen, Cohen, & Bingham, 2020; Lyons & Zhang, 2017) we only consider applicants who made it to the final step of the application process and were almost accepted. Second, we use the ranking in the application process to construct a quasi-experimental regression discontinuity design (D. S. Lee & Lemieux, 2010) to control for active selection and determine the local average treatment effect that program participation has on the dependent variables.

1.3.3 | Data Sources

In our first study, presented in Chapter 2, we use a survey instrument to collect psychometric constructs from participants. In the remaining studies, we forgo data collection through surveys and instead rely on publicly available data from LinkedIn and Crunchbase. We chose this approach to avoid response bias. Given that alumni of the Center for Digital Technology and Management (CDTM) remain well connected to the institute, a survey-based data collection would likely yield unbalanced responses between program participants and rejected applicants. In comparison, all individuals should have an equal interest in maintaining their LinkedIn profiles.

To collected data on startup quality, investment rounds, and, in Chapter 5, on successful exits we used Crunchbase. Crunchbase is a start-up database, containing data on start-ups, VC firms, exits and financing rounds. The data is collected and validated through a community of independent contributors, venture firms and analytics (Dalle, Besten, & Menon, 2017). Previous research regarding the reliability of this database has shown the fit of Crunchbase data for academic research (Dalle et al., 2017; Nylund & Cohen, 2017; Retterath & Braun, 2020).

1.4 | Main Results and Contribution

Collectively, the studies presented in this dissertation provide robust causal evidence that entrepreneurship education programs at university can increase both entrepreneurship rates and startup quality among participating students substantially. They also show that the generated socioeconomical benefits far outweigh the costs for running the program.

1.4.1 | Main Contribution

While the contributions of each study are discussed in detail in the respective chapters, this dissertation, in summary, advances our understanding about entrepreneurship education programs at university in meaningful ways.

First, we contribute a differentiated analysis of the causal effect of participation in entrepreneurship education programs on selection into entrepreneurial careers, entrepreneurship rates, and startup quality. Our quasi-experimental analysis represents a methodological improvement over existing studies, responding to repeated calls for increased rigor in evaluating entrepreneurship education (Neck & Corbett, 2018; Rideout & Gray, 2013; Yi & Duval-Couetil, 2021) and showing that observed effects are a consequence of program participation, not selection.

Second, we examine the driving mechanisms behind the entrepreneurship related outcomes and, across studies, find evidence indicating the importance of social capital development over mere skill development (C. E. Eesley & Lee, 2021). In part these findings may explain, why small-scale programs can lead to increased entrepreneurship rates while broad courses may not, and also why increased entrepreneurship rates are visible long after university graduation.

Third, we juxtapose the cost for running the entrepreneurship program with the socioeconomic returns that alumni-founded companies generate by creating additional jobs. We show that even with conservative assumptions, the generated additional taxes far outweigh the program cost after just ten years and provide empirical evidence for policy makers considering investment into entrepreneurship education programs.

1.4.2 | Methodological Improvements Over Existing Studies

Our approach represents a methodological improvement over existing studies evaluating entrepreneurship education. The main advantage of the RD design we use in Chapter 3 is that it requires milder assumptions than non-experimental approaches to identify causal treatment effects (e.g., instrumental variables, difference-in-differences, matching). The identifying assumption in an RD design is that close to the cutoff, there is some randomness in which side of the cutoff an individual ends (Lee and Lemieux, 2010).[2] Under this condition, which can be checked, for example, by the continuity of the observations around the cut-off point, the RD design is similar to a randomized experiment. This distinguishes the RD design from the instrumental variable approach, which requires the assumption that the instrument is exogenously generated, an assumption that is difficult to justify in most observational studies. For example, the necessary assumption for Eesley and Lee (2021) to measure a causal effect of entrepreneurship education is that the introduction of the CES/STVP entrepreneurship education programs at Stanford was truly random and not driven by a particular demand at the time. Similarly, matching and regression control approaches assume that there are no relevant unobservables conditional on the observables that could introduce omitted variable bias. Previous studies (Lyons and Zhang, 2017; Oosterbeek *et al.*, 2010; Von Graevenitz *et al.*, 2010) have to assume that the observed control variables, such as GPA, prior entrepreneurship experience, and interview score, in a linear regression model fully control for unobservables that may drive the relationship between program participation and entrepreneurship outcomes. The strength of this assumption is the reason why these results are denoted as correlations, not causal effects – and why the studies presented in this dissertation are a methodological step forward compared to extant studies evaluating entrepreneurship education programs at university.

Despite these advantages the RD design also has its disadvantages. The main disadvantage is that the design only identifies a strictly local average treatment effect. That is, we can say that the program would have very likely affected the next 5-10 applicants similarly to the participants in the program. However, it is unclear to what extent our results can be generalized to other programs, institutional backgrounds, other populations, etc. To show in which contexts our results will probably be generalizable, we discuss the results of our study in the following against the findings of existing evaluation studies of entrepreneurship education at university.

1.4.3 | Types of Entrepreneurship Education and Outcomes

Across existing studies, we observe a large variance in outcomes when it comes to whether entrepreneurship education influences entrepreneurial intention (Bae *et al.*, 2014; Oosterbeek *et al.*, 2010; Von Graevenitz *et al.*, 2010) and the likelihood that participants found startups (Eesley and Lee, 2021; Lerner and Malmendier, 2013; Lyons and Zhang, 2017). The collective observations across studies in this dissertation, allow us to interpret the results of past evaluation studies while theorizing about the influence of self-selection and selection on the composition of entrepreneurial aptitude among participants and eventually entrepreneurial outcomes.

[2]See Lee and Lemieux (2010) for an excellent summary of the RD design.

If we look at the reported outcomes of entrepreneurship education at university across recent studies, we observe differences between compulsory courses, non-compulsory courses, and programs (see Table 2). Compulsory courses were shown to negatively affect the entrepreneurial intention among participants (Fretschner and Lampe, 2019; Oosterbeek *et al.*, 2010; Von Graevenitz *et al.*, 2010) and consequently we would also expect a negative impact on founding rates. Similarly, non-compulsory courses, targeting a broad student population were shown to have negative to zero impact on founding rates (Eesley and Lee, 2021; Lerner and Malmendier, 2013). In line with our findings, recent work examining specific entrepreneurship education program, however, report a positive effect on founding rates (Eesley and Lee, 2021; Lyons and Zhang, 2017).

What may cause this variance in outcomes? The analyses presented in this dissertation point to the importance of entrepreneurial social capital formation, for which the composition of the overall participant cohort, e.g. peer effects (Bechthold and Huber, 2020; Eesley and Wang, 2017; Lerner and Malmendier, 2013), and the duration and intensity of the educational intervention, e.g. group social capital and group identity formation (Hallen *et al.*, 2020; Obschonka *et al.*, 2012; Oh, Chung, and Labianca, 2004), may be relevant. Both group composition and intensity vary between different types of entrepreneurship education at university.

Table 2: Types of Entrepreneurship Education and Entrepreneurial Outcomes

	Compulsory Course	**Non-Compulsory Course**	**Program**
Examples	• Von Graevenitz et al. (2010) • Oosterbeek et al. (2010)	• Eesley and Lee (2021) [STVP, CES] • Lerner and Malmendier (2013)	• Eesley and Lee (2021) [Mayfield Fellowship] • Lyons and Zhang (2017)
	Observed Outcomes		
Entrepreneurial Intention	Negative	–	–
Founding Rates	–	Neutral/ Negative	Positive
Startup Quality	–	Positive	Positive
	Selection Effects		
Self-Selection	No	Yes	Yes
Active Selection	No	No	Yes
	Hypothesized Participant Composition		
Interest for Entrepreneurship	Low	Medium	High
Entrepreneurial Aptitude	Low	Medium	High

The group composition between different types of courses may be substantially influenced by self-selection and active selection effects. In non-compulsory courses neither selection is present. Compulsory courses are most commonly part of undergraduate programs when most students have little prior exposure to entrepreneurship. Given that entrepreneurship is a rather scarce career choice, we would expect the group as a whole to have rather low interest and low aptitude for entrepreneurship. For non-compulsory courses, students interested in entrepreneurship self-select. However, most university courses do not employ extensive selection processes to admit participants to single courses. Compared to programs, which require additional workload on top of the existing curriculum, course participation is usually embedded into the existing study programs. Participants thus have lower opportunity costs to consider when joining a single entrepreneurship course. As a result, we would expect somewhat weaker self-selection effects, in summary, leading to medium interest and aptitude for entrepreneurship among the group. Finally, for entrepreneurship programs, we would expect strong self-selection effects as programs require a substantial time investment. Students who apply likely have high confidence that entrepreneurship is the right career path for them. The competitive selection of the most suited participants from a pool of applicants[3] further ensures that the group as a whole is not only characterized by a high interest in entrepreneurship but also by a high entrepreneurial aptitude.

This proposition is compatible with the central theoretical argument in current literature why participation in entrepreneurship education would lead to a decreased likelihood of starting a business, which is that it reveals ability levels among participants (Eesley and Lee, 2021; Lerner and Malmendier, 2013). Participants who underestimate the difficulty of founding a startup or overestimate their own abilities, receive valuable information signals, and update their innate understanding (Fretschner and Lampe, 2019; Von Graevenitz *et al.*, 2010). The reduction in founding rates results from a reduction of unsuccessful entrepreneurial ventures being founded, and thus the average quality of startups is expected to increase (Lerner and Malmendier, 2013). More work examining the outcomes of entrepreneurship education and their driving causal mechanisms would be certainly informative to test these propositions and understand the generalizability of these results.

[3]Both Lyon & Zhang (2017) and the program evaluated in our study employ a multi-stage assessment to select participants from a substantially larger pool of qualified applicants. In an unpublished study, we surveyed applicants to the program (2021 and 2022 cohorts) for their previous experience with entrepreneurship and entrepreneurship education. 59% of applicants worked in a startup prior to their application and, on average, applicants had participated in 2.13 university entrepreneurship.

1.4.4 | Limitations and Generalizability

The presented studies clearly show that entrepreneurship education programs at university can succeed in producing substantial entrepreneurial output and hint at the importance of social capital development as enabling mechanism. However, it is not to say that alternative configurations may not work in increasing entrepreneurial outcomes. To understand which elements, contribute to successful entrepreneurship programs we need further rigorous research evaluating entrepreneurship education (Yi & Duval-Couetil, 2021) while considering the heterogeneity in target groups, program structures, and pedagogical approaches (Nabi et al., 2017).

We discuss the collective results of this dissertation, implications for practice and theory and avenues for future research in more detail in Chapter 6.

2 | Self-Selection into Entrepreneurship Education and Gender Differences

The literature is full […] of stories of the 'entrepreneurial personality' and of people who will never do anything but innovate. […] These discussions are pointless. By and large, people who do not feel comfortable as innovators or as entrepreneurs will not volunteer for such jobs; the gross misfits eliminate themselves. The others can learn the practice of innovation.

Peter Drucker, 1985, Innovation and Entrepreneurship (p. 170)

2.1 | Abstract

Entrepreneurship is a driving force for economic wealth. In past years both interest and investment in entrepreneurship education and training programs has increased substantially. However, research on the impact and success factors of entrepreneurship education remains ambivalent. While some studies find that entrepreneurship programs foster skills relevant for entrepreneurs, others find only weak or even no effects. Part of this ambiguity may be explained by self-selection effects, raising the question of whether students interested in entrepreneurship education are upfront different from those who are not. Understanding this is important to choose adequate control groups when evaluating entrepreneurship education. We address this research gap by testing our hypothesis on a sample of non-applicants (n=359) and applicants (n=495) of a well-known and successful university entrepreneurship program for students in Germany. The dedicated application process allows us to clearly identify candidates who knew the program and decided against applying. Our results indicate that applicants are more "*entrepreneurial*" than non-applicants along several dimensions frequently used to evaluate entrepreneurship education. This suggests that researchers and educators need to pay rigorous attention to select suitable control groups when evaluating the impact of entrepreneurship education.

As of submission of this dissertation, the study presented in this chapter it under review in the Academy of Management Learning & Education (AMLE) journal.

2.2 | Introduction

Entrepreneurship is an important driver for economies all over the world. There is extensive literature linking economic growth and development to entrepreneurship (Acs, Estrin, Mickiewicz, & Szerb, 2018; Audretsch, 2018; Praag & Versloot, 2007; Schumpeter, 1934). In recent years policy makers have focused on the potential of entrepreneurship education in higher education (c.g. European Commission, 2013). In addition, bringing forward entrepreneurs and new ventures are becoming accepted parts of universities' third mission (Nicotra et al., 2021).

In the last two decades the number of entrepreneurship education programs increased considerably. Most academic studies examining their impact focus their evaluation on short-term indicators such as entrepreneurial attitudes, skills, knowledge, perceived feasibility, and entrepreneurial intentions (Nabi et al., 2017). However, recent meta-studies (Bae et al., 2014; Martin et al., 2013) reveal that the research body on the impact of entrepreneurship education provides an overall ambiguous and contradictory picture. Martin et al. (2013) report a small positive relationship on entrepreneurship-related human capital assets but also highlight that studies with lower methodological rigor tend to overestimate the effect. Bae et al. (2014) analyze the relationship between entrepreneurship education and entrepreneurial intentions, finding no significant relationship after controlling for pre-education levels. They highlight the possibility of reverse causation through self-selection effects and argue that "*entrepreneurial intentions may not be determined by entrepreneurship education, but rather by prior beliefs before enrolling*" (Bae et al., 2014, p. 221). Thus, failing to control for potential self-selection might be one reason why the literature has not yet generated consistent findings.

Some studies investigate compulsory programs to avoid potential self-selection biases (Fayolle, Gailly, & Lassas-Clerc, 2006; Oosterbeek, Praag, & Ijsselstein, 2010; Von Graevenitz et al., 2010). However, compulsory courses seem to serve a different purpose than voluntary ones. Von Graevenitz et al. (2010) argue that compulsory courses provide informative signals to participants that allow them to learn about their entrepreneurial aptitude. While not leading to stronger entrepreneurial intentions on average, compulsory courses induce a hidden sorting function by helping students determine whether they are suited for entrepreneurship after the course (Fretschner & Lampe, 2019; Von Graevenitz et al., 2010).

Following this line of argumentation, entrepreneurship education programs with a dedicated application process should be considered distinct from compulsory courses. We can assume that students who actively apply to entrepreneurship education programs likely already see a fit in terms of their career interest and abilities and perceive them as useful for their professional development. Therefore, this self-selection can already be associated with overall stronger prior beliefs regarding entrepreneurship before enrolling (Bae et al., 2014; Liñán et al., 2018). Following this idea, it is surprising that most studies do not consider that participants take a conscious decision to select themselves into entrepreneurship courses. This is problematic as post-educational measures may not reflect the sole outcome of the educational intervention, if an inadequate control group was chosen.

While research has started to address this issue (e.g Liñán et al., 2018), it is not yet evident along which dimensions students who self-select into entrepreneurship education differ from those that don't. A particular challenge in investigating this issue is to clearly identify students who seriously considered entrepreneurship education and then decided against it. We utilize the application process for a well-known entrepreneurship education program at a public German university to close this gap. The dedicated application process allows us to clearly identify candidates who knew the program, considered applying, and decided against. We only consider students in the group of non-applicants that created an account on the application platform and later abandoned their application. This sampling strategy ensures that we avoid including students that simply were not aware of the program but would have applied if they did.

We test our hypotheses on a final sample of 495 applicants and 359 non-applicants. Our results indicate that there are statistically significant differences between applicants and non-applicants along several constructs frequently used to evaluate entrepreneurship education, including entrepreneurial intention, attitudes towards entrepreneurship, and entrepreneurial self-efficacy. In other words, students who decide to apply to entrepreneurship programs have an upfront higher intention to found startups. We also find differences in character traits associated with entrepreneurial personalities and show that applicants have had more exposure to entrepreneurship and entrepreneurship education than non-applicants before applying.

Along all analyses, we find statistically significant difference between genders. Female students are less likely to apply. Among applicants only 25% are female compared to 39% among non-applicants. By taking a second look at differences between gender, we show that female students have lower entrepreneurial intention and attitudes towards entrepreneurship. However, we do not find statistically differences between genders with regards to their entrepreneurial self-efficacy and exposure to entrepreneurship. Our analyses also indicate that differences between genders are smaller than the differences between applicants and on-applicants.

These results suggest that past studies evaluating entrepreneurship education run at risk of self-selection bias. Future evaluation studies of non-compulsory entrepreneurship education should not only utilize pre-/ post-measures, but also select adequate control groups instead of convenience groups to avoid self-selection. For example, for courses or programs that have more applicants than open spots, students who applied but were not admitted can serve as a control group. In cases where participants are selected not randomly, but by some measure of fit or qualification, study designs need to control for the active selection. One approach for this would be to use the rank of applicants in a regression discontinuity design to construct a quasi-experiment (D. S. Lee & Lemieux, 2010).

Our paper seeks to make three contributions. First, we study the difference between applicants and non-applicants at the example of a non-compulsory university entrepreneurship education program. By utilizing the discrete decision of students to apply or not apply after registering for the application process we can clearly identify students who considered applying and decided against it. Our results show that students who self-select into entrepreneurship education differ from those that don't along several dimensions frequently used to evaluate entrepreneurship education.

Second, we take a deeper look at gender differences across both applicants and non-applicants. Gender research in entrepreneurship and female entrepreneurship have both become topics of increased research interest in recent years (Deng, Liang, Li, & Wang, 2021). With female students being less likely to apply, we investigate the differences between male and female students along the measured psychometric constructs.

As a third contribution, we discuss the implications of these results for research seeking to evaluate the impact of entrepreneurship education. Past studies on non-compulsory entrepreneurship courses may suffer from selection biases if inadequate control groups were chosen. Because of self-selection dynamics, future studies need to pay careful attention to select control groups from the same population of entrepreneurial students to isolate the treatment effect of the educational intervention. Finally, future studies should delineate between compulsory and non-compulsory entrepreneurship education at university when discussing their impact.

2.3 | Theoretical Framework and Hypotheses

We hypothesize that students who self-select into entrepreneurship education are more "*entrepreneurial*" than those students who do not apply. We operationalize this concept by looking at three aspects frequently found in entrepreneurship literature: entrepreneurial personality traits, entrepreneurial intentions, and past exposure to entrepreneurship and entrepreneurship education.

2.3.1 | The Entrepreneurial Personality

Entrepreneurship research has long shown interest identifying traits that are associated with entrepreneurial behavior. The word entrepreneurial is commonly used to describe people who are characterized by foresight, creativity and adaptability. Entrepreneurship research often refers to the entrepreneurial personality (Littunen, 2000; Vries, 1977) as a set of personality traits along which founders and non-founders, e.g. employees, differ. While in the working environment the entrepreneurial personality is often distinguished from that of managers (C. C. Chen, Greene, & Crick, 1998; Zhao, Seibert, & Lumpkin, 2010), in the university environment a distinction is usually made between students who are entrepreneurially inclined and those who are not (Gürol & Atsan, 2006; Hansemark, 1998; Kolvereid, 1996). As the entrepreneurial process can be divided into several phases, it is particularly interesting to examine the entrepreneur in the early phases of founding a company, as this is where personality likely has the greatest influence (Frese & Gielnik, 2014; Hambrick, 2007).

Personality traits can amongst other things "*include abilities [...], motives [...], attitudes [...], and characteristics of temperament as an overarching style of a person's experiences and actions*" (Brandstätter, 2011, p. 223). A recent extensive literature review by Salmony & Kanbach (2021) looked at 95 studies between 1985 and 2020 and identified the Five Factor Model (Big 5), Need for Achievement, Innovativeness, Locus of Control, Risk Attitudes, and Entrepreneurial Self-Efficacy as commonly measured traits. While Salmony & Kanbach (2021) highlight that past literature has come short to clearly delineate between different types of entrepreneurs (e.g. agriculture entrepreneurs, nascent entrepreneurs, students with entrepreneurial interest) they find general evidence that many of these traits are more expressed in entrepreneurs. Thus, we hypothesize that students who self-select into entrepreneurship education have more pronounced entrepreneurial character traits compared to students who decide not to.

Hypothesis 1 (H1): *Students who self-select into entrepreneurship educations programs exhibit more expressed character traits associated with* ***the entrepreneurial personality*** *than students who don't.*

Based on recent literature (Salmony & Kanbach, 2021) we hypothesize a positive relationship between applying to the program and *Need for Achievement, Innovativeness, Risk Taking Propensity, Internal Locus of Control, Openness, Conscientiousness,* and *Extraversion*. We hypothesize a negative relationship between applying and the *External Locus of Control* and *Neuroticism*.

2.3.2 | Entrepreneurial Intentions

Along with the growth of entrepreneurship education programs at universities (Kuratko, 2005; Solomon, 2007) researchers have started to study their impact (Nabi et al., 2017). In an extensive systematic literature review on outcomes of entrepreneurship education Nabi et al. (2017) find that most evaluation studies use short-term measures, such as entrepreneurial attitudes and intention, as outcome variables. However, the reported impact of entrepreneurship education evaluated by using short-term measures across studies is overall ambiguous (Bae et al., 2014; Nabi et al., 2017).

Particularly entrepreneurial intention and its antecedents are interesting to look at in the context of self-selection as they have served as theoretical framework for many studies (Bae et al., 2014). Under the Theory of Planned Behavior (Ajzen, 1991) entrepreneurship is framed as planned behavior that is best predicted by observing intentions (Bagozzi, Baumgartner, & Yi, 1992). The formation of intention is preceded by three components, (1) the attitude towards the behavior, (2) subjective norms, and (3) the degree of perceived behavior control (Ajzen, 1991; Y. Zhang, Duysters, & Cloodt, 2014). Attitudes towards the behavior refer to the degree of positive or negative personal valuation an individual holds towards the behavior. Subjective norms refer to the perceived social pressure through relevant friends or family. Perceived behavior control reflects the perceived situational competence (Ajzen, 1991; Y. Zhang et al., 2014).

In the context of entrepreneurship, perceived behavior control and attitude towards entrepreneurship were shown to be robust predictors of entrepreneurial intention (N. F. Krueger, Reilly, & Carsrud, 2000). Subjective norms, however, were shown to be less predictive in the context of entrepreneurship (Autio, Keeley, Klofsten, Parker, & Hay, 2010; Krueger et al., 2000; Y. Zhang et al., 2014). Instead of including subjective norms we therefore include entrepreneurial exposure, following the example of Zhang et al. (2014). In the recent two decades entrepreneurial self-efficacy, a construct embedded within perceived behavior control, has been used in a growing number of entrepreneurship evaluation studies (Newman, Obschonka, Schwarz, Cohen, & Nielsen, 2018). Because of its prevalence we therefore include entrepreneurial self-efficacy.

Building on recent work by Liñán et al. (2018) we expect students who self-select into entrepreneurship education to have higher entrepreneurial intentions compared to students who don’t. We therefore propose the following hypothesis.

Hypothesis 2 (H2): *Students who self-select into entrepreneurship education programs exhibit higher* ***entrepreneurial intention*** *than students who don’t.*

In line with the theory of planned behavior in the context of entrepreneurship (Ajzen, 1991; N. F. Krueger et al., 2000; Liñán & Chen, 2009) we hypothesize that there is a positive relationship between applying to the program and *Entrepreneurial Intention (EI)* as well its antecedents *Attitudes Towards Entrepreneurship (ATE)*, *Entrepreneurial Self-Efficacy (ESE)*, and students' *Entrepreneurial Exposure*.

2.3.3 | Entrepreneurship Education and Entrepreneurship Experience

Looking at a compulsory entrepreneurship course for business students, Von Graevenitz et al. (2010) found that despite entrepreneurial self-efficacy improving, entrepreneurial intentions went down among participating students. They explain this effect by arguing that participation in the course lead to valuable information signals for students about what a potential career as entrepreneur entails and their own entrepreneurial skills. These hidden sorting and alignment functions (Fretschner & Lampe, 2019) help students to assess their own aptitude for entrepreneurship and strengthen their conviction about it.

We would expect that these sorting effects are stronger in situations where students have less information about entrepreneurship before the fact, such as in compulsory courses. Since our empirical context is a non-compulsory program with a relatively long duration of three semesters, a high workload, and a competitive application process that requires upfront investment, we would expect applicants that applicants take a more intentional approach on deciding whether to apply. We would also expect those that do apply have learned about entrepreneurship and their own aptitudes from prior contexts.

Hypothesis (H3): *Students who self-select into entrepreneurship educations programs* ***have more experience with entrepreneurship or entrepreneurship education*** *prior to their application than students who don't.*

Building on previous approaches (N. Krueger, 1993; Von Graevenitz et al., 2010) we operationalize this concept by looking at three types of prior experience: *founding themselves*, *working in a startup*, or *participating in entrepreneurship education*.

2.4 | Data and Method

To test these hypotheses, we utilize the application process for an entrepreneurial add-on study[4] program at a public university in Germany. The program was formally founded in 1998 and has since then accepted 25 students per semester. The goal of the program is to *"Connect, Educate, and Empower the Innovators of Tomorrow"* through a combination of formal coursework, mentorship, interdisciplinary exchange, and access to its network of alumni. The program is to be completed next to regular enrollment in an undergraduate or graduate program at the university – hence add-on program – and comprises 45 ECTs of coursework. Despite its workload and small intake, the program is well-known within the local university landscape to have produced remarkable entrepreneurial output. Some of the most visible startups in the local entrepreneurial ecosystem have been co-founded by alumni of the program. In total, its alumni have co-founded more than 250 startups and raised more than $6 billion in funding.[5]

2.4.1 | Program Context: Application Process

As the program has a limited number of spots each semester, participants are chosen through a competitive application process. The first round of the application consists of a written online application that includes questions on the academic and professional experience of applicants as well as motivational letters. In a double-blind review process each application is scored by multiple people associated with the program. From the initial applicant pool, a set of about 60 finalists are chosen to advance to the next stage of the process. On average around 300 people apply each intake, 60 are invited to the second round, and 25 are admitted to the program.

For the context of this study, we utilize the first step of the application process, the online application. In addition to the around 300 valid applications an additional 500 accounts are created each semester on the online application platform that end up not submitting their application. In other words, in each application round there is a pool of students who know about the program, consider applying and create an account on the application website, only to later abandon their application. This natural event allows us to distinguish between students who decided to pursue entrepreneurial education by submitting their application and those who decided against it.

[4]Entrepreneurship education programs as a form of extra-curricular activity at universities are not uncommon. In literature different accounts at universities across the world can be found: e.g. the Mayfield Fellowship at Stanford University (C. E. Eesley & Lee, 2021), the Manage&More Scholarship at the Technical University of Munich (Schönenberger, 2022), or further examples from Serbia and Portugal (Volkmann & Audretsch, 2017)

[5]See https://crunchbase.com/compare/hub/center-for-digital-technology-and-management-cdtm-alumni-founded-companies/technical-university-of-munich-alumni-founded-companies (last accessed: 2023-01-28)

2.4.2 | Data Collection and Sample Selection

We collected our data with a questionnaire (see Appendix, Table A1), which was distributed after the deadline for the application period had passed and before applicants received feedback. Completing all questions took between 7 and 10 minutes. We were careful to highlight that participation in the study was voluntary, data was collected anonymously, and participation (or the lack thereof) would not have any influence on the application process. To increase response rates, we raffled five vouchers each worth EUR 50 among participants and sent follow-up emails 5 and 12 days after the initial outreach. We collected our dataset in three rounds in May 2021, in December 2021, and again in May 2022. In total we collected 854 valid responses from students. Of those 495 are in the applicant group and 359 in the non-applicant group.

We expect this form of data collection and sample selection to be suitable to test our hypotheses. First, the study program is well known among students within the local university context as it has produced a substantial number of successful founders and is advertised in entrepreneurship related courses at university prior to the application deadline. Second, the dedicated application process via an online platform allows us to capture all students who registered an account regardless of whether a final application is submitted. By distributing our questionnaire to all registered users, we can thus be sure that all participants know about the program and had taken the decision to apply or not apply. This approach allows us to avoid including students in the group of non-applicants that would have applied but were not aware of the program. Finally, we only include responses of students that meet the program selection criteria. Thus, we only consider students that are enrolled in a study program either at the Technical University of Munich or the Ludwig Maximilian Universität in Munich.

2.4.3 | Research Instrument

We developed a web-based questionnaire to collect multiple constructs. Both applicants and non-applicants received the same questionnaire (see Appendix, Table A1). The questionnaire measured the following constructs: *Entrepreneurial Intention*, *Entrepreneurial Self-Efficacy*, *Attitudes Towards Entrepreneurship*, *Innovativeness, Need for Achievement*, *Locus of Control*, *Risk Taking Propensity* and the *BIG Five Personality Traits*. In addition to the main constructs, we collected data on ex-ante experiences with entrepreneurship and entrepreneurship education, as well as demographic data. To ensure the validity of the measures we adapted construct items from previous studies. All questions collected with Likert-Scales (Likert, 1932) were adapted to a 5-point scale, ranging from 1 (Totally Disagree) to 5 (Totally Agree). Constructs measured with several items were combined into an index by calculating the mean from the individual items.

To measure personality traits, we relied on validated scales from prior research. We measured *Need For Achievement* with five questions adapted from Steer & Braunstein (1976). We measured *Innovativeness* with eight items originating from the Jackson Personality Inventory (Paunonen & Jackson, 1996) that were adapted by Mueller & Thomas (2001) for the entrepreneurship context. We measured *Locus of Control* with four items based on Kovaleva (2012). We measured *Risk Taking Propensity* with eight items using the General Risk Propensity Scale by Zhang, Highhouse & Nye (2019). Finally, we measured the *Five Factor Model of Personality* (Big 5) with ten items using the 10-Item-Big-Five-Inventory (BFI-10) by Rammstedt, Kemper, Klein, Beierlein & Kovaleva (2013).

We measured *Entrepreneurial Intention* with three questions adapted from Liñán & Chen (2009). To adapt the item to the university context, we added a time aspect, changing the original item "I have the firm intention to start a firm some day" to "I intend to start a business within the next 5 years". An index was calculated by averaging the scores of these items. A Cronbach's Alpha of 0.88 reflects a strong internal consistency following this adaptation. We measured *Attitudes Towards Entrepreneurship* with five questions adapted from Liñán & Chen (2009). We measured *Entrepreneurial Self-Efficacy* with four questions proposed by Zhao, Seibert, & Hills (2005). We measured *entrepreneurial exposure* by summing up participants' answers (1=yes, 0=no) to the following questions (N. Krueger, 1993; Von Graevenitz et al., 2010): "Did you found a startup in the past?", "Did you work at a startup in the past?", "Did you participate in an entrepreneurship course in the past?", "Among your family, did someone found a startup?", "Among your close friends, did someone found a startup?", 'In your social circle, did someone found a startup?"

2.5 | Results

We find support for H1 to H3. Our results suggest that there are statistically significant differences along all theorized constructs. We fit several regression models to test in how far personality traits, entrepreneurial intention, and past entrepreneurship (education) experience predict program application. Even when including all measured constructs and control variables the estimated probit regression model (Pseudo R-Squared=0.115, $p<0.001$) explains only in 11.5% of the variance in the sample, suggesting that students' decision to select into entrepreneurship education programs is a complex process than cannot solely be captured by psychometric constructs and demographic variables.

2.5.1 | Sample

In total 854 students answered the questionnaire, 495 of whom are in the applicant group and 359 in the non-applicant group. Table 3 provides an overview of the summary statistics and between group differences.

The results suggest that the groups can be considered homogenous with regards to the following demographic measures: whether they are enrolled in graduate program (as compared to an undergraduate program), their total semesters at university, whether their parents have a university degree, and whether their parents at some point founded a business themselves. However, we find statistically significant differences between the following demographic measures: Applicants are slightly younger at the time of application (23.68 vs 24.16 years), are less likely to be female (25% vs 39%), and less likely to be international students (45% vs 54%). Additionally, we also find statistically significant differences at the 10% level with regards to students' study backgrounds. Applicants are more likely to be enrolled in business (37% vs 31%) or computer science and electrical engineering programs (31% vs 27%). Given that the program is run by Professors from exactly these backgrounds, this is not all that surprising.

2.5.2 | Main Results

Table 3 also shows the between group differences concerning each of the hypotheses presented above. The results show that there are statistically significant differences between the groups for all hypothesized constructs.

Personality Traits

We find statistically significant differences between applicants and non-applicants with regards to all theorized personality traits, providing support for H1. Table 3 shows the between group differences. The clearest differences between the groups can be found with regards to Conscientiousness (4.14 vs 3.92, t-stat=4.41), Innovativeness (3.80 vs 3.61, t-stat=5.28), and Need for Achievement (4.29 vs 4.09, t-stat=5.55).

To understand in how far personality traits predict students' decision to apply to the program, we fit three probit regression models, adding the measured variables in steps. The results can be seen in Table 4. Model (1) includes only the BIG Five personality model. Model (2) adds the remaining personality traits related to entrepreneurship, and Model (3) the demographic control variables from Table 3. The overall model fit is statistically significant ($p<0.001$) with pseudo R-Squared values between 0.023 and 0.086. The coefficients of all variables correspond with the

Table 3: Summary Statistics and Difference Between Applicants and Non-Applicants

	Full Sample					Applicants		Non-Applicants		Difference	
	Obs.	Mean	Std. Dev.	Min	Max	Obs.	Mean	Obs.	Mean	Diff.	t-stat.
Demographics											
Age	854	23.88	2.79	19.00	38.00	495	23.68	359	24.16	-0.47	-2.45***
Female	854	0.31	0.46	0.00	1.00	495	0.25	359	0.39	-0.14	-4.45***
International	854	0.49	0.50	0.00	1.00	495	0.45	359	0.54	-0.10	-2.80***
Graduate student	854	0.71	0.45	0.00	1.00	495	0.72	359	0.70	0.02	0.72
Total semesters	854	8.95	2.95	4.00	22.00	495	8.94	359	8.95	-0.01	-0.03
Business major	854	0.35	0.48	0.00	1.00	495	0.37	359	0.31	0.06	1.81*
CS/EE major	854	0.30	0.46	0.00	1.00	495	0.32	359	0.27	0.05	1.70*
University degree parents	854	1.29	0.80	0.00	2.00	495	1.30	359	1.28	0.02	0.30
Entrepreneurship parents	854	0.44	0.50	0.00	1.00	495	0.45	359	0.44	0.01	0.27
Past Entrepreneurship Education											
Founded Startup Prior	854	0.20	0.40	0.00	1.00	495	0.24	359	0.15	0.09	3.18***
Startup Employee Prior	854	0.52	0.50	0.00	1.00	495	0.58	359	0.44	0.14	3.99***
Prior EE participation	854	1.87	1.79	0.00	15.00	495	2.11	359	1.55	0.56	4.56***
Prior EE - positive	685	3.82	1.13	1.00	5.00	420	3.93	265	3.65	0.28	3.14***
Prior EE - learning	686	3.53	1.13	1.00	5.00	421	3.64	265	3.35	0.29	3.31***
Prior EE - inspiration	681	3.79	1.21	1.00	5.00	416	3.95	265	3.54	0.41	4.41***
Prior EE - people	660	3.65	1.32	1.00	5.00	402	3.80	258	3.41	0.40	3.80***
Personality Characteristics											
Agreeableness (BIG 5)	854	4.21	0.63	1.50	5.00	495	4.24	359	4.17	0.07	1.61
Openness (BIG 5)	854	3.75	0.77	1.00	5.00	495	3.79	359	3.69	0.10	1.94**
Extraversion (BIG 5)	854	3.66	0.89	1.00	5.00	495	3.72	359	3.58	0.15	2.39**
Conscientiousness (BIG 5)	854	4.05	0.73	1.00	5.00	495	4.14	359	3.92	0.22	4.41***
Neuroticism (BIG 5)	854	2.31	0.96	1.00	5.00	495	2.25	359	2.39	-0.15	-2.20**
Innovativeness	854	3.72	0.51	2.12	5.00	495	3.80	359	3.61	0.19	5.28***
Risk propensity	854	3.51	0.81	1.25	5.00	495	3.59	359	3.40	0.19	3.45***
Need for achievement	854	4.21	0.52	2.00	5.00	495	4.29	359	4.09	0.20	5.55***
Internal locus of control	854	4.14	0.73	1.00	5.00	495	4.18	359	4.07	0.12	2.34**
External locus of control	854	1.98	0.76	1.00	5.00	495	1.90	359	2.10	-0.20	-3.87***
Entrepreneurial Intention											
EI	854	3.78	1.07	1.00	5.00	495	4.02	359	3.44	0.58	8.02***
ATE	854	4.19	0.80	1.00	5.00	495	4.34	359	3.99	0.35	6.36***
ESE	854	3.79	0.67	1.50	5.00	495	3.91	359	3.64	0.27	5.87***
EEx	854	3.24	1.42	0.00	6.00	495	3.42	359	3.00	0.42	4.27***

Notes: Abbreviations: Entrepreneurial Intention (EI), Attitude Toward Entrepreneurship (ATE), Entrepreneurial Self-Efficacy (ESE), Entrepreneurial Exposure (EEx).* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

hypothesized direction – i.e. a positive coefficient of 0.228 for Conscientiousness indicates that students who score higher on Conscientiousness are more likely to apply. Across the fitted models not all personality traits are statistically significant – only Conscientiousness, Innovativeness, Need for Achievement, and External Locus of Control are. When adding control variables in Model (3), we find that older students (-0.064***), and female students (-0.433***) are less likely to apply. Graduate students (0.243**) and business majors (0.224**) are more likely to apply.

Table 4: Probit Regression – Personality Traits and Program Application

	(1)	(2)	(3)
Agreeableness (BIG 5)	0.051	-0.014	0.011
	(0.73)	(-0.19)	(0.15)
Openness (BIG 5)	0.075	-0.018	-0.018
	(1.30)	(-0.29)	(-0.27)
Extraversion (BIG 5)	0.061	0.009	0.033
	(1.20)	(0.17)	(0.61)
Conscientiousness (BIG 5)	0.228***	0.166**	0.199***
	(3.67)	(2.45)	(2.86)
Neuroticism (BIG 5)	-0.066	-0.009	0.044
	(-1.41)	(-0.19)	(0.85)
Innovativeness		0.310***	0.342***
		(3.05)	(3.29)
Risk propensity		0.083	0.099
		(1.38)	(1.58)
Need for achievement		0.214**	0.205*
		(2.08)	(1.96)
Internal locus of control		0.005	-0.028
		(0.08)	(-0.41)
External locus of control		-0.129**	-0.113*
		(-2.12)	(-1.80)
Controls	No	No	Yes
Observations	854	854	854
Chi-Squared	26.437	58.529	100.452
Prob > F	0.000	0.000	0.000
Pseudo R-Squared	0.023	0.050	0.086

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01.

Entrepreneurial Intention

We find statistically significant differences between applicants and non-applicants with regards to entrepreneurial intention and the theorized antecedents, providing support for H2. The difference between applicants and non-applicants in Entrepreneurial Intention is the highest among all measured constructs (4.02 vs 3.44, t-stat=8.02). Across both groups Entrepreneurial Intention and Attitude Toward Entrepreneurship (4.34 vs 3.99, t-stat=6.36) can be considered as rather high (all items are measured on a 5-point scale where 5 is the highest value), indicating that sthe program succeeds in attracting students interested in entrepreneurship. A comparison to entrepreneurial intentions among business administration students in from 2004 (Franke & Lüthje, 2004) and 2010 (Von Graevenitz et al., 2010) confirm this notion.[6]

[6]Please note that a direct comparison is difficult, since different scales were used to measure the constructs. Nonetheless, the comparison indicates that the program succeeds in attracting students interested in entrepreneurship out of the overall population of students in Munich.

Table 5: Probit Regression – Entrepreneurial Intention and Program Application

	(1)	(2)	(3)
Entrepreneurial Intention (EI)	0.320***	0.232***	0.210***
	(7.66)	(4.07)	(3.61)
Attitude Toward Entrepreneurship (ATE)		0.046	0.034
		(0.60)	(0.43)
Entrepreneurial Self-Efficacy (ESE)		0.196***	0.237***
		(2.63)	(3.10)
Entrepreneurial Exposure		0.047	0.066*
		(1.39)	(1.65)
Controls	No	No	Yes
Observations	854	854	854
Chi-Squared	60.670	72.459	105.823
Prob > F	0.000	0.000	0.000
Pseudo R-Squared	0.052	0.062	0.091

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01.

To understand in how far entrepreneurial intention and its antecedents predict students' decision to apply to the program, we fit three probit regression models, adding the measured variables in steps. The results can be seen in Table 5. Model (1) includes only Entrepreneurial Intention. Model (2) adds the measured antecedents, and Model (3) the demographic control variables from Table 3. The overall model fit is statistically significant (p<0.001) with pseudo R-Squared values between 0.052 and 0.091. The coefficients of all variables correspond with the hypothesized direction – i.e. a positive coefficient of 0.320 for Entrepreneurial Intention indicates that students who score higher on Entrepreneurial Intention are more likely to apply. Across the fitted models only Entrepreneurial Intention and Entrepreneurial Self-Efficacy are consistently statistically significant. When adding control variables in Model (3), we find that older students (-0.071***), female students -0.249**), and international students (-0.190**) are less likely to apply. Graduate students (0.239**) are more likely to apply.

Entrepreneurship Education and Entrepreneurship Experience

We find statistically significant differences between applicants and non-applicants with regards to their experience with entrepreneurship education and entrepreneurship, providing support for H3. Table 3 shows that among applicants 24% have previously founded a startup compared to 15% in the group of on-applicants. Focusing on past experiences with entrepreneurship, we find that applicants have participated in more entrepreneurship education courses (2.11 vs 1.55, t-stat=4.56) and perceived them more positively with regards to several dimensions.

Table 6: Probit Regression – Past EE and Program Application

	(1)	(2)	(3)
Prior EE participation	0.057*	0.041	0.047
	(1.74)	(1.22)	(1.33)
Prior EE - positive	-0.024	-0.015	-0.023
	(-0.33)	(-0.21)	(-0.30)
Prior EE - learning	-0.001	-0.008	0.004
	(-0.01)	(-0.10)	(0.05)
Prior EE - inspiration	0.144**	0.141**	0.159**
	(2.02)	(1.97)	(2.17)
Prior EE - people	0.046	0.044	0.039
	(0.92)	(0.89)	(0.76)
Startup Employee Prior		0.190*	0.204*
		(1.81)	(1.87)
Founded Startup Prior		0.101	0.061
		(0.80)	(0.47)
Controls	No	No	Yes
Observations	854	657	657
Chi-Squared	21.693	23.461	27.983
Prob > F	0.000	0.000	0.000
Pseudo R-Squared	0.019	0.027	0.032

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To understand in how far these past experiences predict students' decision to apply to the program, we fit three probit regression models, adding the measured variables in steps. The results can be seen in Table 6. Model (1) includes past experiences with entrepreneurship education. Model (2) adds first-hand experience with startup (founding or working in a startup), and Model (3) the demographic control variables from Table 3. The overall model fit is statistically significant ($p<0.001$) with pseudo R-Squared values between 0.019 and 0.032. The coefficients of most variables concerning the perception of past entrepreneurship education are close to 0. Across the fitted models only whether prior entrepreneurship education was perceived as inspirational and prior work experience in a startup are consistently statistically significant. The latter one, however, only at the 10% confidence level. The results of the regression thus suggest that students who found past entrepreneurship courses inspirational and have worked in startups before are more likely to apply. When adding control variables in Model (3), we find that older students (-0.053**), female students (-0.394***), and international students (-0.218**) are less likely to apply. Graduate students (0.229*) are more likely to apply.

2.5.3 | Gender Differences

Across all analyses we find statistically significant difference between male and female students. Most notably, among non-applicants 39% of participants are female compared to only 25% among applicants. Gender differences in entrepreneurship research have increasingly become a topic of interest (Deng et al., 2021) with several studies also addressing students (Dabic, Daim, Bayraktaroglu, Novak, & Basic, 2012; Packham, Jones, Miller, Pickernell, & Thomas, 2010; Petridou, Sarri, & Kyrgidou, 2009; Wilson, Kickul, & Marlino, 2007). While these studies examined entrepreneurship related gender differences of general student populations (Dabic et al., 2012), MBA students and adolescent*s* (Wilson et al., 2007), elective courses at university (Petridou et al., 2009) and short enterprise education courses (Packham et al., 2010), our results add to the literature by reporting differences between male and female students along several psychometric constructs in the context of self-selection into entrepreneurship education programs.

Table 7 shows the demographic properties and mean values of the measured constructs split by gender across the full sample, the applicant group, and the non-applicant group. When looking at applicants and non-applicants separately, we generally find more pronounced gender differences in the group of applicants. For example, female applicants are on average older than their male counterparts (24.27 vs 23.49 years), they are more likely to be enrolled in a graduate program (83% vs 68%), have studied longer (9.77 semesters vs 8.67 semesters), and comprise a larger share of international students (62% vs 39%). Overall, gender differences appear to be more expressed among applicants. We also observe that female students are less likely to be enrolled in a study subject related to computer science and engineering across both the applicant group (12% vs 39%) and the non-applicant group (15% vs 34%).

Personality Traits

Across the different groups we find consistent and statistically significant differences of the Big Five dimensions *Extraversion, Conscientiousness,* and *Neuroticism*. Along each dimension, male applicants score lower than their female counterparts. Among non-applicants the difference in *Conscientiousness* loses its statistical significance. We find no differences for *Agreeableness* and *Openness*. The only other personality traits where we observe statistically significant differences between male and female students are their risk propensity and Internal Locus of Control. In both cases female students score slightly lower than male students when looking at the entire sample. However, their statistical significance of diminish when looking at applicants and non-applicants separately.

These observations, to a degree, align with findings from literature. Past research investigating difference between genders of the BIG Five dimensions found that women scored higher than men on *Extraversion*, *Agreeableness*, and *Neuroticism.* Differences in *Openness* and

Table 7: Summary Statistics and Difference Between Genders

	Full Sample (N=854)			Applicants (N=495)			Non-Applicant (N=359)		
	Male (N=593)	Female (N=261)	t-stat	Male (N=373)	Female (N=122)	t-stat	Male (N=220)	Female (N=139)	t-stat
Demographics									
Age	23.65	24.40	-3.62***	23.49	24.27	-2.98***	23.93	24.51	-1.73*
International	0.44	0.61	-4.64***	0.39	0.62	-4.60***	0.51	0.59	-1.41
Graduate student	0.68	0.77	-2.43**	0.68	0.83	-3.10***	0.69	0.71	-0.52
Total semesters	8.69	9.53	-3.86***	8.67	9.77	-3.77***	8.72	9.32	-1.78*
Business major	0.33	0.39	-1.80*	0.35	0.43	-1.44	0.28	0.36	-1.55
CS/EE major	0.37	0.14	6.99***	0.39	0.12	5.56***	0.34	0.15	4.04***
University degree parents	1.33	1.22	1.83*	1.35	1.15	2.41**	1.29	1.28	0.07
Entrepreneurship parents	0.44	0.45	-0.22	0.44	0.48	-0.74	0.45	0.42	0.39
Past Entrepreneurship Education									
Founded Startup Prior	0.23	0.13	3.46***	0.26	0.16	2.23**	0.18	0.10	2.10**
Startup Employee Prior	0.53	0.49	1.09	0.59	0.55	0.79	0.44	0.45	-0.10
Prior EE participation	1.92	1.77	1.11	2.13	2.04	0.44	1.56	1.53	0.16
Prior EE - positive	3.77	3.94	-1.71*	3.87	4.11	-1.97**	3.58	3.77	-1.22
Prior EE - learning	3.47	3.66	-2.01**	3.60	3.77	-1.38	3.22	3.55	-2.30**
Prior EE - inspiration	3.73	3.93	-2.00**	3.89	4.14	-1.92*	3.41	3.73	-1.98**
Prior EE - people	3.60	3.76	-1.42	3.76	3.96	-1.37	3.30	3.58	-1.50
Personality Characteristics									
Agreeableness (BIG 5)	4.21	4.20	0.21	4.24	4.23	0.08	4.16	4.17	-0.13
Openness (BIG 5)	3.75	3.76	-0.22	3.77	3.89	-1.51	3.72	3.65	0.80
Extraversion (BIG 5)	3.59	3.83	-3.63***	3.66	3.91	-2.74***	3.46	3.76	-2.97***
Conscientiousness (BIG 5)	4.01	4.14	-2.56***	4.09	4.30	-3.13***	3.87	4.00	-1.60
Neuroticism (BIG 5)	2.19	2.58	-5.67***	2.16	2.50	-3.50***	2.23	2.65	-4.12***
Innovativeness	3.72	3.70	0.55	3.78	3.85	-1.34	3.63	3.58	1.02
Risk propensity	3.57	3.39	2.92***	3.62	3.50	1.55	3.47	3.30	1.87*
Need for achievement	4.21	4.20	0.31	4.28	4.33	-1.02	4.10	4.09	0.18
Internal locus of control	4.16	4.07	1.71*	4.20	4.15	0.69	4.11	4.00	1.23
External locus of control	1.97	2.01	-0.57	1.88	1.97	-1.20	2.14	2.04	1.16
Entrepreneurial Intention									
EI	3.91	3.47	5.58***	4.08	3.84	2.37**	3.63	3.15	3.97***
ATE	4.30	3.93	6.35***	4.40	4.14	3.68***	4.14	3.75	4.04***
ESE	3.80	3.77	0.71	3.88	3.98	-1.47	3.67	3.59	1.12
EEx	3.29	3.13	1.57	3.45	3.33	0.82	3.03	2.95	0.52

Notes: Male/ Female columns show the respective mean values. Abbreviations: Entrepreneurial Intention (EI), Attitude Toward Entrepreneurship (ATE), Entrepreneurial Self-Efficacy (ESE), Entrepreneurial Exposure (Eex).* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Conscientiousness were only found when looking at subdimensions and the strength of the effects were moderated by age and ethnicity (Weisberg, DeYoung, & Hirsh, 2011). It is, however, important to note that gender differences vary between cultures (they are more pronounced in cultures where traditional sex roles are minimized) and that gender differences are overall small relative to the individual variation within genders (Costa, Terracciano, & McCrae, 2001).

While studies in literature report *"strong evidence"* for gender differences in risk aversion (Charness & Gneezy, 2012) we observe that the statical significance diminishes when only looking at applicants. Comparing the mean score of male non-applicants (3.47) and of female applicants (3.50), the latter even score slightly higher. Existing literature reports little to no difference between genders with regards to Locus of Control (Feingold, 1994; Sherman, Higgs, & Williams, 1997).

Entrepreneurial Intention

When looking at the Entrepreneurial Intention model, we find statistically significant differences between male and female students for Entrepreneurial Intention (EI) and their Attitude Toward Entrepreneurship (ATE), but not for their Entrepreneurial Self-Efficacy (ESE) and Entrepreneurial Exposure. These differences are consistent and statistically significant across all groups. For example, female applicants report lower Entrepreneurial Intention (3.84 vs 4.08, t-stat=2.37) and Attitude Toward Entrepreneurship (4.14 vs 4.40, t-stat=3.86) than their male counterparts. However, it is to note that female students who applied to the program score higher or similarly high on Entrepreneurial Intention (3.84 vs 3.63) and Attitude Toward Entrepreneurship (4.14 vs 4.14) than male students who did not apply. Interestingly, we do not see any statistically significant differences in Entrepreneurial Exposure (EEx) and Entrepreneurial Self-Efficacy. In both cases applicants, regardless of gender, score higher than non-applicants. While not statistically significant, female students even score slightly higher in Entrepreneurial Self-Efficacy than their male students among the applicant group (3.98 vs 3.88).

Previous literature reports higher Entrepreneurial Intention (Dabic et al., 2012; Wilson et al., 2007), higher Attitudes Towards Entrepreneurship (Packham et al., 2010), and higher Entrepreneurial Self-Efficacy among male students (Wilson et al., 2007). However, Wilson et al. (2007) also find that entrepreneurship education has a higher impact on female participants. Among applicants, female and male students both participated in a similar number of entrepreneurship courses prior to their application, which in part might explain the similar scores in Entrepreneurial Self-Efficacy.

It is to note, though, that among the group of applicants the mean scores for Entrepreneurial Intention, Attitudes Towards Entrepreneurship, and Entrepreneurial Self-Efficacy among both female and male students all rank high when compared to previous studies (Franke & Lüthje, 2004; Maresch, Harms, Kailer, & Wimmer-Wurm, 2016; Von Graevenitz et al., 2010). These results suggest that while gender differences in the mean exist for Entrepreneurial Intention and Attitudes Towards Entrepreneurship, the variance of individual differences within genders is substantial. It also shows that while enrollment rates differ between male and female students, the program manages to attract entrepreneurial students regardless of gender.

Entrepreneurship Education and Entrepreneurship Experience

Female students are less likely to have founded a startup prior to their application across all groups. The observed difference is consistent at 10 percentage points. For example, 16% of female applicants founded prior to the application compared to 26% of male applicants. We observe no difference between genders when looking at prior employment at a startup or prior participation in entrepreneurship education.

Previous work indicates that enrollment rates in entrepreneurship education at university are typically male dominated (Bae et al., 2014) which is also reflected when comparing the share of female students among applicants (25%) and non-applicants (39%). However, when looking at the previous participation in entrepreneurship education among applicants, we do not observe any statistically significant differences. In other words, when looking at past behavior of applicants related to entrepreneurship education, both female and male students appear to be similar.

Interestingly, we find that female students across all groups rate the experiences of past entrepreneurship education higher than male students. Except for whether they had met interesting people through participation in entrepreneurship education, these differences are all statistically significant. Previous work lets us speculate about the underlying drivers for these differences. For example, Wilson et al. (2007) show that female students benefit more from entrepreneurship education than their male counterparts. Findings by Petridou et al. (2009) indicate that the upfront motivation for participating in entrepreneurship education might differ between genders. Among others, female students expressed stronger interest in acquiring knowledge and developing skills compared to male students (Petridou et al., 2009). With different ex-ante expectations between male and female students, their ex-post assessment might be different even when joining the same courses and programs.

2.6 | Discussion and Conclusion

We present the first study to explicitly investigate the effect of entrepreneurial constructs and personality characteristics on self-selection in entrepreneurial education. We provide several contributions to the academic discourse and find significant differences between students who self-select into entrepreneurship education and those that don’t.

Study designs in entrepreneurship education research have been repeatedly critiqued (Bae et al., 2014; Rideout & Gray, 2013; Yi & Duval-Couetil, 2021) for, among others, a lax selection of control groups, often resorting to convenience samples (Yi & Duval-Couetil, 2021). When non-compulsory courses or programs on entrepreneurship are taken as research context, self-selection might bias the results if not controlled for. Our work confirms recent research raising this issue, (Bae et al., 2014; Liñán et al., 2018), indicating the possibility of a "*reversed causal influence of entrepreneurial intention on entrepreneurship education*" (Bae et al., 2014, p. 238). The findings presented in this paper strengthen our current understanding of the phenomenon by providing evidence from a highly selective entrepreneurship program, showing that differences between applicants and non-applicants exist not just when looking at intention but also actual behavior to enroll in entrepreneurship education.

Future studies evaluating entrepreneurship education must seek to avoid self-selection bias to capture the true effect of the educational intervention. Mere pre-/ post-study assessments might produce misleading results if no or inadequate control groups are chosen (Yi & Duval-Couetil, 2021). Control groups should be chosen from the same audience as participants to be truly comparable. Particularly in the context of non-compulsory programs with limited spaces, applicants that were not able to secure a spot should be considered a suitable target.

2.6.1 | Avoiding Self-Selection Bias in Evaluation Studies[7]

Scholars can generally follow two approaches to avoid bias through self-selection. Either they can avoid selection all together by looking at compulsory courses and programs or they can choose a control group from the same population as participants, i.e. other applicants that did not receive the treatment. Since differences in pedagogies, methods, and audiences are likely to produce differential outcomes (Nabi et al., 2017) the impact of compulsory and non-compulsory courses should be considered in separation.

Compulsory Entrepreneurship Education

Earlier work attempted to avoid the issue of self-selection by examining compulsory courses (Oosterbeek et al., 2010; Von Graevenitz et al., 2010). However, current research indicates that compulsory courses may have a different effect compared to ones that students actively choose to participate in. For example, Von Graevenitz et al. (2010) report a negative effect of participation in a compulsory entrepreneurship course on participants' entrepreneurial intention. In contrast, recent studies looking at specific experiential entrepreneurship education programs find a positive effect on entrepreneurial outcomes (C. E. Eesley & Lee, 2021; Lyons & Zhang, 2017). Compulsory courses appear to provide information signals to students who in turn adjust their aptitude for entrepreneurship (Von Graevenitz et al., 2010). Following this line of argumentation, compulsory entrepreneurship courses enable participants to gain a better

[7]For a more general discussion on how to design rigorous studies to evaluate entrepreneurship education, recent work by Yi & Douval-Couetil (2021) provides an excellent starting point.

understanding of their *ability* and *preference* (Bae et al., 2014) towards future entrepreneurship and entrepreneurship education (Liñán et al., 2018) and thus enable informed self-selection into additional entrepreneurship courses. As students who self-select into non-compulsory courses perceive them to be more useful, they are likely more engaged during the course, and this in turn might spark different learning outcomes. In other words, because their audience differs, it is likely that compulsory and non-compulsory courses lead to different outcomes.

Non-Compulsory Entrepreneurship Education

To evaluate non-compulsory entrepreneurship education programs and courses, scholars should choose adequate control groups (Yi & Duval-Couetil, 2021). As the presented results show, applicants can be considered up-front more entrepreneurial than students not applying. To avoid bias through self-selection scholars may therefore use applicants who applied for the program or course but were not accepted as control group (Lyons & Zhang, 2017). This strategy seems feasible in practice as many programs have limited spots. From a research design perspective, the most rigorous approach would be to randomly select participants from the population of applicants. However, in practice there is likely an interest to achieve a high program quality and select the students that are most suited for the program.

This consequently raises the issue of active selection. If participants are selected by some metric of merit, it is likely that those who score higher would fare better with regards to the intended outcomes, even without the treatment. For survey-based evaluations looking at change rates in pre- / post-assessments can, to a degree, address this issue. However, if a ranking of applicants exists regression discontinuity designs (RDD) may offer an elegant solution to construct a quasi-experimental evaluating the local average treatment effect at the capacity threshold, while controlling for selection (D. S. Lee & Lemieux, 2010). RDD further provide the advantage that they are closer to the "gold standard" randomized controlled trials compared to other evaluation methods like matching on observables, regressions, and instrumental variables (D. S. Lee & Lemieux, 2010). Similar approaches have been used to evaluate the impact of accelerator programs (Gonzalez-Uribe & Leatherbee, 2018; Hallen et al., 2020).

2.6.2 | Why do students apply?

Our results show that students who self-select in entrepreneurship education differ from those that don't along several psychometric constructs associated with entrepreneurship. However, the presented regressions explain only between 3.2% and 9.1% of the variance between applicants and non-applicants. So why do students decide to (not) enroll in entrepreneurship education?

With the data available, we cannot give a definite answer to that question. However, we can speculate about alternative effects at play. Bae et al. (2014) and Zhang et al. (2013) hypothesize about two mechanisms based on which students select into entrepreneurship education – *ability* or *preference*. Students' perception of their ability can be proxied by their Entrepreneurial Self-Efficacy (ESE) and the preference by their Attitude Toward Entrepreneurship (ATE). We generally observe that applicants score higher among both dimensions compared to non-applicants (see Table 3) indicating that both effects are relevant. In contrast, our regression models (see Table 5) indicate that Entrepreneurial Self-Efficacy (ESE) is the stronger predictor given our empirical context, when controlling for covariates.

However, students with a high entrepreneurial intention, that is they are eager to found, might decide against applying for an entrepreneurship education program for a number of other reasons. They may evaluate the required time-investment of participating in the program against the expected returns, i.e. in how far they benefit from the program compared to alternatives. For students who already have a clear idea in mind, joining such a program might not be as attractive as pursuing the idea directly. The pedagogical setup of the program might be another relevant factor (Nabi et al., 2017). First, the type of entrepreneurship education (e.g. technology entrepreneurship, social entrepreneurship, etc.) may influence students' decision. Second, the duration of the program may play a role. Students who are in the final semester of their studies are likely less inclined to apply for a program that takes another three semesters and would prolong their studies. Third, the required workload, especially when conducted next to their regular studies, may discourage students who are struggling to keep up at university or who need to work next to their studies from applying, despite an appetite for entrepreneurship.

2.6.3 | Limitations

Given our method, the presented differences between applicants and non-applicants should not be interpreted as causality but as correlation. For the correct interpretation additional limitations should be considered.

First, the data was collected from the application process of one entrepreneurship education program targeting university students. While this avoids endogeneity – e.g. variation in entrepreneurial climate at different universities (Sancho, Ramos-Rodríguez, & Vega, 2021) – and ensures comparability among participants, it limits generalizations regarding other contexts. Specific entrepreneurship programs are often very different, sometimes even so that the *"content of syllabi of courses developed by entrepreneurship scholars differs to such an extent that it is difficult to determine if they even have a common purpose"* (Henry et al., 2005, p.103). Future work examining self-selection into entrepreneurship education in different contexts is required to confirm the generalizability of the results.

Second, the pedagogical context of the program should be given consideration (Nabi et al., 2017). We examined an entrepreneurship education program targeting individual university students from different disciplines interested in innovation, technology, and entrepreneurship. The relative long program duration of three semester combined with a relatively high workload in addition to students' main study program likely attracts only a subset of highly ambitious students. This is also reflected in psychometric constructs, such as the high *Need for Achievement* scores. Thus, when relating these results to different forms of entrepreneurship education it is important to consider the program's character, its focus on individuals as opposed to startup teams, and the required workload. Self-selection effects into programs or courses that have a lower entry barrier and require less commitment, i.e. shorter program duration or lower workload, might be less pronounced.

While our data collections allowed us to capture a group of students who considered an application to the program and decided against it, we still miss the group of students who might have been aware of the program but did not consider applying in the first place. Arguably those students are even less interested in entrepreneurship education than the group of non-applicants examined in this study. A comparison of Entrepreneurial Intentions of non-applicants with existing studies (Franke & Lüthje, 2004; Maresch et al., 2016; Von Graevenitz et al., 2010) indicates that non-applicants rank above the typical student population. While indicative, this comparison needs to be taken with a grain of salt. A direct comparison is tricky because of different surrounding university environments (Sancho et al., 2021) and different scales used. A representative survey would be interesting to establish a comparable baseline for future research.

2.6.4 | Conclusion

In this article we present evidence that students who self-select into entrepreneurship education differ along several psychometric constructs associated with entrepreneurship from students that do not. With this work we confirm and strengthen prior work, particularly by using actual behavior to distinguish between both groups. By investigating multiple constructs frequently used to evaluate entrepreneurship education we show how that students interested in entrepreneurship education differ prior to applying to entrepreneurship programs. We highlight the risk of self-selection bias in most entrepreneurship education evaluation studies and discuss how to address implications for researchers and educators.

3 | Impact of Entrepreneurship Education Programs at University: Quasi-Experimental Evidence

Great teams do not hold back with one another. They are unafraid to air their dirty laundry. They admit their mistakes, their weaknesses, and their concerns without fear of reprisal.

Patrick Lencioni, 2002, The Five Dysfunctions of a Team (p. 44)

3.1 | Abstract

We evaluate the impact of participation in an entrepreneurship education program during university on subsequent entrepreneurial activity by comparing career decisions between program participants and the best applicants not accepted to the program using a regression discontinuity design. We find that program participation increases both entrepreneurship rates and startup success. The effect on entrepreneurship rates is visible for several years after the program. Even when program participants do not become entrepreneurs, they are more likely to select into careers related to entrepreneurship. The overall effect is mainly driven by participants who co-found with other participants and, surprisingly, female participants do not benefit from program participation. Overall, these results suggest that entrepreneurship programs can have important real-world impact and highlight the formation of social capital during the program as an important driver.

As of submission of this dissertation, the study presented in this chapter it under review in the Strategic Management Journal (SMJ).

A version of this paper has been accepted at the 83rd Annual Meeting of the Academy of Management (AOM 2023) and was designated as ***Best Paper****.*

3.2 | Introduction

Entrepreneurship has been recognized as engine for economic growth and wealth creation. Increasingly entrepreneurship education has become a policy priority. For example, the 'Skills Agenda for Europe' of the European Commission recognizes entrepreneurial skills to be crucial for sustainable economic development (European Commission & Directorate-General for Employment Social Affairs and Inclusion, 2021; European Commission et al., 2017). Despite the introduction of entrepreneurship programs at many universities (Katz, 2003; Volkmann & Audretsch, 2017) extant research about its effects and outcomes on entrepreneurship rates and startup quality is still relatively sparse (C. E. Eesley & Lee, 2021) and the impact of entrepreneurship programs are ambiguous and partly contradictory.

Recent work finds that the introduction of two entrepreneurship programs at Stanford university had negative to zero impact on entrepreneurship rates, while reducing startup failure rates and increasing firm performance (C. E. Eesley & Lee, 2021). Within the university context, compulsory entrepreneurship courses appear to even decrease the average entrepreneurial intention of students (Oosterbeek et al., 2010; Von Graevenitz et al., 2010). Counter to that the evaluation of a non-profit entrepreneurship training program finds a positive effect on entrepreneurship rates after the program (Lyons & Zhang, 2017). Recent meta-reviews also paint an ambivalent picture. While Martin, McNally, and Kay (2013) report a significant positive relationship between entrepreneurship education and entrepreneurial outcomes, Bae et al. (2014) do not find a significant effect on entrepreneurial intentions when controlling for pre-education levels.

There are several limitations recognized in literature that may explain the variation in results about the effects of entrepreneurship education programs. First, studies have focused predominantly on short-term and subjective outcome measures (e.g. attitude, skills, and abilities) and there is little research available evaluating the impact of entrepreneurship education at actual outcomes of productive entrepreneurship (i.e. number and quality of startups) (Carpenter & Wilson, 2022; C. E. Eesley & Lee, 2021; Nabi et al., 2017). Second, existing literature faces methodological shortcomings. Study designs frequently suffer from self-selection bias and are not fit to make causal claims (Carpenter & Wilson, 2022; Nabi et al., 2017), making it difficult to identify the real treatment effect of entrepreneurship education. Third, "entrepreneurship education" remains a loosely defined term encompassing a wide range of approaches varying with regards to educational goals, target audiences, and pedagogical approaches (Byrne, Fayolle, & Toutain, 2014). Studies in higher education were found to "*severely underdescribe the actual* *pedagogies being tested*" (Nabi et al., 2017, p. 1) which, at least in part, may explain the ambivalent results of recent meta-analyses (Bae et al., 2014; Martin et al., 2013).

One pedagogical aspect that has so far not been addressed concerns the impact of entrepreneurship education programs at university. While the establishment of entrepreneurship centers at school level had little to no impact on entrepreneurship rates, Eesley and Lee (2021) suggest that tailored experiential programs may have a positive effect. Filling this gap is therefore not only important to support policy makers' decisions for the effective allocation of resources to entrepreneurship education at university, but also to inform educational choices for the individual. In this paper, we address these questions and examine how entrepreneurship education programs impact participants' career decisions, their founding rates, and the quality of their startups.

Our empirical setting is an entrepreneurial graduate-level add-on study program open to students of all disciplines in Munich, Germany. It runs over three semesters in parallel to students' regular study programs. It includes experiential project-based courses, mentoring, and components similar to many accelerator and incubation programs like access to a network of investors, successful founders and other mentors. Each semester 25 students start the program, after undergoing a highly competitive application process.

We exploit the fact that there are significantly more applications than program slots. We compare the career decisions of program participants with those of the finalists who were not accepted to the program. By using internal application scores in a regression discontinuity design (RDD) we present the first quasi-experimental evaluation of an entrepreneurship education program at university. Using a pool of comparable applicants allows us to control for self-selection. We can further exclude ecosystem-specific effects as all students were enrolled in a degree program in the same city and continued to study there. And despite the small cohort size of 25 students per semester, the 10-year timeframe, covering applicants between 2011 and 2020, allows us to track their career decisions and evaluate the impact of the program expressed in real-world behavior, not just intention.

Overall, the results show a large and positive relationship between program participation and founding rates and startup performance. We find that program participation is positively correlated with the likelihood to found a company and engage in an entrepreneurial career in the broader sense (e.g. startup employee, venture capital, accelerator). For example, participation in the program resulted in a 15.4% to 27.8% higher chance that individuals would found. Our analyses also show that companies founded by program participants are of higher quality. They are more likely survive, more likely to raise any funding, they raise on average more funding, and employ more people. These results prove robust against several secondary analyses. We find evidence that the effects we observe are likely driven by social capital developed through program participation rather than a mere increase in human capital. Surprisingly, we also find that the program had no effect on founding rates among female participants.

3.3 | Background and Hypotheses

Entrepreneurship has been repeatedly linked to economic growth (Baumol & Strom, 2007; Kane, 2010; Wennekers & Thurik, 1999) and policy makers consequently have interest in fostering the development of new ventures (European Commission et al., 2017). As a result, entrepreneurship education has spread across the world (Katz, 2008; Morris & Liguori, 2016; Neck & Corbett, 2018). Increasingly, the creation of new ventures is also recognized by universities as part of their mission to contribute to society (Nicotra et al., 2021). The effect of entrepreneurship education, however, has remained a topic of discussion in literature (Alsos et al., 2022; C. E. Eesley & Lee, 2021; Lyons & Zhang, 2017; Martin et al., 2013; Nabi et al., 2017). Genetic predisposition of participants (Nicolaou, Shane, Cherkas, Hunkin, & Spector, 2008), potential (self)-selection effects (Bae et al., 2014), a large heterogeneity of pedagogical approaches (Nabi et al., 2017), long times between educational interventions and potential entrepreneurial actions (Hsu et al., 2007), and lack of sufficient data have made it difficult to understand the true treatment effect of entrepreneurship education and establish a clear causal link.

Extant studies have defined the goal of entrepreneurship education in different ways. When framed closely, entrepreneurship education attempts to benefit the economy by creating more and better entrepreneurs (Mwasalwiba, 2010). However, recent literature calls for a broader framing of entrepreneurship education (Neck & Corbett, 2018) arguing for beneficial effects for the economy even when alumni do not become entrepreneurs themselves. There are only few studies that investigate whether and how entrepreneurial students make use of their skills in careers alternative to founding themselves (Alsos et al., 2022). While often overlooked in the evaluation of entrepreneurship programs, this perspective is relevant because of several reasons. A substantial portion of participants of entrepreneurship programs does not go on to found companies (C. E. Eesley & Lee, 2021; Lerner & Malmendier, 2013), even when programs succeed in raising founding rates (Lyons & Zhang, 2017). These participants may look for alternative career paths to benefit from their entrepreneurial competencies and network (Alsos et al., 2022; C. E. Eesley & Lee, 2021; Martin et al., 2013). Their self-selection into entrepreneurship education suggest that they have a favorable attitude towards entrepreneurship (Liñán et al., 2018). With the social network developed through program participation they are likely to have increased access to attractive alternative entrepreneurial careers, such as joining other successful startups (C. Eesley & Wang, 2017) or breaking into adjacent careers, such as venture capital, that are otherwise difficult to access (Dotzler, 2001).

This broader perspective, considering the application of entrepreneurial competencies outside of strict founder careers (Alsos et al., 2022), also connects entrepreneurship education to the management of established firms (Hernández-Perlines, Ariza-Montes, & Blanco-González-Tejero, 2022; Nielsen, Peters, & Hisrich, 1985). Firms need to take decisions on whether to develop strategically important human capital internally or acquire it externally (Arora & Gambardella, 1994). This includes whether to develop entrepreneurial competencies in-house (C. E. Eesley & Lee, 2021; Kim, 2022). Extant literature shows that entrepreneurial human capital of firms is positively associated with their performance (Braunerhjelm & Lappi, 2023; Rauch, Wiklund, Lumpkin, & Frese, 2009) and that firms taking entrepreneurial action have better chances to survive (Teece, Pisano, & Shuen, 1997). At the same time the pool of workers with entrepreneurial and innovation capabilities is limited (Akerlof & Yellen, 1990; Blanchflower & Oswald, 1998) and firms might thus choose to generate the desired skill set among existing employees through training (Lyons & Zhang, 2017). Effective investment in human capital and training was shown to be beneficial for firm performance (Hatch & Dyer, 2004) and the economic value of firms (Riley, Michael, & Mahoney, 2017). However, investment in such training might be wasteful if the tendency to engage in entrepreneurial behavior is driven by genetic predisposition (Nicolaou et al., 2008) or if entrepreneurial training only provides accurate signals of entrepreneurial ability to participants (C. E. Eesley & Lee, 2021; Von Graevenitz et al., 2010). Understanding in which context entrepreneurial competencies can be taught is relevant to take strategic decisions to train employees in-house or hire employees with entrepreneurial traits.

Eesley and Lee (2021) theorize about two fundamental mechanisms related to skill development that may influence founding rates and startup quality among participants. Entrepreneurship education may, first, provide participants with a more accurate picture about their own entrepreneurial ability and, second, allow participants to improve relevant entrepreneurial skills and abilities. The improvement of entrepreneurial human and social capital is expected to positively affect entrepreneurship rates and the quality of founded startups (C. E. Eesley & Lee, 2021). However, if the primary mechanism lies in providing informative signals about the abilities needed to succeed in entrepreneurship (Lerner & Malmendier, 2013) and in revealing ability levels (Von Graevenitz et al., 2010) this could decrease overall founding rates (C. E. Eesley & Lee, 2021).

The outcomes of entrepreneurship education, in particular founding rates and founding quality, may thus vary depending on how these two mechanisms counterbalance within the context of a specific program or course. Furthermore, both increases in entrepreneurial human and social capital through entrepreneurship education, may open participants a pool of attractive alternative entrepreneurial career paths, such as joining successful startups, working in venture capital, or accelerator programs (C. Eesley & Wang, 2017; Lyons & Zhang, 2017) and thus increase the opportunity costs associated with founding a startup.

There are several contextual factors recognized in literature that may influence how these mechanisms balance out. Compulsory courses, for example, seem to reduce the average entrepreneurial intention of students even when self-assessed entrepreneurial abilities improve (Von Graevenitz et al., 2010) indicating a predominance of the ability signaling mechanism. Fretschner and Lampe (2019) explain these observations by distinguishing a "*sorting effec*t" and an "*alignment effect*". The "*sorting effect*" helps students gain a more certain picture of their own entrepreneurial intention and entrepreneurial abilities (Fretschner & Lampe, 2019; Von Graevenitz et al., 2010). The "*alignment effect*" helps students who under- or over-estimate their entrepreneurial abilities to adjust their belief. For both mechanisms, students with little ex-ante information about entrepreneurship education should be more affected. While individual participants may adjust their beliefs, beneficial and detrimental effects may cancel each other out on the whole sample, leading to overall insignificant effects (Fretschner & Lampe, 2019). Since entrepreneurship is a rather scarce career choice – in high-income countries well below twenty percent of people engage in early-stage entrepreneurial activity (Global Entrepreneurship Monitor, 2022) – courses broadly targeting students will likely see stronger sorting and alignment effects and as a second order effect less impact on entrepreneurship rates.

In contrast, there is first evidence that experiential programs may have a positive effect on entrepreneurship rates and startup quality. Eesley and Lee (2021) report tentative findings of the Mayfield Fellowship[8] at Stanford University and Lyons and Zhang (2017) report an increase in entrepreneurship rates and startup performance from a non-profit technology entrepreneurship program. The positive effect could be explained by several mechanisms. First, such programs typically require a dedicated application process and substantial time investment during the program. Applicants thus must be motivated to invest a substantial amount of time upfront, during the program, and believe that this investment has an overall positive return in value for them. Consequently, we would expect a self-selection effect (Liñán et al., 2018), where students who

[8]See https://stvp.stanford.edu/mayfield-fellows-program (last-accessed 2022-06-27)

apply are more certain about their entrepreneurial intentions and entrepreneurial abilities than those who don't. Second, we would expect to see a selection effect as participants are typically chosen from the pool of applicants based on their abilities, motivation, and potential. And finally, we would expect to see the treatment effect of program participation on human and social capital development itself.

Eesley and Lee (2021) call for more research on understanding the effect of specific experiential programs. Evaluating these programs based on actual entrepreneurial outcomes is, however, challenging. Such programs accept only a limited number of participants each term. Typically, there is also a considerable lag-time between university education and startup foundation of university graduates (Azoulay, Jones, Kim, & Miranda, 2020; Hsu et al., 2007). The described self-selection mechanism makes it necessary to identify an adequate control group as applicants likely have an ex-ante predisposition towards entrepreneurship. And the active selection of participants from a pool of applicants makes it difficult to distinguish selection from treatment effects.

Our empirical context allows us to and overcome these challenges and address this gap in literature. First, as opposed to studies evaluating earlier educational levels (Huber, Sloof, & Praag, 2014; Oosterbeek et al., 2010) we focus on entrepreneurship programs at university targeting students (Åstebro et al., 2012). Second, we focus on a program offered as voluntary add-on education as opposed to compulsory courses embedded in a specific study program (Von Graevenitz et al., 2010). Third, we focus on an experiential program with a practice-oriented curriculum that is similar to accelerator or incubator programs in its structure and content yet different in that is situated within university education and focuses on the individual and not startup teams (Alsos et al., 2022; Hallen et al., 2020; Lyons & Zhang, 2017). Finally, this study is the first evaluation of a university entrepreneurship education program using a quasi-experimental design. Internal applicant scores allow us to identify the treatment effect of the program by comparing those accepted into the program with those not accepted, which was not possible in previous studies.[9]

Building on extant literature we derive several hypotheses: Entrepreneurship education programs at university may influence participants through different mechanisms. They provide signals of the challenges of founding a startup and of their respective entrepreneurial abilities to participants. They also allow participants to develop and improve relevant entrepreneurial

[9]See Lee and Lemieux (2010) for an overview of the regression discontinuity design we use, and why it is more closely related to the "gold standard" of randomized experiments than other evaluation methods like matching on observables, regressions, and instrumental variables.

competencies in the form of human and social capital. Key competencies taught in entrepreneurship education are also valuable human capital in career paths beyond founding one's own venture (Alsos et al., 2022; Jones, Pickernell, Fisher, & Netana, 2017). Even when deciding against founding a startup themselves, individuals likely have a favorable attitude towards entrepreneurship (Liñán et al., 2018) and will want to make use of their gained entrepreneurial competencies (Jones et al., 2017). Next to founding startups, program participation should also provide them with the network (C. E. Eesley & Lee, 2021) to access attractive alternative career paths related to entrepreneurship, such as joining established startups as employees or working with startups in venture capital firms, company builders, accelerator and incubator programs, or entrepreneurship centers. We thus expect that program participants are more likely to select into such entrepreneurial careers where they can apply their entrepreneurial competencies and work with startups.

Hypothesis 1 (H1): *Participation in entrepreneurship education programs during university has a positive effect on self-selection into careers related to entrepreneurship.*

Following the argument by Eesley and Lee (2021), the effect programs have on founding rates depends on whether skill and social network development predominates the influence of the ability signaling mechanism. Obtaining a clearer picture about the challenges of founding a company and understanding one's own innate skill in relation could decrease the rate of entrepreneurship. Skill development and the social network on the other hand could increase the rate of entrepreneurship (C. E. Eesley & Lee, 2021). The first effect was shown to be particularly pronounced in compulsory entrepreneurship courses, which overall decreased participants' intention to found (Oosterbeek et al., 2010; Von Graevenitz et al., 2010). Applicants of dedicated experiential programs, however, have likely made first experiences allowing them to learn about their entrepreneurial aptitude and concluded that they see the potential within themselves to become successful entrepreneurs. Consequently, sorting and alignment effects (Fretschner & Lampe, 2019) among those applicants accepted to the program are likely weaker than in compulsory courses. We thus expect that program participants' increase in skills and network outweigh these effects which should lead to increased founding rates.

Hypothesis 2 (H2): *Participation in entrepreneurship education programs during university has a positive effect on founding rates.*

The quality of startups should generally increase to the extent that entrepreneurship education increases entrepreneurial competencies. However, if founding rates increase as result of the program, it could be that less talented entrepreneurs found startups and in turn, on average, decrease the quality of founded startups (Lerner & Malmendier, 2013). Looking at current empirical studies, we expect the first effect to outweigh the second one. Eesley and Lee (2021) report a positive effect at university-level and when taking a tentative look at the Mayfield fellowship. Additionally, Lyons and Zhang (2017) show that entrepreneurial training disproportionally affects participants with no prior experience in technology entrepreneurship, which generally applies to graduate students. Self-selection among students (Liñán et al., 2018) and then active selection of participants from a pool of entrepreneurial applicants should lead to a larger density of entrepreneurial talent within the program. As opposed to individual courses, the program duration over three semesters should allow participants to not only learn about their entrepreneurial talent, but actively develop it through skill and social capital development. We thus expect that the overall quality of startups increases among program participants.

Hypothesis 3 (H3): *Participation in entrepreneurship education programs during university has a positive effect on the quality of startups founded.*

3.4 | Empirical Context

Our empirical setting is an add-on entrepreneurship program offered to students enrolled at the Ludwig Maximilian Universität (LMU) or Technical University of Munich (TUM) in Munich, Germany. The goal of the program is to "*Connect, Educate, and Empower the Innovators of Tomorrow"* through a combination of coursework, mentorship, access to industry partners and alumni of the program. It is offered by the Center for Digital Technology and Management (CDTM), a joint institution of both universities that is supported by 22 professors from both universities and run by a management team of 10 doctoral candidates. Recent work emphasizes the importance to adequately characterize the pedagogical context when evaluation entrepreneurship education (Nabi et al., 2017). In the following, we describe the program context in a similar structure as Lyons and Zhang (2017).

3.4.1 | Program Participants Selection

The program runs twice a year and offers a limited number of spaces. In total ca. 25 students are admitted each cohort, following a three-step selection process. The first round consists of a written online application including questions about demographics, academic performance, work experience, extracurricular engagement, intercultural experiences, an essay, and a motivational letter. Each application is reviewed in a double-blind process by three to four people associated with the program. From the initial pool of applicants, a set of ca. 60 finalists is selected.

These finalists advance to the second round of the application process during which they are randomly assigned to five to eight interviewers. The interviewers are members of the management team of the institute, active students, and alumni of the program. There are two types of interviews each of which are attended by two to four interviewers: First, a personal interview aimed at understanding the applicant's motivation and overall fit to the program; Second, a case interview testing their analytic and subject-specific skills and abilities. All interviewers give an individual score for each applicant. These scores are aggregated to a total interview score by which applicants are ranked. Not knowing their score nor ranking makes it impossible for applicants to manipulate the ranking process. Similarly, given the random assignment and number of interviewers per applicant, interviewers are unlikely to be able to precisely manipulate rankings.

The final step of the selection process is a discussion between interviewers to agree on a final list of applicants to invite. Typically, the applicants ranking higher than the capacity threshold of 25 are selected. However, there is no perfect compliance with this selection rule: not all applicants scoring in the first 25 ranks are accepted and not all accepted applicants rank higher than the threshold. Two reasons explain the less-than-perfect compliance: First, interdisciplinary, internationality, and gender diversity are stated program goals. Participants may receive preference based on these factors depending on the cohort composition. Second, some invited applicants reject the offer. In this case, other – typically lower ranking – applicants are selected.

During the observed period 218.9 valid applications were submitted per cohort, 58.3 finalists were invited to the second round, of which 24.5 finalists were admitted to the program. Typically, the number of suitable finalists far exceeds the number of available slots.[10]

3.4.2 | Program Structure

The program offers participants a structured curriculum comprising three core modules, elective courses, and an abroad stay with a total workload of 45 ECTS.[11] Completing the program typically takes three semesters. The three core modules comprise 60% of overall workload and aim at teaching students in trend research, product development, and go-to-market strategies through

[10]To test this assumption, we asked interviewers in the application process of the 2021 Fall and 2022 Spring cohort whether they would admit the respective applicant if there was no space limit. In the respective cohorts 72% and 75% of finalists would have been admitted this way compared to the actual admission rate of 41%.

[11]The European Credit Transfer and Accumulation System (ECTS) was introduced to standardized academic assessment in higher education in Europe. 60 ECTs correspond to a fulltime academic year (European Commission & Youth Directorate-General for Education and Culture, 2017).

project-based teaching. Within these project courses participants are introduced to and apply entrepreneurial thinking and methods.[12] Elective courses complement the core modules with a broad range of topics spanning from entrepreneurship, working with novel technologies (Christ et al., 2016; Froehlich et al., 2022), to leadership and personal development. In addition to the formalized curriculum various formal and informal networking events expose participants to an active community of alumni, many of which are working in entrepreneurial careers. Thus, the focus of our evaluation is not at course level but at the program level (Souitaris, Zerbinati, & Al-Laham, 2007). Overall, the content and components at program level are comparable to other entrepreneurship programs (Lyons & Zhang, 2017).

In contrast to accelerator or incubator programs which usually focus on developing existing business ideas and startup teams (Pauwels, Clarysse, Wright, & Hove, 2016; Peters, Rice, & Sundararajan, 2004), this program aims at developing individuals. Its stated goal is to equip participants with the mindset, skills, abilities, and network enabling them to innovate, possibly in a range of different careers. Doing so the program adopts a broad framing of entrepreneurship education (Bhatia & Levina, 2020), allowing students to practice entrepreneurial thinking and problem solving and thereby evaluate whether this would be an appropriate career for themselves. Unlike other programs, participants do not work on their own business ideas throughout the core modules. Instead, each core module is conducted in collaboration with project partners from industry introducing a real-world problem context. Courses are organized and managed by doctoral candidates. Lecturers and mentors are typically professionals from varying fields – experienced entrepreneurs, venture capitalists, business angels, consultants, academics, and corporate experts. In combination with an active community of alumni this provides participants with an opportunity to develop a network of people in the regional entrepreneurial ecosystem.

Compared to typical entrepreneurship programs found in university education, there are several features worth mentioning. First, the program has an interdisciplinary orientation with specific focus on the intersection of management and technical disciplines. Second, the program runs as add-on study program in parallel to students' main study programs instead of being integrated into them.[13] Finally, the program requires extensive time commitment. A typical

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[12]Throughout the curriculum, participants develop several business models, investor pitch decks, financial models, go-to-market and pricing strategies. They are introduced to various tools and methods, for example, the Business Model Canvas (Osterwalder & Pigneur, 2010), design thinking (T. Brown, 2008), lean startup principles (Ries, 2011), and methods for agile project management.

[13]Similar add-on programs can be found at other universities. For example, at Stanford University (Mayfield Fellowship), Babson College (Babson Build), the Technical University of Munich (Manage & More), the Technical University of Vienna (Extended Studies in Innovation), and the Hasso-Plattner-Institute (Basic and Advanced Track in Design Thinking).

participant invests 20-30 hours per week during the semester, despite their full-time studies. In combination, these elements facilitate an intensive experiential learning environment for highly motivated management and technology students with an appetite for entrepreneurship.

The overall program structure and curriculum were introduced in 2006 and remained largely the same since then. Over the observed period, there were no major changes in the program structure. Minor changes primarily concerned iterative adjustment in specific courses (e.g. changes of lecturers, session length).

3.4.3 | University Ecosystem

The program is managed by the Center for Digital Technology and Management (CDTM), which is a joint institution of Munich's two universities: The Ludwig Maximilian Universität (LMU) and the Technical University of Munich (TUM). Both universities have been repeatedly ranked among world's top universities[14] and run institutionalized entrepreneurship centers[15] that offer various entrepreneurship courses for students and support for nascent startups (Schönenberger, 2016; Weber & Funke, 2014).

Following the argument of entrepreneurial ecosystem literature, spatially limited ecosystem elements can have substantial influence on emerging startups and their performance (Wurth et al., 2021). In the context of this paper, the surrounding university entrepreneurship ecosystem is relevant for two reasons. First, applicants who are not accepted remain enrolled in their main study program, which allows us to control for ecosystem-specific effects. Second, applicants who are not accepted have several opportunities to pursue entrepreneurial education in the form of other entrepreneurship courses. This allows our evaluation to focus on the impact of entrepreneurship programs in an environment where access to alternative entrepreneurship courses and support services remains open to students not accepted into the program.

3.5 | Data and Methods

Identifying the true treatment effect of entrepreneurship education programs is challenging for two main reasons. First, individuals may self-select into the program based on their underlying preferences and abilities (Bae et al., 2014; Liñán et al., 2018; Lyons & Zhang, 2017). It is likely

[14]For example, in the Times Higher Education Rankings 2022 LMU was ranked number 32 globally and number 1 in Germany and TUM was ranked number 38 globally and number 2 in Germany (Times Higher Education, 2021).
[15]The Ludwig Maximilian Universität runs the "LMU Innovation & Entrepreneurship Center" (see https://iec.uni-muenchen.de/) offering both courses for students and an incubator program open for founders independent of university affiliation. The Technical University of Munich runs a technology transfer office (see https://forte.tum.de/) and one of Europe's largest entrepreneurship centers offering a wide range of services to students and startup founders (see https://unternehmertum.de/).

that those who apply have higher preferences towards entrepreneurial careers and that they would be relatively proficient even without the program (Lyons & Zhang, 2017). Second, by selecting program participants in a competitive application process, it is likely that individuals who are accepted have higher quality human capital and would thus be better entrepreneurs even without participation in the program.

Our research setting allows us to address both concerns. We restrict our analysis to interview finalists, the subset of applicants who progressed to the final step of the application process. Since all applicants have made the decision to apply, this allows us to mitigate potential bias due to self-selection. By limiting our sample to interview finalists, we construct a control group that is of comparable quality to those accepted to the program. Doing so, we follow a similar approach as recent literature to address bias through active selection (Hallen et al., 2020; Lyons & Zhang, 2017). Access to the interview scores at the time of application additionally allows us to use a regression discontinuity design (D. S. Lee & Lemieux, 2010). Similar to Gonzalez-Uribe and Leatherbee (2018) we use the ranking to inspect the discontinuity in dependent variables near the cutoff point. This quasi-experimental approach approximates a randomized experiment and tests the causal effect of program participation on the dependent variables, presenting a substantial methodological improvement over past study (D. S. Lee & Lemieux, 2010).

3.5.1 | Data

Our data set covers 20 application cohorts between 2011 and 2020. During this period 4379 individuals applied and 1050 advanced to the final round of the application process. For applicants who applied multiple times, we only considered their final application. We further excluded the 28 applicants who did not appear to the interview and for which no interview score is present. The final dataset contains 1022 individuals, comprising data on 478 program participants and 544 interview finalists who were not accepted.

We collect data from the original application including the respective ratings in the interviews. To track post-graduation career decisions, we manually collected data from applicants' LinkedIn profiles pages within two weeks in May 2022. To measure firm performance, we additionally collected data about co-founded startups from LinkedIn and Crunchbase[16] between May and June 2022. To define the operating status of co-founded startups we manually collected data from the companies' websites, LinkedIn, and NorthData[17].

[16]Crunchbase is an online database with focus on high-growth start-ups. Previous research has shown the fit of Crunchbase data for academic research (Dalle et al., 2017; Retterath & Braun, 2020).
[17]NorthData is an online database collecting information on the operating status of companies in Germany and other European countries (see https://northdata.com/)

Table 8: Variable Definitions

Variable	Type	Description
		Panel A: Applicant Characteristics
Program participant	**Binary**	1 if the applicant was accepted into the program and completed at least one core module, 0 otherwise
Interview score	**0-1**	Mean of the interview score between 0 (worst) and 1 (best)
GPA	**0-1**	Grade point average at time of application scaled between 0 (worst) and 1 (best)
Age	**Numeric**	Age in years at time of application
International	**Binary**	1 if the applicant has a citizenship other than German, 0 otherwise
Female	**Binary**	1 if the applicant identified as female, 0 otherwise
Business Major	**Binary**	1 if the applicant majors in management, business or economics, 0 otherwise
CS/EE Major	**Binary**	1 if the applicant majors in computer science or electrical engineering, 0 otherwise
Application year	**Numeric**	Year of the application, ranging from 2011 to 2020
Graduate student	**Binary**	1 if the applicant was enrolled in a graduate level program at the time of application
Prior Entrepreneurship	**Binary**	1 if the applicant founded a company prior to their application, 0 otherwise
		Panel B: Career Outcomes (post-application)
Entrepreneurial career	**Binary**	1 if the finalist worked in a full-time position with direct interaction with start-ups after the application in any of the following capacity: co-founding a start-up, employee in a start-up, working in venture capital, working at an incubator, accelerator, or company builder, 0 otherwise
Founded startup	**Binary**	1 if the applicant co-founded a for-profit company after the application, 0 otherwise
Startup survival	**Binary**	1 if the applicant co-founded a for-profit company that was still active or has been acquired at the time of data collection, 0 otherwise
Startup raised any funding	**Binary**	1 if the applicant co-founded a for-profit company that raised at least one funding round publicized on Crunchbase at the time of data collection, 0 otherwise
Startup total funding ($ m)	**Numeric**	The highest amount of funding raised by a for-profit company co-founded by the applicant as publicized on Crunchbase at the time of data collection
Startup employees	**Numeric**	The highest number of employees of a for-profit company co-founded by the applicant as on LinkedIn at the time of data collection
Startup raised > 10m funding	**Binary**	1 if the applicant co-founded a company that raised more than 10m USD by the time of data collection, 0 otherwise
Startup raised > 20m funding	**Binary**	1 if the applicant co-founded a company that raised more than 20m USD by the time of data collection, 0 otherwise
Startup has > 10 employees	**Binary**	1 if the applicant co-founded a company that had a maximum of more than 10 employees by the time of data collection, 0 otherwise
Startup has > 20 employees	**Binary**	1 if the applicant co-founded a company that had a maximum of more than 20 employees by the time of data collection, 0 otherwise

Notes: All applicants identified as either female or male.

Table 8 provides an overview of the variable definitions and their operationalization. We distinguish between applicant characteristics (Panel A) and career outcomes (Panel B). Applicant characteristics were observed at the time of application, whereas career outcomes were observed in May to June 2022 by collecting the aforementioned data from LinkedIn, Crunchbase, and Northdata.

Table 9: Summary Statistics and Differences Between Program Participants and Control Group

	Full Sample		Program participants		Almost accepted		Difference	
	Obs.	Mean	Obs.	Mean	Obs.	Mean	Diff.	t-stat.
Panel A: Applicant characteristics								
GPA	975	0.83	455	0.84	520	0.83	0.02	1.78*
Age	1022	24.21	478	23.81	544	24.56	-0.75	-6.07***
International	1022	0.33	478	0.29	544	0.36	-0.08	-2.56***
Business major	1022	0.33	478	0.34	544	0.33	0.01	0.47
CS/EE major	1022	0.42	478	0.43	544	0.41	0.02	0.56
Female	1022	0.26	478	0.26	544	0.26	0.00	0.08
Application year	1022	2015.64	478	2015.66	544	2015.63	0.03	0.19
Graduate student	1022	0.65	478	0.62	544	0.68	-0.06	-1.98**
Founded startup pre-application	1022	0.06	478	0.08	544	0.05	0.02	1.44
Panel B: Career outcomes								
Entrepreneurial career post-application	1022	0.46	478	0.60	544	0.34	0.26	8.61***
Founded startup post-application	1022	0.26	478	0.36	544	0.18	0.17	6.33***
Startup survival	270	0.47	170	0.56	100	0.31	0.25	4.06***
Startup raised any funding	270	0.52	170	0.63	100	0.34	0.29	4.77***
Startup total funding ($ m)	270	27.11	170	41.07	100	3.37	37.69	2.52***
Startup employees	270	63.65	170	94.44	100	11.30	83.14	2.89***
Startup raised > 10m funding	270	0.14	170	0.21	100	0.03	0.18	4.22***
Startup raised > 20m funding	270	0.10	170	0.14	100	0.03	0.11	2.86***
Startup has > 10 employees	270	0.38	170	0.49	100	0.18	0.31	5.39***
Startup has > 20 employees	270	0.29	170	0.38	100	0.13	0.25	4.57***

Notes: The table presents summary statistics of the main variables used in the analysis. Panel A shows applicant characteristics collected at the time of application. Panel B shows career outcomes based on data collected from LinkedIn and Crunchbase. Interview score and GPA scaled between 0 (worst) and 1 (best). GPA not available for one cohort in 2011 (N=47). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Overall, there is a substantial degree of high-growth entrepreneurship in our sample. The 270 individuals (of the 1,022 interview finalists) who became founders after applying to the program founded 297 unique startups[18] that raised a total of $4.92 billion in funding. Out of these, $4.56 billion in funding was raised by startups co-founded by program participants and $331.9 million by startups co-founded by individuals who were almost accepted. For comparison, all German startups founded after 2011 received $44.9 billion during our sample period between 2011 and 2022[19]. As such, the startups created by the individuals in our sample make up a fair share of the overall startup activity over the 2010's in Germany. Table 9 provides summary statistics of our sample and a comparison between program participants and applicants from the control group.

[18]The number of startups and the number of founders differ because some founders co-founded together to create a startup and others founded multiple times.

[19]According to Crunchbase. See https://crunchbase.com/lists/investments-in-german-startups-founded/7c569f53-00b9-4855-9a3d-453a3e2b1b30/funding_round (last accessed 2023-01-18)

3.5.2 | Method

To estimate the effect of program participation on career outcomes, we use a regression discontinuity design (RDD). We use the discontinuity at the capacity threshold of the program to estimate a local average treatment effect of entrepreneurship education on career choice and startup performance. The central idea behind this identification strategy is that consideration of the sample of individuals within a very small interval around the cutoff point approximates a randomized experiment (Van Der Klaauw, 2002). Because they have essentially the same interview score, we expect individuals just below the cutoff point to be very similar to individuals just above the cutoff point and thus to have similar outcomes in the absence of treatment.

For the approach to be valid, we need to demonstrate three patterns. First, we need to show that the likelihood of program participation changes discontinuously at the cutoff rank (i.e. capacity threshold of the program). Second, we need to demonstrate that ranks are not manipulated. Third, we need to show that applicants immediately above and below this threshold appear similar at the time they applied for the program.

Assumptions for Regression Discontinuity Design (RDD)

The discontinuity to get into the program around the capacity threshold is visible in Figure 3. We plot the share of program participants across the normalized interview score rank, aggregated in bins of 5 participants (plotted as dots). Due to normalization, that is, the ranking of the applicant minus the cohort's capacity threshold, higher ranking applicants are on the right of the capacity threshold, which is 0 on the x-axis.

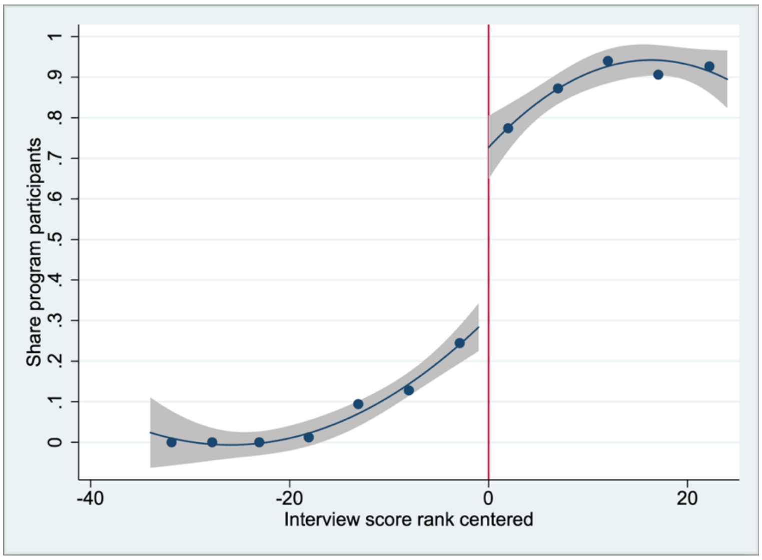

Figure 3: Interview Score and Program Participation

Notes: The figure shows the average share of program participants (dots) in bins of 5 applicants against their interview rank. The line and shaded areas represent fitted values and 95% confidence intervals from estimating equation (1), with a polynomial of degree 2, and no controls. The vertical line represents the cutoff point normalized at 0.

We formally estimate the size of the discontinuity using the following equation:

$$(1) \quad ProgramParticipant_i = \alpha + \delta rank\_above_i + f(rank_i - cutoff)_i + X_i{}' \gamma + \epsilon_i$$

$ProgramParticipant_i$ is a binary variable indicating whether the applicant i was accepted and started the program, $rank_{above_i}$ is a dummy that equals 1 if the applicant ranked higher than the capacity threshold, and X_i is a vector of control variables evident at the time of application, including applicants' grade point average (GPA), age, gender, major, whether the applicant was a graduate student, an international student, and whether they founded a company prior to their application (see Table 8). We control for a flexible function $f(rank_i - cutoff)_i$ of the individual rank of an applicant, either by restricting the sample to a bandwidth b around the cutoff (see Gelman and Imbens, 2019) or higher-order polynomials of the rank of degree p (see Lee and Lemieux, 2008). We consider different bandwidths and polynomial degrees to verify that the results are not dependent on sample choices or functional form (see Table 10).

Table 10: Discontinuity Probability of Program Participation at the Capacity Threshold

	(1)	(2)	(3)	(4)	(5)	(6)
	p=1	p=1 & controls	p=1 & b=15	p=1; b=10	p=2	p=3
Ranked above cutoff	0.573***	0.557***	0.465***	0.422***	0.580***	0.468***
	(12.36)	(11.66)	(6.69)	(4.69)	(12.10)	(7.33)
Controls	No	Yes	No	No	No	No
Application year fixed effects	No	Yes	No	No	No	No
Observations	1022	975	548	363	1022	1022
R-squared	0.672	0.674	0.520	0.420	0.672	0.677

Notes: T-scores in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

The estimated discontinuity is large, highly statistically significant, and robust across an array of specifications. Table 10 shows estimates of δ using different polynomial degrees (Columns 1, 5, and 6), including controls (Column 2), and considering only +/- 10 or 15 applicants round the cutoff (Columns 3 and 4). The coefficient of between 0.42 and 0.58 indicates that ranking above the capacity cutoff of 25 in the interview leads to a discontinuous jump in the likelihood to participate by 42% to 58%, even controlling for the rank and observable differences across applicants. This discontinuity is also graphically evident in Figure 3 (previous page), where we plot the estimated probability of participating with polynomial of order two and no controls (i.e. Table 10, Column 5).

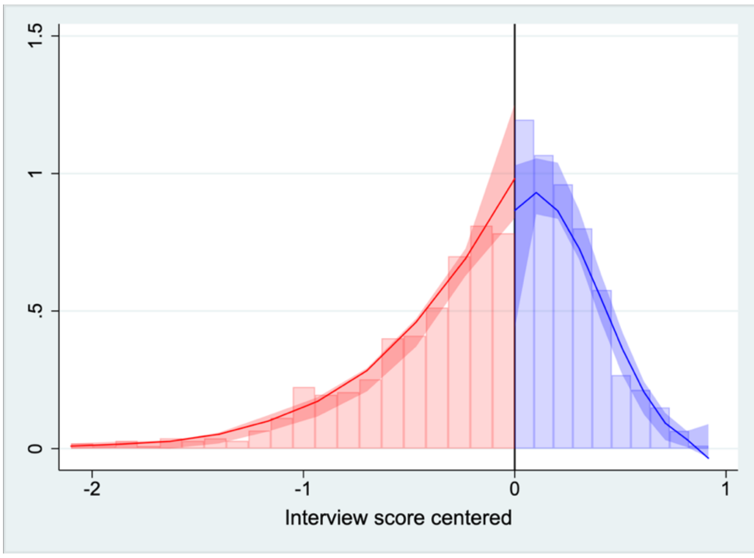

Figure 4: Histogram of Interview Scores

Notes: This figure shows a histogram of normalized interview scores. For each applicant, the score of the capacity-threshold-ranking is subtracted from the original application score. The interview score ranges from 4 (best) to 1 (worst), with scores ranging between 3.95 and 1. The t-statistic of the Cattaneo, Jansson and Ma (2020) test for manipulation is -0.422, giving no statistically significant indication of score manipulation around the threshold. The test uses a local polynomial density estimate (solid) and robust bias corrected confidence intervals (shaded).

As described above, a manipulation of ranks would be difficult in our context. Two tests confirm this notion. First, a histogram of interview scores in Figure 4 shows there is no discontinuity in the distribution of interview scores around the cutoff. Second, the t-statistic of the Cattaneo, Jansson and Ma (2020) test for manipulation is -0.422, giving no statistically significant indication of score manipulation around the threshold.

As an alternative test, we compare mean observable characteristics while narrowing the bandwidth around the cutoff. The results of simple mean difference tests between applicants ranking above and below the cutoff are presented Table 11 (next page). As the bandwidth around the cutoff point narrows, the differences and statistical significances between program participants and almost accepted applicants progressively decrease.

Figure 5 (next page) demonstrates the smoothness of observable covariates at time of application around the threshold. In other words, applicants ranked immediately above and below the capacity threshold are similar. We estimate equation (1) using pre-program covariates as dependent variables and plot the estimates in Figure 5. Across all pre-program variables, we find no statistically significant jump at the capacity threshold.

Table 11: Pre-Existing Differences Between Applicants Above and Below Capacity Threshold

	Mean difference between applicants above and below the capacity threshold		
	Full sample	[-15; +15 applicants around cutoff]	[-10; +10 applicants around cutoff]
	(1)	(2)	(3)
Panel A: Characteristics at application			
GPA	0.02**	0.00	-0.03*
	(2.25)	(0.05)	(-1.88)
Age	-0.64***	-0.37**	-0.22
	(-5.16)	(-2.45)	(-1.20)
International	-0.07**	0.03	0.05
	(-2.37)	(0.82)	(0.98)
Business major	-0.01	-0.06	-0.03
	(-0.29)	(-1.40)	(-0.51)
CS/EE major	0.04	0.06	0.04
	(1.21)	(1.47)	(0.69)
Female	-0.05*	0.00	0.03
	(-1.73)	(0.10)	(0.72)
Application year	-0.06	0.01	0.01
	(-0.33)	(0.05)	(0.03)
Graduate student	-0.08**	-0.11***	-0.13**
	(-2.52)	(-2.77)	(-2.52)
Founded startup pre-application	0.01	-0.03	-0.05*
	(0.95)	(-1.57)	(-1.79)
Panel B: Likelihood to get into program			
Program participant	0.81***	0.71***	0.64***
	(43.81)	(23.38)	(15.66)
Observations	1022	548	363

Notes: T-scores in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

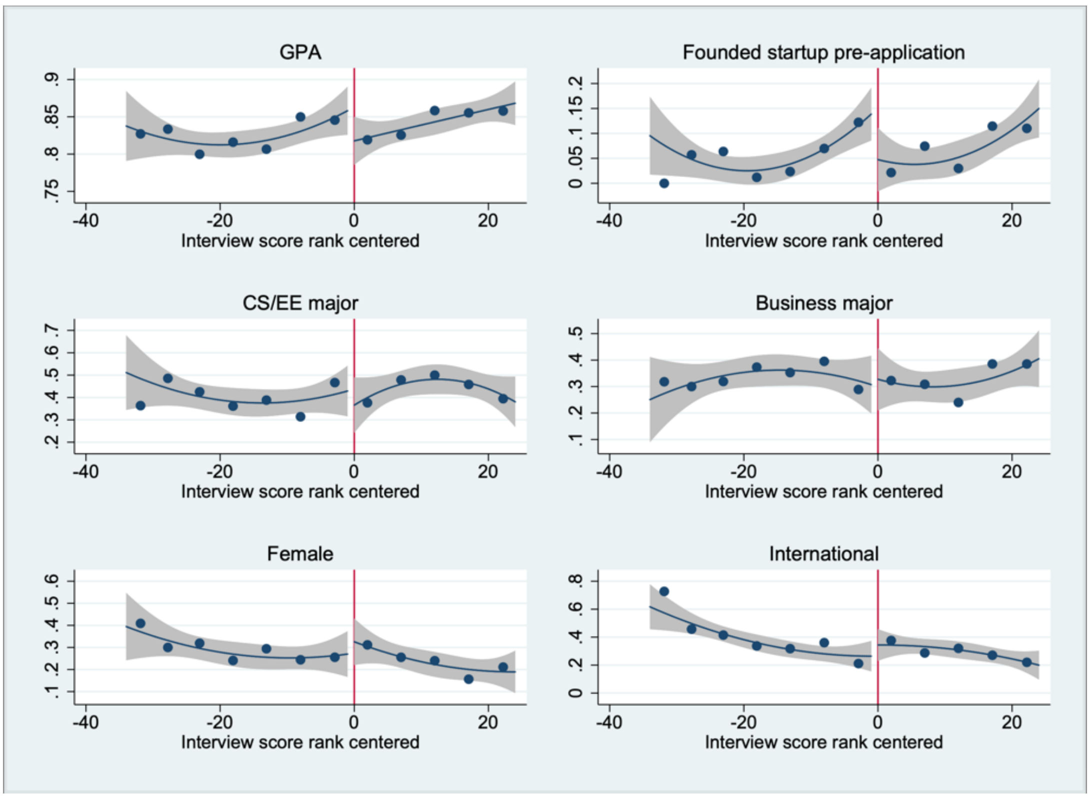

Figure 5: Balanced Sample Around the Capacity Threshold

Notes: The figure shows evidence of a balanced sample near the capacity-threshold-ranking cutoff. The plots show averages grouped in bins of 5 applicants (dots), and the fitted values and 95% confidence interval from estimating equation (1), with a polynomial of degree 2, and no controls. The vertical line represents the cutoff point normalized at 0 for the normalized rank.

Fuzzy Regression Discontinuity Design and Main Analysis

To test our main hypotheses, we estimate two types of models to calculate a local average treatment effect. First, we implement a fuzzy RDD by estimating a regression of the form:

(2) $$Outcome_i = \pi + \beta ProgramParticipant_i + f(rank_i - cutoff)_i + X_i{}'\theta + \epsilon_i$$

where $Outcome_i$ is a career outcome of an applicant. In fuzzy RDD, we use the predicted values from equation (1) for $ProgramParticipant_i$, instead of the actual program participation variable. In other words, we instrument $ProgramParticipant_i$ with the selection rule (i.e. the indicator variable $rank\_above_i$). Under the identification assumption that ranking above the threshold is as good as random for applicants close to the threshold, fuzzy RDD gives an unbiased estimate of the local average treatment effect. The fuzzy RDD estimator implicitly filters out applicants who rank below the threshold but are accepted into the program, and applicants who rank above and are not accepted into the program (i.e. the "non-compliers"). This estimator is unbiased but loses statistical power through not considering the non-compliers. Therefore, we alternatively provide simple mean comparisons (estimated by OLS) of applicants in a given bandwidth around the cutoff.

Table 12: Lowest Ranked Program Participants vs. Highest Ranked Non-Participants.

	10 lowest ranked participants per batch		10 highest ranked non-participants per batch		Difference	
	Obs.	Mean	Obs.	Mean	Diff.	t-stat.
Panel A: Applicant Characteristics						
GPA	190	0.83	190	0.85	-0.02	-1.43
Age	200	23.86	200	24.30	-0.44	-2.59***
International	200	0.30	200	0.29	0.01	0.22
Business major	200	0.32	200	0.32	-0.01	-0.11
CS/EE major	200	0.42	200	0.41	0.01	0.10
Female	200	0.35	200	0.19	0.16	3.65***
Application year	200	2015.50	200	2015.50	0.00	0.00
Graduate student	200	0.61	200	0.68	-0.07	-1.36
Founded startup pre-application	200	0.06	200	0.09	-0.03	-1.17
Panel B: Career Outcomes						
Entrepreneurial career post-application	200	0.60	200	0.38	0.23	4.72***
Founded startup post-application	200	0.36	200	0.20	0.16	3.61***
Startup survival	72	0.54	40	0.42	0.12	1.18
Startup raised any funding	72	0.64	40	0.45	0.19	1.95**
Startup total funding ($ m)	72	29.11	40	7.25	21.85	1.26
Startup employees	72	97.01	40	15.45	81.56	1.63*
Startup raised > 10m funding	72	0.21	40	0.05	0.16	2.27**
Startup raised > 20m funding	72	0.11	40	0.05	0.06	1.08
Startup has > 10 employees	72	0.49	40	0.23	0.26	2.78***
Startup has > 20 employees	72	0.40	40	0.17	0.23	2.52***

Notes: The table presents summary statistics of all main variables. Panel A shows applicant characteristics collected at the time of application. Panel B shows career outcomes based on LinkedIn and Crunchbase data. Interview score and GPA scaled between 0 (worst) and 1 (best). GPA not available for one cohort in 2011 (N=47). * p < 0.1, ** p < 0.05, *** p < 0.01.

While this approach provides higher statistical power, it may be biased by the selection that occurs in the final selection step after ranking. We know from interviews with program managers that one of the purposes of the final selection step is to meet diversity goals. The comparison of the 10 lowest ranked program participants with the 10 highest ranked non-participants in Table 12 shows that this is indeed the case. Among the 10 lowest ranked program participants, 35% are female, whereas among the 10 highest ranked non-participants, only 19% are female. This difference is significant at the 1% level. To the extent that diversity is achieved at the expense of founding performance,[20] the simple OLS estimator provides a lower bound of the true program effect.

3.6 | Results

We find support for all three hypotheses. Robustness tests and secondary analyses confirm and contextualize the main results. The observed effects are a result of participation in the program rather than of selection of the respective students. We find that the increase in founding rates is visible for years after the program.

Secondary analyses suggest that the selection process can identify, to a degree, entrepreneurial aptitude but does not predict which applicants go on to found startups. The observed effect as a result of program participation is likely driven by increases in social capital instead of a mere increase in entrepreneurial skills or competencies. We find that program participants who co-found with one or more other participants are more successful and that founding rates among female participants are not affected by program participation. We conclude this section by discussing participants' perception of the program.

3.6.1 | Main Results

We estimated the effects of participation in the entrepreneurship education program on selection into an entrepreneurial career (H1), on the probability of founding a startup post application (H2), and different measures of startup success (H3). Our results show that program participants consistently outperform rejected finalists. Column 1 to 3 report ordinary least-squares (OLS) estimates with different bandwidths around the cutoff point. Column 4 report estimates using the fuzzy RDD. Panel A reports the base regression results. Panel B includes control variables and application year fixed effects. T-scores are reported in parentheses.

[20]There is good reason to believe, and some evidence later in this paper, that the well-established gender gap in entrepreneurship (see, e.g. Guzman and Kacperczyk, 2019) is also present in our sample.

Table 13: Program Participation and Selection into an Entrepreneurial Career

Dependent variable:	Selection into an Entrepreneurial Career			
	OLS (full sample)	OLS [-15; +15 applicants around cutoff]	OLS [-10; +10 applicants around cutoff]	RDD estimate
	(1)	(2)	(3)	(4)
	Panel A: Base regression			
Program participant	0.260***	0.282***	0.247***	0.204**
	(6.07)	(5.51)	(4.14)	(2.28)
Observations	1022	548	363	1022
R-squared	0.068	0.079	0.061	0.067
	Panel B: With controls			
Program participant	0.261***	0.302***	0.258***	0.279***
	(5.83)	(5.86)	(4.45)	(3.01)
GPA	-0.399***	-0.431**	-0.447**	-0.390***
	(-3.10)	(-2.54)	(-2.15)	(-3.13)
International	-0.025	0.044	0.036	-0.028
	(-0.67)	(0.76)	(0.51)	(-0.81)
Business major	0.044	0.019	0.044	0.044
	(1.02)	(0.38)	(0.79)	(1.07)
CS/EE major	-0.042	-0.022	0.001	-0.041
	(-1.08)	(-0.43)	(0.01)	(-1.08)
Female	-0.133***	-0.119***	-0.091**	-0.136***
	(-5.92)	(-3.78)	(-2.28)	(-6.01)
Graduate student	0.131***	0.083	0.059	0.130***
	(3.22)	(1.59)	(1.20)	(3.30)
Founded startup pre-application	0.219***	0.282***	0.269**	0.222***
	(4.16)	(3.18)	(2.66)	(4.25)
Application year fixed effects	Yes	Yes	Yes	Yes
Observations	975	522	346	975
R-squared	0.172	0.191	0.172	0.173

Notes: This table shows the results of regressions in which entrepreneurial career choice is regressed on participation in the entrepreneurship education program. Panel A presents regression results without any control variables. Panel B includes pre-application observables as controls: GPA and indicators of whether the student is international, female, majors business, majors CS/EE, graduate student, and founded a startup prior to the program. RDD estimate is a fuzzy RDD estimate as described in the main body of the text. T-statistics based on robust standard errors clustered by application batch in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(H1) Entrepreneurial Careers: Table 3 summarizes the estimated effects of program participation on graduates' selection into careers related to entrepreneurship. The results show that program participants are more likely to select a career related to entrepreneurship, providing support for H1. For example, results in Column 1, Panel A indicate that program participants are 26% more likely to choose a career related to entrepreneurship after the program. Across the different models this effect remains stable, varying between 20.3% and 30.9%, and statistically significant. Panel B further reveals stable and statistically significant effects of several control variables. Female gender and the GPA at application have a negative effect, founding prior to the application has a positive one.

Table 14: Program Participation and Startup Founding Rates

Dependent variable:	Startup founded after application			
	OLS (full sample)	OLS [-15; +15 applicants around cutoff]	OLS [-10; +10 applicants around cutoff]	RDD estimate
	(1)	(2)	(3)	(4)
	Panel A: Base regression			
Program participant	0.172***	0.193***	0.154**	0.232**
	(3.80)	(3.55)	(2.53)	(2.29)
Observations	1022	548	363	1022
R-squared	0.038	0.047	0.030	0.035
	Panel B: With controls			
Program participant	0.167***	0.202***	0.157**	0.278**
	(3.59)	(3.54)	(2.32)	(2.41)
GPA	-0.200*	-0.251	-0.361*	-0.187*
	(-1.82)	(-1.52)	(-1.76)	(-1.81)
International	-0.048**	-0.014	0.016	-0.053**
	(-2.42)	(-0.39)	(0.32)	(-2.53)
Business major	0.045	0.011	0.080	0.044
	(1.26)	(0.22)	(1.55)	(1.25)
CS/EE major	0.011	-0.011	0.036	0.011
	(0.43)	(-0.28)	(0.88)	(0.41)
Female	-0.124***	-0.144***	-0.155**	-0.133***
	(-4.37)	(-3.13)	(-2.42)	(-4.64)
Graduate student	0.063**	0.011	0.026	0.066**
	(2.47)	(0.22)	(0.50)	(2.55)
Founded startup pre-application	0.166**	0.184	0.167	0.171**
	(2.25)	(1.73)	(1.63)	(2.33)
Application year fixed effects	Yes	Yes	Yes	Yes
Observations	975	522	346	975
R-squared	0.129	0.176	0.170	0.124

Notes: This table shows the results of regressions in which startup founding is regressed on participation in the entrepreneurship education program. The models are the same as in Table 13. T-statistics based on robust standard errors clustered by application batch in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

(H2) Founding Rates: Table 14 reports the estimated effect of program participation on whether graduates found after their application. The results show that program participants are more likely to found companies, providing support for H2. Column 1, Panel A indicates that participants are 17.2% more likely to found. Across the different models the effect remains stable, varying between 15.4% and 28.1%, and statistically significant. Panel B further reveals that, across both groups, there is a stable and statistically significant negative coefficient for women. This effect is also visible when looking at descriptive statistics. Among men there is a substantial difference between almost accepted applicants (20.79% founded) and program participants (42.37% founded). Among women the difference between almost accepted applicants (12.85% founded) and program participants (16.13% founded) is substantially smaller.

Table 15: Program Participation and Startup Success Indicators

	OLS (full sample)	OLS [-15; +15 applicants around cutoff]	OLS [-10; +10 applicants around cutoff]	RDD estimate
	(1)	(2)	(3)	(4)
	Startup survival			
Program participant	0.249***	0.231**	0.176	0.115
	(4.30)	(2.52)	(1.45)	(0.59)
	Startup raised any funding			
Program participant	0.289***	0.248**	0.253**	0.310
	(4.26)	(2.45)	(2.21)	(1.37)
	LN Startup total funding ($ m)			
Program participant	3.842***	4.315***	4.644***	4.710*
	(3.53)	(3.33)	(3.40)	(1.79)
	LN Startup employees			
Program participant	1.271***	1.287***	1.146**	1.133
	(4.70)	(3.61)	(2.37)	(1.53)
	Startup raised > 10m funding			
Program participant	0.182***	0.206***	0.199***	0.180
	(3.77)	(3.76)	(2.93)	(1.23)
	Startup raised > 20m funding			
Program participant	0.105**	0.111**	0.093	0.013
	(2.36)	(2.29)	(1.71)	(0.11)
	Startup has > 10 employees			
Program participant	0.314***	0.342***	0.287**	0.507**
	(4.80)	(3.72)	(2.36)	(2.36)
	Startup has > 20 employees			
Program participant	0.252***	0.273***	0.253**	0.366*
	(3.91)	(3.49)	(2.46)	(1.91)
Observations	270	149	101	270

Notes: This table shows the results of regressions in which startup success variables are regressed on participation in the entrepreneurship education program. All models are without control variables, except the (fuzzy) RDD estimate which includes a first-order polynomial of the centered interview score rank. T-statistics based on robust standard errors clustered by application batch in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(H3) Startup Success: Table 15 reports the coefficients of each outcome variable proxying startup success regarding the estimated effect of program participation. Program participants consistently outperform rejected applicants. The evidence suggests a large causal effect, providing support for H3. For example, the results in Column 1 indicate of positive effect of program participation on startup survival (25%) and the probability to raise any funding (29%). The coefficients for the log-transformed outcome variables[21] indicate that participation increases the amount of capital raised by a factor of 45 and the number of employees by a factor of 2.5. Since relatively few companies raise most funding and hire the majority of employees,[22] we included dummy variables for the amount of funding raised and the number of employees. The results in Column 1 indicate that program participation increases the probability of raising more than 10 million in funding by 18%. The economic size of this effect is substantial: as the baseline

[21]The effect size of log transformed models can be calculated with $f(\beta) = exp(\beta) - 1$. A coefficient of 3.842 in a log-transformed model results in an effect size of $exp(3.842) - 1 = 45.62$.
[22]The top 10% of founders in our sample account for 94% of total funding raised and 77% of total employees. This ‘power law' distribution is typical for young hyper-growth firms (Crawford *et al.*, 2015).

probability of raising over 10 million in the untreated group is 3%, the estimated program effect implies a 5-fold increase.[23] This large coefficient is stable across startup success variables and model choices. However, statistical significance is reduced by decreasing bandwidth (Column 3) and by fuzzy RDD (Column 4) because of fewer available observations for these rare outcomes.

3.6.2 | Robustness

In the presented results we addressed selection concerns by limiting the analyses to the applicants in the final stage of the selection process, reducing the bandwidth around the cutoff point, and using a RD design. To further test the robustness of our results we repeated the analyses after removing individuals who took part in other entrepreneurship programs from the control group.

After their failed application to the program, rejected applicants may have applied and participated in alternative entrepreneurship education programs at university. Under the assumption that entrepreneurship education programs have a positive effect on our dependent variables, this means that our main analysis could underestimate the effect of program participation and instead only capture the difference in quality between entrepreneurship education programs for those participants.

The assumption behind using a regression discontinuity design is that the assignment to treatment groups around the threshold happens independent of baseline covariates (D. S. Lee & Lemieux, 2010). If the necessary assumptions are met, it is thus not necessary to control for these covariates. As the point of assignment to treatment groups is the application to the program, we decided against including any covariates not available at this point. Considering ex-post information, in particular participation in other entrepreneurship programs, would potentially introduce bias as we hand-select and remove those individuals from the control group that, in hindsight, showed additional entrepreneurial aptitude. In our main analyses we therefore adopted a conservative approach and only considered information available at the point of selection.

To test the robustness of the results, we used the LinkedIn dataset to post-hoc identify rejected applicants who participated in comparable entrepreneurship programs during university and repeated our analyses. We identified 33 out of 544 applicants, who listed participation in comparable entrepreneurship education programs during the period they were enrolled at university in Munich on their LinkedIn profile. Table A2 to Table A6 in the Appendix show the results of the analyses analog to the presented main analyses. We observe no major changes along the different dependent variables, confirming the robustness of the results.

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[23]The relative increase as a result of program participation can be calculated as follows: $(18\% - 3\%)/3\% = 5$

3.6.3 | Founding Activity Over Time

In contrast to previous literature (C. E. Eesley & Lee, 2021) our results show a positive effect of entrepreneurship education on founding rates. Thus far, our analysis does not address when the increase in founding rates manifests. With recent literature showing that startup founders are considerably older than previously thought (Azoulay et al., 2020) and founders generally benefiting from industry experience (Cassar, 2014), we are interested to understand how program participation influences founding rates over time.

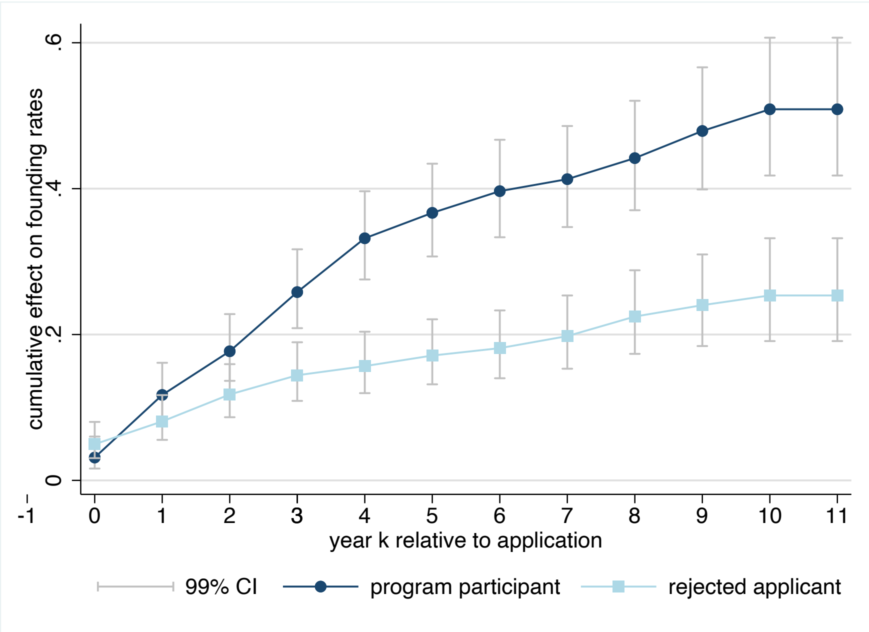

Figure 6: Cumulative Founding Rates Relative to Application Year.

Notes: The figure shows the cumulative founding rate relative to the application year with a 99% confidence interval. Modeled as hazard, individuals can become a founder following their application exactly once. The x-axis depicts the year relative to the application, with 0 being the year of application. The y-axis shows the cumulative rate of founders up to the respective year given the available observations. The confidence intervals increase with distance to the year of application as the number of available observations declines.

We employ a hazard analysis to evaluate the probability that a student will found a startup in the future given that they have not done so already. We select the widely used Cox proportional hazard model to investigate the influence of program participation on founding probability as a function of time (Cox, 1972).The results of the estimated models are reported in Table 16. We report the overall model fit as well as coefficients and hazard rates (in square brackets) for each dependent variable.

All models show a good fit. Model 1, however, violates the proportional hazard assumption, indicated by the Schoenfeld residuals test (Bradburn, Clark, Love, & Altman, 2003; Grambsch & Therneau, 1994). Conceptually, this issue arises because founding rates in the year of application (year 0) are lower for program participants than for rejected finalists, which then reverses for all subsequent years (this is also evident in Figure 6). This effect could be driven by different mechanisms: (1) applicants most eager to found may turn down a place in the program in favor of founding, (2) applicants showing more interest in founding as opposed to the program itself may be less likely to be selected, or (3) selected participants, even when eager to found, may delay their ambitions in favor of completing the program. As the investigated treatment, namely participation in the program itself, is ongoing during year 0, we therefore also fit models excluding it.

Across all models the observed effect of program participation remains stable and statistically significant with hazard rates between 2.12 (Model 3) and 2.78 (Model 4). In the context of our analysis a hazard rate >1 corresponds to an increased probability of founding. A hazard rate of 2.15 (Model 1) indicates that program participants have a 2.15 higher chance of founding compared to rejected finalists.

Table 16: Cox Proportionate Hazard Models of Startup Founding

	Full Sample	Sample Excluding Year = 0	Full Sample	Sample Excluding Year = 0
	(1)	(2)	(3)	(4)
Program participant	0.77 [2.15]*** (6.07)	1.01 [2.75]*** (7.10)	0.75 [2.12]*** (5.66)	1.02 [2.78]*** (6.79)
GPA			-0.95 [0.39]* (-1.95)	-0.81 [0.44] (-1.53)
Age			-0.02 [0.98] (-0.66)	-0.03 [0.97] (-0.81)
International			-0.31 [0.73]** (-2.11)	-0.20 [0.82] (-1.30)
Female			-0.74 [0.48]*** (-4.13)	-0.69 [0.50]*** (-3.61)
Graduate Student			0.23 [1.26] (1.46)	0.24 [1.27] (1.37)
Founded startup pre-application			0.71 [2.03]*** (3.41)	0.71 [2.04]*** (3.04)
Observations	1022	980	975	934
Overall Chi-Squared	38.46***	54.69***	75.66***	80.62***
Log-rank test	40.53***	57.42***	1302.38***	1063.89***
PH assumption (Schoenfeld Residuals)	6.02**	0.08	11.34	6.19

Notes: All models are cox proportional hazard models. The time for founding the first time after the application is measured in years, with the year of application being year 0. Model (1) violates the proportional hazard assumption. As the treatment, participation in the program, is ongoing during the year of application, we fit models excluding year 0 for comparison. Z-Scores in parentheses, hazard ratios in square brackets. * p < 0.1, ** p < 0.05, *** p < 0.01.

We illustrate the estimated effect over time (Model 1) in Figure 6 (previous page). The application year is represented on the x-axis as year 0. The y-axis shows the estimated share of people who have founded in the respective year or in any year before that. In the application year 5.7% percent of rejected finalists found a company, as opposed to 3.3% of program participants. In every year after that, program participants show a higher founding rate. The difference is highest one year after the original application, where 4.0% of rejected applicants and 9.6% of program participants found. In sum, the year-on-year differences in founding rates accumulate to a difference in 20 percentage points between program participants and rejected applicants after ten years.

Overall, these results indicate a strong effect of program participation on founding rates. They also show that participation affects founding rates even years after the program completion.

3.6.4 | Selection vs Treatment Effects

The results of our main analyses indicate that the observed difference between program participants and rejected applicants is driven by a treatment effect. The presence of a selection effect would mean that the observed effect sizes diminish when narrowing the bandwidth around the cutoff point as individuals become increasingly comparable according to the selection function. Since the coefficients remain stable when narrowing the bandwidth this indicates that the effects are a result of the program participation rather than selection of the best applicants.

To further test this argument, we ran additional analyses estimating the predictive power of the interview score. We restrict our analyses to either program participants or rejected finalists. Since within their subgroups they all either received the treatment or not, the estimated effects should capture to which degree the selection at the time of application can identify entrepreneurial potential in applicants. We use estimate equation (2) with the interview score as independent variable. To see how the effect changes when quality between applicants increases, we construct two additional models limiting the analysis to the bottom- and top-ranked individuals.

Table 17 reports the results for each dependent variable. Coefficients of the interview score are not statistically significant for selection into an entrepreneurial career and whether individuals found. For all startup outcomes (Panel C) in the group of program participants coefficients are, while consistently positive, also not statistically significant. This indicates that the original ranking does not predict startup quality for individuals who participated in the program. For rejected applicants, however, coefficients are positive and statistically significant for startup survival, whether the startup raised funding, the amount of funding raised, and the number of employees. In other words, rejected applicants who scored better in the interviews produced startups of higher quality. For example, a coefficient of 1.199 indicates that an improvement of the interview score of 1 increases the probability of startup survival by 119.9%. Since the score

Table 17: Interview Score and Career, Founding, and Startup Outcomes

Dependent variable:	Program Participants			Almost Accepted		
	OLS (full sample)	OLS [bottom 10 vs top 10]	OLS [bottom 5 vs top 5]	OLS (full sample)	OLS [bottom 10 vs top 10]	OLS [bottom 5 vs top 5]
	(1)	(2)	(3)	(1)	(2)	(3)
Panel A: Entrepreneurial Career						
Interview score	0.341	0.378	0.294	-0.023	0.057	-0.013
	(0.87)	(1.03)	(0.74)	(-0.10)	(0.25)	(-0.06)
Observations	478	418	220	544	419	220
R-squared	0.001	0.002	0.002	0.000	0.000	0.000
Panel B: Founded Startup						
Interview score	0.046	0.057	-0.039	0.111	0.177	0.196
	(0.16)	(0.20)	(-0.13)	(0.63)	(1.06)	(1.23)
Observations	478	418	220	544	419	220
R-squared	0.000	0.000	0.000	0.001	0.003	0.005
Panel C: Startup Outcomes						
	Startup survival			Startup survival		
Interview score	0.638	0.706	0.772	1.199**	1.295**	1.190*
	(1.10)	(1.22)	(1.08)	(2.27)	(2.23)	(2.04)
	Startup raised any funding			Startup raised any funding		
Interview score	0.344	0.437	0.632	1.421**	1.488**	1.360**
	(0.65)	(0.81)	(0.98)	(2.52)	(2.47)	(2.18)
	LN Startup total funding ($ m)			LN Startup total funding ($ m)		
Interview score	0.897	1.173	2.340	17.279**	18.015**	17.289**
	(0.09)	(0.12)	(0.22)	(2.63)	(2.64)	(2.32)
	LN Startup employees			LN Startup employees		
Interview score	2.151	2.292	3.415	3.984**	4.075**	3.713*
	(0.87)	(0.92)	(1.24)	(2.42)	(2.33)	(1.95)
	Startup raised > 10m funding			Startup raised > 10m funding		
Interview score	0.426	0.441	0.796	0.299	0.310	0.383
	(0.64)	(0.66)	(1.21)	(1.32)	(1.29)	(1.39)
	Startup raised > 20m funding			Startup raised > 20m funding		
Interview score	0.426	0.401	0.494	0.299	0.310	0.383
	(0.73)	(0.68)	(0.84)	(1.32)	(1.29)	(1.39)
	Startup has > 10 employees			Startup has > 10 employees		
Interview score	0.398	0.491	0.870	0.673	0.700	0.641
	(0.72)	(0.89)	(1.37)	(1.64)	(1.64)	(1.49)
	Startup has > 20 employees			Startup has > 20 employees		
Interview score	0.185	0.188	0.555	0.689**	0.666*	0.566
	(0.35)	(0.35)	(0.88)	(2.10)	(2.04)	(1.55)
Observations	170	154	78	100	81	49

Notes: All models without control variables. Including the control variables from Table 13 results in similar effect sizes across all models. The statistical significance of the coefficients in Panel C, Almost Accepted Finalists diminishes, particularly for the smaller bandwidths. Please note, that in the previous regression tables program participation was a dichotomous variable, while interview score here is a continuous variable between 0 and 1. Therefore the coefficients need to be interpreted slightly different. For example, a coefficient of 1.199 indicates that an improvement of the interview score of 1 increases the probability of startup survival by 119.9%. Since the interview score is scaled between 0 and 1, this translates to a 11.2% percent increase in probability for every 0.1 increase in score. What does this mean in concrete terms? If we compare the mean difference in interview score between the rejected applicants ranking in the bottom and top five of their respective cohorts, we observe a difference of 0.265. This means that startups founded by rejected finalists ranking in the top five, have a 31.8% higher chance of survival compared to those founded in the bottom five. T-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

is scaled between 0 and 1, this translates to a 11.2% percent increase in probability for every 0.1 increase in score. What does this mean in concrete terms? If we compare the mean difference in interview score between the rejected applicants ranking in the bottom and top five of their respective cohorts, we observe a difference of 0.265. This means that startups founded by rejected finalists ranking in the top five, have a 31.8% higher chance of survival compared to those founded in the bottom five.

Overall, these results confirm the findings of our main analyses and provide indicative evidence for three points. First, while the interview score seems to capture entrepreneurial talent, it does not predict whether individuals pursue careers related to entrepreneurship or found themselves. Phrased differently, the statistically significant effects on startup outcomes in the group of rejected finalists show that the selection process can distinguish (to some degree) between students' aptitude for entrepreneurship. Since it does not predict who becomes a founder, it also raises the question to which degree entrepreneurial aptitude and the decision to found coincide. Cognitive theories on entrepreneurial intentions (Ajzen, 1991; N. F. Krueger et al., 2000) include "perceived feasibility" as important antecedent to intention. Our results suggest that self-perception and observed or actual aptitude for entrepreneurship may diverge for individuals who decide to found.

Second, participation in the entrepreneurship education program appears to "level the playing field". In contrast to rejected finalists, the observable differences captured in the interview score do not affect the quality of startups founded by program participants. This indicates that the program is effective in supporting participants to found better startups and that participants with an ex-ante lower interview score benefit to a larger degree from the program. Following the argument of Eesley and Lee (2021) these results, considered in combination with the increase is founding rates, suggest that skill and social network development facilitated through the program clearly outweigh sorting and alignment effects (Fretschner & Lampe, 2019; Von Graevenitz et al., 2010).

Third, the treatment effect appears to be larger than the selection effect for participants of the program. Among program participants all coefficients relating to startup outcomes are greater than zero, suggesting an overall positive correlation between interview score and startup quality. Compared to the equivalent coefficients in the group of rejected finalists, their effect size reduces, most notably for raised capital, and no coefficient remains statistically significant. Overall, this indicates that for program participants the treatment effect outweighs the ex-ante difference in quality as captured by the interview score.

3.6.5 | Program Effect: Education or Network?

Having seen that the program has large positive effects on entrepreneurship rates and startup quality, the question remains: how does the program achieve these results? We propose two main hypotheses: (a) education (i.e. human capital), or (b) network effects (i.e. social capital). Under the human capital hypothesis, the program improves *individual* entrepreneurial skills (e.g. to recognize entrepreneurial opportunities, and execute on opportunities once recognized). Under the social capital hypothesis, program participants get access to resources through their obtained *network and relationships* (e.g. to co-founders, investors, advisers). We present three pieces of evidence that social capital is a main driver of the observed program effects.

Table 18: Heterogeneity of the Program Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables:	Entrepreneurial career	Founded startup	Startup survival	Startup raised any funding	LN Startup total funding ($ m)	LN Startup employees	Startup raised > 10m funding	Startup has > 10 employees
	Panel A: Program effect by course performance							
Top 50% by program grade	0.262***	0.173***	0.192**	0.219**	2.263	0.873***	0.102**	0.261***
	(4.72)	(3.84)	(2.66)	(2.74)	(1.65)	(3.24)	(2.20)	(3.71)
Bottom 50% by program grade	0.254***	0.156**	0.171*	0.279**	3.957**	0.970**	0.152**	0.201*
	(5.69)	(2.85)	(1.93)	(2.85)	(2.75)	(2.27)	(2.25)	(2.07)
H_0: top 50% = bottom 50% (p-value)	0.877	0.699	0.822	0.544	0.182	0.794	0.445	0.542
	Panel B: Program effect by gender							
Male	0.279***	0.208***	0.243***	0.306***	4.069***	1.236***	0.169***	0.322***
	(6.12)	(4.19)	(3.11)	(3.79)	(2.97)	(3.73)	(3.02)	(4.16)
Female	0.102*	-0.006	-0.130*	0.070	0.019	-0.314	-0.044	-0.075
	(1.88)	(-0.12)	(-1.82)	(0.60)	(0.02)	(-1.37)	(-0.94)	(-1.00)
H_0: male = female (p-value)	0.001	0.002	0.001	0.068	0.014	0.000	0.009	0.000
	Panel C: Program effect by co-founder choice							
Not co-founding with other participant	0.192***	0.028	0.031	0.100	1.119	0.228	0.046	0.071
	(3.94)	(0.65)	(0.40)	(1.15)	(0.74)	(0.72)	(0.98)	(0.97)
Co-founding with other participant	0.552***	0.780***	0.325***	0.384***	4.845***	1.567***	0.199***	0.387***
	(14.90)	(22.61)	(4.76)	(5.22)	(4.06)	(5.16)	(3.40)	(4.74)
H_0: not co-founding = co-founding (p-value)	0.000	0.000	0.004	0.005	0.020	0.001	0.019	0.002
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Application year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	975	975	252	252	252	252	252	252

Notes: This table reports estimates from regressions that examine the differential program effect by course performance, gender, and choice of co-founder. All models include control variables for applicant characteristics at application (same as Table 13, Panel B) and application year fixed effects. The H_0 rows report the p-values of tests for the two reported coefficients are equal. T-statistics based on robust standard errors clustered by application batch in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

First, if an increase in skills through education is the main driver of the program effects, we would expect to see a positive relationship between the students' received program grade and program effects. After all, the program grade is the best available measure of how well students achieved the program's educational goals. Table 18, Panel A, shows the differential program effect by students' received program grade. We present OLS estimates with control variables as in Table 3, Panel B, with the only difference that we now separate program participants two buckets: one bucket with the participants in the upper 50% by program grade (per batch), and one below. We find no evidence that the effect of the program differs by program grade – which is not supporting the education hypothesis.[24] An alternative explanation could be that students devoting time to optimizing their grades spend less time on founding related activities.

Second, if education is driving the effect, we would expect the effect to be similar between women and men. Prior findings show that entrepreneurship education disproportionately improves entrepreneurial intention in women (Wilson et al., 2007). If this translates into real behavior, we should find women to disproportionately benefit from the program. Table 8, Panel B shows the program effect by gender.[25] We find that the program has no effect on founding rates and startup success of female participants. While not statistically significant, the coefficients even suggest that program participation has a negative effect on some measures of startup quality.[26] While this result is difficult to explain with the education hypothesis (women should benefit from education about as much as men), the result is consistent with social capital as main mechanism: Fewer female founders within the network acting as role models may reinforce a perceived lack-of fit among female students (Gupta, Goktan, & Gunay, 2014; Rocha & Praag, 2020). The well-documented male dominance in entrepreneur and investor networks (Gompers, Mukharlyamov, Weisburst, & Xuan, 2022; Guzman & Kacperczyk, 2019), together with their bias toward working with same-gender individuals (Ewens & Townsend, 2020), make it likely that compared to men women would benefit less from access to such male-dominated networks if they found startups.

Third, we have direct evidence that the program provides people with entrepreneurial networks, especially co-founders. Of all program participants who found a startup after the program, 50% (85 of 179) co-found their startup with another program participant. When we separate the program effect into participants who co-found with other participants and participants who co-found elsewhere (or not at all), we find that the program effect is driven by the 50% of participants who co-found with other participants (Table 18, Panel C). Program participants who

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[24]We also find no differential effects when we examine the top 33%, 25%, 20%, or 10% (instead of 50%) of participants by course grade.

[25]In addition to the sample splits presented in Table 18, we analyzed the interaction effect between program participation and gender. The corresponding analysis can be found in the Appendix (Table A7 and Figure A1).

[26]Due to the small sample size of female founders, it is difficult to draw definite conclusions, particularly with regards to startup quality. Overall, our sample comprises only 38 female (20 program participants, 18 almost accepted applicants). This corresponds to founding rates of 16.1% among female program participants and 12.85% among female almost accepted applicants. We also find that if female program participants found, they are less likely to found with another program participant (35% among female founders, 52% among male founders).

do not do this are not significantly different from the control group in founding rate and startup quality. It is important to note that the co-founding effect should not be interpreted causally. Instead, it is likely that the intensive collaboration in the program reduces information asymmetries, and a sorting takes place so that those with the best ideas or most complementary skills join forces to found. This observation also speaks to the role of network and group social capital, i.e. participants are used to working together under conditions of complexity and uncertainty (Moore, Payne, Autry, & Griffis, 2018; Oh, Chung, & Labianca, 2004), rather than training effects as the main driver of the program effect. Taken together, the program seems to lead to people finding each other who would not have found each other without the program, and together they accomplish more than the sum of their parts.

3.6.6 | Participant Perceptions

The heterogeneity of the effect suggests that the large causal effects of the program are driven, at least in part, by the formation of social capital for program participants. However, because this evidence is suggestive and not conclusive, we analyze a survey that asks program participants themselves whether and how the program influenced their career success.

Access to the results of an evaluation questionnaire distributed to graduates of the program allows us to explore participant' perceptions. The survey was first distributed in 2020 and covers in total 98 answers with an overall response rate of 47%. As such, the survey does only cover a fraction of main sample but should nevertheless give a representative sample. Answers go back to program participants who completed their last course as early as 2013. The anonymous nature of the questionnaire does not allow us to match answers to specific participants or founders. However, it helps provide a descriptive sentiment of the perceived career impact program participation had. Table 19 summarize the answers to the questionnaire.

Perceived Personal and Career Impact: The questionnaire asked participants whether the program has a positive impact on their personal development and on their career opportunities. Answers were collected on a Likert scale ranging from Strongly Disagree (= 1) to Strongly Agree (= 10). The results indicate that alumni of the program perceive a substantial positive personal and professional impact of the program. 83 of 98 survey participants rated the impact on their personal development with the highest possible answer; 73 of 98 rated the positive impact on their career opportunities with the highest possible answer. We interpret these results with caution due to potential self-selection into survey participation.

Table 19: Program Participant Reported Perception

Panel A: Self-Reported Career Impact				
Program participation had a positive impact on …	N	Median	Mean	Standard Deviation
… my personal development	98	10	9.71*** (61.65)	0.84
… my career opportunities	98	10	9.48*** (40.97)	1.20

Panel B: Coded Statements			
What is the single most valuable thing you took away?	N	Frequency	Common Keywords
network	98	0.55 (54)	*community, network, friends, cofounder*
mindset	98	0.22 (22)	*open mindset, think big, larger career goals, change the world*
attitude	98	0.11 (11)	*confidence, just do it, never settle, work ethic*
knowledge, skills, abilities	98	0.09 (9)	*questioning critically, selling, presenting, conflict management*
personal development	98	0.04 (4)	*growth, choose what I want to do with my life, learn who I am*
inspiration	98	0.02 (2)	*inspiration*

Notes: For Panel A answers were collected on a ten-point Likert scale, with responses ranging from Strongly Disagree (= 1) to Strongly Agree (= 10). A one-sample t-test compares the responses to the neutral midpoint of 4.5. T-values are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Panel B show the frequency of the high-level codes assigned to the collected free text responses.

Perceived Key Benefit: The questionnaire also collected free text answers to the question what "the single most valuable thing" was alumni took away from the program. We coded the responses and organized the emerging codes into the six overarching themes (Braun & Clarke, 2006) reported in Table 19. The most frequent theme relates to the social network. It is present in 54% of answers. These answers are not limited to the professional perspective, but wording of the answers suggests that benefits beyond career development. The most common keywords are "*community*" (22), "*network*" (19), "*people*" (17), and "*friends*" (15), often occurring together.

Statements referring to mindset and attitude are mentioned in 33% of responses. Answers summarized under these themes ranged from specific points – "*confidence*", "*humbleness and hard work*", "*the mindset and willingness to achieve goals I set myself*" – to broader statements – "*daring to take my own path*", "*the security that I could choose what I want to do with my life*", "*perspective on what is possible*". 9% of answers were directly related specific knowledge, skills, and abilities taught within the program. Most of them referred to skills typically considered as soft skills, e.g. *"I became a much better team player"*, "*becoming really good at presenting and* *selling myself and my ideas"*, or "*questioning ideas and approaches critically"*. Finally, some answers referred to personal development (4%) and inspiration (2%). Interestingly only four responses explicitly mention entrepreneurship-specific outcomes as key take-aways from the program, e.g. "*co-founders"*, or *"teaching me founding a company was a viable option*".

What can we learn from these answers? The qualitative responses suggest that a large part of the perceived benefits is related to the social network – consistent with the shown heterogeneity of the program effect. This might be a specific benefit that entrepreneurship programs can deliver compared to individual courses. Does this mean the "education" in entrepreneurship education programs is less important? The wording of the question limits answers to one benefit, while respondents might have benefited along several dimensions. While there are few explicit mentions of the curriculum, many outcomes are likely facilitated through coursework. Responses such as "*a systematic approach and a motivated team can take you places*" are likely rooted in projects and experiences related to the curriculum.

Overall, these responses raise an interesting follow up question for research. To what extent are the effects of entrepreneurship education programs driven by skill development and to what extent the formation of social capital?

3.7 | Discussion and Conclusion

How does participation in entrepreneurship education programs during university affect students' post-graduation career, their likelihood to found, and the quality of their startups? Using application data over a ten-year timeframe and detailed information on applicant's post-graduation career decisions, we construct a quasi-experimental study to address these questions.

We find that program participation increases both founding rates and several indicators of startup quality. The effect of program participation on founding rates is visible for several years after the programs. Even when program participants do not found, they are more likely to select into careers related to entrepreneurship. While not focus of this study, we also find that the interview process can identify students more apt to build higher quality startups, but not who is more likely to found. Participating in the program, however, "levels the playing field" for participants to a degree where the original interview scores lose their explanatory power.

The effect sizes we observe are large and prove robust against several secondary analyses. Our regression discontinuity design (RDD) provides a methodological improvement over past studies and addresses the relative lack of rigorous study designs to evaluate entrepreneurship education. Most importantly, it allows us to distinguish the treatment effect from potential bias through the active selection of participants. Overall, our results suggest a strong positive causal effect between program participation and the measured outcome variables.

Our study fills important gaps in literature. While extant research is ambivalent on whether entrepreneurship education can increase founding rates (Bae et al., 2014; C. E. Eesley & Lee, 2021; Lyons & Zhang, 2017), we show that specific experiential programs succeed in doing so. From our findings arise several implications. First, the effect of specific entrepreneurship education programs should be distinguished from those of singular courses. While compulsory courses may provide valuable information signals about individuals' entrepreneurial aptitude and facilitate sorting and alignment effects (Fretschner & Lampe, 2019; Von Graevenitz et al., 2010), dedicated programs can succeed in increasing founding rates and startup quality. Second, for policy makers and universities, it shows that establishing experiential entrepreneurship education programs is worthwhile, even when only a relatively small number of students benefit from them compared to courses targeting broad student populations. Third, taking a broader perspective on entrepreneurship-specific human capital, our results indicate that graduates of entrepreneurship education programs apply their entrepreneurial competencies in subsequent careers, even when not founding themselves.

When interpreting the presented results, several limitations should be considered. First, specific entrepreneurship programs differ in their pedagogical approach, setup, and scope. The results presented in this study are rooted in one program. Following recent calls (Nabi et al., 2017) we provide a detailed account of the institutional context and pedagogical setup. More work to examining the effects of entrepreneurship education programs in different contexts would be certainly informative to understand the generalizability of these results.

Second, the used startup quality measures, while frequently found in literature, approximate the quality of companies. However, they do not constitute a true measure of long-term success. With the results of our hazard analysis and existing research showing that university graduates found often only decades after their graduation (Hsu et al., 2007), examining the long-term socioeconomic impact over even longer time-periods could yield further insights.

Finally, while our study shows the impact of entrepreneurship education programs at university, it leaves open which mechanism led to these outcomes. For one, these results could be driven by directly increasing participants' human capital and social capital (C. E. Eesley & Lee, 2021; Lyons & Zhang, 2017). An alternative mechanism could also be that past successes of alumni provide a signal for investors allowing emerging founders easier access to financial capital and resources (Hallen et al., 2020; Spence, 1978). Such signals could be especially relevant for early-stage entrepreneurs to signal status (Milanov, 2015) when information on the quality of a venture is limited (Hallen et al., 2020; Podolny, 1994; Stuart, Hoang, & Hybels, 1999) and could have long-lasting effects (Milanov & Shepherd, 2013). While recent work on accelerators suggests that learning, not signaling, is the key mechanism through which ventures are affected (Hallen et al., 2020), we cannot say in how far this transfers to entrepreneurship programs at university.

4 | Entrepreneurship Education, Job Creation, and Generated Tax Revenues

For politicians who worry about technology's geopolitical impact, it's tempting to get the government directly involved in subsidizing venture capital. But this is a mistake. In most cases, four simple steps will pay off more. Encourage limited partnerships. Encourage stock options. Invest in scientific education and research. Think globally.

Sebastian Mallaby, 2022, The Power Law: Venture Capital and the Making of the New Future (p. 417)

4.1 | Abstract

A growing number of universities have adopted entrepreneurship as part of their third mission. Entrepreneurship education programs are frequently used as one mechanism to support students and scientists in transcending the boundaries between the scientific and the professional domain. In particular, small-scale experiential entrepreneurship education programs, with a limited capacity for participants, were shown to increase founding rates and startup quality. Despite their efficacy, the small number of benefactors from these programs raises the question of whether funding them is economically rational. We address this question and juxtapose the cost of running an entrepreneurship education program in Munich over a ten-year period with the tax revenue generated from the jobs created by alumni-founded companies. A control group of almost accepted applicants over the same period allows us to estimate and consider only jobs created because of program participation. We find that even with conservative assumptions every Euro invested into the program generated additional direct annual tax returns of 6.53 Euros in Germany in 2022 alone. By providing first evidence on the impact of entrepreneurship education programs at university on job creation and tax revenues, this study offers quantitative evidence for policy makers that their economic impact is substantial and far exceeds their costs.

As of submission of this dissertation, the study presented in this chapter it under review in Research Policy (RP).

4.2 | Introduction

Universities are engines of regional growth with substantial economic impact (Bramwell & Wolfe, 2008; J. Drucker & Goldstein, 2007; Roessner et al., 2013). Increasingly, contributing to the socioeconomic development through innovation and entrepreneurship is recognized as part of the third mission of universities (Compagnucci & Spigarelli, 2020; Rubens, Spigarelli, Cavicchi, & Rinaldi, 2017; Wissema, 2009). However, most extant research examining the impact of universities under this lens has focused on intellectual property, technology transfer, and spin-offs (Dahlstrand, 1997; Di Gregorio & Shane, 2003; Etzkowitz, 2003) while the economic impact of entrepreneurship education targeting students has received relatively little attention.

This gap in literature is worth addressing, as a substantial number of university alumni go on to create businesses (C. E. Eesley & Miller, 2018; Hsu et al., 2007; Lerner & Malmendier, 2013). The gross flow of startups from recently graduated students was shown to be at least an order of magnitude larger than faculty spin-offs while being of comparable quality (Åstebro et al., 2012). While entrepreneurship education has become a policy priority (European Commission & Directorate-General for Employment Social Affairs and Inclusion, 2021) and spread across universities at an impressive pace (Morris & Liguori, 2016) rigorous research evaluating its impact has remained sparse (Grégoire, Binder, & Rauch, 2019; Neck & Corbett, 2018).

There are generally few studies quantifying the economic impact of entrepreneurship education for university students (Carpenter & Wilson, 2022; C. E. Eesley & Lee, 2021; Nabi et al., 2017). Most studies evaluating entrepreneurship education rather focus on subjective short-term measures (i.e. intentions, self-efficacy, attitudes) instead of objective outcomes of actual entrepreneurship (Nabi et al., 2017). In recent years, a small stream of research has started to emerge that addresses this gap. Eesley & Lee (2021) use a difference-in-difference approach to evaluate the establishment of two entrepreneurship centers at Stanford university at the school level. They find that their creation made little to no difference on the founding rates but increased overall startup quality. They also provide initial evidence that the Mayfield Fellowship, an experiential entrepreneurship education program for a small group of students, is effective in also raising founding rates. In line with their observations, Lyons & Zhang (2017) evaluate a non-profit entrepreneurship education program for undergraduate students and report a positive effect on founding rates and startup quality.

While these studies report the number of founded companies and different measures of startup quality, they, so far, fail to account for the resources that had to be invested into these programs. In other words, entrepreneurship education might succeed in increasing founding rates and startup quality, but remain an economically irrational investment for public funding, if the marginal benefits are outweighed by the overall investment cost. This question is particularly interesting to address in the context of small-scale experiential entrepreneurship programs, because of their high resource investment per participant – i.e. such programs are typically characterized by a focus on a few high-potential individuals and allocate substantial resources to their education instead of reaching a broader audience of students. For policy makers considering funding these programs, it would be important to understand what socioeconomic returns they create in their respective regions.

To address this gap, we analyze the startups founded by participants of a university entrepreneurship education program for students over a ten-year period. We use the tax revenues generated through newly created jobs as the primary measure of socioeconomic return and juxtapose them with the cost of running the program. To estimate the share of jobs that are created as a result of program participation, we follow recent examples from literature (Hallen et al., 2020; Lyons & Zhang, 2017) and use the applicants who were almost accepted to the program as control group of comparable quality.

We show that even with the most conservative assumptions, the socioeconomic returns far outweigh the program cost after a ten-year period. The additionally generated income tax in year ten alone fully covers the accumulated program cost over the entire period and already breaks even between years six and seven. Job creation in our sample follows a power law distribution (Crawford, Aguinis, Lichtenstein, Davidsson, & McKelvey, 2015). We observe that most jobs are created by a few companies producing the most jobs. Most of these jobs remain in regions close to the program. In total, 38% of created jobs are in the Munich metropolitan area in the state of Bavaria where the program is located, 73% in Germany, and 27% in other countries. In summary, our findings make a compelling case for policy makers to invest in and fund specific entrepreneurship education programs for university students to stimulate regional economic development and job creation.

4.3 | Related Work

Universities are a central element in the knowledge-based economy and play an important role in promoting technological change and innovation (Bramwell & Wolfe, 2008). The function and mission of universities have changed over time. Education and research have been traditionally viewed as the core missions of universities. Increasingly, contributing to the socioeconomic development of their region is viewed as universities' third mission (Compagnucci & Spigarelli, 2020; Etzkowitz, 2003; Wissema, 2009). While there is no commonly agreed definition of what activities are included under this third mission (Pinheiro, Langa, & Pausits, 2015), entrepreneurship education and measures to foster entrepreneurship and technology transfer are frequently included (Nicotra et al., 2021; Urbano & Guerrero, 2013).

4.3.1 | The Socioeconomic Impact of Universities

The influence of universities on regional economic development has long been of interest to research and policy makers (Goldstein, Maier, & Luger, 1995; Huggins & Cooke, 1997; Salter & Martin, 2001) and continues to draw attention in the current academic discourse (Robbiano, 2022; Valero & Reenen, 2019).

The key question for any study attempting to quantify the socioeconomic impact of a university is how much better off the considered region is compared to a scenario without the university (Siegfried, Sanderson, & McHenry, 2007). The commonly used analysis method establishes a "counterfactual" scenario in which the university does not exist and estimates which economic activity would remain in the local area (Siegfried et al., 2007). Since universities may contribute to economic development through different mechanisms (J. Drucker & Goldstein, 2007; Goldstein et al., 1995) several measures can be found across existing literature to quantify their socioeconomic contribution: direct expenditure and employment (Huggins & Cooke, 1997; Pastor, Pérez, & Guevara, 2013), regional GDP growth (Roessner et al., 2013; Valero & Reenen, 2019), research and patents (Cowan & Zinovyeva, 2013; Robbiano, 2022), spin-off companies (Åstebro et al., 2012; Landry, Amara, & Rherrad, 2006; Vincett, 2010), and created and supported jobs (Roessner et al., 2013).

Across studies, there is consistent empirical evidence that universities contribute to the economy on global (Valero & Reenen, 2019), national (Cowan & Zinovyeva, 2013; Liu, 2015; Vincett, 2010) and regional levels (Pastor et al., 2013; Robbiano, 2022; Urbano & Guerrero, 2013). For example, Valero & Reenen (2019) report that a 10% increase in the number of universities results in 0.4% increase in future GPD per capita in the respective region. Liu (2015) find a 45% increase in population density and a 57% increase in manufacturing output per worker after 80 years in regions where US land-grant universities were established. Vincett (2010) estimates that the lifetime impact of spin-off companies from Canadian universities exceeds government funding by a substantial margin.

4.3.2 | Entrepreneurship Education at University

Research on the economic impact of companies founded through graduates of university (as opposed to spin-offs founded by faculty members) has only recently started to emerge. The common view in literature followed the assumption that technological advances are created by the academic staff of universities and then diffused to society through a transfer process – i.e. technology licensing, technology transfer offices, spin-off companies – neglecting students as potential creators and diffusors of innovation (Åstebro et al., 2012). However, surveys of university graduates have shown that alumni create a substantial number of firms (C. E. Eesley & Miller, 2018; Hsu et al., 2007; Lerner & Malmendier, 2013) and a small stream of research investigating the phenomenon has started to emerge.

Åstebro et al. (2012) show that recent university graduates found at least an order of a magnitude more companies than faculty members and that these companies are of similar quality. Their analysis shows that this effect is not a consequence of the larger number of students, but that university graduates are twice as likely to found companies compared to faculty staff. When evaluating the role of universities for creating startups, looking exclusively at faculty spin-offs may therefore considerably underestimate their impact. Åstebro et al. (2012) argue that universities and policy makers may therefore consider entrepreneurship education targeting students as potential interventions to stimulate regional entrepreneurship and economic development.

Even though entrepreneurship education programs and courses have proliferated across universities (Katz, 2003) there is little empirical evidence testing this proposition. The literature examining the economic impact of entrepreneurship education in the university context is relatively sparse (C. E. Eesley & Lee, 2021). Most available research evaluating entrepreneurship education uses subjective output measures collected shortly after the intervention (e.g. survey-based measures of entrepreneurial intention or entrepreneurial self-efficacy) instead of observing actual outcomes of entrepreneurship (Nabi et al., 2017). Meta-analyses considering such short-turn outcome measures report somewhat ambivalent results. While Martin, McNally, & Kay (2013) find a positive relationship between entrepreneurship education and entrepreneurial outcomes, Bae, Qian, Miao, & Fiet (2014) find no statistically significant effect of entrepreneurship education at university on entrepreneurial intentions.

A particular issue when trying to aggregate the overall effect of studies evaluating entrepreneurship education at university is that pedagogical differences between educational interventions are only poorly reported (Nabi et al., 2017) and often not adequately distinguished.

For example, compulsory courses at university were shown to reduce students' entrepreneurial intention even while increasing their perceived self-efficacy as they provide students with information signals about their own entrepreneurial aptitude (Von Graevenitz et al., 2010). In comparison, specific experiential entrepreneurship programs were found to increase founding rates among participants (C. E. Eesley & Lee, 2021; Lyons & Zhang, 2017). Considering the effect of entrepreneurship education at university without recognizing the underlying heterogeneity of approaches may contribute to the large variance in results.

Recent studies have started to address limitations in literature and evaluate entrepreneurship education by outcomes of actual entrepreneurial activity. Based on a broad survey of Stanford university alumni, Eesley & Lee (2021) show that the introduction of two entrepreneurship centers at Stanford university did increase the quality of startups founded by alumni while having a negative to zero impact on founding rates among alumni. They also discuss indicative evidence which suggests that participation in one specific entrepreneurship education program, the Mayfield Fellowship, resulted in both increased founding rates and startup quality. These results are in line with a recent study by Lyons & Zhang (2017) evaluating a non-profit entrepreneurship program for undergraduate students. They report that participants were more likely to found after the program compared to a control group of almost accepted applicants.

While these results suggest that entrepreneurship education programs for university students may have a positive effect on founding rates and startup quality more research is needed to confirm the robustness of these results. In addition, there is no data on the cost-effectiveness of such programs. Since entrepreneurship education programs are commonly characterized by small cohort sizes, they allocate substantial resources into the education of a few high-potential individuals. Even if they succeed in increasing founding rates and startups quality, policy makers would need to weigh funding them against alternative measures to stimulate economic development such as R&D subsidies (Lanahan, Joshi, & Johnson, 2021), venture programs (Buffart, Croidieu, Kim, & Bowman, 2020), or entrepreneurship programs for other audiences (Fairlie, Karlan, & Zinman, 2015).

4.4 | Data and Methods

We add to the literature by analyzing the socioeconomic value created through startups founded by participants of an entrepreneurship education program for university students. The following section describes our empirical context, the collected data, and our approach to estimating the additionally generated tax revenue that can be attributed to the program participation.

4.4.1 | Empirical Context

Our empirical setting is an add-on entrepreneurship program offered to students enrolled at the Ludwig Maximilian Universität (LMU) or Technical University of Munich (TUM) in Munich, Germany. The goal of the program is to "*Connect, Educate, and Empower the Innovators of Tomorrow"* through a combination of coursework, mentorship, access to industry partners and alumni of the program. In contrast to accelerator or incubator programs which usually focus on developing existing business ideas and startup teams (Pauwels et al., 2016; Peters et al., 2004), this program aims at developing individual students. Its stated goal is to equip participants with the mindset, skills, abilities, and network enabling them to innovate, possibly in a range of different careers. Completing the program typically takes three semesters. The program structure and curriculum were introduced in 2006 and remained largely the same since then.

The program runs twice a year and offers a limited number of spaces. In each cohort, 25 students are admitted following a competitive selection process. Typically, the number of applicants deemed suitable for the program far exceeds the number of available slots. We exploit this circumstance to construct a control group comprised of the applicants advancing to the final stage of the selection process. By limiting our sample to finalists that were almost accepted to the program, we construct a control group that is of comparable quality to those accepted to the program and avoids bias through self-selection (Liñán et al., 2018). In doing so, we follow a similar approach as recent literature to address bias through active selection (Hallen et al., 2020; Lyons & Zhang, 2017).

This approach also allows us to avoid ecosystem-specific effects (Wurth et al., 2021) as all students stay enrolled in their main study program in Munich, even when not accepted and have equal access to regional entrepreneurial support organizations. Table 20 provides a comparison of group differences between admitted program participants and almost accepted applicants.

To consider the socioeconomic benefits created by the program it is important to also understand the costs of running the program. The Center for Digital Technology and Management (CDTM) has an annual budget of about EUR 1 million (adjusted to 2022). The budget covers personnel costs (ca. 70%), facilities (ca. 15%), and material, travel, and other costs (ca. 15%). Over the observed period the organizational structure and team size remained stable.

Table 20: Applicant Characteristics – Program Participants and Almost Accepted Applicants

	Full Sample		Program participants		Almost accepted		Difference	
	Obs.	Mean	Obs.	Mean	Obs.	Mean	Diff.	t-stat.
Applicant characteristics								
GPA	975	0.83	455	0.84	520	0.83	0.02	1.78*
Age	1022	24.21	478	23.81	544	24.56	-0.75	-6.07***
International	1022	0.33	478	0.29	544	0.36	-0.08	-2.56***
Business major	1022	0.33	478	0.34	544	0.33	0.01	0.47
CS/EE major	1022	0.42	478	0.43	544	0.41	0.02	0.56
Female	1022	0.26	478	0.26	544	0.26	0.00	0.08
Application year	1022	2015.64	478	2015.66	544	2015.63	0.03	0.19
Graduate student	1022	0.65	478	0.62	544	0.68	-0.06	-1.98**
Founded startup pre-application	1022	0.06	478	0.08	544	0.05	0.02	1.44

Notes: The table presents summary statistics of the main variables used in the analysis. Panel A shows applicant characteristics collected at the time of application. GPA scaled between 0 (worst) and 1 (best). GPA not available for one cohort in 2011 (N=47). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4.2 | Data Collection

Our data set covers 20 application cohorts between 2011 and 2020. During this period 4,379 individuals applied and 1,050 advanced to the final round of the application process. After excluding candidates who did not complete the application process and duplicate entries, our final dataset contains 1,022 individuals, comprising data on 478 program participants and 544 applicants who were almost accepted.

To track post-graduation career decisions and identify the startups founded by applicants, we manually collected data from applicants' LinkedIn profile pages within two weeks in May 2022. To measure firm performance, we additionally collected data about co-founded startups from LinkedIn[27] and Crunchbase[28] between May and June 2022. To define the operating status of co-founded startups we manually collected data from the companies' websites, LinkedIn, and NorthData[29]. Considering the overall program duration of three semesters the point of data collection constitutes a ten-year mark since the first cohort in our sample completed the program.

4.4.3 | Estimating Socioeconomic Impact

The program offered by the Center for Digital Technology and Management (CDTM) contributes to the three missions of its universities. First, it employs 10 doctoral candidates pursuing and publishing research. Second, it provides education and training for the students enrolled in the

[27] LinkedIn is a global professional social network. See https://linkedin.com/ (last accessed: 2022-02-02)
[28] Crunchbase is an online database with focus on high-growth start-ups. Previous research has shown the fit of Crunchbase data for academic research (Dalle et al., 2017; Retterath & Braun, 2020). See https://crunchbase.com/ (last accessed: 2022-02-02)
[29] Northdata is a "Company Search Engine". See https://northdata.com/ (last accessed: 2022-02-02)

program. And third, as a second-order effect of entrepreneurship education, it adds to society through the socioeconomic contributions of its alumni-founded companies. Our main analysis evaluates the program's impact primarily through this third lens.

It is important to note that the scholarly perception of the purpose of entrepreneurship education at university emphasizes a more nuanced view than just creating more and better entrepreneurs. Its objective is seen in equipping students with entrepreneurial mindsets and attitudes, having them explore their entrepreneurial aptitude, and understand whether founding a company is the right career for them (Fretschner & Lampe, 2019; Neck & Corbett, 2018; Von Graevenitz et al., 2010). Nonetheless, if entrepreneurship education achieves these goals for the individual, we would expect that the outputs – graduates with higher entrepreneurial human and social capital – over time translate into measurable economic outcomes, namely more and better startups.

Our analysis attempts to proxy the socioeconomic impact of program participation by estimating the tax revenue and social security contributions generated by the jobs created by alumni-founded startups. We omit corporate tax in our analyses as companies in our sample are relatively young and unlikely to make substantial profits. To accurately estimate generated tax returns we need to establish several assumptions. First, we need to consider the mean salary of employees. Second, we need to restrict our analysis to the share of jobs that would not exist in absence of the program. Third, we need to restrict our analysis to jobs in the region of interest. And fourth, we need to consider potential local multiplier effects. To establish reasonable assumptions, we first analyze the characteristics of the founded startups in comparison to the control group and then parameterize several models to estimate the socioeconomic returns over time.

4.5 | Startup Characteristics

In total, our sample comprises 297 companies, 155 of which were founded by program participants and 142 by rejected finalists, serving as the control group. Our sample covers a considerable share of high-growth entrepreneurship. In combination, these startups raised $4.92 billion, of which $4.56 billion are attributed to ones founded by program participants. In comparison, over the same period (2011 – 2022) a total of $44.9 billion was raised by all German startups founded after 2011.[30]

[30]According to Crunchbase. See https://www.crunchbase.com/lists/investments-in-german-startups-founded/7c569f53-00b9-4855-9a3d-453a3e2b1b30/funding_round (last-accessed 2023-01-18)

Table 21 provides an overview of the descriptive statistic of the founded companies. There are statistically significant differences between companies founded by program participants and the control group for almost all variables. Most notably, they are less likely to be inactive (28% vs 41%), are more likely to have raised funding (48% vs 24%), have raised more funding ($ 29.57 million vs $ 2.34 million), and employ 3.95 times more people (51.9 vs 13.12 employees). We additionally included dummy variables indicating how many companies within the sample raised above a certain amount of funding or employed above a certain number of people. The results show that even for high growth outcomes the differences remain statistically significant.

Table 21: Summary Statistics and Differences Between Participant-Founded Startups and Control Group

	Full Sample		Co-founded by Program Participant		Co-founded by Almost Accepted Finalist		Difference	
	Obs.	Mean	Obs.	Mean	Obs.	Mean	Diff.	t-stat.
Startup Characteristics								
Founding year	297	2017.67	155	2017.41	142	2017.94	-0.53	-1.75*
Startup active or acquired	297	0.66	155	0.72	142	0.59	0.13	2.40**
Startup raised any funding	297	0.37	155	0.48	142	0.24	0.24	4.50***
Startup funding rounds	297	0.91	155	1.31	142	0.48	0.83	4.35***
Total funding ($ m)	297	16.55	155	29.57	142	2.34	27.23	2.43**
Startup employees	297	33.36	155	51.90	142	13.12	38.78	2.50***
Startup raised > 5m funding	297	0.11	155	0.19	142	0.02	0.17	4.89***
Startup raised > 10m funding	297	0.09	155	0.15	142	0.02	0.13	3.96***
Startup raised > 20m funding	297	0.07	155	0.11	142	0.02	0.09	3.08***
Startup raised > 50m funding	297	0.04	155	0.08	142	0.01	0.07	3.00***
Startup raised > 100m funding	297	0.03	155	0.06	142	0.01	0.05	2.45***
Startup has > 10 employees	297	0.29	155	0.39	142	0.19	0.20	3.80***
Startup has > 20 employees	297	0.21	155	0.30	142	0.11	0.18	3.99***
Startup has > 50 employees	297	0.11	155	0.16	142	0.06	0.10	2.91***
Startup has > 100 employees	297	0.07	155	0.10	142	0.04	0.06	2.01**
Startup has > 200 employees	297	0.04	155	0.05	142	0.02	0.03	1.39
Startup has > 500 employees	297	0.01	155	0.03	142	0.00	0.03	1.93**

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5.1 | Employees

The comparison of means shows that startups founded by program participants employ significantly more people. In total 9,908 people are employed by startups in our sample. 8,045 or 82% are employed at companies founded by program participants.

It is important to note that we only use the number of employees registered on LinkedIn in our analysis. Therefore, it is likely that the total number of jobs exceeds the numbers we report. Not every employee might have a registered and maintained LinkedIn account. In May 2022 there were 13.73 million LinkedIn users in Germany (Napoleoncat.com, 2022) compared to a workforce of about 42 million (Statistisches Bundesamt (Destatis), 2022). Looking at the German average for people aged between 25 and 34, more than half (56.1%) had a LinkedIn account in May (Napoleoncat.com, 2022). For employees within our sample, the saturation might even be higher. For example, among all applicants in our sample, 94% had a LinkedIn profile.

To better estimate the degree to which program participation affected the number of employees of startups we conducted a regression analysis. Table 22 reports the results. From left to right we add founding year fixed effects and co-founder control variables in steps. All models report positive and statistically significant coefficients if startups were founded by a program participant. Model (1) suggests that startups co-founded by program participants employ 38.7 times more people. By including controls this factor diminishes to 17.1. We additionally estimate models for the log-transformed number of startup employees. The coefficients in model (5) indicate that startups co-founded by program participants employ 1.44 times more people. When including all controls this effect diminishes to 0.925 times more (see Table Notes for an explanation how to calculate the effect size if the dependent variable has been log-transformed).

Table 22: Program Participation and Startup Employees

	Startup employees			LN Startup employees		
	(1)	(2)	(3)	(4)	(5)	(6)
co-founded by program participant	38.784**	36.826**	17.082**	0.834***	0.893***	0.665**
	(2.51)	(2.42)	(2.22)	(3.83)	(3.69)	(2.77)
co-founder application year			-3.313*			-0.125**
			(-2.18)			(-2.56)
co-founder GPA			38.663			0.207
			(1.21)			(0.34)
co-founder international			4.727			-0.375*
			(0.22)			(-2.05)
co-founder business major			66.077			0.601*
			(1.55)			(2.10)
co-founder CS/EE major			45.727			0.629
			(1.20)			(1.77)
co-founder other major			66.933*			1.026**
			(1.90)			(2.89)
co-founder female			-32.962			-0.457
			(-1.79)			(-1.72)
co-founder graduate student			8.397			0.168
			(0.47)			(0.47)
co-founder founded pre-application			-17.837			0.210
			(-0.75)			(0.57)
Controls	No	No	Yes	No	No	Yes
Founding year fixed effects	No	Yes	Yes	No	Yes	Yes
Observations	297	297	276	297	297	276

Notes: GPA scaled between 0 (worst) and 1 (best). GPA missing for one cohort in 2011. The effect size of log transformed models can be calculated with f(β)=exp(β)-1. A coefficient of 0.665 in Model (6) corresponds to an increase in startup employees of 0.925, or 92.5%. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

It is important to note that the log-transformed coefficients are likely lower-bound estimates. Empirical research has established strong evidence that startup growth outcomes follow a power law distribution (Crawford et al., 2015). In simple words, the majority of jobs are created by only a few companies. For example, Shane (2008) argues that 95% of US businesses employ 20 people or fewer and 0.03% of entrepreneurial startups create more than 60% of all new jobs. For outcomes that are driven by outliers, data transformations fitting outlier to a particular distribution will thus rather lead to an underestimation of the effect (Crawford et al., 2015).

We can observe a power law distribution in Figure 7. It juxtaposes the distribution of the number of startups with a certain size to the overall number of people they employ. The x-axis assigns startups into six categories depending on the number of people they have employed. The left side of the figure shows the number of startups in each category on the y-axis. The right side shows the sum of total employees in each category. A few very successful companies employ the majority of people: The top four companies employ 3,474 or 35% of people in our sample, the top ten companies employ 6,249 or 63%, and the top 49 companies cover over 90% of all jobs.

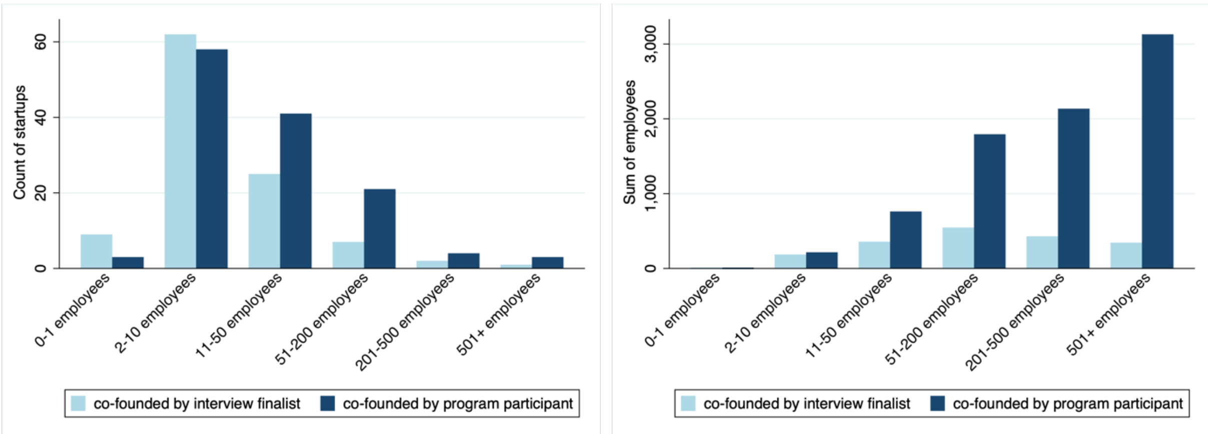

Figure 7: Startups and Employees

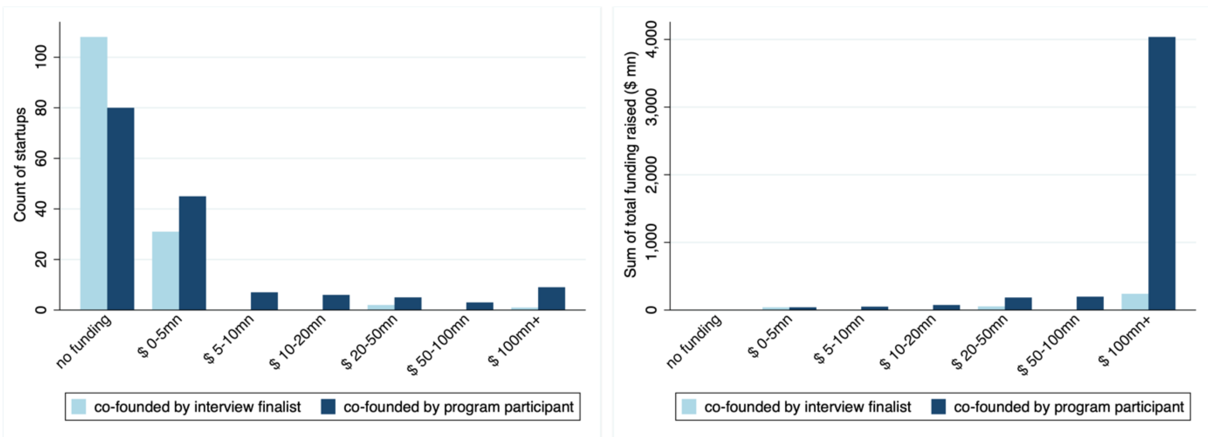

Figure 8: Startups and Raised Funding

4.5.2 | Raised Funding

The startups in our sample raised in total $4.92 billion. Startups with at least one program participant as co-founder raised $4.56 billion which represents 93% of the total funding raised. Figure 8 illustrates the distribution of funding to startups. The x-axis assigns startups into seven categories depending on the amount of total funding raised. The left side of the figure shows the number of startups in each category on the y-axis. The right side shows the sum of total capital raised in each category.

Over the entire sample only 37% of startups raised any funding. Comparing groups shows that 48% of startups founded by program participants have received funding compared to 24% of startups in the control group. Across all categories that raised funding, the number of startups founded by program participants exceeds the number of startups from the control group. This is particularly interesting as the overall amount of total funding is driven by the few outliers at the tail end of the distribution, as illustrated by Figure 8 on the right side. These observations align with the power law distribution commonly observed among venture capital financed growth startups (Crawford et al., 2015).

Table 23: Program Participation and Startup Quality

	(1)	(2)	(3)
	Startup active or acquired		
co-founded by program participant	0.131**	0.170**	0.121
	(2.23)	(2.72)	(1.71)
	Startup raised any funding		
co-founded by program participant	0.244***	0.243***	0.212**
	(4.12)	(3.67)	(3.08)
	Startup funding rounds		
co-founded by program participant	0.831***	0.813***	0.605**
	(4.34)	(3.80)	(3.10)
	Total funding ($ m)		
co-founded by program participant	27.233**	28.377**	25.955**
	(2.93)	(2.98)	(3.00)
	LN Startup total funding ($ m)		
co-founded by program participant	0.644***	0.654***	0.530***
	(5.42)	(5.08)	(4.55)
Controls	No	No	Yes
Founding year fixed effects	No	Yes	Yes
Observations	297	297	276

Notes: GPA missing for one cohort in 2011. The effect size of log-transformed models can be calculated with f(β)=exp(β)-1. A coefficient of 0.530 in Model (3) corresponds to an increase in startup funding of 0.699, or 66.9%. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To better understand the effect size of program participation we conducted a regression analysis on all startup quality measures. We estimate three models and add founding year fixed effects and co-founder level control variables in steps. Table 23 shows the results. With the exception of whether the startup is active or acquired, all coefficients are positive and statistically significant at the 5% level or more. The effect size remains stable when adding founding year fixed effects and the co-founder level control variables.

4.5.3 | Company Age and Growth Outcomes

When looking at growth outcomes, i.e. the amount of funding raised and the number of employees, in relation to a company's age, we would expect older companies to score better. We only find a small correlation between the age of a company in years and its number of employees (Pearson correlation coefficient of 0.2373 with p=0.0008) and no statistically significant correlation between company age and the amount of funding raised (Pearson correlation coefficient of 0.1165 with p=0.1040).

Figure 9 illustrates this relationship graphically in a scatter plot with fitted lines. The x-axis shows the years since a company was founded. The y-axis shows the number of employees (on the left) and the total amount of funding raised (on the right). In both cases it is visible that a few outlier companies are substantially more successful by both metrics than the typical startups in our sample. When looking at the amount of funding raised by these outliers no clear pattern in relation to company age is visible. In comparison, when looking at the number of employees it appears that even outlier companies need time to build their workforce.

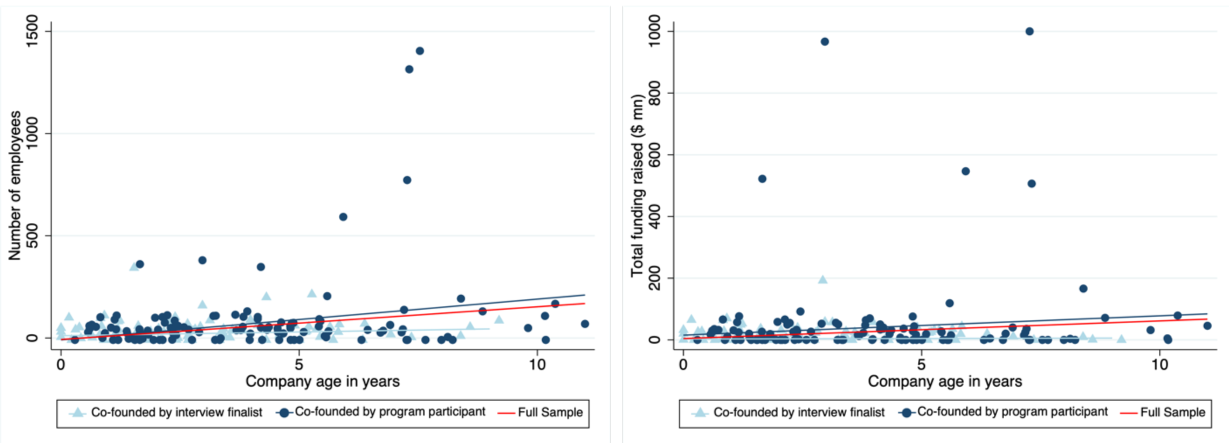

Figure 9: Company Age and Employees

4.5.4 | Geographical Distribution

For universities and policy makers interested in funding entrepreneurship education programs it is interesting to understand where alumni establish their companies. Figure 10 illustrates the locations of jobs created by startups of program participants at European and German level. An advantage of our dataset is that all applicants were students in Munich, Germany. Applicants who were not accepted into the program continued to study in their main study program in Munich. We, therefore, have a control group to explore whether program participants founded their startups in different places.

Table 24 provides an overview of the geographical distribution of the founded companies over three levels. Panel A shows the number of startups and the sum of employees per continent, Panel B for European countries, and Panel C for states within Germany. For 43 startups (14%) we could not identify their location. We did not find any statistically significant differences between both groups with regards to the number of companies founded per region. In other words, startups of program participants and the control group share a similar geographical distribution.

Focusing on the startups founded by program participants, 125 (81%) are located in Europe, 12 (8%) in North America, and 7 (5%) are distributed over the remaining continents. All 12 startups in North America are located in the USA. Six in California, three in New York, two in Boston, and one in Florida. The 125 European startups account for 7,419 (92%) out of the total of 8,045 of jobs created by the startups of program participants. 116 (94%) of the 125 European startups are located in Germany. These startups account for 5,964 jobs. Together with one outlier company located in Sweden, these two countries make up 99% of created jobs in Europe.

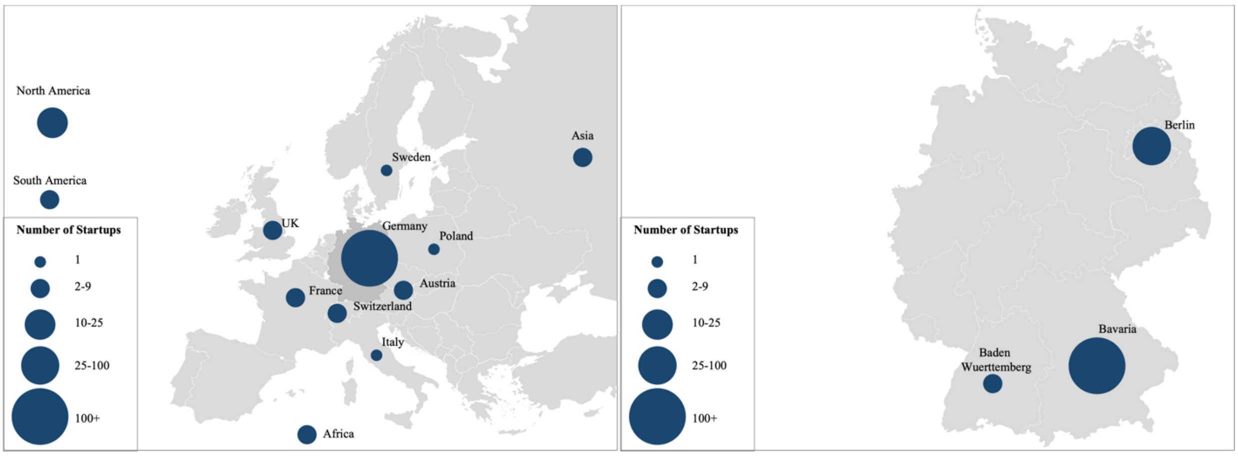

Figure 10: Geographical Distribution of Startups Founded by Program Participants

Within Germany, 85 (74%) of companies are located in Bavaria. They account for 3,633 jobs, which is 61% of jobs in Germany and 45% of total jobs created by startups of program participants. The remaining companies in Germany are located in Berlin and Baden-Wuerttemberg. The large share of startups in Bavaria, particularly in Munich, is not surprising since the program is located in Munich, all participants studied there, and Munich has an attractive entrepreneurship ecosystem (Startup Genome, 2022). Considering that Berlin is the uncontested "startup capital" of Germany (Kollmann et al., 2022) it is also not surprising that many companies are founded there. The 23 (20%) startups located in Berlin account for 38% of jobs created in Germany, indicating that they employ, on average, more people per company than startups located in Bavaria (98.7 in Berlin vs 42.7. in Bavaria). A similar pattern can be observed when looking at funding. Among the observed Berlin startups 70% raised at least one round of investment compared to 51% of Munich startups. On average Berlin startups raised $98.3 million whereas Munich startups raised $23.1 million.

Table 24: Geographical Distribution of Founded Startups

	Full Sample			Founded by Program Participant			Founded by Interview Finalist		
	Freq.	Count	Emp.	Freq	Count	Emp.	Freq	Count	Emp.
Global									
Europe	0.75	222	8766	0.81	125	7419	0.69	97	1347
North America	0.06	17	1052	0.08	12	577	0.04	5	475
South America	0.01	3	10	0.01	2	10	0.01	1	0
Asia	0.03	10	60	0.03	4	38	0.04	6	22
Africa	0.01	2	7	0.01	1	1	0.01	1	6
Australia	0.00	0	0	0.00	0	0	0.00	0	0
–	0.14	43	13	0.07	11	0	0.23	32	13
Europe									
Germany	0.91	201	7222	0.94	116	5964	0.89	85	1258
Switzerland	0.03	6	103	0.02	2	33	0.04	4	70
UK	0.03	6	4	0.02	2	3	0.04	4	1
Austria	0.01	3	9	0.01	1	7	0.02	2	2
France	0.01	2	1	0.01	1	1	0.01	1	0
Sweden	0.00	1	1405	0.01	1	1405	0.00	0	0
Spain	0.00	1	16	0.00	0	0	0.01	1	16
Italy	0.00	1	5	0.01	1	5	0.00	0	0
Poland	0.00	1	1	0.01	1	1	0.00	0	0
Germany									
Bavaria	0.73	146	4407	0.74	85	3633	0.73	61	774
Berlin	0.18	40	2728	0.20	23	2270	0.20	17	458
Baden-Wuerttemberg	0.05	10	69	0.07	8	61	0.02	2	8
Hessen	0.01	2	16	0.00	0	0	0.02	2	16
North Rhine-Westphalia	0.01	2	2	0.00	0	0	0.02	2	2
Lower Saxony	0.00	1	0	0.00	0	0	0.01	1	0

Notes: Overview of the geographical distribution of founded companies according to their headquarters. We found no statistically significant differences in the number of startups per region between companies founded by program participants and the rejected applicants.

4.6 | Job Creation and Generated Tax Revenue

How much tax revenue is generated through jobs created as a result of the program? We estimate six different models with increasingly conservative assumptions and different geographical regions of interest. Using conservative assumptions, we estimate that the additional jobs created in Germany alone generate EUR 18.64 million in income tax and EUR 46.69 million in social security taxes in 2022.

4.6.1 | Model Assumptions and Calculations

Table 25 presents six models estimating additional job creation and generated tax revenues with varying regions of interest. From left to right we apply increasingly conservative assumptions and restrict our analysis to smaller regions of interest.

Annual gross income: For all models we assume a gross annual income of EUR 42,965, which represents the German average including both full-time and part-time employees (Statistisches Bundesamt (Destatis), 2022). This can be considered a conservative estimate for three reasons. First, it doesn't include bonuses and additional forms of payment. Second, most jobs have been created in Bavaria and Berlin, which both rank above the German average (Statistisches Bundesamt (Destatis), 2022). Third, the industries related to the high-growth startups, e.g "Information and Communication", typically rank above the average (Statistisches Bundesamt (Destatis), 2022) and innovative firms were found to pay higher wages (Cirera & Martins-Neto, 2023).

Tax calculation: For the calculation of the income tax, we used the Lohn- und Einkommensteuerrechner[31] maintained by the Federal Ministry of Finance (Bundesministerium der Finanzen) for the year 2022. With an annual gross income of EUR 42,965, this resulted in EUR 6,630 in income tax at a tax rate of 15.43%. Comparing this to the average income tax paid per person in 2018, which was EUR 11,096 for Bavaria, and EUR 8,873 for Berlin, confirms our notion of calculating with a conservative assumption (Statistisches Bundesamt (Destatis), 2022). For the calculation of the social security taxes, we used the federal rates for Germany: 9.3% for pension insurance, 1.2% for unemployment insurance, 7.3% for health insurance, and 1.525% for care insurance. Since all social security taxes must be paid by both the employee and the employer, the rates are effectively doubled. For example, with a gross annual income of EUR 42,965, the employee must pay 9.3% or EUR 3,995.75 in pension insurance. The employer must pay an additional 9.3% or EUR 3,995.75 of the gross annual income.

[31]Available at https://www.bmf-steuerrechner.de/bl/bl2022/eingabeformbl2022.xhtml (last accessed: 2022-12-08)

Observed jobs: All models consider the 8,045 jobs created by startups founded by program participants as foundation. We use the employee-count on LinkedIn as a proxy for the total number of jobs created. Since this number only reflects registered LinkedIn users, not all created jobs might be accounted for.

Share of jobs within a region: For policy makers, different regions within which jobs are created and tax revenue is generated are of interest. In Model (1) – (3) we consider all jobs regardless of company location. In Model (4) – (6) we consider only companies headquartered in Europe, in Germany, and in Bavaria respectively. Since high growth companies are likely to internationalize, we used specific LinkedIn queries for all companies with more than 50 employees to identify the subgroup of employees working in the region of interest.

Share of additional jobs: It is reasonable to assume that even in absence of the program, some students would have founded companies. Across the models we, therefore, apply different assumptions about the share of additional jobs that can be attributed to program participation. Model (1) presents a naïve estimate, where we assume that 100% of jobs would not exist without the program. In Model (2) the share corresponds to the difference in employees that startups in the control group have. In Model (3) – (6) we use the most conservative estimate for additional jobs created through program participation from our regression analysis (see Table 22). Given that job creation is substantially driven by few highly successful outliers, the effect size of the log-transformed regression can be seen as a conservative estimate (Crawford et al., 2015).

Calculation of generated tax revenue: To tabulate the tax revenue generated through the additionally created jobs within a region, we multiply the total number of jobs, the modeled assumptions, and the expected tax revenue per job. For example, to calculate the income tax for model (5) we multiply the total number of created jobs (8,045) with the share of jobs in Germany (0.73), the share of jobs created as a result of program participation (0.48), and the income tax one job generates per year (6,630), resulting in an estimate of EUR 18.64 million.

4.6.2 | Main Results

Table 25 shows the estimated tax revenues for all models. Model (1) presents a naïve estimate, considering all jobs without geographical restriction. It estimates additional tax revenues of EUR 186.93 million in 2022. With the application of more conservative assumptions model (2) adjusts the estimate to EUR 143.64 million, and model (3) to EUR 89.83 million. The accumulated cost of running the program over ten years amounts to about EUR 10 million. Even the conservative estimate for the generated socioeconomic returns exceeds the total costs by a factor of 8.9.

Table 25: Job Creation and Generated Tax Revenue

	(1)	(2)	(3)	(4)	(5)	(6)
Income taxes and social security taxes for a gross income of EUR 42,965 (in EUR)						
Income Tax	6630	6630	6630	6630	6630	6630
Social Security	16606	16606	16606	16606	16606	16606
Total	23236	23236	23236	23236	23236	23236
Number of jobs created by startups of program participants						
	8045	8045	8045	8045	8045	8045
Share of jobs within the considered geographical region						
	(all)	*(all)*	*(all)*	*(europe)*	*(germany)*	*(bavaria)*
Share of jobs in region	1.00	1.00	1.00	0.92	0.73	0.38
Number of jobs in region	8045	8045	8045	7419	5851	3067
Share of jobs created as a result of program participation						
Share of additional jobs	1.00	0.77	0.48	0.48	0.48	0.48
Number of additional jobs	8045	6182	3866	3565	2812	1474
Generated additional annual tax and social security outcomes (in EUR mn)						
Income Tax	53.34	40.99	25.63	23.64	18.64	9.77
Social Security	133.60	102.66	64.20	59.20	46.69	24.48
Total	186.93	143.64	89.83	82.84	65.33	34.25

Notes: EUR 42,965 is the annual mean gross income in Germany in 2022 including full-time and part-time employees. We used the following coefficients according to German law for the tax calculation: Income tax (15.4.%). For social insurance taxes: Pension insurance (9.3%), unemployment insurance (1.2%), health insurance (7.3%), care insurance (1.525%). All social insurance taxes are doubled as employers have to pay them as well. Models from left to right apply increasingly conservative assumptions and reduce the geographical region of interest. In Model (1) the share of additional jobs represents the difference to the control group. In Model (2) - (6) we used the most conservative estimate for additional jobs created through program participation from the regression analysis in Table 22. The share of jobs within the specified regions was calculated by allocating all employees to the companies' headquarters. Since high growth companies are likely to internationalize, we used specific LinkedIn queries for all companies with more than 50 employees to identify the subgroup of employees working in the region of interest and instead use the specific numbers.

However, not all jobs have been created in Germany where the program is located. 73% of all created jobs are in Germany. As shown in model (5), they generate additional tax revenues of EUR 65.33 million, of which EUR 18.64 million are income tax and EUR 46.69 million are social security taxes. Since entrepreneurship programs might be financed through regional funds, we also look at the jobs created within the state of Bavaria. 38% of all jobs or 52% of jobs in Germany are in Bavaria. Model (6) shows that they generate additional tax revenues of EUR 34.25 million, of which EUR 9.77 million are income taxes.

According to the German tax code, income taxes are divided between the federal level (42,5%), the state level (42.5%), and municipalities (15%). Considering model (6) this means that the federal state and the state of Bavaria each collect EUR 4.15 million in 2022. The majority of jobs are created in the greater Munich metropolitan area. Municipalities in this area collect EUR 1.47 million in 2022 through the additional jobs.

4.6.3 | Local Multiplier Effects

The central idea behind local multiplier effects is that an increase in jobs in a region generates increased demand for local services and thus creates additional jobs (Moretti, 2010; Moretti & Thulin, 2013). The multiplier framework distinguishes between two types of jobs. First, jobs in the *local-services* sector such as restaurants, retailers, or construction service local demand. Second, jobs in the *traded* sector such as manufacturing or tradable services create demand in the local economy. The central idea is that an increase in jobs in the traded sector should lead to an increase in jobs in the local-services sector (N. Lee & Clarke, 2019; Moretti & Thulin, 2013). A description of the theory and econometric framework can be found in Moretti & Thulin (2013).

The size of the local multiplier depends on several factors, such as the industry (N. Lee & Clarke, 2019) and the region (Moretti & Thulin, 2013) within which jobs are created. High-tech industries were shown to have particularly high multipliers on the local economy (Moretti & Thulin, 2013). Moretti & Thulin (2013) find that adding one job in a metropolitan area in the US leads to 1.6 new jobs. This effect increases for skilled jobs to 2.5 and for high-tech jobs to 4.9. They repeat their analysis with data from Sweden and find an overall increase of 0.4 to 0.8 jobs in the local-services sector in the long run for every new job created. For new jobs in the high-tech sector, they find an increase of 1.1 jobs, and adding a tertiary education job even creates 3.0 new jobs. Goos, Konings, & Vandeweyer (2018) estimate local high-tech job multipliers for Europe and find that each high-tech job is linked to 3.9 to 4.4 jobs in low-tech sectors in the respective region. In comparison, Lee & Clarke (2019) report a local employment multiplier of 0.7 for each high-tech job in British local labor markets. In parts, the variation in the multiplier effects between these studies can be explained by the use of different definitions of local markets, limited samples, or arbitrary observation periods (Osman & Kemeny, 2022). Moretti & Thulin (2013) use metropolitan areas as their unit of analysis (72 in Sweden), Lee & Clarke (2019) Travel to Work Areas (212 in the UK), and Goos, Konings, & Vandeweyer (2018) NUTS-2 regions (40 in the UK, 8 in Sweden).

We can use the range of reported multipliers in literature (between 4.9 and 0.4) to extend our models and include the induced effects on the labor market. Table 26 tabulates nine different models considering different regions. The calculation follows the same logic as presented before. Panel A considers all jobs regardless of region, Panel B jobs in Europe, Panel C jobs in Germany, and Panel D jobs in Bavaria. We use three different assumptions which share of jobs can be attributed to program participation. 1.0 represents the naïve assumption that all jobs would not exist without the program, 0.73 is the observed difference to the control group, and 0.48 is the most conservative estimate from our regression analysis. We consider local job multipliers of three different sizes. First, a local employment multiplier of 4.9 (as reported for the US for high-tech jobs) represents the upper bound. Second, a multiplier of 1.1 (as reported for Sweden for high-tech jobs) represents a more realistic assumption. And third, a multiplier of 0.4 is the lowest effect that has been reported in recent literature and represents a conservative estimate (Moretti & Thulin, 2013).

Table 26: Jobs Creation and Generated Taxes Considering Multiplier Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel A: All Regions					
Jobs in region	8045	8045	8045	8045	8045	8045	8045	8045	8045
Share of additional jobs	1.00	1.00	1.00	0.73	0.73	0.73	0.48	0.48	0.48
Job Multiplier	4.90	1.10	0.40	4.90	1.10	0.40	4.90	1.10	0.40
Created additional jobs	47466	16895	11263	34521	12287	8191	22810	8119	5413
Income Tax (in EUR mn)	314.70	112.01	74.67	228.87	81.46	54.31	151.23	53.83	35.89
Social Security (in EUR mn)	788.21	280.55	187.03	573.25	204.04	136.03	378.78	134.82	89.88
Total (in EUR mn)	1102.91	392.56	261.71	802.13	285.50	190.34	530.01	188.65	125.77
				Panel B: Europe					
Jobs in region	7419	7419	7419	7419	7419	7419	7419	7419	7419
Share of additional jobs	1.00	1.00	1.00	0.73	0.73	0.73	0.48	0.48	0.48
Job Multiplier	4.90	1.10	0.40	4.90	1.10	0.40	4.90	1.10	0.40
Created additional jobs	43772	15580	10387	31835	11331	7554	21035	7487	4991
Income Tax (in EUR mn)	290.21	103.29	68.86	211.06	75.12	50.08	139.46	49.64	33.09
Social Security (in EUR mn)	726.88	258.72	172.48	528.65	188.16	125.44	349.31	124.33	82.89
Total (in EUR mn)	1017.09	362.01	241.34	739.71	263.29	175.52	488.77	173.97	115.98
				Panel C: Germany					
Jobs in region	5851	5851	5851	5851	5851	5851	5851	5851	5851
Share of additional jobs	1.00	1.00	1.00	0.73	0.73	0.73	0.48	0.48	0.48
Job Multiplier	4.90	1.10	0.40	4.90	1.10	0.40	4.90	1.10	0.40
Created additional jobs	34521	12287	8191	25106	8936	5957	16589	5905	3936
Income Tax (in EUR mn)	228.87	81.46	54.31	166.46	59.25	39.50	109.99	39.15	26.10
Social Security (in EUR mn)	573.25	204.04	136.03	416.92	148.39	98.93	275.48	98.05	65.37
Total (in EUR mn)	802.13	285.50	190.34	583.37	207.64	138.43	385.47	137.20	91.47
				Panel D: Bavaria					
Jobs in region	3067	3067	3067	3067	3067	3067	3067	3067	3067
Share of additional jobs	1.00	1.00	1.00	0.73	0.73	0.73	0.48	0.48	0.48
Job Multiplier	4.90	1.10	0.40	4.90	1.10	0.40	4.90	1.10	0.40
Created additional jobs	18095	6441	4294	13160	4684	3123	8696	3095	2063
Income Tax (in EUR mn)	119.97	42.70	28.47	87.25	31.06	20.70	57.65	20.52	13.68
Social Security (in EUR mn)	300.49	106.95	71.30	218.54	77.79	51.86	144.40	51.40	34.27
Total (in EUR mn)	420.46	149.66	99.77	305.80	108.84	72.56	202.06	71.92	47.95

Notes: Job creation and generated taxes including local employment multipliers estimated across nine configurations for four regions. Considering all regions and all 8,045 jobs (Panel A, Model 1-3), applying the employment multipliers increases estimates of total tax revenue to between EUR 261.71 million and EUR 1,102.91 million for 2022. The more conservative models still estimate total tax revenues between EUR 125.77 million (Panel A, Model 9) and EUR 285.5 million (Panel A, Model 5) for 2022. Considering only jobs in Germany and the most conservative assumptions (Panel C, Model 9) the estimated total tax revenue for 2022 is EUR 91.47 million, which represents 9.1 times the total cost of the program from 2011 to 2020.

Considering all regions and all 8,045 jobs (Panel A, Model 1-3), applying the employment multipliers increases estimates of total tax revenue to between EUR 261.71 million and EUR 1,102.91 million for 2022. The estimates from applying these naïve assumptions represent an upper bound. The more conservative models still estimate total tax revenues between EUR 125.77 million (Panel A, Model 9) and EUR 285.50 million (Panel A, Model 5) for 2022.

Considering only jobs in Germany, our models report total tax returns between EUR 190.34 million (Panel C, Model 3) and EUR 803.13 million (Panel C, Model 1) assuming that all jobs would not exist without the program. Applying more realistic assumptions the estimated total generated tax returns in 2022 in Germany still range between EUR 207.64 million (Panel C, Model 5) and EUR 91.47 million (Panel C, Model 9). Even the most conservative estimate of EUR 91.47 million represents 9.1 times the total cost of the program from 2011 to 2020.

4.6.4 | Program Cost and Break-Even Point

So far, our analysis is restricted to a static view of the tax returns generated in 2022 alone. For policy makers and public funding bodies, it would be of interest to understand the time until the generated additional tax revenues exceed the cost needed to run the program.

While our dataset is limited to the number of people each company employed as of June 2022, we can model the expected tax returns after k years by restricting our sample size to program participants who started the program k years ago. For example, our main analysis considers all companies founded by participants who started the program between 2011 and 2020. Since the program takes three semesters to complete this represents, at the point of data collection in 2022, a ten-year period since the first participants finished the program. To estimate the generated tax revenue after 5 years, we can instead limit our analysis to startups founded by participants who started between 2016 and 2020.

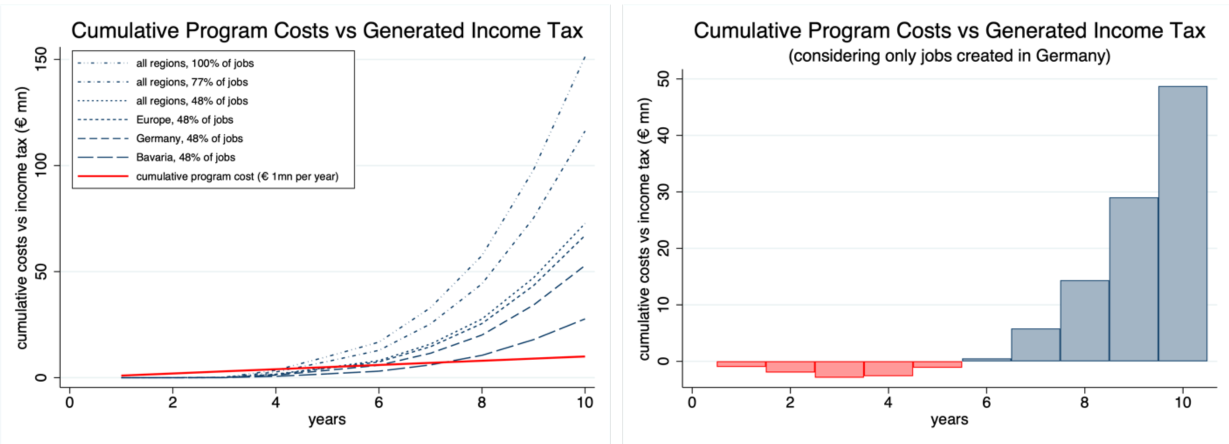

Figure 11: Break-Even Analysis Considering Cumulative Program Cost & Generated Income Tax Revenues

Table 27 tabulates the estimated generated tax revenues for each window of observation from 1 to 10 years for jobs created in Germany and Bavaria. We restrict our analysis to these regions as entrepreneurship programs in the university context are most likely financed by federal or regional funding. We apply the same assumptions as in Table 25, Model 5 (Germany) and model 6 (Bavaria). Thus, we assume that 48% of jobs created by the startups founded by program participants would not exist without the program, reflecting the most conservative assumption. For simplification, we do not consider local employment multipliers.

Table 27: Startups and Job Creation k Years After Program

	Sample		Model (5), Germany			Model (6), Bavaria		
Observed years since application	Founded Startups	Created Jobs	Income Tax	Social Security	Total	Income Tax	Social Security	Total
1 year (2020)	0	0	0.00	0.00	0.00	0.00	0.00	0.00
2 years (2019 – 2020)	2	6	0.01	0.03	0.05	0.01	0.02	0.03
3 years (2018 – 2020)	6	30	0.07	0.17	0.24	0.04	0.09	0.13
4 years (2017 – 2020)	19	495	1.15	2.87	4.02	0.60	1.51	2.11
5 years (2016 – 2020)	35	970	2.25	5.63	7.88	1.18	2.95	4.13
6 years (2015 – 2020)	47	1029	2.38	5.97	8.36	1.25	3.13	4.38
7 years (2014 – 2020)	67	2445	5.67	14.19	19.86	2.97	7.44	10.41
8 years (2013 – 2020)	101	3709	8.59	21.53	30.12	4.51	11.28	15.79
9 years (2012 – 2020)	128	6090	14.11	35.35	49.46	7.40	18.53	25.92
10 years (2011 – 2020)	155	8045	18.64	46.69	65.33	9.77	24.48	34.25

Notes: Our dataset contains only a static view of the number of jobs created by startups of program participants as of June 2022. We can model the expected number of startups and jobs created after k years relative the program application, by restricting the sample to startups who were co-founded by program participants who joined the program in 2022 minus k or later. We tabulate estimated tax returns using the same assumptions as in Model (5) and Model (6) in Table 25 for each year k and do not include employment multipliers. We observe that already after four years relative to program application the additionally generated tax revenues exceed EUR 4.02 million in Germany and EUR 2.11 million in Bavaria.

To estimate the break-even point, we limit our analysis to the generated income tax, since generated social security taxes would also not be available to fund potential entrepreneurship programs. We model the annual program cost at EUR 1 million, which reflects the actual annual budget of the Center for Digital Technology and Management (CDTM) as of 2022. Historically, only about 60% of this overall budget has been financed from public sources. The remaining 40% have been financed through specific industry projects and research grants. To err on the conservative side, we use the full budget of EUR 1 million as the annual cost basis.

Considering jobs created in Germany, the annually generated income tax exceeds the program costs already after year 4 at an estimated EUR 1.15 million. Considering jobs in Bavaria, the same is true after year 5 at EUR 1.18 million (see Table 27). Considering jobs in Germany, the accumulated program costs still exceed the accumulated generated income tax returns slightly after six years (EUR 6 million costs vs EUR 5.86 million income tax). After year seven the accumulated income tax returns (EUR 11.53 million) exceed the accumulated cost (EUR 7 million) for the first time, indicating a break-even point between years six and seven. Considering jobs in Bavaria the break-even point would be between years seven and eight. After year ten the accumulated income tax returns add up to EUR 52.88 million in Germany and EUR 27.72 million for Bavaria.

Figure 11 visualizes the accumulated program costs and accumulated income tax returns over time. The line graph on the right side shows the accumulated program cost and the generated income tax for different regions and with different assumptions regarding the share of jobs that would not exist without the program. The six lines correspond to the six models presented in Table 25. The bar chart on the right side shows the difference in accumulated costs and generated income tax returns over time considering only jobs created in Germany (Table 25 , Model 5). While the accumulated program cost is growing at a linear rate of EUR 1 million per year, Figure 11 shows that the generated income tax return appears to grow at an exponential rate.

4.7 | Discussion and Conclusion

Although entrepreneurship education for university students has become an increasingly widespread phenomenon (Katz, 2003; Neck & Corbett, 2018), there is little published empirical evidence of the actual economic impact it produces (Åstebro et al., 2012; C. E. Eesley & Lee, 2021). Our analysis addresses this gap and provides strong quantitative evidence of the socioeconomic value entrepreneurship education programs targeting university students can provide. Our results contribute to literature in several ways.

First, by confirming indicative evidence showing the effectiveness of entrepreneurship education programs for university students (C. E. Eesley & Lee, 2021; Lyons & Zhang, 2017). Second, by estimating the generated tax revenue we move beyond previous attempts and show that such programs do not only work but have a positive return on investment for society. Our approach builds on previous attempts to quantify the socioeconomic benefits created through universities (Robbiano, 2022; Valero & Reenen, 2019; Vincett, 2010). However, to our knowledge, we are the first to apply such an estimate to a specific entrepreneurship education program and thus add valuable new insight to the research body.

We estimate that a total budget of EUR 10 million over ten years resulted in additional direct tax revenues between EUR 89.83 million and EUR 186.93 million in 2022 through the jobs created by alumni-founded startups (see Table 25). Considering a conservative local employment multiplier of 0.4 (Moretti & Thulin, 2013) the estimates for 2022 increase to between EUR 125.77 million and EUR 261.71 million (see Table 26). Most of the generated jobs remain in geographical proximity to the program location in Munich, Germany. In total 38% of jobs are created in the state of Bavaria, indicating that entrepreneurship education programs may be used as a policy measure to stimulate regional development. When only considering jobs created in Bavaria and applying conservative assumptions, we still estimate that additional tax returns of EUR 34.25 million were generated in 2022.

In summary, these results provide compelling quantitative evidence for university management and policy makers on the socioeconomic contributions entrepreneurship education programs for university students can create.

4.7.1 | Implications for Policy

Several implications for policy makers arise from our findings. Our data provides convincing evidence that funding small-scale entrepreneurship education programs for university students has a positive return on investment. Our analysis suggests that funding such programs can be used as a policy measure to promote regional economic growth.

When funding entrepreneurship education programs policy makers should adopt a long-term perspective considering that it will take several years until the effects will be visible. For example, when only considering income tax generation in Germany, our estimate suggests a break-even point between years six and seven (see Figure 11). However, our analysis also implies that the socioeconomic returns discussed in this paper are a snapshot in time. We observed the generated jobs 10 years after the first cohort in our sample finished the program. An observation point with a longer distance to the original program participation would likely result in even higher returns. In other words, our data suggests that the generated tax revenue will continue to grow in the next years. This is likely for three reasons: (1) some participants, in particular those of more recent cohorts, will found startups in the future and (2) these and existing startups need time to grow and create jobs (see Figure 7) and (3) some startup firms will eventually become profitable and pay corporate taxes. We observe that it takes an average of 3.8 years between the start of the program and participants founding a company, with a considerable variance between startups (e.g. one program participant from 2011 founded only 10 years after their application). These findings are in line with research showing that university graduates often found only years after their graduation (Hsu et al., 2007). Looking at our sample also shows that the average employee size of companies exceeds 100 employees only 6 years after the establishment of the company. Thus, policy makers need to adopt a multi-year perspective until investment in entrepreneurship education programs pays off.

Policy makers should also carefully consider the focus of the entrepreneurship education programs they intend to finance. In line with literature, our sample points at the importance of a few highly successful outlier companies (see Figure 7 and Figure 8) that create a substantial fraction of the observed jobs (Crawford et al., 2015; C. E. Eesley & Miller, 2018). If the policy objective is to stimulate job creation, the focus should therefore be on establishing and supporting entrepreneurship programs that equip participants with the skills and network to build high-growth companies. In line with our findings, recent studies suggest that experiential programs focusing on a few highly talented students fare better to this end compared to broad initiatives (C. E. Eesley & Lee, 2021; Lyons & Zhang, 2017).

Finally, policy makers should not consider entrepreneurship education programs in isolation but within the ecosystems they are embedded in. We find that most jobs created by alumni founded startups are in geographical proximity to the location of the entrepreneurship education program. However, we also observe that a substantial number of founders establish their companies in Berlin, Germany's "startup capital" (Kollmann et al., 2022). Existing research supports both the notion that alumni tend to found companies in proximity to their parent university (C. E. Eesley & Miller, 2018; Heblich & Slavtchev, 2014) and that they take more deliberate choices based on the surrounding ecosystem conditions (Kolympiris, Kalaitzandonakes, & Miller, 2015; Stephens, Butler, Garg, & Gibson, 2019). The decision of whether program participants choose to stay or move to another region may be moderated by the relationship between the local ecosystem attractiveness and the attractiveness of potential competing ecosystems. Therefore, if the goal is to foster regional job creation, policy makers should not only invest in the program itself but also consider supporting elements in the surrounding entrepreneurial ecosystem.

4.7.2 | Limitation and Future Work

As with any empirical study, several limitations should be considered when interpreting the results. We have been careful to apply conservative assumptions in all our models. Ultimately, the validity of our results depends on whether these assumptions reflect reality. While we could ground some assumptions in empirical observations (gross annual income, jobs within certain regions) others are more fraught with uncertainty (share of jobs created as a result of the program, local employment multiplier). By using different methods to derive these assumptions, we attempt to illustrate the range within which the actual effects are likely to be found. We made our models as transparent as possible to allow readers to replicate our calculations with adapted assumptions.

One central assumption is how many jobs would remain in the "counterfactual" scenario, in which the program would not exist. Our approach provides several improvements over existing approaches. The comparison between the control group shows that the startups of program participants employ 4.32 times more people. While the almost accepted applicants in the control group are of similar quality based on observable control variables, program participants were still selected through an active selection process. Using only the best applicants as the control group, given that the number of total applicants far exceeds the available cohort size, allows to soften potential selection bias. The question remains, how large a potential bias is. We address this issue in our model by applying a conservative assumption. We discount the fraction of additionally created jobs from 4.32 to 0.93 accounting for a potentially substantial selection effect.

Our analysis focuses solely on the socioeconomic returns generated by alumni-founded startups. We purposefully excluded other outputs due to a lack of data or difficulty to quantify their economic value. In focusing on one particular outcome, we hope that our analysis gained in depth while staying clear and easy to comprehend. Nonetheless, it would be an interesting avenue for future research to investigate the outputs of entrepreneurship education programs more holistically. In our empirical context, the institute has produced substantial scientific output (90 peer-reviewed publications, 14 doctoral dissertations), contributed to the local startup ecosystem by hosting over 100 public events, and conducted approximately 25 innovation projects per eyar with local industry partners[32]. Furthermore, our analysis focused on founders and their startups, 64% of students in our sample moved on to work as employees. If entrepreneurship education succeeds in increasing the entrepreneurial human and social capital, companies employing graduates of the program should benefit from the competencies they gained as a result of the program (Alsos et al., 2022; Braunerhjelm & Lappi, 2023).

Finally, previous literature has shown a large variance in results evaluating entrepreneurship education. Entrepreneurship education programs differing with regards to their target group, educational goals, and pedagogical approaches may produce different outcomes. Comparable to accelerator programs (Hallen et al., 2020) it is reasonable to expect that some programs, or certain configurations of program elements, produce better outcomes than others. With only a few empirical studies evaluate entrepreneurship education programs by economic outcomes (C. E. Eesley & Lee, 2021; Lyons & Zhang, 2017) more research considering different contexts would certainly be helpful to get a clearer picture of the range of outcomes to expect.

[32]While literature has established the effect of university-industry collaboration (Koch & Simmler, 2020; Laursen & Salter, 2004; Moon, Mariadoss, & Johnson, 2019; Perkmann et al., 2013), so far little research has considered students as actors involved in knowledge diffusion processes (Åstebro et al., 2012).

5 | How do Different Forms of Exits Impact Entrepreneurial Ecosystem Development? Longitudinal Evidence

Founders who have achieved success should be encouraged to continue to engage with the next generation of startups in their community. Don't take your capital, knowledge, and inspiration to the beach (at least not forever). Stay engaged. Help the next generation of entrepreneurs. Do this, especially if no one helped you. Work on leaving your community in a better place than it was when you were building your company. Try to ensure that the next generation of founders following in your footsteps have a smoother journey than you did.

Brad Feld & Ian Hathaway, 2020, The Startup Community Way (p. 139)

5.1 | Abstract

Entrepreneurial ecosystems (EEs) support the emergence of successful startups. But how do startups affect the development of the EE they are embedded in? We investigate the effect of successful exit events on subsequent startup investments by individuals (i.e. business angels) and new venture creation across 46 European cities between 1999 and 2018. We find that an increase in acquisitions positively affects the number of business angel investments and new ventures in the respective ecosystems in the years after. While the increase in business angel investments is observable for two years, the effect on new venture creation is visible for only one year. In contrast to acquisitions, an increase in initial public offerings (IPOs) only affects new venture creation but not business angel investment activity. These results shed light on how EE development is influenced by earlier entrepreneurship: After successful exit events, resources are "recycled" back into the ecosystem. While previous research was limited to case studies, we show that this phenomenon is widespread and that the effect differs between exits by acquisition and IPO. Policy makers interested in developing EEs should consider schemes promoting the reinvestment of proceeds generated through successful startup exits.

As of submission of this dissertation, the study presented in this chapter it under review in the Small Business Economics Journal (SBEJ) for the Special Issue "Opening Entrepreneurial Ecosystem Blackboxes".

A version of this paper was presented at the InnoDays 2022 Conference in Casablanca, Morocco and received ***Best Paper*** *Award.*

5.2 | Introduction

Entrepreneurial ecosystems (EEs) and their influence on productive entrepreneurship are of increasing interest for practice and research (Wurth et al., 2021). Organizations like the WEF and OECD identify EEs as growth lever for regional economic development (Foster et al., 2013; C. Mason & Brown, 2014). Scholars and policy makers have been adopting the EE lens in order to explain and analyze successful entrepreneurship in regions (Spigel & Harrison, 2018; Wurth et al., 2021). Recently, the academic field has seen an explosion of articles on the topic (Alvedalen & Boschma, 2017; Spigel & Harrison, 2018; Vedula & Kim, 2019).

Entrepreneurial ecosystems are defined by interdependencies between elements and entities organized in a way that enables productive entrepreneurship in delimited spatial contexts (Stam & Spigel, 2016). One aspect researchers and policy makers want to understand is how temporal effects influence the evolution of EEs and their lifecycle (Theodoraki, Dana, & Caputo, 2022). Downward causation – the mechanism of outcomes and outputs of an ecosystem feeding back into the ecosystem and in turn influencing its elements – offers a theoretical approach to understanding EE evolution through feedback loops (Stam, 2015). Successful entrepreneurial exits start a feedback loop that fuels the subsequent development of entrepreneurship in their regions (Feld & Hathaway, 2020). After a successful exit event, founders and employees sell (some of) their shares, leave the company, and are able to pursue renewed entrepreneurial activities. This "*entrepreneurial recycling*" process feeds the created resources back into the entrepreneurial ecosystem (C. Mason & Brown, 2014).

The maybe most publicized example of this phenomenon is the *PayPal Mafia*: A group of founders and early employees at Paypal that continued to become some the most successful Silicon Valley entrepreneurs and investors after its acquisition by eBay in 2002.[33] However, this phenomenon is not limited to Silicon Valley but can also found in emerging EEs. Consider the case of Stylight.[34] After its four founders sold their start-up, they used their newly acquired capital and knowledge to invest into, and mentor new start-ups. More than that, they founded again, creating start-ups that by now raised more than EUR 179 million in VC funding. These examples illustrate two ways in which successful exits fuel subsequent entrepreneurial activity in EEs: Founders use their wealth to invest in new startups and may found new companies themselves.

[33]See https://fortune.com/2007/11/13/paypal-mafia/ (last accessed 2022-10-31)

[34]Anselm Bauer, Benjamin Günther, Max-Josef Meier and Sebastian Schuon exited Stylight to ProSiebenSat1 in a EUR 62.4 million deal in 2016. Among many others they have since invested in Personio (today valued at over EUR 8 billion) and TeleClinic (acquired for an undisclosed amount in the medium double digit million value). Bauer, Günther, and Schuon went on to found Alasco that by now raised EUR 50 million and Meier went on to found FINN that by now has raised EUR 132 million in equity and EUR 700 million in debt funding in Munich, Germany.

However, empirical research investigating the path of entrepreneurs and their acquired human and financial capital after successful exits is sparse. Both in the research stream on exits (Parastuty, 2018) and in the literature on entrepreneurial ecosystems the topic is not addressed in recent literature reviews (Cefis, Bettinelli, Coad, & Marsili, 2022; Theodoraki et al., 2022).

The few existing studies that try to determine the influence of start-up exits on regions, concentrate on specific industries (Stuart & Sorenson, 2003), use individual-level case studies (C. M. Mason & Harrison, 2006), do only regard failure as type of exit (Hessels, Grilo, Thurik, & Zwan, 2011; Spigel & Vinodrai, 2021), or are limited to the country-level (Albiol-Sánchez, 2016). Other studies consider the opposite effect, the effect, regional endowments have on exits (Ahluwalia & Kassicieh, 2022; Weterings & Marsili, 2015).

In summary, there is a lack of research concerning exits and their impact on regional development. Research so far, has not been able to empirically show the effect, successful exits have on the investment behavior and new venture creation in local entrepreneurial ecosystems on a broad scale. This gap needs to be filled, since regions are the main container for economic development (Acs, Stam, Audretsch, & O'Connor, 2017; Marshall, 1920), and financing is crucial to increase the capacity of an entrepreneurial ecosystem (Spigel & Vinodrai, 2021).

With this paper, we seek to fill this gap and show that entrepreneurial recycling has a considerable impact on ecosystem development. We address the question: "*How do start-up exits impact the development of entrepreneurial ecosystems?*" with a panel data approach covering 46 European cities over 19 years.

We collected quantitative data on venture establishments, VC investments, Initial Public Offerings (IPOs) and acquisitions activity in European cities between 1999 and 2018 from Crunchbase.[35] Previous research regarding the reliability of this database has shown the fit of Crunchbase data for academic research (Dalle et al., 2017; Nylund & Cohen, 2017; Retterath & Braun, 2020). We included all cities which had at least one acquisition or IPO of a VC-backed company in the observed timeframe. To analyze the data, we used a panel data approach, similar to Audretsch, Belitski, & Desai (2015), applying a fixed effects estimation to determine the influence of acquisitions and IPOs on investing activity by individual investors and new venture creation in subsequent years. In simple words, we analyze whether exit activity in previous years influences the number of angel investments and founded startups in an EE in subsequent years.

[35]Crunchbase is start-up database, containing data on start-ups, VC firms, exits and financing rounds. The data is collected and validated through a community of independent contributors, venture firms and analytics (Dalle et al., 2017).

Our results provide robust evidence that exit activity is positively linked to both subsequent individual investor activity and new venture creation on city level. Regression analysis shows that lagged acquisition activity has a significant and positive influence on individual investment activity both in the first and second year after the exit. In contrast, lagged IPO activity did not show a statistically significant effect on subsequent individual investment activity. With regards to new venture creation, we find that lagged acquisition and IPO activity both have a significant and positive influence. The effect diminishes already in the second year after the exit, indicating that employees found shortly after the exit event. Exits by acquisition seem to be a more important factor for subsequent new venture creation in the next year. These results prove to be robust, when we repeat the regression analysis excluding the three most active cities (London, Paris, Berlin) and when including lagged dependent variables in a dynamic panel analysis.

This study contributes to the literature on entrepreneurial ecosystems. It finds strong evidence for the existence of entrepreneurial recycling and its supportive effect on the regional level. The presented results are in line with the theoretical considerations of downward causation (Stam, 2015; Stam, Suddle, Hessels, & Stel, 2009), and of entrepreneurial recycling in ecosystems (Spigel, 2018; Wurth et al., 2021). These results help explain how successful exit events can serve as catalyst for new entrepreneurship and emphasize the evolutionary character of ecosystems – evolving heterogeneously over time and in different geographic contexts.

5.3 | Theoretical Background

5.3.1 | Entrepreneurial Ecosystems (EEs)

Productive entrepreneurship is important for the development of economies and societies. Over the past decades, scholars and policy makers have pointed out the necessity of entrepreneurship for economies to stay competitive and thriving (Acs et al., 2017). In the last decade, the notion of the genius-entrepreneur that was championed by Schumpeter (Schumpeter, 1934) has been overtaken by the realization that the context of entrepreneurs is playing a crucial role for their success (Stam, 2015). Thus, research regarding entrepreneurial development in different geographic contexts and systems has gained momentum under the name of entrepreneurial ecosystem research (Spigel & Harrison, 2018).

Research on EEs strives to identify critical components, interdependencies, and coordination mechanisms for a regional system to enable productive entrepreneurship and value creation (Stam & Spigel, 2016). Stam (2015) defines EEs as a "*set of interdependent actors and factors coordinated in such a way that they enable productive entrepreneurship within a particular* *territory*" (p. 1765).[36] Productive entrepreneurship is defined as "*any entrepreneurial activity that contributes directly or indirectly to the net output of the economy or to the capacity to produce additional output*" (Baumol, 1996, p. 4). This type of entrepreneurship is often represented by high-growth and innovative entrepreneurship (Leendertse, Schrijvers, & Stam, 2021; Stam & Bosma, 2015). EE research emphasizes the presence and interaction of different context factors for entrepreneurship in regions (Stam, 2015; Wurth et al., 2021). The ecosystem metaphor focuses the discussion on the interdependencies between factors relevant for entrepreneurial development and the new firm establishment (Isenberg, 2016), instead of looking at them in isolation.

To understand the set of actors and factors that interact in EEs, several researchers propose frameworks covering elements important for these ecosystems (Isenberg & Onyemah, 2016; Stam & Ven, 2021; Vedula & Kim, 2019). The frameworks cover between five and eleven elements that are considered crucial. The most established overview of elements can be found in (Stam & Ven, 2021). Multiple scholars recognize the significance of their work; see for example (Audretsch, Colombelli, Grilli, Minola, & Rasmussen, 2020; Karlsson, Rickardsson, & Wincent, 2021; Leendertse et al., 2021; Velt, Torkkeli, & Laine, 2020; Wurth et al., 2021). They divide their ten elements into institutional arrangements and resource endowments. Institutional arrangements are the fundamental physical and socioeconomic arrangements within ecosystems, which legitimize and promote entrepreneurship and innovation. *Institutions*, *entrepreneurial culture*, and *networks* have been identified as necessary to provide a favorable framework for entrepreneurial development. Resource endowments of regions that support entrepreneurship are *physical infrastructure*, *demand*, *intermediaries*, *talent*, *knowledge*, *leadership,* and *finance*. In interrelation with the right institutional arrangements, these resources are responsible for the ecosystems' entrepreneurial output and success (Stam & Ven, 2021).

Figure 12 gives an overview of the different layers and respective mechanisms in EEs. Interdependencies exist not only between the institutional arrangements and resource endowments, but also between all elements in these categories. All these elements support the entrepreneurial development in regions. The interplay of these elements is considered a main driver of ecosystem development (Feldmann, 2001; Johnson, Bock, & George, 2019). The impact of the elements on the outputs is not static over time or across ecosystems (R. Brown & Mason, 2017). It seems to vary with characteristics, maturity, and the overall state of the respective ecosystem (Mack & Mayer, 2016).

[36]For an overview of other definitions for EEs see Cavallo, Ghezzi, & Balocco (2019).

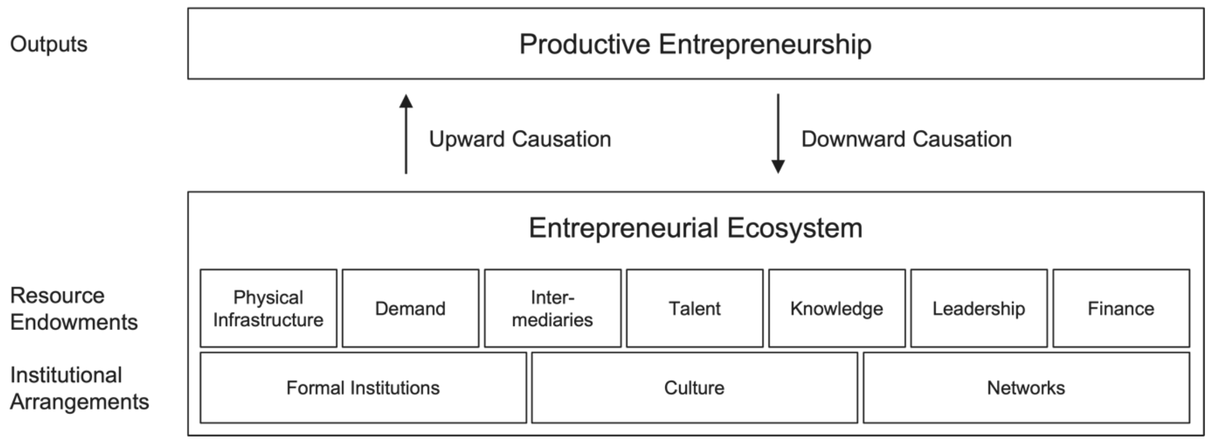

Figure 12: Entrepreneurial Ecosystem (EE) Elements According to Different Studies

The interrelation between different layers of the EE model is just as crucial as the interaction on the same layer. It can be separated into upward- and downward causation (Stam, 2015). Growth-oriented entrepreneurship can be attributed to ecosystem development (upward causation). On the other hand, ecosystem development can be attributed to growth-oriented entrepreneurship (downward causation). The success and value creation of those ventures is circling back to shape the institutional arrangements, or it increases the resource endowments, which enables productive entrepreneurship (Stam & Ven, 2021; Wurth et al., 2021).

Upward causation means that successful EEs lead to more or better firms. It is defined as the interaction between the elements that fosters productive entrepreneurship. The overall state of the ecosystem leads to different forms of economic and social outcomes (Wurth et al., 2021). Several studies point out the positive influence of successful EEs on new firm formation (Audretsch & Belitski, 2017; Stam & Ven, 2021). In addition to firm formation, productive entrepreneurship also covers firm growth and venture survival (R. Brown & Mason, 2017; Vedula & Kim, 2019).

Downward causation means that more or better firms lead to a better EE. It is defined as the influence productive entrepreneurship has on the ecosystem when the created resources are cycling back into the ecosystem (Stam & Ven, 2021). This mechanism is at play when the value created through the ecosystem is feeding back into the ecosystem's elements. Within research on EEs, downward causation has been identified as an enabler for path dependencies, perpetuating entrepreneurial growth in creating a positive cycle that leads to successful systems of entrepreneurship re-enforcing themselves (Wurth et al., 2021). Thus, prior entrepreneurial activity might result in vital externalities for other potential entrepreneurs to engage in entrepreneurial behavior (Chang, Chrisman, & Kellermanns, 2011), which directly influences the dynamics within ecosystems (Autio, Kenney, Mustar, Siegel, & Wright, 2014). Following the argument of downward causation, the outputs of the ecosystem will further influence the ecosystem's development by enabling stakeholders of the ecosystem to shape different ecosystem elements (Stam & Ven, 2021). New ventures can therefore lead to positive feedback effects within the elements of the ecosystem (Wurth et al., 2021).

With initial success, the recycling of resources back into the ecosystem reinforces path dependencies (R. Brown & Mason, 2017; Henning, Stam, & Wenting, 2013). Therefore, recycling could be a substantial success factor in the formation and development of EEs even though research on it remains scarce (Spigel & Harrison, 2018; Wurth et al., 2021).

5.3.2 | Entrepreneurial Recycling and Hypothesis Formulation

One major type of entrepreneurial recycling is the reuse of entrepreneurial resources that are made available through an exit (DeTienne & Robb, 2016; C. M. Mason & Harrison, 2006). Substantial amounts of resources are freed up in successful exits. Successful exits are defined as moments in which entrepreneurs and investors unlock some or all value of their investments by either selling the venture in an acquisition or taking the company public in an IPO (Petty, 2015). Exit events therefore release financial capital to the entrepreneurs, early employees, and shareholders. Case studies suggest that this free capital often stays in the same region. Exited entrepreneurs are not only prone to renascent entrepreneurship but also rarely leave their ecosystem, and thereby foster its development (Albiol-Sánchez, 2016; Bahrami & Evans, 1995; C. M. Mason & Harrison, 2006).

Successfully exited entrepreneurs hold substantial resources (like *finance*, *knowledge*, *talent* that could translate into *leadership* in EEs) that may positively influence the dynamics within EEs. We differentiate between two distinct forms of entrepreneurial recycling. Firstly, entrepreneurial recycling in the form of provision of *leadership* and *finance*, i.e. individual investments in other entrepreneurs also known as angel investing (C. M. Mason & Harrison, 2006). And secondly, recycling in the form of use of *talent*, *knowledge,* and *leadership* for subsequent entrepreneurial endeavors, i.e. new ventures founded by exited entrepreneurs or their leadership team also known as renascent entrepreneurship (Stam, Audretsch, & Meijaard, 2008).

Successfully exited entrepreneurs can financially support ventures in their ecosystems (C. M. Mason & Harrison, 2006). Individual-level studies have found a strong tendency for entrepreneurs who exited to be continuously passionate about entrepreneurship and more likely to engage in subsequent entrepreneurial activities such as investing and mentoring (DeTienne & Robb, 2016; Stam et al., 2008). The exited founders of the venture have enough capital and experience to support other nascent ventures (Ensign & Farlow, 2015). Similar to an acquisition, the founders of a firm and other shareholders can harvest their invested capital once a company went public (Petty, 2015).

Indeed, research shows that a considerable share of individual angel and early-stage investors are former entrepreneurs (C. Mason & Botelho, 2016; C. Mason, Botelho, & Harrison, 2016; C. M. Mason & Harrison, 2006). Evidence from country-level studies supports the notion that a financially successful exit can lead entrepreneurs to either become angel investors or establish VC funds (Honjo & Nakamura, 2019). Harrison, Mason, & Robson (2010) postulate that individual angel investors tend to invest in geographic proximity, given their already established personal networks within their respective ecosystems. This suggests that successful entrepreneurial exits lead to the recycling of financial resources by the entrepreneurs. Hence, there should be a higher concentration of individual investments in regions with high exit rates. Accordingly, our first hypothesis is:

Hypothesis 1 (H1): *There is a positive association between successful exit activity and subsequent investments made by individuals on a regional level.*

The IPO or the acquisition of a venture might lead to changes in the company's organizational culture, which in turn, might lead to some employees or founders looking for new endeavors to use their entrepreneurial resources and abilities. Therefore, employees and founders of an exited company might engage in subsequent entrepreneurial activity (Babina, Ouimet, & Zarutskie, 2017; Hessels et al., 2011; C. M. Mason & Harrison, 2006; Stam et al., 2008).

Entrepreneurs selling successful ventures might be more confident in founding another venture, given that they already showed their ability to build successful ventures (Holmes & Schmitz, 1990; C. M. Mason & Harrison, 2006). Furthermore, since an exit by acquisition or IPO usually leads to the owners becoming financially independent, there might be fewer liquidity constraints in founding a new venture (Stam et al., 2008). Stuart & Sorenson (2003) find the proposed mechanism between exits and new ventures in biotech firms. IPOs and cross-industry acquisitions of biotech firms positively influence the founding rates of new biotech ventures in the same area.

With high exit activity in ecosystems, EEs can profit from individuals pursuing renewed entrepreneurial activities. Additionally, they can foster the development of their local ecosystem by acting as intermediaries and connectors between ecosystem stakeholders. Therefore, high exit rates should be followed by an increased output of productive entrepreneurship shown by an increased number of start-ups being founded in the respective regions. Accordingly, our second hypothesis is:

Hypothesis 2 (H2): *There is a positive association between successful exit activity and subsequent productive entrepreneurship on a regional level.*

5.4 | Data and Methods

To answer our research question and test our hypotheses we study 46 ecosystems in Europe. European entrepreneurial clusters and economies offer a highly diverse set of different attributes, with a multitude of different cultures, economic and social development levels, and distinct regional and national policies for entrepreneurship (Audretsch & Belitski, 2017). Thus, a sample within Europe makes it possible to investigate the potential magnitude of entrepreneurial recycling effects on different ecosystems, regardless of the development stage and maturity (Audretsch & Belitski, 2017).

5.4.1 | Sample and Data

The local unit of analysis in this study is the city. Exact boundaries of EEs are hard to determine since single ecosystem elements and conditions may vary even between small regional contexts (Stam & Ven, 2021). Leendertse et al. (2021) argue that the ecosystem boundaries for measurement should be selected to involve the spatial reach of causal mechanisms. Since cities have been identified as anchors for entrepreneurial development (Bosma, Content, Sanders, & Stam, 2018) we select them as smallest local unit in which entrepreneurial recycling takes place.

Data Sources: We collected the data for this study from multiple sources. Quantitative data on IPOs, acquisitions, venture births, and investments (individual and organizational) were sourced from Crunchbase. Crunchbase focuses on ambitious, high-growth start-ups interested in VC funding and provides an adequate overview of new venture establishments (Dalle et al., 2017; Leendertse et al., 2021). Data on population and economic development was obtained from ARDECO Database.[37] As this database does not contain data from Switzerland, data from municipality statistic offices and the OECD database on metropolitan areas were taken for Zurich, Bern, and Lausanne.

[37] ARDECO was formerly managed and maintained by Cambridge Analytics and is now maintained by the European Commission. See https://knowledge4policy.ec.europa.eu/territorial/ardeco-online (last accessed: 2023-2-20)

Ecosystem Selection: We obtained data for about 13,000 European cities from Crunchbase. We then excluded all cities without records of acquisitions or IPOs of at least one VC-backed company. The final sample comprises 46 European cities in 30 countries.

Timeframe: The collected panel data includes data from 1999 until 2018. Although we originally obtained data up to 2021, we excluded any observations later than 2018 for two reasons. First, recent data might not be fully reported, since Crunchbase is partly contributor (Dalle et al., 2017). Second, we exclude any effects that the Covid-19 pandemic might have had on European ecosystems. In total the final data set contains 82,557 ventures, 48,768 VC deals, 1,877 exits by acquisition, and 1,903 exits by IPO.

5.4.2 | Measures

Dependent Variables

We investigate two primary forms of entrepreneurial recycling: First, the investment of financial capital into nascent ventures by individuals, i.e. angel investments. Second, by reentering the ecosystem with subsequent entrepreneurial activity, i.e. new ventures founded.

We define *individual investments* as investments made by individual people listed on Crunchbase. Partner deals, co-investment with other individuals or companies, were excluded to account for possible network externalities (Botelho, Harrison, & Mason, 2021; C. Mason et al., 2016) capturing only sole individual investors. We collected the data on the deal level and considered all types of investment rounds (i.e. seed investment, Series A, etc.).

We define *venture births* as the number of newly founded companies listed on Crunchbase. In line with EE research, the number of newly founded companies per ecosystem is a proxy for productive entrepreneurship (Leendertse et al., 2021).

Explanatory Variables

Our explanatory variables of interest are successful entrepreneurial exists, measured as number of *acquisitions* and *IPOs* per time period in a given ecosystem. Previous studies define the entrepreneurial exit as general discontinuation of a business (Albiol-Sánchez, 2016; Hessels et al., 2011). We consider only successful exit events. With a financially successful exit, there is motivation for founders and employees to re-enter their respective ecosystems by using their newly acquired resources (Stam et al., 2008).

We measure *acquisitions* as the number of exits by acquisitions listed on Crunchbase. While Crunchbase holds information on the acquirer, acquisition-target, and transaction values, and acquisition types, data is scarce for transaction values. Thus, we did not obtain financial metrics quantifying the size of acquisitions. We only considered acquisitions of companies that previously received VC funding and excluded data on mergers, leveraged buyouts and management buyouts.

We measure *IPOs* as the number of initial public offerings listed on Crunchbase.

Control Variables

First, we control for capital availability in an ecosystem. The importance of VC capital for productive, high-growth, and innovative entrepreneurship is widely agreed upon in academic research. Empirical studies have shown the positive influence of VC investments on firm growth and survival (Colombo & Grilli, 2010), venture establishments, and employment (Samila & Sorenson, 2011).

First, we introduced the number of *investments* and the *investment amount* to control for the availability of financial capital and proxy the overall development of the market in a specific ecosystem. The number of *investments* is defined as the sum of *individual investments* and *organizational investments* in the respective ecosystem. Investments were taken on the deal level, with multiple investments making up one round. The data for the investment amount was derived at the round level, as no information on the amount invested is made available for the individual deal level in the data set. To focus on capital availability for nascent ventures, investments past the IPO stage, non-equity rounds, debt, and corporate rounds were excluded from the sample. We included these controls for two reasons: They address potential network externalities that individual investors might depend on (Lerner, Schoar, Sokolinski, & Wilson, 2018; C. Mason et al., 2016) and they proxy the general maturity of VC markets and market attractiveness for a specific ecosystem at a specific time.

Second, we control for *population*. Public demand is one of the prevailing framework conditions that positively influence development within EEs (Stam, 2015). Hence, to take the potential market size and different sizes of cities in the sample into account, the population of cities was included in the model. Data on population was taken on the NUTS-3 level.[38]

Third, we control for *GRP per capita* (gross regional product per capita) in current prices to account for the economic development of the respective cities potential market size (Stam, 2015). GRP per capita was calculated on the NUTS-3 level.

[38]NUTS is a hierarchical system for dividing up the economic territory of the EU. For cities in Switzerland (Bern, Lausanne, Zurich) we obtained equivalent data from the statistic offices of the respective Cantons. Data for Lausanne was not available for all years.

5.4.3 | Model Definition

We use a panel data approach to investigate the relationship between regional exits and subsequent entrepreneurial activity. Our hypotheses concern the influence of acquisitions and IPOs (explanatory variables) on individual investments and venture births (dependent variables). We defined regression models for each dependent variable (individual investments and venture births). The models include both explanatory variables (acquisitions and IPOs) with time lags of 1 and 2 years, respectively. These lags help to deal with two potential concerns: First, they account for the time needed for resources set free by an exit to circle back into the respective ecosystem (Stam & Ven, 2021). Second, they account for common shocks, i.e. macroeconomic developments that have implications on exit activity as well new venture creation (Phillips & Zhdanov, 2017).

To account for unobserved heterogeneities between cities and years, we use a fixed effects estimator in both models (Wooldridge, 2012). Standard errors are clustered on city level to address the potential serial correlation and heteroscedasticity (Abadie, Athey, Imbens, & Wooldridge, 2017; Wooldridge, 2012). To account for skewness[39] in the data we applied the natural logarithm to all variables across all models (Wooldridge, 2012).

Individual Investments

One form of entrepreneurial recycling is the provision of capital for other ventures in the ecosystem by recently exited founders. H1 assumes that a high number of exits should be positively associated with individual investments thereafter. To test H1, we use a fixed effects estimation with the following regression functions:

$$F1\text{: } \ln ind\_inv_{i,t} = \alpha_i + \lambda_t + \beta_1 \ln \mathrm{acq}_{i,t-1} + \beta_2 \ln ipo_{i,t-1} + \beta_3 \ln org\_inv_{i,t} + \beta_4 \ln grp_{i,t} + \mu_{i,t}$$

$$F2\text{: } \ln ind\_inv_{i,t} = \alpha_i + \lambda_t + \beta_1 \ln \mathrm{acq}_{i,t-2} + \beta_2 \ln ipo_{i,t-2} + \beta_3 \ln org\_inv_{i,t} + \beta_4 \ln grp_{i,t} + \mu_{i,t}$$

The variables i and t indicate city and year. The explanatory variable $ind\_inv_{i,t}$ represents the number of investments made by individuals in a given city i in a given year t. $\mathrm{acq}_{i,t}$ represents the number of acquisitions with the acquired company being based in the city of interest; $ipo_{i,t}$ represents the number of IPOs. F1 introduces a time lag of one year ($t-1$), F2 of two years ($t-2$) for the explanatory variables. To confirm H1, at least one of the coefficients β_1 or β_2 should be positive and statistically significant.

[39]Not all cities in the sample had an observation for either IPO or acquisition for every year. Hence, to apply the natural logarithm, all variables in the sample were incremented by 1 (Samila & Sorenson, 2011).

The functions include several control variables. $org\_inv_{i,t}$ denotes the number of investments made by organizational investors (i.e. not individual investments). Individual investors could be positively influenced by investments made by organizational investors due to network effects (C. Mason et al., 2016). Additionally, this variable proxies general VC market development in a specific ecosystem at a specific time. To control for general economic development GRP per capital in current prices ($grp_{i,t}$) is included. To account for unobserved heterogeneity, city fixed effects (α_i) and dummy variables for each year (λ_t) are included.

Venture Births

In addition to capital being reinvested into ventures, entrepreneurial recycling could happen in the form of exited founders and employees reentering the EE by forming new ventures (Stam et al., 2008). H2 assumes that there is a positive association between exit activity and new venture creation thereafter. To test H2, we use a fixed effects estimation with the following regression functions:

$$F3\text{: } \ln births_{i,t} = \alpha_i + \lambda_t + \beta_1 \ln \mathrm{acq}_{i,t-1} + \beta_2 \ln ipo_{i,t-1} + \beta_3 \ln inv_{i,t} + \beta_4 \ln grp_{i,t} + \beta_5 \ln pop_{i,t} + \mu_{i,t}$$

$$F4\text{: } \ln births_{i,t} = \alpha_i + \lambda_t + \beta_1 \ln \mathrm{acq}_{i,t-2} + \beta_2 \ln ipo_{i,t-2} + \beta_3 \ln inv_{i,t} + \beta_4 \ln grp_{i,t} + \beta_5 \ln pop_{i,t} + \mu_{i,t}$$

The variables i and t indicate city and year. $births_{i,t}$ represents the number of ventures founded per city per year. $\mathrm{acq}_{i,t}$ represents the number of acquisitions with the acquired company being based in the city of interest; $ipo_{i,t}$ represents the number of IPOs. F3 introduces a time lag of one year ($t-1$), F4 of two years ($t-2$) for the explanatory variables. To confirm H3, at least one of the coefficients β_1 or β_2 should be positive and statistically significant.

The functions include several control variables. $inv_{i,t}$ denotes a vector representing investment activity, combining two measures: The number of investments (individual and organizational) and the total amount of capital invested per city (in USD). This variable was chosen to control for the attractiveness of the city for VCs and start-ups. To control for general economic development GRP per capital in current prices ($grp_{i,t}$) is included. Additionally, the population size ($pop_{i,t}$) of the respective cities is included since a larger population size may correspond to a larger pool of potential founders. To account for unobserved heterogeneity, city fixed effects (α_i) and dummy variables for each year (λ_t) are included.

5.5 | Results

Our sample contains 46 different cities. The data set contains in total 82,557 ventures, 48,768 VC deals, 1,877 exits by acquisition, and 1,903 exits by IPO. Observations tend to cluster around few high-activity cities: For instance, London alone makes up 25.85% of all companies founded within the sample. Paris, Berlin, and Amsterdam follow with 7.62%, 4.94%, and 4.93% of all ventures founded. Regarding exits, there is no clear tendency towards one exit route recognizable. Overall, exits by acquisition make up 49.66%, and exits by IPO make up about 50.34% of all exit transactions. Again, London is the most active city, with a share of 24.22% of all exits by acquisition and 34% of exits by IPO. Moreover, the investment activity is dominated by organizational investors (VC funds, corporate investors). In other words, most investments tracked on Crunchbase are not business angel investments (i.e. individual investments) but investments by venture capital firms or other institutional investors.

In total, investments by organizations make up about 82.77% of all closed deals, while investments by individual investors contribute 17.23% to all investments. Descriptive analysis indicates substantial variation between years and cities, with many variables' standard deviation exceeding double the mean. For instance, the mean of the dependent variable venture births is 89.74 (ln = 3.93) per city per year with a standard deviation of 184.28 (ln = 0.916); the mean for individual investments is 9.14 (ln = 0.916) with a standard deviation of 40.25 (ln = 1.30).

Table 28 shows the correlation matrix using Pearson correlation coefficients. Both explanatory variables show statistically significant correlation ($p<0.05$) with individual investments and venture births, providing first indicative evidence for both hypotheses. Looking at the control variables, investment activity (both in terms of number of deals and amount invested), GRP p.c. and population are positively correlated to the dependent variables. Although all variables have significant relationships with each other – likely due to the large sample size – potential problems of multi-collinearity do not arise when calculating regression coefficients.

5.5.1 | Regression Analysis: Individual Investments

Hypothesis 1 assumes a positive influence of exit activity on individual investments. Table 29 shows the results of the fixed effect regression on individual investments as dependent variable. All models consider city and time fixed effects. The explanatory variables are entered in incremental steps into the regression, considering lags of the first and second order (meaning lags of 1 and 2 years). This procedure results in seven respective model instances. All regression models show adjusted R^2-values above 0.63 and p-values below 0.01; the model's fit and statistical significance can thus be considered substantial.

The results provide support for the first hypothesis. The coefficients β_1 for the explanatory variable “acquisitions” are positive and significant across all models, with all p-values below 0.01. The effect increases in magnitude when a second order lag is applied. To illustrate, the results of Model 5 and Model 6 suggest that with a 1.0% increase in the number of acquisitions, there is an increase in individual investments of 0.438% one year later and 0.492% two years later.[40] While the coefficient β_2 is positive for the explanatory variable IPOs across all models, the results are not statistically significant after the stepwise introduction of acquisitions as an explanatory variable (see Model 5 and Model 6).

5.5.2 | Regression Analysis: Venture Births

Hypothesis 2 assumes a positive influence of exit activity on new venture creation. Table 30 shows the results of the fixed effect regression on new venture births as dependent variable. All models consider city and time fixed effects. The explanatory variables are entered in incremental steps, considering first and second order lags (meaning lags of 1 and 2 years). This results in seven model instances. All regression models show adjusted R^2-values above 0.66 and p-values below 0.01; the model’s fit and statistical significance can thus be considered substantial.

The results provide support for the second hypothesis. Lagged acquisition and IPO activity both have a significant and positive influence on new venture births. However, only first order lags of the explanatory variables significantly influence the dependent variable (compare Model 5 and Model 6). With a lag of 1 year both explanatory variables, result in p-values below the 5% threshold across all models. With a two-year lag, both acquisitions and IPOs diminish in impact on the dependent variable and lose statistical significance.

The results indicate that exits by acquisition and IPO seem to be of similar relevance for new venture creation. For instance, Model 5 resulted in a regression coefficient of 0.065 for the explanatory variable “acquisitions” and 0.048 for the variable “IPO”. Hence, with a 1.0% increase in the number of exits by acquisition, there is a 0.065% increase in ventures founded, all else being equal. In comparison, a 1.0% increase in the exits by IPO corresponds with an increase of 0.048% of the explanatory variable, all else being equal.

[40]Due to the log.-log. relationship of the dependent and explanatory variables, regression coefficients are interpreted as direct elasticities throughout this study.

Table 28: Correlation Analysis

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Births (In)	1										
(2) Individual investments (In)	0.711	1									
	(0.000)										
(3) investments (In)	0.741	0.841	1								
	(0.000)	(0.000)									
(4) investment amount (In)	0.534	0.489	0.767	1							
	(0.000)	(0.000)	(0.000)								
(5) Acquisitions (In)	0.706	0.770	0.749	0.459	1						
	(0.000)	(0.000)	(0.000)	(0.000)							
(6) Acquisitions (t-1) (In)	0.677	0.765	0.737	0.443	0.745	1					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
(7) IPOs (In)	0.611	0.457	0.457	0.302	0.507	0.476	1				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
(8) IPOs (t-1) (In)	0.590	0.435	0.432	0.267	0.449	0.459	0.604	1			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(9) Organizational investments (In)	0.737	0.813	0.997	0.766	0.746	0.734	0.458	0.434	1		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(10) Population (In)	0.531	0.366	0.274	0.127	0.344	0.320	0.376	0.362	0.267	1	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(11) GRP p.c. (In)	0.359	0.312	0.425	0.385	0.339	0.332	0.369	0.354	0.427	- 0.177	1
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Notes: N=876/920, Pearson correlation coefficients, p-values in parentheses

Table 29: Individual Investments – Fixed Effects Regression

ln *individual_investments*$_t$ Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
ln *acquisitions*$_{t-1}$	0.441***				0.438***		0.318***
	(0.046)				(0.046)		(0.047)
ln *acquisitions*$_{t-2}$		0.496***				0.492***	0.415***
		(0.048)				(0.048)	(0.048)
ln *IPOs*$_{t-1}$			0.075*		0.054		0.029
			(0.045)		(0.043)		(0.044)
ln *IPOs*$_{t-2}$				0.076*		0.051	0.063
				(0.046)		(0.043)	(0.042)
ln *org_inv*$_t$	0.294***	0.330***	0.330***	0.345***	0.293***	0.327***	0.299***
	(0.036)	(0.037)	(0.038)	(0.039)	(0.036)	(0.037)	(0.036)
ln *grp*$_t$	-0.208	-0.176	-0.418***	-0.391**	-0.218	-0.192	-0.100
	(0.146)	(0.160)	(0.152)	(0.170)	(0.146)	(0.160)	(0.156)
Observations	865	820	865	820	865	820	820
R^2	0.696	0.703	0.663	0.663	0.697	0.704	0.721
Adjusted R^2	0.671	0.677	0.635	0.634	0.671	0.678	0.696
F Statistic	87.094***	89.264***	74.605***	74.080***	83.269***	85.127***	84.317***
	(df = 21; 798)	(df = 20; 754)	(df = 21; 798)	(df = 20; 754)	(df = 22; 797)	(df = 21; 753)	(df = 23; 751)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses; *p<0.1, **p<0.05, ***p<0.01.
The table shows the regression coefficients (β) of the explanatory and control variables following a stepwise introduction of the explanatory variables. Most relevant for testing our hypothesis are the coefficients of Model 5 (1-year lag) and Model 6 (2-year lag), which correspond to the regression functions introduced in section Model Definition. In both Model 5 (β_1 = 0.438***) and 6 (β_1 = 0.492***) the effect is positive and statistically significant, showing that individual investments are positively correlated to acquisition activity both 1 and 2 years before the focal year. The correlation with IPO activity in both Model 5 (β_2 = 0.054) and Model 6 (β_2 = 0.051) is also positive, however not statistically significant.

Table 30: Venture Births – Fixed Effects Regression

ln *venture_births*$_t$ Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
ln *acquisitions*$_{t-1}$	0.067**				0.065**		0.059**
	(0.033)				(0.033)		(0.029)
ln *acquisitions*$_{t-2}$		0.044				0.043	0.031
		(0.035)				(0.035)	(0.030)
ln *IPOs*$_{t-1}$			0.050***		0.048***		0.048***
			(0.015)		(0.014)		(0.016)
ln *IPOs*$_{t-2}$				0.031*		0.029	0.032
				(0.018)		(0.018)	(0.019)
ln *investments*$_t$	0.294***	0.330***	0.330***	0.345***	0.293***	0.327***	0.299***
	(0.036)	(0.037)	(0.038)	(0.039)	(0.036)	(0.037)	(0.036)
ln *investment_amount*$_t$	0.294***	0.330***	0.330***	0.345***	0.293***	0.327***	0.299***
	(0.036)	(0.037)	(0.038)	(0.039)	(0.036)	(0.037)	(0.036)
ln *population*t	0.294***	0.330***	0.330***	0.345***	0.293***	0.327***	0.299***
	(0.036)	(0.037)	(0.038)	(0.039)	(0.036)	(0.037)	(0.036)
ln *grp*$_t$	-0.208	-0.176	-0.418***	-0.391**	-0.218	-0.192	-0.100
	(0.146)	(0.160)	(0.152)	(0.170)	(0.146)	(0.160)	(0.156)
Observations	865	820	865	820	865	820	820
R^2	0.692	0.695	0.691	0.695	0.695	0.696	0.702
Adjusted R^2	0.666	0.668	0.665	0.667	0.668	0.669	0.674
F Statistic	77.902***	78.002***	77.439***	77.766***	75.466***	74.850***	70.589***
	(df = 23; 796)	(df = 22; 752)	(df = 23; 796)	(df = 22; 752)	(df = 24; 795)	(df = 23; 751)	(df = 25; 749)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses; *p<0.1, **p<0.05, ***p<0.01.
The table shows the regression coefficients (β) of the explanatory and control variables following a stepwise introduction of the explanatory variables. Most relevant for testing our hypothesis are the coefficients of Model 5 (1-year lag) and Model 6 (2-year lag), which correspond to the regression functions introduced in section Model Definition. In Model 5 (β_1 = 0.065** and β_2 = 0.048***) the coefficients of lagged acquisition and IPO activity are both positive and statistically significant. In Model 6 (β_1 = 0.043 and β_2 = 0.029) the coefficients are also positive, however not statistically significant. These results show that both acquisition and IPO activity lead to more venture births after 1 year, but not necessarily in later periods.

5.6 | Robustness Checks

To test our models, we conducted several robustness checks. First, we replicated our analysis while systematically removing the most active cities from the sample. While the results changed slightly, our initial analysis proved robust. Second, we created a dynamic panel regression including the dependent variables (individual investments, venture births) with a 1-year lag as explanatory variables. While the influence of the original explanatory variables declined compared to the base model, they remained overall stable and statistically significant. Based on these results we can conclude that both H1 and H2 can be accepted.

5.6.1 | High Activity Areas

Although individual and time fixed effects reduce the potential influence of unobserved heterogeneities between cities and years, the results could potentially be driven by highly active observations in the sample (Samila & Sorenson, 2011). The initial descriptive analysis indicated activity concentration in a few cities. To test the robustness of our results we repeated our regression analysis carrying out a stepwise removal of the most active cities (London, Paris, and Berlin). The results for the model using a 1-year lag time and both explanatory variables are depicted in Table 31 and Table 32 and confirm the robustness of our analysis.

Individual Investments: Our robustness tests shows that the magnitude of effects remains relatively insensitive to the removal of high-activity cities. The statistical significance for both explanatory variables, acquisitions and IPOs, remains stable. We can observe that the explanatory power of acquisitions is diminishing compared to the base model. For example, after removing London, Paris, and Berlin from the sample, a 1.0% increase in the number of acquisitions would result only in a 0.326% increase in the number of individual investments compared to a 0.438% in the base model. Removing high-activity cities also confirms the low statistical significance of IPOs. The impact of control variables remains largely unaffected. Their magnitudes of influence do not change substantially.

Venture Births: Our robustness tests show that the magnitude of the effects remains relatively insensitive to the removal of high- activity cities. However, the statistical significance for the variable acquisitions declines once high-activity cities are removed. The statistical significance for the variable IPOs remains stable. These results suggest that high-activity observations influence the significance of the explanatory variable acquisitions. The magnitude of influence of IPOs remains consistent with the results from the base models, suggesting that high-activity cities do not significantly influence recycling activities through exits by IPO. The impact of control variables remains largely unaffected. Their magnitudes of influence do not change substantially.

5.6.2 | Dynamic Panel Estimates

Another potential concern is that the realization of dependent variables might, to a certain point, depend on the past realization of those variables (Samila & Sorenson, 2011). Downward causation within EEs can be seen as an enabler for path dependencies, indicating self-reinforcing effects with high levels of entrepreneurial output (Stam & Ven, 2021; Wurth et al., 2021). Thus, high levels of productive entrepreneurship measured by new venture creation and individual investing might directly result from past levels of those two indicators. To cope with this concern, we employed a dynamic regression model[41] introducing lagged dependent variables as explanatory variables. Similar to the base fixed effects regressions, both models were set up with year and city fixed effects. Standard errors were again clustered on the city level to account for heteroscedasticity and serial correlation (Abadie et al., 2017). Table 33 shows the dynamic fixed effects regression on new venture creation and individual investments. The models' fit can be deemed satisfactory, with more than 73% of the variation of both explanatory variables being explained by the explanatory variables and p-values in the 1%-confidence interval in all models.

Individual Investments: Overall, the results both indicate a self-reinforcing effect of past individual investment activity and also confirm the results of the original model. Both models (see Table 33, Model 1 and Model 2) show that lagged individual investment activity positively and significantly influences individual investment activity in the next period. Model 1, for instance, indicates that with a 1.0% change in lagged individual investing, the dependent variable changes by 0.451% (0.383% in Model 2). Although the magnitude of influence of the two explanatory variables declines compared to the base models, it also confirms the validity of the initial results. Model 1 still indicates a 1.0% change in the number of acquisitions corresponds to a 0.228% change in the number of individual investments.

This effect also holds with a second order lag of the dependent variable "acquisitions". In both models, the variable shows high statistical significance ($p<0.01$). In addition, the influence of the variable "IPOs" stays positive but, as in the base models, does not show statistical significance.

[41] Initial tests carried out using a Generalized Methods of Moments (GMM) estimator proposed by Arellano & Bond (1991) indicated that autocorrelation in error terms does not significantly influence the dependent variable. Hence the use of a fixed effect estimator with a lagged dependent variable as explanatory variable can be considered substantial and the use of a dynamic panel estimate unnecessary for the main analysis.

Venture Births: Overall the results for the lagged dependent variable "births" indicate the presence a self-reinforcing effect as well. New venture creation is strongly and significantly influenced by venture creation activity in earlier periods in both models (see Table 33, Model 3 and Model 4). For instance, Model 1 indicates that with a 1.0% change in the number of venture births in the previous year, there is a 0.568% (0.581% in Model 2) change in the number of venture births. While the magnitudes of influence of the two explanatory variables both decline compared to the base models, they remain statistically significant, confirming the validity of the initial results.

The insertion of venture births as explanatory variable offers several new insights regarding the influence of the two explanatory variables on new venture births. While the influence of acquisitions on new venture creation declines in magnitude (0.040 in the dynamic estimate compared to 0.065 in the base model), the variable remains statistically significant ($p<0.05$).

The results for the explanatory variable "IPO" stay relatively unaffected in terms of significance. Model 1 indicates that the impact of IPOs on new venture creation remains positive and significant. However, the magnitude of the effect declines (0.037 in the dynamic model compared to 0.048 in the base model).

Table 31: Individual Investments – Robustness Tests

ln *individual_investments*$_t$					
Variables	**All**	**No London (1)**	**No Paris (2)**	**No Berlin (3)**	**No London, Paris, Berlin**
ln *acquisitions*$_{t-1}$	0.438***	0.407***	0.398***	0.423***	0.326***
	(0.046)	(0.075)	(0.070)	(0.079)	(0.079)
ln *IPOs*$_{t-1}$	0.054	0.046	0.065	0.049	0.054
	(0.043)	(0.051)	(0.050)	(0.052)	(0.052)
ln *org_inv*$_t$	0.293***	0.286***	0.293***	0.276***	0.267***
	(0.036)	(0.040)	(0.042)	(0.039)	(0.038)
ln *grp*$_t$	-0.218	-0.186	-0.224	-0.197	-0.168
	(0.146)	(0.180)	(0.181)	(0.181)	(0.181)
Observations	865	846	846	846	808
R^2	0.697	0.690	0.696	0.693	0.676
Adjusted R^2	0.671	0.664	0.670	0.666	0.648
F Statistic	83.269***	75.365***	77.561***	76.196***	67.396***
	(df = 22; 797)	(df = 23; 778)	(df = 23; 778)	(df = 23; 778)	(df = 23; 742)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses; *p<0.1, **p<0.05, ***p<0.01.
The values in the first column (All) correspond to the results of Model 5 in the base model.

Table 32: Venture Births – Robustness Tests

ln *venture_births*$_t$					
Variables	**All**	**No London (1)**	**No Paris (2)**	**No Berlin (3)**	**No London, Paris, Berlin**
ln *acquisitions*$_{t-1}$	0.065**	0.056	0.067*	0.053	0.040
	(0.033)	(0.034)	(0.035)	(0.033)	(0.033)
ln *IPOs*$_{t-1}$	0.048***	0.050***	0.047***	0.047***	0.050***
	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)
ln *investments*$_t$	0.091**	0.090**	0.092**	0.085**	0.083**
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
ln *investment_amount*$_t$	0.001	0.001	0.001	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ln *population*$_t$	-0.063	-0.120	-0.087	-0.010	-0.070
	(0.453)	(0.457)	(0.471)	(0.452)	(0.452)
ln *grp*$_t$	0.079	0.079	0.077	0.074	0.074
	(0.237)	(0.239)	(0.238)	(0.238)	(0.238)
Observations	865	846	846	846	808
R^2	0.695	0.687	0.690	0.686	0.672
Adjusted R^2	0.668	0.660	0.663	0.658	0.643
F Statistic	75.466***	71.119***	72.060***	70.602***	63.224***
	(df = 24; 795)	(df = 24; 777)	(df = 24; 777)	(df = 24; 777)	(df = 24; 741)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses; *p<0.1, **p<0.05, ***p<0.01.
The values in the first column (All) correspond to the results of Model 5 in the base model.

Table 33: Dynamic Panel Estimates – Robustness Tests

	ln *individual_investments*$_t$		ln *venture_births*$_t$	
Variables	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
ln *births*$_{t-1}$			0.568***	0.581***
			(0.046)	(0.045)
ln *individual_investments*$_{t-1}$	0.451***	0.383***		
	(0.041)	(0.041)		
ln *acquisitions*$_{t-1}$	0.228***	0.187***	0.040**	0.040**
	(0.044)	(0.042)	(0.018)	(0.017)
ln *acquisitions*$_{t-2}$		0.268***		-0.001
		(0.062)		(0.023)
ln *IPOs*$_{t-1}$	0.047	0.030	0.037***	0.032**
	(0.049)	(0.052)	(0.013)	(0.015)
ln *IPOs*$_{t-2}$		0.045		0.005
		(0.038)		(0.016)
ln *investments*$_t$			0.029	0.029*
			(0.018)	(0.017)
ln *investment_amount*$_t$			0.001	0.001
			(0.002)	(0.002)
ln *population*$_t$			-0.061	-0.123
			(0.230)	(0.237)
ln *org_inv*$_t$	0.212***	0.228***		
	(0.029)	(0.029)		
ln $_{grpt}$	-0.144	-0.071	0.005	-0.030
	(0.113)	(0.127)	(0.117)	(0.115)
Observations	865	820	865	820
R^2	0.757	0.762	0.791	0.798
Adjusted R^2	0.737	0.740	0.773	0.779
F Statistic	108.021***	100.075***	120.424***	113.538***
	(df = 23; 796)	(df = 24; 750)	(df = 25; 794)	(df = 26; 748)
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses; *p<0.1, **p<0.05, ***p<0.01.
For individual investments the corresponding models from the original analysis (see Table 29) to compare the dynamic panel estimates to are Model 5 (here Model 1) and Model 7 (here Model 2). For venture births the corresponding models from the original analysis (see Table 30) to compare the dynamic panel estimates to are Model 5 (here Model 3) and Model 7 (here Model 4).

5.7 | Discussion

This study contributes to the growing literature on entrepreneurial ecosystems and provides new insights into how acquisitions and IPOs influence subsequent productive entrepreneurship in regions. Increased exit activity in an ecosystem correlates with increased individual investments and venture births in the years thereafter. The effect appears to be limited to a relatively short period: two years for individual investments, and one year for new venture births. However, acquisitions and IPOs differ in their effects. Our analysis reveals that only exits by acquisition result in an increase in subsequent individual investments, while both acquisition and IPOs have a positive effect on subsequent venture births.

These findings confirm theoretical considerations of downward causation in entrepreneurial ecosystems (Stam, 2015; Stam et al., 2009) and shed light on the concrete mechanisms through which entrepreneurial recycling (Spigel & Harrison, 2018; Wurth et al., 2021) after successful exits works. While previous empirical research was limited to individual level case studies (Bahrami & Evans, 1995; C. M. Mason & Harrison, 2006) or industry verticals (Stuart & Sorenson, 2003) our results show that these mechanisms exist across a heterogeneous set of 46 European cities hosting various industries. This is relevant to academics and policy makers as these findings provide first evidence that entrepreneurial recycling is not an isolated phenomenon but common across ecosystems.

Looking at the results in detail, there are three aspects worth discussing: First, the effect size of successful exits is almost a magnitude higher for subsequent individual investments than for subsequent venture births. After increased exit activity we observe a much larger increase in individual investments than venture births in the respective regions. This difference indicates that it is much more likely that founders, employees, and business angels use their newly gained capital to invest into new startups than to found themselves. After a 1% increase in exits by acquisition, individual investments increase by 0.438% and 0.492% in year one and two. In other words, over a two-year period, an increase in acquisitions results in an almost equally large increase in business angel investments. Repeated investments might explain part of this difference. Individuals will likely found at maximum one new venture in the years following the exit, but invest in multiple startups.

Second, our analyses indicate that exits by acquisition are more important than IPOs for subsequent individual investments. In practice IPOs are considered as the most prestigious exit routes for the most successful startups. IPOs were shown to generate the highest returns for investors (Krishnan & Nguyen, 2021) and one would expect that the more financial proceeds are distributed to founders, employees, and investors, the more capital can flow in subsequent business angel investments. However, our analysis shows the opposite. A possible explanation for this is that founders and employees retain large parts of their equity in company shares. The IPO of a startup, in contrast to an exit by acquisition, is a means to finance further growth of the company. Shareholders expect the startup to continue to grow after going public and thus consider holding company shares an attractive investment. In addition, founders may have additional motivation to keep their shares to maintain control of the company (Fattoum-Guedri, Delmar, & Wright, 2018). In contrast, after an exit by acquisition founders, employees, and investors need to look for new opportunities to invest their newly gained financial capital in.

Third, the effect of acquisitions and IPOs on subsequent venture births is of similar magnitude and only statistically significant one year after the exit event. The brief period of the effect indicates that it is likely driven by a direct increase in employee entrepreneurship and not by the improvement of the underlying ecosystems elements. For example, the establishment of new intermediaries (e.g. incubator or accelerator programs) would likely take time to set up and thus only later result in productive entrepreneurship. Empirical research on acquisitions supports this hypothesis. Exits by acquisition are usually connected with founder succession (DeTienne & Robb, 2016). Being released from their responsibilities they may pursue further entrepreneurial activities (Stam et al., 2008). The change in management following an acquisition can also act as catalysts for employees to pursue latent entrepreneurial intentions (Stuart & Sorenson, 2003). Interestingly, the observed increase in employee entrepreneurship following acquisitions seems to be driven disproportionately by founders and top employees (Kim, 2022). Recent work indicates that these findings may generalize to IPOs. After going public employees with stock grants are more likely to depart to start-ups (Babina et al., 2017).

Our interpretation of the results suggests a direct recycling of talent and financial resources back into the ecosystem. However, there might be alternative mechanism causing the observed results. Successful exits could provide a lighthouse effect and attract capital and talent from outside the ecosystem (Feldmann, 2001; Spigel & Harrison, 2018). For example, after a successful exits business angels could become interested in startups from the respective ecosystems or nascent entrepreneurs could move to the ecosystem planning to found their startup there. Our study design cannot exclude this effect. However, following this line of reasoning we would expect IPOs to have a more substantial effect than acquisition which runs counter to the results of our analyses.

5.7.1 | Implications for Theory and Practice

This study has several implications for research and practice. Future research should incorporate entrepreneurial recycling following successful exit events as a potential causal link for entrepreneurial development in regions. Moreover, this study encourages researchers to re-visit the entrepreneurial process and to incorporate successful entrepreneurial exits as significant events in the overall entrepreneurial life cycle (DeTienne & Robb, 2016).

Our results provide valuable insights for policy makers interested in shaping the development of their regional entrepreneurial ecosystems. Resources created through successful entrepreneurial exits flow back into the subsequent development of the ecosystem. Policies favoring the re-investment of proceeds generated through exit events could be an effective tool to accelerate regional startup activity. Our analyses also show that growth entrepreneurship does not just enrich shareholders but benefits our society by enabling new generations of founders. Policy makers should take our findings into account when designing incentives schemes and tools for employee participation in the context of high-growth startups. High-earning employees benefiting from stock grants are more likely to become founders or startup employees after successful exits (Babina et al., 2017; Kim, 2022). Policies allowing startups to implement employee participation schemes may thus be favorable not only to compete for talent against incumbents but also in creating future entrepreneurs – i.e. by enabling more employees to benefit from a successful exit, there will be more who use their financial mobility to found startups themselves.

5.7.2 | Limitations and Future Research

Several limitations need to be considered when interpreting the results. Foremost, these results should be interpreted as correlation, as our data does not permit us to follow exited founders. Our study shows that mechanisms of entrepreneurial recycling exist in EEs with regards to *financial* resources and *talent*. A successful exit may additionally impact various other ecosystem elements not captured by our study design, such as mentoring, guidance, and overall ecosystem attractiveness for outside stakeholders (R. Brown & Mason, 2017) and offer exciting opportunities for future research. Successful exits may impact *culture* by changing the dominant narrative by serving as success stories. Following this assumption, highly visible exits should have a larger impact on subsequent EE development. *Networks* and *leadership* might be strengthened, since the exited individuals act as brokers of talent and ideas. Finally, *knowledge* may be disseminated in new ways as employees leave the company to join or form a new one.

While previous research has shown the fit of Crunchbase data for academic research (Dalle et al., 2017; Nylund & Cohen, 2017; Retterath & Braun, 2020), it is important to acknowledge that data on Crunchbase is community-curated and likely not complete. Data for highly developed ecosystems may be reported more often than for emerging ones and data coverage is likely higher in more recent years. While we cannot eliminate this issue completely, our robustness tests confirm the validity of our results after removing the three most active ecosystems from the sample. To overcome this limitation entirely better data access is needed. Future work would require a complete set of new company formations and investment transactions over a prolonged period of time in the respective ecosystems.

Another limitation arising from the availability of data relates to the value of successful exit events. We were only able to consider the number of acquisitions and IPOs in a given ecosystem, not the transaction value behind them. This is both a limitation and an opportunity for future research. While the number of successful exit events provides a valuable proxy for wealth creation at ecosystem level, the amount of freed up capital can differ substantially between companies.

Additionally, our study considered only successful exit events. Negative exit events – i.e. the liquidation of start-ups – may also effect the development of EEs (Spigel & Vinodrai, 2021). On the one hand, a liquidated startup may release valuable resources in terms of *knowledge* and *talent* back into an EE. On the other hand, it may provide a cautionary tale that discourages nascent entrepreneurs from founding.

5.7.3 | Conclusion

This study contributes to the growing literature on entrepreneurial ecosystems and their mechanisms. It advances previous work on the recycling of financial resources in regions by analyzing a large-scale longitudinal sample of 46 European cities, as opposed case studies limited to specific ecosystems before. It thus provides first evidence that entrepreneurial recycling is prevalent across ecosystems and not an isolated phenomenon. Our empirical results support the notion that effects of downward causation shape the development of entrepreneurial ecosystems. In particular, exits by acquisitions seem to fuel the recycling of financial resources and talent, leading to more startups being founded and more business angel investments being made in subsequent years.

6 | Conclusion

> *Entrepreneurs are everywhere. You don't have to work in a garage to be in a startup. The concept of entrepreneurship includes anyone who works within my definition of a startup: a human institution designed to create new products and services under conditions of extreme uncertainty. That means entrepreneurs are everywhere.*
>
> Eric Ries, 2011, The Lean Startup (p. 17)

Each of the presented studies contributes novel insights to their respective research conversations. In this final chapter, we discuss the collective findings of this dissertation, reflect on implications for research and practice, and chart avenues for future research.

6.1 | Discussion

This dissertation advances the scientific discussion on outcomes of entrepreneurship education at university in meaningful ways. By taking an in-depth look at one successful program for university students, we show that entrepreneurship education can succeed in increasing founding rates and startup quality.

We contribute to theory by empirically confirming the prevalence of self-selection into entrepreneurship education. As recent scholars have hypothesized (Bae et al., 2014; Liñán et al., 2018), this indicates that many existing evaluation studies of entrepreneurship education likely suffer from selection bias. For researchers designing studies to evaluate entrepreneurship education, this implies that control groups need to be constructed from a population of students that is comparable to participants in their entrepreneurial predisposition (Liñán et al., 2018). We discuss how quasi-experimental study designs, using rejected applicants as control group while controlling for active selection, can be used to avoid biasing results through self-selection (D. S. Lee & Lemieux, 2010). These findings add to the ongoing scientific discussion on how to increase rigor in entrepreneurship research (Yi & Duval-Couetil, 2021).

Our main contribution is the evaluation of an experiential entrepreneurship program with regards to different entrepreneurial outcomes – i.e. selection into entrepreneurial careers, entrepreneurship rates, and startup quality – that shows that high-growth entrepreneurship can in fact be taught. The findings present are a methodological step forward compared to previous studies for three reasons. First, we evaluate actual entrepreneurial outcomes instead of changes in entrepreneurial orientation. Second, we base our analyses on a data set of high quality covering 10 years of applicants and participants. This makes it possible to observe startups with a considerable variance in age and size. Third, our quasi-experimental analysis allows us to make causal claims where previous studies only presented correlation designs and show that outcomes are a result of program participation and not a consequence of selecting "better" students. These results strengthen the evidence that small-scale entrepreneurship education programs can succeed in raising founding rates and startup quality (C. E. Eesley & Lee, 2021; Lyons & Zhang, 2017). These results contrast evaluation studies of compulsory university entrepreneurship courses (Fretschner & Lampe, 2019; Von Graevenitz et al., 2010), of entrepreneurship centers at school level (C. E. Eesley & Lee, 2021), and of MBA programs (Lerner & Malmendier, 2013). For scholars, this implies that studies should control for whether students participate in entrepreneurship education by choice or not, and that small-scale experiential programs may lead to differential outcomes compared to other forms of entrepreneurship education. It also hints at the continuing need for more evaluation studies measuring actual entrepreneurial outcomes (Nabi et al., 2017; Yi & Duval-Couetil, 2021).

We contribute multiple analyses that indicate that entrepreneurship education programs work not simply because of skill development, but because of the social capital participants accrue. These findings, while indicative, align with a recent stream of literature emphasizing social capital as an important aspect of entrepreneurship education (C. E. Eesley & Lee, 2021; Yami, M'Chirgui, Spano, & Barykina, 2021). If further confirmed, they are of high significance for scholars, educators, and policy makers alike. First, for scholars they provide a possible explanation why courses and programs may lead to differential outcomes even when the same content is taught with similar methods. Second, educators, should design programs such that there is enough room for participants to interact, network, and build meaningful relationships that last beyond the duration of the program. Third, policy makers, when setting up funding for entrepreneurship education programs, should allocate part of the budget for community building measures in addition to the core educational activities.

With our third study, we show that public funding of entrepreneurship education programs can have a positive return on investment. We show that the socioeconomic benefits created through startups of program participants far outweigh the costs of running the program after ten years, even under the most conversative assumptions. It is reasonable to assume that the socioeconomic benefits will further increase over time. Two reasons speak for this: Program participants found companies often only several years after their participation in the program at university (see Figure 6) and startups, even those that can be considered successful outliers, need several years to meaningfully grow and create jobs (see Figure 7). Thus, we can expect participants from the observed cohorts to found more startups in future years and that the founded startups will continue to create even more new jobs. These finding are relevant for municipal, regional, and national funding bodies, as most startups and jobs are created in geographical proximity to the program. Our analysis suggests that entrepreneurship education programs at university can be used as policy measure to stimulate regional economic development and job creation. By tabulating estimates of the generated additional tax returns, policy makers can weigh funding entrepreneurship education programs against alternative investments while adapting assumptions to their specific context. Or approach builds on previous attempts to quantify the socioeconomic benefits created through universities (Robbiano, 2022; Valero & Reenen, 2019; Vincett, 2010). However, to our knowledge, we are the first to apply such an estimate to a specific entrepreneurship education program and thus add valuable new insight to the research body.

Finally, our excursus investigating successful startup exits and their influence on new venture creation and business angel investment sheds light on one mechanism through which entrepreneurial ecosystems sustain themselves through reinvestment of resources. These results confirm findings from case studies and industry-specific analyses (C. M. Mason & Harrison, 2006; Stuart & Sorenson, 2003) and show that this phenomenon can be observed broadly across ecosystems. The case of the successful exit of Stylight, a startup founded by alumni of the program, further highlights the role of the social network surrounding entrepreneurship education programs in supporting new founders to start their businesses.

6.2 | Future Research

The presented studies provide robust evidence that entrepreneurship programs at university can work in increasing entrepreneurship rates and the quality of the founded startups. However, given that our analysis is based on one specific program, it is important to be careful to generalize to other contexts. While our analyses show that the program works and that social capital seems to be of particular importance, we cannot detail the specific mechanisms how the program achieves the observed outcomes. These limitations are interesting starting points for future research. In the following, we discuss several specific suggestions for future research.

6.2.1 | Variance between Entrepreneurship Education Programs

Further evaluation studies of entrepreneurship education programs would be of interest to understand the variance in entrepreneurial outcomes between programs and to improve our understanding of which configurations of program elements lead to successful program outcomes. As noted in literature, entrepreneurship education programs encompass a wide range of different target groups, program objectives, and pedagogical approaches (Henry et al., 2005; Nabi et al., 2017). Future research may look at both external conditions (e.g. entrepreneurial climate at university, surrounding entrepreneurial ecosystem) as well as internal aspects (e.g. target groups, program objectives, curriculum, duration and intensity).

Entrepreneurial Ecosystem: By focusing on a program open to students in Munich, we avoided heterogeneity regarding the entrepreneurial ecosystem within which the program is embedded in. Following the central argument of entrepreneurial ecosystem literature, it would be interesting to understand the influence of underlying ecosystem elements (Stam & Ven, 2021; Wurth et al., 2021) on outcomes that can be expected from entrepreneurship education. Munich hosts two of the best research universities (Times Higher Education, 2021) and its entrepreneurial ecosystem has developed at a fast pace over the past decade (Startup Genome, 2022). Evaluating programs in different contexts may help us understand the configurations of ecosystem pre-conditions necessary for entrepreneurship education programs to produce desired outcomes.

Target Groups and Program Objectives: The objectives of entrepreneurship education programs likely influence the produced entrepreneurial outcomes (Nabi et al., 2017). For one, programs not focusing on high-growth entrepreneurship, will likely lead to companies with less growth ambition and in turn to fewer created jobs. In addition, different program objectives will attract different groups of students and produce different types of outcomes – e.g. social entrepreneurship vs. technology entrepreneurship (Bacq, Hatog, & Hoogendoorn, 2013). Following our findings regarding self-selection and the importance of social capital, these differences at the top of the funnel may result in substantial differences in the emerging support- and alumni-networks. In our empirical context, we looked at a program for university students at the intersection of technology and management with the objective to "*connect, educate, and empower the innovators of tomorrow"*, instead of specifically creating more or better entrepreneurs. It would be interesting to explore in how far programs with a more direct focus on entrepreneurship compare. The rise of so-called "talent-investors" over the past decade (e.g. Entrepreneur First[42], Antler[43]) would provide an interesting empirical context beyond the university to do so. As these programs target individuals much closer to founding – that is they are expected to found startups with other participants during or shortly after the program – the selection of the right individuals may play a more important role. While our results show mixed results with regards to the predictive power of the interview score on the dependent variables, it would be interesting to understand whether and how entrepreneurial talent can be spotted.

[42]See https://joinef.com/ (last accessed: 2023-02-14)
[43]See https://antler.co/ (last accessed: 2023-02-14)

Program Duration and Intensity: The program we evaluated is characterized by a relatively long duration of three semesters and a high intensity (i.e. workload). On the one hand, this is due to its structural setup as an add-on study program that is completed next to the full-time undergraduate or graduate program. Internal data shows that students spend between 20 to 30 hours per week on program-related tasks (next to being enrolled in a full-time study program). One the other hand, it is driven by group dynamics and working standards developing naturally among ambitious students. We speculate to which degree the duration and intensity of education may moderate outcomes. There are two arguments why this would be plausible.

First, if effects are driven to a large part by social capital developed through program participation, it is plausible to assume that more interaction between participants improves outcomes. After all, interpersonal relationships need frequent interactions and time to develop (Hall, 2019; Marmaros & Sacerdote, 2006). A longer program duration and higher intensity consequently means that program participants spend more time meaningfully working together, have more time to form relationships, and thus build (group) social capital (Oh et al., 2004). For this to result in a positive outcome, it is likely that certain pre-conditions need to be met, e.g. social interaction, mutual trust, and shared goals (M.-H. Chen, Chang, & Hung, 2008). If this is the case, working under time pressure on difficult problems may further strengthen the relationships between participants, as "hard times make for stronger bonds" (Bastian, Jetten, & Ferris, 2014; Brower, 2021).

Second, duration and intensity could be equally relevant when it comes to entrepreneurial skill development and, more so, students' perception of whether they have the aptitude to become successful entrepreneurs. If students enter entrepreneurship education with limited or misguided information about the realities of being an entrepreneur (Fretschner & Lampe, 2019; Von Graevenitz et al., 2010) it could be that they first need to overcome a Dunning-Kruger valley (Dunning, 2011; Mazor & Fleming, 2021) during which their perceived self-efficacy, and consequently their entrepreneurial intention (Ajzen, 1991; N. F. Krueger et al., 2000), drops before eventually regaining and surpassing previous levels. Borrowing from chemistry, this can be compared to the concept of "activation energy" (Logan, 1982). It is usually necessary to first add energy to reactants to activate and start a chemical reaction. If the activation energy does not cross a certain threshold a reaction will not start, and energy already added to the system will slowly dissipate (Logan, 1982; Parrish, 2021). Similarly, for students to consider entrepreneurship as a career path a certain intensity of engagement with the topic might be necessary. If the exposure remains only on a superficial level, the "activation energy" might not cross the threshold necessary to "start the reaction".

6.2.2 | How to Build Successful Entrepreneurship Programs?

With the current literature available we cannot draw direct comparisons to other entrepreneurship education programs. However, comparing the sum of raised venture funding by alumni-founded startups against the overall funding raised by German startups over the same period suggests that the program has produced some extraordinary success (see Figure 1 and Figure 2). For practice it would be valuable to understand how to replicate this success.

Our empirical approach focused primarily on collecting data from LinkedIn and Crunchbase to avoid bias between program participants and the control group. Collecting data on program participants' perception with survey-based instruments comparable to MIT and Stanford alumni surveys (C. E. Eesley & Miller, 2018; Hsu et al., 2007), could help triangulate the results of the presented studies. For one, it would strengthen (or weaken) the causal claim that outcomes can be attributed to program participation. Furthermore, qualitative insight on how participants' careers were influenced by program participation would help untangle the mechanisms that drive the results we presented in this dissertation. One particularly interesting question is the relationship between human capital and social capital development throughout the program.

The Role of Skill Development: Our findings suggest that the observed effects are driven by social rather than human capital development. This naturally raises the question what role entrepreneurial skill development plays and how important the actual educational elements are. At the extreme, one could argue that the courses within the program only serve as a platform to bring likeminded entrepreneurial students together and engage them in meaningful problems through which the build confidence and mutual trust. In such a scenario the content or topic of the program – i.e. technology entrepreneurship education – might act only as a filter for the right students to self-select into the program.

In contrast to this argument, recent research emphasizes the value of entrepreneurial human capital for employees and companies (Alsos et al., 2022; Braunerhjelm & Lappi, 2023; Martin et al., 2013). Research also finds that entrepreneurship education increases the quality of startups being founded (C. E. Eesley & Lee, 2021; Lerner & Malmendier, 2013; Lyons & Zhang, 2017). And pre-/ post- measurements of entrepreneurship courses show that participation increases students' entrepreneurial self-efficacy (Von Graevenitz et al., 2010; Wilson et al., 2007). Future work may further investigate the role of entrepreneurial skill development during entrepreneurship education and its role on entrepreneurship outcomes. For example, by following students' university education over several semesters panel data set could help shed light on entrepreneurial skill development over time.

Understanding Typical Career Paths: Our data shows that the majority of program participants do not go on to found a startup within our timeframe of observation. We know little about the types of careers these participants choose, how they deploy their entrepreneurial human and social capital (Alsos et al., 2022), and which role they play within the alumni network surrounding entrepreneurship programs. For example, they could contribute expertise, act as connectors for startups into establish companies, or directly provide access to capital when working in venture capital. For those students who do found startups, preliminary observations on our dataset suggest that there may be different typical career pathways taken by program participants that lead up to them founding for the first time (e.g. direct after university, career entry into management consulting, career entry as a startup employee).

Following the early careers of participants of entrepreneurship education programs (see Killingberg, Kubberød, & Pettersen, 2022 for a qualitative approach following 10 students) could further improve our understanding of how those university graduates founding startups overcome the intention-behavior gap (Sheeran & Webb, 2016). Understanding typical configurations of post-university career pathways of founders would be helpful for at least two additional reasons. First, it would help explain the mechanisms behind the long-lasting effect on founding rates (see Figure 6) and shed light on the role of certain types of working experiences on later entrepreneurial activity. For example, it might be that certain "entrepreneurial careers" – e.g. working as a startup employee or at a venture capital firm – may act as a springboard to later founding. Second, better knowledge of post-university career paths leading up to entrepreneurship would be valuable to design targeted initiatives supporting those founders in starting their ventures. Set theory approaches, such as fuzzy-set qualitative comparative analysis (fsQCA) may offer promising starting points to further investigate these assumptions (Ge et al., 2022; Kraus, Ribeiro-Soriano, & Schüssler, 2018).

Social Capital and Community Building: Given the suggested importance of social capital development, it would be interesting for practitioners to understand how to design programs such that a community of engaged alumni and supporters develops around it. Future work may open this black box and address the question of how to build communities that retain graduates and alumni far beyond their point of graduation as active members. The brief analysis of survey responses from participants in Chapter 3 indicates that the program achieves this, in part, by not just focusing on career development but also by having participants develop strong social relationships and friendships among each other (see Table 19).

One promising research avenue to explore to this end, is the role of the group- and self-identity of entrepreneurs (Hogg, 2001; Mmbaga, Mathias, Williams, & Cardon, 2020; Shepherd & Patzelt, 2018) and its formation during entrepreneurship education (Donnellon, Ollila, & Middleton, 2014; Leitch & Harrison, 2016). Research suggests that group identification and workplace peers play an important role in the construction of social identity and transition to entrepreneurship (Obschonka, Goethner, Silbereisen, & Cantner, 2012). For example, outside of entrepreneurship research, membership in multiple important social groups was shown to promote positive self-identity (Jetten et al., 2015), members of teams who reported higher group cohesion performed better (Stewart, Courtright, & Barrick, 2011), and a greater sense of belonging to their alma mater was shown to correlate with higher engagement of university alumni (Drezner & Pizmony-Levy, 2021).

A deeper understanding of the social network topologies (Wasserman & Faust, 1994) of program participants would also be interesting to reason about the mechanisms through which social capital influences entrepreneurial outcomes. By modeling points of interaction between program participants and alumni during (e.g. cohorts, courses, mentors) and after (e.g. co-founder, business angel / investor, employee at startup) the program, different layers of career networks could be made visible. Understanding this topology could help shed light on how relationships originating in the program support (or impede) participants entrepreneurial careers. To investigate the role of personal relationships and friendships it would be interesting to overlay the career related social networks of participants with their personal ones.

6.2.3 | Gender Differences

Another research avenue that warrants a deeper investigation pertains to the difference in outcomes regarding male and female students. The studies presented in Chapter 2 and Chapter 3 reveal differences between genders both in terms of psychometric constructs at the point of application as well as in their career choices. In particular, the results of our second study are striking in that they show that female participants appear to not benefit from program participation with regards to most of the measured outcomes. Entrepreneurship rates among female program participants are not affected, and startup quality appears to even be affected negatively (see Table 18, Table A7, and Figure A1).

These results echo findings from literature on entrepreneurship and entrepreneurship education (Cabrera & Mauricio, 2017; Rocha & Praag, 2020; Wheadon & Duval-Couetil, 2019). While recent literature has proposed different mechanisms leading to differential outcomes between genders in entrepreneurship – e.g. stereotype threat (Gupta et al., 2014), access to investor networks (Gompers et al., 2022) – there is still little research explaining the mechanisms leading to differential outcomes in entrepreneurship education and testing interventions to overcoming potential biases. In the empirical context of this dissertation and the with regards to the results presented in our second study, there are several directions for future research.

Founding Rates: With different levels of entrepreneurial intention between genders (see Table 7) at the start of the program, we might not expect the same percentage of female and male participants to found companies after the program. However, we would expect female participants to benefit from the program to the same degree as their male counterparts. However, when looking at the change in founding rates between program participants and the control group by gender this is not the case (see Figure A1). While the percentage of founders increases among men from 20.79% to 42.37%, a change of 22.58 percentage points, the percentage of founders among women only increases from 12.85% to 16.13%, a change of 3.28 percentage points. Possible explanations for this may include a lack of role-models (Bechthold & Huber, 2018) in a male dominated environment that in turn may reinforce a perceived "lack of fit" for a career as startup founder among female participants (Gupta et al., 2014). Potential homophily bias (Ruef, Aldrich, & Carter, 2003) among participants, i.e. a tendency of program participants' to select co-founders from the same gender, may further affect the chances of female participants to attract co-founders among a pool of largely male peers and hamper their chances of founding.

Startup Quality: As for the observed changes in startup quality between genders, the driving mechanisms might be found both within and outside of the entrepreneurship education program. Given that much of the program effect is driven by program participants starting companies together (see Table 18), a homophily bias may also affect startup quality if female program participants are left with no option than founding themselves or access to the network of alumni and supporters is restricted. Potential external factors, such as gender bias within the venture capitals industry (Ewens & Townsend, 2020; Gompers et al., 2022), may further exacerbate the difference between genders. These mechanisms may explain differential effects on program participants by gender. However, they do not explain why startups founded by female participants are of lower quality compared to female founders from the control group (see Figure A1). Given the small sample size – only 38 female founders are in our sample and of those only 20 are program participants – it is important to not jump to conclusions. Nonetheless, a deeper look into the career paths of between female and male participants would be helpful to shine light on these differences. It might be that the most qualified female participants choose to different career paths which would have not been accessible without program participation or that differences are driven by variance in industries within which startups are founded. These questions may be addressed by future research with different approaches. Qualitative methods (e.g. interviews, alumni surveys) may help in understanding the empirical context, quantitative methods (e.g. measurement of network centrality, analysis of career paths) may make differences in first-order outcomes visible, experimental approaches may help to understand the prevalence and causal effects of potential biases (e.g. homophily in co-founder choice), and, finally, the active design and evaluation of interventions may bring forwards ways to overcome gender biases.

Gaining a deeper understanding of gender differences in entrepreneurship education would be valuable for research and practice alike to address potential bias, design better entrepreneurship education, and foster equal opportunities.

6.3 | Concluding Remarks

The studies presented in this dissertation contribute new insights to the longstanding question of "*How can entrepreneurship be taught?*". Our quasi-experimental approach provides robust evidence that entrepreneurship education at university can successfully act as a catalyst and enable students and graduates to start their own ventures and increase the quality of their companies. The tax revenue generated through created jobs more than covers the costs for running the program, showing that investments into entrepreneurship education programs can be an effective policy measure for regional economic development.

Here's to the crazy ones. The misfits. The rebels. The troublemakers. The round pegs in the square holes. The ones who see things differently. They're not fond of rules. And they have no respect for the status quo. You can quote them, disagree with them, glorify or vilify them. But the only thing you can't do is ignore them. Because they change things. They push the human race forward. And while some may see them as the crazy ones, we see genius. Because the people who are crazy enough to think they can change the world, are the ones who do.

Steve Jobs, Apple, 1997
(Think Different Commercial)

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8 | List of Figures

9 | List of Tables

10 | Appendix

A1 | Survey Instrument

Table A1: Survey Instrument

ITEM	TYPE	ADAPTED FROM
	Demographics	
Please enter your **age** in years.	NUMBER	–
Please enter your **gender**.	[m,f,d]	–
Please enter your **highest completed education**.	[High School, Bachelor, Master]	–
Please enter your **nationality**.	TEXT	–
Does either of your **parents** have a **university degree?**	[Both, One, No]	–
What **faculty** are you enrolled in?	TEXT	–
Total **number of semester** you studied at university level (including all previous degrees).	NUMBER	–
Entrepreneurial Intention		
Indicate your level of agreement with the following statements from 1 (Totally Disagree) to 5 (Totally Agree).		
My professional goal is becoming an entrepreneur …	LIKERT	(Liñán & Chen, 2009)
I have very seriously thought of starting a firm …	LIKERT	(Liñán & Chen, 2009)
I intend to start a business within the next 5 years …	LIKERT	(Liñán & Chen, 2009)
Entrepreneurial Exposure		
Please answer the questions regarding your exposure to the following six types of entrepreneurial experience (Yes/No):		
Have your parents ever started or owned a business?	[Yes, No]	(N. Krueger, 1993; Von Graevenitz et al., 2010)
Have your friends ever started or owned a business?	[Yes, No]	(N. Krueger, 1993; Von Graevenitz et al., 2010)
Has anyone else from your social circle ever started or owned a business?	[Yes, No]	(N. Krueger, 1993; Von Graevenitz et al., 2010)
Have you ever worked for a startup?	[Yes, No]	(N. Krueger, 1993; Von Graevenitz et al., 2010)
Have you ever founded/started a company yourself?	[Yes, No]	(N. Krueger, 1993; Von Graevenitz et al., 2010)
Have you been enrolled in an entrepreneurship course at your university?	[Yes, No]	(N. Krueger, 1993; Von Graevenitz et al., 2010)
Prior Entrepreneurship Education		
Have you ever founded/started a company yourself?	NUMBER	–
Indicate your level of agreement with the following statements from 1 (Totally Disagree) to 5 (Totally Agree) and non-applicable.		
I had a **positive experience** with past entrepreneurship courses	LIKERT	–
In previous entrepreneurship courses I **learned a lot**	LIKERT	–
Attending entrepreneurship courses **was inspiring** for me	LIKERT	–
I **met interesting people** in entrepreneurship courses	LIKERT	–

Notes: All items measured on Likert scales were measured with a 5-point Likert scale.

Table A1: Survey Instrument (continued)

ITEM	TYPE	ADAPTED FROM
	(continued)	
	Attitudes Toward Entrepreneurship (ATE)	
Indicate your level of agreement with the following statements from 1 (Totally Disagree) to 5 (Totally Agree).		
Being an entrepreneur implies more advantages than disadvantages to me	LIKERT	(Liñán & Chen, 2009)
A career as entrepreneur is attractive for me	LIKERT	(Liñán & Chen, 2009)
If I had the opportunity and resources, I'd like to start a firm	LIKERT	(Liñán & Chen, 2009)
Being an entrepreneur would entail great satisfactions for me	LIKERT	(Liñán & Chen, 2009)
Among various options, I would rather be an entrepreneur	LIKERT	(Liñán & Chen, 2009)
Entrepreneurial Self-Efficacy (ESE)		
Indicate how much confidence you have in your ability to... from 1 (Very Low Confidence) to 5 (Very High Confidence)		
... identify new business opportunities	LIKERT	(Zhao et al., 2005)
... create new products	LIKERT	(Zhao et al., 2005)
... think creatively	LIKERT	(Zhao et al., 2005)
... commercialize an idea or new development	LIKERT	(Zhao et al., 2005)
Need for Achievement		
At university settings and at work, I... from 1 (Totally Disagree) to 5 (Totally Agree)		
... do my best when my task assignments are quite difficult	LIKERT	(Steers & Braunstein, 1976)
... try very hard to improve on my past performance	LIKERT	(Steers & Braunstein, 1976)
... take risks to get ahead	LIKERT	(Steers & Braunstein, 1976)
... try to avoid any added responsibilities [R]	LIKERT	(Steers & Braunstein, 1976)
... try to perform better than my fellow students & co-workers	LIKERT	(Steers & Braunstein, 1976)
Innovativeness		
Please indicate your level of agreement with the following statements from 1 (Totally Disagree) to 5 (Totally Agree).		
I often surprise people with my novel ideas	LIKERT	(Paunonen & Jackson, 1996)
People often ask me for help in creative activities	LIKERT	(Paunonen & Jackson, 1996)
I obtain more satisfaction from mastering a skill than from coming up with a new idea [R]	LIKERT	(Paunonen & Jackson, 1996)
I prefer work that requires original thinking	LIKERT	(Paunonen & Jackson, 1996)
I usually continue doing a new job in exactly the way it was taught to me [R]	LIKERT	(Paunonen & Jackson, 1996)
I like a job which demands skill and practice rather than inventiveness [R]	LIKERT	(Paunonen & Jackson, 1996)
I am not a very creative person [R]	LIKERT	(Paunonen & Jackson, 1996)
I like to experiment with various ways of doing the same thing	LIKERT	(Paunonen & Jackson, 1996)

Notes: All items measured on Likert scales were measured with a 5-point Likert scale.

Table A1: Survey Instrument (continued)

ITEM	TYPE	ADAPTED FROM
	(continued)	
	Locus of Control	
Please indicate your level of agreement with the following statements from 1 (Totally Disagree) to 5 (Totally Agree).		
If I work hard, I will succeed [ILOC]	LIKERT	(Kovaleva, 2012)
I'm my own boss [ILOC]	LIKERT	(Kovaleva, 2012)
Whether at work or in my private life: What I do is mainly determined by others [ELOC]	LIKERT	(Kovaleva, 2012)
Fate often gets in the way of my plans [ELOC]	LIKERT	(Kovaleva, 2012)
BIG Five		
I see myself as someone who... from 1 (Totally Disagree) to 5 (Totally Agree)		
... is reserved [E] [R]	LIKERT	(Rammstedt et al., 2013)
... is generally trusting [A]	LIKERT	(Rammstedt et al., 2013)
... tends to be lazy [C] [R]	LIKERT	(Rammstedt et al., 2013)
... is relaxed, handles stress well [N] [R]	LIKERT	(Rammstedt et al., 2013)
... has few artistic interests [O] [R]	LIKERT	(Rammstedt et al., 2013)
... is outgoing, sociable [E]	LIKERT	(Rammstedt et al., 2013)
... tends to blame others [A] [R]	LIKERT	(Rammstedt et al., 2013)
... does a thorough/careful job [C]	LIKERT	(Rammstedt et al., 2013)
... gets nervous easily [N]	LIKERT	(Rammstedt et al., 2013)
... has an active imagination [O]	LIKERT	(Rammstedt et al., 2013)
Risk Taking Propensity		
Please indicate your level of agreement with the following statements from 1 (Totally Disagree) to 5 (Totally Agree).		
Taking risks makes life more fun	LIKERT	(D. C. Zhang et al., 2019)
My friends would say that I'm a risk taker	LIKERT	(D. C. Zhang et al., 2019)
I enjoy taking risks in most aspects of my life	LIKERT	(D. C. Zhang et al., 2019)
I would take a risk even if it meant I might get hurt	LIKERT	(D. C. Zhang et al., 2019)
Taking risks is an important part of my life	LIKERT	(D. C. Zhang et al., 2019)
I commonly make risky decisions	LIKERT	(D. C. Zhang et al., 2019)
I am a believer of taking chances	LIKERT	(D. C. Zhang et al., 2019)
I am attracted, rather than scared, by risk	LIKERT	(D. C. Zhang et al., 2019)

Notes: All items measured on Likert scales were measured with a 5-point Likert scale.

A2 | Secondary Analyses

Table A2: Summary Statistics (excluding applicants who participated in other EE programs)

	Full Sample		Program participants		Almost accepted		Difference	
	Obs.	Mean	Obs.	Mean	Obs.	Mean	Diff.	t-stat.
Panel A: Applicant characteristics								
GPA	943	0.83	455	0.84	488	0.83	0.02	1.94**
Age	989	24.20	478	23.81	511	24.56	-0.75	-5.98***
International	989	0.33	478	0.29	511	0.38	-0.09	-2.91***
Business major	989	0.33	478	0.34	511	0.33	0.01	0.41
CS/EE major	989	0.42	478	0.43	511	0.41	0.02	0.51
Female	989	0.26	478	0.26	511	0.26	-0.00	-0.03
Application year	989	2015.62	478	2015.66	511	2015.57	0.09	0.50
Graduate student	989	0.65	478	0.62	511	0.68	-0.06	-1.91*
Founded startup pre-application	989	0.06	478	0.08	511	0.05	0.03	2.01**
Panel B: Career outcomes								
Entrepreneurial career post-application	989	0.45	478	0.60	511	0.32	0.28	9.03***
Founded startup post-application	989	0.26	478	0.36	511	0.16	0.19	7.04***
Startup survival	254	0.49	170	0.56	84	0.35	0.21	3.26***
Startup raised any funding	254	0.55	170	0.63	84	0.38	0.25	3.84***
Startup total funding ($ m)	254	28.79	170	41.07	84	3.96	37.11	2.27**
Startup employees	254	67.63	170	94.44	84	13.37	81.07	2.58***
Startup raised > 10m funding	254	0.15	170	0.21	84	0.04	0.18	3.75***
Startup raised > 20m funding	254	0.10	170	0.14	84	0.04	0.10	2.48***
Startup has > 10 employees	254	0.40	170	0.49	84	0.21	0.28	4.43***
Startup has > 20 employees	254	0.31	170	0.38	84	0.15	0.23	3.79***

Notes: Interview score and GPA scaled between 0 (worst) and 1 (best). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Pre-Existing differences between applicants above and below capacity threshold (excluding applicants who participated in other EE programs)

	Mean difference between applicants ranking above and below capacity threshold		
	Full sample	[-15; +15 applicants around cutoff]	[-10; +10 applicants around cutoff]
	(1)	(2)	(3)
Panel A: Characteristics at application			
GPA	0.02**	0.00	-0.03*
	(2.41)	(0.06)	(-1.89)
Age	-0.64***	-0.35**	-0.16
	(-5.07)	(-2.28)	(-0.84)
International	-0.08***	0.03	0.04
	(-2.64)	(0.77)	(0.87)
Business major	-0.01	-0.05	-0.02
	(-0.27)	(-1.29)	(-0.31)
CS/EE major	0.04	0.06	0.03
	(1.15)	(1.34)	(0.55)
Female	-0.05*	0.00	0.03
	(-1.93)	(0.02)	(0.67)
Application year	0.03	0.12	0.13
	(0.18)	(0.48)	(0.42)
Graduate student	-0.07**	-0.11***	-0.11**
	(-2.41)	(-2.68)	(-2.23)
Founded startup pre-application	0.02	-0.02	-0.03
	(1.55)	(-0.84)	(-1.00)
Panel B: Likelihood to get into program			
Program participant	0.81***	0.70***	0.62***
	(42.79)	(22.26)	(14.78)
Observations	989	530	350

Notes: T-scores in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A4: Program participation and election into an entrepreneurial career (excluding applicants who participated in other EE programs)

Dependent variable:	Entrepreneurial Career?			
	OLS (full sample)	OLS [-15; +15 applicants around cutoff]	OLS [-10; +10 applicants around cutoff]	RDD estimate
	(1)	(2)	(3)	(4)
	Panel A: Base regression			
Program participant	0.275***	0.295***	0.257***	0.235**
	(6.41)	(6.05)	(4.48)	(2.47)
Observations	989	530	350	989
R-squared	0.076	0.087	0.066	0.075
	Panel B: With controls			
Program participant	0.274***	0.322***	0.272***	0.306***
	(6.14)	(7.01)	(4.96)	(2.99)
GPA	-0.389***	-0.391**	-0.412*	-0.377***
	(-2.94)	(-2.40)	(-2.06)	(-2.95)
Age	-0.004	0.014	0.016	-0.005
	(-0.47)	(1.04)	(1.19)	(-0.56)
International	-0.015	0.042	0.027	-0.019
	(-0.42)	(0.75)	(0.41)	(-0.58)
Business major	0.039	-0.001	0.006	0.039
	(0.93)	(-0.03)	(0.11)	(0.97)
CS/EE major	-0.045	-0.026	-0.011	-0.044
	(-1.24)	(-0.49)	(-0.18)	(-1.24)
Female	-0.128***	-0.113***	-0.095**	-0.133***
	(-5.20)	(-3.25)	(-2.11)	(-5.29)
Graduate student	0.138***	0.056	0.022	0.139***
	(3.14)	(1.08)	(0.45)	(3.26)
Founded startup pre-application	0.186***	0.207**	0.166*	0.190***
	(2.99)	(2.46)	(1.76)	(3.16)
Application year fixed effects	Yes	Yes	Yes	Yes
Observations	943	504	333	943
R-squared	0.178	0.194	0.169	0.179

Notes: T-scores in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A5: Program participation and startup founding rates (excluding applicants who participated in other EE programs)

Dependent variable:	Startup founded post?			
	OLS (full sample)	OLS [-15; +15 applicants around cutoff]	OLS [-10; +10 applicants around cutoff]	RDD estimate
	(1)	(2)	(3)	(4)
	Panel A: Base regression			
Program participant	0.191***	0.206***	0.169***	0.267***
	(4.56)	(3.94)	(2.89)	(2.73)
Observations	989	530	350	989
R-squared	0.048	0.053	0.036	0.044
	Panel B: With controls			
Program participant	0.187***	0.220***	0.186**	0.321***
	(4.53)	(4.01)	(2.82)	(2.91)
GPA	-0.217*	-0.248	-0.359	-0.200*
	(-1.93)	(-1.48)	(-1.69)	(-1.87)
Age	-0.003	0.008	0.024**	-0.002
	(-0.49)	(0.91)	(2.29)	(-0.33)
International	-0.041*	-0.018	0.006	-0.046**
	(-2.00)	(-0.48)	(0.12)	(-2.21)
Business major	0.063*	0.030	0.110*	0.062*
	(1.80)	(0.53)	(2.04)	(1.75)
CS/EE major	0.017	0.002	0.068	0.017
	(0.68)	(0.04)	(1.42)	(0.63)
Female	-0.122***	-0.147***	-0.165**	-0.133***
	(-4.22)	(-3.27)	(-2.72)	(-4.53)
Graduate student	0.077**	0.006	-0.000	0.079***
	(2.65)	(0.12)	(-0.01)	(2.75)
Founded startup pre-application	0.177**	0.196*	0.185	0.178**
	(2.35)	(1.74)	(1.60)	(2.35)
Application year fixed effects	Yes	Yes	Yes	Yes
Observations	943	504	333	943
R-squared	0.149	0.197	0.195	0.142

Notes: T-scores in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Program participation and startup success indicators (without controls, excluding applicants who participated in other EE programs)

	OLS (full sample)	OLS [-15; +15 applicants around cutoff]	OLS [-10; +10 applicants around cutoff]	RDD estimate
	(1)	(2)	(3)	(4)
	Startup survival			
Program participant	0.214***	0.203*	0.142	0.052
	(3.73)	(2.07)	(1.12)	(0.23)
	Startup raised any funding			
Program participant	0.248***	0.210*	0.215*	0.270
	(3.53)	(1.95)	(1.81)	(1.06)
	LN Startup total funding ($ m)			
Program participant	3.393***	3.802**	4.084**	3.760
	(3.16)	(2.74)	(2.86)	(1.21)
	LN Startup employees			
Program participant	1.146***	1.184***	1.017*	0.924
	(3.97)	(3.09)	(1.99)	(1.08)
	Startup raised > 10m funding			
Program participant	0.176***	0.202***	0.194**	0.169
	(3.53)	(3.56)	(2.77)	(0.96)
	Startup raised > 20m funding			
Program participant	0.100**	0.107**	0.088	-0.018
	(2.16)	(2.11)	(1.53)	(-0.12)
	Startup has > 10 employees			
Program participant	0.280***	0.313***	0.248*	0.484*
	(3.81)	(3.16)	(1.93)	(1.87)
	Startup has > 20 employees			
Program participant	0.228***	0.252***	0.224*	0.344
	(3.25)	(3.04)	(2.09)	(1.48)
Observations	254	143	96	254

Notes: T-scores in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A7: Heterogeneity and Interaction Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables:	Entrepreneurial career post-application	Founded startup post-application	Startup survival	Startup raised any funding	LN Startup total funding ($ m)	LN Startup employees	Startup raised > 10m funding	Startup has > 10 employees
	Panel A: Program effect by course performance							
Program participant	0.254***	0.156**	0.171*	0.279**	3.957**	0.970**	0.152**	0.201*
	(5.69)	(2.85)	(1.93)	(2.85)	(2.75)	(2.27)	(2.25)	(2.07)
Program participant X top 50% by program grade	0.008	0.016	0.022	-0.061	-1.694	-0.098	-0.050	0.060
	(0.16)	(0.39)	(0.23)	(-0.62)	(-1.39)	(-0.26)	(-0.78)	(0.62)
	Panel B: Program effect by gender							
Program participant	0.279***	0.208***	0.243***	0.306***	4.069***	1.236***	0.169***	0.322***
	(6.12)	(4.19)	(3.11)	(3.79)	(2.97)	(3.73)	(3.02)	(4.16)
Program participant X female	-0.081	-0.167**	-0.416**	-0.413*	-7.091**	-2.187***	-0.299**	-0.610***
	(-1.17)	(-2.29)	(-2.42)	(-1.82)	(-2.45)	(-3.68)	(-2.78)	(-3.83)
	Panel C: Program effect by co-founder choice							
Program participant	0.192***	0.028	0.031	0.100	1.119	0.228	0.046	0.071
	(3.94)	(0.65)	(0.40)	(1.15)	(0.74)	(0.72)	(0.98)	(0.97)
Program participant X co-founded with other program participant	0.360***	0.753***	0.294***	0.283***	3.726**	1.339***	0.153**	0.316***
	(6.43)	(15.30)	(3.32)	(3.22)	(2.56)	(4.14)	(2.58)	(3.65)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Application year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	975	975	252	252	252	252	252	252

Notes: This table reports estimates from regressions that examine the differential program effect by course performance, gender, and choice of co-founder by including interactions between program participation and the respective variables. All models include control variables for applicant characteristics at application (same as Table 13, Panel B) and application year fixed effects. * p < 0.1, ** p < 0.05, *** p < 0.01.

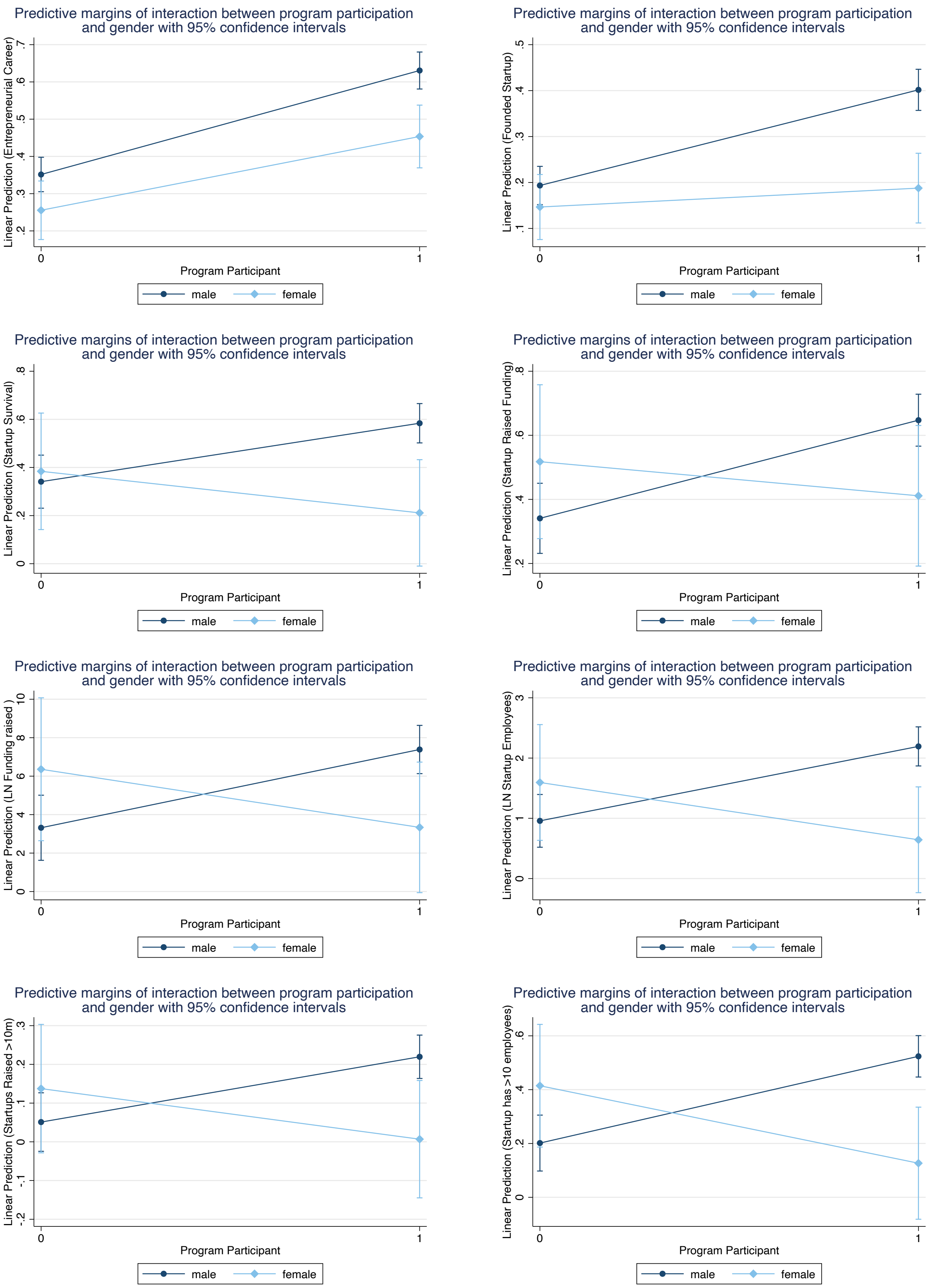

Figure A1: Predictive Margin Plots of the Interaction Between Program Participation and Gender

Notes: It is important to interpret the margin plots relating to startup quality with caution. The number of female founders in our sample amounts to only 38 individuals (20 program participants, 18 control group). Among those only 5 in each group have founded startups that are active or acquired and have any employees. Those active startups founded by female program participants employee on average 46.4 people, startups founded by women in the control group on average 63.4. Those startups that raised funding, raised on average USD 4.4mn (program participants) and USD 6.9mn (control group). Overall, these outcomes are of comparable magnitude. With only 5 observations per group these results are not fit to draw reliable conclusions from.