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Regional crowdfunding and high tech entrepreneurship

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ABSTRACT

Despite extensive though mostly independent literatures on Crowdfunding and regional entrepreneurship, there exists little work that examines how Crowdfunding influences the rate and type of new venture formation in a region, what types of regions are more likely to experience Crowdfunding activity, and what types of regions are more likely to experience additional firm starts following Crowdfunding activity. We argue that Crowdfunding increases high tech and high growth regional firm starts by increasing crucial early-stage funding, providing the opportunity to signal success and legitimacy, facilitating access to entrepreneurial human capital, supporting inexperienced entrepreneurs with education and advice, and providing inexpensive market feedback. Instrumental variable regressions illustrate how Kickstarter campaigns precede an increase in high technology and growth in Crunchbase listings and a weak decrease in more conventional and local business registrations. While more per capita crowdfunding occurs in large cities relative to smaller cities, college towns, and poor regions with weak human capital, the impact per campaign appears greater in the poorer regions.

1. Introduction

Crowdfunding (CF) seeks financing for a commercial, philanthropic, or personal venture by soliciting – that is, running a "campaign" for - many small amounts of money from many people. While the Internet has greatly facilitated the practice, the idea is not new, and can be found historically, for example, in the funding of the Statue of Liberty in 1885 (BBC, 2013). CF provides an alternative to bank loans and equity capital and thus has the potential to increase access to capital for aspiring business and social entrepreneurs and others seeking investment. CF platforms can be organized into four broad categories, including equity, debt-based, charity, and reward-based. Equity platforms may be the iconic CF innovation and were enabled by the JOBS Act of 2012; they allow entrepreneurs to solicit investments from the crowd (as opposed to qualified or wealthier individuals). Debt-based CF allows individuals to ask for personal loans, often secured only by a personal plea, and includes firms such as Prosper and Lending Club. Charity platforms such as GoFundMe ask for money to address a problem. Reward-based platforms often provide a token of appreciation to the investor, such as a product, prize, or service (Cholakova and Clarysse, 2015). Here we focus on reward-based platforms, and in particular, Kickstarter, and illustrate how crowdfunding campaigns in a region precede increased high technology and high growth entrepreneurship in that region, as measured by Crunchbase listings in United States counties. We also show how local Kickstarter campaigns decreased local business registrations, thus shifting entrepreneurial efforts from more conventional entrepreneurship in favor of high technology startups.

Research on CF has recently flourished across a wide variety of topics and many have investigated its relationship with geography. Local networks of friends and family are crucial to early support that leads to eventual success (Agrawal et al., 2015). Given the typically non-corporate and communal sources of projects, CF strongly reflects local cultures and talent pools (Mollick, 2014). The crowd prefers to lend locally and to campaigners of similar cultures (Burtch et al., 2014), though social ties (Dejean, 2017) and media (Guerzoni, 2018) can mitigate this local bias. Local bias appears behavioral and not

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Table 1
Descriptive statistics for county/FIPS-level dataset.

Variable	Obs	Mean	Std. Dev	Min	Max
All KS campaigns	31,390	5.37	38.99	0	1743
Successful KS campaigns	31,390	2.06	17.63	0	685
Funding raised across all KS campaigns	31,390	0.35	0.68	0	44.8
New Crunchbase firms	31,390	2.85	32.2	0	1352
Business registrations	24,227	525.27	2560.93	0	78,201
Angel funding (in millions USD)	31,390	0.78	1.21	0	58.7
VC seed funding (in millions USD)	31,390	0.77	13.7	0	734
Existing firms with <10 employees	31,390	8384.50	32,856.69	0	1229,524
Patents	31,390	44.54	316.53	0	14,037
Citations	31,390	1198.29	8292.37	0	347,501
Population	31,390	101,020.50	323,523.20	45	10,100,000
Median household income	31,390	47,005.91	12,548.03	18,860	140,382
Excluded KS campaigns (Instrument 1)	31,390	3.25	35.35	0	2516
Comments of excluded KS campaigns (Instrument 2)	31,390	21.84	530.17	0	63,500

economically motivated (Lin and Viswanathan, 2015). CF platforms lower, but do not eliminate, the barrier of spatial proximity between investors and the entrepreneur (Mollick, 2013; Mollick and Nanda, 2015).

In addition to helping entrepreneurs gather financial resources, CF platforms such a Kickstarter can enable entrepreneurs to acquire non-pecuniary resources that can contribute to a venture's success, such as building an online presence and fostering a community of potential buyers (Reuber and Fischer, 2011). By launching a campaign, entrepreneurs can signal quality through their fundraising progress and the number of backers. The direct interaction through comments and updates on a campaign page lowers the cost of reaching potential backers and facilitates direct engagement with a user community. Moreover, entrepreneurs can be connected to other like-minded producers or user-innovators to further develop and test their ideas (Franke and Shah, 2003). While these activities typically happen online, there might remain enough geographical localization, such that these campaigns could lower barriers to entry for would-be entrepreneurs in less entrepreneurial or resource-scarce regions (empirically we place CF activity in a region by the geographic listing of the campaigner, and not the funder).

Research on the wider topic of geography and entrepreneurship is well-established and includes many pertinent arguments and findings. Though the argument predates CF, it is plausible that CF (like entrepreneurship) tends to occur in regions with high human capital and creative people (Florida, 2002). Venture capitalists tend to locate in wealthy regions with established entrepreneurial cultures and prior successes, even though returns in those regions can be lower, possibly due to greater competition (Chen et al., 2010). This raises the possibility that CF might provide needed financial and other non-pecuniary resources to constrained entrepreneurs in less entrepreneurial regions (Schwartz, 2012), and indeed, small CF pledges are distributed more uniformly across the country than VC funding (Mollick and Robb, 2016; Sorenson et al., 2016). In addition to very early financing, CF also allows potential entrepreneurs to establish a public signal of legitimacy, meet other entrepreneurs, demonstrate they can deliver a prototype, and gain quick and inexpensive feedback.

Despite the broader literatures on geography and entrepreneurship and these initial results on geography and CF, there remains less work at the intersection between CF and regional entrepreneurship. In particular, there is little research to date on how CF influences the rate and type of new venture formation, what types of regions are more likely to experience CF activity, and what types of regions are more likely to experience additional firm starts following CF activity. While Sorenson et al. (2016) established that technology campaigns have a positive relationship with VC funding in a region, the intermediate mechanisms have not been demonstrated. In particular, the question remains of how local CF increases regional funding and in particular, if it occurs because of entry of firms of interest to investors and VCs, assumedly due to increased access to financing and/or other mechanisms including feedback on prototypes, operational experience, mentoring, access to human capital, and test marketing. It remains even less clear what type of region experiences CF, and what type sees the greatest impact of technology CF, on high tech firm starts. For example, and analogous to the finding that a VC dollar goes further in regions with less VC funding (Chen et al., 2010), regions with an entrepreneurial culture may witness more CF, yet that funding may have less impact per campaign, relative to regions that lack entrepreneurial resources and culture.

Using Kickstarter (KS), Crunchbase, business registration, and U.S. Census data, this paper investigates how local CF campaigns influence regional entrepreneurship. We first investigate the average impact of Kickstarter campaigns in a county upon subsequent firm starts in that county. To strengthen causality, the work creates two instrumental variables, based on campaigns - and comments on campaigns - that are unlikely to affect entrepreneurship. County level IV regressions show positive effects of Kickstarter campaigns, with elasticities between 0.06 and 0.24, on new Crunchbase firm starts. These firms typically seek a high growth trajectory and would be of interest to investors and VCs. We also show that Kickstarter campaigns have a slightly negative effect on more conventional entrepreneurship, as measured by local business registrations. Zip code level regressions allow a finer grained exploration of the data, and illustrate that while CF is less likely in rural and less educated regions, as well as college towns, its impact on new Crunchbase firm formation appears greater, relative to urban regions.

2. Crowdfunding and regional entrepreneurship

We first consider the relationship between CF and high technology regional entrepreneurship, as measured by foundings of new firms listed in Crunchbase. Little work has established correlations, let alone causal relationships, from regional CF to regional economic outcomes (Sorenson et al., 2016). Motivating the exploration of KS and regional entrepreneurship, Mollick and Kuppuswamy (2014) report from a sample of KS campaigners that 59% plan to launch a venture based on their campaign. Since most entrepreneurs found firms where they live (Dahl and Sorenson, 2012), and where they probably launched their CF campaigns, these prior results imply that regional CF activity might influence entrepreneurial intent (Bird 1988) and regional entrepreneurship. Elaborating on the mechanisms that underlie the prior result from Sorenson et al. (2016), if VCs are increasing their investment in a region following an increase in commercially focused CF, then there must be interesting firms in that region for them to invest in.

We propose one hypothesis and a corollary, that *local crowdfunding should increase regional high technology entrepreneurship, through a variety of financial and non-financial mechanisms, and that local crowdfunding should depress non-high technology entrepreneurship, because of reassignment of scarce entrepreneurial resources and the tendency of high technology*

Table 2
Contemporaneous analysis of new Crunchbase firms in a U.S. county using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

DV: New firms	(1) OLS	(2) OLS	(3) First stage	(4) IV Reg	(5) First stage	(6) IV Reg
VARIABLES						
All KS campaigns	0.000134			0.0572***		
	(0.00400)			(0.00945)		
Successful KS campaigns		−0.00812				0.0835***
		(0.00575)				(0.0139)
Instrument 1			0.516***		0.337***	
			(0.0143)		(0.0133)	
Instrument 2			0.0391***		0.0431***	
			(0.00710)		(0.00667)	
Angel funding	0.0888***	0.0905***	0.102***	0.0753***	0.116***	0.0713***
	(0.0229)	(0.0230)	(0.0338)	(0.0228)	(0.0342)	(0.0227)
VC funding	−0.0168	−0.0134	0.299***	−0.0428***	0.304***	−0.0512***
	(0.0129)	(0.0131)	(0.0228)	(0.0136)	(0.0266)	(0.0141)
Existing firms	0.109***	0.109***	−0.0580***	0.111***	−0.0591***	0.113***
	(0.00473)	(0.00472)	(0.00446)	(0.00475)	(0.00411)	(0.00483)
Income	−0.0865***	−0.0913***	−0.645***	−0.0270	−0.304***	−0.0384
	(0.0303)	(0.0304)	(0.0646)	(0.0313)	(0.0479)	(0.0312)
Population	−0.446***	−0.435***	1.676***	−0.563***	1.076***	−0.557***
	(0.0598)	(0.0599)	(0.142)	(0.0646)	(0.102)	(0.0647)
Patents	0.000498	0.000900	0.0525***	−0.00382	0.0324***	−0.00352
	(0.00306)	(0.00306)	(0.00696)	(0.00317)	(0.00459)	(0.00317)
Citations	0.00393	0.00421	0.0472***	0.000299	0.0211***	0.00124
	(0.00258)	(0.00257)	(0.00633)	(0.00268)	(0.00399)	(0.00265)
Constant	4.880***	4.820***				
	(0.666)	(0.666)				
FIPS, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,390	31,390	31,390	31,390	31,390	31,390
F-statistic			3509		2841	
R-squared	0.148	0.148		0.135		0.130
Number of FIPS	3139	3139	3139	3139	3139	3139

Robust standard errors clustered by FIPS in parentheses.
*** $p<0.01$,
** $p<0.05$,
* $p<0.1$.

entrepreneurs to incorporate in Delaware.

Theory for the hypothesis is simple: the number of crowdfunding campaigns in a geographical region, particularly in categories of interest to venture capitalists (Sorenson et al., 2016), should correlate positively with subsequent firm starts. This relationship exists for a number of reasons, only one of which is the possibility of an additional source of finance; CF can also increase entrepreneurship in a region through signaling, education on platform eco-systems, attraction and increased availability of human capital, prototyping and manufacturing experience, and feedback from the market. Foreshadowing the empirical estimations, we estimate two contrasting measures of firms starts, namely, 1) Crunchbase listings for high technology ((Ter Wal et al., 2016); (Samila and Sorenson, 2017)) and 2) business registration (Guzman and Stern, 2020) for more conventional, lower growth, and non-high technology firm starts. We also focus on the Kickstarter reward platform, due to its popularity and prior work that established its impact on venture capital funding in a region (Sorenson et al., 2016).

First, even though the amounts raised are typically meager (on average, \$35k across all campaigns in a fips-year, please see Table 1), even a small amount of funding can enable initial product development and cover other entrepreneurial expenses. Such early dollars are small but crucial resources for getting firms started and ease funding constraints at a critical time in a startup's development. Entrepreneurs may not be seeking salary or remuneration (they may be students or otherwise employed), but access to funds that can pay for supplies and/or experiments can provide seeding support during the initial phases of idea exploration.

Second, entrepreneurs can point to campaign success when they seek additional financial and human resources. The challenge of prototyping and actually shipping a product forces an entrepreneur to confront – and hopefully solve – supply chain and manufacturing issues. Happy customers, as can be observed from the website feedback, provide evidence of at least a minimum of design ability, manufacturing capacity, and operational competence. A successful campaign in particular provides a public signal of organizational acumen, an ability to execute, and an idea worth considering; success conveys legitimacy to the entrepreneurs and their potential startup. Indeed, some venture capitalists look for CF success as part of their due diligence (Hollas, 2015).

Third, in an attempt to increase traffic and build an ecosystem, some platforms (including Kickstarter) have begun to offer a variety of services, advice, and their own research, for example, on branding, structuring funding, securing deals, and fulfilling orders. The CF platform has essentially broadened to offer a more complete and supportive ecosystem, and provides a cheap and potentially easily accessible substitute for business education, incubator or accelerator membership, and experience. This substitute could be especially valuable in lower-income and less entrepreneurial regions, which might lack universities, extensive personal networks and networking opportunities, and an entrepreneurial culture.

Fourth, CF websites offer a virtual platform for interested parties, mainly entrepreneurs but potentially also including active investors, to meet and create opportunities. Consistent with the arguments above, platforms offer community newsletters and communications media for different categories of campaigns; these allow entrepreneurs to interact with and attract fellow founders. Entrepreneurs can connect with early adopters and possibly find a few who are willing to evangelize and spread the word (Cremades, 2019). Virtual CF platforms could thus strengthen the regional infrastructure of personal connections and expertise, by enabling introductions and facilitating the development of social capital. While such regional infrastructure is probably not

Table 3
Lagged (one year) analysis of new Crunchbase firms in a U.S. county using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

DV: New firms	(1) OLS	(2) OLS	(3) First stage	(4) IV Reg	(5) First stage	(6) IV Reg
VARIABLES						
All KS campaigns (1-yr lag)	−0.0237***			0.147***		
	(0.00418)			(0.0240)		
Successful KS campaigns (1-yr lag)		−0.0353***				0.239***
		(0.00618)				(0.0409)
Instrument 1			0.244***		0.135***	
			(0.0150)		(0.0116)	
Instrument 2			0.0194**		0.0252***	
			(0.00807)		(0.00695)	
Angel funding	0.0960***	0.0968***	0.182***	0.0595**	0.146***	0.0512**
	(0.0230)	(0.0230)	(0.0503)	(0.0241)	(0.0486)	(0.0260)
VC funding	−0.0134	−0.0100	0.411***	−0.0869***	0.372***	−0.116***
	(0.0148)	(0.0149)	(0.0336)	(0.0186)	(0.0339)	(0.0231)
Existing firms	0.108***	0.108***	−0.096***	0.121***	−0.058***	0.121***
	(0.00460)	(0.00458)	(0.00572)	(0.00526)	(0.00470)	(0.00541)
Income	−0.0731**	−0.0676**	−0.581***	0.0415	−0.241***	0.0138
	(0.0332)	(0.0331)	(0.0761)	(0.0381)	(0.0560)	(0.0382)
Population	−0.505***	−0.509***	3.708***	−1.158***	2.390***	−1.187***
	(0.0838)	(0.0841)	(0.263)	(0.139)	(0.196)	(0.147)
Patents	−0.00221	−0.00241	0.0556***	−0.0122***	0.0318***	−0.012***
	(0.00327)	(0.00326)	(0.00778)	(0.00378)	(0.00517)	(0.00383)
Citations	0.00516*	0.00497*	0.0326***	−0.000630	0.0167***	0.000170
	(0.00276)	(0.00275)	(0.00792)	(0.00322)	(0.00478)	(0.00322)
Constant	6.121***	6.096***				
	(0.879)	(0.880)				
FIPS, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,251	28,251	28,251	28,251	28,251	28,251
F-statistic			431		289	
R-squared	0.165	0.166		0.054		0.001
Number of FIPS	3139	3139	3139	3139	3139	3139

Robust standard errors clustered by FIPS in parentheses.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

physical, it should still have positive effects on the relationship between the number of CF campaigns and high-tech firm starts in a region.

Finally, campaigns provide market and product development feedback to entrepreneurs. CF platforms provide entrepreneurs a low-cost way to experiment and elicit reactions from potential customers. Some campaigns even offer “rewards” or products to backers, often tiered by the amount of support. These products are often prototypes, and probably built by amateurs or very small firms, yet when successful, indicate an idea worthy of development. CF platforms offer an opportunity for early and cheap “pivots” as bad ideas are quickly winnowed and good ideas are encouraged. CF platforms enable faster iteration and cheaper exploration compared to traditional product development and prototyping methods; they provide market feedback and enable entrepreneurs to found firms around better-validated ideas. In essence, CF supports a model of entrepreneurship as experimentation and option value (Kerr et al., 2014).

To summarize the hypothesis, a variety of mechanisms should contribute to a positive relationship between CF and high technology entrepreneurial firm starts in a region: 1) meager but crucial initial financing, 2) a public signal of (operational) competency and legitimacy, 3) a platform for entrepreneurs to learn from and 4) meet on, 5) prototyping and manufacturing experience, and 6) enhanced, quick, and cheap market feedback, particularly for firms offering prototypes as rewards.

There are two arguments for a corollary to the first hypothesis, that crowdfunding will decrease local business registration. First, to the extent that crowdfunding enables tech capable entrepreneurs to explore a higher tech opportunity, they will be less likely to explore a more conventional opportunity. For example, Kickstarter might encourage an entrepreneur to write a software application for a global market, and found a C Corp, rather than go into business as a personal computer technician. Particularly if entrepreneurial human capital is scare and valuable (Glaeser and Kerr, 2009), then a switch from conventional to higher technology and growth entrepreneurship should be observable in a decrease in the numbers of conventional startups. The second argument is purely mechanical. If crowdfunding increases high technology entrepreneurship, and these entrepreneurs incorporate in Delaware (as most founders of high-tech ventures do, see (Guzman and Stern, 2020)[1], then business registrations within a local region might be depressed.

3. Data and empirical strategy

3.1. Data

Our unit of analysis is the county-year, for U.S. counties, from 2009 to 2018 (time series shorten where data remain unavailable). Our estimations require the integration of geographic, crowdfunding, and entrepreneurship data. CF data came from scraping current and historical Kickstarter campaigns (Yu et al., 2017). Crunchbase, an open-source database of entrepreneurial activity, provided a measure of high technology and high growth firm starts and other measures of regional entrepreneurship activity (Ter Wal, A. L. J. et al. 2016; Sampson and Sorenson 2017). Business registration data was downloaded from the Startup Cartography Project (Andrews et al., 2020; Guzman and Stern, 2020). Economic and demographic characteristics for a region came from the U.S. Census. We collected and integrated data from the year

[1] Besides Guzman and Stern (2020), see the State of Delaware websites: https://corplaw.delaware.gov/why-businesses-choose-delaware/ *and* https://corp.delaware.gov/aboutagency/.

Table 4
Contemporaneous analysis of new Crunchbase firms in a U.S. county excluding highest Angel and VC funded regions (Santa Clara, San Francisco, and New York) using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

DV: New firms	(1) OLS	(2) OLS	(3) First stage	(4) IV Reg	(5) First stage	(6) IV Reg
VARIABLES						
All KS campaigns	−0.000172			0.0567***		
	(0.00400)			(0.00949)		
Successful KS campaigns		−0.00886				0.0829***
		(0.00575)				(0.0139)
Instrument 1			0.515***		0.336***	
			(0.0144)		(0.0133)	
Instrument 2			0.0391***		0.0431***	
			(0.00712)		(0.00668)	
Angel funding	0.0883***	0.0901***	0.100***	0.0752***	0.111***	0.0716***
	(0.0231)	(0.0232)	(0.0343)	(0.0230)	(0.0346)	(0.0229)
VC funding	−0.0206	−0.0171	0.293***	−0.0460***	0.294***	−0.0540***
	(0.0130)	(0.0132)	(0.0225)	(0.0137)	(0.0261)	(0.0142)
Existing firms	0.109***	0.109***	−0.0582***	0.111***	−0.0593***	0.113***
	(0.00477)	(0.00476)	(0.00448)	(0.00479)	(0.00412)	(0.00487)
Income	−0.0881***	−0.0931***	−0.652***	−0.0289	−0.313***	−0.0397
	(0.0303)	(0.0304)	(0.0645)	(0.0313)	(0.0475)	(0.0312)
Population	−0.444***	−0.432***	1.676***	−0.560***	1.077***	−0.554***
	(0.0597)	(0.0599)	(0.142)	(0.0646)	(0.102)	(0.0647)
Patents	0.000354	0.000766	0.0523***	−0.00394	0.0322***	−0.00364
	(0.00306)	(0.00306)	(0.00696)	(0.00317)	(0.00458)	(0.00317)
Citations	0.00384	0.00411	0.0472***	0.000223	0.0209***	0.00117
	(0.00258)	(0.00257)	(0.00632)	(0.00267)	(0.00399)	(0.00265)
Constant	4.871***	4.808***				
	(0.666)	(0.666)				
FIPS, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,360	31,360	31,360	31,360	31,360	31,360
F-statistic			3490		2821	
R-squared	0.147	0.147		0.135		0.129
Number of FIPS	3136	3136	3136	3136	3136	3136

Robust standard errors clustered by FIPS in parentheses.
*** $p<0.01$,
** $p<0.05$,
* $p<0.1$.

Kickstarter was founded, 2009, through 2018 (except for the firm registration data, which ends in 2016). Table 1 provides descriptive statistics.

Kickstarter (KS) is one of the largest and earliest rewards-based CF platforms and includes projects from a diverse set of categories. The CF data was scraped from the Kickstarter website for the years between 2009 and 2018 (in the same manner and with the same tools used for Yu et al., 2017). The dataset includes the title, founder, city, state, campaign year, category, fundraising goal and raised amount (in USD), and status (success, failed, canceled) for each CF project where the founder is located in the U.S. County location is determined by mapping the campaigner's home town to a U.S. county.

Crunchbase is recognized as a comprehensive database of early-stage firms. It positions itself as listing high technology firms that would be of interest to angel and venture capital investors, for example, the most prominent banner on its home page reads, "Discover innovative companies and the people behind them."[2] It is an open source database maintained by TechCrunch, a publisher that covers and promotes the technology industry, and is supported by partnerships with more than 3500 global investment firms and AngelList. Crunchbase is often the first database that founders join since founders can populate as many or as few details about their company that they wish. Consequently, Crunchbase tends to capture many nascent firms that may not yet have funding, employees, or products (Sampson and Sorenson 2017). This makes it preferable for examining new venture formation of ambitious ventures. Most importantly, Crunchbase focuses on technology and potentially high growth ventures, as opposed to restaurants, nail salons, and other more personal, life-style, and conventional entrepreneurship.

Crunchbase covers all states across the time period of study. Data is accessed through an API and includes firm location (city, state, country), founding year, funding milestones (date, type, and amount), and operational status (active, acquired, closed, IPO). In order to capture the number of new firms founded in a region at the county-year level, we only include Crunchbase firms located on the U.S. mainland and founded after 2009, inclusive, and county location is again determined by mapping the firm's home town to a U.S. county.

In order to measure more conventional entrepreneurship, we use the public business registration data collected through the Startup Cartography Project.[3] Specifically, we use the county-level public-access dataset that contains the Startup Formation Rate, which represents for-profit, new business registrants within a county in a given year. This measure mimics metrics obtained through the U.S. Census Business Dynamics Statistics (Andrews et al., 2020; Guzman and Stern, 2020).

In addition to CF activity, various regional factors may also affect entrepreneurial activity; we include a variety of measures as controls, though we also estimate instrumented models without controls and find consistent results (Angrist and Pischke 2009 argue this is the preferred estimation). One of these factors is the availability of funding for entrepreneurs, hence we control for existing funding sources using angel funding and VC funding data from Crunchbase. The number of existing firms in the region comes from County Business Patterns,[4] the median household income comes from the Model based Small Area Income &

[2] https://www.crunchbase.com/.

[3] https://www.startupcartography.com/data.

[4] https://www.census.gov/programs-surveys/cbp/data/datasets.html.

Table 5

Lagged (one year) analysis of new Crunchbase firms in a U.S. county excluding highest Angel and VC funded regions (Santa Clara, San Francisco, and New York) using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

DV: New firms	(1) OLS	(2) OLS	(3) First stage	(4) IV Reg	(5) First stage	(6) IV Reg
VARIABLES						
All KS campaigns (1-yr lag)	−0.0240***			0.146***		
	(0.00419)			(0.0241)		
Successful KS campaigns (1-yr lag)		−0.0360***				0.239***
		(0.00619)				(0.0409)
Instrument 1			0.515***		0.336***	
			(0.0144)		(0.0133)	
Instrument 2			0.0391***		0.0431***	
			(0.00712)		(0.00668)	
Angel funding	0.0968***	0.0976***	0.100***	0.0612**	0.111***	0.0534**
	(0.0232)	(0.0233)	(0.0343)	(0.0243)	(0.0346)	(0.0262)
VC funding	−0.0153	−0.0120	0.293***	−0.0873***	0.294***	−0.115***
	(0.0149)	(0.0150)	(0.0225)	(0.0186)	(0.0261)	(0.0229)
Existing firms	0.108***	0.108***	−0.0582***	0.121***	−0.0593***	0.121***
	(0.00463)	(0.00461)	(0.00448)	(0.00530)	(0.00412)	(0.00545)
Income	−0.0737**	−0.0685**	−0.652***	0.0419	−0.313***	0.0164
	(0.0332)	(0.0332)	(0.0645)	(0.0382)	(0.0475)	(0.0383)
Population	−0.505***	−0.508***	1.676***	−1.157***	1.077***	−1.184***
	(0.0838)	(0.0841)	(0.142)	(0.139)	(0.102)	(0.147)
Patents	−0.00230	−0.00251	0.0523***	−0.0122***	0.0322***	−0.0116***
	(0.00327)	(0.00326)	(0.00696)	(0.00377)	(0.00458)	(0.00382)
Citations	0.00511*	0.00492*	0.0472***	−0.000659	0.0209***	0.000190
	(0.00276)	(0.00275)	(0.00632)	(0.00322)	(0.00399)	(0.00322)
Constant	6.119***	6.092***				
	(0.879)	(0.880)				
FIPS, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,224	28,224	31,360	28,224	31,360	28,224
F-statistic			430		290	
R-squared	0.164	0.165		0.053		0.000
Number of FIPS	3136	3136	3136	3136	3136	3136

Robust standard errors clustered by FIPS in parentheses.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

Poverty Estimates (SAIPE) for School Districts, Counties, and States[5] and county population from the U.S. Census.[6] To control for the technology resources in a region, we include the number of patents in a given county-year (county location is assigned based on the first inventor's home address second and later authors are ignored). To control for the technological success of a region, we include the citations to a regions' patents in the given county-year. Patent data come from Balsmeier et al. (2018) and are updated with the same tools and methods.

3.2. Variables

3.2.1. Dependent variables

New firms is calculated by identifying all the firms in Crunchbase founded in a given year, mapping each firm location from city and state to the corresponding county FIPS code, then aggregating to the FIPS-year level. The data includes firms with founding dates between years 2009–2018.

Business registrations is the count of new business registrants as measured by the Startup Formation Rate from the Startup Cartography Project (Andrews et al., 2020; Guzman and Stern, 2020), which includes the number of new firms registered in a region. This measure differs from Crunchbase measures in that it covers all the firms registered as a corporation, partnership, or limited liability company in a region (for example, new hair salons and restaurants), and thus enables differentiation between high and low tech business starts in a region. We use the county-level data, which is currently available through 2016 so analysis using the business registration data includes years 2009–2016.

3.2.2. Independent variables

KS campaigns is the count of all projects, excluding canceled campaigns, in games, food, technology, fashion, crafts, or journalism, aggregated for 2009–2018 for each county-year. These categories were chosen based on their text-based overlap with VentureXpert categories of venture capital funded firms (analyses pulled directly from Sorenson et al., 2016 Supplementary Materials). We take the founder's location, typically listed as a home town city and state, as the campaign's location and map it to its county.

Successful KS campaigns is a count of KS projects in these same categories that reached their fundraising goals and actually received funds as a result of the CF campaign. As can be seen in the estimates, and not surprisingly, results for successful campaigns typically strengthen.

3.2.3. Control variables

Angel funding and *VC funding* are both measures of the availability of entrepreneurial financing in a given county-year. Angel funding is typically smaller amounts of funding that occur earlier in a new venture's existence, and complement CF. VC funding comes later, typically in staged rounds or series, and typically represents a significant infusion of capital that a new firm would require in order to scale and grow. Here we use VC seed funding to represent early-stage capital. Both variables capture whether a given region has (conventional) financial resources to potentially support new firms in a given county and year. The variables in essence control for alternate sources of funds.

[5] https://www.census.gov/did/www/saipe/.

[6] https://www.census.gov/data/datasets/time-series/demo/popest/intercensal-2000-2010-counties.html and https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-total.html.

Table 6
Contemporaneous analysis of new business registrations in a U.S. county using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

DV: Business registrations	(1) OLS	(2) OLS	(3) First stage	(4) IV Reg	(5) First stage	(6) IV Reg
VARIABLES						
All KS campaigns	−0.0135***			−0.0248***		
	(0.00452)			(0.00913)		
Successful KS campaigns		−0.0127**				−0.0351***
		(0.00528)				(0.0130)
Instrument 1			0.566***		0.367***	
			(0.0156)		(0.0139)	
Instrument 2			0.0468***		0.0579***	
			(0.00845)		(0.00747)	
Angel funding	−0.00209	−0.00233	0.127***	0.000781	0.161***	0.00328
	(0.0114)	(0.0115)	(0.0390)	(0.0116)	(0.0393)	(0.0120)
VC funding	0.00944	0.00821	0.346***	0.0161*	0.356***	0.0200**
	(0.00811)	(0.00820)	(0.0278)	(0.00882)	(0.0313)	(0.00957)
Existing firms	−0.0173	−0.0169	−0.0335*	−0.0176	0.00181	−0.0167
	(0.0244)	(0.0243)	(0.0187)	(0.0246)	(0.0132)	(0.0246)
Income	0.387***	0.395***	−0.746***	0.372***	−0.323***	0.379***
	(0.0577)	(0.0576)	(0.0765)	(0.0587)	(0.0536)	(0.0582)
Population	0.883***	0.866***	2.157***	0.914***	1.225***	0.904***
	(0.105)	(0.104)	(0.170)	(0.108)	(0.119)	(0.107)
Patents	−0.00410	−0.00459	0.0523***	−0.00313	0.0299***	−0.00339
	(0.00521)	(0.00520)	(0.00800)	(0.00525)	(0.00529)	(0.00524)
Citations	−0.00402	−0.00461	0.0609***	−0.00303	0.0280***	−0.00357
	(0.00705)	(0.00704)	(0.00785)	(0.00707)	(0.00468)	(0.00705)
Constant	−9.133***	−9.056***				
	(1.134)	(1.133)				
FIPS, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,227	24,227	24,209	24,209	24,209	24,209
F-statistic			3488		2980	
R-squared	0.165	0.164		0.164		0.164
Number of FIPS	3128	3128	3110	3110	3110	3110

Robust standard errors clustered by FIPS in parentheses.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

We also control for regional characteristics that may increase or decrease entrepreneurial activity. *Existing firms* is the number of firms with less than 10 employees in a given county-year, based on the County Business Patterns data. This variable captures existing competition for resources, including financial, human, legal, and anything associated with entrepreneurship. The *Population* variable is based on the U.S. Census County Intercensal Dataset. We use the time varying population estimates for years 2009–2018 for each county-year. More people mean more potential entrepreneurs. For *Income* on a regional level, we use the median household income amount based on the U.S. Census Small Area Income & Poverty Estimates.

Patents are the number of patents in the region in the year, based on the first inventor's home location on the patent (second and additional authors are ignored), and *Citations* are prior art citations from other patents that are granted outside the region, citing the region's patents in that year. Patents and citations could be positively related to a region's creativity and CF activity, or if they detracted from efforts spent on CF, they might be negatively related. These variables will correlate with the availability of technically trained people who historically have started firms.

3.3. Methodology and identification strategy

Crowdfunding might increase subsequent firm starts in a region, however, a simple regression would likely suffer from omitted variable bias. This is a difficult causal relationship to establish with correlations, as many factors probably influence both the number of CF campaigns and firm starts in a region. Fixed effects models (used here) could account for some of these factors, including relatively static variables such as education levels of a workforce, geographical or institutional influences, or even wealth, assuming these do not change greatly over time. Other co-varying factors could change simultaneously, however, for example, the local economic cycle could encourage both CF and entrepreneurial starts, within a region, which would not be captured by year fixed effects across all regions.

We employ an instrumental variables approach to ameliorate these concerns, using campaigns in film and video, music, comics, and dance to instrument for other types of campaigns that are more likely to have entrepreneurial impact in a region. For campaigns that should influence firm starts, we include games, food, technology, fashion, crafts, and journalism. We chose these two groups based on Sorenson et al. (2016), who showed that the lexical descriptions of these KS projects are relatively uncorrelated and correlated, respectively, with venture capital investment categories (as described by VentureXpert). In other words, Sorenson et al. (2016) show that film and video, music, comics, and dance campaigns are of little or no interest to venture capitalists, in contrast to games, food, technology, fashion, crafts, and journalism, which are much more highly correlated with venture capital investment.[7]

The Sorenson et al. (2016) method took descriptions from KS campaigns and VC firm investments from VentureXpert and established correlations between each lexical population (see the Supplementary Materials of Sorenson et al., 2016 for a detailed explanation). It first tokenized the words in each corpus, reducing each word to its stem. It then identified the most important words that described each category of investments or campaign classification using a standard Term

[7] For additional detail, please see Supplementary Materials for Sorenson et al. (2016): https://science.sciencemag.org/content/sci/suppl/2016/12/21/354.6319.1526.DC1/aaf6989_Sorenson_SM.pdf.

Table 7
Lagged (one year) analysis of new business registrations in a U.S. county using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

DV: Business registrations	(1) OLS	(2) OLS	(3) First stage	(4) IV Reg	(5) First stage	(6) IV Reg
VARIABLES						
All KS campaigns (1-yr lag)	−0.00162			−0.0316*		
	(0.00408)			(0.0179)		
Successful KS campaigns (1-yr lag)		−0.000238				−0.0494*
		(0.00480)				(0.0282)
Instrument 1			0.309***		0.177***	
			(0.0177)		(0.0135)	
Instrument 2			0.0292***		0.0334***	
			(0.00981)		(0.00834)	
Angel funding	−0.00674	−0.00708	0.220***	0.000456	0.214***	0.00403
	(0.0107)	(0.0107)	(0.0599)	(0.0117)	(0.0606)	(0.0129)
VC funding	0.00313	0.00234	0.511***	0.0197	0.453***	0.0259*
	(0.00860)	(0.00872)	(0.0434)	(0.0125)	(0.0431)	(0.0155)
Existing firms	−0.0214	−0.0212	−0.081***	−0.0240	−0.0296**	−0.0229
	(0.0225)	(0.0225)	(0.0208)	(0.0227)	(0.0147)	(0.0228)
Income	0.265***	0.266***	−0.692***	0.240***	−0.315***	0.246***
	(0.0592)	(0.0591)	(0.0974)	(0.0611)	(0.0709)	(0.0603)
Population	0.970***	0.960***	6.096***	1.165***	3.740***	1.156***
	(0.129)	(0.127)	(0.475)	(0.179)	(0.346)	(0.177)
Patents	−0.00499	−0.00508	0.0533***	−0.00320	0.0294***	−0.00344
	(0.00527)	(0.00527)	(0.00921)	(0.00540)	(0.00611)	(0.00539)
Citations	−0.00255	−0.00262	0.0438***	−0.00113	0.0231***	−0.00139
	(0.00757)	(0.00756)	(0.00980)	(0.00759)	(0.00591)	(0.00757)
Constant	−8.428***	−8.344***				
	(1.360)	(1.349)				
FIPS, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,142	21,142	21,118	21,118	21,118	21,118
F-statistic			513		358	
R-squared	0.128	0.128		0.125		0.124
Number of FIPS	3126	3126	3102	3102	3102	3102

Robust standard errors clustered by FIPS in parentheses.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

Table A1
Contemporaneous analysis of new Crunchbase firms in a U.S. county using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

DV: New firms	(1) OLS	(2) OLS	(3) First stage	(4) IV Reg	(5) First stage	(6) IV Reg
VARIABLES						
All KS campaigns	−0.0161***			0.0677***		
	(0.00400)			(0.00925)		
Successful KS campaigns		−0.0347***				0.0972***
		(0.00579)				(0.0134)
Instrument 1			0.546***		0.361***	
			(0.0151)		(0.0142)	
Instrument 2			0.0436***		0.0476***	
			(0.00743)		(0.00694)	
Constant	0.275***	0.275***				
	(0.00383)	(0.00380)				
FIPS, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,390	31,390	31,390	31,390	31,390	31,390
F-statistic			3900		3182	
R-squared	0.052	0.053		0.023		0.012
Number of FIPS	3139	3139	3139	3139	3139	3139

Robust standard errors clustered by FIPS in parentheses.
*** $p<0.01$,
**$p<0.05$,
*$p<0.1$.

Frequency – Inverse Document Frequency algorithm (this removes the influence of common and non-descript words such as "the" and "a"). It then calculated the correlation between categories with a cosine overlap measure. High correlation categories corresponded to areas of interest to both campaigners and investors, and low correlation categories corresponded to areas where investors had little or no interest in CF.

Following Sorenson et al. (2016), we use the categories (and comments in categories) with little overlap as an instrument for categories of greater overlap. The number of campaigns in low overlap categories correlate with higher potential campaigns but are unlikely to become firms and hence should not contribute to firm starts or other entrepreneurial efforts in the region. For example, within dance campaigns, the

Table A2
Lagged (one year) analysis of new Crunchbase firms in a U.S. county using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

DV: New firms VARIABLES	(1) OLS	(2) OLS	(3) First stage	(4) IV Reg	(5) First stage	(6) IV Reg
All KS campaigns (1-yr lag)	−0.0533***			0.277***		
	(0.00423)			(0.0315)		
Successful KS campaigns (1-yr lag)		−0.0700***				0.439***
		(0.00615)				(0.0541)
Instrument 1			0.229***		0.126***	
			(0.0158)		(0.0120)	
Instrument 2			0.0213**		0.0274***	
			(0.00890)		(0.00744)	
Constant	0.176***	0.165***				
	(0.00514)	(0.00518)				
FIPS, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,251	28,251	28,251	28,251	28,251	28,251
F-statistic			358		250	
R-squared	0.067	0.067		−0.399		−0.558
Number of FIPS	3139	3139	3139	3139	3139	3139

Robust standard errors clustered by FIPS in parentheses.
*** $p<0.01$,
** $p<0.05$,
* $p<0.1$.

Table A3
Contemporaneous analysis of new Crunchbase firms in a U.S. county excluding highest Angel and VC funded regions (Santa Clara, San Francisco, and New York) using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

DV: New firms	(1) OLS	(2) OLS	(3) First stage	(4) IV Reg	(5) First stage	(6) IV Reg
VARIABLES						
All KS campaigns	−0.0167***			0.0664***		
	(0.00400)			(0.00928)		
Successful KS campaigns		−0.0358***				0.0956***
		(0.00580)				(0.0135)
Instrument 1			0.544***		0.359***	
			(0.0151)		(0.0141)	
Instrument 2			0.0435***		0.0474***	
			(0.00745)		(0.00694)	
Constant	0.269***	0.269***				
	(0.00382)	(0.00379)				
FIPS, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,360	31,360	31,360	31,360	31,360	31,360
F-statistic			3865		3145	
R-squared	0.051	0.053		0.023		0.012
Number of FIPS	3136	3136	3136	3136	3136	3136

Robust standard errors clustered by FIPS in parentheses.
*** $p<0.01$,
** $p<0.05$,
* $p<0.1$.

most common fundraising goal is for specific performances. Even when the fundraising is used for a physical space (which might indicate the formation of a new dance firm), the funds are typically donated to existing dance companies for renting, repairing, or furnishing an existing studio (as established by reading the campaign descriptions themselves). For example, descriptions such as "Dance With Me is ready to open its 1st dance/rehearsal studio, but we need your backing & support," and "We need a new dance floor and ceiling for a safe and fun dance space…" are representative of the purpose of campaigns under Dance Spaces. The logic of the exclusion restriction is that the projects that are not of interest to investors will correlate with the projects that are of interest, and yet have no impact on subsequent entrepreneurial activity in the region.

We also consider an additional instrument using the comments on film and video, music, comics, and dance campaigns in addition to the number of campaigns. The comments are aggregated by counting the number of words entered for such campaigns. The logic is that discussion of campaigns in areas that are of no interest to entrepreneurs is even further removed from starting a firm.

To test our hypothesis that crowdfunding should increase firms starts in a region, we apply instrumental variables estimations of KS campaigns on new firms (Crunchbase new firms and business registrations), controlling for angel funding, VC funding, existing businesses, median household income, population, patents, citations, and including year and FIPS fixed effects (results are robust to IV models without control variables). In the first stage, we use two instruments—campaigns in low VC overlap categories and the comments in these campaigns; and in the second stage, all KS campaigns or the successful number of KS campaigns is instrumented. Across all specifications, the Cragg-Donald F-statistics are greater than 10, indicating that we do not have weak instruments. As can be seen in the regressions, the comment instrument (Instrument 2) coefficient is smaller than the number of low VC overlap campaigns instrument (Instrument 1), but both instruments always have positive and statistically significant coefficients.

Table A4
Lagged (one year) analysis of new Crunchbase firms in a U.S. county excluding highest Angel and VC funded regions (Santa Clara, San Francisco, and New York) using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

DV: New firms	(1) OLS	(2) OLS	(3) First stage	(4) IV Reg	(5) First stage	(6) IV Reg
VARIABLES						
All KS campaigns (1-yr lag)	−0.0536***			0.274***		
	(0.00424)			(0.0314)		
Successful KS campaigns (1-yr lag)		−0.0707***				0.433***
		(0.00619)				(0.0537)
Instrument 1			0.544***		0.359***	
			(0.0151)		(0.0141)	
Instrument 2			0.0435***		0.0474***	
			(0.00745)		(0.00694)	
Constant	0.170***	0.159***				
	(0.00512)	(0.00516)				
FIPS, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,224	28,224	31,360	28,224	31,360	28,224
F-statistic			359		252	
R-squared	0.067	0.067		−0.389		−0.541
Number of FIPS	3136	3136	3136	3136	3136	3136

Robust standard errors clustered by FIPS in parentheses.
*** $p<0.01$,
** $p<0.05$,
* $p<0.1$.

Table A5
Contemporaneous analysis of new business registrations in a U.S. county using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

DV: Business registrations	(1) OLS	(2) OLS	(3) First stage	(4) IV Reg	(5) First stage	(6) IV Reg
VARIABLES						
All KS campaigns	−0.00852*			−0.0205**		
	(0.00445)			(0.00839)		
Successful KS campaigns		−0.00650				−0.0285**
		(0.00525)				(0.0117)
Instrument 1			0.618***		0.409***	
			(0.0163)		(0.0149)	
Instrument 2			0.0523***		0.0633***	
			(0.00885)		(0.00790)	
Constant	3.887***	3.887***				
	(0.00611)	(0.00612)				
FIPS, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,227	24,227	24,209	24,209	24,209	24,209
F-statistic			4194		3667	
R-squared	0.156	0.155		0.155		0.155
Number of FIPS	3128	3128	3110	3110	3110	3110

Robust standard errors clustered by FIPS in parentheses.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

3.4. Main results

Table 1 contains descriptive statistics. It illustrates that the average number of KS campaigns in a county is only 5 to 6 campaigns, with a large variation between county-years. Less than half of campaigns across all categories are successful and the average number of new Crunchbase firms is even lower, at about 2 to 3 firms in a county-year. The number of new business registrations at 525 is much higher, illustrating how Crunchbase captures a narrow and specific segment of entrepreneurial activity. Control variables vary in significance and magnitude, however, instrumented regressions without possibly bad control variables (Angrist and Pishcke, 2009, pg. 64) show similar and stronger results in the directions hypothesized (please see appendix Table A1:, A2:, A3:, A4:, A5: and A6:).

Table 2 details contemporaneous (same-year) results with all variables logged to account for skewness and robust standard errors clustered at the FIPS level. The instrument using KS campaigns in film and video, music, comics, and dance is statistically significant in the first-stage with the Cragg-Donald F statistic of 3509 and 2841 for all campaigns and successful campaigns in columns 3 and 5. Sargan Hansen tests of overidentification also fail to reject the null for all campaigns and for successful campaigns, with p values of 0.19 and 0.34 respectively, assuming one degree of freedom for a chi-squared distribution. The second-stage IV regressions in columns 4 and 6 indicate strongly significant and positive effects for both, with magnitudes of 0.057 and 0.084. Hence, a 100% increase in campaigns correlates with an approximately 6% and 8% increase in firm starts, for all campaigns and successful campaigns, respectively.

Table 3 illustrates much stronger and highly significant effects in the immediate year following the CF campaigns. This seems reasonable, assumedly because it takes time to progress from a campaign to a Crunchbase listing. The magnitudes are 0.15 and 0.24, implying that a 100% increase in KS campaigns and successful campaigns precedes a 15% and 24% increase in Crunchbase listings. Both instruments remain

Table A6
Lagged (one year) analysis of new business registrations in a U.S. county using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

DV: Business registrations	(1) OLS	(2) OLS	(3) First stage	(4) IV Reg	(5) First stage	(6) IV Reg
VARIABLES						
All KS campaigns (1-yr lag)	0.00834**			−0.0190		
	(0.00380)			(0.0153)		
Successful KS campaigns (1-yr lag)		0.0114**				−0.0292
		(0.00448)				(0.0238)
Instrument 1			0.359***		0.212***	
			(0.0194)		(0.0147)	
Instrument 2			0.0339***		0.0372***	
			(0.0107)		(0.00897)	
Constant	4.205***	4.207***				
	(0.00655)	(0.00561)				
FIPS, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,142	21,142	21,118	21,118	21,118	21,118
F-statistic			626		456	
R-squared	0.121	0.121		0.119		0.118
Number of FIPS	3126	3126	3102	3102	3102	3102

Robust standard errors clustered by FIPS in parentheses.
*** $p<0.01$.
** $p<0.05$,
* $p<0.1$.

Table A7
Descriptive statistics for zipcode-level dataset.

Variable	Obs	Mean	Std. Dev.	Min	Max
All KS campaigns	157,145	0.19	0.58	0	8.23
Successful KS campaigns	157,145	0.09	0.39	0	7.41
Total Population (Log)	157,145	7.79	1.7	2.08	14.93
Median Household Income (Log)	157,145	10.79	0.37	8.3	12.42
Unemployment Rate	157,145	8.22	6.48	0	94.4
Foreign Born Population	157,145	4.39	7.29	0	81
Education - Bachelor Degree	157,145	13.29	8.42	0	100
Education - Graduate/ Professional Degree	157,145	7.16	7.01	0	100
Education - High School Graduate	157,145	35.95	11.5	0	100
Education - Less than 9th Grade	157,145	5.35	5.94	0	97.3
Industry - Agriculture, Forestry	157,145	7.21	10.42	0	100
Industry - Arts, Entertainment	157,145	7.63	6.68	0	100
Industry - Construction	157,145	7.85	5.87	0	100
Industry - Education, Healthcare	157,145	22.41	9.05	0	100
Industry - Information	157,145	1.47	2.24	0	82.6
Industry - Manufacturing	157,145	12.29	9.05	0	100
Industry - Other Services	157,145	4.63	3.97	0	100
Industry - Professional, Scientific	157,145	7.05	5.81	0	100
Industry - Public Administration	157,145	5.38	5.68	0	100
Industry - Retail Trade	157,145	11.06	6.23	0	100
Industry - Transportation	157,145	5.76	5.08	0	100
Industry - Wholesale Trade	157,145	2.55	3.02	0	100
Occupation - Management, Science, Business	157,145	31.27	12.56	0	100
Occupation - Natural Resources, Construction	157,145	13.58	8.34	0	100
Occupation - Production, Transportation	157,145	15.74	9.36	0	100
Occupation - Services	157,145	17.49	8.44	0	100
Population 15–25 Years	157,145	12.23	6.15	0	98.3
Population 25–34 Years	157,145	10.71	4.78	0	76
Population 35–44 Years	157,145	11.99	4.41	0	71.6
Population 45–54 Years	157,145	15.18	5.09	0	91
Population 55–59 Years	157,145	7.63	3.77	0	80.9
Population 60–64 Years	157,145	6.86	3.7	0	93.5
Population 65–74 Years	157,145	9.75	5.19	0	84.4
School Enrollment - High School	157,145	24.32	12.61	0	100
School Enrollment - University	157,145	19.79	14.13	0	100

very strong, with F-statistics greater than 10. This result is consistent with Sorenson et al. (2016) who showed that venture capital funding in a region increased in the immediate years after CF in that region.

As a robustness check to address concerns that results are being driven by regions with high entrepreneurial activity, we estimate models that exclude the top 3 counties in terms of angel and VC funding, namely Santa Clara, San Francisco, and New York counties. Table 4 illustrates contemporaneous results and Table 5 a one-year lag, with very similar results. The coefficients on both instruments are positive and statistically significant in the first-stage. Contemporaneously, there is a positive and highly significant effect. Moreover, after one year, the magnitude of the coefficient is even greater, indicating that a 100% increase in KS campaigns and successful campaigns precedes a 15% and 24% increase in Crunchbase listings, respectively, and very similar to the full sample estimates. These results indicate that the main findings are not a consequence of outlier data points, and provide additional support that CF and its effects are not restricted to already entrepreneurial regions (Mollick and Robb, 2016; Sorenson et al., 2016).

We also regress business registrations (Andrews et al., 2020) on KS campaigns at the county level. Contemporaneous results in Table 6 are negative and significant though the coefficients remain small, implying that a 100% increase in CF correlates with a 2% and 4% decrease in new registrations, for all and successful campaigns, respectively. Table 7 illustrates larger though less precise negative results, indicating the CF depresses local business registrations one year later, by 3% and 5%, respectively. The instruments remain very strong for both sets of models. These results would be consistent with arguments and evidence that human capital is the most crucial input to entrepreneurship if entrepreneurs are starting firms that list on Cruncbase, they are unable to start more conventional firms (such as shops, restaurants, and personal services) that would be observed in the registration data, but not in the Crunchbase data. It is also likely that Crunchbase firms incorporate in Delaware (Guzman and Stern, 2020), thus depressing local registration rates slightly (given that the number of registrations in each county is much greater than the number of Crunchbase listings).

4. Greater detail on where the crowd funds: an exploratory analysis using zip code locations

In order to better understand where crowdfunding occurs and is most effective, and given that counties can encompass a very wide variety of social and economic diversity, we moved to a lower level of

Table A8
Regression of population, unemployment, income, professions, industries, demographics, foreign born, and education on KS campaigns, by zip code.

VARIABLES	(1) All KS Campaigns	(2) Successful KS Campaigns
Total Population (Log)	0.1546**	0.0781**
	(0.0016)	(0.0012)
Unemployment Rate	0.0006**	0.0005**
	(0.0002)	(0.0001)
Median Household Income (Log)	−0.0422**	−0.0243**
	(0.0049)	(0.0034)
Foreign Born Population	0.0049**	0.0022**
	(0.0003)	(0.0002)
Education - Less than 9th Grade	−0.0024**	−0.0008**
	(0.0003)	(0.0002)
Education - High School Graduate	−0.0006**	−0.0002*
	(0.0002)	(0.0001)
Education - Bachelor Degree	0.0024**	0.0014**
	(0.0002)	(0.0002)
Education - Graduate/Professional Degree	0.0034**	0.0021**
	(0.0003)	(0.0002)
School Enrollment - High School	−0.0002*	−0.0001*
	(0.0001)	(0.0001)
School Enrollment - University	0.0008**	0.0004**
	(0.0001)	(0.0001)
Occupation - Management, Science, Business	0.0003	0.0001
	(0.0002)	(0.0001)
Occupation - Services	0.0005*	0.0001
	(0.0002)	(0.0001)
Occupation - Natural Resources, Construction	−0.0003	−0.0002
	(0.0002)	(0.0002)
Occupation - Production, Transportation	0.0003	0.0001
	(0.0002)	(0.0001)
Industry - Agriculture, Forestry	0.0011**	0.0006**
	(0.0003)	(0.0002)
Industry - Construction	−0.0002	−0.0000
	(0.0004)	(0.0002)
Industry - Manufacturing	−0.0007*	−0.0004
	(0.0003)	(0.0002)
Industry - Wholesale Trade	−0.0002	−0.0001
	(0.0004)	(0.0003)
Industry - Retail Trade	0.0004	0.0001
	(0.0003)	(0.0002)
Industry - Transportation	0.0003	0.0001
	(0.0004)	(0.0002)
Industry - Information	0.0012*	0.0006
	(0.0005)	(0.0004)
Industry - Professional, Scientific	0.0012**	0.0006*
	(0.0003)	(0.0002)
Industry - Education, Healthcare	0.0002	0.0001
	(0.0003)	(0.0002)
Industry - Arts, Entertainment	0.0011**	0.0004
	(0.0003)	(0.0002)
Industry - Other Services	0.0004	0.0002
	(0.0004)	(0.0003)
Industry - Public Administration	0.0002	0.0001
	(0.0003)	(0.0002)
Population 15–25 Years	0.0017**	0.0012**
	(0.0003)	(0.0002)
Population 25–34 Years	0.0011**	0.0005*
	(0.0003)	(0.0002)
Population 35–44 Years	−0.0007*	−0.0001
	(0.0003)	(0.0002)
Population 45–54 Years	0.0003	0.0003
	(0.0003)	(0.0002)
Population 55–59 Years	0.0018**	0.0009**
	(0.0003)	(0.0002)
Population 60–64 Years	0.0021**	0.0007**
	(0.0003)	(0.0002)
Population 65–74 Years	0.0021**	0.0006**
	(0.0003)	(0.0002)
Constant	−0.7345**	−0.3533**
	(0.0626)	(0.0430)
Observations	157,145	157,145
Number of zcta	26,910	26,910

geographical analysis. These analyses are exploratory; while we speculate about possible causes and future research opportunities, these analyses are not intended as a deductive test of hypotheses.

Using the United States' approximately 27,000 zip code regions, we illustrate positive correlations between CF and young and old, highly educated, in school, and immigrant populations. We then cluster the zip codes and develop a typology of regions that host crowdfunding, documenting wide disparities in the types of regions that witness high per capita crowdfunding, ranging from large cities, which witness the most, to rural and human capital poor regions, which witness the least. Further zip code level regressions find that KS campaigns precede higher rates of firm founding, and that the less urban regions that witness less CF activity actually benefit more, per CF campaign. While CF appears to be less likely in rural and less educated regions, as well as college towns, the impact of CF on new firm formation appears greater, relative to urban regions.

Table A7 reports descriptive statistics on the zip code data and Table A8 regresses the logs of campaigns and successful campaigns in a U.S. zip code on a variety of regional characteristics, over the years of 2011–2016. The models explore the relationships between the number of campaigns and successful campaigns and a variety of government collected variables (from government sources such as the Census and Bureau of Labor Statistics[8]), including population, unemployment, income, percentage foreign born, education, school enrollment, occupation, industry, and age distribution. The zip code level data are necessarily aggregated, as CF geographical data are entered by the campaigner at the city level. The city location must be mapped to a zip code, which maps directly for small towns where there is a one to one correspondence between zip code and city. This approach does not work well for large cities, where there are many zip codes for the city (for example, Los Angeles has at least 117). Hence, estimations at the zip code level are likely to be noisy, especially for larger cities.

Appendix Table A9 breaks out individual categories (for example, technology, art, comics) of the log contemporaneous number of Kickstarter campaigns and color codes them by significance; quick inspection indicates few differences in the relationships between regional characteristics and the particular type of KS campaign (the colors, which represent p values, are relatively consistent across the different campaign categories, which can be identified by the similar colors within rows). Here we discuss these relationships between the total number of campaigns and regional characteristics, after which we cluster regions and consider the campaigns/person individually for each cluster type.

Population, unemployment, and income: Not surprisingly, simple population correlates strongly with both the total number of campaigns and number of successful campaigns. Urban regions are known to better support innovation and knowledge spillovers, assumedly due to population density ((Roche, 2020)); assuming CF requires creativity and innovation, perhaps the same holds true. Unemployment correlates positively – people out of work might have more time to run campaigns. Median household income correlates negatively – wealthier people appear less likely to run campaigns, perhaps because they have more slack financially, or access to resources, including technological

[8] https://www.bls.gov/lau/#tables.

Table A9
(next page, horizontal): An expansion of Table 7 broken down by CF category, illustrating little variation across CF categories, with regards to correlations with regional (zip code) population, unemployment, income, professions, industries, demographics, foreign born, and education. Dark red covers highly significant correlations ($p< 0.05$), pink covers marginally significant correlations ($p< 0.10$, and white indicates no significant correlation ($p => 0.01$).

	Arts	Comics	Crafts	Dance	Design	Fashion	Film & Video	Food	Games	Journalism	Music	Photography	Publishing	Technology	Theater
Total Population (log)	0.0251	0.0137	0.0085	0.0057	0.0211	0.0177	0.0412	0.0244	0.0256	0.0040	0.0444	0.0132	0.0377	0.0170	0.0122
Civilian Unemployment Rate	0.0000	0.0001	0.0000	0.0000	0.0001	0.0001	0.0000	0.0001	0.0001	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000
Median Household Income	-0.0212	-0.0103	-0.0085	-0.0051	-0.0147	-0.0122	-0.0269	-0.0193	-0.0171	-0.0051	-0.0297	-0.0117	-0.0264	-0.0147	-0.0113
O_Management	0.0002	0.0001	0.0001	0.0001	0.0003	0.0002	0.0001	0.0002	0.0003	0.0000	0.0001	0.0001	0.0003	0.0003	0.0001
O_Services	0.0003	0.0001	0.0001	0.0000	0.0003	0.0001	0.0001	0.0003	0.0002	0.0000	0.0001	0.0001	0.0003	0.0002	0.0001
O_Natural Resources	-0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0002	0.0000	0.0000	0.0000	-0.0002	0.0000	-0.0001	0.0000	0.0000
O_Production	0.0003	0.0001	0.0001	0.0001	0.0003	0.0002	0.0001	0.0003	0.0002	0.0001	0.0001	0.0002	0.0004	0.0003	0.0001
I_Agriculture	0.0007	0.0003	0.0004	0.0001	0.0006	0.0004	0.0007	0.0008	0.0007	0.0001	0.0008	0.0003	0.0009	0.0006	0.0002
I_Construction	0.0003	0.0000	0.0002	0.0000	0.0002	0.0000	0.0002	0.0002	0.0002	0.0000	0.0002	0.0001	0.0002	0.0002	0.0001
I_Manufacturing	-0.0001	-0.0002	0.0000	-0.0001	0.0000	-0.0002	-0.0004	-0.0001	0.0000	0.0000	-0.0002	-0.0001	-0.0003	0.0001	-0.0001
I_Wholesale Trade	0.0000	0.0000	0.0001	0.0000	-0.0001	0.0000	-0.0002	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0001
I_Retail Trade	0.0002	0.0000	0.0001	0.0000	0.0002	0.0000	0.0001	0.0003	0.0002	0.0000	0.0000	0.0000	0.0002	0.0002	0.0000
I_Transportation	0.0002	0.0001	0.0002	0.0000	0.0003	0.0001	0.0002	0.0003	0.0003	0.0000	0.0003	0.0001	0.0003	0.0003	0.0000
I_Information	0.0003	0.0001	0.0002	0.0001	0.0003	0.0002	0.0007	0.0002	0.0004	0.0001	0.0004	0.0001	0.0004	0.0003	0.0002
I_Professional	0.0004	0.0002	0.0003	0.0001	0.0005	0.0003	0.0003	0.0007	0.0006	0.0001	0.0004	0.0002	0.0006	0.0005	0.0001
I_Education	0.0001	0.0000	0.0001	0.0000	0.0001	0.0000	0.0000	0.0002	0.0001	0.0000	0.0002	0.0000	0.0001	0.0001	0.0000
I_Arts	0.0004	0.0001	0.0001	0.0000	0.0003	0.0002	0.0003	0.0005	0.0003	0.0000	0.0004	0.0001	0.0005	0.0003	0.0000
I_Other Services	0.0002	0.0000	0.0001	0.0000	0.0001	0.0001	0.0000	0.0003	0.0002	0.0000	0.0002	0.0001	0.0003	0.0002	0.0000
I_Public Administration	0.0002	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001	0.0002	0.0001	0.0000	0.0001	0.0001	0.0001	0.0001	0.0000
Pop_15to24	0.0007	0.0003	0.0003	0.0001	0.0007	0.0005	0.0012	0.0008	0.0008	0.0001	0.0014	0.0004	0.0010	0.0007	0.0004
Pop_25to34	0.0009	0.0006	0.0006	0.0003	0.0010	0.0009	0.0010	0.0013	0.0012	0.0003	0.0011	0.0007	0.0013	0.0011	0.0006
Pop_35to44	0.0002	0.0002	0.0002	0.0001	0.0002	0.0002	0.0003	0.0002	0.0003	0.0001	0.0004	0.0002	0.0001	0.0002	0.0002
Pop_45to54	0.0002	0.0002	0.0001	0.0001	0.0002	0.0003	0.0004	0.0002	0.0002	0.0001	0.0004	0.0002	0.0003	0.0002	0.0002
Pop_55to59	0.0007	0.0003	0.0003	0.0002	0.0005	0.0005	0.0006	0.0008	0.0006	0.0002	0.0007	0.0004	0.0008	0.0005	0.0002
Pop_60to64	0.0005	0.0003	0.0003	0.0002	0.0006	0.0005	0.0007	0.0008	0.0006	0.0001	0.0008	0.0004	0.0007	0.0005	0.0003
Pop_65to74	0.0006	0.0004	0.0004	0.0002	0.0008	0.0006	0.0007	0.0010	0.0008	0.0002	0.0007	0.0005	0.0010	0.0007	0.0003
Foreign Born	0.0007	0.0005	0.0001	0.0002	0.0011	0.0007	0.0012	0.0007	0.0009	0.0002	0.0009	0.0003	0.0011	0.0009	0.0004
EA_Less than High School	-0.0003	-0.0002	-0.0002	0.0000	-0.0004	-0.0003	-0.0004	-0.0005	-0.0005	0.0000	-0.0003	-0.0002	-0.0007	-0.0004	-0.0001
EA_High School	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0001	0.0000	0.0000	0.0000	-0.0001	0.0000	0.0000
EA_Bachelors	0.0005	0.0001	0.0002	0.0001	0.0006	0.0003	0.0007	0.0005	0.0005	0.0001	0.0008	0.0002	0.0007	0.0005	0.0003
EA_Graduate	0.0010	0.0004	0.0003	0.0003	0.0011	0.0005	0.0014	0.0010	0.0008	0.0002	0.0014	0.0005	0.0011	0.0010	0.0005
SE_High School	0.0000	0.0000	0.0000	0.0000	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	0.0000	-0.0001	0.0000	-0.0001	-0.0001	0.0000
SE_College	0.0003	0.0001	0.0001	0.0001	0.0002	0.0002	0.0004	0.0003	0.0002	0.0001	0.0004	0.0001	0.0004	0.0002	0.0001

business, or entrepreneurial expertise.

Occupations: Occupations are split ranging from management and business to production and transportation. Management and science, services, and production and transportation demonstrate positive correlations and this effect is relatively consistent across the individual Kickstarter categories. People in these occupations may generate more ideas that could result in a startup. Perhaps the most interesting occupational insight from Table A9 is the lack of vertical correlation between occupations and arts campaigns, including Dance, Film and Video, Journalism, Music, and Theater.

Industry: Industry composition in a zip code appears to have little impact on crowdfunding activity (as indicated also by the mostly white space in that row of Table A9). We estimated the proportion of a zip code's industry in a particular subcategory, ranging from agriculture and farming to arts and entertainment. The models indicate that location of scientific industries are positively correlated with local CF, however, a few other industries show positive correlations as well, including agriculture and forestry, retail trade, transportation, education, and the arts. Agriculture and forestry are the strongest, surprisingly. This may result from the college towns and tourism regions, identified below in the clustering exercise. Regions with science industries would obviously be home to technical professionals, who are more likely to run technical CF campaigns.

Population Demographics: In order to study the impact of population distribution on CF, we split the total population into six time of life categories with period lengths of approximately 10 years. Both the number and number of successful campaigns reveal a non-monotonic relationship; regions with younger and older people are more likely to pursue and succeed in pursuing CF. Regions with middle aged people appear to have less CF (the effect is actually negative and significant for the percentage of population between 35 and 44). Young people, possibly in college and not yet married and supporting a family, and old people, done with raising a family and probably retired, may have more time and motivation to pursue CF campaigns. The results are not consistent with a survey from Mollick and Kuppuswamy (2014), who asked CF campaigners their age. One possible explanation is that regional characteristics may not map directly to who ultimately launches a campaign.

Foreign Born: Regions with more foreign-born populations support more crowdfunding. Immigrants may bring higher education and/or higher aspirations to a region, and also be less likely to pursue or have access to conventional types of financing. They may also rely more heavily on friends and family networks and this may be done through crowdfunding. These arguments are very consistent with studies of immigrants and increased entrepreneurship (Kerr and Kerr 2017).

Educational Attainment: Regions with more highly educated inhabitants experience a stark difference in crowdfunding. An increase in the percentage of people with less than 9th grade and high school education in a region demonstrates a negative correlation and the less than 9th grade education is significant; the effect of a bachelors and Masters or professional degree is positive and significant. The coefficient of graduate degrees is also significantly greater than bachelor degrees. The results are consistent for both the number and success of campaigns. This might occur because better educated people are more able to navigate CF platforms, create and craft a pitch for a CF website, or simply be more aware of CF opportunities. These results are consistent with the Mollick and Kuppuswamy (2014) survey that found that 95% of Kickstarter campaigners had some college education. It indicates a stark divide between poorly and better educated people being able to take advantage of CF.

School Enrollment: Consistent with education levels, the proportion of the population currently in high school in a region demonstrates a negative correlation with the number or success of campaigns; the population in college has a positive and significant impact for both. This may result from stark differences in human capital in the regions; counties with many college students may simply support a higher average level of human capital, both amongst students and faculty and staff who live nearby. On the other hand, Agrawal et al. (2018) have shown that CF activity goes up dramatically during school breaks. Consistent with their arguments, students may also generate potential campaigns in the course of their studies and business plan contests, independent of the average level of human capital in the county.

Continuing the exploratory data analysis, we clustered the zip code data by these same variables, though we found very little change in assignment past the inclusion of total population and median income (both forward and stepwise variable selection methods identified these

Table A10
(a): Cluster analysis of KS campaigns at zip code level on new firms using two instruments: 1) excluded KS category campaigns and 2) comments of excluded KS category campaigns. Excluded KS categories include film and video, music, comics, and dance.

Panel A4a. Big cities						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS		IV Reg		IV Reg
VARIABLES	New firms	New firms	First stage	New firms	First stage	New firms
All KS campaigns	−0.0255			0.138		
	(0.114)			(0.194)		
Successful KS campaigns		−0.0331				0.116
		(0.0868)				(0.163)
Instrument 1			0.705***		0.834***	
			(0.133)		(0.182)	
Instrument 2			0.0177		0.0277	
			(0.0275)		(0.0374)	
Angel funding	−0.00437	−0.00452	−0.00132	−0.00455	−0.00670	−0.00398
	(0.00605)	(0.00605)	(0.00546)	(0.00573)	(0.00742)	(0.00579)
Income	0.890*	0.886*	−0.577	1.015**	−0.517	0.995**
	(0.482)	(0.478)	(0.424)	(0.473)	(0.577)	(0.468)
Population	0.496**	0.497**	−0.241	0.491**	−0.305	0.492**
	(0.230)	(0.230)	(0.216)	(0.218)	(0.294)	(0.220)
Constant	−12.15**	−12.09**				
	(6.019)	(5.923)				
ZCTA, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91	91	91	91	91	91
F statistic			14.97		11.6	
R-squared	0.935	0.935		0.933		0.932
Number of zcta	13	13	13	13	13	13
Panel A10b. Not so big cities						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS		IV Reg		IV Reg
VARIABLES	New firms	New firms	First stage	New firms	First stage	New firms
All KS campaigns	−0.0532			0.590*		
	(0.0873)			(0.316)		
Successful KS campaigns		0.0340				0.242
		(0.0640)				(0.508)
Instrument 1			0.297***		0.173**	
			(0.0566)		(0.0802)	
Instrument 2			−0.00202		−0.0200	
			(0.0150)		(0.0212)	
Angel funding	0.00466	0.00489	−0.00198	0.00639	−0.00218	0.00543
	(0.00399)	(0.00399)	(0.00252)	(0.00434)	(0.00357)	(0.00420)
Income	−0.507**	−0.493**	0.00787	−0.444*	−0.187	−0.440
	(0.236)	(0.236)	(0.150)	(0.254)	(0.213)	(0.269)
Population	0.717***	0.702***	−0.0165	0.628***	0.131	0.658***
	(0.193)	(0.193)	(0.125)	(0.210)	(0.177)	(0.220)
Constant	−0.891	−1.118				
	(3.421)	(3.417)				
ZCTA, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	364	364	364	364	364	364
F statistic			14.31		2.4	
R-squared	0.805	0.805		0.769		0.798
Number of zcta	52	52	52	52	52	52
Panel A10c. College towns						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS		IV Reg		IV Reg
VARIABLES	New firms	New firms	First stage	New firms	First stage	New firms
All KS campaigns	0.0154			1.104***		
	(0.0167)			(0.267)		
Successful KS campaigns		−0.0356**				1.920***
		(0.0167)				(0.699)
Instrument 1			0.0892***		0.0307*	
			(0.0181)		(0.0182)	
Instrument 2			0.00175		0.0141*	
			(0.00844)		(0.00847)	
Angel funding	0.00320	0.00339	0.00169	0.00122	0.00447	−0.00551
	(0.00275)	(0.00275)	(0.00272)	(0.00408)	(0.00273)	(0.00680)
Income	0.458***	0.459***	0.0474	0.400***	−0.00940	0.479***
	(0.0610)	(0.0610)	(0.0605)	(0.0909)	(0.0607)	(0.133)
Population	0.594***	0.591***	−0.0868*	0.669***	−0.0756	0.721***
	(0.0464)	(0.0464)	(0.0460)	(0.0707)	(0.0462)	(0.111)
Constant	−11.07***	−11.00***				
	(0.856)	(0.856)				
ZCTA, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4235	4235	4235	4235	4235	4235
F statistic			15.47		5	

(*continued on next page*)

Table A10 (*continued*)

Panel A4a. Big cities						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS		IV Reg		IV Reg
VARIABLES	New firms	New firms	First stage	New firms	First stage	New firms
R-squared	0.312	0.313		−0.493		−2.289
Number of zcta	605	605	605	605	605	605

Panel A10d. Diversified and tourism rural						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS		IV Reg		IV Reg
VARIABLES	New firms	New firms	First stage	New firms	First stage	New firms
All KS campaigns	−0.00346			0.562***		
	(0.00215)			(0.0718)		
Successful KS campaigns		−0.00175				1.172***
		(0.00347)				(0.174)
Instrument 1			0.0483***		0.0219***	
			(0.00687)		(0.00426)	
Instrument 2			0.0135***		0.00739***	
			(0.00394)		(0.00244)	
Angel funding	0.00763***	0.00763***	0.00342	0.00585***	0.00314**	0.00409**
	(0.00108)	(0.00108)	(0.00210)	(0.00163)	(0.00130)	(0.00195)
Income	−0.00280***	−0.00281***	0.00368***	−0.00479***	0.00107	−0.00398***
	(0.000616)	(0.000616)	(0.00120)	(0.000950)	(0.000741)	(0.00108)
Population	0.0226***	0.0226***	0.00974***	0.0165***	−0.000836	0.0229***
	(0.000878)	(0.000878)	(0.00171)	(0.00152)	(0.00106)	(0.00152)
Constant	−0.110***	−0.110***				
	(0.00921)	(0.00920)				
ZCTA, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,005	67,005	67,005	67,005	67,005	67,005
F statistic			56.91		34.2	
R-squared	0.025	0.025		−1.151		−1.915
Number of zcta	9574	9574	9574	9574	9574	9574

Panel A10e. Rich suburbs						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS		IV Reg		IV Reg
VARIABLES	New firms	New firms	First stage	New firms	First stage	New firms
All KS campaigns	−0.00278			1.594*		
	(0.00730)			(0.861)		
Successful KS campaigns		−0.00814				−11.92
		(0.0104)				(69.87)
Instrument 1			0.0212		−0.00164	
			(0.0150)		(0.0105)	
Instrument 2			0.00442		0.000831	
			(0.00829)		(0.00583)	
Angel funding	0.0107***	0.0106***	0.00552**	0.00169	−0.000358	0.00639
	(0.00187)	(0.00187)	(0.00239)	(0.00644)	(0.00168)	(0.0320)
Income	−0.0117***	−0.0116***	0.00611**	−0.0212***	0.00374*	0.0330
	(0.00224)	(0.00224)	(0.00286)	(0.00724)	(0.00201)	(0.263)
Population	0.0824***	0.0824***	0.0107**	0.0642***	−0.00448	0.0287
	(0.00394)	(0.00394)	(0.00503)	(0.0133)	(0.00353)	(0.317)
Constant	−0.360***	−0.359***				
	(0.0387)	(0.0387)				
ZCTA, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,508	13,508	13,508	13,508	13,508	13,508
F statistic			2.13		0.02	
R-squared	0.117	0.117		−3.534		−100.325
Number of zcta	1931	1931	1931	1931	1931	1931

Panel A10f. Poor and mostly rural						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS		IV Reg		IV Reg
VARIABLES	New firms	New firms	First stage	New firms	First stage	New firms
All KS campaigns	−0.000301			0.216***		
	(0.00126)			(0.0318)		
Successful KS campaigns		−0.00571**				0.828***
		(0.00239)				(0.121)
Instrument 1			0.0669***		0.0154***	
			(0.00566)		(0.00298)	
Instrument 2			−0.00129		0.00798***	
			(0.00395)		(0.00208)	
Angel funding	0.0181***	0.0181***	−0.00249	0.0187***	−0.00195	0.0197***
	(0.00106)	(0.00106)	(0.00289)	(0.00124)	(0.00152)	(0.00167)
Income	−0.000349*	−0.000349*	0.000477	−0.000442*	−0.000103	−0.000251
	(0.000197)	(0.000197)	(0.000536)	(0.000229)	(0.000282)	(0.000307)
Population	0.00384***	0.00384***	0.00433***	0.00279***	0.000386	0.00338***
	(0.000372)	(0.000371)	(0.00101)	(0.000457)	(0.000532)	(0.000583)
Constant	−0.0159***	−0.0159***				
	(0.00323)	(0.00323)				
ZCTA, Year FE	Yes	Yes	Yes	Yes	Yes	Yes

(*continued on next page*)

Table A10 (*continued*)

Panel A4a. Big cities						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS		IV Reg		IV Reg
VARIABLES	New firms	New firms	First stage	New firms	First stage	New firms
Observations	99,397	99,397	99,397	99,397	99,397	99,397
F statistic			90.23		40.5	
R-squared	0.007	0.007		−0.336		−1.411
Number of zcta	14,202	14,202	14,202	14,202	14,202	14,202

Standard errors in parentheses.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

two variables as most important). We interpreted and labeled the six clusters as follows. Every data point was assigned to one and only one cluster.

- **Big cities: $n = 13$, 380.5 campaigns/1000 people** (highest population density, highest foreign born and Arts, lowest older population: New York, NY, Chicago, IL, Los Angeles, CA)
- **Not so big cities: $n = 52$, 216.5 campaigns/1000 people** (2nd largest population, highest young population, high Arts: Atlanta, GA, San Francisco, CA, Salt Lake, UT, Minneapolis, MN)
- **College towns: $n = 605$, 68.8 campaigns/1000 people** (high foreign born, high college enrollment and educational attainment, high Arts, 2nd highest young people, Berkeley, CA, Santa Barbara, CA, Corpus Christi, TX, Fort Collins, CO, Boulder, CO, Bloomington, IN, Cambridge, MA, Palo Alto, CA)
- **Diversified and tourism rural: $n = 9574$, 25.6 campaigns/1000 people (**higher older population, high Agriculture and Forestry, low foreign born, low tech, low population density, low unemployment: Mammoth Lakes, CA, Yosemite National Park, CA, Crested Butte, CO, Key Largo, FL)
- **Rich suburbs: $n = 1931$, 30.1 campaigns/1000 people (**almost double median income, high management/professional occupations, high educational attainment, highest management, science, business occupations: Greenwich, CT, Cupertino, CA, Brookline, MA)
- **Poor and mostly rural: $n = 14{,}202$, 18.6 campaigns/1000 people (**lowest income and population density, low enrollment and education, low foreign born, high agriculture, highest older population: Weed, CA, Cortez, CO, Cotton, GA, Roxbury, MA)

Some of the clustering results are unsurprising, given prior research on entrepreneurship, for example, greater entrepreneurship in high human capital, urban, and immigrant rich regions. Other results highlighted differences in CF activity. Big cities are much more likely to host CF (an average of 380.5 campaigns/1000 people), following by not so big cities (216.5 campaigns/1000 people) and college towns (68.8 campaigns/1000 people). Given the attention paid to college student CF (Agrawal et al., 2018), it might appear surprising that college towns are not the highest regions of CF activity. All other categories exhibited ~25 campaigns/1000 people with poor regions coming in last at 18.6 campaigns/1000 people. Surprisingly, tourist regions exhibited higher CF activity than poor regions but less than rich suburbs (all three experienced substantially less than big and small cities and college towns).

5. How does the impact of CF vary across zip codes?

While CF might be more popular in urban and educated areas, it might have less relative impact there because entrepreneurs have alternative means of access to resources, and visibility from those alternative resources, in those regions. For example, urban entrepreneurs might have easier access to capital, richer and denser social networks, opportunities for feedback on their ideas, and other ways to publicize their endeavor and attract talent. Less urban entrepreneurs, on the other hand, may live in poorer regions which investors are more likely to ignore. They are also more likely to lack strong social networks and in general, be socially isolated, experience fewer opportunities for feedback, face greater challenges in publicizing their effort, and have less immediate access to high quality talent. If these mechanisms are present, we might observe greater CF activity in urban and educated areas, yet greater effect of CF in less urban and educated areas.

The six panels in Table A10 detail IV regressions by type of clustered region: a) big cities, b) not so big cities, c) college towns, d) diversified tourism and rural, e) rich suburbs, and f) poor and mostly rural. The two instruments generally hold within regions, and in particular, the number of campaigns in non-entrepreneurial categories holds, with the exception of rich suburbs, where neither instrument holds.

Most interestingly, and consistent with the unchanged results when dropping Silicon Valley and New York, the instrumented regressions on the clustered regions indicate that the effect is not driven by cities (though given the thin 91 data points, it remains difficult to interpret a lack of significance for the big cities). Not so big cities show a marginally significant result for the total number of campaigns, though not for successful campaigns. For a 100% increase in KS projects, college towns experience a 110% increase (implying a surprisingly direct correspondence between campaigns and firm starts), diversified and tourism regions experience a 56% increase, and mostly rural and poor regions, a 22% increase, all significant (Tables A4c, A4d, and A4e, respectively). To put these in perspective, assume that a region had 8 KS campaigns and 2 new firms, on average (motivated by the descriptive statistics in Table A7). If this were a college town, for example, then a doubling of KS campaigns would result in the number of firm starts increasing from two to four. In a rural and diversified region, it would result in an increase from two to three.

6. Discussion

Even though an entrepreneurial culture is often cited as an important factor in regional entrepreneurial success (Saxenian, 1994), it remains challenging to consistently measure culture and mechanisms, particularly across multiple regions and over time. Here we used and make available a measure that is closely related to a region's entrepreneurial culture and mechanisms, namely, the number, types, and success of crowdfunding campaigns. In contrast to government data and formal surveys, crowdfunding campaigns provide a finer grained and almost continuous real-time window on potential entrepreneurs at the earliest stage in their idea development. As an example of the value of this measure, we first establish that CF campaigns precede a shift in regional entrepreneurship, and also describe where crowdfunding campaigns are most likely, and most effective with regards to firm starts. The work remains exploratory, but indicates potentially fruitful avenues for future theorizing and hypothesis testing.

It remains difficult to generalize these results beyond the relatively short time period of observation. The economy grew steadily during the years of observation, as did penetration of digital media and use of the internet.[9] Despite the instrumental variable, the identification strategy remains vulnerable to the possibility that unobserved regional characteristics influenced both commercial and non-commercial CF activity and entrepreneurship. The zip code analyses for towns with more than one zip code are fundamentally noisy as well, due to the need to aggregate data from multiple zip codes into one observation. Finally, there might be some reverse causality, whereby firm starts in a county might increase CF. One could hypothesize that entrepreneurs start firms, or see others start firms, and that they then increase CF, in an effort to generate more possibilities for entrepreneurship. This is certainly plausible theoretically, though our lagged models and IV regressions make this unlikely as explanation for the current results. Further work would be needed to establish whether regional entrepreneurship precedes CF. It would also be interesting to investigate whether CF benefits spill over to other nearby regions.

7. Conclusion

Despite much research on regional entrepreneurship and much research on crowdfunding, less work has connected the two topics, and none has established the relationship between crowdfunding and entrepreneurial firms starts in a region. Using an instrumental variables based on commercial vs. non-commercial crowdfunding campaigns and user comments on those campaigns, this research first established that crowdfunding precedes high tech and high growth entrepreneurship. The positive relationship occurs between commercially oriented CF and high tech and high growth entrepreneurship and the greatest effect occurs one year after a campaign, with elasticities from 0.06 to 0.24. Regional Kickstarter campaigns also appear to decrease more conventional business registrations slightly. Hence it appears that Crowdfunding shifts the nature of entrepreneurship in a region, towards higher tech and higher growth firms that would be incorporated in Delaware, and away from more conventional firm starts, that would be observed in local business registration. Whether this is desirable or not remains an open policy question, and warrants future research which ties types of firm starts to specific regional outcomes, such as jobs, sales, and employment. Such research should investigate the lagged effects as well, for example, if a high-tech firm is less likely to ultimately survive in an isolated region, that region might have benefited more from a more conventional entrepreneurial firm founding, even though long-term very high growth opportunities for conventional entrepreneurship are fewer.

Moving to finer-grained zip code regressions, this research also established that regions with greater CF have higher rates of education, younger, older, college, foreign born, and greater populations, and lower median income. Exploratory clustering by zip code resulted in six clusters, mainly driven by population and income, which we labeled big cities, not so big cities, college towns, diversified tourism and rural, rich suburbs, and poor and mostly rural. Campaign rates per thousand people ranged from 151. 6 in the big cities to 12.3 in the poor and mostly rural counties. Breaking out the regressions by clusters showed that while poorer regions often experience less CF, the impact of a campaign on the region's entrepreneurship was greater.

Regional inequality has increased recently and become an increasingly important issue to social scientists and policy makers (Moretti, 2012). Over the past 50 years, some regions of the United States have witnessed tremendous growth (Moretti, 2012), often fueled by high tech entrepreneurship and well-paying jobs, while others, even physically close by, have witnessed languid economies, falling populations, and stagnant housing prices. Crowdfunding has emerged more recently, and given rise to some staggering anecdotes of entrepreneurial success, for example, Oculus Rift, which raised $2.5 M from the crowd, and was bought by Facebook for $2B (Oculus Rift, 2019). Such stories raise an intriguing possibility, that CF might decrease regional inequality, by providing entrepreneurs in poorer regions with access to very early financing, feedback, experience, and visibility to later investors. Our results also provide nuance to particular types of entrepreneurship, for example, policy makers may prefer Crunchbase firms to more conventional firms - if such firms ultimately generate more wealth and jobs (Moretti, 2012).

These results provide mixed news for policy makers seeking to increase entrepreneurship and firm starts. If the goal is the formation of high growth firms, then regional CF activity appears to precede high tech and high growth entrepreneurship. If the policy concern is helping poor regions with weak human capital, it appears CF activity unfortunately concentrates mainly in urban regions with greater human capital. Returning to the first point, however, it also appears that the limited amount of CF in non-urban regions (and in particular, diversified and tourism and poor rural areas, and college towns) appears to have a stronger positive impact than that in urban regions. The multivariate regression of Table A8 indicates that a region's median wealth correlates negatively with CF, hence, one might infer from this that poor – yet educated – people are motivated by necessity to CF.

Policy makers might apply this research in a number of ways. First, it appears that regions might benefit from raised awareness of CF, for example, schools and other institutions could offer CF classes and workshops. Such efforts might also increase the social and human capital in economically disadvantaged regions, though policy makers should be careful, if they do not wish to shift focus from conventional business registrations to high growth startups. This work also provided an example of how CF can provide regional and real-time measures of entrepreneurial culture and activity, before firms are founded and become visible. Because campaigns can be observed in real time and scraped on a regular basis, this measure could be incorporated into policy dashboards and local business analyses.

Further work should explore the culture and mechanisms of CF and entrepreneurial success and failure in these regions. In particular, it remains an open question why particular regions are able to leverage CF into entrepreneurship and what might be done to help less advantaged regions. It should also explore the mechanisms whereby CF appears to shift the focus of regional entrepreneurs, from conventional firms, to high tech and high growth (and assumedly risky) startups. Future research could also seek to understand the mechanisms within individual CF campaigns and entrepreneurial startups, for example, how many entrepreneurs now use CF campaigns in their development and does running a CF campaign increase the chances of entrepreneurial success? As argued here, many CF mechanisms might increase the chances of entrepreneurial success, including early stage funding, market feedback, legitimacy, experience, and visibility; future work at a lower level of analysis, possibly with qualitative methods, should investigate these possibilities.

Declaration of Competing Interest

None.

Appendix: Instrumented regressions without control variables

Zip code analyses of different types of CF campaigns

The ZIP Code Tabulation Areas (ZCTA) are generalized areas representing the United States Postal Service ZIP code areas [2]. Because the CF campaign data at the city level is entered manually, we developed a concordance containing a combination of United States Postal Service (USPS) ZIP code dataset [3] and a relationship dataset between ZCTA and

[9] https://en.wikipedia.org/wiki/Economic_policy_of_the_Barack_Obama_administration; https://www.statista.com/chart/15355/social-media-users/.

Zip codes (essentially, for cities with more than one zip code, we collapsed and aggregated all data into one observation). The USPS datasets provide a link between Zip codes and city names which when linked with the relationship dataset provides us a direct relation between ZCTA and city names. Only mainland US ZIP codes are considered.

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