

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

Douglas Laporte[†]

Washington University in St. Louis

Rebecca Lester[‡]

Stanford Graduate School of Business

June 12, 2024

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

*We are grateful for comments from John Barrios, Ed deHaan, Jinhwan Kim, Xiang Li (discussant), Xiumin Martin, Joe Piotroski, Kevin Standridge, Rodrigo Verdi, Peng Wang (discussant), and seminar participants at the 2023 BYU Accounting Symposium, 2023 Paris December Finance Meeting, 2024 FARS Midyear Meeting, 2024 Bretton Woods Accounting and Finance Ski Conference, London Business School, Northwestern University, Stanford University, and Washington University in St. Louis. We thank Andy Su for outstanding research assistance.

[†]laporte@wustl.edu

[‡]rlester@stanford.edu

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](#)). By the third quarter of 2023, 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 requirements, permitting younger, pre-revenue firms to obtain financing. Second, the process

¹Specifically, 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](#)).

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, we expect Reg CF 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 capital goes to viable firms or instead to “lemons” ([Akerlof, 1970](#)).

Our empirical analyses shed light on these issues by quantifying the extent to which equity crowdfunding alleviates financial constraints and enables the growth of viable businesses. We 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 allows us to gather detailed financial

²Financial 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.

information, to accurately measure the amount raised, to quantify the effects on survival, and to test the quality and financial performance of firms that receive capital over a sufficient post-period. After imposing all data restrictions, our sample includes 1,598 offerings. The average (median) issuer is 3.2 (2.0) years old, has 6.0 (3.0) employees, earns \$392 thousand (\$5 thousand) of revenue, and holds \$86 thousand (\$11 thousand) of cash. Approximately 71.8% of offerings are successful, meaning that the issuer meets its minimum fundraising target. Conditional on success, the average (median) amount raised is \$362 thousand (\$171 thousand), more than doubling sample firms' assets.

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](#); [Lazos, 2024](#)). We compare crowdfunding firms to firms receiving small business loans and venture capital investments as relevant benchmarks. As formal bank credit is the largest source of capital for entrepreneurs ([Robb and Robinson, 2014](#)), we 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. 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 in democratizing access to capital.

Second, we quantify to what extent Reg CF increases firm survival rates. 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. 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 on the sample platform at the same time. These firms face similar economic forces affecting their subsequent performance, despite experiencing different levels of competition for Reg CF capital. Two falsification tests further support that the exclusion restriction is met.

We find that issuers with a successful Reg CF offering are at least 18.3 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. We also find that a one standard deviation increase in the amount raised is associated with a 4.3 to 13.9 percentage points increase in the likelihood of survival for the average issuer. This translates to a 8.6% to 27.8% increase in survival, given the estimated 50% survival rate for issuers in our sample according to their age and Bureau of Labor Statistics data ([BLS, 2016](#)).

Having quantified increased survival rates for successful issuers, we test whether crowdfunding efficiently allocates capital to 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 \$628 thousand (\$36 thousand) in non-cash assets and \$553 thousand (\$19 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 triples after a successful offering. Together, these results validate the crowd’s investment decisions and extend earlier findings in other settings that the crowd appears “wise” ([Mollick and Robb, 2016](#)). Cross-sectional tests suggest that Reg CF improves access to VC by providing capital for new investments as well as marketing benefits to successful issuers.

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 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 6.5-13.0% 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](#)), 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](#)), and other determinants of success (e.g., [Coakley et al., 2022](#); [Burke, 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 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

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.

⁴For 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, and [Burke \(2023\)](#) examines the crowd's response to analyst reports.

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 to the better 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

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

⁵Only 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.

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

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.

⁶In 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.

⁷Specifically, 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.

2.2.3 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 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 Even though the index is scaled such that 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.

⁸We excluded the platform Republic because alternate meanings unrelated to crowdfunding skew the Google search measure.

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

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 we obtain unemployment rate data 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 1,598 offerings for 1,428 firms. See Table [IA.1](#) for details.¹⁰

Figure 1 Panel A depicts the rapid growth of equity crowdfunding over the sample period. The solid (striped) 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 (dotted bars) shown next to the total number of offerings (striped bars repeated from Panel A). The number of successful offerings generally increases over time,

¹⁰Some issuers pursue multiple offerings on different platforms, which explains why the number of unique issuers in the sample is less than the sum of the breakdown by platform.

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 \$202 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 71.8%, amounting to 1,147 offerings for 1,005 distinct issuers. The average (median) successful offering raises \$362 (\$171) thousand of additional capital. Approximately 68% of issuers are still active in subsequent years. The average (median) issuer is 3.18 (2.04) 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 \$361 thousand (\$67 thousand), with average (median) cash balances of \$86 thousand (\$11 thousand) and revenue of \$392 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 856 (74.6%) of the issuers with successful offerings were still active at the end of April 2023, compared to only 226 (50.1%) for failed offerings. Likewise 7.1% (1.9%) of successful issuers obtain subsequent VC funding (SBA loans), compared to only 1.3% (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 assess their quality based on 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 has two SBA loan recipients, 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.¹¹

3.1 Business Qualification

3.1.1 Industry composition

We first evaluate the industry composition of equity crowdfunding. Figure 2 plots in striped bars 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 (solid bars) and SBA (dotted bars). 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.

¹¹Consistent 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).

3.1.2 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 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 from 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).¹² 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)), 38.0% 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)).¹³ Column (5)

¹²Many 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.

¹³We 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.

shows that only 5.3% of crowdfunding offerings would qualify based on meeting the income, revenue, and age requirements. That proportion drops to 1.6% 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.¹⁴ Likewise, venture capital has mostly been clustered in high population centers, in part because geographically close investments are easier to monitor (Chen et al., 2010).

We perform two analyses to assess whether the fully online fundraising process for 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):

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

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 financing 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), whereas 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, as indicated by 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 have an average Gini coefficient of 97.7%. In contrast, SBA loans

¹⁴Access 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 counterparts.

exhibit less concentration, with an average Gini coefficient of 58.5%.

The high levels of concentration suggest that Reg CF has not yet diversified the allocation of capital across the country as suggested by proponents of the regulation. However, trends show promising patterns for more recent periods; column (2) reports a decline of 1.4 percentage points over a five year period. 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 all Reg CF offerings. Analysis of concentration across zip codes *within* the top 30 counties by number of offerings in columns (3) and (4) of Table 2 Panel B further confirms these patterns.

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, Austin, 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 in 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 allocating capital to 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.¹⁵ Second, starting in 2017, the SBA provides annual statistics on the number 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.¹⁶

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 30.2% 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 18.9% 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 0.8 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 5.6 percentage points). In summary, crowdfunding provides capital to businesses owned by female and minority entrepreneurs at a similar rate as SBA – and

¹⁵This package produces a prediction of gender and race based on millions of names reported to the U.S. 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.

¹⁶To 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.

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 quantify the extent to which Reg CF increases survival rates of small businesses by alleviating financial constraints and test whether crowdfunding enables “good” firms to grow or if it prolongs the life of “lemons” that should have otherwise remained unfunded.

4.1 Empirical Design

4.1.1 Baseline regression

We face an inherent selection bias when studying the effect of equity crowdfunding on survival and subsequent funding: 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:

$$Y_i = \beta_1 \cdot Success_i + \gamma_1 \cdot X_i + quarter_i + industry_i + platform_i + \epsilon_{1i} \quad (2)$$

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 and platform fixed effects to subsume differences in funding across industries and platforms. 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 the logarithm of the dollar amount raised. This latter measure allows us to compare firms based on the extent of capital raised, thereby capturing variation in successful fundraising.

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.¹⁷ 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. We include *\$ target*, the target amount to raise, because it has a direct impact on the likelihood of success. 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 subsequent access to venture or debt capital. For example, if successful issuers

¹⁷We do not scale by assets because it would induce a small denominator problem in many companies.

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.¹⁸

For the first stage, we estimate the following regression:

$$Success_i = \beta_2 \cdot IV_i + \gamma_2 \cdot X_i + quarter_i + industry_i + platform_i + \epsilon_{2i} \quad (3)$$

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.¹⁹ In the second stage, we regress the post-offering outcomes on the instrument and controls:

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

where $\widehat{Success}_i$ is the predicted value 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.²⁰ Second, listing platforms can only

¹⁸Signori 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.

¹⁹We 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).

²⁰At 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.

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 StartEngine, documenting the limited space for investors to observe particular offerings at a given time.

With respect to the exclusion restriction, because we include quarter, industry, and platform fixed effects, our analyses compare issuers in the same industry that are raising capital on the same platform at the 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 financial statement assurance). Thus, after controlling for industry, time, platform, 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.

Prior to estimating Eq. 3, we plot the likelihood of success against the number of competing offerings by platform to further assess the validity of the instrument; see Figure IA.6. We observe the expected inverse relation for Wefunder and StartEngine, with peaks in the number of offerings corresponding to dips in the likelihood of success. However, we observe essentially no variation in the success rate for Republic offerings during the sample period, suggesting that the instrument may not be valid for this platform. Consequently, we drop Republic offerings from the sample for the following analysis, and instead use them in placebo tests. Table IA.3 reports descriptive statistics for this reduced sample and Section 4.5 discusses these placebo tests as well as several analyses that further demonstrate the validity of the instrument for the remaining two platforms.

Table 3 presents results from the first-stage estimation that uses the number of competing offerings to predict crowdfunding success. We continue to observe the predicted negative relation from Figure IA.6 after including control variables: the number of competing offerings exhibits a negative and statistically significant association with the likelihood of a *Successful offering* in column (1) and the natural logarithm of the amount raised in column (2). A one

standard deviation increase in the number of competing offerings is associated with a 5.3% decrease in the likelihood of Reg CF success and a 33% decrease in the amount raised. The F-statistic for the amount raised is 15.9, indicating a strong instrument, but only 6.91 for the binary indicator of success, below the recommended threshold of 10 (Stock et al., 2002). Thus, we conduct several tests to confirm results are robust to weak instruments in the following analyses. Control variables exhibit the expected sign: factors positively correlated with offering success include *VC before*, *Reg CF before*, and *CPA engaged*. Setting a high target or offering debt or convertible securities instead of equity are negatively associated with offering success.

4.2 Reg CF Success and Firm Survival

Firms that receive funding from Reg CF should be no worse off after a successful offering; that is, we should expect them to have higher survival rates than unsuccessful offerings. Thus, we first focus on quantifying the effect of a successful offering on survival by defining Y_i as *Active*, an indicator equal to one if the firm is still in business as of April 2023 (the date we obtained business activity data).

Table 4 reports results from OLS and 2SLS estimations. In column (1), we find that issuers are 18.3 percentage points more likely to be listed as active 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. In column (3), we estimate a statistically significant coefficient of 1.15 from 2SLS. However, because the instrument is weak for the binary indicator of Reg CF success potentially leading to inflated coefficients, we report the Chernozhukov and Hansen (2008) 95% confidence intervals that are robust to weak instruments. The lower bound is 0.408, providing strong evidence that Reg CF improves the survival of successful issuers. We find consistent results in columns (2) and (4) using the continuous measure of Reg CF success: a one standard deviation increase in the amount raised is associated with a 4.3 to 13.9 percentage points increase in the likelihood of

survival for the average issuer.²¹ 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 8.6% to 27.8% increase in the likelihood of survival for a standard deviation increase in the amount raised.

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, whereas 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.²²

4.3 Viability of Successful Issuers

We next conduct two tests to study whether the crowd provides capital to firms with good growth prospects, or if it instead prolongs the life of poor quality firms.

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 financial growth as one metric of future performance.²³ 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, viable firms would use the offering proceeds to

²¹For example, the effect size based on the 2SLS coefficient is computed as follows: $0.133 \cdot \log\left(\frac{0.251+0.463}{0.251}\right)$, where 0.251 is the mean amount raised, and 0.463 the standard deviation, both from Table IA.3.

²²The 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 positive 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.

²³This 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).

acquire productive assets and increase revenue. We use data from publicly filed annual reports (Form C-AR) to measure financial growth. These data are available for approximately 57% of successful issuers in the first year post-offering, and 36% 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 \$177 thousand on average (median of \$7 thousand), and revenue increases by \$143 thousand on average (median of \$1 thousand). Because, in some cases, period t contains only a few months after the close of the offering, we also measure growth through $t + 1$. We find substantial growth in that one year period: non-cash assets increase by \$628 thousand on average (median of \$36 thousand), and revenue increases by \$553 thousand (median of \$19 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 that the average amount raised was \$370 thousand (see Table IA.3).

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 will suffer from upward bias. Thus, we conduct an additional test to assess the crowd's investment decisions.

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). VC-backed companies also account 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, obtaining VC or bank financing can serve as a measure of success for startups in need of external capital (e.g., [Ewens and Townsend \(2020\)](#)).

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. According to [Ueda \(2004\)](#), startups with those characteristics may not be able to obtain bank credit at favorable terms and will instead prefer VC financing. Thus, 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.

Table 6 presents the results of the OLS and 2SLS estimations. Panel A focuses on VC. In column (1), we find that issuers are 3.0 percentage points more likely to raise capital from VC firms after a successful offering. The 2SLS estimate in column (3) is 0.688 and statistically significant. More importantly, the lower bound of the 95% confidence interval that is robust to weak instruments is 0.27, providing evidence that Reg CF success increases the likelihood of subsequently being financed by VC among successful issuers. Column (4) reports consistent effects for the continuous measure of Reg CF success: a one standard deviation increase in the amount raised is associated with a 10.9 percentage point increase in the likelihood of receiving subsequent VC investments for the average issuer. Based on the fact that 3.2% of issuers received VC investments prior to crowdfunding (Table IA.3), this estimate implies that a one standard deviation increase in the amount raised more than triples the likelihood of subsequent VC investment.

Panel B presents mixed results for SBA loans. The OLS estimate in column (1) suggests

a 2.0 percentage point increase in the likelihood of obtaining an SBA loan for successful issuers. As 4.1% of firms have SBA loans prior to crowdfunding (Table IA.3), this translates to a 48.8% 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.²⁴ 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 appears “wise” to the context of equity crowdfunding.

4.4 Mechanisms

A natural question is *why* a successful crowdfunding improves subsequent firm growth and access to capital. One explanation, consistent with prior work on early-stage financing, is that crowdfunding alleviates financial constraints, enabling firms to fund positive NPV projects that they previously could not afford. Another explanation, specific to crowdfunding, is that it provides marketing benefits: having an offering listed on an online platform can both attract new customers and improve the loyalty of existing ones by offering an ownership stake to these individuals.

We conduct two cross-sectional tests to assess if either, or both, of these mechanisms explain the effect of crowdfunding on subsequent performance. To do so, we partition firms based on their *ex ante* expectations of post-offering investment and marketing spending, and re-estimate Eq. 2 separately for firms above and below the median allocation.²⁵ Under the assumption that the intended use of proceeds reflects the firm’s perceived opportuni-

²⁴Untabulated 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.

²⁵We standardize the categories for the intended use of proceeds across firms to include offering fees, marketing expenses, employment, investment, debt repayment, and other general uses. Observations for which the allocation of intended use of proceeds, as reported in Form C, is missing or does not add up to 100% are dropped.

ties and needs, the marketing (financial constraints) benefits of crowdfunding will be more pronounced for firms with a high allocation of proceeds to marketing expenses (investments).

The marketing (investment) results are reported in Table IA.4, Panel A (B). In columns (1) and (2), we observe that the association between Reg CF success and subsequent VC financing is significant only for firms with high (above-median) expected marketing and investment spending. These results are consistent with Reg CF success providing an informative signal to VCs about customer demand or potential firm growth. In contrast, columns (3) and (4) indicate a stronger association between Reg CF success and access to SBA loans for firms with *lower* (higher) marketing (investments) allocations. This evidence, although indirect, suggests that equity crowdfunding improves subsequent performance by alleviating financial constraints and providing marketing benefits to successful issuers.

4.5 Instrument validity and robustness

In this section, we perform several additional analyses to further assess the validity of the instrument and the robustness of our results.

4.5.1 Reduced form regression and falsification tests

First, as suggested by Angrist and Krueger (2001) and Chernozhukov and Hansen (2008), we estimate reduced form regressions which are not biased even in the presence of weak instruments. Specifically, we estimate the following regression:

$$Y_i = \beta_4 \cdot IV_i + \gamma_4 \cdot X_i + quarter_i + industry_i + platform_i + \epsilon_{4i} \quad (5)$$

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 A of Table 7 reports these estimates for our sample of Wefunder and StartEngine offerings. Consistent with our main results, the number of competing offerings has a statistically significant negative association with subsequent survival and VC funding,

and no association with subsequent SBA loans.²⁶ Thus, the reduced form estimates further confirm that Reg CF success improves survival and access to VC.

Next, we conduct two falsification tests to mitigate concerns about the exclusion restriction. If the exclusion restriction is violated – that is, if the number of offerings affects subsequent performance through channels other than Reg CF success – then those other channels should also be apparent in settings where the outcome of the offering is “fixed.” We identify two settings in which this is likely to be the case. Panel B leverages the fact that offerings on the Republic platform consistently have very high levels of success (97% on average). Panel C uses the number of offerings across all platforms in a 3-month window *following completion* of the specified offering as a placebo IV, since at that point the success of the offering is already determined (see Bernstein, 2015 for a similar argument in the context of IPOs). As expected, in both cases, we find no relation between the number of offerings and subsequent survival or VC financing, consistent with the exclusion restriction being satisfied.²⁷

4.5.2 Robustness

Table IA.5 further assesses the robustness of the 2SLS estimation based on the amount raised to different definitions of the IV. Because prior work in rewards-crowdfunding shows that the capital raised in the initial weeks of an offering predicts success (Etter et al., 2013), we repeat the analysis using a shorter 1-month window to compute the number of active offerings. For ease of comparison, column (1) of Panels A and B repeats the first and second stage results from our main specification, respectively, and column (2) reports the coefficient estimates using this alternative definition. Despite a somewhat weaker but still significant instrument (F-statistic of 8.67), the 2SLS results are consistent with our main results.

One potential 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

²⁶Note that the sign of the coefficients in the reduced form should be opposite of those reported in 2SLS because the instrument *decreases* the probability of success.

²⁷There is a marginally significant association with subsequent SBA loans for offerings on the Republic platform, but it is of the opposite sign as the results in the main sample.

launched within the 3-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. While unlikely in the Reg CF setting given that 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), we nonetheless examine this in column (3). Specifically, we repeat the analysis using 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. We find quantitatively similar results for the first and second stage estimations.

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 across the sample period. We exploit this variation in treatment intensity when using a staggered difference-in-differences specification. 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.²⁸

²⁸This 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 regression:

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

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. $D_{ct}^l = \mathbb{I}\{t - \mathcal{G}_c = l\}$ 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 for which data was hand-collected (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 Internet 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.6). 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.²⁹ Second, following Barrios et al. (2022), we capture general interest in entrepreneurship and starting new businesses with Google searches for “entrepreneurship.”

Table 8 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 entrepreneurship. One concern is that these effects are potentially impacted by the Covid-

²⁹As discussed in Section 2, we excluded the third largest platform, “Republic,” because it is a common word with an alternate meaning.

19 pandemic, which unfolded around the same time as the Reg CF market developed and motivated a number of individuals to change jobs and, in some cases, 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 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 available to estimate effects. We observe the same pattern of results for this time period, as seen in columns (2) and (4).

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 8, 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. The results point to a significant 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, 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 9 presents the 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 6.5 to 13.0% in the number of early-stage VC deals in a county following the first Reg CF offering in that county.³⁰ 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 percentage points 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. Together, these results suggest 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. The figure demonstrates both the similarity in pre-trends, as well as the marked change in VC investment and, to a lesser extent, SBA loans, after Reg CF offerings.

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

³⁰Because of the log transformation, the magnitude of the effect for coefficient $\hat{\beta}$ is calculated as $\exp(\hat{\beta}) - 1$.

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. Results for SBA loans, in column (9), are similarly unaffected.

5.4 Robustness

We conduct three additional tests to further assess the robustness of these results. First, we address the concern that counties with Reg CF offerings face different economic trends than those without, and that those trends may not be adequately controlled for with 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 .³¹ We report results in column (1) of Table IA.7 and find the same pattern of results as above: Google searches for equity crowdfunding platforms and entrepreneurship (Panel A), as well as the number of early-stage VC deals (Panel B) are increasing with the count of Reg CF offerings.³²

A second concern relates to measurement. We may observe differing results if we further account for differences in county population or use alternative measures of crowdfunding exposure. Additional tests show that results are unchanged 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* Reg CF offering (columns (4) and (5)).

Finally, an alternative interpretation is that our results are driven by government policies specifically targeted at entrepreneurial activity. For this to be the case, these policies would have to be implemented by local governments (i.e., cities or counties) at the same time as the first (successful) crowdfunding offering within each county, which is staggered across the sample period. While this seems unlikely, we reviewed governmental policies for the 20

³¹Note that this changes means that the estimation is no longer a staggered difference in difference, as we now compare counties on the basis of the treatment intensity, conditional on treatment.

³²The geographic overlap of Reg CF and VC deals means that Reg CF frequently occurs in counties where VC deals are already taking place (see Figure 3B). Thus, when we restrict the analysis to counties with Reg CF, the coefficient on the *binary* indicator of VC activity is, unsurprisingly, statistically insignificant.

counties with the most Reg CF offerings using both county and city websites, as well as the Wayback Machine, to identify policies in place in the years immediately preceding and overlapping with the sample period. We find very limited evidence that this is a concern as only a handful of counties have programs targeted at the same types of entrepreneurial firms in our sample, and the programs that do exist generally provide very little monetary support that would be meaningful enough to motivate individuals to start a small business.³³

Collectively, the evidence in this section 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.

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 quantify the extent to which bridge financing via Reg CF helps sustain small businesses until they can obtain subsequent funding.

³³For example, some programs provide relatively small grants of \$5,000 to \$10,000 (e.g., from the San Francisco county Office of Small Business), and others provide no monetary support and instead only offer business advisory services (e.g., Cook County Small Business Source).

This work 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 while at the same time raising concerns about investor protection. We offer some of the first evidence about the viability of equity crowdfunding issuers and their impact on the local economy.

References

- Abate, L. (2018). One Year of Equity Crowdfunding: Initial Market Developments and Trends. Technical report, U.S. Small Business Administration.
- Akerlof, G. A. (1970). The Market for “Lemons”: Quality Uncertainty and the Market Mechanism*. *The Quarterly Journal of Economics*, 84(3):488–500.
- Aland, J. M. (2023). Equity Crowdfunding and Offering Page Disclosure. *Journal of Financial Reporting*, 8(2):25–53.
- Alois, J. (2023). Reg CF - Crowdfunding Total Tops \$2 Billion In Total Raised. *Crowdfund Insider*.
- Angrist, J. D. and Krueger, A. B. (2001). Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments. *Journal of Economic Perspectives*, 15(4):69–85.
- Armstrong, C., Davila, A., and Foster, G. (2006). Venture-backed Private Equity Valuation and Financial Statement Information. *Review of Accounting Studies*, 11(1):119–154.
- Ashwell, B. (2023). As Bank Lending Tightens, Small Businesses Turn to Customers to Raise Money. *Wall Street Journal*.
- Bai, J. J., Chen, T., Martin, X., and Wan, C. (2023). Platform-provided Disclosure on Investor Base and Entrepreneurial Success: Evidence from Crowdfunding. *The Accounting Review*, Forthcoming.
- Baik, B. K., Berfeld, N., and Verdi, R. S. (2022). Do Public Financial Statements Influence Venture Capital and Private Equity Financing? SSRN 3867958.
- Baker, A. C., Larcker, D. F., and Wang, C. C. Y. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2):370–395.
- Barrios, J. M., Choi, J. H., Hochberg, Y. V., Kim, J., and Liu, M. (2023). Informing Entrepreneurs? Initial Public Offerings and New Business Formation. SSRN 3640736.
- Barrios, J. M., Hochberg, Y. V., and Yi, H. (2022). Launching with a parachute: The gig economy and new business formation. *Journal of Financial Economics*, 144(1):22–43.
- Battisto, J., Lieberman, S., Mills, C. K., Wiersch, A. M., and Zeeuw, M. d. (2019). Report on Employer Firms. *Small Business Credit Survey*. Publisher: Federal Reserve Banks.
- Becker, S. O. (2016). Using instrumental variables to establish causality. *IZA World of Labor*.
- Bernstein, S. (2015). Does Going Public Affect Innovation? *The Journal of Finance*, 70(4):1365–1403.
- Blanchflower, D. G., Levine, P. B., and Zimmerman, D. J. (2003). Discrimination in the Small-Business Credit Market. *The Review of Economics and Statistics*, 85(4):930–943.
- BLS (2016). Entrepreneurship and the U.S. Economy : U.S. Bureau of Labor Statistics.

- Bogdani, E., Causholli, M., and Knechel, W. R. (2022). The Role of Assurance in Equity Crowdfunding. *The Accounting Review*, 97(2).
- Brown, J. D. and Earle, J. S. (2017). Finance and Growth at the Firm Level: Evidence from SBA Loans. *The Journal of Finance*, 72(3):1039–1080.
- Burke, G. (2023). Information Intermediation in Opaque Markets: Evidence from Equity Crowdfunding Analyst Reports. SSRN 4580101.
- Card, D. (1999). Chapter 30 - The Causal Effect of Education on Earnings. In Ashenfelter, O. C. and Card, D., editors, *Handbook of Labor Economics*, volume 3, pages 1801–1863. Elsevier.
- Cascino, S., Correia, M., and Tamayo, A. (2019). Does Consumer Protection Enhance Disclosure Credibility in Reward Crowdfunding? *Journal of Accounting Research*, 57(5):1247–1302.
- Chen, A. J., Dechow, P., and Tan, S. T. (2022). Corporate Response to the Black Lives Matter Movement: Determinants of Speaking Out in Support of Social Causes. SSRN 3921985.
- Chen, H., Gompers, P., Kovner, A., and Lerner, J. (2010). Buy local? The geography of venture capital. *Journal of Urban Economics*, 67(1):90–102.
- Chernozhukov, V. and Hansen, C. (2008). The reduced form: A simple approach to inference with weak instruments. *Economics Letters*, 100(1):68–71.
- Coakley, J., Lazos, A., and Liñares-Zegarra, J. M. (2022). Equity Crowdfunding Founder Teams: Campaign Success and Venture Failure. *British Journal of Management*, 33(1):286–305.
- Cumming, D., Meoli, M., and Vismara, S. (2021). Does equity crowdfunding democratize entrepreneurial finance? *Small Business Economics*, 56(2):533–552.
- Dambra, M., Field, L. C., and Gustafson, M. T. (2015). The JOBS Act and IPO volume: Evidence that disclosure costs affect the IPO decision. *Journal of Financial Economics*, 116(1):121–143.
- D’Ambrosio, M. and Gianfrate, G. (2016). Crowdfunding and Venture Capital: Substitutes or Complements? *The Journal of Private Equity*, 20(1):7–20.
- de Kok, T. (2023). Generative LLMs and Textual Analysis in Accounting: (Chat)GPT as Research Assistant? SSRN 4429658.
- Dolatabadi, I., Fracassi, C., and Yang, L. (2021). Equity Crowdfunding in the U.S. SSRN 3934662.
- Donovan, J. (2021). Financial Reporting and Entrepreneurial Finance: Evidence from Equity Crowdfunding. *Management Science*, 67(11):7214–7237.
- Etter, V., Grossglauser, M., and Thiran, P. (2013). Launch hard or go home! predicting the success of kickstarter campaigns. In *Proceedings of the first ACM conference on Online social networks*, COSN ’13, pages 177–182. Association for Computing Machinery.

- Ewens, M. and Townsend, R. R. (2020). Are early stage investors biased against women? *Journal of Financial Economics*, 135(3):653–677.
- Fairlie, R., Robb, A., and Robinson, D. T. (2022). Black and White: Access to Capital Among Minority-Owned Start-ups. *Management Science*, 68(4):2377–2400.
- Gompers, P. A., Gornall, W., Kaplan, S. N., and Strebulaev, I. A. (2020). How do venture capitalists make decisions? *Journal of Financial Economics*, 135(1):169–190.
- Gong, J., Krishnan, J., and Liang, Y. (2022). Securities-Based Crowdfunding by Startups: Does Auditor Attestation Matter? *The Accounting Review*, 97(2).
- Gonzalez, L. and James, C. (2007). Banks and bubbles: How good are bankers at spotting winners? *Journal of Financial Economics*, 86(1):40–70.
- Kaplan, S. N. and Lerner, J. (2010). It Ain’t Broke: The Past, Present, and Future of Venture Capital. *Journal of Applied Corporate Finance*, 22(2):36–47.
- Kerr, W. and Nanda, R. (2009a). Financing Constraints and Entrepreneurship. NBER 15498.
- Kerr, W. R., Lerner, J., and Schoar, A. (2014). The Consequences of Entrepreneurial Finance: Evidence from Angel Financings. *The Review of Financial Studies*, 27(1):20–55.
- Kerr, W. R. and Nanda, R. (2009b). Democratizing entry: Banking deregulations, financing constraints, and entrepreneurship. *Journal of Financial Economics*, 94(1):124–149.
- Krishnan, K., Nandy, D. K., and Puri, M. (2015). Does Financing Spur Small Business Productivity? Evidence from a Natural Experiment. *The Review of Financial Studies*, 28(6):1768–1809.
- Lambert, T., Ralcheva, A., and Roosenboom, P. (2022). Crowdfunding Entrepreneurship: Evidence from US Counties. SSRN 4244733.
- Lazos, A. (2024). Does equity crowdfunding benefit ventures located in high unemployment regions? *Small Business Economics*.
- Mach, T. L. and Wolken, J. D. (2012). Examining the Impact of Credit Access on Small Firm Survivability. In Calcagnini, G. and Favaretto, I., editors, *Small Businesses in the Aftermath of the Crisis: International Analyses and Policies*, Contributions to Economics, pages 189–210. Physica-Verlag HD.
- Madsen, J. M. and McMullin, J. L. (2019). Economic Consequences of Risk Disclosures: Evidence from Crowdfunding. *The Accounting Review*, 95(4):331–363.
- Mollick, E. and Nanda, R. (2016). Wisdom or Madness? Comparing Crowds with Expert Evaluation in Funding the Arts. *Management Science*, 62(6):1533–1553.
- Mollick, E. and Robb, A. (2016). Democratizing Innovation and Capital Access: The Role of Crowdfunding. *California Management Review*, 58(2):72–87.
- Morgan, D. P., Pinkovskiy, M. L., and Yang, B. (2016). Banking Deserts, Branch Closings, and Soft Information. *Liberty Street Economics*. Federal Reserve Bank of New York.

- Puri, M. and Zarutskie, R. (2012). On the Life Cycle Dynamics of Venture-Capital- and Non-Venture-Capital-Financed Firms. *The Journal of Finance*, 67(6):2247–2293.
- Rashidi Ranjbar, H. (2022). Return-based Crowdfunding and Entrepreneurship. SSRN 4264845.
- Ritter, T. and Pedersen, C. L. (2022). An Entrepreneur’s Guide to Surviving the “Death Valley Curve”. *Harvard Business Review*.
- Robb, A. M. and Robinson, D. T. (2014). The Capital Structure Decisions of New Firms. *The Review of Financial Studies*, 27(1):153–179.
- SBA (2022). 2022 Small Business Profile. Technical report, U.S. Small Business Administration.
- SEC (2015). Crowdfunding. 80 Fed. Reg. 71388-71615.
- Serrano, J. (2023). Does Crowdfunding Success Hinge on Launch Timing? SSRN 4327209.
- Signori, A. and Vismara, S. (2018). Does success bring success? The post-offering lives of equity-crowdfunded firms. *Journal of Corporate Finance*, 50:575–591.
- Sorenson, O., Assenova, V., Li, G.-C., Boada, J., and Fleming, L. (2016). Expand innovation finance via crowdfunding. *Science*, 354(6319):1526–1528.
- Stock, J. H., Wright, J. H., and Yogo, M. (2002). A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments. *Journal of Business & Economic Statistics*, 20(4):518–529.
- Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.
- Tang, H. (2019). Peer-to-Peer Lenders Versus Banks: Substitutes or Complements? *The Review of Financial Studies*, 32(5):1900–1938.
- Ueda, M. (2004). Banks versus Venture Capital: Project Evaluation, Screening, and Expropriation. *The Journal of Finance*, 59(2):601–621.
- Walthoff-Borm, X., Schwienbacher, A., and Vanacker, T. (2018). Equity crowdfunding: First resort or last resort? *Journal of Business Venturing*, 33(4):513–533.

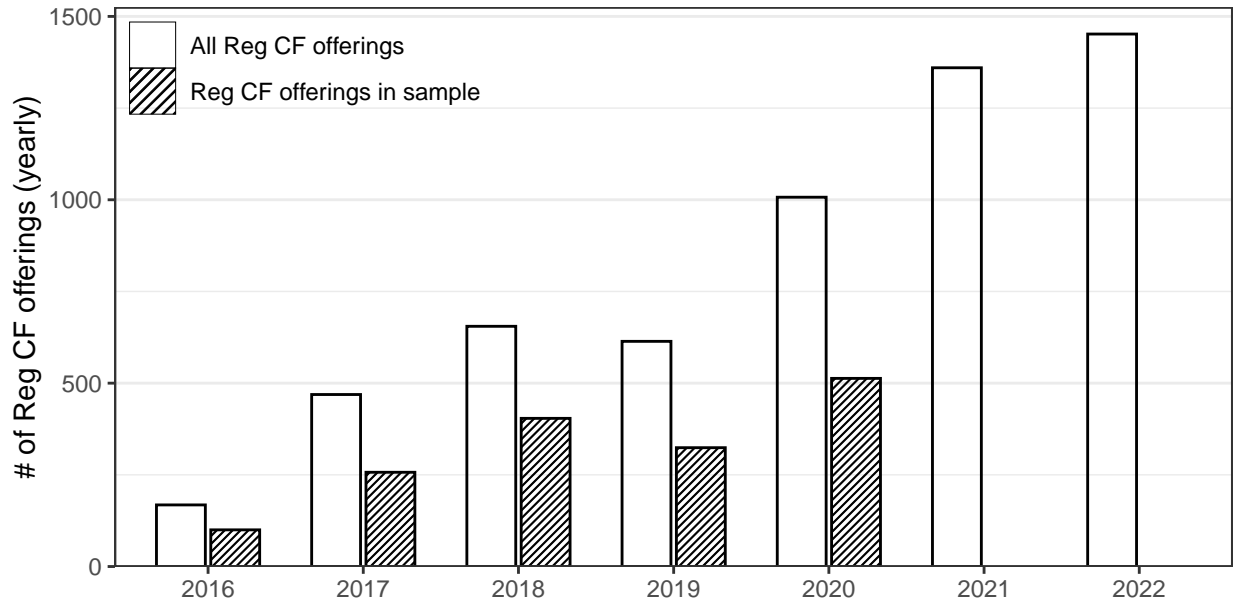
Table A.1: Variable definitions

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

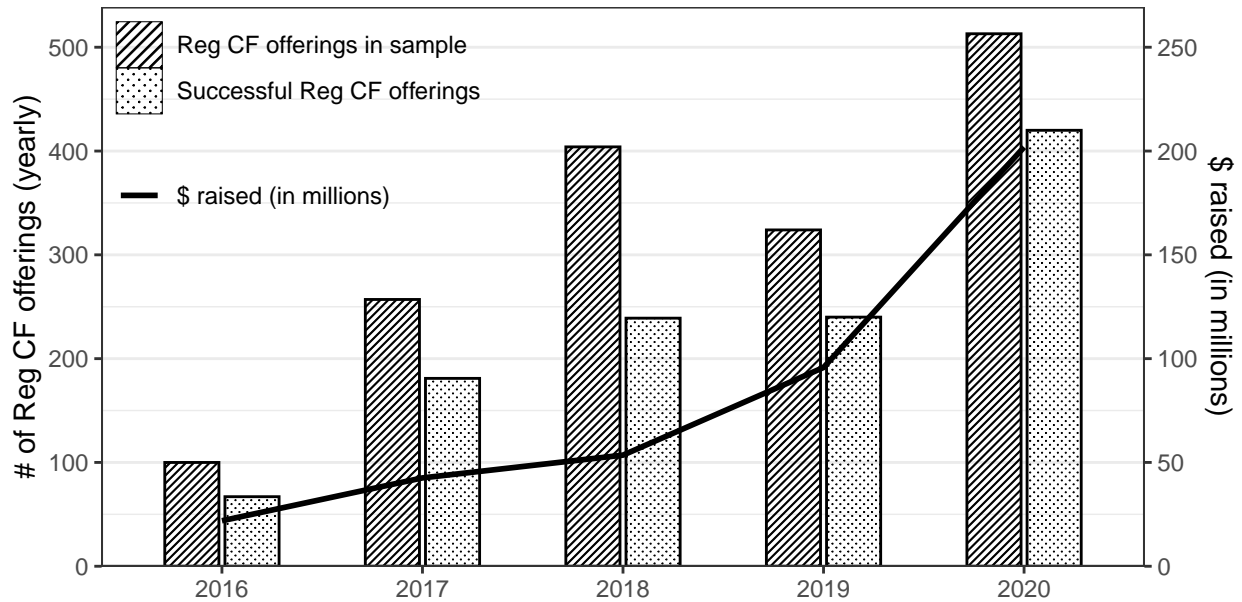
This table describes the variables used in the main analyses and their sources.

Figure 1: Reg CF offerings over time

A: All offerings and in-sample offerings

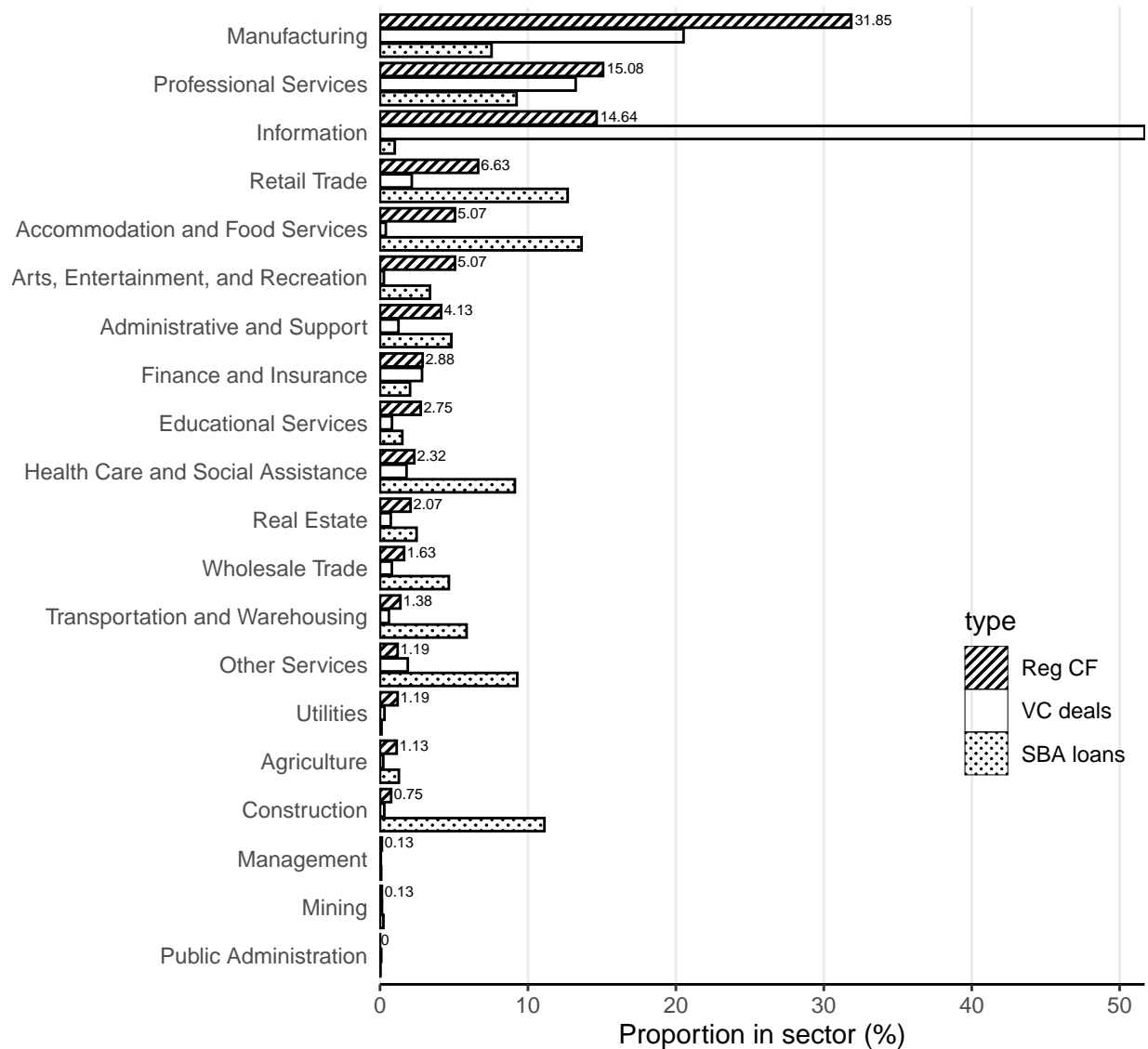


B: In-sample offerings



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.

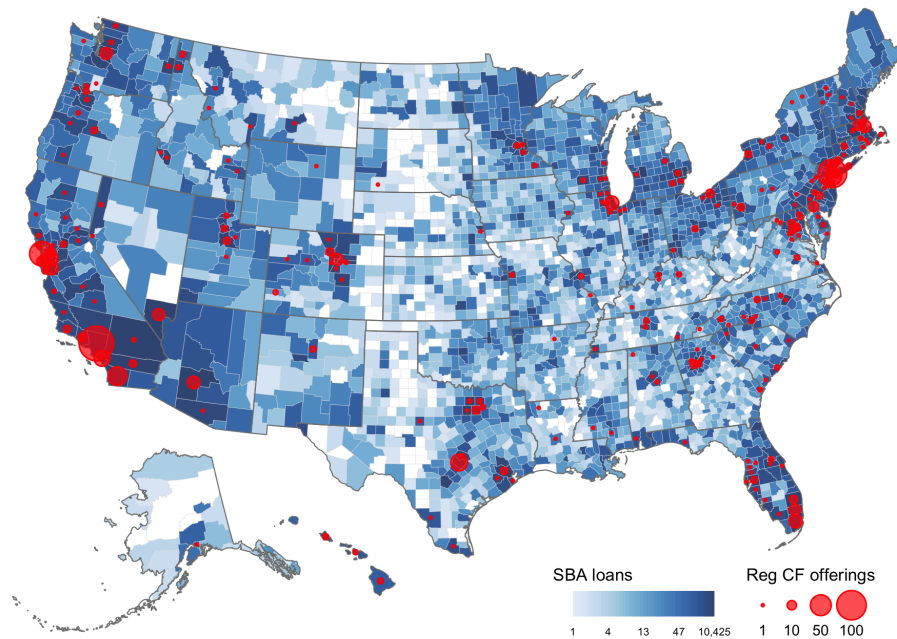
Figure 2: Industry comparison of Reg CF with SBA loans and VC deals



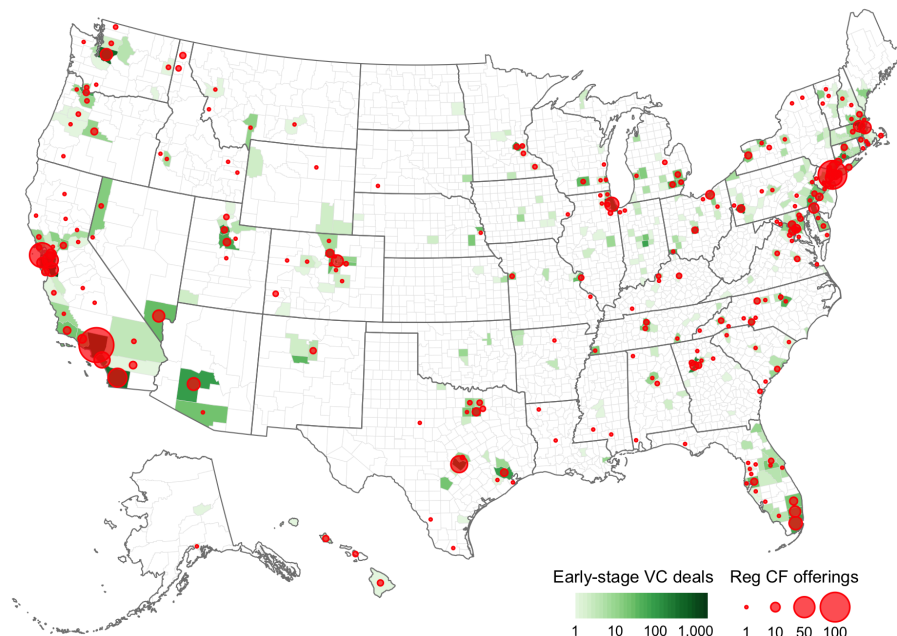
This figure plots the proportion of Reg CF offerings, SBA loans, and VC deals that fall into each of the 2-digit NAICS sectors. The sectors are ordered in decreasing proportion based on Reg CF offerings.

Figure 3: Spatial concentration and overlap

A: Comparison of Reg CF offerings and SBA loans

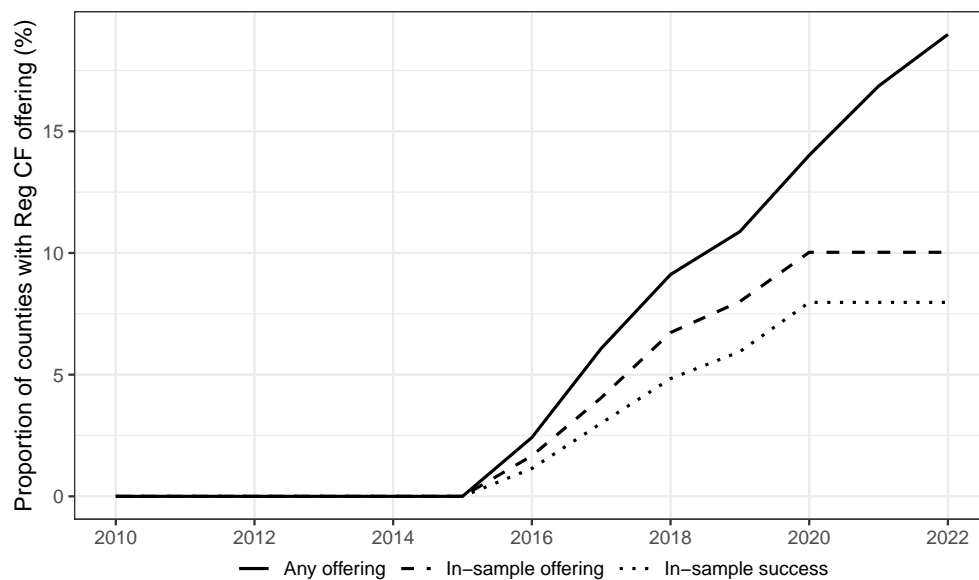


B: Comparison of Reg CF offerings and early-stage VC deals



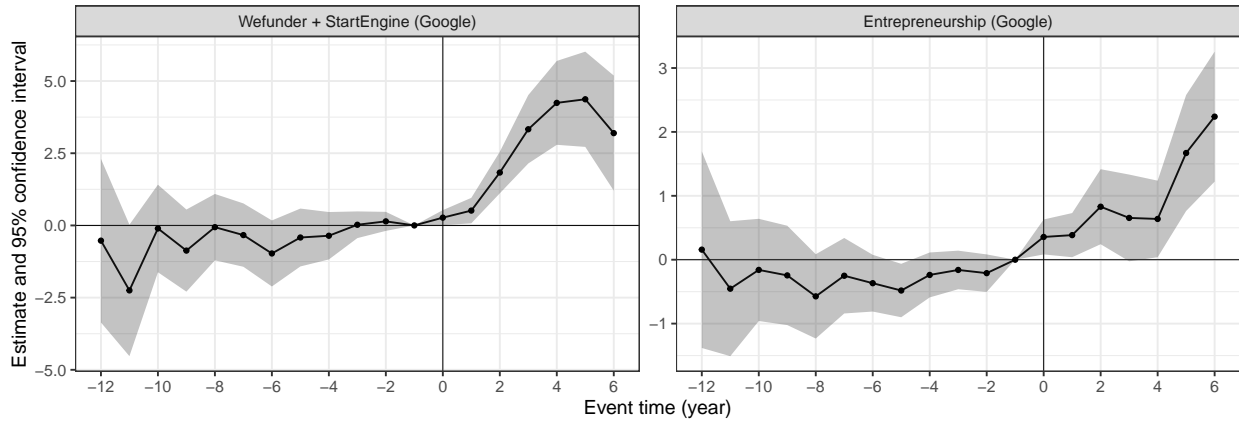
This figure plots the location of Reg CF offerings against the location of SBA loans in Panel A, and early-stage VC deals in Panel B for years 2016 to 2020. The size of the red circles corresponds to the number of successful Reg CF offerings in a given county, and the color shading corresponds to the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

Figure 4: Diffusion of Reg CF over time



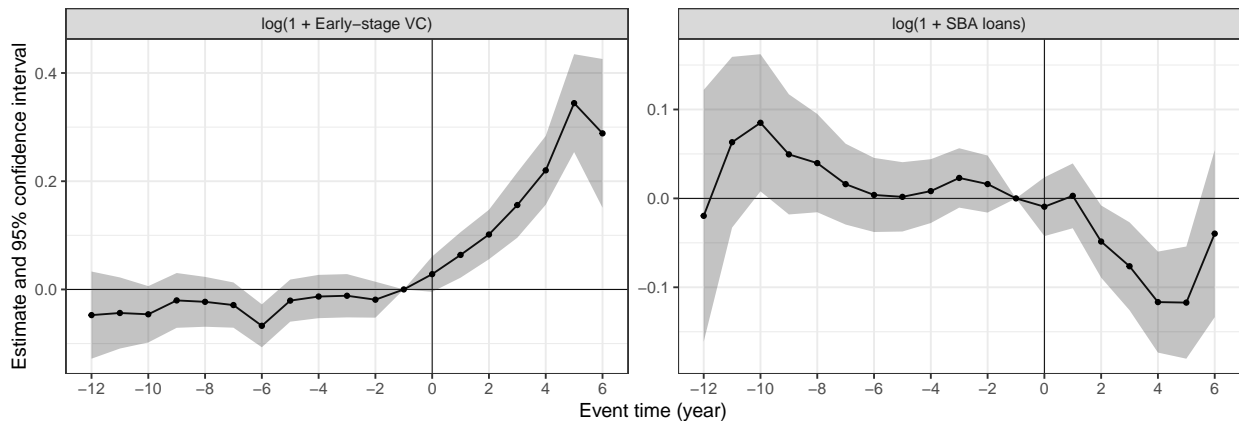
This figure plots the diffusion of Reg CF offerings across U.S. counties for different samples. “Any offering” corresponds to all Reg CF offerings, “In-sample offering” corresponds to the offerings that are in the sample used for the firm-level analysis (offerings launched between 2016 and 2020 in the 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: Offerings on Wefunder, StartEngine, and Republic

	N (1)	Mean (2)	Std. Dev. (3)	25th (4)	Median (5)	75th (6)
Main firm-level variables:						
Successful offering	1,598	0.718	0.450	0.000	1.000	1.000
\$ raised (in millions)	1,598	0.262	0.448	0.013	0.093	0.289
\$ raised success (in millions)	1,147	0.362	0.494	0.076	0.171	0.466
Active	1,598	0.677	0.468	0.000	1.000	1.000
VC after	1,598	0.054	0.227	0.000	0.000	0.000
SBA after	1,598	0.015	0.122	0.000	0.000	0.000
Competing offerings	1,598	106.390	60.532	70.000	97.000	127.000
Firm-level control variables:						
\$ target (in millions)	1,598	0.058	0.080	0.010	0.050	0.050
Age (years)	1,598	3.179	3.930	0.797	2.041	4.164
# of founders	1,598	1.899	1.194	1.000	2.000	2.000
# of employees	1,598	6.066	11.484	2.000	3.000	6.000
VC before	1,598	0.041	0.198	0.000	0.000	0.000
SBA before	1,598	0.041	0.198	0.000	0.000	0.000
RegCF before	1,598	0.106	0.308	0.000	0.000	0.000
CPA engaged	1,598	0.720	0.449	0.000	1.000	1.000
Assets	1,598	0.361	0.757	0.006	0.067	0.331
Cash	1,598	0.086	0.194	0.000	0.011	0.064
Total debt	1,598	0.506	1.075	0.001	0.072	0.461
Revenue	1,598	0.392	1.019	0.000	0.005	0.214
Income	1,598	-0.303	0.664	-0.295	-0.052	-0.001

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

		Full sample	Active		VC after		SBA after	
			Yes	No	Yes	No	Yes	No
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Successful	N	1,147	856	291	81	1,066	22	1,125
	%	[71.8]	[74.6]	[25.4]	[7.1]	[92.9]	[1.9]	[98.1]
Failed	N	451	226	225	6	445	2	449
	%	[28.2]	[50.1]	[49.9]	[1.3]	[98.7]	[0.4]	[99.6]
Chi-squared test			87.89***		19.56***		3.81*	

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)	39,286	2.3	10.9	0.0	0.0	0.0
Entrepreneurship (Google)	39,286	17.6	9.6	13.0	17.0	22.0
Early-stage VC	39,732	0.9	11.8	0.0	0.0	0.0
SBA loans	39,732	17.2	65.0	0.0	2.0	9.0
Reg CF offerings	39,732	0.1	1.7	0.0	0.0	0.0
Per-capita income (lag)	39,732	41.4	12.7	33.3	39.1	46.6
Population (lag)	39,732	103.8	330.1	11.2	26.1	68.6
Bank branches (lag)	39,732	29.7	75.0	5.0	11.0	23.0
Bank deposits (lag)	39,732	3,561.0	26,818.9	188.0	429.6	1,098.1
Unemployment rate (lag)	39,732	6.4	3.0	4.1	5.8	8.1

Panel A reports descriptive statistics for the sample of Reg CF offerings in the three largest platforms (Wefunder, StartEngine, and Republic). 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	38.0	50.6	3.3	5.3	1.6

B: Spatial concentration

Gini coefficient (%)	Across counties		Within county	
	Average	Δ 2020-2016	Average	Δ 2020-2016
	(1)	(2)	(3)	(4)
Successful Reg CF	99.0	-1.4	95.3	-2.2
Early-stage VC deals	97.7	-1	90.6	-1.6
SBA loans	58.5	4.1	63.8	1.8

C: Founders demographics

	Female			Non-white		
	All	Failed	Successful	All	Failed	Successful
	(1)	(2)	(3)	(4)	(5)	(6)
Top 3 platforms	28.8	25.5	30.2	23.6	22.0	24.2
Republic	38.4	14.3	39.1	35.9	42.9	35.7
StartEngine	20.6	24.2	18.9	18.2	17.7	18.5
Wefunder	32.4	26.7	35.4	23.9	24.4	23.6
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 (1)	log(\$ raised) (2)
Competing offerings (in hundreds)	-0.088** (-2.63)	-0.662*** (-3.99)
VC before	0.110** (2.15)	0.362 (1.25)
SBA before	0.133 (1.73)	0.645*** (2.96)
RegCF before	0.119*** (4.32)	0.158* (1.80)
Age	0.002 (0.534)	0.001 (0.113)
# founders	0.010 (0.973)	-0.018 (-0.639)
# employees	0.001 (1.15)	0.0009 (0.176)
Assets	-0.018 (-0.968)	0.047 (0.519)
Cash	0.150 (1.40)	1.47*** (4.03)
Total debt	0.010 (0.582)	-0.043 (-0.626)
Revenue	-0.015 (-1.08)	-0.019 (-0.354)
Income	-0.032 (-1.36)	-0.207** (-2.21)
CPA engaged	0.226*** (7.08)	1.45*** (9.95)
\$ target	-1.11*** (-5.37)	-1.01 (-0.907)
Convertible security	-0.082** (-2.35)	-0.278* (-1.80)
Debt security	-0.072 (-1.50)	-0.262 (-1.43)
Quarter, Industry and Platform FE	Y	Y
Observations	1,353	1,183
Adjusted R ²	0.176	0.423
F-test (1st stage)	6.91	15.9

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 the total amount raised in column (2). We include offering quarter, industry (2-digit NAICS), and platform fixed effects, 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

	Active			
	OLS		2SLS	
	(1)	(2)	(3)	(4)
Successful offering	0.183*** [0.119; 0.247]		1.15** [0.082; 2.22] (0.408; 3.000)	
log(\$ raised)		0.041*** [0.021; 0.060]		0.133*** [0.054; 0.212] (0.052; 0.223)
Quarter, Industry and Platform FE	Y	Y	Y	Y
Control variables	Y	Y	Y	Y
Observations	1,353	1,183	1,353	1,183
Adjusted R ²	0.112	0.097	-	-

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 the amount raised in even-numbered columns. We include offering quarter, industry (2-digit NAICS), and platform fixed effects, as well as firm-level control variables as defined in Table A.1. We report asymptotic 95% confidence intervals based on standard errors clustered at the quarter level in square brackets. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. We also report the Chernozhukov and Hansen (2008) 95% confidence intervals that are robust to weak instruments in parentheses.

Table 5: Financial growth of successful Reg CF issuers

Fiscal years	Δ Non-cash assets		Δ Revenue		Filed C-AR
	Mean	Median	Mean	Median	%
	(1)	(2)	(3)	(4)	(5)
t-1 \rightarrow t	0.177	0.007	0.143	0.001	57.0
t-1 \rightarrow t+1	0.628	0.036	0.553	0.019	36.3

This table summarizes the financial growth of successful Reg CF issuers in our main sample 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	0.030** [0.007; 0.053]		0.688** [0.039; 1.34] (0.270; 2.669)	
log(\$ raised)		0.004 [-0.007; 0.016]		0.104*** [0.047; 0.162] (0.054; 0.180)
Quarter, Industry and Platform FE	Y	Y	Y	Y
Control variables	Y	Y	Y	Y
Observations	1,353	1,183	1,353	1,183
Adjusted R ²	0.108	0.116	-	-
B: SBA loans				
	SBA after			
	OLS		2SLS	
	(1)	(2)	(3)	(4)
Successful offering	0.020*** [0.007; 0.033]		0.108 [-0.187; 0.403] (-0.405; 0.442)	
log(\$ raised)		0.003 [-0.0009; 0.006]		0.019 [-0.027; 0.066] (-0.029; 0.072)
Quarter, Industry and Platform FE	Y	Y	Y	Y
Control variables	Y	Y	Y	Y
Observations	1,353	1,183	1,353	1,183
Adjusted R ²	0.035	0.038	-	-

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 the amount raised in even-numbered columns. We include offering quarter, industry (2-digit NAICS), and platform fixed effects, as well as firm-level control variables as defined in Table A.1. We report asymptotic 95% confidence intervals based on standard errors clustered at the quarter level in square brackets. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. We also report the Chernozhukov and Hansen (2008) 95% confidence intervals that are robust to weak instruments in parentheses.

Table 7: Reduced form regression

A: Wefunder and StartEngine platforms

	Active (1)	VC after (2)	SBA after (3)
Competing offerings (in hundreds)	-0.102*** (-2.99)	-0.061*** (-3.45)	-0.010 (-0.702)
Quarter, Industry and Platform FE	Y	Y	Y
Control variables	Y	Y	Y
Observations	1,353	1,353	1,353
Adjusted R ²	0.088	0.110	0.030

B: Falsification - Republic platform

	Active (1)	VC after (2)	SBA after (3)
Competing offerings (in hundreds)	0.362 (0.787)	0.528 (1.09)	0.157* (1.94)
Quarter and Industry FE	Y	Y	Y
Control variables	Y	Y	Y
Observations	245	245	245
Adjusted R ²	0.120	0.121	-0.042

C: Placebo IV - Subsequent offerings on Wefunder and StartEngine platforms

	Active (1)	VC after (2)	SBA after (3)
Subsequent offerings (in hundreds)	-0.005 (-0.088)	-0.016 (-1.09)	-0.012 (-1.41)
Quarter, Industry and Platform FE	Y	Y	Y
Control variables	Y	Y	Y
Observations	1,353	1,353	1,353
Adjusted R ²	0.085	0.104	0.030

This table reports reduced form results (regression of business outcome on IV) for offerings on the Wefunder and StartEngine platforms in Panel A, on the Republic platform as a falsification test in Panel B, and using as a placebo IV the number of offerings on all platforms in the 3 months following completion of an offering in Panel C. We include offering quarter, industry (2-digit NAICS), and platform fixed effects, 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 8: Reg CF awareness and entrepreneurial interest

	Wefunder + StartEngine (Google)		Entrepreneurship (Google)	
	(1)	(2)	(3)	(4)
Avg. treatment on treated	1.90*** (5.40)	1.67*** (5.91)	0.681*** (3.30)	1.04*** (3.31)
log(1 + Per-capita income) (lag)	2.81*** (3.75)	2.21*** (3.28)	0.123 (0.223)	-0.597 (-0.897)
log(1 + Population) (lag)	14.5*** (7.39)	7.57*** (5.13)	3.06*** (2.70)	3.81** (2.32)
log(1 + Bank branches) (lag)	-1.78*** (-3.04)	-0.919* (-1.95)	-0.329 (-0.772)	-0.003 (-0.005)
log(1 + Bank deposits) (lag)	0.133 (0.493)	-0.173 (-0.663)	0.087 (0.410)	0.290 (0.930)
Unemployment rate (lag)	-0.045 (-0.873)	-0.034 (-0.765)	-0.066 (-1.55)	-0.091* (-1.65)
County FE	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y
Sample	2010-22	2010-19	2010-22	2010-19
# 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 9: Interaction with traditional financing

	log(1 + Early-stage VC)			Early-stage VC > 0			log(1 + SBA loans)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Avg. treatment on treated	0.122*** (6.54)	0.063*** (2.61)	0.119*** (6.13)	0.062*** (4.19)	0.041** (2.17)	0.066*** (4.09)	-0.045*** (-2.76)	-0.024 (-1.25)	-0.044*** (-2.67)
log(1 + Per-capita income) (lag)	0.015 (0.901)	-0.008 (-0.496)	0.003 (0.218)	0.001 (0.087)	-0.0008 (-0.060)	0.004 (0.331)	0.021 (0.429)	0.005 (0.092)	0.021 (0.426)
log(1 + Population) (lag)	0.168*** (3.56)	0.158*** (2.85)	0.149*** (3.27)	0.154*** (4.10)	0.144*** (3.01)	0.145*** (3.83)	0.743*** (8.54)	0.723*** (6.62)	0.740*** (8.49)
log(1 + Bank branches) (lag)	0.010 (0.811)	0.020 (1.47)	0.005 (0.390)	-0.006 (-0.626)	0.006 (0.513)	-0.004 (-0.435)	-0.003 (-0.079)	-0.025 (-0.517)	-0.005 (-0.131)
log(1 + Bank deposits) (lag)	0.033*** (2.90)	0.034** (2.16)	0.038*** (3.63)	0.025*** (2.97)	0.015 (1.60)	0.029*** (3.46)	0.014 (0.888)	0.027 (1.24)	0.015 (0.914)
Unemployment rate (lag)	0.003*** (2.79)	0.0003 (0.195)	0.004*** (3.16)	0.002* (1.72)	0.0006 (0.547)	0.002** (2.06)	-0.0007 (-0.201)	-0.004 (-0.968)	-0.0007 (-0.217)
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sample	2010-22	2010-19	2010-22 & indirect	2010-22	2010-19	2010-22 & indirect	2010-22	2010-19	2010-22 & indirect
# County	3,061	3,061	3,024	3,061	3,061	3,024	3,061	3,061	3,043
Observations	39,732	30,570	39,251	39,732	30,570	39,251	39,732	30,570	39,498
Adjusted R ²	0.889	0.895	0.793	0.659	0.676	0.614	0.905	0.907	0.900

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) to (9). 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 where successful Reg CF issuers received subsequent funding from VCs. In column (9) we drop counties where successful issuers subsequently received SBA loans. 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


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)



Financial Statement Certified


Ralf-Rainer von Albedyll
CEO

B: Balance sheet and income statements for MF Fire

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

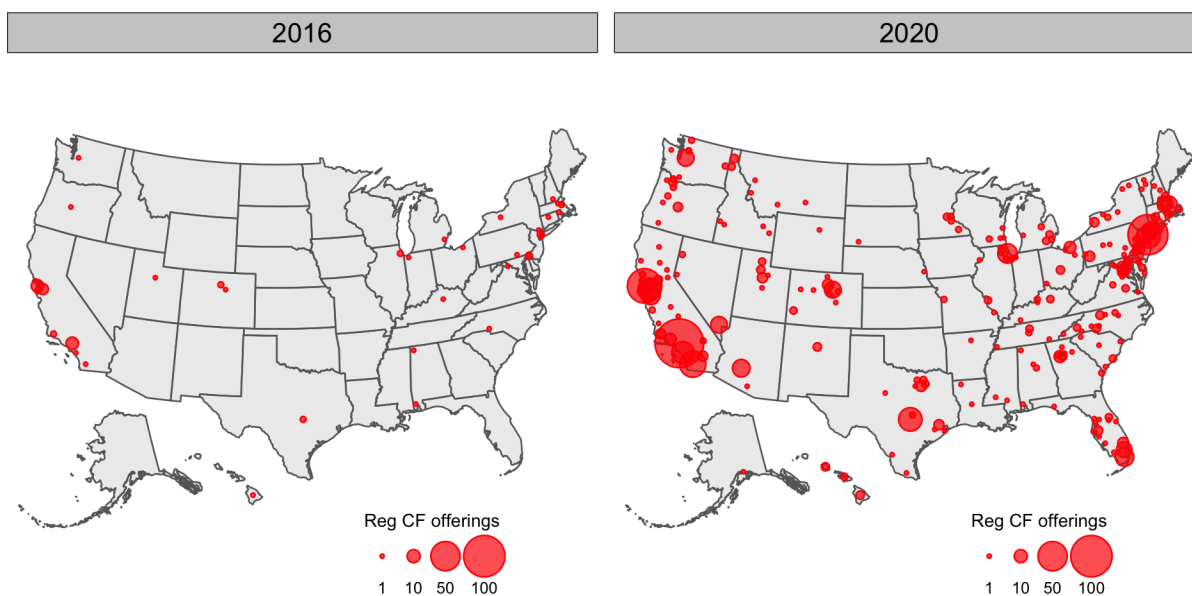
	2015	2014
ASSETS		
Current Assets:		
Cash and cash equivalents	\$ 10,170	\$ 7,321
Total Current Assets	10,170	7,321
TOTAL ASSETS	\$ 10,170	\$ 7,321
LIABILITIES AND MEMBERS' EQUITY (DEFICIT)		
Liabilities:		
Current Liabilities:		
Accounts payable	\$ 24,782	\$ -
Total Liabilities	24,782	-
Members' Equity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

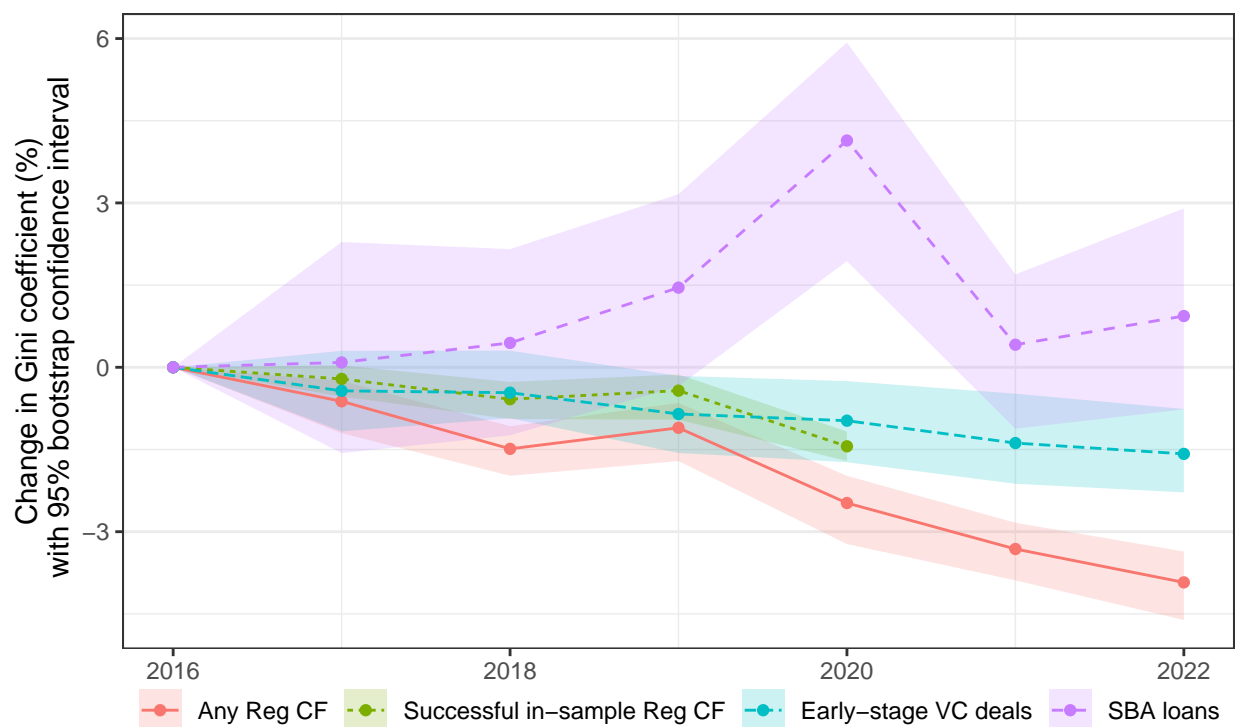
Financial statements filed with Form C on May 16, 2016 for two of the earliest Reg CF offerings. Panel A shows the balance sheet and income statement of NextRx, Inc. for fiscal year 2015. Panel B shows the balance sheet and income statement of MF Fire, Benefit LLC for fiscal years 2014 and 2015.

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.

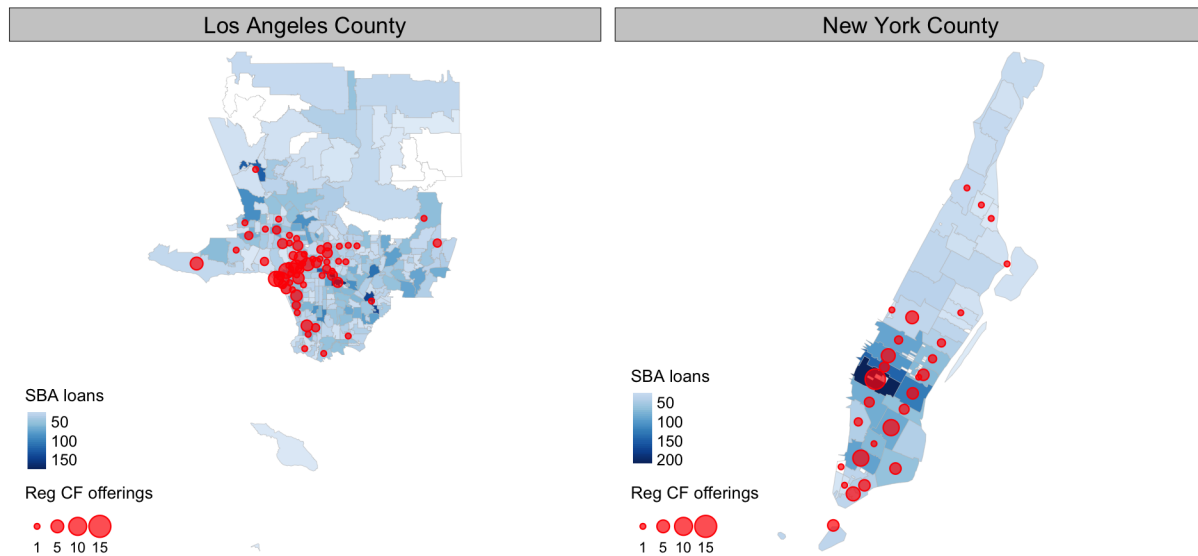
Figure IA.3: Locational Gini coefficients over time



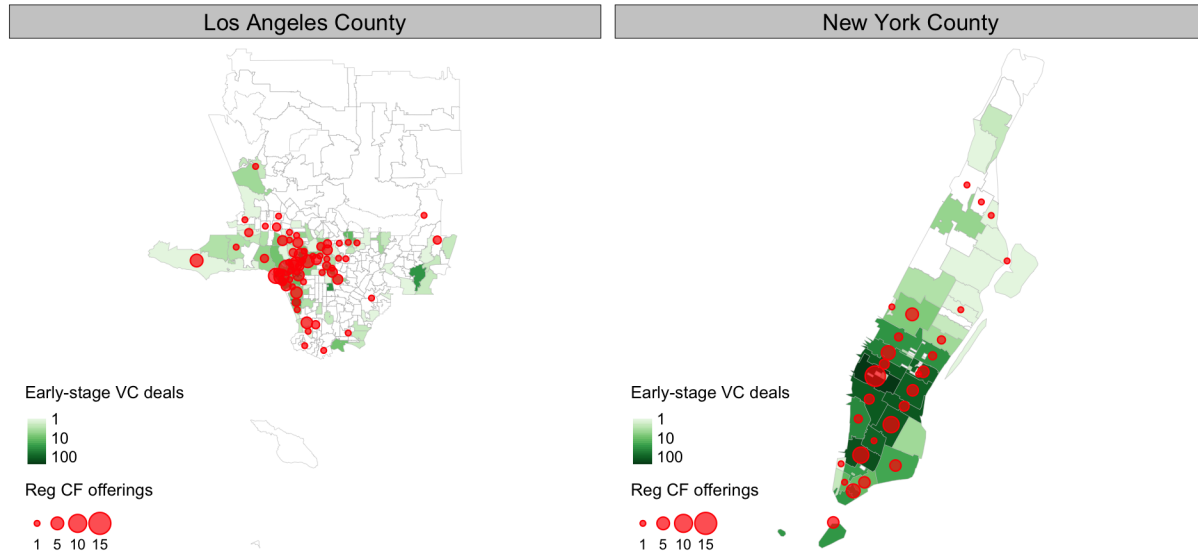
This figure plots the change in locational Gini coefficients across U.S. counties over time for Reg CF offerings (both in-sample successful offerings and all offerings), early-stage VC deals, and SBA loans. The shaded areas denote bootstrapped 95% confidence intervals.

Figure IA.4: Within county spatial concentration and overlap

A: Comparison of Reg CF offerings and SBA loans



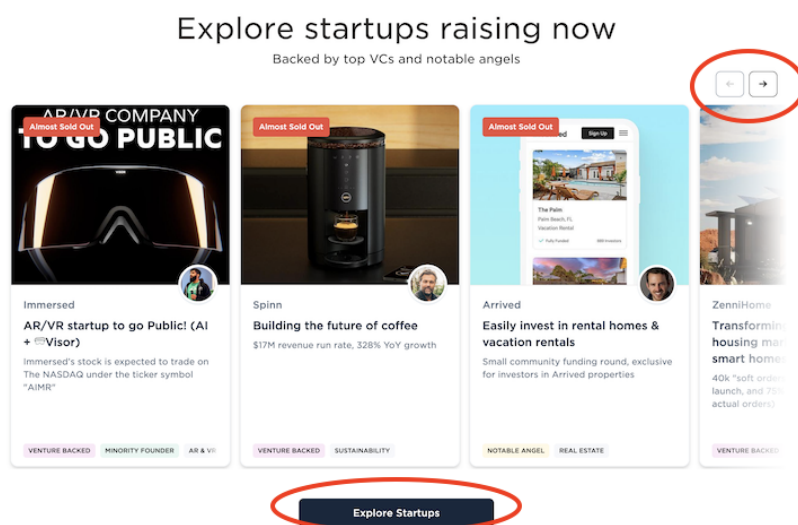
B: Comparison of Reg CF offerings and early-stage VC deals



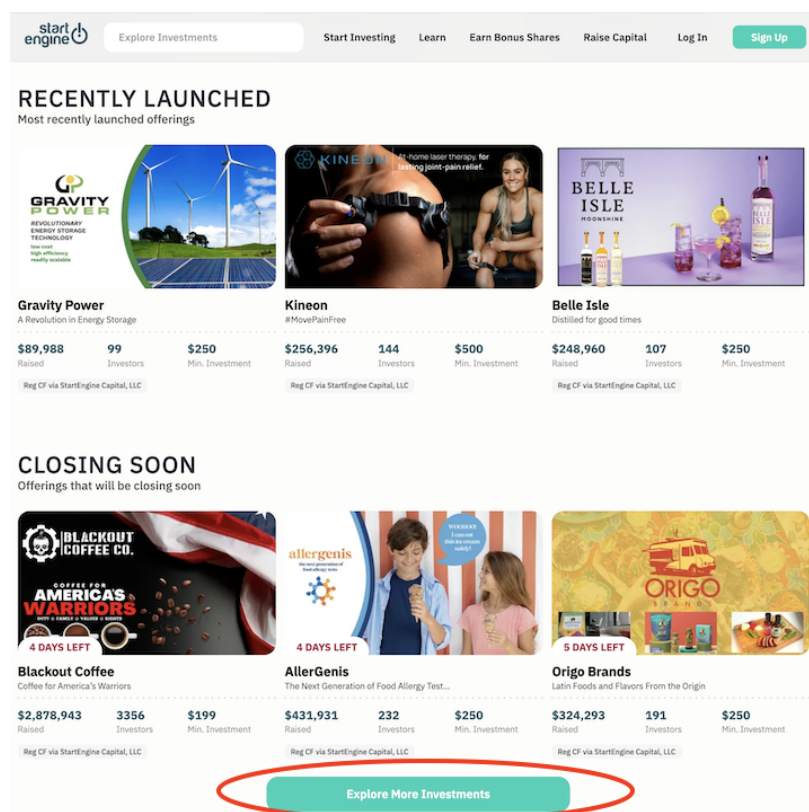
This figure plots the location of Reg CF offerings against the location of SBA loans in Panel A, and early-stage VC deals in Panel B for the two counties with the most Reg CF offerings between years 2016 to 2020. The size of the red circles corresponds to the number of successful Reg CF offerings in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

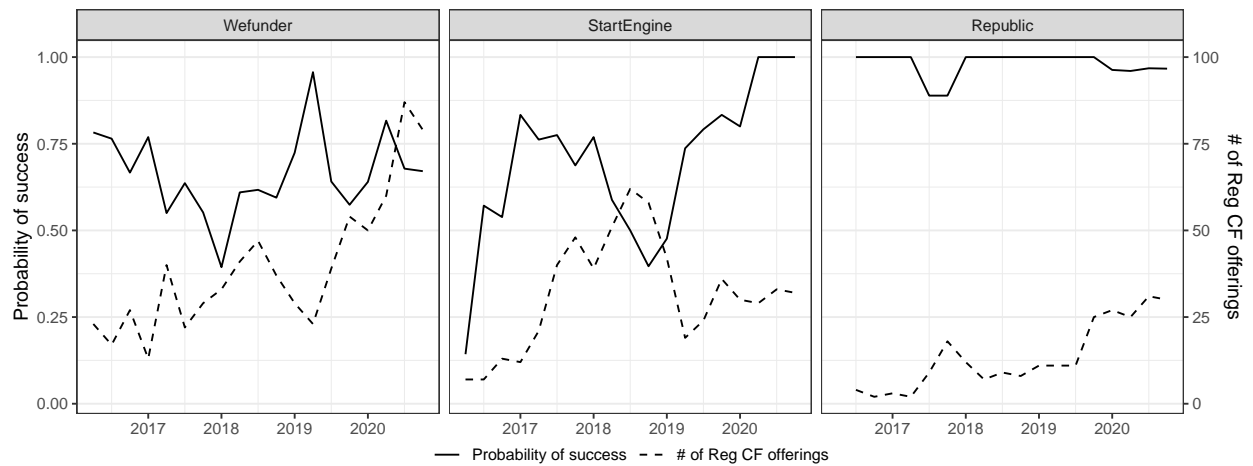


B: StartEngine



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

Figure IA.6: Reg CF success and number of offerings over time



This figure plots the number of offerings in our sample and the probability of Reg CF success across platforms and over time.

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	(122)	(93)
Total qualified offerings	1,622	1,449
Offerings without financial statements	(24)	(21)
Final sample	1,598	1,428
By listing platform:		
Wefunder	750	684
StartEngine	603	549
Republic	245	233

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: Descriptive statistics for IV estimation

	N (1)	Mean (2)	Std. Dev. (3)	25th (4)	Median (5)	75th (6)
Main firm-level variables:						
Successful offering	1,353	0.672	0.470	0.000	1.000	1.000
\$ raised (in millions)	1,353	0.251	0.463	0.008	0.073	0.267
\$ raised success (in millions)	909	0.370	0.525	0.069	0.168	0.484
Active	1,353	0.656	0.475	0.000	1.000	1.000
VC after	1,353	0.039	0.194	0.000	0.000	0.000
SBA after	1,353	0.014	0.118	0.000	0.000	0.000
Competing offerings	1,353	117.015	58.707	84.000	105.000	131.000
Firm-level control variables:						
\$ target (in millions)	1,353	0.062	0.086	0.010	0.050	0.070
Age (years)	1,353	3.218	4.142	0.749	1.936	4.249
# of founders	1,353	1.899	1.235	1.000	2.000	2.000
# of employees	1,353	6.264	11.992	2.000	3.000	6.000
VC before	1,353	0.032	0.175	0.000	0.000	0.000
SBA before	1,353	0.041	0.198	0.000	0.000	0.000
RegCF before	1,353	0.112	0.316	0.000	0.000	0.000
CPA engaged	1,353	0.684	0.465	0.000	1.000	1.000
Assets	1,353	0.362	0.769	0.005	0.062	0.322
Cash	1,353	0.079	0.186	0.000	0.009	0.056
Total debt	1,353	0.504	1.104	0.000	0.063	0.410
Revenue	1,353	0.400	1.053	0.000	0.002	0.208
Income	1,353	-0.286	0.661	-0.252	-0.043	-0.001

This table reports descriptive statistics for the sample of Reg CF offerings from the Wefunder and StartEngine platforms used for the main IV estimation (i.e., excluding offerings from Republic). Financial variables are winsorized at the 1st and 99th percentiles. Variables are defined in Table A.1.

Table IA.4: Potential channels

A: Marketing

	VC after		SBA after	
	Low marketing (1)	High marketing (2)	Low marketing (3)	High marketing (4)
Successful offering	0.023 (1.19)	0.032** (2.81)	0.040*** (3.37)	0.004 (1.02)
Quarter, Industry and Platform FE	Y	Y	Y	Y
Control variables	Y	Y	Y	Y
Observations	660	658	660	658
Adjusted R ²	0.164	0.042	0.023	0.048

B: Investment

	VC after		SBA after	
	Low investment (1)	High investment (2)	Low investment (3)	High investment (4)
Successful offering	0.020 (1.21)	0.044*** (3.79)	0.009 (0.807)	0.027** (2.60)
Quarter, Industry and Platform FE	Y	Y	Y	Y
Control variables	Y	Y	Y	Y
Observations	659	659	659	659
Adjusted R ²	0.102	0.069	0.010	0.033

This table reports the effect of a successful Reg CF offering on issuers subsequent survival and fundraising activity. We use the same OLS specification as column (1) of Tables 4 and 6, but we split the sample based on whether the fraction of proceeds the issuers intend to allocate to marketing (Panel A) or investments (Panel B) is above or below the median. We drop observations for which the allocation of proceeds is missing or does not add up to 100%. We include offering quarter, industry (2-digit NAICS), and platform fixed effects, 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 IA.5: IV robustness

A: First stage regressions

	log(\$ raised)		
	(1)	(2)	(3)
Competing offerings	-0.662*** (-3.99)	-0.883*** (-2.95)	-0.907*** (-3.79)
Quarter, Industry and Platform FE	Y	Y	Y
Control variables	Y	Y	Y
F-test (1st stage)	15.9	8.67	14.4
Time window	3 months	1 month	3 months
Active vs. new	Active	Active	New

B: Two-stage least squares estimates

	(1)	(2)	(3)
	Active		
log(\$ raised)	0.133*** (3.53)	0.127* (1.77)	0.182*** (4.01)
	VC after		
log(\$ raised)	0.104*** (3.82)	0.080** (2.74)	0.124*** (3.33)
	SBA after		
log(\$ raised)	0.019 (0.866)	0.011 (0.399)	0.035 (1.40)
Quarter, Industry and Platform FE	Y	Y	Y
Control variables	Y	Y	Y
Time window	3 months	1 month	3 months
Active vs. new	Active	Active	New

This table reports the robustness of the IV estimation to different specifications. Panels A and B report the first stage and 2SLS estimates, respectively. Each column corresponds to a different definition of the IV, with column (1) being the definition used in the paper. *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. We include offering quarter, industry (2-digit NAICS), and platform fixed effects, 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. Variables are defined in Table A.1.

Table IA.6: 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.7: County-level robustness

A: Reg CF awareness and entrepreneurial interest

	(1)	(2)	(3)	(4)	(5)
	Wefunder + StartEngine (Google)				
log(1 + Reg CF offerings)	1.15*** (2.63)				
Avg. treatment on treated		2.29*** (5.78)	1.72*** (6.00)	2.91*** (5.54)	1.77*** (4.36)
	Entrepreneurship (Google)				
log(1 + Reg CF offerings)	0.913*** (5.10)				
Avg. treatment on treated		0.741*** (3.20)	1.07*** (3.61)	0.721*** (2.81)	0.988*** (3.14)
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

Table IA.7: County-level robustness (continued)

B: Interaction with traditional financing

	(1)	(2)	(3)	(4)	(5)
	log(1 + Early-stage VC)				
log(1 + Reg CF offerings)	0.136*** (7.34)				
Avg. treatment on treated		0.104*** (4.96)	0.063** (2.51)	0.158*** (5.53)	0.066** (2.20)
	Early-stage VC > 0				
log(1 + Reg CF offerings)	0.007 (0.707)				
Avg. treatment on treated		0.052*** (3.21)	0.039** (2.07)	0.061*** (3.04)	0.034 (1.51)
	log(1 + SBA loans)				
log(1 + Reg CF offerings)	-0.008 (-0.802)				
Avg. treatment on treated		-0.064*** (-3.99)	-0.022 (-1.26)	-0.064*** (-2.92)	-0.005 (-0.170)
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, where each column corresponds to a different specification. Panel A focuses on measures of Reg CF awareness and interest in entrepreneurship, while Panel B focuses on measures of VC and SBA fundraising. 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.