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Crowdfunding performance, market performance, and the moderating roles of product innovativeness and experts' judgment: Evidence from the movie industry

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Abstract
Reward-based crowdfunding (CF) has emerged as a method to solicit funds for innovative projects. Yet, little is still known about the ability of reward-based CF to act as a signal in the eyes of future consumers, and thus boost the future market performance of new products that innovators intend to commercialize using the campaign funds. In addition, scant research has clarified the boundary conditions that can magnify or weaken the efficacy of this CF signal. Given the relevance of reward-based CF for supporting innovation, understanding when the CF campaign performance works as an effective signal is of great interest, especially in business settings characterized by high product quality uncertainty. By using the movie industry as a setting, we contribute to fill this gap. Specifically, we argue that the positive effect of the reward-based CF performance is moderated by two important factors influencing consumers' purchase decisions: the degree of product innovativeness and the expert judgment about the product. Elaborating on the effects of product innovativeness, we posit that this product feature should moderate the positive relationship between CF and subsequent market performances in an inverted U-shaped fashion. Favorable expert recommendations, on the other hand, should weaken the efficacy of the CF performance as a signal. Results from a sample of 1059 new movies (of which 152 released in theaters) confirm these predictions and offer several remarkable implications for innovators.

KEYWORDS
expert judgment, movie industry, new product commercialization, product innovativeness, reward-based crowdfunding, signal interplay

1 | INTRODUCTION

In less than a decade, the way of financing innovation and entrepreneurial initiatives has been notably shaped by the rise of the crowdfunding (CF) phenomenon. CF supports individuals, firms, and organizations pursuing innovative projects by soliciting funding from other people (i.e., the crowd), often in exchange for future rewards, equity, or other forms of returns (Belleflamme et al., 2014). Recently, the CF phenomenon has surged so prominently that the global CF market is expected to grow up from 13.9 billion US$ in 2019 to 39.8 billion by the end of 2026 (MarketWatch, 2023).

The rapid growth characterizing this phenomenon and its economic relevance have also merited overwhelming academic interest in the last decade. Researchers have started investigating a number of issues (see Messeni Petruzzelli et al., 2019), such as CF campaign design and performance (e.g., Ahlers et al., 2015; Bapna, 2019; Burtch et al., 2013; Butticé et al., 2017; Chan & Parhankangas, 2017; Colombo et al., 2015; Du et al., 2022; Gleasure et al., 2019; Mollick, 2014; Wei et al., 2021; Zhang & Chen, 2019), choice of funding mechanism (e.g., Cholakova & Clarysse, 2015), funders' behavior and incentives (e.g., Butticé et al., 2017; Colombo et al., 2015; Gleasure et al., 2019; Jiang et al., 2022; Kim, Park, et al., 2022b; Nielsen & Binder, 2021; Testa et al., 2020; Xiao et al., 2021; Zhang & Chen, 2019), as well as relationships and impacts on the financial system and society in general (e.g., Drover et al., 2017; Gao et al., 2021; Mollick & Nanda, 2016; Short et al., 2017; Stanko & Henard, 2017), among others.

Prior literature has suggested that a positive performance in reward-based[1] CF can improve the odds of securing subsequent funding from early-stage venture capitalists (VCs; Colombo & Shafi, 2021; Drover et al., 2017; Roma et al., 2017). The main argument proposed to explain this finding is that, beyond its financing function, a reward-based CF campaign can work as a signal that helps mitigate VCs' uncertainty about the market prospects of the new product the campaign proponent intends to commercialize (Drover et al., 2017; Roma et al., 2017). However, this does not shed light on whether the new product will actually meet consumer preferences and succeed in the final market. Consumers in the final product market are clearly different signal receivers as compared with (early-stage) professional investors, in terms of characteristics, motivations, and type of decisions. Thus, it is not immediately clear whether and under which conditions the performance in reward-based CF can work as a quality signal for consumers, thus affecting the market performance of the new product when commercialized.

For new products, consumers typically confront considerable product quality uncertainty, and thus they need to resort to external information (*signals*) to mitigate the risks associated with such uncertainty (Bharadwaj et al., 2017; Stuart et al., 1999). In a world where the information production and diffusion has been democratized and the "voice" of the crowd has become more relevant, the performance in reward-based CF can arguably be one of these signals able to reduce the inherent quality uncertainty new (crowdfunded) products carry over. However, the efficacy of the CF signal may be favored or curbed by both key new product characteristics and the contextual presence of other influential external signals. The rationale is that both these elements contribute to determine

Practitioner points

- We suggest innovators to invest time and effort designing attractive reward-based crowdfunding (CF) campaigns able to ignite commitments from the crowd, which are not only beneficial per se, but also yield valuable information that can influence consumers' purchase decisions, and thus lead to a positive market performance.
- To improve the odds of success in the market stage, we advise innovators to fine-tune the communication strategy during and after the CF campaign depending on the degree of product innovativeness, trying to soften the downsides of an ultra-innovative product by explaining novel features and increasing consumers' familiarity with new meanings, styles, and technological aspects of the product.
- Innovators should be aware that a good performance in reward-based CF may serve most suitably as a product quality signal for consumers when expert judgments are not particularly favorable.
- It is an essential task for innovators to identify the relevant product quality signals (from both the crowd and experts), understand their interplay, and work to enhance the benefits of favorable signals and mitigate the effects of negative ones.

[1]In reward-based CF, funding is provided in exchange for non-monetary rewards—typically the new product itself (or its customized versions) that the project proponent aims to develop and sell.

the level of product quality uncertainty facing consumers, and consequently the value the latter assign to the CF signal (e.g., Bharadwaj et al., 2017; Lee et al., 2016). Indeed, some intrinsic product attributes may render the overall product quality more difficult for consumers to evaluate, or may confer higher or lower reliability to a signal, thus significantly shaping the resulting uncertainty consumers confront. Likewise, the presence of other influential external signals (in addition to the CF one) may reduce the need to rely on each individual signal to mitigate the uncertainty at hand (Bapna, 2019; Roma, Vasi, & Kolympiris, 2021a). Thus, it is important to *jointly* investigate the role of these two elements to better understand when and why the CF performance can be an effective signal of market performance.

In particular, among product characteristics, the level of product innovativeness is a key feature that has been largely shown to influence (directly or indirectly) the market performance of new products by affecting consumers' views of the new product (Allen et al., 2022; McNally et al., 2010; Szymanski et al., 2007), their status of uncertainty when dealing with something less familiar (Lee et al., 2016), and their consequent need for information (Langerak & Hultink, 2006). In principle, product innovativeness may thus spawn different consumers' perceptions as to the value of certain sources of information, possibly modifying the efficacy of reward-based CF as a signal. Yet, little is known about whether (and in which shape) this will occur.

As for the role of other influential external signals, we note that expert judgment (e.g., conveyed through reviews, ratings, and assessments) has been traditionally deemed the most influential product quality signal in many business settings (Mollick & Nanda, 2016). However, consumers are nowadays largely exposed to both crowd- and experts-generated signals (Mollick & Nanda, 2016). The recent theoretical developments on signal interplay suggest that in presence of multiple signals, the marginal effect of a signal depends on whether the interacting signals convey similar or different type of information (Bapna, 2019; Colombo et al., 2019; Courtney et al., 2017; Roma, Vasi, & Kolympiris, 2021a). Therefore, a natural and important question to ask is whether both crowd- and experts-generated signals influence each other's efficacy when being simultaneously available. Still, the recent literature has been mostly confined to examine the implications of higher or lower agreement among experts, and between crowd and expert judgments (Chakravarthy et al., 2010; Mollick & Nanda, 2016; Wang et al., 2015), leaving the above question largely unanswered.

In this article, we offer a first attempt to fill the above gaps. By grounding on the signaling literature (e.g., Connelly et al., 2011; Kirmani & Rao, 2000; Spence, 1973), and more specifically on third-party signals, that is, signals generated by third parties (e.g., Bapna, 2019; Bharadwaj et al., 2017; Howell, 2017; Megginson & Weiss, 1991), we examine the effect of the signal generated through the reward-based CF campaign on the market performance of a new product. Moreover, we use the theoretical insights available in the product innovativeness literature (e.g., Kleinschmidt & Cooper, 1991; Langerak & Hultink, 2006; Lee et al., 2016; McNally et al., 2010; Szymanski et al., 2007) as well as the logic of signal interplay (e.g., Bapna, 2019; Colombo et al., 2019; Courtney et al., 2017; Vanacker et al., 2020) to investigate how the level of product innovativeness and the experts' judgment magnify or weaken the efficacy of the CF signal.

We study these questions in the movie industry. Since films are *experience goods*, this industry is typically characterized by high product quality uncertainty and high information asymmetry between firms and consumers. Such features make the movie industry an ideal template to assess the efficacy of a new signal (Basuroy et al., 2006; Bharadwaj et al., 2017; Eliashberg & Shugan, 1997). In addition, reward-based CF has become very popular in the movie industry.[2] Toward our scopes, we collected data on movie projects launched on Kickstarter in the years 2010–2017. To gather all required information on movie characteristics, their production, distribution, and market performance, we matched movie projects retrieved from Kickstarter with those available in movie databases, that is, Imdb.com, BoxOfficeMojo, Rotten Tomatoes, and The Numbers. Our final sample includes 1059 movies (152 released in theaters in the years 2010–2018). For each film, we retrieved data regarding both CF and market performance, the level of product innovativeness, critics' rating, and total budget, as well as several other typical controlling factors. To help rule out alternative explanations related to sample selection and unobserved quality, we controlled for several factors related to product quality and CF campaign publicity, as well as used different methods, including the Heckman selection model and instrumental variables regressions.

For new movies launched in reward-based CF, our findings show that campaign performance (measured by the pledged amount) is positively associated with performance at the box office, suggesting its efficacy as a signal for consumers. Interestingly, our findings also reveal that the degree of product innovativeness moderates the positive relationship between the performance in CF and the subsequent market performance in an inverted U-shaped

[2]As of September 2022, projects launched in the cinema and video category of the most popular reward-based CF platform, that is, Kickstarter, have attracted overall funding near 450 million US$.

manner. We explain this moderation as the result of two conflicting effects. On the one hand, higher product innovativeness magnifies consumers' need to rely on third-party signals as they confront higher uncertainty in this case. On the other hand, for highly innovative products risk escalates that the CF campaign produces an unreliable signal. Too innovative products may indeed require consumers to significantly change habits, views, feelings, and/or spend effort to learn and appreciate them (Calantone et al., 2006; Chan & Parhankangas, 2017; Delmestri et al., 2005; Menguc et al., 2014). Therefore, they may result appealing to early adopters (i.e., the crowd in the CF campaign), but not to general consumers. Finally, we find that the positive effect of the CF performance on the market performance falls as the critics' rating becomes more favorable. Indeed, an increase in the CF performance has limited value (as a signal) when consumers observe high ratings from critics, whereas it becomes pivotal to break any hesitation making a purchase in presence of critics' low ratings. Drawing on the notion of signal interplay, we argue that this happens as both signals act to inform potential consumers about the overall product quality, rather than to reduce uncertainty along distinct informational domains.

Our article adds new knowledge mainly to the extant literature on CF. First, we conceptualize the performance in reward-based CF as a signal that may influence the purchase decisions of consumers active in the market stage. By doing so, our study provides initial evidence about the role of the reward-based CF performance not only as a signal that mobilizes later-stage funding as suggested by prior literature (e.g., Drover et al., 2017; Roma et al., 2017), but also as a signal influencing actual product market performance. Considering the clear differences between consumers and VC investors, in terms of characteristics, motivations, and decision types, our study adds, therefore, a first important piece to a fuller characterization of reward-based CF as a signal that may influence different types of actors. Second, we add to the extant knowledge that the signaling efficacy of reward-based CF to consumers nontrivially hinges on a product characteristic, that is, product innovativeness, as well as on the contextual presence of a second external signal possibly affecting consumers, that is, expert judgment. Our contribution here is to reveal new boundary conditions that may enhance or curb the efficacy of reward-based CF as a signal and to explain the underlying mechanism. By conceptualizing the CF performance as a signal and most importantly examining the boundary conditions that may affect its efficacy, we add to Stanko and Henard (2017), who have also studied the role of CF for market performance, but with a focus on how CF supports open innovation. Interestingly, in terms of results, Stanko and Henard (2017) find that the number of backers, but not the amount pledged in the campaign, influences the subsequent market performance of the new product. Our findings instead suggest a positive and significant relationship between pledged amount and market performance.[3]

Examining the above moderating effects allows us to advance two additional streams. First, we add to the literature focusing on the direct or indirect performance implications of product innovativeness (e.g., Calantone et al., 2006; Kleinschmidt & Cooper, 1991; Lee & O'Connor, 2003; Szymanski et al., 2007). Specifically, we are the first to showcase how this feature can drive the market performance of a new product by shaping the informational value that a signal external to the firm can deliver to potential consumers. This sheds new light on the possible collateral effects of product innovativeness, especially in business settings featuring high product quality uncertainty. Second, we also contribute to emergent literature on the interplay of multiple signals (e.g., Bapna, 2019; Colombo et al., 2019; Courtney et al., 2017) as well as to recent literature on the contraposition between crowd and expert opinions (e.g., Mollick & Nanda, 2016), by revealing that the efficacy of the CF signal is diminished by the presence of a favorable signal from the experts.

Our article unfolds as follows. In Section 2, we showcase our theoretical arguments and hypotheses. In Section 3, we describe the data, variables, and methods adopted in this article. In Section 4, we present our findings under both OLS and Heckman-corrected models, as well as the analysis of the marginal effects. In Section 5, we conduct several robustness checks. Finally, in Section 6, we provide implications for theory and practice, concluding with a discussion of limitations and future research directions.

2 | THEORY AND HYPOTHESES

2.1 | The role of reward-based CF as a signal for consumers

In business settings characterized by the presence of product quality uncertainty, parties involved in a

[3]Moreover, from an empirical viewpoint, we complement their study along two directions. First, we use archival data that encompass the actual revenues of crowdfunded products, whereas Stanko and Henard (2017) have combined the CF campaign data with a survey where project proponents were asked to evaluate the market success of their crowdfunded products relative their objectives, using a qualitative scale 1–5. Second, we extend their study to a different product category, that is, movies. These differences may explain the different results.

transaction (e.g., seller and buyer) need to turn to accessible information related to the counterpart's observable attributes "thought to co-vary with their underlying but unknown quality" (Stuart et al., 1999, p. 317), to thus mitigate the uncertainty at hand. Commonly referred to as *signal*, this information is sometimes sent by one party to the other party (Kirmani & Rao, 2000; Spence, 1973; Talay et al., 2017). In many other circumstances, it is provided by or passes through credible, influential third parties, such as VCs in equity investments, critics in the arts, or even the crowd in online product reviews, in which case it is commonly referred to as *third-party signal* (Anglin et al., 2020; Bharadwaj et al., 2017; Howell, 2017; Megginson & Weiss, 1991; Mollick & Nanda, 2016). For example, Howell (2017, p. 1156) conceptualizes the grants awarded to startups by a third party (US government, in her study) "as a signal, conveying market-relevant information about grantee quality".

In either case, a signal may benefit the party who lacks information about the features of the product offered by the other party, by abating inherent uncertainty, and thus leading to more informed decisions, for example, whether to purchase or not (Connelly et al., 2011). The signal may also become beneficial to the other party, that is, the seller, who may otherwise be uncertain about the purchase intentions of the buyer (Connelly et al., 2011; Stiglitz, 2000). By reducing buyer uncertainty, the signal may make purchase intentions clearer, and thus inform, at an aggregate level, the seller on the product market potential.

Based on the considerations above, we maintain that for new products, the reward-based CF performance can work as a signal in the eyes of consumers active at the commercialization stage. It is a third-party signal because it is generated by a third party (i.e., the crowd), which provides a collective "stamp of approval" on the quality of a new product by contributing to its funding (Drover et al., 2017; Lerner, 2002). In fact, broadly speaking, the performance that a new product idea achieves in a reward-based CF campaign provides information on its quality and the appreciation manifested by the crowd (Drover et al., 2017; Roma et al., 2017; Strausz, 2017).

This information should be particularly valuable to consumers active at the commercialization stage because of the nature of reward-based CF. In fact, in reward-based CF, the reward scheme offered to investors typically includes the product that the project proponent intends to commercialize, and people contribute to the campaign mostly out of a desire to obtain this specific reward (Chakraborty & Swinney, 2021; Lin et al., 2022; Roma et al., 2017; Roma, Vasi, Testa, & Perrone, 2021b; Strausz, 2017). Consequently, investors in reward-based CF are essentially *early adopters* who invest money in advance in order to "buy" a product yet to be developed (Chan & Parhankangas, 2017; Kickstarter, 2020; Roma et al., 2017).[4] In other words, the outcome of a CF campaign is the result of *financial commitment* from early adopters, who pre-order a new product so in advance that they even risk new product development proving a failure. Therefore, in line with the vast literature on new product diffusion suggesting a positive influential role of early adopters on later consumers (Abrahamson & Rosenkopf, 1997; Frattini et al., 2014; Ho et al., 2012; Mahajan et al., 1990; Morvinski et al., 2017; van den Bulte & Joshi, 2007; Zhang et al., 2022), we argue that the CF performance can affect market-stage consumers, by providing valuable information about product quality and thus reducing the inherent uncertainty.

Besides being valuable to future consumers, the information generated from the CF campaign is also easily observable to them. Information on crowdfunded products is indeed heavily publicized not only within the CF communities (e.g., Kickstarter), but also across social media and other online media (Colombo et al., 2015; Mollick, 2014).[5] Thus, in principle, for crowdfunded products, consumers active at the commercialization stage are largely exposed to the signal coming from the CF campaign and can consider it in their purchase decisions, similarly to what they typically do with experts-generated information, for example, critics' reviews, (Basuroy et al., 2003; Chakravarthy et al., 2010; Chen et al., 2012; Reinstein & Snyder, 2005) or with other forms of consumer-generated information, such as electronic word-of-mouth (eWOM; Chevalier & Mayzlin, 2006; Hennig-Thurau et al., 2015; Liu, 2006; Trusov et al., 2009). In turn, by mitigating consumer uncertainty, the CF performance may also be useful to firms as a marketing research tool to assess the market potential of new

[4]For instance, for the movies in our sample, on average, 75% of backers contributed an amount entitling them to have free access to the movie (e.g., via DVD, streaming, cinema ticket) when it was commercialized.

[5]Here are some examples of articles in online press mentioning crowdfunded movies: https://www.hollywoodreporter.com/movies/movie-news/wish-i-was-ny-premiere-718742/https://www.indiewire.com/2014/07/from-obvious-child-to-blue-ruin-here-are-9-kickstarter-films-from-2014-that-deserve-your-attention-24269/. In our empirical analysis, we provide evidence of the publicity given to the CF campaigns (and their outcomes) in our sample via social media and film-focused websites. Moreover, it is noteworthy that backers who contributed amounts not entitling them to have free access to the movie when commercialized may be part of the box office market. We believe that the CF performance can still work as a signal for them because they are the first to observe the campaign outcomes and knowing whether other backers' contributions have been large or not will likely influence their purchase decisions.

products (Chemla & Tinn, 2020; Roma et al., 2018; Strausz, 2017; Viotto da Cruz, 2018).

New motion pictures are ideal templates to test the efficacy of reward-based CF performance as a signal. Movies are *experience goods*, and as such are characterized by considerable product quality uncertainty and information asymmetry between firms and consumers (e.g., Basuroy et al., 2006). On the one hand, this implies that consumers must rely on signals through which they can infer the product quality, and thus make their purchase decisions. On the other hand, this also means that firms may find difficult to anticipate how the market will respond to their new products, considering the short product lifecycle (Bharadwaj et al., 2017). As such, the movie industry has often been chosen as an important business setting to test the effects of a variety of signals on the future market performance of a new product (Basuroy et al., 2003, 2006; Bharadwaj et al., 2017; Eliashberg et al., 2006). Prior literature focusing on this industry has identified many firm and product attributes carrying out this informative function, encompassing signals sent by the firm, such as production-advertising budgets and star power, as well as signals generated by or passing through third parties, such as critics judgment, awards, and eWOM (Akdeniz & Berk Talay, 2013; Basuroy et al., 2003, 2006; Bharadwaj et al., 2017; Broekhuizen et al., 2011; Chen et al., 2012; Chintagunta et al., 2010; Duan et al., 2008; Eliashberg & Shugan, 1997; Gemser et al., 2008; Hennig-Thurau et al., 2009, 2015; Karniouchina, 2011a, 2011b; Liu, 2006; Liu et al., 2015; Moon et al., 2010; Reinstein & Snyder, 2005).

According to the underlying mechanism elucidated above, we posit that for firms enlisting reward-based CF to finance their new movie projects, the performance in this funding channel should serve as an added key element to signal product quality to future potential consumers, mitigate their uncertainty, and thus prod their willingness to buy. In turn, this should drive better box office returns. Hence, we formulate as follows:

> **Hypothesis 1. (H1)** The performance of a new movie project in a reward-based CF campaign is positively associated with its subsequent box office performance.

2.2 | The moderating role of product innovativeness

We complement the above argument by proposing that the ability of the reward-based CF campaign to work as a signal for future consumers is moderated in a nontrivial manner by an important feature intrinsic to new products: the degree of product innovativeness. To elaborate in detail our arguments, it is useful to first discuss the effects of product innovativeness on its market performance, both as a direct driver of performance and moderator of other performance determinants.

The effect of product innovativeness on market performance has been a central question in innovation management literature, with surprisingly unclear results (Rubera & Kirca, 2012; Szymanski et al., 2007). Positive, negative, and insignificant effects have all been documented (Henard & Szymanski, 2001; McNally et al., 2010; Song & Montoya-Weiss, 1998; Szymanski et al., 2007). Considering product innovativeness from the consumer perspective, these mixed results may stem from the emergence of two main contrasting effects (Garcia & Calantone, 2002; Story et al., 2015). Product innovativeness from the consumer view refers, indeed, to how novel the product is to consumers and how much they must alter their behavior in adapting to the new product (Garcia & Calantone, 2002; McNally et al., 2010; Menguc et al., 2014).

On the one hand, product novelty and uniqueness can naturally benefit consumers by improved ability to satisfy their needs or wants (Szymanski et al., 2007). As a result, product innovativeness can confer product advantage (i.e., superiority over rival offerings) to firms, thus indirectly influencing market performance (Calantone et al., 2006). Yet, highly innovative products may require changed habits, views, or very high search and learning costs for consumers who are typically unfamiliar with the new product features (Calantone et al., 2006; Langerak & Hultink, 2006; Menguc et al., 2014). In addition, extremely innovative products may prove even too far ahead of their time to be understood (Delmestri et al., 2005), even to the point of failing in the market (Kleinschmidt & Cooper, 1991).

This reasoning is also consistent with the sensations-familiarity framework proposed for hedonic products, such as movies (Allen et al., 2022; Hennig-Thurau & Houston, 2019). According to this framework, when a new product is too familiar (delivering few new sensations), it may prove unappealing to consumers. In the same vein, when the new product is too novel, consumers may be overwhelmed by too many new sensations with little link to the familiar, and thus may fail to appreciate it. Therefore, following this logic, the right balance between novelty and familiarity should be pursued for the new (hedonic) product to succeed (Allen et al., 2022).

Recent CF studies have examined the impact of product innovativeness on the reward-based CF performance, by assimilating the CF campaign to a final market and using arguments like those discussed above (Chan &

Parhankangas, 2017; Oo et al., 2019). Per Chan and Parhankangas (2017), more innovative products are riskier to develop, harder for crowdfunders to understand, thus yielding less favorable funding outcomes.

One stream of literature has also scrutinized product innovativeness as a moderator of other performance determinants. Here, main attention has been devoted to understanding how product innovativeness influences the performance implications of some organizational aspects of new product development (e.g., Langerak & Hultink, 2006; Olson et al., 1995; Salomo et al., 2007).

More closely related to our study, Lee and O'Connor (2003) have documented that, for more innovative products, firms would benefit more from pre-announcing the new product launch as well as from emotional rather than functional advertising. This is partly due to the negative effects of product innovativeness discussed above, that is, the greater uncertainty and fear of unfamiliar product traits consumers face for highly innovative products (Lee & O'Connor, 2003). In their study, both the signal (i.e., advertising) and its moderator (product innovativeness) are firm's decisions, and thus the signal can be strategically fine-tuned by the firm depending on the level of product innovativeness. In our study, the signal is *not* provided by the firm. Rather it is provided by a third-party, that is, the crowd, and thus this strategic fine-tuning can hardly occur. Further, in terms of findings, Lee and O'Connor (2003) study and find a linear (positive) moderation of product innovativeness on certain advertising features. In contrast, our contention here is that the level of product innovativeness modifies the efficacy of the signal generated through a CF campaign in an inverted U-shaped manner.

To derive our hypothesis, we merge our conceptualization of CF as a signal with the traditional effects of product innovativeness. Specifically, when the degree of product innovativeness is relatively low, an increase in the product innovativeness should boost the signal value that a positive CF performance delivers to consumers active in the commercialization stage. That is, the salience that these consumers attribute to a positive CF performance should initially increase with product innovativeness. The rationale is that, as innovativeness increases, consumers become less familiar and knowledgeable about the product (Chan & Parhankangas, 2017; Delmestri et al., 2005; Lee & O'Connor, 2003). They have fewer clues to make accurate assessments and are naturally more vulnerable to product quality uncertainty (Lee et al., 2016; Morvinski et al., 2017). Therefore, they need to rely on *external* sources of information to a greater extent to evaluate whether the product is worth buying (Lee et al., 2016; Micheli & Gemser, 2016; Morvinski et al., 2017). Indeed, signals that curb product quality uncertainty and information asymmetry exert greater impact when consumers' perceptions of such issues are high (Dimoka et al., 2012; Hong & Pavlou, 2014; Spence, 1973). As argued in our first hypothesis, a reward-based CF campaign can be one of those influential sources of information because the reward mechanism helps elicit early consumer preferences through risky financial commitment, making the campaign performance a reliable product quality signal in the eyes of future potential consumers (Chemla & Tinn, 2020; Roma et al., 2018; Strausz, 2017; Viotto da Cruz, 2018).

However, when the level of product innovativeness exceeds a certain threshold, greater product innovativeness should diminish the value of the information that a positive CF performance delivers to future potential consumers. When innovativeness is too high, the outcome generated by the CF campaign becomes indeed a less reliable signal for these consumers. Product quality perceptions of consumers active in the market stage are likely to diverge considerably from those of early adopters (i.e., the crowd active in the campaign) when product innovativeness becomes too high. As theory suggests, highly innovative products may require consumers to change habits, views, feelings, and/or spend effort to learn and appreciate them (Calantone et al., 2006; Menguc et al., 2014), may negatively overwhelm them due to the absence of links to familiar sensations (Allen et al., 2022), and they may even be too far ahead of their time to be understood (Chan & Parhankangas, 2017; Delmestri et al., 2005). Hence, ultra-innovative products may result appealing only to early adopters (i.e., the crowd active in the CF campaign) and other consumer niches (hardcore fans, *aficionados*) who are by nature familiar with such innovative features and their meanings, or possess the special attitudes/knowledge/passion to fully assess and value them (Kickstarter, 2020; Taeuscher et al., 2021). As a result, at the commercialization stage, most consumers will sense that campaign contributors are not necessarily representative of their views for product quality, thus devaluing the information delivered by a positive CF performance when making their purchase decisions. These arguments imply that the positive effect of the reward-based CF performance on market success should be attenuated.

Because of the above conflicting effects connected to product innovativeness, we expect the efficacy of the CF performance as a signal, and thus its effect on the market performance, to arc as an inverted U-shape with rising product innovativeness. Accordingly, we formulate as follows:

> **Hypothesis 2. (H2)** The degree of new movie innovativeness moderates the relationship between reward-based CF performance

and box office performance in an inverted U-shaped fashion.

2.3 | The moderating role of experts' judgment

We also investigate how the role of the reward-based CF performance as a signal affecting market performance is moderated by another influential signal: the judgment of experts. Numerous studies focusing on the movie industry have highlighted the positive effect of critics' reviews as a third-party signal that softens consumer uncertainty about product quality, thus favoring purchases (Bharadwaj et al., 2017; Hadida, 2009). Critics are usually perceived as knowledgeable experts that have also experienced the product prior to its public release (Bharadwaj et al., 2017). Experts have generally occupied a prominent role in many settings including the arts and the funding of science or innovation, by serving as influencers for the general public and other types of involved parties, by predicting commercial success, or by serving as gatekeepers of vital resources (Baum & Silverman, 2004; Eliashberg & Shugan, 1997; Kim & Viswanathan, 2019; Mollick & Nanda, 2016; Reinstein & Snyder, 2005).

Recently, the emergence of peer-to-peer platforms or crowd-based phenomena (e.g., CF, crowdsourcing, online review platforms) has spawned a process of democratization in the production and diffusion of information. On the one hand, this has increased the amount of information available to individuals; on the other hand, it has magnified the influence that individuals can exert directly or indirectly on a multitude of other people (Godes & Mayzlin, 2004; Mollick & Nanda, 2016; Trusov et al., 2009). This growing reliance on the crowd has generated recent interest in the relationship between expert and crowd judgments in various business settings, including the arts (e.g., Mollick & Nanda, 2016), sports (e.g., Butler et al., 2021), politics (Greenstein & Zhu, 2018), and services (e.g., Tat Keh & Sun, 2018). For instance, Mollick and Nanda (2016) have documented an alignment between crowd and experts in art funding decisions. However, in terms of their comparative efficacy as signals, consumers may still give greater weight to the information provided by critics than by the crowd as source expertise and authoritativeness exceed experiential credibility (Flanagin & Metzger, 2013). This may depend on how knowledgeable and familiar consumers are with the product. For instance, frequent moviegoers rely more on critics' reviews, while infrequent moviegoers trust user reviews to a greater extent (Chakravarthy et al., 2010).

Closely related to our work, one stream of literature has examined the interplay between user and expert reviews in the movie industry (Basuroy et al., 2020; Chakravarthy et al., 2010; Kim, Ding, et al., 2022a; Wang et al., 2015; Zhou & Duan, 2016). However, these studies have mostly focused on how the level of disagreement among users or experts and between users and experts shapes the effect of eWOM on movie performance. Although the contraposition between expert and crowd judgments provides valuable insights, how the efficacy of the *early-stage signal* sent by the crowd through the CF campaign is moderated by the signal later sent by the experts through their reviews still needs unraveling.

To build our arguments on this issue, we ground on signal interplay (Bapna, 2019; Courtney et al., 2017). The central tenet is that signal efficacy may be strengthened or weakened by the contextual presence of other signals. Recent studies have started examining this issue, with a particular focus on signals able to facilitate new venture financing (Bapna, 2019; Colombo et al., 2019; Courtney et al., 2017; Plummer et al., 2016; Roma, Vasi, & Kolympiris, 2021a; Scheaf et al., 2018; Stern et al., 2014; Vanacker et al., 2020). According to this literature, signals providing similar information, or pertaining to the same informational domains, reduce similar types of uncertainty, and thus are likely to curb each other's marginal effect (Colombo et al., 2019). In contrast, signals that attenuate distinct types of uncertainties (e.g., market, technology, competition) may add value to each other (Bapna, 2019; Colombo et al., 2019; Roma, Vasi, & Kolympiris, 2021a).

For instance, Bapna (2019) has demonstrated how signals that inform of product features become more effective to investors when coupled with signals conveying market characteristics or investment-related characteristics. To the opposite, in the CF setting, Courtney et al. (2017) have shown that the marginal value of media usage as a signal is diminished by the presence of prior successful experience of the entrepreneur. The reason is that both these two firm-generated signals convey similar information, that is, they both inform about general project quality. We apply the same logic in building our arguments on the interplay of the two signals originated from the crowd and the experts, respectively. However, we differ from prior literature first because the signal receivers (consumers, not financiers) differ. The dynamics driving VC or other equity investments are totally distinct from those guiding consumers to purchase a product. Second, our study is interested in reward-based CF (performance) as a signal itself, not as a mere stage for testing other signals.

Building on the above stream of literature on signal interplay, we propose that—at least in the context of the movie industry—signals sent by the CF campaign and the experts weaken each other's marginal value. More specifically, the positive effect of the reward-based CF performance on the market performance decreases as the critics' rating increases. The reason is that the two signals do not pertain to different specific informational domains. Rather, they convey the same type of information. Indeed, both sources ultimately produce comprehensive signals (e.g., ratings of critics and monies pledged from CF backers) that work to inform future potential consumers of the overall product quality. That is, in line with the arguments of Courtney et al. (2017), they serve more as a global indication of product quality, rather than providing information related to merely distinct, or even independent, informational domains.[6]

If two signals provide similar information, and thus reduce the same type of uncertainty, the marginal value of either signal in the eyes of the signal receiver should be attenuated in the presence of the other signal (Bapna, 2019; Colombo et al., 2019; Courtney et al., 2017). Therefore, we expect the efficacy of the positive indication conveyed by a good CF performance to be weakened by the contextual presence of favorable expert recommendations. In fact, for consumers confronting product quality uncertainty in the market stage, an increase in the CF performance should have limited value (as a signal) when they observe high rating from critics. In line with prior arguments (e.g., Courtney et al., 2017), high critics rating already reassures market-stage consumers as to the product quality, and thus reduce their urge to consider other positive information on the same aspect. As a result, for favorable critics rating, a rise in CF money commitments should not yield a considerable increase in consumers' purchase propensity, and thus in the box office performance. Vice versa, following the same logic, an increase in the CF performance is highly valued by consumers when they observe a low rating from the critics. In fact, such an increase can offset the negative signal sent by the critics and become decisive to break any hesitation making a purchase (i.e., watch the movie). As a result, when critics issue warnings, an increase in the CF performance should be substantially beneficial to the box office performance. Accordingly, we formulate as follows:

Hypothesis 3. (H3) The effect of a movie's reward-based CF performance on its box office performance weakens as the rating provided by critics becomes more favorable.

3 | METHODOLOGY

3.1 | Data

To test the above hypotheses, we collected data on CF campaigns regarding movie projects from the reward-based CF platform Kickstarter. We selected Kickstarter since it is one of the largest and most successful CF platforms with a long record of campaigns promoted, and particular interest also in movie projects. We started by retrieving data on all 15,239 CF campaigns displayed in its category *Cinema & Video* from January 2010 until the end of April 2017.[7] Next, we excluded CF projects improperly categorized by Kickstarter as movies. Beyond subcategories encompassing varied film genres, the category *Cinema & Video* includes project subcategories unrelated to movies, such as Festivals, Music Videos, Television, and Webseries. Moreover, to collect all necessary data on movie characteristics, their production, distribution, and market performance, we checked for listings of movie projects in dedicated and distinguished movie databases: Imdb.com (professional version), BoxOfficeMojo, Rotten Tomatoes, and The Numbers. All these websites have been commonly used in prior related research (e.g., Akdeniz & Berk Talay, 2013; Bharadwaj et al., 2017; Karniouchina, 2011b). One very appealing feature of the movie industry is the availability of information regarding the market performance of single products (i.e., movies). In contrast, such information is scant for other product categories, especially in the context of CF where these products are often developed by new ventures.

Matching the movies retrieved from Kickstarter with those listed in the above movie databases yielded 1059 observations related to actual movie projects for which the necessary information to conduct our study was available. Interestingly, out of these 1059 observations, 152 movies were first released through cinemas, while the rest were commercialized directly through other

[6]Rotten Tomatoes website defines their average critics' rating as an indicator of the overall quality of a movie (https://www.rottentomatoes.com/faq#:~:text=The%20Average%20Rating%20measures%20the,given%20film%20or%20TV%20show). Similarly, numerous studies on CF identified the campaign performance as an indication of overall quality of a project (Agrawal et al., 2014; Colombo & Shafi, 2021; Drover et al., 2017; Roma et al., 2017).

[7]Note that Kickstarter limits the number of campaigns displayed for each category (and subcategory). Specifically, no more 100 pages can be loaded per subcategory. This implies that if the name or the URL of a given project is not known a priori, the researcher cannot access all possible campaigns when such limit is exceeded and must rely only on the "visible" campaigns. Yet, the fact that the number of "visible" campaigns in the *Cinema & Video* category is vast (15,239 campaigns) and encompasses all subcategories (i.e., all possible genres) aptly ensures high reliability in our initial sample.

distribution channels, for example, video streaming platforms, TVs, and so forth.[8]

The goal of this study is to investigate the role of reward-based CF performance as a signal for consumers, and thus as a determinant of market performance of movie projects. As a consequence, we focus mainly on the subsample of 152 CF movie projects released in theaters post-campaign since for these projects the revenue is easily accessible via box office results. In contrast, projects commercialized directly through other distribution channels (i.e., video streaming platforms, TV, etc.) lack public information usually secret in private contracts between film producers and distributors. Note that the size of our theater-released movie sample aligns with relevant literature on the film industry (e.g., Basuroy et al., 2003, 2006; Bharadwaj et al., 2017; Chen et al., 2012; Chintagunta et al., 2010; Gemser et al., 2008; Hennig-Thurau et al., 2015; Karniouchina, 2011a; Liu, 2006; Liu et al., 2015; Moon et al., 2010).

Nevertheless, as explained later in model estimation, we do consider movies commercialized directly through other distribution channels (i.e., the remaining 907 movies) when we enlist the Heckman selection regression model to address potential bias concerns regarding the fact that the distribution channel is a decision variable from movie producers.

3.2 | Variables and operationalization

3.2.1 | Dependent variable

We measure our dependent variable, the market performance of the movies released in theaters in the United States, by accessing box office revenues available in our selected movie databases and computing the variable *Box Office Gross*. We use US box office gross rather than global (or foreign) figures since the former type is much more available (and reliable). This choice should not be problematic in our setting as the great majority of movie projects and CF contributors in the sample are from the US and Kickstarter is a US-based platform. In our sample, 82% of movies are indeed US-based productions, and more than 75% of campaign contributors live in the US. Thus, both box office and CF campaigns mostly reflect the American audience. Moreover, as discussed later, we control for a movie being a US production to account for any possible disadvantage of non-US movies.

3.2.2 | Independent variables of interest

We measure our main independent variable, performance in the reward-based CF campaign, by means of the amount pledged in the CF campaign. This variable, referred to as *Pledged Amount*, is the amount of money reached at the end of the campaign irrespective of goal attainment. This variable has been utilized as measure of campaign performance in many CF studies, emphasizing the informational role of reward-based CF (Drover et al., 2017; Roma et al., 2017; Viotto da Cruz, 2018). By representing the total commitments from campaign contributors who are mostly product early adopters, a campaign may still signal high value if able to attract favorable interest from the crowd, even in the case of unmet goal (Roma et al., 2017). In other words, it is not the actual funds a movie receives from the campaign to finance production and distribution (we control for the budget to account for the financial resources necessary to make and distribute the movie). Rather, it is how much money the crowd commits in the campaign that signals the movie quality to future consumers.[9] Moreover, this measure is preferable to the ratio *amount pledged over goal* because under an all-or-nothing mechanism, the ratio

[8]Matching the movies on Kickstarter with those available in the foregoing movie databases naturally removes a multitude of movie projects never released through any distribution channel since they failed in earlier stages or were simply recreational projects created by hobbyists. We note that disregarding these projects in our study does not introduce any bias. Rather, it helps strengthen our findings. Indeed, the excluded projects display much lower average performance in the CF campaign than those included in our sample: the average amount pledged (the success percentage) is $13,753 (53%) for excluded projects versus $53,385 (88%) for included projects. This implies that we exclude the projects that underperform in CF and, at the same time, fail in the marketplace (not even reaching the market). As shown later, in line with our arguments, we find that the performance in reward-based CF is positively associated with the market performance. Therefore, the inclusion of these excluded projects would have simply reinforced our finding, better discriminating the role of low versus high CF performance in terms of market performance: projects poorly performing in CF being more likely associated with negative market performance, and projects outperforming in CF more likely winning in the market. In other words, excluding these projects yields a rather conservative empirical setting for testing our arguments; and since our results hold in such conservative environment, they would likely hold in less restrictive setting where these projects are included.

[9]In our sample, there are only seven movies (out of 152) that did not reach the target goal, thus failing to receive money from the crowd, given the all-or-nothing mechanism employed by Kickstarter. Nevertheless, they were later produced and released in theaters. Although these movies could not count on CF money, their campaign still provided some (positive or negative) information about people commitments. To show robustness our findings, we ran two additional analyses: one by explicitly controlling for a dummy variable indicating whether the goal was reached in the campaign, and the other one by excluding the seven movies that did not reach the goal. In either case we obtained the same qualitative results as those presented in the article. These analyses are available from the authors.

may be affected by potentially different risk aversion among project creators (Roma et al., 2017). The data regarding our dependent variable were retrieved from Kickstarter.

To test the inverted U-shaped moderating role of the degree of movie innovativeness (Hypothesis 2 (H2)), we introduced the interaction between the variable *Pledged Amount* and both linear and quadratic terms of a complex measure for the degree of movie innovativeness. This measure tracks how frequently the combination of keywords and genres of a given film appears in the entire universe of movies included in Imdb.com. Specifically, we collected data for all movies available in the Imdb.com database. For the entire universe of movies in Imdb.com, we retrieved genres and keywords describing the main characteristics of a movie. In Imdb.com, each movie is assigned one or more genres that identify the main narrative and stylistic categories as well as the chief driving forces behind a movie story arc. Moreover, each movie is described with several keywords that help detail the topics, the plot treated by the film, and sometimes even other aspects such as peculiar visual-sound effects, costumes, and scenography.

Considering all genres and keywords across the entire universe of movies listed in Imdb.com, we were able to build a matrix containing the number of occurrences of each possible genre-keyword couple to thus compute the number of occurrences of the genre-keyword couples for each movie in our sample (1059 movies). The rationale behind using the number of occurrences of its genre-keyword couples to measure the degree of innovativeness of a movie is as follows. A film dealing with less treated topics in the cinematographic history (i.e., less frequent keywords) or one handling known topics under new narrative, stylistic, or even technical perspectives (i.e., frequent keywords rarely pegged to a specific movie genre) are more likely to be deemed "innovative" in the cinematographic landscape. In other words, we believe that two movies distinct in the number of occurrences of genre-keyword couples will also exhibit meaningful differences in originality and consequent ability to uniquely advance the movie industry.

To illustrate, the three-time Academy Awards-winning movie "Life is Beautiful" treated holocaust-related themes (*holocaust*, *concentration camp*, *World War II*) in a very different manner from prior movies featuring similar material (e.g., "Schindler's List"), also using comedy lens. As a matter of fact, this movie is also categorized in the comedy genre, reflecting a very rare blend of genres and keywords. Similarly, the more recent "Get Out," winning an Academy Award for Best Original Screenplay in 2018, tackled a very old topic, that is, racism against African-American people, by mixing horror, thriller, and even satiric elements. Indeed, the movie includes *satire*, *racism*, *African-Americans*, and *white supremacy* as keywords while classed in horror, mystery, and thriller genres. Again, this type of mix is quite rare in the movie universe.

A similar approach in measuring product innovativeness has been used in other studies focusing on innovation issues in the film industry (Perretti & Negro, 2007). To align with our assumption, we weighted the number of occurrences of each genre-keyword couple in our sample by the total occurrences of the given genre and the given keyword. This allowed us to take into account that some genres (keywords) appear more frequently irrespective of any combination with a specific keyword (genre). Then, we summed the weighted number of occurrences across all genre-keyword couples associated with a given movie.[10] Since this frequency-based sum inversely relates to product innovativeness, we obtained a direct measure, *Product Innovativeness*, by inverting it for each movie via its division from the maximum resultant value across all movies in our sample.

Overall, the choice of using this elaborated frequency-related measure of movie innovativeness reflects the well-known challenges in operationalizing product innovativeness (McNally et al., 2010). In the innovation management literature, product innovativeness is usually operationalized by surveying managers or consumers for qualitative assessments (Calantone et al., 2006; Chan & Parhankangas, 2017; Kleinschmidt & Cooper, 1991; McNally et al., 2010)—an approach hardly applicable to our study without purposely watching each movie. Absent surveys, we believe our approach appears the most reasonable (Perretti & Negro, 2007). Still, in Section 5, we verify our findings as robust to the use of an *alternative* measure of product innovativeness, built by evaluating the presence of this feature in critics reviews posted on Rotten Tomatoes.

In addition to introducing the interactions of both linear and quadratic terms of this measure of innovativeness with the main independent variable *Pledged Amount*, we controlled for the direct effect of this measure by including its linear and quadratic level forms consistent with prior literature (Kleinschmidt & Cooper, 1991).

[10]It is important to note that in computing our measure, we summed the weighted number of occurrences across all genre-keyword couples associated with a given movie, rather than taking the average. The reason is that, consistent with the general logic of our approach, film innovativeness depends on the overall "popularity" of the topics (or topics-genres) treated by the focal film, and not on mere "popularity" of single topics (or topics-genres). Thus, computing *all* occurrences associated with a given movie allowed to have a better sense of its originality in terms of topics featured and/or topics treated under new perspectives.

Finally, to test our Hypothesis 3 (H3), we introduced the interaction between variables *Pledged Amount* and *Critics Rating*, where the latter is measured as the average rating of professional critics available on the Rotten Tomatoes website for a focal movie released in theaters. Similar to prior literature (e.g., Basuroy et al., 2003; Bharadwaj et al., 2017; Chintagunta et al., 2010; Eliashberg & Shugan, 1997; Karniouchina, 2011a; Reinstein & Snyder, 2005), critics ratings likely influence consumers' quality perception of a film and their consequent purchase decisions. Therefore, in addition to the interaction with the main independent variable *Pledged Amount*, we controlled for the direct effect of *Critics Rating* by including its level form.

3.2.3 | Control variables

We also added a number of control variables accounting for movie characteristics that may influence its market performance.[11] First, we control for the budget invested in the project by introducing the variable *Movie Budget*. For movie projects successful in CF, the movie budget may naturally include (at least in part) the amount collected through the campaign. We also control for the production country by introducing a dummy variable (*US Production Country*) indicating whether a movie is produced in the US or elsewhere. Controlling for the production country is necessary since the American cinema industry has always been widely considered the most relevant and influential worldwide (Galloway, 2012).

To recognize their different financial and marketing assets, we followed the traditional industry classification and distinguished producers/distributors in Major, Mini-Major, and Independent studios (e.g., Wherry & Schor, 2015) by enlisting two dummies *Major* and *Mini-Major*. Major producers–distributors are companies that have historically released a large number of films accounting for a very significant market share. Dubbed the "Big Six" are: *Universal Pictures*, *Paramount Pictures*, *20th Century Fox*, *Columbia Pictures*, *Warner Bros. Pictures*, and *Walt Disney Pictures* (Katz, 2017).[12] Mini Major production–distribution companies account for lesser market shares at the international level while still having considerable relevance and include: *Lionsgate Films*, *Metro-Goldwyn-Mayer*, *DreamWorks SKG*, and *The Weinstein Company* (Wherry & Schor, 2015).[13] Remaining producers–distributors logically classified as independent studios.

Moreover, we introduced a dummy variable, *Actors/Directors/Writers Nominations/Awards*, indicating whether at least one member of the cast (in the actor, director, and writer categories, respectively) of a given movie had won an award or received a nomination during their entire career before participating in the focal film.[14] To calculate this variable, we enlisted six of the most important film award ceremonies or festivals worldwide, that is, Academy Awards, Golden Globes, and British Academy Film Awards, as well as the Cannes, Berlin International, and Venice Film Festivals. Similar to the case of *Critics Rating*, we included the variable *User rating*, computed as the average vote casted by registered users on Imdb.com per given movie released in theaters. To account for competition faced by each movie when released for the first time in theaters, we also controlled for the variable *N. of Movies in Theaters in the Same Month and Genre* computed as the number of movies of the same genre released in theaters during the month a given film was released. We also controlled for whether the focal movie was a sequel of a prior movie enlisting the dummy *Sequel*, as well as for the CF campaign goal (*Campaign Goal*). We introduced four dummies indicating the genre of each film in our sample per both Kickstarter and Imdb.com movie categorization, that is, *Comedy and Musical*, *Drama*, *Documentary*, and *Other Genres*. In particular, *Other Genres* comprised all movie categories displaying a percentage of occurrences under 3%. Finally, we controlled for the film release year by

[11]Among control variables, we could not include the MPAA rating because in the movie databases it was available only for 57 movies commercialized in theaters (out of 152 in our sample), thus precluding any reliable analysis. This may be due to the fact that MPAA rating is a *voluntary* system. However, the absence of this variable should not prove problematic because we include numerous control variables that can influence directly or indirectly what the MPAA rating helps capture: size of the potential audience.

[12]Note that Walt Disney acquired 20th Century Fox on March 2019. Since the acquisition refers to a period subsequent to the release dates (2010–2018) of movies in our sample, we deem them separate studios.

[13]DreamWorks SKG is a label of Amblin Partners. The Weinstein Company filed for Chapter 11 bankruptcy in August 2018, following the scandal where the company's founder Harvey Weinstein was implicated. At any rate, our sample does not include any movie distributed by The Weinstein Company.

[14]To capture movie quality and marketability, we looked at the past successes (awards and nominations) of the major *cast* components (actors, directors, writers), rather than at awards and nominations achieved by the given movie. We did this to avoid any reverse causality bias. Indeed, awards and nominations are assigned usually after a movie has been released in theaters (e.g., the cases of *Golden Globes*, *Academy Awards*, etc.). Therefore, the market performance of a movie is often realized *before* its potential nominations are announced, and awards are assigned. This would imply the existence of a potential reverse effect from market performance on the odds of nominations/awards assignments. In contrast, looking at past successes of major cast members averts this problem. In addition, while the number of nominations/awards for the crowdfunded movies in our sample is small, the number of past nominations/awards of actors, directors and writers of such movies is certainly higher.

including nine dummies from 2010 to 2018 (*Year of Release*).

Notably, the use of control variables directly associated with product quality—critics' ratings, user ratings, movie budget, cast quality, and type of producers/distributors—helps rule out alternative explanations related to *unobserved* quality, thus increasing the confidence that our results duly stem from the role of reward-based CF as a signal, rather than as a mere predictor. In addition, we use the Heckman selection model and instrumental variables regressions and consider CF campaign publicity to further increase this confidence.

Tables 1 and 2 report the descriptive statistics for the subsample of our main interest that includes only movies released in theaters (152 movies) and for the full sample of 1059 movies (i.e., the sample including also movies commercialized through other distribution channels), respectively. For brevity, the correlation matrix in Table 3 is reported only for the smaller sample ($n = 152$) of movies released in theaters.[15]

3.3 | Model estimation

For our main analysis, we used two approaches. First, we began empirical tests by considering only the sample of movie projects first released in theaters after the CF campaign (i.e., $n = 152$). Given the cross-sectional nature of our dataset and the continuous nature of our dependent variable, we used here robust OLS regression. Second, we verified our results robust to sample selection using the Heckman selection model. In fact, potential bias concerns may arise due to the nonrandom nature of our sample of (152) movies released in theaters. Since the selection of the commercialization channel is a decision variable, movie creators may indeed self-select to first release a film in theaters rather than opting for other channels (or vice versa) based on *unobserved* characteristics that correlate to the main independent and dependent variables. Heckman selection regression model corrects for any potential selection bias by taking into account that different movie projects might have distinct odds of being exposed to different commercialization channels.

To accomplish this, we used the full sample of 1059 movies, comprising, as described earlier, 907 movies commercialized through other channels beyond the 152 theater releases. In the first stage, the probability of being commercialized in theaters after the CF campaign was regressed against a menu of factors expected to affect the likelihood of channel selection. The second stage regressed the specification of our interest corrected by the Heckman procedure. To apply the Heckman selection regression model, the exclusion restriction must be met: the first-stage regression must include at least one additional predictor *not* correlated to the outcome of the second-stage regression. For this predictor, we used a proxy for the growth of the video streaming industry: the number of paying Netflix subscribers (thus using the most important platform in this industry) during the same time our sample films were released.[16] This variable suited our scopes for three reasons.

First, it is well known that the rise of video-streaming industry, and Netflix in particular, has deeply affected the way consumers gain access to movies and other entertainment products (Morgan, 2019). The growing importance of this phenomenon has naturally influenced the commercialization choices of movie creators that have a new, relevant, and in some cases, even more accessible distribution option for product release (Morgan, 2019).[17] In addition, by having movies released in different years (movie release in our sample being 2010–2018), we ably and fully captured the growing trend of this phenomenon and its potentially varied impact on channel choices over these years. Second, while the growing size of the video-streaming industry, as exemplified by Netflix, likely influences the choice of the commercialization channel, it should hardly influence the market

[15]The correlation matrix suggests no serious degree of correlation among the variables employed in this study, except for the correlation coefficient between the variables *Pledged Amount* and *Campaign Goal*. Yet, under the base model, the VIF of these variables does not exceed the usual rule-of-thumb 10 (8.19 and 8.06, respectively), while the mean VIF is near 6. To show that this correlation does not impact our results in any meaningful way, we ran our regression models with and without the control *Campaign Goal* and found that our results are fully robust across all the models irrespective of its inclusion, thus eliminating potential multicollinearity concerns. As Baum (2006, p. 87) states multicollinearity that does not affect key parameters can be safely ignored. Because multicollinearity inflates standard errors, significant coefficients would become more significant if the sample contained fewer collinear regressors. In this article, we provide the results including *Campaign Goal*, while making the alternative analysis available upon request.

[16]The number of paying subscribers was retrieved directly from the Investor Relations section of the Netflix website for the entire period of interest (https://www.netflixinvestor.com/ir-overview/profile/default.aspx). Netflix has always been regarded as the major platform, by far, in the video-streaming (subscription-based) industry worldwide (Kindig, 2019). Therefore, we lose no generality by exemplifying the video streaming industry via the Netflix user base, for which official data were available.

[17]Independent films typically face greater difficulties in accessing theaters. For these movies, Netflix and similar players offer an easier, yet very good, alternative (Morgan, 2019). Movies launched in CF often belong to this category where creators are naturally more keenly affected by the channel-selection decision as the video-streaming sector expands.

TABLE 1 Descriptive statistics (152 observations).

Variables	Mean	SD	Min	Max
Box Office Gross ($) (Dep. variable)	311,265.7	981,314.6	2021	7,449,681
Pledged Amount	141,484.3	528,185.8	4453	5,702,153
Product Innovativeness	3.156	1.185	0	3.814
Critics rating	6.693	1.137	1.8	8.75
User rating	6.894	0.968	3.9	9
N. Movies in Theaters in the Same Month and Genre	458	424.66	43	3593
Movie Budget	482,817	1,125,914	5203	8,000,000
US Production Country	0.816	0.389	0	1
Major	0.033	0.179	0	1
Mini-Major	0.007	0.081	0	1
Actors/Directors/Writers Nominations/Awards	0.072	0.260	0	1
Comedy and Musical	0.046	0.210	0	1
Drama	0.283	0.451	0	1
Documentary	0.638	0.482	0	1
Campaign Goal	117,766.7	314,867.4	3000	2,220,000
Sequel	0.013	0.114	0	1
Release Year 2010	0.013	0.114	0	1
Release Year 2011	0.020	0.140	0	1
Release Year 2012	0.105	0.308	0	1
Release Year 2013	0.224	0.418	0	1
Release Year 2014	0.257	0.438	0	1
Release Year 2015	0.237	0.427	0	1
Release Year 2016	0.125	0.332	0	1
Release Year 2017	0.020	0.140	0	1
Release Year 2018	0.000	0.000	0	0
Product Innovativeness (alternative measure)	1.645	7.927	−8	84
Number of Critics Reviews	29.691	40.454	1	277
Category Aggregated Pledged Amount (million $ — used as IV)	118.0	88.6	1.596	350.000

performance of a specific movie, once released in theaters. As a matter of fact, the box office gross has been quite stable in the time span of our interest despite the burgeoning trend in video streaming platforms.[18] Moreover, the performance of a specific movie more likely depends on its *own* features rather than on general trends in diverse distribution channels (Ryu et al., 2019). Third, our proxy, being a variable that captures industry growth, can hardly be affected by a single movie creator based on its own (latent) traits, which further elevates confidence as to the exogeneity of this variable (Larcker & Rusticus, 2010).

To operationalize of the impact of the video streaming industry growth, we divided the number of paying Netflix subscribers in the year of focal movie release by its budget to introduce the variable *Video Streaming Size Impact* in the first-stage regression. Under this correction, the instrument varies at both year and observation levels (Rossi, 2014). We chose to divide by the movie budget because the impact of the growth of the video streaming industry may not be the same for all movies. High-budget movies may be less affected by growth in video-streaming; thus, the option to commercialize these movies in theaters appears less influenced by this growth. Our results, however, prove robust irrespective of division by the film budget (the analysis is available upon request).

[18] https://www.the-numbers.com/market/.

TABLE 2 Descriptive statistics (1059 observations).

Variables	Mean	SD	Min	Max
Pledged Amount ($)	53,385.5	224,657.1	168	5,702,153
Product Innovativeness	3.012	1.223	0	3.814
Movie Budget (S)	213,150.7	911,009.9	1000	20,000,000
US Production Country	0.829	0.377	0	1
Major	0.010	0.101	0	1
Mini-Major	0.009	0.097	0	1
Actors/directors/writers nominations/awards	0.035	0.184	0	1
Comedy and musical	0.085	0.279	0	1
Drama	0.306	0.461	0	1
Documentary	0.478	0.500	0	1
Campaign goal	44,999.0	142,575.7	62	2,220,000
Sequel	0.004	0.061	0	1
Release Year 2010	0.010	0.101	0	1
Release Year 2011	0.040	0.195	0	1
Release Year 2012	0.085	0.279	0	1
Release Year 2013	0.153	0.360	0	1
Release Year 2014	0.187	0.390	0	1
Release Year 2015	0.216	0.412	0	1
Release Year 2016	0.209	0.407	0	1
Release Year 2017	0.088	0.283	0	1
Release Year 2018	0.012	0.110	0	1
Product Innovativeness (alternative measure)	0.782	5.233	−8	84
Number of Critics Reviews	15.774	29.624	1	277
Video Streaming Industry Size (millions of users – used for Heckman)	65.505	26.132	20	139.26

Note: For the variables *Product Innovativeness* (alternative measure) and *Number of Critics Reviews*, the descriptive statistics are computed using the 367 observations for which the relative information is available.

4 | RESULTS

Results of OLS and Heckman-selection model regressions are reported in Tables 4 and 5, respectively. Specifically, we first introduced in Table 4 the logarithmic transformation of variable *Pledged Amount* in addition to the control variables (Column 1). Next, we feature the interaction terms in a stepwise fashion in Columns 2–4. In Table 5, for ease of exposition, we present the results of first- and second-stage regressions for the models without and with all interaction terms. As can be observed, the results are largely robust across both approaches. Therefore, we only comment on those obtained using the Heckman selection model, completely specified with all interactions (last column of Table 5).

Before discussing the effect of our main variable, we note, as expected in the first-stage regression, that exogenous regressor *Video Streaming Size Impact* proves strongly significant with a negative effect on the probability of releasing the movie in theaters. This confirms its strength as a predictor of the channel selection choice. Moving to the second-stage regression, most coefficients for the controls display the expected sign and significance. For instance, box office gross improves for CF movies with higher budgets, better ratings from critics, a lower campaign goal, and US production. Among other controls, the effect of a prestigious cast, as measured by their prior nominations and awards, proves not significant, perhaps because few artists received such accolades in our sample. Finally, in the presence of interaction terms, the direct effect of product innovativeness appears to trace the inverted U-shaped relationship. But it must be noted that when the interaction terms are introduced, the linear and quadratic coefficients of the variable *Product Innovativeness* capture its effect when the variable *Pledged Amount* is set to zero.

TABLE 3 Correlation matrix (for the sample of 152 movies released in theaters).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Pledged Amount														
(2) Product Innovativeness (Product Innovativeness – Alternative Measure)	−0.005 (−0.134)													
(3) Critics Rating	−0.062	−0.027 (0.426*)												
(4) User Rating	−0.016	0.024 (0.159)	0.425*											
(5) N. Movies in theaters in the same month and genre	0.032	−0.180* (−0.044)	0.047	−0.099										
(6) Movie budget	0.548*	0.126 (0.059)	−0.104	0.024	0.039									
(7) US Production Country	−0.111	−0.049 (−0.147)	−0.139	−0.121	0.038	−0.148								
(8) Major	0.380*	−0.031 (−0.028)	−0.048	0.016	−0.055	0.272*	−0.008							
(9) Mini-Major	0.136	0.027 (0.028)	−0.129	−0.084	0.041	0.115	0.039	−0.015						
(10) Actors/directors/ writers nominations/ awards	0.066	−0.044 (−0.083)	−0.153	−0.043	−0.031	0.114	0.133	0.233*	−0.023					
(11) Comedy and musical	0.167*	0.055 (−0.059)	−0.278*	−0.126	0.160*	0.207*	−0.058	−0.041	−0.018	0.060				
(12) Drama	−0.038	−0.281* (−0.041)	−0.047	−0.310*	0.176*	0.067	0.148	0.130	0.130	0.163*	−0.138			
(13) Documentary	−0.079	0.207* (0.015)	0.265*	0.441*	−0.186*	−0.189*	−0.111	−0.168*	−0.108	−0.212*	−0.292*	−0.834*		
(14) Campaign goal	0.928*	0.018 (−0.152)	−0.125	−0.069	0.076	0.561*	−0.104	0.316*	−0.070	0.118	0.301*	−0.053	−0.115	
(15) Sequel	0.262*	−0.132 (−0.072)	0.006	−0.065	−0.061	0.123	0.055	0.302*	−0.009	−0.032	−0.025	0.056	−0.033	0.213*

Note: The significance level is equal to 0.05. For ease of exposition, we do not include the coefficients related to the *Year of Release* dummies, which, however, display correlation coefficients no larger than 0.321 in absolute value. Moreover, the control variable *Number of Reviews*, used only when the alternative measure of *Product Innovativeness* is considered, exhibits correlation coefficients no larger than 0.327 in absolute value. Finally, we use natural logarithm transformation for the variables: *Pledged Amount*, *Product Innovativeness*, *Budget*, *Campaign Goal*.

TABLE 4 OLS regression models.

	No interactions	*Pledged Amount* × *Product Innovativeness* (both linear and squared terms)	*Pledged Amount* × *Critics Rating*	All interactions
Pledged Amount	0.857*** (0.266)	0.992*** (0.320)	0.945*** (0.267)	1.093*** (0.306)
Pledged Amount × Product Innovativeness	–	1.410** (0.572)	–	1.770*** (0.562)
Pledged Amount × Product Innovativeness^2	–	−1.251** (0.504)	–	−1.565*** (0.495)
Pledged Amount × Critics Rating	–	–	−0.161** (0.080)	−0.191** (0.080)
Product Innovativeness	1.656** (0.791)	2.005** (0.812)	1.510* (0.809)	1.980** (0.822)
Product Innovativeness^2	−1.420** (0.710)	−1.711** (0.704)	−1.275* (0.729)	−1.662** (0.719)
Critics Rating	0.517*** (0.114)	0.533*** (0.116)	0.519*** (0.112)	0.530*** (0.112)
User Rating	0.044 (0.179)	0.054 (0.175)	0.058 (0.175)	0.066 (0.170)
N. Movies in theaters in the same month and genre	−0.337 (0.319)	−0.383 (0.327)	−0.304 (0.322)	−0.301 (0.221)
Movie budget	0.313*** (0.113)	0.312*** (0.113)	0.325*** (0.114)	0.329*** (0.114)
US Production Country	0.444 (0.323)	0.532 (0.334)	0.429 (0.324)	0.526 (0.336)
Major	0.947 (0.921)	1.076 (0.964)	0.849 (0.884)	1.000 (0.946)
Mini-Major	1.609** (0.665)	1.467** (0.706)	1.049 (0.684)	0.838 (0.732)
Actors/directors/writers nominations/awards	0.296 (0.395)	0.298 (0.396)	0.297 (0.400)	0.342 (0.397)
Comedy and musical	1.071 (0.815)	1.070 (0.833)	1.048 (0.815)	1.128 (0.838)
Drama	−0.583 (0.520)	−0.521 (0.560)	−0.557 (0.485)	−0.231 (0.578)
Documentary	−0.321 (0.549)	−0.375 (0.576)	−0.312 (0.518)	−0.130 (0.634)
Campaign Goal	−0.567** (0.260)	−0.604** (0.265)	−0.646** (0.268)	−0.732*** (0.262)
Sequel	0.198 (0.635)	0.462 (0.817)	0.302 (0.635)	0.497 (0.773)
Year of release (dummies)	Included	Included	Included	Included
Constant	−0.585 (0.1.987)	8.878*** (3.091)	12.789*** (3.176)	14.871*** (3.338)
Number of observations	152	152	152	152
R^2	0.411	0.423	0.422	0.443
F (p-value)	0.000	0.000	0.000	0.000

Note: Robust standard errors in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE 5 Heckman selection regression models.

	First stage (no interactions)	Second stage (no interactions)	First stage (all interactions)	Second stage (all interactions)
Pledged Amount	0.235** (0.116)	0.984*** (0.329)	0.235** (0.116)	1.213*** (0.383)
Pledged Amount × Product Innovativeness	–	–	–	1.805** (0.816)
Pledged Amount × Product Innovativeness^2	–	–	–	−1.634** (0.699)
Pledged Amount × Critics Rating	–	–	–	−0.212** (0.099)
Product Innovativeness	0.002 (0.136)	1.687* (0.871)	0.002 (0.136)	1.916** (0.875)
Product Innovativeness^2	–	−1.418* (0.729)	–	−1.602** (0.735)
Critics Rating	–	0.524*** (0.119)	–	0.444*** (0.096)
User Rating	–	0.40 (0.142)	–	0.062 (0.141)
N. Movies in theaters in the same month and genre	–	−0.317 (0.280)	–	−0.335 (0.275)
Movie Budget	0.586 (0.524)	0.360*** (0.112)	0.586 (0.524)	0.342*** (0.110)
US Production Country	−0.058 (0.147)	0.407 (0.313)	−0.058 (0.147)	0.502* (0.301)
Major	0.099 (0.484)	0.797 (0.794)	0.099 (0.484)	0.965 (0.750)
Mini-Major	−0.880 (0.681)	1.121 (1.653)	−0.880 (0.681)	0.482 (1.593)
Actors/directors/writers nominations/awards	0.293 (0.255)	0.494 (0.547)	0.293 (0.255)	0.368 (0.517)
Comedy and musical	0.632* (0.354)	1.375 (0.981)	0.632* (0.354)	1.283 (0.945)
Drama	1.074*** (0.281)	−0.027 (1.028)	1.074*** (0.281)	−0.027 (0.992)
Documentary	1.104*** (0.267)	0.286 (1.074)	1.104*** (0.267)	0.106 (1.044)
Campaign goal	0.103* (0.055)	−0.432 (0.328)	0.103* (0.055)	−0.699** (0.327)
Sequel	1.198 (1.191)	0.345 (1.163)	1.198 (1.191)	0.643 (1.230)
Video streaming size impact	−0.963** (0.404)	–	−0.963** (0.404)	–
Year of release (dummies)	–	Included	–	Included
Constant	−9.877*** (2.501)	−5.210 (6.433)	−9.877*** (2.501)	10.347* (5.323)
Total observations	–	1059	–	1059
Censored	–	907	–	907
Uncensored	–	152	–	152
Wald Chi-square	–	81.900	–	97.330
p-value	–	0.000	–	0.000
Lambda	–	0.769	–	0.279
Rho	–	0.519	–	0.211
Sigma	–	1.481	–	1.320

Note: Standard errors in parentheses.
$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

More importantly, the sign of our main variable *Pledged Amount* is positive with a statistically significant coefficient, suggesting that the performance of a movie launched in the CF campaign is positively associated with its subsequent market performance at the box office. This provides support to our Hypothesis 1 (H1). That is, a better performance of the movie in CF correlates with its market success, thus providing initial evidence of the positive CF influence on consumers. Moreover, the coefficients of the interactions with the linear and quadratic terms for variable *Product Innovativeness* prove significant, displaying the hypothesized signs. That is, the interaction of variable *Pledged Amount* with the linear (quadratic) term of variable *Product Innovativeness* is positive (negative). This confirms our H2, suggesting that as the level of innovativeness of a movie increases, the effect of CF performance on the market performance strengthens, but only up to a certain point. Beyond such a maximum, the effect of the CF performance on the market performance starts decreasing. Finally, the coefficient of the interaction term between the variables *Pledged Amount* and *Critics Rating* proves significant with a negative sign. This supports H3.[19]

Due to the high number of variables, we also conducted a power analysis to check the achieved power when we add our variables of interest (*Pledged Amount* and its interactions) in addition to the control variables. For instance, considering the main model in Table 4, the R^2 without the variable *Pledged Amount* is 0.373, whereas the R^2 after the inclusion of the variable *Pledged Amount* is 0.411. With a sample of 152 observations and an α equal to 5% level of significance, we get a power ($1 - \beta$ probability) of 0.8745, which is significantly larger than 0.8, that is, the default value in Stata. The power is even greater if we also add the three interactions of *Pledged Amount*, raising the R^2 to 0.443 (0.7 increase compared to the model with only control variables). In this case, we get a power of 0.9478. These results reassure us about the predictive power of our variables of interest, despite the limited size of the sample and the sufficiently high number of variables.

4.1 | Marginal effect analysis

To further prove the reliability of our results, we tested the statistical significance of the marginal change in the box office performance when switching from low to high levels of the *Pledged Amount* (i.e., the reward-based CF performance), at different values (within our sample data range) for the variables *Product Innovativeness* and *Critics Rating* with the remaining variables held at their sample means when continuous or integer, or equaling zero when binary (except baseline dummies). This approach is commonly utilized to demonstrate significance of non-linear relationships, such as interaction and U-shaped forms (Cui & Wu, 2016; Keil et al., 2008; Zelner, 2009). Based on the estimates with all interactions, Figure 1 shows that when the variable *Product Innovativeness* increases, the marginal effect of a rise in the amount pledged in CF on the subsequent box office gross proves statistically significant, increasing up to a maximum and reducing afterward. In Figure 1, the value of our (mean-centered) measure *Product Innovativeness* yielding the highest marginal effect equals nearly −0.45. It can be also observed that the increasing part of the effect is larger than the decreasing part, implying that the negative moderating effect prevails only when product innovativeness is quite high. Finally, Figure 2 illustrates the marginal effect of a rise in the amount pledged in CF on the subsequent box office gross decreases with the variable *Critics Rating*.

5 | ROBUSTNESS CHECKS

5.1 | Alternative measure of product innovativeness

Given the importance of the variable *Product Innovativeness* for our theoretical arguments, we checked the robustness of our findings using an alternative measure. As explained earlier, being based on the weighted frequency of keyword-genre couples assigned to the focal movie by Imdb.com, our main variable has the advantage of being an objective measure. At the same time, however, it may end up capturing movie innovativeness mainly in terms of topics treated. Moreover, by construction this measure is naturally skewed, as most films exhibit relatively small keyword-genre occurrences, still there are few films with large keyword-genre frequencies. Thus, to capture product innovativeness more comprehensively and reduce skewness, we resorted to critics' reviews available on Rotten Tomatoes. Specifically, for each movie in our sample, three researchers of our team (not the authors) independently scrutinized all the critics' reviews, assessing whether any feature of innovativeness was described in the reviews. While being informed about the general context of the study, these researchers were

[19]Note that all our results are also robust to inflation adjustments as well as to the removal of movies with outlier CF success. Specifically, inflation adjustments did not impact results because elapsed time between the CF campaign and the commercialization in theaters was no longer than 2 years in our sample, and we are interested in how the monetary value raised in CF relates to the monetary value raised at the box office, and not their absolute values per se. These additional analyses are available from the authors.

not aware of the specific formulation of the hypotheses. Specifically, for each film review (a movie could have many reviews), each researcher assigned a value of 1 if the review highlighted any feature of innovativeness, a value of −1 if the review cited features contrary to the concept of innovativeness (e.g., unoriginality), and a value of 0 if the review was mute as to innovativeness. Notably, not all the 1059 movies included in the full sample had at least one review on Rotten Tomatoes. Actually, only 367 movies (out of 1059) had at least one review, but all 152 movies commercialized in theaters had at least one. Overall, 6093 extensive reviews of 367 films were analyzed. Each researcher in charge of the evaluation was instructed how to consider the

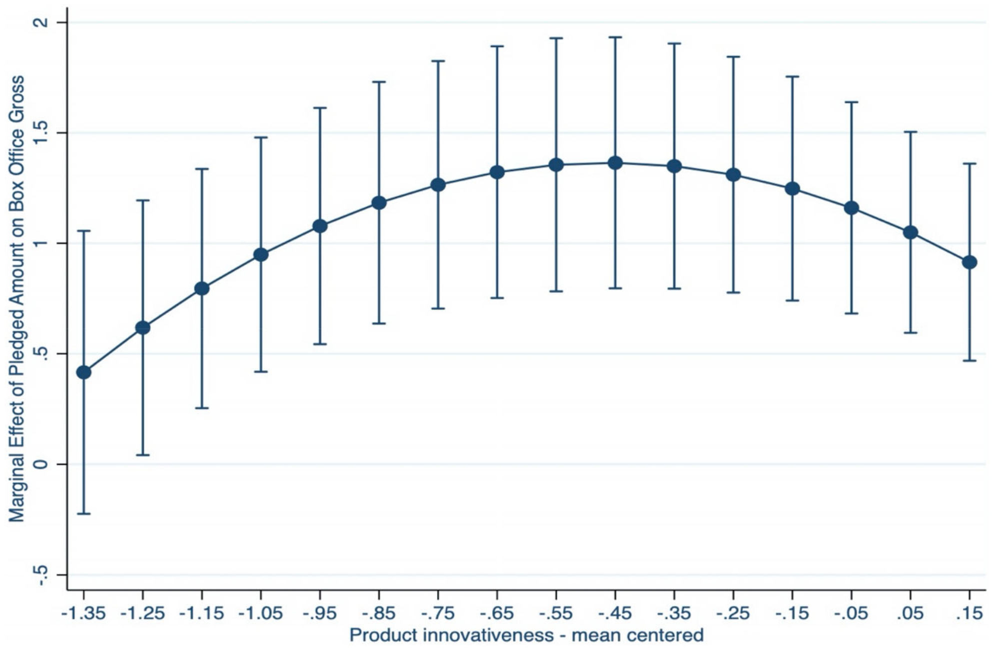

FIGURE 1 Marginal effects analysis of the variable *Pledged Amount* for different levels of the variable *Product Innovativeness*.

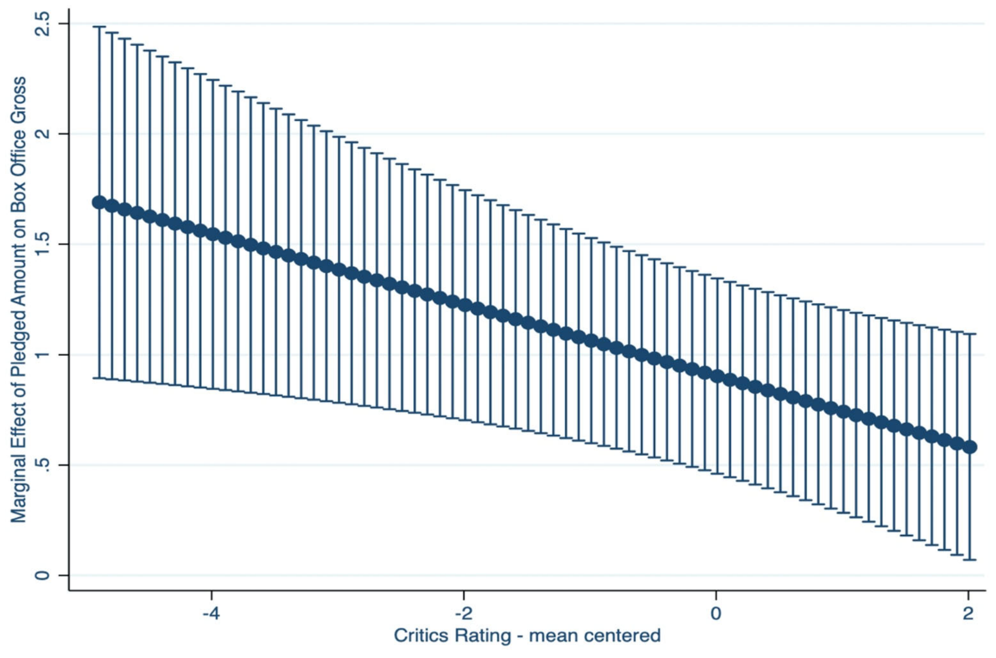

FIGURE 2 Marginal effects analysis of the variable *Pledged Amount* for different levels of the variable *Critics Rating*.

presence of innovative features (or opposite ones) in each review.[20]

After the evaluation step, majority rule was adopted in cases of disagreement, or in rare cases of three different judgments re-evaluation was conducted to reach agreement. Overall, the Cronbach's alpha, commonly used to evaluate inter-rater reliability, equaled 0.76—a value in line with prior CF studies (e.g., Calic & Mosakowski, 2016). Then, we built our alternative measure of innovativeness by summing for each movie the values across all reviews pertaining to the same movie. We chose the sum rather than the average for two important reasons. First, we believe that more "voices" highlighting the innovativeness of a film (or its opposite) more strongly and reliably indicate the true presence of such feature.[21] Of course, our regressions controlled for the number of reviews per movie when using this alternative measure of innovativeness to avoid any possible disproportionate increase in its value for a film having many reviews. Second, had we used the average, movies with more reviews would have naturally tended toward a more dispersed measure, possibly yielding artificially lower (higher) levels of innovativeness than for films with fewer reviews—even where two types of movies proved equally innovative (or equally unoriginal).

By thus using the sum across the reviews for each movie and controlling for the number of reviews, we believe we best captured the feature of innovativeness without creating any dangerous distortion. Descriptive statistics of our alternative measure of product innovativeness and the number of reviews (serving as control variable here) are reported in Tables 1 and 2. Further, due to the differences highlighted above, the correlation between main and alternative measures of product innovativeness is quite low (coefficient near 0.07). More importantly, Tables 6 and 7 report the results for this alternative measure under OLS and Heckman-selection regression models, respectively. Our findings remain qualitatively unchanged.

5.2 | Instrumental variables regression approach

We captured product quality through several controls, including movie budget, critics' rating, user rating, cast quality, and type of producer–distributor. These should significantly reduce, if not eliminate, any potential bias from omitted variable related to product quality or budget size. Moreover, the Heckman selection model should additionally account for unobserved heterogeneity. However, we also resorted to instrumental variables (IVs) regression approach to further reduce these bias concerns and enhance confidence that our results fairly isolate the role of reward-based CF as a signal. In choosing the instrument for our supposedly endogenous independent variable *Pledged Amount*, we followed similar works using aggregate measures of variables computed in prior periods (e.g., Colombo et al., 2019; Roma et al., 2017).

Specifically, for each movie, we computed the overall amount pledged by all contributors in the entire *Cinema & Video* category in the period from Kickstarter inception until the month preceding the campaign launch of the focal movie (*Total Category Pledged Amount*). This variable essentially captured the total amount of money allocated to the movie category on Kickstarter slightly before the campaign of the focal movie project was launched. As such, this variable very likely influences a movie CF performance. On the one hand, it may capture growing overall interest of the Kickstarter community for the movie category until that point, and thus may improve the odds of success for any later campaign, ceteris paribus. On the other hand, it also captures the growing overall funding effort of the Kickstarter community for the movie category until that point. This may imply saturation effects that, combined with temporal increase in project competition, may negatively influence the success for any subsequent campaign. Moreover, because of its aggregate nature and the fact that it pertains to dynamics internal to the Kickstarter community, this variable should influence the box office performance of the single movie *only* via its effect on the CF performance (Roma et al., 2017; Ryu et al., 2019). Thus, the exclusion restriction assumption is presumably met. In addition, we show in the first stage regressions (Tables 8 and 9 for the main measure of product innovativeness and its alternative, respectively) that this instrument strongly predicts (mostly at the 1% level) CF performance, increasing our confidence in the salience of this instrument.

[20]Researchers had to carefully read the entire review, interpret possible ironic views and/or implicit meanings in the review, pay attention to the use of certain words such as innovative, novel, original, and so forth, as well as to any type of innovativeness described including the plot, themes, narrative style, technical, cast, visual/sound effects, costumes, and so forth. To illustrate, we report an example of sentences taken from film reviews that were unanimously identified as innovative: *Charlie Victor Romeo is worth seeking out, as a thought-provoking, original, form-breaking film, is a rare thing.* (*John Fink on movie "Charlie Victor Romeo"*). Here are sentences taken from reviews of movies that were unanimously identified as unoriginal: *That's really Clement and Waititi's core joke*: *These neck-biters have been at it so long that they are only imitating old vampire stereotypes.* (*Brian Miller on movie "What we do in the shadows"*).

[21]That is, it is reasonable to consider a movie with 10 reviews (out of 10) indicating the presence of innovative features as more innovative than a film with a single review (out of one) indicating the presence of such features.

TABLE 6 OLS regression models with alternative measure of innovativeness.

	No interactions	***Pledged Amount* × *Product Innovativeness* (both linear and squared terms)**	***Pledged Amount* × *Critics Rating***	All interactions
Pledged Amount	0.822*** (0.256)	0.884*** (0.265)	2.109*** (0.672)	1.347*** (0.326)
Pledged Amount × Product Innovativeness	–	0.207** (0.080)	–	0.391*** (0.114)
Pledged Amount × Product Innovativeness^2	–	−0.096** (0.039)	–	−0.139*** (0.038)
Pledged Amount × Critics Rating	–	–	−0.180** (0.087)	−0.264** (0.132)
Product Innovativeness	−2.196** (1.004)	−2.946** (1.231)	−1.575 (1.029)	−0.832 (1.945)
Product Innovativeness^2	0.466** (0.223)	0.735*** (0.272)	0.391* (0.212)	0.272 (0.394)
Critics Rating	0.458*** (0.124)	0.468*** (0.124)	0.413*** (0.130)	0.487*** (0.113)
User Rating	0.035 (0.170)	0.052 (0.169)	0.050 (0.167)	0.060 (0.064)
N. Movies in theaters in the same month and genre	−0.384 (0.325)	−0.348 (0.328)	−0.332 (0.325)	−0.334 (0.224)
Movie budget	0.269** (0.112)	0.267** (0.114)	0.277** (0.112)	0.304*** (0.066)
US Production Country	0.458 (0.320)	0.491 (0.324)	0.466 (0.319)	0.498 (0.307)
Major	−0.073 (0.950)	0.006 (1.153)	−0.071 (0.989)	−0.226 (1.196)
Mini-Major	1.567** (0.700)	1.746** (0.712)	0.757 (0.779)	0.449 (0.723)
Actors/directors/writers nominations/awards	−0.235 (0.342)	−0.056 (0.350)	−0.162 (0.361)	0.168 (0.373)
Comedy and musical	1.773** (0.820)	1.551* (0.827)	1.802** (0.799)	1.144 (0.930)
Drama	0.033 (0.527)	−0.370 (0.559)	0.177 (0.458)	−0.131 (0.386)
Documentary	0.307 (0.530)	−0.045 (0.558)	0.440 (0.463)	−0.303 (0.395)
Campaign goal	−0.548** (0.255)	−0.587** (0.257)	−0.631** (0.266)	−0.519*** (0.310)
Sequel	0.416 (0.837)	−0.030 (0.498)	0.452 (0.811)	−0.222 (0.310)
Number of reviews (control)	0.288*** (0.097)	0.270*** (0.097)	0.281*** (0.094)	0.221** (0.087)
Year of release (dummies)	Included	Included	Included	Included
Constant	2.284 (3.506)	12.105*** (3.455)	11.068*** (3.428)	25.641** (9.939)
Number of observations	152	152	152	152
R^2	0.457	0.466	0.466	0.527
F (p-value)	0.000	0.000	0.000	0.000

Note: Robust standard errors in parentheses.
$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 7 Heckman selection regression models with alternative measure of innovativeness.

	First stage (no interactions)	Second stage (no interactions)	First stage (all interactions)	Second stage (all interactions)
Pledged Amount	−0.103 (0.188)	0.825*** (0.269)	−0.103 (0.188)	1.259*** (0.282)
Pledged Amount × Product Innovativeness	–	–	–	0.387*** (0.133)
Pledged Amount × Product Innovativeness^2	–	–	–	−0.139** (0.056)
Pledged Amount × Critics Rating	–	–	–	−0.231** (0.112)
Product Innovativeness	0.272 (0.318)	−2.340* (1.230)	0.272 (0.318)	−0.599 (0.387)
Product Innovativeness^2	–	0.487* (0.254)	–	0.378 (0.371)
Critics Rating	–	0.460*** (0.132)	–	0.487*** (0.112)
User Rating	–	0.039 (0.137)	–	0.100 (0.128)
N. Movies in theaters in the same month and genre	–	−0.387 (0.268)	–	−0.384 (0.248)
Movie budget	−0.836 (1.121)	0.245** (0.100)	−0.836 (1.121)	0.296*** (0.059)
US Production Country	0.306 (0.208)	0.384 (0.323)	0.306 (0.208)	0.355 (0.307)
Major	−0.190 (0.558)	0.061 (0.849)	−0.190 (0.558)	−0.060 (0.863)
Mini-Major	−1.184* (0.711)	1.888 (1.550)	−1.184* (0.711)	1.419 (1.456)
Actors/directors/writers nominations/awards	0.007 (0.350)	−0.240 (0.471)	0.007 (0.350)	0.128 (0.471)
Comedy and musical	0.520 (0.515)	1.670* (0.893)	0.520 (0.515)	1.013 (0.870)
Drama	0.480 (0.416)	−0.118 (0.773)	0.480 (0.416)	−0.547 (0.743)
Documentary	0.678* (0.406)	0.089 (0.833)	0.678* (0.406)	−0.268 (0.775)
Campaign goal	0.093 (0.089)	−0.592** (0.274)	0.093 (0.089)	−0.870*** (0.270)
Sequel	0.888 (1.218)	0.394 (1.068)	0.888 (1.218)	−0.624(1.342)
Number of reviews (control)	0.180*** (0.023)	0.177 (0.226)	0.180*** (0.023)	−0.035 (0.197)
Video streaming size impact	−1.915*** (0.746)	–	−1.915*** (0.746)	–
Year of release (dummies)	–	Included	–	Included
Constant	−8.269** (3.959)	3.604 (3.561)	−8.269** (3.959)	17.954 (3.997)
Total observations	–	367	–	367
Censored	–	215	–	215
Uncensored	–	152	–	152
Wald Chi-square	–	90.300	–	119.770
p-value	–	0.000	–	0.000
Lambda	–	−0.394	–	−0.899
Rho	–	−0.300	–	−0.668
Sigma	–	1.312	–	1.347

Note: Standard errors in parentheses.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

We enlisted a GMM (generalized method of moments) regression with instrumental variables,[22] that

[22]We use GMM command in Stata rather than ivregress command because GMM allows giving structural form to the first and second stage regressions, specifying which variable should be included in which stage and which should work as instruments. This cannot be done using ivregress command. Note that the 2SLS estimator used when applying the ivregress command is essentially a one-step GMM estimator. We instead used the GMM 3SLS estimator, which grants us the above advantage (see Wooldridge, 2010, chap. 8 or https://www.stata.com/manuals13/rgmm.pdf). We are aware of potential specification problems associated with specifying the variables to be included in the

TABLE 8 GMM instrumental variable regressions with all interactions.

	First stage (*Pledged Amount* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness*^{2} as dependent variable)	First stage (*Pledged Amount* × *Critics Rating* as dependent variable)	Second stage (*Box Office Gross* as dependent variable)
Pledged Amount	–	–	–	–	1.448** (0.664)
Pledged Amount × Product Innovativeness	–	–	–	–	1.235** (0.517)
Pledged Amount × Product Innovativeness^2	–	–	–	–	−0.993** (0.449)
Pledged Amount (ln) × Critics rating	–	–	–	–	−0.238** (0.091)
Product Innovativeness	0.000 (0.036)	0.616*** (0.049)	0.715*** (0.059)	−0.038 (1.826)	2.067** (0.984)
Product Innovativeness^2	–	–	–	–	−1.989** (0.831)
Critics Rating	–	–	–	–	0.703*** (0.171)
User Rating	–	–	–	–	0.010 (0.160)
N. Movies in theaters in the same month and genre	–	–	–	–	−0.337 (0.306)
Movie budget	–	–	–	–	0.744*** (0.170)
US Production Country	0.079 (0.376)	−0.056 (0.106)	−0.014 (0.132)	−0.052 (2.045)	0.582* (0.346)
Major	1.433 (0.913)	0.595** (0.259)	0.860*** (0.321)	1.053** (0.494)	1.883** (0.871)
Mini-Major	4.566*** (1.747)	1.220** (0.512)	1.391** (0.633)	1.884** (0.954)	0.438 (1.823)
Actors/directors/writers nominations/awards	−0.309 (0.573)	−0.192 (0.165)	−0.218 (0.204)	−0.278 (0.312)	0.020 (0.514)
Comedy and musical	−1.168 (1.051)	−0.598** (0.298)	−0.802** (0.369)	−5.947 (5.690)	0.696 (1.007)
Drama	−0.637 (0.838)	−0.341 (0.240)	−0.385 (0.297)	−1.012 (4.574)	−0.201 (0.781)
Documentary	−0.372 (0.812)	−0.223 (0.232)	−0.293 (0.287)	0.415 (4.429)	0.171 (0.779)
Campaign goal	0.136*** (0.040)	0.772*** (0.096)	0.946*** (0.119)	0.091*** (0.034)	−0.593 (0.735)
Sequel	3.318 (4.000)	−0.523 (0.397)	−0.762 (1.471)	0.965 (0.723)	0.448 (0.287)
Category Aggregated Pledged Amount	1.615*** (0.160)	3.284*** (0.399)	3.907*** (0.492)	2.986*** (0.309)	–
Category Aggregated Pledged Amount × Product Innovativeness	–	−3.920*** (0.342)	−4.291*** (0.422)	–	–

TABLE 8 (Continued)

	First stage (*Pledged Amount* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness*^{2} as dependent variable)	First stage (*Pledged Amount* × *Critics Rating* as dependent variable)	Second stage (*Box Office Gross* as dependent variable)
Category Aggregated Pledged Amount × Product Innovativeness^2	–	0.008 (0.125)	−0.215 (0.154)	–	–
Category Aggregated Pledged Amount × Critics Rating	–	–	–	−0.567** (0.163)	–
Year of release (dummies)	–	–	–	–	Included
Constant	−10.13*** (1.656)	−14.08*** (1.68)	−17.07*** (2.08)	−53.83*** (8.35)	−0.14*** (2.25)
Total observations	152	152	152	152	152

Note: Standard errors in parentheses.
$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

regressed *Pledged Amount* (and its interactions with *Product Innovativeness* and *Critics Rating*) against some of the control variables plus the instrument(s). When our interactions of interest were considered, our regressors included interactions of the instrument with the respective variable(s) interacted in the second stage with the supposedly endogenous regressor (*Pledged Amount*), as usually done when potentially endogenous regressors are interacted with other variables. We did this because we cannot exclude a priori that the interaction terms might also suffer from the same endogeneity concerns. Finally, in the GMM estimation, we regressed, of course, our dependent variable *Box Office Gross* against our set of control variables along with the "adjusted" values of the variable *Pledged Amount* and its interaction terms. In Tables 8 and 9, we report the results of the analysis with all interactions specified for the models with the main measure of product innovativeness and its alternative, respectively. Our main findings remain qualitatively unchanged.

5.3 | Checking for CF campaign publicity

Our argument about the role of CF performance as a signal relies on the assumption that future viewers of the focal film are aware of its CF campaign outcomes. We have argued that this should hold for crowdfunded movies as CF information is heavily hyped not only within the CF communities (e.g., Kickstarter), but also across social media and other online media (Colombo et al., 2015; Mollick, 2014). In addition, because of the innovative nature of CF and the small nature of crowdfunded films, consumers who self-select to watch them naturally seek more information before deciding. Thus, in principle, for crowdfunded movies, these consumers should be as exposed to this information as they are to other movie signals, such as critics ratings or eWOM.

first stage. However, as the first stage regression seeks to explain the determinants of CF performance, including variables measuring something not yet available at the time of the CF campaign is hardly sensible. For instance, variables such as the critics rating, user rating, movie budget, number of movies released in theaters in the same period as the focal movie, capture features not yet occurred at the time of the CF campaign. Indeed, the making of the movie has not started or been completed yet, no movie evaluation by critics has been made, and there is no budget available. Therefore, to explain the CF performance, we only included those variables that, being available at the time of the campaign, could reasonably drive backer decision to fund the movie project. GMM gives the flexibility to do this, while addressing endogeneity via IVs.

TABLE 9 GMM instrumental variable regressions with all interactions and alternative measure of innovativeness.

	First stage (*Pledged Amount* as dependent variable)	First stage (*Pledged Amount × Product Innovativeness* as dependent variable)	First stage (*Pledged Amount × Product Innovativeness*^{2} as dependent variable)	First stage (*Pledged Amount × Critics Rating* as dependent variable)	Second stage (*Box Office Gross* as dependent variable)
Pledged Amount	–	–	–	–	1.477*** (0.257)
Pledged Amount × Product Innovativeness	–	–	–	–	0.168*** (0.044)
Pledged Amount × Product Innovativeness^2	–	–	–	–	−0.070*** (0.021)
Pledged Amount × Critics Rating	–	–	–	–	−0.258** (0.131)
Product Innovativeness	−0.392 (0.862)	−2.726 (3.588)	−7.577 (7.739)	0.509* (0.261)	−0.621** (0.305)
Product Innovativeness^2	–	–	–	–	0.218*** (0.073)
Critics rating	–	–	–	–	0.462* (0.264)
User rating	–	–	–	–	−0.126 (0.205)
N. movies in theaters in the same month and genre	–	–	–	–	0.188 (0.411)
Movie budget	–	–	–	–	0.326** (0.137)
US Production Country	−0.735 (0.837)	0.319 (1.294)	0.997 (2.753)	−0.292 (1.860)	0.927* (0.549)
Major	3.947* (2.101)	1.942*** (0.356)	4.386*** (0.757)	4.183 (4.451)	−5.579** (2.573)
Mini-Major	1.537*** (0.390)	−1.413 (6.190)	−0.322 (13.173)	−0.407 (0.898)	−7.146** (2.914)
Actors/directors/writers nominations/awards	0.068 (1.269)	−1.021 (2.024)	−0.672 (4.302)	1.671 (2.824)	2.922*** (1.028)
Comedy and musical	−3.415 (2.395)	−0.348 (0.362)	−0.951 (0.770)	−0.677 (0.515)	2.958 (1.842)
Drama	−3.379* (1.833)	−0.041 (0.288)	−0.473 (0.612)	−0.324 (0.438)	−1.480 (1.511)
Documentary	−1.926 (1.803)	−0.222 (0.283)	−0.791 (0.612)	−0.251 (0.436)	−0.571 (1.472)
Campaign goal	0.862*** (0.131)	0.323*** (0.057)	0.684*** (0.122)	−3.200*** (0.819)	−0.631*** (0.118)
Sequel	3.091 (2.966)	0.419*** (0.046)	0.865*** (0.098)	6.293 (6.455)	−1.416*** (0.447)

TABLE 9 (Continued)

	First stage (*Pledged Amount* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness*^{2} as dependent variable)	First stage (*Pledged Amount* × *Critics Rating* as dependent variable)	Second stage (*Box Office Gross* as dependent variable)
Number of reviews (control)	−0.054 (0.272)	0.561 (0.427)	0.997 (0.908)	−0.422 (0.597)	0.036 (0.182)
Category Aggregated Pledged Amount	1.809*** (0.266)	−1.120** (0.478)	−2.357** (1.027)	2.295*** (0.775)	–
Category Aggregated Pledged Amount × Product Innovativeness	–	1.420 (1.563)	4.089 (3.373)	–	–
Category Aggregated Pledged Amount × Product Innovativeness^2	–	0.225*** (0.059)	−0.326*** (0.126)	–	–
Category Aggregated Pledged Amount × Critics Rating	–	–	–	−0.091** (0.042)	–
Year of release (dummies)	–	–	–	–	Included
Constant	−31.14 (5.34)	−10.77 (8.28)	−20.06 (17.67)	6.45 (12.36)	74.03*** (15.08)
Total observation	152	152	152	152	152

Note: Standard errors in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE 10 OLS regression models with subsample.

	No interactions	*Pledged Amount* × *Product Innovativeness* (both linear and squared terms)	*Pledged Amount* × *Critics Rating*	All interactions
Pledged Amount	0.794*** (0.300)	0.893** (0.357)	0.779*** (0.299)	0.968*** (0.356)
Pledged Amount × Product Innovativeness	–	1.973*** (0.756)	–	2.185*** (0.741)
Pledged Amount × Product Innovativeness^2	–	−1.652*** (0.632)	–	−1.877*** (0.621)
Pledged Amount × Critics Rating	–	–	−0.169** (0.084)	−0.194** (0.081)
Product Innovativeness	1.757* (0.888)	1.907** (0.870)	1.684* (0.896)	1.810** (0.874)
Product Innovativeness^2	−1.435* (0.781)	−1.617** (0.752)	−1.359* (0.787)	−1.514** (0.755)
Critics rating	0.486*** (0.116)	0.500*** (0.121)	0.476*** (0.114)	0.494*** (0.116)
User rating	0.049 (0.187)	0.069 (0.183)	0.073 (0.186)	0.104 (0.179)
N. Movies in theaters in the same month and genre	−0.291 (0.325)	−0.343 (0.335)	−0.275 (0.331)	−0.333 (0.341)
Movie budget	0.313** (0.117)	0.290** (0.118)	0.312*** (0.119)	0.309*** (0.118)
US Production Country	0.295 (0.345)	0.383 (0.352)	0.315 (0.346)	0.404 (0.353)
Major	1.968*** (0.642)	2.250*** (0.677)	1.986*** (0.571)	2.133*** (0.555)
Mini-Major	1.716** (0.687)	1.498** (0.720)	1.109 (0.719)	0.843 (0.715)
Actors/directors/writers nominations/awards	0.082 (0.391)	0.084 (0.390)	0.042 (0.403)	0.065 (0.397)
Comedy and musical	1.089 (0.889)	1.083 (0.910)	1.137 (0.877)	1.082 (0.876)
Drama	−0.367 (0.568)	−0.291 (0.612)	−0.348 (0.490)	−0.280 (0.514)
Documentary	−0.143 (0.594)	−0.179 (0.627)	−0.134 (0.522)	−0.203 (0.541)
Campaign goal	−0.565* (0.303)	−0.665** (0.304)	−0.563* (0.294)	−0.719** (0.310)
Sequel	0.104 (0.466)	0.450 (0.827)	0.071 (0.477)	0.526 (0.818)
Year of release (dummies)	Included	Included	Included	Included
Constant	−0.282 (2.143)	9.711*** (3.401)	9.319*** (2.449)	13.160*** (3.564)
Number of observations	141	141	141	141
R^2	0.405	0.421	0.415	0.436
F (p-value)	0.000	0.000	0.000	0.000

Note: Robust standard errors in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE 11 Heckman selection regression models with subsample.

	First stage (no interactions)	Second stage (no interactions)	First stage (all interactions)	Second stage (all interactions)
Pledged Amount	0.258** (0.120)	0.924*** (0.362)	0.258** (0.120)	0.858** (0.412)
Pledged Amount × Product Innovativeness	–	–	–	1.980** (0.983)
Pledged Amount × Product Innovativeness^2	–	–	–	−1.637** (0.788)
Pledged Amount × Critics rating	–	–	–	−0.200** (0.100)
Product Innovativeness	0.014 (0.143)	1.726* (0.943)	0.014 (0.143)	1.470* (0.887)
Product Innovativeness^2	–	−1.383* (0.781)	–	−1.138 (0.738)
Critics Rating	–	0.490*** (0.125)	–	0.391*** (0.117)
User Rating	–	0.044 (0.150)	–	0.114 (0.140)
N. movies in theaters in the same month and genre	–	−0.272 (0.288)	–	−0.354 (0.266)
Movie Budget	0.551 (0.540)	0.339*** (0.119)	0.551 (0.540)	0.373*** (0.075)
US Production Country	−0.023 (0.154)	0.268 (0.331)	−0.023 (0.154)	0.302 (0.301)
Major	−0.029 (0.534)	1.698* (0.989)	−0.029 (0.534)	−0.340 (1.053)
Mini-Major	−0.895 (0.689)	1.246 (1.655)	−0.895 (0.689)	0.713 (1.475)
Actors/directors/writers nominations/awards	0.261 (0.263)	0.262 (0.572)	0.261 (0.263)	−0.251 (0.507)
Comedy and musical	0.594 (0.365)	1.348 (0.985)	0.594 (0.365)	1.071 (0.891)
Drama	1.014*** (0.284)	0.122 (0.985)	1.014*** (0.284)	0.110 (0.894)
Documentary	1.081*** (0.268)	0.412 (1.050)	1.081*** (0.268)	0.245 (0.937)
Campaign goal	0.096* (0.058)	−0.449 (0.349)	0.096* (0.058)	−0.692** (0.324)
Sequel	1.409 (1.282)	0.109 (1.193)	1.409 (1.282)	0.284 (1.266)
Video streaming size impact	−1.267*** (0.466)	–	−1.267*** (0.466)	–
Year of release (dummies)	–	Included	–	Included
Constant	−9.651*** (2.620)	−4.099 (6.349)	−9.651*** (2.620)	15.451*** (4.578)
Total observations	–	1048	–	1048
Censored	–	907	–	907
Uncensored	–	141	–	141
Wald Chi-square	–	78.690	–	121.220
p-value	–	0.000	–	0.000
Lambda	–	0.711	–	−0.127
Rho	–	0.487	–	−0.103
Sigma	–	1.461	–	1.234

Note: Standard errors in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Because of the importance of the above assumption for our theoretical arguments, we checked robustness of our findings when explicitly considering the publicity CF campaigns of our 152 movies received across online media. Specifically, as a proxy for this publicity, we checked the presence of posts regarding the CF campaign on the official pages of our 152 films available on three main social media namely, Facebook, Twitter, and YouTube (trailer included), as well as on two of the most important movie-dedicated websites, that is, Imdb.com and Rotten Tomatoes, in the timespan between the CF campaign and the movie release in theaters. We found that only 11 of 152 movies did not display any CF information in any of the five

TABLE 12 OLS regression models with subsample and alternative measure of innovativeness.

	No interactions	***Pledged Amount*** × ***Product Innovativeness*** (both linear and squared terms)	***Pledged Amount*** × ***Critics Rating***	All interactions
Pledged Amount	0.718** (0.299)	0.806** (0.317)	2.035*** (0.717)	1.153*** (0.346)
Pledged Amount × Product Innovativeness	–	0.199** (0.091)	–	0.363*** (0.124)
Pledged Amount × Product Innovativeness^2	–	−0.095** (0.045)	–	−0.127*** (0.048)
Pledged Amount × Critics Rating	–	–	−0.190** (0.095)	−0.261** (0.130)
Product Innovativeness	−1.966** (0.921)	−2.206* (1.154)	−1.169 (0.921)	−0.513 (2.043)
Product Innovativeness^2	0.422** (0.203)	0.604** (0.242)	0.315* (0.181)	0.195 (0.395)
Critics rating	0.426*** (0.132)	0.391*** (0.101)	0.356** (0.142)	0.458*** (0.118)
User rating	0.040 (0.179)	0.071 (0.174)	0.041 (0.084)	0.057 (0.072)
N. Movies in theaters in the same month and genre	−0.365 (0.339)	−0.324 (0.339)	−0.329 (0.335)	−0.400 (0.318)
Movie budget	0.251** (0.119)	0.250** (0.123)	0.266** (0.120)	0.295*** (0.069)
US Production Country	0.292 (0.339)	0.381 (0.359)	0.332 (0.334)	0.402 (0.339)
Major	0.769 (0.579)	1.106* (0.653)	0.868* (0.508)	0.788 (0.849)
Mini-Major	1.715** (0.741)	1.773** (0.771)	0.831 (0.845)	0.743 (0.755)
Actors/directors/writers nominations/awards	−0.414 (0.374)	−0.163 (0.374)	−0.371 (0.392)	−0.050 (0.405)
Comedy and musical	1.755* (0.899)	1.401 (0.905)	1.804** (0.874)	1.452 (1.019)
Drama	0.146 (0.578)	−0.517 (0.687)	0.261 (0.500)	−0.076 (0.478)
Documentary	0.388 (0.591)	−0.202 (0.687)	0.492 (0.530)	−0.504 (0.465)
Campaign goal	−0.506* (0.303)	−0.554* (0.301)	−0.526* (0.307)	−0.430** (0.199)
Sequel	0.181 (0.659)	−0.139 (0.429)	0.144 (0.558)	−0.340 (0.328)
Number of reviews (control)	0.273*** (0.095)	0.258*** (0.095)	0.269*** (0.091)	0.219** (0.085)
Year of release (dummies)	Included	Included	Included	Included
Constant	2.998 (2.725)	5.414 (4.014)	7.199 (7.333)	21.833** (10.467)
Number of observations	141	141	141	141
R^2	0.443	0.453	0.455	0.514
F (p-value)	0.000	0.000	0.000	0.000

Note: Robust standard errors in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE 13 Heckman selection regression models with subsample and alternative measure of innovativeness.

	First stage (no interactions)	Second stage (no interactions)	First stage (all interactions)	Second stage (all interactions)
Pledged Amount	−0.061 (0.193)	0.712** (0.308)	−0.061 (0.193)	1.074*** (0.323)
Pledged Amount × Product Innovativeness	–	–	–	0.348** (0.140)
Pledged Amount × Product Innovativeness^2	–	–	–	−0.127** (0.061)
Pledged Amount × Critics Rating	–	–	–	−0.232** (0.117)
Product Innovativeness	0.310 (0.325)	−2.111 (1.365)	0.310 (0.325)	−0.459 (0.767)
Product Innovativeness^2	–	0.436 (0.281)	–	0.290 (0.394)
Critics Rating	–	0.434*** (0.140)	–	0.468*** (0.120)
User Rating	–	0.049 (0.146)	–	0.102 (0.139)
N. movies in theaters in the same month and genre	–	−0.372 (0.276)	–	−0.398 (0.259)
Movie budget	−0.873 (1.192)	0.213** (0.107)	−0.873 (1.192)	0.282*** (0.061)
US Production Country	0.330 (0.216)	0.176 (0.352)	0.330 (0.216)	0.237 (0.335)
Major	−0.340 (0.627)	1.039 (1.110)	−0.340 (0.627)	0.986 (1.195)
Mini-Major	−1.207* (0.719)	2.176 (1.581)	−1.207* (0.719)	1.605 (1.486)
Actors/directors/writers nominations/awards	−0.006 (0.357)	−0.412 (0.520)	−0.006 (0.357)	−0.052 (0.518)
Comedy and musical	0.488 (0.522)	1.598* (0.930)	0.488 (0.522)	1.144 (0.897)
Drama	0.421 (0.417)	−0.058 (0.786)	0.421 (0.417)	−0.408 (0.758)
Documentary	0.643 (0.404)	0.068 (0.859)	0.643 (0.404)	−0.147 (0.791)
Campaign goal	0.090 (0.092)	−0.565* (0.312)	0.090 (0.092)	−0.757** (0.303)
Sequel	1.023 (1.271)	0.101 (1.145)	1.023 (1.271)	−0.731(1.354)
Number of reviews (control)	0.173*** (0.023)	0.123 (0.219)	0.173*** (0.023)	−0.018 (0.190)
Video streaming size impact	−2.173*** (0.795)	–	−2.173*** (0.795)	–
Year of release (dummies)	–	Included	–	Included
Constant	−8.314** (4.109)	12.690*** (4.616)	−8.314** (4.109)	16.402*** (4.370)
Total observations	–	356	–	356
Censored	–	215	–	215
Uncensored	–	141	–	141
Wald Chi-square	–	76.450	–	105.770
p-value	–	0.000	–	0.000
Lambda	–	−0.555	–	−0.867
Rho	–	−0.412	–	−0.642
Sigma	–	1.348	–	1.350

Note: Standard errors in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

consulted sources. We re-ran all models (OLS, Heckman, and GMM regressions for both main and alternative measures of product innovativeness), considering only the 141 movies that had the information about the CF campaign publicized through the above sites. Restricting only to these movies should increase the confidence that our findings can be mostly ascribed to the signaling role of CF, given the publicity received through different channels. Tables 10–15 suggest that all three hypotheses are again supported.

TABLE 14 GMM instrumental variable regressions with subsample and all interactions.

	First stage (*Pledged Amount* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness*^{2} as dependent variable)	First stage (*Pledged Amount* × *Critics Rating* as dependent variable)	Second stage (*Box Office Gross* as dependent variable)
Pledged Amount	–	–	–	–	1.510** (0.693)
Pledged Amount × Product Innovativeness	–	–	–	–	1.733*** (0.649)
Pledged Amount × Product Innovativeness^2	–	–	–	–	−1.327*** (0.518)
Pledged Amount (ln) × Critics rating	–	–	–	–	−0.266*** (0.091)
Product Innovativeness	0.007 (0.069)	0.627*** (0.054)	0.778*** (0.068)	−0.097 (1.734)	1.498 (1.038)
Product Innovativeness^2	–	–	–	–	−1.535* (0.861)
Critics rating	–	–	–	–	0.569*** (0.171)
User rating	–	–	–	–	0.118 (0.162)
N. movies in theaters in the same month and genre	–	–	–	–	−0.367 (0.305)
Movie Budget	–	–	–	–	0.655*** (0.163)
US Production Country	0.300 (0.768)	0.015 (0.106)	0.065 (0.133)	0.683 (1.942)	0.576 (0.367)
Major	2.245 (2.222)	0.814*** (0.292)	1.233*** (0.366)	1.427*** (0.534)	3.635*** (1.113)
Mini-Major	8.944*** (3.366)	1.209** (0.484)	1.390** (0.605)	1.759** (0.857)	0.303 (1.807)
Actors/directors/writers nominations/awards	−1.205 (1.173)	−0.347** (0.166)	−0.436** (0.208)	−0.514* (0.298)	−0.575 (0.548)
Comedy and Musical	−1.085 (2.077)	−0.226(0.291)	−0.325 (0.364)	−0.942 (5.255)	1.206 (1.008)
Drama	−1.430 (1.642)	−0.325 (0.228)	−0.361 (0.286)	−0.288 (4.157)	−0.016 (0.770)
Documentary	−0.900 (1.584)	−0.175 (0.220)	−0.213 (0.276)	1.458 (4.015)	0.343 (0.777)
Campaign Goal	0.524*** (00.134)	0.816*** (0.098)	0.980*** (0.123)	0.125*** (0.036)	−0.420 (1.001)
Sequel	1.560 (7.935)	−0.680* (0.394)	−1.061 (1.441)	0.577 (0.660)	0.462 (0.302)
Category Aggregated Pledged Amount	3.136*** (0.326)	3.416*** (0.430)	4.356*** (0.537)	2.809*** (0.298)	–
Category Aggregated Pledged Amount × Product Innovativeness	–	−3.980*** (0.408)	−4.852*** (0.509)	–	–

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TABLE 14 (Continued)

	First stage (*Pledged Amount* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness*^{2} as dependent variable)	First stage (*Pledged Amount* × *Critics Rating* as dependent variable)	Second stage (*Box Office Gross* as dependent variable)
Category Aggregated Pledged Amount × Product Innovativeness^2	–	−0.001 (0.135)	−0.100 (0.168)	–	–
Category Aggregated Pledged Amount × Critics rating	–	–	–	−0.643*** (0.164)	–
Year of release (dummies)	–	–	–	–	Included
Constant	−19.71*** (3.00)	−14.88*** (1.72)	−18.34*** (2.15)	−51.23*** (7.96)	0.18 (2.26)
Total observations	141	141	141	141	141

Note: Standard errors in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

6 | DISCUSSION AND CONCLUSION

In this article, we have investigated the role of reward-based CF performance as a signal for consumers of new products. We have also examined how the efficacy of this signal is nontrivially moderated by the degree of product innovativeness as well as by expert judgment. In addressing our questions, we have focused on movies as they are characterized by significant product quality uncertainty. This feature makes the movie industry ideal to assess the role of signals. Moreover, CF has gained popularity for financing the commercialization of these products.

For products launched in reward-based CF, our findings provide initial evidence that CF campaign performance likely acts as an effective signal for consumers, thus positively affecting market performance. In addition, our findings reveal that the efficacy of the CF signal is reduced in the presence of more favorable expert judgments and is moderated by the level of product innovativeness in an inverted U-shaped fashion. Next, we discuss the implications for both theory and practice.

6.1 | Implications for theory

Our article offers remarkable implications for extant literature on CF. In highlighting the role of reward-based CF as a signal, prior CF studies have focused on its effect on venture capital search. Our study adds another piece to the puzzle and complements this stream by (a) preliminarily documenting that the performance in reward-based CF works as a signal able to influence consumers' purchase decisions at the market stage and (b) informing on important boundary conditions that may magnify or dampen its efficacy. This is new "food for thought" for academics studying CF because they have mostly cast reward-based CF as a signal for VCs, rather than for consumers active in the final market (e.g., Colombo & Shafi, 2021; Drover et al., 2017; Roma et al., 2017; Roma, Vasi, & Kolympiris, 2021a). These two signal receivers differ substantially since the motives driving VC funding decisions diverge from those guiding consumers to purchase a product. For instance, prior literature has suggested that boundary conditions making the CF signal effective for VCs are essentially related to a comprehensive assessment that targets managerial competencies and a startup's technological capabilities (e.g., Roma, Vasi, & Kolympiris, 2021a). We instead suggest that the efficacy of the CF performance as a signal for consumers depends on mechanisms typically

TABLE 15 GMM instrumental variable regressions with subsample, all interactions, and alternative measure of innovativeness.

	First stage (*Pledged Amount* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness*^{2} as dependent variable)	First stage (*Pledged Amount* × *Critics Rating* as dependent variable)	Second stage (*Box Office Gross* as dependent variable)
Pledged Amount	–	–	–	–	1.689*** (0.348)
Pledged Amount × Product Innovativeness	–	–	–	–	0.133*** (0.045)
Pledged Amount × Product Innovativeness^2	–	–	–	–	−0.069*** (0.024)
Pledged Amount × Critics rating	–	–	–	–	−0.273** (0.110)
Product Innovativeness	−0.207 (0.819)	−0.851 (3.923)	−2.691 (8.246)	1.711*** (0.573)	0.667* (0.373)
Product Innovativeness^2	–	–	–	–	−0.024 (0.066)
Critics rating	–	–	–	–	0.511* (0.285)
User rating	–	–	–	–	−0.244 (0.242)
N. movies in theaters in the same month and genre	–	–	–	–	0.262 (0.474)
Movie budget	–	–	–	–	0.495*** (0.164)
US Production Country	−0.595 (0.802)	1.356 (1.304)	3.438 (2.732)	0.098 (0.510)	1.243* (0.705)
Major	1.643 (2.452)	3.080*** (0.433)	6.982*** (0.908)	0.719 (1.395)	3.691 (4.540)
Mini-Major	1.432*** (0.355)	−3.027 (5.952)	−3.261 (12.472)	−0.354 (0.236)	−8.605*** (3.196)
Actors/directors/writers nominations/awards	−0.836 (1227)	−1.316 (2.048)	−1.125 (4.290)	−0.243 (0.789)	3.945*** (1.212)
Comedy and musical	−2.581 (2.210)	−0.227 (0.353)	−0.679 (0.740)	0.007 (0.140)	0.985 (1.756)
Drama	−3.460** (1.679)	−0.071 (0.276)	−0.576 (0.577)	0.026 (0.117)	−2.010 (1.753)
Documentary	−2.100 (1.652)	−0.163 (0.294)	−0.662 (0.566)	0.043 (0.117)	−1.203 (1.597)
Campaign goal	1.244*** (0.156)	0.399*** (0.062)	0.830*** (0.129)	−0.314 (0.242)	−0.664*** (0.157)
Sequel	0.349 (2.758)	0.348*** (0.046)	0.710*** (0.096)	0.691 (1.713)	−0.173 (0.343)

TABLE 15 (Continued)

	First stage (*Pledged Amount* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness* as dependent variable)	First stage (*Pledged Amount* × *Product Innovativeness*^{2} as dependent variable)	First stage (*Pledged Amount* × *Critics Rating* as dependent variable)	Second stage (*Box Office Gross* as dependent variable)
Number of reviews (control)	−0.078 (0.245)	0.590 (0.403)	1.063 (0.845)	−0.087 (0.155	0.198 (0.171)
Category Aggregated Pledged Amount	1.618*** (0.160)	−1.405*** (0.499)	−2.895*** (1.046)	0.511** (0.211)	–
Category Aggregated Pledged Amount × Product Innovativeness	–	0.659 (1.707)	2.058 (3.589)	–	–
Category Aggregated Pledged Amount × Product Innovativeness^2	–	−0.348*** (0.061)	−0.604*** (0.129)	–	–
Category Aggregated Pledged Amount × Critics rating	–	–	–	−0.046*** (0.012)	–
Year of release (dummies)	–	–	–	–	Included
Constant	−27.87*** (5.09)	−14.68* (8.33)	−28.18 (17.45)	0.644 (3.35)	59.83*** (19.15)
Total observations	141	141	141	141	141

Note: Standard errors in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

related to consumer purchase behavior, for example, peer-to-peer influence dynamics, consumer attitudes toward more or less innovative products, and the role of expert influencers.

By showing that the product innovativeness first boosts and then curbs the efficacy of the crowd signal, we offer further implications also to the copious body of literature studying the performance implications of this key product feature. Beyond its direct effect, this literature has also pinpointed the role of product innovativeness as a moderator of the performance implications of organizational aspects in new product development (e.g., Langerak & Hultink, 2006; Olson et al., 1995; Salomo et al., 2007) or those of some firm's communication strategies (Lee & O'Connor, 2003). We summon this literature to consider in future advancements that, in settings featuring high product quality uncertainty, product innovativeness may also impact market performance via its influence on the efficacy of signals external to the firm—especially where these signals originate from committed early adopters (i.e., the crowd).

Finally, recent literature examined the interplay of signals that mitigate uncertainties in specific informational domains, for example, market, technology, human capital, and so forth (Bapna, 2019; Colombo et al., 2019; Roma, Vasi, & Kolympiris, 2021a). It has been argued that signals that primarily help resolve uncertainty along the distinct informational domains (e.g., patents versus connections with prominent customers) tend to strengthen each other, while signals providing similar information (e.g., research grants versus affiliation with universities) may reduce their marginal effects (Bapna, 2019; Colombo et al., 2019; Courtney et al., 2017). Both CF performance and expert judgment can be viewed as expressions of global assessment of a product from two third parties, where one tends to reflect the collective tastes of the consumption market and may activate herding behavior (Chen et al., 2020), while the other provides the professional and authoritative voice. Conventional wisdom may suggest that the efficacy of the signal sent via the CF campaign may be reinforced by positive expert judgment, which would lift crowd opinion to higher levels of authority. We reveal in contrast that, being indications of the overall product quality, the CF signal proves less salient in the presence of more favorable expert judgment.

6.2 | Implications for practice

Considering the rising popularity of CF for financing innovation, our findings seem quite important toward business settings featuring high product quality uncertainty. This is true for movies, but also is the case for many products or services that debut "new-to-world." The first practical implications for innovators who intend to launch a reward-based CF to finance their innovative projects? Invest time and effort designing attractive campaigns able to ignite commitments from the crowd, which are not only beneficial per se, but also yield valuable information that can lead to successful product commercialization and positive market performance. For instance, paying attention to align the communication strategies for both campaign and commercialization stages could increase the efficacy of the signal, since the crowd targeted for the campaign would better reflect the population of consumers targeted for the commercialization stage.

Developing this further, we offer more detailed implications considering boundary conditions that may boost or harm the efficacy of the signal possibly generated from a CF campaign. Specifically, we advise innovators to fine-tune the communication strategy during and after the campaign depending on the degree of product innovativeness to improve the odds of success in the market stage. For instance, innovators could anticipate the potential drawback of highly innovative products and modify their communication in the CF campaign to attract consumers more representative of the future market to fund the campaign. The communication during and after the campaign could be oriented to soften the downsides of an ultra-innovative product by explaining novel features, simplifying the layout, and increasing the familiarity with new meanings, styles, and technological aspects of the product. By doing so, innovators would soften the different views of product quality possibly emerging for highly innovative products between the crowd and commercialization-stage consumers. This would benefit the innovators not only because reducing these downsides may attract more consumers to fund, but also because will increase the efficacy of the CF performance as a signal for consumers in the market stage.

Finally, innovators should be aware that a good performance in reward-based CF may serve most suitably as a signal for consumers when expert judgments are not particularly favorable. In this case, they could leverage on the CF performance by exerting even more effort in publicizing the good campaign results during the commercialization stage. This elevated effort could help compensate for unfavorable expert reviews and activate positive online buzz around the new product that will boost the benefits of a positive CF campaign. More in general, our study suggests that the impact of a (third-party) signal is not simply the result of its *stand-alone* effect, but most often the outcome of an entwined interplay with other third-party signals. Therefore, it is an essential task for innovators to identify the relevant third-party signals (from both the crowd and experts), understand their interplay and their degree of (mis)alignment, and thus activate communication efforts that will enhance the benefits of favorable signals and mitigate the effects of negative ones.

6.3 | Limitations and future research directions

Our study has, of course, some limitations that may serve as opportunities for future research. First, our study relies on archival data to examine the role of CF as a signal that drives market performance. However, as explained, an alternative explanation could be that CF performance just acts as a predictor of future market performance. This would be the case where consumers do not observe or consider the CF signal, and both performances are driven by unobserved product quality. To mitigate this risk, we have shown robustness of results after controlling for many factors related to product quality and CF publicity, as well as by means of Heckman-selection model and IVs regressions. This should increase the confidence that our results can be ascribed to the signaling role of CF. Nevertheless, in line with recent CF studies (Acar et al., 2021), we urge future studies to address the same questions studied here using an experimental setting, which would naturally eliminate the effect of unobservables, thus overcoming the intrinsic limitations of the current approach.

Second, our study setting is the movie industry. Besides the easier access to data, the main reason for this choice is that movies are experience goods. This feature places signals at center stage for consumers seeking to evaluate products before purchase. We expect that our findings would still hold for other experience goods and, in general, for other settings (e.g., new-to-world products) characterized by high product quality uncertainty. Future research addressing our questions in other business settings would help shed light on the generalizability of our findings. Different measures of product innovativeness than those used in this article could also be configured depending on the specificity of the business setting under consideration. Third, we examined CF campaigns launched on Kickstarter confined to the period from 2010 to 2017. Future studies could consider projects launched on other platforms or perform a multi-platform analysis. Moreover, future replications of our study may help unravel the emergence of novel peculiar phenomena in CF. Fourth, we studied market performance considering the US box office gross as data were easily accessible and reliable. This measure of market performance could put the few non-US movies in our sample at a disadvantage vis-à-vis the American ones. While controlling for the production country helps diminish the inherent bias, future research could extend the analysis to consider global or multi-country revenues. Fifth, in this article we examine the moderating role of expert judgment by considering the average critics' rating. It is of great interest to examine whether the degree of agreement among experts (i.e., the variance of individual critics' ratings) can shape the efficacy of the CF signal. We were unable to explore this issue due to the absence of (homogeneous) information at individual rating level. Still, we conjecture that a higher level of disagreement among experts should imply higher need to search for an additional signal (i.e., the CF performance) to mitigate the inherent uncertainty. Finally, our findings and relative implications are valid for innovators engaging in reward-based CF. To distill the absolute effect of reward-based CF as an informative mechanism, future efforts could compare firms successfully engaging in reward-based CF with similar firms not using this funding channel.

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The authors have read and agreed to the Committee on Publication Ethics (COPE) international standards for authors.

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