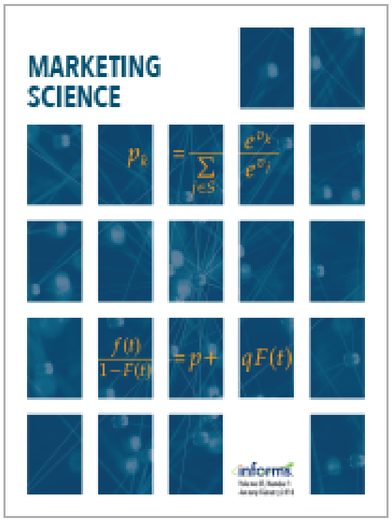

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Modeling Dynamics in Crowdfunding

Chul Kim,[a] P. K. Kannan,[b] Michael Trusov,[b] Andrea Ordanini[c]

[a] Department of Marketing, Baruch College, City University of New York, New York, New York 10010; [b] Department of Marketing, Robert H. Smith School of Business, University of Maryland, College Park, Maryland 20742; [c] Department of Marketing, Bocconi University, 20136 Milan, Italy

Contact: chul.kim@baruch.cuny.edu, https://orcid.org/0000-0002-2927-5740 (CK); pkannan@rhsmith.umd.edu, https://orcid.org/0000-0003-0738-0766 (PKK); mtrusov@rhsmith.umd.edu, https://orcid.org/0000-0003-2154-9695 (MT); andrea.ordanini@unibocconi.it, https://orcid.org/0000-0002-7915-1359 (AO)

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Abstract. We investigate various dynamics characterizing the crowdfunding process: stagnation after friend-funding, gradual increase through crowd participation, and acceleration in the last phase. We propose three mechanisms as major drivers of the crowdfunding dynamics: forward-looking delaying investment behavior, contemporaneous social interactions, and forward-looking social interactions. We apply the rational expectations equilibrium of the approximate aggregation approach to model the underlying mechanisms. Using the Bayesian IJC method, we analyze individual-level investment data from a crowdfunding platform, Sellaband. We find strong evidence for the three mechanisms and confirm that they contribute to the contrasting dynamic patterns observed in our data. We also simulate counterfactuals to derive optimal policy decisions for both fundraisers and platforms. For fundraisers, we infer the optimal goals that ensure goal completion while raising the maximum capital. For platforms, we suggest an optimal targeting strategy that identifies those crowdfunders who contribute the most to the crowding process and, ultimately, goal success. Also, we provide critical input for various resource allocation decisions by accurately predicting whether the project will succeed and when it will succeed at the time when 50% of the goal has been achieved.

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Keywords: crowdfunding • forward-looking • social interactions • rational expectations equilibrium • approximate aggregation

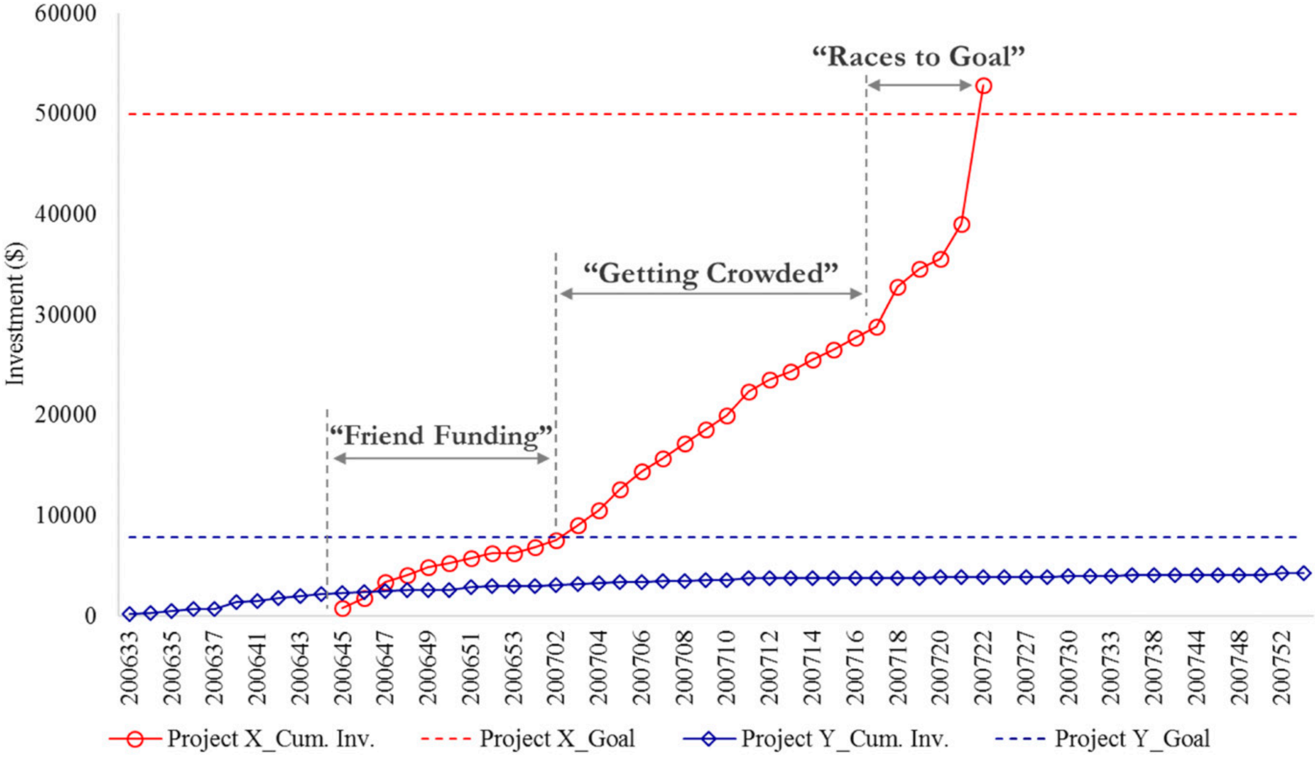
1. Introduction

Crowdfunding is the process of raising capital from a crowd of investors through an online platform in order to produce new products (Agrawal et al. 2014). Once a fundraising project reaches its goal, investors receive terminal payoffs in return for their investments in advance of receiving final rewards. These terminal payoffs may take the form of rights and/or stocks that bestow exclusive eligibility for receiving the final rewards. The final rewards may be new products and/or the profit generated by the new products (e.g., profit sharing and dividends).

Crowdfunding has attracted much attention as a valuable alternative source of financing and marketing for new products (Moisseyev 2013, Belleflamme et al. 2014, Brown et al. 2017, Bitter and Schreier 2018). Fundraisers not only gather enough capital to develop and produce the new products but also get direct access to the market before the products are launched or perhaps even developed. As the crowdfunding process embraces decision-making that straddles finance, marketing, and social networking, individual investors exhibit multiple roles simultaneously. For instance, they may act as donors and supporters who invest their money to support, encourage, and help fundraisers out of goodwill. At the same time, they may play the role of rational investors who are motivated by the prospect of earning terminal payoffs, and ultimately, final rewards. Furthermore, they interact socially, tied by their common goal, influencing others while being influenced by others at the same time. We use the term "crowdfunder" in this paper to capture the different roles investors in crowdfunding may play.

The multifaceted roles of crowdfunders result in various dynamic investment patterns. Previous studies (Ordanini et al. 2011, Agrawal et al. 2014) identify three phases of crowd fundraising: a "friend-funding phase," where the funds are mostly contributed by closely related people such as friends and family; a "getting crowded phase," where the cascading process and network effect kick in to motivate the crowd's participation; and a "race to the goal phase," where the fundraising gains rapid momentum until the goal is achieved. Interestingly, distinct patterns are often observed depending on whether a project successfully completes its goal or not. Figure 1 shows the dynamic investment patterns of two crowdfunding

Figure 1. (Color online) Dynamic Patterns in Crowdfunding



Project X: artist Maitreya, Project Y: artist Simeon

projects (X and Y) from our data set, representing a success case (goal completion) and a failure case, respectively. We observe all three phases in project X, whereas project Y never moved beyond the "friend-funding phase." Because the dynamic patterns are informative about whether the fundraising project is successful, a better understanding of the underlying mechanisms behind the crowdfunding dynamics provides substantive implications for crowdfunders, platforms, and fundraisers. For instance, as revealed by the underlying mechanisms: Crowdfunders maximize their returns by identifying the projects that are most likely to succeed; fundraisers maximize the chance to meet their goals by optimizing the policy settings (e.g., goal amount); and platforms maximize their profits by optimizing their promotional activities and resource allocation to spur investment demand.

This paper investigates the underlying mechanisms of crowdfunding behavior, which lead to the crowdfunding dynamics (stagnation after friend-funding, gradual increase through crowd participation, acceleration in the last phase, etc.). Our premise is that crowdfunders exercise dynamic decision-making. Specifically, they trade-off early investments against late investments. Early investments may secure a desired amount of stocks and/or rights that will be exclusively given to the crowdfunders at the end of fundraising as terminal payoffs and make the crowdfunders eligible for profit-sharing (dividends) and/or new products. However, early investments incur opportunity costs by requiring the crowdfunders to lock in their investment until the project either succeeds or fails. On the other hand, late investments are less subject to the opportunity cost of the deposited investments. However, crowdfunders who procrastinate and delay their investment as long as possible might lose the chance to participate and receive the terminal payoffs. Thus, rational crowdfunders delay participation for as long as possible in the early stage and finally commit participation when the project is close enough to the goal (i.e., forward-looking delaying investment behavior).

Another important premise is that individual crowdfunders engage in social interactions with other crowdfunders (i.e., the "crowd") by paying attention to and reacting to the crowd's behavior. For instance, a crowdfunder passively mimics the crowd's current behavior, because goal completion highly depends on the crowd's movement (Zhang and Liu 2012) (i.e., contemporaneous social interactions). Furthermore, crowdfunders take the crowd's future participation into account in their current decision-making (i.e., forward-looking social interactions). For instance, a crowdfunder might expect that her current investment will encourage future crowd participation by advancing the project toward its goal and making the project more promising and appealing. In turn, such expectation feeds back into her current decision-making, because the project would then be perceived as more appealing to her as well. A related premise is that crowdfunders are bounded-rational in a sense that they lack knowledge about each crowdfunder's optimal behavior but have a rational belief about the crowd's optimal behavior. This is imperative because having complete knowledge of the optimal behavior of each crowdfunder is an unrealistic assumption that imposes a large informational burden on individual crowdfunders (Krusell and Smith 1998, Lee and Wolpin 2006, Ahn et al. 2015).

On the basis of these premises, we propose three underlying mechanisms of crowdfunding behavior as drivers of the crowdfunding dynamics: forward-looking delaying investment behavior, contemporaneous social interactions, and forward-looking social interactions. The forward-looking delaying investment behavior is caused by the trade-off between the opportunity cost and the terminal payoff. Therefore, it may result in stagnation (to reduce the opportunity cost) and/or acceleration (not to miss out on the chance to participate and to receive the terminal payoff). The contemporaneous social interactions imply the interdependences of current decisions between an individual crowdfunder and the crowd (e.g., the effect of the crowd's current decision on an individual crowdfunder's current decision). On the other hand, the forward-looking social interactions imply the intertemporal dependences of decisions between an individual crowdfunder and the crowd (e.g., the effect of expectation about the crowd's future decision on an individual crowdfunder's current decision). It is important to note that these two types of social interactions generate both social spillovers (a stimulus to a focal agent spreads out to the other agents) and social multipliers (a stimulus to a focal agent is reinforced by the feedback effect through the other agents) (Hartmann et al. 2008). Therefore, both the contemporaneous social interactions and the forward-looking social interactions may play an important role in generating various dynamic patterns such as initial investments (through social multiplier) and the gradual increase and acceleration (through social spillover and social multiplier).

Several drivers behind crowdfunding dynamics have been suggested in the crowdfunding literature, ranging from friend-funding (Agrawal et al. 2014) and bystander effects (Agrawal et al. 2014, Kuppuswamy and Bayus 2015) to payoff externalities (Zhang and Liu 2012), herding (Freedman and Jin 2011, Zhang and Liu 2012, Mollick 2014, Agrawal et al. 2015, Kuppuswamy and Bayus 2015), and free-riding incentives (Hu et al. 2015). However, to the best of our knowledge, such mechanisms (forward-looking delaying investment behavior, contemporaneous social interactions, and forward-looking social interactions) have not yet been investigated as a source of crowdfunding dynamics. This is because previous studies rely on descriptive and static approaches where the suggested mechanisms are incompatible. As a result, extant studies investigate only a few pieces of the mechanisms behind the crowdfunding dynamics and thus lack a holistic and systematic view.

In this paper, we propose a structural microfoundation that incorporates the three mechanisms. To model the investment behavior of forward-looking and socially interacting crowdfunders, we adopt the rational expectations equilibrium of the approximate aggregation approach (Ahn et al. 2015). In this approach, we model the equilibrium of the crowd's behavior based on the premise that crowdfunders have a rational belief about the crowd's optimal behavior but not about each individual crowdfunder's behavior. This approach fits very well into our context where social interactions between an individual and the crowd take place.

We apply our model to individual-level investment data from Sellaband, a crowdfunding platform for musicians. We allow for consumer heterogeneity by using the random-effect specification and estimate individual-level parameters using the Bayesian IJC method (Imai et al. 2009, Ching et al. 2012). The rich specification for heterogeneity helps the identification of the social interactions from other correlations (e.g., homophily, correlated unobservables, and simultaneity) (Manski 1993, Hartmann et al. 2008, Nair et al. 2010). The empirical analysis provides five key findings. First, crowdfunders delay their investments to minimize the future opportunity cost that will be incurred by their current investments (i.e., forward-looking delaying investment behavior). Second, from the exploratory analysis and the results of the proposed model, we obtain the consistent finding that the interactions between the individual crowdfunders' current decisions and the crowd's current decision (i.e., contemporaneous social interactions) are asymmetric. Specifically, the results show a significant effect of the crowd's current decision on the individual crowdfunders' current decisions but not vice versa. Third, we find that crowdfunders commit initial or early investments to encourage future participation by the crowd, which ultimately benefit themselves (i.e., forward-looking social interactions). Fourth, we find that the proposed mechanisms (forward-looking investment behavior, contemporaneous social interactions, and forward-looking social interactions) contribute to better capturing the distinct and contrasting dynamic crowdfunding patterns of different projects. Fifth, we identify crowdfunders' characteristics contributing to the successful project completion. Specifically, we show that crowdfunders who invested in successful projects are more altruistic and socially interactive and who perceive smaller risk, opportunity cost, and satiation.

The counterfactual analyses also provide practical and actionable insights into both fundraisers and platforms. First, fundraisers can maximize both the chance of success and the amount of capital by optimizing their goals. In our institutional context, we find that the goals of the successful projects could have been increased by 16.3%, while still ensuring success. We also find that the goals of the unsuccessful projects should have been decreased by 52.5%. Interestingly, the optimal goal of the unsuccessful projects is 46.2% larger than the naively chosen goal based on the actual amount of investments raised. Second, platforms can optimize their targeting strategies in promotional campaigns (e.g., investment matching). We find that platforms can increase the investment demand by 21.7% and reduce the length of fundraising period by 164 days by identifying and targeting the crowdfunders who are more altruistic and socially interactive and who perceive smaller risk, opportunity cost, and satiation. Third, platforms can optimize their resource allocations by focusing more on potentially successful projects while deprioritizing the laggards based on the proposed model's prediction on the goal completion and its timing. We show that the proposed model provides good predictive performance for the final success of a crowdfunding project and its timing of goal completion at the time when the project reaches 50% of goal completion (i.e., using only the data before 50% of goal completion of the project).

To summarize, we make three contributions. First, from the theoretical viewpoint, to the best of our knowledge, this study is the first to propose and confirm empirically the three mechanisms (forward-looking delaying behavior, contemporaneous social interactions, and forward-looking social interactions) as the major sources of crowdfunding dynamics. Second, from the methodological viewpoint, we propose a structural microfoundation that exhaustively accommodates the underlying mechanisms and adequately captures the contrasting crowdfunding dynamics simultaneously within a single unified framework. The holistic approach uncovers the underlying mechanisms behind the crowdfunding dynamics and provides a better understanding of crowdfunding, which may not be obtained under the extant descriptive and static approaches. Third, from the substantive viewpoint, we provide practical and actionable insights into both fundraisers and platforms. Specifically, they can significantly benefit by utilizing the findings of this study (e.g., revealed mechanisms and key success factors for goal completion) and by optimizing their policy designs (e.g., goal setting, targeting strategies, and resource allocations).

2. Crowdfunding Dynamics

2.1. Extant Literature

The extant research has pointed to several drivers behind the crowdfunding dynamics—stagnation after friend-funding, gradual increase through the crowd's participation, and acceleration in the last phase. Agrawal et al. (2014) provide empirical evidence of friend-funding by observing that friends and family disproportionately invest early in the funding cycle, generating a signal for later funders through accumulated investments. Stagnation or slowdown after friend-funding is partially explained by the bystander effect, a reduction in the propensity to fund by new crowdfunders because of the perception that the target will be reached regardless (Agrawal et al. 2014, Kuppuswamy and Bayus 2015). Meanwhile, payoff externalities partially explain the acceleration, which imply that a crowdfunding project that has received a higher amount of funding may be more desirable because of its greater likelihood of goal completion (Zhang and Liu 2012). Herding behavior is also suggested as an alternative explanation of the acceleration (Freedman and Jin 2011, Zhang and Liu 2012, Mollick 2014, Agrawal et al. 2015, Kuppuswamy and Bayus 2015). In addition, Hu et al. (2015) raise the possibility of free-riding incentives of subsequent crowdfunders as the driver for the acceleration.

Despite the wide attention to dynamics in crowdfunding indicated in the studies above, to the best of our knowledge, no study has fully captured all the three dynamic patterns in a single unified framework. We believe that this is partially because in the absence of a holistic and systematic view, the contrasting dynamic patterns are disparate and incompatible in the extant descriptive and static approaches. For instance, the bystander effect might be able to explain the stagnation after the friend-funding stage. However, it is not flexible enough to explain the acceleration, which might operate in the opposite direction to stagnation. This paper demonstrates how such complex dynamics of the crowdfunding process can be effectively captured by the proposed mechanisms.

2.2. Key Drivers of Crowdfunding Dynamics

In this section, we present the three mechanisms (forward-looking delaying investment behavior, contemporaneous social interactions, and forward-looking social interactions) as key drivers that lead to crowdfunding dynamics.

2.2.1. Forward-Looking Delaying Investment Behavior. Crowdfunders face trade-offs between early investments and late investments. Early crowdfunders can secure a desired amount of stocks and/or rights that will be exclusively given to the crowdfunders at the end of fundraising as terminal payoffs, making them eligible for profit sharing (dividends) and/or new products. However, the deposited investments locked in the platform cannot be used for any other purposes, thereby incurring future opportunity costs until the project turns out to be either a success or a failure. On the other hand, although late investments may incur smaller future opportunity costs, crowdfunders who procrastinate too long may miss out on the chance to receive the terminal payoffs. This is because the investment opportunity may be lost if the project reaches its goal. Thus, rational crowdfunders compare the future cumulative opportunity cost that will be incurred until goal completion against the benefit they will receive (e.g., terminal payoff). In the early stage, crowdfunders might delay their investments because they expect a longer time remaining until the goal is achieved and therefore perceive a larger future cumulative opportunity cost compared with the benefit. In the late stage, however, crowdfunders might be less inclined to delay because they expect a shorter time until the goal is met and therefore perceive a smaller future cumulative opportunity cost compared with the benefit. Such delaying investment behavior that aims to avoid and/or minimize the future cumulative opportunity cost can explain the pattern of stagnation. Conversely, the eventual commitment of delayed investments at the last phase of fundraising so as not to miss out on the opportunity to participate and to receive terminal payoffs can explain the pattern of acceleration.

2.2.2. Social Interactions. Individual crowdfunders necessarily monitor and refer to the crowd's movement as a descriptive social norm and ultimately follow the crowd's movement, because goal completion is highly dependent on the crowd's movement (Zhang and Liu 2012). Therefore, social interactions between an individual crowdfunder and the crowd may arise under the crowdfunding context.[1] Specifically, two types of social interactions may arise: contemporaneous social interactions or forward-looking social interactions. First, the contemporaneous social interactions are the interdependences of current decisions between an individual crowdfunder and the crowd. It is important to note that the contemporaneous social interactions tend to be asymmetric under the crowdfunding context. This is because the focal crowdfunder passively mimics the crowd's current decision (e.g., herding), and her current decision will not be strong enough to move the crowd, which consists of a large number of crowdfunders, into a certain direction in the current period (Zhang and Liu 2012).[2] Second, the forward-looking social interactions are the intertemporal dependences of decisions between an individual crowdfunder and the crowd that arise by means of crowdfunders being forward-looking (Hartmann et al. 2008). More specifically, a crowdfunder might expect that her current investment will elevate the project's goal achievement level closer to the goal, making the project more promising and appealing. Thus, she may expect that her very act of investing will trigger subsequent future participation by the crowd. Finally, her expectation of the crowd's future participation will incite her current decision, as the project would be more appealing to her as well because of the expectation on the elevated goal achievement level by crowd's participation.

These social interactions are of primary importance to crowdfunding platforms and fundraisers, because they can generate both social spillovers and social multipliers and therefore trigger the crowding process. According to the previous literature, a social spillover in a dyadic relationship between two agents arises when a focal agent's decision affects the other agent's decision so that a stimulus to the focal agent spreads out to the other agent (Hartmann et al. 2008). Moreover, a social multiplier arises when the social interaction between the two agents includes a feedback effect of the focal agent's decision through the other agent. In this case where the feedback loop exists, the stimulus to the focal agent is reinforced by the feedback effect through the other agent. Under our context, social spillovers and social multipliers arise through the contemporaneous social interactions and the forward-looking social interactions, respectively. For instance, a focal crowdfunder's current decision may be reinforced by the expectations of the crowd's future participation (social multipliers through the forward-looking social interactions). Furthermore, the triggered future participation by the crowd will spread out again over the network and affect other individual crowdfunders' future decisions (social spillovers through the contemporaneous social interactions). Thus, social spillovers and social multipliers can vastly increase the compounding effect of stimuli to crowdfunders and thereby lead the crowding process and ultimately goal completion.

The interplay of the contemporaneous social interactions and the forward-looking social interactions may generate crowdfunding dynamics. For instance, the forward-looking social interactions can generate crowdfunders' early participation and ignite the crowding process, because the crowdfunders can benefit from the early participation while expecting the crowd's future participation (social multipliers).

Also, the combined effect of the contemporaneous and forward-looking social interactions can convert the crowd's small early phase movements (the ignited crowding process) into a gradual increase in the middle phase and finally a strong herding in the last phase by continuously and simultaneously encouraging crowdfunders to internalize the feedback effects of their own decisions (social multipliers) and to follow the crowd (social spillovers).

3. Institutional Setting and Data

3.1. Sellaband

In this study, we focus on a music crowdfunding platform, Sellaband. Since its launch in 2006, Sellaband raised over $4,500,000 from 35,000 crowdfunders among 70,000 potential registered crowdfunders (Ordanini et al. 2015). On this platform, artists raise funds from crowdfunders in order to cover the costs of making new music albums. To start the fundraising process, a fundraiser (artist) uploads up to three sample songs with the self-introduction of the new music album, specifies the funding goal, and sets the proportion of stocks of the project to be shared with crowdfunders. When the goal is achieved, the crowdfunders receive the stocks of the project depending on their shares as terminal payoffs of the crowdfunding process. Meanwhile, Sellaband provides the fundraiser with professional resources for recording and selling the new music album such as a recording facility, mixing engineering, distribution channels, marketing, etc. Once the new music album is recorded and generates profits, the crowdfunders receive the profit sharing as a form of dividends and a limited edition of the new music album. If the project fails to meet the funding goal,[3] the deposited investments are credited to the crowdfunders' account. However, the credits cannot be exchanged back into real money. Instead, the credits may be used to support other fundraising projects.

The data that are obtained from Sellaband.com contain individual investment histories from 2006 to 2011. An individual's investment history contains what, when, and how much a crowdfunder has invested in the past. In addition, we have the general profiles of 300 fundraising projects[4] (i.e., the artists), including information such as country, genre, goal amount, percentage of stocks to be shared with crowdfunders, launch date, number of sample songs, photos, videos, and artist blog posts. We also have the general profile of 25,547 crowdfunders including information such as country, number of page views, sign-up date, etc.[5]

3.2. Dynamic Data Patterns

We introduce dynamic data patterns resulting from the forward-looking investment behavior of socially interacting crowdfunders using the entire data set collected. Figure 2 shows the histogram of the goal achievement level. We observe that there are only a few projects whose goal achievement level is between 50% and 100%. That is, most of the projects (83.7%) that moved beyond 50% of their goal ultimately got funded. Also, the skewness shows a funding velocity where a project "sits longer" at early stages and passes more quickly through later stages, because we observe more projects sitting in the early stage than in later stages. This finding is consistent with the literature that shows crowdfunding is highly skewed (Agrawal et al. 2014). More importantly, the skewed distribution shows the three dynamic patterns: stagnation (between 0% and 10% of goal achievement level), gradual increase (between 10% and 80% of goal achievement level), and the acceleration (between 80% and 100% of goal achievement level). Figure 3 presents the three dynamic patterns more clearly. We can see that both the average conversion rate and the average investment amount stagnate around 10% of goal achievement level and slowly increase until 80% of goal achievement level. Finally, these metrics dramatically increase as projects near their goal (after 80% of goal achievement level). Specifically, when the goal achievement level is between 20% and 30%, only 3% of individuals among active crowdfunders have invested.[6] However, 21% of active individuals have invested when the goal achievement level is between 90% and 100%.

3.3. Exploratory Analysis

We also conduct an exploratory analysis to find empirical evidence of the proposed mechanisms behind the crowdfunding dynamics using the entire data

Figure 2. Histogram of Goal Achievement Level

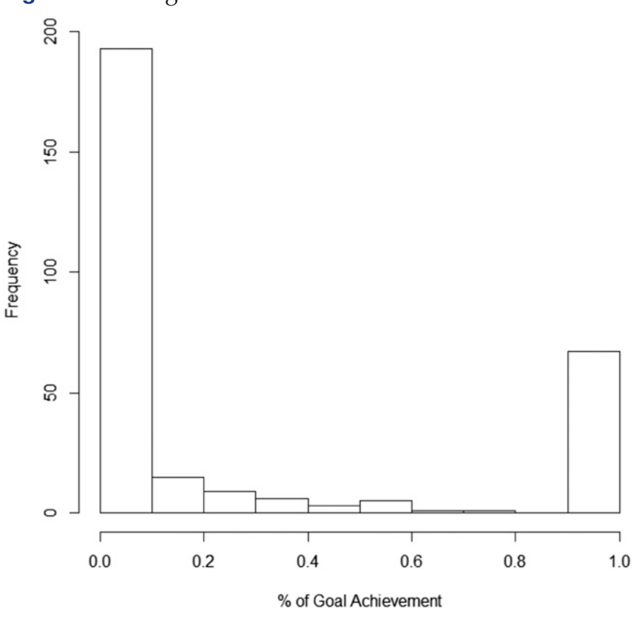
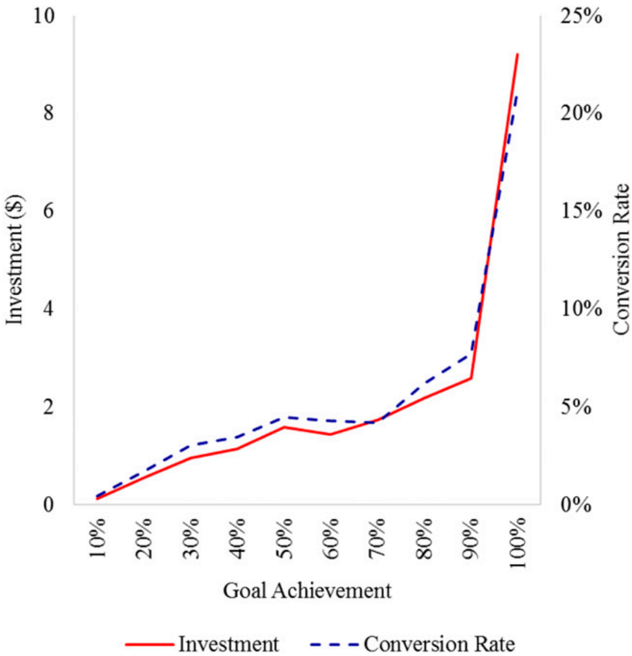


Figure 3. (Color online) Investment Patterns Depending on Goal Achievement Level



set collected. Specifically, we follow the approaches suggested by previous studies to show the patterns related to dynamic behaviors (Chintagunta et al. 2012, Ahn et al. 2015) and social interactions (Manski 1993, Van den Bulte and Lilien 2001, Hartmann et al. 2008, Nair et al. 2010) with reduced-form regressions. Following these approaches, we simply run fixed-effects regressions of the individual investment amount on the three variables: the remaining amount left until the goal at the next period (forward-looking delaying investment behavior), the total investment amount by others at the current period (contemporaneous social interactions), and the total investment amount by others at the next period (forward-looking social interactions). The fixed-effects regression can be represented as

$$Y_{ijt} = \beta_0 + \beta_1 R_{jt+1} + \beta_2 Y_{-ijt} + \beta_3 Y_{-ijt+1} + \delta_i + \gamma_j + w_t + \xi_{ijt}, \quad (1)$$

where Y_{ijt} is the investment amount of individual i in project j in week t (unit: \$1); R_{jt+1} is the remaining amount left until the goal of project j in week $t+1$ (unit: \$1,000); Y_{-ijt} is the total investment amount by others in project j in week t (unit: \$1,000); Y_{-ijt+1} is the total investment amount by others in project j in week $t+1$ (unit: \$1,000); δ_i is the individual fixed effect; γ_j is the project fixed effect; w_t is the week fixed effect; and ξ_{ijt} is the error term. We discuss how the regression shows empirical evidence of the three mechanisms one by one.

First, we examine the dynamic delaying behavior by following the approaches suggested by Ahn et al. (2015) and Chintagunta et al. (2012), which regress the current decisions on the future states. The remaining investment amount left until the goal at the next period (R_{jt+1}) represents the future status of fundraising progress. Thus, it shows how individual crowdfunders' decisions may differ depending on the future fundraising progress. We can expect that the larger the remaining amount left until the goal at the next period, the less a focal crowdfunder will invest at the current period (forward-looking delaying investment behavior). In a similar vein, the focal crowdfunder might invest more when the remaining amount left until the goal in the next period is small (acceleration due to the eventual commitments of delayed investments in the last phase).

Second, we examine the contemporaneous social interactions by investigating the effect of others' current decision (Y_{-ijt}) on a focal crowdfunder's current decision (Y_{ijt}). The contemporaneous social interactions may potentially be confounded with other correlations: homophily, correlated unobservables, and simultaneity. In order to sort out the causal peer effects from those correlations, we follow the identification strategies suggested by previous studies (Manski 1993, Van den Bulte and Lilien, 2001, Hartmann et al. 2008, Nair et al. 2010).[7] Homophily may arise when individuals have similar tastes. Following the previous studies that control for homophily by directly capturing individuals' tastes with the individual fixed effects (Manski 1993, Nair et al. 2010), we include the individual fixed effects and the project fixed effects to capture individuals' tastes to specific music (homophily). Also, other factors (correlated unobservables) could influence individuals to make similar decisions. Previous studies control for the correlated unobservables with time fixed effects, which may pick up the common trends of comovements (Van den Bulte and Lilien 2001). We also control for correlated unobservables by including the time fixed effects. Simultaneity may arise because individuals' decisions are contemporaneously interdependent. For instance, an individual can affect others, while being affected by the decision of the others simultaneously. However, the contemporaneous social interactions between an individual crowdfunder and the crowd tend to be asymmetric under the crowdfunding context (Zhang and Liu 2012). Furthermore, we find empirical evidence that the effect of the individual crowdfunder's current decision on the crowd's current decision is not statistically significant.[8] Therefore, we assume that simultaneity is unlikely under our context.

Third, we examine the forward-looking social interactions by investigating the effect of others' future decision (Y_{-ijt+1}) on a focal crowdfunder's current decision (Y_{ijt}). It represents how the expectation of future participation by others affects the focal crowdfunder's current decision. We argue that a focal crowdfunder will invest more when larger future participation by others is expected, as it would increase the likelihood of successful goal completion, and, accordingly, benefit the crowdfunder.

Table 1 shows the results of the regressions of the individual investment amount on the three variables. We run four regressions by cumulatively adding the fixed effects one by one to see how heterogeneity facilitates homophily and correlated unobservables. All the effects of the three variables are statistically significant in all models. The effect of the remaining amount left until the goal at the next period is negative and significant, showing that a focal crowdfunder invests less (delay) when the remaining amount left until the goal in the next period is large. Also, the effect of the total investment amount by others at the current period is positive and significant. Thus, this result implies that a focal crowdfunder's current decision is affected by the current decisions of others (contemporaneous social interactions). Interestingly, the effect of the contemporaneous social interactions decreases as we add more fixed effects (5.46, 5.36, 4.77, and 3.90 for OLS 1, OLS 2, OLS 3, and OLS 4, respectively). These results show that including fixed effects can help sort out social interactions from homophily and correlated unobservables, and, more importantly, the contemporaneous social interactions are still significant after controlling for these correlations. Furthermore, the effect of the total investment amount by others at the next period is also positive and significant, showing that a focal crowdfunder invests more in the current period when there are more future investments from others (the forward-looking social interactions).

4. Model

In this section, we demonstrate the proposed model that incorporates the proposed underlying mechanisms of crowdfunding behavior.

4.1. State Transitions

Individual crowdfunder i decides how many shares to buy (Q_{ijt}) in crowdfunding project j in period t. The state of the system can be defined as $S_{ijt} = (C_{ijt-1}, A_{jt-1}, a_{jt})$. C_{ijt-1} is the cumulative individual shares invested in project j of individual i until $t-1$ (the beginning of period t). It represents how many shares she has invested in the past in project j. Thus, it is a degenerate continuous state variable, which evolves deterministically depending on each crowdfunder's decision, $C_{ijt} = C_{ijt-1} + Q_{ijt}$. A_{jt-1} stands for the cumulative total shares invested in project j until $t-1$ (the beginning of period t). It represents how many shares project j has collected in the past from all crowdfunders. The value a_{jt} is the period total shares invested in project j during period t (i.e., $a_{jt} = \Sigma_i Q_{ijt}$). Thus, the transition of the cumulative total shares can be defined as $A_{jt} = A_{jt-1} + a_{jt}$.

4.2. Rational Expectations Equilibrium

The social interactions may continue to arise until a steady state is attained (Hartmann et al. 2008). Thus, the period total shares (a_{jt})m which aggregates all players' optimal decisions, is an equilibrium outcome. We model the equilibrium of the aggregate behavior (crowd behavior) by adopting the rational expectations equilibrium of the approximate aggregation approach suggested by Ahn et al. (2015). Under this approach, we assume that crowdfunders have a rational belief about the transition of the crowd's behavior in lieu of each individual crowdfunder's behavior and that the belief is consistent with the actual transition of the crowd's behavior.

Table 1. Linear Regressions of the Individual Investment Amount on the Three Drivers

	OLS 1		OLS 2		OLS 3		OLS 4	
	Est	SE	Est	SE	Est	SE	Est	SE
Intercept	3.79	0.20	2.70	2.45	10.87	2.76	17.52	2.96
Remaining amount left until goal at the next period (R_{jt+1})	−0.09	0.01	−0.12	0.01	−0.31	0.01	−0.44	0.02
Total investments by others at the current period (Y_{-ijt})	5.46	0.15	5.36	0.15	4.77	0.16	3.90	0.17
Total investments by others at the next period (Y_{-ijt+1})	1.85	0.15	1.70	0.15	1.08	0.16	1.24	0.17
Individual fixed effects (δ_i)			Yes		Yes		Yes	
Project fixed effects (γ_j)					Yes		Yes	
Week fixed effects (w_t)							Yes	

Note. Est, estimates; SE, standard error.

We specify the rational belief about the transition of the crowd's behavior in the aggregate-level model in Equation (2). More specifically, following the approach of Ahn et al. (2015), we model the transition of the crowd's behavior (the period total shares) as a first-order Markov process:[9]

$$a_{jt} = \phi_j^{(0)} + \phi_j^{(1)} a_{jt-1} + \eta_{jt}, \tag{2}$$

where $\phi_j^{(0)}$ and $\phi_j^{(1)}$ are determined by the rational expectations equilibrium and η_{jt} is the zero-mean random error captures the uncertainty in the evolution of the period total shares. The evolution of the period total shares captures the speed of goal achievement. Thus, crowdfunders predict the amount of time remaining until goal completion based on the rational belief about the evolution of the aggregate participation.

4.3. Period Utility and Terminal Payoff

Next, we specify the individual-level model of crowdfunders' dynamic investment behavior. When individual crowdfunder i makes an investment decision about project j in period t (beginning of period t), two scenarios may arise. Project j might either continue to collect additional investments (ongoing) or have achieved the goal already (success). Whether a project remains ongoing or successfully completes the goal depends on the cumulative total shares (A_{jt-1}). If the cumulative total shares collected until $t-1$ (the beginning of period t) is larger or equal to the goal amount ($A_{jt-1} \geq G_j$), then the fundraising process is terminated at period t, and additional investments are no longer possible. In this case, she receives her own share of stocks of the project and becomes eligible for profit sharing (dividends). The terminal payoff of the end-in-success case (u^F_{ijt}) that she would receive right after the goal completion can be represented as

$$u^F_{ijt} \big| S_{ijt} = M_j R_j C_{ijt-1} / G_j, \tag{3}$$

where M_j is the total market value of stocks of project j, R_j is the promised proportion of stocks to be shared with crowdfunders, C_{ijt-1}/G_j is her share of project j. G_j and R_j are determined by the fundraiser before fundraising. The total market value (M_j) may reflect the rewards that will be finally shared to crowdfunders (e.g., dividends and new products).[10]

On the other hand, if the cumulative total shares collected until $t-1$ (beginning of period t) is smaller than the goal ($A_{jt-1} < G_j$), then project j will continue to collect additional investments in period t. In this case, she perceives the per-period utility of investing Q_{ijt} shares in project j in period t irrespective of goal completion. Thus, the per-period utility (u^P_{ijt}) is the function of Q_{ijt}. Specifically, we employ a concave quadratic function to account for the optimal investment decision of a risk-averse crowdfunder as

$$\begin{aligned} u^P_{ijt}(Q_{ijt} \big| S_{ijt}) = {} & \left(\alpha_{ij} e^{-k_{ij} C_{ijt-1}} + \pi_{ij} a_{jt}/G_j - H_j\right) Q_{ijt} - \upsilon_{ij} Q^2_{ijt} \\ & - \theta_{ij} C_{ijt-1} + \varepsilon_{ijt}(Q_{ijt}). \end{aligned} \tag{4}$$

The linear terms include any benefit and cost she perceives in proportion to the number of shares (Q_{ijt}) such as the altruistic utility, the contemporaneous social interactions, and the actual cost. The individual- and project-specific intercept (α_{ij}) captures the altruistic utility to support, encourage, and help the crowdfunding project out of goodwill (Ordanini et al. 2011). It also controls for homophily by directly capturing individual crowdfunders' tastes in music.[11] In addition, we take satiation into account by allowing for the diminishing baseline utility for additional investments with the rate of $e^{-k_{ij} C_{ijt-1}}$.[12] In addition, π_{ij} captures the effect of the crowd's current decision on the focal crowdfunder's current decision (contemporaneous social interactions). We normalize the aggregate investments of all crowdfunders at period t (a_{jt}) by the size of the goal (G_j) to capture the relative impact of the crowd's movement compared with the goal. H_j is the actual cost (price) per share that is predetermined by the fundraiser before fundraising. On the other hand, the quadratic term (ν_{ij}) captures all potential sources of risk of the current decision (Q_{ijt}). For instance, she might perceive risk concerned with the credibility and transparency of the fundraisers and platform. A fundraiser might "dine and dash," never sharing the promised rewards. Also, the platform and fundraisers might fabricate the profit and revenue. The perceived risk makes her avoid investments. In addition, θ_{ij} captures the opportunity cost of the money previously invested (C_{ijt-1}). Lastly, $\varepsilon_{ijt}(Q_{ijt})$ is the Type 1 extreme value error, which accounts for the factors that are unobservable to researchers.

By putting the terminal payoff and the per-period utility together, the value function must satisfy the following Bellman equation:

$$\begin{aligned} & V_{ij}(S_{ijt}) \\ & = \max_{Q_{ijt} \in \mathbf{Q}} \Big\{ I(A_{jt-1} \geq G_j) \cdot u^F_{ijt} \Big| S_{ijt} + I(A_{jt-1} < G_j) \\ & \qquad \times \Big[u^P_{ijt}\big(Q_{ijt} \big| S_{ijt}\big) + \rho E\Big[V_{ij}\Big(S_{ijt+1} \Big| S_{ijt}, Q_{ijt}\Big)\Big]\Big]\Big\} \\ & = \max_{Q_{ijt} \in \mathbf{Q}} \left\{ \begin{array}{l} I(A_{jt-1} \geq G_j) \cdot M_j R_j C_{ijt-1}/G_j \\ + I(A_{jt-1} < G_j) \cdot \left[\begin{array}{l} \left(\alpha_{ij} e^{-k_{ij} C_{ijt-1}} + \pi_{ij} a_{jt}/G_j - H_j\right) \\ \quad \times Q_{ijt} - \upsilon_{ij} Q^2_{ijt} - \theta_{ij} C_{ijt-1} \\ + \varepsilon_{ijt}(Q_{ijt}) \\ + \rho E\Big[V_{ij}\Big(S_{ijt+1} \Big| S_{ijt}, Q_{ijt}\Big) \end{array} \right] \end{array} \right\}, \end{aligned} \tag{5}$$

where ρ is the discount factor, $\mathbf{Q} = \{0,1,2,\cdots,\bar{q}\}$, and $\bar{q}$ is the maximum number of shares to invest. Note that the terminal payoff is realized at the end of the fundraising process only after the goal completion, whereas the per-period utility is perceived for every investment regardless of goal completion. That is, once the goal is met and the fundraising is terminated, the investor receives the terminal payoff and no more future period utility is expected. On the other hand, if the project continues to collect investments, the investor can continue to perceive the current period utility, expecting both the future period utility through additional investments and the terminal payoff after the goal completion.

4.4. Mechanisms

In this section, we discuss how the proposed models account for the underlying mechanisms behind the crowdfunding dynamics: forward-looking delaying investment behavior, contemporaneous social interactions, and forward-looking social interactions.

4.4.1. Forward-Looking Delaying Investment Behavior. The proposed model captures the trade-off between the gain obtained from the current investment and the loss caused by the current investment. For instance, if a crowdfunder decides to invest q shares at period t (i.e., $Q_t = q$),[13] then she gains the current period utility induced by the current investment, $(\alpha e^{-kC_{t-1}} + \pi a_t/G - H)q - vq^2$ and expects the future terminal payoff contributed by the current investment, MRq/G. However, she also expects some loss of the future opportunity cost induced by the current investment θq, which will be incurred every period until the goal completion. Thus, she will invest only if the expected gain of the current investment is larger than the expected loss of the current investment.

This trade-off captures the delaying behavior. For instance, if she expects that the goal is far beyond than the current cumulative total shares (early stage), then the expected cumulative future opportunity cost induced by the current investment would be very large compared with the expected future terminal payoff contributed by the current investment. This is because the future opportunity cost induced by the current investment is expected to be incurred for a long time, and the future terminal payoff would be discounted more. On the other hand, if the goal is expected to be achieved soon (late stage), then the expected future terminal payoff would become dominant. This is because the future opportunity cost induced by the current investment is expected to be incurred for a very short period and the future terminal payoff would be discounted less.

It is also important to note that the current opportunity cost (θC_{t-1}) is not a function of the current decision (Q_t) but the past decisions (C_{t-1}). That is, the current opportunity cost is determined by previous investments (C_{t-1}) but not the current investment (Q_t). Therefore, even though the investor perceives the current opportunity cost incurred by the previous investments, she does not take the current opportunity cost into account in making the current investment decision. Furthermore, myopic crowdfunders would not expect any future opportunity cost induced by their current investments and therefore tend not to delay their investments at all.

We can formulate the trade-off more formally. Let's consider the case where a crowdfunder decides when and how many shares to buy for a project. Without loss of generality, we assume that she decides to either buy q shares or invest nothing at all in every period until project success and that the project achieves its goal after two periods (in period $t + 2$). Then, four choice scenarios may arise over the first two periods as depicted in Table 2: $(Q_t, Q_{t+1}) = (0, 0), (q, 0), (0, q)$, or (q, q). In addition, we assume the same crowd's behavior across periods to clearly see the delaying behavior ($a_t = a$). Also, for simplicity, we drop subscript i and j and assume no errors. The values $\tilde{\alpha}$ and $\tilde{\alpha}'$ are the coefficients of first-order term in Equation (4) when $C = 0$ and $C = q$, respectively: $\tilde{\alpha} = \alpha + \pi a/G - H$ and $\tilde{\alpha}' = \alpha e^{-kq} + \pi a/G - H$.

Let's compare Case 2 and Case 3. If she invests only in period t (Case 2), then she would perceive the period utility, $\tilde{\alpha}q - vq^2$ in period t and the opportunity

Table 2. Dynamic Behavior

Case	(Q_t, Q_{t+1})	Returns: t	$t + 1$	$t + 2$	Discounted sum of returns
Case 1	(0, 0)	0	0	0	0
Case 2	$(q, 0)$	$\tilde{\alpha}q - vq^2$	$-\theta q$	qMR/G	$V_1 = (\tilde{\alpha} - \rho\theta + \rho^2 MR/G)q - vq^2$
Case 3	$(0, q)$	0	$\tilde{\alpha}q - vq^2$	qMR/G	$V_2 = (\rho\tilde{\alpha} + \rho^2 MR/G)q - \rho vq^2$
Case 4	(q, q)	$\tilde{\alpha}q - vq^2$	$-\theta q + \tilde{\alpha}'q - vq^2$	$2qMR/G$	$V_1 + V_3 = (\tilde{\alpha} - \rho\theta + \rho^2 MR/G)q - vq^2$ $+ (\rho\tilde{\alpha}' + \rho^2 MR/G)q - \rho vq^2$

cost, $-\theta q$ in period $t+1$. Instead, if she delays her investment and invests only in period $t+1$ (Case 3), then she would perceive the period utility, $\tilde{\alpha} q - vq^2$ in period $t+1$. Thus, simply speaking, what she trades off between the early investment (Case 2) and the delayed investment (Case 3) is the discounted amount of the period utility from the current investment, $(\tilde{\alpha} q - vq^2)(1-\rho)$ and the discounted future opportunity cost induced by the current investment $\rho\theta q$. Thus, under the context where crowdfunders decide the investment timing only (every crowdfunder should invest the same amount once and no investment is not allowed: either Case 2 or Case 3), the terminal payoff does not affect the investment decision, because the terminal payoff is the same regardless of investment timing (qMR/G for both cases). However, under our context, crowdfunders may have other options to consider. In this example, crowdfunders may invest in every period (Case 4) or choose not to invest at all (Case 1). Therefore, they necessarily take the terminal payoff into consideration in their decision-making by comparing all the possible choice options. For instance, compare Case 1 and Case 2. If the expected terminal payoff contributed by the current investment ($\rho^2 MRq/G$) is not large enough to cover the losses induced by the current investment (risk in the current period utility from the current investment: $-vq^2$; and the expected future opportunity cost induced by the current investment: $-\rho\theta q$), then she might not invest at all (choose Case 1). Thus, all those model components (current period utility from the current investment, future opportunity cost induced by the current investment, and terminal payoff contributed by the current investment) contribute to capturing the dynamic investment behavior.

4.4.2. Social Interactions. The asymmetric nature of the contemporaneous social interaction between a focal crowdfunder and the crowd is incorporated by the approximate aggregation approach. Specifically, the effect of the crowd's current decision (a_{jt}) on the focal crowdfunder's current decision (Q_{ijt}) is captured by π_{ij}. On the other hand, the effect of the focal crowdfunder's current decision on the crowd's current decision is not directly modeled. Instead, the crowd's current decision is modeled as the equilibrium of the aggregate behavior based on the rational belief.

The forward-looking social interactions are incorporated into both the aggregate-level model, which models the belief about the transition of crowd's behavior, and the individual-level model, which models the dynamic investment behavior of individual crowdfunders. In the aggregate-level model (Equation (2)), a focal crowdfunder's current decision (Q_{ijt}) is incorporated in the crowd's future participation ($a_{jt+1} = \phi_j^{(0)} + \phi_j^{(1)} \cdot \sum_i Q_{ijt} + \eta_{jt+1}$). Also, the feedback effect of the focal crowdfunder's current decision through the expected crowd's future participation is incorporated into in the individual-level model (Equation (5)). More specifically, the expected crowd's future participation is expected to push the future cumulative total shares closer to the goal ($A_{jt+1} = A_{jt} + a_{jt+1}$). Therefore, the expectation on the increased future cumulative total shares will increase the expected sum of discounted future returns, $\mathrm{E}[V_{ij}(S_{ijt+2}|S_{ijt})]$ and, in turn, increase the investor's current investment, because the expected terminal payoff would be less discounted and the future opportunity cost would be small.

4.4.3. Rational Expectations Equilibrium. The rational expectations equilibrium fully reflects the three mechanisms (forward-looking delaying investment behavior, contemporaneous social interactions, and forward-looking social interactions). Note that an individual crowdfunder's optimal decision is endogenously determined by the crowd's decision. Also, the crowd's decision is the aggregation of all crowdfunders' optimal decision (including her own decision), which considers the three mechanisms. Therefore, under the equilibria where the aggregation of all crowdfunders' optimal decision converges to the crowd's decision, the optimal decision of a forward-looking individual crowdfunder is the result of considering the effect of the crowd's current decision (contemporaneous social interactions), internalizing the effect of her own decision through the crowd's future decisions (forward-looking social interactions), and trading off the future opportunity cost and the terminal payoff (forward-looking delaying investment behavior).

The crowdfunding dynamics can be recovered through the equilibrium process. For instance, in the early stage, a few investments may arise through the forward-looking social interactions, encouraging future participation by the crowd and benefiting the early crowdfunders. The early investments will elevate the crowd's future participation, and the elevated crowd's future participation will also increase individual crowdfunders' decisions in the following periods through the contemporaneous social interactions. In addition, the feedback effect through the forward-looking social interactions and the social spillovers through the contemporaneous social interactions accelerate, as crowdfunders expect the larger future participation by the crowd. Finally, the decreased future opportunity cost with the shorter amount of time expected to complete the goal leads to more commitments of delayed investments in the later stages. Therefore, the equilibrium process that embraces all those mechanisms helps us to recover the crowdfunding dynamics such as early investments (incentives through the forward-looking social interactions),[14] the gradual increase in the middle stage (combined effect of the contemporaneous and forward-looking social interactions), and the acceleration in the last phase (social interactions and the eventual commitments of delayed investment participation).

4.5. Identification

4.5.1. Structural Parameters. We discuss the identification of the structural parameters using the example introduced in the previous section. We can observe all four cases in Table 2 from our data. Thus, we can separately identify V_1, V_2, and V_3.[15] Because we can identify the linear and quadratic coefficients in V_1, V_2, and V_3, we can identify $\tilde{\alpha} - \rho\theta + \rho^2 MR/G$, $\rho\tilde{\alpha} + \rho^2 MR/G$, $\rho\tilde{\alpha}' + \rho^2 MR/G$, and v. According to previous literature, the discount factor ρ is not identified in dynamic discrete choice models (Manski 1993, Magnac and Thesmar 2002, Ahn et al. 2015). Thus, we set the discount factor in our empirical analysis. To separately identify $\tilde{\alpha}$, $\tilde{\alpha}'$, and θ, we also set M in our empirical study. Finally, we can identify k by the difference between $\tilde{\alpha}$ and $\tilde{\alpha}'$. Furthermore, we can identify α and π, because $\tilde{\alpha} = \alpha + \pi a/G - H$, and G and H are determined by the fundraiser. In sum, the model parameters (α_{ij}, π_{ij}, v_{ij}, θ_{ij}, and k_{ij}) can be statistically identified if we set M_j and ρ. We show the true model parameters are recovered very well in the simulation study (see Online Appendix E).

To empirically identify the structural parameters from data, some variations are necessary. For instance, we need variations in the size of investments to identify the risk parameter (v_{ij}). If only one investment option is available (1:invest or 0:not), then we cannot identify the linear coefficient from the quadratic coefficient, because q is equal to q^2 (when $q = 1$). Also, the intercept (α_{ij}) and satiation parameter (k_{ij}) can be identified separately by the difference in patterns between early investments and subsequent investments, because α_{ij} is more likely to be state-independent (i.e., $C_{ijt} = 0$). If the size and frequency of subsequent investments tend to be small, then satiation would be large. The social interaction parameter (π_{ij}) can be identified by variations in participation by the crowd over time. The opportunity cost (θ_{ij}) is determined by investment timing. If an individual invests early, then the opportunity cost would be small. Because early investment necessarily incurs the future opportunity cost for a long time, the early investments would not have been made unless the opportunity cost is small. On the other hand, if the investor waits and invests later rather than earlier, then the opportunity cost would be large.

4.5.2. Identification of Social Interactions. In observational data, social interactions (causal peer effects) are likely to be confounded with other correlations: homophily, correlated unobservables, and simultaneity (Manski 1993, Hartmann et al. 2008, Wang et al. 2013). If the confounding factors are not properly addressed, social interactions tend to be overidentified. Therefore, identifying the true causal effect of social interactions from the confounding factors is one of the key problems in social interaction studies. We address these correlations one by one.

Under our context, crowdfunders are able to pick up the characteristic of artists' music by listening to the sample music and reading the self-introduction. Thus, homophily may arise when crowdfunders who have similar tastes in music invest in the same artist. These correlations may lead to an upward bias in the estimates of π_{ij}. Previous studies control for homophily by facilitating heterogeneity (Manski 1993, Hartmann et al. 2008, Nair et al. 2010). In this study, we directly capture individual tastes in music with the individual- and project-specific intercepts (α_{ij}). By doing so, we sort out the crowdfunders' tastes in music from the unobservable factors (ε_{ijt}) and thereby control for the portion of unobservable factors that are correlated with α_{ij}.

There may exist factors other than homophily (correlated unobservables) that engender comovements of crowdfunders simultaneously. One possible source of these correlations is marketing activities targeted to specific individuals to encourage them to invest by giving actual benefits (e.g., price discounts). These marketing activities may drive the targeted individuals to behave in a similar fashion. Thus, the causal peer effects may be biased without regard for the correlations derived by marketing activities. Because not all marketing activities are observable, previous studies control for these correlations by using secondary data or time fixed effects (Van den Bulte and Lilien 2001, Nair et al. 2010). However, there were very limited marketing activities under our context because the platform did not differentiate the price per share for different crowdfunders or investment timing. That is, all crowdfunders who invested the same amount of money should receive the same number of shares regardless of their investment timing. Some platforms do indeed undertake certain marketing actives (e.g., incentivizing early investments to trigger the crowding process with price discounts, or giving extra shares to the original investment akin to our counterfactual application in the empirical study). However, to the best of our knowledge, this platform has never engaged in such marketing activities that give actual benefits to targeted crowdfunders. Thus, our context is less subject to such correlations derived by marketing activities.

Furthermore, additional correlated unobservables that generate common trends in comovement of crowdfunders should be considered. For instance, crowdfunders may time their investments coincidently. The common trends in comovement can be captured by the individual- and project-specific dynamic structure of the proposed model (individual- and project-specific intercept, satiation, opportunity cost, risk, etc.), separating these effects from social interactions.

Simultaneity may arise when individual crowdfunders' decisions are contemporaneously interdependent. As we mentioned earlier, the contemporaneous social interactions are somewhat passive under our context where individual crowdfunders' decisions are affected by the aggregate behavior of the crowd but not vice versa. Also, as we showed in Online Appendix B, we find an asymmetric relationship between the focal crowdfunder and the crowd. Thus, we assume that simultaneity is not present under our context and adopt the concept of the rational expectations equilibrium of approximate aggregation approach. This approach, which has the passive flavor of social interactions, fits into our crowdfunding context very well where the cotemporaneous social interactions between a crowdfunder and the crowd are passive.

4.6. Likelihood

The choice probability of buying q_{ijt} shares can be derived as

$$P(Q_{ijt} = q_{ijt} | S_{ijt}) = \frac{\exp\left(u^P_{ijt}(q_{ijt}|S_{ijt}) + \rho\tilde{E}[V_{ij}(S_{ijt+1}|S_{ijt}, q_{ijt})]\right)}{\sum_{\tilde{q}_{ijt}\in\mathbf{Q}} \exp\left(u^P_{ijt}\left(\tilde{q}_{ijt}|S_{ijt}\right) + \rho\tilde{E}\left[V_{ij}\left(S_{ijt+1}|S_{ijt}, \tilde{q}_{ijt}\right)\right]\right)}, \quad \text{if } A_{jt-1} < G_j, \tag{6}$$

where $\tilde{E}[V_{ij}(S_{ijt+1}|S_{ijt}, q_{ijt})]$ is the pseudo-expected value function obtained by the Bayesian IJC method (see Online Appendix C for the detailed estimation procedure). If we extend this choice probability to multiple projects, then the likelihood function can be written as

$$L(\mathbf{\Omega}_i) = \prod_t \prod_i \prod_j P\left(Q_{ijt} = q_{ijt} | S_{ijt}; \Omega_{ij}\right), \tag{7}$$

where $\Omega_{ij} = \{\tilde{\alpha}_{ij}, \tilde{\pi}_{ij}, \tilde{v}_{ij}, \tilde{\theta}_{ij}, \tilde{k}_{ij}\}$, $\alpha_{ij} = \exp(\tilde{\alpha}_{ij})$, $\pi_{ij} = \exp(\tilde{\pi}_{ij})$, $v_{ij} = \exp(\tilde{v}_{ij})$, $\theta_{ij} = \exp(\tilde{\theta}_{ij})$, $k_{ij} = \exp(\tilde{k}_{ij})$, and $\mathbf{\Omega}_i$ is the vector of Ω_{ij}. We estimate individual parameters by using the Bayesian MCMC methods. Heterogeneity is captured by the following distribution

$$\mathbf{\Omega}_i \sim MVN\left(\bar{\Omega}, V_\Omega\right). \tag{8}$$

4.7. Estimation

We adopt a two-step estimation approach suggested by Ahn et al. (2015). First, we estimate the aggregate-level model, which is the transition of the period total shares represented in Equation (2). Because the observed data imply the current equilibrium where crowdfunders actually played under the current underlying primitives, we do not need to estimate the evolution of the aggregate state nor obtain equilibria at every iteration of the estimation of the individual-level model in the second stage. However, the current equilibria may not hold for counterfactuals that assume different underlying primitives from the current underlying primitives in the data. Thus, in our counterfactual analysis we reestimate the aggregate state transition and obtain rational expectations equilibria that never happened but could arise under the new underlying primitives, by recursively simulating individuals' optimal behaviors at each iteration until they converge to the aggregate demand.[16]

Second, we estimate the structural parameters of the individual-level model (altruistic utility, social interactions, risk, opportunity cost, and satiation) specified in Equation (5). In this stage, the aggregate-level model estimated in the first stage is used to form the belief about the crowd's future participation for each individual crowdfunder's decision-making in estimating the individual structural parameters. Also, we adopt the Bayesian IJC method and estimate individual parameters in order to separately identify the social interactions from other confounding correlations (e.g., homophily, correlated unobservables, and simultaneity). The Bayesian IJC method consists of two components: the inner loop and the outer loop. The inner loop approximates the expected value function using a set of value functions obtained from past iterations. The outer loop computes the likelihood functions using the expected value functions obtained from the inner loop and estimates the individual parameters using the Bayesian MCMC method. The Bayesian IJC method significantly reduces computational costs, because it applies the Bellman operator only once in inner loops. On the other hand, the traditional methods such as the nested fixed point algorithm (Rust 1987) repeatedly apply the Bellman operator until convergence in inner loops. Because considering the MCMC outer loop requires many iterations to estimate the individual parameters, the traditional methods that utilize MCMC to estimate individual parameters might be infeasible. See Online Appendix C for the detailed estimation procedure.

5. Empirical Analysis

For our empirical analysis, we randomly select two successful projects that completed their goals and two unsuccessful projects that failed to meet their goals from each of the four genres (alternative, rock, pop, and electronic) in order to tabulate the differences between genres and goal achievement.[17] We also select 1,015 individuals who have invested more than once in those 16 projects. We aggregate the data at the day-level. Because there is no limitation on the investment amount, $\bar{q}$, the maximum number of shares invested in a day is large (the maximum number of shares invested is 100 in our sample data set). However, 90% of the observations show that the number of shares invested in a day is less than 10. Thus, we handle the exact number of shares up to 10. For the cases where the number of shares is larger than 10, we order the investment shares for every 50. That is, in our empirical analysis, the kth choice option indicates purchasing $k-1$ shares (for $k \leq 11$). On the other hand, the 12th choice option and 13th choice option indicates the purchases of shares between 11 and 50 and between 51 and 100, respectively. We set ρ as 0.9 and M_j as 10,000 for identification purpose.[18] Table 3 summarizes the descriptive statistics of the sample data used in the empirical analysis.

We estimate two models: (1) the null model (no forward-looking delaying investment behavior and no social interactions) and (2) the proposed model (both forward-looking delaying investment behavior and social interactions). Table 4 compares the performances between the models. We find that the proposed model outperforms the null model in terms of log marginal density (LMD) and model fit (sum of squared error), which is defined as

$$\text{Model Fit} = \sum_t \sum_j \left(\sum_i q_{ijt} - \sum_i \hat{q}_{ijt} \middle| \Omega_{ij} \right)^2, \qquad (9)$$

where $\hat{q}_{ijt}$ is the simulated number of shares invested by individual i in project j at period t. Note that when simulating individual investment demands, we use the same procedure for simulating counterfactuals.[19] Figure 4 shows the real and predicted cumulative total shares by project. To calculate the predicted cumulative total shares at the project-level, we need to simulate individual investment demands first ($\hat{q}_{ijt}$) and then aggregate the individual investment demands into each project's demand. We find that the proposed model captures the distinct dynamics of each crowdfunding project very well. For instance, the proposed model captures the acceleration of Project A2 and the stagnation of Project E4 very well, but the null model does not.

Table 5 shows the estimation results of the state transition of the period total sales (aggregate-level model). We find the positive and significant lagged dependent variables in most of the projects. Furthermore, following the approach of Ahn et al. (2015), we conduct the Durbin-Watson test to check the autocorrelations of the residuals of the AR(1) model. The results show that the autocorrelations for 16 projects are not significantly different from zero. Thus, the results support the assumption that the rational belief about the state transition of the period total sales follows AR(1). Furthermore, the results confirm a partial path of the mechanisms of the forward-looking social interactions. Table 6 shows the estimation results of the structural parameters (individual-level model). We find that individual crowdfunders' current decisions are affected by the crowd's current decision (contemporaneous social interactions). Furthermore, we find that crowdfunders perceive the opportunity cost (forward-looking delaying investment behavior). In sum, all

Table 3. Sample Data

Category	Artist	Project	Goal	Total shares collected	Stocks to be shared with crowd (%)	Cost per share ($)	Days until success (#)	Shares collected in early stage (%)	Shares collected in middle stage (%)	Shares collected in last stage (%)
Alternative	mystimayhem	A1	5,000	5,673	50	10	448	12	13	75
Alternative	cubworld	A2	5,000	5,251	50	10	123	6	39	55
Alternative	agnieszkaholm	A3	5,076	1,992	50	7.88		22	16	62
Alternative	sylvainzebo	A4	2,500	841	50	10		20	50	30
Rock	civilized-tears	R1	3,100	5,977	50	10	491	25	16	59
Rock	juliamarcell	R2	5,000	5,165	50	10	95	42	16	43
Rock	wetwerks	R3	5,000	3,288	50	7.88		61	36	3
Rock	dandelium	R4	5,000	701	50	7.88		61	36	3
Pop	sowhat	P1	5,000	5,580	50	10	456	19	11	70
Pop	clemence	P2	5,000	5,134	50	10	85	12	23	66
Pop	thefakes	P3	5,000	2,180	50	7.88		97	2	1
Pop	laudanum	P4	3,008	911	70	7.88		39	47	15
Electronic	secondperson	E1	5,000	5,472	50	10	162	20	19	62
Electronic	sandbox1	E2	2,335	2,974	50	7.88	246	71	28	1
Electronic	kirt	E3	5,000	3,462	50	7.88		47	26	27
Electronic	emilyplayground	E4	5,000	251	50	7.88		93	7	0

Note. Early stage, the first 33% of fundraising period; last stage, the last 33% of fundraising period; middle stage, between the early stage and last stage.

Table 4. Model Performances

Model	Description	LMD	SSE
Model 1	Null	−32,942	2,597,923
Model 2	Proposed (forward-looking and social interactions)	−31,483	1,773,393

Note. LMD, log marginal density; SSE, sum of squared errors.

these results support our premise that the suggested mechanisms are present and that they also contribute to capturing the crowdfunding dynamics. The proposed models, which incorporate the three underlying mechanisms (forward-looking delaying behavior, contemporaneous social interactions, and forward-looking

Figure 4. (Color online) Real and Predicted Aggregate Investment Pattern

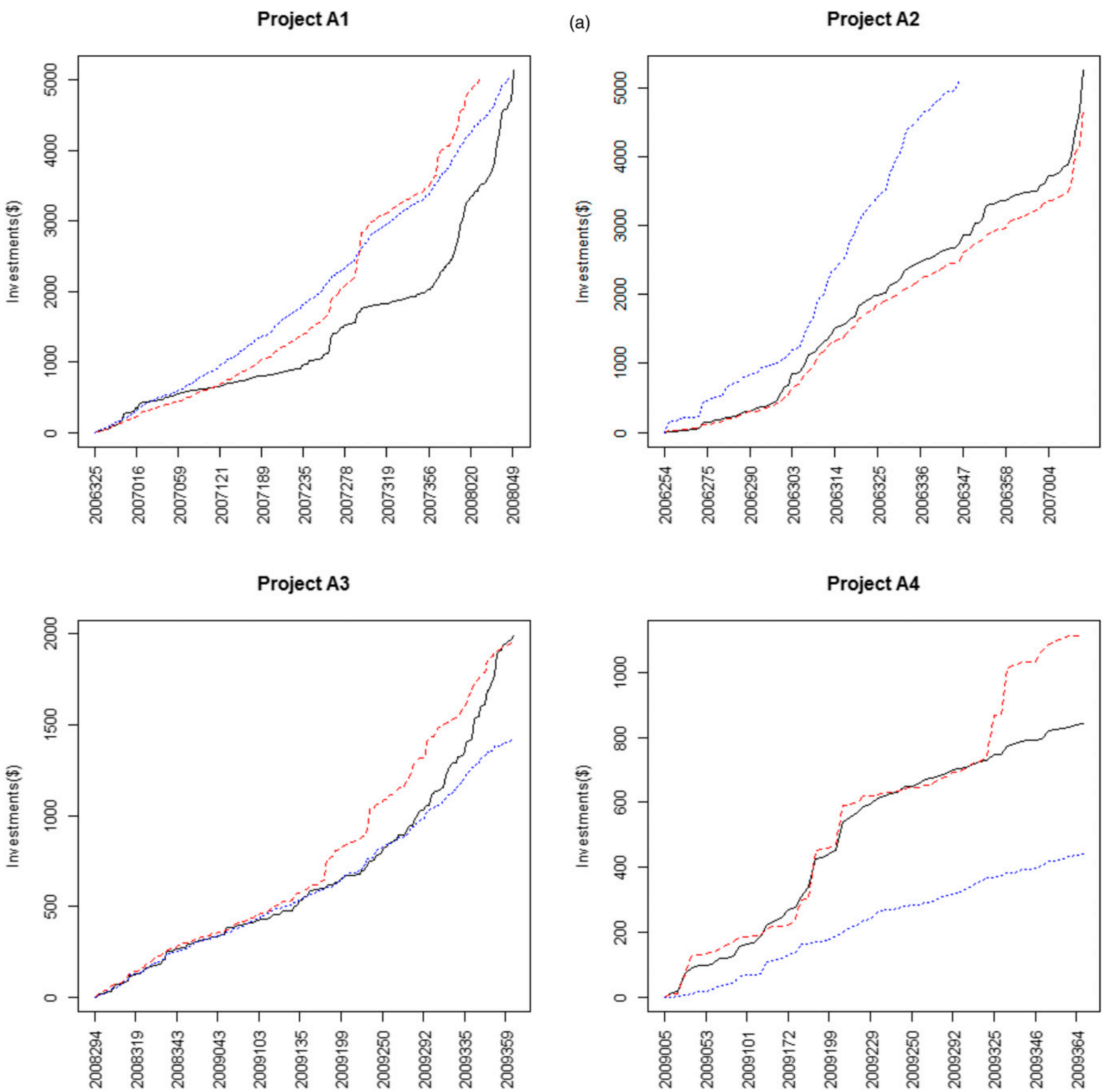
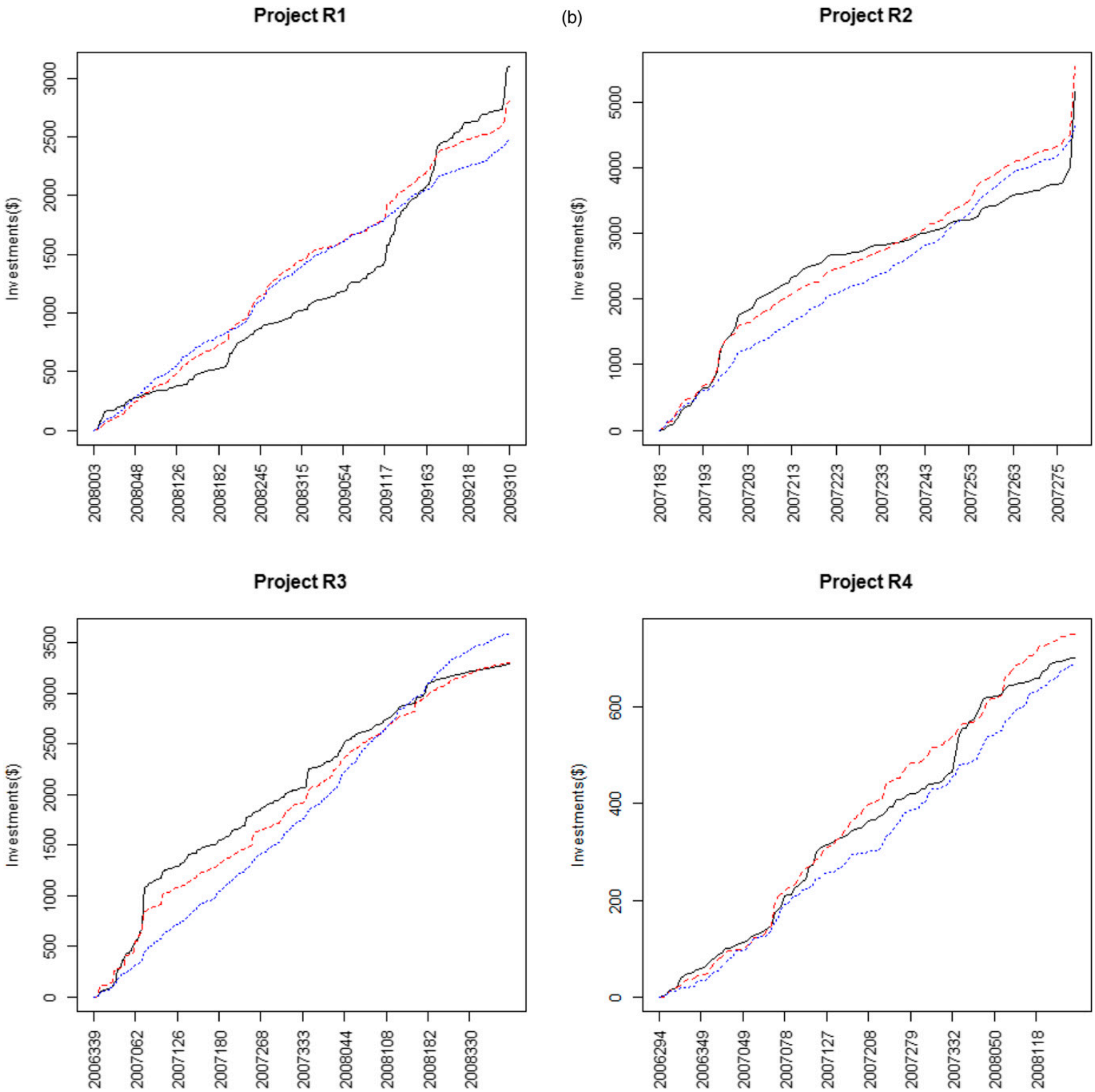


Figure 4. (Continued)



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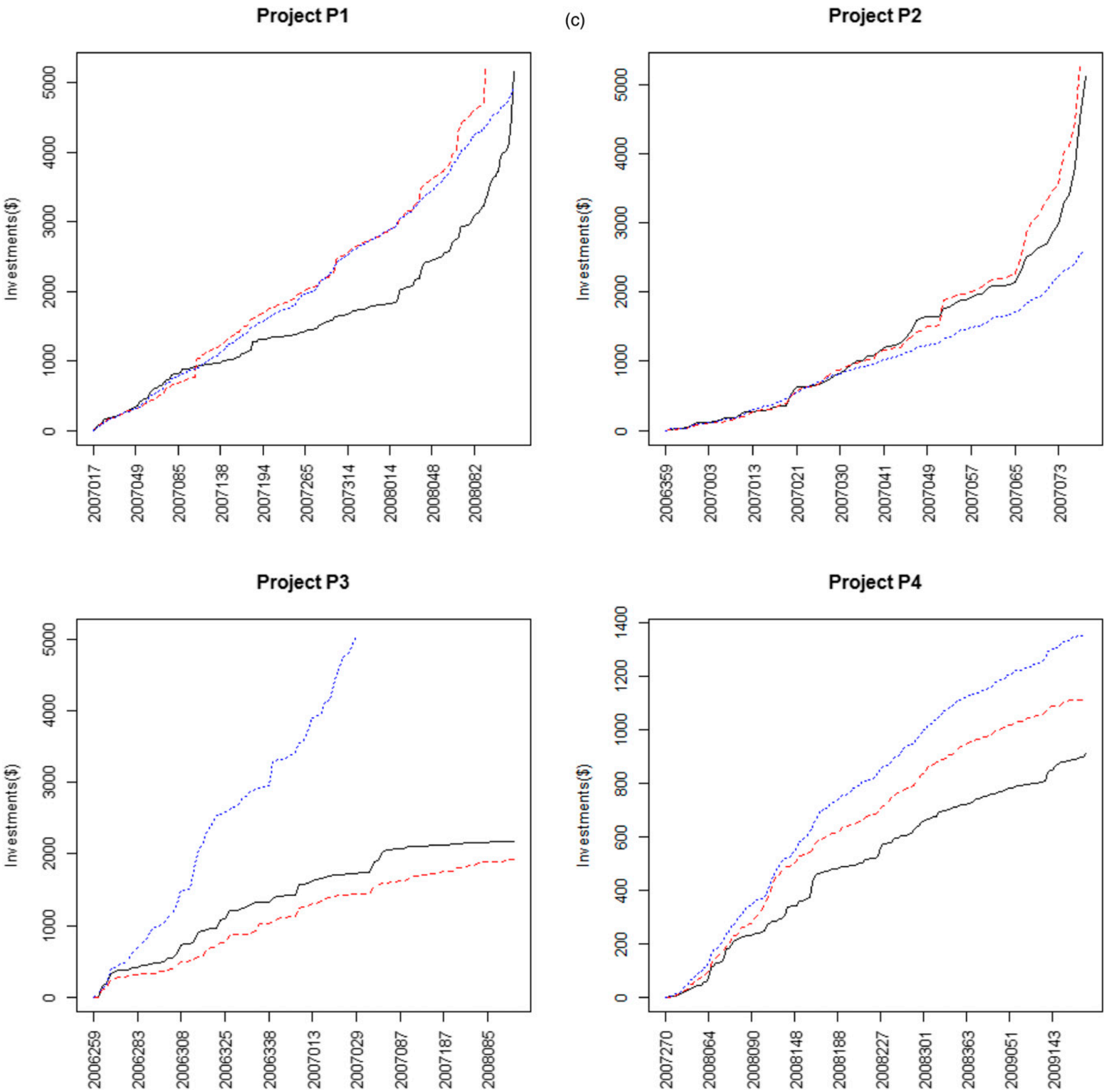

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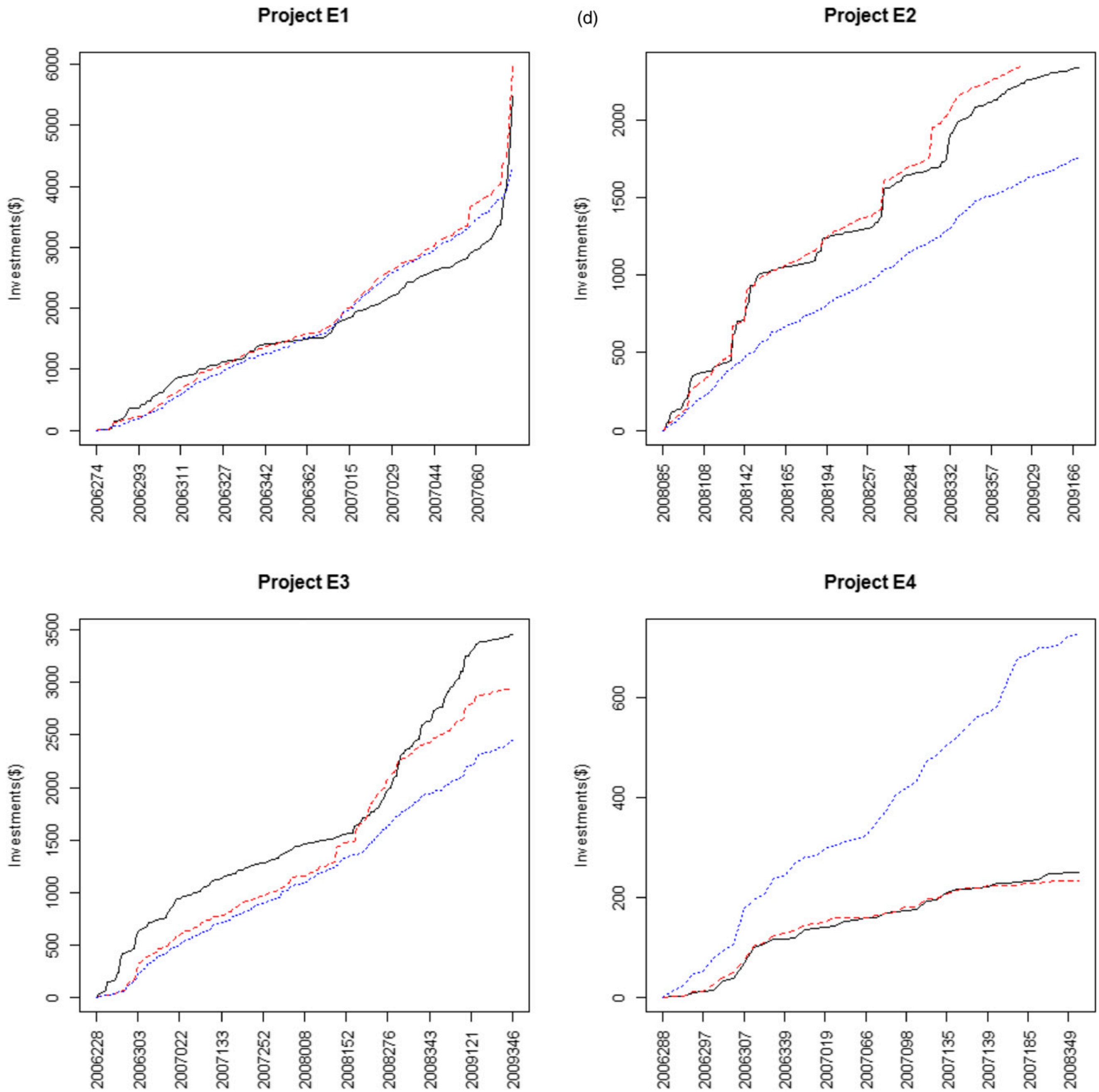

Notes. (a) Alternative: solid and black, real cumulative investments; square dot and blue, predicted cumulative investments based on the null model (Model 1); dashed and red, predicted cumulative investments based on the proposed model (Model 2). The top two projects were successful, whereas the bottom two projects were unsuccessful. The goal of project A1, A2, A3, and A4 is 5,000, 5,000, 5,076, and 2,500, respectively. (b) Rock: solid and black, real cumulative investments; square dot and blue, predicted cumulative investments based on the null model (Model 1); dashed and red, predicted cumulative investments based on the proposed model (Model 2). The top two projects were successful, whereas the bottom two projects were unsuccessful. The goal of project R1, R2, R3, and R4 is 3,100, 5,000, 5,000, and 5,000, respectively. (c) Pop: solid and black, real cumulative investments; square dot and blue, predicted cumulative investments based on the null model (Model 1); dashed and red, predicted cumulative investments based on the proposed model (Model 2). The top two projects were successful, whereas the bottom two projects were unsuccessful. The goal of project P1, P2, P3, and P4 is 5,000, 5,000, 5,000, and 3,008, respectively. (d) Electronic: solid and black, real cumulative investments; square dot and blue, predicted cumulative investments based on the null model (Model 1); dashed and red, predicted cumulative investments based on the proposed model (Model 2). The top two projects were successful, whereas the bottom two projects were unsuccessful. The goal of project E1, E2, E3, and E4 is 5,000, 2,335, 5,000, and 5,000, respectively.

Table 5. State Transition of Period Total Shares

	Intercept ($\phi^{(0)}$)		Lagged period total shares ($\phi^{(1)}$)		DW test	
Projects	Estimate	Std. error	Estimate	Std. error	DW	*p*-value
A1	6.12	1.63	0.67	0.04	2.21	0.96
A2	16.04	5.71	0.66	0.09	2.11	0.69
A3	10.37	0.97	0.09	0.05	2.02	0.58
A4	9.30	1.47	0.30	0.07	2.16	0.85
R1	9.06	1.60	0.33	0.05	2.04	0.65
R2	20.31	5.34	0.55	0.09	1.85	0.22
R3	4.75	0.63	0.26	0.04	1.99	0.46
R4	3.28	0.50	0.18	0.07	2.03	0.58
P1	3.03	1.88	0.90	0.05	2.05	0.67
P2	8.65	10.12	1.00	0.12	2.15	0.74
P3	7.91	1.46	0.24	0.07	2.06	0.65
P4	3.68	0.51	0.16	0.07	2.02	0.54
E1	13.14	4.14	0.63	0.09	2.16	0.84
E2	9.83	1.65	0.13	0.06	2.03	0.59
E3	7.07	0.84	0.14	0.05	2.00	0.51
E4	2.70	0.65	0.21	0.12	1.97	0.45

social interactions), not only show better fitting and prediction performance, but they also better capture the crowdfunding dynamics. In addition, we find strong evidence of the three underlying mechanisms from both the aggregate-level model and the individual-level model.

Furthermore, we provide managerial and substantive implications about key success factors for goal completion by analyzing the difference in crowdfunders' behavior between successful projects and unsuccessful projects. For instance, we find that the effects of the crowd's current decision on an individual crowdfunder's current decision for the successful projects are larger than those for the unsuccessful projects (average of the successful projects, 10.3; average of the unsuccessful projects, 5.3). This is partially because unsuccessful projects may mostly gather independent crowdfunders who make investment decisions based on their own judgement and taste in music independent of others. Therefore, independent crowdfunders are less likely to successfully trigger social interactions and the crowding process. As a result, the observed effects of contemporaneous social interactions among the independent crowdfunders of the unsuccessful projects might be relatively smaller than those of the successful projects. Furthermore, this result may imply that if significant contemporaneous social interactions are present, then the project is likely to ignite the crowding process and therefore meet the goal. In a

Table 6. Estimates of Structural Parameters

	Intercept ($\bar{\bar{\alpha}}$)		Contemporaneous social interactions ($\bar{\bar{\pi}}$)		Risk ($\bar{\bar{v}}$)		Opportunity cost ($\bar{\bar{\theta}}$)		Satiation ($\bar{\bar{k}}$)	
Project	Posterior mean	Posterior std. dev.	Posterior mean	Posterior std. dev.	Posterior mean	Posterior std. dev.	Posterior mean	Posterior std. dev.	Posterior mean	Posterior std. dev.
A1	–2.36	0.29	11.78	0.19	7.6	0.14	0.09	0.38	–4.19	0.44
A2	–0.23	0.31	9.85	0.30	6.53	0.15	–3.14	0.92	0.42	0.46
A3	0.56	0.45	2.29	0.78	7.66	0.24	–0.97	0.49	0.62	1.48
A4	–9.23	1.02	12.26	0.54	5.23	0.64	3.56	1.34	–11.52	1.85
R1	1.81	0.55	7.39	0.60	7.7	0.15	0.73	0.43	–4.79	0.36
R2	–0.65	0.34	10.53	0.19	6.91	0.13	–0.72	0.37	–1.74	0.52
R3	–2.46	0.64	6.53	0.36	8.22	0.13	0.79	0.26	–0.82	0.28
R4	–3.81	0.95	9.79	1.30	7.52	0.29	–3.18	0.95	1.73	0.46
P1	–1.12	0.28	11.02	0.75	7.94	0.12	–2.81	0.55	–1.96	0.42
P2	–1.97	0.27	11.03	0.22	6.98	0.17	0.07	0.53	–0.09	0.32
P3	–1.12	0.55	–1.52	0.42	5.82	0.34	–1.54	0.47	2.46	0.69
P4	2.79	0.83	0.58	0.55	8.01	0.21	2.07	0.64	–0.75	0.51
E1	1.25	0.76	10.5	0.27	6.85	0.14	0.7	0.23	–3.11	0.40
E2	–0.75	0.37	10.17	0.44	7.66	0.18	–4.88	0.76	–2.58	0.72
E3	2.99	0.37	2.04	0.62	7.06	0.24	1.79	0.54	–3.33	0.88
E4	3.3	2.09	10.52	1.02	–3.34	1.07	3.11	1.42	–1.86	1.03

similar vein, we find that crowdfunders who invest in the successful projects perceive smaller opportunity costs than those who invests in the unsuccessful projects (average of the successful projects, −1.2; average of the unsuccessful projects, 0.7). This result implies that if crowdfunders keep delaying their investments because of the higher opportunity cost, then it would be difficult for the project to meet its goal. Also, crowdfunders who invest in the successful projects get satiated less easily and are more altruistic than those who invest in the unsuccessful projects. Thus, altruistic participation that supports the project out of goodwill, and additional investments from the crowdfunders who have already invested in the project might also be very important for driving the crowd fundraising to success. We utilize these findings in our counterfactual analysis to identify the most effective crowdfunders whom promotions should be targeted to in Section 6.3.

6. Counterfactual Analysis

We provide counterfactual insights to both fundraisers and platforms. It is important to note that the current equilibria found in the observed data may not hold anymore in the counterfactual analysis, because different equilibria from the observed equilibria in the data would have occurred under the altered underlying primitives (e.g., new goal amount). Thus, when simulating counterfactuals, new equilibria under the altered underlying primitives need to be attained. The equilibria can be obtained by recursively simulating each individual crowdfunder's optimal decision based on a crowd's decision until the aggregation of the simulated optimal decision of all crowdfunders converges to the crowd's decision. These steps are iterated back and forth until the aggregate-level model and individual-level model converge (Ahn et al. 2015).[20] Because each crowdfunder's optimal decision is plugged into the crowd's decision in simulating the equilibria, we can explore unrestricted counterfactuals by examining individual crowdfunders' behavior altered by the changes in the underlying primitives. In the counterfactual analysis, we investigate the prediction performance of the proposed approach with the limited data (observed dynamics prior to achieving 50% of goal), the optimal policy settings (e.g., goal amount), and the efficient promotion strategies (e.g., targeting).

6.1. Predicting Project Success

The ability to predict which projects are more or less likely to complete the goal and the time to completion will directly benefit the crowdfunding platform. For example, the platform can stimulate promising projects that need additional help to spur investments – either through promotions or through changes in the project characteristics (e.g., goal, percentage of stocks to share) – or it can deprioritize (completely ignore) projects with low expected success rates. Moreover, being able to estimate the timing of completion would dramatically increase the efficiency of various resource allocation decisions for successful projects (e.g., booking recording facilities, mixing engineering, editing, packaging, and marketing)

To demonstrate the practical value of our approach, we estimate the proposed model and null model using partial data (i.e., observed dynamics prior to achieving 50% of goal) and predict whether the project eventually succeeds, and if so, when the project meets the goal.[21] We find that the proposed model performs better in predicting both the final success of crowd fundraising (hit ratio, 100% versus 70%) and the timing of goal completion (mean absolute error, 20.5 versus 49.5 days) compared with the model that ignores forward-looking delaying investment behavior and the two types of social interactions (see Table 7). This predictive power demonstrates the potential of the proposed model as a diagnostic tool for predicting the success of crowdfunding projects. We find this result particularly encouraging. In contrast to the predictive models based on aggregate demand, our microfoundation approach carries additional benefits of counterfactual analyses that we demonstrate next.

6.2. Optimal Goals

Collecting a large fund to develop and produce new products might be the most important issue for fundraisers. So, fundraisers may attempt to maximize their funding goal to attain as much capital as possible. However, they should also set their goal at an attainable level. Otherwise, the projects may fail because goals that are set too high may lower the crowdfunders' motivation to participate. Thus, fundraisers face a trade-off between a larger goal versus a smaller goal. Using counterfactuals, we identify the amount of the largest possible goal, that is, the largest amount of capital that can be raised while still ensuring project success.

To optimize the goal, we simulate investment demands under different goal settings. Note that the aggregate participation, a_{jt} is policy dependent, because the aggregate participation is endogenously determined by individual crowdfunders' optimal decision, which takes policy settings (e.g., goal) into account. Thus, we can truly examine the altered investment behavior by changing the goal setting in this counterfactual analysis. Figure 5 shows the simulated investment demand (solid and black) and its corresponding goal (square dot and green). Also, it shows the current goal (dash dot and blue) and the optimized goal (dash and red). For instance, Project A1

Table 7. Prediction

	Real		Proposed model (Model 2)			Null model (Model 1)		
	Success	Goal completion date	Success	Goal completion date	Difference	Success	Goal completion date	Difference
A1	True	2008_050	True	2008_049	−1	True	2008_013	−37
A2	True	2007_013	True	2007_045	32	True	2007_075	62
R1	True	2009_310	True	2010_213	268	False		
R2	True	2007_279	True	2007_242	−37	True	2007_283	4
R3	False		False			False		
P1	True	2008_110	True	2008_070	−40	False		
P2	True	2007_078	True	2007_078	0	True	2007_202	124
E1	True	2007_072	True	2007_111	39	True	2007_142	70
E2	True	2010_280	True	2010_294	14	False		
E3	False		False			False		
MAE					20.5			49.5
Hit ratio					100%			70%

Note. Goal completion date: [Year]_[Day]; MAE, mean absolute error (exclude R1, R3, and P1).

achieved its goal of 5,000. However, it would still meet its goal even if the goal were increased to 7,500. On the other hand, Project R3 failed to meet its goal of 5,000 and collected only 3,288. If Project R3's goal had been 3,288, the goal would have been met, because it is the exact amount that the project actually collected. However, the goal need not be reduced to 3,288. Using counterfactuals, we find that the optimal goal for Project R3 is 4,000, which is 21.7% larger than the naively chosen goal (3,288) based on the actual amount raised.

Table 8 summarizes the optimality gap (the difference between the original goal and the optimal goal) and the improvement compared with the naively chosen goal (the difference between the cumulative total shares collected and the optimal goal). We find that, on average, the successful projects could have increased their goals by 16.3%, while still ensuring success. Also, the unsuccessful projects would have been successful if they had decreased their goals by 52.5%. This is 46.2% larger than the naively chosen goal. The counterfactual analysis demonstrates that the goal setting of crowdfunding projects is far from optimal in the absence of optimization efforts. This finding might be one of the reasons why many crowdfunding platforms struggled in the market or went bankrupt (Sellaband included). These results are generalizable to other projects, categories, and platforms beyond our sample data, because the optimality gaps are consistent across categories (successful projects, between 10% and 50%; unsuccessful projects, between −90% and −20%).

6.3. Targeting Promotions

In this counterfactual analysis, we explore more effective targeting strategies under the investment matching promotion campaign where the platform or fundraiser provides crowdfunders with credits that match their exact investment amount. We take advantage of the rich specification for heterogeneity of the proposed approach to target crowdfunders. More specifically, we utilize the empirical findings that attracting crowdfunders who are more altruistic and socially interactive and who perceive smaller risk, opportunity cost, and satiation is more beneficial for goal completion. We rank the crowdfunders in descending order by the altruistic utility and social interactions parameters, and in ascending order by the risk, opportunity cost, and satiation parameters. Then, we compute the targeting score of each individual by adding the order of the five parameters. Finally, we select the bottom 30% (targeting option 1) and the top 30% (targeting option 2) of crowdfunders in ascending order by the targeting score for the targeting promotions. The top 30% crowdfunders (targeting option 2) are more altruistic and socially interactive and who perceive smaller risk, opportunity cost, and satiation than the bottom 30% crowdfunders. Thus, targeting option 2 would be the best performing targeting strategy, whereas targeting option 1 would be the least performing targeting strategy. The targeted crowdfunders in both options would perceive the doubled altruistic utility ($2\alpha_{ij}e^{-k_{ij}C_{ijt-1}}Q_{ijt}$), social interactions ($2\pi_{ij}a_{jt}Q_{ijt}/G_j$), and terminal payoff ($2C_{ijt-1}M_jR_j/G_j$) but with the same cost (H_jQ_{ijt}), opportunity cost ($\theta_{ij}C_{ijt-1}$), and risk ($v_{ij}Q_{ijt}^2$). We simulate counterfactuals under the targeted investment matching promotions and compare the performance of the two targeting scenarios: the top 30% and bottom 30%. Table 9 shows that for unsuccessful projects, targeting option 2 (top 30%) increases the investment demand by 21.7%, which is 4.6% larger than under targeting option 1. Also, Table 10 shows that for successful projects, targeting

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Figure 5. (Color online) Optimal Goals

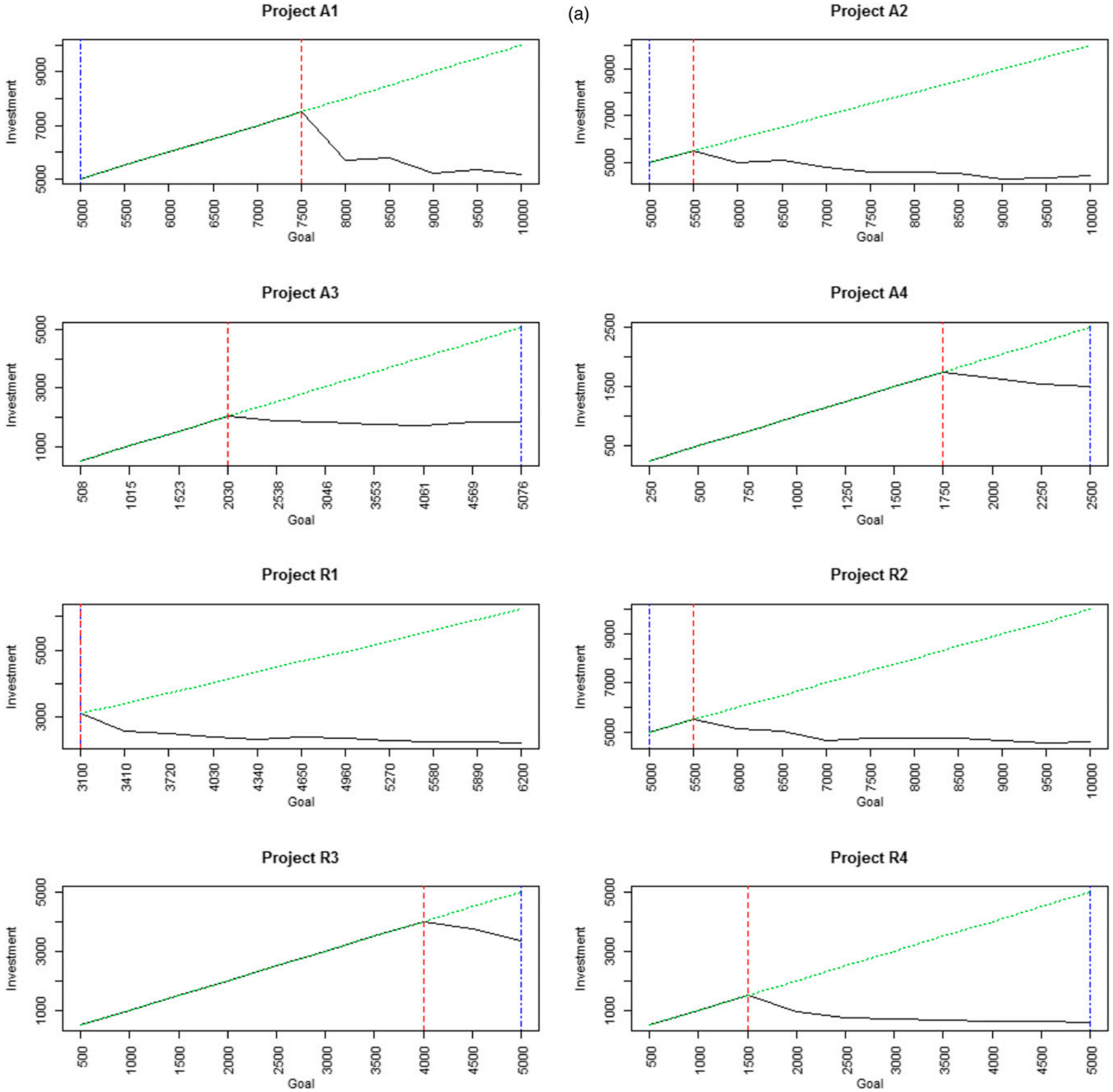
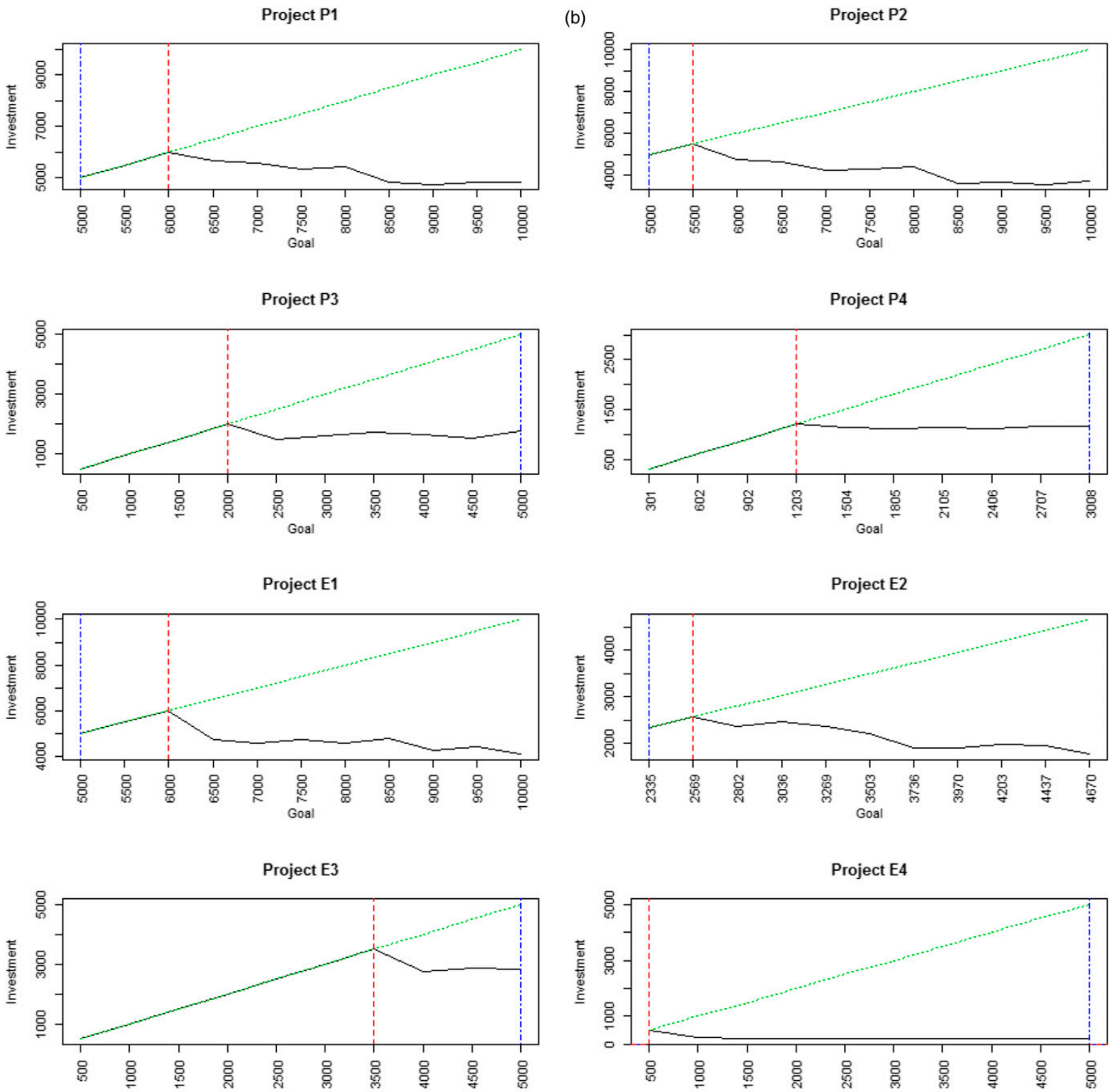


Figure 5. (Continued)



Notes. (a) Alternative and rock: solid and black, simulated investment demand (y axis); square dot and green, goal amount (y axis), dash and red, optimal goal based on the proposed model (Model 2) (x axis); dash dot and blue, current goal (x axis). (b) Pop and electronic: solid and black, simulated investment demand (y axis); square dot and green, goal amount (y axis); dash and red, optimal goal based on the proposed model (Model 2) (x axis); dash dot and blue, current goal (x axis).

option 2 (top 30%) reduces the fundraising duration by 164 days, which is 60 days shorter than in targeting option 1. These results imply that the platforms or fundraisers can increase investment demand and also decrease fundraising duration (accelerate the goal completion) by utilizing the individual information obtained from the proposed model; and targeting crowdfunders who are more altruistic and socially interactive and who perceive smaller risk, opportunity cost, and satiation. Furthermore, we cannot identify any differences in performance of the targeting promotions across categories, supporting the robustness of our results.

7. Conclusion

This paper examines the underlying mechanisms of crowdfunding behavior that lead to crowdfunding

Table 8. Optimal Goal

	Original goal	Total shares collected	Optimal goal	Optimality gap (opt. goal – goal)	Improvement (opt. goal – total shares)
A1	5,000	5,673	7,500	50%	
A2	5,000	5,251	5,500	10%	
A3	5,076	1,992	2,030	–60%	1.9%
A4	2,500	841	1,750	–30%	108.1%
R1	3,100	5,977	3,100	0%	
R2	5,000	5,165	5,500	10%	
R3	5,000	3,288	4,000	–20%	21.7%
R4	5,000	701	1,500	–70%	114.0%
P1	5,000	5,580	6,000	20%	
P2	5,000	5,134	5,500	10%	
P3	5,000	2,180	2,000	–60%	–8.3%
P4	3,008	911	1,203	–60%	32.1%
E1	5,000	5,472	6,000	20%	
E2	2,335	2,974	2,569	10%	
E3	5,000	3,462	3,500	–30%	1.1%
E4	5,000	251	500	–90%	99.2%
Successful projects				16.3%	
Unsuccessful projects				–52.5%	46.2%

dynamics (stagnation, gradual increase, and acceleration). From the theoretical viewpoint, to the best of our knowledge, this study is the first to propose and confirm empirically the three mechanisms (forward-looking delaying investment behavior, contemporaneous social interactions, and forward-looking social interactions). From the methodological viewpoint, adopting the rational expectations equilibrium of the approximate aggregation approach, we provide a structural microfoundation that models the three underlying mechanisms and captures the contrasting dynamic patterns within a single unified framework. In addition, we apply the Bayesian IJC method to separately identify the social interactions from other confounding correlations (e.g., homophily, correlated unobservables, and simultaneity) by taking advantage of the rich specification for heterogeneity.

The empirical findings and counterfactual analyses provide meaningful implications and actionable insights to both crowdfunding platforms and fundraisers. Fundraisers can dramatically increase their chances of success by optimizing their goals. Platforms can spur growth by better allocating resources to the projects that are likely to be successful, while deprioritizing laggards that have little potential to meet their goals. Also, platforms can increase the investment demand and make the goal completion more quickly by targeting crowdfunders who are more altruistic and socially interactive and who perceive smaller risk, opportunity cost, and satiation. The unified structure of the proposed approach, which exhaustively and simultaneously models the underlying mechanisms, enables us to provide these meaningful managerial implications and practical insights, which may not be obtained under the extant approaches without the holistic view to crowdfunding dynamics.

Table 9. Investment Demand Change (Targeting Promotion)

Projects	Targeting option 1	Targeting option 2	Difference
A3	2.5%	8.8%	6.3%
A4	86.9%	93.1%	6.2%
R4	5.2%	7.5%	2.3%
P3	2.1%	6.2%	4.2%
P4	11.1%	16.7%	5.6%
E3	2.6%	5.8%	3.2%
E4	9.5%	13.9%	4.4%
Average	17.1%	21.7%	4.6%

Finally, we address opportunities for future research and some limitations of our study. Further studies may explore the dynamic portfolio optimization of multiple crowdfunding projects. In this approach, we model that crowdfunders dynamically optimize their investment decisions within a single project rather than across multiple projects given the evidence from the data that crowdfunders handle only one active project on average at any given time. Nevertheless, generalizing the proposed single-project dynamic optimization approach to multiple-project dynamic optimization problems may greatly increase the understanding of crowdfunding behavior across projects. For instance, the multiple-project dynamic optimization approach may provide insights about the role of budget under the dynamic portfolio optimization and the crowdfunders' dynamic budget allocations across different crowdfunding projects. Moreover, the investigation on crowdfunding behavior over the sequence of

Table 10. Days Until Success (Targeting Promotion)

Projects	Real	Targeting option 1	Targeting option 2	Difference
A1	448	97	77.8	19.2
A2	123	100.4	106	–5.6
R1	491	351	156.8	194.2
R2	95	90.8	83.4	7.4
R3		366	264.2	101.8
P1	456	276.6	137.2	139.4
P2	85	73.8	50.8	23
E1	162	138	133.6	4.4
E2	246	140	45.6	94.4
Average[a]	263.3	158.5	98.9	59.6

[a]Excludes R3.

interrelated and conditional investments on a series of projects may reveal how crowdfunding behavior changes over time. For instance, we can examine how the crowdfunders' motivation and perception of the opportunity cost may change in a subsequent project contingent upon the success of other previous projects.

The availability of postfundraising information (e.g., financial performance, the delivery, and/or quality of final products) may unlock the potential of these approaches to examine the interdependences across projects and also between projects on a series. For instance, it may uncover how crowdfunders differentiate (vary) their expectations on the future financial performance of different projects depending on observable characteristics of the projects. Also, it may unveil how crowdfunders learn about the future financial performance of a crowdfunding project depending on the crowd's movement or on the success of projects previously invested over the course of investments on a series of projects.

In addition, in our context, if a project fails to meet its funding goal, the deposited investment is refunded to the crowdfunder's account in the form of credits. The credits cannot be exchanged back into real money but can be used to support other fundraising projects. Therefore, it would be interesting to examine how "cash" crowdfunders might behave differently from the crowdfunders who put forth with credits (e.g., perceive more risk and less opportunity cost). Unfortunately, our data set does not include investments made with credits. Future studies may examine the investment behavior of crowdfunders who own credits and how to utilize their investments to trigger the crowding process.

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Endnotes

[1] These interactions can be considered as the interactions between an agent and its reference group as is the case in many other contexts of social interactions. In this case, an individual crowdfunder can be viewed as an agent, and the crowd can be regarded as her reference group.

[2] We also find empirical evidence of the asymmetric contemporaneous social interactions. See Online Appendix B for details.

[3] This platform does not require any deadline for goal completion. Thus, the failure may be determined by the agreement between Sellaband and an artist. That is, the artist can raise funds until both Sellaband and the artist agree to cease fundraising.

[4] We collected the top 50 artists (according to the amount of funds raised) in each of the six genres: alternative, electronic, hip hop/R&B, pop, rock, and world.

[5] See Online Appendix A for more details about our data.

[6] We define active investors who have shown at least one investment in this platform (across all projects) during a week.

[7] Note that these identification strategies are only be applied to this exploratory analysis. Because the exploratory analysis is not our main goal and the purpose of the exploratory analysis is to show empirical evidence, we briefly introduce the approaches suggested by the previous studies and discuss how we sort out the contemporaneous social interactions from other correlations in this exploratory analysis. We discuss more detailed identification strategies for the proposed model in Section 4.5.

[8] See Online Appendix B for details.

[9] In empirical analysis, we conduct the Durbin-Watson test to check the autocorrelation of the residuals of the AR(1) model. We find that the autocorrelations of the residuals are not significantly different from 0, implying that the AR(1) model is a reasonable approximation of the aggregate transition of the period total shares. See Section 5 for details.

[10] Investors may learn signals about the total market value of stocks by observing other investors' investment behavior. For instance, investors might learn that a project that is quickly collecting investments will generate more revenue and share more profit (dividends) to the stakeholders and therefore might increase their expectations for the total market value of the project. Thus, learning through signaling may potentially be confounded with social

interactions, because the signal is based on the others' behavior. However, learning through signaling would be fairly limited under our context for the following two reasons. First, the entire crowdfunding process (fundraising, product development, sales, etc.) takes a very long period of time, and thus the learning through signaling that occurs over the course of actual rewards received from different projects (profit share, dividends, etc.) may become less prominent over the lengthy crowdfunding process (diluted or forgotten). Second, the limited availability of the post-fundraising information of past projects (e.g., financial performance) hinders investors from learning from past cases. Thus, they are able to learn only from their own investments and the actual rewards received from the corresponding investments. These facts also make it difficult for us to empirically capture the learning through signaling, because our data set is not long enough to capture the learning through signaling and more importantly does not include the post-fundraising information regarding the financial performance. In sum, the signaling effect is not present under our context and in our data set. Therefore, we assume the total market value (M_j) does not vary with time but is constant (independent of other investors' investment patterns).

[11] We discuss how the individual- and project-specific intercept control for homophily in Section 4.5.

[12] The satiation parameter partially captures the project-level portfolio management behavior in our single-project dynamic optimization framework. We focus on the dynamic optimization of quantity decisions within a single project (single-project dynamic optimization of quantity decisions in a project) rather than over multiple projects (multiple-projects dynamic optimization of quantity decisions across multiple projects). Thus, we model that crowdfunders maximize the utility from each project separately, not the utility from multiple projects. This is realistic because dynamically optimizing quantity decisions across multiple projects requires a tremendous amount of computational and cognitive burden for investors. Also, the data support our assumption. According to the data, the average number of active projects for an investor per week is only 1.28 (we define a project as active for an individual in a week when the focal week is in between the first and last investment of the focal individual in the focal project). This finding implies that there is very little overlap in the active investment period of different projects. Thus, it supports our assumption that investors focus on only one project at a time for a certain period of time and dynamically optimize their decisions within the project (single-project dynamic optimization). If investors dynamically optimized their quantity decisions over multiple projects simultaneously (multiple-projects dynamic optimization), then the average number of active projects per week would be significantly larger than 1 (at least 2). Meanwhile, this finding can be also the result of the strategic portfolio management behavior under the budget (project-level decisions). For instance, investors might choose a single project to focus for a while and then dynamically optimize their quantity decisions for the chosen project, setting aside a certain amount of money for future projects. Consequently, we observe the pattern that investors invest less (save money for future projects), once they have invested enough money in a project. Thus, we introduce the satiation parameter to partially capture this effect (the project-level portfolio management under the budget) in our single-project dynamic optimization framework by allowing for decreasing baseline utility for the additional investments.

[13] We drop subscripts i and j and assume no errors for simplicity.

[14] Indeed, practitioners understand the power and importance of such incentives. This is the reason why a number of crowdfunding platforms are offering tangible incentives in the form of additional shares or products upon project completion in their efforts to ignite early investments and create a chain reaction in the early phase.

[15] By comparing Case 1 and 2, we can identify V_1. Under a similar logic, by comparing Case 1 and 3, we can identify V_2. By comparing Case 1 and 4, we can identify $V_1 + V_3$. We can separately identify V_1, therefore we can identify V_3 as well.

[16] See Online Appendix D for the detailed procedure for simulating counterfactuals and obtaining the rational expectation equilibrium.

[17] We sample our data for expositional reasons. Composition of the selected genres and projects does not affect the main results. As we show in the simulation study in Online Appendix E, our approach can identify each project's distinct investment patterns uniquely.

[18] In our empirical study, we assume that individual investors expect the same total market value ($M_j = M$) across different projects and have set M as 10,000. The value (10,000) is chosen for numerical reasons, considering the mode of R (percentage of stocks to be shared with crowdfunders) and G (goal amount) is 50% and 5,000, respectively. We also try different values for M and find that the main results remain unchanged. The assumption on the same total market value for different projects is predicated on the fact that self-provided artist information might be too subjective and limited for individual investors to successfully utilize for evaluating the total market values of different projects. Furthermore, we focus on dynamic decisions within a single project not the interdependences between projects. More importantly, the post-fundraising information about the financial performance is not available in our data. Thus, we set the same M across different projects.

[19] See Online Appendix D for the detailed procedures on obtaining the rational expectations equilibrium and on simulating individual investment demands.

[20] See Online Appendix D for the detailed procedures on obtaining the rational expectations equilibrium and on simulating counterfactuals.

[21] Note that any information other than the estimates of the structural parameters and policy settings are not used in simulating counterfactuals (e.g., actual goal success), because investment demands are generated chronologically from $t = 1$ and the aggregate-level model is reestimated using the simulated demands in each step. See Online Appendix D for the detailed procedure.

References

Agrawal A, Catalini C, Goldfarb A (2014) Some simple economics of crowdfunding. *Innovation Policy Econom.* 14:63–97.

Agrawal A, Catalini C, Goldfarb A (2015) Crowdfunding: Geography, social networks, and the timing of investment decisions. *J. Econom. Management Strategy* 24:253–274.

Ahn D-Y, Duan JA, Mela CF (2015) Managing user-generated content: A dynamic rational expectations equilibrium approach. *Marketing Sci.* 35:284–303.

Belleflamme P, Lambert T, Schwienbacher A (2014) Crowdfunding: Tapping the right crowd. *J. Bus. Venturing* 29:585–609.

Bitter S, Schreier M (2018) When consumers become project backers: The psychological consequences of participation in crowdfunding. *Internat. J. Res. Marketing* 35(4):673–685.

Brown TE, Boon E, Pitt LF (2017) Seeking funding in order to sell: Crowdfunding as a marketing tool. *Bus. Horizons* 60:189–195.

Ching AT, Imai S, Ishihara M, Jain N (2012) A practitioner's guide to Bayesian estimation of discrete choice dynamic programming models. *Quant. Marketing Econom.* 10:151–196.

Chintagunta PK, Goettler RL, Kim M (2012) New drug diffusion when forward-looking physicians learn from patient feedback and detailing. *J. Marketing Res.* 49:807–821.

Freedman SM, Jin GZ (2011) Learning by doing with asymmetric information: Evidence from Prosper.com. Working paper, National Bureau of Economic Research, Cambridge, MA.

Hartmann WR, Manchanda P, Nair H, Bothner M, Dodds P, Godes D, Hosanagar K, Tucker C (2008) Modeling social interactions: Identification, empirical methods and policy implications. *Marketing Lett.* 19:287–304.

Hu M, Li X, Shi M (2015) Product and pricing decisions in crowdfunding. *Marketing Sci.* 34:331–345.

Imai S, Jain N, Ching A (2009) Bayesian estimation of dynamic discrete choice models. *Econometrica* 77:1865–1899.

Krusell P, Smith AA Jr (1998) Income and wealth heterogeneity in the macroeconomy. *J. Political Econom.* 106:867–896.

Kuppuswamy V, Bayus BL (2015) Crowdfunding creative ideas: The dynamics of project backers in Kickstarter. Research paper, University of North Carolina Kenan-Flagler Business School, Chapel Hill.

Lee D, Wolpin KI (2006) Intersectoral labor mobility and the growth of the service sector. *Econometrica* 74:1–46.

Magnac T, Thesmar D (2002) Identifying dynamic discrete decision processes. *Econometrica* 70:801–816.

Manski CF (1993) Identification of endogenous social effects: The reflection problem. *Rev. Econom. Stud.* 60:531–542.

Moisseyev A (2013). Crowdfunding as a marketing tool. Accessed September 15, 2019, https://www.socialmediatoday.com/content/crowdfunding-marketing-tool.

Mollick E (2014) The dynamics of crowdfunding: An exploratory study. *J. Bus. Venturing* 29:1–16.

Nair HS, Manchanda P, Bhatia T (2010) Asymmetric social interactions in physician prescription behavior: The role of opinion leaders. *J. Marketing Res.* 47:883–895.

Ordanini A, Miceli L, Pizzetti M, Parasuraman A (2011) Crowdfunding: transforming customers into investors through innovative service platforms. *J. Service Management* 22:443–470.

Ordanini A, Kim C, Trusov M, Kannan PK, Joshi Y, Wang L (2015) Co-investment network dynamics in crowdfunded ventures. Preprint, submitted June 6, https://ssrn.com/abstract=2657674.

Rust J (1987) Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica* 55:999–1033.

Van den Bulte C, Lilien GL (2001) Medical innovation revisited: Social contagion vs. marketing effort. *Amer. J. Sociol.* 106:1409–1435.

Wang J, Aribarg A, Atchadé YF (2013) Modeling choice interdependence in a social network. *Marketing Sci.* 32:977–997.

Zhang J, Liu P (2012) Rational herding in microloan markets. *Management Sci.* 58:892–912.