Do Learning Benefits Accrue Equally Over Successive Fundraising Attempts?

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Abstract

In the management literature, the role of learning from experience and its effect on performance has been highlighted. However, little is known about the effects of strategic changes on performance due to aspects retaining to the mobility of learning. Building on different learning theories, we theorize about the effect of strategic change on performance when: i) strategic change does not require the mobilizing of resources, ii) strategic change does not involve exposure to a new set of stakeholders, and iii) time commitment to previous strategies is low. We confront our contentions with data on serial campaign launchers in crowdfunding. The data indicates that changing industry adversely affects fundraising performance due to the specificity of a portion of the accrued learning. This adverse effect is mitigated by venture launching experience and exacerbated following failure. Implications for practitioners and scholars are discussed.

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1. Introduction

The role of learning and its effect on performance has been highlighted in different contexts (Barnett & Ceci, 2002; Lee & Chiravuri, 2019; Parker, 2013). Whether learning benefits do accrue with experience or not has been a subject of debate (Hmieleski & Baron, 2009; Hsu, 2007; Rocha, Carneiro, & Amorim Varum, 2015). Indeed, management scholars have identified different effects that experience might have on performance. While some studies suggested that individuals learn from experience (Delmar & Shane, 2006; Toft-Kehler, Wennberg, & Kim, 2014), others have highlighted that experience could adversely affect performance (Betton, Branston, & Tomlinson, 2019; Eggers, 2012; Simon, Houghton, & Aquino, 2000). To enhance our understanding of learning from experience in the business context, scholars have turned to the study of serial entrepreneurs. However, a caveat to prior analysis is that not all serial entrepreneurs' endeavors culminate into business ventures. The lack of information on venturing attempts that do not see fruition hinders our understanding of serial entrepreneurs' learning dynamics (Li & Martin, 2019; Sewaid, Parker, & Kaakeh, 2021). Moreover, some strategic changes might be the reason why entrepreneurs might be unable to secure funds to launch the subsequent venture in first place (Lee & Chiravuri, 2019). To gain better insight into learning dynamics in the business context, we turn to serial fundraisers on crowdfunding platforms. The strength of leveraging data from crowdfunding platforms is the ability to track both successful and unsuccessful venturing attempts , a feature not available in other contexts (Li & Martin, 2019; Sewaid et al., 2021).

Crowdfunding has emerged as a viable source of funding for entrepreneurs (Ahlers, Cumming, Guenther, & Schweizer, 2015; Belleflamme, Lambert, & Schwienbacher, 2014; Cumming & Johan, 2013; Guenther, Johan, & Schweizer, 2018; Mollick, 2014). The number of entrepreneurs that have returned to crowdfunding for their subsequent ventures has grown rapidly in recent years (Butticè, Colombo, & Wright, 2017). On Kickstarter, serial crowdfunders, that is entrepreneurs who launch multiple projects on the platform, have successfully raised $859 million up to November 2016 which accounts for more than 30% of the amount successfully raised on the platform. Serial crowdfunding research has highlighted that serial crowdfunders have increased access to platform-specific capital (i.e., social ties and prior crowdfunding experience) enhancing subsequent campaign performance (Butticè et al., 2017; Sewaid et al., 2021; Skirnevskiy, Bendig, & Brettel, 2017). Thus, serial crowdfunders benefit from their prior crowdfunding experience.

But do learning benefits accrue equally from prior experience, independently of what this experience was? The transfer of knowledge between ventures is not a simple process and depends on multiple dimensions. For example, Barnett & Ceci (2002) pose that learning can be hindered due to contextual differences between previous experience and current application; i.e., where this learning is transferred from and to. Management scholars take the same stance and identify the industry context as an important cornerstone of the venturing process (Eesley & Roberts, 2012). Furthermore, they highlight the implications of strategic changes, such as changing industries, on firm performance (Parker, 2013; Toft-Kehler et al., 2014). Similarly, between campaigns, crowdfunders might change the category of their new launches, making prior experience different to current efforts. Despite the relevance of the categorical context on campaign performance (Butticè, Orsenigo, & Wright, 2018), it has attracted limited scholarly attention. In particular, we still lack an understanding on how category change between campaigns affects fundraising performance. To this end, we adapt different learning theories to the crowdfunding context and contribute to the management literature through exploring three facets of serial crowdfunding and category change. First, we start by investigating the effect of the strategic decision, category change, on fundraising performance. Second, we explore how this effect differs given accumulated experience. Third, we examine how the effect of the given strategic change differs following failure. Our findings can be generalized to contexts where strategic change does not require a significant mobilizing of resources, does not involve exposure to a new set of stakeholders, and for cases where time commitment to prior strategies was limited.

We probe our research questions using the universe of Kickstarter's serial crowdfunders since its start up to November 2016. In that time period, we have a sample of 28,749 serial crowdfunders with 72,000 fundraising attempts. Our analysis reveals that learning from experience can be deconstructed into two segments: general learning and category-specific learning. By changing category, the entrepreneur foregoes category-specific learning benefits. However, there is still some general learning benefits that the entrepreneur could capitalize on. Additionally, we find evidence that individuals with higher levels of experience are less harmed by changing category. Thus, experience moderates the negative relationship between category change and fundraising performance. Regarding previous failure, our findings support the notion that the adverse effect of category change is intensified following failure. Entrepreneurs that respond to failure by changing category are less likely to recognize their own flaws and might be attributing failure to external factors. Therefore, they are less likely to learn from their failure. Moreover, one could also think that changing category adds another layer of complexity that intensifies barriers to learning.

In theoretical terms, our study seeks to make a twofold contribution to the management literature. First, we apply a new theoretical lens to further extend the management literature on learning. Building on different learning theories, our study aims to provide a more holistic overview of the effects of strategic changes in contexts where a strategic change does not require mobilizing own resources (Murray, Kotha, & Fisher, 2020), does not involve exposure to a new set of stakeholders (Kuppuswamy & Bayus, 2018), and where time commitment to prior strategies is limited (Butticè et al., 2017; Mollick, 2014). Our findings contradict those of prior studies that investigated the effect of contextual change without accounting for experience (Lee & Chiravuri, 2019), and studies that investigated the effect of experience without accounting for contextual changes between campaigns (Yang & Hahn, 2015). Specifically, we find that category change is negatively associated with fundraising performance and that entrepreneurs do not rebound after failure. On the contrary, failure is negatively associated with subsequent campaign performance. Second, in addition to the direct effects of experience, we suggest that similarities in the venturing process can alleviate barriers to learning that stem from contextual differences. This provides new insights for the management literature and complements prior work that investigated contextual similarities as an alleviator of barriers to learning from venturing differences (Gick & Holyoak, 1987; Toft-Kehler et al., 2014).

The rest of this paper is organized as follows. In Section 2 we present the underlying theoretical framework and develop the hypotheses that we will empirically test in this paper. In Section 3 we present the data that we will build our analysis on, as well as define the variables of interest to us in this study. The results of our main analysis along with the robustness checks, are discussed in Section 4. In Section 5 we discuss the implications of our findings, the limitations, and the possible areas for fruitful future research. Section 6 concludes our paper.

2. Theoretical Development

Constructing a campaign involves taking decisions regarding many factors: the rewards offered (Colombo, Franzoni, & Rossi-Lamastra, 2015; Du, Li, & Wang, 2018), prices (Hu, Li, & Shi, 2015; Schwienbacher, 2018), pitch style (Anglin, Wolfe, Short, McKenny, & Pidduck, 2018; Johan & Zhang, 2020; Parhankangas & Renko, 2017), and media content (Courtney, Dutta, & Li, 2017; Scheaf et al., 2018). It seems natural to expect that prior campaign launching experience might help when developing the current campaign (Butticè et al., 2017; Sewaid et al., 2021; Yang & Hahn, 2015). However, between campaigns, serial crowdfunders might make behavioral decisions (Sewaid et al., 2021) affecting current performance or strategic decisions (Lee & Chiravuri, 2019) that deem previously launched campaigns different or even irrelevant.

The most prominent change that an entrepreneur could take when re-venturing is to change industry (Delmar & Shane, 2006; Klepper, 2002). In the traditional venturing context, the role of the entrepreneur's prior industry experience has been extensively studied. Several studies have shown the association of industry experience with new firm survival and performance (Bosma, van Praag, Thurik, & de Wit, 2004; Brüderl & Preisendörfer, 1998; van Praag, 2003). These findings suggest that many of the skills required to launch a venture and effectively exploit an opportunity are industry-specific (Delmar & Shane, 2006). Indeed, Eggers & Song (2015) highlight, through an analysis of serial entrepreneurs, the effect that changing industry has on performance.

In the crowdfunding context, when launching a campaign, crowdfunders identify the category to which the project belongs. The category to which a project belongs has been widely used as a proxy for industry (Allison, Davis, Webb, & Short, 2017; Butticè et al., 2017; Oo, Allison, Sahaym, & Juasrikul, 2019; Scheaf et al., 2018). Soliciting funds for a new project in a different category changes the contextual domain of the current campaign (Toft-Kehler et al., 2014). Previous studies that have looked into the effect of changing category failed to account for the value that prior experience might have (Lee & Chiravuri, 2019). While studies that have investigated the role of experience failed to account for category changes between campaigns (Yang & Hahn, 2015). If we turn to findings from the serial entrepreneurship literature (Wright, Robbie, & Ennew, 1997), we know that their analyses fail to account for venturing efforts that do not culminate into actual ventures. We acknowledge that crowdfunding campaigns do not resemble all traditional venturing activity. However, our arguments and findings are extendable to traditional contexts that share three main characteristics with crowdfunding. Namely, 1) contexts where strategic change does not require a significant mobilizing of resources, 2) contexts where strategic change does not involve exposure to a new set of stakeholders, and 3) contexts where time commitment to prior strategic choices is limited.

Following the above description, we have three goals in this section. First, we sort among different learning theories to offer the most plausible effect that category change could have on fundraising performance. Second, we scrutinize the moderating role of experience to identify whether it amplifies or mitigates the effect of category changes. Third, we consider different behavioral theories of learning from failure to analyze whether the effect of changing category varies with previous outcome.

2.1 Learning Theories, Category Change, and Performance

In the crowdfunding context, Butticè et al. (2018) argue that learning benefits are diminished and that serial crowdfunders do not acquire knowledge over campaigns. Their argument builds on the fact that crowdfunding platforms publicly host crowdfunding campaigns after their completion. Hence, crowdfunders can easily learn by observing prior campaigns and replicate the "winning" strategies. Butticè et al. (2017) and Skirnevskiy et al. (2017) attribute serial crowdfunders' superior fundraising performance to the community developed on the platform rather than to learning benefits from prior launching experience. This approach considers that there is too little to learn from prior experience, and that campaign launching experience, by itself, yields no durable learning benefits (Parker, 2013; Weick, Sutcliffe, & Obstfeld, 1999). Given that the community of backers on the platform are mobile across categories and given that no learning benefits accrue from prior category experience, these arguments suggest that changing category yields no benefits nor harms in terms of campaign performance.

Yet, other scholars have highlighted that prior experience is both relevant and significantly affects fundraising performance (Anglin, Short, et al., 2018; Scheaf et al., 2018; Sewaid et al., 2021), casting some doubt on the prior argument that changing category does not affect performance. Yang & Hahn (2015) found that, although prior experience enhances campaign performance, an increase in the number of successful launches decreases current performance. They argue that an increase in the number of successful launches fosters overconfidence. Indeed, overconfidence is well documented in the crowdfunding context (Mollick & Kuppuswamy, 2014). The venturing process is complicated and mere replication of previous practices may lead to inaccurate inferences and generalizations (Betton et al., 2019; Levitt & March, 1988). By changing category between campaigns, the entrepreneur will more likely indulge in acts of reflection on previous experience, rather than replicate previous strategies. Hence, changing category could enhance current campaign performance through countering the adverse effects of overconfidence and the improper generalizations made from prior crowdfunding experience.

Nonetheless, we doubt the positive effects that changing category might have among serial crowdfunders due to three main reasons. First, if a serial entrepreneur exhibits overconfidence, costly strategic choices that involve mobilizing financial resources will likely temper down this overconfidence (Forbes, 2005). Thus, leading to positive effects of category change. Nevertheless, crowdfunders do not need to mobilize their own financial resources when changing category (Murray et al., 2020). In case the campaign fails to raise the needed capital, the crowdfunder's financial risk will be limited to campaign preparation expenses (prototype development, video shooting, photo editing, content proofing). These expenses are relatively low compared to the costs associated with actually launching a venture. However, if the campaign is successful in raising the required funds, backers will assume the risk associated with reward delivery (no delivery, late delivery or low quality). Thus, the downside risk for crowdfunders is limited and there is no additional financial risk attributed to changing category that can counter the adverse effects of overconfidence.

Second, if the strategic choice involved exposure to a new set of stakeholders, this could stimulate proper preparation (i.e., industry and market analysis) countering any improper generalizations made from prior experience (Betton et al., 2019). However, what if the adopted strategic choice does not involve exposure to a new set of stakeholders? Crowdfunders interact with a relatively stable population of backers on the platform, whom are stable across categories. Moreover, reputation built on the platform is public and easily visible by new potential backers regardless of the category (Li & Martin, 2019). This feature will likely lead serial crowdfunders to "rest on their laurels" rather than being more "pro-active" when launching a new campaign in a new category. Thus, changing category in the crowdfunding setting might not help in countering any adverse effects of the improper generalizations or overconfidence.

Third, if time commitment to prior strategies was extensive, the entrepreneur would have spent enough time developing one venture in order to fully apprehend its dynamics. However, in crowdfunding, campaign duration is capped at 60 days (Mollick, 2014). Moreover, campaign launches are rapid, with serial crowdfunders launching more than one campaign in a year (Butticè et al., 2017; Skirnevskiy et al., 2017). Rapid relaunching involves no sufficient time between ventures in order to reflect on previous outcome and effectively reapply it to a different context These time-related issues cast additional doubt on the notion that serial crowdfunders can effectively reflect on previous crowdfunding experience and reapply it to a different context.

That being said, we expect that, among serial crowdfunders, changing category will be negatively associated with campaign performance since changing category can act as a barrier to the transfer of learning between campaigns (Toft-Kehler et al., 2014). Given that research has highlighted differences in the drivers of fundraising performance across categories (Butticè et al., 2018), if the generalizations made from prior experience were improper, they should be more applicable to a venture in the same category. Additionally, an alternative explanation is associated with the type of knowledge accumulated over ventures: general and category-specific knowledge. On the one hand, if serial crowdfunders remain in the same category, they will benefit from both the category-specific and the general knowledge accrued over ventures. However, those serial crowdfunders who change category will lose their category-specific knowledge and will be able to capitalize only on the general knowledge acquired over ventures. If this was true, then we would expect the prior experience's effect to be positive for both category and non-category changers. These arguments culminate in the following hypotheses:

Hypothesis 1a. *Changing category is negatively associated with fundraising performance.*

Hypothesis 1b. *Prior experience is positively associated with fundraising performance for both category changers and non-changers.*

One final remark is in order. It is possible that hypothesis 1a is supported and, at the same time, hypothesis 1b does not follow. If hypothesis 1b is supported, then we will have some empirical evidence suggesting that learning benefits in crowdfunding has two dimensions: a general knowledge dimension and a category-specific knowledge dimension. The general knowledge dimension is mobile across contexts, while the category-specific knowledge remains immobile. However, if hypothesis 1b is not supported, we will conclude that learning benefits in crowdfunding are exclusively category-specific and that they are immobile across contexts.

2.2 Experience and Category Change

Cope (2005) defines entrepreneurial learning as a task where much of the learning is context-specific, where prior experience within a context can directly affect performance. Besides the direct effects of experience, a strand in the literature also suggests that experience plays a moderating role in different contexts (Anglin, Short, et al., 2018; Brunel, Laviolette, & Radu-Lefebvre, 2017; Chaston & Sadler-Smith, 2012; Farmer, Yao, & Kung-Mcintyre, 2011; Hmieleski & Baron, 2009; Hughes, Hughes, & Morgan, 2007; Sommer & Haug, 2011). The moderating role that experience might play depends on the learning benefits that accrue with experience. If learning is difficult or if there are no benefits from learning (Butticè et al., 2018; Parker, 2013), then it will follow that experience should have no direct or indirect effects on performance. However, if there are learning effects that accrue with experience (positive or negative), then it will be plausible that experience could indirectly affect performance.

As we have previously argued, although the benefits of learning diminish when changing category there are still some learning benefits associated with prior experience. This suggests that a share of the learning benefits is transferable across categories. These learning benefits could be attributed to the similarity in those tasks required to identify an opportunity and launch a venture (Barnett & Ceci, 2002). With higher levels of experience, the entrepreneur has a wider set of previous experiences that act as a reference for the tasks to be carried out in the current venture (Tversky &

Kahneman, 1992). Indeed, it has been shown that serial entrepreneurs with higher levels of experience are able to respond quicker to a challenge and generate fast and effective heuristics (Ucbasaran, Westhead, & Wright, 2008). Serial entrepreneurs are better able to effectively apply knowledge from their prior efforts to their current endeavors (Toft-Kehler et al., 2014). Furthermore, learning from prior experiences also strengthens entrepreneurs' ability to process and respond to complex information (Lord & Maher, 1990) and stimulates creativity (Amabile, 1997).

Along similar lines, we argue that crowdfunders with higher levels of experience can draw better inferences from the knowledge acquired through previous exposure to the tasks involved in launching a campaign. Additionally, given their familiarity with the crowdfunding platform and its dynamics, they can identify opportunities better even if these opportunities are not within the same category of their prior ventures. Therefore, in addition to the direct effect of experience on performance, we expect experience to lessen the negative relationship between category change and fundraising performance. Thus, we predict:

Hypothesis 2. *Experience mitigates the adverse effects of category change on fundraising performance.*

2.3 Learning from Failure, Failure Attribution, and Category Change

Entrepreneurs might face cognitive limitations when learning from previous venturing experience. This is due to the complex nature of the venturing process (Levinthal & March, 1993). These cognitive limitations might act as a barrier to learning, such that learning does not occur regardless of the previous venture performance. Prior performance might be irrelevant in contexts where learning yields no sustainable benefits (Butticè et al., 2018; Parker, 2013). When prior performance is irrelevant, then the effect of changing category will not differ given the previous campaign outcome.

Behavioral theories of learning suggest asymmetry in learning, where entrepreneurs *learn from* and *respond to* different outcomes differently (Cope, 2011). This is corroborated by Yang & Hahn's (2015) where the authors suggest that even though learning takes place as crowdfunders accumulate crowdfunding experience, this learning could be cyclical in nature. Following success, crowdfunders may fall into "complacency traps" which adversely affect subsequent campaign performance (March, 1991), while following failure crowdfunders become more proactive, enhancing subsequent campaign performance (Kim, Kim, & Miner, 2009; Rerup, 2009). Taking this evidence into consideration, when hypothesizing about the possible effect that category changes might have, we consider that the negative effect of changing category should be less, in absolute terms, following failure compared to the case of following success, given the entrepreneur's proactive behavior and the caution when deciding to change category. However, two main arguments derived from the literature on learning from failure and failure attribution question the validity of this presumption.

First, the literature shows that learning from failure is not a straightforward process and improper inferences can be made (Denrell & March, 2001; Eggers, 2012). As a result of failure, an entrepreneur learns what does not work rather than what works. Furthermore, failure might drive entrepreneurs into downward performance spirals (Singh, Corner, & Pavlovich, 2007) rather than represent the "fire that tempers the steel" (Timmons, 1999). This suggests that learning from failure is more complex than learning from success (Baumard & Starbuck, 2005). In any case, introducing a contextual change to the process of new campaign launch increases the complexity of the information that the entrepreneur needs to process (Lord & Maher, 1990). When we combine more complexity with previous venture failure, the entrepreneur will face more obstacles in transferring knowledge among ventures. As a result, the adverse effect of previous failure is amplified by a change in category.

Second, learning from failure would require the recognition of the causes of failure for it to yield any benefits (Cannon & Edmondson, 2001). According to attribution research, individuals tend to take credit for success, while blame factors beyond their control for failure (Jones & Harris, 1967). This behavior has been well documented in the venturing context (Eggers & Song, 2015). By blaming failure on external factors (e.g., industry, competition, customers, suppliers), entrepreneurs fail to recognize internal reasons for failure (e.g., strategy, management, planning) impeding their ability to learn from failure. In search for success, these entrepreneurs will take actions that change their exposure to the blamed external factors, rather than reflect on the internal causes of failure. Following this approach, entrepreneurs who respond to failure by changing category will more likely fail to recognize previous causes of failure. Hence, they are less likely to reflect and learn from their previous failure. Due to the above considerations, we suspect that the adverse effect of changing category is intensified following failure. Thus, we hypothesize:

Hypothesis 3. *The negative association between changing category and fundraising performance is amplified following failure.*

3. Data and Methodology

To examine the role of category change on fundraising performance we collect data from Kickstarter, the leading reward-based crowdfunding platform which has been widely used in previous crowdfunding research (e.g., Butticè et al., 2017; Colombo et al., 2015; Courtney et al., 2017; Kuppuswamy & Bayus, 2017; Mollick, 2014). Our initial dataset covers all observations (297,884 projects) between April 21st, 2009 and November 29th, 2016. Out of these, 75,654 projects were launched by 29,788 serial crowdfunders. During that period, serial crowdfunders successfully raised $859 million, accounting for more than 30% of the funds raised on Kickstarter. Since category change is defined as a change in category from that of the prior campaign, we drop the first observation for all crowdfunders. This reduces the sample to 45,866 projects.

In Table 1 we provide some insight into the serial crowdfunders' performance presented by the number of projects launched by each serial entrepreneur. The average success rate of entrepreneurs with 5 projects or more is 61.72% compared to a 38.65% success rate of entrepreneurs with 2 projects. Additionally, successful entrepreneurs with 5 projects or more raise, on average, $30,376 compared to $20,571 raised on average by those entrepreneurs with 2 projects. This preliminary evidence suggests that those entrepreneurs with higher levels of experience are more likely to be successful in their crowdfunding efforts and raise more funds on average.

[Table 1: About Here]

To conduct our analysis, following Mollick (2014), we drop non-serious crowdfunding attempts from our sample. Specifically, we drop campaigns with goals less than $100 or greater than $1,000,000. This leaves us with a final sample of 43,251 subsequent campaigns launched by 28,749 serial crowdfunders.

3.1 Dependent Variables

We examine the effect that category change has on two outcomes of interest in crowdfunding research: the success of the campaign and the amount raised. Unlike other platforms with a Keep-it-All mechanism, Kickstarter is a crowdfunding platform with an All-or Nothing mechanism. In such a setting, the campaign goal must be met in order for the funds to be disbursed to the entrepreneur. This suggests that an appropriate measure of campaign performance is whether the campaign was successful in reaching its goal or not. Given this, we have our dependent variable defined as *Success*, which takes the value 1 if the campaign goal is met and 0 otherwise. Past crowdfunding research has also used continuous measures of success, such as the amount of funds raised and the number of backers (e.g., Anglin, Short, et al., 2018; Anglin, Wolfe, et al., 2018; Butticè et al., 2017; Colombo et al., 2015; Courtney et al., 2017) to evaluate the performance of crowdfunding campaigns. In line with this research, we additionally measure campaign performance with a continuous variable accounting for the amount of funds raised during the campaign. This variable presents a positive skewness which poses analytical challenges and adversely affects the model's performance. The most popular approach in this case is to apply a natural log transformation to correct for the skewness. However, since this variable has zero values, this prevents us from using the natural log transformation. To transform right-skewed variables that include zero values, the inverse hyperbolic sine transformation is frequently applied in the literature since it is defined at zero. Moreover, its interpretation remains identical to that of variables transformed using the natural log (Burbidge, Magee, and Robb, 1988; Franke and Richey, 2010; Sauerwald, Lin, and Peng, 2016). Thus, we follow Anglin, Short et al. (2018) and use the inverse hyperbolic sine transformation to treat this variable, $\sinh^{-1}(y) = \log\,[y + (y^2 + 1)^{1/2}]$. We denote this additional measure of fundraising performance as *Amount Raised*.

3.2 Independent Variables

Entrepreneurs on the crowdfunding platform have the freedom to launch campaigns in different categories, with no platform-specific barriers. Given the absence of restrictions and the proximity between some of these categories, there are instances where entrepreneurs relaunch a failed campaign in a different category. Launching the same campaign in a different category does not imply a strategic change and should not be treated as change in category. Hence, capturing category change using a dummy variable is prone to misspecification. To circumvent this issue, we operationalize our independent variable, *Category Change*, using two components. First, we construct the variable *Category Switch* that captures switches in category affiliations and takes the value 1 if the current campaign category differs from the previous campaign's category and 0 otherwise. Second, we construct the variable *Project Similarity* that compares the textual similarity between the current and previous campaign using the Levenshtein textual similarity algorithm. This construct takes a value between 0 and 100%. In the extremes, campaigns with identical description would score 100% whereas campaigns with no textual similarity would score 0%. Finally, using these components we construct our independent variable *Category Change, where*:

Category Change = *Category Switch* x (*1 – Project Similarity*)

This category change distance measure overcomes issues related to the use of the dummy variable *Category Switch*. Relaunching an identical campaign in a different category would no longer be treated as a change in category. Additionally, similar campaigns launched in different categories would score lower on this construct relative to dramatically different category switches.

3.3 Interaction Variables

In our hypothesis we posit that more experienced crowdfunders suffer less from changing context. Thus, we expect that the degree of task similarity arising from prior experience will moderate the negative effects of category change. To account for this, we first collect information on the number of campaigns launched by the entrepreneur prior to the current project. We denote it by *Crowdfunding Experience*. Then we examine the interaction between crowdfunding experience and category change. We denote it by: *Crowdfunding Experience* x *Category Change*. In Figure 1 we present the success rate of projects (with and without category switches) over the number of ventures launched, an increasing pattern in the success rate over the number of ventures can be noticed. However, the increasing patterns do not seem to exhibit the same slope.

[Figure 1: About Here]

We also hypothesize that the effect of changing category following failure is more severe. To capture this effect, we control for previous campaign outcome using the variable *Failure* which will take the value 1 if the previous campaign goal is not met, and 0 otherwise. We additionally interact this variable with category change, *Failure* x *Category Change*. In Table 2, we present the percentage of category switches grouped by previous campaign outcome along with the success rate of their current campaigns. We note that, following failure, the percentage of crowdfunders that switch category is higher by 48.97% (from 17.50% to 26.07%). Moreover, the adverse effect of category switch becomes more severe following failure where the average success rate is 41.45% lower (from 33.63% to 19.69%) than that of campaigns that do not switch category. In contrast, following a success, the average success rate is only 13.62% lower (from 76.06% to 65.70%) than that of campaigns that do not change category.

[Table 2: About Here]

3.4 Control Variables

To account for other determinants of fundraising performance, we include several control variables that are consistent with previous literature on crowdfunding (Anglin, Wolfe, et al., 2018; Butticè et al., 2017; Colombo et al., 2015; Courtney et al., 2017; Mollick, 2014). First, we start by controlling for factors related to previous crowdfunding attempts. We construct *Project Similarity* to control for the percentage of textual similarity between the current and previous campaign description using the Levenshtein textual similarity algorithm. We control for *Time between Projects* by counting the number of days that have passed since the end of the previous campaign and the start of the current campaign. We also control for whether the campaign is launched in a different location relative to the previous campaign, Location Change *(0 = no location change, 1 = location change)*. Second, we control for factors attaining to the campaign's content. We control for the project goal size and call it *Project Goal*. Due to the significance of the number of rewards offered by an entrepreneur in a reward-based crowdfunding setting, we control for the number of rewards by using the variable *Rewards*. We additionally account for whether the project has a video pitch or not, using a dummy variable *Video Pitch (0 = no video pitch, 1 = video pitch available)*. Furthermore, we also control for the count of videos on the campaign page and denote it by *Video Count*. The variable *Image Count* refers to the number of images in the campaign webpage and *Text Length* is the length of the text included in the campaign's webpage in thousands. Additional control variables in our analysis are the *Duration* of the campaign, *Category* to which the project belongs, and the *Year* of launch. Finally, due to the right skewed distribution and the zero values observed in some of the continuous variables in our control, we treat these variables using the inverse hyperbolic sine transformation which is defined at zero values (Anglin, Short, et al., 2018).

3.5 Estimation Models

To test the effects of category change, previous campaign outcome, and the interaction terms on campaign performance, our analysis relies on the analysis of the entrepreneur's subsequent launches. However, the decision to relaunch a campaign might not be independent from previous campaign's outcome, thus posing some major self-selection issues (Chen, 2013). To address this, we adopt the two-stage Heckman sample-selection correction to our panel data structure through estimating a system of equations (Heckman, 1979). In the first stage, using a probit model, we estimate the probability of launching a subsequent campaign given current campaigns' and entrepreneurs' characteristics. This is conducted using the population of crowdfunders (serial and non-serial). Variables pertaining to subsequent relaunch (project similarity, time between projects, and location change) are omitted since such information is not available for the crowdfunders' first campaign. This estimation model is used to generate the inverse Mills ratio (IMR) which we associate with the subsequent campaign (if any). In the second stage, we include the IMR as an independent variable in our main estimation models to correct for any selection bias (if present). Since the two-stage Heckman sample-selection correction grants identification by an exclusion restriction, at least one parameter included in the selection equation should be excluded from the main analysis. Absent better exclusion restrictions, subcategory dummies (Z) were only included in the selection equation (Cumming, Meoli, & Vismara, 2021). The econometric specification of the first-stage (selection equation) is represented by Equation (1), and the general main model econometric specification is represented in Equation (2):

$$Pr(Relaunch_{i,t}) = X_{i,t}\gamma_1 + Z_{i,t}\gamma_2 + u_{i,t} \tag{1}$$

$$E\left[Fundraising\ Performance_{i,t} \middle| X_{i,t},\ Relaunch_{i,t} = 1\right] = X_{i,t}\beta + \lambda\ IMR_{i,t} + \varepsilon_{i,t} \tag{2}$$

To model the probability of crowdfunding success we use a panel logistic regression model which we denote as Model A in Table 5. We report the coefficients and clustered standard errors (the latter ones in between brackets) and continue with an analysis of the marginal effects. In Model B in Table 6, we use a panel ordinary least squares (OLS) estimation with clustered standard errors to estimate the amount of capital raised (*Amount Raised*). Both Models A and B are specified with random effects because including individual fixed effects would eliminate the variance in our individual-level predictor, crowdfunding experience (Toft-Kehler et al., 2014).

4. Results

Table 3 provides the descriptive statistics of our sample. Table 4 presents the correlations and the variance inflation factors (VIFs) of our independent variables. The average VIF (1.24) and the maximum VIF (1.50) are well below the thresholds established in the literature (Hair, Black, Babin, & Anderson, 2010; McDonald & Moffitt, 1980; Neter, Wasserman, & Kutner, 2018; Tabachnick & Fidell, 2007). Therefore, these results indicate no concerns regarding multicollinearity issues with our subsequent analyses. In Tables 5 and 6 we start by reporting the selection model used to generate the IMR that we apply to subsequent models. In Model A (I), presented in Table 5, we consider the effects of crowdfunding experience and the control variables on the probability of success. In Model B (I), presented in Table 6, we observe similar effects on the amount of funds raised. The only difference between the two approaches is that although a larger campaign goal is negatively associated with the probability of success, it exhibits an opposite relationship with the amount of funds raised. The results provided for these two dependent variables are consistent with the findings of previous literature.

[Table 3: About Here]

[Table 4: About Here]

Hypothesis 1a suggested that changing category will be negatively associated with fundraising performance. In Model A (II) and Model B (II), the coefficient of *Category Change* was negative and significant (*p-value* < 0.01). Therefore, these results provide support for hypothesis 1a. The results of the marginal effects indicate that, on average, changing category (from 0 to 1) is associated with a 31.00% reduction in the probability of success (from 48.22% to 33.27%) and a 51.46% decrease in the amounts of funds raised. Hypothesis 1b suggested that if learning has both general and category-specific benefits, then the role of crowdfunding experience will be significant for both category changers and non-changers. In Model A (III-IV) and Model B(III-IV), the coefficient of *Crowdfunding Experience* is positive and significant (*p-value* < 0.01), for both groups supporting hypothesis 1b. Category changers suffer from inferior campaign performance due to abandoning category-specific knowledge acquired over previous campaigns. However, they are still able to capitalize on the general knowledge acquired over previous launches.

Hypothesis 2 suggested that the negative effect of changing category becomes less severe with an increase in launching experience. In Model A (V), the interaction term between *Crowdfunding Experience* and *Category Change* is positive and significant (*p-value* < 0.10). Concerning Model B (V), the moderating effect of crowdfunding experience on the amount of funds raised is also positive and significant (*p-value* < 0.01). Therefore, these results support hypothesis 2. We plot the interactions in Figures 2a and 2b. At the average crowdfunding experience, we find that a change in category is associated with a 31.01% decrease in the probability of success (from 48.21% to 33.26%) and a 52.62% decrease in the amount of funds raised. When we increase crowdfunding experience by 1 SD (standard deviation), we find that the effects of changing category are relatively less severe, such that a change in category is now associated with a 27.18% decrease in the probability of success (from 50.99% to 37.13%) and a 41.85% decrease in the amounts of funds raised. From the interaction plots, we also note that for extremely high levels of crowdfunding experience the entrepreneur is able to raise higher levels of funding when changing category, but the probability of meeting the minimum capital requirement is lower. Hence, even though experienced crowdfunders can benefit by changing category through capitalizing on backers from the previous category, acquiring new backers from the new category will be a relatively-risky strategy.

[Figure 2a and 2b: About Here]

Finally, hypothesis 3 suggested that the negative effect of changing category is more severe following a failed campaign. In Model A (VI) and Model B (VI), the coefficient of the interaction term between *Failure* and *Category Change* is negative and significant (*p-value* < 0.01). More specifically, changing category after a failed campaign is associated with a 36.80% decrease in the probability of success (from 35.78% to 22.61%) and a 54.39% decrease in the amount of funds raised. However, following success, changing category is only associated with a 16.61% decrease in the probability of success (from 66.56% to 55.50%) and a 32.08% decrease in the amount of capital raised. Our results indicate that, first, changing category is negatively associated with campaign performance, regardless of previous campaign outcome and, second, as hypothesized, this negative effect is more severe following failure, thus supporting hypothesis 3.

[Table 5: About Here]

[Table 6: About Here]

4.1 Robustness Tests

To ensure the robustness of our results, we run series of additional tests. First, our analysis focuses on learning effects in serial crowdfunding and does not control for social capital measures due to high correlation ($\rho > 0.60$). However, prior literature shows the significant role that *social capital*, the community of backers that serial crowdfunders accumulate on the platform, plays in subsequent campaigns' performance (Butticè et al., 2017; Skirnevskiy et al., 2017). To rule out an alternative explanation that our results might have been driven by social capital rather than learning effects, we repeat our analysis using social capital. The result shows that our main finding holds, changing category adversely affects campaign performance. Interestingly, social capital does not mitigate the adverse effects of changing category. Hence, only learning through launching mitigates the adverse effect of changing category and not the social capital accumulated on the platform. The results are reported in Table 7 Columns (I – II). Second, endogeneity concerns might arise given that current strategic choices might be affected by previous performance or accumulated experience (Cumming, Leboeuf, & Schwienbacher, 2019). To that end, serial crowdfunders changing categories might differ from their counterparts. For instance, “worse” or “inexperienced” entrepreneurs who failed in identifying the correct category in the first campaign might respond by changing category in the subsequent campaign. If this is the case, then experience and previous outcome are confounding factors biasing our results. To that end, we proceeded with two approaches to fully validate our results. We split our sample into campaigns following failure and campaigns following success and repeated our analysis. The results are reported in Table 7 Columns (III-IV). Additionally, we performed coarsened exact matching (Iacus, King, & Porro, 2012) and matched campaigns with a change in category with campaigns without a change in category along the constructs associated with category change (previous campaign performance and crowdfunding experience). Out of a total of 9,634 campaigns with a category change, 9,629 campaigns were matched with similar campaigns with no category change (a match could not be identified for 5 campaigns). We repeat our main analysis for our two main dependent variables and report the results in Table 8. The results of both approaches garner confidence in the main results initially reported.

[Table 7: About Here]

[Table 8: About Here]

Third, the crowdfunding literature has used different proxies for campaign performance. Although in our analysis we have consistent results for the two dependent variables investigated, success and amount raised, we proceed by investigating the main effects discussed earlier on an alternative campaign performance measure, the number of backers. Once again, we find no differences in the effects presented with the main results. The results are reported in Table 7 Columns (V-VII). Fourth, we relax some of the restrictions in our main analysis. Namely, we repeat our analysis using the dummy variable *Category Switch*, which is not scaled by current and previous campaign similarity. The analysis is run on the full dataset of serial crowdfunders on Kickstarter and similar findings are reported in Table 9. Fifth, in our analysis we have looked at change in category relative to the previous campaign. However, what we measure as a change in category could be a return to a category where the crowdfunder had previous experience. In order to get a more "accurate" measure of category change, we repeat our analysis using serial crowdfunders' second campaigns. Our initial results regarding the adverse effects of category change hold. Finally, in our analysis we have used panel regressions to account for the panel-level variance component. As a robustness check, we replicate the process used to yield the results in Table 5 and 6 by using pooled logistic and OLS regression models. The results are also in line with our prior findings.

[Table 9: About Here]

5. Discussion

In this study we examine how changing category negatively affects fundraising performance and how this barrier to learning can either be alleviated by the accumulated crowdfunding experience, or intensified by previous campaign failure. We pose that entrepreneurs with higher levels of experience are able to make better generalizations when venturing into a new category relative to others with lower levels of experience (Tversky & Kahneman, 1992). We find supporting evidence that the effect of changing category is moderated by experience. Regarding previous failure, previous studies have suggested that serial crowdfunders exhibit cyclical learning, such that success predicts underperformance while underperformance contains the seeds of future over-performance (Yang & Hahn, 2015). We argue that even though serial crowdfunders' fundraising performance exhibits a cycling trajectory (Sewaid et al., 2021) this is not explained by cyclical learning. Furthermore, we also consider that learning from failure is not a straightforward process and that entrepreneurs need to acknowledge the reasons for failure in order to learn. Entrepreneurs who respond to failure by changing category are less likely to learn from their failure and, hence, they are more severely affected by category change.

Our study seeks to make a twofold contribution to the management literature. First, we apply a new theoretical lens to further extend the management literature on learning. Building on different learning theories, our study provides a more holistic overview of the effects of strategic changes in contexts where strategic change does not require mobilizing own resources, does not involve exposure to a new set of stakeholders, and where time commitment to prior strategies is limited. Indeed, these contexts are of essence given the developments in the entrepreneurial landscape. In a study conducted by Lee and Chiravuri (2019), they investigate the effect of category change on campaign performance and find positive association between category change and performance. However, their analysis fails to control for main antecedents of fundraising performance. After controlling for the main antecedents of performance and conducting our analysis on the population of serial crowdfunders rather than a restricted sample (28,749 serial crowdfunders vs 2,406 serial crowdfunders), we find that changing category is negatively associated with campaign performance, contradicting prior findings. Another intriguing result of our analysis is that when controlling for changes in categories between campaigns, we find that entrepreneurs do not rebound after failure as suggested by Yang and Hahn (2015). On the contrary, following failure, entrepreneurs experience downward fundraising performance spirals. The findings of our study contribute to the debate on learning dynamics in different contexts and the possible effects of strategic changes.

Second, in addition to the direct effects of experience, we suggest a moderating role that experience could play in easing some barriers to learning, which provides new insights to the literature. Barriers to learning from venturing differences were shown to be alleviated by contextual similarities (Gick & Holyoak, 1987; Toft-Kehler et al., 2014). Our work complements these results since we investigate how similarities in the venturing process can alleviate barriers to learning stemming from contextual changes. We suggest that, as entrepreneurs accumulate venture launching experience, the tasks required to launch a new venture become more similar due to the multiple reference points that they have (Tversky & Kahneman, 1992). An increase in the task similarities can, in turn, facilitate the transfer of knowledge between contexts. Thus, in contrast to novice entrepreneurs, experienced entrepreneurs are able to make better generalizations and apply them, more effectively, to different contexts. Our results indicate that entrepreneurs benefit from the knowledge drawn from their prior experience, even if it is not within the same industry.

Fruitful venues for future research are best viewed in light of the limitations of our current approach. First, we focus our research on a single reward-based crowdfunding platform, Kickstarter. Thus, we do not have information on funding campaigns launched by the same entrepreneur on other platforms and this might lead to a possible underestimation in the number of serial entrepreneurs in our sample. Second, although our analysis draws important insights into the preliminary stage of serial crowdfunders' projects, the financial resources acquisition stage, it does not track serial crowdfunders' post-campaign performance. Although prior research has investigated the effects of industry change and experience on firm performance (Cooper, Gimeno-Gascon, & Woo, 1994; Eggers & Song, 2015; Toft-Kehler et al., 2014), it is still not clear how these findings can be extended to crowdfunded projects where moral hazard problems are amplified. Third, our main analysis investigates one dimension of change between campaigns. Although we think this is the most prominent contextual dimension in the traditional venture launching setting, there exist other dimensions (i.e., temporal, functional …) that can be considered in future serial crowdfunding studies. Fourth, given our findings, we encourage research on how entrepreneurs can apply previous experience to effectively launch ventures in different contexts. Finally, future research can investigate the generalizability of our findings to different learning transfer contexts.

6. Conclusion

Our study is the first to investigate the effects of entrepreneurial experience, category change, and previous performance on current fundraising performance while taking into consideration entrepreneurial endeavors that do not reach fruition. From our analysis of 28,749 serial crowdfunders on Kickstarter, we show that experience moderates the adverse effects of category change. Moreover, we find evidence that failure adds a new level of complexity to the effective application of prior knowledge. Furthermore, our research indicates that entrepreneurs who respond to failure by changing category are less likely to learn from their failure and are more severely affected by category change. For scholars, our study motivates the need to acknowledge contextual differences when investigating the role of experience and learning. We also suggest that experience can be used to ease barriers to learning. For entrepreneurs, our study suggests that entrepreneurs can improve their performance by extensively launching in the same industry. Additionally, following failure entrepreneurs should not focus so quickly on blaming external factors and should rather consider changing aspects regarding their venture.

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Figures and Tables

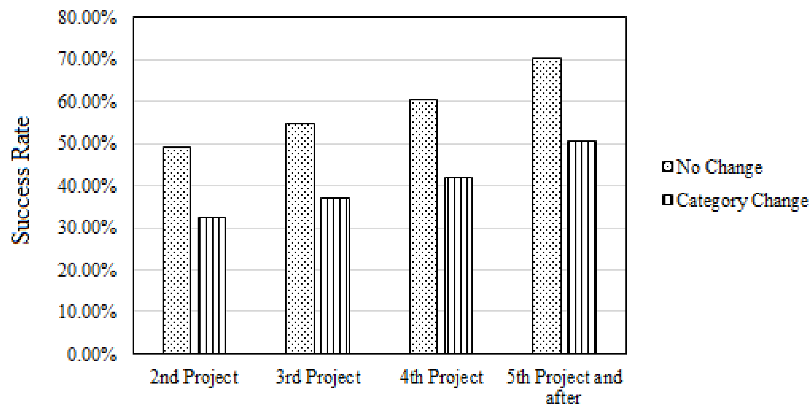
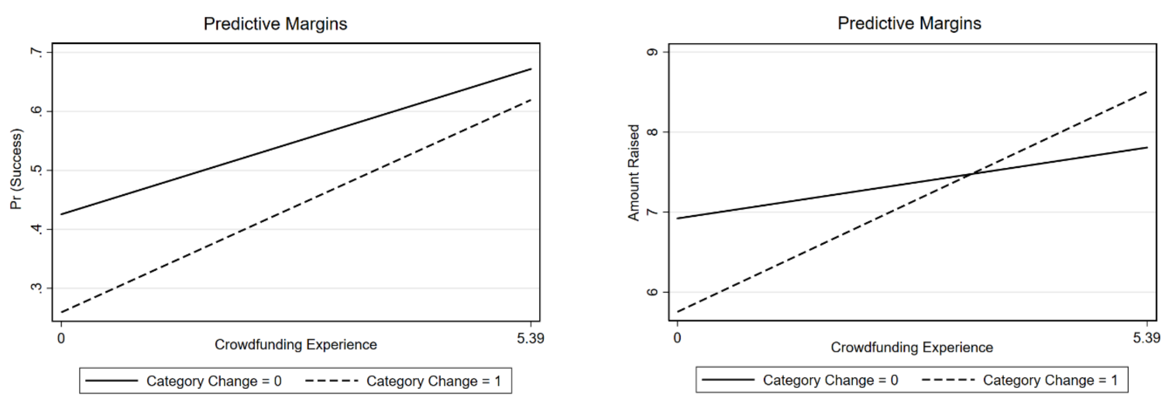


Figure 1. Success Rate for Projects Over the Number of Ventures



Figures 2a and 2b. Interactions between Category Change and Crowdfunding Experience

Table 1
Insight on Serial Crowdfunders in Kickstarter

Projects Launched by Entrepreneur	Number of Entrepreneurs	Number of Projects	Success Rate	Successful Amount Raised (in thousands)	Average Amount Raised
2	22,116 (74.24%)	44,232 (58.47%)	38.65%	$ 351,668 (40.91%)	$ 20,571
3	4,570 (15.34%)	13,710 (18.12%)	45.50%	$ 199,304 (23.18%)	$ 31,950
4	1,498 (5.03%)	5,992 (7.92%)	49.62%	$ 88,932 (10.35%)	$ 29,911
5 or more	1,604 (5.38%)	11,720 (15.49%)	61.72%	$ 219,725 (25.56%)	$ 30,376
Totals	29,788	75,654		$ 859,629	

Table 2
Category Switch and Success Rate by Previous Campaign Outcome

Previous Campaign Outcome	**Failure**		**Success**	
	# of Campaigns	Success Rate	# of Campaigns	Success Rate
No Category Switch	17,965 (73.93%)	33.63%	15,562 (82.50%)	76.06%
Category Switch	6,334 (26.07%)	19.69%	3,300 (17.50%)	65.70%
Total	24,299		18,862	

Table 3
Descriptive Statistics

Variable	Mean	S.D.	Min	Max	Variable	Frequency	% of Sample	Variable	Frequency	% of Sample
Success	0.49	0.50	0	1	Year:			Category:		
Amount Raised	$15,000.68	$159,080.50	0	$20,338,986	2009	107	0.25%	Art	3,104	7.18%
Category Change	0.19	0.36	0	1	2010	937	2.17%	Comics	2,567	5.94%
Crowdfunding Experience	2.13	4.38	1	110	2011	3,060	7.07%	Crafts	844	1.95%
Previous Failure	0.56	0.50	0	1	2012	5,412	12.51%	Dance	587	1.36%
Project Similarity	0.28	0.28	0	1	2013	7,106	16.43%	Design	3,757	8.69%
Time between Projects	283.98	321.15	0	2516	2014	10,417	24.08%	Fashion	1,941	4.49%
Location Change	0.27	0.44	0	1	2015	9,694	22.41%	Film and Video	7,288	16.85%
Rewards	9.02	6.56	1	179	2016	6,518	15.07%	Food	1,667	3.85%
Project Goal	$13,677.93	$44,486.18	$100	$1,000,000				Games	6,475	14.97%
Video Pitch	0.74	0.44	0	1				Journalism	340	0.79%
Video Count	0.34	1.08	0	21				Music	5,039	11.65%
Image Count	7.43	11.74	0	166				Photography	1,101	2.55%
Text Length	2.84	2.97	0	186.97				Publishing	4,256	9.84%
Duration	33.22	13.32	1	92				Technology	2,840	6.57%
								Theater	1,445	3.34%

Table 4
Correlation Matrix and VIFs

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	VIF
1	Success	1.00															DV
2	Amount Raised	0.65***	1.00														DV
3	Category Change	-0.15***	-0.18***	1.00													1.13
4	Crowdfunding Experience	0.15***	0.15***	-0.03***	1.00												1.15
5	Previous Failure	-0.44***	-0.48***	0.10***	-0.22***	1.00											1.35
6	Project Similarity	0.02***	0.01	-0.29***	-0.05***	0.17***	1.00										1.22
7	Time between Projects	0.21***	0.31***	0.02***	-0.11***	-0.36***	-0.27***	1.00									1.35
8	Location Change	-0.04***	-0.06***	0.09***	-0.07***	0.00	-0.11***	0.14***	1.00								1.04
9	Rewards	0.26***	0.44***	-0.09***	0.05***	-0.24***	0.01	0.20***	-0.02***	1.00							1.29
10	Project Goal	-0.15***	0.21***	-0.01*	-0.07***	0.00	-0.02***	0.11***	0.03***	0.20***	1.00						1.20
11	Video Pitch	0.20***	0.33***	-0.08***	-0.01**	-0.16***	0.01**	0.19***	-0.01	0.27***	0.19***	1.00					1.16
12	Video Count	0.10***	0.21***	-0.07***	0.06***	-0.07***	0.00	0.07***	-0.01***	0.14***	0.17***	0.14***	1.00				1.12
13	Image Count	0.21***	0.45***	-0.05***	0.17***	-0.19***	0.00	0.12***	-0.07***	0.35***	0.21***	0.20***	0.27***	1.00			1.50
14	Text Length	0.20***	0.38***	-0.07***	0.05***	-0.17***	0.03***	0.14***	-0.02***	0.34***	0.25***	0.23***	0.25***	0.50***	1.00		1.46
15	Duration	-0.16***	-0.03***	0.02***	-0.13***	0.11***	-0.01**	0.01	0.01	0.05***	0.25***	0.03***	0.01	0.00	0.04***	1.00	1.09

** p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001*

Table 5

Panel Logistic Regressions

	Selection Model	Model A (Dependent Variable : Success)					
		I	II	III	IV	V	VI
Category Change			-0.9215*** (0.0505)			-1.0938*** (0.1151)	-0.5225*** (0.0586)
Crowdfunding Experience x Category Change						0.1405* (0.0841)	
Previous Failure x Category Change							-0.1907** (0.0774)
Previous Failure							-1.4261*** (0.0332)
Crowdfunding Experience	0.6288*** (0.0055)	0.2956*** (0.0376)	0.3048*** (0.0374)	0.3306*** (0.0417)	0.4055*** (0.0778)	0.2795*** (0.0403)	0.2052*** (0.0291)
Project Similarity		1.1714*** (0.0721)	0.8017*** (0.0733)	0.7742*** (0.0773)	1.9050*** (0.2304)	0.8003*** (0.0734)	0.9610*** (0.0595)
Time between Projects		0.4305*** (0.0133)	0.4283*** (0.0133)	0.4310*** (0.0152)	0.4755*** (0.0303)	0.4289*** (0.0133)	0.2211*** (0.0111)
Location Change		-0.2570*** (0.0375)	-0.2164*** (0.0373)	-0.2528*** (0.0428)	-0.1396* (0.0776)	-0.2160*** (0.0373)	-0.1480*** (0.0303)
Rewards	0.0145*** (0.0054)	1.0556*** (0.0328)	1.0336*** (0.0324)	1.0416*** (0.0370)	1.0176*** (0.0731)	1.0347*** (0.0325)	0.7220*** (0.0256)
Project Goal	-0.0151*** (0.0021)	-0.7082*** (0.0171)	-0.6993*** (0.0169)	-0.6741*** (0.0193)	-0.7584*** (0.0395)	-0.7006*** (0.0169)	-0.5391*** (0.0128)
Video Pitch	-0.1005*** (0.0076)	1.0674*** (0.0453)	1.0536*** (0.0449)	1.0029*** (0.0511)	1.2137*** (0.0982)	1.0545*** (0.0450)	0.7775*** (0.0355)
Video Count	-0.0015 (0.0068)	0.2403*** (0.0327)	0.2331*** (0.0324)	0.2207*** (0.0358)	0.2838*** (0.0783)	0.2340*** (0.0324)	0.2063*** (0.0261)
Image Count	0.0488*** (0.0030)	0.2800*** (0.0161)	0.2717*** (0.0160)	0.2581*** (0.0183)	0.3481*** (0.0344)	0.2718*** (0.0160)	0.2040*** (0.0128)
Text Length	-0.0056* (0.0033)	0.3682*** (0.0263)	0.3618*** (0.0261)	0.3347*** (0.0292)	0.4866*** (0.0600)	0.3622*** (0.0261)	0.2654*** (0.0208)
Duration	-0.0571*** (0.0417)	-0.8531*** (0.0417)	-0.8433*** (0.0413)	-0.9012*** (0.0470)	-0.7323*** (0.0907)	-0.8449*** (0.0414)	-0.6124*** (0.0331)
Inverse Mills Ratio		-0.1660 (0.1394)	-0.1656 (0.1395)	-0.1954 (0.1412)	0.6628 (1.0481)	-0.1542 (0.1393)	-0.0658 (0.1327)
Subcategory Dummies	Yes	No	No	No	No	No	No
Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Population	Full Sample	Full Sample	Non-changers	Category-Changers	Full Sample	Full Sample
Observations	294,500	43,251	43,251	33,617	9,634	43,251	43,251
Wald Chi^2	28386.6	4119.5	4249.6	3006.8	715.3	4233.4	7518.8

** p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01*

Table 6
Panel Ordinary Least Squares Regression

	Selection Model	Model B (Dependent Variable : Amount Raised)					
		I	II	III	IV	V	VI
Category Change			-0.7229*** (0.0348)			-1.1679*** (0.0758)	-0.3869*** (0.0520)
Crowdfunding Experience x Category Change						0.3462*** (0.0524)	
Previous Failure x Category Change							-0.3983*** (0.0644)
Previous Failure							-0.9892*** (0.0295)
Crowdfunding Experience	0.6288*** (0.0055)	0.2224*** (0.0257)	0.2244*** (0.0257)	0.2126*** (0.0276)	0.3581*** (0.0616)	0.1643*** (0.0272)	0.1637*** (0.0256)
Project Similarity		0.8037*** (0.0502)	0.5083*** (0.0520)	0.4874*** (0.0531)	1.4712*** (0.1769)	0.4965*** (0.0520)	0.7493*** (0.0520)
Time between Projects		0.3525*** (0.0085)	0.3524*** (0.0084)	0.3360*** (0.0097)	0.4270*** (0.0180)	0.3515*** (0.0084)	0.2755*** (0.0086)
Location Change		-0.2513*** (0.0267)	-0.2239*** (0.0267)	-0.2064*** (0.0299)	-0.2784*** (0.0596)	-0.2229*** (0.0267)	-0.1997*** (0.0264)
Rewards	0.0145*** (0.0054)	1.0584*** (0.0208)	1.0449*** (0.0207)	1.0331*** (0.0229)	1.0496*** (0.0463)	1.0425*** (0.0207)	0.9868*** (0.0204)
Project Goal	-0.0151*** (0.0021)	0.1120*** (0.0094)	0.1166*** (0.0093)	0.1649*** (0.0106)	0.0090 (0.0194)	0.1176*** (0.0093)	0.1153*** (0.0092)
Video Pitch	-0.1005*** (0.0076)	1.0650*** (0.0304)	1.0528*** (0.0303)	1.0251*** (0.0340)	1.0960*** (0.0653)	1.0507*** (0.0302)	1.0164*** (0.0298)
Video Count	-0.0015 (0.0068)	0.2490*** (0.0235)	0.2452*** (0.0235)	0.2291*** (0.0249)	0.2933*** (0.0638)	0.2468*** (0.0234)	0.2569*** (0.0232)
Image Count	0.0488*** (0.0030)	0.4046*** (0.0116)	0.3994*** (0.0115)	0.3657*** (0.0130)	0.5399*** (0.0256)	0.3982*** (0.0115)	0.3878*** (0.0114)
Text Length	-0.0056* (0.0033)	0.3329*** (0.0188)	0.3323*** (0.0187)	0.2997*** (0.0206)	0.4883*** (0.0436)	0.3318*** (0.0187)	0.3174*** (0.0184)
Duration	-0.0571*** (0.0417)	-0.2326*** (0.0290)	-0.2303*** (0.0289)	-0.2724*** (0.0318)	-0.0991 (0.0669)	-0.2343*** (0.0289)	-0.1879*** (0.0286)
Inverse Mills Ratio		0.2008** (0.0851)	0.2027** (0.0852)	0.1913** (0.0809)	-0.0234 (0.4960)	0.2298*** (0.0852)	0.2597*** (0.0865)
Subcategory Dummies	Yes	No	No	No	No	No	No
Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Population	Full Sample	Full Sample	Non-changers	Category-Changers	Full Sample	Full Sample
Observations	294,500	43,251	43,251	33,617	9,634	43,251	43,251
Wald Chi^2	28386.6	20692.4	21479.3	15712.5	5795.3	21547.9	24783.6
R-Squared: Within		0.0977	0.0971	0.0892	0.1223	0.0972	0.0570
Between		0.4330	0.4436	0.4168	0.4379	0.4437	0.5015
Overall		0.4159	0.4264	0.4088	0.4153	0.4258	0.4818

** p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01*

Table 7
Robustness Checks: Social Capital, Split Sample, and Alternative Dependent Variable

Dependent Variable	**Success**		**Success**		**Number of Backers**		
	I	II	III	IV	V	VI	VII
Category Change	-0.6534*** (0.0448)	-0.6249*** (0.0576)	-0.8643*** (0.0757)	-0.6270*** (0.0757)	-0.6043*** (0.0228)	-0.6356*** (0.0499)	-0.1461*** (0.0288)
Social Capital x Category Change		-0.0160 (0.0204)					
Crowdfunding Experience x Category Change						0.0246*** (0.0035)	
Previous Failure x Category Change							-0.3671*** (0.0356)
Previous Failure							-2.0425*** (0.0162)
Crowdfunding Experience			0.3721*** (0.0617)	0.0647 (0.0540)	0.1396*** (0.0169)	0.1354*** (0.0180)	0.0087 (0.0142)
Social Capital	0.2054*** (0.0241)	0.2054*** (0.0241)					
Project Similarity	0.8971*** (0.0648)	0.8996*** (0.0649)	1.2089*** (0.0953)	1.0045*** (0.1469)	0.0219 (0.0340)	0.0211 (0.0340)	0.5168*** (0.0286)
Time between Projects	0.3309*** (0.0116)	0.3307*** (0.0116)	0.2062*** (0.0173)	0.3754*** (0.0268)	0.3444*** (0.0055)	0.3444*** (0.0055)	0.1701*** (0.0047)
Location Change	-0.1190*** (0.0329)	-0.1194*** (0.0330)	-0.2505*** (0.0553)	-0.1030* (0.0552)	-0.2116*** (0.0175)	-0.2116*** (0.0175)	-0.1570*** (0.0145)
Rewards	0.8175*** (0.0281)	0.8178*** (0.0281)	1.0820*** (0.0508)	0.5972*** (0.0469)	0.3968*** (0.0135)	0.3967*** (0.0135)	0.2728*** (0.0112)
Project Goal	-0.7014*** (0.0147)	-0.7017*** (0.0147)	-0.8987*** (0.0304)	-0.4704*** (0.0253)	0.0431*** (0.0061)	0.0432*** (0.0061)	0.0453*** (0.0050)
Video Pitch	0.8423*** (0.0389)	0.8428*** (0.0389)	1.0034*** (0.0635)	0.8155*** (0.0708)	0.3960*** (0.0198)	0.3958*** (0.0198)	0.3244*** (0.0164)
Video Count	0.1492*** (0.0287)	0.1486*** (0.0288)	0.3165*** (0.0474)	0.1955*** (0.0470)	0.0903*** (0.0154)	0.0904*** (0.0154)	0.1154*** (0.0128)
Image Count	0.1108*** (0.0142)	0.1109*** (0.0142)	0.4176*** (0.0244)	0.0526** (0.0242)	0.2528*** (0.0075)	0.2527*** (0.0075)	0.2229*** (0.0062)
Text Length	0.3170*** (0.0230)	0.3171*** (0.0230)	0.3927*** (0.0377)	0.2796*** (0.0397)	0.1203*** (0.0122)	0.1202*** (0.0122)	0.0817*** (0.0101)
Duration	-0.5951*** (0.0360)	-0.5949*** (0.0360)	-0.7777*** (0.0559)	-0.6039*** (0.0680)	-0.4448*** (0.0189)	-0.4451*** (0.0189)	-0.3321*** (0.0157)
Inverse Mills Ratio	-0.3061** (0.1328)	-0.3084** (0.1329)	-0.3598 (0.2859)	-0.0112 (0.1568)	0.0380 (0.0572)	0.0399 (0.0573)	0.1585*** (0.0493)
Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full Sample	Full Sample	Previous Failure	Previous Success	Full Sample	Full Sample	Full Sample
Observations	43,251	43,251	24,299	18,952	43,251	43,251	43,251
Wald Chi^2	5642.05	5641.65	1272.78	897.65	17794.60	17796.37	48786.38

** p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01*

Table 8
Robustness Check: Coarsened Exact Matching Sample

	CEM Matched Sample					
Dependent Variable:	**Success**			**Amount Raised**		
	I	II	III	IV	V	VI
Category Change	-0.8001*** (0.0672)	-0.8726*** (0.1495)	-0.5712*** (0.0769)	-0.6600*** (0.0500)	-0.9392*** (0.1084)	-0.5305*** (0.0739)
Crowdfunding Experience x Category Change		0.2438*** (0.0413)			0.2264*** (0.0780)	
Previous Failure x Category Change			-0.4315*** (0.0959)			-0.1734* (0.0886)
Previous Failure			-1.5435*** (0.0613)			-1.4649*** (0.0576)
Crowdfunding Experience	0.3839*** (0.0545)	0.1822*** (0.0508)	0.1742*** (0.0420)	0.3324*** (0.0418)	0.2374*** (0.0531)	0.2148*** (0.0410)
Project Similarity	0.9513*** (0.1234)	0.9491*** (0.1235)	1.0049*** (0.0978)	0.6451*** (0.0941)	0.6318*** (0.0942)	0.9192*** (0.0926)
Time between Projects	0.4410*** (0.0205)	0.4413*** (0.0206)	0.2236*** (0.0161)	0.4064*** (0.0129)	0.4060*** (0.0129)	0.3060*** (0.0130)
Location Change	-0.1656*** (0.0553)	-0.1652*** (0.0554)	-0.0840* (0.0441)	-0.2392*** (0.0423)	-0.2376*** (0.0423)	-0.1962*** (0.0411)
Rewards	1.0535*** (0.0504)	1.0538*** (0.0504)	0.7251*** (0.0383)	1.0731*** (0.0326)	1.0728*** (0.0326)	0.9709*** (0.0318)
Project Goal	-0.7011*** (0.0262)	-0.7013*** (0.0262)	-0.5548*** (0.0191)	0.0590*** (0.0139)	0.0595*** (0.0139)	0.0618*** (0.0135)
Video Pitch	1.1153*** (0.0679)	1.1151*** (0.0680)	0.8115*** (0.0523)	1.1026*** (0.0466)	1.1018*** (0.0466)	1.0271*** (0.0453)
Video Count	0.2080*** (0.0506)	0.2084*** (0.0506)	0.1849*** (0.0399)	0.2745*** (0.0404)	0.2758*** (0.0404)	0.2926*** (0.0392)
Image Count	0.3286*** (0.0240)	0.3286*** (0.0241)	0.2392*** (0.0188)	0.4730*** (0.0179)	0.4723*** (0.0179)	0.4441*** (0.0174)
Text Length	0.4136*** (0.0400)	0.4137*** (0.0400)	0.2878*** (0.0312)	0.4181*** (0.0298)	0.4175*** (0.0298)	0.3800*** (0.0290)
Duration	-0.8324*** (0.0626)	-0.8331*** (0.0627)	-0.5562*** (0.0487)	-0.2132*** (0.0462)	-0.2157*** (0.0462)	-0.1301*** (0.0450)
Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,258	19,258	19,258	19,258	19,258	19,258
Wald Chi^2	1,517.0	1,514.6	2,756.6	11,281.4	11,294.7	13,633.8
R-Squared: Within				0.1049	0.1052	0.0548
Between				0.4401	0.4399	0.5030
Overall				0.4207	0.4207	0.4815

** p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01*

Table 9
Robustness Check: Panel Logistic Regressions for Full Data Sample using Category Switch

	Dependent Variable : Success					
	I	II	III	IV	V	VI
Category Switch		-0.8567*** (0.0396)			-1.0426*** (0.0902)	-0.5357*** (0.0484)
Crowdfunding Experience x Category Switch					0.1495** (0.0650)	
Previous Failure x Category Switch						-0.2247*** (0.0632)
Previous Failure						-1.2761*** (0.0323)
Crowdfunding Experience	0.2140*** (0.0343)	0.2362*** (0.0341)	0.2419*** (0.0384)	0.3491*** (0.0692)	0.2033*** (0.0370)	0.1290*** (0.0271)
Time between Projects	0.3495*** (0.0117)	0.3665*** (0.0118)	0.3656*** (0.0134)	0.4327*** (0.0271)	0.3671*** (0.0118)	0.1795*** (0.0102)
Location Change	-0.3021*** (0.0361)	-0.2461*** (0.0359)	-0.2799** (0.0417)	-0.1713** (0.0733)	-0.2454*** (0.0360)	-0.1841*** (0.0298)
Rewards	1.0038*** (0.0310)	0.9819*** (0.0306)	0.9937*** (0.0353)	0.9697*** (0.0668)	0.9835*** (0.0307)	0.7114*** (0.0248)
Project Goal	-0.6466*** (0.0146)	-0.6443*** (0.0145)	-0.6310*** (0.0170)	-0.6768*** (0.0316)	-0.6457*** (0.0146)	-0.5043*** (0.0114)
Video Pitch	1.0365*** (0.0428)	1.0150*** (0.0425)	0.9773*** (0.0489)	1.1293*** (0.0898)	1.0163*** (0.0426)	0.7786*** (0.0345)
Video Count	0.2290*** (0.0316)	0.2205*** (0.0313)	0.2138*** (0.0349)	0.2564*** (0.0746)	0.2217*** (0.0314)	0.1998*** (0.0258)
Image Count	0.2691*** (0.0154)	0.2614*** (0.0153)	0.2470*** (0.0177)	0.3457*** (0.0324)	0.2613*** (0.0154)	0.1999*** (0.0126)
Text Length	0.3858*** (0.0253)	0.3732*** (0.0251)	0.3445*** (0.0284)	0.4889*** (0.0564)	0.3735*** (0.0252)	0.2894*** (0.0205)
Duration	-0.0292*** (0.0013)	-0.0288*** (0.0013)	-0.0307*** (0.0015)	-0.0255*** (0.0029)	-0.0289*** (0.0013)	-0.0216*** (0.0011)
Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full Sample	Full Sample	Non-changers	Category-Changers	Full Sample	Full Sample
Observations	45,866	45,866	35,319	10,547	45,866	45,866
Wald Chi^2	4436.29	4609.80	3202.59	827.75	4585.80	7710.47

** p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01*