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Segmented receivers? preferences and the response to signals. An empirical test in film-crowdfunding

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Abstract

This paper studies the response to signals when the receivers have to face asymmetric information and have segmented preferences. We argue that signals of reliability are preference-neutral and trigger always a positive response. Conversely, signals of product characteristics are not preference neutral and trigger responses that vary depending on the preferences of the receivers. Specifically, preference-reinforcing signals trigger a positive response, while preference-dissonant signals trigger a negative response. We test our conjectures by analyzing the response to quality signals in a sample of 610 film crowdfunding campaigns. We run an algorithm of content analysis to measure the extent to which a film project is targeted to the mass-market audience or to the artistic movie audience. In line with our predictions, the signal of the artistic value of a filmmaker triggers a positive response when the film is targeted to the

artistic movies audience, but it triggers a negative response when the film is targeted to the mass-market audience. Conversely, the allure of the filmmaker in the star system triggers a positive response when the film is targeted to the mass-market and a negative response when the film is targeted to the artistic movie audience. Reliability signals trigger the expected positive response, regardless of the audience to which the project is aimed.

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Keywords: Signaling theory, quality signal, crowdfunding, movie industry

1. Introduction

It is well established in a wide array of research contexts that signals –such as a good reputation, a proved experience or a good customers' feedback- influence transactions in contexts of high information asymmetry (see Connelly et al., 2011 and Bergh et al., 2014 for comprehensive reviews). Signals allow inferring quality of a good or an investment, whenever quality is not directly observable, and mitigating concerns of moral hazard whenever the counterpart cannot effectively be monitored (Akerlof 1970; Spence, 2002). Signals are especially important when the content of the transaction (i.e., the object being traded) is an experience-good, whose value is unknown until after purchase (Nelson 1970) or when the transaction value depends on future courses of action and is exposed to uncertainty, thus paving the way to opportunistic behavior.

Among the many contexts in which signals have been investigated, two are of main relevance in this paper. The first context is entrepreneurial finance, where several empirical studies have documented the importance of signals about the competence and preparedness of the venture's founders in eliciting support from venture capitals (Gompers, 1995; Shane and Cable, 2002) and from providers of informal finance (e.g., business angels, crowdfunders, Conti et al., 2012, Ahlers et al., 2014). A second context is offered by online transactions, such as web-auctions, e-commerce and online microcredit loans, in which potential customers typically have to deal with an unknown counterpart (Ba, 2001; Doney and Cannon, 1997; Fueller et al., 2007). Several empirical studies have demonstrated that Internet users react strongly to positive or negative customer's feedback (e.g., sellers on eBay or borrowers on the microcredit platform Prosper.com), albeit perhaps with different intensity (Cabral and Hortacsu, 2010; Dimoka et al., 2012; Jin and Kato, 2005; Resnick et al., 2006; Standifird, 2001; Xie and Shugan, 2001).

One hallmark of most - if possibly all - of the mentioned studies is that the receivers of the signals are always assumed to respond univocally and uniformly to the signal that they observe. Specifically, when they observe a positive signal, they may or may not react, but if they do, they respond positively. When they observe a negative signal, they may or may not react, but, if they do, they respond negatively. For example, a buyer in Ebay.com typically wants a reliable seller and consequently offers higher bids to sellers with a high-percentage of positive ratings and offers no or low bids to sellers with negative ratings (Standifird, 2001). A lender in Prosper.com invariably wants a borrower that redeems the loan and responds to scores of creditworthiness accordingly (Zhang and Liu, 2012).

In this paper, we claim that the assumption of univocal and uniform response to signals may fit reasonably well the above-mentioned contexts, but it does not fit equally well all those contexts in which receivers have diverse preferences concerning the – unobserved - quality of the object of the transaction. As the quality of the object results from an array of multiform characteristics, we maintain that, when the preferences of the receivers are heterogeneous, rather than homogenous, and – for example - they can be grouped into segments that value differently different characteristics, the response to a signal would not be easily predictable, because different segments of receivers would react in different ways. Therefore, the same signal could trigger different (and even opposite) responses from different segments of receivers if this signal is associated to characteristics that are liked by one segment, but disliked by the other segment. Accordingly, we posit that the response in the presence of a segmented audience would not be signal-specific, but rather depend on whether the signal is coherent with the preferences of the segment (preference-reinforcing), or incoherent with the segment preferences (preference-dissonant), or else if it is unrelated to the preferences of the market segment (preference-neutral). We argument our hypotheses based on the insights of the theory of cognitive dissonance and peer pressure (Haider, 1946; Osgood and Tannenbaum, 1955; Festinger, 1957; Festinger, 1962) and maintain that receivers respond univocally to signals that are preference-neutral, they responde positively to signals that are preference-reinforcing, and negatively to signals that are preference-dissonant.

In general, segmented response to signals can be encountered in all markets in which a) there are segmented customers' or audience' preferences and b) the buyers have to take decisions under asymmetric information. In this paper we investigate the market for the crowdfunding of films and videos. This is a market characterized by an audience with segmented preferences concerning movie types (Holbrook, 1999; Bryant and Thorsby, 2006) and by severe information asymmetries, because the movies are yet to be filmed. We identify three different (and commonly used) reputational signals, of which one –the prior experience in movie making- is preference-neutral, and the other two –the filmmaker's popularity and the awards and prizes received by the movie critic- can be preference-reinforcing or preference dissonant depending on the segment of the audience to which they are directed. While the response to positive preference-neutral signals is always positive, irrespective to the audience to which the movie is directed, the two preference-specific signals trigger mixed responses. Specifically, each of the two reputational signals triggers a positive response in the segment of audience where that signal is preference-reinforcing and a simultaneous negative response in the segment of audience where the signal is preference-dissonant.

Other examples of markets that likely meet the aforementioned criteria are those of expensive software, personal computers and other durable hardware, where, for example, expert and non-expert users, or Windows and Apple users, typically form different market segments (Bapna et al., 2004).[1] In the automobile industry, a similar situation exists between customers interested in driving power and customers interested in low emissions (Berry et al., 1998). A further example of market where these conditions are likely to be met is that of angels financing, where investors appear to have nuanced preferences with respect to desirable venture characteristics (Blake et al, 2014).

In the rest of the paper, we present the film crowdfunding as a context characterized by frequent use of signals and having a segmented audience (mass-market and artistic movies lovers) (Section 2.1). We then build three hypotheses. The first concerns the response to signals of reliability (Section 2.2). The other two concern the response to signals of product characteristics (Section 2.3). We test our hypotheses on a dataset, which includes a sample of 610 crowdfunding campaigns conducted in Kickstarter.com, combined with individual records about the characteristics of the filmmaker available in IMDb.com at the time of the campaign. The dataset and variables are described in Section 3.1 and 3.2. We adopt a methodology of content analysis to assess whether the film was target to the artistic audience or to the mass-market. This is presented in Section 3.3. We then estimate OLS and Tobit models capturing the impact of the three signals within the two segments of audience and show that, while the preference-neutral signal is univocally (positively) received, the other two signals trigger simultaneously a positive response in the one segment in which the signal is preference-reinforcing and a negative response in the other segment in which the signal is preference-dissonant (Section 4.1). We comment the implication of our findings and maintain that, to the best of our knowledge, this is the first contribution that challenges the assumption of univocal responses to signals (Section 5).

[1] For example, the segment of skilled users may react negatively to observing a large number of positive customers ratings for a software because these could reflect the preferences of the mass-market of unskilled users who are thought to like easy-to-operate software with simple functions.

2. Conceptual framework and research hypotheses

2.1. The Context: Film crowdfunding

The context of our study is the crowdfunding of films and videos (hereafter: film crowdfunding), where filmmakers seek to raise the budget for the making of a new movie (or documentary, cartoon, short-movie, etc.) in the pre-production stage. The practice of funding films through online campaigns has become increasingly widespread since after 2010, by means of platforms such as Indieagogo.com, Kickstarter.com, Gogetfunding.com and several other country-specific websites. To date, Kickstarter alone has hosted about 39 thousands of film crowdfunding campaigns, making films its largest category of projects. Crowdfunding is becoming one of the major vehicles of financing for young and emerging filmmakers, but it has occasionally been used by known movie stars, such as Spike Lee and Zach Braff.

For the purpose of this paper, we wish to characterize film crowdfunding as a context affected by high asymmetric information and in which the audience has segmented preferences concerning the characteristics of the movies that they wish to fund. In film crowdfunding, the filmmakers typically seek to raise money for their movies in the pre-production phase, i.e. at a very early stage of development. At this stage, there is almost always a movie pitch, but less often a complete script. The casting is usually not yet decided. In about nine out of ten cases the filmmaker is also the director of the movie. The movie description includes usually an inspiration and sometimes a few images or a short video, giving hints about the possible staging of the movie.

The audience of the film industry is known for being highly segmented concerning movie preferences (De Vany and Lee, 2001; De Vany 2006; Kim and Jensen, 2014). The project description would therefore provide a first indication concerning the gender and the audience to which the film is targeted. Given the early stage of development at which projects are crowdfunded, the decision of the crowdfunders on whether or not to finance a movie are based on their general interest for the project, in light of their preferences for different types of movies. The crowdfunders also take their decisions under conditions of severe information asymmetries. In addition to not knowing what the movie will really be once filmed, the crowdfunders are clearly exposed to the risk that the filmmakers fail to deliver the movie, either because of cheating (moral hazard) or simply because of unanticipated difficulties, which are very common in the production phase (De Vany and Lee, 2001).

In sum, film crowdfunding offers a context characterized by: a) an audience with highly segmented preferences, facing uncertainty about the characteristics of the movie that will be filmed and b) exposure to high information asymmetries and moral hazard.

2.2. Response to signals of reliability

To partly cope with these conditions, the crowdfunders typically make use of signals. There are two kinds of signals that are going to be particularly salient in the context just described. The first and relatively straightforward kind of relevant signals concerns the reliability of the filmmakers, i.e. their capability to accomplish the difficult and perilous task of completing the movie. In his lucid review, De Vany (2006) describes the many perils that may occur in the production and in the post-production stage, resulting in an impressive number of films being left unfinished. Since the value of a film is zero unless it is completed, one standard signal for reliability is typically offered by whether or not the filmmakers have a prior track record of completed projects (Hadida, 2010). This is similar to signals of creditworthiness used in virtually all financing contexts (Duarte et al, 2012; Jin and Kato, 2006). In the film industry, experience is visible from the records of film credits of the filmmakers (Del Mestri et al. 2005). Film credits are individual records showing all roles taken by any individual who has ever participated in the production or making of any movie since the film industry inception (De Vany and Lee, 2001; De Vany 2006). They are extremely important in forming once reputation within the film industry (Baker and Faulkner, 1991; Watts and Strogats, 1998; Uzzi and Spiro, 2005).

In this paper, we argue that signals of reliability can be assumed to operate identically, irrespective of the preferences of the crowdfunders for the quality and characteristics of the movie, in the sense that –all other things being equal- crowdfunders always prefer to fund a movie that will likely be completed, rather than funding a movie that will likely not be completed (Zhang, 2006). In this paper, we call preference-neutral the signals that trigger the same response from all receivers, irrespective of their preferences for film characteristics. In this sense, the filmmaker's prior track record of experience is a preference-neutral signal. A preference-neutral signal operates according to the standard predictions of the signaling theory, i.e. a positive (preference-neutral) signal would trigger a positive response. This leads us to formulate our first hypothesis:

H1: A preference-neutral signal triggers always a positive response, irrespective of the *receivers' preferences.*

I.e. a filmmaker's prior experience in movie making is always likely to trigger a positive response in a crowdfunding campaign.

2.3. Response to signals of product characteristics

The second kind of relevant signals relates to the characteristics of the movie that will be produced. We have stressed before that these are unobservable at the time of the campaign, because the project is still underdeveloped. Accordingly, the crowdfunders would be prone to respond to signals that mitigate the paucity of information concerning the characteristics that the movie will have, once it is finished. The scholarly literature about the film industry has suggested that, in the absence of information concerning the movie, a typical movie audience would resort to information about the director, the producer and the other main film roles (Baker and Faulkner, 1991). In that respect, there are at least two signals commonly used: the prizes and the awards that the filmmakers have received from the movie critic for past works (Nelson et al., 2001) and the popularity that the filmmakers have achieved within the star system (Ravid, 1999).

Unlike for the signals of reliability, which apply consistently to all receivers, these two signals cannot be assumed to be preference-neutral, in the sense that their impact would likely depend on the preferences of the receivers concerning what kind of film they like. In other words, two receivers with diverse preferences would react to an identical signal in two potentially different ways, to the extent that the signal allows inferring a characteristic that one likes and the other does not like. Therefore, in order to understand the likely response to the two signals above, we also need to understand the preferences of the receivers.

The literature on film industry has extensively described the large segmentation that exists in the global film market (Kim and Jensen, 2014; De Vany, 2006). A segmentation of primary importance distinguishes between the segment of the audience that sees films as a form of art and the segment of the audience that sees films as a commercial product for consumption (Holbrook, 2005; Holbrook and Addis, 2008; Cattani and Ferriani, 2008).

According to the scholarly studies of art, these two segments are not just different, but they also trade off against each other. To understand why this is so, we should refer more broadly to the studies of art, which portrait the work of artists as based on the duality between creating products of artistic or commercial value (Holbrook, 1999; Bryant and Thorsby, 2006). Based on this literature, a product has an artistic value when it is the result of a search for an original aesthetic (Boden, 1991, Menger 1999). An original aesthetic, by definition, is one that has never been expressed before. A truly original aesthetic has a value as a piece of art, but it typically does not have a market, because the general public is trained to like only the existing aesthetics (Pearce and Wiggins, 2004). Therefore, the challenge of the artists or creators is to develop their own new aesthetic and then work to spread it and make it progressively understood by the general public (Bryant and Thorsby, 2006). As the creators succeed in spreading an original aesthetic, they progressively create a market niche for consumption, and cash-in the value of their work (De Vany, 2006). However, as a corollary of progressive market spread, the creators own aesthetic ceases to be original and looses value as a piece of art. In sum, a work that has a mass-market value does not have a value as a piece of art and vice versa. Accordingly, the spectrum of a film audience distributes between two extremes: At one extreme stands the audience interested at art works (hereafter: artistic movie audience) and at the other extreme stands the audience interested at commercial products (hereafter: mass-market audience).

We are now interested at understanding how the two segments of the audience would respond when they are exposed to the two signals of product characteristics that we introduced above, namely the awards/prizes received from the critic and the popularity in the star-system. In general, the literature sees awards and prizes as a signal pointing at the artistic value of a movie. In fact the awards and prizes express the appraisal of experts and film critics, who judge the artistic merits (Faulkner and Anderson, 1987; Holbrook and Addis, 2008). Conversely, the popularity in the star system reflects the mass-market allure for the filmmaker (Thorsby, 2001). Hence popularity signals the potential value of the movie as a commercial product. It is therefore straightforward to assume that the segment represented by the artistic movie audience would respond positively to the signal offered by prizes and awards and the mass-market audience would respond positively to the popularity in the star system. To generalize, each audience segment responds positively to the signals that are consistent to the preferences of that specific segment. Accordingly, we call signals that are consistent to segment preferences preference-reinforcing and formulate the following hypothesis:

H2: A signal triggers a positive response when it is consistent to the preferences of the segment (preference-reinforcing).

I.e. A filmmaker's artistic quality is likely to trigger a positive response when the project is aimed at an artistic movie audience and a filmmaker's popularity in the star system is likely to trigger a positive response when the project is aimed at a mass-market audience.

Until now we have maintained that the signals of product characteristics trigger a positive response from a segmented audience of receivers whenever the signal reinforces the preferences of that specific audience segment. We now need to determine what happens when the receivers in a certain audience segment are exposed to signals that are not consistent with their preferences. In other words, how would the mass-market audience respond to signals of awards and prices and how would the artistic movie audience respond to signals of popularity in the star-system? A first answer is offered by the theory of cognitive dissonance (Haider, 1946; Osgood and Tannenbaum, 1955; Festinger, 1957), which describes the behavior of single individuals. This theory, largely accepted in psychology of consumers behavior, suggests that the individuals who face a misalignment between actions and preferences (i.e. a dissonance) experience a state of psychological tension, which generates discomfort (Festinger, 1957). They consequently prefer to conform their actions to their own preferences as a strategy to avoid psychological tension (Festinger, 1962). A second insight is offered by the literature of social psychology and homophily (see McPherson et al. 2001 for a review), which describe the behavior of individuals in social groups whose members share consistent preferences (Raegans, 2012). Social groups have been shown to play a predominant role in shaping consumers' purchasing decisions (Centola, 2010; Aral and Walker, 2014) because group members enjoy a feeling of belonging when they conform their consumption decisions to the preferences expressed by their group (Park and Lessig, 1977)[1]. A final argument of consumers behavior is that, once a set of preferences are formed, these tend to endure because

[1] Conformism to group preferences has been shown to endure over time and generating consumption inertia, even after a group disaggregates (Oliver, 1999)

consumers prefer to avoid the costs of switching (Colgate e Lang, 2001) or the risk and the additional investments necessary to fully appreciate unfamiliar products (Dowling and Staelin, 1991).

In sum, we maintain that each audience responds negatively to the signals of product characteristics that are inconsistent to the preferences of the specific segment of audience. Accordingly, we call signals that are inconsistent to segment preferences preference-dissonant and formulate the following hypothesis:

H3: A signal triggers a negative response when it is inconsistent to the preferences of the segment (preference-dissonant).

*I.e. A filmmaker's artistic quality is likely to trigger a n*egative response when the project is aimed at a mass-*market audience and a filmmaker's popularity in the star system is likely to* trigger a negative response when the project is aimed at an artistic audience.

3. Data and methods

3.1. Sample

We use a sample of 610 projects of crowdfunding of film and videos launched by individual filmmakers in Kickstarter.com during 2013. The sample was built to include all projects launched in Kickstarter.com in the months of January and February 2013 in the film and video class, whose campaigns were conducted by individual filmmakers[2] and whose filmmakers had an individual credit profile in IMDb.com at the time of the campaign. From an initial set of 683 projects having these characteristics, we omitted using 66 projects that were canceled before the closure of the campaign and 7 projects that required a minimum pledge of $100 for support and remain with a final sample of 610 observations.

Focusing on Kickstarter offers several advantages. First, the platform is a common source of film funding. About 39,000 projects of firms and videos have been lunched in the platform so far, and of these about 16,000 have been successfully funded. Second, for each film campaign we can observe the number of backers who have pledged money and claimed a

[2] We chose not to include campaigns launched by groups of individuals because measuring groups signals would have posed methodological problems.

reward, which gives us information about the support that films receive from their perspective audience. Third, the setting offers an ideal tested for empirical search, because it allows us to control for virtually each and all the information that the crowdfunders could use at the time they took the decision on whether or not to fund the project. Finally, Kickstarter.com data have been used in several prior studies of crowdfunding (Mollick, 2013; Kuppuswamy & Bayus, 2013; Colombo et al., 2014), making the results comparable and potentially replicable.

Individual signals variables were coded from the individual profiles of the filmmakers recorded in IMDb.com. We used IMDb.com because it is the most popular source of film credit information among those available online and free of charge to the non-professional audience. Interviews with movie professionals and amateurs confirmed that IMDb.com is the most common source of information used by the general public. Sine the link to the IMDb.com filmmaker's page is very often provided in the project webpage of Kickstarter.com or alternatively in the Facebook.com profile of the filmmaker, choosing IMDb.com allows us to assume that the information we coded was available to crowdfunders when taking the financing decision. Search in IMDb.com was conducted through direct links, when links where available, or was based on searching the first and last name of the filmmaker in case it was not. We cleaned our data by cross-checking the information with those available in Kickstarter.com and Facebook.com.

3.2. Variables

Table 1 provides a summary description of the variables construction and reports the respective descriptive statistics for all the variables used in the models.

Dependent variable. The dependent variable of our econometric models is the number of backers of each crowdfunding project that claimed a reward in exchange of the pledge. Specifically, we coded separately the number of crowdfunders that supported a project and claimed a reward and the number of crowdfunders that supported a project without claiming a reward. In computing our dependent variable, we only take into account the former because we wish to minimize the incidence of those who support merely for reasons of friendship (Agrawal et al., 2013) or philanthropy (Belleflamme et al., 2014). As the variable has a highly skewed distribution, in the models, we used its logarithmic transformation (ln_rewback).

Independent variables. Independent variables include explanatory variables, accounting for reputational (quality) signals, moderating variables and a wide set of control variables about the project and its proponent, as identified by prior studies (e.g., Mollick, 2014).

Explanatory variables. Explanatory variables are measures of reputational signals obtained from IMDb.com. We coded the filmmaker's experience (exp_j) based on the filmmaker's credits in two main roles: The director and the producer (ln_experience). For robustness, we further coded film credits as cinematographer, writer, and actor. These roles were identified as the most important ones in the movie industry, based on interviews with experts[3] and prior studies (Faulkner and Anderson, 1987). However, roles rather than those as director and producer never resulted significant in the estimates and were consequently omitted. The search in the IMDb.com database was conducted between February and March 2014. We cleared film credit information from any credits that the filmmaker had gained after the project start, but before our search, based on the project start date and on the credits date.

To measure popularity (pop_j), we retrieved the STARmeter™ from IMBbPro.com, which allows retrieving retrospective records.[4] The STARmeter™ is a measure that captures the ranking of each individual from the most to the least prominent in the star system. We considered this measure as particularly appropriate for our purposes, because it indicates the level of public allure of the person at the time of starting the campaign. Since the ranking has small numbers for top celebrities and high numbers for less popular individuals, we generated our popularity variable (popularity) by reverting the index to make it growing as popularity increases. Since the STARmeter™ is computed daily, we retrieved for each project the value registered at the day prior to the date of project launch.

We measure artistic capability (aw_j) by the logarithm of the number of prizes and awards received in festivals and other circles of film critics by the proponent before the launch of the focal project (ln_awards).

[3] We conducted two interviews, of which one with a movie producer and one with a professor of History of Cinema during Fall 2013.

[4] STARmeterTM is a proprietary index computed daily by IMDbPro.com. The metric ranks all individual profiles listed in the database in descending order of popularity. The ranking is dynamic and fluctuates considerably over time. The algorithm is not disclosed. IMDb states that one important metric component is the frequency of name search on the web.
http://www.imdb.com/search/name?gender=male%2Cfemale&ref_=nv_tp_cel_1. Accessed September 1, 2014

Moderator variable. A crucial moderator variable concerns whether the project is aimed at an artistic movie audience or rather to a mass-market audience. The construction of this variable required building a measure of artistic content of each project. We based our measure on a semantic analysis of the projects verbal description contained in Kickstarter.com. The methodology is based on a search of terms denoting artistic content used in the textual description of the projects. We used a standard algorithm of content analysis that scores the project description based on the occurrence and frequency of a set of terms included in a dictionary. To compute the score, we use the Term Frequency/Inverse Document Frequency (TF/IDF, [5] see e.g., Manning and Schütze, 1999; Loughran and McDonald, 2011; Jegadeesh and Wu, 2014), which is a standard index adopted in semantic analysis. The score increases with both the number of occurrences in a document and with the relative rarity of the term across the entire collection of documents. This score is considered a better measure of term significance than the simple frequency count. In order to eliminate the potential bias due to documents length, we normalized the TF/IDF score, by following the approach of Singhal et al. (1996).

As a dictionary of terms denoting artistic quality, we used the Harvard IV-4[6], a freely accessible and widely used resource in content analysis that contains terms used to describe arts (Insch et al., 1997; Tetlock, 2007). Once the normalized TF/IDF score is obtained, we generate a binary variable (d_art) that partitions the sample into two sub-samples of projects each aimed at a separate audience segment. We code d_art as 1 for projects having a value of the normalized TF/IDF greater or equal to the 75-th percentile of the score distribution within the project sub-category. This give us a partition composed by 440 projects oriented to the mass-market audience and 170 projects oriented to the artistic movie audience. In the robustness checks we also use the normalized score taking continuous values (harart).

We tested the appropriateness of this methodology by collecting the verbal movie description of two samples of films. A first sample is composed of films presented at the Sundance Film Festival that belonged to the category "new frontiers". Films in this section represent the avant-garde of the international movie scene and cross the boundaries of

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[5] The algorithm uses the formula: $w_{t,d} = (1+\log tf_{t,d})\,[\log (N/df_t)]$; where $tf_{t,d}$ is the frequency of the term t in the document d, N is the total number of documents, and df_t is the frequency of the term t among the documents.

[6] www.wjh.harvard.edu/~inquirer/homecat.htm

traditional storytelling. A second sample is composed of high budget films (e.g., super-heroes movies) that are usually aimed at a mass-market audience (De Vany and Walls, 2003). The dictionary performed well in separating the films aimed at an artistic movie audience from those targeted to the mass-market audience.

Control variables. We collected a first set of information about the projects. This information include: the size of the project, based on three dimensional classes of target capital (c_size), the minimum pledge required by the proponent to support the project (w_minimum_pledge), the number of visuals (video plus images) attached to the project description (ln_visuals), the length of the verbal description (ln_text_lenght), and the project sub-category (being a full movie V. a short-movie or other project) (d_film).[7] Several other information concerning the project (e.g. the duration of the campaign, the external links provided in the project description, the number of different rewards offered) were initially collected but these were omitted from the report because they were not significant in any of the estimates. A second set of control variables concerns information on the filmmaker. We coded the filmmaker's gender with a dummy variable (d_female), taking the value 1 if the proponent is a female and 0 otherwise. We further code the location of the filmmaker by separating proponents located in the Hollywood area (d_holliwood), from those located within the US, but outside the Hollywood area, and from those outside of the US (d_foreign). Following the nascent crowdfunding literature, we also controlled for the proponent's social capital using two measures of individual social capital shown to be important in prior studies. These are the (logarithm of) the number of Facebook friends (ln_facebook, see e.g., Agrawal et al., 2013), which we model as conditional to having a Facebook account (no_facebook) (see Mollick, 2014), and the number of projects that a proponent has previously backed on Kickstarter (ln_internal_sc) (see Colombo et al., 2014). The first variable proxies the social capital that a proponent has outside the crowdfunding platform, while the second one indicates the social capital that one had previously built internally to the community of crowdfunders by backing other projects within the platform (Colombo et al. 2014). Finally we controlled for the proponent's experience with the crowdfunding platform, measured by the number of projects launched prior to the focal project (d_crowd_exp), and by the number of these that resulted successful (d_succ_proj).

[7] Note that, in case of highly skewed distribution, we applied the logarithmic transformation to the variable. Complete variables descriptions are provided in Table 1.

[Table 1 about here]

4. Results

4.1. Estimates

We test our hypotheses by means of a set of robust OLS regressions, whose results are reported in Table 2. Columns I-III report the step-wise estimates computed over the full sample of 610 observations. Specifically, the model in Column I includes only the control variables (which are project- and proponent- specific). As the variable measuring a filmmaker's experience (ln_experience) is correlated with those accounting for popularity and reception of awards,[8] we included these variables separately. In particular, the model in Column II includes ln_experience, while model in Column III includes popularity and ln_awards. Column IV reports the estimates computed only within the sub-sample of the 440 movies aimed to a mass-market audience and Column V reports the estimates computed only for the sub-sample of the 170 aimed at the artistic movie audience.

Results in model I indicate that all control variables signs are in line with those expected or found in the prior crowdfunding literature. As expected, the number of backers is positively related with the proponent's social capital both internally to the crowdfunding community (Colombo et al., 2014) and externally. As regards to the external social capital, we replicate the results of Mollick (2014): ln_facebook has a positive and significant coefficient (p value< 0.01), while having no Facebook account is better than having few contacts¬. In line with the findings of Colombo and colleagues (2014), the number of crowdfunding projects that a proponent has backed prior to the focal project has a positive impact on the attraction of backers. All other variables have the expected signs. The number of images and videos (ln_visuals) in the project description, which may be regarded as an indicator of campaign quality (see again Mollick, 2013), exhibit positive and significant coefficients (p value <0.01), although images and videos seem irrelevant for project aimed at an artistic movie audience. A longer verbal description is always associated to more backers, as shown by the positive coefficient of the variable ln_textlenght in all models (p value < 0.01). The same holds for the variable w_minimum_pledge. Higher minimum rewards raise fewer backers and this result is consistent across all model specifications. Female proponents have a

[8]Correlation (ln_experience; popularity)=0.65. Significant at 99%. Correlation (ln_experience; ln_awards)=0.28. Significant at 99%.

tendency to raise more supporters (p value < 0.1), although the coefficient of d_female is not always significant. These results are in line with the nascent crowdfunding literature, which shows not consistent findings on the role of gender in the financing of crowdfunding projects (see e.g., - Barasinska and Schafer, 2014; Marron et al., 2014). Unsurprisingly, Hollywood-based projects (d_hollywood) raise on average more backers than projects located elsewhere in the US but the latter raise in turn more support compared to foreign movies (d_foreign). Prior success in crowdfunding campaigns is associated to more backers (d_succ_proj). Conversely, the variable assessing target capital through projects' class size (c_size) is significant only in the model I-II-II, and this is true even by using other variable specifications like the (log of) target capital.

Let us now turn attention to the explanatory variables. The proponent's experience (measured by prior credits as a director or producer) has a positive effect on the number of backers, in all model specification, and independently of the artistic V. mass-market audience to which the movie is targeted. Thus, we find support for hypothesis H1, which predicted that a filmmakers' prior experience, being preference-neutral, would always exert a positive influence, regardless of the targeted film audience. The magnitude of this effect is moderate: A one percent increase of the variable ln_experience is associated to an increase of the number of backers ranging from +0.28% for projects aimed at the mass-market to +0.56% for projects aimed at the artistic movie audience.

In Model III we see that the coefficient of the variables representing the signals of popularity and artistic merit are both positive in the total sample, although the standard error of ln_award is high, making the estimate not statistically significant. When we split the sample, based on the audience of reference (Models IV and V), the four coefficients turn significant and show compelling support to our predictions. In particular, the signal of popularity in the sample aimed at the mass-market audience and the signal of awards in the artistic movie audience are positive and significant ($p<0.01$ and $p<0.05$, respectively). This confirms our hypothesis H2 that preference-reinforcing signals trigger a positive response from the related audiences. The effects are different in magnitude. Holding all other independent variables constant, an increase of one thousand units of the popularity metric produces a quite modest (0.16%) increase in backers for movies targeting a mass-market audience. Concerning ln_award, a one percent increase in the number of awards is associated with a 0.48% increase of backers in films targeted to the artistic movie audience.

Conversely, the coefficient of popularity is negative and significant in the sample of projects aimed at an artistic movie audience. Symmetrically, the coefficient of ln_award exerts a negative influence on the number of backers attracted when the movie was aimed at a mass-market audience. In both cases, the coefficients exhibit a moderately large standard error, making them significant at the 90% confidence interval (p value<0.1). Collectively, the two confirm our HP3 that preference-dissonant signals have a negative impact on the related audience. In terms of magnitude, holding all other independent variables constant, an increase of one thousand units of the popularity metric produces a 0.15% reduction of backers in project targeted to the artistic movie audience. An increase of 1% in ln_awards produces a 0.25% decrease in the number of backers in the movies aimed at the mass-market audience.

4.2. Robustness checks

To assess the robustness of the results, we perform a number of supplementary estimates. A first set of checks concerns the robustness of our estimates to the choice of the metric used to assess the artistic orientation of a movie. In the model just presented, we chose to partition the sample based on a threshold in the TF/IDF score and coded as movies aimed at an artistic audience all those projects that scored grater or equal than the value of the score at the 75-th percentile. We first test the sensitivity to a 5% change in the choice of this threshold. When we re-estimated the models with a less-restrictive threshold for artistic movies, fixed at the 70-th percentile, all results hold invariant.[9] However, when we fix a more restrictive threshold, represented by the 80-th percentile in the TF/IDF score distribution, some results (popularity and ln_experience) loose significance, albeit the sign of the coefficients remain as expected. To further investigate this problem, we performed a second kind of check. We modeled the entire spectrum of projects in a unique regression, rather than splitting the sample and running separate regressions. In this case, we estimate a model that includes the continuous moderation effect by looking at the interaction between the continuous TF/IDF score (harart) and each of the two quality signals popularity and ln_award. Results are

[9] Results are available upon request to the authors.

presented in Table A1 in the Appendix. Our main findings of the positive impact of preference-reinforcing signals and negative impact of presence-dissonant signals confirmed. The coefficient of popularity is significant at the 99% confidence level (p-value<0.01) and the coefficient ln_awards is significant at the 95% confidence level (p-value>0.05). It is also confirmed that ln_experience does not vary in dependence of harart (p<0.01).

A second set of robustness checks relates to modeling a dependent variable (ln_rewback) that is left-bound to zero. These are 50 cases in which a project at the end of the campaign had not received support form any backer claiming a reward and represent the 8.2% of the distribution, unevenly split between movies aimed at the artistic (2,9%) and mass-market (10.2%) audiences. To cope with potential biases due to censoring, we estimated a Tobit model with left bound at zero. Results of the estimates are shown in Table A2 in the Appendix. All findings are largely further confirm all our hypotheses.

As a final robustness check, we re-estimated the Tobit model with the inclusion of the continuous variable harart. Results are reported in Table A3 of the Appendix and the confidence level of the interaction effects of harart with popularity and ln_award are visualized in Figure A1. Also in this case, our results are confirmed. The graphs show quite visibly that the effect of popularity is positive for low values of the TF/IDV score (movies aimed at the mass-market) and shifts from positive to negative at a score of about 11 or up (88-th percentile of the distribution). The opposite happens for the marginal effect of the signal of artistic quality of the filmmaker (ln_award). This goes from having a negative marginal effect for projects with a low TF/IDV score (directed to the mass-market) to having a positive marginal effect for artistic movies. The lower-bound of the confidence interval crosses the x-axis at a score of about 7, representing the 63-rd percentile of the distribution.

5. Conclusions and limitations

Signalling theory has been widely used in studies of transactions under condition of high information asymmetries. In a recent survey of the literature on the topic, Connelly and colleagues (2011) highlighted the growing interest of scholars for the effects of multiple signals, but showed that virtually no research yet exists on multiple receivers. Recently, Kim and Jensen (2014) looked at international film markets and investigated how audience heterogeneity influences the effectiveness of commercial performance and artistic acclaim as market signals. Our work is similar to that of Kim and Jensen in that we have notion of audience heterogeneity. We contribute to the debate by suggesting that, in case of audience heterogeneity –which we described in terms of segmentation- the impact of signals would be explained based on their consistency V. dissonance with the preferences of the related market segment. Whenever the signal reinforces the preferences of the market segment, the receivers would respond positively to the signal. Conversely, whenever the signal is inconsistent with the preferences of the market segment, the receivers would respond negatively to the signal. We also show that, regardless of the audience, the response to positive signals that are unrelated to the audience preference, are always positive.

The paper contributes to several research streams. First, it adds to the literature on reputation in online marketplaces (Bolton et al., 2004; Jin and Kato, 2005; Resnick et al., 2006). This literature has widely recognized the paramount importance of reputational signals to enable transactions among strangers, but has until now tended to assume that signals' receivers have univocal and quite straightforward preferences. For example, eBay customers generally prefer reliable sellers and Prosper lenders have a clear preference for borrowers who redeem their loans. While this assumption may fit relatively well some marketplaces (for example e-commerce platforms where sellers offer mass-market goods), it appears to be unsatisfactory in online environments, where the audience consists of segments with diversified and nuanced tastes. Crowdfunding is a case in point. Internet users financing projects on the Web act out of heterogeneous motivations and thus likely attach a different value to different project's characteristics and dimensions, thus responding in potentially different ways to diverse reputational signals. Second, the paper advances the literature on seed and venture funding (e.g., by Business Angels and Venture Capitals, Amit et al., 1990; Hsu, 2004; Conti et al., 2013). Usually, this literature models funders as homogeneous concerning the preferences for projects and entrepreneurs to be funded. We are confident that more accurate models can be developed if preference diversity (e.g. for liquidity, exit-time, risk) is taken into account.

Finally, the paper offers interesting insights to the nascent literature on crowdfunding. The fact that information asymmetries between a proponent and the crowd of Internet users have a critical importance in the context of crowdfunding is widely recognized by scholars and practitioners. Prior studies have singled out several factors that may contribute to reduce information asymmetries, including proponents' social capital (Colombo et al., 2014; Mollick, 2014), proximity with supporters (Agrawal et al., 2011), and human capital (Alhers et al., 2012). However, to date, research on crowdfunding has overlooked the role of proponents' reputation, which mainstream literature on entrepreneurial finance has acknowledged as being of crucial importance.

The paper has several limitations that pave the way to further research. For a start, we cannot observe directly the preferences and tastes of potential backers. We assume that movies having an artistic content would provoke the response from the artistic movie audience and that movies having a non-artistic content would provoke the response from the mass-market audience. One can hardly deny that our assumptions are reasonable and in line with mainstream theory (Holbrook, 2005; Bryant and Thorsby, 2006; Kim and Jensen, 2014). However, the availability of more fine-grained information about the tastes of the crowd and/or its motivations would certainly contribute to shed light on the topic. Second, we consider the effect of diverse reputational signals separately. However, a filmmaker may have a good critic appreciation and be very popular or vice versa. We do not account for interactive effects, partly because of the relatively scarce incidence of top celebrities among filmmakers seeking crowdfunding. Third, following a well-established research design in the nascent crowdfunding literature, our paper focuses on projects hosted on the Kickstarter platform. However, to date, there are many diverse platforms both in the United States and in Europe. Investigating more platforms would shed light on the generalizability of our results. In a similar vein, although crowdfunding projects in the movie and video category are an interesting test-bed for our study; other categories exist where projects may have both a commercial and an artistic content (e.g., design, fashion, art or dance). Are our results generalizable to these contexts?

Despite these limitations, our paper has interesting implications for project proponents and managers of crowdfunding platforms. Crowdfunding is raising a growing amount of attention both as an innovative financing means and as a tool to empower innovativeness from creative individuals. As the phenomenon took momentum, several celebrities like Spike Lee and Zach Braff have launched very successful campaigns, raising considerable amounts of capital in matters of hours and leaving many wondering whether a proponent that cannot account on the head-start of a sparking reputation can nonetheless be successful in raising money from the crowd. Our results suggest that reputation matters, particularly for what concerns evidence of prior experience. However, we also show that –due to market segmentation- not being popular in the star system may not necessarily mean bad news, and can even be good news if the project that one seeks to finance is not primarily targeted to the mass-market audience. Similarly, having collected awards from the film critics may give a head start to a project, but only if the movie audience to which one aims is the artistic-movie audience, whereas it can be harming if one wants to fund a movie for the mass-market.

In light of our results what matters more is not scoring high in all dimensions of reputation, but rather showing coherence between the one's reputation and one's target audience.

The results may incidentally bring implications for platform managers, as they indicate that proponents should probably be helped to think carefully about targeting projects to the right audience. It is possible that the platforms will want to develop custom tools for profiling project supporters in the future. Finally, our results are potentially generalizable to other contexts characterized by market segmentation and asymmetric information. Think for example at Amazon, where the readers feedback reflects a largely diversified range of readers' tastes or at Tripadvisor.com, where signals of customer's feedback may mean different things, depending on the preferences of traveler.

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TABLES

Table 1 – Summary statistics

	Obs.	Mean	St. Dev.	Min.	Max.	Variable description
ln_rewback	610	3.0290	1.6564	0	9.2446	Ln[Number of backers that claim a reward+1]
ln_experience	610	0.3559	0.4422	0	1.0986	Ln[Number of credits for film direction or production(winsorized at 95-th percentile) +1].
popularity	610	0.4836	0.1280	0.0760	0.5998	(6000000- STARmeter^{TM})/1000000
ln_award	610	0.1287	0.4223	0	3.4011	Ln(Number of awards+1).
no_facebook	610	0.2672	0.4428	0	1	Dummy=1 if the proponent does not have a Facebook page.
ln_facebook	610	4.6324	2.9241	0	8.5225	Ln(Number of Facebook friends+1).
ln_internal_sc	610	0.9502	0.9941	0	4.8362	Ln(Number of projects supported by the proponent at the time of project launch+1).
d_hollywood	610	0.1704	0.3763	0	1	Dummy=1 if project location is in the Holliwood area.
d_foreign	610	0.1491	0.3565	0	1	Dummy=1 if project location is outside of the US.
d_female	610	0.1934	0.3953	0	1	Dummy=1 if proponent is female; 0 if male.
d_crowdf_exp	610	0.2590	0.4384	0	1	Dummy=1 if the proponent had presented at least one other project before the launch of the focal project.
d_succ_proj	610	0.1163	0.3209	0	1	Dummy=1 if the proponent had presented. at least one successful project before the launch of the focal project.
ln_visuals	610	1.3730	0.7625	0.6931	4.4184	Ln(Number of pictures and videos in project description+1).
ln_textlenght	610	5.9933	0.6344	4.9344	6.9469	Ln[Number of words in the project Description (winsorized at 95-th percentile)+1].
c_size	610	2.4409	1.0876	1	4	Categorical variable=1 if project target capital<=25-percentile; =2 if project target capital>25-percentile and <=50-percentile; =3 if project target capital > 50-percentile and<=75-percentile; =4 if project target capital >75-percentile j
w_minimum_pledge	610	6.6245	5.6963	1	20	Minimum pledge required by proponent for backing a project, winsorized at the 95-th percentile.
d_film	610	0.3082	0.4621	0	1	Dummy=1 if the project is a film; 0 if the project is a short, a documentary, an animation, a fiction or a web fiction.
harart	610	6.1074	4.1636	0	20.076	TF/IDF score of project, based on the occurrence of words in the Harvard IV list of artistic terms.

Table 2 – Model estimate

Sample:	Full sample			Mass-market	Artistic
	I	II	III	IV	V
ln_experience		0.4241***		0.2850*	0.5607**
		(0.123)		(0.151)	(0.233)
popularity			0.9921**	1.5866***	-1.5697*
			(0.449)	(0.516)	(0.856)
ln_award			0.1039	-0.2503*	0.4856**
			(0.138)	(0.133)	(0.213)
ln_facebook	0.2806***	0.2698***	0.2851***	0.2084***	0.4099***
	(0.063)	(0.062)	(0.063)	(0.077)	(0.099)
no_facebook	1.8479***	1.7988***	1.8783***	1.4381***	2.5278***
	(0.416)	(0.407)	(0.414)	(0.500)	(0.694)
ln_internal_sc	0.5483***	0.5476***	0.5314***	0.5016***	0.5651***
	(0.066)	(0.066)	(0.067)	(0.084)	(0.103)
d_hollywood	0.3910**	0.3268**	0.3498**	0.3561*	0.3585
	(0.155)	(0.154)	(0.154)	(0.182)	(0.283)
d_foreign	-0.3629**	-0.4135***	-0.3399**	-0.4707***	-0.1265
	(0.148)	(0.147)	(0.148)	(0.172)	(0.266)
d_female	0.2034	0.2417*	0.1968	0.2723*	0.0103
	(0.125)	(0.124)	(0.125)	(0.150)	(0.237)
d_crowdf_exp	-0.4932***	-0.5172***	-0.4741***	-0.4589**	-0.8825**
	(0.159)	(0.159)	(0.160)	(0.180)	(0.347)
d_succ_proj	0.7704***	0.7043***	0.7395***	0.6636**	1.0184**
	(0.223)	(0.224)	(0.224)	(0.264)	(0.426)
ln_visuals	0.3331***	0.3217***	0.3162***	0.4057***	0.0760
	(0.097)	(0.096)	(0.095)	(0.112)	(0.172)
ln_textlenght	0.2826***	0.2551**	0.2759***	0.2153*	0.4381**
	(0.100)	(0.100)	(0.099)	(0.120)	(0.179)
c_size	0.1396**	0.1248**	0.1277**	0.0776	0.1650
	(0.056)	(0.056)	(0.057)	(0.066)	(0.104)
w_minimum_pledge	-0.0400***	-0.0406***	-0.0416***	-0.0349***	-0.0622***
	(0.010)	(0.010)	(0.010)	(0.012)	(0.019)
d_film	-0.1775	-0.2039*	-0.2219*	-0.1627	-0.4050*
	(0.121)	(0.121)	(0.122)	(0.148)	(0.218)
Constant	-1.4721**	-1.3052*	-1.8578***	-1.4077*	-2.1392
	(0.675)	(0.666)	(0.689)	(0.836)	(1.341)
Observations	610	610	610	440	170
R-squared	0.3989	0.4105	0.4056	0.3805	0.5174
R-sq	0.3857	0.3966	0.3906	0.3570	0.4670
F stat	36.3978	34.1073	32.7532	18.4417	14.9693

Dependent variable: Ln_reward_backers. Robust standard errors in parentheses. Significance: *, **, *** at: 90%, 95%, 99%.

APPENDIX

Table A1- OLS model with continuous interaction

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Sample	Full sample		
	I	II	III
ln_experience		0.3998***	1.3979
		(0.127)	(0.219)
harart			0.1116**
			(0.050)
ln_experience x harart			0.2020
			(0.029)
Popularity		0.8508*	2.5048***
		(0.447)	(0.719)
popularity x harart			-0.2765***
			(0.100)
ln_award		0.3201	-0.3848**
		(0.133)	(0.185)
ln_award x harart			0.0609**
			(0.027)
ln_facebook	0.2826***	0.2754***	0.2744***
	(0.063)	(0.062)	(0.062)
no_facebook	1.8694***	1.8436***	1.8174***
	(0.417)	(0.407)	(0.404)
ln_internal_sc	0.5568***	0.5404***	0.5374***
	(0.067)	(0.067)	(0.066)
d_foreign	-0.4352***	-0.4458***	-0.4540***
	(0.145)	(0.143)	(0.143)
d_female	0.2248*	0.2498**	0.2142*
	(0.127)	(0.125)	(0.127)
d_crowdf_exp	-0.5257***	-0.5264***	-0.5394***
	(0.159)	(0.160)	(0.160)
d_succ_proj	0.8058***	0.7131***	0.7151***
	(0.225)	(0.225)	(0.225)
ln_visuals	0.3493***	0.3216***	0.3214***
	(0.099)	(0.096)	(0.095)
ln_textlenght	0.2668***	0.2391**	0.2576**
	(0.101)	(0.101)	(0.108)
c_size	0.1679***	0.1371**	0.1312**
	(0.055)	(0.056)	(0.055)
w_minimum_pledge	-0.0402***	-0.0419***	-0.0413***
	(0.010)	(0.010)	(0.010)
d_film	-0.1606	-0.2276*	-0.2222*
	(0.123)	(0.123)	(0.125)
Constant	-1.4179**	-1.6030**	-2.3260***
	(0.679)	(0.687)	(0.723)
Observations	610	610	610
R-squared	0.3967	0.4131	0.4259
F stat	35.37	30.14	25.61

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TABLE A2 – Tobit model

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Sample	Full sample		Mass-market	Artistic
	I	II	III	IV
ln_experience		0.4220***	0.3234**	0.6253***
		(0.134)	(0.159)	(0.237)
Popularity		0.8953*	1.7883***	-1.6734*
		(0.498)	(0.575)	(0.867)
ln_award		0,1347	-0.2743*	0.4748**
		(0.141)	(0.150)	(0.206)
ln_facebook	0.3029***	0.2957***	0.2475***	0.3970***
	(0.069)	(0.068)	(0.085)	(0.102)
no_facebook	1.9637***	1.9417***	1.6588***	2.4230***
	(0.460)	(0.449)	(0.556)	(0.716)
ln_internal_sc	0.5658***	0.5513***	0.5144***	0.5871***
	(0.069)	(0.069)	(0.086)	(0.104)
d_hollywood	0.4022**	0.3065*	0.3447*	2.6166
	(0.162)	(0.160)	(0.192)	(0.277)
d_foreign	-0.4086**	-0.4413***	-0.5477***	-0.1464
	(0.165)	(0.163)	(0.192)	(0.276)
d_female	0.2305*	0.2619**	0.3123**	0.0044
	(0.133)	(0.132)	(0.157)	(0.244)
d_crowdf_exp	-0.5162***	-0.5248***	-0.4804**	-0.9250***
	(0.174)	(0.174)	(0.197)	(0.353)
d_succ_proj	0.8014***	0.7138***	0.6691**	1.0606**
	(0.232)	(0.233)	(0.274)	(0.419)
ln_visuals	0.3501***	0.3270***	0.4287***	0.6298
	(0.101)	(0.099)	(0.114)	(0.176)
ln_textlenght	0.3089***	0.2754**	0.2530*	0.4391**
	(0.108)	(0.108)	(0.129)	(0.184)
c_size	0.1360**	0.1105*	0.5104	1.0506
	(0.061)	(0.061)	(0.071)	(0.106)
w_minimum_pledge	-0.0451***	-0.0468***	-0.0400***	-0.0674***
	(0.011)	(0.011)	(0.013)	(0.020)
d_film	-0.1797	-0.2455*	-0.1853	-0.3913*
	(0.130)	(0.130)	(0.159)	(0.214)
Constant	-1.8113**	-1.9902***	-2.0102**	-2.0427
	(0.740)	(0.750)	(0.927)	-1.329
Observations	610	610	440	170
R-squared	0.1252	0.1326	0.1227	0.1741
F stat	31.34	26.50	16.18	14.23

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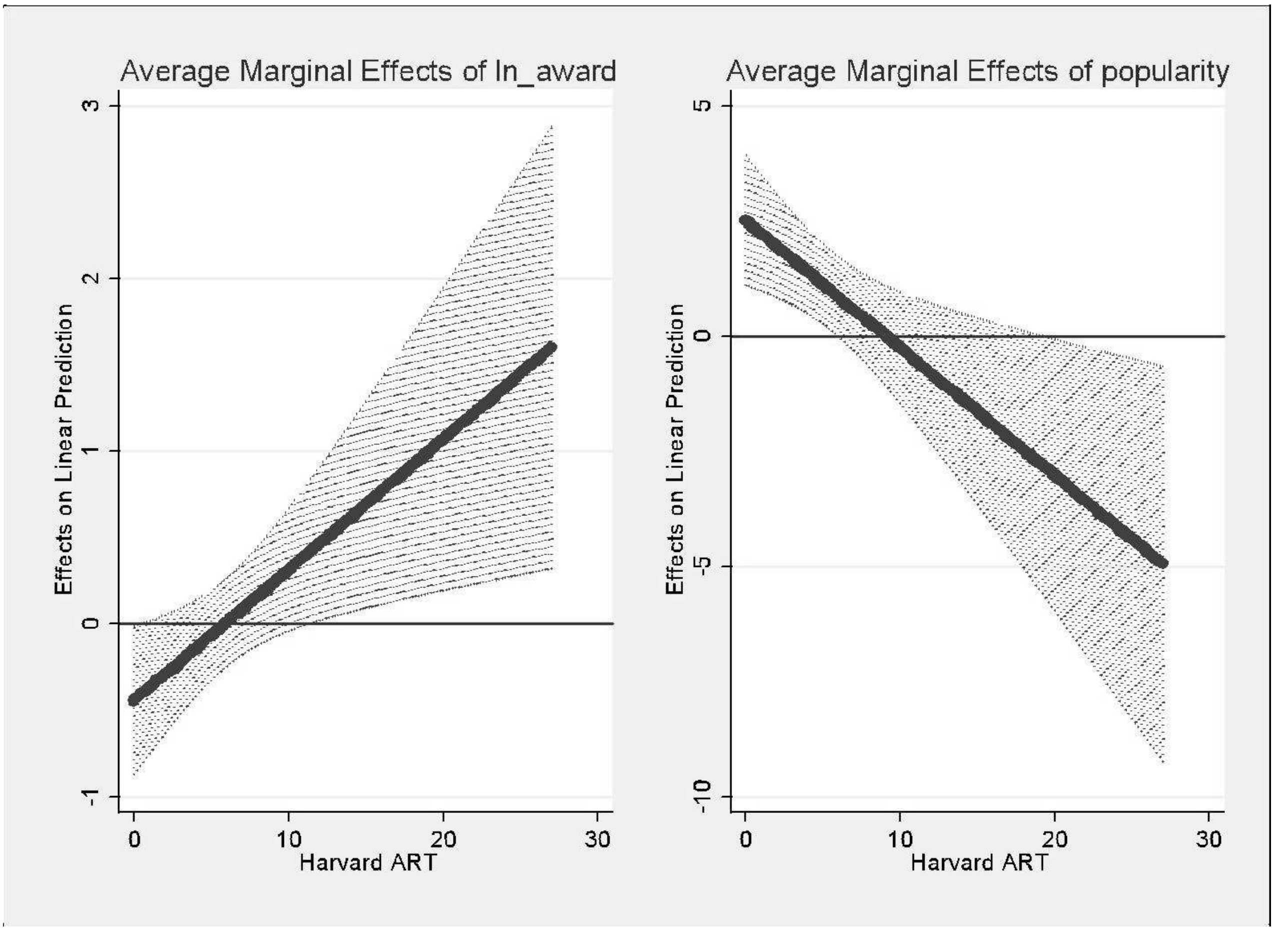
Table A3 – Tobit model with continuous interaction

Sample	Full sample		
	I	II	III
ln_experience		0.4220***	1.5638
		(0.134)	(0.235)
Harart			0.1407**
			(0.056)
ln_experience x harart			0.1993
			(0.031)
Popularity		0.8953*	2.9071***
		(0.498)	(0.838)
popularity x harart			-0.3365***
			(0.112)
ln_award		0.1347	-0.4493**
		(0.141)	(0.220)
ln_award x harart			0.0654**
			(0.031)
ln_facebook	0.3029***	0.2957***	0.2949***
	(0.069)	(0.068)	(0.067)
no_facebook	1.9637***	1.9417***	1.9157***
	(0.460)	(0.449)	(0.442)
ln_internal_sc	0.5658***	0.5513***	0.5469***
	(0.069)	(0.069)	(0.068)
d_hollywood	0.4022**	0.3065*	0.3285**
	(0.162)	(0.160)	(0.157)
d_foreign	-0.4086**	-0.4413***	-0.4539***
	(0.165)	(0.163)	(0.162)
d_female	0.2305*	0.2619**	0.2218*
	(0.133)	(0.132)	(0.133)
d_crowdf_exp	-0.5162***	-0.5248***	-0.5378***
	(0.174)	(0.174)	(0.174)
d_succ_proj	0.8014***	0.7138***	0.7125***
	(0.232)	(0.233)	(0.232)
ln_visuals	0.3501***	0.3270***	0.3266***
	(0.101)	(0.099)	(0.098)
ln_textlenght	0.3089***	0.2754**	0.2963**
	(0.108)	(0.108)	(0.115)
c_size	0.1360**	0.1105*	0.1032*
	(0.061)	(0.061)	(0.060)
w_minimum_pledge	-0.0451***	-0.0468***	-0.0463***
	(0.011)	(0.011)	(0.011)
d_film	-0.1797	-0.2455*	-0.2371*
	(0.130)	(0.130)	(0.132)
Constant	-1.8113**	-1.9902***	-2.8953***
	(0.740)	(0.750)	(0.806)
Observations	610	610	610
R-squared	0.1252	0.1326	0.1383
F stat	31.34	26.50	22.25

Figure A1- Average marginal effect of ln_award and popularity



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