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Reward-based Crowdfunding in a Pandemic

By
Matthew Grace, University of South Florida

How the COVID-19 pandemic has impacted entrepreneurship in America is a critical question. Despite the pandemic, entrepreneurs have been, and still are, looking to finance their ongoing, established businesses, as well as finance new ventures. Reward-based crowdfunding has filled an important gap in alternative finance since the 2008 financial crisis, and many are wondering if it can do the same for the current crisis. By examining 114,838 Kickstarter projects spanning more than a decade, including through the COVID-19 pandemic, this paper tries to answer the following questions: how has the COVID-19 pandemic impacted crowdfunding campaigns in America, and how have different product categories been affected? The analyses show that reward-based crowdfunding campaigns on Kickstarter have reached a global maximum in terms of success rates. Furthermore, the number of backers, the ratio of a campaign's funds raised to its goal, and the average funds pledged per campaign, have also increased during the pandemic. Furthermore, some product categories have performed dramatically better than others. Each of these findings alone would contribute towards an increased understanding of the effects of the pandemic on crowdfunding; however, taken together, these results contribute substantially towards an understanding of the dynamics of crowdfunding with implications for academics as well as practitioners.

In early 2020, many entrepreneurs were ready to turn to alternative financing such as crowdfunding. But were the 'crowd' financing campaigns like they used to? They were not; paradoxically, they were helping projects succeed at a never-before-seen rate.

Keywords: Entrepreneurship, Crowdfunding, Alternative Finance, Pandemic, COVID-19, Finance, Startup, Financial Crisis

The birth of the web 2.0 shook the world and allowed entrepreneurs seeking capital to use online sources to fund their ventures, sources such as Crowdfunding (CF) (A. K. Agrawal, Catalini, & Goldfarb, 2011; Belleflamme, Lambert, & Schwienbacher, 2010). CF is one of many types of alternative finance (AF) that permit fundraisers to seek funds in a slightly different fashion than ventures seeking funds in traditional financing, for example from a venture capitalist, bank, or angel investor. CF casts a wide net, often through online platforms, permitting funds to be raised from a large number of individuals (Belleflamme, Lambert, & Schwienbacher, 2014). So while individually large sums from a few investors are rare in CF, smaller amounts from many investors are common (E. Mollick, 2014). CF is not new. Before the web, and especially before web 2.0, CF took place offline, such as in the case of the Statue of Liberty. America's shining beacon needed a pedestal, and the 'crowd' came together, collectively donating small sums to purchase one. CF is not just used for singular projects, established businesses use CF to fund individual projects as well. In fact, CF could be seen as an extension of crowdsourcing, where work, ideas, and solutions for problems can be sought from others, also now often online (Belleflamme et al., 2010).

There are a number of both coarse and granular definitions of the various types of AF, and the same holds true for CF. Broadly CF models can be classified as non-investment, or as investment (Shneor & Vik Amy, 2020). But one of the more common categorizations of CF types is: donation, equity, lending, and reward (Belleflamme et al., 2014; Kshetri, 2015; E. Mollick, 2014).

Equity CF concerns raising funds with the promise of equity or profit-sharing. In the United States, common equity CFPs include WeFunder, StartEngine, and Republic; while overseas, Crowdcube, Seedrs, WiSEED, and Seedmatch are leading sites (Yasar, 2021). Originally, fundraisers might have used equity CF for early funding or as a first step in a larger strategy involving future funding (Belleflamme, Omrani, & Peitz, 2015). There have been some interesting developments in the Equity CF space. As an example of equity CF in film, Legion M was founded several years ago as a self-proclaimed co-op. Legion M is an entertainment studio that allows fans to invest directly and have limited influence on future movies through offering class A common stock with each share representing a vote, although the exact influence funders have in practice is likely limited (Wroldsen, 2016). Lastly, real estate crowdfunding, which allows ownership of property through shares, has emerged as a sub-group of equity CF in recent years (Ziegler et al., 2021)

Lending CF funders seek a possible interest on their pledged capital. Prosper and LendingClub are two popular lending platforms (Dushnitsky & Fitza, 2018). Lending CF can be seen as the type of CF most comparable to traditional bank lending (Belleflamme et al., 2015).

Donation CF concerns charitable giving without monetary or non-monetary reward. GoFundMe is a prominent donation platform that had an early start in the donation CF space in the United States (Belleflamme et al., 2015). Humanitarian, ecologically friendly, and artistic projects typify the most common campaigns on GoFundMe. Warm-glow, as a resulting feeling from prosocial behavior, can be seen as analogous to an experiential reward and is a motivator for funders in donation CF (Cecere, Le Guel, & Rochelandet, 2017).

Of primary interest in this paper are questions about non-investment CF, specifically reward-based crowdfunding (RBCF), where the fundraiser essentially presells rewards, often tangible products, but sometimes also experiences. In America, Kickstarter (Kickstarter.com) (KS) is the largest, and one of the more well-known RBCF platforms. As of August 2021, KS has recorded over 6 Billion USD pledged (Kickstarter, 2021, August 8). RBCF also allows for co-creation, that is collaborative development, between funders and fundraisers, of new products. Co-creation, through the crowdsourcing aspects of CF, has been extended from e-commerce into the RBCF context (Ryu & Kim, 2016).

> **Crowdfunding is one of many types of alternative finance that permit fundraisers to seek funds in a slightly different fashion than ventures seeking funds in traditional financing.**

There are usually three principal components of CF that receive attention: the capital seeker, the capital provider, and intermediaries (Moritz & Block, 2016). The first, the capital seeker, is known as the fundraiser. The fundraiser can be an individual, a group of individuals, or even an already established business. The second, the capital provider, is often called the funder. The funder finances the fundraiser's proposed campaign, sometimes known as a project. The third, an intermediary, is the Crowdfunding Platform (CFP) which can act as a bridge between funders and fundraisers (Belleflamme et al., 2015). This 3-way relationship can be seen in Figure 1. Although CFPs receive a large amount of attention in CF, and although they are extremely common, CFPs need not be present. Some fundraisers have attempted to engage directly with funders. This direct relationship can be seen in Figure 2. Take as an example

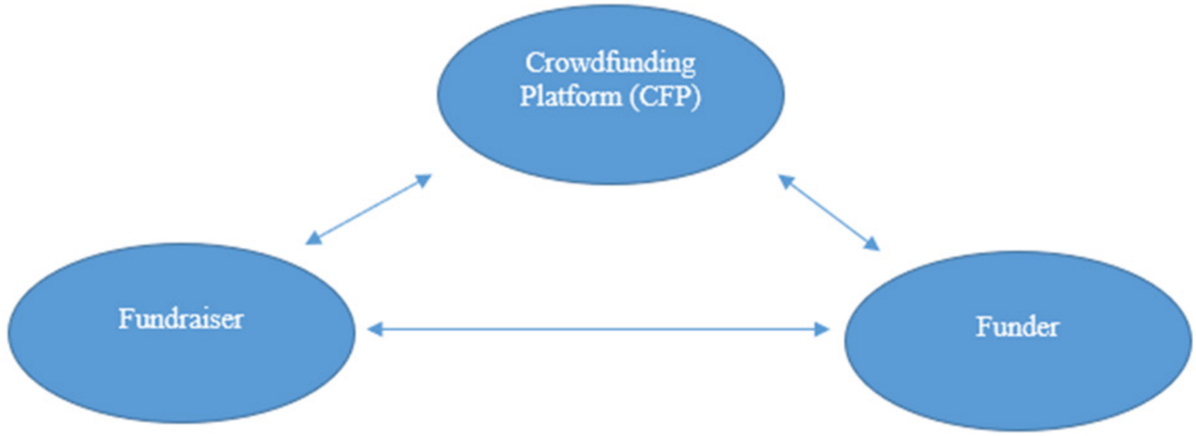

Figure 1: Relationship when a fundraiser uses a crowdfunding platform (most common).

Figure 2: Relationship when a crowdfunding campaign is self-hosted (uses the company's own website, not a CF platform) by the fundraiser.

Star Citizen, an in-development video game, which, although an anomaly in its success, is worth studying as an atypical success story. Star Citizen, which is still collecting funds as of August 2021, has raised 379 million USD during a protracted campaign (Belleflamme et al., 2015; "Stretch Goals - Roberts Space Industries," 2021). When a CFP is present, it acts as an intermediary that charges fees to the fundraiser, usually around 5% and an additional 3-5% for payment processing, and in exchange allows fundraisers to host their campaign on their website. Depending on the business model and the type of CF, CFPs can also act as advisors to fundraisers by providing structure to the CF process and suggestions (Belleflamme et al., 2015).

CFPs today are organized by the collection model they permit on their site. The all-or-nothing (AON) model allows fundraisers to keep the funders' pledged funds only if they achieve a predetermined threshold known as the campaign goal. If they do not achieve the campaign goal, then no funds are collected from the funders and the campaign fails. KS employs this model. Keep-it-all (KIA) allows fundraisers to keep any funds raised during the campaign. Some CFPs, such as Indiegogo (Indiegogo.com) permit fundraisers to choose between AON and KIA when they are designing their campaign.

Of key interest to entrepreneurs, and examined in this article, is how the alternative finance environment has changed due to the COVID-19 pandemic. This paper will present an up-to-date examination of data from KS. Academically framed research questions and hypotheses are presented in this paper, but most practitioners will be asking themselves a much simpler question: "Is now a good time to use CF to finance my new project or venture, or will the pandemic hurt my chances of success?" The answer to that question is both surprising and unexpected.

This paper presents a natural experiment with the period after the beginning of the pandemic acting as the experimental condition. The goal is to examine the data to discover if the COVID-19 pandemic disrupted CF and thus entrepreneurial ventures. It is hoped that this paper contributes in some small way towards examining the phenomena and the new data, alerting other researchers to new and interesting information, and leading to further theoretical insights.

Review of Research

A brief history of CF is in order. CF research has been published in top Association of Business School (ABS) ranked journals (Shneor & Vik Amy, 2020). Worldwide RBCF accounted for 1.2 Billion USD in 2020, a fraction of the tens of billions of dollars that all CF types combined (Ziegler et al., 2021). CF is a new and hot topic. It is on its way to becoming a dominant research field (Barbi & Bigelli, 2017).

First, the role of geography in CF will be examined; next, two popular theories in CF literature; third, the role of web scraped data in CF observational studies;

fourth, the role of experiments in CF; fifth, research related to the 2008 financial crisis; sixth, the growth of e-commerce during the COVID-19 pandemic; lastly, the current scarcity of COVID-19 CF research and how such research might begin.

One focus in CF literature has been understanding the role that geography plays in CF. Traditional financing success has been shown to be determined by geographic factors (Chen, Gompers, Kovner, & Lerner, 2010; Stuart & Sorenson, 2003). Some research has found that CF has a very large geographic dispersion of investors, that is that funders and fundraisers are located thousands of miles apart from one another (A. K. Agrawal et al., 2011). Contrasting this is other research showing that distance remains quite important in CF (Dejean, 2019; Lin & Viswanathan, 2016). Other research has focused on the proximity of fundraisers that pledge early. Those fundraisers do tend to be closer to the fundraiser than those that pledge later (A. K. Agrawal et al., 2011). Friends and family of fundraisers also tend to exhibit different pledge patterns, being less impacted by the campaign's performance and funds raised than other investors (A. Agrawal, Catalini, & Goldfarb, 2015). Geography can play an oversized role in the project mix that comes out of certain cities, near which the CF campaign is based. (E. Mollick, 2014). In addition, creative geographic concentrations of individuals are associated with campaign success (E. Mollick, 2014). Some research has examined the theoretical underpinnings of such geographic dependence in CF, finding that altruism and social capital play an important role (Giudici, Guerini, & Rossi-Lamastra, 2018). Yet others have examined the discriminatory or undemocratic distribution of funds, with rural or less affluent areas experiencing low success rates (Gallemore, Nielsen, & Jespersen, 2019).

A number of theoretical perspectives have been taken to understand CF. Several of the most popular will be examined here. The first, the elaboration likelihood model of persuasion (ELM) has been used to study what the theory terms the central and peripheral routes and has extended the original theory of attitude change into persuasion in CF (Allison, Davis, Webb, & Short, 2017; Bi, Liu, & Usman, 2017; Z. Wang & Yang, 2019; Xiang, Zhang, Tao, Wang, & Ma, 2019; Zheng, Hung, Qi, & Xu, 2016). The second, signaling theory was adapted from its original intent of studying signals sent between job seekers and employers and extended into CF to look at the signals that fundraisers and their campaigns send to potential funders (Belleflamme et al., 2015; Calic & Shevchenko, 2020; Davies & Giovannetti, 2018; Kromidha & Robson, 2016; W. Wang, He, Wu, & Goh, 2021; Yeh, Chen, & Lee, 2019).

Data sources and methodology in CF vary, but observational studies using data sourced directly from CFPs, often extracted with the assistance of web crawling algorithms, compose a large proportion of the CF literature including the most well-known paper in CF literature by Ethan Mollick in 2014 (E. Mollick, 2014). Some researchers have shown that these publicly available campaign factors of goal size, social media network size, pictures, videos, comments, and updates, to name a few, are obvious predictors of CF success, and for those using signaling theory, signals of campaign quality (Calic & Shevchenko, 2020; Davies & Giovannetti, 2018; Kromidha & Robson, 2016).

However, contrasting those observational studies, innovative experiments have recently proven invaluable for CF, allowing researchers to tap into the minds of funders and discover things that an observational study would have trouble finding such as purchasing decisions based on rewards and reward structure (Weinmann, Mishra, Kaiser, & vom Brocke, 2020). Researchers exploring motivations beyond rewards have seen success in experiments as well (Cholakova & Clarysse, 2015; Herrero, Hernández-Ortega, & San Martín, 2020; Nielsen & Binder, 2020; Zvilichovsky, Danziger, & Steinhart, 2018). Some researchers have made extensions of decades-old research such as the decoy effect in an online CF setting (Tietz, Simons, Weinmann, & vom Brocke, 2016). Herding theory has been introduced into experimental CF research as well showing that early contributions and positive opinions matter and can create a strong 'herd' which goes a long way towards explaining some of the nonlinear pledging relationships seen in CF (C. S. R. Chan, Parhankangas, Sahaym, & Oo, 2020; Comeig Ramírez, Mesa Vázquez, Sendra-Pons, & Urbano, 2020). Experimental studies into privacy issues have produced mixed, counterintuitive results where a loss of privacy can increase donations, but decrease the size of donations (Burtch, Ghose, & Wattal, 2015). What is apparent is that CF research is poised to develop much further in the near future (Moritz & Block, 2016).

RBCF is unique in that it is both a means of financing and a form of e-commerce where the funder pre-purchases a product. An examination of the

Some researchers have shown that these publicly available campaign factors of goal size, social media network size, pictures, videos, comments, and updates, to name a few, are obvious predictors of Crowdfunding success

2008 financial crisis with comparisons to the current pandemic and its impacts on financing is in order. Access to credit is essential for entrepreneurs (Aparicio, Urbano, & Audretsch, 2016). The 2008 financial crisis was devastating to some groups seeking financing (Block & Sandner, 2009). In many ways, the financial crisis gave way to alternative finance and CF, or at least hastened the adoption (Zhang, Wardrop, Rau, & Gray, 2015). Credit constraints were common not only in the U.S., but also worldwide, with firms taking drastic measures to preserve cash, and cut costs, all while seeking loans that in many cases never came (Campello, Graham, & Harvey, 2010). Large firms received the most attention, but small and medium enterprises (SMEs) were impacted as well, with many of those able to, seeking trade credit or engaging in a variety of traditional and alternative finance options available at the time (Casey & O'Toole, 2014). Firms with fewer tangible assets were affected more by the shocks from the financial crisis (Popov & Udell, 2012). Many startups and entrepreneurs have very few tangible assets available. The COVID-19 pandemic is similar to the 2008 financial crisis in several ways. First, the current crisis has already caused global financial markets to have nearly the same volatility and declines as those in 2008 (Fernandes, 2020) In addition, the pandemic had a negative effect on bank consumer lending (Cumming, Martinez-Salgueiro, Reardon, & Sewaid, 2021).

> **In many ways, the 2008 financial crisis gave way to alternative finance and crowdfunding, or at least hastened their adoption**

As mentioned previously, RBCF permits a pre-purchase of a product in a manner similar to transactions in e-commerce. Understanding the effects of the COVID-19 pandemic on e-commerce is thus essential to gaining insight into the relationship between the pandemic and CF. The World Trade Organization released an information note in May of 2020 stating that e-commerce, specifically business-to-consumer, and business-to-business, sales spiked due to social distancing and lockdowns in response to the COVID-19 pandemic ("E-COMMERCE, TRADE AND THE COVID-19 PANDEMIC," 2021). The World Bank Group released a guidance note in May of 2020 with insights and practical measures for governments on using e-commerce to mitigate the impact of the COVID-19 pandemic, in part focusing on the sale of goods and services online as a major pillar (Ungerer, Portugal, Molinuevo, & Rovo, 2020).

There is a paucity of CF research that has directly examined the effects of the COVID-19 pandemic, although that is starting to change. In 2021, there have been several attempts to study the pandemic, although primarily by examining donation-based CF data, such as from the CFP GoFundMe (Elmer, Ward-Kimola, & Burton, 2020; Rajwa et al., 2020; Saleh, Lehmann, & Medford, 2021). And yet others have used a broader perspective to develop new theories around events like the pandemic in general, their effects on businesses, and the various attempts at a post-crisis recovery, through the perspective of CF (Chandler, Short, & Wolfe, 2021). At this time, there has been no published paper specifically examining RBCF performance and the COVID-19 pandemic.

To begin such an examination, some preliminary reviews must be made concerning the economy and the government pandemic stimulus measures. According to the U.S. Department of Commerce's Bureau of Economic Analysis, The impact of The Coronavirus Aid, Relief, and Economic Security Act of 2020 also provided relief funds to qualifying individuals in April of 2020 ("How are federal economic impact payments to support individuals during the COVID-19 pandemic recorded in the NIPAs? | U.S. Bureau of Economic Analysis (BEA)," 2021). The Coronavirus Response and Relief Supplemental Appropriations Act of 2021 provided a similar supplemental tax credit to qualifying individuals, and although the distribution did not occur until January 2021, households were able to plan and budget for the then-upcoming payments. Furthermore, by May 2020, households of all income levels experienced large increases in asset balances (Cox et al., 2020).

Based on these above analyses the following research questions and hypotheses are proposed:

RQ1: How has the COVID-19 pandemic affected crowdfunding in America?

H1.1: Success rates will increase. In light of the examined nature of CF as a hybrid e-commerce and alternative finance activity, and due to the examination of the performance of e-commerce and alternative finance activity during the pandemic, as shown above, specifically due to the lack of traditional financing, and the increase in e-commerce levels, CF success rates will similarly increase.

H1.2: Similarly, the number of funders per campaign will increase.

H1.3: Similarly, the ratio of funds raised to a campaign's goal will increase.

H1.4: Pledge size will decrease slightly. Although more consumers will begin engaging in CF as funders, constraints from the pandemic on discre-

The Protocol

This paper seeks to provide initial evidence of the nature of CF and how that has changed due to the COVID-19 Pandemic. This paper and the data can help to springboard future research into the effects of the pandemic on other CFPs, other types of CF (i.e., equity, lending), or even other types of alternative finance.

To begin, KS was chosen as this researcher's primary source of data due to its prominence and dominance in the CF space. KS Datasets were obtained from Web Robots a well-known repository for CF Data used by many CF researchers (de Larrea, Altin, & Singh, 2019; Patel, Wolfe, & Manikas, 2021b; Song, Berger, Yosipof, & Barnes, 2019; Wolfe, Patel, & Manikas, 2021). Web Robots, a company that provides data services such as scraping, or migration, maintains the data and makes their KS datasets publicly available on their site for free ("Kickstarter Datasets," 2021).

The data obtained spanned the timeframe from April 2009 to April 2021 and contained nearly a quarter-million projects in one of four distinct states: failed, successful, canceled, and live. These projects contained over 7 million data points and would contain nearly 10 million after certain derived values of interest were calculated.

Next, the data was cleaned; first, removing any duplicate project IDs, missing records, live projects, and canceled projects. Next, countries outside of the United States of America were removed. This was done for two purposes. The first, in order to create homogeneity between campaigns since the foreign projects might be atypical similar to Mollick's seminal work in 2014 (E. Mollick, 2014). Second, in particular, to also ensure the creation of a clearly defined "*Pandemic Period*" for when the COVID-19 pandemic impacted the United States of America, explained in further detail below. Lastly, campaigns with large and small fundraising goals were removed as most researchers have done (E. Mollick, 2014). Projects with goals larger than 2 million USD and less than 200 USD were eliminated. Upon examination, these projects did not represent serious attempts to crowdfund. It is also worth noting that no project with a goal larger than 2 million USD was successful, but that a number of projects larger than 1 million USD were successful, with some of those projects being rather recent. It is supposed that this demonstrates increasingly large, authentic, campaigns representing serious attempts at using CF to fund large capital projects or new business ventures outright. Figure 3 presents summaries of this data.

tionary income and increased attempts to save money will make pledges more conservative.

RQ2: How have campaigns in different product categories been impacted by the COVID-19 pandemic?

H2.1: Product categories will vary dramatically in their success, including the ratio of funds raised to goal, and the number of backers. Product categories that provide more tangible products as rewards will perform better than those that are more experiential, or that require going out and socializing.

May 1st, 2020, was chosen as the date that best represented the COVID-19 pandemic period of interest in this study. This date was chosen since it occurred well after the first cases of COVID-19 were confirmed, and slightly after the WHO declared a worldwide pandemic in March (Morens, Daszak, Markel, & Taubenberger, 2020). It was in May that the Washington Post, one of America's largest news outlets declared that 100,000 Americans had died as a result of COVID-19 and that Americans were living daily life aware of the virus ("U.S. coronavirus death toll surpasses 100,000," 2021). Furthermore, on May 1st, the FDA issued emergency use authorization for the investigational drug Remdesivir for COVID-19, the CDC launched the SHERES consortium for genomic sequencing of the COVID-19 virus and launched the PPE burn rate calculator for healthcare facilities (Cdcgov, 2021). Lastly, by May 2nd the World Health Organization (WHO) issued a renewal declaration stating that the pandemic was a Global Health Crisis.

Just under 120,000 campaigns were considered suitable to be included in the analysis. The factors of interest are summarized below. As will be mentioned below again specifically, any of the below variables that were nonnormal were transformed with the natural log, and in all cases, any troublesome skewness was resolved.

Pandemic Period: A dichotomous variable, and the focus of this paper. Projects that had an end date occurring before May 1st, 2020, were defined as pre-pandemic, and those occurring after through the remainder of 2020 were determined to be in the COVID-19 pandemic period.

Prep Time Days: preparation time, was calculated as the difference between when the campaign page was created and when the campaign was launched. The days that the fundraiser spent preparing for the campaign has, in some research, been determined to increase the odds of a campaign succeeding (Kunz, Bretschneider, Erler, & Leimeister, 2017). This variable is logged in the regressions presented.

Campaign Length Days: The campaign duration, or runtime, or length, is often associated with a decreased chance of success (Barbi & Bigelli, 2017; Du, Li, & Wang, 2019; Frydrych, Bock, Kinder, & Koeck, 2014). In particular, signaling theory has been em-

	Category														
	Art	Comics	Crafts	Dance	Design	Fashion	Film & Video	Food	Games	Journal..	Music	Photog..	Publishi..	Technol..	Theater
Avg. Campaign length days	32	30	32	31	32	31	33	35	31	34	34	32	32	36	31
Std. dev. of Campaign length days	13	9	11	11	12	11	12	12	11	13	12	12	11	12	12
Avg. Goal	9,839	7,190	7,971	7,245	25,231	12,576	32,536	30,083	24,015	18,420	9,874	11,680	8,229	43,500	16,397
Std. dev. of Goal	47,479	20,852	24,323	23,311	106,617	40,839	130,647	87,099	78,448	59,316	42,041	45,390	33,111	112,747	88,072
Avg. Num Backer	78	268	45	57	396	136	128	74	416	66	79	58	121	367	57
Std. dev. of Num Backer	308	554	244	103	2,083	560	1,215	361	2,017	231	238	154	562	1,769	97
Avg. Pledge/Backer	63	46	46	81	76	76	93	74	58	46	68	61	60	130	77
Std. dev. of Pledge/Backer	84	38	77	82	139	109	150	143	164	86	78	84	134	251	83
Avg. Prep time days	41	76	37	32	58	55	50	58	65	34	52	41	51	67	41
Std. dev. of Prep time days	133	198	127	78	159	142	158	159	174	115	153	129	143	162	158
Avg. Pledged	6,002	13,740	2,834	4,769	41,188	13,652	12,551	7,475	27,349	4,627	5,914	6,340	7,293	51,597	5,451
Std. dev. of Pledged	30,064	39,000	11,605	6,771	245,065	83,827	117,626	39,638	194,679	15,166	17,583	29,064	69,395	227,786	11,424
Count of Category	13,836	4,516	3,896	2,418	3,380	5,396	16,364	10,441	5,048	2,536	20,280	3,218	10,818	10,274	2,417
Avg. RATIO pledged/goal	1.465	2.443	1.091	0.974	4.346	2.425	0.807	0.626	2.179	0.491	0.919	0.732	1.236	2.486	0.797
Std. dev. of RATIO pledged/goal	3.806	5.465	3.008	0.542	17.687	7.992	1.062	3.110	5.831	0.863	1.020	1.469	2.610	9.234	0.613
% Success	62.14%	89.24%	36.42%	81.22%	53.31%	63.34%	59.87%	33.06%	62.74%	32.29%	69.63%	37.97%	68.36%	45.74%	63.84%

Frequencies for Successful or Failed

Successful or Failed	Frequency	Percent	Valid Percent	Cumulative Percent
failed	47393	41.269	41.269	41.269
successful	67445	58.731	58.731	100.000
Missing	0	0.000		
Total	114838	100.000		

Frequencies for Pandemic Period?

Pandemic Period?	Frequency	Percent	Valid Percent	Cumulative Percent
No	106736	92.945	92.945	92.945
Yes	8102	7.055	7.055	100.000
Missing	0	0.000		
Total	114838	100.000		

Frequencies for Staff Pick

Staff Pick	Frequency	Percent	Valid Percent	Cumulative Percent
No	98974	86.186	86.186	86.186
Yes	15864	13.814	13.814	100.000
Missing	0	0.000		
Total	114838	100.000		

Figure 3: Summary statistics

ployed to understand how fundraisers are signaling quality to funders (Kunz et al., 2017). Others have viewed campaign length from an entrepreneurial legitimacy theory perspective (Frydrych et al., 2014).

Goal: The campaign goal, or project goal, is the amount of money (or the minimum amount of money) that the fundraisers declare that they are seeking to raise using CF. As a reminder, KS uses an AON model where the campaign needs to meet the goal threshold in order to receive funds. When they do so, then the funds are collected from the funders and subsequently released to the fundraiser. Previous research has investigated this factor and determined that a larger goal is usually associated with a higher failure rate (Barbi & Bigelli, 2017; Dikaputra, Sulung, & Kot, 2019; E. Mollick, 2014; Oo, Allison, Sahaym, & Juasrikul, 2019). Although paradoxically, it is also associated with more funds raised, more backers, and a higher chance of being promoted on a CFP (H. F. Chan, Moy, Schaffner, & Torgler, 2021). In order to eliminate any possibly troublesome dispersion of goal values, a transformation in the form of the natural logarithm was used on the goal data in line with other researchers (E. Mollick, 2014).

Staff Pick: KS employs a 'Staff Pick" that acts as a form of promotion on the KS CFP. Sometimes also studied as a response variable in CF literature. It has been shown to increase a campaign's chance of success (Kunz et al., 2017; E. Mollick, 2014).

Category: KS groups similar projects into categories. The possible classification into categories that a campaign may have are: comics, crafts, dance, design, fashion, film & video, food, games, journalism, music, photography, publishing, technology, and theater. In many studies, project category is a control variable (Koch & Siering, 2019; E. Mollick, 2014). In this paper, however, we consider the categories and their interrelations with other variables because there is no reason to suspect that the pandemic would not have affected the categories differently. This will potentially create a substantially larger model; however, it was deemed essential.

Successful or Failed: this study's response variable, a dichotomous 'successful / failed', is determined by the campaign's ability to achieve its fundraising goal by the campaign deadline date chosen before the project launches. As CF theory established itself, dozens of studies have identified a plethora of factors that possibly influence the success of a campaign, (Shneor & Vik Amy, 2020). Furthermore, a campaign's success on an AON CFP determines if the fundraiser is able to collect any funds from funders. Only when pledged funds exceed the campaign goal, are funds collected by the CFP and distributed to the Fundraiser.

NumBacker: The number of funders (backers) of a CF campaign. A lesser studied response variable with the exception of a few insightful studies (Bi et al., 2017; H. F. Chan et al., 2021; Z. Wang & Yang, 2019). The number of campaign backers, by itself, does not indicate the amount of funds raised, or the success or failure of a campaign, which is of prime importance in an AON campaign. This variable was transformed using the natural logarithm.

Ratio: A ratio formed by dividing the pledge funds by the campaign goal. A lesser studied response variable that can act as an alternate to the more commonly studied binary measure of success or failure, since ratios larger than or equal to 1 indicate campaign success as well (Zheng et al., 2016; Zheng, Li, Wu, & Xu, 2014). This variable was transformed using the natural logarithm.

Pledge/Backer: Individual pledges are not available for KS campaigns however, since the total pledged funds and the number of backers are available, this response variable can be derived. This variable was transformed using the natural logarithm.

Preliminarily, to begin, summary statistics by KS category were compiled, along with frequencies for the categorical variables. Second, a visual analysis of the success or failure of a campaign over time was conducted. Third, tests for proportions and means were conducted preliminarily following the advice of Thad Dunning on simplicity and transparency in natural experiments, since by reporting the 'raw' difference in proportions and means between the two periods in addition to our other primary tests, the causal inference is strengthened (Dunning, 2010).

Four regression analyses were conducted. First, a logistic regression was carried out on *Successful or Failed*. Next, three separate linear regressions (OLS) were completed on *LN NumBacker, LN Ratio, and LN Pledge/Backer*. Before beginning each analysis, correlations were checked. There were no complicating correlations. The same factors of *Category, Staff Pick, LN Goal, Campaign Length Days, LN Prep Time, and Pandemic Period,* were chosen for all 4 models. In addition, *Pandemic Period* was interacted with each other variable in all 4 models. In particular, and of key interest is if the pandemic had an influence on each model and if it had varying effects on each of the categories?

The first analysis proceeded using a generalized linear model logistic regression. Logistic regression is appropriate for studying *Successful or Failed* because the response variable is dichotomous. This method has been employed in the vast majority of CF Literature, including in certain key seminal research (E. Mollick, 2014). Logistic regression allows for a determination of the success factors available from the dataset and can allow for a comparison between the two time periods of interest by including the time period of interest as a dichotomous variable.

OLS regression is the appropriate method to model *LN NumBacker, LN Ratio,* and *LN Pledge/Backer* as other key research in the CF space has created insights that would not otherwise be available through logistic regression alone, using this method (H. F.

Descriptive Statistics

	LN(Goal)	Campaign length days	LN(Prep time)	LN NumBacker	LN Ratio	LN Pledge /backer
Valid	114838	114838	114838	114838	114838	114838
Missing	0	0	0	0	0	0
Skewness	0.254	1.035	−0.642	−0.571	0.020	−1.733
Std. Error of Skewness	0.007	0.007	0.007	0.007	0.007	0.007
Kurtosis	0.092	1.626	0.626	0.068	−0.609	2.542
Std. Error of Kurtosis	0.014	0.014	0.014	0.014	0.014	0.014

Figure 4: Skewness and kurtosis statistics. Note that all variables are approximately normal, with even LN Pledge/backer being less than moderately non-normal (Curran et al., 1996)

Chan et al., 2021; Raab, Schlauderer, Overhage, & Friedrich, 2020; Ryu & Kim, 2018). To begin, normality was assessed using measures of skewness and kurtosis (see **Table 2).** *LN Ratio* and *LN NumBacker* were approximately normal. *LN Pledge/Backer* was less than moderately nonnormal, which was sufficient to proceed (Curran, West, & Finch, 1996). Following other research, because some campaigns have no funders, they have no funds, and thus for *LN NumBacker, LN Ratio,* and *LN Pledge/Backer,* their inclusion, and the logarithmic transformations were permitted by adding 0.1 to each value, before transformation, in the model. i.e. LN(NumBacker+0.1), LN(Ratio+0.1), LN(Pledge/Backer+0.1). (H. F. Chan et al., 2021).

Findings

Please refer to the appendix for detailed statistical analysis and visualizations. What follows is an extremely brief description of key findings specifically with the practitioner in mind. A pie chart of projects by KS defined categories can be found in Figure 5, and visualizations of factors by pre-pandemic and pandemic period are found in Figure 6. For the results of the visualizations and tests of proportions and means of interest between the pre-pandemic and pandemic periods see Figure 7, Figure 8, Figure 9, and Figure 10.

Overall, all 4 models were significant ($p<.001$). They also explained a significant portion of the variance in each case. The pseudo R-squared of the logistic regression for the success or failure of a campaign was .222. The linear regression for the number of backers had an R-squared value of .274. The linear regression for the ratio of funds raised had an R-squared value of .308. The linear regression for the pledge per backer had an R-squared value of .109.

Paradoxically, and as the main finding of this paper, the logistic regression model shows that CF during the pandemic substantially increased the odds of a

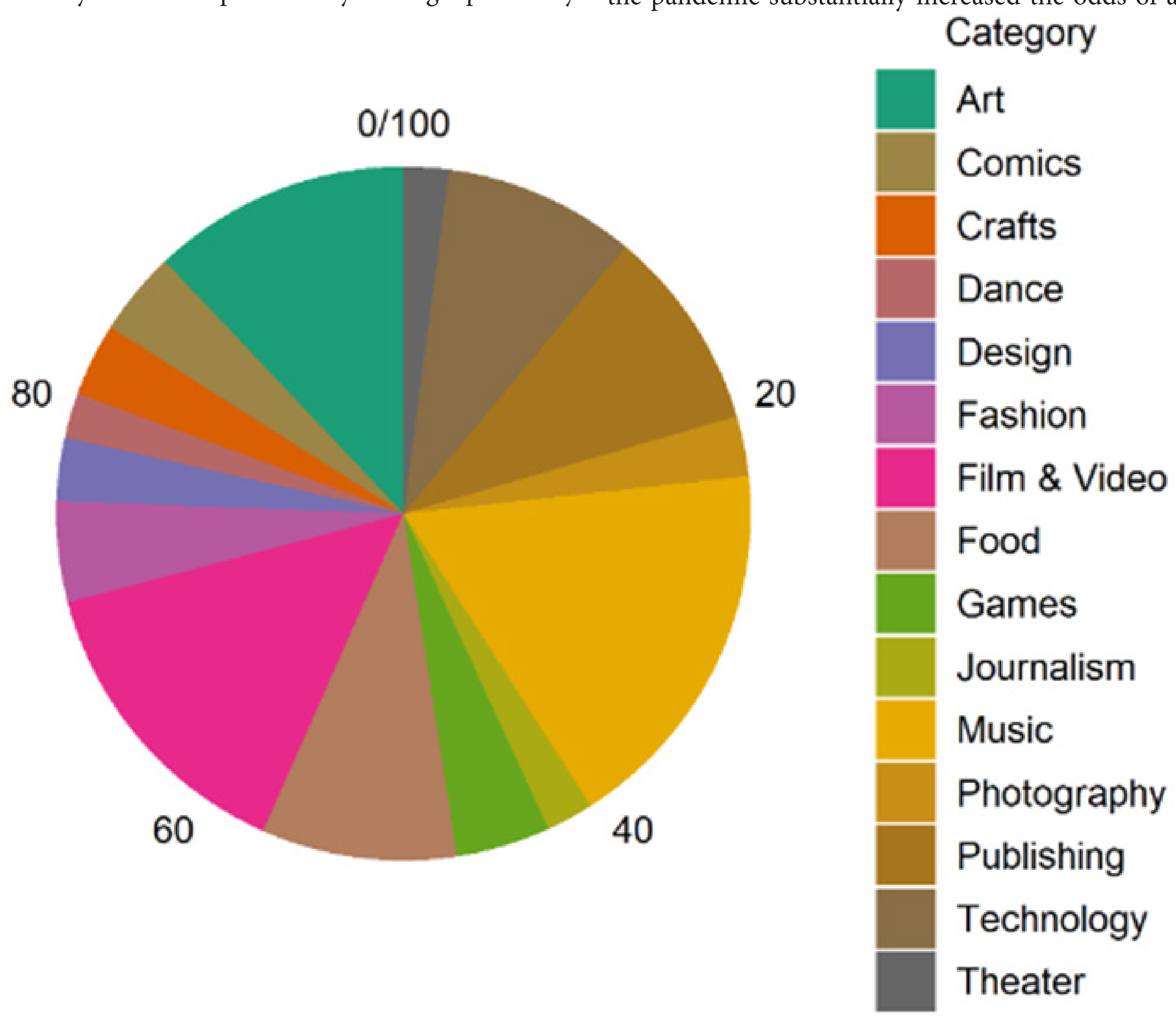

Figure 5: Pie chart of projects by Kickstarter category type

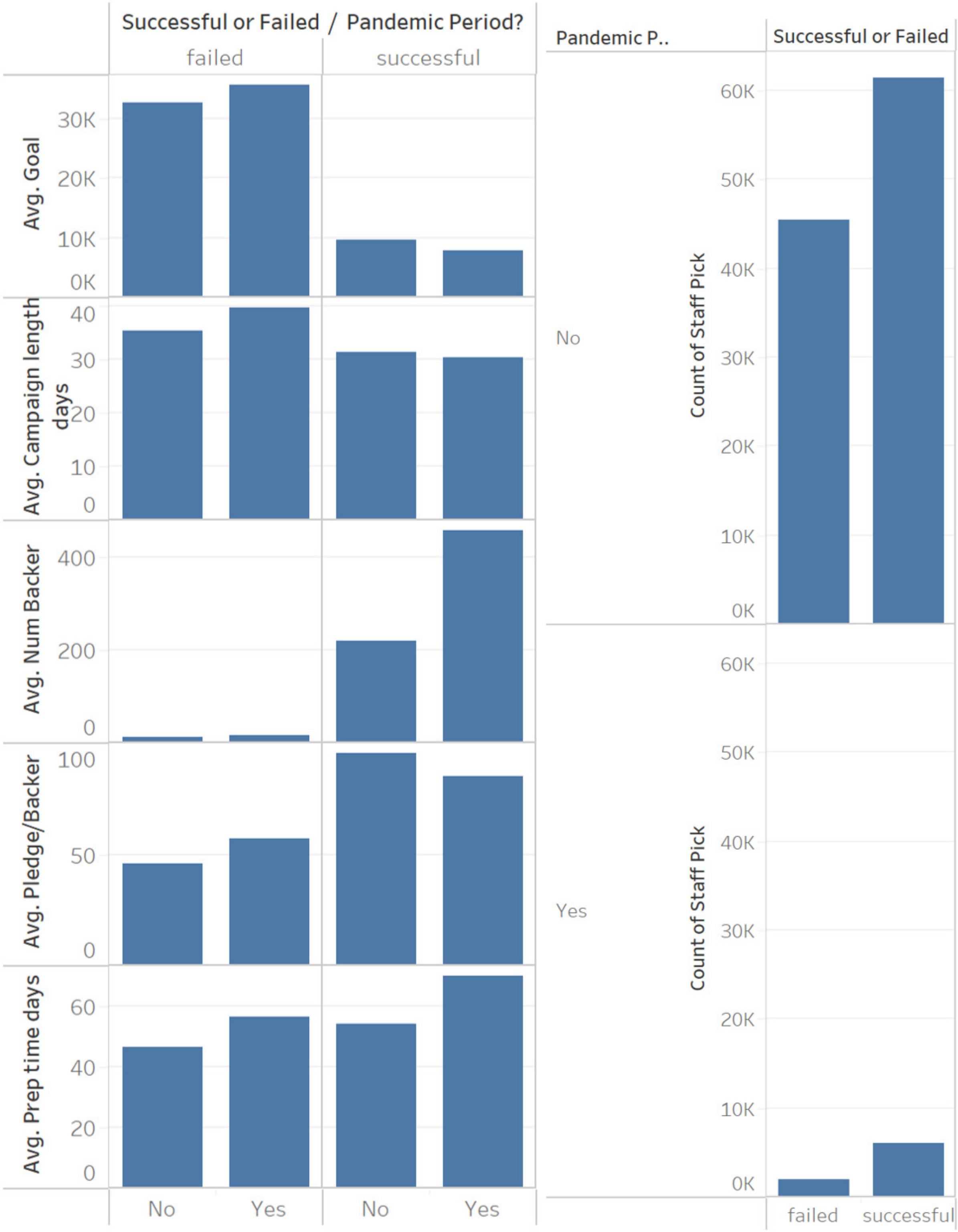

Figure 6: Visualization of success factors by pre-pandemic period and pandemic period

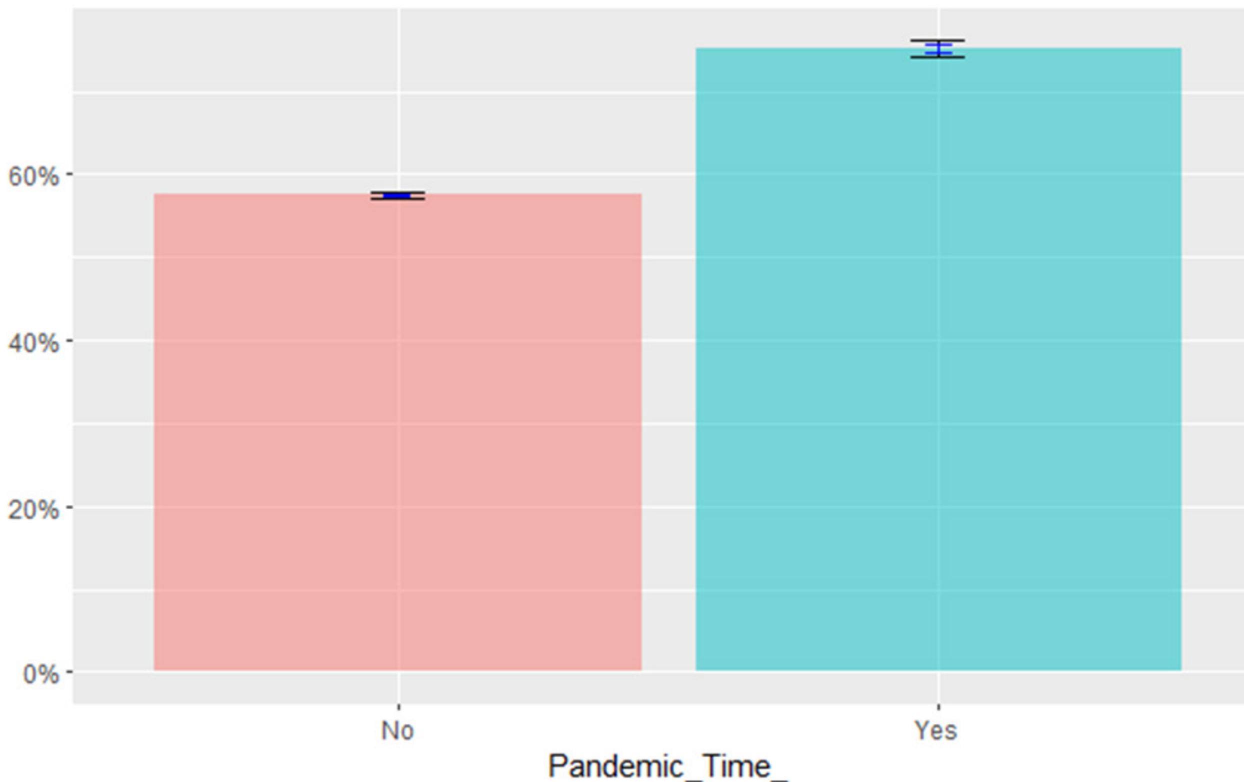

Figure 7: Successful campaign proportions by pre-pandemic and pandemic period

successful campaign over pre-pandemic periods (OR% = 1096%, p<.001). Correlations and the results of this model can be found in Figure 11. H1.1 is thus supported. In addition, to make the results more convincing, the variable Pandemic Period was altered in supplemental tests. First, it was altered to begin in April, and then to June of 2020. The main variable of interest, Pandemic Period, was still significant at p<.001 in both cases. Thus, there can be additional confidence that the defined Pandemic Period represents a true effect. Visualizations of the data show that the increase in success rates during the pandemic is, in fact, dramatic. Success rates never declined from May to December 2020, reaching a global maximum at the end of 2020, surpassing success rates at all other times since the data began in 2009. See Figure 12 and Figure 13. There had never been a better time to use RBCF in terms of improving your chance of succeeding.

Other factors of significance for that model are as follows. The (logged) time that the fundraiser spent preparing their campaign page before launching it increased the chance of success. The logarithm of the fundraising goal, that is the project's requested funds, was also significant. A large fundraising goal dramatically decreased a campaign's chance of success. If the project was promoted on the site as a staff pick during the pandemic, then the chances of the campaign succeeding increased. A longer campaign length minorly decreased a campaign's chance of success. Concerning interaction effects of significance, preparation time was even more important during the pandemic, as was the negative effect of longer campaigns and larger goals during the pandemic.

The KS product categories deserve special attention. All of the KS project categories (relative to the chosen category of art) were significant, with some categories having increased odds of success rates: comics, dance, fashion, film & video, games, music, publishing, and theater. Other categories had the opposite effect, decreasing success rates: crafts, design, food, journalism, photography, and technology. The interaction effects between categories and the pandemic are as follows. Comics, crafts, dance, film & video, food, journalism, music, publishing, technology, and theatre all had negative interaction effects. But so powerful was the direct P*andemic Period* effect that even those categories had a higher chance of success overall. One specific effect worth spotlighting is that the design category fared very well during the pandemic period with an interaction odds ratio increase of 757.9%.

Concerning the first of the OLS regressions, paradoxically, the number of backers for campaigns increased during the pandemic (B= .427, p=.002).

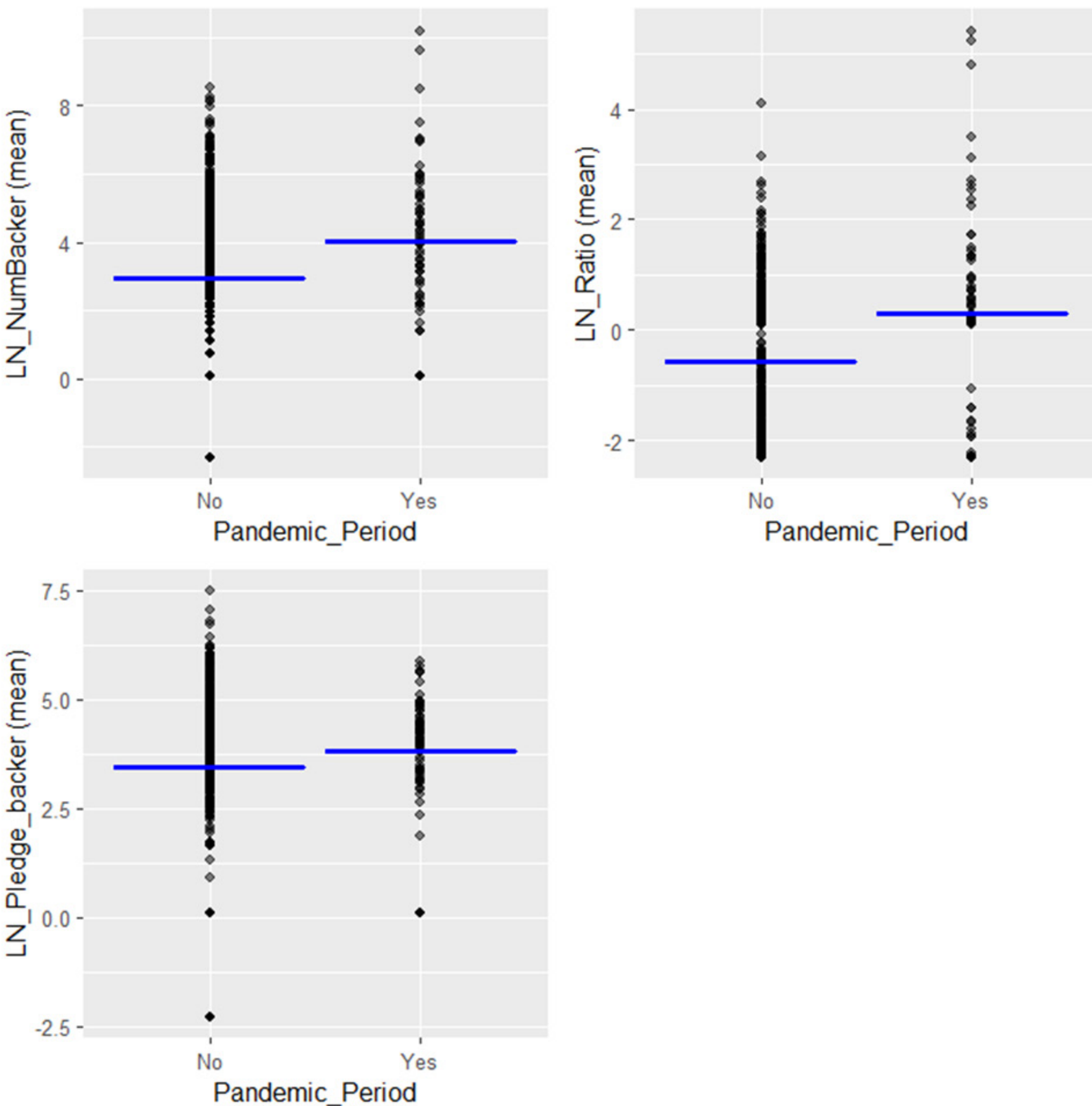

Figure 8: Visual comparisons of means for the 3 linear regressions in this study by pandemic period

Correlations and the results of this model can be found in Figure 14. Thus, H1.2 is supported. Similarly. the time that the fundraiser spent preparing their campaign before launching it also increased the number of backers. Longer campaigns had fewer backers especially so during the pandemic. And KS spotlighting a campaign increased the number of backers. Surprisingly the larger a campaign's goal, the more backers it gained, especially so during the pandemic (interaction effect) which contrasts with the first model that showed the chance of a campaign failing increased as the funding goal increased. Thus, we can likely conclude that even though campaigns with larger goals gain more backers it does not offset the additional amount of funds required to succeed, or simply that although a large campaign may gain backers, they may pledge fewer funds. This subject will be revisited in the next two models.

The pandemic effect on backers in each KS category was not as strong as in the logistic regression model. The number of backers during the pandemic in a few categories was higher or lower. To present a few of the interesting findings, film & video and technology were among the worst-performing categories with regard to the pandemic, whereas the design category during the pandemic performed the best of any category.

The second OLS regression, the ratio of funds raised to a campaign's goal, was similar to the model for the number of backers. The Pandemic Period's direct effect improved the ratio of funds dramatically (B= 1.401, p<.001). Correlations and the results of this

Contingency Tables

Successful or Failed		Pandemic Period? No	Yes	Total
failed	Count	45380.000	2013.000	47393.000
	Expected count	44049.350	3343.650	47393.000
successful	Count	61356.000	6089.000	67445.000
	Expected count	62686.650	4758.350	67445.000
Total	Count	106736.000	8102.000	114838.000
	Expected count	106736.000	8102.000	114838.000

Chi-Squared Tests

	Value	df	p
X^2	970.102	1	< .001
Likelihood ratio	1028.191	1	< .001
N	114838		

Log Odds Ratio

	Log Odds Ratio	95% Confidence Intervals Lower	Upper	p
Odds ratio	0.805	0.753	0.857	
Fisher's exact test	0.805	0.753	0.858	< .001

Figure 9: Successful and failed campaigns by pre-pandemic and pandemic period

model can be found in Figure 15. Thus, H1.3 is supported. Preparation time increased the ratio of funds raised, especially so during the pandemic (interaction effect). Whereas the length of the campaign and the campaign goal had a negative impact on the ratio of funds raised, again especially so during the pandemic. Staff Pick, as seen in each previous model, was dramatically favorable for campaign performance. Category performance was similar to the previous model for the number of backers. The ratio of funds raised by design during the pandemic was impressive (B= .987, p<.001), while technology and film & video performed more poorly than normal.

The third OLS regression concerning the average pledge per backer (funder) for a campaign, required a more nuanced interpretation. Where an initial examination of the data showed that the average pledge per backer had been very slightly higher during the pandemic, and where that would have broadly agreed with the previous three models, Pandemic Period in the final OLS regression model showed a negative effect on the average pledge per backer (B= -.430, p=.001.). Correlations and the results of this model can be found in Figure 16. Thus, H1.4 is supported. A further examination of the data shows potential reasons that might be. First, it must be acknowledged that the model might not account for unknown and unaccounted-for variables. In fact, the R-squared value for this model is the lowest of the four models presented. However, another likely explanation for why the average pledge per backer appears higher in the pandemic period, but is not attributable to the pandemic period directly, is that at least partially the increased percentage of staff picks,

```
Pairwise mean comparisons (t-test)
Data      : LN_all_3_pand_period_ratio_backer_dv
Variables : Pandemic_Period, LN_NumBacker
Samples   : independent
Confidence: 0.95
Adjustment: None

 Pandemic_Period  mean       n n_missing    sd    se    me
              No 2.894 106,736         0 2.310 0.007 0.014
             Yes 4.092   8,102         0 1.873 0.021 0.041

 Null hyp.  Alt. hyp.            diff   p.value
 No = Yes   No not equal to Yes   -1.198 < .001  ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Pairwise mean comparisons (t-test)
Data      : LN_all_3_pand_period_ratio_backer_dv
Variables : Pandemic_Period, LN_Ratio
Samples   : independent
Confidence: 0.95
Adjustment: None

 Pandemic_Period   mean       n n_missing    sd    se    me
              No -0.561 106,736         0 1.284 0.004 0.008
             Yes  0.262   8,102         0 1.487 0.017 0.032

 Null hyp.  Alt. hyp.            diff   p.value
 No = Yes   No not equal to Yes   -0.824 < .001  ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Pairwise mean comparisons (t-test)
Data      : LN_all_3_pand_period_ratio_backer_dv
Variables : Pandemic_Period, LN_Pledge_backer
Samples   : independent
Confidence: 0.95
Adjustment: None

 Pandemic_Period  mean       n n_missing    sd    se    me
              No 3.347 106,736         0 2.021 0.006 0.012
             Yes 3.800   8,102         0 1.179 0.013 0.026

 Null hyp.  Alt. hyp.            diff   p.value
 No = Yes   No not equal to Yes   -0.452 < .001  ***

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 10: Comparisons of means (T-Test) for the 3 linear regressions in this study by pandemic period

Pearson's Correlations

Variable		LN(Prep time)	Campaign length days	LN(Goal)
1. LN(Prep time)	Pearson's r	—		
2. Campaign length days	Pearson's r	−0.005	—	
3. LN(Goal)	Pearson's r	0.183***	0.209***	—

* p < .05, ** p < .01, *** p < .001

```
Logistic regression (GLM)
Data                 : LN_all_3_pand_period_ratio_backer_dv
Response variable    : Successful_or_Failed
Level                : successful in Successful_or_Failed
Explanatory variables: Pandemic_Period, LN_Prep_time_, Campaign_length_days, LN_Goal_, Staff_Pick, Category
Null hyp.: there is no effect of x on Successful_or_Failed
Alt. hyp.: there is an effect of x on Successful_or_Failed

                                           OR      OR% coefficient std.error z.value p.value
 (Intercept)                                                 3.876     0.050  78.012  < .001 ***
 Pandemic_Period|Yes                   11.960 1,096.0%       2.482     0.237  10.467  < .001 ***
 LN_Prep_time_                          1.273    27.3%       0.241     0.004  66.700  < .001 ***
 Campaign_length_days                   0.980    -2.0%      -0.020     0.001 -32.717  < .001 ***
 LN_Goal_                               0.644   -35.6%      -0.440     0.006 -77.668  < .001 ***
 Staff_Pick|Yes                        12.973 1,197.3%       2.563     0.032  79.437  < .001 ***
 Category|Comics                        3.750   275.0%       1.322     0.058  22.638  < .001 ***
 Category|Crafts                        0.353   -64.7%      -1.041     0.043 -24.344  < .001 ***
 Category|Dance                         2.883   188.3%       1.059     0.060  17.759  < .001 ***
 Category|Design                        0.443   -55.7%      -0.815     0.050 -16.444  < .001 ***
 Category|Fashion                       1.124    12.4%       0.117     0.038   3.085   0.002 **
 Category|Film & Video                  1.468    46.8%       0.384     0.027  13.969  < .001 ***
 Category|Food                          0.442   -55.8%      -0.815     0.032 -25.341  < .001 ***
 Category|Games                         1.100    10.0%       0.095     0.040   2.357   0.018 *
 Category|Journalism                    0.345   -65.5%      -1.065     0.053 -19.934  < .001 ***
 Category|Music                         1.988    98.8%       0.687     0.026  26.128  < .001 ***
 Category|Photography                   0.402   -59.8%      -0.911     0.046 -19.597  < .001 ***
 Category|Publishing                    1.327    32.7%       0.283     0.031   9.152  < .001 ***
 Category|Technology                    0.870   -13.0%      -0.139     0.032  -4.377  < .001 ***
 Category|Theater                       1.357    35.7%       0.306     0.051   5.951  < .001 ***
 Pandemic_Period|Yes:LN_Prep_time_      1.094     9.4%       0.090     0.019   4.719  < .001 ***
 Pandemic_Period|Yes:Campaign_length_days 0.984  -1.6%      -0.016     0.003  -5.978  < .001 ***
 Pandemic_Period|Yes:LN_Goal_           0.851   -14.9%      -0.161     0.028  -5.799  < .001 ***
 Pandemic_Period|Yes:Staff_Pick|Yes     1.085     8.5%       0.081     0.162   0.501   0.617
 Pandemic_Period|Yes:Category|Comics    0.752   -24.8%      -0.286     0.176  -1.621   0.105
 Pandemic_Period|Yes:Category|Crafts    0.794   -20.6%      -0.231     0.210  -1.096   0.273
 Pandemic_Period|Yes:Category|Dance     0.720   -28.0%      -0.328     0.721  -0.456   0.649
 Pandemic_Period|Yes:Category|Design    8.579   757.9%       2.149     0.174  12.388  < .001 ***
 Pandemic_Period|Yes:Category|Fashion   1.577    57.7%       0.456     0.178   2.554   0.011 *
 Pandemic_Period|Yes:Category|Film & Video 0.333 -66.7%     -1.101     0.143  -7.725  < .001 ***
 Pandemic_Period|Yes:Category|Food      0.998    -0.2%      -0.003     0.151  -0.017   0.987
 Pandemic_Period|Yes:Category|Games     2.954   195.4%       1.083     0.165   6.566  < .001 ***
 Pandemic_Period|Yes:Category|Journalism 0.623  -37.7%      -0.474     0.304  -1.559   0.119
 Pandemic_Period|Yes:Category|Music     0.820   -18.0%      -0.198     0.147  -1.345   0.179
 Pandemic_Period|Yes:Category|Photography 1.925  92.5%       0.655     0.273   2.396   0.017 *
 Pandemic_Period|Yes:Category|Publishing 1.217   21.7%       0.196     0.142   1.379   0.168
 Pandemic_Period|Yes:Category|Technology 0.385  -61.5%      -0.955     0.129  -7.421  < .001 ***
 Pandemic_Period|Yes:Category|Theater   1.129    12.9%       0.122     0.511   0.238   0.812

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Pseudo R-squared: 0.222
Log-likelihood: -60521.078, AIC: 121118.157, BIC: 121484.905
Chi-squared: 34637.799 df(37), p.value < .001
Nr obs: 114,838
```

Figure 11: Correlations and logistic regression of successful or failed campaigns

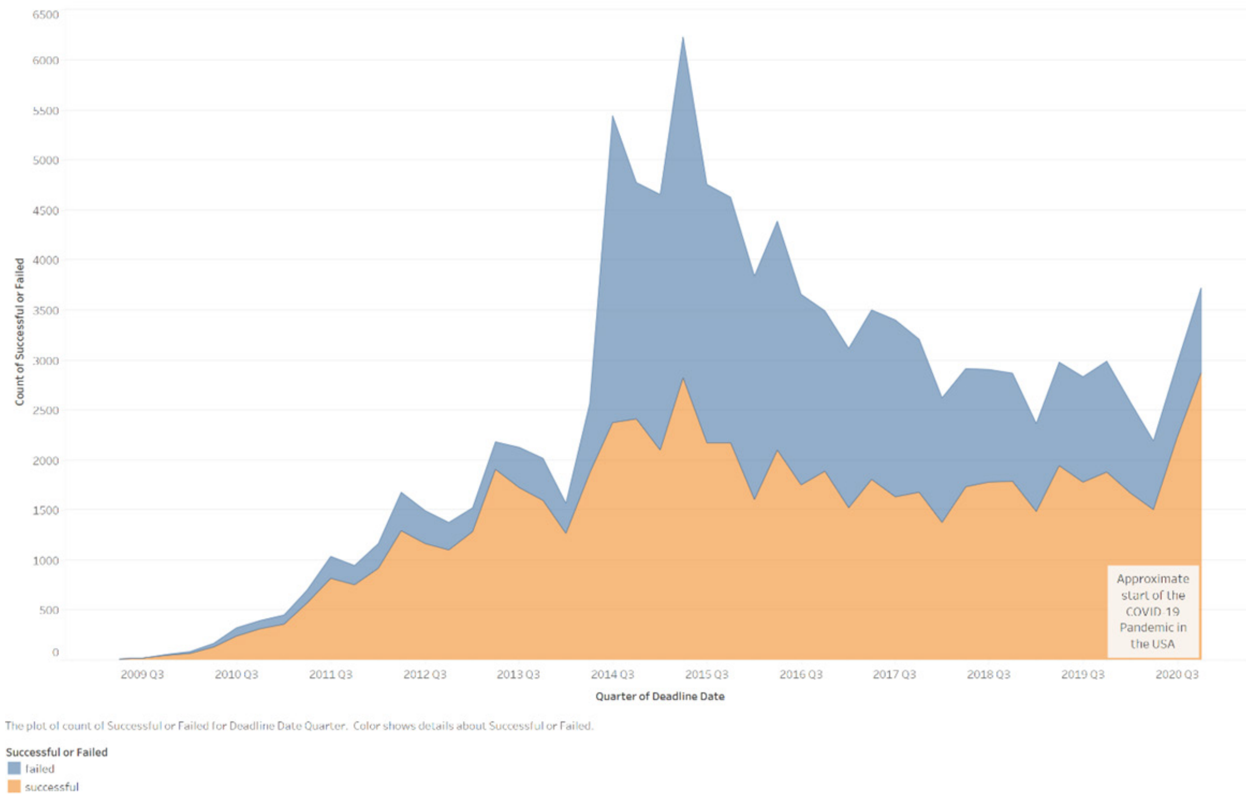

Figure 12: Campaigns by deadline date From 2009 until December 31st, 2020

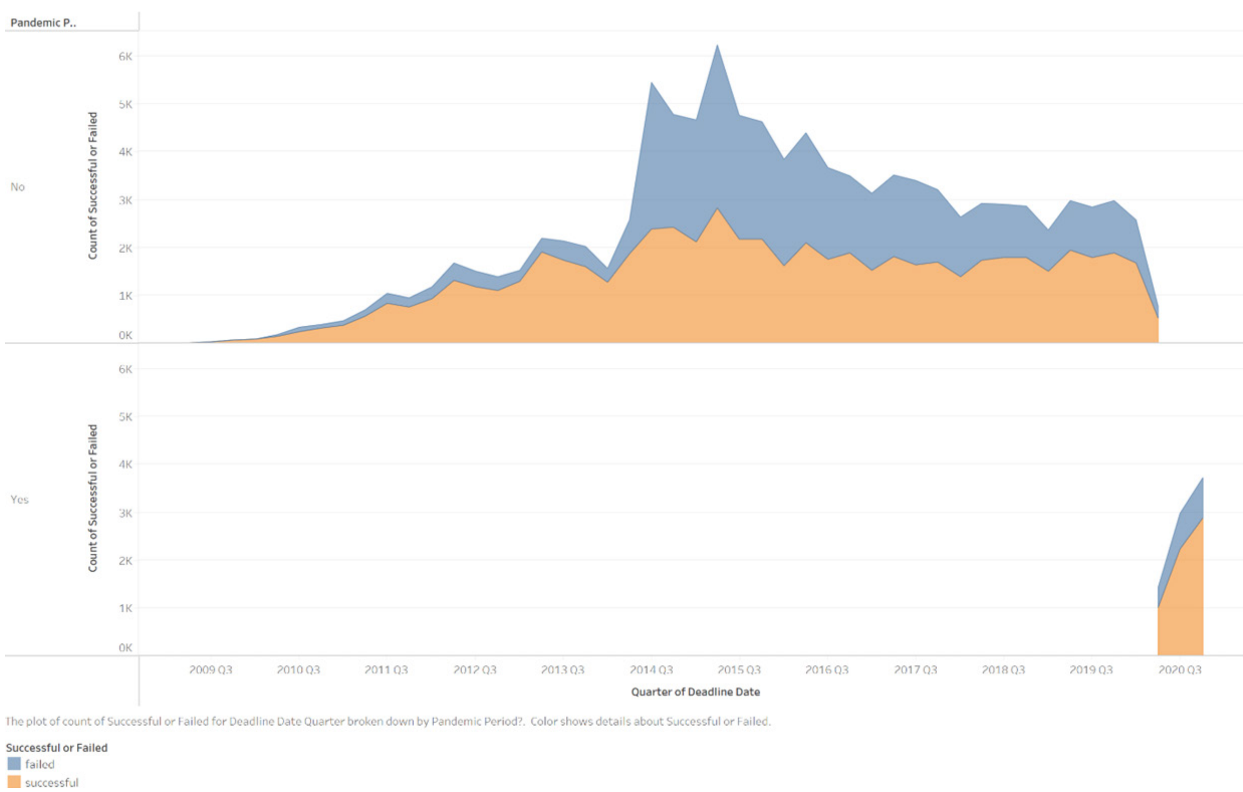

Figure 13: Campaigns by deadline date from 2009 until December 31st, 2020, separated by pre-pandemic period above, and pandemic period below

Pearson's Correlations

Variable		LN(Prep time)	Campaign length days	LN(Goal)	LN NumBacker
1. LN(Prep time)	Pearson's r	—			
2. Campaign length days	Pearson's r	−0.005	—		
3. LN(Goal)	Pearson's r	0.183***	0.209***	—	
4. LN NumBacker	Pearson's r	0.331***	−0.090***	0.078***	—

* p < .05, ** p < .01, *** p < .001

```
Linear regression (OLS)
Data     : LN_all_3_pand_period_ratio_backer_dv
Response variable    : LN_NumBacker
Explanatory variables: Pandemic_Period, LN_Prep_time_, Campaign_length_days, LN_Goal_, Staff_Pick, Category
Null hyp.: the effect of x on LN_NumBacker is zero
Alt. hyp.: the effect of x on LN_NumBacker is not zero

                                          coefficient std.error t.value p.value
 (Intercept)                                    2.236     0.039  56.710  < .001 ***
 Pandemic_Period|Yes                            0.427     0.141   3.032   0.002 **
 LN_Prep_time_                                  0.278     0.003  95.349  < .001 ***
 Campaign_length_days                          -0.013     0.001 -25.594  < .001 ***
 LN_Goal_                                       0.011     0.004   2.415   0.016 *
 Staff_Pick|Yes                                 2.212     0.018 122.885  < .001 ***
 Category|Comics                                1.198     0.037  31.967  < .001 ***
 Category|Crafts                               -0.729     0.037 -19.944  < .001 ***
 Category|Dance                                 0.261     0.044   5.985  < .001 ***
 Category|Design                               -0.152     0.042  -3.585  < .001 ***
 Category|Fashion                               0.211     0.033   6.392  < .001 ***
 Category|Film & Video                          0.129     0.024   5.435  < .001 ***
 Category|Food                                 -0.512     0.027 -19.078  < .001 ***
 Category|Games                                 0.486     0.035  13.816  < .001 ***
 Category|Journalism                           -0.958     0.043 -22.094  < .001 ***
 Category|Music                                 0.361     0.022  16.137  < .001 ***
 Category|Photography                          -0.708     0.039 -17.999  < .001 ***
 Category|Publishing                            0.190     0.026   7.234  < .001 ***
 Category|Technology                            0.291     0.028  10.539  < .001 ***
 Category|Theater                               0.029     0.044   0.654   0.513
 Pandemic_Period|Yes:LN_Prep_time_             -0.061     0.013  -4.841  < .001 ***
 Pandemic_Period|Yes:Campaign_length_days      -0.007     0.002  -3.679  < .001 ***
 Pandemic_Period|Yes:LN_Goal_                   0.151     0.017   8.702  < .001 ***
 Pandemic_Period|Yes:Staff_Pick|Yes            -0.718     0.066 -10.815  < .001 ***
 Pandemic_Period|Yes:Category|Comics           -0.775     0.096  -8.087  < .001 ***
 Pandemic_Period|Yes:Category|Crafts           -0.199     0.172  -1.158   0.247
 Pandemic_Period|Yes:Category|Dance            -0.630     0.497  -1.268   0.205
 Pandemic_Period|Yes:Category|Design            1.032     0.104   9.931  < .001 ***
 Pandemic_Period|Yes:Category|Fashion          -0.030     0.111  -0.273   0.785
 Pandemic_Period|Yes:Category|Film & Video     -1.215     0.109 -11.128  < .001 ***
 Pandemic_Period|Yes:Category|Food             -0.197     0.116  -1.691   0.091 .
 Pandemic_Period|Yes:Category|Games             0.433     0.098   4.398  < .001 ***
 Pandemic_Period|Yes:Category|Journalism       -0.532     0.230  -2.312   0.021 *
 Pandemic_Period|Yes:Category|Music            -0.638     0.103  -6.179  < .001 ***
 Pandemic_Period|Yes:Category|Photography       0.244     0.197   1.240   0.215
 Pandemic_Period|Yes:Category|Publishing       -0.338     0.094  -3.594  < .001 ***
 Pandemic_Period|Yes:Category|Technology       -1.389     0.099 -14.044  < .001 ***
 Pandemic_Period|Yes:Category|Theater          -0.875     0.379  -2.309   0.021 *

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-squared: 0.274,  Adjusted R-squared: 0.274
F-statistic: 1170.738 df(37,114800), p.value < .001
Nr obs: 114,838
```

Figure 14: Campaigns by deadline date from 2009 until December 31st, 2020, separated by pre-pandemic period above, and pandemic period below

Pearson's Correlations

Variable		LN(Prep time)	Campaign length days	LN(Goal)	LN Ratio
1. LN(Prep time)	Pearson's r	—			
2. Campaign length days	Pearson's r	−0.005	—		
3. LN(Goal)	Pearson's r	0.183***	0.209***	—	
4. LN Ratio	Pearson's r	0.228***	−0.178***	−0.272***	—

* p < .05, ** p < .01, *** p < .001

```
Linear regression (OLS)
Data     : LN_all_3_pand_period_ratio_backer_dv
Response variable    : LN_Ratio
Explanatory variables: Pandemic_Period, LN_Prep_time_, Campaign_length_days, LN_Goal_, Staff_Pick, Category
Null hyp.: the effect of x on LN_Ratio is zero
Alt. hyp.: the effect of x on LN_Ratio is not zero

                                          coefficient std.error  t.value p.value
 (Intercept)                                    1.639     0.022   74.490  < .001 ***
 Pandemic_Period|Yes                            1.401     0.079   17.831  < .001 ***
 LN_Prep_time_                                  0.131     0.002   80.802  < .001 ***
 Campaign_length_days                          -0.009     0.000  -32.668  < .001 ***
 LN_Goal_                                      -0.276     0.002 -111.455  < .001 ***
 Staff_Pick|Yes                                 1.109     0.010  110.319  < .001 ***
 Category|Comics                                0.534     0.021   25.530  < .001 ***
 Category|Crafts                               -0.461     0.020  -22.619  < .001 ***
 Category|Dance                                 0.182     0.024    7.479  < .001 ***
 Category|Design                               -0.158     0.024   -6.695  < .001 ***
 Category|Fashion                               0.202     0.018   10.934  < .001 ***
 Category|Film & Video                          0.077     0.013    5.831  < .001 ***
 Category|Food                                 -0.372     0.015  -24.839  < .001 ***
 Category|Games                                 0.152     0.020    7.723  < .001 ***
 Category|Journalism                           -0.607     0.024  -25.071  < .001 ***
 Category|Music                                 0.172     0.012   13.758  < .001 ***
 Category|Photography                          -0.443     0.022  -20.169  < .001 ***
 Category|Publishing                            0.060     0.015    4.108  < .001 ***
 Category|Technology                            0.208     0.015   13.514  < .001 ***
 Category|Theater                               0.006     0.024    0.233   0.816
 Pandemic_Period|Yes:LN_Prep_time_              0.019     0.007    2.705   0.007 **
 Pandemic_Period|Yes:Campaign_length_days      -0.006     0.001   -5.560  < .001 ***
 Pandemic_Period|Yes:LN_Goal_                  -0.053     0.010   -5.473  < .001 ***
 Pandemic_Period|Yes:Staff_Pick|Yes            -0.121     0.037   -3.276   0.001 **
 Pandemic_Period|Yes:Category|Comics           -0.540     0.054  -10.089  < .001 ***
 Pandemic_Period|Yes:Category|Crafts           -0.360     0.096   -3.762  < .001 ***
 Pandemic_Period|Yes:Category|Dance            -0.594     0.277   -2.142   0.032 *
 Pandemic_Period|Yes:Category|Design            0.987     0.058   17.006  < .001 ***
 Pandemic_Period|Yes:Category|Fashion           0.032     0.062    0.521   0.602
 Pandemic_Period|Yes:Category|Film & Video     -0.828     0.061  -13.589  < .001 ***
 Pandemic_Period|Yes:Category|Food             -0.253     0.065   -3.894  < .001 ***
 Pandemic_Period|Yes:Category|Games             0.289     0.055    5.258  < .001 ***
 Pandemic_Period|Yes:Category|Journalism       -0.471     0.128   -3.670  < .001 ***
 Pandemic_Period|Yes:Category|Music            -0.514     0.058   -8.926  < .001 ***
 Pandemic_Period|Yes:Category|Photography       0.110     0.110    1.002   0.316
 Pandemic_Period|Yes:Category|Publishing       -0.384     0.052   -7.321  < .001 ***
 Pandemic_Period|Yes:Category|Technology       -0.738     0.055  -13.358  < .001 ***
 Pandemic_Period|Yes:Category|Theater          -0.448     0.212   -2.119   0.034 *

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-squared: 0.308,  Adjusted R-squared: 0.307
F-statistic: 1378.994 df(37,114800), p.value < .001
Nr obs: 114,838
```

Figure 15: Correlations and OLS linear regression of the natural logarithm of the ratio of funds raised to the campaign goal (pledged/goal) by campaigns

Pearson's Correlations

Variable		LN(Prep time)	Campaign length days	LN(Goal)	LN Pledge /backer
1. LN(Prep time)	Pearson's r	—			
2. Campaign length days	Pearson's r	−0.005	—		
3. LN(Goal)	Pearson's r	0.183***	0.209***	—	
4. LN Pledge /backer	Pearson's r	0.262***	−0.047***	0.051***	—

* p < .05, ** p < .01, *** p < .001

```
Linear regression (OLS)
Data     : LN_all_3_pand_period_ratio_backer_dv
Response variable    : LN_Pledge_backer
Explanatory variables: Pandemic_Period, LN_Prep_time_, Campaign_length_days, LN_Goal_, Staff_Pick, Category
Null hyp.: the effect of x on LN_Pledge_backer is zero
Alt. hyp.: the effect of x on LN_Pledge_backer is not zero

                                              coefficient std.error t.value p.value
 (Intercept)                                        3.167     0.037  84.510  < .001 ***
 Pandemic_Period|Yes                               -0.430     0.134  -3.216   0.001 **
 LN_Prep_time_                                      0.221     0.003  79.830  < .001 ***
 Campaign_length_days                              -0.007     0.000 -13.521  < .001 ***
 LN_Goal_                                          -0.019     0.004  -4.472  < .001 ***
 Staff_Pick|Yes                                     0.831     0.017  48.576  < .001 ***
 Category|Comics                                   -0.090     0.036  -2.536   0.011 *
 Category|Crafts                                   -0.558     0.035 -16.063  < .001 ***
 Category|Dance                                     0.417     0.042  10.040  < .001 ***
 Category|Design                                   -0.320     0.040  -7.958  < .001 ***
 Category|Fashion                                  -0.050     0.031  -1.600   0.110
 Category|Film & Video                              0.194     0.023   8.619  < .001 ***
 Category|Food                                     -0.255     0.026  -9.980  < .001 ***
 Category|Games                                    -0.355     0.033 -10.620  < .001 ***
 Category|Journalism                               -0.920     0.041 -22.325  < .001 ***
 Category|Music                                     0.110     0.021   5.184  < .001 ***
 Category|Photography                              -0.522     0.037 -13.957  < .001 ***
 Category|Publishing                               -0.161     0.025  -6.431  < .001 ***
 Category|Technology                                0.150     0.026   5.712  < .001 ***
 Category|Theater                                   0.221     0.042   5.320  < .001 ***
 Pandemic_Period|Yes:LN_Prep_time_                 -0.077     0.012  -6.383  < .001 ***
 Pandemic_Period|Yes:Campaign_length_days          -0.003     0.002  -1.401   0.161
 Pandemic_Period|Yes:LN_Goal_                       0.139     0.016   8.451  < .001 ***
 Pandemic_Period|Yes:Staff_Pick|Yes                -0.564     0.063  -8.938  < .001 ***
 Pandemic_Period|Yes:Category|Comics               -0.234     0.091  -2.572   0.010 *
 Pandemic_Period|Yes:Category|Crafts                0.253     0.163   1.547   0.122
 Pandemic_Period|Yes:Category|Dance                -0.220     0.472  -0.466   0.642
 Pandemic_Period|Yes:Category|Design                0.694     0.099   7.025  < .001 ***
 Pandemic_Period|Yes:Category|Fashion               0.082     0.106   0.772   0.440
 Pandemic_Period|Yes:Category|Film & Video         -0.350     0.104  -3.371  < .001 ***
 Pandemic_Period|Yes:Category|Food                  0.258     0.111   2.328   0.020 *
 Pandemic_Period|Yes:Category|Games                 0.198     0.094   2.117   0.034 *
 Pandemic_Period|Yes:Category|Journalism            0.167     0.219   0.762   0.446
 Pandemic_Period|Yes:Category|Music                -0.076     0.098  -0.778   0.437
 Pandemic_Period|Yes:Category|Photography           0.844     0.187   4.506  < .001 ***
 Pandemic_Period|Yes:Category|Publishing            0.120     0.089   1.341   0.180
 Pandemic_Period|Yes:Category|Technology           -0.499     0.094  -5.306  < .001 ***
 Pandemic_Period|Yes:Category|Theater              -0.026     0.360  -0.071   0.943

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-squared: 0.109,  Adjusted R-squared: 0.109
F-statistic: 380.052 df(37,114800), p.value < .001
Nr obs: 114,838
```

Figure 16: Correlations and OLS linear regression of the natural logarithm of the average pledge per backer

during the pandemic, and the Staff Pick large effect size, compared to the pre-pandemic time frame. For a contingency table of staff picks by pre-pandemic and pandemic periods see Figure 17. One last surprising effect was the interaction between Pandemic Period and Staff Pick where the positive effect was moderated somewhat.

Longer preparation time increased the average pledge per backer, although slightly less so during the pandemic. A longer campaign length decreased the average pledge per backer and during the pandemic that decrease was slightly larger an effect. A larger campaign goal decreased the average pledge per backer; however, during the pandemic, a larger campaign increased the average pledge per backer. The average pledge per backer in each of the KS categories was impacted similarly to Model 2, the ratio model presented previously. Film & video, and technology, were among the worst-performing categories with regard to the pandemic, whereas the design category during the pandemic performed the best of any category. Full category details can be found in the attached tables. Thus, there is partial support for H2.1. Categories such as design and games which provide typically tangible rewards, performed better than those that do not such as the food, theater, or film categories. However, the extreme positive effect size of the pandemic period factor was enough to outweigh many category-specific effects on success, funds raised, and backer count.

Discussion

CF, as an online activity is a relatively new form of financing. Given its rapid rise and undeniable importance, its study is warranted. This paper offers unique insight into the previously unexamined impact of the COVID-19 pandemic. This paper has contributed to the broader academic literature by confirming some recognized success factors. Furthermore, this paper has demonstrated a previously unexplored factor, the pandemic, and proven it to be highly significant, and with a large effect on campaign success. The pandemic period beginning fully in May 2020, can be considered unique and worthy of further exploration.

Returning to the practitioner's most important questions, outlined at the beginning of this paper: "Is now a good time to use CF to finance my new project or venture, or will the pandemic hurt my chances of success?" We can answer it authoritatively now. It is indeed a great time to use RBCF to start a new venture or begin a project, with success rates being at an all-time high. Campaigns are seeing a higher number of backers, and projects are experiencing better overall funding, as a percent to goal, as a result of the pandemic. How long that continues to be the case, has yet to be seen.

And although these results are of great comfort to practitioners seeking funding, it represents just a first examination of RBCF, its success factors, and the influence of the pandemic. It did not examine any of the other types of CF, namely the investment models, equity, and lending. These are limitations in part, but realistically just represent future opportunities for other researchers to explore. There are many reasons to suppose that the results of this paper might not extend to the other CF models, as previous systematic literature reviews have demonstrated that while CF may share some success factors, others are unique to the CF model (Shneor & Vik Amy, 2020). One interesting avenue of exploration would be in testing some conclusions of researchers who have stated that RBCF funders are essentially acting as a traditional investors (A. K. Agrawal et al., 2011). By testing the effects of the pandemic on investment and non-investment CF, something more might be added to that discussion.

As a brief aside, two points are worth mentioning concerning the findings on goal size and campaign length on RBCF success. The effect of goal size and campaign length has not been entirely consistent across prior CF studies (Shneor & Vik Amy, 2020), despite many studies finding, similar to this study, that goal size and duration decrease chances of success, backers, or funds raised (Barbi & Bigelli, 2017; Du et al., 2019; Kunz et al., 2017; Oo et al., 2019; Zheng et al., 2016). This discrepancy likely indicates nonlinear effects, or even yet-undiscovered factors (Shneor & Vik Amy, 2020). Although there have been suggestions that longer campaigns or larger goals signal to the funder a lack of confidence, or an overreach, there has been research into this nonlinear relationship worth exploring briefly here. The seminal research of Kuppuswamy and Bayas explains some of the inconsistency, where they state that there is a nonlinear, dynamic, interaction between funders and prior contributions over the length of the campaign and that funders are more inclined to fund a campaign if their contributions will make an impact, which likely occurs when a realistic and lower goal is set as the target and this 'goal gradient' effect can be achieved (Kuppuswamy & Bayus, 2017).

An examination of individual fundraisers whose campaigns failed could also prove fruitful. Sometimes a fundraiser will launch another campaign, or go on to seek traditional financing if they have not already, or another type of CF. But if success rates elsewhere are also low, and funding scarce, then there might not be as many alternative outlets for an entrepreneur to check. A replication, and extension, of some of Mollick & Kuppuswamy's 2014 study could create valuable insights into what occurs 'after the campaign', but in light of the Pandemic (E. R. Mollick & Kuppuswamy, 2014).

Some of the findings relating to the RBCF product type categories in this article might also illuminate future research. Further study of ideas generated by previous research examining rewards as strategic assets in CF (Thürridl & Kamleitner, 2016) might be able to draw distinctions between tangible (material/physical goods) and intangible rewards (immaterial/experiential) by product category that could further explain the success of some categories such as Design compared to the poorer performers during the pandemic such as film & video or technology.

Also interesting is the potential impact on CFPs. When a campaign succeeds on an AON CFP, then the CFP makes money through fees, usually around 5%, drawn from the funds raised by the fundraiser. If success rates and total projects have increased, then the CFP is seeing a similar increase in its revenue. It is not unforeseeable that more CFPs would join the

Contingency Tables

		Staff Pick		
Pandemic Period		No	Yes	Total
No	Count	92126.000	14610.000	106736.000
	Expected count	91991.230	14744.770	106736.000
	% within row	86.312 %	13.688 %	100.000 %
Yes	Count	6848.000	1254.000	8102.000
	Expected count	6982.770	1119.230	8102.000
	% within row	84.522 %	15.478 %	100.000 %
Total	Count	98974.000	15864.000	114838.000
	Expected count	98974.000	15864.000	114838.000
	% within row	86.186 %	13.814 %	100.000 %

Chi-Squared Tests

	Value	df	p
X^2	20.258	1	< .001
Likelihood ratio	19.664	1	< .001
N	114838		

Log Odds Ratio

		95% Confidence Intervals		
	Log Odds Ratio	Lower	Upper	p
Odds ratio	0.144	0.081	0.207	
Fisher's exact test	0.144	0.080	0.207	< .001

Figure 17: Contingency table of staff pick by pandemic period

market. Another question ff interest to the already established CFPs is how they can maintain those revenues as the pandemic winds down.

How will the fundraisers deliver on their rewards and campaign promises? Previous research has already shown that many campaigns fulfill their promises late, and a few do not at all (E. Mollick, 2014; E. R. Mollick & Kuppuswamy, 2014). Furthermore, fundraisers are not necessarily in the position to budget, schedule appropriately, or adjust their business plans as they become more informed, as many do not have any business to speak of, or even estimates before beginning the CF campaign (E. Mollick, 2014). Further research could examine if there is an increase in the number of campaigns that did not put serious effort into thoughts of how to fulfill those promises being suddenly put into a position to deliver?

There will likely need to be a reexamination of fraud rates in the face of this changing landscape. Without one, and if there has been a corresponding increase in fraud as a result of the higher than pre-pandemic success rates, CF may face a decline due to lost trust from funders, or from increased regulation (Cumming, Hornuf, Karami, & Schweizer, 2020). In fact in late 2021, Indiegogo, another large CFP announced that they would begin manually reviewing campaigns, and were actively working on ideas to combat fraud and deceit ("10 Years, 1 Takeaway: It's All About Community & Trust," 2021)

While these results are all intriguing, this study has several limitations which are outlined, or highlighted again, here. First, this study only looked at one CFP. Although the dates were comprehensive of most of the modern RBCF timeline, other CFPs were operating before KS, and are worthy of attention. Second, only non-investment CF, specifically RBCF, was examined and only those projects that were extractable from available data. Third, how the CF landscape continues to change into 2021 and onwards was left unexamined. In addition, no international CFPs were examined, and no conclusions about the broader CF market in other countries were drawn. It is certainly conceivable that what was discovered would apply to other countries, but further investigation is warranted.

Further economic measures have not been considered in the models and might be examined in more detail in future studies. Exploration of the effects of factors such as GDP, CPI, housing prices, stock market measures, unemployment, and average hourly earnings might add additional insight. It is already acknowledged that there is a paucity of research relating to macro-level factors in the CF literature (Shneor & Vik Amy, 2020). An examination of macroeconomic factors in the RBCF space is lacking in particular.

Lastly, all of the various unique anomalies during the pandemic taken together might give credence to the proposition that increased relief funds, and tax credits, could explain, in part, increased CF spending during the pandemic. However, caution must be taken as personal income and disposable personal income, although volatile during 2020, did not increase dramatically for an extended period of time, with only April seeing a truly large temporary spike ("Personal Income and Outlays, December 2020 | U.S. Bureau of Economic Analysis (BEA)," 2021; "Personal Income and Outlays, July 2020 | U.S. Bureau of Economic Analysis (BEA)," 2021). Further research, again, likely tying into the macroeconomic factors just mentioned, is needed.

Conclusions

This paper was an empirical research effort. In the same vein as other natural experiments, the goal was to uncover evidence of how the COVID-19 pandemic, acting as a treatment in an experiment, might have affected the subject of interest, RBCF. Comparing the pandemic period, between May and December 2020, to all of the data from the pre-pandemic period from when KS first launched in 2009, provided a great opportunity to answer important questions.

The evidence examined in this paper suggests that entrepreneur success rates, the number of backers, the ratio of funds raised, and the funds pledged per backer, have all changed during the heart of the COVID-19 pandemic. Entrepreneurs were rightfully concerned that the pandemic might induce another financial crisis similar to the one that began in 2008. That financial crisis endangered many firms and hurt or delayed many entrepreneurial dreams. Fortunately, the COVID-19 pandemic proved to be far different for those willing to use RBCF.

During the COVID-19 pandemic, it has been demonstrated that despite the average pledge per backer being negatively impacted by the pandemic, the odds of a campaign succeeding were much higher and that the pandemic also positively affected the ratio of funds raised to a campaign's goal and the number of campaign backers. The pandemic can now be said to be a truly unique period of time. Contrasting with the financial crisis in 2008, where it was seen as difficult for many entrepreneurs to raise capital, 2020 can be viewed as a period of time where the 'Crowd' did what traditional financial institutions struggled to do roughly a decade earlier: fund new business ventures, and keep entrepreneurial hope alive.

References

10 Years, 1 Takeaway: It's All About Community & Trust. (2021). Retrieved from https://go.indiegogo.com/blog/2021/11/10-years-1-takeaway-community-trust.html

Agrawal, A., Catalini, C., & Goldfarb, A. (2015). Crowdfunding: Geography, social networks, and the timing of investment decisions. *Journal of Economics & Management Strategy, 24*(2), 253-274.

Agrawal, A. K., Catalini, C., & Goldfarb, A. (2011). *The geography of crowdfunding* (0898-2937). Retrieved from

Allison, T. H., Davis, B. C., Webb, J. W., & Short, J. C. (2017). Persuasion in crowdfunding: An elaboration likelihood model of crowdfunding performance. *Journal of business venturing, 32*(6), 707-725.

Aparicio, S., Urbano, D., & Audretsch, D. (2016). Institutional factors, opportunity entrepreneurship and economic growth: Panel data evidence. *Technological Forecasting and Social Change, 102*, 45-61. doi:https://doi.org/10.1016/j.techfore.2015.04.006

Barbi, M., & Bigelli, M. (2017). Crowdfunding practices in and outside the US. *Research in International Business and Finance, 42*, 208-223. doi:https://doi.org/10.1016/j.ribaf.2017.05.013

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2010). *Crowdfunding: An industrial organization perspective*. Paper presented at the Prepared for the workshop Digital Business Models: Understanding Strategies', held in Paris on June.

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of business venturing, 29*(5), 585-609. doi:https://doi.org/10.1016/j.jbusvent.2013.07.003

Belleflamme, P., Omrani, N., & Peitz, M. (2015). The economics of crowdfunding platforms. *Information Economics and Policy, 33*, 11-28. doi:https://doi.org/10.1016/j.infoecopol.2015.08.003

Bi, S., Liu, Z., & Usman, K. (2017). The influence of online information on investing decisions of reward-based crowdfunding. *Journal of Business Research, 71*, 10-18. doi:https://doi.org/10.1016/j.jbusres.2016.10.001

Block, J., & Sandner, P. (2009). What is the effect of the financial crisis on venture capital financing? Empirical evidence from US Internet start-ups. *Venture Capital, 11*(4), 295-309.

Burtch, G., Ghose, A., & Wattal, S. (2015). The hidden cost of accommodating crowdfunder privacy preferences: A randomized field experiment. *Management Science, 61*(5), 949-962.

Calic, G., & Shevchenko, A. (2020). How signal intensity of behavioral orientations affects crowdfunding performance: The role of entrepreneurial orientation in crowdfunding business ventures. *Journal of Business Research, 115*, 204-220.

Campello, M., Graham, J. R., & Harvey, C. R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics, 97*(3), 470-487. doi:https://doi.org/10.1016/j.jfineco.2010.02.009

Casey, E., & O'Toole, C. M. (2014). Bank lending constraints, trade credit and alternative financing during the financial crisis: Evidence from European SMEs. *Journal of Corporate Finance, 27*, 173-193. doi:https://doi.org/10.1016/j.jcorpfin.2014.05.001

Cdcgov. (2021). CDC Museum COVID-19 Timeline | David J. Sencer CDC Museum | CDC. Retrieved from https://www.cdc.gov/museum/timeline/covid19.html

Cecere, G., Le Guel, F., & Rochelandet, F. (2017). Crowdfunding and social influence: an empirical investigation. *Applied Economics, 49*(57), 5802-5813.

Chan, C. S. R., Parhankangas, A., Sahaym, A., & Oo, P. (2020). Bellwether and the herd? Unpacking the u-shaped relationship between prior funding and subsequent contributions in reward-based crowdfunding. *Journal of business venturing, 35*(2), 105934. doi:https://doi.org/10.1016/j.jbusvent.2019.04.002

Chan, H. F., Moy, N., Schaffner, M., & Torgler, B. (2021). The effects of money saliency and sustainability orientation on reward based crowdfunding success. *Journal of Business Research, 125*, 443-455. doi:https://doi.org/10.1016/j.jbusres.2019.07.037

Chandler, J. A., Short, J. C., & Wolfe, M. T. (2021). Finding the crowd after exogenous shocks: Exploring the future of crowdfunding. *Journal of Business Venturing Insights, 15*, e00245.

Chen, H., Gompers, P., Kovner, A., & Lerner, J. (2010). Buy local? The geography of venture capital. *Journal of Urban Economics, 67*(1), 90-102. doi:https://doi.org/10.1016/j.jue.2009.09.013

Cholakova, M., & Clarysse, B. (2015). Does the Possibility to Make Equity Investments in Crowdfunding Projects Crowd Out Reward–Based Investments? *Entrepreneurship Theory and Practice, 39*(1), 145-172. doi:10.1111/etap.12139

Comeig Ramírez, I., Mesa Vázquez, E., Sendra-Pons, P., & Urbano, A. (2020). Rational Herding in Reward-Based Crowdfunding: An MTurk Experiment. *Sustainability, 2020, vol. 12, num. 9827.*

Cox, N., Ganong, P., Noel, P., Vavra, J., Wong, A., Farrell, D., . . . Deadman, E. (2020). Initial impacts of the pandemic on consumer behavior: Evidence from linked income, spending, and savings data. *Brookings Papers on Economic Activity, 2020*(2), 35-82.

Cumming, D. J., Hornuf, L., Karami, M., & Schweizer, D. (2020). Disentangling crowdfunding from fraudfunding. *Max Planck Institute for Innovation & competition research paper*(16-09).

Cumming, D. J., Martinez-Salgueiro, A., Reardon, R. S., & Sewaid, A. (2021). COVID-19 bust, policy response, and rebound: equity crowdfunding and P2P versus banks. *The Journal of Technology Transfer*, 1-22.

Curran, P. J., West, S. G., & Finch, J. F. (1996). The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. *Psychological methods, 1*(1), 16.

Davies, W. E., & Giovannetti, E. (2018). Signalling experience & reciprocity to temper asymmetric information in crowdfunding evidence from 10,000 projects. *Technological Forecasting and Social Change, 133*, 118-131.

de Larrea, G. L., Altin, M., & Singh, D. (2019). Determinants of success of restaurant crowdfunding. *International Journal of Hospitality Management, 78*, 150-158.

Dejean, S. (2019). The role of distance and social networks in the geography of crowdfunding: evidence from France. *Regional Studies*.

Dikaputra, R., Sulung, L. A. K., & Kot, S. (2019). Analysis of success factors of reward-based crowdfunding campaigns using multi-theory approach in ASEAN-5 countries. *Social Sciences, 8*(10), 293.

Du, Z., Li, M., & Wang, K. (2019). "The more options, the better?" Investigating the impact of the number of options on backers' decisions in reward-based crowdfunding projects. *Information & Management, 56*(3), 429-444. doi:https://doi.org/10.1016/j.im.2018.08.003

Dunning, T. (2010). Natural Experiments. *Draft entry for the International Encyclopedia of Political Science. Consultado el, 5*.

Dushnitsky, G., & Fitza, M. A. (2018). Are we missing the platforms for the crowd? Comparing investment drivers across multiple crowdfunding platforms. *Journal of Business Venturing Insights, 10*, e00100. doi:https://doi.org/10.1016/j.jbvi.2018.e00100

E-COMMERCE, TRADE AND THE COVID-19 PANDEMIC. (2021). Retrieved from https://www.wto.org/english//tratop_e/covid19_e/ecommerce_report_e.pdf

Elmer, G., Ward-Kimola, S., & Burton, A. G. (2020). Crowdfunding during COVID-19: An international comparison of online fundraising. *First Monday*.

Fernandes, N. (2020). Economic effects of coronavirus outbreak (COVID-19) on the world economy. *Available at SSRN 3557504*.

Frydrych, D., Bock, A. J., Kinder, T., & Koeck, B. (2014). Exploring entrepreneurial legitimacy in reward-based crowdfunding. *Venture Capital, 16*(3), 247-269.

Gallemore, C., Nielsen, K. R., & Jespersen, K. (2019). The uneven geography of crowdfunding success: Spatial capital on Indiegogo. *Environment and Planning A: Economy and Space, 51*(6), 1389-1406.

Giudici, G., Guerini, M., & Rossi-Lamastra, C. (2018). Reward-based crowdfunding of entrepreneurial projects: the effect of local altruism and localized social capital on proponents' success. *Small Business Economics, 50*(2), 307-324.

Herrero, Á., Hernández-Ortega, B., & San Martín, H. (2020). Potential funders' motivations in reward-based crowdfunding. The influence of project attachment and business viability. *Computers in Human Behavior, 106*, 106240. doi:https://doi.org/10.1016/j.chb.2019.106240

How are federal economic impact payments to support individuals during the COVID-19 pandemic recorded in the NIPAs? | U.S. Bureau of Economic Analysis (BEA). (2021). Retrieved from https://www.bea.gov/help/faq/1409

Kickstarter. (2021, August 8). Kickstarter Stats. Retrieved from https://www.kickstarter.com/help/stats

Kickstarter Datasets. (2021). Retrieved from https://webrobots.io/kickstarter-datasets/

Koch, J.-A., & Siering, M. (2019). The recipe of successful crowdfunding campaigns. *Electronic Markets, 29*(4), 661-679.

Kromidha, E., & Robson, P. (2016). Social identity and signalling success factors in online crowdfunding. *Entrepreneurship & Regional Development, 28*(9-10), 605-629.

Kshetri, N. (2015). Success of Crowd-based Online Technology in Fundraising: An Institutional Perspective. *Journal of International Management, 21*(2), 100-116. doi:https://doi.org/10.1016/j.intman.2015.03.004

Kunz, M. M., Bretschneider, U., Erler, M., & Leimeister, J. M. (2017). An empirical investigation of signaling in reward-based crowdfunding. *Electronic Commerce Research, 17*(3), 425-461. doi:10.1007/s10660-016-9249-0

Kuppuswamy, V., & Bayus, B. L. (2017). Does my contribution to your crowdfunding project matter? *Journal of business venturing, 32*(1), 72-89.

Lin, M., & Viswanathan, S. (2016). Home bias in online investments: An empirical study of an online crowdfunding market. *Management Science, 62*(5), 1393-1414. doi:https://doi.org/10.1287/mnsc.2015.2206

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of business venturing, 29*(1), 1-16. doi:10.1016/j.jbusvent.2013.06.005

Mollick, E. R., & Kuppuswamy, V. (2014). After the campaign: Outcomes of crowdfunding. *UNC Kenan-Flagler Research Paper*(2376997).

Morens, D. M., Daszak, P., Markel, H., & Taubenberger, J. K. (2020). Pandemic COVID-19 joins history's pandemic legion. *MBio, 11*(3), e00812-00820.

Moritz, A., & Block, J. H. (2016). *Crowdfunding: A literature review and research directions*.

Nielsen, K. R., & Binder, J. K. (2020). I am what I pledge: the importance of value alignment for mobilizing backers in reward-based crowdfunding. *Entrepreneurship Theory and Practice*, 1042258720929888.

Oo, P. P., Allison, T. H., Sahaym, A., & Juasrikul, S. (2019). User entrepreneurs' multiple identities and crowdfunding performance: Effects through product innovativeness, perceived passion, and need similarity. *Journal of business venturing, 34*(5), 105895. doi:ARTN 105895

10.1016/j.jbusvent.2018.08.005

Patel, P. C., Wolfe, M. T., & Manikas, A. S. (2021a). Logic is (Somewhat) Overrated: Image-Based Versus Concept-Based Rhetoric in Crowdfunding Narratives. *Entrepreneurship Theory and Practice, 45*(3), 600-625.

Patel, P. C., Wolfe, M. T., & Manikas, A. S. (2021b). Talk is cheap?! The value of a ban on product simulations and renderings on a crowdfunding platform. *Applied Economics*, 1-22.

Personal Income and Outlays, December 2020 | U.S. Bureau of Economic Analysis (BEA). (2021). Retrieved from https://www.bea.gov/news/2021/personal-income-and-outlays-december-2020

Personal Income and Outlays, July 2020 | U.S. Bureau of Economic Analysis (BEA). (2021). Retrieved from https://www.bea.gov/index.php/news/2020/personal-income-and-outlays-july-2020

Popov, A., & Udell, G. F. (2012). Cross-border banking, credit access, and the financial crisis. *Journal of International Economics, 87*(1), 147-161. doi:https://doi.org/10.1016/j.jinteco.2012.01.008

Raab, M., Schlauderer, S., Overhage, S., & Friedrich, T. (2020). More than a feeling: Investigating the contagious effect of facial emotional expressions on investment decisions in reward-based crowdfunding. *Decision Support Systems, 135*, 113326. doi:https://doi.org/10.1016/j.dss.2020.113326

Rajwa, P., Hopen, P., Mu, L., Paradysz, A., Wojnarowicz, J., Gross, C. P., & Leapman, M. S. (2020). Online Crowdfunding Response to Coronavirus Disease 2019. *Journal of general internal medicine, 35*, 2482-2484.

Ryu, S., & Kim, Y.-G. (2016). A typology of crowdfunding sponsors: Birds of a feather flock together? *Electronic Commerce Research and Applications, 16*, 43-54.

Ryu, S., & Kim, Y.-G. (2018). Money is not everything: A typology of crowdfunding project creators. *The Journal of Strategic Information Systems, 27*(4), 350-368.

Saleh, S. N., Lehmann, C. U., & Medford, R. J. (2021). Early crowdfunding response to the COVID-19 pandemic: Cross-sectional study. *Journal of medical Internet research, 23*(2), e25429.

Shneor, R., & Vik Amy, A. (2020). Crowdfunding success: a systematic literature review 2010–2017. *Baltic Journal of Management, 15*(2), 149-182. doi:10.1108/BJM-04-2019-0148

Song, Y., Berger, R., Yosipof, A., & Barnes, B. R. (2019). Mining and investigating the factors influencing crowdfunding success. *Technological Forecasting and Social Change, 148*, 119723. doi:ARTN 11972310.1016/j.techfore.2019.119723

Stretch Goals - Roberts Space Industries (2021). Retrieved from https://robertsspaceindustries.com/funding-goals

Stuart, T., & Sorenson, O. (2003). The geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms. *Research Policy, 32*(2), 229-253. doi:https://doi.org/10.1016/S0048-7333(02)00098-7

Thürridl, C., & Kamleitner, B. (2016). What goes around comes around? Rewards as strategic assets in crowdfunding. *California management review, 58*(2), 88-110.

Tietz, M., Simons, A., Weinmann, M., & vom Brocke, J. (2016). The decoy effect in reward-based crowdfunding: Preliminary results from an online experiment.

U.S. coronavirus death toll surpasses 100,000. (2021). Retrieved from https://www.washingtonpost.com/graphics/2020/national/100000-deaths-american-coronavirus/

Ungerer, C., Portugal, A., Molinuevo, M., & Rovo, N. (2020). Recommendations to Leverage E-Commerce During the COVID-19 Crisis.

Wang, W., He, L., Wu, Y. J., & Goh, M. (2021). Signaling persuasion in crowdfunding entrepreneurial narratives: The subjectivity vs objectivity debate. *Computers in Human Behavior, 114*, 106576. doi:https://doi.org/10.1016/j.chb.2020.106576

Wang, Z., & Yang, X. (2019). Understanding backers' funding intention in reward crowdfunding: An elaboration likelihood perspective. *Technology in Society, 58*, 101149.

Weinmann, M., Mishra, A., Kaiser, L., & vom Brocke, J. (2020). The Attraction Effect in Reward-Based Crowdfunding: Evidence from Four Experiments. *Available at SSRN 3630514*.

Wolfe, M. T., Patel, P. C., & Manikas, A. S. (2021). Shock and awe: Loudness and unpredictability in Twitter messages and crowdfunding campaign success. *Journal of Innovation & Knowledge*.

Wroldsen, J. (2016). Crowdfunding investment contracts. *Va. L. & Bus. Rev., 11*, 543.

Xiang, D., Zhang, L., Tao, Q., Wang, Y., & Ma, S. (2019). Informational or emotional appeals in crowdfunding message strategy: An empirical investigation of backers' support decisions. *Journal of the Academy of Marketing Science, 47*(6), 1046-1063.

Yasar, B. (2021). The new investment landscape: Equity crowdfunding. *Central Bank Review, 21*(1), 1-16. doi:https://doi.org/10.1016/j.cbrev.2021.01.001

Yeh, T.-L., Chen, T.-Y., & Lee, C.-C. (2019). Investigating the funding success factors affecting reward-based crowdfunding projects. *Innovation, 21*(3), 466-486.

Zhang, B., Wardrop, R., Rau, P. R., & Gray, M. (2015). Moving mainstream: Benchmarking the European alternative finance market. *Journal of Financial Perspectives, 3*(3).

Zheng, H., Hung, J.-L., Qi, Z., & Xu, B. (2016). The role of trust management in reward-based crowdfunding. *Online Information Review*.

Zheng, H., Li, D., Wu, J., & Xu, Y. (2014). The role of multidimensional social capital in crowdfunding: A comparative study in China and US. *Information & Management, 51*(4), 488-496. doi:https://doi.org/10.1016/j.im.2014.03.003

Ziegler, T., Shneor, R., Wenzlaff, K., Suresh, K., Paes, F. F. d. C., Mammadova, L., . . . Wang, B. (2021). The 2nd Global Alternative Finance Market Benchmarking Report.

Zvilichovsky, D., Danziger, S., & Steinhart, Y. (2018). Making-the-product-happen: A driver of crowdfunding participation. *Journal of Interactive Marketing, 41*, 81-93.

Review

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Authors

Matthew Grace is currently enrolled in the Doctor of Business Administration Program at the University of South Florida's Muma College of Business with a 2023 anticipated completion date. Matthew Grace is the award-winning author of the International Case Management Conference's Best Case Award for "Crowdfunding When The Crowd Makes Demands." Matthew's principal research interests are entrepreneurship, innovation, alternative finance, crowdfunding, strategy, and gamification. Matthew is the Director of Marketing Research, and Director of Innovation at By Night Studios, a roleplaying game design, and publishing company.