

Klarl, Torben; Kritikos, Alexander S.; Poghosyan, Knarik

Working Paper

Complementary Funding: How Location Links Crowdfunding and Venture Capital

GLO Discussion Paper, No. 1654

Provided in Cooperation with:

Global Labor Organization (GLO)

Suggested Citation: Klarl, Torben; Kritikos, Alexander S.; Poghosyan, Knarik (2025) : Complementary Funding: How Location Links Crowdfunding and Venture Capital, GLO Discussion Paper, No. 1654, Global Labor Organization (GLO), Essen

This Version is available at:

<https://hdl.handle.net/10419/324487>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Complementary Funding: How Location Links Crowdfunding and Venture Capital*

Torben Klarl^{1,2}, Alexander S. Kritikos^{3,4}, and Knarik Poghosyan³

¹University of Bremen, Max-von-Laue-Straße 1, 28359 Bremen

²SPEA, Indiana University, Bloomington

³DIW Berlin, Mohrenstr. 58, 10117 Berlin

⁴University of Potsdam and GLO Essen

July 30, 2025

Abstract

While Equity Crowdfunding (ECF) platforms are a virtual space for raising funds, geography remains relevant. To determine how location matters for entrepreneurs using equity crowdfunding (ECF), we analyze the spatial distribution of successful ECF campaigns and the spatial relationship between ECF campaigns and traditional investors, such as banks and venture capitalists (VCs). Using data from the two leading German platforms – Companisto and Seedmacht – we employ spatial eigenvalue filtering and negative binomial estimations. In addition, we introduce an event study based on the implementation of the Small Investor Protection Act in Germany allowing us to obtain causal evidence. Our combined analysis reveals a significant geographic concentration of successful ECF campaigns in some, but not all, dense areas. ECF campaigns tend to cluster in dense areas with VC activity, while they are less prevalent in dense areas with high banking activity, and are rarely found in rural areas. Thus, rather than closing the so-called regional funding gap, our results suggest that, from a spatial perspective, ECF fills the gap when firms in dense areas seek external financing below the minimum equity threshold offered by VCs and when there are few banks offering loans.

Keywords: Crowdfunding, Finance Geography, Entrepreneurial Finance, Venture Capital (VC) Proximity

JEL Classification: G30, L26, M13

*The authors declare that they have no conflict of interest. The authors did not receive any external funding. The data on the ECF campaigns were collected from publicly available sources. All other data used in this study are freely accessible. The authors are grateful to Johannes Weinert for excellent data preparation.

1 Introduction

Entrepreneurs entering markets with the aim to launch new products and services are a key element of innovation, job creation, and economic growth (see *inter alia* Fonseca et al. (2001) and Kritikos (2015)). When they are constrained by their own capital, external finance becomes a crucial ingredient for them to be able to realize their business ideas. Entrepreneurs then must rely on access to credit via their local banks or access to equity via venture capitalists (VCs) and private equity firms, which are usually located in specific, more dense geographic areas (Sorenson and Stuart 2001). Remotely located individuals with entrepreneurial ideas face higher access barriers to capital as the geographical distance between investors and entrepreneurs still constitutes a severe obstacle in venture financing (Agrawal et al. 2010). This is particularly pronounced in peripheral regions, where the "regional funding gap" limits access to capital, leaving entrepreneurs with fewer institutional options for financing (Martin et al. 2005). Without access to formal financial sources, these entrepreneurs more often turn to informal funding.

Equity crowdfunding (ECF), a platform-oriented innovation that offers finance for entrepreneurs through social networks, is seen as having the potential to address this funding gap. Starting in the late 2000s, the first platforms provided equity through digital marketplaces, where the platform replaces the traditional local middleman (Vulkan et al. 2016). It opens up the possibility for entrepreneurs to obtain - irrespective of their location - fast and efficient access to equity for financing their business ideas by interested, mostly small-scale, investors, characterized as "the crowd," to whom entrepreneurs are virtually connected. ECF may thus have the potential to close the regional funding gap as it may offer equity to those who might have been excluded before for reasons of distant proximity to their investors (Cumming et al. 2021; French and Poterba 1991; Mollick and Robb 2016). Yet, there is an established literature emphasizing that the location of entrepreneurs is not only determined by the access to external finance but by the overall entrepreneurial ecosystem (Stam 2009), which leads to certain entrepreneurial clusters in, for instance, cities.

This yields the first research question of this contribution: where are entrepreneurial firms physically located that raise equity through campaigns on ECF platforms? More specifically, are remotely located firms also able to raise funds through such campaigns? Using data on the German ECF market, in this paper we systematically investigate from a spatial point of view where the firms of the ECF campaigns are located in the German context and what the spatial distribution of these financed campaigns is.

Beyond the benefits of reducing transaction costs by using digital capital markets in comparison to offline offers, ECF must be seen as an additional source of external finance. The main potential competitors (but also cooperators), are - as mentioned before - banks, where entrepreneurs may obtain loans, or VC companies, where entrepreneurs may also raise equity. While several studies have examined the relationship between equity crowdfunding and traditional forms of entrepreneurial finance—such as venture capital and bank lending, the spatial

dimension of these dynamics has not been investigated. Little is known about how the substitutive or complementary roles of ECF evolve across different regional contexts. Pollack et al. (2019), for instance, stress the need to investigate under which conditions crowdfunding complements or substitutes other financing channels. Therefore, in our second research question, we aim to put our analysis from a spatial point of view in the overall context of the capital market for entrepreneurs and investigate the nature of the spatial relationship between ECF-financed companies and more traditional sources of entrepreneurial finance, be it venture capitalists or traditional banks. By doing so, we aim to determine in what way location matters for entrepreneurs who use ECF platforms to successfully finance their firms and aim to understand whether ECF campaigns tend to be rather complements or rather substitutes to the traditional funding sources of equity through VCs and of debt through banks, or whether their location happens to be independent of VCs and banks.

More specifically, we examine the spatial localization of companies that are ECF-financed through one of the two central platforms in Germany (Companisto and Seedmacht) and the geographical context in which the two platforms operate. We include in our analysis the location of banks and VCs, typical traditional early-stage investors. Using data covering about 90% of the German ECF market between 2012-2018, we analyze the locations of entrepreneurial ECF campaigns and further investigate their spatial relationship with these traditional investors. Using the number of active early-stage investors and the number of banks in a region as proxies for available venture capital and available loans in the same region, we compare its geographic distribution with the geographic distribution of successfully launched ECF campaigns. By applying spatial eigenvector filtering combined with negative binomial estimations, we account for regional interdependencies and correct for spatial autocorrelation—thereby addressing potential endogeneity due to unobserved spatial spillovers. This filtering approach enhances the credibility of our estimates by removing bias from omitted spatial variables that may otherwise confound inference. To further reinforce our findings and establish causal claims, we exploit the 2015 implementation of the Small Investor Protection Act (Kleinanlegerschutzgesetz, KASG) as a policy shock. Leveraging this exogenous event, we use an event study design paired with Coarsened Exact Matching (CEM) to compare ECF-active and non-active regions before and after the reform, isolating the impact of regulatory change on crowdfunding dynamics.

We contribute to the ECF literature in three ways. First, we provide a systematic analysis of the geography of ECF-funded firms. Second, we analyze the spatial interplay between ECF activity and the presence of traditional funding sources, identifying conditions under which ECF serves as a complement or substitute. Third, and most critically, we implement a rigorous empirical framework that combines spatial filtering with causal identification tools—CEM and event study methods—allowing us to draw more robust conclusions about how location and local financial ecosystems influence the success of ECF campaigns.

We find that the number of successful equity crowdfunding (ECF) campaigns is heavily clustered, however, not in all dense areas in general, but only in three cities in Germany (Berlin,

Hamburg, and Munich), while there are nearly no successful ECF campaigns in rural areas. This argues against ECF closing the regional funding gap. Moreover, our spatial approach reveals that successful ECF campaigns in a region are positively correlated with the number of venture capitalists in the same region, while it tends to be negatively correlated with the number of monetary financial institutions (i.e., banks), subject to the ECB's minimum reserve requirements, covering cities like Frankfurt, Cologne or Stuttgart. This picture – that successful ECF-financed firms are more likely located in those highly dense areas, where the concentration of VCs is high – did not really change with the introduction of KASG. Within those regions where the VC market is well developed, ECF then generally tends to act as a complement to VCs, with one exception in the year after the KASG has been introduced. This clarifies that there is no linear relationship between the likelihood of ECF campaigns and the density of an area. Rather than density, it is the local financial ecosystem that plays a crucial role in determining where ECF campaigns thrive.

2 Theoretical Background and Hypotheses

While some entrepreneurs may establish their firms in areas with a strong financial environment, others in more remote areas may suffer from a lack of access to external finance. This disparity aligns with the concept of the "regional funding gap," which describes the systematic disadvantages firms in peripheral regions face when seeking capital (Martin et al. 2005). Traditional sources of funding, such as venture capital (VC) and bank loans, tend to be concentrated in financial hubs, leaving entrepreneurs in less-developed regions with fewer financing options. Before the design of ECF platforms, the importance of spatial proximity was well documented for the investment decisions of venture capitalists (VC). Earlier studies indicate that venture capital firms prefer investments in their local areas (Cumming and Dai 2010; Kolympiris et al. 2015). This is known as the home bias phenomenon, documented across different domains in the financial and economic literature (Ahearne et al. 2004; French and Poterba 1991). It may exist for various reasons, such as reduced information asymmetries, more affordable due diligence capabilities, decreased transaction costs (Cumming and Dai 2010; Sorenson and Stuart 2001), or regional embeddedness such as the connection to regional actors, network, environment, and established culture Birkholz (2024).

Restrictive regulations are applied when it comes to financial assistance to entrepreneurs, small firms, and startups by banks. For instance, in Germany, local or regional savings and cooperative banks adhere to a policy known as the "regional principle," which imposes strict limitations on their lending activities. Specifically, these banks are required by law to provide loans exclusively to businesses located within their local regions (Gramlich et al. 2020). This regulatory constraint further exacerbates the regional funding gap, making alternative financing sources such as ECF particularly attractive. By contrast, ECF platforms, which facilitate digital mediation between small-scale investors and entrepreneurs seeking equity, appear capable of

addressing these so-called home-bias-related investment decisions and eliminating distance-related economic frictions apparent in early-stage VC markets (Agrawal et al. 2010; Agrawal et al. 2015; Lin and Viswanathan 2016). Notably, ventures from high-unemployment areas tend to perform better in ECF campaigns, despite facing higher failure risks (Lazos 2024).

Through ECF, entrepreneurs can make a public call to sell a specified amount of equity or bond-like shares in their company online, to attract numerous investors (Ahlers et al. 2015). According to Correia et al. (2024), the pre-investment period is important and involves strategic decisions shaped by entrepreneurs' funding needs, the regulatory environment, and the characteristics of crowdfunding platforms. The key distinction between equity crowdfunding and traditional fundraising lies in its digital nature: Entrepreneurs openly solicit funding on a crowdfunding platform and investors base their decisions on the provided information. Additionally, the platform facilitates transactions by offering standardized investment contracts, handling payments, and allowing for information updates (Block et al. 2018), thus reducing the transaction costs (Belleflamme et al. 2014; Estrin et al. 2024). Research also suggests that presenting structured information on these platforms enhances investor engagement and increases campaign success, particularly in financially constrained settings (Yang et al. 2025).

Once platform administrators grant entrepreneurs access, platforms become accessible at relatively low costs. Information collection, due diligence on proposed projects, and monitoring of entrepreneurial activities occur within the virtual exchange facilitated by the platforms. This digital marketplace effectively addresses most economic requirements typically demanded by investors while simultaneously offering lower transaction and search costs (Hornuf et al. 2022). Crowdfunding investors usually make relatively small investments and do not acquire the monitoring or control rights typically granted to accredited investors like venture capitalists (Belleflamme et al. 2014; Cumming and Johan 2007; Lerner 1995). Cultural background may also shape investor behavior in ECF. Barbi et al. (2023) show that individuals born in Italian provinces with high levels of social capital are more likely to invest in riskier campaigns, underscoring the influence of inborn trust-based traits over environmental factors.

However, there are other studies arguing that the preference for local investments may remain prevalent (Agrawal et al. 2010; Agrawal et al. 2015; Guenther et al. 2017; Lin and Viswanathan 2016). Hortaçsu et al. (2009) observe a similar trend on other platforms, revealing that despite the distance-independent nature of online platforms like eBay, the likelihood of a purchase is still inversely correlated with distance.

This is discussed from both sides of the market, from the perspective of entrepreneurs, who are the main focus of this analysis, as well as from the perspective of investors. Entrepreneurs are more likely to choose to establish their companies in regions characterized by a good local infrastructure ecosystem as well as functioning social and cultural ecosystem (Stam 2009; Stam and Spigel 2016). This preference is more prevalent in urban areas, largely due to the advantages they offer over rural counterparts. One key benefit is the large population size and density, which earlier research shows to positively influence entrepreneurial activity (Wagner and Sternberg

2004). It allows for easier access to both customers and the necessary resources such as capital, labor, and suppliers, facilitated by the concentrated population (Stam 2009). However, recent evidence by Kim and Orazem (2025) shows that the impact of population, industrial diversity, and skilled labor on new firm formation has declined more sharply in rural areas than in urban ones, contributing to a further widening urban–rural gap in firm entry rates.

Furthermore, according to the classic ‘incubation hypothesis’ in urban economics, cities offer the availability of labor, rentable space, and services, etc. to small-scale production (Stam 2009). Urban areas also facilitate interactions with skilled individuals, increasing human capital and entrepreneurial opportunities (Glaeser 1999; Glaeser 2007). The presence of universities and research centers in urban areas generates new knowledge, crucial for innovative entrepreneurs, thus increasing the propensity for entrepreneurship (Audretsch et al. 2006). Additionally, the abundant employment opportunities in cities reduce the risk for entrepreneurs by providing a fallback option if their ventures fail (Stam 2009). An essential factor influencing entrepreneurial decisions, particularly in crowdfunding, is access to high-speed internet. According to Bertschek et al. (2023), this access is generally superior in urban areas compared to rural areas.

Given the discussion indicating a higher likelihood of finding entrepreneurs in urban compared to rural areas, we expect that equity crowdfunding (ECF) campaigns initiated by entrepreneurs should also be more prevalent in urban areas.¹ Following this reasoning, we derive:

Hypothesis 1: The denser an area, the greater the likelihood of successful ECF-funded firms.

Conversely, with finance remaining highly concentrated in specific locations, urban areas also see a significant presence of other funding sources, such as venture capital (Martin et al. 2002; Martin et al. 2005) and traditional banking (Hegerty 2015). Since recent evidence by Fasano et al. (2025) suggests that ECF alone may not boost firm performance—especially as financially constrained firms often use ECF funds to stabilize finances rather than pursue growth—it is important to examine how ECF interacts with other funding sources, specifically whether banks and venture capital act as substitutes or complements to equity crowdfunding.

According to the pecking order theory (Myers and Majluf 1984), entrepreneurs prioritize financing options based on the costs associated with information asymmetry, relying first on internal funds, then debt, and only turning to external equity as a last resort. This theory is further supported by Walthoff-Borm et al. (2018): firms resort to ECF as a last option when they have exhausted internal funds and lack additional debt capacity.²

¹There is also suggestive first evidence that the majority of successful ECF campaigns are initiated in major cities (Gallemore et al. 2019; Langley 2016; Mollick 2014), known for their diverse and sophisticated human capital (Florida 2003). Guenther et al. (2017) provide further evidence with their study on the Australian Small Scale Offerings Board (ASSOB), one of the world’s largest investment crowdfunding platforms. They observe that firms located near metropolitan areas were more likely to achieve funding targets than firms in remote areas. (Similar results are reported by Maymoni and Solodoha (2025) for the Israeli platform Headstart.)

²However, this framework may not fully apply to early-stage startups, which often lack access to both internal funds and traditional debt.

This raises the question of how ECF interacts with other financing options. Although Bernardino and Santos (2020) affirm that there is a pecking order where entrepreneurs turn to crowdfunding after being rejected by banks, they also highlight a reverse pecking order where entrepreneurs opt for bank financing due to a lack of awareness about ECF. Miglo (2022) further corroborates these findings through a theoretical model that examines a firm's choice between crowdfunding and traditional banking. His results suggest that bank financing is more prevalent, as crowdfunding often becomes impractical due to moral hazard problems, thus supporting the substitution argument between ECF and bank financing.

Finally, Cole et al. (2019) offer further explanations as to why ECF and banks may serve as substitutes. First, both banks and crowdfunding markets have the capacity to raise similar amounts of funds. Second, crowdfunding platforms offer a wider variety of fee arrangements (Cumming and Zhang 2016), allowing entrepreneurs to find more attractive fee structures in contrast to those offered by banks. Third, in contrast to crowdfunding markets, traditional banking experiences a pronounced investor bias, particularly regarding age, location, gender, and ethnicity (Bellucci et al. 2010; Wang and Prokop 2024). ECF may also reduce gender bias in financing. While female entrepreneurs often face greater challenges in securing traditional venture funding, recent evidence shows they perform equally well as male peers in initial equity crowdfunding campaigns but encounter a gender gap in subsequent rounds, which may be mitigated by more ambitious funding targets and promotion strategies (Prokop and Wang 2021). This is supported by evidence from China showing that female-led teams perform as well as male-led ones, and gender diversity within teams improves crowdfunding success (Chuang et al. 2025). Additionally, team dynamics and composition, including family ties, also positively impact crowdfunding achievement (Campopiano et al. 2025; Troise et al. 2024).

When entrepreneurs are unable to meet the criteria for bank debt financing, they frequently turn to external funding sources like venture capital (VC), which has similarities to equity crowdfunding (ECF). Both financing types involve investing in businesses in exchange for a share of profits and show similar clustering tendencies (Agrawal et al. 2015; Guenther et al. 2017; Kolympiris et al. 2015). Similarly, ECF investors share a comparable risk profile, as they understand and accept high risks, anticipating that a few successful investments will offset multiple failures (Estrin et al. 2018). Furthermore, the presence of active VC markets not only pushes VC-backed startups toward riskier scaling strategies but also incentivizes non-VC-backed firms to take risks, hoping for follow-on VC funding opportunities (Norbäck et al. 2024).

However, there are significant differences between them. Beyond the typical VC monitoring, they offer larger amounts of funding, starting at around 1 million Euros, while ECF generally provides smaller amounts of equity, usually far below 1 million Euros (Belleflamme et al. 2014; Cumming and Johan 2007; Hornuf and Schwienbacher 2018).³ Additionally, they target different sectors, with the VCs preferring to invest in more high-tech firms than the crowd

³According to Hornuf and Schwienbacher (2018), the typical funding amount of crowdfunding campaigns in Germany is on average set for 50,000-100,000 EUR.

(Stevenson et al. 2018). However, when the crowd supports ventures in sectors typically associated with VC, the two funding sources may complement each other, as ECF investments may attract subsequent VC funding (Sorenson et al. 2016).

One explanation for this complementarity lies in signaling theory. Vismara (2018) find that investors who make their profile public are more likely to attract other investors in the initial days of the campaign. Ahlers et al. (2015) highlight that retaining equity and providing more detailed information about risks may be interpreted as effective signals and may therefore impact the probability of funding success. Hence, in the context of ECF, successful fundraising serves as a signal of firm quality, reducing uncertainty for institutional investors such as VCs.

Building on these insights, we propose that ECF and venture capital are spatial complements and that bank loans act as substitutes. In light of these considerations, we formulate the following hypotheses:

Hypothesis 2a: From a spatial standpoint, in comparison between regions, bank-provided loan financing will tend to act as a substitute.

Hypothesis 2b: From a spatial standpoint, equity through venture capital will tend to serve as a complement to successful ECF campaigns.

Existing research predominantly explores the home bias pattern in ECF and those factors influencing location choice (Agrawal et al. 2010; Agrawal et al. 2015; Guenther et al. 2017). With this paper, we aim to address the identified gap in the literature by offering a systematic analysis of the geographical patterns of successful ECF campaigns, particularly exploring the geographical clustering of ECF campaigns and traditional financing institutions. Furthermore, we provide evidence on the nature of the relationship between ECF and traditional financing methods (e.g., banks, venture capitalists). Within our empirical strategy, we also exploit the 2015 implementation of the Small Investor Protection Act (Kleinanlegerschutzgesetz, KASG) in Germany as an exogenous event to further test Hypothesis 2.

3 2015 Small Investor Protection Act (KASG) in Germany

The introduction of the Small Investor Protection Act (Kleinanlegerschutzgesetz, KASG) in Germany in 2015 marked a turning point for equity crowdfunding (ECF) regulation within the country. Prior to KASG, Germany had largely taken a laissez-faire approach to crowdfunding, operating within the framework of existing securities law without specific regulation. This allowed equity crowdfunding to grow under the general provisions of the German Securities Prospectus Act (WpPG) and the Investment Act (VermAnlG). These laws exempted issuers from filing a prospectus for security and investment issues under €100,000, though the definition of "investment" was narrow and excluded subordinated profit-participating loans (Hornuf and Schwienbacher 2017).

This regulatory gap enabled issuers to bypass prospectus requirements by structuring contracts around subordinated loans, allowing campaigns to raise unlimited amounts without filing requirements. However, concerns over investor protection and the integrity of crowdfunding markets prompted reform. In April 2015, the German Parliament passed KASG, explicitly targeting equity crowdfunding and expanding the regulatory oversight for small investor protection. KASG allowed firms to raise up to €2.5 million without a prospectus and provided specific conditions on investment limits for individual investors. Generally, investors could contribute up to €1,000 per campaign, with exceptions for wealthier individuals, who could invest up to €10,000 if they had a net worth over €100,000 (Hornuf and Schwienbacher 2017).

Importantly, while the KASG introduced stricter rules for some investment vehicles, it preserved important exemptions for subordinated profit participation loans - the most common instrument in crowdfunding - allowing firms using this model to continue raising funds with minimal regulatory burden. By explicitly protecting the rights of smaller firms that rely on these instruments, KASG facilitated their access to crowdfunding markets while ensuring greater investor protection. As a result, smaller companies gained a competitive advantage by being subject to fewer regulatory restrictions than those relying on more complex investment structures (i.e. silent partnerships or non-securitized participation rights). For the latter, the €100,000 threshold remained intact.

In this context, KASG has reshaped both the structure of crowdfunding campaigns and their accessibility for early-stage investors and firms in Germany. From an analytical perspective, KASG represents an exogenous regulatory shock to the crowdfunding market, as it was an unexpected policy intervention not driven by the market itself. This exogeneity allows us to apply an event study approach to assess its impact, particularly on the number and regional distribution of successful ECF campaigns, which will be discussed in the following sections.

4 Data

The financial market in Germany for investing in entrepreneurial activities is relatively diverse. Traditionally, in Germany (in contrast to the Anglo-Saxon countries), regional banks run numerous publicly supported loan programs to finance entrepreneurs with their newly founded firms. Germany's venture capital market is comparably small and the amounts invested are below those in the UK and the USA (Estrin et al. 2024). Equity crowdfunding emerged in Germany in 2011, with regulatory control of it being imposed since 2015 through the KASG.

In our analysis, we use three kinds of data: the number of Equity Crowdfunding campaigns that were successfully launched on the two major German platforms, the number of early-stage venture capital investors (VCs), and the number of monetary financial institutions (MFIs)⁴. As for equity crowdfunding, we include two German platforms: Companisto and Seedmatch.

⁴Monetary Financial Institutions (MFIs) are referred to as banks.

Both together lead the market in terms of total amounts raised and the number of successful funding rounds. Seedmatch was launched in 2011 and Companisto in 2012. Although there are differences between the organizational arrangements for funding on the platform, both platforms adhere to funding equity investments with similar upper limits, and both apply the all-or-nothing funding model. Moreover, both have established screening processes that lead to very high rates of successful campaigns of around 98 percent, such that the number of approved campaigns is the same as the number of successful campaigns (Löher 2016).

The whole sample comprises 266 campaigns. Campaigns launched in either 2011 or 2019, as well as campaigns financing motion pictures, real estate projects, or venture debt, are excluded since this analysis focuses exclusively on entrepreneurial equity crowdfunding. We also do not include any campaigns after 2019 as the COVID-19 pandemic affected entrepreneurship and, thus, ECF platforms. Moreover, Companisto underwent a fundamental transformation in its business model starting in 2019, shifting from a traditional equity crowdfunding platform to an active investor community model, known as the Companisto Investment Club. Given this structural change, which significantly altered investor behavior, platform dynamics, and the nature of startup financing, we conclude our analysis in 2018. This ensures that our findings reflect a consistent market environment before the onset of these substantial modifications. The resulting sample consists of 193 start-up campaigns, run by 171 companies between 2012 and 2018. Collectively, €80 million was invested in these ECF campaigns.⁵

Second, we use data on the location of early-stage venture capital investors. Given that VCs' investment decisions are influenced by spatial determinants, it is reasonable to assume that the number of early-stage investors in a region and the amount of venture capital invested in the same region are correlated (French and Poterba 1991). The final sample consists of 411 investors who invested in early-stage companies at least once or if no kind of investment record is publicly available, stated that they are investing in early-stage companies in general. The sample comprises accelerators, incubators, venture capitalists, corporate venture capitalists, government offices, private equity firms, family offices, micro VCs, publicly known angel groups, SME-holding companies ('Mittelstaendische Beteiligungsgesellschaften'), and hybrids. Business angels are excluded. The sample comprises data from the BVK, complemented by data from Crunchbase. Founding dates of the early-stage investors, if not available, were gathered from the German Handelsregister ('trade register'). The correlation between the number of early-stage investors in one region and the amount of venture capital invested in the same region is fairly high (see Appendix C). Thirdly, in addition to the early-stage investor variable, the number of monetary financial institutions subject to the European Central Bank's minimum

⁵The German ECF market consists of more Equity Crowdfunding platforms and the overall number of platforms and the estimated accumulated market volume of ECF may vary in the literature, depending on the market-segmentation approach chosen for each respective study. One author reports 59 Equity Crowdfunding platforms for 2016, while many of them did not launch a single successful campaign (Dorfleitner et al. 2017). The most active platforms, however, in each and every sample used in the literature, are Seedmatch and Companisto. These have a joint market share of about 90% (Löher 2016). Counting pure equity-crowdfunding portals that have not implemented a sector restriction, it is most likely that the high market-share numbers are still valid in 2024.

reserve requirement will serve as an indicator of the development of the financial intermediation infrastructure across regions.

As we investigate regional phenomena that are related to entrepreneurial activities looking for external finance and as entrepreneurial activities are, per se, also influenced by regional factors, we control, in our estimation approach for various factors at the NUTS 2-level, among others, for the income per capita that a region generates. We use disposable rather than national income or GDP as this is closer to the concept of income generally understood in economics. Moreover, we control for population and population density, the latter being important for capturing economic effects related to dense versus remote areas. To control for the experience of entrepreneurs, we include the region’s specific median age of entrepreneurs in our analysis. We also use information on the local unemployment rate provided by the Federal Employment Agency which is defined as the share of registered unemployed over the entire working population, consisting of all employed plus the registered unemployed.

Table 1 is approximately here.

Table 1 provides descriptive statistics based on 266 observations. Values for all activity variables are separately calculated for successful ECF campaigns, early-stage investors, and MFIs. The data also reveal that regions have an average disposable income of 19,249.82 EUR, an unemployment rate of 4.5%, and a start-up rate of 1.40%. Additionally, these regions have a population density⁶ of 446.61 people per square kilometer and a total population of 2,145,107. The median age of entrepreneurs in these regions is about 46 years.

5 Empirical Framework

5.1 Spatially filtering procedure

Our empirical strategy consists of two steps: In the first step, we use the so-called eigenvector spatial filtering (esf) approach. Essentially, this approach is used to remove regional interdependencies from a specific variable. The advantage of the esf approach is that, unlike referring to the Spatial Durbin Model, it does not require any distributional assumptions about the error term (see Koley and Bera 2024). Pace et al. (2013) further argue that the esf approach is particularly beneficial for models where the dependent variable represents – as in our case – binary outcomes, discrete choices, or Poisson-distributed counts.

Afterward, we employ conventional econometric tools that are based on the assumption of spatially uncorrelated errors, such as zero-inflated Poisson and negbin approaches (second step). The literature provides two well-established filtering methods (for a review, see Getis and Griffith 2002). The first approach is based on the local spatial autocorrelation statistic (Getis

⁶The division of the number of people in an area by kilometers.

and Ord 1992), while the second is based on an eigenfunction decomposition that is related to the global spatial autocorrelation statistics, known as Moran’s I . As pointed out by Badinger et al. (2004), both approaches are equally effective. As the Getis and Ord (1992) approach is computationally simpler, we use it in our estimations and provide a brief description of the approach. In a nutshell, if we apply this filtering method to all variables used in the regression models introduced below, spatial autocorrelation that is isolated in \hat{X} should not significantly affect the regression results. For further details, see Appendix B.1.

5.2 Event Study

In this analysis, we examine the impact of the Small Investor Protection Act of 2015 (Kleinanlegerschutzgesetz, KASG) on the number of successful equity crowdfunding campaigns across German regions from 2012 to 2018, using the event study model as outlined by Callaway and Sant’Anna (2021) and Goodman-Bacon (2021). A key purpose of excluding ECF-funded firms from KASG’s regulatory restrictions is to stimulate startup growth and innovation by providing easier access to capital without imposing regulatory burdens. Hence, for ECF firms, KASG acts as a supportive measure, creating a more favorable environment for startups and actively encouraging ECF activity. In this framework, we define the treatment group as regions where firms first achieved successful ECF campaigns only after the enactment of KASG in 2015, while the control group includes regions without any successful ECF campaigns before or after the KASG. This definition ensures that the treatment group had no ECF activities before KASG, allowing us to isolate the impact of KASG and not confuse it with pre-existing trends. Further, because the treatment and control groups had no ECF activity prior to 2015, we expect their trends to have been parallel in the absence of the law. By comparing these two groups, we are able to attribute the observed increase in ECF activity in the treatment group to the KASG.

To control for potential confounding variables, we use Coarsened Exact Matching (CEM) to align regions on key pre-treatment characteristics (see Appendix B.2). Combined with an event study design, we strengthen our ability to attribute differences in ECF activity to KASG and not to other factors. This approach allows us to make robust causal claims and assess its impact on the regional distribution of successful campaigns. For further details on how the event study was conducted, see Appendix B.3.

6 Results

6.1 A descriptive view on equity crowd-funding in Germany

We start our analysis by investigating how equity crowd-funding is localized in Germany. For this purpose, we make use of a global Moran’s I analysis to obtain a descriptive overview of whether ECF activities are clustered in German regions. In contrast to earlier research (Breznitz

and Noonan 2020), our data set also allows for exploiting the time dimension to examine whether a potential clustering behavior of the number of successful ECF campaigns has become more or less relevant over the 2012-2018 period. The results of this analysis are depicted in Table 2.

Moran's I is a standard measure for spatial correlation and ranges between -1 and 1, where positive (negative) values indicate positive (negative) spatial autocorrelation. Moran's I is a global statistic that allows us to test whether the spatial correlation is significantly different from zero (Cliff and Ord 1981). The Moran's I analysis in Table 2 shows that, for each period, the Moran's I coefficient remains negatively stable over the 2012-2018 period, indicating negative spatial autocorrelation. However, the small z -statistics and corresponding large p -values show that this negative spatial correlation is not significantly different from zero. In other words, the small z statistic over all time periods shows that ECF activities are very localized activities and these observations are rather stable throughout the 2012-2018 period.

Table 2 is approximately here.

Figure 1 is approximately here.

Nevertheless, successful ECF activities are densely clustered within a specific Nuts-2 region, which is in line with a large body of literature pointing to the fact that digital finance is also clustered. Our finding is graphically supported by Figure 1. Besides successful ECF campaigns (yellow), this Figure depicts the geographical distribution of monetary financial institutions (blue) and early-stage investors (green) aggregated on the German state level (Nuts-1) from 2012-2018. Overall, the sample accounts for the 193 campaigns that were launched. Figure 1 indicates three major hot spots for Equity Crowdfunding. It is concentrated around Berlin, Hamburg, and Munich. Overall, little less than 60% (111) of all ECF campaigns are launched by companies located within these three cities, not counting their peripheries. To a lesser extent, Equity Crowdfunding campaigns also take place in Baden-Wuerttemberg (ca. 13%, 26 campaigns), where they are not concentrated in a single city. Across the rest of Germany, ECF campaigns are relatively rare.

Similarly distinctive is the geographic distribution of early-stage investors. The three Equity Crowdfunding hot spots accommodate a large number of early-stage investors. In particular, Berlin and Munich are home to registered early-stage investor offices. Berlin hosts 104 early-stage investors, approximately 25% of the sample (411 investors). Another 109 (27%) are located in Bavaria, with around 75 (18%) in the greater Munich area. Between 2012 and 2018, annually about €880 million were invested in venture capital in Germany; 67% of it in Berlin and Bavaria. Only 6% of the capital was invested in the eight German states with low venture capital shares, indicating distinctive spatial heterogeneity across Germany.

Regarding registered monetary financial institutions, Frankfurt, with its stock exchange, accommodates the highest number of MFIs for a single German city (140 – 9% of the sample; greater Frankfurt totals 163). A large number of MFIs are also registered in the populous Ruhr

area and Stuttgart, where again Equity Crowdfunding plays a negligible role, while a strikingly low number (17, ca. 1% of the sample) is registered in Berlin. Munich is an exception in the sense that it hosts a relatively large number of both MFIs and early-stage investors. All in all, it seems the MFIs in Germany are mostly registered across southern and western Germany.

The data in Figure 1 might be spatially correlated.⁷ After removing the potential spatial correlation between Nuts-2 regions with the procedure explained in Section B, Figure 2 represents the regression line of a simple OLS regression of successful ECF campaigns on early-stage investors and MFIs, respectively. These regression lines are embedded into so-called hexagon plots to visualize the density of data points. Hexagon plots have a similar interpretation as scatter plots. However, scatter plots do not provide information regarding the relative concentration of points in particular locations, which is due to the overplotting problem related to our dataset.⁸ To address this problem, we produce hexagonal bin plots, where the data range is covered by equally sized hexagons. The color gradient in Figure 2 indicates the density of data points that fall inside a specific hexagon, where brighter colors show a higher density.

We start by focusing on ECF campaigns and early-stage investors. Turning to the left panel of Figure 2, we see that the observations are most dense near the origin. This density rapidly decreases if we move in the northeast direction. We also observe that regions with a large number of successful ECF campaigns benefit from a relatively large number of early-stage investors (points above the regression line). However, these regions (with five or more ECF campaigns per year) are rather the great exception. Berlin, Munich, and Hamburg are responsible for the most severe outliers.

Next, we turn to the right panel in Figure 2, where we focus on ECF campaigns and traditional MFIs. Compared to the left panel, the picture is different. Performing a simple OLS regression of ECF campaigns on MFIs reveals that there is virtually no correlation between these variables. Further, and in contrast to early-stage investors, even for regions with a large number of MFIs, the number of ECF campaigns is close to zero. As visualized by the hexagon plot, this holds for the great majority of data points (see non-blue-colored hexagons below the regression line). Before we continue our analysis, it is worth summarizing the most important findings:

Result: *Successful ECF campaigns are densely clustered in three regions, namely Berlin, Munich, and Hamburg. The spatial distribution of traditional financing supplied by financial monetary institutions is more widespread across the country, while early-stage investors are geographically closely connected to successful ECF campaigns, particularly in Berlin, Munich, and Hamburg.*

One implication of these findings is that the location of early-stage investors matters for

⁷The Moran's I analysis depicted in Table 1 suggests that spatial autocorrelation is not a relevant issue for the ECF-campaign variable. However, this does not need to be true for the remaining variables as well. Indeed, we show that some of the controls that we use later in the regression analysis exhibit significant spatial autocorrelation. Results are presented in Appendix D.1. Therefore, for every considered year, we filter all variables based on the procedure outlined in section 3.

⁸We use these plots to address the overplotting problem originating in the fact that, for most regions, no or only a few ECF campaigns and early-stage investors are observed.

the locational choice of ECF-financed companies. To obtain a better understanding of this potentially interesting relationship, in the next subsection, we examine the spatial localization of ECF-financed companies and the geographical context in which they operate. Thus, we include in our analysis the location of traditional early-stage investors that consist of banks and VCs and investigate their spatial relationship with these traditional investors.

Figure 2 is approximately here.

6.2 Regression results

The dependent variable in our approach is the number of ECF campaigns. As some regions in our sample did not launch an ECF campaign between 2012 and 2018, the distribution of this variable is heavily right-skewed toward zero, implying that we cannot assume that the error of the outcome variable follows a normal distribution. Therefore, we rely on zero-inflated Poisson and negbin model regressions,⁹ where the latter approach takes a possible overdispersion of count data into account. The zero-inflated Poisson/negbin model addresses the issue when data contain a higher fraction of zeros than is likely what we expect to be “produced” by a Poisson/negbin model.¹⁰ We suspect that the number of zeros may be inflated since only a small fraction of regions successfully launched ECF campaigns between 2012-2018. This could be either because ECF campaigns failed in some regions (which we can exclude as almost all campaigns that were approved also succeeded) or, what is highly likely, because a region has not yet been engaged in an ECF campaign.¹¹ A standard Poisson or negbin model would treat these types of zero observations as homogenous, which, in turn, leads to biased statistical results. We apply these models to our spatially filtered data set X^* . Filtering our data should be interpreted as a procedure to obtain more precise estimates, where the filtering procedure, per se, provides a substantial amount of information on the spatial dependence regarding the distribution of successful ECF campaigns, as shown below.¹²

The zero-inflated Poisson models in Tables 7 strengthen the descriptive analysis presented in subsection 6.1. First, our dependent variable, ECF campaigns, shows an excess of zero observations (79 of 266 observations). We suspect that the number of zeros may be inflated for two reasons: first, in some regions, no ECF campaigns were approved during our sample period; or, second, no campaigns were started on either of the platforms between 2012 and 2018. Of course, treating these two events as homogeneous would lead to biased results. Hence, we separately present the result of a Poisson regression in Part I of Table 7 and that of a logit

⁹For the analysis, we use the Stata-packages *zinb* and *zip*.

¹⁰See Long (1997), pp. 242-247 and Cameron and Trivedi (2005, May), pp. 680-681.

¹¹We should add that we cannot observe potential ECF campaigns that were not admitted to the platforms.

¹²Alternatively, one could ignore the overdispersion and estimate a fixed effects Poisson model. However, we opt against this alternative. First, the standard panel fixed-effects Poisson model ignores the conditional overdispersion of our data. Second, we lose 63% percent of our regional areas due to zero outcomes and, third, the time dimension is rather short ($T=7$). Therefore we pool the data and rely on the zero-inflated Poisson model.

regression in Part II of Table 7.¹³ In other words, Part I of Table 7 corresponds to the standard Poisson model for ECF campaigns that have been indeed undertaken, while Part II of Table 7 contains the “real” zeros, i.e. regions that have never undertaken an ECF campaign. We follow Cameron and Trivedi (2010) and compute robust standard errors for all regressions.

To connect the results from our descriptive analysis executed in the previous subsection, we start by regressing the number of ECF campaigns on population density to test Hypothesis 1 (see column 1). The first column in Part II of Table 7 shows a highly significant (1% level) coefficient of -0.00119 for population density that is difficult to interpret. Thus, we compute marginal effects. The associated marginal effect with population density is -0.0002674 , which implies that an increase in the population density of a region implies a significantly higher probability of conducting successful ECF campaigns compared to a region where the population density remains the same. Thus, successfully ECF-financed firms are more likely to be located in a highly dense area than in a remote area, confirming Hypothesis 1.

Next, we regress the number of ECF campaigns on MFIs and early-stage investors (column 2). The results of this regression are again found in Parts I and II of the first column of Table 7. The second column of Part I of Table 7 shows that c.p. the existence of MFI significantly decreases the expected log count on a 5% level by 0.008, while for each unit increase of early-stage investors, the expected log count of a region-specific ECF-campaign increases significantly on a 1% significance level by 0.0242 c.p. Part II of Table 7 models if a region does not pursue an ECF campaign. Based on the results of Part II of Table 7, we compute marginal effects by estimating the probability of a “real zero” or, in our example, the probability of *not* performing an ECF campaign. We find that it is more likely for a region to pursue an ECF campaign if this region consists of early-stage investors, while it is less likely to be engaged in an ECF campaign if the region has only financial access to traditional MFIs. While the former effect is highly statistically significant on a 1% level of significance, the latter is not anymore.¹⁴

We further examine whether an additional early-stage investor affects the expected number of ECF campaigns. For this purpose, we compute the expected number of ECF campaigns for a region that moves from no early-stage investors to one investor while still holding the number of MFIs at its mean of 45.01. The significant difference in ECF campaigns for regions with and without early-stage investors is 0.19. In general, the expected number of ECF campaigns exponentially increases as the number of early-stage investors grows (see Figure 3). This figure further reveals that the expected number of ECF campaigns is lower the higher the number of MFIs. For example, if there would be 90 early stage investors, we could expect 10 ECF campaigns if there would be 40 banks in the same region, but only 3 ECF campaigns if there would exist 160 banks.

Figure 3 is approximately here.

¹³The detailed regression results summarized with Table 7 are relegated to the Appendix D.1.

¹⁴The computed marginal effect for *not* conducting an ECF campaign for early-stage investors is -0.0444 , while it is 0.0018 for MFIs.

However, the effect of early-stage investments on ECF campaigns might be affected by a different set of confounding factors. Therefore, we add controls for population, socioeconomic factors, and employment in our regression. The results of this regression are summarized in columns 3-6 in Table 7, respectively. In column 3, we additionally include the household income (log), total population, as well as startup rate as additional regressors. As evident from the third column of Part I of Table 7, only the startup rate is statistically significant on a 1% level. If regions actively engaged in ECF campaign activities experience a 1% increase in their start-up rate, this is associated with a significant rise in the expected number of ECF campaigns by approximately 5 times ($\exp(1.611) \approx 5.00$), holding all other covariates constant. This finding is qualitatively robust even if we control for the regional unemployment rate (column 5 of Part I of Table 7) or if we exclude Berlin from the sample (column 6 of Part I of Table 7). The median age of entrepreneurs has not related to ECF campaigns (column 4 of Part I of Table 7).

Moreover, we make use of Part II of Table 7 to obtain a better understanding of why regions are not engaged in ECF campaigns ("real zero" case). We compute the marginal effects of potentially influential factors, such as unemployment rate or start-up rate, to quantify the probability of regions to not be engaged in ECF activities. Important is the respective sign of the estimated coefficients presented in Part II of Table 7. For all regressions, the sign of the early-stage investment is negative, indicating that it is more likely to conduct ECF campaigns if the number of early-stage investors (MFIs) increases (decreases). Additionally, it seems that densely populated areas are more likely to conduct ECF campaigns. However, as we argued before, ECF campaigns are highly concentrated, especially in Berlin. Therefore, in the subsequent subsection, we investigate whether our findings still hold if Berlin is excluded from the sample.

6.3 Berlin stands out

Berlin's crowdfunding scene is substantial, hosting a quarter of all German crowdfunding projects in 2018. Over the past decade, Berlin became a hub for various crowdfunding types, including donations, rewards, equity, and real estate. Major platforms like Companisto (equity), BetterPlace (donations), StartNext (rewards), and Funding Circle have established operations within the city limits (Langley et al. 2020). The city's vibrant creative and digital start-up economy supports its unique crowdfunding scene. With 35,000 to 40,000 start-ups annually since 2008, notable companies like Soundcloud, 6Wunderkinder, ResearchGate, and Delivery Hero have emerged. Berlin hosts many co-working spaces and accelerators, bolstered by universities and a significant influx of migrants (Langley et al. 2020).

Hence, we ask whether our main findings still hold if Berlin is excluded from the regression (see in column 6 in Table 7). Again, we compute marginal effects for early-stage investors, MFIs, disposable income, total population, population density, and the unemployment rate with and without Berlin. We use estimation results stored in columns 5 and 6 in Part II of Table 7.

Table 3 is approximately here.

Results are summarized in Table 3. First, irrespective of whether we exclude or include Berlin, we find that it is more likely for a region to pursue an ECF campaign if this region includes early-stage investors, while it is less likely to be engaged in an ECF campaign if the region has financial access to traditional MFIs. This confirms our finding in the basic regression.

Second, we find that increasing the start-up rate decreases the chance that a region engages in future ECF campaigns. This might be interpreted as a competition between startups and ECF campaigns for regions that have not been engaged in ECF campaigns thus far. Third, if Berlin is excluded from the sample, a lower unemployment rate increases the likelihood of a region being engaged in future ECF campaigns. It should be noted that Berlin has relatively high unemployment rates. Fourth, we observe that increasing the population density significantly increases the likelihood of pursuing an ECF campaign only if Berlin is included.

Our analysis demonstrates that the regional drivers of ECF campaign activity extend beyond the Berlin effect. By conducting the analysis both with and without Berlin, we show that the presence of early-stage investors, local startup dynamics, and labor market conditions remain significant predictors of ECF activity, indicating that these dynamics are not solely driven by Berlin’s exceptional position but reflect broader patterns across German regions.

6.4 Event Study: The impact of KASG on ECF

One drawback of our analysis could be that our main finding that successful ECF campaigns act as a complement for VC is not causally established by our regression analysis. Therefore, we make use of the KASG implementation as an exogenous event to corroborate our findings. This section presents the results of our event study model analyzing the effects of the KASG on the number of ECF campaigns.

Figure 4 is approximately here.

Table 4 is approximately here.

In Figure 4, the estimation captures the impact of the KASG introduction on ECF campaigns. We observe significant increases in campaign numbers immediately following the policy’s implementation. At period $t = 1$, the treatment effect is positive (0.451, significant at the 5% level), indicating that KASG spurred a notable rise in ECF campaigns in the short term. However, this effect declines in magnitude over time, with the coefficients at $t = 2$ and $t = 3$ remaining positive but diminishing in strength and no longer being statistically significant (see Table 4 for more details). This suggests that while KASG initially boosted ECF activity, the effect is short-lived, with its influence fading after the first period. In summary, these findings highlight a significant, yet short-lived impact of KASG on ECF campaigns.

We also perform a sensitivity analysis using Honest DID, applying two types of restrictions: the relative magnitude restriction and the smoothness restriction. This allows us to evaluate the robustness of our results in the face of potential violations of the parallel trends assumption. Under both restrictions, even when the parallel trends assumption is relaxed, the treatment effect remains positive and statistically significant (see Appendix [D.2](#)).

7 Discussion, limitations and further research

Employing spatial eigenvalue filtering, negative binomial estimations, and an event study design, we investigate the spatial distribution of successful equity crowdfunding campaigns (ECF) as well as the spatial relationship between the locations of ECF campaigns and traditional investors, comprising banks (MFIs) and other early-stage investors like VCs.

Our three main findings are: there is a significant geographic concentration of successful ECF campaigns in dense areas, while they are rarely found in rural areas. However, this observation does not hold for dense areas in general, but is limited to three major German cities: Berlin, Munich, and Hamburg. This finding partly aligns with Hypothesis 1, which posits that successful ECF campaigns tend to cluster in developed urban areas and strengthens descriptive evidence reported in earlier studies by Gallemore et al. (2019), Guenther et al. (2017), Langley (2016), and Mollick (2014). Yet, in contrast to earlier research, we observe that while urban density is a necessary condition for ECF activity, it is not the only determining factor. We observe a distinct spatial distribution of financial institutions. Banks (MFIs) are to a certain extent more concentrated in Southern and Western Germany, particularly in city areas like Frankfurt, Stuttgart, the Ruhrgebiet area, including Cologne, whereas early-stage investors, such as venture capitalists (VCs), are geographically concentrated in different highly dense regions. It turns out that ECF activities are closely tied to the strength of the VC infrastructure in specific cities, as the number of successful ECF-campaigns is high where VCs are concentrated; i.e. in Berlin, Munich, and Hamburg. Thus, as illustrated in Figure [3](#), our findings indicate a negative correlation between MFIs and ECF platforms, while VCs show a positive correlation with ECF platforms. These results confirm Hypothesis 2, suggesting that ECF campaigns tend to complement VCs in a spatial context (Hypothesis 2b), whereas traditional banks tend to act as substitutes (Hypothesis 2a).

Finally, leveraging the exogenous nature of the KASG implementation, our event study largely confirms and strengthens our findings. While ECF and VC complemented each other before the introduction of the KASG, the policy only temporarily disrupted this dynamic, with the effect dissipating shortly after its implementation.

These findings have several implications for entrepreneurs, politics, and financial institutions. First, the hope that equity crowdfunding would alleviate the home bias and increase financing opportunities for entrepreneurs in remote locations has not been fulfilled. Geographically speaking, we have to reject the expectation that ECF would close the regional funding gap

in Germany. Replacing the local middleman with a digital marketplace is not sufficient to generate access to finance for entrepreneurs in remote areas. Thus, ECF does not reduce the concentration of access to equity for firms and start-ups in dense areas.

Secondly, there is no simple relationship between the likelihood of a successful ECF campaign and the density of an area in Germany. ECF campaigns are primarily concentrated in cities with strong VC infrastructure, such as Berlin, Munich, and Hamburg. This indicates that in cities where traditional financing options through banks are limited, entrepreneurs are more likely to seek alternative funding from VCs and now from ECF. There are other cities where banks are numerous and where ECF structures are weak. In these cities, banks may be willing to provide loans to start-ups and entrepreneurial firms that are often subsidized by public banks like the federal KfW (Kreditanstalt für Wiederaufbau) or regional public banks through various programs¹⁵. This also means that if all German cities had strong bank structures, we probably would have seen a weaker ECF development in Germany.

In that sense, the phenomenon of ECF growth is closely tied to the strength of the VC infrastructure in specific cities. Thus, arguably, ECF is filling a different market gap than originally thought; it complements the existing VC infrastructure. As VCs usually offer equity starting at amounts of €1 m., ECF offers seem to be able to fill the gap when firms are seeking external finance through equity below that threshold. The observed complementarity between ECF and VCs challenges the expectation that ECF would be more effective in regions where VC funding is scarce. Moreover, considering that VCs and ECF investors share a comparable risk/return profile (Estrin et al. 2018), this further reinforces the notion that ECF is not just filling a gap but complementing the existing VC landscape. Much in contrast to this, there is probably no such funding gap in those regions where banks are strong and offer publicly subsidized loans.

Setting these results in a wider context of start-up activities, our results clarify another interesting pattern. Kritikos and Mattes (2017) observe that, during this period, Berlin, Hamburg, and Munich had similar start-up rates as cities like Cologne, Frankfurt, and Stuttgart, where MFIs are more concentrated and access to equity via VCs and ECF is rather limited. Thus, despite their similar start-up activity, cities like Cologne, Frankfurt, and Stuttgart do not follow the same pattern of VC and ECF concentration seen in Berlin, Munich, and Hamburg. In these cities, where traditional banks are more numerous, banks appear to act as substitutes for VCs and ECF platforms, limiting the need for alternative funding options. This suggests that while these cities are also startup hubs, their well-established banking infrastructure may be serving as a primary source of funding, preventing a stronger role for VCs and ECF.

Our results partially align with previous research linking urban areas to crowdfunding activity, but differ in important ways. While digital platforms have been seen as a means to overcome

¹⁵For the loan programs, KfW offers through MFIs, see KfW Group (2024) (www.kfw.de); for the regional programs offered through regional MFIs, see Federal Ministry for Economic Affairs and Climate Action (Germany) (2024) (www.foerderdatenbank.de)

geographic barriers and provide more equal access across regions Agrawal et al. (2010), Agrawal et al. (2015), and Lin and Viswanathan (2016), we observe that equity crowdfunding campaigns remain highly concentrated in a few cities, with limited reach in peripheral or rural areas. Additionally, contrary to the common view of equity crowdfunding as a substitute for traditional finance, particularly venture capital, our findings suggest a spatial complementarity between these funding sources. Unlike many earlier studies relying on descriptive or non-spatial methods (Agrawal et al. 2015; Guenther et al. 2017), our approach explicitly accounts for spatial interdependencies, allowing us to move beyond correlation and uncover structural relationships in the geography of entrepreneurial finance. By explicitly modeling spatial interdependencies, we are able to account for unobserved regional spillovers and spatial autocorrelation, which are key sources of endogeneity.

These findings have policy implications. The concentration of successful ECF campaigns in major urban areas with VC infrastructure clarifies that new financial institutions, like platforms for ECF, are not reducing the clustering of start-ups and entrepreneurial firms, they probably rather benefit of such clustering. If politics should aim to address such concerns, it cannot leave it to the market. Policies would still need to foster regional entrepreneurial ecosystems outside these hubs. Secondly, based on our event study design, we find that the introduction of the KASG had only a temporary impact on the number of successful ECF campaigns. This suggests that the shift from complementarity to substitution after the KASG is also a transient phenomenon. Therefore, our findings confirm that, at the regional level, there continues to be a complementarity between ECF and VC in Germany. Thirdly, given the rather complementary role of VCs to ECF platforms, encouraging collaboration between them might be another policy measure to focus upon, if VCs and ECF platforms have not already initiated cooperation by themselves. Measures for inducing cooperation may include tax incentives, co-investment schemes, or networks facilitating interaction. Such policies can enhance ECF platform's effectiveness and support early-stage ventures.

Our approach is not without limitations. First, in our dataset, most ECF campaigns are clustered in large cities, aligning with earlier findings (Breznitz and Noonan 2020; Gallemore et al. 2019; Langley 2016; Mollick 2014), which demonstrate that crowdfunding tends to cluster in regions with high industry concentration, education, income, and population, as confirmed by Sorenson et al. (2016). If these regions also have above-average early-stage venture capital investors or MFIs, these omitted variables imply an upward bias of our estimates. Although we have spatially filtered our data, the omission of non-spatially filtered unobserved characteristics, such as endogenous amenities, still induces spatial correlation between endogenous and exogenous characteristics of the early-stage venture capital landscape in German regions. The standard procedure addressing omitted variables is to add spatial fixed effects (see Kuminoff et al. (2013)). However, we cannot follow this strategy as there is not sufficient within-variation of the ECF campaigns and MFI variables. Also, we have no information on the selection of startups, such as whether the distribution of locations is a result of the available startups, local

preferences of managers, or other reasons.

Future research can build on our findings by conducting longitudinal studies to understand how the spatial dynamics of ECF campaigns evolve and identify factors contributing to their long-term success across regions and the dynamic interactions with VCs. In that context, it would also be important to get information on the location of firms that applied for one of the ECF platforms but were not accepted. Currently, platforms do not provide information on these firms, as they aim to protect the firms from facing disadvantages if the information of being rejected would become public. Additionally, investigating the broader economic impact of ECF on regional development – such as its effects on job creation, innovation, and economic growth – will provide insights into its regional benefits. Moreover, future research on the spatial distribution of ECF campaigns and on the spatial relationship between ECF and other financial institutions should start investigating other countries, for instance, the Anglo-Saxon countries whose financial markets for entrepreneurs, start-ups, and small firms differ significantly from continental Europe (Estrin et al. [2024](#)).

Another crucial area for future research is evaluating the effectiveness of policy interventions promoting ECF across different regions. Comparative studies of various policy frameworks can help identify best practices and guide policymakers in enhancing the ECF ecosystem. Our event study is pointing in that direction. Lastly, investigating the impact of geographic distribution on investor networks, particularly how proximity affects investor engagement and campaign outcomes, will shed light on spatial factors influencing ECF success. Understanding how the concentration of venture capitalists and early-stage investors in specific areas contributes to the growth and success of ECF ventures is also essential. By addressing these research areas, future studies can deepen our understanding of ECF's spatial dynamics and its potential to foster entrepreneurial activity and to drive economic growth across diverse regions.

8 Conclusion

We show that there is a strong geographic concentration of ECF campaigns in select major cities of Germany. Successful ECF campaigns are not simply concentrated in dense areas. This indicates that in cities where financing options through banks are limited, entrepreneurs are more likely to seek funding from VCs and, more recently, from ECF. Thus, the phenomenon of ECF growth is closely tied to the strength of VC infrastructure in specific cities, rather than a broad urban-rural divide. We use the implementation of KASG as an exogenous event and observe that ECF tends to act as a complement to VCs. As shown with the event study, ECF in Germany is not able to reduce the concentration of access to equity for firms and start-ups. In a spatial context, instead of reducing the regional funding gap, ECF is filling a different gap when entrepreneurial firms are seeking equity below the threshold of minimum equity offers of VCs.

References

- Agrawal, A., Catalini, C., & Goldfarb, A. (2010). The geography of crowdfunding. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.1692661>
- Agrawal, A., Catalini, C., & Goldfarb, A. (2015). Crowdfunding: Geography, social networks, and the timing of investment decisions. *Journal of Economics & Management Strategy*, 24(2), 253–274. <https://doi.org/10.1111/jems.12093>
- Ahearne, A. G., Grier, W. L., & Warnock, F. E. (2004). Information costs and home bias: An analysis of us holdings of foreign equities. *Journal of International Economics*, 62(2), 313–336. [https://doi.org/10.1016/s0022-1996\(03\)00015-1](https://doi.org/10.1016/s0022-1996(03)00015-1)
- Ahlers, G. K., Cumming, D. J., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship Theory and Practice*, 39(4), 955–980. <https://doi.org/10.1111/etap.12157>
- Audretsch, D., Keilbach, M., & Lehmann, E. (2006). *Entrepreneurship and economic growth*. Oxford University Press. <https://EconPapers.repec.org/RePEc:oxp:obooks:9780195183511>
- Badinger, H., Müller, W., & Tondl, G. (2004). Regional convergence in the European Union, 1985–1999: A spatial dynamic panel analysis. *Regional Studies*, 38(3), 241–253. <https://doi.org/10.1080/003434042000211105>
- Barbi, M., Febo, V., & Giudici, G. (2023). Community-level social capital and investment decisions in equity crowdfunding. *Small Business Economics*, 61(3), 1075–1110. <https://doi.org/10.1007/s11187-022-00724-4>
- Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of Business Venturing*, 29(5), 585–609. <https://doi.org/10.1016/j.jbusvent.2013.07.003>
- Bellucci, A., Borisov, A., & Zazzaro, A. (2010). Does gender matter in bank-firm relationships? Evidence from small business lending. *Journal of Banking & Finance*, 34(12), 2968–2984. <https://ideas.repec.org/a/eee/jbfina/v34y2010i12p2968-2984.html>
- Bernardino, S., & Santos, J. F. (2020). Crowdfunding: An Exploratory Study on Knowledge, Benefits and Barriers Perceived by Young Potential Entrepreneurs. *JRFM*, 13(4), 1–24. <https://ideas.repec.org/a/gam/jjrfrm/v13y2020i4p81-d349009.html>
- Bertschek, I., Block, J., Kritikos, A. S., & Stiel, C. (2023). German financial state aid during covid-19 pandemic: Higher impact among digitalized self-employed. *Entrepreneurship & Regional Development*, 36(1–2), 76–97. <https://doi.org/10.1080/08985626.2023.2196267>
- Birkholz, J. (2024). Regional embeddedness is the key: Quantity and quality of regional business opportunity perception. *Small Business Economics*, 64(3), 1083–1109. <https://doi.org/10.1007/s11187-024-00936-w>

- Block, J., Hornuf, L., & Moritz, A. (2018). Which updates during an equity crowdfunding campaign increase crowd participation? *Small Business Economics*, 50(1), 3–27. <https://doi.org/10.1007/s11187-017-9876-4>
- Breznitz, S. M., & Noonan, D. S. (2020). Crowdfunding in a not-so-flat world. *Journal of Economic Geography*, 20(4), 1069–1092. <https://doi.org/10.1093/jeg/lbaa008>
- Callaway, B., & Sant’Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200–230. <https://doi.org/10.1016/j.jeconom.2020.12.001>
- Cameron, A., & Trivedi, P. (2010). *Microeconometrics using Stata* (Vol. 5).
- Cameron, A. C., & Trivedi, P. K. (2005, May). *Microeconometrics: Methods and applications*. Cambridge University Press. <https://doi.org/10.1017/cbo9780511811241>
- Campopiano, G., Lo Monaco, V., Minola, T., & Vismara, S. (2025). Survival of family start-ups seeking equity crowdfunding: Family nuances in entrepreneurial teams. *Small Business Economics*. <https://doi.org/10.1007/s11187-025-01086-3>
- Chuang, H.-L., Zhao, Y., & Zhu, T. (2025). Entrepreneurial teams and gender roles: Evidence from equity crowdfunding achievement. *Small Business Economics*, 65(1), 287–314. <https://doi.org/10.1007/s11187-024-00990-4>
- Cliff, A., & Ord, J. (1981). *Spatial processes: Models & applications*. Pion.
- Cole, R. A., Cumming, D. J., & Taylor, J. (2019). Does fintech compete with or complement bank finance? *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3302975>
- Correia, S., Sousa, M., & Brandão, E. (2024). What do we know about the choices of entrepreneurs before the equity crowdfunding campaign? *Small Business Economics*, 63(4), 1471–1501. <https://doi.org/10.1007/s11187-023-00868-x>
- Cumming, D. J., & Dai, N. (2010). Local bias in venture capital investments. *Journal of Empirical Finance*, 17(3), 362–380. <https://doi.org/10.1016/j.jempfin.2009.11.001>
- Cumming, D. J., & Johan, S. A. b. (2007). Advice and monitoring in venture finance. *Financial Markets and Portfolio Management*, 21(1), 3–43. <https://doi.org/10.1007/s11408-006-0041-3>
- Cumming, D. J., Vanacker, T., & Zahra, S. A. (2021). Equity crowdfunding and governance: Toward an integrative model and research agenda. *Academy of Management Perspectives*, 35(1), 69–95. <https://doi.org/10.5465/amp.2017.0208>
- Cumming, D. J., & Zhang, Y. (2016). Are crowdfunding platforms active and effective intermediaries? *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2882026>
- Dorfleitner, G., Hornuf, L., Schmitt, M., & Weber, M. (2017). Definition of fintech and description of the fintech industry. In *Fintech in Germany* (pp. 5–10). Springer International Publishing. https://doi.org/10.1007/978-3-319-54666-7_2
- Estrin, S., Gozman, D., & Khavul, S. (2018). The evolution and adoption of equity crowdfunding: Entrepreneur and investor entry into a new market. *Small Business Economics*, 51(2), 425–439. <https://doi.org/10.1007/s11187-018-0009-5>

- Estrin, S., Khavul, S., Kritikos, A. S., & Löher, J. (2024). Access to digital finance: Equity crowdfunding across countries and platforms (S. Porcher, Ed.). *PLOS ONE*, 19(1), e0293292. <https://doi.org/10.1371/journal.pone.0293292>
- Fasano, F., La Rocca, M., Sánchez-Vidal, F. J., & Boutouar, Y. (2025). Why smes go to crowdfunding? the role of financial constraints and agency issues. *Small Business Economics*. <https://doi.org/10.1007/s11187-025-01046-x>
- Federal Ministry for Economic Affairs and Climate Action (Germany). (2024). Foerderdatenbank [Accessed: 2024-09-12]. <https://www.foerderdatenbank.de/FDB/DE/Home/home.html>
- Florida, R. (2003). Cities and the creative class. *City & Community*, 2(1), 3–19. <https://doi.org/10.1111/1540-6040.00034>
- Fonseca, R., Lopez-Garcia, P., & Pissarides, C. A. (2001). Entrepreneurship, start-up costs and employment. *European Economic Review*, 45(4–6), 692–705. [https://doi.org/10.1016/s0014-2921\(01\)00131-3](https://doi.org/10.1016/s0014-2921(01)00131-3)
- French, K., & Poterba, J. (1991). *Investor diversification and international equity markets*. <https://doi.org/10.3386/w3609>
- Gallemore, C., Nielsen, K. R., & Jespersen, K. (2019). The uneven geography of crowdfunding success: Spatial capital on Indiegogo. *Environment and Planning A: Economy and Space*, 51(6), 1389–1406. <https://doi.org/10.1177/0308518x19843925>
- Getis, A., & Griffith, D. A. (2002). Comparative spatial filtering in regression analysis. *Geographical Analysis*, 34(2), 130–140. <https://doi.org/10.1111/j.1538-4632.2002.tb01080.x>
- Getis, A., & Ord, J. K. (1992). The analysis of spatial association by use of distance statistics. *Geographical Analysis*, 24(3), 189–206. <https://doi.org/10.1111/j.1538-4632.1992.tb00261.x>
- Glaeser, E. L. (1999). Learning in cities. *Journal of Urban Economics*, 46(2), 254–277. <https://doi.org/10.1006/juec.1998.2121>
- Glaeser, E. L. (2007). *Entrepreneurship and the City* (NBER Working Papers No. 13551). National Bureau of Economic Research, Inc. <https://ideas.repec.org/p/nbr/nberwo/13551.html>
- Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254–277. <https://doi.org/10.1016/j.jeconom.2021.03.014>
- Gramlich, L., Gluchowski, P., Horsch, A., Schäfer, K., & Waschbusch, G. (2020). *Gabler banklexikon (a – j): Bank – Börse – Finanzierung*. Springer Fachmedien Wiesbaden. <https://doi.org/10.1007/978-3-658-20041-1>
- Guenther, C., Johan, S., & Schweizer, D. (2017). Is the crowd sensitive to distance?—how investment decisions differ by investor type. *Small Business Economics*, 50(2), 289–305. <https://doi.org/10.1007/s11187-016-9834-6>

- Hegerty, S. W. (2015). Commercial bank locations and “banking deserts”: A statistical analysis of Milwaukee and Buffalo. *The Annals of Regional Science*, 56(1), 253–271. <https://doi.org/10.1007/s00168-015-0736-3>
- Hornuf, L., Schmitt, M., & Stenzhorn, E. (2022). The local bias in equity crowdfunding: Behavioral anomaly or rational preference? *Journal of Economics & Management Strategy*, 31(3), 693–733. <https://doi.org/10.1111/jems.12475>
- Hornuf, L., & Schwienbacher, A. (2017). Should securities regulation promote equity crowdfunding? *Small Business Economics*, 49(3), 579–593. <https://doi.org/10.1007/s11187-017-9839-9>
- Hornuf, L., & Schwienbacher, A. (2018). Market mechanisms and funding dynamics in equity crowdfunding. *Journal of Corporate Finance*, 50, 556–574. <https://doi.org/10.1016/j.jcorpfin.2017.08.009>
- Hortaçsu, A., Martínez-Jerez, F. A., & Douglas, J. (2009). The geography of trade in online transactions: Evidence from eBay and MercadoLibre. *American Economic Journal: Microeconomics*, 1(1), 53–74. <https://doi.org/10.1257/mic.1.1.53>
- Iacus, S. M., King, G., & Porro, G. (2011). Multivariate matching methods that are monotonic imbalance bounding. *Journal of the American Statistical Association*, 106(493), 345–361. <https://doi.org/10.1198/jasa.2011.tm09599>
- Iacus, S. M., King, G., & Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political Analysis*, 20(1), 1–24. <https://doi.org/10.1093/pan/mpr013>
- KfW Group. (2024). Gründen und nachfolgen - KfW Bank [Accessed: 2024-09-12]. <https://www.kfw.de/inlandsfoerderung/Unternehmen/Gr%C3%BCnden-Nachfolgen/Gr%C3%BCnden/>
- Kim, Y., & Orazem, P. F. (2025). What increases the urban–rural gap in firm entry rates? *Small Business Economics*. <https://doi.org/10.1007/s11187-025-01044-z>
- Koley, M., & Bera, A. K. (2024). To use, or not to use the spatial durbin model? – that is the question. *Spatial Economic Analysis*, 19(1), 30–56. <https://doi.org/10.1080/17421772.2023.2256810>
- Kolympiris, C., Kalaitzandonakes, N., & Miller, D. (2015). Location choice of academic entrepreneurs: Evidence from the US biotechnology industry. *Journal of Business Venturing*, 30(2), 227–254. <https://doi.org/10.1016/j.jbusvent.2014.02.002>
- Kritikos, A. S. (2015). Entrepreneurship and economic growth. In *International Encyclopedia of the Social & Behavioral Sciences* (pp. 675–680). Elsevier. <https://doi.org/10.1016/b978-0-08-097086-8.94004-2>
- Kritikos, A. S., & Mattes, A. (2017). In Deutschland sinkt die Zahl der Betriebsgründungen weiterhin, nicht aber in Berlin. *DIW Wochenbericht* (26) 539–547.

- Kuminoff, N. V., Smith, V. K., & Timmins, C. (2013). The new economics of equilibrium sorting and policy evaluation using housing markets. *Journal of Economic Literature*, 51(4), 1007–1062. <https://doi.org/10.1257/jel.51.4.1007>
- Langley, P. (2016). Crowdfunding in the United Kingdom: A Cultural Economy. *Economic Geography*, 92(3), 301–321. <https://doi.org/10.1080/00130095.2015.113>
- Langley, P., Lewis, S., McFarlane, C., Painter, J., & Vradis, A. (2020). Crowdfunding cities: Social entrepreneurship, speculation and solidarity in Berlin. *Geoforum*, 115, 11–20. <https://doi.org/10.1016/j.geoforum.2020.06.014>
- Lazos, A. (2024). Does equity crowdfunding benefit ventures located in high unemployment regions? *Small Business Economics*, 64(2), 575–598. <https://doi.org/10.1007/s11187-024-00908-0>
- Lerner, J. (1995). Venture capitalists and the oversight of private firms. *The Journal of Finance*, 50(1), 301–318. <https://doi.org/10.1111/j.1540-6261.1995.tb05175.x>
- LeSage, J. P. (2004). A family of geographically weighted regression models. In *Advances in Spatial Science* (pp. 241–264). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-05617-2_11
- Lin, M., & Viswanathan, S. (2016). Home bias in online investments: An empirical study of an online crowdfunding market. *Management Science*, 62(5), 1393–1414. <https://doi.org/10.1287/mnsc.2015.2206>
- Long, J. S. (1997). Regression models for categorical and limited dependent variables.
- Löher, J. (2016). The interaction of equity crowdfunding platforms and ventures: An analysis of the preselection process. *Venture Capital*, 19(1–2), 51–74. <https://doi.org/10.1080/13691066.2016.1252510>
- Martin, R., Sunley, P., & Turner, D. (2002). Taking risks in regions: The geographical anatomy of Europe's emerging venture capital market. *Journal of Economic Geography*, 2(2), 121–150. <https://doi.org/10.1093/jeg/2.2.121>
- Martin, R., Berndt, C., Klagge, B., & Sunley, P. (2005). Spatial proximity effects and regional equity gaps in the venture capital market: Evidence from Germany and the United Kingdom. *Environment and Planning A: Economy and Space*, 37(7), 1207–1231. <https://doi.org/10.1068/a3714>
- Maymoni, L., & Solodoha, E. (2025). Crowdfunding beyond borders: Geographic disparities in crowdfunding success. *Journal of Business Venturing Insights*, 23, e00520. <https://doi.org/10.1016/j.jbvi.2025.e00520>
- Miglo, A. (2022). Crowdfunding and bank financing: Substitutes or complements? *Small Business Economics*, 59(3), 1115–1142. <https://doi.org/10.1007/s11187-021-00571-9>
- Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing*, 29(1), 1–16. <https://doi.org/10.1016/j.jbusvent.2013.06.005>

- Mollick, E., & Robb, A. (2016). Democratizing innovation and capital access: The role of crowdfunding. *California Management Review*, 58(2), 72–87. <https://doi.org/10.1525/cmr.2016.58.2.72>
- Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2), 187–221. [https://doi.org/10.1016/0304-405x\(84\)90023-0](https://doi.org/10.1016/0304-405x(84)90023-0)
- Niebuhr, A. (2001). Convergence and the effects of spatial interaction. *Jahrbuch für Regionalwissenschaft*, 21.
- Norbäck, P.-J., Persson, L., & Tåg, J. (2024). Risky business: Venture capital, pivoting and scaling. *Small Business Economics*, 64(3), 1285–1319. <https://doi.org/10.1007/s11187-024-00944-w>
- Ord, J. K., & Getis, A. (1995). Local spatial autocorrelation statistics: Distributional issues and an application. *Geographical Analysis*, 27(4), 286–306. <https://doi.org/10.1111/j.1538-4632.1995.tb00912.x>
- Pace, R. K., Lesage, J. P., & Zhu, S. (2013). Interpretation and computation of estimates from regression models using spatial filtering. *Spatial Economic Analysis*, 8(3), 352–369. <https://doi.org/10.1080/17421772.2013.807355>
- Pollack, J. M., Maula, M., Allison, T. H., Renko, M., & Günther, C. C. (2019). Making a contribution to entrepreneurship research by studying crowd-funded entrepreneurial opportunities. *Entrepreneurship Theory and Practice*, 45(2), 247–262. <https://doi.org/10.1177/1042258719888640>
- Prokop, J., & Wang, D. (2021). Is there a gender gap in equity-based crowdfunding? *Small Business Economics*, 59(3), 1219–1244. <https://doi.org/10.1007/s11187-021-00574-6>
- Sorenson, O., Assenova, V., Li, G.-C., Boada, J., & Fleming, L. (2016). Expand innovation finance via crowdfunding. *Science*, 354(6319), 1526–1528. <https://doi.org/10.1126/science.aaf6989>
- Sorenson, O., & Stuart, T. (2001). Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology*, 106(6), 1546–1588. <https://doi.org/10.1086/321301>
- Stam, E. (2009). Entrepreneurship, evolution and geography. *Max Planck Institute of Economics, Evolutionary Economics Group, Papers on Economics and Evolution*.
- Stam, F., & Spigel, B. (2016). *Entrepreneurial Ecosystems* (Working Papers No. 16-13). Utrecht School of Economics. <https://ideas.repec.org/p/use/tkiwps/1613.html>
- Stevenson, R. M., Kuratko, D. F., & Eutsler, J. (2018). Unleashing main street entrepreneurship: Crowdfunding, venture capital, and the democratization of new venture investments. *Small Business Economics*, 52(2), 375–393. <https://doi.org/10.1007/s11187-018-0097-2>

- Troise, C., Giovando, G., Jabeen, F., & Bresciani, S. (2024). Unveiling the role of entrepreneurial teams in the equity crowdfunding journey. *Small Business Economics*, 63(4), 1517–1538. <https://doi.org/10.1007/s11187-024-00873-8>
- Vismara, S. (2018). Information cascades among investors in equity crowdfunding. *Entrepreneurship Theory and Practice*, 42(3), 467–497. <https://doi.org/10.1111/etap.12261>
- Vulkan, N., Åstebro, T., & Sierra, M. F. (2016). Equity crowdfunding: A new phenomena. *Journal of Business Venturing Insights*, 5, 37–49. <https://doi.org/10.1016/j.jbvi.2016.02.001>
- Wagner, J., & Sternberg, R. (2004). Start-up activities, individual characteristics, and the regional milieu: Lessons for entrepreneurship support policies from german micro data. *The Annals of Regional Science*, 38(2), 219–240. <https://doi.org/10.1007/s00168-004-0193-x>
- Walthoff-Borm, X., Schwienbacher, A., & Vanacker, T. (2018). Equity crowdfunding: First resort or last resort? *Journal of Business Venturing*, 33(4), 513–533. <https://doi.org/10.1016/j.jbusvent.2018.04.001>
- Wang, D., & Prokop, J. (2024). Gender homophily and local bias in equity crowdfunding. *Small Business Economics*, 64(3), 805–836. <https://doi.org/10.1007/s11187-024-00949-5>
- Yang, J., Xin, J., Zeng, Y., & Liu, P. J. (2025). Signaling and perceiving on equity crowdfunding decisions—a machine learning approach. *Small Business Economics*, 65(1), 315–356. <https://doi.org/10.1007/s11187-024-00991-3>

Tables and Figures

Table 1: Descriptive statistics ($N = 266$)

Variable	Mean	Std.	Min	Max
ECF campaigns	0.76	2.01	0	19
earlstage	8.22	16.41	0	99
MFI	45.01	33.41	6	184
disposable income	19,249.82	1,930.80	15,189.65	26,320.88
population density	446.61	730.62	74.32	4238.68
population total	2,415,107	1,118,296	521,808.8	5,232,901
startup rate	1.40	0.37	0.70	51.55
unemployment rate	4.46	1.85	1.78	10.88
median age	45.89	2.05	40.99	51.55

Note: Descriptive statistics based on $N = 266$ region-period observations. All monetary values are in euros. The startup rate, unemployment rate, and median age are expressed in percent and years, respectively.

Table 2: ECF localization in Germany through Moran's I analysis

Year	Moran's I	z -statistic	p -value
2012	-0.024	0.204	0.581
2013	-0.027	0.000	0.499
2014	-0.027	0.000	0.500
2015	-0.027	0.000	0.499
2016	-0.027	-0.217	0.414
2017	-0.026	0.004	0.501
2018	-0.028	-0.402	0.343

Note: Moran's I measures spatial autocorrelation of ECF campaign occurrences across German regions. Values close to zero indicate no spatial clustering, while positive (negative) values suggest clustering (dispersion). The z -statistic and p -value test the significance of the spatial autocorrelation for each year.

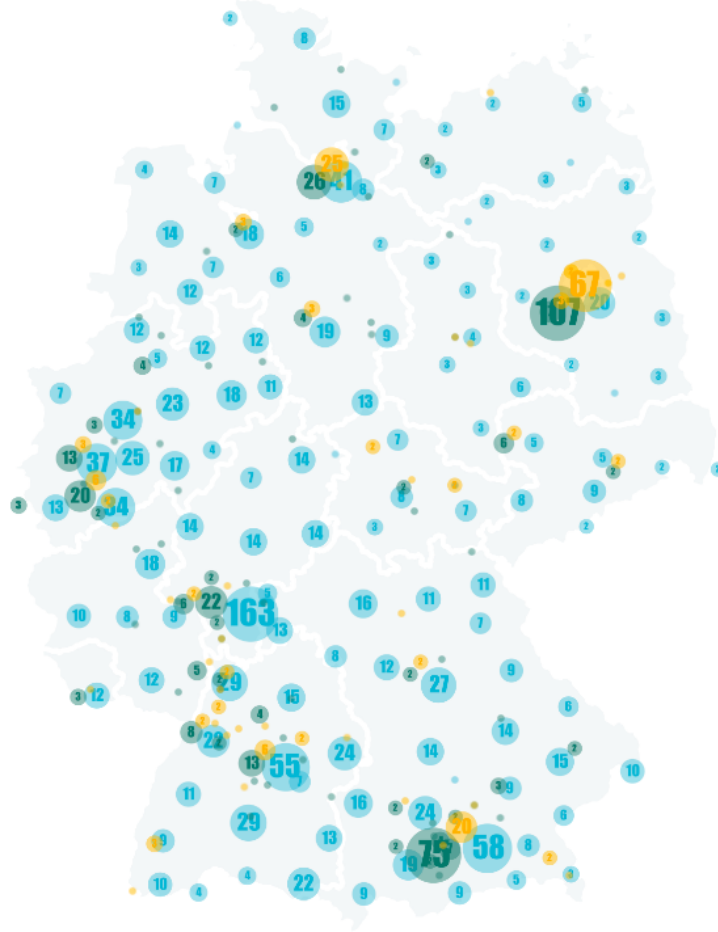


Figure 1: Geographical Distribution of successful Equity Crowdfunding Campaigns (yellow), Monetary Financial Institutions (blue), and Early Stage Investors (green) in Germany, from 2012-2018. NUTS-1 Regions (States)

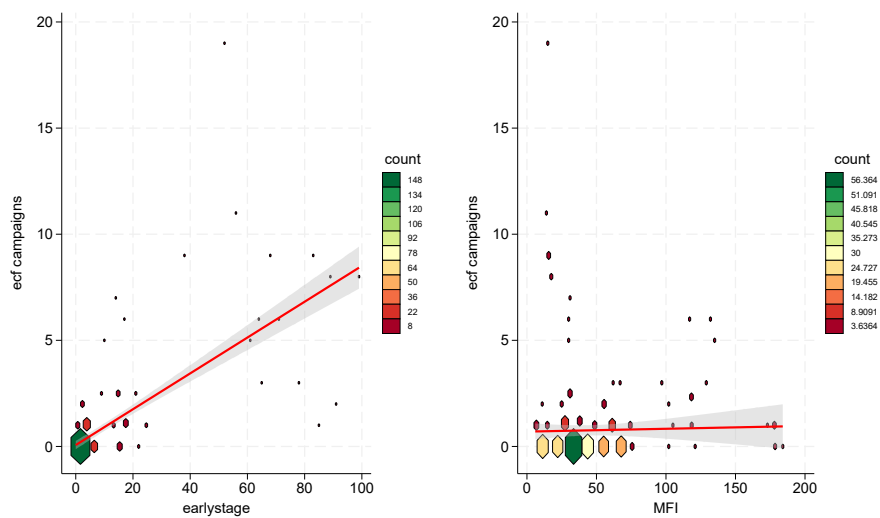


Figure 2: Hexagon plots for ECF campaigns vs early stage investments/MFIs

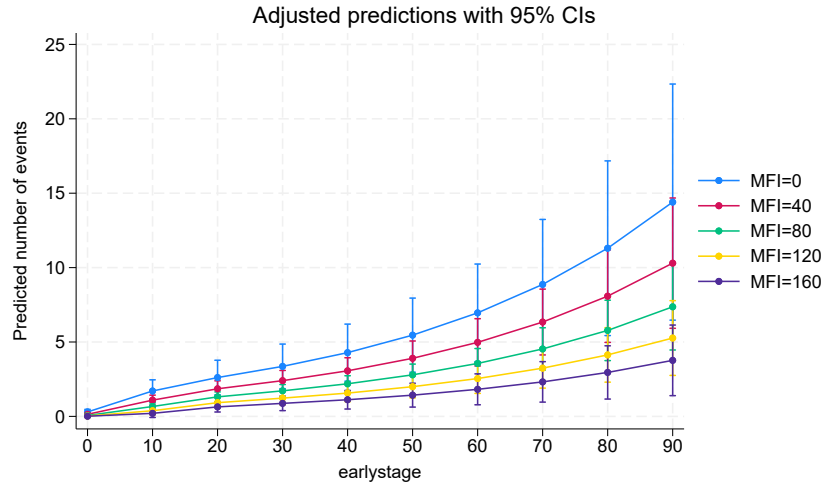


Figure 3: The expected number of ECFs in the region with and without early-stage investors

Table 3: Average marginal effects with and without Berlin

Variable	Without Berlin		With Berlin	
	Average marginal effect	p-Value	Average marginal effect	p-Value
earlystage	-.0389085	0.019	-.0431834	0.002
MFIs	.0048607	0.013	.0050178	0.044
disposable income	-1.735658	0.089	.4171076	0.718
population total	-1.38e-07	0.088	-1.93e-07	0.007
population density	-.0000964	0.464	-.0003144	0.001
unemployment rate	-.1408631	0.022	.0256987	0.622
startup rate	.3606429	0.000	.3659673	0.017

Note: This table reports average marginal effects from probit regressions estimating the likelihood of ECF campaign presence in a region. Results are shown with and without including Berlin.

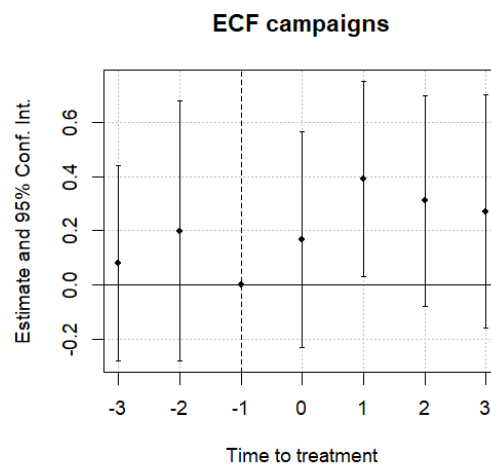


Figure 4: Event study estimates

Table 4: Event study: The impact of KASG on ECF

Dependent Variable: Model:	log(1+ECF campaigns) (1)
<i>Variables</i>	
treat × time_to_treat = -3	0.1089 (0.1893)
treat × time_to_treat = -2	0.2129 (0.1772)
treat × time_to_treat = 0	0.1323 (0.1723)
treat × time_to_treat = 1	0.4510** (0.2116)
treat × time_to_treat = 2	0.3520** (0.1768)
treat × time_to_treat = 3	0.3079* (0.1719)
GDP per capita	8.08×10^{-6} (1.93×10^{-5})
population total	-1.18×10^{-6} (1.78×10^{-6})
startup rate	0.0904 (0.2111)
HRST total	-0.0018 (0.0262)
earlystage	-0.0355* (0.0186)
MFIs	-0.0074 (0.0130)
<i>Fixed-effects</i>	
Region	Yes
<i>Fit statistics</i>	
Observations	137
R ²	0.71817
Within R ²	0.18609
<i>Heteroskedasticity-robust standard-errors in parentheses</i>	
<i>Signif. Codes: ***: 0.01, **: 0.05, *: 0.1</i>	

Table 5: The description of variables

Variable	Description
ECF campaigns	The number of successful ECF campaigns
earlystage	The number of early stage investors
MFI	The number of monetary financial institutions (i.e. banks)
disposable income	Income available after taxes and mandatory deductions, used for spending or saving.
population density	Number of people per square kilometer.
population total	Total number of people residing in a given area.
startup rate	Ratio of new businesses to the total number of firms in a given period.
unemployment rate	Share of registered unemployed over the entire working population, consisting of all employed plus the registered unemployed.
median age	Regions' specific median age of entrepreneurs

Note: This table provides definitions of the main variables used in the analysis. All variables are measured at the regional level and refer to annual values unless otherwise stated.

Table 6: Cross-correlation table

Variables	ECF campaigns	earlystage	MFIs	disposable income	population total	population density	unemployment rate	startup rate	median age
ECF campaigns	1.000								
earlystage	0.689	1.000							
MFIs	0.022	0.363	1.000						
disposable income	0.041	0.323	0.548	1.000					
population total	0.324	0.580	0.687	0.281	1.000				
population density	0.751	0.573	-0.105	-0.003	0.224	1.000			
unemployment rate	0.299	0.092	-0.323	-0.766	0.067	0.357	1.000		
startup rate	0.402	0.243	0.082	-0.083	0.059	0.471	0.202	1.000	
median age	-0.364	-0.447	-0.402	-0.547	-0.273	-0.492	0.282	-0.481	1.000

Note: This table displays the pairwise Pearson correlation coefficients between the main variables used in the analysis. While some variables, such as early-stage investors and ECF campaigns, show strong positive correlations, others, like median age, exhibit negative relationships with key variables.

Table 7: Regression results

I. Part: Poisson regression		(1)	(2)	(3)	(4)	(5)	(6)
	ECF campaigns	ECF campaigns	ECF campaigns	ECF campaigns	ECF campaigns	ECF campaigns	ECF campaigns
earlystage		0.0242*** (0.00291)	0.0157*** (0.00505)	0.0133** (0.00448)	0.0157*** (0.00498)	0.0279*** (0.00768)	
MFIs		-0.00838** (0.00282)	-0.00210 (0.00381)	0.00132 (0.00364)	-0.00208 (0.00375)	0.000595 (0.00356)	
disposable income			1.229 (1.104)	1.258 (2.976)	2.822 (2.315)	-6.310* (2.956)	
population density	0.000625*** (0.0000704)		0.000131 (0.000154)	-0.0000721 (0.000229)	0.0000835 (0.000154)	0.000666* (0.000266)	
population total			1.97e-08 (0.000000111)	-7.66e-08 (0.000000107)	-2.22e-08 (0.000000115)	-5.02e-09 (0.000000108)	
startup rate			1.161*** (0.274)		0.998** (0.330)	0.818** (0.313)	
unemployment rate				0.292** (0.107)	0.120 (0.147)	-0.564*** (0.164)	
median age				-0.249 (0.172)			
cons	-0.183 (0.210)	0.485* (0.247)	-14.00 (10.82)	-2.346 (35.97)	-29.91 (23.00)	62.89* (29.52)	

II. Part: Logit regression ("Real zeros")					
	(1) ECF campaigns	(2) ECF campaigns	(3) ECF campaigns	(4) ECF campaigns	(5) ECF campaigns
					(6) ECF campaigns
earlystage		-0.304*** (0.0657)	-0.375* (0.147)	-0.287* (0.120)	-0.361* (0.141)
MFIs		0.0128 (0.0111)	0.0434 (0.0231)	0.0417 (0.0232)	0.0419 (0.0238)
disposable income			0.531 (5.043)	-4.911 (11.91)	3.486 (9.452)
population density	-0.00119** (0.000438)		-0.00251* (0.000983)	-0.00261** (0.000842)	-0.00263** (0.000919)
population total			-0.00000160* (0.000000745)	-0.00000131* (0.000000614)	-0.00000162* (0.000000721)
startup rate			3.389* (1.442)		3.058* (1.496)
unemployment rate				0.324 (0.341)	0.215 (0.426)
median age				-0.778 (0.503)	
cons	0.727* (0.293)	1.488*** (0.430)	-6.247 (49.41)	85.95 (135.8)	-35.72 (93.53)
N	266	266	266	266	266
AIC	515.8	494.1	437.0	447.5	440.0
BIC	530.2	515.6	487.2	504.9	497.3

Note: This table presents results from a Zero-Inflated Poisson regression estimating the number of equity crowdfunding (ECF) campaigns across regions. The first part models the count of campaigns (Poisson), and the second part models the probability of observing excess zeros (logit). Model (1) includes only population density; Model (2) includes early-stage inventors and the presence of MFIs; Model (3) further includes disposable income, population total, population density, and startup rate; Model (4) adds unemployment rate and median age; Model (5) includes all covariates; and Model (6) is identical to Model (5) but excludes Berlin from the sample to check for robustness. Standard errors are reported in parentheses, with significance levels denoted by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Descriptive Statistics

Variables	Before Matching			After Matching		
	ECF Regions (N= 147)	Non-ECF Regions (N= 91)	Overall (N= 238)	ECF Regions (N= 67)	Non-ECF Regions (N= 70)	Overall (N= 137)
Number of ECF campaigns						
Mean (SD)	1.33 (2.56)	0 (0)	0.819 (2.11)	0.881 (1.35)	0 (0)	0.431 (1.04)
Median [Min, Max]	0 [0, 19.0]	0 [0, 0]	0 [0, 19.0]	0 [0, 6.00]	0 [0, 0]	0 [0, 6.00]
Number of early-stage investors						
Mean (SD)	13.2 (20.7)	1.69 (1.89)	8.81 (17.2)	12.4 (21.8)	2.10 (1.96)	7.12 (16.1)
Median [Min, Max]	3.00 [0, 99.0]	1.00 [0, 6.00]	3.00 [0, 99.0]	4.00 [0, 91.0]	1.00 [0, 6.00]	3.00 [0, 91.0]
MFIs						
Mean (SD)	52.6 (41.1)	36.3 (16.5)	46.4 (34.7)	50.9 (31.8)	39.7 (16.5)	45.2 (25.7)
Median [Min, Max]	38.0 [6.00, 184]	36.0 [12.0, 71.0]	37.0 [6.00, 184]	46.0 [6.00, 135]	38.0 [14.0, 71.0]	40.0 [6.00, 135]
Disposable income						
Mean (SD)	19500 (2180)	18900 (1550)	19300 (1980)	19800 (2270)	19000 (1690)	19400 (2030)
Median [Min, Max]	19300 [15600, 26300]	19000 [15200, 22800]	19100 [15200, 26300]	19600 [16000, 26300]	19100 [15200, 22800]	19100 [15200, 26300]
GDP (mil)						
Mean (SD)	101000 (63700)	52100 (20200)	82200 (56700)	98500 (63800)	58800 (17300)	78200 (50200)
Median [Min, Max]	77100 [26500, 270000]	46100 [13700, 89400]	65900 [13700, 270000]	77200 [26500, 270000]	57600 [34500, 89400]	69800 [26500, 270000]
GDP per capita						
Mean (SD)	38400 (9360)	33900 (5740)	36600 (8440)	37000 (7810)	34600 (6170)	35800 (7090)
Median [Min, Max]	36800 [23400, 65400]	34100 [22700, 48900]	35500 [22700, 65400]	35900 [23900, 58700]	35300 [22700, 48900]	35400 [22700, 58700]
HRST (total)						
Mean (SD)	36.7 (4.22)	33.6 (2.43)	35.5 (3.94)	36.7 (4.02)	33.3 (2.57)	35.0 (3.74)
Median [Min, Max]	36.2 [28.8, 49.7]	33.5 [28.9, 38.7]	35.0 [28.8, 49.7]	36.5 [28.8, 47.1]	33.2 [28.9, 38.7]	34.7 [28.8, 47.1]
HRST (employment)						
Mean (SD)	46.2 (4.59)	42.4 (2.77)	44.7 (4.38)	45.8 (3.72)	42.0 (2.81)	43.8 (3.79)
Median [Min, Max]	45.4 [38.5, 60.2]	42.2 [37.1, 47.5]	43.9 [37.1, 60.2]	44.9 [39.6, 56.1]	41.6 [37.1, 47.4]	43.4 [37.1, 56.1]
Population (total)						
Mean (SD)	2540000 (1280000)	1540000 (567000)	2160000 (1170000)	2540000 (1240000)	1720000 (497000)	2120000 (1020000)
Median [Min, Max]	2210000 [652000, 5230000]	1460000 [522000, 2660000]	1830000 [522000, 5230000]	2260000 [974000, 5140000]	1600000 [1070000, 2660000]	1840000 [974000, 5140000]
Population (density)						
Mean (SD)	658 (929)	182 (81.9)	476 (767)	298 (197)	192 (88.9)	244 (160)
Median [Min, Max]	268 [82.0, 4240]	165 [74.3, 379]	227 [74.3, 4240]	245 [82.0, 968]	179 [74.3, 379]	222 [74.3, 968]
Unemployment rate						
Mean (SD)	4.74 (1.97)	4.00 (1.74)	4.46 (1.91)	4.37 (1.87)	4.15 (1.91)	4.26 (1.89)
Median [Min, Max]	4.30 [1.78, 10.6]	3.61 [1.89, 10.9]	4.08 [1.78, 10.9]	3.96 [1.78, 9.70]	3.90 [1.89, 10.9]	3.91 [1.78, 10.9]
High-tech employment						
Mean (SD)	4.31 (1.53)	3.16 (1.13)	3.87 (1.49)	4.40 (1.50)	3.13 (1.14)	3.76 (1.47)
Median [Min, Max]	3.73 [2.11, 7.79]	2.80 [1.49, 5.83]	3.47 [1.49, 7.79]	4.05 [2.49, 7.79]	2.77 [1.49, 5.83]	3.37 [1.49, 7.79]
Median age						
Mean (SD)	45.6 (2.23)	46.1 (1.90)	45.8 (2.12)	45.7 (1.66)	46.1 (2.12)	45.9 (1.91)
Median [Min, Max]	45.0 [41.0, 50.7]	45.4 [43.4, 51.5]	45.3 [41.0, 51.5]	45.7 [43.1, 50.2]	45.3 [43.4, 51.5]	45.4 [43.1, 51.5]
Startup rate						
Mean (SD)	1.42 (0.408)	1.40 (0.325)	1.42 (0.378)	1.38 (0.173)	1.35 (0.205)	1.36 (0.190)
Median [Min, Max]	1.40 [0.701, 2.59]	1.40 [0.856, 2.31]	1.40 [0.701, 2.59]	1.40 [1.06, 1.61]	1.40 [0.856, 1.61]	1.40 [0.856, 1.61]
ln (Funding amount)						
Mean (SD)	13.4 (0.802)	13.4 (0.0465)	13.4 (0.630)	13.2 (1.02)	13.6 (0.258)	13.2 (0.981)
Median [Min, Max]	13.4 [10.5, 15.8]	13.4 [13.3, 13.8]	13.4 [10.5, 15.8]	13.4 [10.5, 14.5]	13.6 [13.3, 13.8]	13.4 [10.5, 14.5]
Funding levels						
Low	36 (24.5%)	1 (1.1%)	37 (15.5%)	10 (14.9%)	0 (0%)	10 (7.3%)
Medium	85 (57.8%)	90 (98.9%)	175 (73.5%)	16 (23.9%)	1 (1.4%)	17 (12.4%)
High	26 (17.7%)	0 (0%)	26 (10.9%)	4 (6.0%)	2 (2.9%)	6 (4.4%)
Companisto						
No	28 (19.0%)	2 (2.2%)	30 (12.6%)	10 (14.9%)	2 (2.9%)	12 (8.8%)
Yes	42 (28.6%)	1 (1.1%)	43 (18.1%)	20 (29.9%)	1 (1.4%)	21 (15.3%)
Seedmatch						
No	21 (14.3%)	1 (1.1%)	22 (9.2%)	12 (17.9%)	1 (1.4%)	13 (9.5%)
Yes	49 (33.3%)	2 (2.2%)	51 (21.4%)	18 (26.9%)	2 (2.9%)	20 (14.6%)

Note: This table presents summary statistics for key variables in ECF and non-ECF regions before and after matching, allowing assessment of covariate balance.

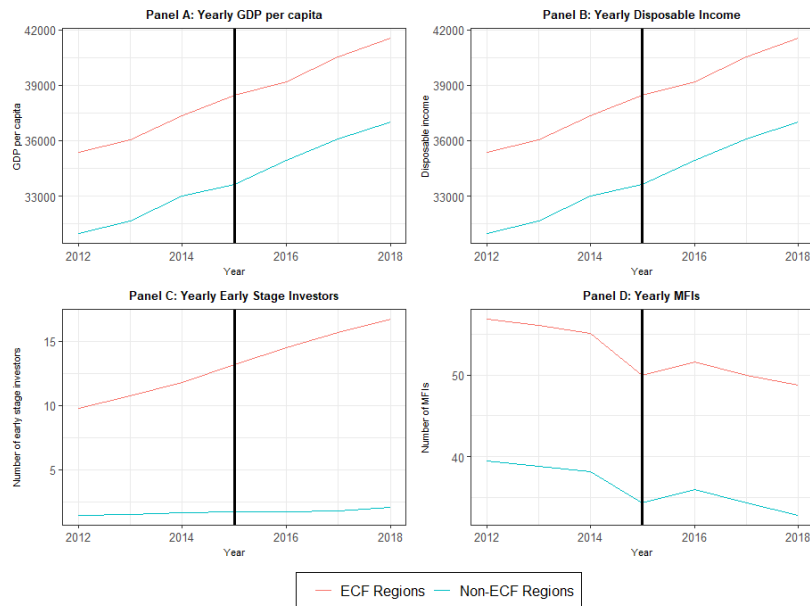
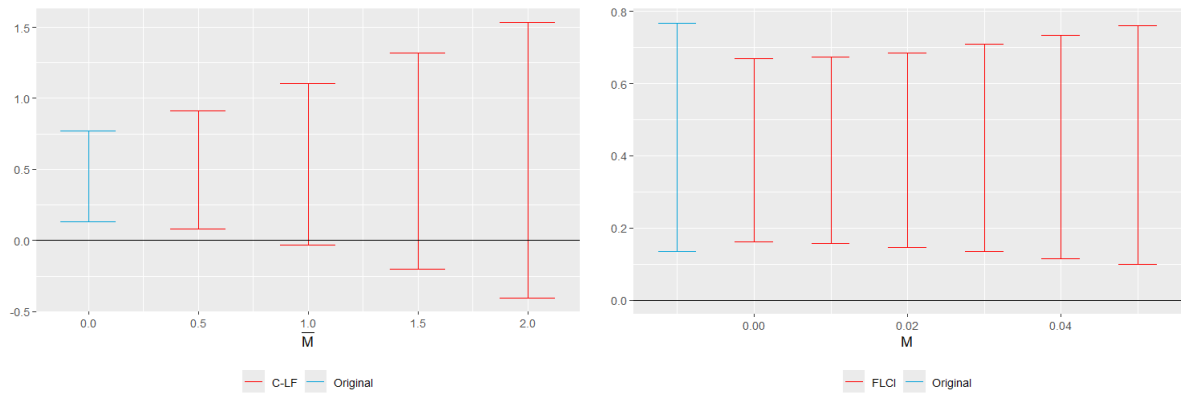


Figure 5: Raw means after Coarsened-Exact Matching



(a) Relative Magnitude Restriction

(b) Smoothness Restriction

Figure 6: Honest DID

Table 9: Honest DID

(a) Relative Magnitude Restriction

lb	ub	method	Delta	\bar{M}
0.0809661	0.9100589	C-LF	DeltaRM	0.5
-0.0291478	1.1043776	C-LF	DeltaRM	1.0
-0.2040346	1.3181281	C-LF	DeltaRM	1.5
-0.4048305	1.5318786	C-LF	DeltaRM	2.0

(b) Smoothness Restriction

lb	ub	method	Delta	M
0.1619685	0.6686433	FLCI	DeltaSD	0.00
0.1577928	0.6728190	FLCI	DeltaSD	0.01
0.1453857	0.6852261	FLCI	DeltaSD	0.02
0.1344460	0.7099195	FLCI	DeltaSD	0.03
0.1157795	0.7332165	FLCI	DeltaSD	0.04
0.0986724	0.7604612	FLCI	DeltaSD	0.05

Note: The table presents confidence intervals obtained from the Honest DiD method using the Relative Magnitude restriction (a) and Smoothness restriction (b) across varying values of \bar{M} and M respectively.

Appendix

A Data

Table 5 is approximately here.

B Empirical Framework

B.1 Spatially filtering procedure

The eigenvector spatial filtering approach consists of the following local filtering statistics:

$$G_i(\delta) = \sum_j w_{ij}(\delta) \left[\sum_j x_j \right]^{-1}, i \neq j, \quad (1)$$

where $w_{ij}(\delta)$ denotes the elements of the row-standardized spatial weights matrix W , while $\delta > 0$ represents the distance decay parameter. The x_j represents observations of a random variable X_j . The choice of δ is delicate as $G_i(\delta)$ is directly affected by this parameter. Ord and Getis (1995) discusses techniques on how to choose δ . A rather intuitive choice would be to choose δ that maximizes the following objective function:

$$\delta^{opt} = \text{Arg max}_{\delta} \sum_i |z_{G_i}(\delta)|, 0 < \delta < \infty, \quad (2)$$

where $z_{G_i}(\delta)$ is an asymptotically normally distributed z-standardized $G_i(\delta)$ statistic. Having determined δ^{opt} , this parameter can be used in the following, frequently employed, distance decay function (among others see LeSage (2004) or Niebuhr (2001)):

$$w_{ij}(\delta) = \exp(-\delta d_{ij}), 0 < \delta < \infty, \quad (3)$$

where d_{ij} reflects the geographical distance between centers of region i and region j . Finally, the spatially filtered observations can be calculated in the following manner:

$$x_i^* = \frac{x_i \left[\frac{\sum_j w_{ij}(\delta)}{(N-1)} \right]}{G_i(\delta)}, \quad (4)$$

where N is the number of observations. Thus, purely spatial effects can be stored in $(\hat{X} = X - X^*)$. If δ is chosen properly, the corresponding z-standardized Moran's I^{16} statistic z_1 applied to the

¹⁶Moran's I is a standard measure of spatial correlation and is calculated as $I = \frac{N}{W} \frac{\sum_i \sum_j w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{(\sum_i (y_i - \bar{y})^2)}$, where N is the number of observations and W is the sum of all pairwise spatial weights w_{ij} between observations i and j .

spatially filtered variables stored in X^* should be insignificant (see, for instance, Getis and Griffith (2002)).

B.2 Coarsened-Exact Matching (CEM)

The exclusion of equity crowdfunding (ECF) firms under the Small Investor Protection Act (KASG) complicates the comparison between treated and non-treated regions, as it introduces significant differences in outcomes that may skew the analysis. We are particularly interested in examining whether regions that had no prior ECF activity were incentivized to initiate ECF campaigns as a result of this exclusion. Hence, we define regions that had ECF activity after 2015 but not before as our treatment group, while regions without ECF activity both before and after 2015 serve as our control regions.

To mitigate these differences and address potential selection biases, we employ Coarsened Exact Matching (CEM) as outlined by Iacus et al. (2011) and Iacus et al. (2012). It is important to note, that CEM is used only in the second part of the analysis, where we examine the effect of KASG on the number of ECF campaigns in a region. This method enables us to pair each region with successful ECF campaigns with an appropriate control region. To ensure that each ECF region is matched with only one control region, we utilize the Nearest Neighbor matching algorithm within the CEM framework, specifically setting $k2k = TRUE$ and applying Mahalanobis distance.¹⁷ As a result, we achieve a balanced sample of 20 regions by successfully matching 10 ECF-active regions (representing 47.61% of the total 21 regions with ECF campaigns—with 10 suitable control regions (in total 17 non-ECF regions)).¹⁸

The selection of potential control regions for each ECF region comprises all non-ECF regions that have not engaged in ECF campaigns either before or after the implementation of KASG in 2015. Through CEM, we ensure that matches are made precisely based on GDP per capita,¹⁹ population density, and startup rate, all assessed in the year preceding KASG's implementation (2014). Matching on startup rate is particularly crucial, as it plays a significant role in influencing a region's propensity to adopt ECF. Additionally, aligning GDP per capita and population density guarantees that each ECF region is paired with a control region of comparable size, investment capacity, and developmental potential.

Table 8 (see Appendix B.2) summarizes the descriptive statistics for ECF and non-ECF

¹⁷This matching procedure effectively minimizes discrepancies between treated and control regions, enhancing the robustness of our analysis.

¹⁸Germany comprises a total of 38 NUTS-2 regions, and our data includes all of them. In our setting, 21 are classified as ECF-active, having implemented ECF campaigns after the introduction of the KASG in 2015. In contrast, 13 regions are identified as non-ECF regions, which did not engage in any ECF campaigns before or after 2015. We exclude four regions that had ECF campaigns prior to 2015 but not afterward, as these regions do not align with the treatment introduced by the KASG. Excluding them ensures that our analysis focuses on regions that are directly impacted by the policy change, allowing for a clearer assessment of the KASG's effects on ECF activity.

¹⁹GDP per capita is binned into four categories—Low GDP, Middle-Low GDP, Middle-High GDP, and High GDP—to capture variations in regional wealth.

regions both before and after the matching process. The first three columns present summary statistics for the ECF and non-ECF regions prior to matching, while columns four through six illustrate the statistics after matching.

Table 8 is approximately here.

Before matching, ECF regions show distinct differences compared to non-ECF regions in terms of economic and population characteristics. For GDP per capita, ECF regions have a higher average of €38,400 compared to €33,900 in non-ECF regions, indicating greater economic activity in ECF-supported areas. Population density also stands out, with ECF regions being much denser (average 658) than non-ECF regions (182), highlighting the urban focus of ECF activity. The startup rate in ECF regions averages 1.42%, slightly higher than the 1.4% in non-ECF regions.

After matching, these differences narrow considerably, indicating that the matching process effectively controlled for the key economic and demographic variables associated with ECF presence. The GDP per capita difference between ECF and non-ECF regions slightly reduces to €37,000 for ECF and €34,600 for non-ECF regions, population density drops to 298 and 192, respectively, while the startup rate is similarly aligned at 1.38% in ECF regions and 1.35% in non-ECF regions. This similarity suggests that the matching process minimized initial discrepancies, aligning ECF and non-ECF regions in terms of economic activity, density, and entrepreneurial environment.

Comparing the remaining variables, we find that prior to matching, ECF regions generally exhibit a higher number of early-stage investors, monetary financial institutions (MFIs), and a more highly skilled workforce (HRST). After matching, most of these differences decrease, indicating successful alignment on these additional variables, with ECF and non-ECF regions becoming more comparable across financial and workforce metrics.

Figure 5 is approximately here.

Figure 5 (see Appendix B.2) presents the annual means of GDP per capita, disposable income, the number of early-stage investors, and MFIs in both ECF-active regions and their matched control regions from 2012 to 2018. Notably, the pre-KASG trends for ECF-active regions and their matched controls are strikingly similar after the matching, indicating that the matching procedure for selecting an appropriate control group was effective.

Overall, Figure 5 (see Appendix B.2) illustrates that the KASG has positively influenced the growth of GDP per capita (panel A) and disposable income (panel B). Interestingly, while the number of early-stage investors shows an upward trend exclusively in ECF-active regions (panel C), the number of MFIs demonstrates a downward trend across both treatment and control groups (panel D). This observation supports our expectation that the KASG has enhanced the appeal of ECF-active regions for early-stage investors.

B.3 Event Study

We employ an event study framework to estimate the dynamic effects of KASG on the number of successful ECF campaigns across different regions in Germany over the period of 2012-2018. In the following, i indexes the region, $t \in \{1, \dots, T\}$ the time period, $y_{i,t}$ denotes the outcome variable, and $D_{i,t}$ is a binary treatment indicator equal to one if region i had a successful ECF campaign in period t after the implementation of KASG. We assume that once a region is treated, that unit will remain treated in future time periods.

The target parameter is the average treatment effect

$$ATT(t) \equiv \mathbb{E} [y_{i,t}(1) - y_{i,t}(0) \mid D_{i,t} = 1 \text{ for } t \geq 2016]. \quad (5)$$

that report the average difference in potential outcomes under treatment ($y_{i,t}(1)$) and no treatment ($y_{i,t}(0)$) for regions that had successful ECF campaigns after the implementation of the KASG in 2015, specifically for the period $t \geq 2016$. Notice that the average treatment effects capture both leads ($t < 2015$), lags ($t > 2015$), and the instantaneous ($t = 2015$) effect of treatment.

The $ATT(g, t)$ are estimated via the following regression:

$$y_{i,t} = \alpha_i + \sum_{\ell=-K}^{-2} \mu_{\ell} D_{i,t}^{\ell} + \sum_{\ell=0}^L \mu_{\ell} D_{i,t}^{\ell} + \theta X_{it} + \varepsilon_{i,t}, \quad (6)$$

where $y_{i,t}$ is the outcome of interest (the number of successful ECF campaigns) for region i at time t , α_i denotes region-fixed effects. $D_{i,t}^{\ell}$ is equal to 1 for region i in period t if region i has been exposed to treatment for exactly ℓ periods in period t . We refer to ℓ as the period since the treatment. The interest lies in the coefficients μ_{ℓ} that identify (under appropriate assumptions) the average treatment effects. Notice that the coefficients μ_{ℓ} should be interpreted as the effect of treatment relative to the omitted reference period $\ell = -1$.²⁰ Finally, $\varepsilon_{i,t}$ is the error term (robust standard errors are adjusted for both heteroscedasticity and clustering at the region level).

In this context, we outline the following identification assumptions (see Goodman-Bacon (2021) and Callaway and Sant'Anna (2021)):

Assumption 1 (Irreversibility of Treatment (Staggered Adoption)): This assumption asserts that once treatment is assigned, it cannot be reversed.

Assumption 2 (Random Sampling): This assumption posits that the sample units are randomly selected from the target population. This ensures that the estimated treatment effects can be generalized to the larger population without bias from non-random selection.

Assumption 3 (Parallel Trends): The average potential outcomes in the absence of treatment follow parallel trends over time for all regions and time periods.

Assumption 4 (No/Limited Anticipatory Behavior Prior to Treatment): This assumption

²⁰As is common in practice, we drop the first relative period before the treatment ($t = 2014$) to avoid multicollinearity.

indicates that firms do not exhibit anticipatory behaviors in any period leading up to the initial treatment in 2015. Combined with the parallel trends assumption, this implies that the coefficients μ_ℓ should equal zero for $\ell < 0$. In other words, any non-zero μ_ℓ for $\ell < 0$ would indicate a violation of the parallel trends assumption.

C Correlations

Table 6 is approximately here.

D Results

D.1 Regression results

Table 7 is approximately here.

D.2 Honest DID

We further conduct a sensitivity analysis using Honest DID with two different types of restrictions: relative magnitude restriction and smoothness restriction. This method helps to assess how robust our results are to violations of the parallel trends assumption.

Sensitivity analysis using relative magnitudes restriction: In the Honest DID framework, this restriction focuses on the period directly following the treatment to ensure that post-treatment confounding factors do not exceed the pre-treatment trend deviations significantly in magnitude.

Figure 6a illustrates the impact of KASG on the number of successful ECF campaigns in the initial post-treatment period, with robust confidence intervals capturing differences in trend. For specific coefficient details, see Table 9. The original event study estimate (in blue) suggests a positive effect on successful ECF campaigns, with confidence intervals excluding zero. When imposing the restrictions (in red), the significance still maintains at $\Delta = 0.5$ (lower bound of 0.0809 and upper bound of 0.91). However, as Δ increases further, the significance diminishes, reaching a “breakdown value” around 1.

These findings indicate that with modest assumptions (lower Δ), the treatment effect remains positive and statistically significant. However, as we permit greater deviations from parallel trends, the lower bound moves into negative values, suggesting that the treatment effect might diminish or even reverse under stronger trend deviations.

Sensitivity analysis using smoothness restriction: Figure 6b presents the results of the KASG impact on ECF campaigns in the first post-treatment period, along with robust confidence intervals assessing the non-linearity of trend differences (see Table 9 for more details on coefficients). In blue, the original event study confidence intervals for μ^1 are depicted from specification 6. In red, fixed length confidence intervals (FLCIs) are shown for different values

of M , where $M = 0$ signifies linear violations of parallel trends, and larger M values allow for greater deviations from linearity. In Model 1 (see Figure 6b), the original event study estimate shows a positive effect on the number of ECF campaigns, with the confidence interval excluding the 0 effect. Under the smoothness restriction, the treatment effect remains positive and significant, even when we relax the assumption of parallel trends. This suggests that the results are more robust under smoothness assumptions compared to the relative magnitudes restriction.

Figure 6 is approximately here.

Table 9 is approximately here.