
Crowdfunding the next hit: Microfunding online experience goods

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Abstract

The combination of limited individual information and costly information acquisition in markets for experience goods leads us to believe that significant peer effects drive demand in these markets. In this paper we model the effects of peers on the demand patterns of products in the market experience goods microfunding. By analyzing data from an online crowdfunding platform from 2006 to 2010 we are able to ascertain that peer effects, and not network externalities, influence consumption.

1 Introduction

The goal of this paper is to estimate the extent to which demand for crowdfunding projects is driven by peer effects. In these markets sellers enlist a crowd of consumers to help finance new projects or products. However, product quality is difficult to establish prior to consumption and consumption cannot happen until projects successfully complete their funding. We focus on situations where quality is both state-dependent (i.e. contingent on funding status) and difficult to *ex ante* determine, and where investors hold a prior on quality, which they may update based on information from their investor social network. This information has two potential delivery channels: through directly communicating with peers who have already consumed, or alternatively by observing peers consumption decisions. If consumers receive independent quality signals for the projects, then consumption decisions of individuals provides valuable information to other consumers, as individuals use the information contained in others actions to update their own quality expectations [1]. It seems particularly important to investigate peer effects as it relates to crowdfunding. Predicting crowdfunding success is hard partly because peer effects is poorly modeled as well as non-deterministic. Peer effects denotes any social process where group behavior (thought, action, consumption, communication) influences individual outcome (thought, action, etc.). We believe peer effects to a large extent drive demand because 1) Sellaband is a large market with many choices, and 2) knowledge about the experience goods is low. These market characteristics suggest that investors suffer from information overload and that learning about goods is costly. Additionally, it does not help that the quality of experience goods is inherently unknown.

Why is this not observational learning? Observational learning only requires that agents observe predecessors' actions, and does not consider the effect of agent communication. Agents observe so

much more than simply outcome. They have access to artist information, they can listen to sample tracks, and they can communicate with one another. This is a much richer setting than observational learning assumes.

Network externalities provides an alternate explanation for product adoption or investing in a crowdfunding project. Network externalities arise when each consumer’s utility directly depends on the consumption of others [2]. Whether and to what extent network externalities plays a role in influencing demand in the markets we study remains an empirical question we also seek to address.

We are unaware of any work that examines how differences in network location give rise to variations in the demand for experience goods in a state-dependent investment model, where consumption cannot take place until a threshold investment level has been met. Recent online market forms using such a model include Sellaband, Kiva, and Groupon. Most previous work examines how network location affects outcomes in a pay-as-you-go model [4]-[5]. Additionally, little previous work has examined models of peer effects with both local and global strategic complementarity. Most prior literature relies on a framework such as that of [3] of local strategic complementarity and global strategic substitutability. We seek to fill both these gaps.

2 Model

We adapt a simple model of peer effects from [6]: the popularity of project a at time t is a function of three components: an unobserved correlated effect (α); from local peer effects (L), capturing the effects of neighboring projects on project a ’s popularity, where a neighboring project is defined as a project whom a shares a direct link; and from global uniform effects (X), capturing the extent to which the popularity of project a is driven by the project’s own characteristics [2][6]. This model follows the classical linear endogenous social effects model analyzed in [7]. For tractability we assume that the network is static for each t , and no resale of shares is possible. We assume the popularity function is well-behaved, i.e. twice-differentiable and strictly concave: $p(0) = 0$, $p'(\cdot) > 0$, and $p''(\cdot) < 0$. We use the following notation:

- p_{it} : popularity of project i at time t
- \mathbf{p}_t : the $n \times 1$ vector (p_{it}) representing popularity of all projects
- \mathbf{g}_a : the network neighborhood of a , defined as $g_a(a, b) = 1$ if a and b share a link, and 0 otherwise
- X : the $n \times K$ matrix of project characteristics, where K is the number of characteristics and x_{aj} is the value of characteristic j for project a .

The model, in matrix notation, can be specified as follows:

$$p_{it} = \alpha + \lambda \mathbf{g}_a \mathbf{p}_{t-1} + X\gamma + \varepsilon \quad (1)$$

where λ measures the peer effects on a and γ measures the the effects of the project’s own characteristics on its popularity (demand). Let us define the local peer effects matrix L as follows:

$$L = \mathbf{g}_a \mathbf{p}_{t-1} \quad (2)$$

Then we can rewrite Equation 1 as follows:

$$p_{it} = \alpha + L\lambda + X\gamma + \varepsilon \quad (3)$$

2.1 Data source

This study uses archival data from the online crowdfunding website Sellaband.com. This website facilitates crowdfunding of music artists and is the oldest and most prominent website in this domain. Our data set encompasses the activities of 8,836 music fans and 3,865 artistic projects, from August 2006 to February 2010, capturing a total of 86,766 investment transactions and 112,978 comments.

We note with interest that mean number of days since signup for projects is in excess of 500 days, and in excess of 900 days for fully funded projects.

Figure 1 shows some of the aggregate investor dynamics in our data, and clearly shows an exponentially decaying trend in both level of activity (panel *a*) and network location of investors (panels *b*). Panel *c* shows the cumulative diffusion process across weeks. It is interesting to note the adoption process in our data is inverse of typical S-shaped adoption curves, possibly reflecting the threshold investment model used by Sellaband.

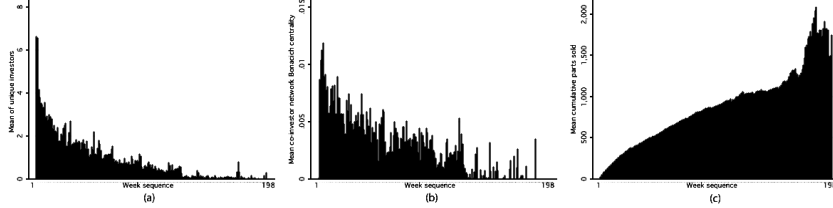


Figure 1: Aggregate investor dynamics across time.

2.2 Empirical models

Based on the theoretical model we seek to test the following empirical implications:

1. In the presence of peer effects, projects increase in popularity the longer they are available for funding.
2. The new information contained in peer feedback should be more important when investors face a higher degree of uncertainty for a project.
3. In the presence of peer effects, the marginal amount of learning decrease over time.
4. Peer effects has a greater effect on popularity than network externalities.

We rely on the results in [6], who prove that under certain conditions peer effects can be completely identified, to examine these empirical implications. We operationalize project popularity as project demand. Project characteristics are divided into two sets: those intrinsic to the project and those that are network-based. The intrinsic characteristics include the following: price, goal fundraising amount, project age (in weeks). The network-based characteristics include indegree and bibliographic coupling. Indegree is calculated as the number of parts bought in the prior week. Bibliographic coupling is a similarity measure, and measures the fraction of investors shared with competing projects. Peer learning can take several avenues: though observing the popularity of neighboring (competing) projects, or though peer feedback. We operationalize peer feedback three ways: as number of investor comments, number of project updates, and whether a project is listed on a top-5 popularity list for fundraising and number of sample tracks played. Additionally, we control for traffic seasonality to the website, using weekly Alexa traffic rankings for Sellaband during our data collection window. Based on these variables, our model translates to the following econometric specification:

$$p_{it} = \alpha + \lambda_1 L_1 + \lambda_2 L_2 + \lambda_3 L_3 + \lambda_4 L_4 + \gamma_1 X_1 + \gamma_2 X_2 + \gamma_3 X_3 + \beta_1 B_1 + \varepsilon \quad (4)$$

We control for unobserved correlated effects using a fixed-effects model and take advantage of the panel-nature of our data set to partially account for simultaneity.

3 Discussion and conclusions

Significant peer effects drive consumption in the markets we study due to the combination of limited individual information and costly information acquisition in markets for experience goods. We modeled the effects of peers on the consumption patterns of investors in the market experience goods microfunding. By analyzing data from an online crowdfunding platform from 2006 to 2010

Table 1: Estimation results. Dependent variable: Demand for project shares

Variable	Description	(1)	(2)	(3)	(4)
L_1	Demand for neighborhood projects	0.0003*** (0.000)			
L_2	Number of investor comments, lagged	0.0002 (0.000)***	0.033 (0.013)***	0.042*** (0.014)	
L_3	Number of project blog updates, lagged	0.029*** (0.0003)	5.600*** (0.141)	5.564*** (0.143)	
L_4	On a top-5 chart, lagged	1.349*** (0.006)			
X_1	Indegree, lagged	0.002*** (0.000)			
X_2	Bibliographic coupling, lagged	3.971*** (0.020)			
X_3	Project age (weeks)	-0.013*** (0.000)	-0.135*** (0.005)	-0.135*** (0.005)	-0.029*** (0.009)
X_3^2	Project age, squared				0.000 (0.000)
X_4	Fraction of funding goal reached, lagged				3.236† (1.750)
X_4^2	Fraction of funding goal reached, lagged squared				-3.661* (1.852)
B_1	Unique pages viewed/user/day to Sella-band	0.028*** (0.002)			
$X_3 \times L_2$		-0.0005*** (0.0001)	-0.0009*** (0.0003)		
$X_3 \times L_3$			-0.017*** (0.002)	-0.012*** (0.005)	
$(X_3 \times L_2)^2$				0.000 (0.000)	
$(X_3 \times L_3)^2$				0.000 (0.000)	

Standard errors in parenthesis. *** p < .001, ** p < .01; * p < .05; † p < .1

we are able to ascertain that peer effects, and not network externalities, influence consumption. Specifically, we find that investors are more influenced by information aggregating devices, such as top-5 popularity lists and by the information provided by projects in blog updates than by more granular information sources, possibly due to information overload. We also ascertain that projects quickly go out of favor with the investment community unless the projects are able to maintain momentum in their funding drive. This provides one explanation for why so few projects are able to complete funding. It remains to discover how projects can overcome this "cold start" problem. We leave this as an exercise for a later version of our paper.

We find that investors are influenced by the success or failure of related projects and use the actions of other investors as a source of information in their funding decisions (Table 1 column 1). This is reinforced in Table 1 column (4): investors buy increasingly more number of parts as a group per week when the project successfully fundraises. Second, investors are more influenced by information aggregating devices, such as top-5 popularity lists, and by the information provided by projects in blog updates, than by more granular information sources and other investor comments. This informational effect decreases with age (table 1 columns (2) and (3)). Finally, projects quickly go out of favor with the investment community unless the projects are able to maintain momentum in their funding drive. This provides one explanation for why so few projects are able to complete funding.

Our findings have implications for market design: successfully completing microfunding of a project requires fundraising momentum or else projects quickly fall out of favor with investors. How projects can ensure this remains a question we wish to investigate further, but our preliminary results indicate that increased blogging activity on part of the projects has a positive effect on investing activity. Second, aggregate information measures, such as top-5 charts of funding progress are more effective at positively driving demand than more granular measures, such as individual investor actions.

It remains to discover how projects can overcome this cold start problem. We leave this as an exercise for a later version of our paper. The effect of large early investments might provide an avenue for investigating this issue. A second shortcoming of our study is that we do not consider the social welfare implications of the observed peer effects for the market as a whole. Empirical regularities in network-based social welfare remain a largely unsolved research question [8].

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References

- [1] Banerjee, A. V. (1992): A simple model of herd behavior. *Quarterly Journal of Economics* 107(3), 797-817.
- [2] Moretti, E. (2010): Social learning and peer effects in consumption: Evidence from movie sales. *UC Berkeley working paper*.
- [3] Ballester, C., Calvó-Armengol, A., and Zenou, Y. (2006): Who's who in networks. Wanted: the key player. *Econometrica* 74(5), 1403-1417.
- [4] Calvó-Armengol, A., Patacchini, E., and Zenou, Y. (2009): Peer effects and social networks in education. *Review of Economic Studies* 76(4), 1239-1267.
- [5] Ghiglino, C. and Goyal, S. (2010): Keeping up with the neighbors: social interaction in a market economy. *Journal of the European Economic Association* 8(1), 90-119.
- [6] Oestreicher-Singer, G. and Sundararajan, A. (2010): The visible hand of peer networks in electronic markets. *SSRN working paper*.
- [7] Manski, C. F. (1993): Identification of endogenous social effects: The reflection problem. *Review of Economic Studies* 60(3), 531-542.
- [8] Bala, V. and Goyal, S. (1998): Learning from neighbours. *Review of Economic Studies* 65(3), 595-621.