Are We Missing the Platforms for the Crowd?
Comparing Investment Drivers Across Multiple Crowdfunding Platforms

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Abstract

Crowdfunding platforms have attracted the attention of practitioners and scholars alike. The term ‘crowdfunding’, first coined in the early 2000s, describes a new institutional form in the financial markets which utilizes digital platforms to originate and aggregate funding. There is abundant research on the topic. Yet extant work mainly consists of single-platform studies. We argue that observing patterns on one platform does not necessarily advance our understanding of other platforms. Specifically, we use data from eight major crowdfunding platforms to conduct a variance decomposition analysis of funding success. The findings suggest factors associated with success in a given platform do not replicate to the other platforms. It underscores the generalizability challenge facing the crowdfunding literature. We therefore highlight the need to complement single-platform studies with cross-platform studies.

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Are We Missing the Platforms for the Crowd?
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The crowdfunding phenomenon has grabbed the attention of scholars in the fields of entrepreneurship, strategy, and beyond. The term "crowdfunding" was coined in the late 2000s to describe a new institutional form which utilizes digital platforms to originate and aggregate funding. It covers a wide set of activities ranging from the facilitation of for-profit start-up investments to the charitable funding of social ventures in faraway continents. Although a recent phenomenon, the academic archive SSRN lists over six hundred entries on the topic, with half of the posts dated 2015 or later.[1] The work exhibits many virtues. For example, recent studies document success drivers on the reward-based platform Kickstarter (Mollick, 2014; Mollick and Nanda, 2016), or fundraising pricing on the lending-based platform Prosper (Lin, Prabhala, Viswanathan, 2013; Hildebrand, Puri, Rocholl, 2016). Each study presents insights based on analyses of detailed transactions within a single platform. Yet, it often remains silent as to the rationale for selecting the focal platform to begin with. The issue is exacerbated as there are hundreds of crowdfunding platforms across the world (Dushnitsky et al., 2016).

This observation raises questions regarding generalization. Why is that an issue? Because platforms differentiate. Specifically, the proliferation of crowdfunding platforms stimulated research on the topic, but extant work has yet to acknowledge platform differentiation (Figure 1). The fact that platforms differentiate suggests empirical patterns observed on one platform cannot be assumed to generalize to other platforms. Indeed, practitioners are apprehensive that funding patterns vary across platforms. Consider a Quora posting contrasting two prominent lending platforms (e.g., "*What's the difference between Lending Club and Prosper?*"), and similar posts regarding donation and reward platforms.[2] They underscore the fact each platform seeks to

[1] SSRN searched on March 31, 2018.
[2] A post suggesting donation platforms differ ("*Why would anyone choose GoFundMe over YouCaring…*"), and anther contrasting two reward platforms ("*Which is better and why: Kickstarter or IndieGoGo?*"). Quora links accessed on 18.5.2018; www.quora.com/Whats-the-difference-between-Lending-Club-and-Prosper; www.quora.com/Which-is-better-and-why-Kickstarter-or-IndieGoGo; www.quora.com/Why-would-anyone-choose-GoFundMe-over-YouCaring-when-GoFundMe-takes-8%E2%84%85-and-YouCaring-takes-3-from-your-donation-amount

differentiate itself from the competition. Its choices affect (a) the crowds that self-select to go on the platform, and (b) the drivers of funding success within the platform. It begs the question whether patterns observed within a given platform necessarily advance our understanding of investment drivers in other crowdfunding platforms.

What are the implications to research? The situation described above suggests that crowdfunding is a complex phenomenon, and using one term "crowdfunding" to describe it can be counter-productive because it overlooks the heterogeneity of the context. In fact, doing so can hinder the accumulation of knowledge across studies. To see that, recall Thorngate (1976) who notes it is impossible for a theory of social behaviour to simultaneously pursue (a) *accuracy*, (b) *parsimony*, and (c) *generality*. The current approach which focuses on detailed examinations within single platforms results in *accurate* analyses and *parsimonious* theory. Per Thorngate's argument, however, this approach raises the question of *generalisability* as it remains unclear whether the accurate data from within one platform carries general insights to other – differentiated – crowdfunding platforms. A review of the literature illustrates this conundrum. For example, a popular assertion is that investment location will become irrelevant because crowdfunding platforms are easily accessible by individuals across the world. Yet, the impact of location remains inconclusive. A few studies report crowdfunding does indeed attract funding from faraway (e.g., Agrawal, Catalini and Goldfarb, 2017; Stroube, 2017), while others record a strong preference to invest locally (Lin and Viswanathan, 2016; Gunther, Johan, and Schweizer, 2017). Crucially, each of these studies uses data from a different platform.

The purpose of this study is to explore generalizability in the crowdfunding literature. How does the current 'modus operandi' of single-platform studies affect generalizability? To that end, we investigate whether factors that are common across platforms also exhibit comparable impact on ultimate funding success. We accomplish this by using a variance decomposition methodology (e.g., McGahan and Porter, 2002; Rumelt, 1991; Fitza et al., 2009). The results inform the question of generalizability. For example, we find that on one platform, the location of the project explains over a third of the variance in its ultimate funding success, while location has no explanatory impact on other platforms. Similarly, most of the platforms group projects into categories as a way of helping contributors search for projects of interest. Yet there is a remarkable disparity in the association of such categories with funding success; the impact of category differs a hundred-fold across the platforms we analysed. We discuss the implication to the accumulation of knowledge in the conclusion section.

Before turning to our study, we would like to highlight its contributions by addressing a common criticism; "*The study compares apples to oranges. It is not surprising that investment patterns differ across platforms. It is because of the varied goals across such platforms which in turn may have very different investors self-selecting and participating in these platforms.*" Our response is threefold. First, we emphasize the difference are observed not only across crowdfunding types (i.e., reward vs. lending), but also between platforms of a similar type (e.g., differences between lending platforms). Second, we are in full agreement with the argument; crowdfunding platforms are so different that scholars should not generalize from one platform to another. Unfortunately, our reading of the literature is that such generalization takes place, if not explicitly then implicitly. We believe that what may be viewed as intuitive upon seeing our findings, is actually non-trivial given the current state of the literature. In short, we provide evidence-based support for that intuition. Third, the criticism rightfully hints that participants self-select onto a platform that fit their interests. It is well-understood that failure to account for self-selection could lead to erroneous inferences. However, we are not aware of studies that account for self-selection of crowdfunders onto the studied platform. Hopefully, this study will stimulate further work and richer understanding of crowdfunding success.

------- Insert Figure 1 about here -------

THE CROWDFUNDING PHENOMENON

Crowdfunding refers to the practice of funding a project or a venture by raising small amounts of money from a large number of people via the Internet. Formally, a crowdfunding platform features five traits: (a) it is a digital platform, (b) aggregating funds from multiple individuals, where (c) each individual generally contributes a small fraction of the requested amount, (d) based on a set of goals and objectives (e.g., securing financial gains, seeking material gain (rewards), donating to social cause) and (e) his/her assessment of the focal project.

Unfortunately, the term “crowdfunding” is often extended to include many fundamentally different activities. It is partly because digital platforms exhibit similar “look and feel”. At the extreme, this is because the same exact website interface is duplicated across different platforms. For example, “*With Thrinacia Atlas you can quickly create white label CrowdFunding portals. Build fundraising, reward, donation, real estate, loan or equity CrowdFunding websites*” (www.thrinacia.com/). More often, the reason is not outright duplication, but merely an outcome of being a digital platform with similar interface and user experience. Oftentimes, platforms feature identical fields; e.g., they usually list projects by categories and location.

As a result, the term “crowdfunding” is often extended to include many different digital platforms. It can be misleading. Platforms critically differ on four traits (i.e., aforementioned traits (b) through (e)). Ignoring this may result in an incomplete understanding of the factors associated with crowdfunding success. Crucially, the differences are not only between different crowdfunding types (e.g., reward vs. lending), but also within a given type (e.g., different donation platforms). For example, donation platforms (where contributions are given in the form of donations) differ substantially in their focus and goals; Kiva facilitates pro-social donations based on individuals giving to projects in faraway emerging markets; whereas FundRazr enables crowdfunding by sharing one’s local project or cause with friends and family; and DonorsChoose focuses on a particular cause of supporting US public schools. Likewise, there are notable differences among reward platforms[3], as well as lending platforms.[4]

A careful review of scholarly work uncovers incongruent findings. Below, we focus on three broad factors that attracted much attention in extant work, but have yet to accumulate a consistent set of results. These factors are the impact of projects' location, category and year. Consider the role of project location. Because crowdfunding is an Internet-based phenomenon, there is an expectation that location need not affect funding success. Many platforms include data-fields for crowdfundees and projects location. Past work leveraged these data. Yet, the impact of location remains ambiguous. A few studies investigate the prevalence of home bias; a common investment bias in offline setting denoting investors' inclination to finance projects located nearby. They find that home bias persists online; both on the lending platform, Prosper (Lin and Viswanathan, 2016) as well as the equity platform, ASSOB (Gunther, Johan, and Schweizer, 2017). At the same time, other studies allude to an opposite pattern. Analysis of a China-based lending platform finds a preference for distant projects (Stroube, 2017). And investment in distant projects is common on the equity-like platform Sell-A-Band, where it is also associated with herding behaviour (Agrawal, Catalini and Goldfarb, 2017).

Next, consider the role of project category. Many platforms group projects into categories as a way of helping crowdfunders find projects of interest. It is probably the first field they use to filter through projects. As such, category considerations have been incorporated into many crowdfunding studies. Yet, the impact of category affiliation features inconclusive observations. First, we know little about the way category information is utilized. Leung and Sharkey (2013)

[3] Reward platforms differ in their approach to funding success. To this date, Kickstarter follows an 'All or Nothing' (AoN) approach where a crowdfundee sets a funding threshold and collects the proceeds if and only if total funds exceeds the threshold. Indiegogo, in contrast, allows participants to opt for an alternative approach; under 'Keep it All' (KiA) a crowdfundee receives whatever amount was contributed irrespectively of the threshold.

[4] Lending platforms differ significantly in the nature of loans they facilitate. Some platforms follow a peer-to-peer focus (e.g., Lending Club); providing loans solely to individuals (e.g., consolidating credit card debt). Other platforms facilitate peer-to-business lending (e.g., Funding Circle), where crowdfundees are small or medium size companies (e.g., purchasing equipment or inventory). Others yet support both approaches (e.g., Zopa and Prosper).

report that Prosper's decision to conceal category information had a notable impact on funding success. If platforms vary in their approach to category information, it may result in meaningful cross-platform heterogeneity in funding patterns. Second, some studies' findings are category agnostic. For instance, a positive association between professional investors and crowdfunders on Kickstarter is observed both in the Arts category (Mollick and Nanda, 2015) and the Technology category (Roma et al., 2017). Yet, others report nontrivial category-by-category variation; such as the likelihood of funding CleanTech projects on Indiegogo (Cumming, Leboeuf, and Schwienbacher, 2015), or the effect of crowdundees' narratives in Kickstarter (Manning & Bejarano, 2017; Parhankangas & Renko, 2017).

Finally, consider the year of funding. We note investment patterns vary annually, and to a different extent for different platforms. First, crowdfunding is a nascent industry. During the mid 2000s, Kiva, Zopa and Kickstarter were crowdfunding pioneers. A handful of platforms were educating the market about crowdfunding and mainly attracted enthusiasts. The landscape changes in the following decade as it gained substantial media coverage and regulatory legitimacy. Hundreds of platforms entered, competed and sought to differentiate (Dushnitsky et al., 2016). Second, annual fluctuation in macroeconomic conditions and government policy critically affect crowdfunding. For example, investment patterns on the lending platform Prosper are shaped by fluctuation in interest rates (Rigbi, 2013) and access to bank loans (Butler et al., 2016). Taken together, the observations suggest a strong temporal (i.e., year) effect.

In sum, the discussion illustrates open puzzles in the crowdfunding literature. It shows findings based on examination of one platform need not necessarily generalise to all platforms.

METHODOLOGY

Our analysis explores whether drivers of crowdfunding success generalize across platforms. Whereas past work 'goes deep' with detailed data from a single platform, we aim to 'go broad' and employ consistent data-fields across multiple platforms (Figure 2). We ask, do factors common across crowdfunding platforms equally explain funding success in each and every platform? To that end, we identify a set of data-fields that appear in many crowdfunding platforms; category, location and project year. A variance decomposition analysis uncovers the impact these factors on ultimate fundraising success. The analysis is repeated for every platform. We then compare the impact of each factor across the different platforms.

Variance decomposition has been used frequently in the strategy and management literatures (Bowman and Helfat, 2001; Brush et al., 1999; McGahan and Porter, 2002; Rumelt, 1991) and more recently adopted by entrepreneurship scholars (Fitza et al., 2009; Short et al., 2009). It is used to estimate the proportion of variance in a dependent variable that can be attributed to, or explained by, certain factors called "effect-classes". The methodology is particularly advantageous for cross-platform analysis because it (a) addresses limited data availability across platforms and (b) facilitates meaningful cross-platform comparisons. We expand on these advantages below.

First, consider the issue of data availability. Recall that any one study cannot be simultaneously accurate, general and parsimonious (Thorngate, 1976). In the crowdfunding literature, most studies focus on a single platform. A major strength of single-platform studies is the rich and fine-grained data they collect. Inevitably, a study of multiple platforms sacrifices some level of accuracy. The variance decomposition methodology enables us to get around this issue. It estimates the overall impact of each effect-class and does not require fine-grained measures thereof.[5] Table 1 shows the effect-classes we use in our study and provides some general information for each class across the eight crowdfunding platforms.

Second, the methodology facilitates meaningful cross-platform comparisons. We can understand and compare the impact of an effect-class while being agnostic of the specific values

[5] To illustrate the benefit, consider an example from the well-known profitability variance decomposition studies (Bowman and Helfat, 2001; McGahan and Porter, 1997, 2002). Among other effects, these studies estimate the industry effect. Certain industry features such as market size, economies of scale, regulatory intensity, etc. might affect firm profitability. However, it is often impossible to collect fine grained information on every possible industry feature. A variance decomposition methodology does not require information on each feature. Instead it looks at the overall effect of industry by measuring the amount of variance in firm performance that can be explained by the industry to which firms belong. Our study uses variance decomposition for similar reasons.

that effect-class undertakes on any given platform. For example, consider the effect-class of project location. On one platform, the location variable may take the values "New York City" and "San Francisco", while on another platform it takes the values "Berlin" and "Frankfurt". Our paper does not study the marginal contribution of specific effect values (e.g., NYC versus SF). Rather, we study the impact of the location effect-class; the extent to which funding success is sensitive to variation in project location. Thus for the purpose of our analyses, the specific values within a given effect-class are irrelevant. Rather, all that matters is whether the dependent variable varies as a function of variation in the effect-class. To the extent that a past study included a given effect (e.g., category) in its analysis, it implicitly assumes that the effect can be informative in explaining funding success. It is not clear, however, whether the impact of the effect in one platform is telling us anything about its role in another platform. Our analyses allow for direct comparisons of effect sizes across platforms. It thus informs the generalizability of results across platforms.

Study Sample. The data comes from eight major crowdfunding platforms; Lending Club (lending), Funding Circle (lending), Prosper (lending), Zopa (lending), Kickstarter (rewards), Indiegogo (rewards), Kiva (donations), and FundRazr (donations).

Analysis: We follow McGahan and Porter (2002), and Fitza (2015) and use a simultaneous ANOVA approach to determine the sizes of the individual classes of effects (see also: McGahan and Victor 2010, Fitza 2014; Ma et al, 2013; Quigley and Hambrick, 2014; Graffin and Quigley, 2017; Fitza and Tihanyi, 2017). For each crowdfunding platform we capture the amount of variance in funding success that can be explained by three effects: year, location and category. We estimate the following equation for each platform: $IV_{p,s} = \mu_s + \alpha_{y,s} + \beta_{cat,s} + \nu_{l,s} + \varepsilon_{o,s}$, where $IV_{p,s}$ represents the dependent variable of interest for each project p on crowdfunding platform s. On the right-hand side, the first term μ_s is a constant equal to the grand mean of the dependent variable for each platform. The other terms on the right side represent our effects of interest. The term $\alpha_{y,s}$ represents the *Year* effect for each crowdfunding platform; $\beta_{cat,s}$ depicts the *Category* effect, and $\nu_{l,s}$ captures how much of the variance in the dependent variable of each crowdfunding platform can be attributed to the *Location* of the projects; and finally, $\varepsilon_{p,s}$ represents the residual for each crowdfunding platform. As indicated by the subscript *s*, we apply this model to each crowdfunding platform separately.

All effects are represented by vectors of dummy variables. The size of a specific effect is determined by measuring the increase in the explained variance of the model, once a vector of dummies representing this effect has been included. To compensate for the fact that our sample sizes, as well as the degrees of freedom for each effect, differ between different crowdfunding platforms, we follow recent studies and use the adjusted R^2 as our measure of the explained variance (e.g., Fitza, 2009, Graffin and Quigley, 2017). The simultaneous ANOVA controls for covariance between the individual effects (e.g., Fitza 2014, McGahan and Victor 2010). Some recent studies have used hierarchical linear modeling (HLM) (Misangyi et al., 2006; Short et al., 2007) to control for such covariance. However, HLM assumes a clear hierarchical or nested structure in the data. Our effects of interest are year, category, and location; these three effects are not in any hierarchical relationship because year cuts across all observations, and categories and location are not nested in each other either. Our use of a simultaneous ANOVA allows us to measure all effects without the need for a nested structure.[6]

Measures of Crowdfunding Success: The dependent variable is a measure of a project's funding success. For each crowdfunding platform, we employ a measure of success which is appropriate for that crowdfunding type. To that end, we are guided by extant work for the main crowdfunding types.[7] For reward-based (e.g., Burtch, Ghose, Wattal, 2015) and donation-based (e.g., Galak, Small, Stephen, 2011) platforms, we follow past work and use the total amount contributed (US$) as our measure of funding success. As for lending crowdfunding, past work has focused on the

[6] When both approaches can be used HLM usually yields somewhat smaller effect (e.g., Quigley and Graffin 2017, Fitza 2017). While this is important for certain research questions, the absolute magnitude of the effect size is not the focus of our study. Instead, we examine the relative effect size; namely, how does the magnitude of the focal effect-class (e.g., location) compares across the eight crowdfunding sites we study.
[7] Past variance decomposition studies also utilized multiple performance measures. For example, variance decomposition studies in the strategy literature used at least three measures, including firm profitability based on accounting data, market share, or financial returns based on Tobin's Q (e.g., Bowman and Helfat, 2001).

cost of the loan – rather than the loan amount – as a measure of success. The lower the interest rate necessary to attract funding, the more successful the crowdfundee is considered to be (Pope and Sydnor, 2011; Duarte et al., 2012; Lin et al., 2013). Hence, we use the mean interest rate on a project as a dependent variable in our analysis of lending platforms.

RESULTS

Table 2 summarizes descriptive statistics by platform. Although Kickstarter and Indiegogo pursue a reward-based model, the average project size, or amount pledged for each project, differs substantially: $7,557 for Kickstarter versus $2,948 for Indiegogo. Likewise, discrepancies are observed for lending platforms; Lending Club has an average interest rate of 14.0% (St.Dev. 4.4%), while Zopa has an average rate of 7.0% (St.Dev 1.3%).

------- Insert Figure 2 and 3, and Tables 1-3 about here -------

The preceding table, Table 1, offers insights into common effect-classes such as project category and location. Specifically, six of the eight platforms include a project category field. A similar number of platforms also include a location field. Given that location and category are prevalent fields across different platforms, it is not surprising that most scholarly studies incorporate them in their analyses. We do observe a certain degree of disparity in terms of values or levels within each effect-class. The category effect-class takes as little as 15 unique values on Kiva, and as many as 58 unique values on reward platform Kickstarter. The values for location effect-class range from a low of 15 (Zopa) to a high of over 9,000 (Kickstarter). Our methodological approach controls for the resulting differences in degrees (also see Appendix A).

Table 3 reports our results, the size of the year, category and location effect for each platform. The key takeaway is twofold. First, the total variance explained by all three effects is different for each and every platform. Taken together, the three effect-classes of interest explain 44.54% of the dependent variable variance on the donation platform Kiva. They explain between about 7% and 11% in the lending platforms (i.e., LendingClub, Prosper, Zopa, and Funding

Circle), and only very small magnitude of variance on reward platforms (i.e., FundRazr, Kickstarter, and Indiegogo).

Second, while location, year, and category are common across platforms, they play different roles within each one. The magnitude of the effect-classes varies across platforms. For easier comprehension we demonstrate these magnitudes graphically in Figure 3. Consider the impact of location; while it explains about 43% of the variance in funding success in the donation-based Kiva, it exhibits negligible explanatory power for the other platforms. The category effect exhibits an important, yet smaller, impact. It explains only 0.03% of the variance in funding success on the reward-based Indiegogo and has over a hundred-fold larger effect on LendingClub, where it explains 3.82% of funding success. Finally, the year effect is relatively small for the reward platforms (0.16% for Kickstarter and 0.0% for Indiegogo), while it is larger on average for lending platforms (from a low 3.96% for LendingClub, to high 10.77% for Zopa).

Importantly, the results underscore significant disparity in funding patterns even within each crowdfunding type. Consider the size of the category effect on lending platforms. It accounts for 3.82% of the variance in funding success on LendingClub, yet it is almost tenfold smaller for the other USA-based lending platform, Prosper (only 0.48% of explained variance). We observe similar differences for the location effect. While the location effect explains 0.01% of the variance for Zopa, it is almost a fifty-fold larger on the other UK-based platform Funding Circle, where it accounts 0.49% of the full model variance. The year effect shows similar differences even within one crowdfunding type, ranging for example from a low of 3.96% for Lending Club to high of 10.77% for UK Zopa.

CONCLUSIONS

Our understanding of crowdfunding platforms is at a critical juncture. We explore whether crowdfunding patterns are generalizable across platforms. The results are striking. For example many platforms report the location of the project or its owner. We find that the association between location and ultimate funding success differs across platforms; on some platforms, it informs over a third of the variance, yet it has no explanatory impact on others. Similarly, most platforms group projects into categories as a way of speeding up and supporting funding allocation. We document a notable disparity in the ability to explain funding success; the impact of category varies a hundred-fold across the platforms we analyzed.

Our findings carry immediate implications. Consider a scholar who leverages crowdfunding data to study the role of location. Kickstarter and Indiegogo are two immediate choices as each platform lists over 8,000 locations. However, in our analysis Kiva is the platform where location explains the highest percentage of variance in funding success. Similarly, consider a scholar who studies the effect of sectoral affiliation (e.g., the impact of gender in traditionally feminine vs masculine sectors). Again, Kickstarter and Indiegogo emerge as the ideal setting as they have the largest number of sectors and categories. It is Lending Club, however, where funding success is most sensitive to project categories. Taken together, our results suggest scholars should carefully contemplate whether a platform's main dimension of variation fits with their theoretical focus.

Our work also highlights the opportunity for future crowdfunding work. At the current juncture, the literature has amassed studies that are both accurate and parsimonious. It now stands to benefit from work that is generalizable (Thorngate, 1976), such as in the opportunity to add to current studies which offer insights based on rich transactional data from a single platform and complement them with cross-platform studies that explicitly test for the heterogeneity among platforms (for notable exception, see Anglin et al., 2018; Cumming and Zhang, 2018). We hope whatever is lost in the way of accuracy is compensated by way of addressing issues of generalizability. The current study documents heterogeneity in funding patterns across platforms. Future work can build on this effort to advance a deeper understanding of crowdfunding investment drivers and contingencies.

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Table 1. Characteristics of each crowdfunding platform

	Kiva	FundRazr	Kickstarter	Indigogo	Lending club	Prosper	UK Zopa	Funding Circle
Type	Donation	Donation	Reward	Reward	Lending	Lending	Lending	Lending
Geographic focus	Africa/ Asia	Mostly North America	Mostly USA	Global	Mostly USA	USA	United Kingdom	United Kingdom
Dependent variable	Amount pledged	Amount pledged	Amount pledged	Amount pledged	Interest Rate	Interest Rate	Interest Rate	Interest Rate
Available effects	Year category location	-- category --	Year category location	Year category location	Year category --	Year -- location	Year -- location	Year category location
Period (years) in dataset	2005-14	n.a.	2009-14	2008-14	2014-17	2014-15	2011-13	2010-17
Number of different categories	15	21	58	31	22	29	n.a.	23
Number of different locations	2,586	n.a.	9,133	8,762	n.a.	79	15	32

Table 2. Descriptive statistics for each crowdfunding platform

	Kiva	FundRazr	Kickstarter	Indigogo	Lending club	Prosper	UK Zopa	Funding Circle
Number of observations	518,047	14,846	105,598	44,323	275,064	108,422	13,924,547	29,543
Dependent variable mean	453.4	1,247	7,557.2	2,948.37	14.0%	19.3%	7.0%	9.8%
Dependent variable standard deviation	228.8	3,331	70,880.1	61,338	4.4%	7.5%	1.3%	2.3%

Table 3. Variance Decomposition results for each crowdfunding platform

Effect	Kiva	Fund-Razr	Kick-starter	Indigogo	Lending Club	Prosper	UK Zopa	Funding Circle
Year[a]	0.86	n.a.	0.16	0.00	3.96	9.25	10.77	4.05
Category[a]	0.87	0.23	1.32	0.03	3.82	0.48	n.a.	2.19
Location[a]	42.81	n.a.	0.00	0.00	n.a.	0.51	0.01	0.49
Full Model[a]	44.54	0.23	1.48	0.03	7.78	10.24	10.78	6.73

Notes: a: In percent

Figure 1: Forces Shaping the Crowdfunding Phenomenon: Platform Proliferation and Differentiation

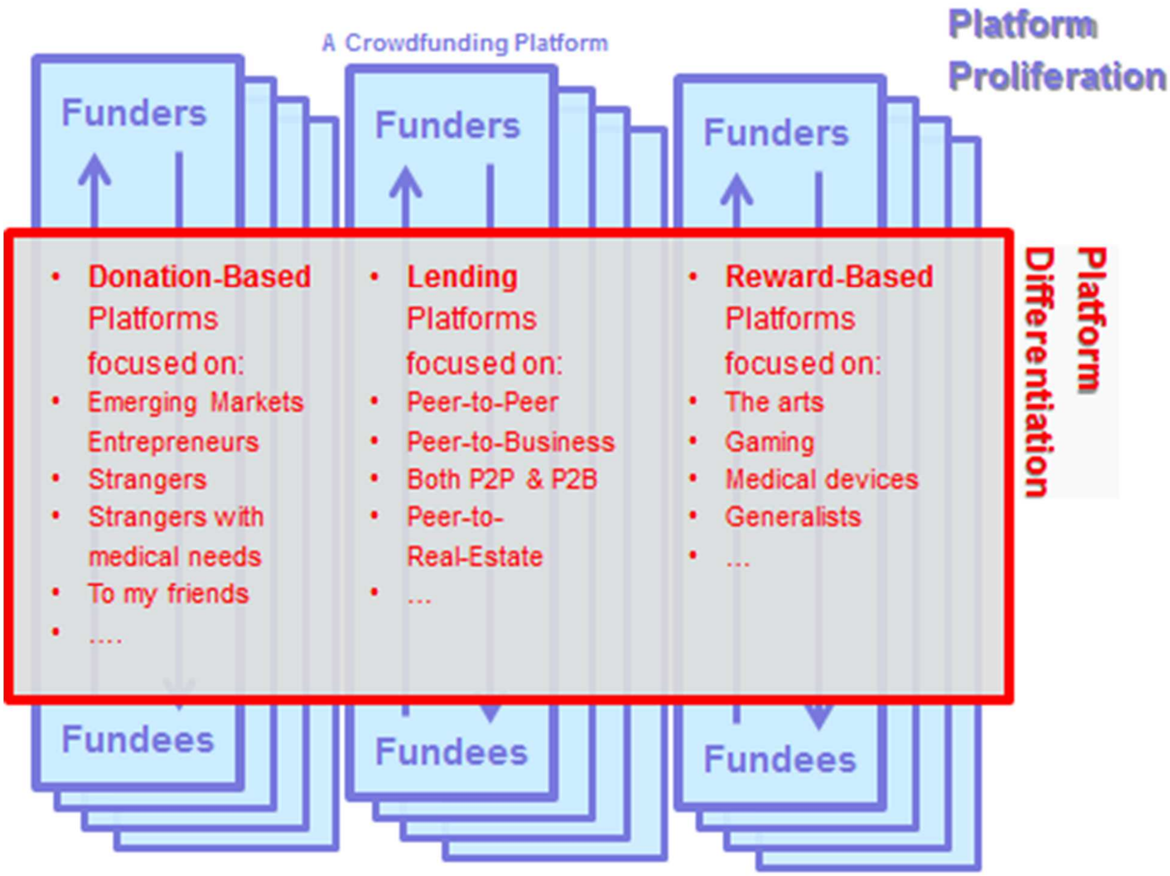


Figure 2: Looking Within a Platform versus Looking Across Platforms.

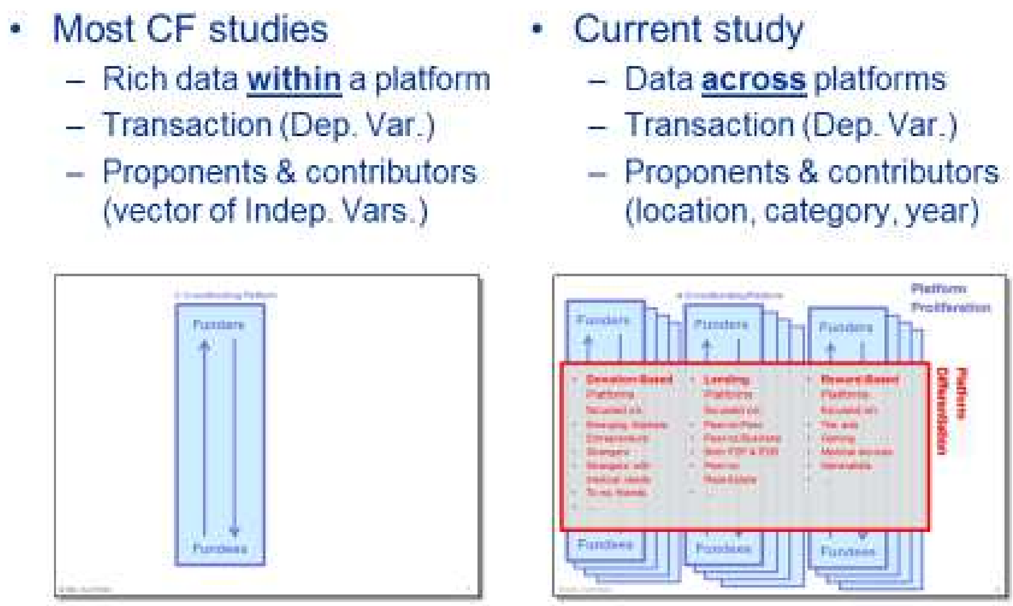
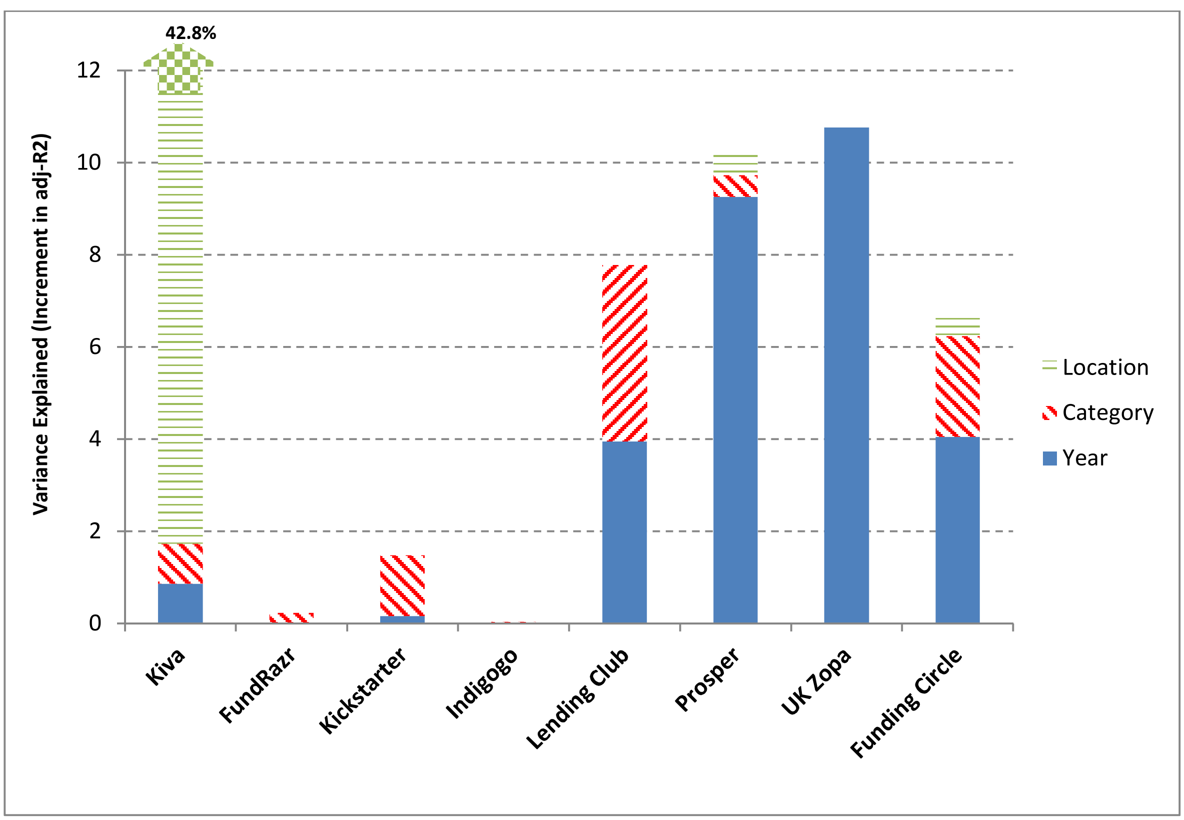


Figure 3: Graphical Comparison of Effect Sizes by Platform and Effect-Class.



Appendix A -- Sensitivity Analyses

We report a couple of robustness tests. The first addresses any concerns regarding the varying number of specific values for the location effect-class. The second tackles concerns regarding the fact there is a high variation in platform sample size across the eight platforms.

First, consider the issue of specific values for the location effect-class. Recall that our main analysis finds a large location effect for the Kiva platform. We are mindful of the fact that, on this platform, location is reported at the fine-grained level of a town, and because the platform covers projects from many different countries, the location effect undertakes some 2,586 different values (i.e., the names of 2,586 distinct towns). Other platforms report location at a coarser level (e.g., the state or the country). Therefore, one may be concerned that our results are merely an artifact of "location inflation", that the Kiva findings are merely due to the platform's use of town-level location effect of which there are 2,586 distinct values.

This concern is assuaged for the following reasons. First, there are two other platforms which utilize fine-grained location information: Kickstarter, with 9,133 unique values, and Indiegogo, with 8,762 unique values. Yet the location effect for these two platforms is an order of magnitude lower than that of Kiva's. Second, we conducted additional sensitivity analyses whereby we "aggregated up" Kiva's location from the town to the country level. The exercise yielded 64 distinct location values instead of the 2,586 unique values at the level of the town. We ran the variance decomposition again using these country-level location effect. The variance explained by location effect is now 32.2%. It is lower than the 42.8% we report for the original analysis based on town-level location effect. That said, at 32.2%, the location effect on the Kiva platform continues to dwarf the effect size on any other platform. Therefore, the additional analysis offers comfort that the location effect is not merely an artifact of "location inflation", but rather is indicative of the deep and meaningful role location has for participants on the Kiva platform. We conducted a similar analysis for Kickstarter. We "aggregated up" location, which decreased the number of unique location values from 9,133 to only 96. The results of the additional variance decomposition did not reveal any change to the location effect.

Second, consider the fact that sample size varies across the eight platforms. It ranges from 14,846 observations for the FundRazr platform to 13,924,547 for the Zopa platform. Our methodological approach controls for these differences (e.g., see Fitza, 2015, Graffin and Quigley, 2017). Nonetheless, we conducted additional analyses to further examine whether the results are an artifact of different sample sizes. To do so, we drew random subsamples of 15.000 observations from each crowdfunding dataset. Thus, in this analysis, the sample size for each platform has the same number of observations. To ensure that any specific subsample analysis is not an artifact of the specific subsamples, we followed Fitza and Tihanyi (2017) and conducted this analysis on multiple (100) subsamples for each platform and aggregated the results.

Table App-A. Results based on 100 randomly drawn samples from each platform of equal size.

Effect	**Kiva**	**Fund-Razr**	**Kick-starter**	**Indi-gogo**	**Lending Club**	**Prosper**	**UK Zopa**	**Funding Circle**
Year	0.78	n.a.	0.55	0.28	3.91	9.30	10.72	4.07
Category	0.65	0.23	1.75	0.29	3.74	0.47	n.a.	1.94
Location	42.20	n.a.	0.19	0.73	n.a.	0.54	0.02	0.46

Notes: a: In percent

Appendix B – More detailed results

Table App-B. Detailed description of variance decomposition results for each crowdfunding platform

	Kiva	**Fund-Razr**	**Kick-starter**	**Indigogo**	**Lending Club**	**Prosper**	**UK Zopa**	**Funding Circle**
Year Effect								
Fraction of full model variance explained be the effect	1.93	n.a.	10.94	0.00	50.90	90.41	99.89	60.15
F Value	38.29	n.a.	28.12	0.73	1688.05	1398.02	560028.00	184.06
Pr>F	<.0001	n.a.	<.0001	0.65	<.0001	<.0001	<.0001	<.0001
Category Effect								
Fraction of full model variance explained be the effect	1.95	1.00	89.06	100.00	49.10	4.64	n.a.	32.53
F Value	24.83	2.69	26.95	1.48	877.34	29.69	n.a.	7.86
Pr>F	<.0001	<.0001	<.0001	0.06	<.0001	<.0001	n.a.	<.0001
Location Effect								
Fraction of full model variance explained be the effect	96.12	n.a.	0.00	0.00	n.a.	4.95	0.11	7.32
F Value	7.65	n.a.	0.31	0.03	n.a.	13.23	169.76	18.26
Pr>F	<.0001	n.a.	1.00	1.00	n.a.	<.0001	<.0001	<.0001
Variance explained by full model[a]	44.54	0.23	1.48	0.03	7.78	10.24	10.78	6.73

Notes:
a: in percent