U.S. Equity Crowdfunding: Real Effects of Financing Small Entrepreneurs*

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Abstract

Equity crowdfunding allows small businesses to raise capital from the public via online platforms. We find that, despite having limited impact on diversifying entrepreneurship, it improves access to capital by financing younger firms compared to banks. Using the number of competing offerings as an instrument for equity crowdfunding success, we show that equity crowdfunding alleviates financial constraints of viable businesses. Successful issuers survive longer, are more likely to receive venture capital, and exhibit subsequent financial growth. We also find that equity crowdfunding activity is associated with both increased interest in entrepreneurship and increased venture capital investment in the local area.

Keywords: Equity crowdfunding, entrepreneurship, fundraising

JEL Codes: G23, G28, L26, M13

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1 Introduction

Small businesses represent over 90% of all U.S. firms, and the health of these businesses impacts the local communities in which they operate (SBA, 2022). Yet, more than half of these businesses have inadequate access to financing (Battisto et al., 2019), which directly affects their survival (Mach and Wolken, 2012), productivity (Krishnan et al., 2015), employment (Brown and Earle, 2017), and spillover effects on local startup activity (Kerr and Nanda, 2009b). As such, understanding how capital market frictions affect the growth and survival of young firms is a central question of entrepreneurial finance (Robb and Robinson, 2014; Kerr and Nanda, 2009a). In this paper, we study whether and to what extent an alternative financing channel for entrepreneurs, known as equity crowdfunding, affects small business financing at the firm and local level.

Regulation Crowdfunding (Reg CF) was included as part of the 2012 Jumpstart Our Business Startups (JOBS) Act and went into effect on May 16, 2016. It is intended to improve small businesses' access to capital by allowing firms to raise capital from the public while remaining private.[1] Unlike *rewards-based* crowdfunding, in which donors contribute to campaigns with no expectation of a financial return (e.g., Kickstarter), investors in *equity* crowdfunding obtain a financial stake in the company's future performance. Other key differences include SEC oversight (because crowdfunding entails the issuance of securities) and requirements to publicly disclose financial, strategic, and ownership information. Reg CF has grown rapidly. In its first twelve months, 326 firms filed for Reg CF offerings, raising over $30 million (Abate, 2018). At the time of writing, seven years after its launch, over 7,400 offerings had raised $2 billion in aggregate (Alois, 2023).

Several features make Reg CF a potentially attractive financing option for entrepreneurs. First, capital allocation is determined by the "crowd" rather than by formulaic lending

[1] Specifically, U.S. regulators stated that "the statute [...] may increase both capital formation and the efficiency of capital allocation among small issuers by expanding the range of methods of external financing available to small businesses and the pool of investors willing to finance such types of businesses" (SEC, 2015).

requirements, permitting younger, pre-revenue firms to obtain financing. Second, the process takes place completely online, potentially increasing firms' access to capital and reaching a larger pool of investors. Finally, the crowd's investment decision reflects product viability and customer demand, providing valuable information to founders and potential investors.

As a new source of capital, Reg CF has the potential to alleviate financial constraints of small businesses, enabling firms to survive and grow. Entrepreneurial businesses are often first financed by founders and a close group of friends and family. Once sufficiently mature, the business may access external financing via bank loans and venture capital (VC). However, many firms die in the "valley of death" – the period between the initial "bootstrapping" and the point at which firms qualify for external financing (e.g., Ritter and Pedersen, 2022). Reg CF can provide critical bridge capital during this period, supporting viable businesses that are otherwise unfunded by traditional financing channels.

On the other hand, Reg CF suffers from adverse selection and moral hazard issues, potentially resulting in the inefficient allocation of capital to low quality businesses. Reg CF imposes fewer reporting requirements than initial public offerings (IPOs) and does not offer the same access to management typically available to banks and VC firms.[2] In fact, based on evidence from a small sample of U.K. companies, equity crowdfunding may be a last resort for unprofitable firms (Walthoff-Borm et al., 2018). Further, Reg CF investors – many of whom are likely customers or friends and family – could invest for motives other than generating high returns. Thus, it is unclear whether and to what extent Reg CF enables the growth of viable startups.

Our empirical analyses rely on Reg CF offerings data obtained from the SEC's EDGAR. We supplement the limited information available in machine-readable format on EDGAR by hand-collecting a wide range of data points for offerings launched before the end of 2020 on the top three platforms by volume (Wefunder, StartEngine, and Republic). This

[2]Financial statement audits are often not required, resulting in substantial heterogeneity in the amount and quality of information provided. In addition, many investors obtain non-voting securities or do not acquire a sufficiently large stake to have a say in business operations.

allows us to gather detailed financial information, to accurately measure the amount raised, and to observe subsequent survival and financial performance for a sufficient post-period. After imposing all data restrictions, our final sample includes over 1,600 offerings. The average (median) issuer is 3.2 (2.0) years old, has 6.0 (3.0) employees, earns \$389 thousand (\$5 thousand) of revenue, and holds \$86 thousand (\$11 thousand) of cash. Approximately 68.9% of offerings are successful, meaning that the issuer meets its minimum fundraising target. The average (median) amount raised is \$404 thousand (\$172 thousand), more than doubling the assets of sample firms.

First, we descriptively evaluate the types of businesses seeking funding via Reg CF. We focus on evaluating whether Reg CF fills critical financing gaps along three dimensions often cited by proponents of this new financing alternative: business qualifications, geographic access to capital, and demographic profiles of founders (e.g., Mollick and Robb, 2016; Cumming et al., 2021). We compare crowdfunding firms to firms receiving small business loans and venture capital investments as relevant benchmarks. Because formal bank credit is the largest source of capital for entrepreneurs (Robb and Robinson, 2014), we first measure the proportion of Reg CF issuers that would also qualify for bank lending at the time of the crowdfunding offering. When applying typical revenue, income, and age requirements obtained from six small business lenders and marketplaces, we find that at most 5% of issuers would qualify. This relatively low proportion confirms the need for these firms to seek alternative funding sources. Consistent with this, only 4% of sample companies actually received Small Business Administration (SBA) loans before seeking capital via equity crowdfunding.

We also assess whether Reg CF capital flows to new communities and new groups of business owners. Geographically, we find that Reg CF is more concentrated than SBA loans and substantially overlaps with the location of early-stage VC investment. Demographically, the proportion of female small business owners receiving Reg CF capital is similar to SBA loan recipients but higher than VC-backed companies. Thus, to date, Reg CF appears to have had only a limited effect on providing capital to a more diverse group of entrepreneurs.

Second, we study whether and to what extent Reg CF success alleviates financial constraints, focusing on firm survival. There are two potential selection biases that make this analysis challenging: (i) firms that seek capital via Reg CF could differ systematically from other small businesses that do not, and (ii) successful and failed offerings could differ on a number of unobservable dimensions that also affect survival. We address the first selection bias by comparing firms with successful offerings to firms that also tried to raise capital via Reg CF, but were ultimately unsuccessful. To address the second selection bias, we follow Signori and Vismara (2018) and instrument for Reg CF success with the number of competing offerings on the same equity crowdfunding platform. Our expectation is that, similar to rewards-based crowdfunding (Serrano, 2023), the success of a Reg CF offering is inversely related to the number of competing offerings because of investors' limited information processing ability (i.e., they focus on the most salient offerings) and limited funds (i.e., the SEC placed income-based limits on investments).

As validation of the instrument, we document the expected negative association between the number of competing offerings and the likelihood of success, with first-stage F-statistics ranging from 69.4 to 120. Satisfying the exclusion restriction requires the number of competing offerings to not affect an issuer's subsequent performance except through the likelihood of Reg CF success. While this cannot be empirically verified, we mitigate concerns by comparing survival rates for issuers in the same industry that are raising capital at the same time. These firms face similar economic forces affecting their subsequent performance, despite experiencing different levels of competition for Reg CF capital.

We find that issuers with a successful Reg CF offering are between 17.1 and 27.6 percentage points less likely to become inactive in subsequent years. For comparison, Kerr et al. (2014) find that survival rates increase by a similar amount, 20 to 25 percentage points, for firms that receive angel financing. Given an estimated 50% survival rate for issuers in our sample according to their age and Bureau of Labor Statistics data (BLS, 2016), our estimates imply an increase in survival of 34% to 55%. We also find consistent effects using the amount raised in excess of the firm's target as an alternative measure of success.

Having shown increased survival for successful issuers, we next perform two analyses to determine whether the crowd selects viable businesses, or if the funds flow to poor quality firms that should have remained unfunded. First, we provide descriptive evidence on the financial growth of successful issuers. If most Reg CF issuers are "lemons" or frauds, we should find little to no growth in non-cash assets and revenue following the offering. Using annual reports filed by successful Reg CF issuers, we find an average (median) increase of \$509 thousand (\$43 thousand) in non-cash assets and \$499 thousand (\$36 thousand) in revenue two years after the offering, suggesting that Reg CF provides capital to firms with good growth prospects. Second, we assess whether "smart money" provides follow-on capital to successful Reg CF issuers. In particular, VC firms play an important role in the financing of successful startups, and their performance relies on their skill in the deal selection process (e.g., Puri and Zarutskie, 2012; Kaplan and Lerner, 2010; Gompers et al., 2020). Our estimates suggest that the likelihood of obtaining subsequent financing from VCs more than doubles after a successful offering. Taken together, these results validate the crowd's investment decisions.

Finally, we study the effect of Reg CF activity on the local economy. Equity crowdfunding offerings can encourage local entrepreneurship by increasing awareness of this alternative source of capital, and by providing relevant information to local startups through public filings (Barrios et al., 2023). Consistent with these informational benefits, we find that the occurrence of a Reg CF offering in a county is associated with increased awareness of equity crowdfunding (measured with Google searches for Reg CF platform names) and increased interest in entrepreneurship (also measured with Google searches) in subsequent years. Informational benefits also extend to VC investors because the improved information environment for local startups reduces search costs (Baik et al., 2022). Specifically, we find that equity crowdfunding activity in a county is associated with a 6.6-13.1% increase in the likelihood of VC investment into the same area (Sorenson et al., 2016 document a similar effect for rewards-based crowdfunding). Interestingly, we observe 4.4% *fewer* SBA loans in the county after a Reg CF offering, but this decline is insignificant in the period before the Covid-19 pandemic. This suggests either a post-pandemic tightening of bank credit, or a substitution by firms from SBA loans to Reg CF.[3]

This paper makes two key contributions. First, we contribute to the growing literature on equity crowdfunding. Thus far, the empirical finance and accounting literature has focused on studying rewards-based crowdfunding (e.g., Bai et al., 2023; Cascino et al., 2019; Lambert et al., 2022; Madsen and McMullin, 2019; Sorenson et al., 2016), analyzing the factors driving entrepreneurs to seek capital via equity crowdfunding (Walthoff-Borm et al., 2018; Cumming et al., 2021), or documenting the role of financial statement disclosures for successful equity crowdfunding offerings (e.g., Bogdani et al., 2022; Gong et al., 2022; Donovan, 2021; Aland, 2023).[4] Beyond this work, we have very little evidence about the first-order impact of this new financing channel on firm survival and viability, aside from a small sample of successful U.K. issuers in a very different regulatory setting (Signori and Vismara, 2018).

Our analysis complements two closely related concurrent working papers. Dolatabadi et al. (2021) also study subsequent survival and VC fundraising, but their regression discontinuity design compares issuers just above and below an endogenously-selected target threshold, potentially limiting generalizability and causal inferences. Instead, we use an instrumental variable approach to study the effect of equity crowdfunding success on subsequent firm performance, including access to bank credit. We also quantify the economic impact of equity crowdfunding activity on the local area. This last set of results is related to Rashidi Ranjbar (2022), who analyzes how the adoption of Reg CF and intrastate crowdfunding regulations impacted business applications across states. Our analysis considers a

[3] Ashwell (2023) provides anecdotal evidence of this second interpretation, although as noted previously, only a small fraction of issuers in our sample would have qualified for SBA loans.

[4] For example, Bogdani et al. (2022) and Gong et al. (2022) show that higher levels of assurance on financial statements are associated with a higher likelihood of a successful offering. In the U.K. equity crowdfunding market, Donovan (2021) finds that voluntary financial disclosures are positively associated with capital raised. Aland (2023) studies the determinants of disclosures available on online listing platforms and their association with offering success.

different set of outcomes related to entrepreneurial finance and exploits county-level variation in exposure to Reg CF instead of the timing of new legislation.

More broadly, we contribute to the literature on the growth of private capital markets and their impact on entrepreneurship (e.g., Kerr and Nanda, 2009b; Robb and Robinson, 2014). Recent lines of research investigate how the crowd's investing decisions interact with traditional sources of capital (e.g., Mollick and Nanda, 2016; Tang, 2019; D'Ambrosio and Gianfrate, 2016) and the effect of public disclosures by private firms on entrepreneurship (e.g., Baik et al., 2022; Barrios et al., 2023). We extend this literature to the equity crowdfunding setting, which resembles traditional financing more closely than rewards-based crowdfunding. Our analyses provide policy-relevant evidence to evaluate whether this new financing channel can effectively allocate capital to small businesses despite severe adverse selection and moral hazard issues. This is particularly important in light of the recent increase in the statutory cap that permits issuers to now raise up to $5 million in the U.S., as well as significant reforms seeking to harmonize crowdfunding in the E.U.

2 Background and Data

2.1 Institutional Details

The 2012 JOBS Act included a number of provisions intended to facilitate the capital formation and expansion of small businesses across the United States. Prior literature primarily focuses on the effect of the JOBS Act on relatively larger "start up" businesses. For example, Dambra et al. (2015) document that the JOBS Act motivated more firms to engage in traditional IPOs.

Equity crowdfunding is one of the key JOBS Act provisions targeted at smaller companies. It is similar in spirit to the more well-known rewards-based crowdfunding, in that it allows entrepreneurs to raise funds from a large and disperse "crowd" to fund a particular project, idea, or business. However, unlike rewards-based crowdfunding, in which the backer contributes with no expectation of a financial return (effectively a non-charitable donation), backers in equity crowdfunding obtain a security (i.e., stock, debt, or convertible securities) in exchange for their contribution and thus become shareholders or debtholders of the business.

To initiate a crowdfunding offering, firms must complete and file a Form C with the SEC. Form C is similar in spirit to Form S-1 that is filed for traditional IPOs, in that it requires companies to provide a description of the business, its ownership structure, and financial information. However, Form C generally requires less information. For example, while Form S-1 filings require three pre-IPO years of audited financial statements, Reg CF filers must include only up to two years of prior activity; see Figure IA.1 for examples. The level of assurance provided for these financial statements also varies with the amount the company intends to raise. In most cases, audits are not provided; instead, financial statements are certified by management or reviewed by a certified public accountant (CPA). Filing Form C with the SEC initiates an offering, which is then hosted by an online listing platform.

On Form C, a Reg CF issuer must indicate minimum and maximum target fundraising amounts and select a deadline for the offering. Through 2020, firms could raise up to $1.0 million over a 12-month period; this amount has since increased to $5.0 million. Reg CF offerings are "all-or-nothing" in that the issuer collects all the money raised if it meets or exceeds the intended target, but otherwise receives no funds. Once the offering is complete, which is the earliest of when the maximum target is raised or the deadline is reached, the issuer is required to file Form C-U and disclose the total amount raised. Successful issuers are also required to publicly file annual reports (Form C-AR) for one year, three years, or an indefinite period after the offering, depending on the number of shareholders and assets.[5]

[5]Only one year is required if the issuer has fewer than 300 holders of record; 3 years are required if total assets do not exceed $10 million. The requirement to file Form C-AR also ends if the issuer becomes public, liquidates, or sells/redeems all securities.

2.2 Data

2.2.1 Equity crowdfunding filings

Data on equity crowdfunding offerings come from Forms C, C-U, and C-AR available on the SEC's EDGAR. A subset of the information contained in these forms is provided in machine-readable format by the Division of Economic and Risk Analysis. We supplement these data with hand-collected information from the offering memorandum and listing platforms. This hand-collection is necessary to either fill in information often missing on EDGAR (e.g., the amount raised), or to obtain additional information not provided on EDGAR (e.g., the industry of the issuer).[6]

We assign each firm to an industry based on their business description. Because the SEC regulatory filings do not provide industry details, we collect business descriptions for all issuers from Form C and use the GPT 3.5 Turbo API to assign a 3-digit NAICS based on the first 500 words of the business description. We then use the coarser 2-digit sectors in our empirical analyses to retain a manageable number of industry classifications given the size of our data.[7]

[6] In practice, many issuers do not report the amount raised on Form C-U. This lack of compliance is an important reason why we supplement data from SEC filings with hand-collected information from listing platforms and from KingsCrowd, a leading data aggregator, to ensure that we correctly identify successful offerings.

[7] Specifically, we use the following prompt: `You will be provided with business descriptions, and your task is to determine the corresponding 3-digit NAICS industry code. Return the results in the following JSON format:`

```
["index": ..., "naics": ...]
JSON =
```

and set the temperature to 0 to make the algorithm's output less subject to random variation. See de Kok (2023) for guidelines on using large language models for research. To ensure the consistency and quality of the industry classification, we also employ a second approach, in which we use business descriptions to manually assign keywords to each issuer and then map each keyword to a 3-digit NAICS code. For example, we assign Aptera, a company that manufactures solar-powered cars, NAICS code 336 for Transportation Equipment Manufacturing. The two classification schemes lead to overlapping 2-digit NAICS sectors for over 54% of observations. Of the remaining observations, more than 20% of the differences stem from classifications into similar sectors (e.g., retail vs. wholesale trade). We use the industry classification generated by GPT for the remainder of the analysis since it takes into account more information and is easier to reproduce, but the results are qualitatively similar with the classification based on industry keywords.

2.2.2 Business survival

We measure firm survival through April 30, 2023 using the business status of Reg CF issuers from the OpenCorporates database. To do so, we use the OpenRefine reconciliation algorithm provided by the OpenCorporates API to match Reg CF issuers with business status from state registers. We match based on name and either the state of incorporation or business operations. For cases where business status is missing, which is mostly for companies registered in Delaware, we measure future survival based on whether the company's website is still active.

2.2.3 Traditional funding sources

Our empirical tests include a comparison of equity crowdfunding with two traditional funding sources: SBA loans and VC investments. We download SBA data from the SBA website for the period 2010 to December 2022. We use Refinitiv to obtain data on VC deals for the period 2010 to May 31, 2023. In addition to obtaining these data as comparison groups for equity crowdfunding firms, we also match issuers with SBA loan recipients and VC-funded companies based on their name and state of incorporation. We first obtain a list of candidate matches for each issuer by fuzzy-matching on names, and then we manually review the best matches for each issuer, retaining those for which the names and states match.

2.2.4 Reg CF awareness and entrepreneurial interest

We measure local awareness of Reg CF with Google searches for "Wefunder + StartEngine," the two largest and most well-known equity crowdfunding platforms.[8] These searches could be driven by entrepreneurs seeking to raise capital via Reg CF or by potential investors, but in both cases, a higher search index reflects greater awareness of Reg CF as a way to raise capital. Similar to Barrios et al. (2022), we measure entrepreneurial interest with Google searches for "entrepreneurship." The intuition is that individuals interested in starting a new

[8]We excluded the platform Republic because of its alternate meanings that would skew Google searches.

company are likely to seek information on entrepreneurship via Google.

Because the actual search volume on Google is not publicly available, we use the Google Trends index that ranges from 0 to 100 based on the relative popularity of the specified search term across different geographic regions in a given time period. We collect the Google Trends index annually between 2010 and 2022 across Nielsen's Designated Market Areas (DMAs) and match the DMAs to counties based on a publicly available crosswalk.[9] While the index is scaled and its magnitude does not represent actual search volume, we can still use it to compare the relative popularity of a search term across counties in a given year.

2.2.5 Local area activity

Because entrepreneurship and economic activity is driven in part by population dynamics, wealth, access to capital, and employment, we obtain annual county-level data to construct control variables for the local spillover tests. specifically, we obtain information on population and per-capita income from the Bureau of Economic Analysis, and unemployment rates from the BLS Local Area Unemployment Statistics (LAUS). Data on bank branches and bank deposits come from the FDIC Summary of Deposits data (SOD).

2.3 Sample Construction and Descriptive Statistics

We identify 6,557 offerings for 5,617 firms from May 2016, the inception of Reg CF, through December 2022. To ensure sufficient post-offering data, we drop offerings that start in 2021, as well as offerings that end in 2022 or later. Due to the requisite hand-collection, we focus on offerings on the top three platforms in terms of deal volume, dropping an additional 1,467 offerings. We further drop offerings related to foreign issuers, token securities, firms that withdraw their offering, and offerings that erroneously exclude financial information. The final sample includes 1,612 offerings for 1,442 firms. See Table IA.1 for details.

Figure 1 Panel A depicts the rapid growth of equity crowdfunding over the sample period.

[9] The crosswalk can be found at: https://www.kaggle.com/code/kapastor/google-trends-dma/input.

The green (pink) bars show the annual number of offerings without (with) sample restrictions. The number of annual offerings has increased over eight fold, from 168 in 2016 to 1,452 in 2022. Our sample follows a similar growth pattern and captures a substantial proportion of all offerings (between 51% and 62%), confirming that our focus on the top three equity crowdfunding platforms – Wefunder, StartEngine, and Republic – is likely representative of equity crowdfunding in the U.S.

Panel B plots the annual observations for our main sample, with the yearly number of *successful* offerings (blue bars) shown next to the total number of offerings (pink bars repeated from Panel A). The number of successful offerings generally increases over time, with a slight dip in 2019. The black line plots the total amount raised among our sample firms in each year, which has grown from approximately $22 million in the second half of 2016 to almost $225 million in 2020.

Figure IA.2 shows the geographic diffusion of equity crowdfunding across the U.S. over the sample period for our sample. In 2016, Reg CF offerings primarily occurred in higher population centers (e.g., Los Angeles, San Francisco, New York, Boston). However, by the end of 2020, offerings occurred across the United States, including in the Southeast, the Midwest, Texas, and the Pacific Northwest.

Table 1 Panel A reports descriptive statistics for the sample of Reg CF offerings. The rate of success in our sample is 68.9%, amounting to 1,111 offerings for 973 distinct issuers. The average (median) successful offering raises $404 ($172) thousand of additional capital. Approximately 32% of issuers are listed as inactive in subsequent years. The average (median) issuer is 3.16 (2.03) years old, with 1.9 founders and 6.0 employees. Further underscoring the small size of these companies, the average issuer has average (median) assets of $360 thousand ($67 thousand), with average (median) cash balances of $86 thousand ($11 thousand) and revenue of $389 thousand ($5 thousand). Most issuers in the sample are loss firms, with negative values for both mean and median income.

In Panel B, we tabulate firm-level outcomes by Reg CF success. In particular, we find that 75.1% of the issuers with successful offerings were still active at the end of April 2023, compared to only 51.9% for failed offerings. Likewise 7.3% (2.0%) of successful issuers obtain subsequent VC funding (SBA loans), compared to only 1.2% (0.4%) for failed offerings. Chi-squared tests reject the null of independence between Reg CF success and subsequent firm outcomes. While descriptive, this tabulation motivates the analysis in Section 4, in which we quantify the impact of Reg CF success on firm survival and subsequent performance.

Panel C reports descriptive statistics for county-level variables between 2010 and 2022. The median county-year observation has a Google Trends index of 17 for "entrepreneurship" and two SBA loans, but no early-stage VC deal nor Reg CF offering. The median observation also has per-capita income of $39.1 thousand, a population of 26.1 thousand, 11 bank branches, and an unemployment rate of 5.8%. Given their right skew, we log-transform county-level variables other than Google searches for the remaining analyses.

3 Improving Access to Capital

We descriptively assess the factors motivating firms to seek external financing via equity crowdfunding. Specifically, we explore whether equity crowdfunding addresses three funding gaps attributable to: (i) relatively strict *business qualification* requirements, (ii) *spatial concentration* of traditional financing sources, and (iii) biases related to *founder demographics*. Throughout this section we compare Reg CF to SBA loans and VC investments as relevant benchmarks.[10]

[10] Consistent with this analysis, the SEC identified the lack of access to bank credit and VC investments due to financial, industry, or geographic factors as potential motivations for entrepreneurs to use Reg CF (SEC, 2015).

3.1 Business Qualification

3.1.1 Industry composition

We first evaluate the industry composition of equity crowdfunding. Figure 2 plots in purple the industry distribution of Reg CF issuers in our sample at the 2-digit NAICS level. The figure portrays notable differences in composition compared to VC (teal) and SBA (yellow). For example, the most common sectors for Reg CF issuers are manufacturing (32%), professional services (15%), and information (15%) firms. By comparison, over 52% of venture capital recipients are in the information sector, but only 1% of SBA loan recipients. We also observe moderate proportions of Reg CF issuers and SBA loan recipients in retail trade, arts/entertainment, and accommodation/food services, but few VC investments in those sectors. These sectors in which either SBA or VC are essentially absent highlight the potential for Reg CF to improve access to capital.

3.1.2 Lending criteria

We next focus specifically on SBA loans, which are subsidized by the U.S. government and provide an important source of capital for entrepreneurial firms (see Robb and Robinson, 2014 for survey evidence on the importance of formal bank credit for entrepreneurs). These loans typically rely on historical revenue, collateral, and the owner's credit score or personal guarantees to ensure the credit-worthiness of the borrower.

To understand whether these traditional SBA loan requirements preclude crowdfunding firms from obtaining external financing, we estimate the proportion of the Reg CF issuers that would qualify for formal bank credit. While the SBA website lists general principles for eligibility, it does not specify minimum thresholds, thereby leaving the final determination to the lender. Thus, we access websites of several online banks and loan marketplaces to compile typical requirements for small business loans and create a minimum profile for a company to qualify. Table IA.2 provides the requirements for six different websites. We focus on requirements for profitability, revenue, age, and the ability of a firm to pay debt service costs (i.e., the debt service coverage ratio or DSCR).[11] As shown in the appendix, the most lenient lending requirements are from SmartBiz, an online provider of SBA loans. This company typically requires firms to be two years old, to have at least $50,000 in revenue, and to report positive income.

These requirements, as well as a typical debt service coverage ratio of 1.15, form the basis for Table 2, Panel A, in which we determine the proportion of Reg CF issuers that would have qualified for SBA loans based on the financial information provided at the time of fundraising. Only 9.8% of issuers in our sample are profitable (column (1)), 37.9% have revenues in excess of $50,000 (column (2)), over 50% are at least two years old (column (3)), and only 3.3% meet the minimum debt coverage service ratio (column (4)).[12] Column (5) shows that only 5.27% of crowdfunding offerings would qualify based on meeting the income, revenue, and age requirements. That proportion drops to 1.61% in column (6) when also imposing the DCSR requirement. In short, most Reg CF issuers would not qualify for SBA loans at the time of their offering, highlighting the need to seek alternative sources of capital.

3.2 Spatial Concentration

Access to capital has long been a function of a firm's proximity to banking or venture capital centers. For example, banking is relationship-based and heavily reliant on brick-and-mortar branches.[13] Likewise, venture capital has mostly been clustered in high population centers because geographically close investments are easier to monitor (Chen et al., 2010). In con-

[11] Many lenders also require good credit and no recent bankruptcy, but because these are not easily measured for the sample firms, we exclude these criteria. Thus, the requirements we use may over-estimate the ability of companies to qualify for loans.

[12] We compute the debt service coverage ratio as net income, divided by the sum of short term debt and the interest cost on long-term debt, including the target amount to be raised. We assume an interest rate of 8% corresponding to the average prime rate of 4.26% between 2016 and 2020, plus a 3.74% premium at the low end of the 3% to 6.5% range for the maximum premium allowed by the SBA.

[13] Access to credit has become particularly problematic since the 2008 financial crisis, as many banks consolidated or failed, leaving areas – mostly low-income – with limited banking presence, so-called banking deserts (Morgan et al., 2016). In the past few years there has been an uptick in small businesses seeking loans from online lenders (32% of applicants), but those loans can have worse terms than their brick-and-mortar counterpart.

trast, Reg CF offers a fully online fundraising process, potentially eliminating geographical hurdles to capital.

We perform two analyses to assess whether Reg CF has expanded geographic access to capital relative to SBA loans and VC. We first calculate a locational Gini coefficient across time following Sorenson et al. (2016):

$$Gini_t^k = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}|x_{i,t}^k - x_{j,t}^k|}{2N\sum_{j=1}^{N} x_{j,t}^k} \tag{1}$$

where $k \in \{Reg\ CF,\ SBA\ loans,\ VC\ deals\}$, N is the number of counties, and $x_{i,t}^k$ is the number of successful capital raising events in county i at time t via channel k normalized by the population of county i. A Gini coefficient equal to one indicates extreme concentration (all capital raising events happen in one county), while a coefficient of zero indicates an even distribution across all counties.

We report these statistics in Table 2 Panel B. We observe that Reg CF is highly concentrated between 2016 and 2020, with an average Gini coefficient of 99.0% in column (1). This is even higher than early-stage VC deals (defined as "seed" and "early stage" in Refinitiv), which report an average Gini coefficient of 97.7%. In contrast, SBA loans have an average Gini coefficient of 58.5%.

The high levels of concentration suggest that Reg CF has not diversified the allocation of capital across the country as suggested by proponents of the regulation. However, trends show promising patterns for more recent periods; in column (2), we observe that crowdfunding concentration declines by 1.4 percentage points over five years. This change appears larger than the change in venture funding (1.0 percentage point decline) and starkly contrasts with changes in SBA loan concentration, which *increases* by 4.1 percentage points between 2016 and 2020. Figure IA.3 depicts these trends by plotting the change in locational Gini coefficients over an extended period of time and for a larger sample of Reg CF offerings.Analysis of concentration across zip codes *within* the top 30 counties by number of offerings further confirms these patterns; see columns (3) and (4).

In a second analysis, we study the geographic overlap with SBA loans and early-stage VC deals. Figure 3 Panel A plots the location of Reg CF offerings against the distribution of SBA loans across the country. A few patterns emerge. First, Reg CF offerings are concentrated on the coasts and a few other major population centers (i.e, Texas, Chicago, Denver), while SBA loans are much more dispersed throughout the country. Second, there is substantial overlap between SBA loans and Reg CF offerings, with greater density for both in the largest population centers. We find similar patterns in Panel B when comparing to early-stage VC deals. Figure IA.4 depicts the overlap across zip codes *within* the two counties with the most Reg CF offerings – Los Angeles and New York. There is less overlap *across* zip codes, with Reg CF funds flowing to areas receiving relatively less investment from banks or VCs. Thus, while Reg CF is very concentrated in counties served by traditional financing channels, this descriptive analysis suggests possible spatial diversification within a locality.

3.3 Founder Demographics

A growing body of evidence shows that banks are biased against women- and minority-owned businesses, resulting in lower approval rates and distrust of the banking system among minority entrepreneurs (e.g., Fairlie et al., 2022; Blanchflower et al., 2003). Proponents of crowdfunding suggest that these biases may potentially be reduced because anyone can participate in the Reg CF crowd, possibly distributing funding across a more diverse set of businesses (Mollick and Robb, 2016).

We use three data sources to provide descriptive evidence on whether equity crowdfunding provides capital to a more diverse set of entrepreneurs than traditional fundraising channels. First, we obtain the names of equity crowdfunding founders and executives who are required to sign Form C, and we identify their gender and race using the `predictrace` package in R.[14] Second, starting in 2017, the SBA provides annual statistics on the number

[14] This package produces a prediction of gender and race based on millions of names reported to the U.S.

of loans issued to businesses with female and minority owners. Third, Pitchbook's U.S. VC female founders dashboard reports annual statistics on the number of businesses with female founders receiving venture capital.[15]

Table 2 Panel C shows that 28.8% of Reg CF offerings in our sample have a female executive (column (1)), and 23.6% have a non-white executive (column (4)). These proportions increase to 29.9% and 24.2%, respectively, once we restrict the sample to successful offerings. This means that founders with diverse demographic backgrounds are more likely to receive funding via equity crowdfunding. In addition, Panel C reveals heterogeneity across platforms: 39.1% (35.7%) of successful offerings on Republic have a female (non-white) executive, whereas on StartEngine these proportions are 18.8% and 18.5%, respectively. Finally, the last two rows of Panel C suggest that successful Reg CF offerings have a slightly less diverse executive team than SBA loan recipients (by 1.1 and 1.4 percentage points for female and non-white executives), but they are more diverse than VC-backed businesses in terms of female ownership (by 5.3 percentage points). In summary, crowdfunding provides capital to businesses owned by female and minority entrepreneurs at a similar rate as SBA – and a higher rate for female-owned businesses than VC – but the focus on diversity is highly platform-specific.

4 Effects on Survival and Subsequent Performance

We next determine whether Reg CF alleviates the financial constraints of small businesses, enabling viable firms to survive and grow.

Census. To assess the accuracy and sensitivity of this method, we also independently selected a random sample of executive names, visually checking the gender and race based on profile pictures, available either on the firm's crowdfunding website or on other sites. We find that the two methods lead to the same classification for approximately 90% of cases, validating the use of the R package to predict gender and race. See also Chen et al. (2022), who use this methodology to determine the race of Board of Director members.

[15] To facilitate the comparison of potentially changing demographic trends across different data sources, we report numbers for similar time periods: years 2016 to 2020 for equity crowdfunding and VC deals, and years 2017 to 2020 for SBA loans.

4.1 Empirical Design

4.1.1 Baseline regression

We face an inherent selection bias when studying the effect of equity crowdfunding on subsequent performance: the choice to seek capital via equity crowdfunding, as well as the timing of the offering, are endogenous. For example, equity crowdfunding may be a last resort for firms on the brink of bankruptcy, or a source of capital for young innovative firms, or both. Thus, we compare firms with a successful offering to firms that also tried to raise capital via Reg CF but were unsuccessful. Our baseline specification is:

$$Y_i = \beta_1 \cdot Success_i + \gamma_1 \cdot X_i + quarter_i + industry_i + \epsilon_{1i} \tag{2}$$

where Y_i is one of three measures of business outcomes capturing subsequent survival and access to capital, as described in Sections 4.2 and 4.3, respectively. $Success_i$ is one of two measures of crowdfunding success, and X_i is a vector of offering-specific controls. Because we measure Y_i at the same point in time for all offerings, we include offering-year-quarter fixed effects to subsume differences in the length of the post-offering period. We also include industry fixed effects to subsume differences in funding across industries. We cluster standard errors by offering-year-quarter.

We measure $Success_i$ in two ways. First, we use an indicator equal to one if the issuer has a successful offering (i.e., raised capital in excess of the target amount reported in its offering documents), and zero otherwise. Second, we calculate a measure equal to the logarithm of one plus the amount raised, scaled by the targeted amount. This allows us to compare firms based on the extent to which the capital raised exceeded the minimum threshold, and capture greater variation in successful fundraising as compared to the indicator variable.

We include several control variables when estimating Eq. 2 following prior work (Bogdani et al., 2022; Gong et al., 2022; Donovan, 2021; Signori and Vismara, 2018). The variables *VC before* and *SBA before* control for previously received venture or bank funding, as a signal of more viable companies. *RegCF before* is an indicator equal to one for companies with multiple offerings. *Age* is equal to the number of years the firm has been in business. We control for the size of the issuer with the number of founders and employees (*# of founders* and *# of employees*, respectively) and with total assets (*Assets*). *Cash* controls for the amount of internal liquidity the firm has at the time of the offering. We include *Total debt*, *Revenue*, and *Income* as additional financial characteristics reflecting the firm's financial status and the demand for external capital.[16] We winsorize financial variables at the 1st and 99th percentile to mitigate the influence of outliers. We also include *CPA engaged*, an indicator for whether the issuer engaged a CPA to review or audit its financial statements (Bogdani et al., 2022; Gong et al., 2022). Beyond its documented relation with offering success, CPA involvement could signal the issuer's intention to pursue traditional fundraising channels for which reviewed financial statements are often required. Finally, we include *Convertible security* and *Debt security*, which are indicator variables equal to one if the firm uses crowdfunding to issue securities other than straight equity. All variables are defined in Table A.1.

4.1.2 Instrumental variable

Unobserved characteristics correlated with a successful offering could affect the firm's future survival and access to venture or debt capital. For example, if successful issuers have more viable business plans or are better managed, OLS estimates could be biased to the extent that these effects are not otherwise controlled for in Eq. 2. We use two-stage least squares (2SLS) to address this endogeneity concern, instrumenting for crowdfunding success with the number of competing offerings on the same platform during a 3-month window from the start of the specified offering.[17]

[16] We do not scale by assets because it would induce a small denominator problem in many companies.

[17] Signori and Vismara (2018) use a similar instrument to study the incidence of acquisitions, secondary offerings, and failures after crowdfunding offerings in a small sample of U.K. companies. Our analysis differs not only because of the much larger sample of U.S. firms, but also because of its focus on subsequent venture and SBA funding, as well as examination of local area effects.

For the first stage, we estimate the following regression:

$$Success_i = \beta_2 \cdot IV_i + \gamma_2 \cdot X_i + quarter_i + industry_i + +\epsilon_{2i} \tag{3}$$

where IV_i is the instrumental variable, which is computed as the number of active Reg CF offerings in the first three months after the launch of offering i and on the same platform.[18] In the second stage, we regress the post-offering outcomes on the instrument and controls:

$$Y_i = \beta_3 \cdot \widehat{Success}_i + \gamma_3 \cdot X_i + quarter_i + industry_i + \epsilon_{3i} \tag{4}$$

where $\widehat{Success}_i$ are the predicted values of Reg CF success from the first stage.

To be valid, the instrument must (i) affect the likelihood of Reg CF success and (ii) only affect subsequent business outcomes – Y_i – through the likelihood of success (i.e., the exclusion restriction). With respect to the first criterion, there are two main reasons why the number of active offerings should be (negatively) associated with the likelihood of success: congestion and salience. First, when more issuers compete for a limited amount of capital from Reg CF investors, it is more difficult for any particular firm to raise capital. This congestion problem is amplified in this setting due to SEC rules that cap the amount investors can invest across all offerings in a given calendar year.[19] Second, listing platforms can only display a small number of offerings on their front page. Thus, when there are more active offerings, some offerings will receive less attention from investors. Figure IA.5 provides an example of the homepages from Wefunder and Republic, documenting the limited space for investors to observe particular offerings at a given time.

With respect to the exclusion restriction, because we include quarter and industry fixed effects, our analyses compare issuers in the same industry that are raising capital at the

[18] We use OLS even though the dependent variables are binary because consistency of the second-stage estimation is not dependent on the functional form of the first-stage (Angrist and Krueger, 2001).

[19] At the time of writing, non-accredited investors with income or net worth below (above) \$124 thousand can invest up to the greater of 5% (10%) of their income or net worth not to exceed \$124 thousand. These caps were lower for most of the sample period in this paper.

same time, but that are also experiencing different levels of competition for Reg CF capital. These issuers likely face similar economic forces impacting their subsequent performance and fundraising, especially after controlling for observable differences in issuer characteristics (e.g., age, available cash, and assurance provided on financial statements). Thus, after controlling for industry, time, and firm-specific characteristics, the number of competing offerings is plausibly uncorrelated with the issuer's subsequent survival and fundraising, except through the success of the Reg CF offering. In section 4.4, we conduct several analyses to further demonstrate the validity of the instrument.

Table 3 presents results from the first-stage estimation, where we use the number of competing offerings to predict crowdfunding success. The instrument exhibits the predicted negative sign: the number of competing offerings is negatively associated with the likelihood of a *Successful offering* in column (1) and the amount raised in excess of the target in column (2). F-statistics of 69.4 and 120.0 provide strong support that the instrument is relevant. Control variables exhibit the expected sign: factors positively correlated with offering success include *SBA before*, *Reg CF before*, *Cash*, and *CPA engaged*. Offering debt or convertible securities instead of equity is negatively associated with offering success. Figure IA.6 presents graphical evidence on the univariate association between Reg CF success and the number of competing offerings, confirming that the probability of success declines as the number of competing offerings increases.

4.2 Reg CF Success and Firm Survival

Because more than 30% of companies fail within the first three years, being active three or more years after crowdfunding is a substantial hurdle (BLS, 2016). As such, the first firm outcome Y_i we consider is *Inactive*, an indicator equal to one if the firm is no longer in business as of April 2023 (the date we obtained business activity data). If Reg CF alleviates financial constraints, we expect a higher rate of survival among successful offerings ($\beta < 0$).

Table 4 reports results from OLS and 2SLS estimations. In columns (1) and (3), we find that issuers are between 17.1 and 27.6 percentage points less likely to be listed as inactive after a successful offering. For comparison, Kerr et al. (2014) find that survival rates increase by a similar amount, 20 to 25 percentage points, after receiving angel financing. Given BLS (2016) reports a survival rate of approximately 50% after six years, which is the median age issuers would have been in April 2023, our estimates suggest a 34% to 55% increase in the likelihood of survival. We find consistent results in columns (2) and (4) using the continuous measure of Reg CF success.

The larger magnitudes for the 2SLS estimates can be explained by the fact that the 2SLS coefficients capture the effect on issuers for which the treatment (i.e., the number of competing offerings) affects crowdfunding success, while OLS coefficients capture the average effect across the full sample (Becker, 2016; Card, 1999). Specifically, the 2SLS coefficients capture the effect for issuers that would have been successful were it not for the many competing offerings.[20]

4.3 Viability of Successful Issuers

Our finding that a successful Reg CF offering increases the likelihood of survival raises the question of whether the crowd provides capital to firms with good growth prospects, or instead prolongs the life of poor quality firms. We address this question with two different tests.

4.3.1 Subsequent financial growth

First, we examine the post-offering financial performance of successful issuers. Because crowdfunding firms are not publicly traded, we unfortunately cannot estimate market returns to assess the efficiency of the crowd's investment decision. Instead, we calculate post-offering

[20] The primary concern that we address when using 2SLS is that firm viability is an unobserved and important factor correlated with both the likelihood of Reg CF success and firm survival. As such, its omission from Eq. 2 would induce a negative bias for the OLS coefficient β_1, as it would capture some of the effect of firm viability on survival. Because the IV estimation corrects for this bias, we would expect the 2SLS coefficients to be smaller in magnitude than the OLS coefficients. The fact that we find larger magnitudes with 2SLS suggests that this is not the dominant force driving the difference in coefficients.

financial growth as one metric of future performance.[21] If most firms raising capital via Reg CF are "lemons" or frauds, we should find little to no growth in non-cash assets and revenue following the offering. On the other hand, we expect viable firms to use the offering proceeds to acquire assets and generate revenue. We use data from publicly filed annual reports (Form C-AR) to measure financial growth. These data are available for approximately 61% of successful issuers in the first year post-offering, and 40% in the second year.

Table 5 reports the average and median growth in non-cash assets and revenue from year $t-1$ to year $t+1$, where t is the year in which the offering took place. We use non-cash assets to explicitly measure the extent to which cash raised in the offering was invested by the firm and not only retained as cash holdings. Revenue growth captures whether there is increasing demand for a firm's products and services. Between years $t-1$ and t, non-cash assets increase by \$144 thousand on average (median of \$10 thousand), and revenue increases by \$138 thousand on average (median of \$6 thousand). Note that in some cases, period t contains only a few months after the close of the offering. Thus, we also measure growth through $t+1$ and find, as expected, larger effects: non-cash assets increase by \$509 thousand on average (median of \$43 thousand), and revenue increases by \$499 thousand (median of \$36 thousand). The average and median increase in non-cash assets and revenue is consistent with successful issuers using the capital raised via Reg CF to purchase new assets and finance growth, particularly when considering the average amount raised of \$404 thousand from Table 1.

While helpful in assessing the viability of the issuers funded by the crowd, we acknowledge that this test estimates financial growth only for issuers filing annual reports. If only the healthiest issuers comply with the filing requirement, these estimates could suffer from upward bias. Thus, we conduct an additional test to assess the crowd's investment decisions.

[21] This approach is consistent with prior work that shows a strong association between the valuation of VC-backed firms and financial statement information (Armstrong et al., 2006).

4.3.2 Subsequent access to capital

Specifically, we assess whether "smart money" provides follow-on capital to issuers that successfully raised capital from the crowd. VC firms specialize in financing risky startups, with VC-backed companies having a lower failure rate (Puri and Zarutskie, 2012), and accounting for an abnormally large proportion of IPOs (Kaplan and Lerner, 2010), in part due to a careful deal selection process (Gompers et al., 2020). Likewise, banks screen businesses based on their creditworthiness, and Gonzalez and James (2007) show that tech firms with banking relationships prior to an IPO survive longer and grow faster. As such, being financed by VCs or banks serves as a measure of success for startups in need of external capital.[22]

To conduct this test, we re-estimate Eq. 2 and 4, replacing the dependent variable Y_i with two measures of external financing. The first measure is *VC after*, which is an indicator variable equal to one if the issuer receives venture capital investment after the start of the Reg CF offering. The second measure is *SBA after*, which is an indicator variable equal to one if the issuer is approved for an SBA loan after the start of the Reg CF offering.

To the extent that successful offerings signal strong customer demand or provide bridge financing until viable issuers can obtain alternative funding, we should observe a positive association with access to VC and bank capital. We expect this association to be stronger for VC because many issuers in the sample are risky startups that are unprofitable and have low collateral. According to the model of Ueda (2004), startups with those characteristics may not be able to obtain bank credit at favorable terms and prefer VC financing.

Table 6 presents the results of the OLS and 2SLS estimations. Panel A focuses on VC. In columns (1) and (3), we find that issuers are between 4.4 and 21.7 percentage points more likely to raise capital from VC firms after a successful offering. Based on the fact that 4.1% of issuers have received VC investments prior to crowdfunding (Table 1), this effect implies that the likelihood of VC investment more than doubles after a successful offering. Columns (2) and (4) report consistent effects with the continuous measure of Reg CF success.

[22] Ewens and Townsend (2020) use a similar approach to study gender bias in early stage investors.

Panel B presents mixed results for SBA loans. The OLS estimate in column (1) suggests a 1.9 percentage point increase in the likelihood of obtaining an SBA loan for successful issuers. As 4.0% of firms have SBA loans prior to crowdfunding (Table 1), this translates to a 47.5% increase. However, we observe statistically insignificant coefficients in columns (2) through (4). These weak effects for SBA loans could be driven by issuers remaining unable to obtain bank credit despite a successful offering.[23] Alternatively, many issuers in the sample may prefer to meet their financing needs with non-debt securities (Ueda, 2004; Kerr and Nanda, 2009a), in which case equity crowdfunding could substitute for SBA loans.

Taken together, our findings of subsequent financial growth and increased likelihood of VC financing provide validation for the crowd's investment decisions, and extend Mollick and Nanda (2016)'s finding that the crowd is "wise" to the context of equity crowdfunding.

4.4 Robustness

We perform several additional analyses to confirm the observed results and further assess the validity of the instrument and report the results in Table IA.3. One concern when instrumenting with the number of competing offerings, which includes both offerings active at the time of the focal offering, as well as new offerings launched within the three-month window of measurement, is that skilled entrepreneurs could strategically time their offering to occur when there is less competition. Such strategic timing would violate the exclusion restriction. This strategic timing is unlikely because most issuers have very little cash to finance their operations and cannot wait for the opportune time to raise capital (the median issuer has $11 thousand in cash). Nonetheless, we perform a robustness test in which we define the instrument to be equal to the number of *new* (not concurrent) offerings launched on the same platform, which entrepreneurs would be unlikely to anticipate at the time of their own offering. Column (1) of Panels A and B repeats the first and second stage results from

[23]Untabulated analyses reveal that there is almost no overlap between issuers that receive VC funding and issuers that receive SBA loans, suggesting that these effects (or the lack thereof) are driven by different groups of issuers.

our main specification for ease of comparison, and column (2) reports the coefficient estimates from using this alternative construction for the instrument. Inferences are unchanged.

Second, we estimate results after constructing the instrument based on the number of active offerings within both shorter and longer windows. We select one month because prior work in rewards-crowdfunding shows that amount of capital raised in the initial weeks of an offering predict success (Etter et al., 2013), and and we also use six months because 75% of offerings last less than 179 days. Columns (3) and (4) of Panel A indicate a strong instrument, with F-statistics ranging from 29.4 to 104.6 across the two columns. In Panel B, we continue to observe consistent results, but with slightly weaker effects for *Inactive* when using the instrument based on the 6-month window (t-statistics of -1.52 and -1.56).

Third, we address the concern that platforms may differ based on how they screen potential issuers, and that such differences could affect subsequent survival, VC fundraising, or access to SBA loans. To do so, we repeat the analysis but include platform fixed effects, although we caution that doing so absorbs a substantial amount of variation because the instrument is also constructed at the platform level. We present the first and second stage results in column (5) of Panels A and B. We find qualitatively similar results, but the instrument becomes weaker, especially in the case of the binary measure of success (F-stat of 1.25). Two additional tests mitigate concerns about this weaker instrument. First, when using the continuous measure of success, we observe that the instrument is moderately strong in the first stage (F-stat of 8.24), and that the second stage coefficients are statistically significant and of similar magnitudes as those reported in the main specification. Second, we estimate reduced form regressions which are not biased in the case of weak instruments (Chernozhukov and Hansen, 2008). These tests regress business outcomes directly on the instrument as follows:

$$Y_i = \beta_4 \cdot IV_i + \gamma_4 \cdot X_i + quarter_i + industry_i + +\epsilon_{4i} \tag{5}$$

The exclusion restriction implies that the reduced form coefficient β_4 should equal zero if Reg CF success has no impact on subsequent performance and should be statistically significant otherwise. Panel C reports these estimates for the different specifications, including those with platform fixed effects in column (5). Consistent with our main results, we find that even when we include platform fixed effects, the number of competing offerings has a statistically significant positive (negative) association with subsequent survival (venture capital), and no association with subsequent SBA loans.[24] Thus, the reduced form estimates further confirm that Reg CF success helps issuers remain in business longer and improves access to VC.

5 Effects on the Local Area

In addition to the direct effect on issuers, equity crowdfunding offerings could also lead to positive spillovers on the local economy by providing relevant information to potential investors and entrepreneurs. We study two channels through which this could occur: increased interest in entrepreneurship, and increased private sector investment in local businesses.

5.1 Empirical Design

While Reg CF became available in all U.S. counties during the second quarter of 2016, counties differ in their exposure to equity crowdfunding as a fundraising channel across the sample period. We use a staggered difference-in-differences specification, where the treatment captures exposure to equity crowdfunding. We address concerns about standard two-way fixed effects specifications by following Sun and Abraham (2021), where the cohorts correspond to the years in which equity crowdfunding offerings take place.[25]

[24]Note that the sign of the coefficients in the reduced form should be opposite those reported in 2SLS because the instrument *decreases* the probability of success.

[25]This specification improves on the commonly used two-way fixed effects regression with leads and lags of the treatment when the timing of the treatment varies across units (see Baker et al., 2022 for a comprehensive discussion).

Specifically, we estimate the following staggered difference-in-differences regression:

$$Y_{ct} = \alpha_c + \mu_{st} + X_{ct} + \sum_{g \notin \mathcal{C}} \sum_{l \neq 1} \beta_{gl} \cdot (\mathbb{I}\{\mathcal{G}_c = g\} \cdot D^l_{ct}) + \epsilon_{ct} \tag{6}$$

where Y_{ct} is one of four measures of local entrepreneurship or financing described in Sections 5.2 and 5.3. The subscript c denotes the county in state s, and t is a year. The time period in which a county c receives the treatment is $\mathcal{G}_c$, the amount of time since treatment is denoted by l, and cohorts are denoted by g, where $\mathcal{C}$ captures the cohort of counties that are never treated. $D^l_{ct} = \mathbb{I}\{t - \mathcal{G}_c = l\}$ is an indicator variable for a county c in cohort $\mathcal{G}_c$ that is l periods from the treatment in period t. This specification estimates cohort-specific coefficients for each period of time; the estimates are then averaged across cohorts, or across cohorts and time, with weights corresponding to the size of each cohort.

We consider two different measures of a county's exposure to equity crowdfunding: (i) the occurrence of a Reg CF offering (regardless of its outcome), and (ii) the occurrence of a successful Reg CF offering. While successful offerings are likely to have stronger spillover effects than unsuccessful ones, we accurately measure success only for the offerings from the sample used in the previous analyses (i.e., the top 3 crowdfunding platforms and through 2020). Limiting our analysis to this sample could potentially introduce non-random noise in the measurement of the timing and exposure of certain counties to equity crowdfunding. Consequently, in the following analysis, we measure a county's exposure to equity crowdfunding based on the occurrence of *any* Reg CF offering, but we report the robustness of our results to this choice in the Appendix. Figure 4 illustrates the diffusion of equity crowdfunding over time – i.e., the treatment intensity leveraged in our tests – and shows that the different measures of exposure follow similar trends.

For Eq. 6 to identify the average treatment effect of equity crowdfunding on the treated counties, the error term ϵ_{ct} must not be correlated with our measure of exposure to equity crowdfunding in county c. However, counties with Reg CF offerings differ significantly from those without along several demographic dimensions, including poverty rates, higher median incomes, and a larger population (see Table IA.4). Thus, we include county fixed effects (α_c), which subsume time-invariant differences across counties. We also control for national and state-specific economic changes over time with state-year fixed effects (μ_{st}). Further, we include time-varying county controls (X_{ct}): per-capita income, population, the number of bank branches, bank branch deposits, and the unemployment rate.

5.2 Reg CF Awareness and Interest in Entrepreneurship

First, we analyze whether equity crowdfunding activity provides relevant information to potential entrepreneurs. The occurrence of Reg CF offerings in an area can increase awareness about small businesses and this new source of capital among the local community, thereby encouraging entrepreneurship. This could happen through advertising, rewards for investors, and word-of-mouth. There is also considerable information generated by issuers that is publicly available on the SEC website and listing platforms. Prior work shows that these types of disclosures are informative to entrepreneurs (Barrios et al., 2023), suggesting that we would observe increased interest in both Reg CF and in entrepreneurship more generally in the local area following Reg CF offerings.

We measure increased local awareness of Reg CF in county c at time t with Google searches for "Wefunder + StartEngine" in the DMA that contains county c. These searches could be driven by entrepreneurs seeking to raise capital via Reg CF or by potential investors, but in both cases, more searches reflect greater awareness of Reg CF.[26] Second, following Barrios et al. (2022), we capture general interest in entrepreneurship and starting new businesses with Google searches for "entrepreneurship."

Table 7 presents results using the Google Trends indices for Reg CF platforms in column (1) and entrepreneurial interest in column (3). In both cases, we find that Reg CF offerings in a county are associated with more Google searches for Reg CF platforms and

[26] As discussed in Section 2, we excluded the third largest platform, "Republic", because it is a common word with an alternate meaning.

entrepreneurship. One concern is that these effects are potentially impacted by the Covid-19 pandemic, which motivated a number of individuals to change jobs and professions, possibly seeking to start their own business. Thus, we repeat the analysis after restricting the sample to years 2010 through 2019 to mitigate concerns that the Covid-19 pandemic, which unfolded around the same time as the Reg CF market developed, confounds our inferences. While this helps assess the effect of Reg CF absent the pandemic, the trade-off is that it truncates the post-period for measuring these effects. We report these results in columns (2) and (4) and observe the same pattern of results.

Figure 5 plots the annual coefficients in an event study graph, where the vertical line indicates the timing of the first exposure to equity crowdfunding in a county. Consistent with Table 7, we find an increase in Google searches for "Wefunder + StartEngine" and "entrepreneurship" in the post-period. Importantly, we also observe no statistical differences in the pre-period between counties with Reg CF offerings and those without, suggesting that the changes in the post-period are not driven by pre-existing differences across the counties used in the analysis. The results point to an important information effect on the local entrepreneurial community.

5.3 Venture Capital Investment and SBA Lending

We also study whether equity crowdfunding provides relevant information to traditional capital providers – VCs and banks – thereby attracting new capital to the area. Reg CF offerings reduce search costs for investors in two ways. First, as discussed above, the amount of publicly available information about small businesses increases. Further, the crowd's investments reveal the demand for an issuer's products and services, quantifying the potential market for that issuer. This increased information lowers search costs and reduces information frictions, potentially attracting new investments to an area in ways similar to that shown by prior work in rewards-based crowdfunding (Sorenson et al., 2016) and in non-crowdfunding settings (Baik et al., 2022).

To test the interaction between equity crowdfunding and traditional financing in the local area, we re-estimate Eq. 6, replacing the dependent variable Y_{ct} with the number of early-stage VC deals or SBA loans in county c during year t. We log transform both variables to mitigate the impact of outliers, and, because VC deals are spatially concentrated, we also use a binary indicator of whether a county has an early-stage VC deal in a given year.

To the extent that equity crowdfunding reduces information frictions for local investments, we should observe an increase in the number of VC deals and SBA loans in the local area following a Reg CF offering. Alternatively, equity crowdfunding could substitute for those traditional sources of capital, decreasing local investments by VCs and banks. In fact, Tang (2019) finds that peer-to-peer lending substitutes for traditional bank loans.

Table 8 presents these results. As before, we estimate the regression on the full sample as well as for the subsample of observations prior to the Covid-19 pandemic in columns (2), (5), and (8). The estimates in columns (1) and (2) suggest an increase of approximately 6.6 to 13.1% in the number of early-stage VC deals in a county following the first Reg CF offering in that county.[27] In columns (4) and (5), we replace the dependent variable with an indicator variable for the presence of an early-stage VC investment in a county; the estimates suggest an increase of 4.1 to 6.2% in the likelihood of early-stage VC deals following a Reg CF offering.

We observe differing effects for SBA loans. The estimate in column (7) indicates a decline of 4.4% in the number of SBA loans approved in a county following Reg CF, but this association is statistically insignificant in column (8) for the pre-pandemic period. This suggests that the decline in SBA loans may be driven by a post-pandemic tightening of credit, or that Reg CF substituted for SBA loans once credit became more difficult to obtain.

Figure 6 plots the event study coefficients for the number of early-stage VC deals and SBA loans and confirms those findings. We also observe no statistical differences in the pre-period trends for counties with and without Reg CF offerings.

[27] Because of the log transformation, the magnitude of the effect for coefficient $\widehat{\beta}$ is calculated as $\exp(\widehat{\beta})-1$.

One concern is that the increase in VC investment could simply be driven by the firm-level results documented in Section 4.3 instead of a spillover effect on the local community. Thus, in columns (3) and (6), we drop counties where successful Reg CF issuers received VC investments after their offering. We continue to find a statistically significant result, meaning that the local increase in VC investment relates to firms beyond those that obtain VC investment after Reg CF.

5.4 Robustness

Another potential concern with the above analysis is that counties with Reg CF offerings could face different economic trends than those without, and that those trends may not be adequately controlled for through the inclusion of control variables and the fixed effects structure. Even though we observe parallel trends in the pre-treatment period, we repeat the analysis including only those counties with crowdfunding offerings. With this estimation, we substitute the binary treatment variable with the number of Reg CF offerings in county c and year t.[28] We report results in column (1) of Table IA.5 and find the same pattern of results as above: Google searches for equity crowdfunding platforms and entrepreneurship, as well as the number of early-stage VC deals are increasing with the count of Reg CF offerings.[29] In additional tests, we also find unchanged results when weighting observations by county population (columns (2) and (3)) or when measuring a county's exposure to crowdfunding with the occurrence of a *successful* Ref CF offering (columns (4) and (5)).

Collectively, the evidence in Tables 7 and 8 corroborates an important information effect of crowdfunding on the local community. The increased information provided through crowdfunding leads to increased awareness of this new fundraising channel and interest in entrepreneurship. We also find a positive effect on venture funding, suggesting that crowdfunding reduces search costs for investors, attracting more VC investments to the area.

[28] Note that this is no longer a staggered difference in difference, as we now compare counties on the basis of the treatment intensity, conditional on treatment.

[29] Given the geographic overlap of Reg CF and VC deals (see Figure 3B), the coefficient on the binary indicator of VC activity is, unsurprisingly, statistically insignificant.

6 Conclusion

We study the economic effects of equity crowdfunding offerings. The increasing number of offerings, as well as the amount of capital raised, suggest growing interest in equity crowdfunding as an alternative financing channel. Despite this growth, the empirical evidence on the U.S. crowdfunding market is limited. We provide new evidence about whether equity crowdfunding improves access to capital. We then quantify the extent to which a successful offering improves the survival of viable businesses, and we examine whether these offerings are associated with increased local area entrepreneurial activity via an information channel.

Not only does this evidence inform the equity crowdfunding literature, but it more broadly provides a setting in which to understand the capital formation decisions of small businesses. We document the characteristics of firms that seek this type of funding and show that bridge financing via Reg CF helps sustain small businesses until they can obtain subsequent funding.

This work thus provides new evidence in the literature on small business financing and also provides policy relevant information about the impact of equity crowdfunding on entrepreneurial finance. The recent increase in the fundraising cap to \$5 million in the U.S. as well as crowdfunding reforms in the E.U. reflect interest by regulators in facilitating investment into small businesses, but governments also voice substantial concerns over investor protection. We offer some of the first evidence about the viability of equity crowdfunding issuers and their impact on the local economy.

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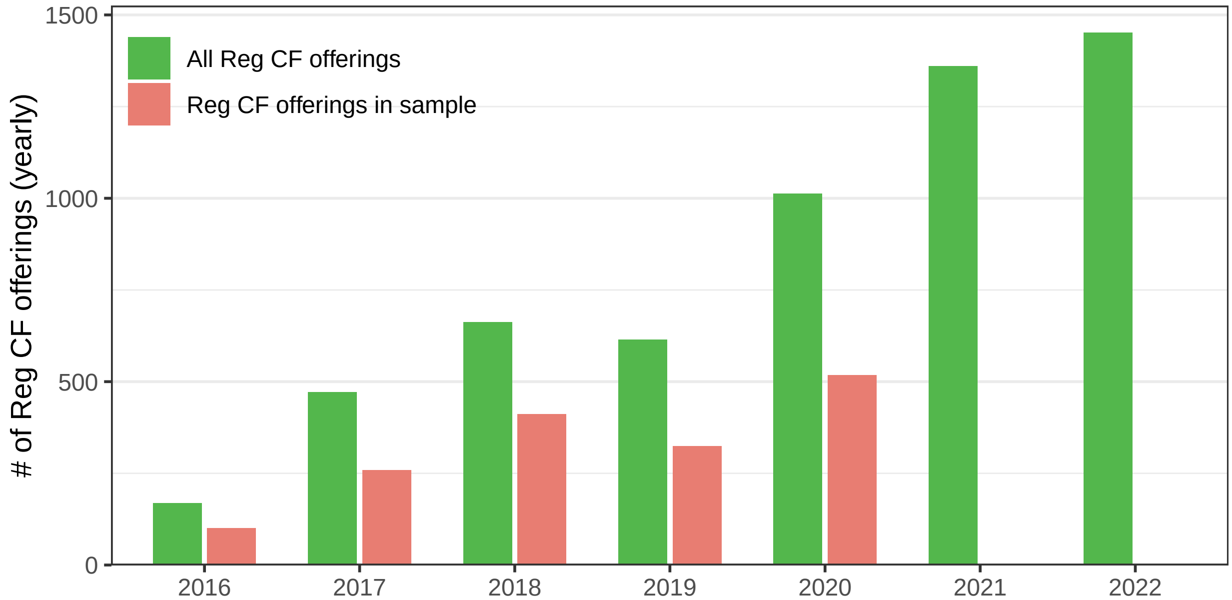
Table A.1: Variable definitions

Name	Definition	Source
	Main firm-level variables:	
Successful offering	Indicator equal to 1 if the issuer raised more than the minimum target before the deadline and 0 otherwise.	SEC + hand-collected
$ raised	Amount raised.	SEC + hand-collected
$ target	Minimum target amount to raise.	SEC + hand-collected
Inactive	Indicator equal to 1 if the issuer has ceased business activities as of April 30, 2023 based on the OpenCorporates website. Issuers are matched based on name and state using the OpenRefine algorithm with the OpenCorporates API. If the status is missing, we assess whether the company's website is still active.	OpenCorporates
SBA after	Indicator equal to 1 if the issuer has received an SBA loan after the start of the Reg CF offering (plus 7 days) and 0 otherwise.	SBA website
VC after	Indicator equal to 1 if the issuer has received venture capital funding after the start of the Reg CF offering (plus 7 days) and 0 otherwise.	Refinitiv
Competing offerings	Number of Reg CF offerings on the same platform and within 3 months of launch.	SEC + hand-collected
	Firm-level control variables:	
Age (years)	Number of years between the offering start date (Form C filing date) and incorporation date.	SEC + hand-collected
# of founders	Number of signatures on Form C.	SEC + hand-collected
# of employees	Number of employees reported on Form C.	SEC + hand-collected
Assets	Assets at time of Reg CF offering.	SEC + hand-collected
Cash	Cash at time of Reg CF offering.	SEC + hand-collected
Total debt	Total debt (short-term and long-term) at time of Reg CF offering.	SEC + hand-collected
Revenue	Revenue in fiscal year before Reg CF offering.	SEC + hand-collected
Income	Income in fiscal year before Reg CF offering.	SEC + hand-collected
RegCF before	Indicator equal to 1 if the issuer ran another Reg CF offering before and 0 otherwise.	SEC + hand-collected
CPA engaged	Indicator equal to 1 if the issuer engaged a CPA to either review or audit its financial statements and 0 otherwise.	SEC + hand-collected
SBA before	Indicator equal to 1 if the issuer has received an SBA loan before the start of the Reg CF offering (minus 7 days) and 0 otherwise.	SBA website
VC before	Indicator equal to 1 if the issuer has received venture capital funding before the start of the Reg CF offering (minus 7 days) and 0 otherwise.	Refinitiv
	County-level outcomes:	
Wefunder + StartEngine (Google)	Google Trends index for "Wefunder + StartEngine" in the Nielsen's Designated Market Area (DMA) that contains county c in year t.	Google Trends
Entrepreneurship (Google)	Google Trends index for "entrepreneurship" in the Nielsen's Designated Market Area (DMA) that contains county c in year t.	Google Trends
Early-stage VC	Number of early-stage VC deals in county c in year t.	Refinitiv
SBA loans	Number of SBA loans in county c in year t.	SBA website
	County-level control variables:	
Per-capita income	Income per capita in county c in year t.	BEA
Population	Population in county c in year t.	BEA
Bank branches	Number of bank branches in county c in year t.	FDIC SOD
Bank deposits	Total bank deposits in county c in year t.	FDIC SOD
Unemployment rate	Unemployment rate in county c in year t.	BLS LAUS

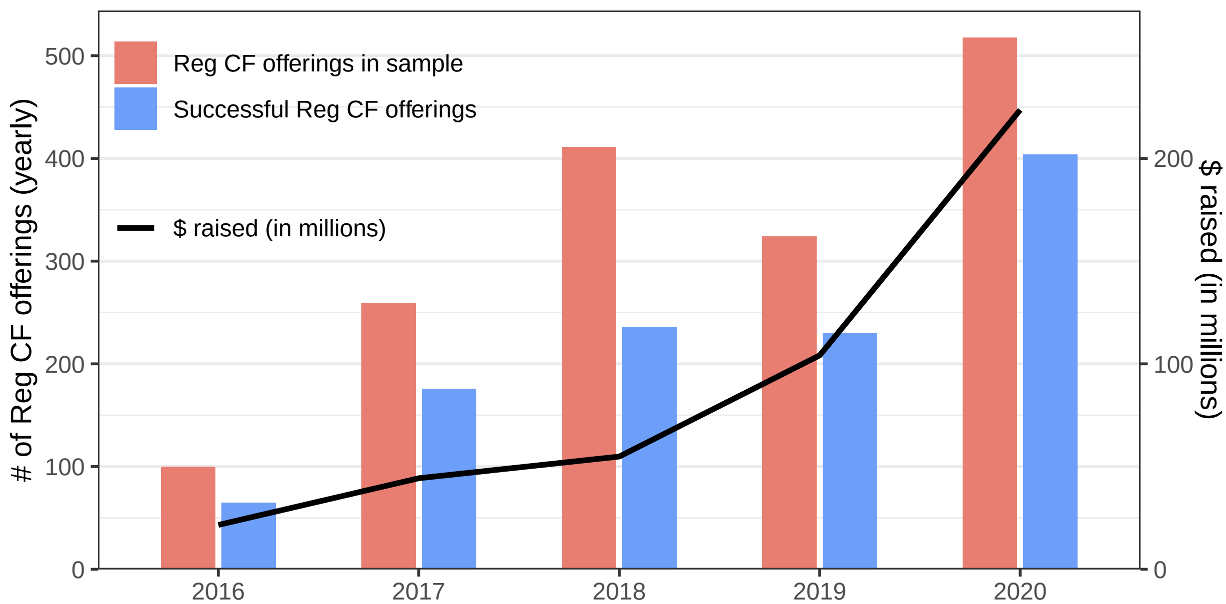
This table describes the variables used in the main analyses and their sources.

Figure 1: Reg CF offerings over time

A: All offerings and in-sample offerings

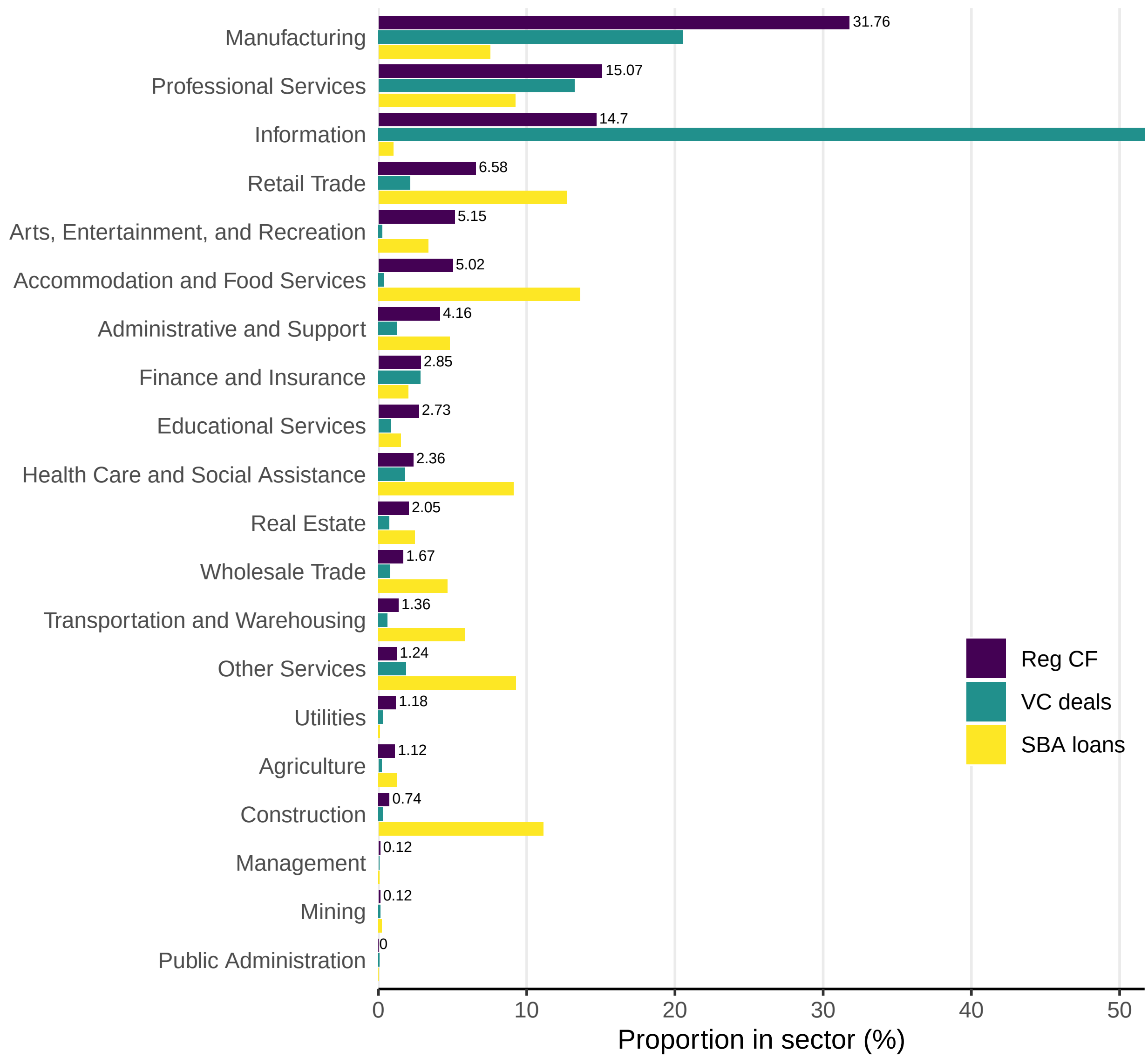


B: In-sample offerings



This figure plots the evolution of the number of Reg CF offerings and fundraising over time. Panel A contrasts the yearly number of Reg CF offerings across all platforms with the number of offerings in our main sample for which we collect detailed fundraising and financial information. Panel B focuses on our main sample and plots the number of successful offerings as well as the amount raised in each year (not cumulative) between 2016 and 2020.

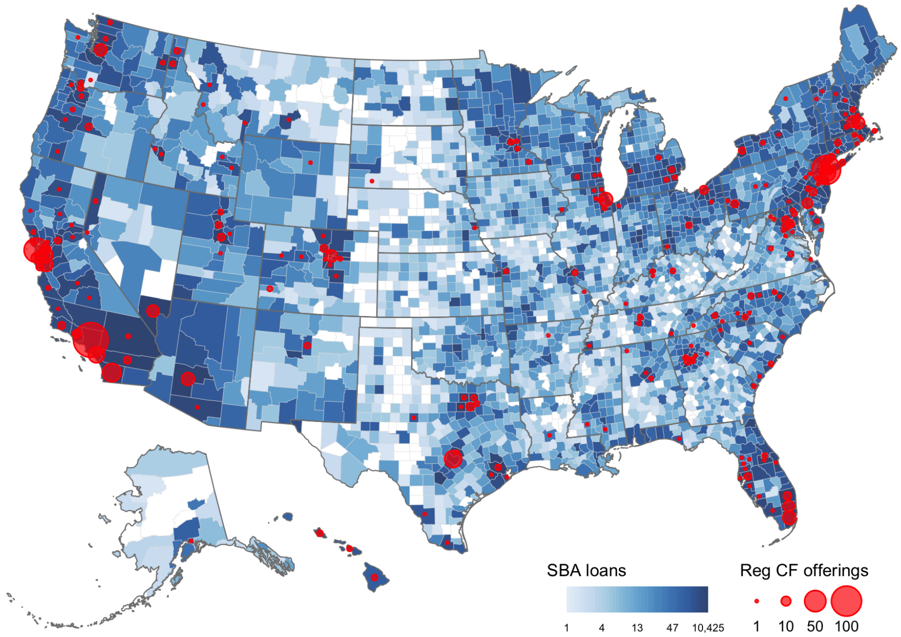
Figure 2: Industry comparison of Reg CF with SBA loans and VC deals



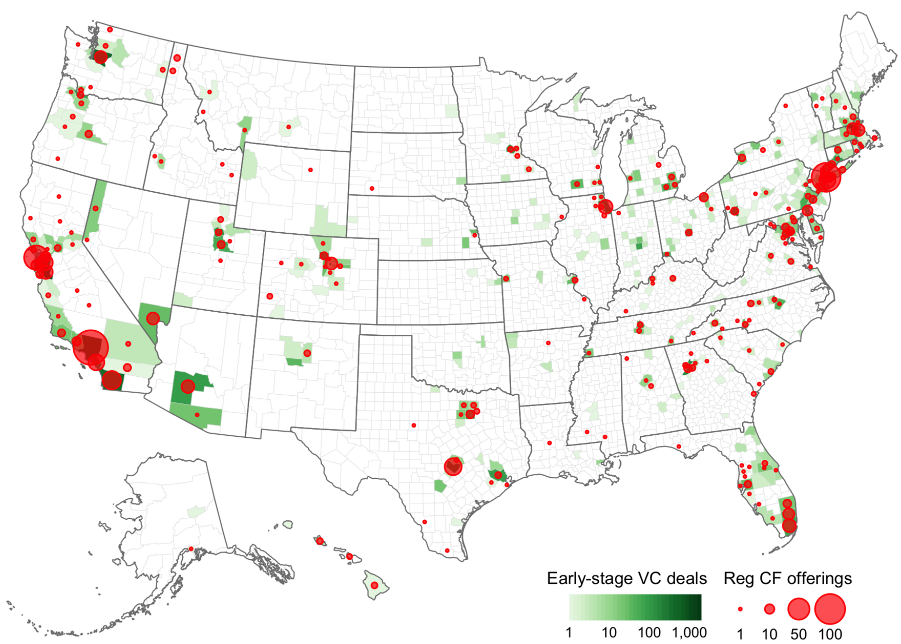
This figure plots the proportion of Reg CF offerings, SBA loans, and VC deals that fall into each of the 2-digit NAICS sectors. The sectors are ordered in decreasing proportion based on Reg CF offerings.

Figure 3: Spatial concentration and overlap

A: Comparison of Reg CF offerings and SBA loans

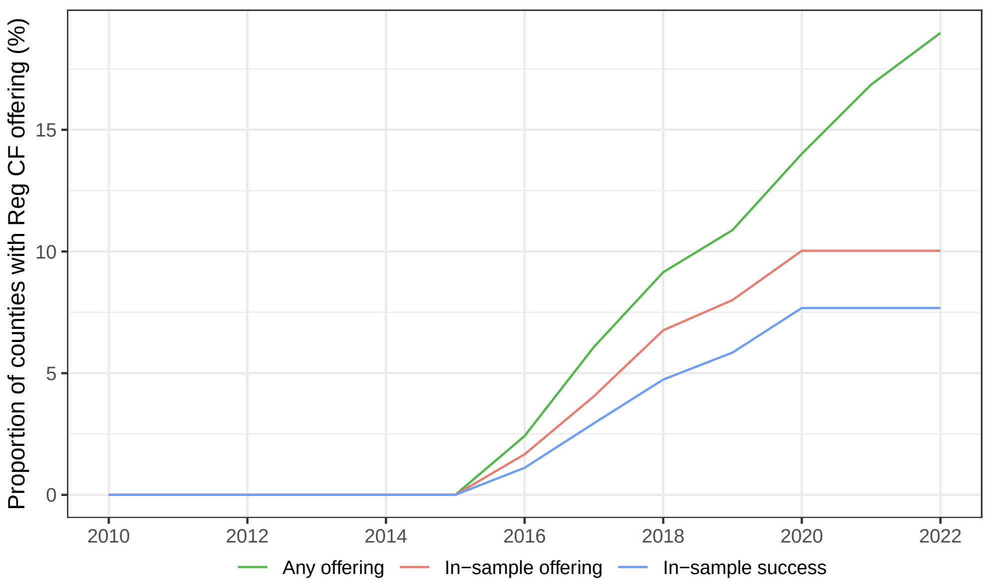


B: Comparison of Reg CF offerings and early-stage VC deals



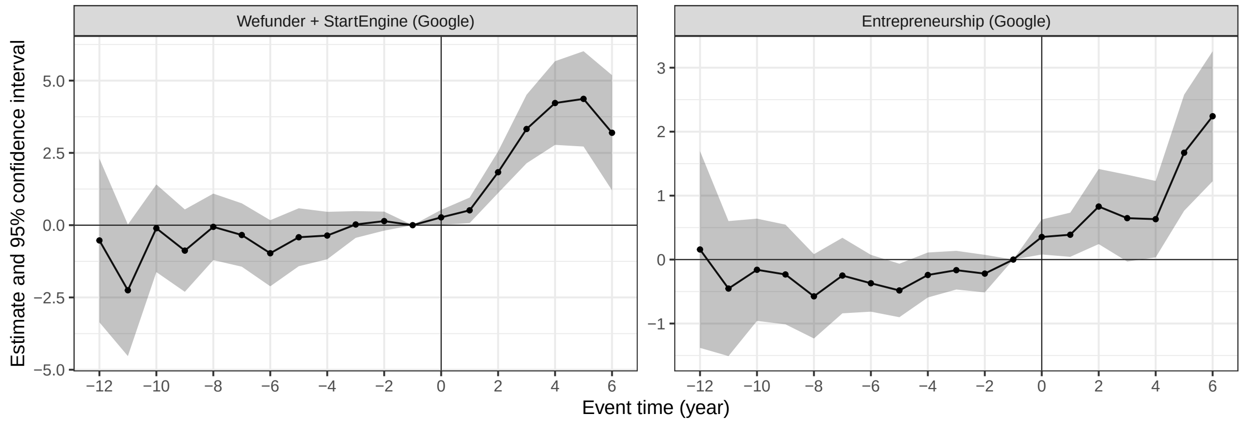
This figure plots the location of Reg CF offerings against the location of SBA loans in Panel A, and early-stage VC deals in Panel B for years 2016 to 2020. The size of the red circles corresponds to the number of successful Reg CF offerings in a given county, and the color shading corresponds to the number of SBA loans or early-stage VC deals.

Figure 4: Diffusion of Reg CF over time



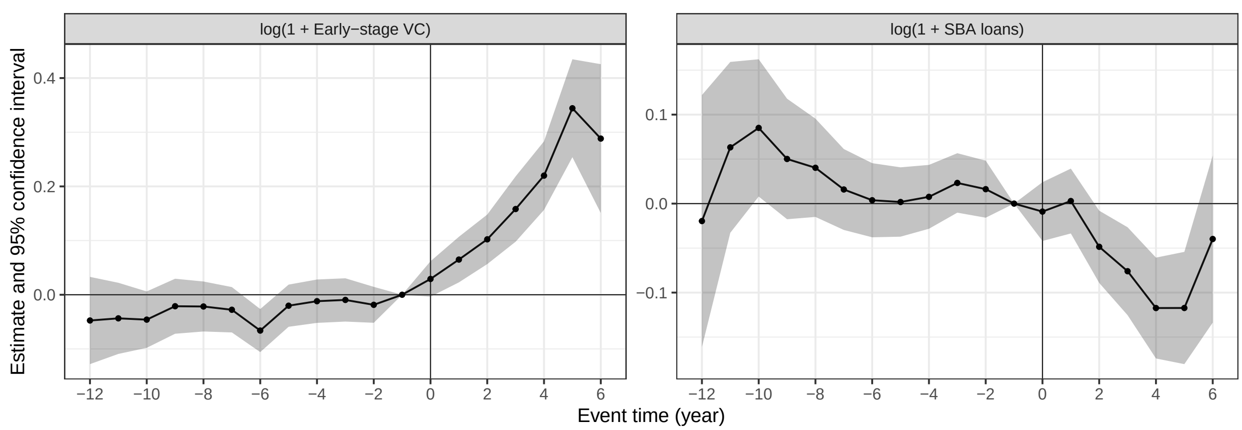
This figure plots the diffusion of Reg CF offerings across U.S. counties for different samples. "Any offering" corresponds to all Reg CF offerings, "In-sample offering" corresponds to the offerings that are in the sample used for the firm-level analysis (offerings launched between 2016 and 2020 in the top 3 platforms by volume), and "In-sample success" corresponds to those in-sample offerings that were successful.

Figure 5: Reg CF awareness and entrepreneurial interest - Event study



This figure plots the event study coefficients and 95% confidence intervals from the county-year staggered difference-in-differences regression of Eq. 6. The dependent variables are the Google Trends index in the corresponding Nielsen's Designated Market Area (DMA) for the two largest equity crowdfunding platforms ("Wefunder + StartEngine") in the left panel, and for "entrepreneurship" in the right panel. Variables are defined in Table A.1.

Figure 6: Interaction with traditional financing - Event study



This figure plots the event study coefficients and 95% confidence intervals from the county-year staggered difference-in-differences regression of Eq. 6. The dependent variables are the number of early-stage VC deals in the left panel, and the number of SBA loans in the right panel. Variables are defined in Table A.1.

Table 1: Descriptive statistics

A: Firm-level

	N (1)	Mean (2)	Std. Dev. (3)	25th (4)	Median (5)	75th (6)
Main firm-level variables:						
Successful offering	1612	0.689	0.463	0.000	1.000	1.000
$ raised (in millions)	1111	0.404	0.628	0.077	0.172	0.489
$ target (in millions)	1612	0.058	0.080	0.010	0.049	0.050
Inactive	1612	0.321	0.467	0.000	0.000	1.000
VC after	1612	0.054	0.226	0.000	0.000	0.000
SBA after	1612	0.015	0.121	0.000	0.000	0.000
Competing offerings	1612	107.511	60.788	71.000	98.000	129.000
Firm-level control variables:						
Age (years)	1612	3.162	3.919	0.789	2.029	4.109
# of founders	1612	1.897	1.193	1.000	2.000	2.000
# of employees	1612	6.050	11.439	2.000	3.000	6.000
VC before	1612	0.041	0.198	0.000	0.000	0.000
SBA before	1612	0.040	0.197	0.000	0.000	0.000
RegCF before	1612	0.105	0.307	0.000	0.000	0.000
CPA engaged	1612	0.719	0.450	0.000	1.000	1.000
Assets	1612	0.360	0.754	0.006	0.067	0.331
Cash	1612	0.086	0.194	0.000	0.011	0.064
Total debt	1612	0.504	1.070	0.001	0.072	0.461
Revenue	1612	0.389	1.013	0.000	0.005	0.212
Income	1612	-0.303	0.662	-0.294	-0.052	-0.001

B: Tabulation of firm-level outcomes by Reg CF success

	Full sample	Inactive		VC after		SBA after	
		No	Yes	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Successful	1111	834	277	81	1030	22	1089
	[68.9]	[75.1]	[24.9]	[7.3]	[92.7]	[2.0]	[98.0]
Failed	501	260	241	6	495	2	499
	[31.1]	[51.9]	[48.1]	[1.2]	[98.8]	[0.4]	[99.6]
Chi-squared test		83.95***		23.93***		4.86**	

Table 1: Descriptive statistics (continued)

C: County-level (annual)

	N (1)	Mean (2)	Std. Dev. (3)	25th (4)	Median (5)	75th (6)
Wefunder + StartEngine (Google)	39286	2.3	10.9	0.0	0.0	0.0
Entrepreneurship (Google)	39286	17.6	9.6	13.0	17.0	22.0
Early-stage VC	39732	0.9	11.8	0.0	0.0	0.0
SBA loans	39732	17.2	65.0	0.0	2.0	9.0
Reg CF offerings	39732	0.1	1.7	0.0	0.0	0.0
Per-capita income (lag)	39732	41.4	12.7	33.3	39.1	46.6
Population (lag)	39732	103.8	330.1	11.2	26.1	68.6
Bank branches (lag)	39732	29.7	75.0	5.0	11.0	23.0
Bank deposits (lag)	39732	3561.0	26818.9	188.0	429.6	1098.1
Unemployment rate (lag)	39732	6.4	3.0	4.1	5.8	8.1

Panel A reports descriptive statistics for the sample of Reg CF offerings used for the firm-level analyses. Financial variables are winsorized at the 1st and 99th percentiles. Panel B tabulates the firm-level outcomes by Reg CF success. Proportions are reported in brackets, and, except for the full sample, are computed within a row for each outcome. The last row reports the results of Chi-squared tests with continuity correction testing the independence of Reg CF success and firm-level outcomes. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Panel C focuses on county-level variables (not log-transformed). Variables are defined in Table A.1.

Table 2: Comparison of Reg CF with SBA loans and VC deals

A: Loan qualifications

	Income>0	Revenue>$50k	Age>2 years	DSCR>1.15	Combined	
	(1)	(2)	(3)	(4)	(5)=(1) to (3)	(6)=(1) to (4)
% Reg CF offerings	9.8	37.9	50.4	3.3	5.3	1.6

B: Spatial concentration

	Across counties		Within county	
Gini coefficient (%)	Average (1)	Δ2020-2016 (2)	Average (3)	Δ2020-2016 (4)
Successful Reg CF	99.0	-1.4	95.4	-2.1
Early-stage VC deals	97.7	-1	90.9	-1.3
SBA loans	58.5	4.1	63.8	1.7

C: Founders demographics

	Female			Non-white		
	All (1)	Failed (2)	Successful (3)	All (4)	Failed (5)	Successful (6)
Top 3 platforms	28.8	26.3	29.9	23.6	22.2	24.2
Republic	38.4	14.3	39.1	35.9	42.9	35.7
StartEngine	20.6	24.4	18.8	18.3	17.8	18.5
Wefunder	32.4	27.9	35.2	23.9	24.6	23.4
SBA loans			31.0			25.6
VC deals			24.6			-

This table compares Reg CF issuers in the sample to SBA loans or VC deals along three dimensions. Panel A lists the proportion of Reg CF offerings that meet various requirements to qualify for SBA loans. Columns (5) and (6) report the proportion of offerings that satisfy multiple requirements. Panel B reports the average and change in locational Gini coefficients between 2016 and 2020 for Reg CF issuers, SBA loans, and early-stage VC deals. Columns (1) and (2) focus on concentration across U.S. counties, while columns (3) and (4) focus on concentration within the 30 counties with the highest number of Reg CF offerings (across zip codes). Panel C reports the proportion of businesses with a female and non-white founder or executive. Columns (1) and (4) report the numbers for all Reg CF offerings, columns (2) and (5) for failed offerings, and columns (3) and (6) for successful offerings as well as SBA loans and VC deals.

Table 3: First stage regression

	Successful offering	$\log\left(1+\frac{\$\text{ raised}}{\$\text{ target}}\right)$
	(1)	(2)
Competing offerings (in hundreds)	-0.225***	-0.758***
	(-5.05)	(-9.01)
VC before	0.056	0.170
	(1.59)	(0.859)
SBA before	0.133*	0.132
	(2.07)	(0.987)
RegCF before	0.142***	0.399***
	(6.20)	(4.59)
Age	0.003	0.005
	(0.799)	(0.732)
# founders	0.006	-0.081***
	(0.703)	(-3.36)
# employees	0.001	0.003
	(1.38)	(0.893)
Assets	-0.026	-0.010
	(-1.54)	(-0.175)
Cash	0.143*	0.980***
	(1.90)	(4.65)
Total debt	0.016	0.013
	(1.35)	(0.348)
Revenue	-0.019	-0.030
	(-1.60)	(-0.618)
Income	-0.019	-0.150**
	(-0.887)	(-2.37)
CPA engaged	0.179***	0.715***
	(6.03)	(10.4)
Convertible security	-0.051*	-0.672***
	(-2.03)	(-8.06)
Debt security	-0.097**	-0.660***
	(-2.27)	(-4.68)
Offering quarter FE	Y	Y
Industry FE	Y	Y
Observations	1,612	1,612
Adjusted R^2	0.170	0.373
F-test (1st stage)	69.4	120.0

This table reports the first stage estimation for the instrumental variable analysis. The instrument is the number of competing offerings in the 3 months following the start of a Reg CF offering. We consider two measures of success of a Reg CF offering: an indicator variable equal to 1 if the issuer raised more than the fundraising target (*Successful offering*) in column (1), and the natural logarithm of 1 plus the ratio of the total amount raised and the fundraising target in column (2). We include fixed effects for the offering quarter, the industry (2-digit NAICS), as well as firm-level control variables as defined in Table A.1. Standard errors are robust and clustered at the offering quarter level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 4: Effect of Reg CF success on issuer survival

	Inactive			
	OLS		2SLS	
	(1)	(2)	(3)	(4)
Successful offering	-0.171***		-0.276**	
	(-5.15)		(-2.76)	
$\log\left(1+\frac{\$\text{ raised}}{\$\text{ target}}\right)$		-0.039***		-0.082**
		(-3.56)		(-2.63)
Offering quarter FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Control variables	Y	Y	Y	Y
Observations	1,612	1,612	1,612	1,612
Adjusted R^2	0.111	0.094	0.101	0.084

This table reports the effect of a successful Reg CF offering on the issuer's subsequent survival. The dependent variable is an indicator of whether the issuer is still in operation as of April 2023. Columns (1) and (2) report results from ordinary least squares, and columns (3) and (4) from two-stage least squares using the number of competing offerings in the 3 months following the start of an offering as an instrumental variable. Reg CF success is measured with a binary indicator in odd-numbered columns, and as the logarithm of one plus the amount raised scaled by the minimum target in even-numbered columns. We include fixed effects for the offering quarter, the industry (2-digit NAICS), as well as firm-level control variables as defined in Table A.1. Standard errors are robust and clustered at the offering quarter level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 5: Financial growth of successful Reg CF issuers

	ΔNon-cash assets		ΔRevenue		Filed C-AR
	Mean	Median	Mean	Median	%
Fiscal years	(1)	(2)	(3)	(4)	(5)
t-1 $\rightarrow$ t	0.144	0.010	0.138	0.006	60.9
t-1 $\rightarrow$ t+1	0.509	0.043	0.499	0.036	39.9

This table summarizes the financial growth of successful Reg CF issuers from year $t-1$ to year $t+1$, where t is the year in which the Reg CF offering took place. Columns (1) and (2) report the mean and median change in non-cash assets (in millions). Columns (3) and (4) report the mean and median change in revenue (in millions). Column (5) reports the proportion of successful issuers filing an annual report (Form C-AR).

Table 6: Effect of Reg CF success on subsequent external financing

A: Venture capital

	VC after			
	OLS		2SLS	
	(1)	(2)	(3)	(4)
Successful offering	0.044***		0.217***	
	(4.11)		(3.32)	
$\log\left(1 + \frac{\$\text{ raised}}{\$\text{ target}}\right)$		0.016**		0.064**
		(2.82)		(2.68)
Offering quarter FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Control variables	Y	Y	Y	Y
Observations	1,612	1,612	1,612	1,612
Adjusted R^2	0.122	0.122	0.013	0.064

B: SBA loans

	SBA after			
	OLS		2SLS	
	(1)	(2)	(3)	(4)
Successful offering	0.019***		0.017	
	(4.33)		(0.504)	
$\log\left(1 + \frac{\$\text{ raised}}{\$\text{ target}}\right)$		0.003		0.005
		(1.31)		(0.506)
Offering quarter FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Control variables	Y	Y	Y	Y
Observations	1,612	1,612	1,612	1,612
Adjusted R^2	0.030	0.026	0.030	0.026

This table reports the effect of a successful Reg CF offering on the issuer's subsequent external financing. The dependent variable is an indicator of whether the issuer subsequently receives venture capital in Panel A, and an SBA loan in Panel B. For both panels, columns (1) and (2) report results from ordinary least squares, and columns (3) and (4) from two-stage least squares using the number of competing offerings in the 3 months following the start of an offering as an instrumental variable. Reg CF success is measured with a binary indicator in odd-numbered columns, and as the logarithm of one plus the amount raised scaled by the minimum target in even-numbered columns. We include fixed effects for the offering quarter, the industry (2-digit NAICS), as well as firm-level control variables as defined in Table A.1. Standard errors are robust and clustered at the offering quarter level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 7: Reg CF awareness and entrepreneurial interest

	Wefunder + StartEngine (Google)		Entrepreneurship (Google)	
	(1)	(2)	(3)	(4)
	2010-22	2010-19	2010-22	2010-19
Avg. treatment on treated	1.89***	1.66***	0.679***	1.03***
	(5.39)	(5.90)	(3.29)	(3.31)
log(1 + Per-capita income) (lag)	2.80***	2.20***	0.124	-0.597
	(3.74)	(3.28)	(0.223)	(-0.897)
log(1 + Population) (lag)	14.5***	7.56***	3.06***	3.82**
	(7.39)	(5.13)	(2.70)	(2.32)
log(1 + Bank branches) (lag)	-1.78***	-0.915*	-0.328	-0.003
	(-3.04)	(-1.94)	(-0.770)	(-0.004)
log(1 + Bank deposits) (lag)	0.133	-0.174	0.087	0.290
	(0.492)	(-0.664)	(0.408)	(0.929)
Unemployment rate (lag)	-0.045	-0.034	-0.066	-0.091*
	(-0.877)	(-0.770)	(-1.55)	(-1.65)
County FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
# County	3,025	3,025	3,025	3,025
Observations	39,286	30,230	39,286	30,230
Adjusted R^2	0.805	0.789	0.775	0.765

This table reports the results of county-year staggered difference-in-differences regressions for measures of Reg CF awareness and entrepreneurial interest, where the treatment corresponds to the first occurrence of a Reg CF offering in a county (see Eq. 6). The dependent variables are the Google Trends index in the corresponding Nielsen's Designated Market Area (DMA) for the two largest equity crowdfunding platforms ("Wefunder + StartEngine") in columns (1) and (2), and for "entrepreneurship" in columns (3) and (4). Odd-numbered columns are estimated for the full sample from 2010 to 2022, while even-numbered columns are estimated for years through 2019 before the Covid-19 pandemic. We include county and state-year fixed effects as well as lagged time-varying county-specific controls. Standard errors are robust and clustered at the county level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Variables are defined in Table A.1.

Table 8: Interaction with traditional financing

	log(1 + Early-stage VC)			Early-stage VC > 0			log(1 + SBA loans)	
	(1) 2010-22	(2) 2010-19	(3) 2010-22	(4) 2010-22	(5) 2010-19	(6) 2010-22	(7) 2010-22	(8) 2010-19
Avg. treatment on treated	0.123***	0.064***	0.120***	0.062***	0.041**	0.066***	-0.045***	-0.024
	(6.59)	(2.66)	(6.18)	(4.19)	(2.17)	(4.09)	(-2.77)	(-1.25)
log(1 + Per-capita income) (lag)	0.015	-0.008	0.003	0.001	-0.0008	0.004	0.021	0.005
	(0.905)	(-0.492)	(0.222)	(0.086)	(-0.061)	(0.329)	(0.430)	(0.092)
log(1 + Population) (lag)	0.168***	0.157***	0.149***	0.154***	0.144***	0.145***	0.743***	0.723***
	(3.55)	(2.84)	(3.26)	(4.09)	(3.01)	(3.83)	(8.54)	(6.62)
log(1 + Bank branches) (lag)	0.010	0.020	0.005	-0.006	0.006	-0.004	-0.003	-0.025
	(0.809)	(1.47)	(0.387)	(-0.624)	(0.515)	(-0.434)	(-0.081)	(-0.518)
log(1 + Bank deposits) (lag)	0.034***	0.034**	0.038***	0.025***	0.015	0.029***	0.014	0.027
	(2.90)	(2.17)	(3.63)	(2.97)	(1.60)	(3.46)	(0.888)	(1.24)
Unemployment rate (lag)	0.003***	0.0002	0.004***	0.002*	0.0005	0.002**	-0.0007	-0.004
	(2.79)	(0.187)	(3.16)	(1.72)	(0.543)	(2.06)	(-0.199)	(-0.966)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
# County	3,061	3,061	3,024	3,061	3,061	3,024	3,061	3,061
Observations	39,732	30,570	39,251	39,732	30,570	39,251	39,732	30,570
Adjusted R^2	0.889	0.895	0.793	0.659	0.676	0.614	0.905	0.907

This table reports the results of county-year staggered difference-in-differences regressions for measures of fundraising, where the treatment corresponds to the first occurrence of a Reg CF offering in a county (see Eq. 6). The dependent variables are the number of early-stage VC deals in columns (1) to (3), an indicator variable equal to 1 if there is an early-stage VC deal in columns (4) to (6), and the number of SBA loans in columns (7) and (8). Columns (2), (5), (8) are estimated for years through 2019 before the Covid-19 pandemic, while the remaining columns are estimated from 2010 to 2022. In columns (3) and (6) we drop counties in which successful Reg CF issuers were subsequently funded by VCs. We include county and state-year fixed effects as well as lagged time-varying county-specific controls. Standard errors are robust and clustered at the county level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Variables are defined in Table A.1.

Internet Appendix

Figure IA.1: Financial statements filed with Form C

A: Balance sheet and income statements for NextRx

Balance Sheet

NextRX Inc.
As at 31 December 2015

	31 Dec 2015
Assets	
Cash and Cash Equivalents	
NextRX Capital	25,079
NextRX Checking	2,224
Total Cash and Cash Equivalents	**27,303**
Property, Plant and Equipment	
Computer & Office Equipment	2,271
Software Development	6,300
Total Property, Plant and Equipment	**8,571**
Total Assets	**35,873**
Liabilities and Equity	
Liabilities	
Current Liabilities	
Amex Open	10,202
Total Current Liabilities	**10,202**
Non-Current Liabilities	
Shareholder Loan	63,799
Total Non-Current Liabilities	**63,799**
Total Liabilities	**74,001**
Equity	
Current Year Earnings	(48,127)
Owner's Capital: Owner's Investment	10,000
Total Equity	**(38,127)**
Total Liabilities and Equity	**35,873**

Financial Statement Certified

Ralf-Rainer von Albedyhll
CEO

Income Statement

NextRX Inc.
1 January 2015 to 31 December 2015

	31 Dec 15
Gross Profit	-
Operating Income / (Loss)	-
Other Income and Expense	
Accounting	(1,455)
Automobile Expense	(1,891)
Bank Service Charges	(241)
Business License & Fees	(794)
Dues & Subscriptions	(2,097)
Insurance	(10,811)
Interest Expense	(658)
Legal Fees	(739)
Marketing	(7,034)
Meals & Entertainment	(4,126)
Miscellaneous	(479)
Office Supplies	(727)
Printing	(1,266)
Rent	(9,385)
Software	(3,767)
Travel	(1,114)
Utilities	(1,543)
Total Other Income and Expense	**(48,127)**
Net Income / (Loss) before Tax	**(48,127)**
Net Income	**(48,127)**
Total Comprehensive Income	**(48,127)**

B: Balance sheet and income statements for MF Fire

MF FIRE, BENEFIT LLC
BALANCE SHEETS
As of December 31, 2015 and 2014

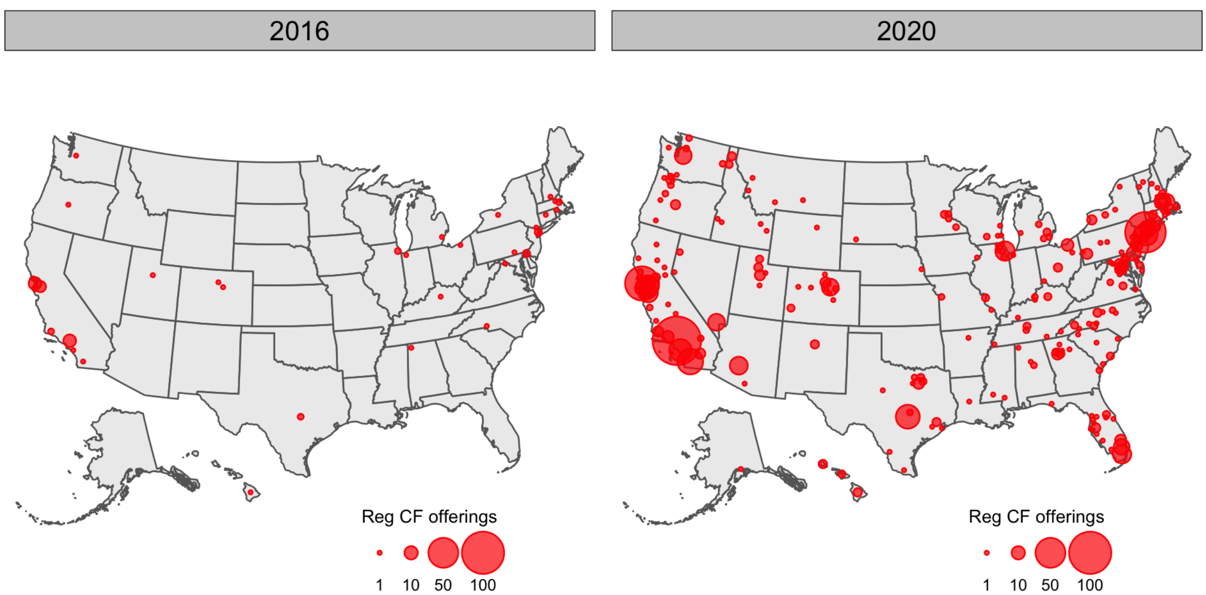
	2015	2014
ASSETS		
Current Assets:		
Cash and cash equivalents	$ 10,170	$ 7,321
Total Current Assets	10,170	7,321
TOTAL ASSETS	$ 10,170	$ 7,321
LIABILITIES AND MEMBERS' EQUITY (DEFICIT)		
Liabilities:		
Current Liabilities:		
Accounts payable	$ 24,782	$ -
Total Liabilities	24,782	-
Members' Equity (Deficit):	(14,612)	7,321
TOTAL LIABILITIES AND MEMBERS' EQUITY (DEFICIT)	$ 10,170	$ 7,321

MF FIRE, BENEFIT LLC
STATEMENTS OF OPERATIONS
For the year ended December 31, 2015 and for the period from April 23, 2014 (inception) to December 31, 2014

	2015	2014
Grant revenues	$ 100,000	$ -
Competition revenues	-	28,500
Net Revenues	100,000	28,500
Cost of net revenues	-	-
Gross Profit	100,000	28,500
Operating Expenses:		
Research and development	108,588	-
General and administrative	25,921	17,495
Professional fees	2,263	8,755
Total Operating Expenses	136,772	26,250
Net Income (Loss)	$ (36,772)	$ 2,250

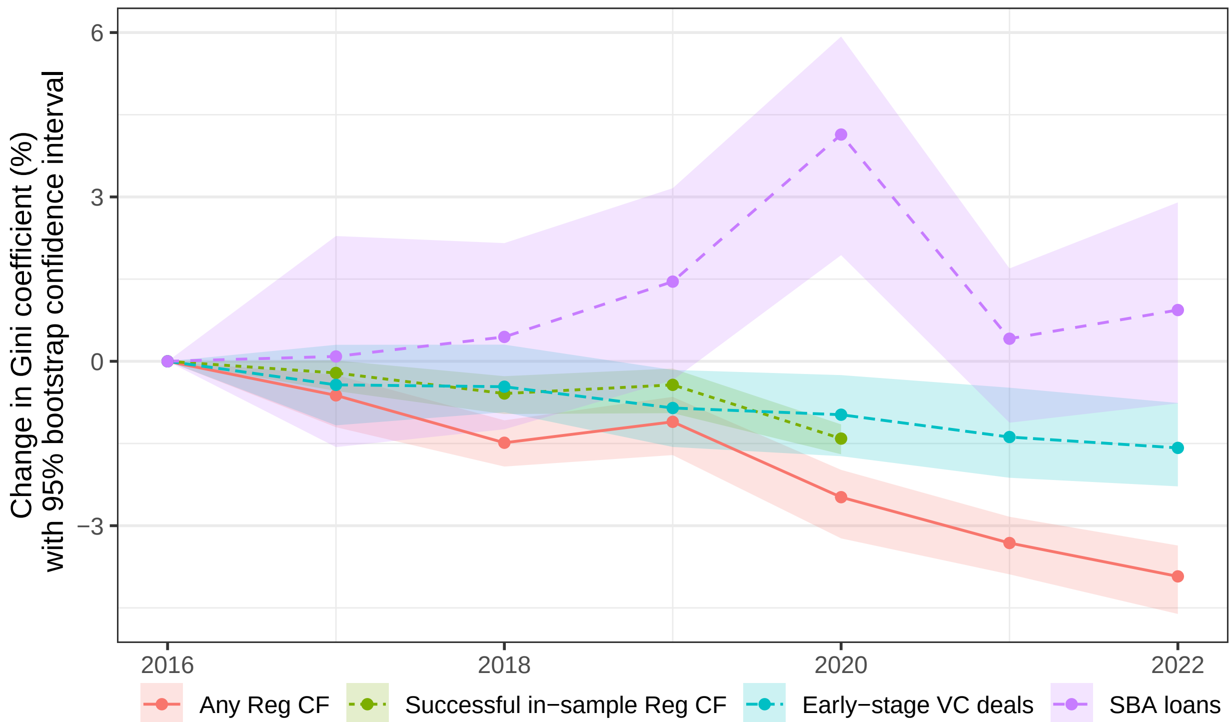
Financial statements filed with Form C on May 16, 2016 for two of the earliest Reg CF offerings. Panel A shows the balance sheet and income statement of NextRx, Inc. for fiscal year 2015. Panel B shows the balance sheet and income statement of MF Fire, Benefit LLC for fiscal years 2014 and 2015.

Figure IA.2: Geographic distribution of Reg CF offerings over time



This figure plots the location of successful Reg CF offerings in 2016 and 2020. The size of the red circles corresponds to the number of Reg CF offerings (cumulative) in a given county.

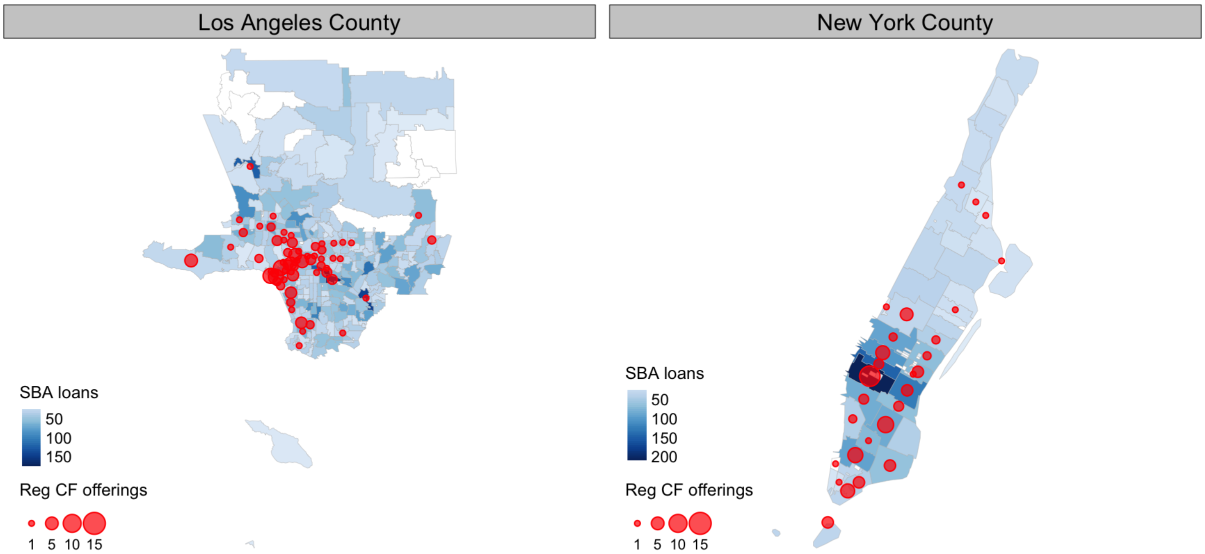
Figure IA.3: Locational Gini coefficients over time



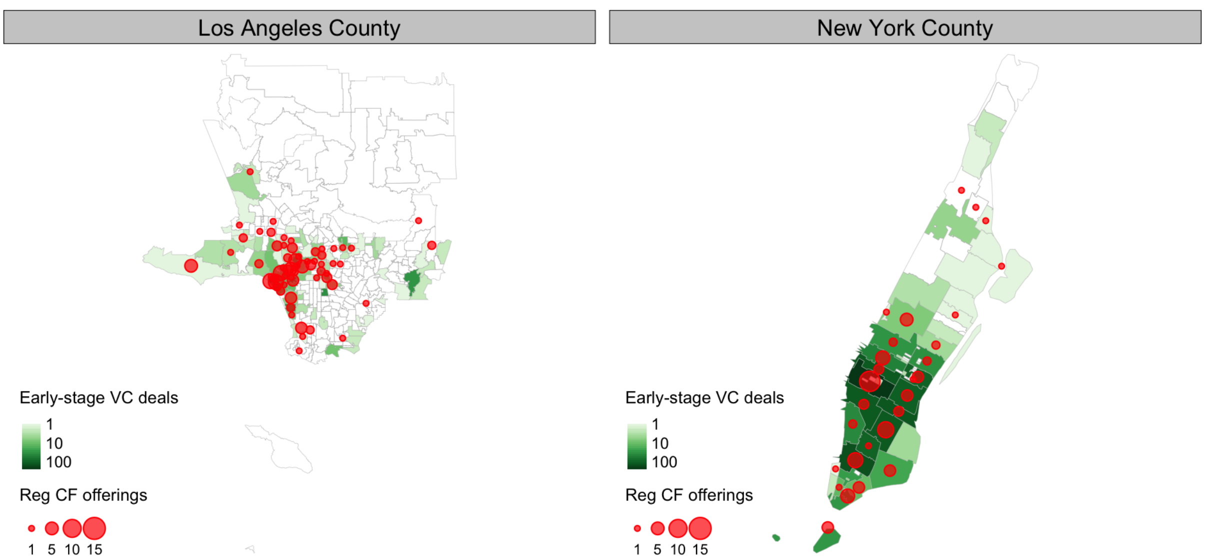
This figure plots the change in locational Gini coefficients across U.S. counties over time for Reg CF offerings (both in-sample successful offerings and all offerings), early-stage VC deals, and SBA loans. The shaded areas denote bootstrapped 95% confidence intervals.

Figure IA.4: Within county spatial concentration and overlap

A: Comparison of Reg CF offerings and SBA loans



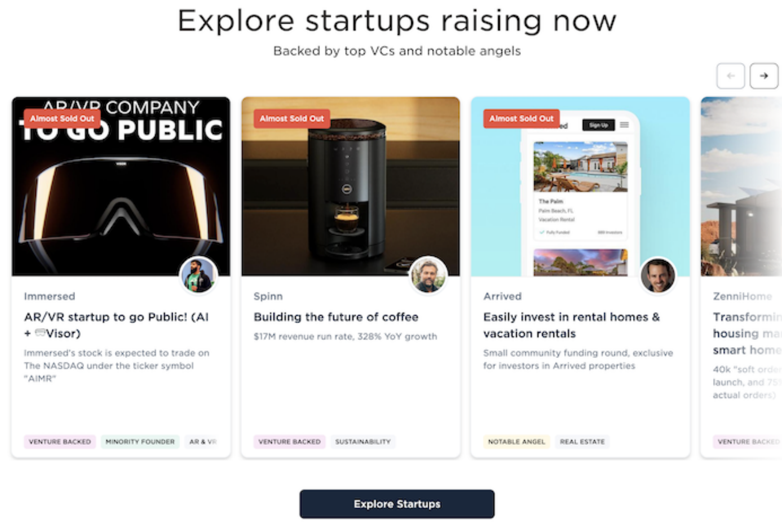
B: Comparison of Reg CF offerings and early-stage VC deals



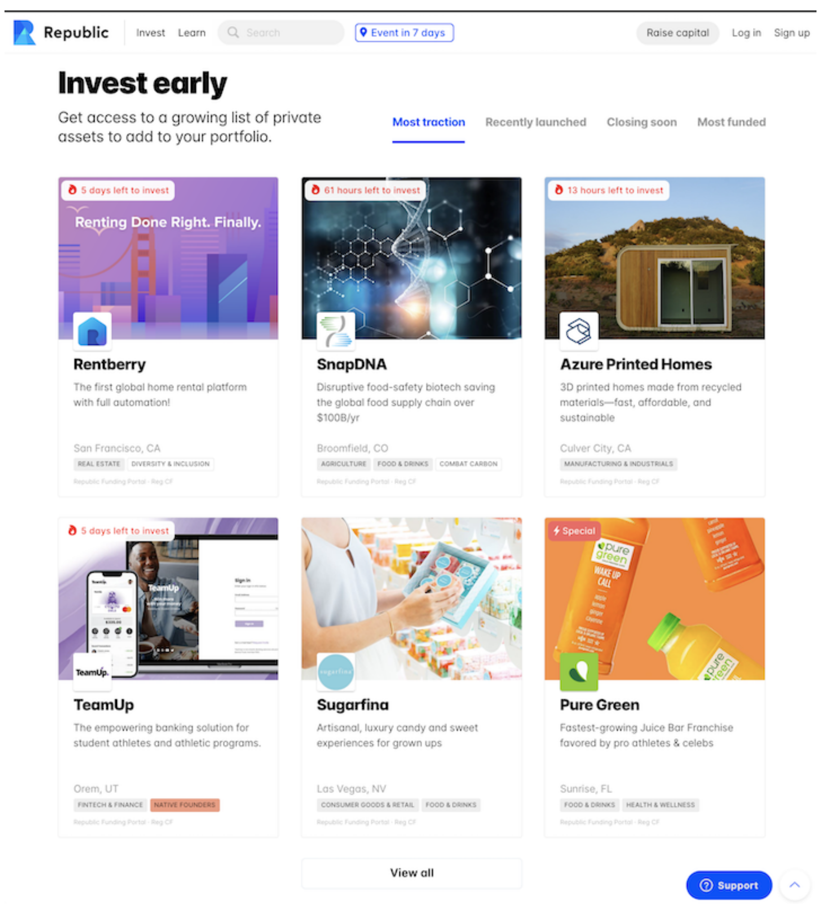
This figure plots the location of Reg CF offerings against the location of SBA loans in Panel A, and early-stage VC deals in Panel B for the two counties with the most Reg CF offerings between years 2016 to 2020. The size of the red circles corresponds to the number of successful Reg CF offerings in a given zip code, and the color shading corresponds to the number of SBA loans or early-stage VC deals.

Figure IA.5: Examples of congestion on Reg CF platforms

A: Wefunder



B: Republic

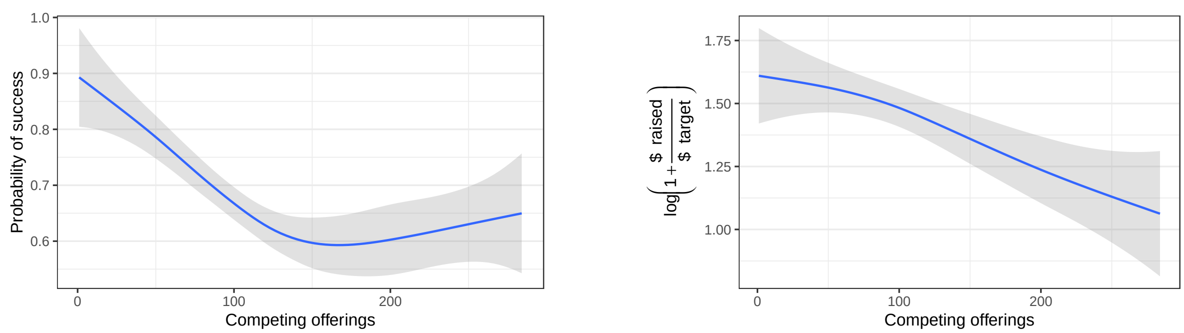


Homepage of two Reg CF platforms displaying only a limited number of ongoing offerings (captured in August 2023).

Figure IA.6: Non-parametric association between Reg CF success and competing offerings

A: Probability of success

B: Amount raised in excess of target



This figure plots the non-parametric association between the number of competing Reg CF offerings during the first three months after the start of an offering and the probability of success in Panel A or the amount raised in excess of the target in Panel B. Variables are defined in Table A.1.

Table IA.1: Sample construction

	Total # of offerings	Total # of unique issuers
All offerings from May 2016 to December 2022	6,557	5,617
Less:		
Offerings that start after 2020-12-31	(3,204)	(2,633)
Offerings that end after 2021-12-31	(92)	(84)
Total offerings in sample period	3,261	2,900
Less:		
Offerings from non-top 3 platforms	(1,467)	(1,310)
Total offerings in top 3 platforms	1,794	1,590
Less:		
Foreign issuers	(8)	(8)
Token	(42)	(40)
Withdrawn offerings	(108)	(79)
Total qualified offerings	1,636	1,463
Offerings without financial statements	(24)	(21)
Final sample	1,612	1,442

This table reports the sample construction criteria and the number of Reg CF offerings and issuers at each step.

Table IA.2: SBA loan requirements for various lenders/marketplaces

Lender or marketplace	Income	Revenue	DSCR	Age (years)	Credit score	Other requirements
Smartbiz	Positive	$50k		2	650	No bankruptcies or tax liens
Funding Circle		$400k		2	650	No tax liens
Kapitus	Positive			2	680	
Janover			"sufficient"	2	680	Collateral
National Business Capital		$500k		2	685	
Nerdwallet		"strong"	1.15	2	690	Collateral and no tax liens

This table reports the minimum requirements to qualify for SBA loans according to the websites of various online small business lenders or marketplaces.
In addition, the SBA program's official requirements are:

- Be an operating business.
- Operate for profit.
- Be located in the U.S.
- Be small under SBA size requirements (based on industry-specific revenue or employee thresholds).
- Not be a type of ineligible business.
- Not be able to obtain the desired credit on reasonable terms from non-federal, non-state, and non-local government sources.
- Be creditworthy and demonstrate a reasonable ability to repay the loan.

Table IA.3: IV Robustness

A: First stage regressions

	(1)	(2)	(3)	(4)	(5)
Successful offering:					
Competing offerings	-0.225***	-0.341***	-0.331***	-0.115***	-0.046
F-test (1st stage)	69.4	43.5	73.9	29.4	1.25
$\log\left(1+\frac{\$\text{ raised}}{\$\text{ target}}\right)$:					
Competing offerings	-0.758***	-1.38***	-1.01***	-0.431***	-0.294**
F-test (1st stage)	120.0	110.5	104.6	62.7	8.24
Control variables	Y	Y	Y	Y	Y
Offering quarter FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Platform FE	N	N	N	N	Y
Time window	3 months	3 months	1 month	6 months	3 months
Active vs. new	Active	New	Active	Active	Active

B: Two-stage least squares estimates

	(1)	(2)	(3)	(4)	(5)
Successful offering:					
Inactive	-0.276**	-0.421***	-0.235**	-0.257	-1.55
VC after	0.217***	0.277***	0.179***	0.358***	0.800
SBA after	0.017	0.038	0.013	0.033	-0.004
$\log\left(1+\frac{\$\text{ raised}}{\$\text{ target}}\right)$:					
Inactive	-0.082**	-0.104***	-0.077**	-0.068	-0.244**
VC after	0.064**	0.068***	0.058**	0.095**	0.126**
SBA after	0.005	0.009	0.004	0.009	-0.0006
Control variables	Y	Y	Y	Y	Y
Offering quarter FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Platform FE	N	N	N	N	Y
Time window	3 months	3 months	1 month	6 months	3 months
Active vs. new	Active	New	Active	Active	Active

Table IA.3: IV Robustness (continued)

C: Reduced form regressions

	(1)	(2)	(3)	(4)	(5)
Inactive	0.062**	0.143***	0.078*	0.029	0.072*
VC after	-0.049**	-0.095***	-0.059*	-0.041**	-0.037*
SBA after	-0.004	-0.013	-0.004	-0.004	0.0002
Control variables	Y	Y	Y	Y	Y
Offering quarter FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Platform FE	N	N	N	N	Y
Time window	3 months	3 months	1 month	6 months	3 months
Active vs. new	Active	New	Active	Active	Active

This table reports the robustness of the IV estimation to different specifications. Panel A reports the first stage regression coefficient and F-statistic. Panel B reports the 2SLS estimates. Panel C reports reduced form results (regression of business outcome on IV). Each column corresponds to a different specification, with column (1) being the specification used in the paper. The specifications differ with respect to the definition of the IV and the inclusion of platform fixed effects. *Time window* is the number of months after the start of an offering over which we measure the number of competing offerings. *Active vs. new* refers to whether an offering was already active at the start of the focal offering. Standard errors are robust and clustered at the offering quarter level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Variables are defined in Table A.1.

Table IA.4: Comparison of counties with and without Reg CF offerings

	Counties without Reg CF (N=2551) (1)	Counties with Reg CF (N=591) (2)	Difference (3)
Population	34.54	400.30	365.76***
Median HH income	50.51	66.27	15.76***
% urban	33.68	74.34	40.66***
% white	83.86	78.85	-5.01***
% with college education	28.63	41.67	13.04***
% below poverty threshold	15.72	12.49	-3.23***
% employed	94.63	95.02	0.39***
Gini index (0 to 100)	44.37	45.29	0.92***

This table reports the demographic characteristics of counties with and without Reg CF offerings. The demographic characteristics are obtained from the American Community Survey (ACS) conducted between 2015 and 2019, or the 2010 Decennial Census of Population and Housing. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table IA.5: County-level Robustness

	(1)	(2)	(3)	(4)	(5)
Wefunder + StartEngine (Google)	1.15***	2.29***	1.72***	3.02***	1.83***
	(2.63)	(5.77)	(5.99)	(5.60)	(4.44)
Entrepreneurship (Google)	0.914***	0.740***	1.07***	0.764***	1.01***
	(5.11)	(3.19)	(3.61)	(2.93)	(3.21)
log(1 + Early-stage VC)	0.136***	0.105***	0.064**	0.167***	0.071**
	(7.34)	(5.01)	(2.55)	(5.74)	(2.33)
Early-stage VC > 0	0.007	0.052***	0.039**	0.063***	0.036
	(0.712)	(3.21)	(2.08)	(3.03)	(1.54)
log(1 + SBA loans)	-0.008	-0.064***	-0.022	-0.070***	-0.008
	(-0.794)	(-3.99)	(-1.26)	(-3.14)	(-0.305)
County FE	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y
Control variables	Y	Y	Y	Y	Y
Sample	Treat=1	2010-22	2010-19	2010-22	2010-19
Treatment	Any	Any	Any	Success	Success
Weights	Ew	Pop	Pop	Ew	Ew

This table reports the robustness of the county-level analysis to different specifications. The *rows* correspond to the coefficient of interest for various outcome variables, and the *columns* correspond to different specifications. In column (1) we restrict the sample to counties that have a Reg CF offering between 2016 and 2022 and substitute the binary treatment variable with the logarithm of one plus the number of Reg CF offerings in a county-year. In columns (2) and (3) we estimate Eq. 6 for the full sample and the pre-Covid sample weighing observations by population. In columns (4) and (5) we replace the treatment with the first occurrence of a *successful* Reg CF offering in a county and restrict the analysis to counties that have either no Reg CF offering or in-sample offerings described in Table IA.1. In all specifications we include county and state-year fixed effects as well as lagged time-varying county-level controls. Standard errors are robust and clustered at the county level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. Variables are defined in Table A.1.