The “Experts” in the Crowd: The Role of Experienced Investors in a Crowdfunding Market

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Abstract

Using a data set on individual investments in an online crowdfunding platform for mobile applications, this study examines whether an early investor’s experience within the platform serves as credible signals of quality for the other investors in the crowd and if so under what conditions. We find that early investors with experience – particularly, investors with app development experience and investors with app investment experience - have a disproportionate influence on later investors in the crowd. Investors with app development experience who are likely to have a better knowledge of the product are found to be more influential for “concept apps” (apps in the pre-release stage), while investors with app investment experience with a better knowledge of market performance are found to be more influential for “live apps” (apps that are already being sold in the market). Our findings show that the majority of investors in this market – *the crowd* – although inexperienced in this market, are rather sophisticated in their ability to identify and exploit nuanced differences in the underlying expertise of the early investors – informational signals that align well with the informational needs they face in the different stages of a venture. In examining the ex-post performance of apps, we find that apps with investments from investors with experience are positively associated with ex-post app sales. More importantly, we find that these investors with experience indeed have the ability to select better apps, making their investment choices credible signals of quality for the crowd. Contrary to popular perceptions of crowdfunding platforms as substitutes for traditional expert-dominated mechanisms, our findings indicate that the participation by individuals with experience can be beneficial to these markets.

Keywords: crowdfunding, investor experience, quality signals, information asymmetry, herding, market design.

The "Experts" in the Crowd: The Role of Experienced Investors in a Crowdfunding Market

Online crowdfunding markets have grown rapidly in recent years, attracting an expected $34.4 billion worldwide in 2015 alone,[1] and have emerged as a viable alternative to traditional sources of financing by financial institutions, venture capitalists (VCs), and angel investors. Online crowdfunding markets are similar to traditional funding markets in many ways, but also differ from them in some key aspects. Online crowdfunding markets, by dramatically reducing the transactions costs as well as the investment thresholds for participation, have enabled smaller, less-sophisticated individual investors (the crowd) to participate in these markets (Agrawal et al. 2014; Ahlers et al. 2015). In contrast to traditional financial markets that are largely intermediated by experts including VCs, angel investors, and financial institutions - who provide not only the resources/capital, but also their expertise in evaluating, monitoring, and managing risk (Huang and Knight 2017; Sorenson and Stuart 2001) - online crowdfunding markets enable startup ventures and entrepreneurs to bypass these financial intermediaries and seek funds directly from the crowd. Further, unlike professional investors in traditional markets who are able to develop affective relational ties to the entrepreneurs to reduce their risks (Huang and Knight 2017), investors in online crowdfunding markets have to primarily rely on the information provided by the entrepreneurs and be content with an arms-length approach to investing. The diversity in the nature and quality of ventures seeking funding, the lack of established intermediaries, the participation by the crowd, the lack of negotiable contracts, and the arms-length approach to investing, exacerbate the issues of information asymmetry in online crowdfunding markets. All of these are likely to increase the value of visible informational cues

[1] http://www.crowdsourcing.org/editorial/global-crowdfunding-market-to-reach-344b-in-2015-predicts-massolutions-2015cf-industry-report/45376

in online crowdfunding markets, and more so for the crowd, to help mitigate the risks they face in these markets. Understanding the dynamics of investor behavior in these markets and the role of mechanisms that help investors manage risks in these nascent markets is crucial to the design of successful crowdfunding platforms. While there are several studies of traditional financial markets and decision making by experts (Engelberg et al. 2012; Nahata 2008), there is very limited research on factors that influence the crowd's investment decisions. The implications of participation by the crowd rather than just traditional experts, and their associated dynamics are unclear, and is one that motivates our study.

While online crowdfunding markets are characterized by significant informational asymmetries, an important feature of these markets is the heightened digital visibility of granular information. In particular, granular information about the actions or inactions of investors within the market is often visible to other participants in the market – information that is difficult to obtain in traditional financial markets. Thus for instance, in an IPO (initial public offering) market, a classic example of traditional crowdfunding mechanism, information about other investors is rarely available to the crowd (i.e., retail investors). This lack of visibility of individual behaviors has also limited the ability of researchers to study the behaviors of individual investors in traditional markets. The increased digital visibility relating to the current and historical transactions of peers and their activities, lacking in most traditional markets, has the potential to play an important role in online crowdfunding markets (Burtch et al. 2015).

Recent research has found that investments by early investors in online crowdfunding campaigns can have a significant influence on later investors. Drawing upon the literature on herding (Banerjee, 1992) as well as "follow-the-leader" informational cascades model (Bikchandani et al 1992) wherein individuals with less-accurate information tend to follow the lead of individuals with more-accurate information, recent empirical studies (e.g., Herzenstein et al 2011, Lee and Lee 2012, Zhang and Liu 2012) have found broad evidence of herding behaviors in online crowdfunding markets. However, these studies do not shed light on the types of early investors that are influential. A related body of research has started to examine the value of other signals unique to online crowdfunding markets (Ahlers et al. 2015, Lin et al. 2013, Liu et al. 2015) and their potential impacts on investors in these markets. These studies along with other emerging evidence[2] from online crowdfunding markets indicate that less-experienced investors may benefit from a variety of informational cues, including the visibility of investment decisions of the more-experienced investors.

Whereas a significant number of market participants in online crowdfunding markets tend to be less-sophisticated individual investors, a few participants in these markets tend to have relevant expertise or experience that could potentially be valuable to the others. Given the availability and visibility of a variety of informational cues to investors in an online crowdfunding market, our study seeks to examine whether the investment choices of peer investors with experience within the market can significantly influence the investment decisions of the crowd. More specifically, we study (i) whether early investments by individuals with experience within a market serve as signals of quality for the crowd, (ii) whether the value of these signals differs depending on the stage of the investment and the type of experience possessed by early investors, and (iii) whether these signals are indeed credible as measured by the ex-post performance of these investments.

[2] There is evidence from crowdfunding platforms that investors actually browse a variety of items relating to a campaign. According to a survey of crowdfunders in the U.K., when making investment decisions, most respondents stated that they look at who had already invested in these projects and also read comments by other investors (Baeck et al. 2014). A qualitative study of equity crowdfunding by Moritz et al. (2015) also provides evidence that investors read through the questions and answers section to decide whether to invest in a particular venture.

We examine these questions in the context of an online crowdfunding market for mobile apps. The data for this study comes from Appbackr, one of the earliest online crowdfunding marketplaces for mobile apps. Started in October 2010, Appbackr had emerged as the primary online crowdfunding marketplace for entrepreneurs seeking funding for "concept apps" (apps in their conceptual stage of development) as well as for "live apps" (apps that have already been launched and are in need of additional funds for marketing and distribution). We collect data on Appbackr listings posted from Aug 2010 through June 2013. For each project, the data set contains time-invariant characteristics related to an app (e.g., price, category, developer identity, platform where the app is (or will be) listed, whether the app is live in store) and the funding status of the project (e.g., the amount requested, the amount backed, the number of backers, days left, return on investment). Our dataset comprises of 532 apps listed by 396 app developers, funded by over 3,500 specific investments for approximately $1 million. We further collect data about the app developer and app characteristics such as total downloads of each app.

We examine the investment choices made by investors with experience (viz. the "experts" in our market) as well as the other investors (i.e., the crowd). Two categories of investors with experience are visible to others in our market. The first is investors with experience related to *app development* within this market whom we denote as App Developer Investors, and the second is investors with experience related to *app investments* within this market, whom we denote as Experienced Investors. We find that App Developer Investors and Experienced Investors tend to invest early. Despite the presence of multiple informational cues in this market including information about the app developer as well as the app among others, we find that the crowd is influenced by the investments made by early investors. However not all early investors are equally influential. We find that the crowd is more likely to follow App

Developer Investors for *concept apps*, and Experienced Investors for *live apps*. Additional analyses also find that the influence of these investors with experience further depends on their past performance on the platform. Variations in the degree of digital visibility or depth of an individual's experience serve as a valuable identification mechanism. Finally, we find that these investors with experience are indeed good at selecting quality apps to invest in, providing supporting evidence that the quality signals conveyed by their experiences are credible.

Our study makes a number of significant contributions. Earlier research on financial markets has focused on the role of traditional experts who have an established reputation and are recognized by their peers as well as the public for their expertise. Our study is among the first to examine the role of experts within the platform and their disproportionate influence on the crowd's investment decisions. It is also among the first to provide systematic evidence of the crowd's ability to identify and act upon the signals implicit in the investment behaviors of individuals with experience despite their lack of any peer or public recognition as experts. More interestingly, the App Developer Investors as well as Experienced Investors in our market have limited experience in this market – experience or expertise that might go unnoticed in larger traditional contexts with well-established experts. The signals conveyed by the limited experience of App Developer Investors and Experienced Investors within the platform are subtle compared to the gross signals possessed by established experts such as VCs, and Wall Street analysts. Yet, we find that the later investors in the crowd are able to infer informative signals implicit in the investment choices of these early investors with experience within this platform. In the process, our study adds to the literature on signaling which has largely focused on the role of traditional quality signals.

Our study also adds to the literature on signaling by identifying the differential impacts of different types of experience possessed by early investors on the crowds' investment decisions and outcomes. While earlier work (Zhang and Liu, 2012) suggests that investors herd behind early investors, our study finds that the crowd is more discerning. We find that the crowd, rather than following the herd, has the ability to infer the informative signals conveyed by the actions of the different types of early investors and are selective in who they follow for the different types of investments on this platform. Our findings also indicate that informational cues serve as credible signals of quality when the information contained in the signal is aligned with the nature of uncertainty as implied by the stage of the venture (i.e., early or later stages) – highlighting the importance of such alignment for the signals' effectiveness. Our study also contributes to the emerging literature on digital visibility (Rhue and Sundararajan 2013) which has shown that increased visibility can influence economic actions and outcomes in a variety of contexts, from product adoptions (Aral and Walker 2012) to charitable contributions (Andreoni and Bernheim 2009). The role of digital visibility is evidenced by our test of falsifiability wherein we find that the experience of early investors lose their effectiveness as a credible signal of quality when their identity and experience is no longer visible to other investors in the markets. Our study also contributes to the small but growing body of research in online crowdfunding markets (e.g., Ahlers et al. 2015; Lin et al. 2013) by empirically identifying a new and credible signal of quality and its implications for the crowd's behavior. Finally, as discussed later, the findings of our study also have significant implications for the design of online crowdfunding markets and for the development of policy and prescriptive guidelines for such markets.

2. THEORETICAL BACKGROUND AND RELATED RESEARCH

2.1. Information Asymmetry and Signaling

Our study builds on well-established theories of adverse selection in markets with information asymmetry and the value of signals in reducing such asymmetry. As noted by Spence (2002), the theory of signaling has its roots in the seminal work of Akerlof (1970) that studies the used car market. Akerlof studies the role of information asymmetry between sellers with better knowledge of the car's quality and the buyers, and how such information asymmetry can lead to a market for "lemons". This eventually causes the market to breakdown as high quality sellers are unable to credibly communicate the quality of their products to buyers and withdraw from the market. According to Spence (1973), the Akerlof adverse selection problem can be mitigated in such markets if buyers can avail of *signals* that can communicate quality. More importantly, these signals are credible when they help buyers separate the high type sellers from the low types. Spence studies the role of education as a signal of a worker's productivity, and this has been followed by a rich literature on signaling spanning multiple disciplines. The signaling framework makes both ex-ante and ex-post predictions. For instance, when education serves as a signal of the worker's quality, educated workers should be more likely to find employment and get paid more if their signals are effective (Spence 1973). Further, ex-post, these workers should be more productive, which serves to validate that the signal (i.e., their education) is indeed useful. These tests readily map to our context.

We add to the signaling literature pioneered by Akerlof (1970) and Spence (1973). Our contribution to this body of work is to offer new empirical evidence on the importance of signaling in online crowdfunding markets. Our evidence is especially interesting because of the unique aspects of online crowdfunding markets. As noted earlier, unlike traditional markets dominated by experts such as VCs or professional investors, online crowdfunding markets are dominated by the crowd comprised largely of less sophisticated investors. This exacerbates the adverse selection (Spence 2002) in online crowdfunding markets, due to the increased information asymmetry between the borrowers and the investors who might lack the necessary expertise. Consequently, credible quality signals that can help such investors better distinguish the high types from the low types, become very valuable and have the potential to make these nascent market more efficient.

Further, experts in traditional markets play a prominent role, with their prominence stemming from well-established reputation that provide them high visibility (Shapiro 1986). However, despite online crowdfunding markets being dominated by largely anonymous individuals, a few of these peer investors might possess specific experience relevant to these markets. Unlike traditional experts, investors in our crowdfunding market, even those with experience, do not have an established reputation within the market. In fact, in many instances, very limited information about them other than their experience within this market is visible to the other market participants, and when their experience is invisible they are indistinguishable from the crowd. Further, their experience within this market is limited. Added to this, different investors could have different types of experience. Inferring its relation to the quality of a specific investment requires sophisticated reasoning. Yet, we find that the crowd's investment decisions align well with the predictions of the theories of signaling.

2.2. The Role of Experts in Entrepreneurial Finance

Our study is also closely related to the work on adverse selection in markets for funding and venture capital. The literature on financial markets as well as the literature on entrepreneurial financing argue that information asymmetry is an important feature of these markets (see, e.g., Gorton and Winton (2003) for a review). Studies based on cognitive decision theories suggest that individuals in such setting with limited information rely on informational cues[3] for decision making (Rosch 1975). A number of studies in entrepreneurship have focused on empirically identifying valid informational cues associated with successful outcomes in financing startup ventures. As noted by Kirsch et al (2009), different attributes possess varying levels of 'cue validity' and in uncertain environments high validity cues (or credible signals) may be difficult to identify even for entrepreneurs and experienced traditional investors. For instance, previous studies have examined the role of signaling by the entrepreneurial firms themselves (Kirsch et al. 2009; Sanders and Boivie 2004), and have shown that higher quality signals such as founders' education are associated with better outcomes (Ahlers et al. 2015; Conti et al. 2013; Cosh et al. 2009). Whether an experienced peer's investment choice serves as a credible informational signal for the crowd, from among a larger set of potential signals in the market, is an open empirical question that we address.

Another body of work examines the role of opinion leaders and how influential individuals accelerate the diffusion of products, innovations, and behaviors (Valente 1995; Watts and Dodds 2007). While most of the work on opinion leadership is in the context of non-financial markets (Kohler et al. 2011; Nair et al. 2010) that lack objective measures of ex-post rationality[4], a stream of research in financial markets (Barber et al. 2001; Engelberg et al. 2012; Hogan 1997; Hsu 2004; Mikhail et al. 1997; Nahata 2008) has examined the role of established intermediaries as well as the role of traditional experts including equity analysts, reputed investment bankers, venture capitalists and angel investors in influencing outcomes in these

[3] While the term "cue" has its origins in psychology (Rosch 1975), the term "signaling" has its origins in economics (Spence 1973). Both streams of research seek to understand, "when is information A a reliable indicator that B is true?" (Kirsch et al. 2009).

[4] Ex-post performance measures (e.g,. the success of projects post-funding) are important to assess the credibility of signals in a given market. Such objective performance measures are, for the most part, absent in non-financial contexts limiting their usefulness in understanding the credibility of different signaling mechanisms.

markets. The focus of these studies have been on the role of investors who are recognized by their peers and the market as leaders or established experts. Further, due to the lack of granular data about anonymous individuals in traditional financial markets the focus has largely been on the role of experts in influencing the ability of these ventures to raise funds rather than on understanding their influence on other individual investors. Our study adds to this literature by empirically identifying the investment choices of peer investors with experience as credible signals of quality for the crowd, despite the presence of other informational cues in the market.

2.3. Venture Life Cycle and Risk

Our study also draws upon research relating to the types of risks faced by entrepreneurs and investors at different stages in a new venture's life cycle. While there is a large literature on risk and uncertainty and the kinds of risks faced by entrepreneurs as well as investors in startups, research in entrepreneurship, management, and economics identifies two broad categories of risk/uncertainty faced by entrepreneurs and investors – (i) internal risks or uncertainty related to technology/product (henceforth, *technology risk*) and (ii) external risks or uncertainty related to market demand and competition (henceforth, *market risk*) (see Ansoff (1988; 1965); Moriarty and Kosnik (1989); Chen et al (2005); Tatikonda and Montoya-Weiss (2001)). Technology risk broadly refers to the extent to which product form, features, performance, costs, manufacturing, and operational aspects, are understood (Lynn and Akgün 1998). Market risk, on the other hand, refers to the uncertainty about demand for the product/innovation and includes uncertainty about the target market, market size, customer preferences, pricing, competition, and environmental factors, among others (Lynn and Akgün 1998). Our market for mobile apps is characterized by novelty (newness) as well as turbulence (rate of change) – two key determinants of technology risk as well as market risk (Chen et al. 2005). Clearly, entrepreneurs (i.e, the app developers seeking funding) as well as investors in this market face significant technology as well as market-demand risks. As noted by Huang and Pearce (2015), early stage investors in high-tech firms face extreme uncertainty that the risks qualify as unknowable. Under such circumstances of extreme uncertainty and noise, investors focus on the information that is available to them and the risks that they can manage. Thus, while all types of risks are the highest at the very early stages of a venture's development, the risks related to product conception and development are addressable in the early stages, while those related to product commercialization and growth remain "unknown unknowns" (Diebold et al. 2010) in the early stages. This is consistent with the view of organizational theorists (see for instance, Kazanjian (1988)) who find that the dominant problem faced by a new venture in the early stage relates to the conception and development of the product or technology, while the later stages focus on market commercialization and growth.

The theory that the focus of entrepreneurs and investors differs depending on the stage of the venture's growth is also the subject of a well-established stream of research on staged financing (e.g., Gompers (1995)). In the very early stages, pre-seed/seed funding helps the entrepreneur to reduce or eliminate technology/product related risks, while late stage funding focuses on product commercialization and scaling up operations (Aram 1989; Elango et al. 1995; Ruhnka and Young 1991). Consequently, both entrepreneurs as well as investors in the later stages are more concerned with market risks, as risks relating to product/technology development have typically been reduced by then.[5]

This difference in the early stage and later stage focus of entrepreneurs as well as investors is also strongly echoed by practitioners. According to the "onion theory of risk"

[5] One of the objectives of staged financing is to reduce risks at each stage. Ventures that have progressed beyond the initial stages of product development and testing typically return to seek additional funding in later stages of product commercialization and scaling operations.

popularized by Marc Andreseen (2007)[6], co-founder of Netscape and an investor in startups, investors in startups should "look at the risk around an investment as if it's an onion. Just like you peel an onion and remove each layer in turn, risk in a startup investment comes in layers that get peeled away - reduced - one by one." And with each milestone, you're peeling away a layer of risk. So you raise seed money in order to peel away the first two or three risks, the founding team risk, the product risk, maybe the initial watch risk".

A number of other notable investors echo Marc Andreseen's view. Angels, or early stage investors, largely take a product risk (they bet on the product or idea and your ability to build it). Late-stage seed investors take market risk (they want to see the product, vision and maybe even the first customers, and they bet on there being a big enough market).[7] Paul Singh, Investor and co-founding Partner at 500 Startups, also notes that "at the earliest stage of the company (e.g., a company's first outside fundraise or a company raising money pre-product), an investor ought to spend 80% of their time determining product risk. The remaining 20% of time should be spent on understanding market and distribution risk. At the next stage of the company (often called the bridge or Series A stage), 80% investor's time should be spent on understanding the market risk. The remaining time should be spent understanding product and distribution risk."

In our context, "concept apps" – apps that are still in the early/conceptual stages of development - correspond to ventures in the early stages seeking seed funding, while "live apps" – apps that have already been released but are still seeking funding to meet operational or marketing expenses - correspond to ventures seeking late stage funding for market expansion and scaling. The focus of entrepreneurs and investors in these two stages are different, with

[6] Source: PMARCA Guide to Startups. http://pmarchive.com/guide_to_startups_part2.html
[7] Source: Get Inside the Mind of an Angel Investor. https://bothsidesofthetable.com/get-inside-the-mind-of-an-angel-investor-34df04dbe8aa#.chezewmlu

managing technology/product risks being the primary focus in the case of concept apps and managing market risks being the primary focus in the case of live apps.[8] Given the differences in the focus on managing risks for entrepreneurs as well as investors in these two different categories of apps, we would expect different signals (i.e., different types of experiences) to be credible to investors in each of these categories of apps. Whether the crowd is able to hone in on the signals that align with the stage in the lifecycle of the venture remains an empirical question, and is one that is answered by our analyses.

App development investors have experience in conceptualizing and developing an app on this platform and are likely to be more informed about the product and technology related aspects as compared to Experienced Investors. Experienced Investors, on the other hand, have no prior experience in developing an app on this platform. However, their prior investments on this platform would have provided them more information about factors that are conducive to an app's popularity and success. In accordance with this, we find that the experience possessed by app developer investors serves as a credible signal of quality in the case of "concept apps", while the experience of experienced investors serves as a credible signal of quality in the case of "live apps". Our findings demonstrate that the crowd, although inexperienced, are rather sophisticated in their ability to identify and exploit nuanced differences between different signals within the same market. Thus we add to literature on signaling by showing that it is not just any experience, but the specific type of experience possessed by early investors that matter (Connelly et al. 2011). This provides a more nuanced view of signals and the circumstances under which they are effective compared to the role of experts in traditional venture capital markets.

2.4. Crowdfunding

[8] This is also reinforced by our text analysis. For details see tables A8 – A10 of the Appendix.

Our study is also related to the body of research on online crowdfunding markets. Given that online crowdfunding is a relatively new phenomenon, early studies present conceptual and descriptive overviews of the market mechanisms (Mollick 2014) and their implications for participants (Belleflamme et al. 2014). An increasing body of research on crowdfunding markets has examined issues such as the role of geography in contribution patterns (Agrawal et al. 2015; Burtch et al. 2014; Lin and Viswanathan 2015), an entrepreneur's incentive to create a project (Kim and Hann 2017), the effect of social media on success of crowdfunding campaigns (Mollick 2014), and the importance of information provision mechanisms (Burtch et al. 2015), as well as different types of crowdfunding, including equity-based crowdfunding (Agrawal et al. 2014; Stemler 2013).

Recent studies have started to examine the role of different sources of social influence, and how they impact the behaviors of investors and consequent outcomes in a variety of online crowdfunding markets including donation-based markets (Burtch et al. 2013), reward-based markets (Kuppuswamy and Bayus 2017), revenue sharing-based markets (Agrawal et al. 2015), financial lending markets (Lin et al. 2013; Liu et al. 2015; Zhang and Liu 2012) and equity crowd funding markets (Ahlers et al. 2015; Bapna 2017). Our study contributes to this research stream on online crowdfunding markets in a number of ways. Our findings show that an investor can be a part of the crowd, a peer, and yet her experience within the market can influence the crowd's behavior, despite the lack of an established reputation or other third-party signals of quality.

3. RESEARCH CONTEXT AND DATA

Our data comes from Appbackr, a crowdfunding marketplace for mobile applications that started operations in October 2010. Since then, it has provided a market where developers of mobile apps can list their apps to obtain funding from potential investors. Compared to other crowdfunding markets that host a variety of different projects, Appbackr focuses on mobile apps and has attracted a considerable number of mobile app developers and investors. By June 2013, Appbackr has attracted around 396 app developers listing 532 mobile apps and over 1,116 members investing around $1,030,000 in total.

Listing and investing on Appbackr proceed as follows. An app developer seeking funding for her app can post her listing - either a "concept app" that is not yet available for sale, or a "live app" that is available for sale in a mobile app store – for potential investors. The listing specifies the maximum amount of funding she seeks, the minimum amount that must be raised before she receives the fund (called 'reserve'), and the duration for which the listing will remain active. The app developer also includes a written statement providing a brief description of her app, why the app should be backed, and what the funds will be used for. App developers typically use the money for development and/or promotion.

An investor decides whether to fund an app and if so, how much to contribute and when. The timing of investment is important for the investor in this "first-come-first-served" market, since investors get paid in the sequence they invest in an app. For example, an investor who is the first to fund 10,000 copies of the app at Appbackr, profits when the first 10,000 copies of the app are downloaded in the app store. After all 10,000 copies have been downloaded, the next investor profits. This makes early investors more likely to get paid than later investors.[9]

[9] While early investors are more likely to get paid than later investors, they are also faced with greater uncertainties. Later investors, on the other hand, run the risk of not being able to recoup their investments, but benefit from being able to learn from earlier investors.

The return on investments on Appbackr depends on whether the app is a concept or a live app. An investor gets a fixed return of 27% when a concept app invested is sold successfully.[10] However, it is possible that the app does not sell well enough to cover the investment. Similarly, investors get a return of 54% for concept apps. If an app listed on Appbackr does not get funded successfully (i.e., reserve not met), all investors receive their contributions back.

Crowdfunders on this platform are likely to invest in the listed apps mainly for monetary incentives. On other crowdfunding platforms such as Kickstarter, crowdfunders are also likely to participate because of other non-monetary motivations, including their desire to support socially oriented initiatives, preferential access to the creators, and early access to new projects (Agrawal et al. 2014). However, these motivations, if any, are likely to be minimal for investors on our context. Since there is limited community activity on Appbackr, easier access to the app developers or recognition within the platform is not likely to be a major motivation for them. Lastly, early access to new products is unlikely to be important, as what they get in return is not new apps, but monetary profits.

We track all listings posted on Appbackr from October 2010 through June 2013. The resulting sample contains 532 listings with 3,501 specific investments.[11] For each listing, we collect a set of its attributes and gather information on its funding progression, including the amount of funding it has received and the number of backers. We drop all listings that were live

[10] Suppose that an investor wants to invest in a live app that is available for sale in the Apple app store for $0.99. The investor funds a copy of the app for $ 0.45. After Appbackr takes a commission of $0.10 for each copy sold, it transfers the rest, $0.35, to the app developer listing the app. When the app later gets sold on the app store, Appbackr receives $0.70 (after Apple's commission of 30%), and retains $0.03 as its commission. Appbackr distributes the rest, with $0.57 going to the investors, and $0.10 going to the app developer. Thus, an investor gets a fixed return of 27% when the app is sold successfully.

[11] We dropped over 20 apps that had limited visibility and information.

at the time of date collection to address potential biases that can arise from simply ignoring censored observations (Van den Bulte and Iyengar 2011).

Table 1 presents the summary statistics for all listings. In this sample, the average price is $3.64, ranging from $0 to $599.99.[12] The total amounts investors actually pledged to each project are between $0 and $101,249, with an average of $1,892. If we consider only successful projects, the average increases to $3,891. The number of backers ranges from 0 to 116, with an average of 6.15. Furthermore, our data suggest that concept apps comprising 42% of total apps attract more money and investors. The ratio of successfully funded apps is higher in concept apps (50%) than in live apps (44%).

3.1. Investors, Experience, and Timing of Investments

We are interested in understanding whether the relevant experience possessed by investors within this platform serves as credible signals of quality for the later investors in the crowd. In this regard, investors on Appbackr fall into three categories. Broadly, there are investors who have experience within this platform that is visible to the others, and those who are either anonymous or have little experience (the crowd). In our context, investors with two different categories of experience within the market are visible. The first category is investors with experience in investing in other apps within the market. Investors with such app investment experience are investors who have invested in prior apps listed on Appbackr. As noted earlier, we call investors with significant app investment experience *Experienced Investors*. Our measure of investment experience is consistent with prior research wherein an investor's experience has

[12] Free apps with in-app purchases use $0.99 pricing structure to determine the price that an investor pays. For example, a $4.99 in-app purchase will pay back 5 backed copies.

been measured by the cumulative amount of investments (Hochberg et al. 2007), the cumulative number of investments (Hsu 2004; Sørensen 2007), and age (Gompers 1996).

The second category of investors with experience comprises of those with experience in developing Apps and listing them on Appbackr. We call investors with prior App Development experience as *App Developer Investors*. App Developer Investors are investors who have developed and listed at least one app on Appbackr and are thus likely to have experience relating to the product – particularly about apps in the developmental stage. We also find that App Developer Investors are not heavy investors but those with their own apps. Finally, the third category of investors - the crowd, consists of the others who have no App Development experience or little experience in investing in apps in this marketplace.

Investors with experience typically tend to focus on specific categories that reflect their experience. For example, investors might invest only in apps in the game category and accumulate some expertise specific to gaming-related apps. To measure the extent to which she concentrates her investments on certain categories, we calculate investment concentration in a way similar to calculating the Herfindahl index used to measure industry concentration. The average investment concentration is 0.83 for App Developer Investors while it is 0.44 for Experienced Investors. App Developer Investors tend to be more specialized in a specific app category compared to Experienced Investors, who have a lower investment concentration and are less likely to focus on a specific category of apps.

Given the existence of investors with different types of experience in this market, our study first seeks to understand if there are significant differences in the investment behaviors of these investors. We begin by examining if investors with experience within this market are more likely to invest early as compared to the crowd. We then seek to understand if these early investments by investors with experience serve as credible signals of quality for later investors, and if so, do the differences in their experience matter?

4. EMPIRICAL ANALYSIS

We begin by examining whether investors with experience in our market are more likely to invest early. We use hazard modeling as the main statistical approach to examine this question. We operationalize the time of adoption as the time of first investment, i.e., we consider only the first investment by an investor for a given app. We create a binary adoption indicator variable y_{ijt} that is set to zero if investor *i* has not invested by period *t* in list *j* and is set to one if he has. The discrete time hazard of investment is then modeled as

$$P(y_{ijt} = 1 | y_{ijt-1} = 0) = F(x_{ijt}\beta) \qquad (1)$$

where x_{ijt} is a row vector of covariates, β is a column vector of parameters to be estimated, and F is a cumulative distribution function (e.g., logistic or standard normal). Our model includes dummies for days to investment within a listing and thus has a flexible baseline hazard rate. For each app, the population of interest consists only of investors who will invest in the app at least once while it remains active. Thus, an investor who eventually makes an investment in the app is at the “risk” of investing in the app. We include monthly dummies to capture the effect of any platform-wide shock, such as changes in the popularity of Appbackr.

In addition, because each investor can invest in multiple apps over time, we might have to account for possible correlation between investments by the same investor across apps. This can happen if heterogeneity among investors is not completely explained by our observed covariates. If such unobserved heterogeneity exists and is temporally stable, then the occurrence of an investor’s subsequent investments will not be independent of prior investments. We address this in multiple ways. We first use standard errors clustered by investor. This enables us to account for the correlation within investor across time, in the error structure. We also include a flexible baseline hazard rate by including dummies for days to investment to provide a nonparametric control for duration dependence. This controls for much of the effects of possible unobserved heterogeneity in hazard models (Dolton and von der Klaauw 1995). Third, we include the number of investments made prior to the current investment as an additional control variable in some specifications (Willett and Singer 1995). This can dampen the dependency of the investment timing on an investor's previous history. Lastly, we include a random individual-level hazard parameter in our hazard model and estimate the standard random-effects model.[13]

As highlighted earlier, our primary focus is to examine the role of investors with experience within this market. We exploit the panel data to examine whether the investors with the two categories of experience influence later investors. To construct the panel data, we collect information about timing and amount of all investments in each listing and calculate time-variant variables on a daily basis. The base equation for testing the effect of investors with experience on later investments is:

$$y_{jt} = \beta_1 A_{jt-1} + \beta_2 E_{jt-1} + \gamma_1 X_{jt-1} + u_j + d_t + v_{jt} \qquad (2)$$

y_{jt} represents the log of the amount of funding that listing j receives during its *t*th day.

We denote the overall experience of App Developer Investors (and Experienced Investors) in listing *j* up to day *t* as A_{jt} and E_{jt}. Since our analysis for the role of these investors with experience is conducted at the project and day level, we need to aggregate the experiences of all of the existing App Developer Investors (or Experienced Investors) for a particular listing.

[13] When we conduct fixed-effects models, *App developers* variable is dropped because of multicollinearity. Thus, we report random-effects estimates.

Since each investor with experience might differ in her experience, when aggregating to get the overall experience of each group in listing *j* at day *t* we use the following formula:

$$overall\ experience\ for\ E\ (or\ A) = \sum_{i=1}^{n} w_i I(i = E\ or\ A)$$

We use the cumulative amount of prior investments of an existing investor with experience for listing *j* as the weight (i.e., w_i) of the investor in the main analysis. The weight represents the experience of the particular investor.[14] As robustness checks, we use different weighting schemes later. We consider no weighting, the cumulative number of prior investments as a weight, and weighting based on the ex-post investment performance. Identity function *I* becomes 1 when investor *i* is an Experienced Investor for the aggregate experience of the group of Experienced Investors or an App Developer Investor for the aggregate experience of the group of App Developer Investors. This measure is log-transformed in our main specifications.

Our independent variables only include time-varying listing attributes X_{jt-1}, since we conduct a fixed-effects model to capture unobserved heterogeneity across listings. The time-varying listing attributes include three variables related to herding. The *cumulative amount of funding* at day *t-1* is used as a measure of herding momentum investors at day *t* face. The cumulative amount reflects previous investors' collective evaluations of a listing as manifested in their funding allocation decisions. We also include the *cumulative number of investments* as another measure of herding momentum.[15] Since payoff externalities may be responsible for herding, it is important to address both mechanisms when empirically measuring herding effects

[14] Potential backers may consider only recent backers. To test this we consider only 15 (or 25) investments in a project prior to a focal investment. Our main findings are robust to this.
[15] Since only a small fraction of the total investments in a listing are made by any given investor, the cumulative number of investments serves a good proxy for the cumulative number of investors.

in certain contexts (Zhang and Liu 2012). This is important in our case, because our sample faces both positive information externality and negative payoff externalities. Positive externalities are common in the case of technologies and software. Examples of negative payoff externalities include bank runs and overcrowding (Hirshleifer and Hong Teoh 2003). Our study, in examining the effect of investors' experience on subsequent investors, controls for both possibilities. Nevertheless, it is pertinent to note that our primary focus is not on identifying herding behavior, but on measuring the influence of investors' experience on subsequent investments, after controlling for average herding. Including both measures helps us account for both effects. Also, following Zhang and Liu (2012) we include the percentage of the amount requested by listing j that is left unfunded at the end of day t-1.[16] To capture any platform-wide shock on Appbackr, we also include time dummies, d_t.

The available data are unlikely to capture every source of heterogeneity across listings. Thus, we control for unobserved listing heterogeneity by including listing fixed effects u_j. The identification assumption is that the unobservable listing heterogeneity is time invariant. Based on this assumption, we identify the effect of investors with experience using within-listing variations in the amount received each day, the sum of cumulative amount of existing App Developer Investors or Experienced Investors prior to current listing, and observable time-varying listing attributes in X_{jt}. The effect of time-invariant listing attributes such as price, reserve, and developer type, cannot be separately estimated from listing fixed effects because of the perfect multi-collinearity between them, and thus we drop them in our analysis.

[16] To further address the concern that duration left to campaign end can affect investment intensity we include a linear time-trend variable and its squared term in a robustness check. Our main findings are robust to this.

Note that we are primarily interested in the role of investors with experience after controlling for peer effects. However, typical identification issues in the traditional peer effects literature are still likely to be a concern (Manski 1993). To the extent that the influence of investors with experience and peer effects are correlated, it can affect our estimates of the influence of investors with experience. Furthermore, prior investments of investors with experience are likely to reflect their preferences and hence may be correlated with current investments of the crowd who share similar preferences.

Endogenous group formation (i.e., homophily) arises if an investor selects peers based on shared traits or preferences. If co-investments in the same listing are more likely between similar investors, their investments could be correlated because of inherent similarities in their preferences rather than as a consequence of their interactions. This is often a key challenge in identifying true contagions from homophily-driven correlations (Aral et al. 2009). We address this issue in several ways. First, to the extent that homophily is driven by listing-related factors, having listing fixed effects can account for this. For example, an early investor with experience and a later investor in the crowd could both prefer investing in a listing that has a professional video, thus making them make an investment in the same listing. If so, co-investment among the two can be driven not by the early investor's influence but by their similar preferences. This can be accounted for by including listing fixed effects. However, it is also possible that the two investors are similar in other dimensions that have nothing to do with listings, such as demography. We believe that this is likely to be less of a concern in our context where most investors release little information and are arm's-length investors funding small portions of a borrower's (app developer's) request. Moreover, there is little room for direct communication among investors during and after campaigns. Thus, it is unlikely that they make investments in the same listing due to unobservable shared traits that are unrelated to listings.

Another concern is the existence of correlated unobservables that lead to the dependency of investments within a listing across time. One source of correlation is marketing efforts directed at the listing. We include time fixed effects to control for common trends in platform marketing efforts to investors. Nonetheless, we acknowledge that this does not completely control for app developer marketing efforts, although such efforts are limited in the platform. Our setting also mitigates concerns from any spatially correlated location-specific shocks to investment behaviors that may generate co-movements in investments. Investors on our online platform are likely to be geographically dispersed and unlikely to be co-located. Thus, any co-movements in investments from location-specific shocks are less of a concern. Lastly, simultaneity is less of a concern in our context, since we do not examine contemporaneous influence between investors. Influence and peer effects are one-day lagged in our analysis.

In addition to these, an important mechanism to identify the impact of an investor's experience on the investment behaviors of subsequent investors is to examine the signaling role of her experience on the platform. More specifically, when an early investor's experience on the platform is visible to subsequent investors, her actions are likely to influence subsequent investors. However, when the investor's experience on the platform is not yet visible to the crowd, the investor's actions should not have a significant influence on subsequent investors. This variation in the digital visibility of an early investor's experience serves as a valuable falsification test. Our data enables us to exploit this difference in information about experience available to subsequent investors to help us identify the role of investors' experience in these markets.

5. RESULTS

5.1. The Experience in the Crowd

Table 2 presents the results of our analysis of the differences in investment behaviors by investor type. As noted earlier, App Developer Investors are investors with at least one app posted at Appbackr while Experienced Investors are investors that have more than $2,000 in investments and at least 5 specific investments.[17] In our sample, we have 67 App Developer Investors who made 168 investments and 17 Experienced Investors with 213 investments. Experienced Investors are heavy investors investing an average of about $15,000. On the other hand, App Developer Investors are not as active, as compared to Experienced Investors. The typical App Developer Investor makes an investment of $330 with slightly less than 3 investments. Since most of App Developer Investors are not heavy investors, our two categories of experienced investors are distinct from each other.

Table 2 also provides evidence of the investment timing of these investors. As shown in Table 2 both types – App Developer Investors as well as Experienced Investors - are likely to invest earlier than the crowd. When we further divide the sample into concept and live apps, we still see the same pattern in each group. These findings are also confirmed by the survival estimates in Figures 1 and 2. As shown in the Figure 1 (panel A), the survival curve drops faster for these investors, implying that both categories of investors are likely to invest earlier than the others. Furthermore, as shown in Figure 1 (panel B), we find that even among Experienced Investors, the investors with more experience tend to invest earlier than those with less experience. When we divide the sample into concept and live apps, we still observe the same

[17] We also vary these cutoffs and examine the impact of alternative definitions of reputable investors. Our main findings are robust to these.

pattern in concept apps (see panel A of Figure 2). However, for live apps, Experienced Investors are still early investors, whereas App Developer Investors look quite similar to the crowd in investment timing. Note that App Developer Investors still tend to invest slightly early in the first 20 days of live apps, as shown in panel B of Figure 2.

Table 3 reports the estimates of the discrete-time hazard model relating to investment timing. Column (2) shows that App Developer Investors and Experienced Investors have a significant and positive effect, which confirms that these investors do invest early. This finding is robust when we add monthly dummies, as shown in column (3). Comparing columns (2) and (3) illustrates the importance of including monthly dummies. Our findings in column (3) suggest that controlling for app characteristics, the estimated odds of investing early are about 46% (76%) higher for App Developer Investors (Experienced Investors), compared to the crowd. The Pseudo R^2 statistic increases with monthly dummies and, as discussed above, including them also helps us to control for all cross-temporal variations in the mean tendency to invest.

We further test whether our finding varies by the type of apps. As shown in columns (4)-(5), we find that these two categories of investors both invest early for concept apps, whereas only Experienced Investors invest early for live apps, findings consistent with Figure 2.[18] This suggests that App Developer Investors are more confident about investing in concept apps which are in the developmental stages, while Experienced Investors being active participants invest early in both types of apps. Lastly, we provide some evidence that our findings are robust even after accounting for investor heterogeneity (see column 6).[19]

[18] The numbers of observations in columns (4) and (5) do not sum up to the number of observations in column (3), because some observations are dropped due to several dummies perfectly predicting success or failure.
[19] In unreported results, we also include the number of investments made prior to the current investment by a given investor as a proxy for her experience. Our main findings are qualitatively similar. Note that this variable is, by definition, highly correlated to *Experienced Investors* who have at least 5 investments and more than $2,000.

5.2. The Role of Experience

We next examine whether App Developer Investors and Experienced Investors have a similar or disproportionate influence on the subsequent crowd. Table 4 reports the panel data model estimates with listing-specific fixed-effects. We first examine the investments of all subsequent investors. As shown in column (1) both variables are positively associated with later investments after controlling for peer effects, even though the influence of investors with App development expertise is likely to be greater. This indicates that the experience of both App Developer Investors as well as Experienced Investors influence investment decisions of subsequent investors. Furthermore, their influences differ with the type of apps. Columns (2) - (3) show that App Developer Investors are influential for both types of apps, while Experienced Investors are more influential for live apps.

Since we are more interested in examining the influence of these two categories of investors on the subsequent crowd rather than on all investors, we next turn to findings that consider only the crowd in subsequent investors.[20] The findings shown in columns (4)-(6) highlight the differential effects of App Developer Investors and Experienced Investors - a likely reflection of the differences in their experience on this platform. App Developer Investors are influential mainly for concept apps, while Experienced Investors are influential mainly for live apps.

The estimates from columns (5) and (6) allow us to evaluate the magnitude of influence. Column (5) suggests that, ceteris paribus, a 10% increase in prior cumulative investments by app developer investors is associated with a 1.73% increase in investments for the app on the

[20] We cluster standard errors at app level for our main specifications. When we cluster standard errors at app developer level, our main findings are qualitatively the same.

following day.[21] Similarly, a 10% increase in prior cumulative investments by Experienced Investors generates a 0.52% increase in investments for the focal app.

We perform additional analyses to gain further insights into the source of influence of App Developer Investors and Experienced Investors and report results in Table 5. The influence of these investors likely stems from their prior experience within this market which makes them a more credible source of information. Since the influence of App Developer Investors is likely to stem from their prior app development experience in this market, we first test whether App Developer Investors are more influential when they have at least one successfully funded app. Columns (1)-(2) of Table 5 show that the crowds' investments are more significantly influenced by App Developer Investors who have their own *successfully* funded apps than by those without.[22]

Furthermore, in columns (3)-(4) we decompose the influence measure for App Developer Investors into those in the same category and those in different categories to examine whether their experience in this platform is category-specific. We expect App Developer Investors to have a stronger influence on the crowd when they have a successfully funded app in the same category as the focal project they invest in. For instance, if an App Developer Investor has developed a successfully funded app in the 'gaming' category, his influence as an investor should be stronger in that category. Our findings suggest that the influence of App Developer Investors is category-specific, although statistically weak. We find that App Developer Investors

[21] $330.1 is the average of the overall influence of existing App Developer Investors and $41.5 is the average daily amount of funding made by the crowd. This is a very conservative estimate, as the influence of an app developer investor or an experienced investor is likely to extend beyond just the following day. Note that calculating the aggregate effect by the end of a listing's duration is challenging since we should take into consideration the recursive nature of herding.

[22] The difference is statistically significant at 10% level for concept apps, while it is not statistically significant for live apps.

have a stronger influence on the crowd when they make an investment in a category where they have their own successfully funded apps. This more nuanced finding further corroborates the credibility based claim.

As noted earlier, an important falsification test is the visibility (or lack thereof) of the investor's experience. In other words, when subsequent investors are unaware of the expertise of an early investor, they are unlikely to be influenced by the specific investor's investment decisions. To examine this, we exploit informational variation in our dataset wherein some App Developer Investors invest in apps before their own app is listed in this marketplace. It is pertinent to note that all App Developer Investors eventually have their own apps listed on the platform. However, some App Developer Investors participate in the platform as an investor before listing their own apps. It is possible that some of these App Developer Investors have app-development related experience and this information could be available through their profile page. However, when an App Developer has listed her own apps on Appbackr, her investments in other apps are made under the same "profile name" as her own listing, making it easier for subsequent investors to gather information about her related experience within the platform. In examining the impact of these seemingly "inexperienced" App Developers on the crowd, we find that App Developer Investors without prior in-platform app development experience have little influence on the investment decisions of the crowd while those with, have a strong influence (see columns (5) – (6)). This indicates that the credibility of an App Developer's investments as a quality signal crucially depends on the ability of the crowd to observe and verify her experience in the focal platform. Furthermore, the visibility of her experience and credentials outside the platform do not significantly influence the later investors in the crowd.

In the case of App Developer Investors, their prior experience within this platform is typically a dichotomous variable – they either have an app listed on this platform earlier or they do not. However, in the case of Experienced Investors, there is some variation in their experience on this platform – both in terms of the number of investments as well as in the amount of investments. Similar to the case of App Developer Investors, we find that Experienced Investors with more experience are more influential than ones with less experienced on the platform. These results are presented in Table A4 in the Appendix. We also examine if the outside profile information available about App Developer Investors and Experienced Investors (rather than their experience within the platform) influence the crowd. We collect data on the App Developer Investors and Experienced Investors who have disclosed relevant information on outside platforms such as LinkedIn and use this in our analysis. We find that even after controlling for the presence of outside profile information, the investors' experience within the platform has a significant influence. Table A3 in the Appendix reports these results.

For Experienced Investors, their experience stems from their prior investments on this platform. In this regard, they are likely to learn more from prior investments in successfully funded apps, as they get monthly updates about those apps and monitor their performance of their investments. Hence, we would expect that Experienced Investors with more successful investments are more influential than those with investing in unsuccessful listings. Columns (7)-(8) of Table 5 show that investments by Experienced Investors in successfully funded apps are more significantly associated with later investments by the crowd than those in unsuccessfully funded are not, although statistically weak.

Until now our measures of experience were a function of the investors' prior amount of investments. We now use different measures of experience to show that our results are robust. As for App Developer Investors, their influence is likely to stem from their prior app developer experience, rather than from their prior investments in this market. Thus, we use an un-weighted measure of experience for both categories of investors, which is the number of existing App Developer Investors or Experienced Investors. This measure assumes that each investor has the same level of experience regardless of her prior investment. Table 6, columns (1)-(2) show results with this measure. The results suggest that our main findings do not change qualitatively. In columns (3)-(4) we use the cumulative number of prior investments as the measure of experience (Hsu 2004; Sørensen 2007). We find that our results are qualitatively the same. Finally, we consider the ex-post investment performance as a measure of an investor's potential influence (Nahata 2008). For this, we collect app sales data as on June 2013 from xyo.net, which reports the cumulative and current monthly estimated sales for apps in Apple and Android app stores.[23] This data tell us whether a particular investment for an app could be successfully recouped. Since Appbackr is a "first-come-first-served" market in payment, there are cases that early investments for an app were successfully recovered, whereas later investments for the same app were not. Once we know which investments were successful based on the ex-post sales, our new measures for experience can be calculated. In other words, we use the cumulative amount of ex-post successful prior investments (in columns (5)-(6)) and the cumulative number of ex-post successful prior investments (in columns (7)-(8)). The columns in Table 6 show that our findings are robust and become stronger.

5.2.1. Robustness Checks

Addressing Endogeneity Concern from Serial Correlation

[23] As of Feb 2013, xyo.net covers 1,951,130 apps and 547,387 app developers. Among 532 apps in our sample, we obtain cumulative sales data for 376 apps. When we can't find the sales data for an app, we assume that it's not launched yet. In this case, investors for this app do not get any returns.

One identification assumption for Equation (2) is that the error terms are not correlated across time. Under this assumption, our key independent variables are contemporaneously uncorrelated with the error terms, although they may be correlated with past shocks. However, if the error terms are serially correlated, they may be correlated with these lagged independent variables through past shocks, thus raising endogeneity concerns.

We assume that the unobserved error terms consist of a first-order autoregressive component with parameter ρ and a random component, w_{jt}. In other words, $v_{jt} = \rho v_{jt-1} + w_{jt}$. Thus, the updated model is

$$y_{jt} = \beta_1 A_{jt-1} + \beta_2 E_{jt-1} + \gamma_1 X_{jt-1} + u_j + \rho v_{jt} + w_{jt} \qquad (3)$$

A serial correlation adjustment allows us to remove the autocorrelation effect v_{jt-1}, thereby leaving us with only the contemporaneous shock.

$$y_{jt} = \rho y_{jt-1} + \beta_1 A_{jt-1} - \beta_1 \rho A_{jt-2} + \beta_2 E_{jt-1} - \beta_2 \rho E_{jt-2} + \gamma_1 X_{jt-1} - \gamma_1 \rho X_{jt-2} + u_j(1 - \rho) + w_{jt} \qquad (4)$$

After estimating ρ with fixed-effect estimation for Equation (4), we construct a new dataset with variables that are corrected for serial correlation and conduct the fixed-effect estimation with the new dataset. Columns (1)-(3) of Table 7 show that our main findings do not change qualitatively even after rho-differencing to remove serial correlation.

We can also address this concern in the dynamic GMM framework. The idea of dynamic GMM is to use lagged independent variables as instruments in the first-differenced model by assuming an orthogonal relationship between the instrumental variables and residuals in the first-difference model. This approach allows us to statistically test whether the instruments satisfy exclusion restrictions. We conducted the dynamic GMM regressions and report the estimation results in columns (4)-(6) in Table 7. The results are qualitatively similar to those from fixed-effects models. App Developer Investors are influential mostly for concept apps, and Experienced Investors for live apps. We checked the validity of the moment conditions required by system GMM using the Hansen test for exogeneity of our instruments (Blundell and Bond 1998; Roodman 2009).

5.3. Ex-post Performance and Tests for the Source of an Investor's Influence

Here, we first examine the performance of the Apps after they are funded and if the apps with investments from App Developer Investors and Experienced Investors perform better than the others. We also examine if their ability to select better apps is a source of their influence on the crowd. Our study of Appbackr for mobile apps benefits from the opportunity to measure the quality of listings as revealed by subsequent app sales. To examine ex-post performance, we use the app sales data as of June 2013 from xyo.net. We could obtain cumulative sales data for 376 apps out of 532 apps in our sample. In addition, some apps do not have app- or app developer-characteristics needed for our selection analysis. So our final data consists of 297 apps.

In our data, slightly over 10% of apps have at least one App Developer Investor and around 30% of apps have at least one Experienced Investor. If we compare raw sales numbers across different groups of apps, apps with at least one App Developer Investor, on average, have about 467,000 cumulative downloads, those with at least one Experienced Investor have about 173,000, and the rest without either of these category of investors have 37,000 downloads. This suggests that these investors with experience, especially App Developer Investors, tend to invest in apps that have greater ex-post sales and provide supportive evidence of the ex-post rationality and the credibility of their investments as signals of quality in this market.

It is possible that App Developer Investors and Experienced Investors are good at selecting better performing apps (hereafter, *selection effect*). It is also possible that they invest more efforts such as promoting or marketing an app after they have invested in a particular app that leads to better app performance (hereafter, *outcome effect*). In this section, we attempt to further separate the source of their influence and determine if these investors with experience indeed select better apps in the first place. To disentangle the two sources of effects, we model a selection process of investors and then employ a counterfactual decomposition approach (Liu et al. 2015).

We first explain the counterfactual decomposition approach (Blinder 1973; Oaxaca 1973). Simply stated, we ask: what would an app's sales be if the crowd had instead participated in another app with the same characteristics that an experienced investor-involved app possess, or vice versa? This counterfactual decomposition approach divides the differences in mean sales between apps with and without an App Developer Investor (or Experienced Investor) into two parts: the differences from the selection effect (i.e., the observed differences in characteristics of apps with and without an investor with experience) and the differences from the outcome effect (i.e., the additional causal effects that investors with experience can generate over the crowd from these characteristics). For example, let S^E and S^N be the sales of an app with (E) and without (N) an investor with experience, respectively. The difference in mean sales of the two groups can be decomposed as follows:

$$E(S^E) - E(S^N) = E(X^E)\beta^E - E(X^N)\beta^N$$
$$= \underbrace{[E(X^E) - E(X^N)]\beta^E}_{\text{Expert selection effect}} + \underbrace{[E(X^N)(\beta^E - \beta^N)]}_{\text{Expert outcome effect}} \qquad (5)$$

where X^E and X^N are characteristics of app involving investors with experience versus crowd apps. β^E and β^N are the causal effects that an investors with experience and the crowd can generate on these characteristics, respectively and are measured using the estimates of covariates in our selection models we will discuss soon. The first part in the final decomposition model captures the selection effect and the second part captures the outcome effect. Thus, the selection effect comes from differences in app-specific and developer-specific observable characteristics each group prefers. For example, in our data App Developer Investors and Experienced Investors tend to like concept apps more than the crowd. If concept apps are on average better sold than live apps, by just selecting concept apps more, these investors can have better sales without having any better outcome effect. We want to emphasize that the selection effect we care about in this study is on observable variables while the selection effect on unobservable variables is something to be controlled for by using a two-stage Heckman style selection model. To the best of our knowledge, we are the first in the Information Systems discipline to adopt the counterfactual decomposition approach to differentiate the selection effect on observable characteristics from the outcome effect and quantify the selection effect.

On the other hand, the outcome effect comes from differences in the causal effects of each group. Going back to the example of concept apps, let us suppose that there is no significant difference in preferences toward concept apps between our investors with experience and the crowd (i.e., there is no selection effect.) Yet, App Developer Investors and Experienced Investors may exert more time and effort into concept apps than the crowd, thus generating greater sales, which is an outcome effect on the characteristic, *concept apps*. This implies that to quantify the outcome effect, we need to have a model to capture the differences in the causal effects on each characteristic between our two categories of investors with experience and the crowd. Thus, included in our model are the interaction terms between observable characteristics and participation by investors with experience.

Based on the above discussion, we consider the following model to explain the causal effect of participation of investors with experience on the ex-post app sales:

$$S_i = \delta_0 + \delta_1 \boldsymbol{X}_i + \delta_2 D_i + \delta_3 \boldsymbol{X}_i D_i + e_i \qquad (6)$$

where $\boldsymbol{X}_i$ is a set of exogenous observable characteristics of app i and D_i is a dummy variable that takes the value of 1 if at least an App Developer or Experienced Investors invested in the app and 0 otherwise. As discussed above, we have the interaction terms in the model to reflect the possibility that there are potentially systematic differences in the causal effects of App Developer Investor and Experienced Investors and the crowd on each observable characteristic.[24] This is necessary to measure the outcome effect as well as the selection effect correctly. When we do not have the interaction terms, D_i would just represent the overall effect of the two categories of investors beyond the crowd's effect conditional on a set of observable characteristics.[25]

An investor with experience will consider observable app and app developer characteristics to evaluate whether an app's outcome potential is attractive enough to recoup her investment. Her decision to invest thus makes the sample of apps attracting App Developer Investors and Experienced Investors nonrandom and their decision to participate in an app (i.e.,

[24] We also considered the endogenous switching regression framework for our data. In other words, a selection model is estimated in the first stage, producing a selection correction term for each app in the sample with participation by App Developer or Experienced Investors, and in the sample with apps without the participation of these two groups of investors. These corrections are added to the second stage models estimating the effect of observable characteristics on app sales for each subsample. However, the framework was difficult in this setting because we have relatively few App Developer Investor-participated apps.
[25] We conducted the analyses without the interaction terms and found that the causal effects of investors with experience are positive and significant only for the App developer investors group.

D_i) is potentially endogenous. To correct for the selection process, we assume that these investors' decision to invest in app *i* is determined by

$$D_i^* = \beta Z_i + \mu_i \qquad (7)$$

$$D_i = 1 \ \ if \ D_i^* \geq 0$$

$$D_i = 0 \ \ if \ D_i^* < 0$$

where D_i^* is an unobserved latent variable, Z_i is a set of app and app developer characteristics that affect the decision to invest in, and μ_i is an error term. We only observe whether an app attracts an investment from an App-Developer/Experience Investor or not. These investors invest in an app when D_i^* exceeds zero in our case. Based on Equations (6) and (7), we control for the self-selection of these investors using Heckman style two stage procedure (Heckman 1979). We first estimate Equation (7) using a probit model to get consistent estimates of β denoted by $\hat{\beta}$. These are then used to get estimates of the correction for self-selection, λ_1 and λ_2, where $\lambda_1(\beta Z_i) = \frac{\phi(\beta Z_i)}{\Phi(\beta Z_i)}$ and $\lambda_2(\beta Z_i) = \frac{-\phi(\beta Z_i)}{1-\Phi(\beta Z_i)}$ (Campa and Kedia 2002).[26] In the second step, we estimate δ by using the following model:

$$S_i = \delta_0 + \delta_1 X_i + \delta_2 D_i + \delta_3 X_i D_i + \delta_\lambda[\lambda_1(\beta Z_i) D_i + \lambda_2(\beta Z_i)(1 - D_i)] + \eta_i$$

$$= \delta_0 + \delta_1 X_i + \delta_2 D_i + \delta_3 X_i D_i + \delta_\lambda \lambda + \eta_i \qquad (8)$$

In the selection model of Equation (7), we include a set of observable app and app developer characteristics. We have price, category, developer identity, platform where the app is listed, whether the app was live in store in the funding stage, app age, and app rating for app

[26] $\phi(.)$ and $\Phi(.)$ are the density and cumulative distribution functions of the standard normal, respectively.

characteristics and global rank for app developer characteristics.[27] Table 8 reports results from the selection model in the first stage. As shown in columns (1) and (2), both types of investors (App Developer Investors as well as Experienced Investors) have similar strategies of selecting apps for their investment. They both are more likely to invest in apps (i) for the Apple app store, (ii) in development in the funding stage, and (iii) with better ratings. In column (3) we report results when we consider any type of investor with experience, which show similar findings.

In Table 9 we report the estimated effects of observable characteristics and their interactions with App Developer/Experienced investor involvement using Heckman's two stage selection correction framework. For the sample of apps without their involvement, young apps, apps from top-ranked app developers, and apps with higher rating, are positively associated with ex-post app sales. As for the interactions, we find that the interaction with *Global rank* is negative and significant[28] suggesting that participation by App Developer Investors and Experienced Investors leads to more sales for apps from top ranked app developers than when they are not involved in those apps. App Developer Investors are further able to benefit apps for the Apple app store and those developed by app companies. This implies that App Developer Investors might be more active and effective in providing additional services after investing and thus making these apps more popular. Interestingly, the selection correction terms are positive but not significant, suggesting that the selection bias from unobservables is not a serious concern.

Table 8 and Table 9 show that there are selection and outcome effects. To disentangle the selection effects on observable characteristics from the outcome effects, we now carry out the

[27] For category, we grouped 20 categories into four broad categories- Entertainment, Life & Health, Games, and Business & Utilities. Xyo reports *Global rank*, which represents the performance of app developers in terms of their recent sales. Lower *Global rank* means a better app developer in recent sales.
[28] When we log transform *Global rank*, our main findings are qualitatively the same.

counterfactual decomposition approach in Equation (5) (Blinder 1973; Oaxaca 1973). To measure β^E and β^N, we use the estimates of covariates in Equation (8). The decompositions of the difference in ex-post app sales are presented in Table 10 . As discussed above, the estimated total differences in ln(sales) are positive, suggesting that the sales is higher for apps with App-Developer/Experienced Investors than for those without. In addition, both the selection and outcome effects are positive. The contribution of the selection effect to the total differences is about 60% in column 3 where we consider either App Developer Investors or Experienced Investors, implying that the selection effect takes a significant share of the total differences. This provides supporting evidence that App Developer Investors and Experienced Investors are indeed good at selecting quality apps with observable app and app developer characteristics.

6. CONCLUSION

Given the lack of traditional quality assurance mechanisms in online markets, researchers have highlighted the need for more studies to examine how the crowd makes investment choices in crowdfunding markets. Our study in answering this call, finds that despite lacking the sophistication of traditional experts, the crowd is not only able to leverage the information contained in early investments by investors with experience, but also identify and exploit nuanced differences between the signals provided by different types and degrees of experience within the same market. Our study also sheds light on an important role played by investors with experience in crowdfunding markets. Unlike a traditional market where experts tend to be those with established reputation and prominent highly-visible signals of their expertise, the “experts” in our market - App Developer Investors and Experienced Investors - do not have established reputations within this platform. Yet, we find that investors with such experience, although constituting a small fraction of the market, have a disproportional effect on the investment behaviors of the crowd. Our findings suggest that encouraging such investors with experience to participate in these online crowdfunding markets can make these markets more efficient.

Our study, in examining the role of experience as a credible signal of quality, also highlights some of the conditions under which signals are more or less effective. Variables such as education or employment in a reputed firm that serve to signal an expert in traditional contexts tend to be gross compared to the underlying experience or specialization they signal. Our focus on experience rather than established reputation stemming from third-party signals, helps us examine the effectiveness of these signals at a more granular level. We find that despite the limited depth of experience for App Developer Investors as well as Experienced Investors in this market, the visibility of their experience within the platform significantly impacts the influence their actions (investments) have on the crowd. Our findings highlight the importance of the specificity and alignment of these signals with the nature of the investments. Investors with prior experience that is in the same category as the focal investment are more influential and investors whose experience credibly aligns with the informational needs of the later investors are more influential. Our findings are consistent with prior theoretical work relating to the management of risks faced by investors in new ventures. The effectiveness of signals provided by App Developer Investors in the case of concept apps where product/technology is the dominant focus, and the effectiveness of signals provided by Experienced Investors in the case of live apps where market factors are the dominant focus, highlight the importance of alignment between the dominant informational needs and the nature of the signal.

As for policy implications, our findings indicate that the crowdfunding market works in a largely rational manner. This is particularly impressive since investors in the crowdfunding market are arguably less sophisticated. Crowdfunding investors in our platform are attentive to credible sources of quality and discern the more credible signals by identifying the nuances in the experiences of early investors. Thus, as long as the crowdfunding market provides a sufficient amount of information about investors and their investments, potential risks in crowdfunding markets of concern to regulators could be significantly mitigated.

Our study also has implications for the design on online crowdfunding markets. While it is feasible for a potential investor to obtain information on early investors and their investments, our findings suggest that identifying and highlighting informative signals in the market can be very beneficial for these markets and its participants, particularly in their nascent stages. Careful design of online crowdfunding markets that enables greater digital visibility of more muted and subtle, but nonetheless specific and credible informational cues, would benefit the crowd. Our findings further highlight the value in making granular information such as the depth and specificity of an investor's experience easily accessible to potential investors.

Our findings also have important implications for the design of nascent equity crowdfunding markets. Some emerging equity-based online crowd-funding markets have proposed a tiered system that seek to create separate markets for sophisticated investors (such as venture capitalists, angel investors, and other investment experts) and for the less-sophisticated investors (i.e., the crowd). Our findings suggest that there are significant positive information externalities from individuals with experience that benefit the crowd as well as the start-up ventures, and providing greater visibility about individual investors' actions and their identities could lead to more efficient markets. However, it would also be important for regulators to pay attention to the potential for misuse in the longer run. Future studies could examine the evolutionary dynamics of these markets.

Our research is not without limitations. It is important to highlight that our research context has its idiosyncrasies. First, the investments sought for the apps in this market are smaller compared to other crowdfunded projects and therefore the risks faced by investors in this market might be relatively low. Further, the two types of experienced investors form a small percentage of all investors. Therefore, the influence of experienced investors and experts might vary quantitatively in other crowdfunding markets. It is also possible that experienced investors could use offline channels to influence some investors to invest in the app. In such cases, these subsequent investments could be driven by word of mouth rather than purely by the visibility of the early investors' experience. Future research can examine the role of offline friendships and influence, and their impact on outcomes in online crowdfunding platforms. In keeping with a large body of empirical studies of quality signals, our study draws upon the theory of revealed preferences (Samuelson, 1948), which enables us to infer the value of quality signals in this marketplace. However, it would be useful to complement this with surveys and interviews as well as analyses of detailed browsing behaviors of participants in these markets to better understand how various informational signals are incorporated into the decision making behaviors of market participants.

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Table 1: Summary Statistics for Listings

Variable	All		Concept		Live	
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**
Listing attributes						
Price	3.64	26.28	5.30	40.43	2.45	3.86
Max. Amount	18,895	34,500	23,453	38,279	15,549	31,095
Reserve	3,980	11,120	4,501	10,028	3,606	11,845
Apple (1=yes)	0.77	0.42	0.79	0.41	0.76	0.43
Company (1=yes)	0.62		0.67		0.58	
Concept (1=yes)	0.42					
Funding Outcome						
Amount funded	1,892	6,865	2,795	7,048	1,245	6,667
Number of investors	6.15	13.65	10.20	19.14	3.26	6.17
Fully funded (1=yes)	0.46		0.50		0.44	
Number of observations	532		222		310	

Table 2: Investment Behavior by Investor Type

Variable	App Developer Investors		Experienced investors		Crowd	
	Mean	**No. obs**	**Mean**	**No. obs**	**Mean**	**No. obs**
Investment intensity						
Cumulative amount of investments	330.13	67	14,641.82	17	209.76	1,030
Cumulative number of investments	2.52	67	22.24	17	1.82	1,030
Investment concentration						
Investment concentration	0.83	28	0.44	17	0.84	318
Investment timing						
Days to investment	18.89	168	21.28	213	24.51	3,120
Days to investment (Concept)	17.42	114	21.55	146	24.92	2,038
Days to investment (Live)	21.98	54	20.69	67	23.97	1,066

Note: The investment concentration is equal to $\sum_{k=1}^{20}(\frac{investment\ at\ cate\ k}{total\ investment})^2$. For this measure, we drop investors with only one investment, since they have the investment concentration of 1 mechanically.

Table 3: Investment Timing and Investor Type

	Logit	Logit	Logit	Logit	Logit	OLS with Investor RE
	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	All	concept	Live	All
App Developer Investors	0.279***	0.312**	0.381***	0.536***	-0.237	0.016***
	(0.102)	(0.119)	(0.098)	(0.105)	(0.207)	(0.005)
Experienced Investors	0.399***	0.534***	0.566***	0.656***	0.384**	0.027***
	(0.101)	(0.109)	(0.082)	(0.121)	(0.185)	(0.005)
Ln(Price)		-0.028	-0.050	-0.025	-0.325**	-0.001
		(0.029)	(0.037)	(0.037)	(0.141)	(0.002)
Ln(Reserve)		0.052***	-0.015	0.003	-0.183***	0.001
		(0.013)	(0.016)	(0.026)	(0.039)	(0.001)
Ln(Maximum funding)		-0.197***	-0.176***	-0.342***	0.046	-0.010***
		(0.026)	(0.033)	(0.053)	(0.061)	(0.002)
Apple		-0.165**	-0.147	-0.471***	0.806***	-0.003
		(0.069)	(0.098)	(0.123)	(0.290)	(0.004)
Company		0.126*	0.353***	0.099	0.182	0.013***
		(0.073)	(0.083)	(0.133)	(0.188)	(0.004)
Concept		0.046	0.059			0.002
		(0.077)	(0.096)			(0.005)
Category fixed effects	No	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes	Yes	Yes
Pseudo R2	0.1499	0.1638	0.1847	0.2015	0.2219	
N	50999	49814	49814	36587	12724	49942

Note: The table reports discrete-time models of investments. Standard errors are clustered by investors. *App Developer Investors* (*Experienced Investors*) are a binary variable equals to 1 if an investor is an App Developer Investors (or an Experienced Investor) and 0 if otherwise. We also include 100 dummies for the first 100 days after the listing of a project to have a flexible baseline hazard rate. *** significant at 1%; ** significant at 5%; * significant at 10%

Table 4: Influence of Investors with Experience on the Crowd

	All subsequent investors			Only the subsequent crowd		
DV: Ln (Amt of backing in day t)	All	Concept	Live	All	Concept	Live
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Overall experience of App Developer Investors)	0.184***	0.208***	0.129**	0.151***	0.180***	0.059
	(0.056)	(0.063)	(0.051)	(0.054)	(0.060)	(0.054)
Ln (Overall experience of Experienced Investors)	0.050**	0.065	0.092***	0.024	0.037	0.054*
	(0.025)	(0.042)	(0.031)	(0.022)	(0.041)	(0.028)
Cumulative amount/1000	-0.004	-0.016	-0.022	0.019	0.006	-0.021
	(0.026)	(0.028)	(0.045)	(0.020)	(0.024)	(0.044)
Cumulative num. of specific investments	-0.002	-0.000	-0.047**	-0.004	-0.002	-0.042**
	(0.005)	(0.004)	(0.020)	(0.005)	(0.004)	(0.018)
Percentage needed	0.006**	0.011*	0.000	0.003	0.004	-0.002
	(0.003)	(0.006)	(0.003)	(0.002)	(0.005)	(0.003)
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.1554	0.1761	0.1306	0.1402	0.1655	0.1062
N	10438	4994	5444	10438	4994	5444

Note: The table reports app-fixed effects regressions. Standard errors are clustered by apps. The influence is calculated as the sum of cumulative amounts of investments in prior projects made by reputable investors in a listing. *** significant at 1%; ** significant at 5%; * significant at 10%

Table 5: Source of Influence of Investors with Experience on the Crowd

DV: Ln (Amt of backing by the crowd in day t)	**Concept**	**Live**	**Concept**	**live**	**Concept**	**Live**	**Concept**	**live**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Ln (Overall experience of App Developer Investors with successfully funded apps)	0.160**	0.184*						
	(0.078)	(0.109)						
Ln (Overall experience of App Developer Investors without successfully funded apps)	-0.031	0.017	-0.102	-0.001				
	(0.066)	(0.048)	(0.077)	(0.051)				
Ln (Overall experience of App Developer Investors with successfully funded apps in the same category)			0.227*	0.204				
			(0.123)	(0.124)				
Ln (Overall experience of App Developer Investors with successfully funded apps in the different categories)			0.100	-0.001				
			(0.089)	(0.077)				
Ln (Overall experience of App Developer Investors with listed apps when investing)					0.160**	0.107		
					(0.070)	(0.070)		
Ln (Overall experience of App Developer Investors without listed apps when investing)					-0.130	-0.040		
					(0.088)	(0.028)		
Ln (Overall experience of App Developer Investors)							0.136**	0.055
							(0.066)	(0.056)
Ln (Overall experience of Experienced Investors)	0.046	0.054*	0.070	0.053*	0.050	0.049*		
	(0.043)	(0.028)	(0.050)	(0.028)	(0.044)	(0.028)		
Ln (Overall experience of Experienced Investors in successfully funded apps)							0.104**	0.068***
							(0.052)	(0.026)
Ln (Overall experience of Experienced Investors in non-successfully funded apps)							0.109	0.024
							(0.120)	(0.055)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.1636	0.1072	0.1670	0.1064	0.1640	0.1074	0.1710	0.1065
N	4994	5444	4994	5444	4994	5444	4994	5444

Note: The table reports app-fixed effects regressions. Standard errors are clustered by apps. The influence is calculated as the sum of cumulative amounts of investments in prior projects made by reputable investors in a listing. In columns (1)-(2) we split the influence of App Developer Investors into two groups in terms of whether App Developer Investors have their own successfully-funded apps. In columns (3)-(4) we further split the influence of App Developer Investors with their own successfully funded apps into two groups in terms of whether App Developer Investors have their own successfully funded apps in the category where they invest in. In columns (5)-(6) we split the influence of App Developer Investors into two groups in terms of whether App Developer Investors have their own listed apps when investing. In columns (7)-(8) we split the influence of Experienced Investors into two groups in terms of whether Experienced Investors made an investment in a successfully funded apps. *** significant at 1%; ** significant at 5%; * significant at 10%

Table 6: Different Measures of the Experience

	Overall experience - the number of investors with experience		Overall experience - the number of investors with experience weighted by their cumulative number of prior investments		Overall experience - the number of investors with experience weighted by their cumulative amount of ex-post successful prior investments		Overall experience - the number of investors with experience weighted by their cumulative number of ex-post successful prior investments	
DV: Ln (Amt of backing by the crowd in day t)	**Concept**	**Live**	**Concept**	**Live**	**Concept**	**Live**	**Concept**	**Live**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Ln(Overall experience of App Developer Investors)	0.251***	0.125	0.300*	0.126	0.389***	0.117	1.088***	0.195
	(0.088)	(0.089)	(0.169)	(0.192)	(0.119)	(0.104)	(0.111)	(0.314)
Ln (Overall experience of Experienced Investors)	0.070	0.303**	0.227*	0.180**	-0.014	0.053**	-0.087	0.193***
	(0.062)	(0.117)	(0.122)	(0.088)	(0.034)	(0.025)	(0.076)	(0.068)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4994	5444	4994	5444	4994	5444	4994	5444

Note: The table reports app-fixed effects regressions. Standard errors are clustered by apps.
*** significant at 1%; ** significant at 5%; * significant at 10%

Table 7: Addressing Endogneity Concern

	Rho-Differencing			Dynamic GMM		
DV: Ln (Amt of backing by the crowd in day t)	**All**	**Concept**	**Live**	**All**	**Concept**	**Live**
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (Overall experience of App Developer Investors)	0.157***	0.191***	0.056	1.531*	1.736*	-0.476
	(0.055)	(0.061)	(0.053)	(0.911)	(0.953)	(1.882)
Ln (Overall experience of Experienced Investors)	0.027	0.046	0.052*	0.186	0.070	0.780*
	(0.023)	(0.043)	(0.028)	(0.300)	(0.325)	(0.436)
Cumulative amount/1000	0.017	0.002	-0.016	-0.374*	-0.129	-0.437
	(0.020)	(0.025)	(0.041)	(0.223)	(0.131)	(0.297)
Cumulative num. of specific investments	-0.004	-0.003	-0.041**	0.135**	0.085**	0.217*
	(0.005)	(0.004)	(0.018)	(0.053)	(0.033)	(0.126)
Percentage needed	0.004	0.005	-0.002	0.007	0.016***	0.005
	(0.002)	(0.005)	(0.003)	(0.005)	(0.006)	(0.006)
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	10437	4994	5443	9730	4814	4916

Note: The table reports app-fixed effect regressions. Standard errors are clustered by apps. The influence is calculated as the sum of cumulative amounts of investments in prior projects made by reputable investors. For columns (1)-(3) we first rho-difference our models and again conduct app-fixed effect regressions using the rho-differenced variables. *** significant at 1%; ** significant at 5%; * significant at 10%

Table 8: Selection Model (Probit Model)

DV: a dummy for whether an expert invested in a focal app	App Developer Investor	Experienced Investor	Either
	(1)	(2)	(3)
Ln(Price)	0.144	0.096	0.078
	(0.123)	(0.111)	(0.110)
Apple	1.102***	0.810***	0.857***
	(0.356)	(0.235)	(0.234)
Company	0.280	0.127	0.178
	(0.233)	(0.180)	(0.180)
Concept	0.533**	0.967***	1.000***
	(0.267)	(0.222)	(0.224)
App age	-0.002	-0.004*	-0.004
	(0.003)	(0.002)	(0.002)
Global Rank	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
App rating	0.009***	0.007***	0.007***
	(0.003)	(0.003)	(0.003)
Entertainment	0.069	0.131	0.233
	(0.317)	(0.243)	(0.241)
Life & Health	0.211	0.035	0.056
	(0.420)	(0.361)	(0.363)
Games	-0.183	-0.003	0.006
	(0.294)	(0.212)	(0.213)
Log likelihood	-85.56	-156.28	-156.57
N	299	299	299

Note: The table reports Probit regressions at an app level. *** significant at 1%; ** significant at 5%; * significant at 10%

Table 9: Results with Interactions While Accounting for Selection

DV: Ln(Cumulative Num of App Downloads)	App Developer Investor	Experienced Investor	Either
	(1)	(2)	(3)
Ln(Price)	-0.193	-0.202	-0.195
	(0.138)	(0.165)	(0.151)
Apple	-0.052	0.667	0.483
	(0.447)	(0.942)	(0.927)
Company	0.304	0.446*	0.414
	(0.226)	(0.261)	(0.283)
Concept	0.322	1.779	1.244
	(0.405)	(1.563)	(1.485)
App age	0.007**	0.003	0.004
	(0.003)	(0.006)	(0.005)
Global Rank	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
App rating	0.023***	0.030***	0.028***
	(0.004)	(0.009)	(0.009)
Entertainment	0.500*	0.659*	0.716*
	(0.270)	(0.351)	(0.395)
Life & Health	0.090	0.285	0.283
	(0.386)	(0.356)	(0.360)
Games	0.019	0.022	0.044
	(0.209)	(0.233)	(0.230)
exp.	-7.741	-4.667	-3.933

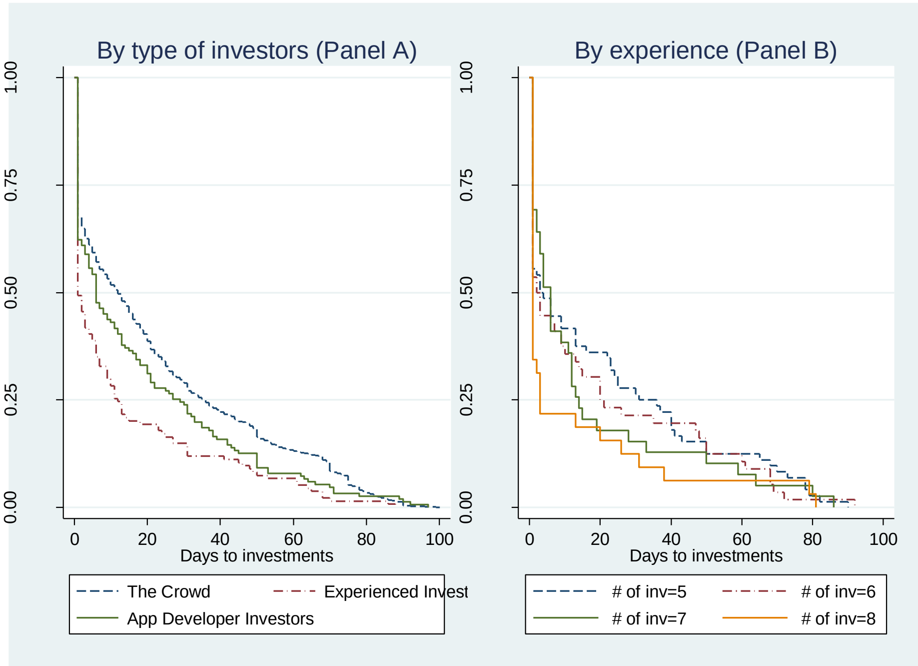
	(5.111)	(5.510)	(5.139)
Ln(Price) * exp.	0.092	0.341	0.206
	(0.249)	(0.234)	(0.231)
Apple * exp.	4.079***	0.421	0.389
	(1.472)	(0.965)	(0.920)
Company * exp.	1.765***	0.169	0.307
	(0.666)	(0.413)	(0.420)
Concept * exp.	1.124	-0.142	0.217
	(0.804)	(0.669)	(0.620)
App age * exp.	0.008	-0.001	0.004
	(0.009)	(0.007)	(0.006)
Global Rank * exp.	-0.000**	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)
App rating * exp.	0.017	0.006	0.005
	(0.012)	(0.007)	(0.006)
Entertainment * exp.	-0.776	-0.598	-0.542
	(0.950)	(0.630)	(0.645)
Life & Health * exp.	-0.652	-1.296	-1.263
	(0.774)	(1.186)	(1.181)
Games * exp.	-0.771	-0.153	-0.080
	(0.671)	(0.539)	(0.544)
Lambda(exp.)	1.272	2.830	2.222
	(1.756)	(2.830)	(2.594)
Adjusted R2	0.3971	0.3611	0.3703
N	297	297	297

Note: The table reports OLS regressions at an app level using a Heckman-style selection correction. Exp. is a dummy variable which is equal to 1 if an app has at least one investor with experience and 0 otherwise. *** significant at 1%; ** significant at 5%; * significant at 10%

Table 10: Decomposition with Selection Corrections

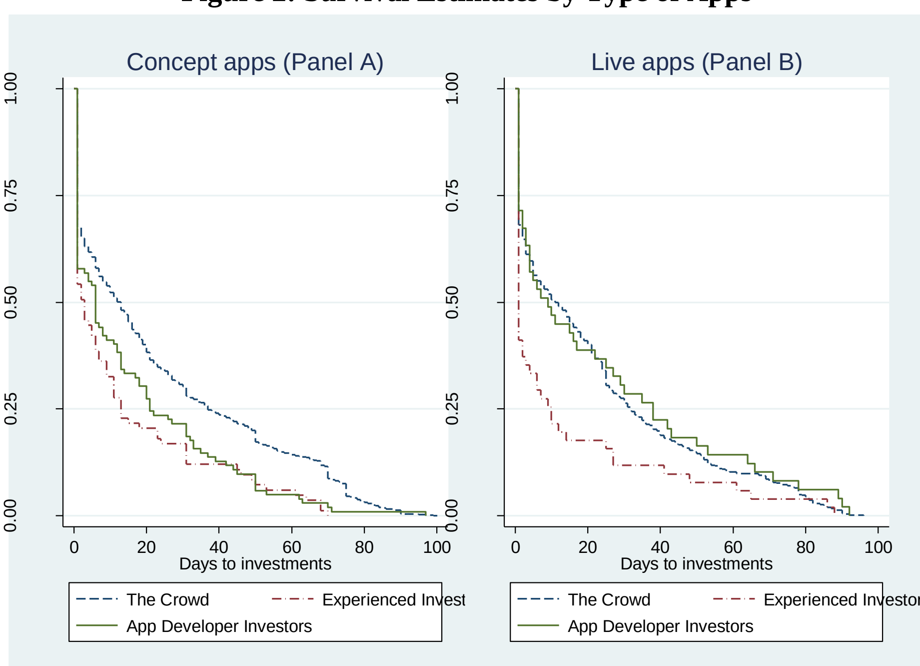
	Ln(Cumulative Num of App Downloads)		
	App Developer Investor	**Experienced Investor**	**Either**
Effect sources	**(1)**	**(2)**	**(3)**
Total effect	6.752	1.168	1.479
Selection effect	2.142	0.954	0.889
Outcome effect	4.610	0.214	0.590

Figure 1: Survival Estimates by Type of Investors and by Experience



Note: The x axis represents the number of days since an app is listed. The y axis represents the cumulative proportion of investors who have not adopted. Y value is one at the start of the first day since no one has made any investment yet.

Figure 2: Survival Estimates by Type of Apps



Note: The x axis represents the number of days since an app is listed. The y axis represents the cumulative proportion of investors who have not adopted.

The “Experts” in the Crowd: The Role of Experienced Investors in a Crowdfunding Market

Appendix

1. Additional Robustness Tests

In this section, we provide additional robustness checks to establish the validity of the results presented in the paper. These include the use of fixed effects Poisson models, the examination of social network effects as a confounding factor, the examination of source of influence of experienced investors, the use of different cutoff values for experienced investors, the potential for collusion, the inclusion of apps only up to Dec 2012, the log-transformation of two herding-related control variables, and the assessment of product- and market-related risk using text mining. In each case, we show that our central relationships of interest are robust.

1.1 Fixed effects Poisson

Since the daily amount that a listing receives cannot be negative and not all listings get funded on a given day, we also estimate a fixed effects Poisson model to examine the effect of investors with experience on subsequent investors. We assume that the daily amount of funding (in dollars) in each listing can be drawn from a different Poisson distribution. As shown in Table A1, we find that our main findings are qualitatively similar. We note that we could not include time fixed effects in columns 2 and 3, because including them does not lead to converged results.

Table A1: Fixed Effects Poisson Models

DV: Amt of backing in day t	**All**	**Concept**	**Live**
	(1)	(2)	(3)
Ln(Overall experience of App Developer Investors)	0.732***	1.136**	0.259*
	(0.247)	(0.455)	(0.135)
Ln(Overall experience of Experienced Investors)	0.093	0.155	0.183*
	(0.086)	(0.134)	(0.096)
Controls	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	No	No
N	9688	4819	5379

Note: The table reports app-fixed effects regressions. Standard errors are clustered by apps. The influence is calculated as the sum of cumulative amounts of investments in prior projects made by investors with experience in a listing. *** significant at 1%; ** significant at 5%; * significant at 10%

1.2 Social network effect as a confounding factor

One could argue that the experienced investors, being active on the platform, also send a lot of referrals to invite subsequent investors to invest in that app. In that case, the subsequent investment may be driven by word of mouth, rather than signaling. We first note that there is no network of investors visible on the platform. Thus, it is little likely that an investor will invite her friends made within the platform. Still, it is possible to invite friends from her other social networks such as Facebook friendship network. To examine this we gather data on investors' social network. The data show that investors with experience do not have a significantly larger social network than the crowd. If any, the crowd has a larger social network than the investors with experience. The group mean-comparison tests between the crowd and either group for either Facebook or Twitter show that p-values are all greater than .5 (see Table A2). The results are based on a set of 243 investors (out of over 1,000 distinct investors) whose friendship network on either Facebook or Twitter is revealed publicly. Out of 243 investors, 40 investors are App Developer Investors and 7 investors are Experienced Investors.

In addition, our nuanced findings imply that this omitted variable will not drive our findings. For example, our falsification test suggests that App Developer Investors are influential mainly when their ownership of apps is publicly shared within the platform so visible to potential investors on the platform. If the friendship network of investors with experience drive our findings, we should not have this nuanced finding, because the social network effect should be similar regardless of this information. Overall, we believe that this should not be a serious concern in our paper based on our additional analysis as well as the original set of analyses.

Table A2: Social Networks of Investors by Groups

		App Developer Investor	Experienced Investor	The Crowd
Twitter followers	Mean	4781	1120	61594
	p-value for group mean-comparison test with the crowd	0.553	0.778	
	Median	499	488	281
Facebook friends	Mean	555	174	906
	p-value for group mean-comparison test with the crowd	0.627	0.639	
	Median	392	114	364

1.3 Source of influence of Investors with experience

We conduct an additional test to verify if the influence of investors with experience comes mainly from their activities within the platform, rather than from their activities outside the platform (e.g., their education background and experience). Some investors with experience in our sample make their relevant outside experiences or credentials available online. If potential investors access such information, those investors could be more influential than those not releasing it. To examine this possibility, we first identified who among our investors with experience disclosed their outside activities based on various external sources including LinkedIn. For App Developer Investors, we then created a dummy for whether an App Developer Investor is reported to be an app/software developer or representing an app development firm. It is likely that those investors are more influential if their outside profile information is accessible. Finally, we generated and added a variable to represent the number of those App Developer Investors at a particular day for each project. If investors care primarily about outside expertise of these investors but dismiss their experiences accumulated within the platform, we should expect that our main overall experience variables become insignificant with the addition of this new variable. Similarly, for Experienced Investors we generated and added a variable to capture the number of Experienced Investors with relevant and significant outside experiences disclosed. As shown in Table A3, the coefficients for the new variables are not significant. More interestingly, our main quality signals based on the activities within the platform are still significant and influential in our context.

Table A3: Controlling for the relevant outside experience of Investors

DV: Ln (Amt of backing in day t)	**Concept**	**Live**	**Concept**	**Live**
	(1)	(2)	(3)	(4)
Ln(Overall experience of App Developer Investors)	0.202***	0.059	0.183***	0.053
	(0.065)	(0.054)	(0.064)	(0.054)
Ln(Number of App Developer Investors with relevant outside experiences disclosed)	-0.296	0.020		
	(0.422)	(0.368)		
Ln(Overall experience of Experienced Investors)	0.033	0.054*	0.036	0.061**
	(0.043)	(0.029)	(0.042)	(0.030)
Ln(Number of Experienced Investors with relevant outside experiences disclosed)			0.143	-0.454
			(0.476)	(0.351)
Controls	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	4994	5444	4994	5444

Note: The table reports app-fixed effects regressions. Standard errors are clustered by apps. The influence is calculated as the sum of cumulative amounts of investments in prior projects made by reputable investors in a listing. *** significant at 1%; ** significant at 5%; * significant at 10%

1.4 Different cutoff values to define Experienced Investors

Based on our main criteria, Experienced Investors invest more than $2000 and had at least 5 investments. We report our results with different cutoff values in Table A4. As shown in the table, robust is our main finding that App Developer Investors are more crucial in concept apps, while Experienced Investors in live apps. The table also suggests that Experienced Investors with more experience are more influential. When we define Experienced Investors most strictly like in columns 3-4 and 7-8, the effects of Experienced Investors are strongest in magnitude, while with the least strict definition in columns 5-6, the effect becomes smaller in statistical significance and magnitude.

Table A4: Different Definition of Experienced Investors

	$2,000 with 4 invs		**$2,000 with 7 invs.**		**$1,500 with 5 invs.**		**$2,500 with 5 invs.**	
DV: Ln (Amt of backing in day t)	**Concept**	**Live**	**Concept**	**Live**	**Concept**	**Live**	**Concept**	**Live**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Overall experience of App Developer Investors)	0.138**	0.059	0.140**	0.056	0.142**	0.066	0.140**	0.056
	(0.065)	(0.054)	(0.065)	(0.053)	(0.065)	(0.057)	(0.063)	(0.053)
Ln (Overall experience of Experienced Investors)	0.097*	0.054*	0.100**	0.059*	0.094*	0.041	0.100**	0.059*
	(0.050)	(0.028)	(0.050)	(0.031)	(0.048)	(0.028)	(0.045)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4994	5444	4994	5444	4994	5444	4994	5444

Note: The table reports app-fixed effects regressions. Standard errors are clustered by apps. The influence is calculated as the sum of cumulative amounts of investments in prior projects made by reputable investors in a listing. *** significant at 1%; ** significant at 5%; * significant at 10%

1.5 Apps only up to Dec 2012

For apps which ended their funding cycle close to July 2013, the sales data may not be credible. An app, which has been in the market for a shorter time, will have fewer sales. To dampen this concern, we conducted the same set of analyses only with apps listed up to Dec. 2012. As you see in Table A4 and A5, all the significances in both the first and the second stages are almost the same.

Table A5: Selection model only with listed apps up to Dec 2012

DV: a dummy for whether an investor with experience invested in a focal app	**App Developer Investor**	**Experienced Investor**	**Either**
	(1)	**(2)**	**(3)**
Ln(Price)	0.141	0.088	0.070
	(0.123)	(0.110)	(0.110)
Apple	1.116***	0.837***	0.884***
	(0.358)	(0.236)	(0.235)
Company	0.276	0.123	0.176
	(0.236)	(0.182)	(0.182)
Concept	0.514*	0.942***	0.975***
	(0.268)	(0.223)	(0.225)
App age	-0.002	-0.004*	-0.004*
	(0.003)	(0.003)	(0.002)
Global Rank	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
App rating	0.009***	0.007***	0.007***
	(0.003)	(0.003)	(0.003)
Entertainment	0.065	0.129	0.231
	(0.318)	(0.245)	(0.243)
Life & Health	0.194	0.011	0.032
	(0.421)	(0.363)	(0.364)
Games	-0.183	-0.011	-0.001
	(0.294)	(0.213)	(0.213)
Log likelihood	-85.56	-156.28	-156.57
N	294	294	294

Note: The table reports Probit regressions at an app level. *** significant at 1%; ** significant at 5%; * significant at 10%

Table A6: Sales outcomes only with listed apps up to Dec 2012

DV: Ln(Cumulative Num of App Downloads)	**App Developer Investor**	**Experienced Investor**	**Either**
	(1)	**(2)**	**(3)**
Ln(Price)	-0.175	-0.187	-0.184
	(0.136)	(0.158)	(0.146)
Apple	0.051	0.914	0.696
	(0.453)	(0.962)	(0.948)
Company	0.275	0.405	0.382
	(0.230)	(0.263)	(0.421)
Concept	0.351	1.981	1.412
	(0.402)	(1.498)	(1.423)
App age	0.006**	0.001	0.002
	(0.003)	(0.006)	(0.005)
Global Rank/1000	-0.008***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)
App rating	0.024***	0.033***	0.030***
	(0.004)	(0.009)	(0.009)
Entertainment	0.468*	0.638*	0.709*

	(0.273)	(0.354)	(0.395)
Life & Health	0.054	0.204	0.209
	(0.385)	(0.347)	(0.351)
Games	-0.021	-0.022	0.004
	(0.211)	(0.236)	(0.233)
Exp.	-8.703	-5.645	-4.753
	(5.084)	(5.371)	(5.020)
Ln(Price)*Exp.	0.100	0.337	0.200
	(0.249)	(0.233)	(0.230)
Apple*Exp.	4.270***	0.481	0.429
	(1.479)	(0.959)	(0.914)
Company*Exp.	1.854***	0.237	0.382
	(0.664)	(0.415)	(0.421)
Concept*Exp.	1.203	-0.121	0.232
	(0.793)	(0.662)	(0.615)
App age*Exp.	0.009	-0.001	0.004
	(0.009)	(0.007)	(0.006)
Global Rank/1000*Exp.	-0.016**	-0.006*	-0.007**
	(0.007)	(0.003)	(0.003)
App rating*Exp.	0.018	0.006	0.005
	(0.012)	(0.007)	(0.006)
Entertainment*Exp.	-0.727	-0.551	-0.487
	(0.951)	(0.633)	(0.647)
Life & Health*Exp.	-0.580	-1.280	-1.239
	(0.766)	(1.185)	(1.180)
Games*Exp.	-0.776	-0.124	-0.048
	(0.671)	(0.539)	(0.544)
Lambda(Exp.)	1.586	3.296	2.596
	(1.750)	(2.766)	(2.540)
Adjusted R2	0.402	0.365	0.375
N	291	291	291

Note: The table reports OLS regressions at an app level using a Heckman-style selection correction. Exp. is a dummy variable which is equal to 1 if an app has at least one investor with experience and 0 otherwise. *** significant at 1%; ** significant at 5%; * significant at 10%

1.6 Two herding-related control variables log-transformed

The control variables for herding, "cumulative amount / 1000" and "cumulative number of specific investments", are not log transformed, while the key independent variables are log transformed. As a robustness check, we also log transform the two control variables for herding. Table A6 shows that our main findings are qualitatively the same.

Table A7: Influence of Investors with Experience on the Crowd with two herding-related control variables log-transformed

	All subsequent investors			**Only the subsequent crowd**		
DV: Ln (Amt of backing in day t)	**All**	**Concept**	**Live**	**All**	**Concept**	**Live**
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Overall experience of App Developer Investors)	0.167***	0.192***	0.098**	0.140***	0.171**	0.030
	(0.053)	(0.071)	(0.049)	(0.053)	(0.068)	(0.053)
Ln(Overall experience of Experienced Investors)	0.080***	0.097*	0.093***	0.042*	0.057	0.051*
	(0.027)	(0.051)	(0.033)	(0.024)	(0.046)	(0.030)
Ln(Cumulative amount/1000)	-0.381***	-0.517***	-0.244**	-0.308***	-0.396***	-0.189**
	(0.093)	(0.162)	(0.102)	(0.084)	(0.147)	(0.089)
Ln(Cumulative num. of specific investments)	0.128	0.177	-0.027	0.151*	0.153	-0.017
	(0.094)	(0.121)	(0.101)	(0.081)	(0.110)	(0.085)
Percentage needed	-0.000	0.001	-0.001	-0.002	-0.004	-0.002
	(0.003)	(0.001)	(0.003)	(0.003)	(0.006)	(0.003)
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.042	0.068	0.019	0.032	0.058	0.010
N	10438	4994	5444	10438	4994	5444

Note: The table reports app-fixed effects regressions. Standard errors are clustered by apps. The influence is calculated as the sum of cumulative amounts of investments in prior projects made by reputable investors in a listing. *** significant at 1%; ** significant at 5%; * significant at 10%

1.7 Assessment of Product- and Market-related Risk Using Text Mining

We performed a text mining analysis of the textual descriptions of all the listings to see what terms dominate the descriptions of concepts apps and live apps. We first extracted all the textual descriptions under the two sections, "Why should you back this app" and "What will the money be used for". We collected the descriptions of 181 concept apps and 171 live apps for the main analysis. After performing the typical text pre-processing including stemming and removal of stop words, we find that development-related words dominate the description of concept apps. A normalized comparison of the terms for Live Apps indicates that marketing related terms dominate the description of Live Apps.

Table A8 shows the top 20 words in terms of the cumulative number of mentions of words in the entire set of texts.

Table A8: Term Frequency of the Top 20 Most Popular Words by Type of Apps

	Concept		Live	
Rank	Words	Frequency	Words	Frequency
1	Game	269	Game	159
2	Develop	228	Develop	115
3	Marketing	166	Marketing	112
4	Design	103	Feature	77
5	Version	77	Version	73
6	Application	74	Market	49
7	Website	72	Update	48
8	Store	67	Create	43
9	Market	55	Improve	41
10	Success	55	Store	41
11	Feature	53	Advertise	40
12	Social	52	Promote	39
13	Android	51	Android	35
14	Release	48	Add	33
15	Create	47	Free	33
16	Advertise	46	Ipad	33
17	Promote	44	Review	32
18	Video	40	Potential	31
19	First	38	Support	30
20	Add	36	Iphone	29

For a deeper analysis, we chose three key product development-related words (i.e., Develop, Design, and Create) and three marketing-related words (i.e., Marketing, Promotion, and Advertise), and reported in Table A9 their frequency of usage. Overall, we observe that the product development-related words are used much more frequently in concept apps but marketing-related words are used slightly more frequently in live apps. This further implies that concept apps have more of a product-related focus, while live apps have more marketing and demand-related focus. In Table A10, we further show how many apps have at least one product development- or marketing-related words and find a qualitatively similar pattern.

Table A9: Term Frequency of Key Product Development and Marketing-related Words by Type of Apps

Product development			Marketing		
	Concept	Live		Concept	Live
Develop	228	115	Marketing	166	112
Design	103	13	Promote	44	39
Create	47	43	Advertise	46	40
All	378	171	All	256	191
Average per app	2.088	1.000	Average per app	1.414	1.117

Table A10: Use of Key Product Development and Marketing-related Words of Apps by Type of Apps

Product development			Marketing		
	Concept	Live		Concept	Live
Develop	114	84	Marketing	102	81
Design	53	10	Promote	35	26
Create	34	33	Advertise	33	25
At least one	136	101	At least one	127	104
% of apps	75.1	59.1	% of apps	70.2	60.8

We have further used word pairs to better capture the nature of product development. We found that for concept apps, words indicating the development of new products are used frequently. These include ‘application development’, ‘finish development’, and ‘create product’. In contrast, for live apps, words relating to development refer to updates to exisiting products. These include ‘add features’, ‘continue develop’, ‘add new’, ‘develop update’, ‘improve game’, and ‘further update’. We further note that ‘update’, ‘add’, and ‘improve’ are rarely used in concept apps as shown in Table A8.

2. Campaign and Investor pages

Figure A1 shows a snapshot of a crowdfunding campaign page. As shown in Figure A1, investors can obtain several campaign-specific characteristics such as price, category, and platform. Moreover, the list of current investors is also very public to potential investors. Clicking on the 'View All' button, provides information on the list of 80 backers. Clicking on any particular investor, leads to the investor profile page shown in Figure A2. The right-hand side provides information on which projects this investor has invested in thus far and whether this investor has also posted her own app on the platform. An investor can also describe their identity in more detail on the left-hand side. They can use this space to describe their education, job experiences, skills, and etc. We manually verified the textual description of experienced investors. Out of 67 App Developer Investors in our data, 50 App Developer Investors had provided some textual description. Interestingly, none of the 17 Experienced Investors provided any description on their profile page.

Figure A1: A Snapshot of a Crowdfunding Campaign Page

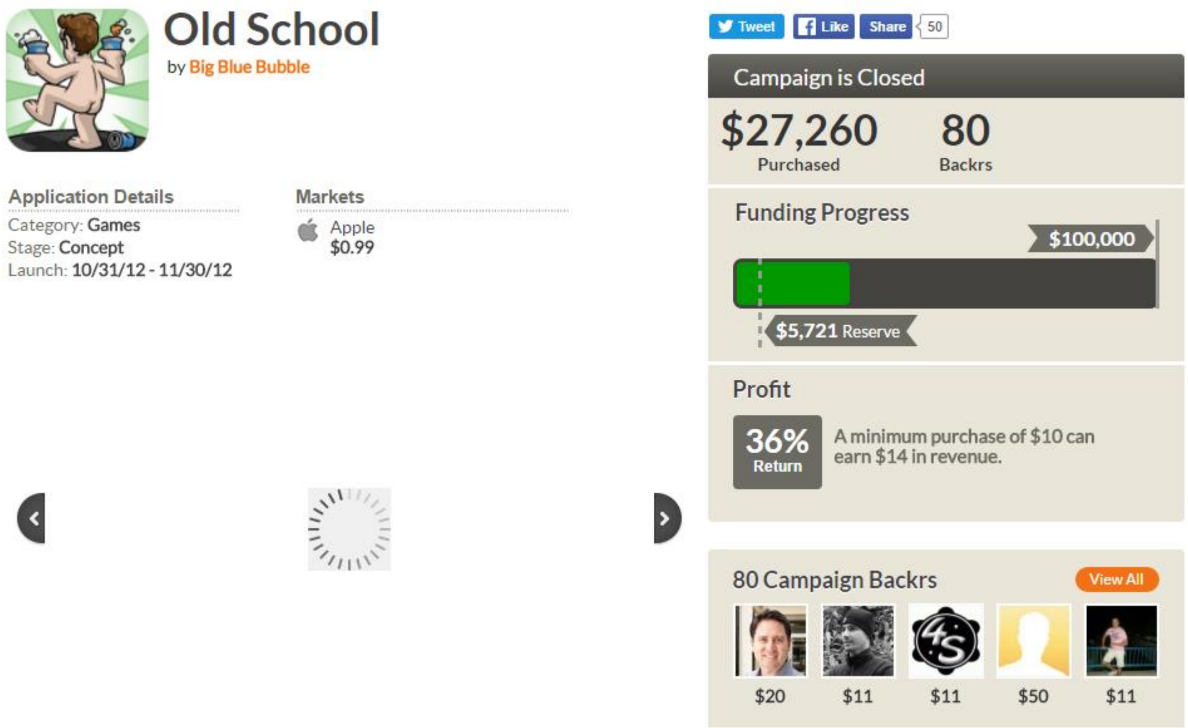


Figure A2: A Snapshot of an Investor Profile Page