New sources of entrepreneurial finance

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A thesis submitted for the degree of

Doctor of Philosophy (Ph.D.) in Finance

Essex Business School

University of Essex

October 2023

Abstract

Small, young firms often face significant challenges in accessing external equity finance – the equity gap – to scale up and fuel their growth. The three papers of this PhD thesis investigate different aspects of new forms of entrepreneurial finance – equity crowdfunding (ECF) and angel platforms where firms raise funds digitally – in addressing this gap in both normal times and during the COVID-19 crisis. The first main paper (Chapter 2) analyses the gender structure of equity crowdfunding (ECF) initial campaigns on the Crowdcube platform and finds that female entrepreneurs are simultaneously less and more successful than their male counterparts. They are less successful in that they are underrepresented in ECF campaigns and that all female (Solo female and Female team) entrepreneurs run just one in seven (14.5%) successful ECF campaigns. However, the results also reveal that solo female entrepreneurs running ECF campaigns are more successful than their male counterparts in ECF outcomes. This signifies the democratizing role of equity crowdfunding in facilitating access to equity capital for female founders and reducing the gender bias documented in early-stage finance via traditional sources. However, it does not address the issue of the underrepresentation of female founders in ECF initial campaigns. The second paper (Chapter 3) examines the access of small firms to equity through ECF platforms during the COVID-19 pandemic. Contrary to expectations, initial equity crowdfunding (ECF) campaigns not only survived but thrived during COVID-19, demonstrating significant growth in funding volume, investor participation, and overfunding rates. This indicates a paradigm shift where external equity, traditionally funding of last resort, became the preferred option. This paper demonstrates that government-backed loan guarantees acted as a liquidity certification for ECF campaigns, particularly benefiting seed ventures, highlighting ECF's role as a digital lifeline. It also underscores the positive interaction between public support mechanisms and private equity, supporting the notion of a reverse pecking order where equity is the funding of choice. These findings emphasize ECF crucial role in providing equity capital to small firms during periods of economic uncertainty. The third main paper (Chapter 4) analyses the modus operandi of the Angels@Essex (A@E) platform as a locale-specific channel for investment by contributing to the advancement of the University Enterprise Zone (UEZ). Business angels are known as patient capital, serving as primary sources of seed capital and providing services that extend beyond financial measures. Angels@Essex, as part of the UEZ, has an additional motivation to support an innovative startup ecosystem. The results indicate that Angels@Essex has mainly invested in younger startups highlighting the positive impact of an angel platform within an UEZ. Moreover, although online digital platforms tend to mitigate geographical barriers, the majority of successful firms originate from Essex County. Finally, the analysis reveals a significant certification effect for prior funding from diverse financial sources including Innovate UK.

Acknowledgements

I want to extend my sincere thanks to my supervisors, Professor Jerry Coakley and Dr. Jose Linares Zegarra, whose extensive knowledge and patient guidance played a pivotal role in making this achievement possible. Their unwavering support has smoothed my learning journey and I'm profoundly appreciative of their support.

I'd also like to express my deep gratitude to my family and friends for their constant encouragement, which has consistently inspired and motivated me.

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Chapter 1
Introduction

This thesis comprises three essays on entrepreneurial finance each of which investigates a different topic on new sources of equity funding and their accessibility to nascent businesses. The topics analysed in the three substantive chapters are chosen because they are innovative within the entrepreneurial finance domain, and each has practical implications that are relevant to policy discussions.

Small young firms play a pivotal role in the economy and investment in these, which differs from that in more established firms, plays a crucial role in the evolution of the entrepreneurship ecosystem. However, despite their significance, small firms often encounter challenges in accessing external equity for their growth and development (Harrison et al., 2016, Fraser et al., 2015, Cowling et al., 2015). Various factors contribute to the difficulties encountered by entrepreneurs when trying to secure external equity capital and information asymmetry is a significant factor among these. This asymmetry can result in increased costs related to assessing the quality of and related risks of smaller firms, ultimately reducing the availability of external funds for these fledgling ventures (Fraser et al., 2015, Coakley and Lazos, 2021, Farag and Johan, 2021). This highlights the crucial, role of early-stage investors with expertise in supporting small firms to bridge the gap. Fortunately, new entrants to the entrepreneurial finance landscape are emerging, potentially lowering the barriers to accessing finance. This thesis focuses on two of the most recent financial innovations, specifically equity crowdfunding (ECF) and angel platforms.

ECF has now established itself emerging as a significant source of external funding for early-stage unlisted firms, gaining increasing prominence in the field of entrepreneurial finance. Researchers and policymakers are showing greater interest in ECF because it is a novel and disruptive financing method with the potential to reduce barriers to entry and more generally to democratize the provision of equity finance (Cumming et al., 2021a, Coakley and Lazos, 2021, Cumming et al., 2020). The rise of ECF has been enabled by online platforms operating as multi-sided markets that provide transparent systems to enable both individual and experienced investors to finance early-stage ventures (Mollick, 2013, Vismara, 2016, Cumming et al., 2020, Coakley et al., 2021a).

The first paper (Chapter 2) of this thesis examines the democratizing effects of ECF by analyzing its gender-related impact on equity funding outcomes. It addresses the pronounced challenges faced by female founders in securing external equity capital, often referred to as the gender gap. This issue holds significant importance, as highlighted by Rose (2019) and Rose (2023), who stress that capital raising is identified as the most critical barrier faced by female entrepreneurs. Addressing this issue has the potential to contribute around £250 billion in new value to the UK economy.

The existing literature has highlighted a well-established gender-driven disparity in capital-raising outcomes within traditional financing sources, with female entrepreneurs achieving less success compared to their male counterparts (Guzman and Kacperczyk, 2019, Dutta and Mallick, 2022, Alesina et al., 2013). However, ECF investors comprise a diverse range of individuals and other players including less-experienced investors - often referred to as the "crowd" - as well as established figures from traditional investment circles such as Business Angels (BA) and Venture Capitalists (VC) and new players such as family offices and regional developments agencies. Importantly, the risk profiles and motivations of ECF investors differ from those of both the crowd in reward-based crowdfunding and traditional investors (Coakley and Lazos, 2021, Coakley et al., 2021b). ECF has the potential to democratize this aspect of entrepreneurial finance by introducing a blend of crowd and traditional investors, thereby potentially influencing the proportion of investment directed toward female-led ventures. This is because the crowd's less biased perceptions of female founders differ from those of traditional investors who typically exhibited more traditional preferences (Bapna and Ganco, 2021).

The first paper makes several contributions to the existing literature. It utilises a comprehensive ECF sample to assess potential gender effects. This sample encompasses 524 initial campaigns on Crowdcube, from its inception in 2011 up until May 2018 during which time ECF has both expanded its funding scope and evolved its operational models. The second contribution lies in its consideration of the founder team structure when examining gender effects. The composition of founder teams can differ based on the number and gender of team members, potentially influencing the human capital signals they convey. The comparison between solo founders and founder teams has been explored by Coakley et al. (2022b), indicating that teams tend to outperform solo entrepreneurs across the three major UK ECF platforms.

This paper utilises the unique feature of our dataset of being comprised of mainly solo founders (more than 60%) and compares the performance of these founders with their male peers to provide a cleaner and less contaminated (by team structure) comparison. This distinctive feature facilitates a comparison of the performance of these solo founders with their male counterparts, providing a more focused comparison that is not influenced by team structure. Further, this paper contributes to the existing literature on gender effects (Kleinert and Mochkabadi, 2021, Hellmann et al., 2021b, Lin and Pursiainen, 2022, Prokop and Wang, 2021) by taking into account the goal setting behaviour of female founders. This suggests that female founders may receive less because they ask for less (Cumming et al., 2021a) or male founders are less successful because of their overestimation (Lin and Pursiainen, 2022) in initial ECF campaigns which becomes more realistic in follow-on rounds. The primary descriptive statistics for solo founders indicate that there is no significant difference between solo female and male founders in terms of their target setting. This highlights the importance of our main contribution of distinguishing between solo versus teams and various gender compositions.

The Heckman selection model is employed to address the potential selection bias arising from the focus on solo founders relative to founder teams. This study employs two approaches in studying gender effects for robustness purposes. In the first, a categorical variable is integrated into the model, allowing for the inclusion of the entire sample when comparing solo female and male founders. The second robustness method involves the use of the propensity score matching (PSM) technique. With the latter approach, a comparison between solo female founders and their male counterparts is conducted by matching firms based on education, founders' average age, pre-money valuation, the percentage of offered equity, and the funding goal (£m).

Our findings indicate that solo female founders are simultaneously more and less successful than their male counterparts in certain aspects. They are successful in raising higher amounts, attracting more investors, and achieving a higher funding ratio and are more likely to exceed their funding targets. However, they are underrepresented in campaigns, with more than 75% of campaigns having no female founder. These results build upon the work of Hellmann et al. (2021b) by using a more comprehensive dataset and conducting a clear comparison between solo female and male founders using the unique feature of a dataset that comprises mainly solo founders. Additionally, it aligns with the recommendations of the Rose review (2019) to examine in more detail the female founders' access to sources of finance and in particular digital sources such as equity crowdfunding (ECF). Like all studies, this paper has its limitations. Summary statistics indicate that all-female founder teams, which constitute only 2.29% of our sample of 524 campaigns, attract the least capital and fewest funders. This calls for further investigation, as the overall team effect (human capital) appears to differ when male and female teams are analyzed separately.

The second paper (Chapter 3) explores the impact of the COVID-19 pandemic on ECF and assesses how resilient ECF was both during and in the wake of the pandemic. Even though ECF platforms represents a novel means for small firms accessing external equity, its role in facilitating capital-raising for young firms during periods of heightened uncertainty such as that induced by COVID-19 has not been explored. Indeed, COVID-19was the first major exogenous shock (Brexit was less impactful) faced by ECF platforms and the outcomes were unpredictable. This is particularly important because small ventures are especially vulnerable to external crises, such as COVID-19, that can significantly disrupt markets and impact their operations. (Eggers, 2020). COVID-19 was different from other crises as it affected firms' human capital and demand for their goods and services as well as the overall economy (Calabrese et al., 2022, Puthusserry et al., 2022). In addition, the distinctive attributes of smaller firms have made it challenging to predict how startups would respond to the pandemic as, in principle, they are more agile than bigger firms but have potentially less resilient business model (Eggers, 2020).

The key contribution of this chapter is its in-depth investigation of startup performance on ECF platforms around the COVID-19 period. Only a handful of studies has specifically explored the impact of Covid on ECF firm performance (Cumming et al., 2021b, Cumming and Reardon, 2022, Vu and Christian, 2023). This paper stands out from existing research in several ways. First, it encompasses three distinct periods, pre-, during COVID-19, and post- COVID-19. To our knowledge, it is the first study to analyse the full COVID-19 period and the post-COVID-19period effects on ECF firms. The samples in extant studies include data only for part of the COVID-19period (Cumming et al., 2021b, Cumming and Reardon, 2022, Vu and Christian, 2023) and none for the post- COVID-19 period. Second, it establishes a crucial link between the take up of government support programs like the Bounce Back Loan Scheme (BBLS) and the Coronavirus Business Interruption Loan Scheme (CBILS) and startup demand for outside equity. Young venture take up of the government loan schemes resulted in increased gearing ratios leaving them severely under-capitalised and in need of outside equity. By a happy coincidence, ECF platforms were willing to supply the necessary equity as the government guarantees reduced venture risk (increased their credit ratings) for firms with loan guarantees. This implies that government loan schemes, initially aimed at smaller firms, indirectly facilitated their survival and success in raising equity from ECF platforms.

The paper's final contribution is that its analysis of the COVID-19disaster and accessibility to alternative finance sources for small firms differs from other natural disasters examined in the literature (Baltas et al., 2022). COVID-19 is unique in that it exerted a widespread impact on all firms in the economy. Therefore, identification methods based on finding similar unaffected counterparts cannot be applied. The paper resolves this issue by treating COVID-19 as an exogenous shock, allowing the coefficients of the main explanatory variable (the COVID-19 categorical variable representing the three periods of pre, Covid, and post) to be considered as the Average Treatment Effect (Baltas et al., 2022). However, several robustness tests are performed.

The findings from this chapter indicate that the amount raised on ECF platforms remained unaffected during the pandemic. Surprisingly, campaigns attracted more investors which is partly because COVID-19 restrictions made face-to-face due diligence problematic and online investment became a convenient alternative (Agrawal et al., 2016, Cumming et al., 2021a). There was a surge in the number of seed stage firms in ECF campaigns which led to the highest funding ratio of campaigns during COVID-19. This overperformance can be explained by UK government swift and unparalleled support/loan schemes targeted at smaller firms. This paper contributed to literature in several aspects. It complements the works of Cumming et al. (2021b) and Vu and Christian (2023) by using a sample that includes the whole COVID-19 and post-COVID-19 periods with comparable numbers of campaigns making an evaluation of the Covid period possible. It addresses the research question offered by Brown et al. (2020) and establishes that ECF as an alternative source of finance is resilient to external shocks.

Furthermore, there was a surge in the number of seed-stage firms running ECF campaigns during the pandemic. These campaigns also exhibited the highest funding ratio during the full period. This overperformance has been examined by both comparing the performance of seed firms with more established firms and also with their counterparts from non- COVID-19 period employing various empirical methods. The success of seed firms can be explained by the swift and unparalleled support and loan schemes from the UK government (BBLS and CBILS), which were primarily targeted at smaller firms and were offered at the first year of COVID-19. The findings of this paper suggest that ECF indeed remained resilient during the COVID-19 pandemic, providing valuable insights into its role in entrepreneurial finance during times of crisis. This study has limitations. Primarily, the dataset is confined to Crowdcube, one of the two major UK ECF platforms. Nevertheless, Crowdcube's status as the longest-established platform in the UK lends credibility to the generalizability of our findings. Additionally, although more than 90% of SMEs relied on government guarantee schemes to secure debt during the first year of the pandemic (Calabrese et al., 2022), the UK government's policy of withholding the identities of recipients of state-backed COVID-19 loans prevents a direct linkage between our ECF dataset and the COVID-19 loan data

The third paper (Chapter 4) focuses on Angel platforms and investigates the dual role of Angels@Essex (A@E) platform within University Enterprise Zone (UEZ). Angel investors, often referred to as business angels, are individuals with substantial net worth who employ their personal capital to invest in newly established privately-owned businesses that are typically beyond their immediate family and social networks (Harrison et al., 2016, Bonnet and Wirtz, 2012, Mason and Botelho, 2016, Wilson, 2011). The equity gap, which arises when internal sources of funding are depleted and limited collateral restricts external debt options for young entrepreneurs, has drawn the attention of policymakers. Business angels, as the traditional primary contributors of seed capital, play a crucial role in addressing this issue. BA typically possess entrepreneurial experience and in-depth industry knowledge, allowing them to offer both financial and non-financial support to firms (Fiet, 1995, Kelly and Hay, 2003, Lindsay, 2004, Harrison et al., 2016, Wilson, 2011). BA actively engage with their investments, mentoring the funders and helping firms expand their social and human capital (Politis, 2008, Lerner et al., 2018).

Angel platforms have been relatively underexplored in the entrepreneurial finance literature with a few notable exceptions (Agrawal et al., 2016, Bonini and Awuni, 2023, Coakley and Kazembalaghi, 2023). This is somewhat surprising considering the significant early impacts of digitalization on BA which mainly involved the emergence of angel crowdfunding platforms like AngelList in the USA and SyndicateRoom in the UK. The utilization of these new online platforms has the potential to reduce barriers to access to finance, including those related to geography. This is due to the ability to conduct monitoring online, reducing the dependence on face-to-face meetings, as noted by Agrawal et al. (2016). This effect has been reported in equity crowdfunding platforms (Cumming et al., 2021a), where both crowd and institutional investors invest in firms situated in diverse geographical locations. It is also observed on business angel platforms, facilitated by the use of angel connections to various geographic regions (Catalini and Hui, 2018, Agrawal et al., 2016). The focus of this chapter is on Angels@Essex (A@E) platform, established in May 2020 to connect entrepreneurs possessing innovative concepts with angel (and other) investors. This platform is an integral part of the Knowledge Gateway Research and Technology Park at the University of Essex, an institution that was founded in 2010. Subsequently, the innovation centre was inaugurated in 2019, and in the same year, the University of Essex was granted the University Enterprise Zone (UEZ) status making it one of the 20 UEZs in the UK (UEZ Annual Report, 2022). Farla. K (2018) have demonstrated the established role of UEZs in fostering localized innovation and in bolstering the regional economy through their efforts to engage with and support potential high-growth ventures.

The first contribution of this paper is its examination of the particular operational procedures and functions of Angels@Essex as an angel funding platform located outside large conurbations in Colchester. Thus, given that Angels@Essex is a regional platform, it is surprising to learn that the mean (median) amounts of equity raised per round is some £670k (£450k). The second contribution is in contrasting the Angels@Essex platform with ECF platforms to analyse how the characteristics of the 45 startups (for which data are available) funded over the 2019-2023 period are similar to and contrast with those on ECF platforms. It identifies two major operational differences. On one hand, it charges no listing fees in contrast to ECF platforms. The logic behind this is to attract listings on a regional funding platform that is located outside the London-Cambridge-Oxford Golden Triangle. One the other, it adopts the Keep-It-All (KIA) funding approach. Under this, entrepreneurs retain the full amount they have raised, regardless of whether they achieve their initial funding targets. This entrepreneur-friendly approach eliminates the pressure on startups to meet specific targets to access equity capital on ECF platforms for example. In contrast, ECF platforms implement the All or Nothing (Wirtz et al.) strategy which requires startups to reach (or exceed) their funding goals to access the capital imply sharing of investment risk between firms and investors (Cumming et al., 2020). By contrast, the KIA approach and the absence of platform fees underscore the startup-friendly nature of Angels@Essex as an integral part of the Essex University Enterprise Zone UEZ. Our investigation uncovers an intriguing observation: while the amount raised by firms on both Angels@Essex and ECF platforms is similar, the dynamics differ significantly. On Angels@Essex, a relatively small group of backers - ranging from 3 to 4 - funds rounds by making very large contributions whereas ECF campaigns involve an average of 740 investors. The big contrast here is between how information asymmetry problems are resolved by the funders (backers) both types of platforms. The Angels@Essex platform relies fully on the industry expertise of the lead investor and handful of other professional investors, all of whom have substantial skin in the game. By contrast, ECF platforms achieve this by a combination of the wisdom of the crowd and the industry expertise of both the lead investor and other professional investors. Furthermore, the funding ratio on Angels@Essex is lower. This could be attributed to realistic target setting in contrast to ECF platforms where the All or Nothing (Cumming et al., 2020) mechanism leads to quite cautious goal setting.

This paper also has limitations due to its exclusive focus on a single angel platform, potentially limiting the broader applicability of our findings. Future research should explore more extensive datasets and intraplatform variations to enhance the generalizability of our conclusions. Additionally, investigating startup success rates could reveal how a platform's primary selection criteria and its role as an investment facilitator for angel investors influence startup achievements, offering important policy implications.

Chapter 2
Why female entrepreneurs are simultaneously less and more successful in equity crowdfunding!

Abstract

This paper analyses the gender structure of a sample of 524 ECF initial campaigns on the Crowdcube platform 2012-2018 and finds that female entrepreneurs are simultaneously less and more successful than their male counterparts. They are less successful in that they are underrepresented in ECF campaigns – while one in three entrepreneurs are female, our data reveal that all female (Solo female and female team) entrepreneurs run just one in seven (14.5%) successful ECF campaigns. In this respect, female entrepreneurs are less successful at accessing private equity on ECF platforms, albeit this is much higher than their VC success rate. By contrast, our results also reveal that solo female entrepreneurs running ECF campaigns are more successful than their male counterparts based on three important criteria. They attract significantly more investors, enjoy a significantly higher Amount-to-goal ratio, and have a higher proportion of overfunded campaigns. While this may suggest a positive bias in favour of female founder campaigns, it seems at odds with the low percentage of female founder campaigns overall. It may be possible that the onboarding process - whereby the platforms select the campaigns that can run ECF campaigns – is subconsciously tougher for female founders or that the latter may be less overconfident than males in selling their campaigns.

1. Introduction

In modern economies, startups and young ventures play an essential role in creating jobs, accelerating innovation and productivity, and increasing employment (Block et al., 2018). Yet startups and smaller firms struggle to fund their activities during different stages of their development, and there is a well-recognized funding gap in the form of either credit, debt, or equity due to information asymmetry issues that are a result of entrepreneurs having more information than investors (Wilson et al., 2018). New players have emerged in entrepreneurial finance that provides outside equity to startups and other ventures at various stages of their growth path. It is important to investigate both how and to what degree startups' struggle to fund their activities can be alleviated by these new players, such as equity crowdfunding (ECF) platforms (Mochkabadi and Volkmann, 2020). The difficulties in raising equity are more pronounced for female entrepreneurs seeking to grow their ventures, and these are variously referred to as gender bias, gender gap, or the gender parity gap. Based on the Rose (2019) report, financial difficulties are the number one barrier for women intending to start or grow their businesses. This estimated that if female entrepreneurs start and scale their businesses at the same rate as men, they could add £250 billion new value to the UK economy.

There is a well-established gender-driven difference in capital-raising outcomes in entrepreneurship and females raise almost one-third less than their male peers (Guzman and Kacperczyk, 2019). Smaller ventures may initially use their own (and family and friends) savings, but at later stages, they have to raise outside capital to scale up their ventures. How gender influences the complicated interaction of investors (outside providers of the fund) and entrepreneurs during this process is an open question (Ewens, 2022). Traditional sources of entrepreneurial finance seem to favour male owners, and bank credit is more expensive for women even though there is no evidence they are riskier (Alesina et al., 2013). Although venture capitalists (VC) are important sources of outside equity, female entrepreneurs rarely receive funds from VCs, and less than 1% of funding goes to all female founders (BVCA, 2019). Female entrepreneurs in startups face a double effect of constraints. Smaller ventures are more constrained than medium or larger firms and, at the same time, ventures with majority female ownership experience more financial barriers than firms with minority female ownership (Dutta and Mallick, 2022).

Fortunately, the entrepreneurial finance landscape is dramatically changing due to technological advances and new players such as Equity Crowd Funding (ECF) and angel platforms, are emerging (Block et al., 2018). Practitioners and policymakers identify potentially new disruptive and democratizing attributes within crowdfunding. Equity crowdfunding, which has attributes of both private and public equity (Cummings et al., 2020), is now one of the most widely used sources of new equity by young ventures in the UK. It is profit-based and highly risky, as investors can potentially lose all their investments (Coakley and Lazos, 2021). Interestingly, investment in such platforms is becoming a strategic option for both young ventures and professional investors such as business angels (BA), and venture capital (VC) funds (Coakley et al., 2021b). Venture capital, for instance, prefer funding closely located ventures due to the required screening and due diligence process. The use of online platforms may make the distance less relevant and thus alleviate geography-related discrimination (Mollick and Robb, 2016, Cumming et al., 2021a). Coakley and Lazos (2021) highlight that ECF can have a potential democratization role in terms of being accessible to small investors. Cumming et al. (2021a) investigate the democratization promise of ECF by comparing the attributes leading informationally opaque firms to choose ECF over an IPO and looking at similar attributes as determinants of campaign outcome. They conclude that geography-related bias is improved in ECF platforms, but ECF has not been able to improve the chance of female entrepreneurs in fundraising. Also, regardless of attracting larger numbers of investors, ECF does not raise minorities' chances of raising the amount of equity they require.

In equity crowdfunding, investment decision-making has shifted from a few professional experts to a combination of the crowd and these investors in coinvestment ECF campaigns. This shift could result in a change in the proportion of investment in female-run ventures as crowds differ from traditional investors in their skills, experience, and perceptions about the gender of a firm owner (Bapna and Ganco, 2021). This innovation-driven change could result in a different attitude towards female entrepreneurs as the perceptions shaping mindsets of traditional investors about female-led firms diverge from those held by the crowd. The crowd tends to follow more of a community-based logic, whereas professional investors are inclined toward the market logic (Cumming et al., 2021a). Equity crowdfunding investors consist of both sophisticated and inexperienced individuals seeking profit by investing in high-potential ventures. This mixture contributes to not easily predictable investor behavior. Enjoying the certification effects of traditional investments and leveraging the wisdom of the crowd leads to a unique investment dynamic in equity crowdfunding campaigns. Equity crowdfunding investors seek financial benefits similar to traditional investors and, at the same time, are less experienced and dominated in terms of numbers by the crowd.

There are several prior studies on gender effects in entrepreneurial finance compared with the few gender studies focusing on crowdfunding platforms. The founder team structure has been examined by comparing the performance of solo founders versus founding teams (Coakley et al., 2022b, Greenberg and Mollick, 2018, Ahlers et al., 2015). Gender effects studies compare the performance of female and male entrepreneurs (Prokop and Wang, 2022, Cumming et al., 2021a, Johnson et al., 2018), to examine whether, after controlling for a number of proxies, there is an underperformance which is explained by the gender of founders. However, there is a prevalent problem in gender studies that is the low presence of female entrepreneurs (Rose, 2019); also, the presence of solo founders and founding teams is not the same across both genders, which makes the comparison of female led firms with male led firms inclined towards the more prevalent type of founder structure. Conceptualizing and testing for gender impact in UK equity crowdfunding is not straightforward due to the diverse nature of ECF founder teams. The quality of human capital is potentially affected by the gender and composition of founder teams (Barbi and Mattioli, 2019). Greenberg and Mollick (2018), using a Kickstarter project sample, postulate that solo founders outperform founder teams. By contrast, Coakley et al. (2022b) employ a sample of 1291 UK ECF campaigns on the three leading platforms UK 2011-2018 to establish that founder teams outperform solo founders. The implication is that differences between female and male led ventures cannot automatically be imputed to gender impact.

The paper makes several contributions to the literature, The first is that it investigates gender effects in initial ECF campaigns for a large and interesting sample of 524 successful and unsuccessful ECF campaigns on the Crowdcube platform. It is considerably larger than the samples used in extant studies and has a greater presence of female entrepreneurs. Hellmann et al. (2021b) utilized the data of campaigns held in Seedrs from 2012 to 2017, and only 9% of all campaigns had female founders, which is equivalent to 33 campaigns, including both teams and solo founders. The female participation rate is substantially higher on ECF platforms than in UK VC deals, where only about 4% of all deals go to female founders (Rose, 2019), and in the US, where only 7% of deals have a female founder (Gafni et al., 2021). Still, ECF platforms do not have a female participation rate as high as reward-based crowdfunding platforms. Gafni et al. (2021) establish that on the Kickstarter platform (a reward-based crowdfunding platform), one-third of all projects have a female leader. But, a sample of French ECF campaigns, Andrieu et al. (2021), reported that about 9.73% of all campaigns were female led which is much lower than the percentage of newly founded firms by women (39%) in France. Also, this paper pays particular attention to the founder's gender as it can more aptly capture potential obstacles entrepreneurs must confront in raising outside equity.

The second contribution is that it takes account of the founder team structure in testing for gender effects. This is because team structures can vary and Coakley et al. (2022b) show that teams outperform solo entrepreneurs on the three major UK ECF platforms. Most extant studies on gender bias (effects) in ECF ignore this factor. Analysis of founder team structure reveals that some 322 (61.5% of the total) ventures have solo founders. The vast majority of these (80%) are solo male founders, and the remaining 20% (64) of them are female founders. Moreover, just 2.29% (12) of all campaigns are run by female founder teams. This is fortuitous as it facilitates a clean test of gender effects for the majority of our sample that is not contaminated by, for example, team effects. Accordingly, the main analysis focuses on comparing the performance of solo female and solo male founder entrepreneurs.

The final contribution provides insights on the goals set by female founders. Target setting strategy is a contributing factor to entrepreneur success, and studies on gender impact in ECF are divided on the effect of target-setting levels and the success of firms during ECF campaigns (Kleinert and Mochkabadi, 2021, Hellmann et al., 2021b, Lin and Pursiainen, 2022, Prokop and Wang, 2021). Although the prior literature suggests that female founders set lower initial goals (Hellmann et al., 2021b) and that male founders overestimate their firm’s need for funds (Lin and Pursiainen, 2022), our data contradict this for solo founders. They show that the mean and median goals and success of solo male and female entrepreneurs are not significantly different at conventional levels, but when they are compared beyond their targets, our findings reveal that solo female founders are found to enjoy an advantage over their male peers in terms of greater Amount-to-goal and having a higher proportion of campaigns exceeding their goal. Success dummy is a measure to categorize the firms into two groups based on reaching or not reaching the targets in campaigns. But this binary variable does not provide any information on the extent of success or failure. The extent of success can make a difference in understanding the existing dynamics and contributors. There is a difference between firms barely making their targets, and those exceed much more than their goals. So, as well as Success and Number of funders (an indicator of firms networking with crowd and investors), two more proxies, namely Amount-to-goal and Overfund_d, are used here. The first one is an alternative measure of the Amount raised, and the second one offers information about the proportion of overfunded firms.

Heckman's model is used to account for potential selection bias stemming from considering solo founders only. Our findings reveal that solo female founders enjoy an advantage over their male peers in terms of attracting more investors or better engaging with the crowd, raising higher Amounts-to-goal, and running a higher proportion of campaigns that exceed their goal. Two robustness analysis methods are employed here. The first one uses the whole sample, and a categorical variable, Founder type, is defined for categorizing the ventures based on the founders' gender composition. The categories measure the difference between Solo female founders and Team with respect to Solo male founders. The results of this robustness analysis confirm the overperformance of Solo female founders. The Second robustness analysis method is Propensity Score Matching (PSM). PSM is employed as an identification method for the comparison between female and male Solo founders who are matched based on their education (Advanced degree), team average Age, Pre-money valuation, percentage of offered Equity, and Goal (£m).

This paper is structured as follows. Section 2 reviews the existing literature and develops the hypotheses to be tested. Section 3 outlines the methodology adopted and the empirical models employed to test the hypotheses. Section 4 discusses the empirical results. The final section concludes.

2. Literature review and hypotheses

Among different reasons leading to lower access of entrepreneurs to capital, including limited internal funds and difficulty providing collateral for bank loans, information asymmetry is perhaps the most challenging. This makes access to external equity particularly difficult for startups. Tomboc (2013) stresses that the lemon problem in the ECF market is more acute than in traditional markets for three main reasons. First, entrepreneurs are less willing to pitch their detailed business ideas to the public rather than a few professional investors. Second, the crowd has less expertise in screening firms than professional investors. Third, the average investor is less experienced or professional in investing. This information imbalance makes observable signals more important for startups in an attempt to demonstrate their quality to investors.

Signaling theory proposed by Spence (1976) postulates that financiers can investigate the quality of new firms from observable and costly signals. The crowd of less experienced investors tends to rely on credible quality signals from entrepreneurs, such as their human capital, which is one of the most critical aspects in the evaluation of early-stage firms (Barbi and Mattioli, 2019, Colombo and Grilli, 2005). Signals include those related to firm characteristics - internal signals – and those related to outside firm accreditation signals sent by third parties such as angel investors. Researchers fit these into categories of firm, campaign, venture, and entrepreneur-related characteristics (Colombo and Grilli, 2005). Higher opportunity exploitation, the skill of the venture team, and better chances of success are indicators of higher human capital capabilities (Ahlers et al., 2015). The rationalization -using signals for quality investigation- stems from the fact that signalling high-quality human capital is both costly, as qualities such as experience and leadership are not easily obtained and are observable through team reports of the firm (Kleinert and Mochkabadi, 2021). Human capital is mainly examined by previous researchers by looking into the educational background and experience of founders (Coakley et al., 2022b, Barbi and Mattioli, 2019, Piva and Rossi-Lamastra, 2018). However, founder gender is another important aspect of the human capital (Barbi and Mattioli, 2019, Hellmann et al., 2021b) that has received less attention than other attributes in ECF literature.

The extant literature provides mixed results on gender effect as crowdfunding is a novel form of outside equity. Equity crowdfunding is one of three main pre-IPO entrepreneurial finance options, alongside Venture Capital (VC) and Business Angels (BA), and its investor seeks profit (Coakley and Lazos, 2021). So, it is possible to observe analogous gender bias patterns with institutional investors, which is discrimination again female founders. Based on Gender Role Congruity Theory (GCRT), there is prejudice toward female leaders, which stems from the incongruity between perceived leadership roles and the gender role of females (Eagly and Karau, 2002). There are assumptions about female management capabilities in spite of their previous working experiences, which leads to a lower success in securing private capital (Amatucci and Sohl, 2004). Drawing on GCRT, Kleinert and Mochkabadi (2021) found that, even with similar features as their male peers, female entrepreneurs are less successful in signaling a high-quality business. All female founding teams that are active in the technology sector raise about 0.81 of raised capital and have 0.72 of attracted investors when they are compared with their male counterparts. Cumming et al. (2021a) conjecture that ECF does not improve women's odds of success even though it is their preferred choice compared with IPO.

On the other hand, based on activist homophily, female founders can enjoy higher support from female investors in a crowd setting such as crowdfunding (Greenberg and Mollick, 2017). Homophily is a fundamental force shaping the structure of social networks suggesting the importance of both individual and group attractions and acting through various underlying mechanisms. Under more specific situations, activists choice homophily relates to social identity based on a common group social barrier resulting in a wish to help one another to overthrow it (Greenberg and Mollick, 2017). This group-level sense of disadvantage is of more relevance in the context of lower-stake crowdfunding and where female investors are inclined to support peer founders. Interestingly, in reward-based crowdfunding campaigns, gender bias favors women, and gender positively affects the outcome of campaigns (Johnson et al., 2018, Greenberg and Mollick, 2017). Differentiating between ECF and other lower stake crowdfunding methods, Bapna and Ganco (2021) discuss that activist homophily, and the use of heuristics is of more relevance in the context of less experienced investors. More experienced investors demonstrate gender-neutral behavior, which is an improvement compared with similar traditional markets. Equity crowdfunding investors are still considered unsophisticated investors when compared with traditional sources of capital for younger firms (Barbi and Mattioli, 2019), which requires attention when looking into their traits and suggests a possible inclination toward bias alleviation. This positive gender effect is not limited to reward-based platforms. Employing the stereotype content model, Johnson et al. (2018) discuss two types of stereotypes, namely trustworthiness toward female entrepreneurs, and competence toward male entrepreneurs. This sense of trustworthiness is a key element when investors are the crowd with limited or no due diligence and screening possibilities and fear of fraud. Looking into founder data on 416 deals from Kickstarter (a reward-based platform) and follow-up experiments, Johnson et al. (2018) found that females are advantaged because of stereotypical trustworthiness. A similar effect of trustworthiness in reward based platforms exists in peer lending platforms such as prosper.com, where individuals' photos that look more trustworthy raise more money and receive better credit rating (Duarte et al., 2012).

There is an analogous pattern of possible positive gender effect in favor of female founders in equity crowdfunding platforms. Barbi and Mattioli (2019) employ the data on 521 successfully funded campaigns from Crowdcube and confirm that, as well as education and prior experience, founder team gender composition affects the amount of capital raised and added women to founding teams contributes to higher capital. Vismara et al. (2017) posit that ECF enjoys higher gender diversity compared with other markets offering entrepreneurial finance, and gender is indeed a factor in the demand or supply sides of equity crowdfunding based on their research on a sample of 58 projects in the Seedrs platform. Prokop and Wang (2021) suggest that in seasoned equity crowdfunding female ratio (female managing directors relative to the whole board) is negatively related to the capital and number of investors, in which a higher number of women on the board is associated with a lower success rate but the underperformance does not appear in initial campaigns.

The number of funders is one of the key performance measures in ECF campaigns. The participation of the crowd in campaigns could be a signal of the firm's quality and lower adverse selection problems or a good networking of ventures with crowd (Vismara, 2018). In ECF, female founders can benefit from the mix of crowd alongside professional investors, and they can attract more funders when compared to their male peers. One contributing factor is the homophily between female investors and female entrepreneurs, and another factor is the stereotyped crowd trust in female entrepreneurs (Johnson et al., 2018), which leads to attracting higher numbers of funders. Prokop and Wang (2021) suggest that a higher female ratio does not affect the number of investors in initial campaigns, which is an improvement considering they attract lower numbers of investors in later offerings when investors know the firm better, and gender becomes of less impact. Zhao et al. (2021) emphasize the role of maximising warm glow, and the utility investors enjoy by investing in female founders. They notice that this leads to female founders' advantage in having more potential investors. As the focus of this paper is initial campaigns, it is possible that Solo female founders also benefit from a similar advantage in attracting a higher number of investors comprising mainly small investors or the "crowd". This leads to our first hypothesis:

H1: *Startups run by solo female founders attract more investors than their male peers*.

The target of venture owners should be based on the evaluated needs, but this is also affected by later strategies for succeeding in the campaign (Cumming et al., 2020). In a study of Kickstarter Gafni et al. (2021), found that female entrepreneurs do not set lower targets than their male peers, and still, they have a higher success rate. But the targets in reward based platforms are much lower than ECF platforms, and the investors have different motivations. 'Crowd" of less professional investors who make relatively smaller investments in ventures are less affected by stereotypes prevailing among professional investors about the lower competency of female founders, and they have a higher trustworthiness perception about female entrepreneurs, which leads to a higher willingness of investors in funding female led firms (Johnson et al., 2018) and higher success rate (Lin and Pursiainen, 2022). The Success rate of the ECF platform is different from reward based platforms in size, outlook, and motivations and expectations of investors (Vismara, 2019). Even though the Success rate of female founders is higher in reward based crowdfunding platforms, they might have lower success rates in ECF platforms. In most ECF gender studies, Success seems to be at the same level for both genders(Cumming et al., 2021a). The primary summary statistic of this article also shows no difference in Success level for Solo female versus Solo male founders in both mean and median tests. This leads to the second hypothesis for the Solo female founders:

H2: *Solo female founders enjoy a similar likelihood of success as their male peers.*

Ventures prefer ECF to other forms of external finance when their required target capital is relatively small (Mochkabadi and Volkmann, 2020). The amount raised by successful companies during the campaigns starts from their target and could be much more than what they asked for. The effect of target goal on the outcome of the campaign is controversial. Setting a lower target could signal that it is more feasible to reach the funding goal and so more investors become eager to contribute. On the other hand, it could signal lower confidence of the founders in their firm (Prokop and Wang, 2021). Vulkan et al. (2016) find that setting higher goals in Seedrs campaigns has a negative effect on the outcome of the campaign, namely success in reaching the goal.

The goal-setting behavior of male founders is different from female founders. Male firm owners tend to have overconfidence in their products and firms' growth prospects which leads to setting higher goals. For the same over-optimism, they have a lower proportion of exceeding their targets when compared to their female peers (Lin and Pursiainen, 2022). Prokop and Wang (2021) utilized data collected about 483 projects from 22 German platforms and recommended setting a higher funding value, and bolder promotions to benefit female managing directors more than their male peers. Hellmann et al. (2021b) postulate that female founders set lower targets, but they wait longer after announcing the end of their campaign; There is no clear reason why female founders set lower targets and if it is rooted in their expectations and they underestimate their firms' growth rate or they believe they cannot raise more in ECF platforms? In another study, Rossi et al. (2020) examine the determinants of success, and a target value and platform effect on US and UK equity crowdfunding campaigns suggest that teams of both genders raise about the same amount of capital. Their results were significant only for the UK platforms, and at the same time, they found a significantly negative relationship between being a female entrepreneur on UK platforms and setting goals implying that female founders set lower initial goals. Finally, literature suggests that female founders set lower goals compared to male founders, who overestimate their firm's needs; and at the same time, they both have a similar success rate (previous hypothesis). These two factors contribute to a higher proportion of female founders receiving more than what they asked for. This leads to our third and fourth hypotheses:

H3: *Solo female founders set a higher Amount/Goal than their male peers.*

H4: *Solo female founders are more likely to enjoy overfunded campaigns than their male counterparts.*

3. Methodology and hypotheses

This paper employs four outcome proxies to investigate gender effects in ECF campaigns and examine the hypotheses. The first Success proxy is the number of funders, as the aim of ECF campaigns is to attract as many funders as possible. However, this ignores the amount contributed by each investor, as a higher mean amount contributed makes reaching the goal easier. Ln(Funders) or the natural logarithm of the number of investors, is used to control for right skewness (Prokop and Wang, 2022). The second proxy is Success which is a dummy variable that takes one if the campaign reaches the initial target.

The third proxy is the Amount/Goal ratio. This includes both unsuccessful campaigns that fail to reach the goal and successful campaigns that meet and/or exceed the goal. It also specifies the extent of the failure of unsuccessful campaigns and the degree of success of successful campaigns.

The *Overfunding* dummy takes the value one for those campaigns meeting or exceeding the goal and is zero otherwise (Coakley et al., 2018). This clearly differentiates between successful campaigns that meet and/or exceed the goal and unsuccessful campaigns that fail to reach the goal (and the extent of failure). Regarding the explanatory variables, two are considered. The variable Solo_female is a binary indicator that takes the value of one for solo female founders and zero for solo male founders. Founder type is a categorical variable that assigns a value of 1 to solo male founders (serving as the reference category), 2 to solo female founders, and 3 to teams. This variable is utilized in the robustness analysis.

Our models include several control variables to take account of variation among entrepreneurs seeking funds in ECF campaigns. Two control variables are used to account for the effect of experience on ECF success: Advanced degree and team age (years). Advanced degree is a dummy that takes one for firms if their owners have higher education (Dr. or Professor) and zero otherwise. Team age (years) refers to the average age of the founding team. The percentage of equity offered by small firms is another important signal to investors, and it is captured by the variable *Equity(%)*. Entrepreneurs signal higher quality of their firm by retaining a higher equity percentage for themselves (Ahlers et al., 2015). We control for the age of the firm by considering Firm Age (years) variable in our model to capture the exact (early) stage of the firm. Pre_money valuation (£m) refers to the firm's value just prior to its campaign.

To study the gender effect, three methods are used here (Heckman method plus two robustness check methods). The first method is employed to study Solo founders. Heckman's method (Heckman, 1979) is used to account for the non-random intentional bias of focusing on the Solo founders only. In the first hypothesis, the dependent variable is Ln(funders) which is a continuous variable. The Stata Heckman routine is employed for coefficient estimation (StataCorp, 2015). The Heckman selection estimation method assumes that there is an underlying regression as follows:

$$\mathrm{y}_j = X_j\beta + u_{1j}$$

The dependent variable is observed in observation j if only:

$$Z_j\gamma + u_{2j} > 0 \qquad \text{(selection equation)}$$

where,

$$u_1 \sim N(0,1), u_2 \sim N(0,1) \ \& \ corr(u_{1j}, u_{2j}) = \rho$$

The regression equation estimates the determinants of Ln(funders) and is observed only when founders are Solo. X_j includes the explanatory variables for Solo_female and the control variables. Z_j, includes the control variables plus the industry dummy (identification variable). Apart from the identification variable, the same control variables are used in both the selection and main models to examine whether the same attributes affecting solo versus team status also influence the campaign outcomes, potentially biasing the results. The Heckman routine employs the Maximum Likelihood Estimation (MLE) method and instead of reporting ρ, it reports this transformed version of ρ:

$$athrho = \frac{1}{2} \ln \left(\frac{1+\rho}{1-\rho}\right)$$

If the χ^2statistic is highly significant (at 1%), the null of ρ=0 is rejected, and because of the correlation between the error term in the main and selection equations, the Heckman selection model is employed here instead of OLS.

The dependent variable for testing the second hypothesis is a Success dummy. Therefore, to account for the sample selection bias of focusing on Solo founders and estimating unbiased consistent coefficients, the Heckprobit routine of Stata is employed (StataCorp, 2015). This routine is used for Probit models with sample selection following Van de Ven and Van Praag (1981). This method assumes an underlying relationship as follows:

$$y_j^* = x_j\beta + u_{1j} \quad \text{(latent equation),}$$

such that we observe only a binary outcome (conducting a successful campaign)

$$y_j^{probit} = (y_j^* > 0)$$

The dependent variable in observation j is only observed if the selection equation (Solo founder versus Team) satisfies

$$y_j^{select} = (z_j\gamma + u_{2j} > 0)$$

where we assume:

$$u_1 \sim N(0,1), u_2 \sim N(0,1) \ \& \ corr(u_{1j}, u_{2j}) = \rho$$

When ρ is equal to zero, and or the error terms of the first and second equations are uncorrelated, the standard Probit model can be used instead of Heckprobit. But when it is non-zero, employing the standard Probit leads to biased estimation. In addition, the model setup should be such that the selection model has at least one more variable than the outcome model. In this paper, Industry dummies are considered in the selection model. The standard errors are clustered at the industry level for possible between-cluster correlation. Therefore, Wald test results are reported. Here the null hypothesis is that the selection and outcome equations are independent or that ρ is equal to zero. The Heckprobit routine employs the Maximum Likelihood Estimation (MLE) method, and $atrho = \frac{1}{2}\ln\left(\frac{1+\rho}{1-\rho}\right)$ is reported. The χ^2statistic is not significant, and the null of ρ=0 cannot be rejected. The correlation between the latent regression and selection equation can be neglected, and Probit can be employed. Here the Heckman results are compared with Probit model and they are similar.

For our third hypothesis test, the dependent variable is Amount/Goal, and similar to the first test, the Heckman routine is implemented. In our fourth hypothesis test, the dependent variable is an Overfunding dummy. Therefore, a similar method to the second hypothesis is employed to estimate unbiased consistent coefficients using the Heckprobit routine of Stata (StataCorp, 2015).

Two robustness methods are employed in addition to the Heckman method to examine gender effects. To utilize data from all campaigns and avoid the explicit non-random selection bias of focusing on Solo founders, a categorical variable name Founder type has been constructed, and the performance of Solo founders and Teams is compared to Solo male founders.

$$Ln(Funders_i) = \alpha_1 + \beta_1 Founder\_type_i + \Gamma_1 Controls_i + \varepsilon_1 \quad (1)$$

$$\Pr(Success_i) = \alpha_2 + \beta_2 Founder\_type_i + \Gamma_2 Controls_i + \varepsilon_2 \quad (2)$$

$$Amount/goal_i = \alpha_3 + \beta_3 FFounder\_type_i + \Gamma_3 Controls_i + \varepsilon_3 \quad (3)$$

$$\Pr(Overfund\mathrm{\_d}_i) = \alpha_4 + \beta_4 Founder\_type_i + \Gamma_4 Controls_i + \varepsilon_4 \quad (4)$$

where i denotes campaign i and $\mathrm{Controls_i}$ represents a vector of control variables as defined in Table 1. The coefficients of the first and third models are computed by OLS estimation method while a Probit model is employed for the second and fourth models. Founder team size is added to above list of controls as the focus here is not the Solo founders and the whole sample has been employed.

The second robustness check method is the Propensity Score Matching technique. Endogeneity is an important concern in any study in management and business research. Our primary data include both successful and unsuccessful ECF campaigns (564 successful and 300 unsuccessful campaigns) that should help ameliorate sample selection bias concerns. However, while we control for a rich set of covariates to explain crowdfunding outcomes, the existence of unobservable characteristics that may still bias the gender effect cannot be completely ruled out. Here we aim to answer the following question: Are solo female entrepreneurs, ceteris paribus, less (Maxwell and Lévesque) likely to succeed (using four success proxies) compared with their male peers with comparable characteristics? A potential selection bias emerges as the decision to be a female entrepreneur is likely to be endogenous and related to various other observable and unobservable characteristics. As such, we follow Rosenbaum and Rubin (1983) in using Propensity Score Matching (PSM) as a means of addressing such concerns. This method has been successfully employed in other ECF studies to confront endogeneity (Walthoff-Borm et al., 2018, Vismara, 2019).

4. Data and empirical analysis

In the empirical analysis, the paper employs a dataset of 524 ECF campaigns on Crowdcube, a leading UK equity crowdfunding platform, from 2011 to 2018. Our data about firms' founders is extracted via a self-written program for scraping data based on information provided on the Crowdcube platform. Wherever data cannot be extracted by web scraping, we have checked manually for information in both Crowdcube and available LinkedIn profiles of founders or other publicly available data on their websites. For gender detection, the data are matched against gender information in a well-recognized source http://genderize.io/ which is a common tool in literature (Geiger and Oranburg, 2018, Mohammadi and Shafi, 2018, Greenberg and Mollick, 2017). This source checks the given first name against its comprehensive name library (over one hundred million names and gender from different countries) and returns the gender and the likelihood of it. Wherever there was a lower probability or results were inconclusive, the image of owners in their LinkedIn profile has been used for verification.

4.1 Descriptive statistics

Table 1 reports the name and description of all variables used in our empirical models.

[Tables 1 around here]

Table 2 presents the descriptive statistics for our sample. Table 2 provides summary statistics of all variables in our models, including the number of observations, mean, median, standard deviation, as well as minimum and maximum values.

[Table 2 around here]

This shows that the data are right skewed (mean>median) in variables such as Number of funders, Amount-to-goal, or Goal because of the impact of large campaigns. For instance, the maximum number of funders is 3.5k which implies that the mean value of 0.35k is close to double that of the median of 0.19k. The average Amount-to-goal ratio is an impressive 1.43 (median 1.28). About 20 percent of all solo founders are female solo founders. Only 6 percent of all ventures have a founder with a Dr. or Professor title. Ventures raising capital offer about 15.08% (median 14.12) of their Equity in exchange for funds. The mean pre-campaign Valuation is almost £4.05m (median £1.3m), and the mean venture Age is 3.2 years (median 2.31). The founder team's mean and median Age exceed 42 years. Finally, the average initial Goal is £330k (median £170k).

Table 3 presents the founder structure of the teams by gender category.

[Table 3 around here]

Three features stand out from Table 3. First, the dominant founder structure in terms of initial ECF campaigns is Solo male entrepreneurs, who account for virtually half the sample or 49.2%. Given this, the category Solo male entrepreneurs is used as a baseline against which to analyse both Solo female entrepreneurs and teams. The next largest category is Male teams (2 or more cofounders) who make up over a quarter of the sample (26.3%). Together, males only (solo and teams) conducted over three-quarters of all campaigns. Second, female-only (solo and teams) conducted just one in seven or 14.5% of all campaigns. In this respect, female entrepreneurs are heavily underrepresented on ECF initial campaigns and so are less successful than their male counterparts. Even if one adds mixed (gender) teams that conducted 52 initial campaigns (10%), the total female representation on ECF initial campaigns is just 22%. Vismara et al. (2017) also report that more than 83% of Seedrs platform deals have male CEOs and about one-fourth of TMT are female managers.

Tables 4 and 5 present equality of means and medians test results, respectively, for solo male founders versus solo female founders. Testing for equality of medians in ECF campaigns is beneficial, as the mean can be influenced by the value of large campaigns, and the dataset remains right-skewed even after correcting for outliers.

[Tables 4 and 5 around here]

The tables show that ECF data are typically right skewed driven by a handful of very large campaigns and that these inflate the mean values of important variables. For instance, the mean Solo male (female) Amount raised at £0.39m (£0.4m) and the Number of funders at 0.28k (0.29k) in Table 4 are both large and virtually identical. By contrast, the corresponding median results are considerably smaller – indicating that the data are right skewed - and more varied. For example, the median number of funders for Solo male founders at 0.144k is smaller than the corresponding number for solo female founders at 0.214k and this is significant at the 5% level. The equality of median results also shows that the Amount/goal is lower for Solo male founders and that Solo male teams are older than Solo female founders, albeit both are significant at the 10% level only. Our findings for Amount and Goal differ from those of for Hellmann et al. (2021b) the Seedrs platform. They find that female teams ask for less and raise less but our findings on Success are comparable. The differences may be explained by the fact that Hellmann et al. (2021b) base their analysis on the females (%) variables that in turn are disaggregated into female-only teams (including solo females) and female mixed teams. The median values of the other variables for solo male and solo female campaigns are overwhelmingly similar. For binary variables of Success and Overfund_d the proportion test was also employed to compare the proportion of Successful/overfunded Solo female founders (equal to one) with their male peers. Results are the same as those from the equality of means test.

Table 6 is the pairwise correlation matrix which reports the correlation coefficient between all variables of the study to test the presence of multicollinearity.

[Tables 6 around here]

The table shows no evidence of significantly high correlations between variables to suggest multicollinearity.

4.2 Regression analysis

Table 7 reports the regression results for testing hypotheses one to four by implementing the Heckman method.

[Tables 7 around here]

To test the first hypothesis, the results of Model (1) are examined. This model has two parts. The first part is the selection equation of the Heckman method, and the marginal effects are reported here. The industry dummies are significant, suggesting the relevance of extra independent variable (Civera et al.) for the selection equation (observing Solo founders versus Teams) with respect to the outcome model. In the outcome equation of Model (1), Ln (Funders) is the dependent variable. The effect of the explanatory variable of interest or Solo_female on the natural logarithm of the number of Funders is positive and highly significant. The coefficient is 0.298, and it is significant at a 1% level, suggesting that Solo female founders attract a higher number of investors in ECF campaigns than their male peers. The estimated athrho is -1.378 and is highly significant (p-value <0.01), which implies that there is selection bias and that not using the Heckman method could lead to biased coefficients. In addition, higher offered equity is positively correlated with the number of investors, and younger entrepreneurs have more funders. Higher Premoney valuation and Goal lead to more funders. Their coefficient is 0.0418 and 1.677, respectively, and they both are highly significant at a 1% level.

Model (2) results are related to the second hypothesis. The first column is the Heckman equation, and the effect of control variables plus the industry dummies on being Solo founder versus a Team is examined. The reported coefficients in both selection and outcome (Success) equations are marginal effects as the dependent variable is Solo founder and Success dummy, and the models are Probit models. The outcome equation or second column in Model (2) includes the effect of Solo_female founder binary on the probability of Success. The coefficient is insignificant, with a very low t-statistic (0.030), implying no difference between Solo female and male founders in their Success rate. The estimate athrho is 0.986 and is insignificant (p-value > 0.1), suggesting that there is no selection bias of focusing on Solo founders when Success is investigated, and the results of Heckman are comparable with the simple probit model.

Model (3) is for testing the third hypothesis. The first equation is the selection equation (Solo versus Team) of the Heckman method and the second equation provides the effect of variable of interest (Solo_female) on the Amount/Goal (Regression equation). Again, most of the industry dummies are highly significant in the selection model. The solo female coefficient is 0.159 and highly significant (p-value < 0.01). solo female is a binary, and its coefficient is the changes in outcome when the type of solo founder is changed from solo male to solo female. Therefore, the results of this model strongly suggest that solo female founders have a higher Amount/Goal ratio than their male peers. Ventures' valuation prior to the campaign (Premoney valuation) is positively associated with having a higher Amount/Goal ratio. The estimated athrho is equal to -0.267 and is significant at a 5% level. This means that not using the Heckman method could result in biased coefficient estimates.

Model (4) results are related to testing the fourth hypothesis. The first column or the selection equation, includes both control variables and industry dummies which are highly significant. The second column is the probit model or the outcome equation that is of interest here. In both equations, the models are probit, and the marginal effect is reported. The estimated athrho is 0.559 and it is not significant, which implies that there is no selection bias of focusing on solo founders when Overfund_d is investigated, and the results of Heckman are comparable with simple probit model. The coefficient of Solo_female in the outcome equation (dependent variable = Overfund_d) is 0.135, and this is highly significant at a 1% level. It implies that solo female founders have a higher proportion of overfunded campaigns than their male counterparts.

Overall, results of comparing solo female founders with solo male founders imply that solo female founders attract a higher number of investors, get more than what they primarily asked for and have a higher proportion of campaigns that exceed their goal, but there is no significant difference between them and their male peers in term of Success. This overperformance of Solo female founders with respect to their targets and also attracting a higher number of investors, which are mainly crowds, is consistent with Bapna and Ganco (2021) the postulation that gender gaps prevailing in traditional markets are decreasing in the ECF context where the investors have a different mindset from traditional investors. Zhao et al. (2021) find that capital raising outcome is indeed in favor of female firm owners in ECF's initial campaign. From their point of view, one of the main contributing reasons is that people are inclined to assume that women are more trustworthy than men (Du Rietz and Henrekson, 2000). Trustworthiness is a key factor in a first offering when investors do not know startups yet, and the level of uncertainty is high. These results are also comparable with Prokop and Wang (2021) study that firms with a higher number of female founders do not underachieve during ECF initial campaigns, and the underperformance appears in later offerings. Therefore, in initial campaigns female founders seem to have an advantage over their male counterparts.

These results are in line with Rossi et al. (2020) and Cumming et al. (2021a) in that both of them found no significant difference between female and male founders in Succeeding in ECF campaigns. However, Rossi et al. (2020) have some reservations about the initial targets of female founders in the UK and mention that they set lower goals. They found that with similar Success rates, females set lower targets. Cumming et al. (2021a) also reported that there is no significant relationship between female leadership and success. Hellmann et al. (2021b) states that female founders set lower goals which leads to a lower Amount raised, but their Success is the same for both genders.

The regressions in Table 7 include Goal as one of the control variables which, one might argue, is affected by gender. Thus, regressions have been rerun for all models without Goal and the results are similar.

4.3 Robustness analysis

Two methods are employed to perform the robustness analysis of results presented in previous section. In the first method, a categorical variable (Founder_type) divides all campaigns into three gender compositions of Solo male founders (1), Solo female founders (2) and Teams (3) and the concern for selection bias of focusing on Solo founders becomes irrelevant.

Table 8 reports the results with t-statistics in parentheses for various ECF campaign outcome variables regressed on founder team characteristics and a set of controls.

[Table 8 around here]

All models include two gender variables (Founder_type = Solo female, and Founder type = Teams) to capture gender effects. The coefficient of Solo_female gives the changes in dependent variables when Solo females are compared to Solo male founders. Teams give the analogous response of Teams relative to Solo male founders. The Model (1) results reveal that the Teams coefficient is positive and significant at the 5% level. This suggests that Teams – 94% of Teams are majority male-led firms - raise a larger Amount than Solo male founders. By contrast, the Solo_female coefficient is insignificant. The Model (2) results show that both Solo_female founders and Teams attract significantly more investors than Solo male founders at the 5% and 1% levels, respectively. The former result is interesting in that it demonstrates that Solo_female founders are more successful at attracting more investors than their Solo_male counterparts. The model (3) results indicate that the Success dummy is insignificant in all cases.

In Model (4), the coefficient on Solo female is 0.155 and is significant at the 5% level. This implies that Solo_female founders enjoy a 15.5% higher Amount-to-goal ratio than Solo male founders. The regression estimation method is Probit in model (5), and for ease of interpretation, marginal effects are reported. Now the coefficient on Solo female founders is significantly positive and implies that these founders have an 11.4% higher proportion of exceeding their targets relative to their male counterparts. Teams also enjoy a significantly higher probability of overfunding than Solo male founders.

The second robustness analysis method is Propensity Score matching. This method has been employed in other ECF studies (Vismara, 2019) to deal with endogeneity concerns. Table 9 reports the Propensity Score Matching (PSM) results.

[Table 9 around here]

Propensity Score Matching suggests Solo female founders attract a significantly higher number of investors (Model (2)). There is no significant difference in Success between Solo female and male founders (Model(3)). Solo female owners enjoy higher Amount-to-goal ratios and have a greater proportion of campaigns that exceed their goals based on the Models (4) and (5) results, respectively. Results are reported for one, three, and five matches per observation. For all three matching scenarios, the effect of being a Solo female founder is positive and significant, whereas Success remains indifferent to the matching method and is insignificant for one, three, or three matches per observation.

Table A1 presents the t-test results before and after matching. This table reports the t-statistics and p-values for the difference in means between treated and control groups before and after matching. The bias percentage is reported to examine the covariate imbalance prior to and after matching.

[Table A1 around here]

Following the suggestion of Rosenbaum and Rubin (1983), all covariates have a bias percentage of less than 5% after the matching is performed. Here bias refers to the average value of the treated and control group. The overall mean bias in the Unmatched group is 13.1% which has reduced to 3.2% after the matching.

Figure A1 illustrates the Propensity scores overlap before and after matching for Treated and Untreated/Control groups (Solo female vs. Solo male) for visual inspection of common support assumption in the the PSM method.

[Fig A1 here]

Propensity Score Matching results confirm our primary regressions, implementing the Heckman method and the first robustness analysis method, utilizing the data of the whole sample by defining the categorical variable of Founder_type.

5. Conclusions

This study contributes to the existing literature by considering the founder gender heterogeneity and using a unique set of data that not only points out the noticeable presence of Solo founders (both genders) in the ECF campaigns but also the rich data set makes the comparison of Solo female founders with their male counterparts possible albeit after correcting for selection bias. Results are robust, as not only the Heckman method has been implemented in our regressions, but also two more methods are used for robustness analysis methods.

The gender impact on firms' performance in ECF campaigns requires a clean comparison, which is not affected by the existing dynamic of the team or the gender composition of founders. Differentiating between different founders' compositions, this article focuses on Solo founders. In addition, the performance of firms is largely affected by their targets. Target setting behavior of founders differs, and male founders tend to overestimate firms capital requirement in their first offerings on ECF platforms (Lin and Pursiainen, 2022). This paper takes account of this difference and compares the performance of both genders based on the Amount/Goal and proportion of Overfunding. These two additional proxies are helpful in shedding light on the question of the extent of success.

In comparing the performance of startups in ECF campaigns, Solo female founders attract more investors, enjoy a higher Amount-to-goal ratio and have a higher probability of raising more than what they asked for. But they have the same odds of succeeding in their campaign. This implies that considering the strategies set by both firms and platforms that influence the campaign characteristics so that more firms succeed (Cumming et al., 2020), gender impact is insignificant in the Success of firms. However, gender impact becomes more evident when the extent of Success is investigated. Solo female founders have a clear advantage over their male peers when their Success is relative to their goals.

It is worth noting that despite the advantage of Solo female founders compared to their male counterparts, female entrepreneurs have a lower share of all campaigns on the Crowdcube platform, and male-led firms comprise 75.58% of total deals. Also, there are almost four times more Solo male founders than Solo female founders. The lower presence of female founder teams is consistent with Rose (2019), which points out that female entrepreneurs are less likely to pursue entrepreneurship compared with their male peers at almost every stage. Still, it requires further investigation into factors contributing to this under-presence.

Similar to all studies, this study has limitations. All female founder teams were not compared with their male counterparts, as they comprise only 2.29% of our sample of 524 campaigns. Based on the summary statistics, All-female teams attract the lowest capital and number of funders. This requires further examination, as the overall team effect is positive (Coakley et al., 2022b), but it seems to be different when male or female teams are compared.

Table 1: Variables and definitions

Variable name	Description
Dependent variables	
Ln(Funders)	Natural logarithm of the number of investors at the end of the campaign
Success	A dummy variable that takes 1 for those campaigns that reach their target and zero otherwise
Amount-to-goal	Amount raised divided by target amount
Overfund_d	A dummy variable that takes 1 for those campaigns raising money over the target value and is zero otherwise
Explanatory variables	
Solo_female	A dummy variable that takes value 1 for solo female founder and 0 for solo male founders
Founder type	A categorical variable that takes 1 for Solo male founders (reference category) and 2 for Solo female founders and 3 for Teams
Solo_founder	A dummy variable that takes value 1 for solo female founder and 0 for Teams
Control variables	
Advanced Degree	A dummy variable that takes value 1 if at least 1 member holds the title Dr or Professor, zero otherwise
Equity (%)	Equity issued during the campaign in percentage
Firm age (year)	The age of the firm on public launch date in year
Pre_money Valuation (£m)	Firm valuation (£m) prior to the crowdfunding campaign.
Team Age (year)	The average age of team members in year
Team Size (number)	The number of founders
Goal (£m)	Target goal (£m) of firms at the beginning of a campaign

Table 2: Descriptive statistics

Variable	N	Mean	SD	Median	Min	Max
Number of funders (k)	524	0.35	0.48	0.19	0	3.5
Success	524	0.94	0.24	1	0	1
Amount/goal	524	1.43	0.55	1.28	0.04	6.2
Overfunding dummy (%)	524	0.84	0.37	1	0	1
Solo_female	322	0.2	0.4	0	0	1
Founders type	524	1.89	0.93	2	1	3
Advanced degree	524	0.06	0.24	0	0	1
Equity (%)	494	15.08	7.85	14.12	0.39	54.27
Firm Age (years)	524	3.2	3.01	2.31	0.02	18.28
Pre-money Valuation(£m)	484	4.05	8.79	1.3	0	68.6
Team age (years)	524	42.24	9.71	42.99	20.34	70.19
Team size(number)	524	2.46	1.5	2	1	7
Goal(£m)	524	0.33	0.52	0.17	0.01	5

Table 3: ECF founder structure

Founder gender structure	Campaigns	Share (%)
Solo female	64	12.2
All female teams	12	2.3
Solo + All female	***76***	***14.5***
Solo male	258	49.2
All male teams	138	26.3
Solo + All male	***396***	***75.6***
Mixed teams	52	9.9
Total	524	

Note: This table reports the founder gender structure for the 524 ECF campaigns conducted on Crowdcube. Just one of the 52 mixed gender mixed campaigns had a majority of female founders.

Table 4. Equality of means test (Solo female versus Solo male founders)

Variables	Solo Male	Solo Female	Difference
Number of funders(k)	0.28	0.29	-0.01
Success	0.94	0.94	0.00
Amount/goal	1.37	1.5	-0.13**
Overfunding_d (%)	0.79	0.89	-0.10*
Advanced degree	0.05	0.02	0.03
Equity (%)	15	14.22	0.78
Firm Age (years)	3.1	3	0.11
Pre-money Valuation(£m)	3.4	2.16	1.23
Team age (years)	43.22	40.85	2.37*
Goal(£m)	0.27	0.26	0.01

Note: This table presents equality of means test results for Solo female founders versus Solo male founders.

Table 5. Equality of medians test (Solo female versus Solo male founders)

	Solo Male	Solo Female	Difference
Number of funders (k)	0.144	0.214	-0.071**
Success	1.00	1.00	0.00
Amount/goal	1.260	1.381	-0.121*
Overfunding dummy (%)	1.000	1.000	0.00
Advanced degree	0.000	0.000	0.00
Equity (%)	14.000	13.595	0.405
Firm Age (years)	2.301	2.175	0.126
Pre-money Valuation(£m)	0.975	1.077	-0.102
Team age (years)	44.497	41.093	3.404*
Goal(£m)	0.150	0.150	0.00

Note: This table presents equality medians (nonparametric Pearson Chi-square) test results for Solo female founders versus Solo male founders.

Table 6. Correlation Matrix

Variables	Ln(funders)	Success	Amount/goal	Overfund_d	Solo_female	Founder	Advanced degree	Equity	Firm Age	Premoney Valuation	Team age	Team size	Goal
Ln(funders)	1												
Success	0.164*	1											
Amount/goal	0.485*	0.271*	1										
Overfund_d	0.403*	0.566*	0.395*	1									
Solo_female	0.103*	-0.001	0.113*	0.102*	1								
Founder type	0.214*	0.015	0.101*	0.110*	1.000*	1							
Advanced degree	0.039	-0.04	0.016	0.002	-0.068	0.064	1						
Equity (%)	-0.100*	-0.045	-0.067	-0.002	-0.039	0.026	0.006	1					
Firm Age (years)	0.329*	0.117*	0.160*	0.063	-0.014	0.044	0.051	-0.256*	1				
Pre-money Valuation (£m)	0.513*	0.014	0.280*	0.056	-0.075	0.110*	0.046	-0.346*	0.346*	1			
Team age (years)	0.036	0.027	0.042	-0.013	-0.095*	-0.088*	0.150*	-0.181*	0.328*	0.174*	1		
Team size	0.185*	-0.03	0.066	0.037		0.786*	0.127*	0.025	0.056	0.117*	0.004	1	
Goal(£m)	0.436*	0.037	0.055	-0.016	-0.014	0.158*	0.058	-0.061	0.220*	0.622*	0.117*	0.145*	1

Note: Pairwise correlation method is used to investigate the dependence between all variables in the research. In the pairwise correlation method, the observations with missing data are also considered in the correlation calculation. So, the results are a better representative of the sample. Significance levels are denoted as * when $p < 0.10$, ** when $p < 0.05$ and *** when $p < 0.01$.

Table 7. ECF outcomes and founder team composition (Heckman model)

	Model (1)		Model(2)		Model(3)		Model(4)	
Variables	Selection	Ln(funders)	Selection	Success	Selection	Amount/Goal	Selection	Overfund_d
Solo_female		**0.298*** **		**0.00072**		**0.159*** **		**0.135*** **
		(2.875)		(0.030)		(3.340)		(2.950)
Advanced degree	-0.142**	0.202	-0.146***	0.518**	-0.149***	0.0757	-0.146***	0.156
	(-2.570)	(0.743)	(-4.380)	(4.070)	(-4.380)	(0.666)	(-4.47)	(0.980)
Equity (%)	-0.005**	0.0146**	-0.005**	-0.001	-0.005**	0.00265	-0.005**	0.004
	(-2.070)	(2.306)	(-2.270)	(-0.59)	(-2.260)	(-2.286)	(-2.3)	(-1.54)
Team age (years)	0.006***	-0.0144**	0.006***	0.0002	0.006***	0.000845	0.006**	-0.001
	(3.120)	(-2.218)	(2.620)	(0.210)	(2.640)	(0.380)	(2.580)	(0.600)
Firm Age (years)	-0.002	0.0371	-0.004	0.012	-0.004	0.0146	-0.005	0.007
	(-0.190)	(1.206)	(-0.370)	(1.270)	(-0.330)	(1.247)	(-0.43)	(0.640)
Pre-money Valuation(£m)	-0.005	0.0418***	-0.004	-0.004*	-0.004	0.0143***	-0.004	0.001
	(-1.370)	(8.036)	(-1.060)	(-1.510)	(-1.100)	(5.274)	(-1.113)	(0.580)
Goal(£m)	-0.164	1.677***	-0.198**	0.015	-0.198**	0.00608	-0.191**	-0.001
	(-1.600)	(5.126)	(-2.590)	(-0.340)	(-2.560)	(0.039)	(-2.5)	(-0.09)
	(-3.460)		(-2.230)		(-7.890)		(-9.26)	
atrho		-1.378***		0.986		-0.267**	0.549	
		(-4.39)		(1.37)		(-2.29)	(1.55)	
Industry dummies	YES	NO	YES	NO	YES	NO	YES	NO
Observations	481	302	481	302	481	302	481	302
Log pseudolikelihood	-624.57	-624.57	-356.62	-356.62	-482.84	-482.84	-436.94	-436.94

Note: The reported coefficients in selection models are marginal effects (dy/dx). The dependent variable in models (1) and (3) are Ln(Funders), and Amount/Goal, respectively, and Heckman is employed. In Models 2 and 4 the dependent variable is Success and Overfund_d. The heckprobit is used here, and marginal effects are reported. Significance levels are denoted as * when p < 0.10, ** when p < 0.05, and *** when p < 0.01. The standard errors are clustered at the industry level.

Table 8. ECF outcome and founder team composition (Robustness Analysis_1)

Variables	Model (1) Ln(Funders)	Model (2) Success	Model (3) Amount/Goal	Model (4) Overfund_d
Founder_type: Solo_female	0.299**	-0.00932	0.155**	0.114***
	(2.569)	(-0.277)	(2.944)	(4.160)
Founder_type: Teams	0.293***	0.00279	0.0708	0.0816**
	(5.873)	(0.094)	(1.006)	(1.964)
Advanced degree	-0.0899	-0.0413**	0.00451	-0.00992
	(-0.665)	(-2.312)	(0.033)	(-0.201)
Equity (%)	0.003	-0.00191	0.00345*	0.00118
	(0.757)	(-0.888)	(1.947)	(0.897)
Firm Age (years)	0.0468***	0.0159*	0.0172**	0.00917
	(3.543)	(1.921)	(2.552)	(0.924)
Pre-money Valuation(£m)	0.0308**	-0.0022	0.0233***	0.00527**
	(3.151)	(-1.060)	(4.100)	(2.175)
Team age (years)	-0.0102**	-0.00014	-0.000832	-0.00057
	(-2.498)	(-0.298)	(-0.480)	(-0.466)
Goal(£m)	0.958**	0.0239	-0.304**	-0.091
	(2.779)	(1.015)	(-3.165)	(-1.185)
Team size(number)	0.0484	-0.000537	0.0355	0.0125
	(1.852)	(-0.0616)	(1.511)	(1.289)
Constant	4.878***		1.242***	
	(23.830)		(12.530)	
Observations	481	418	481	481
R-squared	0.429		0.14	
Pseudo R-squared		0.0847		0.048
Industry dummies	Yes	Yes	Yes	Yes

Note: This table reports the results with t-statistics in parentheses for various ECF campaign outcome variables regressed on founder team characteristics and a set of controls. Models (1), (2) and (4) employ OLS. The dependent variables in Models (3) and (5) are a Success and an Overfund(ing) dummy, respectively, and the Probit estimation method is employed. All variables are winsorized at the 1% level except for Ln(Amount) which is winsorized at the 5% level. Significance levels are denoted as * when $p < 0.10$, ** when $p < 0.05$ and *** when $p < 0.01$. The standard errors are clustered at the industry level.

Table 9: Propensity score matching (Robustness Analysis_2)

	Ln(Funders)	Success	Amount/Goal	Overfund_d
One match per observation				
ATET	0.41**	0.065	0.23**	0.145*
	(2.31)	(1.13)	(2.29)	(1.91)
N	302	302	302	302
Three match per observation				
ATET	0.36**	0.043	0.201**	0.145**
	(2.56)	(1.07)	(2.32)	(2.35)
N	302	302	302	302
Five match per observation				
ATET	0.32**	0.032	0.163*	0.116**
	(2.39)	(0.86)	(1.95)	(2.07)
N	302	302	302	302

Note: This table reports the Average Treatment Effect on Treated (ATET), along with the t-statistics in parentheses. The matching method is the nearest neighbor match method, and the Solo female firms have been matched with 1, 3, and 5 counterfactuals based on their propensity score. The treatment and control groups are matched based on Advanced degree, Equity (%), Premoney Valuation, Team Age, and Goal.

Appendices Chapter 2

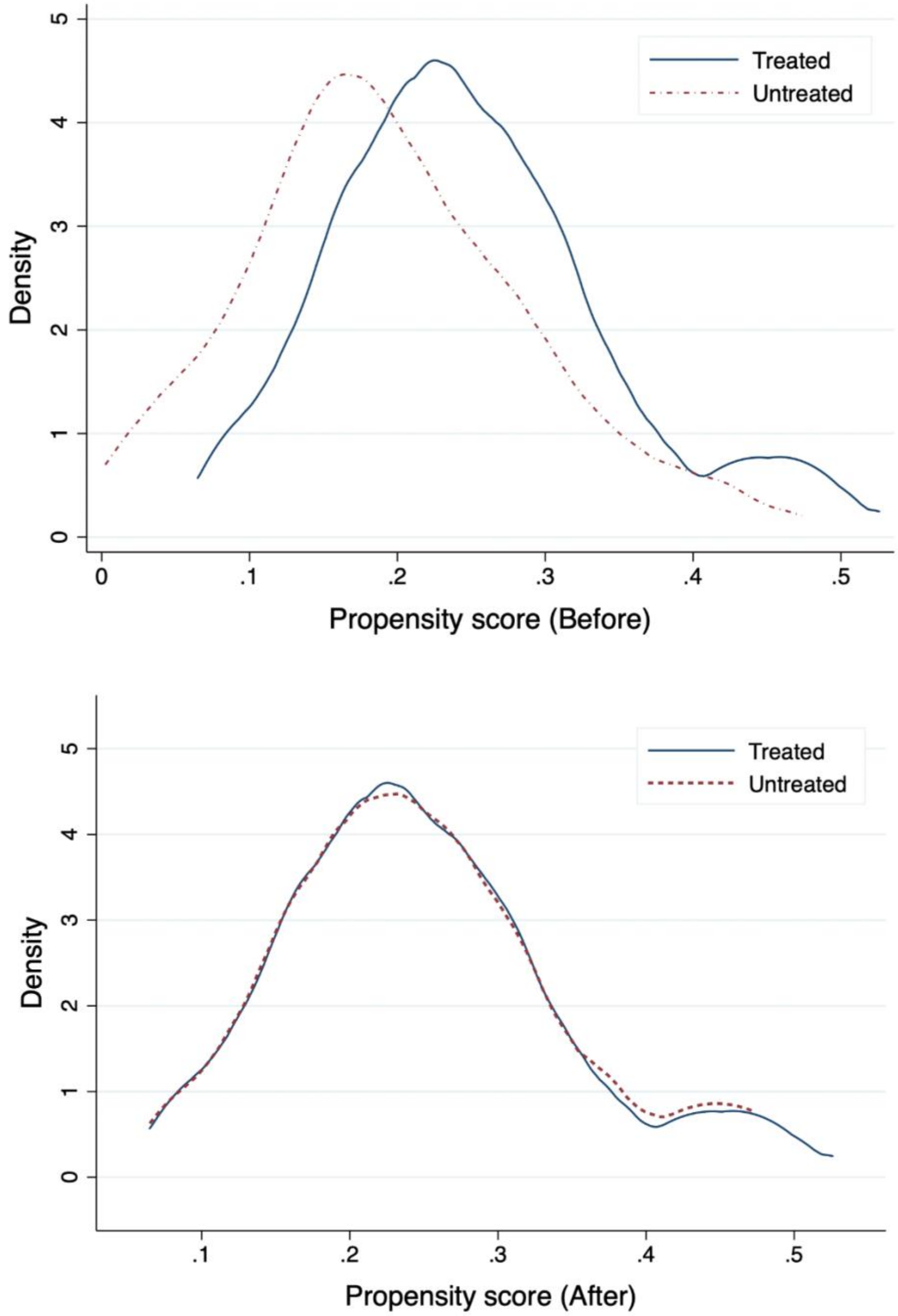
Table A1 : t-test before and after matching

Variable	Unmatched Matched	Treated (Mean)	Control (Mean)	% Bias	% Bias reduction	t-statistics	p-value
Advanced degree	U	0.0161	0.05	-19.0		-1.17	0.243
	M	0.0161	0.023	-3.6	81	-0.26	0.796
Premoney_valuation	U	2.164	3.412	-22.6		-1.31	0.191
	M	2.164	2.021	2.6	88.5	0.30	0.765
Equity (%)	U	14.219	14.73	-7.4		-0.47	0.637
	M	14.219	14.58	-5.2	29.3	-0.32	0.746
Team Age (years)	U	40.75	43.253	-27.2		-1.80	0.073
	M	40.75	40.665	0.9	96.6	0.05	0.959
Firm Age (years)	U	3.04	3.029	0.4		0.03	0.979
	M	3.04	3.140	-3.5	-815.8	-0.20	0.842
Goal(£m)	U	0.253	0.259	-2.1		-0.14	0.886
	M	0.253	0.243	3.5	-70.5	0.22	0.829

Sample	Pseudo R^2	LR χ^2	P - value	Mean bias %	Median bias %
Unmatched	0.045	13.78	0.032	13.1	13.2
Matched	0.002	0.35	0.999	3.2	3.5

Note: this table reports the t-statistics and p-value for the difference of mean between treated and control groups before and after matching. Bias percentage is reported to examine the covariate imbalance prior and after matching.

Figure A1: Propensity Score of Treated and Untreated



Note: The figure at the top is the Propensity Score of Treated (Solo female founders) vs. Untreated (Solo male founders) before matching, whereas the figure at the bottom is After matching. The propensity Score refers to the probability of a firm being in the Treated group (Solo female founders) or Untreated (Solo female founders) given the covariates calculated based on Advanced degree, Equity (%), Premoney Valuation, Team Age, and Goal.

Chapter 3
Responses to COVID-19: the role of digital equity and government loan schemes

Abstract

The advent of COVID-19 portended a dire liquidity crunch for small firms as traditional funding sources were curtailed. Defying expectations, initial equity crowdfunding (ECF) campaigns not only withstood the pandemic's onslaught but also saw unprecedented growth in funding volume, investor participation and overfunding (amount/target). This anomaly suggests a paradigm shift. External equity, the traditional funding of last resort, became the first choice. This paper documents that government-backed loan guarantees served as a liquidity certification effect for ECF campaigns, especially for seed ventures, thus substantiating ECF's potential as a digital lifeline. The paper highlights the unanticipated positive interplay between public support mechanisms and private equity dynamics bolstering the thesis of a reverse pecking order where equity is funding of first choice. These developments underscore ECF's instrumental role in channelling equity capital to small firms during a period of heightened economic uncertainty.

Keywords: Equity crowdfunding, COVID-19, Digital finance, Seed firms

1. Introduction

The COVID-19 pandemic was a major exogenous shock to all economies worldwide and it raised the spectre of a doomsday scenario for small firms hit by a combination of lockdown restrictions and an obvious lack of external funding sources (Belitski et al., 2022). The severity of the economic downturn and the scale of the related mortality numbers were unprecedented in recent decades (Altig et al., 2020, Baker et al., 2020). In the UK, the COVID-19 pandemic and related government lockdown restrictions impacted both new startup formation and the survival prospects of existing ventures. (Calabrese et al., 2022, Brown et al., 2020, Eggers, 2020, Altig et al., 2020, Brown and Cowling, 2021). This paper examines how equity crowdfunding (ECF) as a leading form of digital finance (Block et al., 2018, Block et al., 2021) helped young small firms meet the complex challenges the pandemic posed using a sample of 660 successful Crowdcube initial ECF campaigns, 2018-2023. The findings reveal a puzzling surge in ECF performance during COVID-19. The amount of equity raised, number of funders, and the degree of overfunding (amount/target) all rose by double-digit figures in contrast to underperforming public equity activity (Paterson et al., 2024) and to the pecking order theory that views external equity as funding of last resort.

This paper builds on recent calls to explore the impact of digitalization on resource mobilization by focusing on ECF as a form of digital equity (e.g., Estrin et al., 2018; Inceoglu et al., 2024). It makes two contributions to the literature. The first is that it explains why ECF, as a form of digital equity, flourished during COVID-19. This was partly because a digital platform proved more adaptable and resilient than traditional equity providers like business angels (BA) and venture capital (VC) funds and partly because a digital platform became an attractive outlet for professional investors whose traditional day-to-day activities were curtailed during the pandemic (Bellavitis et al., 2021). Both BA and VC initial funding rounds were adversely affected by the pandemic's lockdown restrictions due to restrictions on in-person meetings required for their due diligence (Mason and Botelho, 2021, Harrison et al., 2016). All this took place against a bleak mainstream financial market backdrop, where the FTSE 100 and the pound sterling posted record-breaking losses (Paterson et al., 2024). The digitalization process was the key to ECF success during COVID-19 as argued below.

A key feature of the recent (post-2016) UK digital equity model is that the ECF campaign lead investor undertakes her own due diligence as she has to organise a syndicate to pledge 20% of the target – a new provision point mechanism (PPM) – before the campaign can go public (Coakley et al., 2024). Here the impact of the lead investor – typically a business angel or venture capitalist – is akin to that of a third-party prior financing effect (Kleinert et al., 2020). These factors imply that low-quality ventures typically fail to meet the PPM while successful high-quality ventures attract professional investors even in times of increased uncertainty. Conveniently, lockdown measures – that interrupted the in-person due diligence practices of BA and VC investors – also shifted their investment towards ECF platforms (Mason and Botelho, 2021). Moreover, VC involvement in ECF campaigns had increased as a result of their diversification ("spray and pray") strategy over the past decade where they invested smaller amounts of funding and governance across a broader array of startups (Ewens et al., 2018). Digital ECF platforms are an ideal outlet in this context because their ownership and exit rights are almost identical to those of typical VC syndicates but within a digital framework. The digitalization of equity finance played a pivotal role in the boost to ECF performance during COVID-19 with platforms predominantly utilizing pre-campaign big data analytics for due diligence, facilitating online funding through ECF platforms, and implementing post-campaign digital ownership, monitoring, and corporate governance systems (Kleinert et al., 2022, Coakley et al., 2024, Inceoglu et al., 2024). The resultant increased involvement of professional investors on ECF platforms triggers cascading effects among the crowd and contributes to enhanced ECF performance (Vismara, 2018). The increase in ECF funding also reflects a broader trend in Western economies involving a shift from public to private equity and where innovative young firms benefit from staying private longer (Ewens and Farre-Mensa, 2022).

The paper's second contribution is that it highlights how a digital platform leveraged the government loan guarantee scheme (LGS) liquidity certification effect to provide equity funding to enable small and especially seed firms to flourish at the height of the pandemic. Seed firms are considered distinctive due to their higher innovation levels, presence in high-growth sectors, and a stronger emphasis on cutting-edge technology compared to other small firms. Kleinert et al. (2020) stress that prior financing by BA or VC exerts a strong signaling effect on seed firms. The latter also have lottery stock properties (Bali et al., 2011) such as right-skewed returns which make them highly attractive to professional investors like VCs. In this context, the government LGS helped young startups and seed firms in particular to overcome the liquidity crisis and related challenges arising during the pandemic (Brown and Cowling, 2021). While Bounce Back Loan Scheme (BBLS)[1] loans cannot be viewed as a prior certification effect (Kleinert et al., 2020) due to lack of time for due diligence and looser eligibility criteria[2], they provided a liquidity certification effect for recipient startups. This lowered their venture risk ratings by credit rating agencies, thereby making them more appealing to ECF platforms.

In this context, the increased demand for equity capital by small firms are more consistent with the reverse pecking order theory (POT) – where equity is funding of first choice – for the smallest firms (Frank and Goyal, 2003) and with the theoretical model predictions of Fulghieri et al. (2020). The ECF literature provides some evidence of ECF as funding of last resort as the POT predicts (Blaseg et al., 2021, Walthoff-Borm et al., 2018) but their samples do not extend beyond 2015. In other words, they applied to the period of pure ECF (Vismara, 2016) with mainly crowd investors when serious adverse selection problems persisted because due diligence was hampered by the collective action problem. Finally, the Fulghieri et al. (2020) model predicts that firms with pre-existing debt are likely to use equity in follow-on offerings An unintended consequence of government-backed loans at a time of falling equity valuations was an increase in seed firm gearing ratios. Successful ECF campaigns then directly assisted them in recapitalizing and nudging their gearing ratios back to tolerable levels. The role of ECF funding in this context sharply contrasts with the pre-COVID-19 funding of seed firms. Historically, BA and VC funds would invest in seed firms via convertible (loan) notes[3] that offer no immediate ownership or control rights but can be converted to equity at a future Series A round (Weiss, 2023).

The findings on the outperformance of ECF campaigns during the COVID-19 period link to the related literature. They support the early COVID-19 period ECF findings of Vu and Christian (2023) for the UK and the Cumming et al. (2021b) ECF and P2P lending results for

[1] During COVID-19, the UK government introduced three major Loan Guarantee Schemes (LGSs) two of which aimed at supporting small firms, namely the Bounce Back Loan Scheme (BBLS) and the Coronavirus Business Interruption Loan Scheme (CBILS). These three initiatives helped over 1 million UK businesses, with BBLS being the most widely utilized (Cowling et al., 2023, Cowling et al., 2022). For further details on BBLS and CBILS, see: https://www.gov.uk/guidance/apply-for-a-coronavirus-bounce-back-loan and https://www.gov.uk/guidance/apply-for-the-coronavirus-business-interruption-loan-scheme

[2] Eligibility criteria for BBLS: https://www.gov.uk/guidance/apply-for-a-coronavirus-bounce-back-loan#eligibility

[3] Detailed information on VC investments is extremely difficult to obtain. See this link for UK VC. https://www.osborneclarke.com/insights/vc-focus-why-vcs-and-companies-use-convertible-loan-notes-and-bridging-rounds-uk . Weiss (2023) confirms a similar pattern in the USA.

the USA. It validates the conjecture of Walthoff-Borm et al. (2018) that ECF can theoretically serve as the primary funding source for private firms during crises (Guenther et al., 2018) as it fosters founder control and provides value-added services like digital corporate governance to investors (Estrin et al., 2018).

The paper's seed firm findings link to the related COVID-19 literature. Calabrese et al. (2022) examined the role of COVID-19 government loan guarantee schemes (LGS) in supporting UK SMEs and established that the most significant proportion of loans were directed to better-performing micro and small businesses. Brown et al. (2020) found that seed firms accounted for most of the equity funding of small firms during COVID-19. Our paper also contributes to the literature on the effectiveness of UK government LGS during the COVID-19 crisis (Cowling et al., 2023, Cowling et al., 2022, Wilson et al., 2023). ECF outperformance was particularly notable during the government LGS period, suggesting a direct impact of government intervention on crowdfunding success, particularly among seed firms.

The remainder of this paper is organised as follows. Section 2 reviews the literature and outlines the hypotheses to be examined. Section 3 provides an overview of the methodology and describes the empirical models employed to test the hypotheses. Section 4 analyses and discusses the empirical findings. The final section concludes.

2. Literature review and hypotheses

2.1 Funding responses to natural disasters

The crises following natural disasters typically have the most detrimental impact on smaller and younger firms' day-to-day business and on their ability to access traditional funding sources such as bank lending (Nguyen and Wilson, 2020, Cortés and Strahan, 2017, Casey and O'Toole, 2014). Similar to a natural disaster, COVID-19 represents a major exogenous shock (Li et al., 2023, Baltas et al., 2022, Chandler et al., 2021) that offers a quasi-natural setting to explore shifts in the digital capital raising outcomes of smaller firms. By contrast to a natural disaster, a pandemic involves the outbreak of an infectious disease over entire economies – the world *in extremis* – that generally affects a significant proportion of the population and leaves huge numbers of fatalities in its wake over a prolonged period. The related economic crises lead to more extreme information asymmetries impacting particularly young startups, making access to external – including digital – finance even more challenging. However, recent research indicates that alternative financing might exhibit distinct behavioural patterns during periods of heightened uncertainty (Baltas et al., 2022, Zhang et al., 2015).

COVID-19 highlighted a sharp contrast between the modus operandi of ECF and traditional sources of equity for small firms. Due diligence by traditional VC and BA investors relies on face-to-face contact over a period of time to perform detailed evaluations of prospective startups seeking equity (Agrawal et al., 2016, Cumming et al., 2021b). By contrast, ECF platforms rely heavily on digital and word of mouth (for example, networks of accountants and lawyers that deal with such ventures) due diligence. Consequently, many professional investors migrated their investments to online ECF platforms during the pandemic (Mason and Botelho, 2021). This was a general trend that had earlier gained momentum with business angels (Wright et al., 2015) and with the "spray and pray" venture capital strategy over the past decade where small investments are spread over a wider range of startups (Ewens et al., 2018). Note here that such investments by BA or VC would serve as a strong prior financing signalling effect leading to potential cascading behaviour by other investors (Vismara, 2018).

2.2 Pecking order theory

The traditional pecking order theory (POT) posits that firms prefer internal to external funds due to adverse selection costs (Myers, 1984, Myers and Majluf, 1984) and, among external funds, they prefer debt to equity. POT was developed at a time when public equity – given by stock exchange flotation – was in the ascendancy. However, recent decades have witnessed a move in the opposite direction with a fall in public (listed) firms and a simultaneous rise in private firms which Doidge et al. (2017) refer to as the listing gap. The empirical study of Lattanzio et al. (2023) confirms this trend for developed economies and shows that it emerged earlier (in the mid-1990s) in the UK and USA relative to other developed economies. The shift in Western economies from public to private equity is driven by factors such as the increased costs of regulation on stock markets (public equity) and the fact that the deregulation (e.g. allowing the establishment of ECF platforms) of the private equity markets enhances the benefits for small firms of remaining private (Ewens and Farre-Mensa, 2022).

The COVID-19 pandemic had a dual effect on the equity financing of firms. On the one hand, it exerted a direct effect on the professional investors (VC and BA) that traditionally supplied private equity but who suffered due to lockdown restrictions (Mason and Botelho, 2021, Brown et al., 2020). More generally, COVID-19 led to sharply increased uncertainty for public equity (Brown and Rocha, 2020) which drove down stock exchange valuations and hampered the IPO markets. The latter are quite sensitive to the negative mood in the markets. Paterson et al. (2024) report that the FTSE 100 and pound sterling witnessed record-breaking losses during the COVID-19 period that would have depressed the IPO market also. In other words, traditional equity finance was severely rationed during COVID-19.

On the other hand, the pandemic-induced shift from traditional to digital finance is clearly illustrated by the performance of ECF campaigns. How does this link to POT? Researchers such as Walthoff-Borm et al. (2018) and Blaseg et al. (2021) find that ECF was the funding of last resort for ECF samples of UK and German firms, respectively, which is in line with the traditional POT. However, their ECF samples end in 2015 and so belong to the pure ECF era (Vismara, 2016) where small crowd investors dominated ECF campaigns giving rise to the collective action problem. By contrast, the post-2016 syndicated ECF model with a lead investor (Coakley et al., 2024) has transformed the role of professional investors in ECF as it has leveraged their due diligence and monitoring skills to attract high-quality investors to their campaigns. In particular, the new PPM of requiring the lead investor syndicate to garner pledges for a minimum of 20% of the target prior to the campaign going public is a game changer in terms of sharply improving the quality of small firms permitted to run initial ECF campaigns. Moreover, Kleinert et al. (2022) provide survey evidence that the stringent due diligence standards imposed by ECF platforms across a range of countries imply that only high-quality ventures are permitted to run ECF campaigns. For such firms, ECF is funding of first resort or what Fulghieri et al. (2020) call the reverse POT. In this context, Walthoff-Borm et al. (2018) were prescient in arguing that ECF could theoretically be funding of first resort as it permits founder control and offers value-added services like visibility and feedback.

2.3 Hypotheses

The development and growth of digital finance platforms such as ECF, P2P and others (e.g. market invoice or the prepayment of invoices for a fee) began in the wake of the Great Financial Crash. The COVID-19 lockdown restrictions curtailed traditional investor activities which relied heavily on face-to-face due diligence. This provided ECF platforms with a unique opportunity to attract more professional investors, thereby enhancing campaign performance through a BA or VC certification effect. These investors responded by investing in ECF either as lead investors in syndicated ECF campaigns or by diversifying their investment risk across a range of ECF campaigns in a period of heightened risk. Additionally, they were drawn to the bespoke value-added services provided by the platform (Walthoff-Borm et al., 2018). These include a digital nominee corporate governance structure that monitors ECF firms and protects the ownership and exit rights of all investors (Coakley et al., 2024, Agrawal et al., 2016).

The COVID-19 boost to digital finance is exemplified by initial ECF campaigns run by high-quality startups during the pandemic period. These new equity injections would help to boost their funding performance relative to those in the pre-COVID-19 period as outlined in H1A:

H1A: *Initial ECF campaigns launched during the COVID-19 period outperform those of the pre-COVID-19 period.*

During the post-COVID-19 period, the crisis factors that previously boosted ECF outcomes no longer apply, and so funding outcomes tended to revert to their pre-COVID-19 patterns. This leads to H1B:

H1B: *Initial ECF campaigns launched during the post-COVID-19 period perform similarly to those of the pre-COVID-19 period.*

The other novel factor that impacted ECF during COVID-19 was government intervention on an unprecedented scale aimed at reducing capital-raising barriers for small firms generally but for seed firms in particular (OECD, 2020, Feyen et al., 2020, Cowling et al., 2023, Calabrese et al., 2022). The UK government supported SMEs financially through schemes like the BBLS, CBILS (Coronavirus Business Interruption Loan Scheme) and others. These were aimed at addressing market imperfections by offering government loan guarantee schemes (LGS) to smaller (seed- and early-stage) firms during the systemic liquidity crisis resulting from the COVID-19-induced sudden drop in revenues (Cowling et al., 2023). Calabrese et al. (2022) find that some 92% of the debt funding provided during this period was backed by the UK government, swamping the usual support level of under 5%.

Jibril et al. (2021) using survey data from the SME Finance Monitor for Q3 and Q4 2020 report a positive short-term effect of the policy instruments employed by the UK government. Wilson et al. (2023) observed that patterns of insolvency during the COVID-19 pandemic differed from those of previous crises. Notably, there was an initial decline in insolvency rates, particularly in the first year of COVID-19, which contributed to the liquidity certification effect of such loan schemes. Moreover, by lowering the risk of startup debt, LGS prompted credit rating agencies to give the recipients improved credit rating scores that are a critical component of platform due diligence.[4] This leads to the following hypothesis on the government LGS and their impact on ECF campaigns.

H2A*: *The government loan guarantee schemes in the first year of COVID-19 positively impacted ECF campaign performance.

The LGS targeted small and young startups. Among the latter, seed firms are typically younger, riskier, and often more innovative than early-stage and growth firms. The literature suggests seed firms usually struggle to secure outside funding, especially during periods of heightened uncertainty (Fraser et al., 2015, Baltas et al., 2022, Berger and Udell, 1998). The substantial challenges encountered by such firms at the onset of the COVID-19 crisis (January 2020 - March 2020) are consistent with these observations, as noted by Brown et al. (2020). The traditional investors in seed firms in normal times are mostly BA (Block et al., 2019) and VC (Weiss, 2023). ECF platforms during the pandemic presented such investors with two unique advantages for investing directly in seed firms.

First and crucially, investors could immediately acquire direct equity stakes in seed firms via ECF instead of potential deferred equity acquired via convertible notes. While the government support packages exerted an overall positive effect on seed firms, they had one unintended side effect: the resultant debt increases inflated their leverage ratios, especially at a time of falling equity valuations. This made equity injections all the more urgent (Calabrese et al., 2022, Jibril et al., 2021, Cowling et al., 2023). The related second advantage of ECF in this context was that government-backed loans provided a liquidity certification effect that paved the way for a private equity injection by BA of VC. Since higher-performing micro and small firms were the primary beneficiaries of government loans (Calabrese et al., 2022), these firms were able to pass both ECF platform checks (Kleinert et al., 2022) and lead investor due diligence in raising initial ECF funds during the COVID-19 period. Fulghieri et al. (2020) offer another rationale that applies in this

[4] See Cumming et al. (2019) on the critical details of due diligence.

context. Firms that already have debt are more likely to use equity in follow-up offerings. This leads to H2B on the outperformance of seed firms.

H2B. *Seed firms exhibit improved ECF performance compared to other ECF firms during COVID-19.*

3. Methodology

The COVID-19 pandemic was an exogenous shock that provides a singular research opportunity for examining the capital-raising performance of firms on ECF platforms. This study employs a categorical variable regression to analyse differences in performance between campaigns in the pre-COVID-19, COVID-19, and post-COVID-19 periods. Variations in ECF performance are given by the logged values of the Amount raised, the number of Funders, and Overfunding (Amount/Goal) outcomes. All regressions take account of industry-fixed effects. The categorical variable (COVIDcat) takes the value of 1 for campaigns conducted during the pre-COVID-19 period (January 2018 – February 2020), 2 for campaigns during COVID-19 (March 2020 December 2021), and 3 for post-COVID-19 campaigns (December 2021 – October 2023). A dummy variable (LGS_d), taking the value of 1 for the duration of the government's COVID-19 loan schemes in 2020, is employed to examine their effects.[5]

The empirical setting of this study comprises 660 initial ECF offerings on Crowdcube between January 2018 and October 2023. Since our attention is directed exclusively towards ECF offerings, we do not include those that offer convertibles or debt (bonds), but only equity-related offerings. Furthermore, the dataset comprises initial ECF campaigns as follow-on ECF campaigns can potentially benefit from a positive certification effect from a successful initial campaign (Coakley et al., 2022a). The choice of the platform and the sampling criteria are in line with most previous studies on ECF (Cerpentier et al., 2022, Estrin et al., 2018, Walthoff-Borm et al., 2018). Several control variables are included to account for the observable heterogeneity in firms seeking to raise ECF funds. Ln(Goal (£m)) refers to the natural logarithm of the goal (target) set at the beginning of the campaign. Under the All-or-Nothing provision point mechanism, startups can retain the raised capital if and only if they reach or exceed this threshold (Burtch et al., 2018, Cumming et al., 2020). Equity offered (%) is a reliable signal of the entrepreneur's confidence in

[5] As part of a robustness check, additional analysis incorporating the interaction of LGS_d and COVIDcat was conducted. The results are consistent with those presented in our main model in Table 8.

the firm. Ceteris paribus, the more confident she is about her firm (project), the smaller the equity share she is prepared to sell to outsiders (Ahlers et al., 2015, Vismara, 2016).

Firm-related characteristics include Pre-money Valuation (£m), which is the agreed valuation of a firm (by the founder(s) and platform) prior to the initial ECF campaign and is a proxy for the size (Coakley et al., 2022a). Firm size is positively associated with the ability to survive disasters or crises (Baltas et al., 2022). Firm stage is a categorical variable for three types of young firms involved in ECF campaigns: seed, early stage, and growth stage. Founder Team size can affect ECF outcomes and the literature suggests that a higher number of founders is associated with higher success in ECF (Coakley et al., 2022b). An Enterprise Investment Scheme (Weiss) tax relief dummy, which equals one for firms using this scheme and zero otherwise (Vu and Christian, 2023), captures potential professional investor involvement. The number of Views and Followers of the campaign on the Crowdcube platform is used to proxy for the social capital and visibility of firms. This has an important signalling role from the investor's perspective (Vismara, 2016) and a visibility role from the firm’s viewpoint (Walthoff-Borm et al., 2018). Finally, industry dummies are used to control for industry-fixed effects and capture the unobservable traits of each industry.

3.1 Regression models

The estimation method employed is ordinary least squares (OLS) and robust standard errors are reported in all Tables. The following model is used to test hypotheses H1A and H1B, where the ECF performance for each campaign is proxied by the natural logarithm of Amount, Funders and Overfunding (Amount/Goal) ratio:

$$\mathrm{Ln(ECF\ performance_i)} = \alpha_1 + \beta_1\,\mathrm{COVIDcat} + \Gamma_1\mathrm{Controls_i} + \varepsilon_1 \qquad (1)$$[6]

where i denotes campaign i and $\mathrm{Controls_i}$ represents a vector of control variables as defined in Table A1. The categorical variable COVIDcat can be rewritten in the form of two dummies with associated β_{11} and β_{12} coefficients, respectively:

$$\mathrm{Ln(ECF\ performance_i)} = \alpha_1 + \beta_{11}\,\mathrm{COVID\_Pre} + \beta_{12}\,\mathrm{Post\_Pre} + \Gamma_1\mathrm{Controls_i} + \varepsilon_1 \qquad (1.1)$$

[6] The estimation results of this model using a post-COVID-19 dummy (post-COVID-19 campaigns vs. COVID-19 campaigns) are presented in Table A6 in the Appendix for the robustness tests of H1A and H1B.

The coefficients β_{11} and β_{12} respectively capture the initial and net impacts of COVID-19, compared to the performance metrics of the pre-COVID-19 period.

The following two models are employed to test hypotheses H2A and H2B:

$$\mathrm{Ln(ECF\ performance_i)} = \alpha_2 + \beta_2\mathrm{LGS\_d} + \Gamma_2\mathrm{Controls_i} + \varepsilon_2 \tag{2}$$

$$\mathrm{Ln(ECF\ performance_i)} = \alpha_3 + \beta_{31}\mathrm{Seed\_d} + \beta_{32}\mathrm{COVID\_d} + \beta_{33}\mathrm{Seed\_d} * \mathrm{Covid\_d} + \Gamma_3\mathrm{Controls_i} + \varepsilon_3 \tag{3}$$

The primary explanatory variable in Model (2) is LGS_d which is equal to 1 for the period during which the UK government loan schemes (BBLS and CBILS) were offered and 0 otherwise (both during the COVID-19 period). The main coefficient of interest in Model (3) is β_{33} which is the interaction of seed firm campaigns with the COVID-19 period. This shows the effect of being a seed stage firm for ECF initial campaign outcomes during COVID-19 compared to the non-COVID-19 period.

3.2 Robustness analysis

Several robustness tests were performed to evaluate the robustness of the results. Model (1) is re-estimated using a COVID-19 dummy to examine the results of the hypotheses H1A and H1B. Here, the comparison is between the COVID-19 sample (Covid_d=1) period campaigns and the remaining campaigns (Covid_d =0). As a robustness test of H2A, Model (2) is re-estimated for the first year of COVID-19 (March 2020–December 2021), contrasting the period when government loan schemes were available with all other periods. Propensity Score Matching (PSM) is employed to examine the robustness of the H2B results. This method has been used by several ECF and COVID-19 studies to deal with endogeneity (Coakley et al., 2022b, Vismara, 2019, Li et al., 2023). The use of PSM here seeks to answer the following question: are seed firms during the COVID-19 period, ceteris paribus, less/more likely to outperform when compared with counterfactuals in the non-COVID-19 period matched on Goal(£m), Equity(%), Pre-money Valuation(£m), and Team Size.[7] Here the sample includes seed firms.

4. Data and empirical analysis

The analysis utilises a dataset comprising 660 initial ECF campaigns on Crowdcube, the leading

[7] The post-estimation results of this method are available in Table A7 and Figure A1 in the Appendix.

UK-based ECF platform. Data were collected from the platform using a customised program designed for information scraping. When the necessary information is unavailable, the dataset is supplemented by data obtained from Companies House (Cerpentier et al., 2022, Vismara, 2016). The dataset covers three distinct periods, as shown in Table 1.

[Insert Table 1 around here]

This gives the distribution of campaigns across the three (approximately) 2-year sample periods. Nearly one-third (33.66%) of the campaigns were conducted during the actual COVID-19 period, with a greater number occurring pre-COVID-19 and fewer afterwards. It also shows that the government LGS were available for over half (54%) of COVID-19 period campaigns.

4.1 Descriptive statistics

Table 2 reports the summary statistics for the variables that are defined in Table A1 in the Appendix.

[Insert Table 2 around here]

Table 2 highlights the presence of right-skewness for the outcome variables Amount, Funders, and Overfunding, as their means are all substantially greater than their corresponding medians. Hence, these variables are logged in the empirical analysis to mitigate the impact of outliers. Table 2 shows that firms offer, on average, 11.11% (median of 9.37%) of their equity capital, implying that founders clearly retain majority control. The median Pre-money Valuation is £4.53m, and the median Team Size is 1, indicating that solo founders predominate. Approximately 73% of the campaigns include an EIS option to attract professional investors through tax relief schemes.

Figure 1 shows the mean value of the ECF campaign outcomes and the campaign goals over the three COVID-19 periods.

[Insert Figure 1 around here]

The Amount raised in initial campaigns increased in the pre-COVID-19 period and continued to grow thereafter. Simultaneously, the average funding goal (the amount requested by ventures) is on the rise. This ongoing increase in funding goals chimes with the Beauhurst (2022) observation that the ECF market is increasingly attracting more established firms. As the market evolves, it attracts an increased presence of professional investors (Coakley et al., 2024) alongside the crowd. The observed decrease in the median value of funding goal during the COVID-19 period, contrasted with an increase in its mean value, can be attributed to a higher number of successful initial campaigns by seed firms during the pandemic, while outliers have concurrently driven up the average value. The COVID-19 period attracted the highest number of Funders and the greatest degree of Overfunding (Amount/Goal) and both of these exhibit concave patterns over the sample period.

Table 3 provides a breakdown of ventures running initial ECF campaigns into seed, early-stage, and growth categories. Prior to COVID-19, just over half (52%) of the ventures were early stage, with the remaining firms distributed between seed (26%) and growth-stage (23%) categories. The proportion of seed firms jumped to 39% during the pandemic but fell sharply to just 14% during the post-pandemic period. Correspondingly, the share of early-stage firms rose from 39% during COVID-19 to some 63% post-COVID-19. The share of growth-stage firms remained stable at 22-23% over the sample period. Table A2 in the Appendix presents the pairwise correlation coefficients between all variables included in the regression analysis. Except for the first three columns involving the dependent variables, none of the pairwise correlations exceeds 0.6.

[Insert Table 3 around here]

Table 4 displays the test results for equality of mean and median (nonparametric Pearson Chi-square) for COVID-19 vs. pre-COVID-19 and post-COVID-19 vs. pre-COVID-19 variables. Panel A shows that the COVID-19 mean and median values of Funders, Overfunding and Pre-money Valuation are significantly larger than their pre-COVID-19 counterparts at the 5% level or better (the mean Amount is also considerably larger). Panel B shows that both the post-COVID-19 mean and median values of Amount, Goal and Pre-money Valuation are significantly larger than their pre-COVID-19 levels at a 5% significance level or better, while the Equity (%) share sold is significantly smaller. The mean and median difference of Funders and degree of Overfunding are both insignificant.

[Insert Table 4 around here]

4.2 Regression results

Table 5 presents the results of the categorical variable regression models. These serve to evaluate the performance of ECF campaigns over both the COVID-19 and post-COVID-19 periods relative to the baseline pre-COVID-19 period. The primary explanatory variables are *COVID_Pre* and

Post_Pre in these models. The former gives the COVID-19 effect or the difference between the COVID-19 and pre-COVID-19 periods. The coefficient on Post_Pre gives the difference between the post-COVID-19 and pre-COVID-19 periods, or the net COVID-19 effect. The dependent variables are the performance metrics *Ln(Amount)*, *Ln(Funders)*, and *Ln(Overfunding)* in Models 1 and 2, 3 and 4, and 5 and 6, respectively. The second model in each pair (for example, Model 1 in the 1 and 2 pair) adds industry-fixed effects (FE) to the relevant regression.

[Insert Table 5 around here]

Virtually all small firm capital gearing ratios were sharply inflated during COVID-19 by a combination of increasing debt levels and lower equity valuations as a result of increasing risk levels and little or no retained earnings. Debt levels rose due to the liquidity crisis from falling sales revenue and the need for additional funds, including from government-backed loans. Note that the Amount of ECF funds raised directly increases a firm's equity and, ceteris paribus, improves its gearing ratio. Thus, the Amount raised is considered the most salient performance metric in our regression analysis. It should be noted that the mean (median) Amount raised was a considerable £790k (£480k) for the full sample.

The COVID-19 effect (*COVID_Pre*) is significantly positive at the 1% level in Models (1) and (2), indicating that the COVID-19 period campaigns raised a significantly larger Amount (of equity) than their pre-COVID-19 counterparts. In Model (2) with industry FE, the coefficient is 0.136, suggesting that Amount raised by COVID-19 campaigns is 14.6% ($e^{.136} - 1 = 0.146$) higher than their pre-COVID-19 counterparts. Such considerable levels of new equity helped to reduce gearing ratios. This supports H1A.

The performance variable used in Models (3) and (4) is the natural logarithm of Funders(k). The COVID-19 effect (*COVID_Pre*) is significant at the 1% level in Model (4). Its value implies that the number of funders during COVID-19 was some 32% ($e^{.281} - 1 = .324$) higher than in the pre-COVID-19 period. This is an impressive increase in funders and likely reflects large numbers of crowd investors attracted by the increasing involvement of BA and VC investors in ECF campaigns generally as noted by Wang et al. (2019) for an earlier period. Models (5) and (6) employ *Ln(Overfunding)* as the dependent variable. The COVID-19 effect (*COVID_Pre*) in equation (6) is significantly positive at the 1% level. This implies that COVID-19 campaigns enjoyed a 13% ($e^{.122} - 1 = 0.13$) increase in the Overfunding ratio relative to pre-COVID-19 campaigns. Both Model (4) and (6) results also clearly support H1A. Our findings for the full pandemic period extend the results of Cumming et al. (2021b) and Vu and Christian (2023) for the early months of COVID-19 in the USA and UK, respectively. They showcase the outperformance of ECF campaigns during the full COVID-19 period using three different metrics. The increases reported above range from 13% for Overfunding and 14.6% for Amount raised to 32% for Funders.

Finally, note that the coefficients on *Post_Pre* are statistically insignificant across all six regressions in Table 5. These imply that the post-COVID-19 funding performance was not significantly different from the pre-COVID-19 funding performance, indicating a return to the *status quo ante.* This supports H1B. These results provide initial evidence of the post-pandemic resilience of the ECF ecosystem to the COVID-19 shock and the agility of digital platforms in adapting to increased demands for outside equity from smaller firms. Summing up, the Table 5 regression results show that initial ECF campaigns exhibited an unexpected surge in funding performance during the full COVID-19 period relative to the pre-COVID-19 period which returned to pre-COVID-19 levels in the post-COVID-19 period.

The coefficients on *Ln(Goal)* are significantly positive at the 1% level in Models (1) to (4), indicating that Goal exerts a positive impact on both the Amount raised and the number of Funders. *Ln(Goal)* is excluded from Models (5) and (6) due to endogeneity concerns. The other two control variables that are mostly significant across models are EIS and Followers. The significantly positive coefficients of EIS in Models (1) to (6), but excluding (4), underline the direct impact of (tax relief for) professional investors on Amount raised, Funders and Overfunding. The control variable, Followers, is significantly positive at the 1% level in all regressions underlining the important impact of campaign visibility (Walthoff-Borm et al., 2018) and social capital (Cumming et al., 2020, Vu and Christian, 2023, Vismara, 2019) on performance.

Overall, the results reported in Table 5 suggest a heightened interest in equity capital on ECF platforms, suggesting a surge in private equity demand during the crisis. This uptick coincides with the lockdown-induced constraints on traditional entrepreneurial finance sources like BA and VC (Mason and Botelho, 2021), and the scarcity of funding for small firms (Baltas et al., 2022, Zhang et al., 2015, Cumming et al., 2021b). They also underline the positive impact of COVID-19 on ventures' use of ECF as a viable source of equity finance (Cumming and Reardon, 2022, Vu and Christian, 2023).

Table 6 compares ECF campaign outcomes during the April 2020 – March 2021 period, when both the BBLS and CBILS government LGS were available, versus the second year of COVID-19 when they were withdrawn. An LGS dummy variable (*LGS_d*) is employed to capture this effect. The coefficient of *LGS_d* is positive and highly significant across all regressions, suggesting a novel liquidity certification effect of the BBLS (and CBILS) government loan guarantee schemes, which backed most of SME debt finance during the first year of COVID-19 (Calabrese et al., 2022). The coefficient of 0.133 in Model (2) indicates that, during the government support period, campaigns raised 14.2% ($e^{0.133} - 1$) higher Amounts of funds than during the second year of COVID-19. Model (4) suggests that during the first year of COVID-19, the number of investors was 26.1% ($e^{0.232} - 1$) higher than in the second year. Along similar lines, the Model (6) Overfunding coefficient implies a 20.2% ($e^{0.184} - 1$) increase in the Amount-to-goal ratio in the first relative to the second year of COVID-19. These results highlight the overall positive impact of the UK government's support of small firms during COVID-19 (Jibril et al., 2021, Calabrese et al., 2022) and support H2A.

[Insert Table 6 around here]

Table 7 reports the results of the interaction of a COVID-19 period dummy with a seed dummy to examine the performance of seed versus more established firms during COVID-19.[8] The coefficients of *Covid_d* align with our previous regression results. The negative *Seed_d* coefficient is significant at the 5% level in (6), insignificant in (4), and significant at the 10% level only in (2). These indicate that seed firms generally underperform compared to more established firms which is in line with the typical information asymmetry problems of smaller firms (Coakley and Lazos, 2021, Wilson et al., 2018). In Model (2) with *Ln(Amount(£m))* as the dependent variable, the interaction term coefficient is positive but significant at the 10% level only, while it is insignificant in (4). However, it is statistically significant at the 5% level in Model (6), suggesting that seed firms enjoy an 18.2% ($e^{0.168} - 1$) increase in Overfunding relative to early-stage and growth firms during COVID-19. Overall, COVID-19 had a positive effect on Overfunding, and, at a lower significance level, the Amount raised by seed firms in comparison to their more established counterparts. These results lend some support to H2B.

[8] The robustness of the analysis is confirmed by examining both seed firms exclusively and in combination with early-stage firms to mitigate any influence the platform's definition of 'seed firms' might have on our findings.

[Insert Table 7 around here]

The findings in Tables 5, 6 and 7 are consistent with BA and VC funds leveraging the due diligence of ECF platforms and of the lead investor in campaigns to invest in seed startups. ECF platforms enable them to gain a direct equity stake in seed firms rather than an indirect one via convertible loan notes that they traditionally employed. The findings are also consistent with an element of the "spray and pray" approach of VC funds diversifying their approach to seed firms with smaller investments and limited involvement in governance (compared to their traditional approach) across more startups over the past decade or so in the USA (Ewens et al., 2018). Moreover, these funds could leverage both digital ECF platform governance and the liquidity certification effect of LGS loans by investing in seed firms. They are in line with the findings of Jibril et al. (2021) on the positive impact of the policy instruments used by the UK government to support SMEs (Calabrese et al., 2022, Cowling et al., 2023, Wilson et al., 2023). Here, the prospect of using ECF campaigns for debt and capital gearing ratio reduction likely led to additional successful campaigns during COVID-19. Indeed, this observation aligns with the finding that ECF platforms emerged as the most active investors in early-stage equity in the UK in 2020 (Beauhurst, 2022, Cerpentier et al., 2022)

4.3 Robustness Tests

This section discusses the results of robustness tests. First, Table A3 in the Appendix presents the robustness test results for H1A and H1B. The *Covid_d* coefficient compares the performance of COVID-19 period campaigns versus non- (pre-and post-) COVID-19 campaigns. These results reconfirm that ventures attract significantly larger Amounts of capital, more Funders, and higher Overfunding ratios during the COVID-19 than the non-COVID-19 periods.

Table A4 in the Appendix presents the results of comparing the first year of COVID-19 with all other periods. The coefficient of the government *LGS_d* is positive and significant in the models, reconfirming the H2A hypothesis.

Table A5 in the Appendix presents the results of utilising Propensity Score Matching to compare the performance of seed firms during the COVID-19 period with those in the other periods. For robustness purposes, this analysis is conducted using two routines in Stata – *psmatch2* (Panel A) and *teffects* (Panel B) – which utilize different approaches for calculating standard errors.

The Average Treatment Effect on Treated (ATET), capturing the causal impact of COVID-19 on seed performance, is reported using one, three and five matches per observation. The significantly positive coefficients across all three measures of performance suggest that, during COVID-19, seed firms outperformed their counterparts in non-Covid-periods. These findings are consistent with those in Table 7, demonstrating that during the COVID-19 period, seed firms' access to ECF was unrestricted and they significantly outperformed.

5. Conclusions

This paper provides clear evidence of an unexpected surge in ECF performance during the COVID-19 period relative to that of the pre-COVID-19 period. One explanation for this is the ECF platform evolution towards attracting high-quality firms, a task at which it was less successful during its early years (Blaseg et al., 2021, Walthoff-Borm et al., 2018). The pandemic's constraints inadvertently tipped the scales in favour of digital equity platforms, eclipsing traditional avenues such as BA and VC. This pivot is compounded by a broader, seismic shift from public to private equity, reshaping the investment landscape over recent decades.

These findings, while rather unexpected in this context, are in step with the burgeoning and positive impact of digitalization on entrepreneurial finance which has created new financial avenues that complement traditional intermediaries as discussed by Bertoni et al. (2022). Digitalisation serves a dual purpose. First, it empowers nascent firms, even those with limited financial track records and no audited accounts, to secure financial resources through internet platforms (Inceoglu et al., 2024). This corroborates the democratizing influence of ECF (Cumming et al., 2021a, Wang et al., 2019) and its leading role during the COVID-19 period (Cumming et al., 2021b). The latter period offered a unique laboratory setting for testing the performance of ECF at a time of heightened uncertainty and limited access for smaller firms to traditional entrepreneurial finance sources due to lockdown restrictions (Baltas et al., 2022, Zhang et al., 2015, Cumming et al., 2021b).

Second, the disruption wrought by the pandemic, unlike that of natural disasters, precipitated a shift in due diligence practices - digital access to funding became a necessity (Agrawal et al., 2016, Cumming et al., 2021a). This situation, marked by intensified information asymmetries, favoured digital channels like ECF and P2P lending. Consequently, ECF platforms thrived by catering to high-calibre small private firms that met exacting due diligence standards.

ECF thus emerged as a lifeline for these ventures, ensuring their survival and prosperity. For traditional and professional investors, the pandemic served as an impromptu nudge for transitioning to online services offered by digital platforms. This paves the way for future research on post-pandemic online investment tactics of BAs and VCs who have unwittingly test-driven the value added by ECF platforms during the COVID-19 pandemic.

This paper reveals an unforeseen positive consequence of government loan guarantee schemes (LGS), notably the BBLS Bounce Back Loan Scheme) with full repayment guarantees, on equity sources for small firms. Contrary to initial concerns about potential negative effects on SME lending and other finance sources[9], the findings highlight the beneficial impact on small firms' access to equity capital—an outcome not anticipated at the scheme's inception. The paper underlines the pivotal role of LGS during the initial year of the COVID-19 crisis. By providing repayment guarantees ranging from 80% to 100%, these schemes not only offered vital liquidity support for equity crowdfunding (ECF) campaigns by recipient firms but also significantly bolstered the performance of seed firms. This outperformance among young seed firms stands out as particularly surprising, given that traditional investors typically favour more established firms, a preference intensified by the financial crisis (Vismara, 2018). The resilience and adaptability of ECF platforms during COVID-19 further underscore their critical role in mitigating the impacts of external disruptions. This dual effect of LGS and ECF platforms in facilitating small firms' access to equity capital highlights their importance, offering policymakers evidence of the effectiveness of LGS, particularly in supporting seed firms.

This paper provides a complementary perspective to that of Savio et al. (2024) who analyze government financial support mechanisms in Italy from 2008 to 2014, specifically examining temporary debt suspension. Our study focuses on loan guarantees. While both debt moratoria and loan guarantees are forms of financial support, they influence firm strategies in a distinct manner. Savio et al. (2024) discuss how debt moratoria – pausing debt payments – can bolster SME long-term growth. Conversely, loan guarantees acted as a short-term buffer against the COVID-19 crisis by providing much-needed working capital and liquidity and potentially boosting the related ECF surge via a liquidity certification effect during the pandemic. While Savio et al. (2024) investigate

[9] Please refer to
https://assets.publishing.service.gov.uk/media/5ee11ef3d3bf7f1eb4a1b4eb/200501_AO_Direction_letter_on_Bounce_Back_Loans_Scheme.pdf

principal-principal conflicts within a large SME sample, our study suggests that such conflicts are less prevalent in digital ECF funding, given the equitable share ownership and exit rights ensured by digital nominee shareholding (Coakley et al., 2024).

This study has some limitations. For example, the dataset is confined to just one of the two major UK ECF platforms – the Crowdcube platform. However, this is the longest established and largest UK platform which vouches for the broad applicability of our findings. Moreover, although more than 90% of SMEs utilized the government guarantee schemes for raising debt during the first year of the pandemic (Calabrese et al., 2022), the UK government's policy of withholding the identities of state-backed COVID-19 loan recipients[10] restricts directly linking our ECF dataset with that for the COVID-19 loans. Nonetheless, given excess demand for ECF funding and the huge numbers of firms that availed of LGS schemes, it is highly likely that the platform choose such firms due to their lower firm-specific risk.

The findings suggest two areas for future research. First, the empirical results are consistent with ECF as funding of first resort for small private firms during a crisis period. The question is whether this is driven by the crisis effect or whether it is a more general phenomenon for young, high-quality private firms. More research is warranted on a possible reverse POT (Fulghieri et al., 2020) for such firms. Second, it would be interesting to explore the relative performance during the COVID-19 period of ventures that received a combination of ECF, and other digital funding (e.g. market invoice finance) compared to ventures that received ECF funding only. However, this currently would face data challenges.

[10] https://www.theguardian.com/business/2023/jan/05/names-of-uk-covid-business-loan-applicants-to-stay-secret-tribunal-rules

Table 1. Campaign distribution

Sub-sample periods

		No. Campaigns	Percent
Pre- COVID-19	January 2018 – February 2020	256	40.65%
COVID-19	March 2020 – December 2021	209	33.66%
	LGS available	113	
	LGS unavailable	96	
Post- COVID-19	December 2021 – October 2023	195	25.69%
Total		660	

Note: The Covid-19 period ended in mid-December 2021.

Table 2. Descriptive statistics

Variable	Mean	Median
Amount(£m)	0.79	0.48
Funders (k)	0.67	0.38
Overfunding	1.82	1.43
Goal(£m)	0.44	0.3
Equity (%)	11.11	9.37
Pre-money Valuation(£m)	12.25	4.53
Team size	1.35	1
Firm Stage	1.95	2
EIS	0.73	1
Followers(k)	1.21	0.7
Views(k)	28.49	19.26

Note: This table displays the summary statistics for the variables used in our empirical analysis.

Table 3. Firm stage and COVID-19

	Pre-COVID-19 Campaigns		COVID-19 Campaigns		Post-COVID-19 Campaigns		All Campaigns	
	(N)	(%)	(N)	(%)	(N)	(%)	(N)	(%)
Seed	48	26%	81	39%	20	14%	149	28%
Early-stage	96	52%	81	39%	92	63%	269	50%
Growth-stage	42	23%	45	22%	33	23%	120	22%
Total	186	100%	207	100%	145	100%	538	100%

Note: This table presents the number (%) of campaigns based on firm stage for the pre-COVID-19, COVID-19, and post-COVID-19 periods. The total COVID-19 campaigns is 207 as firm stage data are missing for 2 firms.

Table 4. Equality of means and median tests

Panel A. COVID-19 vs. Pre-COVID-19

	COVID-19		Pre-COVID-19			
Variables	Mean	Median	Mean	Median	Mean Difference	Median Difference
Amount(£m)	0.82	0.48	0.66	0.41	0.16**	0.07
Funders (k)	0.79	0.47	0.55	0.34	0.24***	0.13***
Overfunding	2.07	1.58	1.72	1.42	0.35***	0.16***
Goal(£m)	0.42	0.25	0.38	0.3	0.04	-0.05
Equity (%)	12.79	9.24	11.83	11.78	0.96	-2.54**
Pre-money Valuation(£m)	11.89	4.31	7.58	3	4.31**	1.31**
Team size	1.4	1	1.31	1	0.09	0
Firm Stage	1.83	2	1.97	2	-0.14*	0
EIS	0.68	1	0.72	1	-0.04	0
Followers(k)	1.38	0.84	1.12	0.65	0.25	0.19*
Views(k)	32.5	19.33	28.75	20.87	3.76	-1.54

Panel B. (Post-COVID-19 vs. Pre-COVID-19)

	Post- COVID-19		Pre-COVID-19			
Variables	Mean	Median	Mean	Median	Mean Difference	Median Difference
Amount(£m)	0.93	0.567	0.66	0.413	0.27***	0.154***
Funders (k)	0.7	0.371	0.55	0.335	0.15	0.036
Overfunding	1.66	1.303	1.72	1.424	-0.06	-0.121
Goal(£m)	0.54	0.4	0.38	0.3	0.16***	0.1***
Equity (%)	8.27	6.31	11.83	11.78	-3.56***	-5.47***
Pre-money Valuation(£m)	18.97	7.5	7.58	3	11.39***	4.5***
Team size	1.35	1	1.31	1	0.04	0
Firm Stage	2.09	2	1.97	2	0.12*	0
EIS	0.78	1	0.72	1	0.06	0
Followers(k)	1.05	0.6	1.12	0.65	-0.11	-0.05
Views(k)	22.61	16.15	28.75	20.87	-5.96*	-4.72***

Note: Significance at the 10%, 5%, and 1% levels is indicated by *, ** and ***, respectively

Table 5. ECF campaigns: COVID-19 vs. Pre-COVID-19, Post- vs. Pre-COVID-19 result

Variables	(1) Ln(Amount(£m))	(2) Ln(Amount(£m))	(3) Ln(Funders(k))	(4) Ln(Funders(k))	(5) Ln(Overfunding)	(6) Ln(Overfunding)
COVID_Pre	0.139***	0.136***	0.273***	0.281***	0.117***	0.122***
	(3.24)	(3.12)	(4.89)	(5.05)	(2.62)	(2.66)
Post_Pre	0.0661	0.0734	-0.0063	-0.00428	-0.00927	0.00229
	(1.41)	(1.60)	(-0.0857)	(-0.0612)	(-0.208)	(0.05)
Ln(Goal(£m))	0.840***	0.835***	0.222***	0.192***		
	(29.10)	(29.05)	(5.16)	(4.96)		
Equity (%)	0.00350**	0.00357**	-0.000147	-0.00103	0.00148	0.00156
	(2.49)	(2.29)	(-0.0519)	(-0.355)	(1.14)	(1.10)
Pre-money Valuation(£m)	0.00049	0.000628	-0.000887	-0.000927	-0.000605	-0.000416
	(0.39)	(0.50)	(-0.486)	(-0.539)	(-0.634)	(-0.429)
Team size	-0.00927	-0.0058	0.00107	0.00702	-0.0156	-0.00964
	(-0.402)	(-0.249)	(0.03)	(0.22)	(-0.651)	(-0.392)
Firm Stage	0.0539*	0.0566*	0.0626	0.0639	-0.021	-0.02
	(1.87)	(1.91)	(1.48)	(1.64)	(-0.814)	(-0.758)
EIS	0.0970**	0.0924**	0.125**	0.091	0.0821**	0.0752*
	(2.54)	(2.39)	(2.24)	(1.63)	(2.13)	(1.93)
Views(k)	0.000587	0.000667	0.00554**	0.00570***	0.000209	0.000219
	(0.67)	(0.77)	(2.40)	(2.62)	(0.28)	(0.30)
Followers(k)	0.111***	0.103***	0.213***	0.196***	0.107***	0.100***
	(4.07)	(4.05)	(3.43)	(3.56)	(4.74)	(4.68)
Constant	-0.122	-0.0349	5.592***	5.528***	0.319***	0.459***
	(-1.089)	(-0.209)	(33.77)	(28.82)	(4.41)	(2.90)
Industry FE	NO	YES	NO	YES	NO	YES
Observations	487	487	487	487	487	487
Adjusted R-squared	0.851	0.852	0.596	0.642	0.222	0.228

Note: The dependent variable in models (1), (3), and (5) is the natural logarithms of Amount, Funders, and Overfunding (Amount/Goal), respectively, and the key coefficients of interest are those of COVID_Pre and Post_Pre. The estimation method is Ordinary Least Squares (OLS). Models (2), (4), and (6) are the same as (1), (3), and (5), respectively, but include industry-fixed effects. The standard errors are robust. The dataset consists of successful initial ECF campaigns on Crowdcube from January 2018 to October 2023. Significance at the 10%, 5%, and 1% levels is indicated by *, ** and ***, respectively.

Table 6. Loan guarantee scheme (LGS) vs. non LGS campaigns

Variables	(1) Ln(Amount(£m))	(2) Ln(Amount(£m))	(3) Ln(Funders(k))	(4) Ln(Funders(k))	(5) Ln(Overfunding)	(6) Ln(Overfunding)
LGS_d	0.0916	0.133**	0.206**	0.232***	0.151***	0.184***
	(1.62)	(2.29)	(2.52)	(2.86)	(2.67)	(3.10)
Ln(Goal(£m))	0.796***	0.784***	0.219***	0.184***		
	(16.75)	(14.73)	(3.46)	(2.84)		
Equity (%)	0.00423**	0.00390*	0.00105	-0.00029	0.000898	0.0008
	(2.32)	(1.71)	(0.41)	(-0.0837)	(0.54)	(0.36)
Pre-money Valuation(£m)	0.0036	0.0036	0.00380*	0.00314	0.00154	0.00163
	(1.53)	(1.38)	(1.66)	(1.31)	(0.78)	(0.76)
Team size	-0.00073	-0.0082	0.0449	0.022	-0.00651	-0.00129
	(-0.0254)	(-0.293)	(0.95)	(0.48)	(-0.201)	(-0.0391)
Firm Stage	0.0422	0.0473	0.00346	0.0171	-0.0715*	-0.0631
	(0.85)	(0.91)	(0.06)	(0.31)	(-1.838)	(-1.580)
EIS	0.219***	0.212***	0.182**	0.164*	0.174***	0.145**
	(3.59)	(3.18)	(2.16)	(1.87)	(2.88)	(2.25)
Views(k)	-0.000426	-0.000208	0.00262	0.00322*	-0.00052	-0.000538
	(-0.597)	(-0.268)	(1.55)	(1.86)	(-0.804)	(-0.753)
Followers(k)	0.126**	0.114**	0.226**	0.198**	0.122***	0.115**
	(2.56)	(2.35)	(2.42)	(2.32)	(2.81)	(2.52)
Constant	-0.196	-0.249	5.764***	5.827***	0.357***	0.51
	(-1.233)	(-0.667)	(30.09)	(16.87)	(3.78)	(1.61)
Industry FE	No	Yes	No	Yes	No	Yes
Observations	207	207	207	207	207	207
Adjusted R-squared	0.85	0.852	0.617	0.652	0.257	0.265

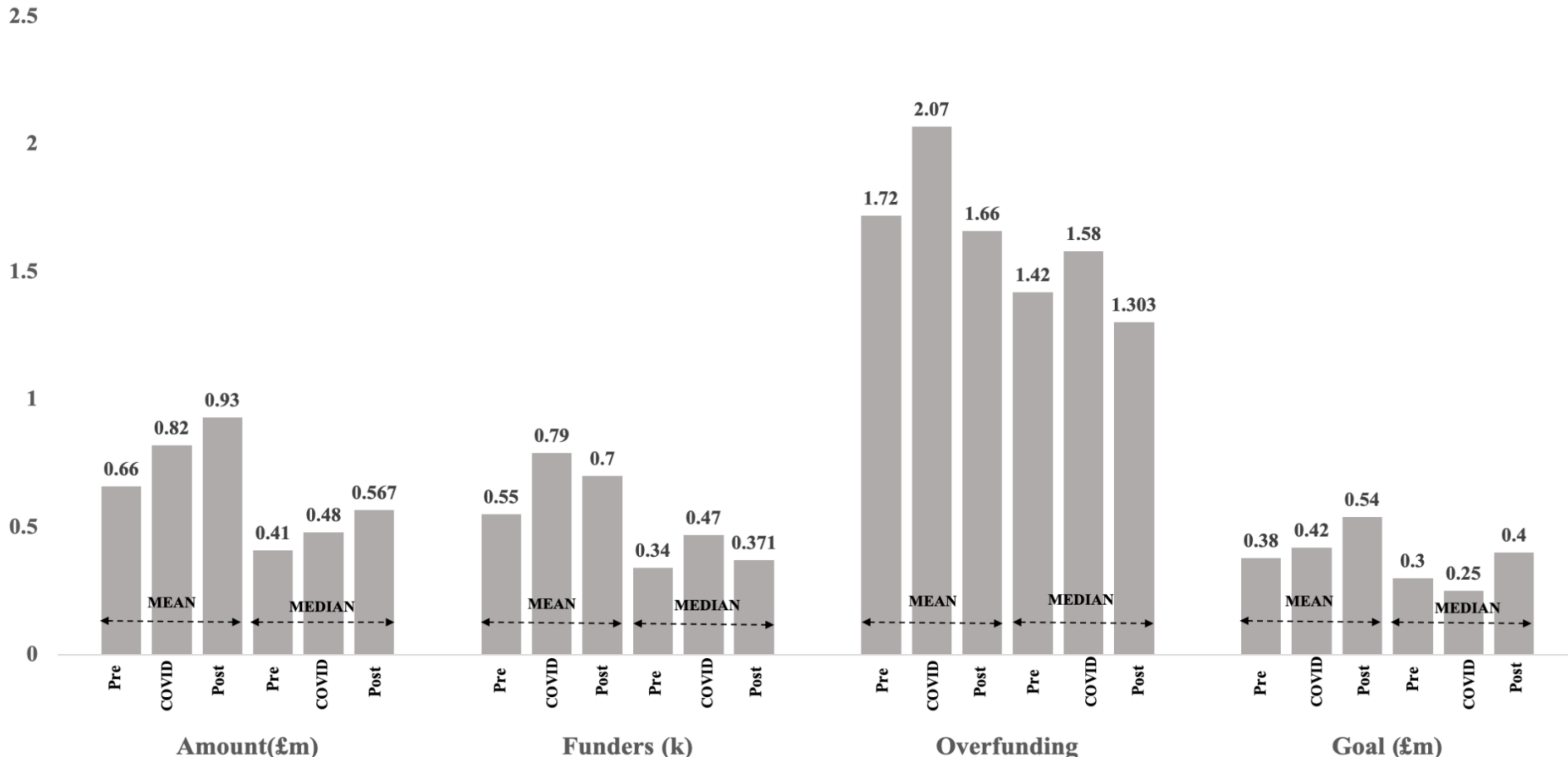
Note: The dependent variables in models (1), (3), and (5) are the natural logarithms of Amount, Funders, and Overfunding (Amount/Goal), respectively, where the key coefficient of interest is that of a Loan Guarantee Scheme dummy, LGS_d. The estimation method is Ordinary Least Squares (OLS). Models (2), (4), and (6) represent the same models as (1), (3), and (5), respectively, but they include industry-fixed effects. The standard errors are robust. The dataset includes successful initial ECF campaigns for the full COVID-19 period (March 2020 – Dec 2021). Significance at the 10%, 5%, and 1% levels is indicated by *, ** and ***, respectively.

Table 7. COVID-19 period and seed firm ECF outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Ln(Amount(£m))	Ln(Amount(£m))	Ln(Funders(k))	Ln(Funders(k))	Ln(Overfunding)	Ln(Overfunding)
Covid_d	0.190*	0.0645	0.376***	0.229**	0.105**	0.0757
	(1.90)	(1.46)	(3.83)	(2.82)	(2.15)	(1.61)
Seed_d	-0.696***	-0.141*	-0.394***	-0.0923	-0.114**	-0.159**
	(-6.381)	(-1.849)	(-3.890)	(-0.708)	(-2.450)	(-1.984)
Covid_d×Seed_d	-0.144	0.139*	0.00624	0.179	0.162**	0.168**
	(-0.873)	(1.85)	(0.04)	(1.41)	(1.99)	(2.10)
Ln (Goal(£m))		0.847***		0.195***		
		(31.31)		(4.82)		
Equity (%)		0.00354**		-0.00113		0.00157
		(2.25)		(-0.680)		(1.08)
Pre-money Valuation(£m)		0.000819		-0.00109		-0.000393
		(0.66)		(-0.929)		(-0.406)
Team size		-0.00489		0.00721		-0.0098
		(-0.208)		(0.18)		(-0.390)
Firm Stage		0.016		0.0635		-0.06
		(0.33)		(0.84)		(-1.270)
EIS tax		0.0866**		0.0832		0.0653*
		(2.19)		(1.41)		(1.66)
Views(k)		0.000626		0.00581***		0.000341
		(0.77)		(4.29)		(0.47)
Followers(k)		0.102***		0.197***		0.101***
		(4.13)		(5.86)		(4.68)
Constant	-0.551***	0.155	6.020***	5.590***	0.475***	0.611***
	(-9.830)	(0.81)	(113.10)	(20.63)	(18.78)	(3.14)
Industry FE	No	Yes	No	Yes	No	Yes
Observations	538	487	538	487	538	487
Adjusted R-squared	0.122	0.853	0.064	0.643	0.03	0.236

Note: This table presents the OLS regression results with robust standard errors of the interaction of Seed_d and Covid_d. Covid_d×Seed_d is the main variable of interest. The dependent variables in Models (1), (3), and (5) are the natural logarithms of Amount, Funders, and Overfunding (Amount/Goal), respectively. Models (2), (4), and (6) add control variables and industry-fixed effects to previous models. The dataset includes successful initial ECF campaigns on Crowdcube from January 2018 to October 2023. Significance at the 10%, 5%, and 1% levels is indicated by *, ** and ***, respectively.

Figure 1. ECF outcomes (Pre-, COVID-19 and Post-COVID-19)



Note: This bar chart depicts the mean and median values for Amount (£m), Funders (k), Overfunding, and Goal(£m) for the pre-, COVID-19 and post-COVID-19 periods. The dataset includes successful initial ECF campaigns on Crowdcube from January 2018 to May 2023.

Appendices Chapter_3

Table A1. List of variables

Dependent variables	
Amount(£m)	Total Amount raised in the campaign
Funders (k)	The number of funders (investors) at the end of the campaign
Overfunding	Amount raised divided by goal.
Explanatory variables	
COVIDcat	A categorical variable that takes 1 for campaigns pre- COVID-19, 2 during COVID-19, and 3 post-COVID-19
COVID_Pre	A dummy variable that takes 1 for the COVID-19 period and zero for pre-COVID-19
Post_Pre	A dummy variable that takes 1 for the post-COVID-19 period and zero for pre-COVID-19
Covid_d	A dummy variable that takes 1 for the COVID-19 period and zero otherwise
LGS _d	A dummy variable that takes 1 for the period BBLS/CBILS was offered (April 2020-March 2021) by the UK government and 0 otherwise.
Seed_d	A dummy variable that takes 1 for seed firms and zero for early-stage and growth firms
Other variables	
Ln(Goal (£m))	The natural logarithm of funding Goal that firms set at the beginning of a campaign
Equity (%)	Equity (%) of firm's equity issued during the campaign
Pre-money Valuation(£m)	Firm valuation (£m) before the crowdfunding campaign
Team Size	The number of founders
Firm Stage	A categorical variable that takes 1 for seed-, 2 for early- and 3 for growth-stage
EIS	A dummy that takes 1 if firms use the Enterprise Investment Scheme tax relief and zero otherwise
Views (k)	Number of viewers of the firm on the Crowdcube platform
Followers (k)	Number of followers of the firm on the Crowdcube platform

Table A2. Correlation matrix

Variables	Amount	Funders	Overfunding	COVIDcat	LGS_d	Goal	Equity	Valuation	Team size	Firm Stage	EIS	Followers	Views
Amount (£m)	1												
Funders (k)	0.780*	1											
Overfunding	0.467*	0.511*	1										
COVIDcat	0.123*	0.063	-0.012	1									
LGS_d	-0.015	0.046	0.182*	0.04	1								
Goal(£m)	0.754*	0.372*	-0.026	0.153*	-0.097*	1							
Equity (%)	0.03	-0.052	0.048	-0.118*	0.144*	0.061	1						
Pre-money Valuation(£m)	0.594*	0.655*	0.215*	0.176*	-0.05	0.436*	-0.243*	1					
Team size	0.024	0.059	0.046	0.028	0.007	0.003	0.136*	-0.014	1				
Firm Stage	0.429*	0.298*	0.041	0.057	-0.104*	0.444*	-0.073*	0.380*	-0.077*	1			
EIS	-0.126*	-0.084*	-0.003	0.054	-0.055	-0.106*	-0.068	-0.199*	0.07	-0.073*	1		
Followers(k)	0.700*	0.933*	0.461*	-0.025	0.053	0.315*	-0.012	0.570*	0.082*	0.216*	-0.074	1	
Views(k)	0.540*	0.686*	0.245*	-0.064	0.106*	0.374*	0.077*	0.532*	0	0.302*	-0.157*	0.586*	1

Note: This table presents the correlation matrix detailing the relationships among all variables utilized in this study. Significance at the 10%, 5%, and 1% levels is indicated by *, ** and ***, respectively

Table A3. COVID-19 vs. non-COVID-19 period campaigns (Robustness H1A and H1B)

Variables	(1) Ln(Amount(£m))	(2) Ln(Amount(£m))	(3) Ln(Funders(k))	(4) Ln(Funders(k))	(5) Ln(Overfund)	(6) Ln(Overfund)
Covid_d	0.107***	0.101***	0.276***	0.283***	0.121***	0.120***
	(3.10)	(2.80)	(5.35)	(5.79)	(3.34)	(3.28)
Ln (Goal(£m))	0.848***	0.844***	0.221***	0.191***		
	(31.37)	(31.18)	(5.44)	(5.23)		
Equity (%)	0.00349**	0.00356**	-0.000147	-0.00103	0.00147	0.00161
	(2.51)	(2.30)	(-0.0517)	(-0.355)	(1.14)	(1.13)
Pre-money Valuation(£m)	0.000658	0.00081	-0.000903	-0.000937	-0.000638	-0.000356
	(0.54)	(0.66)	(-0.501)	(-0.555)	(-0.681)	(-0.376)
Founding Team size	-0.00826	-0.00455	0.000974	0.00694	-0.0158	-0.00801
	(-0.361)	(-0.197)	(0.03)	(0.22)	(-0.658)	(-0.340)
Firm Stage	0.0537*	0.0563*	0.0626	0.0639	-0.0215	-0.0185
	(1.86)	(1.90)	(1.48)	(1.64)	(-0.838)	(-0.717)
EIS tax relief	0.0995***	0.0957**	0.125**	0.0908	0.0816**	0.0789**
	(2.59)	(2.46)	(2.25)	(1.64)	(2.11)	(2.13)
Number of Views(k)	0.00046	0.000526	0.00555**	0.00570***	0.000225	0.00035
	(0.55)	(0.65)	(2.42)	(2.66)	(0.30)	(0.48)
Number of followers(k)	0.110***	0.102***	0.213***	0.196***	0.107***	0.0899***
	(4.15)	(4.15)	(3.45)	(3.58)	(4.75)	(4.15)
Constant	-0.0786	0.00734	5.588***	5.526***	0.316***	0.458***
	(-0.794)	-0.046	-36.41	-29.98	-4.628	-2.924
Industry FE	NO	YES	NO	YES	NO	YES
Observations	487	487	487	487	487	487
Adjusted R-squared	0.85	0.852	0.597	0.643	0.224	0.224

Note: The dependent variables in models (1), (3), and (5) are the natural logarithms of Amount(£m), Funders, and Overfunding (Amount/Goal), respectively, with the key coefficient of interest being Covid_d. The estimation method used is Ordinary Least Squares (OLS). Models (2), (4), and (6) are the same as (1), (3), and (5), respectively, but include industry-fixed effects. The standard errors are robust. The dataset includes successful initial campaigns on Crowdcube from January 2018 to October 2023. Significance at the 10%, 5%, and 1% levels is indicated by *, ** and ***, respectively.

Table A4. Loan guarantee scheme (LGS) vs. non LGS campaigns (Robustness H2A)

Variables	(1) Ln(Amount(£m))	(2) Ln(Amount(£m))	(3) Ln(Funders(k))	(4) Ln(Funders(k))	(5) Ln(Overfunding)	(6) Ln(Overfunding)
LGS_d	0.134***	0.127***	0.310***	0.309***	0.170***	0.165***
	(2.94)	(2.67)	(5.66)	(5.51)	(3.62)	(3.35)
Ln (Goal(£m))	0.855***	0.849***	0.235***	0.201***		
	(31.46)	(31.33)	(5.61)	(5.35)		
Equity (%)	0.00315**	0.00327**	-0.000864	-0.00165	0.00112	0.00124
	(2.22)	(2.06)	(-0.306)	(-0.568)	(0.85)	(0.85)
Pre-money Valuation(£m)	0.000717	0.000884	-0.000785	-0.000775	-0.000475	-0.000253
	(0.58)	(0.71)	(-0.444)	(-0.470)	(-0.502)	(-0.259)
Team size	-0.00522	-0.00214	0.00874	0.0134	-0.0119	-0.00641
	(-0.228)	(-0.0938)	(0.24)	(0.42)	(-0.496)	(-0.263)
Firm Stage	0.047	0.0501*	0.045	0.0465	-0.0245	-0.0239
	(1.64)	(1.70)	(1.09)	(1.20)	(-0.958)	(-0.919)
EIS	0.0998***	0.0970**	0.125**	0.0937*	0.0835**	0.0780**
	(2.63)	(2.52)	(2.26)	(1.70)	(2.19)	(2.02)
Views(k)	0.000376	0.000454	0.00539**	0.00558***	0.000109	0.00012
	(0.45)	(0.57)	(2.36)	(2.63)	(0.15)	(0.17)
Followers(k)	0.111***	0.102***	0.216***	0.199***	0.108***	0.101***
	(4.22)	(4.23)	(3.52)	(3.67)	(4.86)	(4.83)
Constant	-0.0424	0.0175	5.683***	5.558***	0.332***	0.451***
	(-0.431)	(0.11)	(36.91)	(30.28)	(4.90)	(2.87)
Industry FE	No	Yes	No	Yes	No	Yes
Observations	487	487	487	487	487	487
Adjusted R-squared	0.851	0.852	0.594	0.639	0.231	0.236

Note: The dependent variables in models (1), (3), and (5) are the natural logarithms of Amount (£m), Funders (k), and Overfunding (Amount/goal), respectively, with the key coefficient of interest being LGS_d. The estimation method used for these three models was Ordinary Least Squares (OLS). Models (2), (4), and (6) represent the same models as (1), (3), and (5), respectively, but with the inclusion of industry-fixed effects. The standard errors are robust. The dataset includes successful initial ECF campaigns on Crowdcube from January 2018 to October 2023. Significance at the 10%, 5%, and 1% levels is indicated by *, ** and ***, respectively.

Table A5. Propensity Score Matching (Robustness H2B)

Panel A: Results using *psmatch2* routine in Stata.

	(1) Ln(Amount)	(2) Ln(Funders)	(3) Ln(Overfunding)
ATET (One match per observation)	0.04	0.27*	0.17*
	(0.24)	(1.66)	(1.86)
ATET (Three matches per observation)	0.09	0.39***	0.194***
	(0.61)	(3.02)	(2.59)
ATET (Five matches per observation)	0.15	0.38***	0.209***
	(1.09)	(3.01)	(2.92)
Obs.	149	149	149

Panel B: Results using *teffects* routine in Stata.

	Ln(Amount)	Ln(Funders)	Ln(Overfunding)
ATET (One match per observation)	0.348***	0.647**	0.243*
	(7.27)	(2.55)	(1.88)
ATET (Three matches per observation)	0.389**	0.525***	0.227**
	(2.46)	(3.62)	(2.26)
ATET (Five matches per observation)	0.423***	0.535***	0.232***
	(2.91)	(4.54)	(2.66)
Obs.	143	143	143

Note: This table reports the Average Treatment Effect on Treated (ATET) and the *t*-statistics in parentheses using two routines in Stata. Seed firms during COVID-19 are matched with one, three, and five counterfactuals based on their propensity scores. The treatment and control groups are matched based on the Goal (£m), Equity (%), Pre-money Valuation (£m), and Team Size.

Table A6. ECF Post-COVID-19 vs. COVID-19 outcomes

Variables	(1) Ln(Amount(£m))	(2) Ln(Amount(£m))	(3) Ln(Funders(k))	(4) Ln(Funders(k))	(5) Ln(Overfunding)	(6) Ln(Overfunding)
Post_COVID	-0.0771*	-0.0842*	-0.281***	-0.314***	-0.126***	-0.134***
	(-1.861)	(-1.946)	(-3.842)	(-4.747)	(-3.055)	(-3.109)
Ln (Goal(£m))	0.839***	0.842***	0.215***	0.210***		
	(23.44)	(21.68)	(3.89)	(4.17)		
Equity (%)	0.00308**	0.00290*	0.000341	-0.000832	0.00114	0.00104
	(2.33)	(1.92)	(0.12)	(-0.277)	(0.91)	(0.72)
Pre-money Valuation(£m)	0.000476	0.000761	0.0000371	0.000212	-0.000459	-0.0000795
	(0.36)	(0.56)	(0.02)	(0.12)	(-0.430)	(-0.0709)
Team size	-0.0146	-0.0123	-0.000994	0.00408	-0.0219	-0.0151
	(-0.616)	(-0.514)	(-0.0248)	(0.11)	(-0.850)	(-0.570)
Firm Stage	0.0601	0.0527	0.0394	0.0239	-0.0272	-0.0323
	(1.59)	(1.32)	(0.70)	(0.48)	(-0.859)	(-0.999)
EIS tax relief	0.154***	0.149***	0.143*	0.106	0.132***	0.121***
	(3.44)	(3.16)	(1.96)	(1.45)	(2.95)	(2.61)
Views(k)	0.000716	0.00075	0.00528**	0.00528**	0.000433	0.000419
	(0.76)	(0.86)	(2.14)	(2.38)	(0.51)	(0.54)
Followers(k)	0.108***	0.0994***	0.199***	0.180***	0.107***	0.0985***
	(3.72)	(3.81)	(3.14)	(3.34)	(4.09)	(4.15)
Constant	-0.0221	0.0724	5.900***	6.143***	0.416***	0.564***
	(-0.171)	(0.33)	(31.02)	(23.00)	(5.22)	(2.88)
Industry FE	NO	YES	NO	YES	NO	YES
Observations	352	352	352	352	352	352
Adjusted R-squared	0.841	0.844	0.56	0.622	0.266	0.283

Note: The dependent variables in Models (1), (3), and (5), are the natural logarithm of Amount (£m), Funders (k), and Overfunding, respectively, with the key coefficient of interest being that on Post_COVID. This is a dummy that takes 1 for the post-COVID-19 period and zero for the COVID-19 period. The estimation method is Ordinary Least Squares (OLS). Models (2), (4), and (6) are the same as models (1), (3), and (5), respectively, but add industry fixed effects. The standard errors are robust. The dataset includes successful initial ECF campaigns for COVID-19 (March 2020 – Dec 2021) and post-COVID-19 (Dec 2021 – Oct 2023) periods. Significance at the 10%, 5%, and 1% levels is indicated by *, ** and ***, respectively.

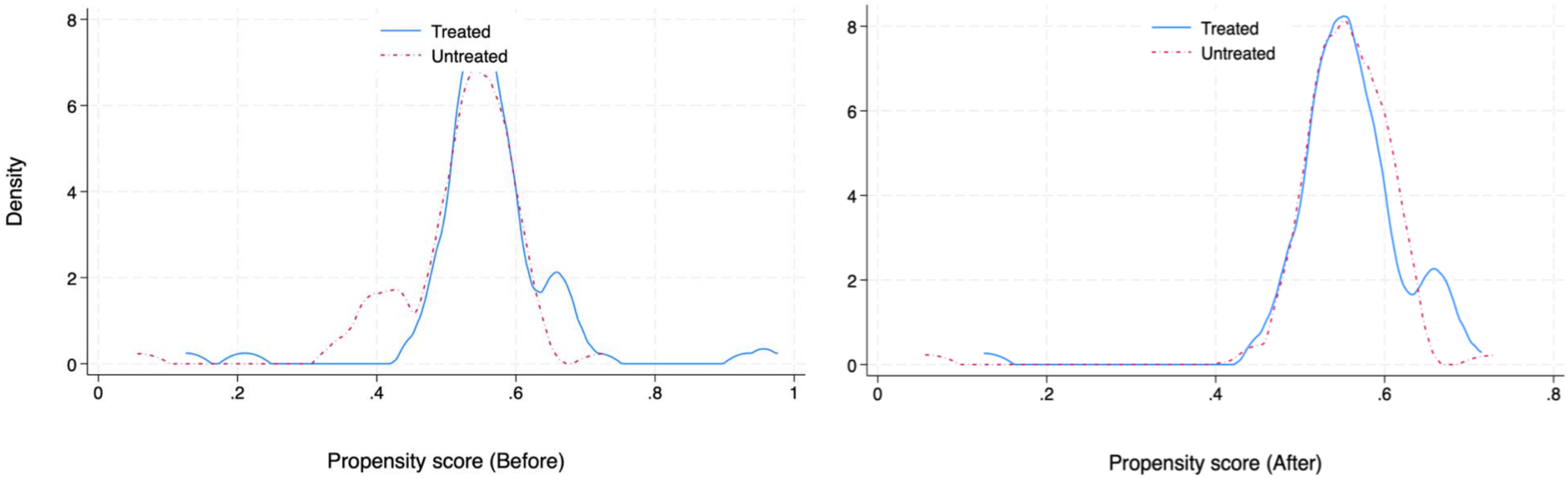
Table A7. PSM post-estimation tests

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%bias reduction	t	P> | t|	V(T)/ V(C)
Goal(m)	U	0.22179	0.2735	-21.3		-1.3	0.196	0.75
	M	0.19889	0.20563	-2.8	87	-0.22	0.83	0.75
Equity (%)	U	13.322	12 .212	11.8		0.7	0.484	3.56*
	M	12.305	12 .54	-2.1	82.1	-0.19	0.847	1.14
Pre-money Valuation (£m)	U	3.7744	3.5233	4.3		0.26	0.798	3.81*
	M	2.9955	2.8172	3.1	29	0.4	0.688	0.87
Team size	U	1.4321	1.3824	6		0.36	0.717	1.41
	M	1.4487	1.4197	3.5	41.6	0.22	0.827	1.5

Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Median Bias	B	R	%Var
Unmatched	0.031	6.42	0.17	1.9	8.9	39.5*	1.78	50
Matched	0.4	0.77	0.942	2.9	2.9	14	1.16	0

Note: This table reports the *t*-statistics and *p*-value for the difference in mean between the treated and control groups before and after matching. The bias percentage is reported to examine covariate imbalance before and after matching.

Figure A1. Propensity score of treated and untreated firms before and after matching



Note: The figure on the left shows the Propensity Score of Treated (seed firms during COVID-19) versus Untreated (seed firms in the non-COVID-19 period) before matching, whereas the figure on the right shows it after matching. The propensity score refers to the probability of a firm being in the Treated (seed firms during COVID-19) or Untreated (seed firms in the non-COVID-19 period) group given the covariates calculated based on Goal (£m), Equity (%), Pre-money Valuation (£m), and Team Size.

Chapter 4

Angels@Essex: A digital platform in a University Enterprise Zone

Abstract

Utilizing data from 71 startups on the Angels@Essex (A@E) platform, this paper makes three contributions to the literature. The first contribution is an analysis of the modus operandi of A@E, a distinctive online angel platform as a locale-specific channel for investment by contributing to the advancement of the University Enterprise Zone (UEZ) at Essex and fostering growth in the greater Colchester region. Second, it compares the investment outcomes in A@E with an ECF platform (Crowdcube) and highlights the differences. Finally, the paper investigates the funding success of startups on the A@E, their location, and their prior funding history. The results indicate that A@E has mainly invested in younger startups. Some 63% of startups have successfully secured funding, surpassing (on average) their initial funding targets. Over 10% of these startups are University Spin-Offs (USOs) and this highlights the positive impact of an angel platform within an UEZ. Moreover, although online digital platforms tend to mitigate geographical barriers, the majority of successful firms originate from Essex county. The analysis reveals a significant certification effect for prior funding rounds. Specifically, almost half (47%) of all successful startups on A@E platform enjoy a history of prior fundraising from diverse financial sources including Innovate UK. These startups raise more capital and enjoy a higher probability of success and a higher funding ratio. This aligns with the primary role of the angel platform as a facilitator of BA deals.

1. Introduction

Angel investors or business angels are high net-worth individuals who utilize their personal funds to invest in privately-owned businesses that lie outside their family and social circles (Harrison et al., 2016, Bonnet and Wirtz, 2012, Mason and Botelho, 2016, Wilson, 2011). They typically adopt a medium to long-term investment horizon (Wilson, 2011) and, in contrast Private Equity (PE) and Venture Capital (VC), exhibit more moderate return expectations and more extensive time horizons (Harrison et al., 2016, Wilson, 2011). BA investors, unlike VC, exhibit a closer alignment with entrepreneurs, primarily due to their typical status as former business owners who possess extensive industry insights stemming from their prior professional engagement (Fiet, 1995, Kelly and Hay, 2003, Lindsay, 2004, Harrison et al., 2016, Wilson, 2011). Their diverse educational background mixed with entrepreneurship experience renders them distinctive backers of early-stage firms (Cumming et al., 2016, Botelho et al., 2023). In contrast to VC, who predominantly bring financial expertise to the table, BAs act as former entrepreneurs driven by the desire to invest their personal funds to foster the emergence of new and existing startups (Bonnet and Wirtz, 2012). Moreover, their approach to risk assessment differs from that of VC managers. The main risks can be classified as market and agency risks. While venture capitalists emphasize market risk, BAs are more subject to the moral hazard and adverse selection inherent in agency risks, specifically pertaining to the misalignment of interests between startup owners and investors (Fiet, 1995, Harrison et al., 2016, Maxwell and Lévesque, 2014).

BAs play a paramount role as primary sources of early-stage funding. For example, in the United States, BA have contributed nearly twentyfold more capital to young enterprises than VC, underscoring their pivotal significance in entrepreneurial finance and the promotion of emerging ventures (Bonnet and Wirtz, 2012, Wiltbank et al., 2009, Sohl, 2012, Mason and Botelho, 2016, Harrison et al., 2016, Mason and Harrison, 2000, Bonnet et al., 2022). An accurate assessment of the magnitude of the angel market may even surpass current figures, as some angel investments remain undisclosed (Lerner et al., 2018).

BA support goes beyond mere financial investment and spans strategic guidance and mentorship. This involvement fosters the growth of human and social capital within these enterprises, extending their contribution beyond just financial assistance. (Harrison et al., 2016, Politis, 2008, Lerner et al., 2018). BA investment embodies the characteristics of patient capital across multiple dimensions, encompassing their investment objectives, the extent of their involvement in shaping the decisions of the founder management team to align with investor interests within the invested firm, and their approach toward exit strategies (Harrison et al., 2016). These characteristics render them an indispensable component of the entrepreneurial finance ecosystem. Despite the vital role that BA financial and non-financial contributions play in ensuring the survival of young ventures, the existing research on the operational methods and investment strategies employed by BAs in startups remains limited (Bonnet et al., 2022, Hellmann et al., 2021a, Bonini et al., 2018, Mason et al., 2019, Hellmann et al., 2013)

This chapter makes three contributions to the entrepreneurial finance literature. The first is that it investigates the specific modus operandi and role of an angel funding platform – Angels@Essex - located in Colchester and outside the London-Cambridge-Oxford Golden Triangle. As such it sheds light upon the evolving UK entrepreneurial finance ecosystem in which BA play multiple roles. They are both making more investments and are contributing more significant amounts to young ventures (Mason and Botelho, 2016, Mason et al., 2019, Lerner et al., 2018). They can operate independently - as solo angels – or as members of networks (e.g., UKBAA or UK Business Angel Association), groups, syndicates or platforms (Bonini et al., 2018). For example, angel syndicates refer to a lead angel working with other angels to assess and invest in startups. This leads to BA pooling their funds and making more significant contributions. By contrast, angel networks only facilitate the relationship between investors and investees (Wilson, 2011). The formal coinvestment between angels mainly happens through syndicates (OECD, 2016).

Since around 2015/2016 angels have co-invested alongside the crowd on online ECF platforms such as Crowdcube and Seedrs (Coakley and Lazos, 2021, Coakley and Kazembalaghi, 2023). A@E distinguishes itself from these ECF platforms through two distinctive attributes. On one hand, it does not charge any fees for listing a funding round on A@E. On the other, it adopts the Keep-It-All (KIA) funding approach, which signifies that start-ups retain the all – however small - the pledged funds, diverging from the All-or-Nothing policy implemented on ECF platforms (Cumming et al., 2020). These characteristics indicate that the A@E platform exhibits a high degree of start-up-friendliness in comparison to both ECF platforms and, more notably, in contrast to angel syndicate platforms (Coakley and Kazembalaghi, 2023) like AngelList in the USA. To the best of our knowledge, the existing literature primarily centres around the BA groups (Carpentier and Suret, 2015, Croce et al., 2017, Mason and Botelho, 2016, Lerner et al., 2018), networks (Bonini et al., 2018, Payne and Macarty, 2002), and syndicates (Agrawal et al., 2016). This paper fills the gap by shedding light on the performance of the A@E platform utilizing a unique and comprehensive dataset.

Although the significant early effects of digitalization on BA primarily encompassed the emergence of angel crowdfunding platforms such as AngelList in the USA and SyndicateRoom in the UK, these platforms have received little attention within the literature on entrepreneurial finance with a few notable examples (Agrawal et al., 2016, Coakley and Kazembalaghi, 2023). The use of these platforms is democratising access to finance by pooling networks of angels with connections to diverse geographical locations (Catalini and Hui, 2018, Agrawal et al., 2016) where startups are more constrained than those located in industrial or financial hubs.

The second contribution is it compares outcomes on the A@E angel platform with those on the UK's leading ECF platform - Crowdcube (Coakley and Lazos, 2021). Successful firms on A@E and ECF exhibit similar median Amounts raised over the same sample period, with figures of £450k and £500k, respectively. However, this is in stark contrast with the number of Backers, with A@E firms typically having an average of only 3-4 backers, while Crowdcube campaigns attract a mean of some 740 backers. This difference suggests that the contributions on A@E come from a relatively small group of traditional investors, setting it apart from ECF platforms. The Keep It All (KIA) policy on A@E has influenced the target setting of startups compared to Crowdcube. KIA prompts higher targets on A@E while All or Nothing policy on Crowdcube tends to lead to lower targets to improve their success rate (Cumming et al., 2020). Additionally, the absence of available information on some unsuccessful campaigns, which are eventually removed from the platform, contributes to these variations (Vu and Christian, 2023).

The third contribution is that the chapter analysed the other role of the A@E platform as a component of the University of Essex Innovation Centre within the Essex UEZ (University Enterprise Zone). This role involves promoting the advancement of transformative technologies specifically in the Greater Colchester Area including the surrounding counties (UEZ, 2022). The platform is successfully meeting this goal to the extent that some 8 (out of the 37) funded startups are based in Essex with a further 17 in the three neighbouring counties of Greater London, Cambridgeshire and Suffolk. What about the advancement of transformative technologies? The platform is meeting this goal in that 14 of the 37 funded startups focus on ICT accounts and a further 8 on manufacturing. Finally, A@E helps to promote university spin-offs (USOs) and to date has funded 4 USOs. While 4 may seem a small number, one has to bear in mind that this is a new activity for the University of Essex.

This paper employs firm Age, Location, and Funding history to analyze the role of the A@E platform within UEZ. An augmented dataset collected from the A@E platform and

Beauhurst is utilized to investigate whether funding is primarily directed towards young startups in need of external capital. It also compares the funding outcomes for local and non-local firms. Further, it investigates whether ventures that successfully secure funding on A@E benefit from a certification effect stemming from prior funding rounds, underscoring the prevalence of investor (BA) oriented criteria in their selection.

The structure of the paper includes as follows: Section 2 gives the background to the Knowledge Gateway Research and Technology Park (hereafter the Knowledge Gateway) at the University of Essex, and the establishment of the Angels @Essex platform and the approval of the Essex University Enterprise Zone in 2019. Section 3 presents the literature review and outlines the hypotheses to be tested. Section 4 presents the sample data and the methodology employed. Section 5 discusses the hypothesis testing in the light of the findings while a final section concludes.

2. Background

Young ventures constitute a vital component of the economy and investment in them plays a pivotal role in nurturing entrepreneurial ecosystems (Harrison et al., 2016). Their funding diverges significantly from that of well-established counterparts across various dimensions. Small ventures face unique challenges when seeking external equity and these can negatively impact their performance and place constraints on their growth trajectory (Fraser et al., 2015, Cowling et al., 2015). However, from an investor perspective, investment in small startups with limited or no financial records is highly risky. Market failure due to the high fixed costs of screening smaller firms with higher levels of information asymmetry is partly to blame for the lower supply of external equity for these firms (Fraser et al., 2015, Coakley and Lazos, 2021).

The equity gap, which emerges when internal sources of finance become depleted and inadequate collateral limits external debt for young entrepreneurs, has attracted attention from policymakers (Wilson et al., 2018). Various initiatives have been established to stimulate the availability of equity finance and facilitate the expansion of startups. For example, within the UK, the support for smaller firms in bridging the funding gap is not a recent development. Exemplary cases span the range from the introduction of the Small Firms Loan Guarantee (SFLG) in 1981 to more contemporary loan programs instituted in response to the COVID-19 pandemic (Calabrese et al., 2022, Fraser et al., 2015). Nevertheless, the need for external investors persists as firms seek equity capital to fuel their growth trajectory. In this context, BA have played a significant role in furbishing external funding for emerging enterprises.

The University of Essex established the Knowledge Gateway Research and Technology Park in 2010 as part of its key role in establishing Colchester as a hi-tech hub. In 2019 it opened its Innovation Centre which provides high-quality, flexible offices and coworking for young start-ups. Managed by Oxford Innovation, its services include mentoring and strategic business support for start-ups, backed up by access to leading research at the University of Essex. In recognition of this, Research England granted it University Enterprise Zone (UEZ) status in 2019, making it one of 24 UEZs in the UK. As well as establishing the A&E platform, the Knowledge Gateway helps to make startups investment ready for A&E rounds. For example, it engages in training, coaching, and aiding startups in presenting their concepts to potential investors on the platform.

The contribution of UEZs to place-based innovation and in supporting the local economy by connecting with and helping potential high growth ventures has been established by Farla. K (2018). The report adds that the nurturing environment of UEZ tries to facilitate the interaction between local businesses and academics by building a vibrant community. As part of this, the role of the Angels@Essex platform in providing access to outside equity for start-ups is vital. This is an accredited investor platform with 96 BA and 40 VC funds as registered investors. The University Enterprise Zone at Essex has two main Enterprise tasks. The first one is "Investment Readiness" which offers business support via webinars, one-on-one support, and utilization of the expertise of their partners to help startups get ready to access investment. The second one is Angels@Essex which is an investment platform that has raised more than £19m for some 38 deals from over 110 investors either individual, syndicate, or fund managers. At the same time, this platform has advised and supported about 338 firms/founders and it follows a policy of total inclusion (UEZ, 2022).

The Angels@Essex platform was seen as playing a key role in the development of the Knowledge Gateway and the Essex UEZ. More specifically, its role was to provide external equity for young startups needing capital to grow and expand. Since its launch in May 2020, it has been involved in the funding a relatively large number of start-ups which are analysed in a later section. The platform is distinctive in its characteristics as it represents a part of the ongoing transformation in the angel market. This transformation includes a shift from individual investors who primarily rely on informal word-of-mouth information to more structured collectives, networks, and now angel platforms.

This shift not only enhances interactions within entrepreneurial finance – VC and other investors like family offices and regional development agencies are investing via platforms - but it also diminishes transaction costs and results in higher value deals (Mason et al., 2019). The angel platform shares similar attributes to both angel networks and more recent forms of equity crowdfunding (ECF) platforms. It resembles angel networks in its role as a facilitator of equity financing rather than a direct investor. Similarly, it mirrors the recently evolving, multi-sided version of Equity Crowdfunding (ECF) platforms by actively participating in the entire investment process, transitioning from mere introductions to performing due diligence and maintaining an active involvement throughout (Coakley et al., 2021a, Wilson, 2011).

3. Literature review and hypotheses

3.1 Startups versus later-stage ventures

There is an increasing interest among policymakers in recent decades in transferring university knowledge to industry via start-ups that encompass the created knowledge and technology (Mustar et al., 2008). Mathisen and Rasmussen (2019) suggest that university spinoffs (USOs) need not have a unique definition and can be defined in a broader or narrower format, depending on the research question. USOs are rewarded by policy regulators almost regardless of their level of economic performance and it is not surprising to see they might not perform as well as other start-ups. However, when they are established on the basis of a market-oriented rationale, they contribute to the local economy and overall economic growth by generating added value. Moreover, when they are necessity-oriented, they contribute mainly by job creation (Civera et al., 2020). The primary sources of capital for these small firms is owner savings and Friends and Family capital (Ang, 1991). However, this internal source of capital is limited and due to challenges in securing debt eventually, many high-potential small firms eventually turn to external equity sources of capital. This is where BA and other providers can play a key role in boosting the capital structure of these young ventures alongside grants offered by the government (Wright et al., 2015).

BAs are known for prioritizing the significance of the entrepreneurs over other factors when compared to venture capitalists in the context of investing in smaller ventures (Harrison et al., 2010, Bonnet and Wirtz, 2012). They are recognized as the primary contributors of seed-stage capital (Block et al., 2019). Therefore, it is anticipated that younger firms or startups have a higher likelihood of securing BA funding compared to that of other traditional sources of entrepreneurial finance. Catalini and Hui (2018) posit that on online angel platforms in the USA, traditional investors are able to identify and support high-potential startups that might otherwise go unnoticed due to high information asymmetry concerns. This implies that the valuable information provided by BA networks in introducing undervalued startups could take precedence and override their preference for more established firms. Additionally, considering the tendency for less experienced angels to participate in online platforms (Wright et al., 2015, OECD, 2016), they may also display less sensitivity to the investment criteria typically employed by more experienced BAs or VCs.

Moreover, being situated within Essex UEZ offers A@E the opportunity to uncover and attract a greater number of innovative young startups. Universities often encourage the exploration of opportunities within less established firms that could benefit from the support of angels in providing patient capital (Harrison et al., 2016). This leads to our first hypothesis:

***H1**: Startups have better investment outcomes on A@E than more established firms.*

Literature on the importance of location in making investment decisions by BA is not conclusive. While some research suggested the preference of angels to invest locally to better monitor their investments and efforts of entrepreneurs (Prowse, 1998, Freear et al., 1994, Shane, 2005), others suggest that BA are willing to invest in high quality but distant startups (Harrison et al., 2010, Van Osnabrugge and Robinson, 2000). This can be partly attributed to the fact that investing through groups and networks has revolutionized the approach for individual angel investors. Previously dependent on their personal social networks, funds, and expertise to back promising startups, these investors can now join forces with other angels, pooling resources to make larger investments across diversified portfolios (Mason et al., 2019). For instance, in syndicate deals, the lead investor leverages her networks to present opportunities to angels who might not otherwise consider those investments. This tactic serves to broaden the geographical range of successful fundraising startups an individual angel can engage with by reducing information asymmetry (Agrawal et al., 2016, Agrawal et al., 2011, Hortaçsu et al., 2009). Therefore, the belief that BA and VC investors prefer local investment and companies in distant locations suffer from access to this capital raising source can be countered to an extent by the rise of online platforms such as BA and ECF platforms. This trend is further facilitated by the convenience of using online platforms where both investors and investees can create profiles, broadening the geographical scope of investment opportunities.

Lerner et al. (2018) explore variations in the risk profile, developmental stage, or industry concentration among the pool of startups seeking angel funding from angel groups in regions characterized by a less supportive entrepreneurial ecosystems. Harrison et al. (2010) employ data on 109 business angels who made 373 investments in the UK and draw conclusions based on different pattens of locations of investors and startups. Cumming et al. (2021a) examine whether ECF platforms democratise finance by reducing geographical distance related barriers and conclude they indeed achieve this goal. These findings collectively suggest that BA investors (on online platforms) maybe becoming less sensitive to the locality of their investments.

On one hand, the convenience of online investing and changing BA investing pattern from solo investors to coinvestment in groups, syndicates and platforms (Agrawal et al., 2016, Agrawal et al., 2011, Coakley et al., 2021b) means that ventures located in proximity of A@E might not have a geography-related advantage over firms located further away. On the other hand, this proximity might even encourage less viable startups to approach A@E resulting in a lower overall success rate in securing funds on this platform. This leads to our second hypothesis:

H2*: Ventures located close to the A@E platform exhibit a lower success rate than those in other locations.*

3.2 Angel platforms and startup funding history

Business angels employ a set of investment criteria when considering investments in smaller firms. These criteria tend to be more systematic in the case of BA groups, networks, syndicates, or platforms compared to solo angels who may have higher personal motivations driving their investment decisions (Mason et al., 2019, Wilson, 2011, Mason and Botelho, 2017). The conventional BA investment procedure comprises deal sourcing and screening, showcasing firms to potential investors, conducting thorough due diligence, negotiating investment contracts, making the investment, and ultimately offering post-investment support and, finally, an exit (Wilson, 2011, Bonnet et al., 2022). However, this process has been transformed by BA groups and syndicates by including investor-specific screening prior to generic and later detailed evaluations or due diligence (Mason et al., 2019). Block et al. (2019) identify the investment criteria of private equity investors, including VCs, BAs, and Family Offices (FOs). They highlight the importance of an existing investor's reputation as a key factor used by PE investors to assess the quality of their investment. This principle extends beyond BAs or VCs/PE. In crowdfunding platforms, backers also rely on the investment decision patterns of prior investors with a significant history of as a valuable indicator when making their own investment choices (Vismara, 2018, Signori and Vismara, 2018).

Business angels and venture capitalists, and especially the latter, often opt to invest in startups across multiple stages. This strategy aims to minimize potential losses in case their investment does not meet their expectations (Signori and Vismara, 2018, Sahlman, 2022). Drawing on the substitute and complement hypotheses, Hellmann et al. (2013) compare the interrelationship of BA with VC and conclude that these two investors are inclined to be substitutes rather than complements. However, they also mention that this is more evident in firms funded by less experienced BAs. Hellmann and Thiele (2015) states that BA and VC could be friends in the sense that they rely on each other's investment certification effect, but they do not have this dynamic in later-stage investments when VCs go for follow-on investments.

Investments made in later funding rounds, as opposed to initial offerings, can generate a certification effect that mitigates the adverse selection problem when investing in smaller firms, as highlighted by Coakley et al. (2022a) in their assessment of seasoned equity crowdfunding offerings (SECO) versus initial ECF offerings. We postulate that this same favorable impact of a prior funding round can influence the fundraising performance of startups on an online angel platform. This leads to our final hypothesis:

H3: *Ventures with prior angel funding history enjoy more favorable investment outcomes on A@E than those without any prior funding.*

4. Data and Methodology

The Angels@Essex platform is physically located within the Innovation Centre at the University's Knowledge Gateway. Some 338 startups have engaged with the Innovation Centre from the platform's establishment in May 2020 up to February 2023. All of these received some form of mentoring, training, and assistance. From these startups, a total of 71 have sought to secure financial backing. The dataset encompasses investment outcomes on the A@E platform and is supplemented by information from the Beauhurst database, encompassing firm-level, deal-level, and investor-related characteristics.

***Dependent variable*:** Three proxies are employed to capture startups investment outcomes on the A@E platform. The first, *Amount(£m)*, is the total value of capital raised on A@E platform. The second, *Success*, is a dummy that takes value of 1 if the startups have raised a positive amount of capital. The third proxy, *funding ratio*, is the ratio of Amount over the Target.

***Independent variables*:** Three variables are utilized to test the hypotheses. *Startup_d* is a dummy that takes 1 for ventures aged below 30 months and zero otherwise. This explanatory variable is used to test the first hypothesis (Coakley et al., 2022b). *PreFund* is a dummy that takes 1 for ventures with a successful funding record prior to applying to A@E.

Control variables: Several control variables are used to capture firm level as well as deal related characteristics. *Target(£m)* is the initial goal of the entrepreneurs. Regressions are reported with or without including this control variable. The reason is that *Target* reflecting the startup's need for capital may an important factor affecting the *Amount* raised but at the same time it could be influenced by other factors and thus also be an outcome variable (Cumming et al., 2020, Cumming et al., 2019a). Views refers to the number of views on the platform to capture the level of startup social networking among investors (Vismara, 2016, Colombo et al., 2015) and the attractiveness of their pitch. The *Credit rating* of startups at the time of data collection captures their potential access to debt capital. Pre PE/VC is the amount raised by firms from private equity or venture capital prior to approaching A@E. The same goes for Pre-BA and Pre-Innovate UK rounds. These three variables are used to proxy the effect of prior funding record on investment outcomes on A@E. In robustness tests, *Firm status* (a categorical variable that takes 1 for active startups, 2 dissolved, 3 dormant, and 4 liquidations to capture the current status of startups, *USO* (a dummy that distinguishes between University spin-offs (*USO*) and other ventures) and *Employees* (a proxy to capture human capital) are utilised.

4.1 Models

Multivariate regressions are employed to investigate the characteristics of startups that successfully raised equity on the A@E platform. The models used to test the hypotheses are:

$$Investment\ outcome_i = \alpha_1 + \beta_1 \mathbf{Startup\_d} + \Gamma_1 Controls_i + \varepsilon_1 \qquad (1)$$

$$Investment\ outcome_i = \alpha_2 + \beta_2 \mathbf{Location\_d} + \Gamma_2 Controls_i + \varepsilon_2 \qquad (2)$$

$$Investment\ outcome_i = \alpha_3 + \beta_3 \boldsymbol{PreFund} + \Gamma_3 Controls_i + \varepsilon_3 \qquad (3)$$

where i denotes firm i and $\mathrm{Controls_i}$ represents a vector of control variables. Investment outcomes are proxied by *Amount(£m)*, *Success*, and *funding ratio*. The estimation method is Ordinary Least Square (OLS) for models with dependant variable of Amount and funding ratio and robust standard errors are used. In models where dependent variable is Success dummy the Probit estimation method is employed and standard errors are cluster at location level. All models are reported with and without industry dummies to capture industry fixed effects. Place dummies are included in first and third models to capture location heterogeneity but are excluded from second model for multicollinearity.

5. Empirical analysis

5.1 Descriptive statistics

Table 1 presents list of variables, their definition, and data collection source.

[Table 1 around here]

5.1.1 Startups on A@E platform and USOs (University spin-offs)

This subsection comprises two parts. First, it examines the characteristics of startups that made pitches seeking equity on A@E. Second, it investigates the fundraising history and performance of USOs. Tables 2.1 to 2.5 present an analysis of the attributes of all startups engaging with A@E, regardless of the eventual fundraising outcome.

Table 1.1 summarises the characteristics of start-ups using the A@E platform to raise capital. Overall, 71 firms made pitches on the platform. The credit rating of start-ups is on average about 28 which falls well within the lowest credit band (<40), indicating that they pose the highest risk for funders. This could be partly due to not having audited financial records (Dedman and Kausar, 2012). The combination of a low credit rating, small credit limits of less than £12k, and limited access to collateral presents a challenge for these startups in accessing debt and leads to higher interest rates (OECD, 2016). As a result, external equity becomes a crucial factor for their development especially smaller knowledge-based firms (Berger and Udell, 1995, Wilson et al., 2018, Cumming and Zhang, 2019, Baltas et al., 2022). Gender diversity is examined at three levels. All three exhibit to a similar level of 15% representation of women among directors, founders, and firms' key people. Interestingly this is similar to what Wright et al. (2015) find in a survey of UK BAs. A@E platform offers the "Female Founders & Investors" program as a part of its mentorship to promote the entrepreneurial spirit among women to contribute both as investors and investees.

Our data on the investor side is limited. The 15% gender diversity in firms corresponds to a considerably lower success rate by female entrepreneurs in securing angel investments compared to their male peers (Rose, 2019). On average, the start-up value before their latest fundraising is £3.48m and more than half of them have a value over £2.3m. The mean firm age is 5.5 years. There are three spin-offs among the 63 firms with information on Beauhurst and we identified another on the platform. Finally, the mean (median) time to raise the first round of external finance or grant is 2 (1.7) years. This together with the low credit scores or startups underlines the importance of early-stage support by either government or traditional investor funding for the survival of young ventures.

[Table 2.1 around here]

Beauhurst classifies the firms into active, dissolved, dormant, and liquidation stages. Almost 4 out of 5 firms were active and less than 10% were dissolved, dormant, or liquidated. Just under 11% of startups had no information on Beauhurst.

[Table 2.2 around here]

Table 2.3 shows the number of employees distributed into four categories. Firms applying to the A@E platform are in the “micro enterprise” and “small enterprise" categories based on the OECD classification. Except for four startups with 25-49 employees, the rest have fewer than 25 employees with quite a similar distribution (around 30%) among the three categories of less than 5 employees, 5-9 employees and 10-24 employees.

[Table 2.3 around here]

Table 2.4 classifies deals into five distinct firm stages as defined by Beauhurst: seed, venture, growth, zombie, and dead. The majority of the sample startups fall into the seed (51%) and venture (36%) categories, with 1 in the growth stage, 1 Dead, and 4 Zombies (not dead but in financial trouble). BA are renowned for their role as seed capital providers (Mason et al., 2019) which aligns with the finding that over half of the firms are at the seed stage. In total, 87% of the sample firms fall within the seed and venture stages, further confirming this trend. This also aligns with the findings of Lerner et al. (2018) that indicate that, firms seeking BA funding in countries with more supportive entrepreneurial environments tend to be early stage, less established, and generate lower revenue.

[Table 2.4 around here]

The A@E platform commenced business in mid-2019 and the COVID-19 pandemic hit the UK in early 2020 (Official platform start date is May 2020). For that reason, the COVID-19 impact on these startups is reported in Table 2.5 to examine how they coped with the COVID-19 crisis.

[Table 2.5 around here]

The COVID-19 impact is mainly low (63% of startups), moderate (16%) and, interestingly for some startups (11%), it is positive. This positive performance could be explained by the fact that startups that successfully underwent the due diligence process at the A@E platform are innovative, technology-intensive companies. Figure 2 shows that nearly 40% are in the ICT (Information Communication and Technology) sector. This positioning might have worked to their advantage, allowing them flexibly to adjust their business models during the COVID-19 pandemic. This is in line with the Beauhurst (2021) report on the impact of COVID-19 on performance of small firms which implies some small firms did exceptionally well during the pandemic. Interestingly, only 3% and 8% were “critically” and “severely” impacted by the COVID-19 pandemic.

Table 3 presents data on the four USOs identified among successful startups on the A@E platform.

[Table 3 around here]

The presence of four USOs in our sample point to the A@E platform as a vital source of risk capital (Lerner et al., 2018, Prowse, 1998) in nurturing university-affiliated businesses. The first USO emerged in 2018. Currently, this startup is categorized as being at the "venture" stage and has enjoyed a total of four successful fundraising rounds, including two external equity fundraisings and two Innovate UK grants. The first round entailed an investment of £60k by unidentified investors in exchange for a substantial equity share of 49%. The second round involved a co-investment with BA and PE/VC, totalling £760k. Following these investment rounds, the startup obtained two Innovate UK grants.

The second spin-off in March 2021 has completed three fundraising rounds, all in return for equity holdings. The most substantial contribution was from the first round, totalling £130k, facilitated by BA. In total, the startup has raised £195k. Currently, this startup remains at the Seed stage. The third spin-off is at the Venture stage, having raised a total of £484k. While there are records of four external fundraising rounds, the identity of one (second) round source has been disclosed. This involved investors on the Seedrs (ECF) platform contributing £190k in exchange for a 4% stake. All four fundraising rounds were executed within a span of approximately two years, highlighting the startups early-stage appetite for external capital. The fourth spin-off has a history of five fundraising rounds, accumulating a total amount of £1.17m. The investors involved in the first, second, and fourth rounds remain unidentified. BAs invested £332k in the third round and PE/VC alongside a BA network invested £500k in the fifth round. This is consistent with the finding that coinvestment leads to larger contributions (Wilson, 2011)

5.1.2 Startups on A@E

This subsection focuses on the startups and ventures that applied to the A@E platform. The data includes both successful and unsuccessful deals. Some 45 out of 71 startups (63% of the total) succeeded in raising funds. By employing the Keep-It-All (KIA) strategy, the A@E platform has achieved a remarkable success rate, securing funds for 63% of all firms. This success can be attributed to allowing entrepreneurs to keep whatever they have raised in contrast to the All-or-Nothing policy employed in (ECF) campaigns (Cumming et al., 2020, Burtch et al., 2018). It also reflects the angel platform's adeptness in streamlining the investment process between potential investors and startups, akin to the functioning of Angel networks. This alignment highlights the risk reduction effect achieved through information dissemination, networking, and monitoring – characteristics commonly associated with angel networks (Bonini et al., 2018).

Tables 4.1 and 4.2 provide detailed information on fundraising outcomes for both the A@E and Crowdcube platforms. They include Crowdcube campaigns only for the period from the inception of A@E up to February 2023.

Tables 4.1 provides the results of the equality of means and median tests, encompassing both successful and unsuccessful firms.

[Table 4.1 around here]

It suggests that the mean (median) amount raised by all firms on A@E is £420k (£90k), whereas on Crowdcube, it is £820k (£480k). This implies that the amount raised on both A@E and Crowdcube is disproportionately affected by a few large campaigns, leading to a right-skewed distribution. However, the difference is not significant. On average, the number of investors in A@E campaigns ranges from 2 to 3, while Crowdcube campaigns have more than 700 investors. The difference in both the equality of means and medians for the number of backers is highly significant at a 1% level. The mean (median) target amount on A@E is £680k (£500k), in contrast to Crowdcube's £460k (£300k) and the difference between both means and medians are highly significant at a 1% level. The funding ratio mean (median) is 0.68 (0.5) for all firms on A@E, which is significantly different from mean (median) of 1.84 (1.43) on Crowdcube. It's important to note that while 63% of firms are successful on A@E, Crowdcube have a significantly higher success rate of 92%. This difference in success rates on Crowdcube could be attributed to platform strategies aimed at encouraging firms to establish attainable campaign targets, enhancing their likelihood of success under the All or Nothing (Wirtz et al.) funding policy (Cumming et al., 2020, Burtch et al., 2018).

Tables 4.2 provides the results of the equality of means and median tests, focusing solely on successful firms.

[Table 4.2 around here]

It indicates that successful firms raise a higher mean (median) Amount of £860k (£500k) on Crowdcube compared to £660k (£450k) on A@E but the differences are insignificant in both cases. The amounts raised are achieved by a mean (median) of 704 (438) backers on Crowdcube compared to just 3.73 (3), respectively, on A&E. Interestingly, the mean (median) Target of £670k (£500) on A@E is significantly larger at the 1% level than the corresponding figures of £470k (£300k) on Crowdcube. This difference is consistent with the inflation and downsizing of targets on A@E and Crowdcube, respectively, induced by the KIA and AON provision point (funding) mechanisms (Cumming et al., 2020). This also has direct implications for the Funding ratio (Amount/Target). The mean (median) Funding ratios are 1.91 (1.49) on Crowdcube. These are significantly larger at the 1% level than the corresponding ratios of 0.67 (0.5) on A@E and these reflect the inflation and downsizing of targets on A@E and Crowdcube, respectively.

Figure 1 depicts the location by county of the funded ventures.

[Figure 1 around here]

Colchester city is the largest urban area in Essex which is the adjoining county to the east of Greater London. As such, is just outside Golden Triangle for startups that is comprised of the area bounded by the London, Oxford, and Cambridge triangle. Figure 1 shows that, while some 22% funded startups are based in Essex, the influence of the Golden Triangle is evidenced by one third of funded startups are from this area - 19% in Cambridgeshire and 14% in Greater London. BA investment on the A@E platform is affected by two location factors. Firstly, angel platforms alleviate the expenses associated with knowing about deals and conducting due diligence for remote firms by depending on the lead investor's information (Agrawal et al., 2016). While A@E may lack this specific mechanism (lead investor), its investor network could nevertheless mitigate the challenges linked to geographical distance by the overall effect of the networking (Bonini et al., 2018). Secondly, the prevalence of viable startups for potential investors is greater in urban centres and especially in high tech hubs like London or Silicon Valley. For instance, Wilson et al. (2019) in their examination of the regional allocation of equity finance, highlight that the likelihood of a firm securing equity funding is significantly lower - by as much as 50% - in regions outside London.

Table 4.3 gives a breakdown of funded startups by the Amount raised, number of Backers, Target and Funding ratio (Amount/target)

[Table 4.3 around here]

This shows that the median amount raised is just in excess of £540k except for Suffolk (£720k) and other counties (£270k). The median target amount implies that Greater London and Suffolk deals are overfunded (exceed their target) and these deals involve a median of 5 investors each. By contrast, those in Essex, Cambridgeshire and Other are all underfunded and these boast a median of just 3 investors.

Figure 2 gives the industry sector of the funded firms by SIC code.

[Figure 2 around here]

The three main industries include Information and communication (40%), Manufacturing (20%), and Professional, scientific, and technical activities (14%). Due to their background as former entrepreneurs, BA tend to concentrate primarily on industries within their area of expertise (Botelho et al., 2023, Politis, 2008); However, platforms appear to transcend this constraint by engaging with ventures from various industries, regardless of the expertise of a single investor. Still, the substantial majority of A@E deals occur within technological sectors, accounting for approximately 74% of the total. This tendency can be attributed in part to A@E's affiliation with the University Enterprise Zone (UEZ) which positions it in proximity to technology-intensive enterprises.

Table 5 provides a listing of investors in startups categorized into two groups: solo investments and co-investments.

[Table 5 around here]

Approximately 95% of all funding rounds feature solo investors. The highest number of such deals with available information involve ventures with Innovate UK grants (35%) or with prior BA investment (11%). PE/VC investors account for around 7% of the rounds, totalling approximately 13, while ECF rounds represent 4% of the total, consisting of 7 rounds. Co-investments make up about 5% of all rounds, equivalent to 10 rounds.

Table 6 presents data regarding the mean and median values of investment amounts and the equity percentage requested by investors in exchange for capital.

[Table 6 around here]

This information is based on the fundraising records of all rounds by successful startups on the A@E platform. These rounds encompass all investment rounds both within and outside of the platform. In addition to the Amount raised, investor type and the equity offered is presented. The data from 8 rounds involving BA indicate that, on average, they invest £320k (with a median of £290k) and request approximately 14% equity in return. However, the median equity is much lower at about 4.5%. In the case of the 10 rounds involving PE/VC investors, startups have secured an average of £720k (with a median of £410k) in exchange for relinquishing, on average, 14.9% of the firm's ownership control (with a median equity share of 14%).

Startups are increasingly using online platforms and our dataset included 4 rounds of ECF in which a e mean (median) of £580k (£510k) was given to entrepreneurs in return for 19% (10%) equity. Almost 65 rounds of investment had no information about the investors where a mean (median) of £270K (£130K) was invested in exchange for 10.12% (6%) equity. In rounds involving a single type of investor, the average investment is £470k (with a median of £330K), with an average equity share of 14.51% (with a median of 8.63%). Conversely, in co-investment rounds, a significant amount averaging £1.44m (with a median of £500k) is invested in return for an average equity share of 13.88% (with a median of 15%). This difference in Amount is expected as co-investment relies on pools of capital from different investors, leading to shared risk, higher portfolio diversification, and a more substantial contribution from each investor.

Angel investments are undergoing a transition from individual, solo investments to collaborative initiatives within groups, networks, and joint funding with other sources of seed capital increasing both the amount invested and portfolio diversification (Bonnet et al., 2022). Our dataset includes 10 instances of co-investment involving various combinations of investors within the fundraising history of successful startups. These collaborations encompass diverse co-investors, such as angel investors alongside PE/VC firms, ECF platforms, university, and undisclosed investors (representing a varied range of affiliations). Angels demonstrate the credibility and expertise to partake in co-investments alongside both institutional and government-based seed and venture funds, particularly within more extensive syndicated deals (Mason and Botelho, 2021).

5.1.3 Fundraising records of successful startups and Pre-A@E

This section aims to quantify the A@E contribution to the overall fundraising record of startups. Tables 7.1 to 7.3 examine the overall capital-raising performance of successful startups on A@E via all sources of finance while Tables 8.1 and 8.2 highlight the prevalence of prior rounds and identifies the typical investors who participated in startup funding prior to engaging with the A@E platform.

Table 7.1 analyses the Amount raised, which includes fundraising (excluding Grants) involving equity exchange for capital, grants, and contributions from the Angels@Essex platform.

[Table 7.1 around here]

Successful startups exhibit a mean fundraising amount of £1.44m, while the median is about one-third of that value at £490k. This indicates that the mean is influenced by a few larger fundraising events. The average capital raised through Angels@Essex is approximately half of the Fundraising total (£720k), with a median of £500k. Startups have obtained an average of £240k from Innovate UK as innovation grants, with nearly half of them not receiving any grants. Some firms have secured substantial grants, reaching up to £1.64m. Innovate UK grant supports innovation-driven young businesses (Baldock and Mason, 2015) that are unlikely to raise debt finance and in this dataset is the main contributor of grants.

Table 7.2 presents the number of rounds for all fundraisings, which encompass both external fundraisings and grants. Successful ventures, on average, had five rounds with a median of four rounds. Among these five rounds, approximately one to two rounds involved grants, while the remaining three to four rounds were associated with fundraising in exchange for startup equity.

[Table 7.2 around here]

Table 7.3 examines the sources of finance using dummy variables, which are set to 1 if startups have a record of receiving money from a specific funding source. Innovate UK has granted money to more than half of successful firms (51%), while approximately 30% of successful startups have received investments from BAs. These percentages may appear somewhat confusing since all these firms have also raised money on the A@E platform. The explanation lies in the fact that the list of successful firms is derived from the A@E platform, and not all of them have been published in Beauhurst yet. Additionally, some fundraisings are classified as 'undisclosed,' a classification that applies across all categories of investors. We have considered this aspect as a factor affecting all sources of finance and reported the values accordingly. Approximately 1 in 5 (19%) of startups have a record of raising capital from PE/VC investors. Additionally, 11% of firms have successfully raised funds on Equity crowdfunding platforms, namely Crowdcube and Seedrs. These findings align with the diverse landscape of entrepreneurial finance. Government support, in the form of grants, emerges as the primary source of capital, accounting for 51% of the cases, followed by Business Angels at 30%. PE/VC investors stand at 19%, and Equity Crowdfunding represents a newer source of funds for entrepreneurs, contributing to 11% of the rounds. The most frequent external investors among startup investors are Innovate UK, BA, PE/VC and finally ECF. A@E's financial contribution is substantial when compared with all funding sources for startups that have established collaborations with this platform.

[Table 7.3 around here]

Based on Table 8.1 overall, 21 out of the 45 successful firms (our data are limited to 37 firms) had prior funding. About half of them received a grant from Innovate UK and almost the same percentage (19%) had record of capital raising from BA or PE/VC.

[Table 8.1 around here]

Table 8.2 reports more details of prior rounds in terms of type of investor and their contribution. These 21 firms raised a total amount of £28.74m in 51 rounds. The mean (median) value of the prior round is £1.44m (£0.52m). Interestingly, close to half of successful startups in A@E have an average of 3 prior rounds of funding before being able to receive capital from A@E. Some 4 startups had been previously funded by PE/VC and 4 had received capital from BA. The 4 PE/VC funded startups received a total of £6.46m but the mean (median) is £1.61m (£1.33m) which is larger than the mean (median) of capital received from BA for the 4 star-ups with prior BA funding. Moreover, some 10 out of 21 firms have received a total of 26 Innovate UK grants in addition to the above-reported prior rounds. The grant mean (median) value is £443k (£325k) which, as expected, much smaller than the mean value of PE/VC and BA rounds.

[Table 8.2 around here]

5.2 Regression analysis

Table 9 presents the pairwise Pearson product-moment correlation coefficients between variables included in the study.

[Table 9 around here]

Apart from the (understandably) very high Amount/Target correlation with Amount, no other correlation coefficient exceeds 0.51 and so multicollinearity is not likely to be an issue.

Table 10 presents the regression results testing the first hypothesis that startups enjoy better investment outcomes than more established firms on the A@E platform. Investment outcomes are proxied by the *Amount(£m), Success* and *Funding ratio*.

[Table 10 around here]

The table show the output from six regressions where the primary explanatory variable is *Startup_d* or startup dummy. In regressions (1) to (3), the dependent variable is *Amount(£m)* and the estimation method is OLS. In all three regressions, the coefficient on *Startup_d* is positive and statistically significant at the 5% level with and without industry and place fixed dummies. The coefficients are also economically significant. For example, the regression (3) results imply that startups raised 50% higher amounts of funds compared to established firms. Importantly, this coefficient remains significant with and without controlling for Target (£m).

The *Startup_d* coefficient is not significant in models (4) to (6) suggesting that there is no significant difference between startups and older firms in terms of securing fund on A@E. In Models (7) through (9), where the outcome variable is the *Funding ratio*, all of the *Startup_d* coefficients are significant at the 1% or 5% level. This indicates that startups have higher Amount-to-goal ratio than non-startup firms in A@E platform. When industry and place fixed effects are included, this coefficient is 1.35. This suggests that, on average, startups enjoy a funding ratio that is 1.35 times higher than that of more established ventures. These results lend support to the first hypothesis (H1).

Similar to the findings in the ECF literature (Coakley et al., 2022b), a higher *Target* is associated with a higher *Amount* raised and a lower *Funding ratio*. As expected, a higher number of *Views* is associated with a higher *Amount* raised and a higher *Success* rate, which is similar to the positive effect of social capital on ECF platforms. Additionally, *Credit rating* has a positive and significant relationship with all outcome variables. Startups with a higher credit rating are more likely to enjoy more successful outcomes. Prior investment record (*PreFund*) is a control variable proxying for the certification effects of successful prior funding rounds. The coefficient of *PreFund* is positive and highly significant, mostly at the 1% level. The outperformance of startups in comparison to more established firms align with the mission of the A@E platform to support startups as highlighted in the UEZ Annual Report of 2022. Additionally, it reflects the fact that business angels are the most accessible source of seed capital (Mason et al., 2019, Block et al., 2019). The coefficient of *Pre-BA* (£m) is negative and significant at the 10% level when the outcome variable is *Amount* or *Funding ratio*. This is consistent with the A@E preference not to invest in firms that are not already supported by their peers (Hellmann et al., 2013, Hellmann et al., 2021a). These results lend support to the second hypothesis (H2).

Table 11 presents the regression results on location designed to test the second hypothesis that ventures located close to the A@E platform exhibit a lower success rate than those in other locations.

[Table 11 around here]

This table displays the results of regressions with the primary explanatory variable being a location dummy (Location_d). In Models (1) to (3) and (7) to (9), the Location_d variable is insignificant, suggesting no significant difference between the amount raised and the funding ratio in the Essex region and those outside this region. However, the coefficient of Location_d is negative and highly significant in models (4) to (6). These lend partial support to hypothesis H3. This indicates that the success rate is lower within the Essex region. It is important to note that this, combined with the fact that Essex has the highest presence as the location of successful firms, suggests that there are more applications from the Essex region, and the most successful ones are in this region. Additionally, a higher number of local firms approach A@E, regardless of their quality. This raises the probability of low-quality applications for startups close to the platform. Firms that secure investments from A@E, even if they are not located in proximity to the platform, are likely representing high-quality potential investments, often originating from cities within the "Golden Triangle" (Wilson et al., 2019). Having these firms on the A@E platform is also one of the positive effects of investing via online platforms which reduces geography- and distance-related barriers and is intended to garner attention of investors in the platform (Agrawal et al., 2016, Agrawal et al., 2011).

Table 12 presents the regression results for testing the third hypothesis that ventures with prior angel funding history enjoy more favourable investment outcomes on A@E than those without any prior funding.

[Table 12 around here]

In the initial three models, the dependent variable is *Amount(£m)*, and OLS estimation is employed. In these models, the coefficient on *PreFund* is 0.73 and highly significant at the 1% level. Model (2) controls for Target but this variable is not significant. Model (3) controls for industry and location fixed effects and PreFund is now highly significant at a 1% level. This suggests that ventures with a successful prior track record attract some 73% more capital on A@E compared to those with no such track record. In Models (4) to (6), the dependent variable is *Funding ratio* and the coefficient of around 1.8 is significant at the 5% level. The latter implies that startups with prior funding have a 1.8 times higher funding ratio. All models used to examine the performance of startups with a successful prior investment record in comparison to those without one suggest that A@E, as an online angel (BA) platform, places value on startups that exhibit prior investment records from other sources of finance. Such a successful prior track record certifies them as less risky investments. It also aligns with previous literature on online investment in Equity Crowdfunding (ECF) platforms (Vismara, 2018, Signori and Vismara, 2018).

6. Conclusions

The early success of the A@E platform has provided startups in Colchester and nearby regions with the opportunity of securing outside equity, particularly when accessing finance poses challenges for small firms. A@E distinguishes itself from ECF online platforms in several key aspects. To start, it utilizes the Keep It All policy, while ECF platforms typically employ the All or Nothing (Wirtz et al.) policy. Additionally, the Amount raised in A@E primarily comes from a small number of angels, with an average of 3 to 4 contributors, yet the total capital raised is comparable to ECF platforms, which often have a mean number of backers exceeding 700 (including both crowd and traditional investors). In addition, our results suggest that A@E primarily invests in startups at their early stages, namely seed and venture stages. Notably, the platform has achieved a success rate of around 63% in raising equity for startups that have pitched their ideas on the platform. This achievement is partly attributed to its utilization of the Keep It All policy, enabling firms to retain the raised funds without being subject to any threshold requirements.

In 2019, Research England designated the University of Essex as one of only 24 University Enterprise Zones (UEZs) in the UK. Angels@Essex (A@E) stands out as the first angel platform within a UEZ, emphasizing the significance of my work for other UEZs and policymaking. This study underscores the contributions of UEZs to place-based innovation and the broader UK economy. The platform aligns with the entrepreneurial spirit fostered by UEZ schemes by not imposing a minimum investment value, a requirement often found in angel groups (Mason et al., 2019), which typically ranges between 250,000 to 1 million pounds. Our dataset also reveals the presence of four University Spin-Offs (USOs) that have achieved successful fundraising outcomes within a span of around three years, aligning with the mission of University Enterprise Zones to foster entrepreneurship among university graduates. This highlights the roles of A@E as a part of the UEZ in addressing the equity gap that these emerging ventures encounter. This is also supported by the fact that startups which are riskier firms have received more capital and enjoyed a higher overfunding ratio compared to older, more established firms and it highlights the platform's pivotal role in the fundraising process of startups within the Essex UEZ. The A@E support for startups is consistent with the findings of Block et al. (2019) who reported that 70% of their sample BAs invested in seed stage startups, the highest percentage among all categories of early-stage investments.

The A@E platform's role as a locale-specific channel for investment in the Essex UEZ has been reflected in Essex county having the highest number of successful firms, however this has not detracted it from its primary function as an angel platform dedicated to identifying high-potential startups and attracting investors to the platform. Being situated outside the "Golden Triangle" of London, Oxford, and Cambridge, A@E has broadened its scope beyond local firms to include some from neighbouring counties. This strategic move likely aims to generate investment interest from a broader range of investors by introducing high-quality startups from regions renowned for their vibrant entrepreneurial activity, such as London and Cambridge.

A significant proportion of successful startups has already secured at least one investment round before seeking capital through the A@E platform. Furthermore, ventures with a previous investment track record tend to raise more capital, exhibit higher success rates, and achieve greater overfunding ratios compared to those presenting their ideas on the A@E platform for the first time. This phenomenon can be interpreted as a form of certification effect for subsequent investments, underscoring the platform's role in this regard (Cumming and Zhang, 2019, Bonini et al., 2018). The notable prevalence of A@E investments in startups with an established funding history suggest the platform's effort to mitigate risk for its members, aligning with its primary role as an angel platform. Interestingly, pre-A@E investments extend beyond government backed Innovate UK grants, encompassing contributions from other angels, PE/VC investors, and, in a few cases, an ECF platform.

Our study has limitations as our focus is solely on one angel platform, thereby potentially limiting the broader applicability of our findings. Research conducted on more extensive datasets, along with the exploration of intraplatform variations, could augment the generalizability of our conclusions. Further investigations could explore avenues such as disentangling the success rates of startups, similar to the approach taken by Lerner et al. (2018) in their examination of angel groups. Such research holds potential policy implications, offering insights into the extent to which a startup's achievements are influenced by the platform's primary selection criteria and its adherence to its core role as an investment facilitator for angels. Angels@Essex platform was launched in May 2020, with COVID-19 lockdown measures starting in March 2020 and continuing until December 2021. Given that the data collection period primarily coincides with the COVID-19 period, our findings could be influenced by the effects of the pandemic on both the demand and supply sides of the Angels@Essex platform as was the case with ECF campaigns during COVID-19. Future research could include a more updated dataset for the post-pandemic lockdown period and compare it with the pandemic period to assess how this angel platform accommodated the demand from entrepreneurs during the pandemic. Additionally, a longer period would result in a higher number of deals and the possibility of follow-on rounds on the platform, benefiting from the prior certification effect of the first successful round of equity investment. This represents another avenue for future research.

Table 1. List of variables and source of data

Variable	Data source	Explanation
Outcome variables		
Amount(£m)	A@E	Amount raised on A@E platform
Success	A@E	A dummy variable that takes value 1 for a positive Amount raised and 0 otherwise
Funding ratio	A@E	Amount raised divided by Target set by startups at the beginning of a deal
Backers	A@E	Number of backers/investors in each A@E deal
Target (£m)	A@E	Target (£m) of startups at the beginning of a deal
Credit Rating	Beauhurst	Credit rating of startups at time of data collection
Previous credit rating	Beauhurst	Previous credit rating of startups
Credit limit(£K)	Beauhurst	Credit limit (£k) of startups
Director gender	Beauhurst	Percentage of women among firm directors
Founder gender	Beauhurst	Percentage of women among firm founders
Key people gender	Beauhurst	Percentage of women among firm key people
Pre-money Valuation(£m)	Beauhurst	Firm value before its latest fundraising
Age (years)	Beauhurst	Duration between firm establishment date and data collection date in years
USO	Beauhurst	Dummy variable that takes value 1 if firm is a spin out from university, and 0 otherwise
Time Fund (years)	Beauhurst	Duration between firm establishment date and firm fundraising round
Status	Beauhurst	Categorical variable that takes 1 for Active, 2 Dissolved, 3 Dormant and 4 in Liquidation
Stage	Beauhurst	Categorical variable that takes 1 for Seed, 2 Venture, 3 Growth, 4 Zombie, and 5 for Dead startups
Employees	Beauhurst	Categorical variable: 1 for < 5 Employees, 2 for 5-9, 3 for 10-24, and 4 for 25-49 Employees
Views	A@E	Number of views of pitches on A@E platform by backers on the platform
Pre A@E		
PreFund	Beauhurst	A dummy variable that takes 1 if firm has prior fundraising record, 0 otherwise
Pre PE/VC (£m)	Beauhurst	Amount raised from PE/VC prior to A@E platform
Pre BA (£m)	Beauhurst	Amount raised from other BA prior to A@E platform
Pre_Innovate (£m)	Beauhurst	Amount raised from Innovate UK prior to A@E platform

Table 2.1 Startups on A@E

Variable	Obs.	Mean	Median	Min	Max
Credit Rating	62	27.56	23	0	92
Previous credit rating	46	32.04	31	0	90
Firm credit limit(£K)	62	11.56	0	0	434.02
Director gender (% female)	54	14.99	0	0	100
Founder gender (% female)	38	14.47	0	0	100
Key people gender (% female)	39	14.81	0	0	100
Pre-money Valuation(£m)	35	3.48	2.3	0.01	10
Firm Age (years)	62	5.52	4.95	0.54	20.68
University Spin Off (USO)	63	0.05	0	0	1
Time to raise fund (years)	40	2.04	1.66	0.12	6.11

Table 2.2 Startup status

Startup status	Startups	Percent
Active	56	79%
Dissolved	2	3%
Dormant company	3	4%
Liquidation	2	3%
No data	8	11%
Total	71	100%

Table 2.3 Startup employees

Number of Employees	Startups	Percent
< 5 Employees	20	32%
5-9 Employees	18	29%
10-24 Employees	21	33%
25-49 Employees	4	6%
Total	63	100%

Table 2.4 Startup stage

Startup Stage	Startups	Percent
Seed	24	51%
Venture	17	36%
Zombie	4	9%
Dead	1	2%
Growth	1	2%
Total	47	100%

Table 2.5 Covid impact on startups

Covid impact	Startups	Percent
Critical	1	3%
Severe	3	8%
Low	24	63%
Moderate	6	16%
Potentially positive	4	11%
Total	38	100%

Table 3. University spin-offs

	Fundraising/grant	Date	Amount	Equity (%)	Investors
Spin off 1	First round	26/06/2018	£60k	49%	Undisclosed Investors
	Second round	26/06/2020	£760k	N/A	BA and PE/VC coinvestment
	Innovate UK	31/03/2021	£487k	-	Innovate UK
	Third round	03/08/2021	£265k	6%	Undisclosed Investors
	Fourth round	23/08/2022	£500k	6%	PE/VC coinvestment with undisclosed investors
	Innovate UK	01/11/2022	£50k	-	Innovate UK
	Total (round)		£1.585m		
	Total (Grant)		£537k		
Spin off 2	First round	28/02/2022	£130k	76%	BA
	Second round	21/06/2022	£35k	4%	Undisclosed investors
	Third round	20/02/2023	£30k	77%	Undisclosed investors
	Total (round)		£195k		
Spin off 3	First round	15/03/2020	£150k	11%	Undisclosed investors
	Second round	03/02/2021	£190k	4%	ECF (Seedrs)
	Third round	17/12/2021	£126k	2%	Undisclosed investors
	Fourth round	17/09/2022	£17.5k	2%	Undisclosed investors
	Total (round)		£483.5		
Spin off 4	First round	19/08/2019	£10k	1%	Undisclosed investors
	Second round	01/04/2020	£203k	14%	Undisclosed investors
	Third round	30/06/2021	£332k	N/A	BA
	Fourth round	20/05/2022	£125k	4%	Undisclosed investors
	Fifth round	14/12/2022	£500k	14%	PE/VC coinvestment with Angel network
	Total (round)		£1.170m		

Total Amount (Grant)	£537k
Total Fundraising	£3,433.5m
Average Equity (%)	19%

Table 4.1 Equality of means and medians for A@E Essex versus Crowdcube ECF (All firms)

Variables	Obs. ECF	Mean ECF	Median ECF	Obs. A@E	Mean A@E	Median A@E	MeanDiff	MedianDiff
Amount (£m)	348	0.82	0.48	71	0.42	0.09	0.40***	0.39***
Funders	348	704.97	401	71	2.45	2	703***	399***
Target(£m)	346	0.46	0.3	71	0.68	0.5	-0.21***	-0.2***
Funding ratio	346	1.84	1.43	71	0.68	0.5	1.16***	0.93***
Success	346	0.93	1	71	0.63	1	0.29***	0

Table 4.2 Equality of means and medians for A@E Essex versus Crowdcube ECF (Successful firms)

Variables	Obs. ECF	Mean ECF	Median ECF	Obs. A@E	Mean A@E	Median A@E	MeanDiff	MedianDiff
Amount (£m)	322	0.86	0.5	45	0.66	0.45	0.196	0.05
Funders	322	737.4	437.5	45	3.73	3	733.67***	434.5***
Target(£m)	320	0.47	0.3	45	0.67	0.5	-0.2***	-0.2***
Funding ratio	320	1.91	1.49	45	0.67	0.5	1.24***	0.99***
Success	320	1	1	45	1	1	0	0

Table 4.3 Location and outcome on Angels@ Essex

Location	Mean Amount(£m)	Median Amount(£m)	Mean Backers	Median Backers	Mean Target(£m)	Median Target (£m)
Essex	0.97	0.55	4.25	3.50	0.72	0.68
Greater London	0.47	0.59	4.00	5.00	0.66	0.50
Suffolk	1.32	0.72	5.80	5.00	0.51	0.50
Cambridgeshire	0.55	0.54	2.86	3.00	0.72	0.65
Other	0.51	0.27	3.33	3.00	0.78	0.50

Table 5. Single investment versus coinvestment rounds

	Investors type	Number of rounds	Percent	Cum.
Single Investment	BA	20	10.81	10.81
	Innovate UK Grant	64	34.59	45.41
	PE/VC	13	7.03	52.43
	ECF	7	3.78	56.22
	Undisclosed investor	68	36.76	92.97
	University	1	0.54	93.51
	None	2	1.08	94.59
Coinvestment rounds	BA coinvestment with PE/VC	2	1.08	95.68
	BA coinvestment with Undisclosed investor	2	1.08	96.76
	BA Coinvestment with University	1	0.54	97.3
	PE/VC coinvestment with ECF	1	0.54	97.84
	PE/VC coinvestment with Undisclosed Investor	2	1.08	98.92
	BA coinvestment with ECF (Innovate UK is a part of deal)	1	0.54	99.46
	BA coinvestment with PE/VC and Undisclosed Investors	1	0.54	100
	Total	185	100	

Note: This table reports the investor types for each round of fundraising.

Table 6. Investment rounds and equity offered (%)

Investor type	Number of rounds	Mean Amount (k)	Median Amount (k)	Mean Equity (%)	Median Equity (%)
Business Angels	8	£320	£290	14.01 %	4.50 %
Private Equity/Venture Capital	10	£710	£410	14.90 %	14.00 %
Equity crowdfunding	4	£580	£510	19.00 %	10.00 %
Undisclosed investors	65	£270	£130	10.12 %	6.00 %
Single investments (Total)	87	£470	£330	14.51 %	8.63 %
Coinvestments	8	£1,440	£500	13.88 %	15.00 %

Note: This table presents the Amount (k) raised in rounds and Equity offered for each round by investor category. This only includes the external investments which are made in return for equity, and it excludes the grants (Innovate UK grant)

Table 7.1 Amount of capital raised by successful startups

Variable	N	Mean	Median	Min	Max
All Fundraisings(£m)	36	1.44	0.49	0.04	11.56
Grant(£m)	37	0.24	0.03	0	1.64
A&E platform (£m)	37	0.72	0.5	0.04	4.03

Table 7.2 Number of rounds and grants by successful startups

Variable	N	Mean	Median	Min	Max
All rounds (Grants & Fundraisings)	36	5.08	4	1	18
Grants	37	1.62	1	0	7
Fundraisings	37	3.27	3	0	11

Table 7.3 Sources of finance by successful startups

Variable	N	Mean	Median	Min	Max
Innovate UK Grant	37	0.51	1	0	1
BA	37	0.3	0	0	1
PE/VC	37	0.19	0	0	1
ECF	37	0.11	0	0	1

Table 8.1 Prior rounds and grants by successful startups

Variable	Number	Percent
Startups with prior rounds	21	
Startups with prior PE/VC	4	0.19
Startups with prior BA	4	0.19
Startup with prior Innovate UK grant	10	0.48

Table 8.2 Detail of pre-Angels@Essex rounds and grants

	Total	Mean	Median
All 21 startups with prior rounds			
Amount (£m)	28.74	1.44	0.52
Prior rounds	51	2.83	2.5
4 startups with prior VC rounds			
Amount (£m)	6.46	1.61	1.33
Prior rounds	5	1.13	1.25
4 startups with prior BA rounds			
Amount (£m)	3.76	0.94	0.305
Prior rounds	8	2	1
10 startups with Innovate UK grants			
Amount (£m)	4.43	0.443	0.325
Prior grants	26	2.6	1.5

Table 9. Correlation matrix

Variables	Amount	Success	Funding ratio	Startup_d	Location_d	PreFund	Target(£m)	Views	Pre	Pre PE/VC	Pre BA	Pre Innovate	Credit Rating
Amount(£m)	1												
Success	0.417*	1											
Funding ratio	0.811*	0.301*	1										
Startup_d	-0.07	0.007	-0.03	1									
Location_d	0.025	-0.19	-0.03	0.122	1								
PreFund	0.456*	0.503*	0.373*	-0.283*	-0.08	1							
Target(£m)	0.230*	-0.017	-0.13	-0.072	0.013	0.062	1						
Views	0.154	0.349*	0.139	-0.076	-0.106	0.104	0.078	1					
Pre	0.456*	0.503*	0.373*	-0.283*	-0.08	1.000*	0.062	0.104	1				
Pre PE/VC (£m)	0.103	0.141	0.093	-0.081	-0.104	0.285*	-0.068	-0.220*	0.285*	1			
Pre BA (£m)	0.038	0.109	-0.01	-0.062	0.198*	0.220*	0.053	0.15	0.220*	-0.022	1		
Pre Innovate Uk (£m)	0.145	0.210*	0.003	-0.12	-0.155	0.425*	0.374*	0.136	0.425*	0.218*	-0.03	1	
Credit Rating	0.403*	0.17	0.315*	-0.351*	0.026	0.298*	0.006	0.059	0.298*	0.201*	0.097	0.13	1

Note: The method employed in this table is pairwise correlation. The number of observations is reported for each variable in blue color (*** p<0.01, ** p<0.05, * p<0.1)

Table 10. Startups and A@E platform

Variables	(1) Amount(£m)	(2) Amount(£m)	(3) Amount(£m)	(4) Success	(5) Success	(6) Success	(7) Funding ratio	(8) Funding ratio	(9) Funding ratio
Startup_d	0.423**	0.438**	0.505**	0.606	0.605	0.474	1.080***	1.053***	1.354**
	(2.32)	(2.55)	(2.63)	(1.33)	(1.12)	(0.64)	(2.75)	(2.69)	(2.57)
Target(£m)		0.240**	0.260**		-0.249	-0.336*		-0.428	-0.289
		(2.06)	(2.49)		(-1.500)	(-1.891)		(-1.289)	(-0.892)
Views	0.150*	0.146	0.132*	0.584***	0.605***	0.623***	0.373	0.381	0.293
	(1.68)	(1.63)	(1.68)	(8.00)	(8.05)	(4.73)	(1.22)	(1.23)	(1.16)
Credit Rating	0.0164**	0.0162**	0.0174**	0.0179***	0.0180***	0.0209***	0.0317**	0.0322**	0.0353**
	(2.32)	(2.30)	(2.44)	(5.16)	(6.05)	(7.06)	(2.33)	(2.36)	(2.35)
PreFund	0.690**	0.734***	0.786***				2.134**	2.055**	2.217**
	(2.48)	(2.72)	(2.88)				(2.04)	(2.04)	(2.20)
Pre PE/VC (£m)	-0.0414	-0.00736	-0.156				-0.00342	-0.0641	-0.611
	(-0.385)	(-0.0675)	(-0.981)				(-0.0129)	(-0.229)	(-1.047)
Pre BA (£m)	-0.213	-0.246*	-0.216				-0.879*	-0.820*	-0.701
	(-1.559)	(-1.835)	(-1.468)				(-1.717)	(-1.686)	(-1.642)
Pre Innovate Uk (£m)	-0.239	-0.518	-0.322				-2.175	-1.678	-1.148
	(-0.445)	(-1.186)	(-0.976)				(-1.616)	(-1.349)	(-1.366)
Constant	-0.595**	-0.737***	-0.714**	-1.377***	-1.264***	-1.771**	-1.390*	-1.138	-1.476
	(-2.268)	(-2.937)	(-2.199)	(-4.067)	(-3.140)	(-2.080)	(-1.679)	(-1.561)	(-1.226)
Industry FE	No	No	Yes	No	No	Yes	No	No	Yes
Location FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	69	69	69	69	69	69	69	69	69
Adjusted R-squared	0.332	0.349	0.386				0.193	0.19	0.236
Pseudo R-squared				0.141	0.148	0.202			

Note: In models (1) to (3) and (7) to (9) dependent variable is Amount(£m) and Funding ratio, respectively, and OLS estimation is utilised. In Models (4) to (6) the dependent variable is a Success dummy and probit estimation is employed. Models (2), (5) and (8) include Target. Target, industry, and location fixed effect are included in Models (3), (6), and (9).

Table 11. Location and A@E platform

Variables	(1) Amount(£m)	(2) Amount(£m)	(3) Amount(£m)	(4) Success	(5) Success	(6) Success	(7) Funding ratio	(8) Funding ratio	(9) Funding ratio
Location_d	0.2	0.177	0.104	-0.459***	-0.456***	-0.461***	0.0517	0.102	-0.109
	(0.96)	(0.84)	(0.48)	(-2.685)	(-2.630)	(-2.757)	(0.12)	(0.23)	(-0.198)
Target(£m)		0.215*	0.198		-0.0867	-0.17		-0.465	-0.513
		(1.77)	(1.66)		(-0.481)	(-1.415)		(-1.453)	(-1.351)
Views	0.164*	0.158*	0.150*	0.509***	0.512***	0.581***	0.377	0.388	0.379
	(1.86)	(1.80)	(1.70)	(7.22)	(7.21)	(5.10)	(1.27)	(1.29)	(1.22)
Credit Rating	0.635**	0.672**	0.669**				1.974*	1.895*	1.882*
	(2.32)	(2.54)	(2.63)				(1.91)	(1.89)	(1.95)
PreFund	-0.0119	0.0169	-0.0461				0.0314	-0.0309	-0.172
	(-0.122)	(0.17)	(-0.371)				(0.12)	(-0.109)	(-0.462)
Pre PE/VC (£m)	-0.259*	-0.282*	-0.183				-0.879*	-0.828*	-0.605
	(-1.688)	(-1.868)	(-1.365)				(-1.770)	(-1.744)	(-1.514)
Pre BA (£m)	-0.206	-0.459	-0.356				-2.169	-1.621	-1.344
	(-0.396)	(-1.075)	(-0.930)				(-1.583)	(-1.284)	(-1.212)
Pre Innovate Uk (£m)	0.0140**	0.0137**	0.0151**	0.0118***	0.0116***	0.0130**	0.0259*	0.0265**	0.0297**
	(2.14)	(2.10)	(2.30)	(2.87)	(3.04)	(2.54)	(2.00)	(2.05)	(2.09)
Constant	-0.527**	-0.641**	-0.614**	-0.847***	-0.792**	-1.033*	-1.05	-0.804	-0.848
	(-2.004)	(-2.536)	(-2.432)	(-3.249)	(-2.096)	(-1.772)	(-1.411)	(-1.211)	(-1.012)
Industry FE	No	No	Yes	No	No	Yes	No	No	Yes
Location FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	69	69	69	70	70	70	69	69	69
Adjusted R-squared	0.307	0.318	0.348				0.164	0.163	0.17
Pseudo R-squared				0.123	0.124	0.158			

Note: In models (1) to (3) and (7) to (9) the dependent variable is Amount(£m) and Funding ratio, respectively, and OLS estimation method is utilised. In Models (4) to (6) dependent variable is a Success dummy and probit estimation is employed. Models (2), (5) and (8) include Target. Target, industry fixed effect are included in Models (3), (6), and (9).

Table 12. Prior investment record and A@E platform

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Amount(£m)	Amount(£m)	Amount(£m)	Funding ratio	Funding ratio	Funding ratio
Pre	0.739***	0.726***	0.739***	1.767**	1.814**	1.811**
	(3.046)	(2.893)	(2.893)	(2.223)	(2.25)	(2.347)
Target(£m)		0.186	0.239		-0.632*	-0.440*
		(1.205)	(1.649)		(-1.725)	(-1.726)
Constant	0.174***	0.056	0.0944	0.319***	0.720***	0.395
	(3.291)	(0.749)	(0.3)	(3.834)	(2.877)	(0.586_
Industry FE	No	No	Yes	No	No	Yes
Location FE	No	No	Yes	No	No	Yes
Observations	70	70	70	70	70	70
Adjusted R-squared	0.196	0.204	0.216	0.127	0.14	0.17

Note: In models (1) to (3) the dependent variable is Amount(£m) and in models (4) to (6) it is the Funding ratio. OLS estimation is utilised in all models. In. Models (2), and (5) Target is included. In Models (3), and (6) industry and location fixed effects are included.

Figure 1. Angels@Essex startup location

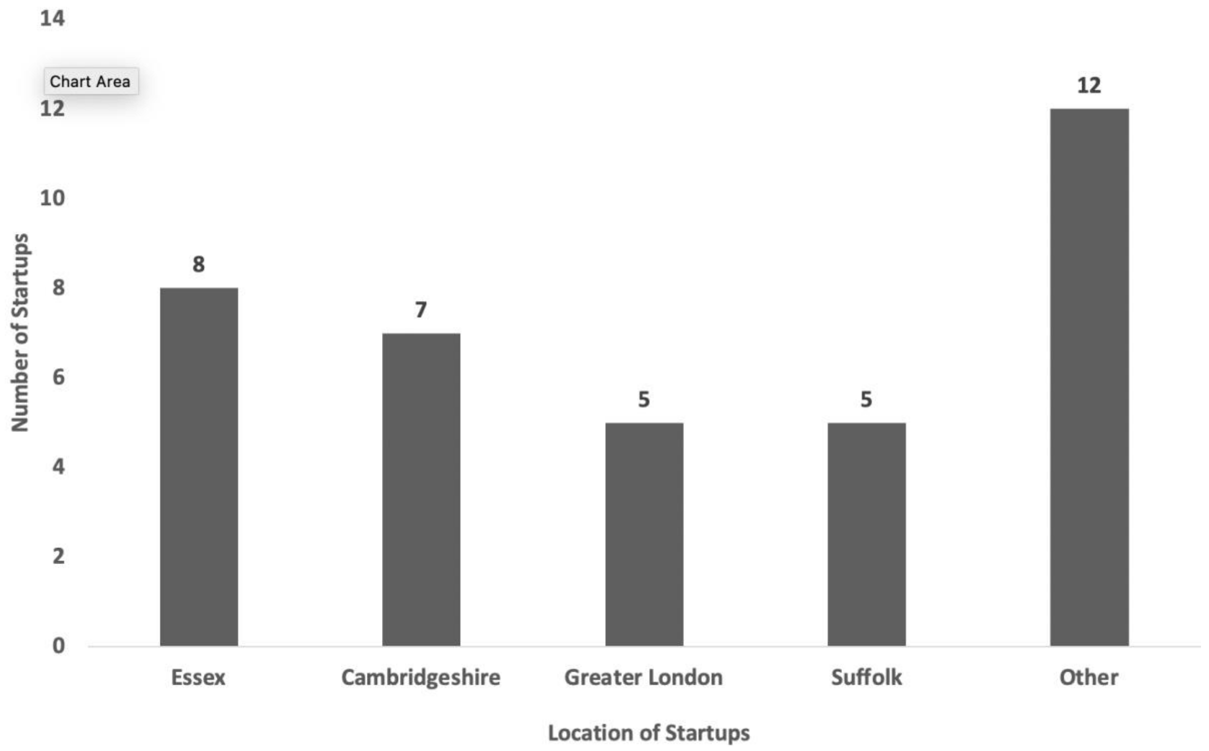
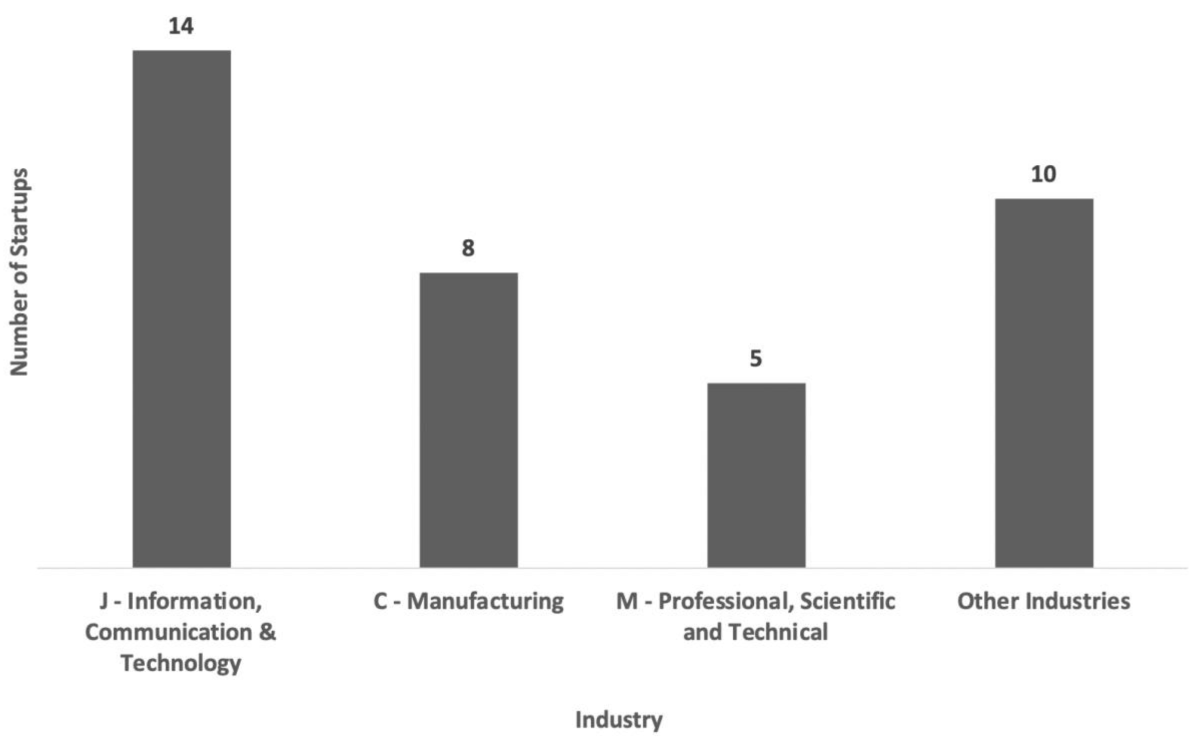


Figure 2. Angels@Essex startups by Industry (SIC)



Chapter 5
Conclusions

This chapter summarises the finding of all three papers on different aspects of entrepreneurial finance and outlines areas for further research. All three paper focus on issues linked to the provision of digital outside equity to startups and other young ventures via online platforms. Two papers (Chapters 2 and 3) investigate current issues relating to equity crowdfunding platforms while a third (Chapter 4) provides a discussion of issues relating to a novel angel funding platform located in the Essex University Enterprise Zone.

The first paper (Chapter 2) examines the effect of gender on equity crowdfunding outcomes. In particular, it analyses whether online equity crowdfunding platforms can reduce the well-documented gender gap present in traditional equity finance channels like business angels and venture capital. The empirical results reveal some positive findings for female entrepreneurs raising funds via crowdfunding. Female founders running solo ventures attract more investors, achieve higher ratios of funds raised over their target amounts, and have a greater likelihood of surpassing their fundraising goals compared to solo male founders. These results contrast with previous research in traditional sources of finance showing that women receive less equity investments than men when pursuing outside financing through conventional means like angel investors and VC firms (Alesina et al., 2013, BVCA, 2019, Rose, 2019, Dutta and Mallick, 2023), however it aligns with crowdfunding literature and democratising effect of ECF (Zhao et al., 2021, Cumming et al., 2021a). However, this positive gender effect does not extend to the probability of equity crowdfunding campaign success, as success might be influenced by platform-specific strategies (Cumming et al., 2020). Solo female founders demonstrate a clear advantage when their performance is compared relative to their funding goals. Nevertheless, when it comes to the number of campaigns with female entrepreneurs, there is a disadvantage, with female-founded firms having a smaller presence across all campaigns. In the case of Crowdcube (2011-2018), approximately 76% of all campaigns had no female founder. This underrepresentation aligns with the findings of the Rose (2019) concerning female entrepreneurs in the UK. Interestingly, female founders have a stronger presence in ECF compared to traditional investment sources but less so when compared to reward-based crowdfunding. The reasons behind this underrepresentation warrant further investigation. Similar to other studies, this study has limitations when comparing all-female founding teams with their male counterparts since only 2.29% of all campaigns had exclusively female founding teams. A potential avenue for future research could involve examining the performance of all-female teams as our dataset descriptive statistics suggest that the positive team effect seems to be favouring all male founding teams and not female founders.

The second paper (Chapter 3) focuses on the impact of the COVID-19 pandemic on equity crowdfunding on the UK's largest platform - Crowdcube. This paper presents evidence of an unexpected increase in ECF performance during the COVID-19 period compared to the pre-COVID-19 period. One reason for this is the improved ability of ECF platforms to attract higher-quality firms, a task they initially struggled with. The pre-COVID-19 stablished online practices of ECF platforms and disruptions in BA and VC face to face due diligence was another contributing factor. These findings are consistent with the positive effects of digitalization on entrepreneurial finance, which has created new financial pathways that complement traditional intermediaries. Digital platforms enable nascent firms with limited financial histories to secure resources, illustrating ECF's democratizing role and its crucial importance during the pandemic. The paper also uncovers an unexpected positive impact of government loan guarantee schemes (LGS), such as the Bounce Back Loan Scheme (BBLS), on small firms' access to equity capital. Contrary to initial concerns, LGS provided essential liquidity support for ECF campaigns, significantly benefiting seed firms. Interestingly, seed firms benefited more from the boost than their more established counterparts. This is evidenced by an increase in the number of deals and the positive mediating effect of the COVID-19 period on ECF performance when compared to early-stage and growth-stage firms during the same period. This resilience underscores the importance of LGS and ECF platforms in enabling small firms to access equity capital during periods of external disruption.

The third paper (Chapter 4) explores the functioning of a novel type of funding platform based - Angels@Essex - at Essex University Enterprise Zone (UEZ). This is an angel funding platform where only accredited investors like business angels and venture capital can invest. This examination provided insights into how this platform operates as a locality-specific channel for investment and as an Angel platform that aligns with the evolving landscape of Angel investors, who are now actively engaging with online platforms, networks, and syndicates rather than functioning solely as Solo Angels. The findings indicate that Angels@Essex (A@E) has achieved significant success, providing funding to more than 63% of the startups that have approached the platform. A@E operates with a "Keep It All" policy, which allows firms to retain the funds they raise without being subjected to threshold requirements. While this approach demonstrates the platform's friendliness towards startups, it does carry a moral hazard risk, as noted by Cumming et al. (2020), particularly for campaigns that do not reach their full funding target. However, Angel platforms differ from ECF platforms in the sense that the former exclusively comprise Angel members and benefit from their extensive network to conduct more detailed due diligence. A@E has invested in younger firms with a prior record of funding. These, in addition to the main industry focus on technology, indicate that A@E has leveraged its role as a part of the University Enterprise Zone (UEZ) to identify potential high-quality firms, regardless of their location. This demonstrates one of the advantages of being an online platform and the evolution of investment by business angels.

In summary, the results of this thesis indicate that recent advances in information communication technologies such as digital funding platforms have contributed to and, in some cases, reshaped the evolution of the entrepreneurial finance ecosystem. This evolution has led to increased accessibility to equity finance for smaller firms by addressing challenges like market failure resulting from significant information asymmetries, thus reducing the equity gap for young, innovation-driven businesses (Cumming et al., 2021a, Wilson et al., 2018). These technological advances have introduced new markets, such as equity crowdfunding (ECF), and angel platforms which may lower the sensitivity to gender differences and, in the case of the former, leverage the collective wisdom of the crowd. They have also provided an alternative source of finance (ECF) that has demonstrated resilience during periods of heightened uncertainty, serving as a potential external capital source when other traditional sources are limited. Additionally, these advances have transformed the methods and strategies employed by business angels (BAs) when investing in smaller firms. BAs are now investing via platforms and syndicates rather than relying solely on personal networks. They are making more diverse contribution as platforms facilitate risks sharing with their peers and other professional investors such as VC and family offices.

This thesis is subject to some particular overall limitations. The dataset employed in this thesis is confined to a single ECF platform and one Angel crowdfunding platform. The former could benefit from incorporating datasets from other UK-based platforms to enhance the generalizability of the findings. However, the latter, as part of the University Enterprise Zone (UEZ), is unique and would benefit from a more detailed examination of the performance of startups funded through the Angels@Essex (A@E) platform after their success in securing equity capital from A@E. Moreover, future studies could explore the democratizing role of ECF by examining its performance for minorities, given the recent evolution of this emerging market and the increased involvement of professional investors such as Business Angels (BA) and Venture Capitalists (VC). In such contexts and with the active role of BA and VC in ECF deals, the Gender Role Congruity Theory (GCRT) becomes more relevant as female founders compete with their male counterparts in securing external capital. More, two chapters of this thesis focus solely on the UK ECF market. It would be interesting to compare these research questions in the context of the US market, given the rapid increase in the US ECF market size and the number of deals since its inception on May 16th, 2016, when Title III of the Jumpstart Our Business Startups (JOBS) Act went into effect. Furthermore, given the thesis's focus on new sources of entrepreneurial finance, the democratizing role of digital finance could be explored in the context of marketplace (peer-to-peer) lending.

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