ABSTRACT

Title of Document:	THE TRANSFORMATIONAL ROLE OF IT IN ENTREPRENEURSHIP: CROWDFUNDING AND THE DEMOCRATIZATION OF ACCESS TO CAPITAL AND INVESTMENT OPPORTUNITY
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My dissertation examines the strategic impacts of IT-enabled platforms on entrepreneurial and innovation activities. Specifically, I explore the behaviors of both investors and entrepreneurs in online crowdfunding markets that have the potential to democratize access to capital and investment opportunities. In my first essay, I examine the role of experts in a crowdfunding market. While conventional wisdom considers a crowdfunding market as a mechanism to democratize decision making and reduce reliance on experts, I find that experts still play a pivotal role in these markets. In particular, I find that the early investments by experts serve as credible signals of quality for the crowd, and have

a significant impact on the crowd's investment decisions. In my second essay, I analyze whether crowdfunding democratizes access to capital for entrepreneurs. I find that difficult access to credit from traditional sources induces entrepreneurs to rely more on crowdfunding as a viable alternative, while this effect varies across project types and across areas. In each essay, I analyze micro-level data from online crowdfunding markets with a variety of econometric methods. The results have important theoretical and practical implications for questions ranging from the design of online crowdfunding markets to competition between online and offline channels for funding and regional dynamics of crowdfunding.

THE TRANSFORMATIONAL ROLE OF IT IN ENTREPRENEURSHIP: CROWDFUNDING AND THE DEMOCRATIZATION OF ACCESS TO CAPITAL AND INVESTMENT OPPORTUNITY

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Dedication

I would like to dedicate my work to my amazing Mom, Dad, and beloved wife Jooyoung for their endless encouragement, patience and belief in me.

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Table of Contents

List of Tables

List of Figures

CHAPTER 1: OVERVIEW

Advances in basic digital technologies, along with global business trends, are enabling more people to have easier access to ideas and resources from around the world. Especially, the ability of online ‘crowdsourcing’ markets to bring together individuals and businesses has transformed and redefined the way innovation is conducted. Crowdsourcing “represents the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call. This can take the form of peer-production (when the job is performed collectively), but is also often undertaken by sole individuals.” (Howe 2006). This technology has been used in a variety of areas such as online labor market, innovation contest, and distributed knowledge, thereby enabling wider and easier access to ideas and resources.

Crowdfunding derives from the concept of crowdsourcing and has emerged as a viable alternative to traditional sources of financing by financial institutions, venture capitalists, and angel investors. The objective of crowdfunding is to raise funds from a large number of investors for a variety of projects. In contrast to the traditional model of raising funds from a small number of sophisticated investors, crowdfunding seeks to obtain smaller amounts of funding from a number of individual investors – the crowd. This can take the form of donations, lending, rewards, and equity purchases.

Crowdfunding, as a phenomenon, has grown rapidly in recent years, attracting an estimated $5.1 billion worldwide in 2013 alone.[1] Kickstarter, one of the leading online crowdfunding marketplaces, had received about $480 million in pledges in 2013 alone.[2] It has been widely used to support a variety of projects including entrepreneurial ventures, social ventures, creative works, citizen journalism, and scientific research. Recently, the World Bank commissioned a study on how crowdfunding could be applied internationally and what its potential could be for affecting entrepreneurship in developing countries. The study predicts a $93 billion equivalent crowdfunding market by 2025.[3]

With the Jumpstart Our Business Startups (JOBS) Act, crowdfunding has also begun to attract a lot of attention from policy makers and regulators. It makes it easier for ordinary investors to participate in entrepreneurial ventures that were up-to-now only reserved to sophisticated investors. When signing the JOBS Act in April 2012, President Obama announced that "Startups and small businesses will be allowed to raise up to $1 million annually from many small-dollar investors through web-based platforms, democratizing access to capital".[4] Despite the rapid growth and popularity of online crowdfunding marketplaces as well as their potential to democratize access to capital and investment opportunity, there have been very few systematic studies of these markets.

[1] http://research.crowdsourcing.org/2013cf-crowdfunding-industry-report
[2] http://www.kickstarter.com/year/2013
[3] http://www.pbs.org/mediashift/2013/12/world-bank-crowdfunding-investment-market-to-hit-93-billion-by-2025/
[4] http://www.whitehouse.gov/the-press-office/2012/04/05/president-obama-sign-jumpstart-our-business-startups-jobs-act

My dissertation examines the strategic impacts of online crowdfunding markets on entrepreneurial and innovation activities. Specifically, I explore the behaviors of both investors and entrepreneurs in online crowdfunding markets that have the potential to democratize access to capital and investment opportunities. In my first essay, I examine the role of experts in a crowdfunding market. In crowd-driven markets like crowdfunding markets, the conventional wisdom says that the crowd has the powerful tool to help them access ideas and resources more efficiently and effectively, thereby making them have more independent decision and rely less on experts in these markets. Thus, my first essay examines the role of experts in a crowdfunding market by examining dynamic behaviors of investors in the market. In my second essay, I now focus on entrepreneurs' behaviors and analyze whether crowdfunding democratizes access to capital for entrepreneurs by exploiting geographical variation in crowdfunding activity in the U.S.

The first essay in my dissertation examines the role of experts in an online crowdfunding market. Using a novel data set on individual investments in a crowdfunding market for mobile applications, I investigate whether early investments serve as signals of quality for later investors, and if the value of these signals differs depending on the identity of early investors. I also investigate if these signals are indeed credible as measured by the ex-post performance of these projects and investments.

I find that while early investors have a significant influence on later investors, not all early investors are equally influential. Specifically, I find that among the early investors, two categories of experts — *app developer investors and experienced investors*—have a significant influence on the later investors - *the crowd*. More interestingly, the specifics of their expertise determine their influence. App developer investors who have a better knowledge of the product are found to be more influential for “concept apps” (apps in the pre-release stage), while experienced investors – investors 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). My findings show that the majority of investors in this market – *the crowd* – although inexperienced, are rather sophisticated in their ability to identify and exploit nuanced differences in the informational content of the investments made by these different experts. In examining the ex-post performance of apps, I find that successful funding in the market is positively associated with ex-post app sales and that the quality signals provided by the experts’ investment choices are indeed credible.

This essay makes a number of significant contributions. It is among the first to provide systematic evidence of the role of experts in crowd-based markets with detailed individual-level data. In addition to highlighting the role of experts, this essay also shows how their influence can vary depending on their expertise, an issue overlooked in the existing literature on opinion leadership. This study also adds to the literature on signaling by showing the nuanced effects of the signals provided by different types of investors in an online crowdfunding market. Lastly, given the infancy of online crowdfunding, understanding investor behavior in these nascent markets is important for their success. Conventional wisdom considers crowdsourcing and crowdfunding markets as mechanisms for empowering the masses and democratizing expertise. Contrary to popular perceptions, our initial findings indicate that despite the freedom of choice provided by these decentralized markets, the crowd's decisions are highly influenced by experts participating in these markets.

The second essay examines the role of crowdfunding in democratizing access to capital by looking how geography affects the formation of crowdfunded projects. I collect data on housing prices and local credit markets that are closely related to the cost of accessing traditional sources of credit and matched these data to a novel data set from a leading crowdfunding market. I then examine whether entrepreneurs with limited access to traditional sources of financing have a higher propensity to use crowdfunding. In order to identify the causal effect of the credit availability proxied by housing prices I instrument for the change in housing prices between 2009 and 2012 using the measure of housing supply elasticity developed by Saiz (2010), which exploits exogenous geographical and regulatory restrictions on housing supply. Next, I investigate whether this effect varies across different cities with a particular attention paid to income differences. Third, I examine whether this effect varies across categories.

I find that small cities appear to get a disproportionate benefit from crowdfunding. My findings also show that difficult access to credit from local banks induces entrepreneurs to rely more on crowdfunding. Moreover, tighter credit constraints due to a drop in housing prices have a stronger effect on entrepreneurs who initiate large projects and live in high income areas. The impact of a local credit market structure is almost entirely via 'location-independent' projects that attract less funding from local people. Overall, I provide evidence that web-enabled crowdfunding has the potential to democratize access to capital in that it can be a viable option for entrepreneurs having difficulty accessing traditional offline channels of credit.

This study makes several significant contributions to the relevant literature. First, my study is the first to show systematic evidence of a significant relationship between local credit conditions and the use of crowdfunding in the local region. In this regard, my study complements recent empirical studies shedding light on the importance of geography in the context of crowdfunding (Agrawal et al. 2011; Lin and Viswanathan 2013; Mollick 2012). Second, my study contributes to a body of empirical literature on the consumer substitution between online and offline channels (Anderson et al. 2010; Brynjolfsson et al. 2009; Choi and Bell 2011; Ellison and Ellison 2009; Forman et al. 2009; Ghose et al. 2012; Goolsbee 2000, 2001; Langer et al. 2012). Finally, and more broadly, this study extends the growing body of literature that examines how IT-mediated online platforms contribute to consumer welfare. The literature has shown how online platforms benefit consumers with increased product variety (Brynjolfsson et al. 2003), lower transaction costs (Overby and Jap 2009), higher price elasticity (Granados et al. 2012) and better information about product quality (Mudambi and Schuff 2010). I contribute to this literature by showing that online crowdfunding platforms have the potential to democratize access to capital.

In conclusion, in each essay I analyze micro-level data from online crowdfunding markets with a variety of econometric methods. The results have important theoretical and practical implications for questions ranging from the design of online crowdfunding markets to competition between online and offline channels for funding and regional dynamics of crowdfunding.

CHAPTER 2: THE EXPERTS IN THE CROWD: THE ROLE OF REPUTABLE INVESTORS IN A CROWDFUNDING MARKET

ABSTRACT

This paper examines the role of experts in an online crowdfunding market. Using a novel data set on individual investments in a crowdfunding market for mobile applications, we investigate whether early investments serve as signals of quality for later investors, and if the value of these signals differs depending on the identity of early investors. We find that while early investors have a significant influence on later investors, not all early investors are equally influential. Specifically, we find that among the early investors, two categories of experts — app developer investors and experienced investors—have a significant influence on the later investors - the crowd. More interestingly, the specifics of their expertise determine their influence. App developer investors who have a better knowledge of the product are found to be more influential for “concept apps” (apps in the pre-release stage), while experienced investors – investors 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, are rather sophisticated in their ability to identify and exploit nuanced differences in the informational content of the investments made by these different experts. In examining the ex-post performance of apps, we find that successful funding in the market is positively associated with ex-post app sales and that the quality signals provided by the experts’ investment choices are indeed credible. Contrary to

popular perceptions of crowdfunding markets as means for democratizing expertise and as substitutes for traditional expert-dominated mechanisms, our findings indicate that despite the choice provided by these crowd-based markets, the crowd's decisions are highly influenced by experts participating in these markets.

2.1 Introduction

Online crowdfunding markets have emerged as a viable alternative to traditional sources of financing by financial institutions, venture capitalists, and angel investors. Crowdfunding derives from the concept of crowdsourcing, which refers to the process of obtaining ideas, opinions, and solutions from an anonymous crowd (Howe 2008). The objective of crowdfunding is to raise funds from a large number of investors for a variety of projects. In contrast to the traditional model of raising funds from a small number of sophisticated investors, crowdfunding seeks to obtain smaller amounts of funding from a number of individual investors – the crowd. This can take the form of donations, lending, rewards, and equity purchases. Crowdfunding, as a phenomenon, has grown rapidly in recent years, attracting an estimated $2.8 billion worldwide in 2012 alone,[5] and has been widely used to support a variety of projects including entrepreneurial ventures, social ventures, creative works, citizen journalism, and scientific research. With the Jumpstart Our Business Startups (JOBS) Act, crowdfunding has also begun to attract a lot of attention from policy makers and

[5] http://www.crowdsourcing.org/document/crowdfunding-industry-report-abridged-version-market-trends-composition-and-crowdfunding-platforms/14277

regulators. Despite the rapid growth and popularity of online crowdfunding marketplaces, there have been very few systematic studies of 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.

Crowdfunding differs from traditional mechanisms for financing in a number of ways. First, a key difference lies in the investors who participate in crowdfunding markets (Agrawal et al. 2013a; Ahlers et al. 2012). Traditional investors such as financial institutions, venture capitalists, and angel investors are professionals with substantial resources and expertise in evaluating and performing stringent reviews of potential investment opportunities. In contrast, the vast majority of investors in crowdfunding markets – the crowd - are often retail investors who have neither the resources nor the expertise to evaluate the risks of competing investment opportunities. Further, the geographical separation between the project owner and the investor prevents the investor from conducting a stringent on-site review process (Agrawal et al. 2011). Online crowdfunding markets overcome some of these limitations by allowing many small investors to pool their resources, thereby reducing their risks. However, with a wide variety of geographically dispersed projects and startups competing for funds, investors in these noisy markets could always benefit from reliable signals of quality that help mitigate their risks (Ahlers et al. 2012). Given the heightened information asymmetries in online crowdfunding markets, it is crucial to understand the factors that drive investors' choices and funding decisions.

An important feature of online crowdfunding markets is the availability of information about investments made by other investors in a given project. In particular, given that each project attracts a number of investors, information about early investors and their investments in a project is available to subsequent investors. Thus, information about peers and their funding activities has the potential to play an important role in online crowdfunding markets (Burtch et al. 2013).

Our study seeks to examine if the investment decisions by early investors influence later investments in these markets, especially by those who are less sophisticated. More specifically, we study whether early investments serve as signals of quality for later investors and if the value of these signals differs depending on the identity of early investors. We also investigate if these signals are indeed credible as measured by the ex-post performance of these projects and investments.

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 has 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 been launched and are in need of additional funds). 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 Developer Investors, funded by over 3,500 specific investments for approximately $1 million. For each listing, we collect a detailed set of its attributes and gather information on its funding progression, including the amount of funding it has received and the number of investors. In addition, we also collect data about app developer- and app-specific characteristics such as total downloads of each app.

We examine the investment choices made by different types of investors. We identify three categories of investors – *App Developer Investors* or investors who have sought prior funding for a different app in this market; *Experienced Investors* or investors who have invested in at least 5 prior apps and more than $2,000 investments; and the remaining investors – *the Crowd*. In examining each of their investment patterns we find that the experts – the App Developer Investors and Experienced Investors – tend to invest early. Given the presence of these experts, our study seeks to examine if the investments made by these reputable investors serve as quality signals for the crowd, and if so, whether these signals are indeed credible.

Our findings indicate that the crowd indeed learns from the investments made by the early investors. However not all early investors are equally influential. We find that the crowd is more likely to follow App Developer Investors and Experienced Investors, although each for a different category of apps that matches their expertise. The crowd is more likely to follow App Developer Investors for concept apps, and Experienced Investors for live apps. The two categories of experts – App Developer Investors and Experienced Investors – are likely to differ in their expertise, the former with a better knowledge of the product (product expertise) and latter with a better knowledge of market performance (market expertise). Additional analyses also find that the influence of these experts further depends on their past performance, which is consistent with the conjecture that their influence most likely stems from their credibility based on past experience on the platform. 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.

This study makes a number of significant contributions. It is among the first to provide systematic evidence of the role of experts in crowd-based markets with detailed individual-level data. Recent studies have raised doubts about the importance of opinion leaders in non-financial contexts (Godes and Mayzlin 2009; Watts and Dodds 2007). Our paper builds on prior studies on the value of opinion leaders by demonstrating their importance in a decentralized financial marketplace. In addition to highlighting the role of experts, our study also shows how their influence can vary depending on their expertise, an issue overlooked in the existing literature on opinion leadership. This study also adds to the literature on signaling by showing the nuanced effects of the signals provided by different types of investors in an online crowdfunding market. While online crowdfunding markets lack the sophisticated quality signaling mechanisms available in well-developed traditional markets, investors in these online markets are able to observe the investment decisions of other individual investors for a given venture or startup. The investment decisions made by some of these early investors might serve as valuable signals of quality of the investments under consideration. If so, these early investors could help mitigate the risks faced by the less experienced investors (Agrawal et al. 2011; Ahlers et al. 2012; Lin et al. 2013). Our study is among the first to examine these issues in one of the earliest and largest online crowdfunding markets for apps.

This study also contributes to the literature on herding behavior by providing evidence of rational herding in crowdfunding markets. While previous studies (Bikhchandani and Sharma 2000; Cipriani and Guarino 2005) have identified the influence of early movers or later investors, ours is among the first study to provide evidence of the importance of the identity of these early investors. We find that not all early investors are equally influential – only the experts among these early investors have a significant influence on the investments by later investors. Lastly, given the infancy of online crowdfunding, understanding investor behavior in these nascent markets is important for their success. Conventional wisdom considers crowdsourcing and crowdfunding markets as mechanisms for empowering the masses and democratizing expertise. Contrary to popular perceptions, our initial findings indicate that despite the freedom of choice provided by these decentralized markets, the crowd's decisions are highly influenced by experts participating in these markets. Our findings have practical implications for the design of crowdfunding markets and, more importantly, for the development of policy and prescriptive guidelines for such markets.

2.2 Literature Review

Our study draws on a number of streams of research – one being the literature on opinion leadership. One argument in this literature is the "influential hypothesis"- the idea that influential individuals accelerate the diffusion of products, innovations, and behaviors (Valente 1995; Watts and Dodds 2007). A growing body of literature in marketing and sociology has attempted to identify and test the role of influentials or opinion leaders. Some studies show that the opinion leaders, identified by self-reported measures, sociometric measures, and usage volume, tend to have a disproportionate influence on others' adoptions (Iyengar et al. 2011; Nair et al. 2010; Weimann 1994). Iyengar et al. (2011) find that sociometric and self-reported measures of leadership are likely to capture different constructs and that heavy users are more influential. Nair et al. (2010) also use a sociometric approach to identify influentials and find asymmetric peer effects that opinion leaders exert a significant effect on other physicians, but not the other way around. Trusov et al. (2010) develop a methodology to identify influential users based on their activity level in online social networks and show significant heterogeneity in the level of influence among users. Aral and Walker (2012), using a randomized experiment on Facebook, further separate influence from susceptibility. In constrast, a small body of literature has recently questioned the role of opinion leaders. Adopting a simulation approach, Watts and Dodds

(2007) find that influence is not a key driver for peer effects. Also, Godes and Mayzlin (2009) show that heavy users are likely to be less effective sources of influence for low-risk products.

However, there has been no substantive research on the role of opinion leaders in financial markets. Furthermore, even the small body of literature examining the role of influential entities often assumes that big investment banks, experienced venture capitals, and top-rank mutual funders are influential and examines whether investees report superior subsequent performance or whether these investees outperform the market (Barber et al. 2001; Hogan 1997; McLaughlin et al. 2000; Nahata 2008). However, there is, to the best of our knowledge, little research that has empirically examined the influence of opinion leaders in financial markets. This is in part related to the lack of detailed individual-level data in financial markets. This study attempts to fill this gap by identifying two types of reputable investors, and examining their investment decisions and their effects on subsequent investors.

Our study also builds on the literature on signaling (Akerlof 1970; Spence 1973). The signaling literature suggests that a high information asymmetry between sellers and buyers has a potential to lead to a "lemons" market and eventually, a market failure. Consequently, credible quality disclosure mechanisms from sellers and third parties are necessary to make such markets work (Dranove and Jin 2010). The literature further observes that a signal is more effective when the cost of acquiring it is greater (Spence 2002). Thus when experts' credentials are visible to others, their signals are likely to be more credible. A stream of literature has looked at direct quality disclosure by sellers and empirically shown that sellers with better signals are associated with better outcomes. Specifically, several studies have focused on signaling by entrepreneurial firms and the outcomes of the such signaling (Ahlers et al. 2012; Conti et al. 2013; Cosh et al. 2009; Hsu and Ziedonis 2013; Lin et al. 2013; Michael 2009). These studies suggest that better quality signals help entrepreneurial firms to obtain funding. A growing body of research has also focused on signals from third parties and buyers to examine their effect on individual behaviors and outcomes (Dranove and Jin 2010; Stuart et al. 1999). Our paper is closely related to this stream of research. Our study examines the value of the quality signals coming from informed investors rather than from the entrepreneurs themselves. In the context of entrepreneurial finance, several studies have shown that the endorsement by high-status investors can lead to performance benefits of invested startups (Hsu 2004; Meggison and Weiss 1991; Nahata 2008). However, there is little research about how investors' responses to these quality signals depend on the source of these signals. Our study contributes to this stream of research by highlighting two distinct sources of quality signals from experts and their differential effects on subsequent investors.

Our study is also related to the literature on herding behavior – especially, studies focusing on the mechanism of observational learning in financial markets. The concept of herding encompasses many mechanisms through which individuals may be influenced by other individuals. In particular, it includes two main mechanisms- the information-based mechanism (often called observational learning) and the mechanism based on payoff externalities.[6] There is an extensive literature on observational learning starting with the seminal works of Banerjee (1992) and Bikhchandani et al. (1992). A body of literature shows that observational learning can explain a large variety of social behaviors such as consumer demand, technology adoption, and kidney transplantation (Conley and Udry 2010; Moretti 2011; Nanda and Sørensen 2010; Salganik et al. 2006; Zhang 2010).[7] For instance, several studies find that popularity information affects consumers' behavior in an e-commerce context (Tucker and Zhang 2011) and in the context of restaurants (Cai et al. 2009).

Reflecting the difficulty of identifying observational learning in non-experimental settings, another stream of research uses experiments to examine herding. Through field experiments with market professionals, Alevy et al. (2007) find that, because of their ability to better discern the quality of public signals, professionals are less likely to be involved in overall cascades than students. In a laboratory setting, Cipriani and Guarino (2005) find that herding rarely occurs when the price is flexible. However, due to lack of individual investment data in financial markets, there have been very few studies attempting to identify observational learning in financial markets, especially at the individual level. Our study complements recent empirical studies with detailed data showing information-based herding in emerging online financial platforms such as peer-to-peer lending markets (Zhang and Liu 2012) and crowdfunding markets (Agrawal et al. 2011).

[6] Herding may also arise through such means as preferences for conformity and sanctions.
[7] See also Cai et al. (2009) and Hirshleifer and Teoh (2003) for discussions of the herding literature.

Payoff externalities may also be responsible for herding. Positive externalities are common in the case of technologies and software. On the other hand, bank runs involve negative payoff externalities in which withdrawal by one depositor reduces the expected payoffs of others (Hirshleifer and Hong Teoh 2003). Negative payoff externalities may also be caused by overcrowding (e.g., in restaurants where one's utility decreases with the number of predecessors in the same restaurant).[8] Thus, it is important to address both mechanisms when empirically measuring herding effects in certain contexts (Zhang and Liu 2012). Our study, in examining the effect of reputable investors 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 experts on subsequent investments, after controlling for average herding.

Lastly, our study adds to the emerging research on online crowdfunding platforms. In one of the early studies on online crowdfunding, Lin et al (2013) find that a borrower's social network can serve as a credible signal of quality to potential investors. Subsequent studies have also examined the role of social influence in a number of online crowd-based markets including donation-based markets (Burtch et al. 2013), reward-based markets (Kuppuswamy and Bayus 2013), and lending-based markets (Zhang and Liu 2012). Researchers have also begun to examine the role of location and geography on outcomes in crowd-funding markets (Agrawal et al. 2011; Kim and Hann 2013; Lin and Viswanathan 2013). There has also been an increasing interest in understanding equity-based

[8] Reputational herding, pioneered by Scharfstein and Stein (1990), also falls within this category. But, it is less important in our setting, because, unlike security analysts and fund managers, our investors are less likely to face career concerns.

crowdfunding markets (Agrawal et al. 2013a; Stemler 2013). For instance, Ahlers et al. (2012) examine the role of different factors in signaling quality in equity-based crowdfunding markets. Our study adds to this nascent but rapidly growing stream of research by examining the role of experts and more importantly the differential role of expertise in signaling the quality of investments to the crowd.

2.3 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.[9]

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

[9] Some investors remain anonymous and we are unable to verify their identities.

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.

The return on investments on Appbackr depends on whether the app is a concept or a live app. 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. 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. 2013a). However, these motivations, if any, are likely to be small for investors on our context. Also, 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 not likely to be important, because what they get in return is not new apps, but monetary profits. Thus, non-monetary incentives are likely to be less important on our context. It is also worth noting that our main focus here is to examine the role of experts on subsequent investments by the crowd.

We track all listings posted on Appbackr from October 2010 through June 2013. The resulting sample contains 532 listings with 3,501 specific investments.[10] 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 dropped all listings that were live at the time of date collection to address potential biases that can arise from simply ignoring censored observations (Van den Bulte and Iyengar 2011).

[10] We dropped a few apps that had limited visibility and information.

Table 1 presents the summary statistics for all listings. In this sample, the average price is \$3.64, ranging from \$0 to \$599.99.[11] The minimum amount listings request ranges between \$0 and \$157,500, with an average of \$3,980. The maximum amount for funding is from \$45 to \$350,000. On the other hand, 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. An average concept app receives \$2,795 from about 10 investors while an average live app gets \$1,245 from over 3 investors. As a result, the ratio of successfully funded apps is higher in concept apps (50%) than in live apps (44%).[12] Finally, about 77% of the listed apps are Apple iOS apps, whereas about 62% comes from app development companies.[13]

2.3.1 Investor Types and Timing of Investments

Investors on Appbackr fall into three categories. We identify two categories of experts. The first category of experts is App Developer Investors. App Developer Investors are investors who have developed and listed at least one other app on Appbackr and are thus likely to have expertise about the product –

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[11] 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.
[12] Our sample has about 8% of apps that meet their maximum funding amounts set initially.
[13] To determine whether an app developer belongs to an app development company or is an individual, we rely on multiple sources, such as profiles at Appbackr, developer information at app stores, and Google search. When it comes to the category of apps, game is the largest category taking around 40% of total apps, even though apps in our sample come from 20 different categories. The distribution of apps across categories is comparable to that in the overall app market.

particularly about apps in the developmental stage. The second category of experts are experienced investors. Experienced investors are investors who have invested in prior apps listed on Appbackr, and are more likely to have expertise about the market performance of apps. Finally, the third category of investors - the crowd, are the others who are neither App Developers nor Experienced Investors.

Experts typically tend to focus on specific categories that reflect their expertise. 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. Experienced investors tend to have a lower investment concentration, and are less likely to focus on specific categories.

While early investors are more likely to get paid than later investors, they are also faced with greater uncertainties – particularly given the intense competition among mobile apps and their low success rate. However, an important aspect of the online crowdfunding market is the visibility of information about early investors and their investments, to later investors. Thus, while on the one hand later investors run the risk of not being able to recoup their investments, on the other, they benefit from being able to learn from earlier investors.

Given the existence of investors with different types of expertise, our study seeks to understand if there are significant differences in the investment behaviors of these investors. In particular, we seek to examine if experts are more likely to invest early as compared to the crowd. Further, if these experts indeed invest early, are their investments likely to serve as signals of quality for later investors, and if so, do the differences in their expertise matter?

2.4 Empirical Analysis

We begin by examining whether experts 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 every investor 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 (Meyer 1990). 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.[14]

As highlighted earlier, our primary focus is to examine the role of experts in this crowdfunding markets. We exploit the panel data to examine whether the two categories of experts 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

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

effect of reputable investors on later investments is:

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

y_{jt} represents the amount of funding that listing j receives during its *t*th day. We denote the influence of App Developer Investors (Experienced Investors) in listing *j* from day 1 to day *t* as A_{jt} and E_{jt}, To operationalize the influence of both groups, we use an aggregate measure of influence at a day. The measure is the sum of cumulative amounts of investments in prior projects of existing App Developer Investors (Experienced Investors) investing in listing *j* at day *t*. This measure assumes that the influence of the two groups of investors is proportional to their past investments. This is consistent with prior studies using investment experience (Chemmanur et al. 2010; Hsu 2004) and age (Gompers 1996) as a proxy for venture capital reputation.

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] This is important in our case, because our sample faces both positive information externality and negative payoff externality. Including both measures will help us

[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.

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. To capture any platform-wide shock on Appbackr, we also include time dummies.[16]

It is unlikely that we capture every source of heterogeneity across listings with our available variables. 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 reputable investors 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.

Note that we are primarily interested in the role of reputable investors 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 reputable investors and peer effects are correlated, it can affect our estimates of the influence of reputable investors. Furthermore, prior investments of reputable investors are likely to reflect their preferences and hence may be correlated with current investments of the crowd who share similar

[16] We include monthly dummies in our main models. However, our main findings remain robust to including weekly dummies.

preferences.

Endogenous group formation (i.e., homophily) arises if an investor selects peers based on shared traits or preferences. If coinvestments 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 some listing-related factors, having listing fixed effects can account for this. For example, a reputable investor and an unsophisticated later investor could both prefer investing in a listing that has a professional video, thus making them make an investment in the same listing. If so, coinvestment among the two can be driven not by the reputable 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 an 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 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. Obvious sources of correlation are marketing efforts directed at the listing and the change in ratings of live apps. We include time fixed effects to partly control for some variations in a project. Nonetheless, we acknowledge that this does not completely control for variations in some project characteristics over time, although the marketing effort is limited in the platform. In addition, our setting mitigates a concern from any spatially correlated location-specific shocks to investment behaviors that may generate comovement in investments. Investors on our online platform are likely to be geographically dispersed and rarely likely to be located in similar regions. 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 expert investor on the investment behaviors of subsequent investors is to examine the signaling role of "expertise". More specifically, when an early investor's expertise is visible to subsequent investors, her actions are likely to influence subsequent investors. However, when the crowd is unaware of an investor's expertise (i.e. the crowd is unaware that the early investor is indeed an expert), the expert's actions should not have a significant influence on subsequent investors. This serves as a valuable falsification test. Our data enables us to exploit this difference in information about expertise available to subsequent investors to help us identify the role of experts and their expertise in these markets.

We also conduct ex-post performance tests at the app level to examine whether herding driven by reputable investors is rational or not. If herding is rational, well-funded apps should indeed have more sales. To examine this, we use app sales data provided by xyo.net. Xyo provides estimated cumulated monthly sales data for an app or an app developer. We conduct several regressions of the number of cumulative downloads of apps listed at Appbackr on funding status at the app level. An obvious concern is lack of measures of the true quality of an app which drives both funding and sales. We include an app's consumer rating as a proxy for its perceived quality.

2.5 Results

2.5.1 The Experts 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 having 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

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

heavy investors, our two categories of reputable investors are distinct from each other.

Table 2 also provides some evidence of the investment timing of reputable investors. As shown in Table 2 both types of experts – 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. 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. As shown in the Figure 1 (panel A), the survival curve drops faster for experts, implying that both Experienced Investors and App Developer 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 more experienced investors tend to invest earlier than less experienced investors. When we divide the sample into concept and live apps, we still observe the same 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. We find that both groups of experts tend to invest earlier after accounting for possible covariates. Column (2) shows that *App developer Investors* and *Experienced Investors* have a significant and positive effect, which confirms that these experts 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 with 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 the two types of reputable investors both invest early for concept apps, whereas only the experienced investors invest early for live apps, the finding consistent with Figure 2.[18] This might suggest 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.

2.5.2 The Role of Expertise

We next examine whether both categories of experts have a 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. In column (1) both variables are positively associated with later investments after controlling for peer effects, even though the influence of app developers are likely to be greater. This indicates that both have some expertise and reputation in this market so later investors imitate their investment decisions. 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 – a likely reflection of the differences in their expertise. The R^2 Statistic is higher in concept apps than in live apps. This may imply that the influence of peer investors including experts is stronger in concepts as compared with live apps.

Since we are more interested in examining the influence of reputable investors on the subsequent crowd rather than on all investors, we next turn to findings that consider only the crowd in subsequent investors. 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 expertise. App Developer Investors are influential only for concept apps, while Experienced Investors are influential only for live apps. This may reflect the fact that App Developer Investors are more likely to have expertise with respect to the creation and development of apps, while Experienced Investors are more likely to have expertise with respect to market dynamics including sales and performance of the product.

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 following day. In other words, if a listing's App Developer Investors, on average, have an additional $33.0 (from the mean of $330.1) in prior investments, it will, on average, generate an additional $0.72 (=1.73%*$41.50) for the listing on the following day.[20] Similarly, a 10% increase in prior cumulative investments by an Experienced Investor, generates an additional $0.21 in investments for the focal app.

We perform additional analyses to gain more insights into the source of influence of reputable investors and report results in Table 5. The influence of experts is likely to depend on their prior experience which in turn makes them a more credible source of information. Since the expertise of App Developer Investors is likely to come from their prior app development experiences, we first test whether App Developer Investors are more influential when they have at least a successfully funded app. Columns (1)-(3) of Table 5 show that the crowds' investments are significantly influenced only by App Developer Investors with their own successfully funded apps and that this effect is stronger for concept apps.

[20] $345.4 is the average of the overall influence of existing App Developer Investors and $42.84 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 experience 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.

Furthermore, in columns (4)-(6) we decompose the influence measure for App Developer Investors into those in the same category and those in different categories to examine whether the expertise of App Developer Investors is category-specific. We expect that App Developer Investors should 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 a successfully funded app in ‘game’ category, his influence as an investor should be stronger in that category. Our findings suggest that the expertise of App Developer Investors is somewhat category-specific, although statistically weak. We find that App Developer Investors 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 an expert investor’s expertise. 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 anonymous App Developer investors have apps listed on other platforms.

Without prior knowledge of the identity of these App Developers, it is very costly for the crowd to verify the expertise of these otherwise anonymous investors. 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 expertise. In examining the impact of these anonymous App Developers on the crowd, we find that these potential App Developers do not have a significant influence on the investment decisions of the crowd (see Columns 7 – 9). This indicates that the credibility of an App Developer’s investments as a quality signal crucially depends on the ability of the crowd to verify her expertise.

For Experienced Investors, their expertise, if any, is likely to come from their prior investments. 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 may be more active in promoting them. Thus, we expect that investing in successfully funded apps makes Experienced Investors more influential than investing in unsuccessfully funded ones. Columns (10)-(12) of Table 5 show that investments by Experienced Investors in successfully funded apps are significantly associated with later investments by the crowd than those in unsuccessfully funded. This implies that their prior investments in successfully funded apps are perceived as a more credible source of influence. Furthermore, unreported analyses indicate that the “expertise” of Experienced Investors is less likely to be category specific. As compared to App Developer Investors, Experienced Investors are more likely to invest in a wider variety of promising apps regardless of which category they belong to and their experience regardless of the category serves as a credible signal for later investors. The investment concentration shown in Table 2 highlights this. It is pertinent to note that the total investments and unrelated investments for Experienced Investors are highly correlated, since a significant share of investments are unrelated investments.

Until now our influence measures assume that the influence of the experts is a function of their prior investments. While it is likely to be reasonable for Experienced Investors, it might not be a reasonable assumption for App Developer Investors. Their influence is likely to come from their prior app developer experience, not from their prior investments. Thus, we also use an un-weighted measure of influence of App Developer Investors, which is the number of existing App Developer Investors. This measure assumes that each App Developer Investor has the same level of influence regardless of their prior investment. Table 6 shows results with this measure. Note that we use the same measure for Experienced Investors as in our main model. Table 6 suggests that our main findings do not change qualitatively. This further reinforces the assertion that the influence of App Developer Investors derives mainly from their prior app development experience.

2.5.3 The Credibility of Experts: An Analysis of Ex Post Performance

We then examine the performance effects of crowdfunding investments. Our study of Appbackr for mobile applications benefits from the opportunity to measure the quality of listings as revealed by subsequent app performance. To examine ex-post performance, we use the 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.[21] Among 551 apps in our sample, we obtain cumulative sales data for 376 apps. We conduct an OLS regression of the cumulative number of downloads on app- and app developer-specific characteristics.

Column (1) of Table 7 reports the relationship between the amount of funding and total app sales. As expected, the relationship is significantly positive. We add app-specific characteristics in column (2). We still see a significant and positive association between total funding and total app sales, implying that well-funded apps are likely to have better sales after controlling for observable app attributes. This finding is robust when we add an app developer attribute- *global rank*.[22] The coefficient in column (3) suggests that for 1% increase in funding on Appbackr, the number of downloads increases on average by 0.15%. *Global rank* at xyo represents the performance of app developers in terms of their recent sales. The lower the *global rank*, the better the app developer. We then include an app's consumer rating as a proxy for its perceived quality. The positive relationship could be driven by both the selection effect and the causal effect. In other words, experts can be good at selecting better apps in the first place. However, crowdfunding may also causally lead to better apps because investors may help promote the apps they are investing in, for example, by sharing them on their social networking pages. Also, investors, especially App Developer Investors, may provide other app developers with some tips about product development. It is

[21] As of Feb 2013, xyo.net covers 1,951,130 apps and 547,387 app developers.
[22] Xyo stopped providing this measure on Mar 2013. Thus, when we add this variable, we lose some apps whose developers appear in our sample after the period.

challenging to separate out the two effects. However, to the extent that an app's consumer rating is a good proxy for its quality, the reduction in the coefficients for the success of funding after including the consumer rating indicates that there exist some levels of selection effects. Comparing column (3) with column (5), we find the coefficient for the total funding is lower. This suggests that the experts on Appbackr indeed have expertise in selecting better apps in the first place. Thus their early investments serve as a credible signal of quality to the subsequent crowd. In addition, when we compare the raw ex-post sales between apps with investments by experts and those without, we find that apps with investments from experts, especially App Developer Investors, have more sales, further indicating the credibility of their expertise.[23] We then examine whether the relationship varies with type of apps and find little difference between concept and live apps.

2.5.4 Robustness Checks

Addressing Endogeneity Concern from Serial Correlation

Our identification strategy for Equation (2) assumes 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

[23] The average number of downloads is 159,342 for apps with app developer investors, 66,353 for those with experienced investors, 61,153 for those with only the crowd, 11,422 for those apps without any investor.

correlated, they may be correlated with these lagged independent variables, thus raising endogeneity concerns.[24]

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

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

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

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

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 8 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 with multiple lagged levels as instruments and report the estimation results in columns (4)-(6) in Table 8. The

[24] We conducted the Wooldridge test for autocorrelation in panel data with the Stata command, *xtserial*, and find that there is a significant first-order autocorrelation in our main model.

results are qualitatively similar to those from fixed-effects models. App Developer Investors are influential mostly for concept apps, whereas 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).

Potential for Collusion

Since a listing with App Developer Investors will attract more money from subsequent investors, app developers might collude among themselves by exchanging investment favors. In such a case, signals from app developers can lead to sub-optimal results. We do not find evidence for this in our context. First, the suggestive evidence of rational herding driven by app developers dampens this concern, since low quality app developers are more likely to participate in collusion, if any, thus making well-funded apps have lower sales ex-post. Second, in our sample there are only two instances where app developers mutually invest in each other's app. Lastly, in examining which app developers are more likely to be investors, we find that the only significant factor is the quality of the app developers. High quality app developers are more likely to invest in other apps. This suggests that investing in other apps is unlikely to derive from a need for reciprocity.

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 experts on subsequent investors. We assume that the daily amount of funding (in dollars) in each listing can be drawn from a different Poisson distribution. In unreported results, we find that our main findings are robust.

2.6 Conclusion

In this paper, we study investors' behaviors in an online crowdfunding market for mobile apps. We show that early investments by experts serve as credible signals of quality for later investors, especially for those who are less experienced. More importantly, the value of these signals depends on the nature of their expertise. In particular, early investments by App Developer Investors are more influential for concept apps, while Experienced Investors are more influential for live apps. Furthermore, we find that App Developer Investors are more influential when they have successfully funded apps, especially in the category where they make an investment, while the experience of Experienced Investors determines the strength of their influence. These present a clear contingency argument in the effectiveness of quality signals for investors – quality signals may be credible only if senders possess related expertise and experience. Last, we find that well-funded apps are more likely to have better sales ex-post.

The findings of our study have a number of interesting implications. As highlighted earlier, investors in crowdfunding markets are faced with significant information asymmetries. Given the lack of traditional quality assurance mechanisms, it is interesting to examine how individual investors that comprise the crowd make investment choices in a noisy market (Agrawal et al. 2013a). We find that despite the crowd lacking the sophistication and expertise of traditional investors such as financial institutions, VCs, etc., the crowd is not only able to leverage the information contained in early investments by expert investors, but also identify and exploit nuanced differences between different signals within the same market.

Our study also sheds light on an important role played by experts in crowdfunding markets. While it is well known that experts play an important and prominent role in traditional financial markets, online crowdfunding is often considered to be largely driven by the crowd of anonymous participants. While the crowd constitutes the vast majority of the investors in online crowdfunding markets, we find that experts, although few in number, play a disproportionate role in influencing the behavior of investors in these markets.

In examining the role of experts in a crowdfunding markets, our study also contributes to research on opinion leadership. Our empirical evidence indicates that product expertise is an overlooked dimension of opinion leadership that is quite different from another measure, investment experience (i.e., usage volume), which has been used rather frequently. Furthermore, our finding on credibility of product experts complements recent studies showing that opinion leadership is related to the stage of the product life cycle (Godes and Mayzlin 2009; Iyengar et al. 2011; Susarla et al. 2012). Our finding extends the literature by showing that, in a nascent crowdfunding market, product experts might be at least as credible as heavy users, which are experienced investors in our context.

With respect to 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 appear to pay much attention to credible sources of quality and discern more credible signals by looking at expertise and experience of senders. Thus, as long as the crowdfunding market provides a sufficient amount of information about investors and products, potential risks in crowdfunding that some regulators are concerned about might be significantly mitigated.

Finally, 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 providing more sophisticated search tools that facilitate seamless access to such information might be crucial for these markets, particularly in their nascent stages. However, it is also important for regulators to pay attention to the potential for misuse in the longer run. Our data does not find any evidence of fraud among project owners. Nonetheless, if the cost of quality signaling is small, an improved understanding of this dynamic could lead to its misuse. Future studies could examine the evolutionary dynamics of these markets. Furthermore, as in many other online platforms, in crowdfunding platforms reputation-building systems for both investors and project owners would be particularly important in the long term.

CHAPTER 3: CROWDFUNDING AND THE DEMOCRATIZATION OF ACCESS TO CAPITAL: A GEOGRAPHICAL ANALYSIS

ABSTRACT

One aspect of crowdfunding that has garnered large interest of late is the ability of crowdfunding to 'democratize' access to capital. Entrepreneurs initiating crowdfunded projects, located anywhere, are able to access sources of capital from anywhere. As such, entrepreneurs who face less attractive credit environments may on the margin choose to engage in crowdfunding. Similarly, projects in geographically less populated areas may benefit from crowdfunding. In this paper, we examine how geography affects the formation of crowdfunded projects. We collected data on housing prices and local credit markets that are closely related to the cost of accessing traditional sources of credit and matched these data to a novel data set from a leading crowdfunding market. We find that small cities appear to get a disproportionate benefit from crowdfunding. Our findings also show that difficult access to credit from local banks induces entrepreneurs to rely more on crowdfunding. Moreover, tighter credit constraints due to a drop in housing prices have a stronger effect on entrepreneurs who initiate large projects and live in high income areas. The impact of a local credit market structure is almost entirely via 'location-independent' projects that attract less funding from local people. Overall, we provide evidence that web-enabled crowdfunding has the potential to democratize access to capital in that it can be a viable option for entrepreneurs having difficulty accessing traditional offline channels of credit.

3.1 Introduction

In a knowledge-based economy, economic prosperity and job creation rests on its ability to foster innovation. Innovation leads to new products, production processes, intellectual property and industries. One of the main drivers of innovation is access to capital. Traditionally, private individuals, banks, and venture capital funds have supported high-risk projects through loans or investments. Previous studies have shown that these investments often target few industries and/or have a very narrow geographic scope (Petersen and Rajan 2002; Sorenson and Stuart 2001).

The proliferation of Internet based platforms has created an additional channel of capital – crowdfunding. In these markets, an individual requests funding for an idea and a large number of unaffiliated individuals contribute to fund the project. Crowdfunded projects range from small creative projects to social and entrepreneurial ventures seeking millions of dollars in capital. The crowdfunding marketplaces have grown rapidly in recent years, attracting an estimated $5.1 billion worldwide in 2013.[25] Kickstarter, one of the leading online crowdfunding marketplaces, had received about $480 million in pledges in 2013 alone.[26]

This massive growth has received enormous attention from policy makers. Until now, if funders of Kickstarter projects were to earn a return on their money, they would be subject to federal and state laws governing the sale of securities. The Jumpstart Our Business Startups (JOBS) Act in the United States (US) allows

[25] http://research.crowdsourcing.org/2013cf-crowdfunding-industry-report
[26] http://www.kickstarter.com/year/2013

an exemption to this rule. It makes it easier for ordinary investors to participate in entrepreneurial ventures that were up-to-now only reserved to sophisticated investors. When signing the JOBS Act in April 2012, President Obama announced that “Startups and small businesses will be allowed to raise up to $1 million annually from many small-dollar investors through web-based platforms, democratizing access to capital”.[27] This democratization of access to capital has attracted even greater attention in recent economic downturns. The recent financial crisis and economic downturns have led to a significant reduction in the availability of capital and credit, especially for cash-strapped individuals and small businesses (Greenstone and Mas 2012; Laderman and Reid 2010). As a consequence, providing small businesses with needed capital has been more crucial and crowdfunding has been viewed as a viable alternative for raising capital.

However, academic research on crowdfunding has largely neglected this important question of whether and how crowdfunding helps in democratizing access to capital. What would the democratization of access to capital look like? We could say that crowdfunding contributes to democratizing access to capital if it provides a new channel of capital to entrepreneurs who have promising ideas but are difficult to raise money from conventional funding sources. Entrepreneurs may get financially disadvantaged because of several factors such as their race, education, and social groups. In this paper, we are focusing on geography, since the literature suggests that geography is playing a significant role in determining

[27] http://www.whitehouse.gov/the-press-office/2012/04/05/president-obama-sign-jumpstart-our-business-startups-jobs-act

access to capital and credit from conventional funding sources (Kerr and Nanda 2011). Furthermore, geography is a right dimension to investigate, because online crowdfunding markets are believed to reduce geographical constraints on funding which are often shown in conventional funding sources (Agrawal et al. 2011; Petersen and Rajan 2002; Sorenson and Stuart 2001). Obviously, the role of geography in accessing capital and credit can take different forms. Projects in small cities may have lower odds of being funded. Similarly, local market conditions may lower the availability of credit to individuals and thus limit the feasibility of their ventures. In addition, not all projects and entrepreneurs may benefit equally from crowdfunding as an alternative source of capital. In this endeavor, this paper examines conditions under which such venture activities benefit more from online crowdfunding markets as an alternative source of financing. Specifically, we ask the following three questions: 1) *What is the geographic distribution of crowdfunded projects between small and large cities?* 2) *How does the availability and cost of traditional sources of financing influence the propensity to use crowdfunding?* 3) *What variables moderate the decision to seek crowdfunding over traditional financing?*

Little is known regarding the factors that contribute to the initiation of crowdfunded projects. However, previous literature on entrepreneurship suggests that access to capital and credit is a primary factor in spurring entrepreneurship (Combes and Duranton 2006; Samila and Sorenson 2011). Previous work has shown that household wealth is vital for the creation of new businesses (Evans and Jovanovic 1989; Hurst and Lusardi 2004). In particular, housing wealth, which represents the bulk of household wealth, has been shown to ease credit constraints for entrepreneurs and thereby boost entrepreneurship (Fairlie and Krashinsky 2012; Fan and White 2003). Following prior literature (Adelino et al. 2013; Mian and Sufi 2011), we focus on housing prices as a proxy for credit availability for entrepreneurs. We expect that housing price decline during the recent economic downturn has driven entrepreneurs facing tough credit constraints to seek alternative sources of financing such as crowdfunding.[28] We also examine the number of banks in a local market that can affect the cost of accessing credit from traditional sources (Guiso et al. 2004). It is well known that small business lending often relies on “soft” information, which would be collected through long-term relationships with borrowers (Petersen and Rajan 2002). As such, geographical proximity should matter in this kind of lending. Thus, when entrepreneurs live farther from their local banks, they are likely to pay higher (monetary and non-monetary) costs for funding projects, thus making them use crowdfunding more.

This paper studies the research questions in the context of an online crowdfunding market. The data for this study was collected from Kickstarter, one of the leading online crowdfunding marketplaces. Since its beginning in April 2009, Kickstarter has emerged as the major online crowdfunding marketplace for entrepreneurs initiating various projects, especially creative projects. We collected data on Kickstarter projects from April 2009 through January 2013; overall, we gathered data on 70,654 projects that have attracted more than $450 million in

[28] The Survey of Consumer Finances has recently shown that median household net wealth during the period 2007-10 dropped significantly and that the drops have been mainly driven by significant decline in house prices (Ackerman et al. 2012).

pledges from about 2.47 million contributors. We use the term of entrepreneurs to refer to project creators on Kickstarter. The entrepreneurs on this market include musicians, film makers, dancers, game developers, and hardware product developers, most of whom are different from technologically innovative entrepreneurs that many people typically have in mind.

We investigate whether we can find support for the notion that crowdfunding 'democratizes' access to capital and if so, how. In order to do this, we first report the geographical distribution of crowdfunded projects. We then examine whether entrepreneurs with limited access to traditional sources of financing have a higher propensity to use crowdfunding. In order to identify the causal effect of the credit availability proxied by housing prices we instrument for the change in housing prices between 2009 and 2012 using the measure of housing supply elasticity developed by Saiz (2010), which exploits exogenous geographical and regulatory restrictions on housing supply. Next, we investigate whether this effect varies across different cities with a particular attention paid to income differences. Third, we examine whether this effect varies across categories. We focus on two major category characteristics- the share of local contributions and the average project size. Last, we conduct several robustness tests to rule out alternative explanations.

We find that small cities appear to get a benefit from crowdfunding that is disproportionate to that which they receive from traditional means: compared to venture capital investments, smaller cities get disproportionately more projects and contributions in crowdfunding. We also show that tighter credit constraints due to housing price decline or fewer banks in a market increase the use of crowdfunding. This is consistent with the notion that crowdfunding is serving as an alternative to traditional sources of financing. We further observe that the effect of a decline in housing prices on crowdfunding is stronger for categories that require larger funding, confirming that our main finding is driven by the collateral effect. Next, we find that the effect of changing housing prices is significant mainly for high income (and high education) Metropolitan Statistical Areas (MSAs). This implies that crowdfunding will be helpful mainly for entrepreneurs who are facing a temporary credit shock because of a drop in housing prices but have a certain level of skills and wealth. Finally, we see that the impact of competition among local banks is almost entirely via 'location-independent' projects that attract less from local people.

This study makes several significant contributions to the relevant literature. First, our study is the first to show systematic evidence of a significant relationship between local credit conditions and the use of crowdfunding in the local region. In this regard, our study complements recent empirical studies shedding light on the importance of geography in the context of crowdfunding (Agrawal et al. 2011; Lin and Viswanathan 2013; Mollick 2012). Second, our paper contributes to a body of empirical literature on the consumer substitution between online and offline channels (Anderson et al. 2010; Brynjolfsson et al. 2009; Choi and Bell 2011; Ellison and Ellison 2009; Forman et al. 2009; Ghose et al. 2012; Goolsbee 2000, 2001; Langer et al. 2012). Most of this prior work focuses on consumer substitution between the two channels in the context of non-financial products. Our paper explores how local credit market conditions affect the propensity of entrepreneurs to use web-based crowdfunding. Third, our study advances a small body of literature showing that the geographical distance in online transactions matters more for certain products (Blum and Goldfarb 2006; Brynjolfsson et al. 2009; Hortacsu et al. 2009; Sinai and Waldfogel 2004). We not only report significant variation in contribution patterns across categories, but also provide evidence that this can affect behaviors of market participants in crowdfunding. Finally, and more broadly, this study extends the growing body of literature that examines how IT-mediated online platforms contribute to consumer welfare. The literature has shown how online platforms benefit consumers with increased product variety (Brynjolfsson et al. 2003), lower transaction costs (Overby and Jap 2009), lower prices (Baye et al. 2006), more liquid markets for information goods (Ghose et al. 2006), higher price elasticity (Granados et al. 2012) and better information about product quality (Mudambi and Schuff 2010). We contribute to this literature by showing that online crowdfunding platforms have the potential to democratize access to capital.

3.2 Literature Review

3.2.1 Crowdfunding

A growing body of literature has examined the concept of online crowdfunding platforms. In general, crowdfunding platforms differ in terms of the funder's primary motivation. Funders participate in expectation of some sort of financial return (e.g., in *Crowdcube*), no monetary compensation (e.g., in *Kiva*), or tangible, but non-financial, benefits (e.g., in *Kickstarter*) for their financial contributions. Market participants are expected to behave differently depending on different types of incentives (Kuppuswamy and Bayus 2013). Existing work on crowdfunding has provided conceptual and legal analysis (Belleflamme et al. 2010; Schwienbacher and Larralde 2010). For example, Agrawal et al. (2013b) provide a good overview of the economics of crowdfunding, especially crowdfunding for equity, which is often called equity-based crowdfunding. They consider crowdfunding as a puzzling market, since funders appear to make contributions in the market with high levels of information asymmetry and risks without practicing careful due diligence. They describe incentives of all participants in crowdfunding (i.e., creators, funders, and platforms) and discuss market mechanisms that may be effective in reducing potential market failures.

A small body of literature has provided empirical evidence of the behavior of market participants in different crowdfunding markets. Social influence among funders has been the most examined factor in the literature. This topic has been examined in donation-based markets (Burtch et al. 2013), reward-based markets (Kuppuswamy and Bayus 2013), revenue sharing-based markets (Agrawal et al. 2011), and lending-based markets (Lin et al. 2013; Zhang and Liu 2012). Altogether, the literature shows that social influence does matter for crowdfunders but the direction of the influence varies depending on the funders' incentives. Agrawal et al. (2011) further examined the role of geography in contribution patterns and suggested a reduced role for geographical proximity. Lin and Viswanathan (2013) have also looked at a similar question in an online lending-based market, showing there is still a significant “home bias” in the market. Though an increasing body of literature has been examining crowdfunding markets, almost all the studies have focused mainly on crowdfunders. Thus, we know little about what drives entrepreneurs to use crowdfunding. Specifically, whether and how geography affects the incentive of entrepreneurs to use crowdfunding are important issues but have remained unknown so far. Our study attempts to fill this gap.

3.2.2 Geography and Entrepreneurship

Since creating a crowdfunded project can be thought of as a new form of entrepreneurship, our study also relies on the literature on entrepreneurship, especially examining the role of geography in entrepreneurship. The existing literature offers several explanations on why entrepreneurship differs by geography. The first explanation focuses on the supply of potential entrepreneurs. This theory suggests that the level of initial human capital base in an area affects the entrepreneurial rate in the area. A second explanation highlights the importance of a large customer base. Entrepreneurs may start businesses to cater to this customer base (Glaeser 2007). Customers may also play a role in providing capital and investment support to certain projects (Ordanini et al. 2011). This is particularly plausible for our context. Many consumers who are really enthusiastic about a project are likely to become crowdfunders, who contribute a small amount of money to the project. The ability of some areas to foster new ideas is another potential reason why they become hubs of entrepreneurship. Entrepreneurial ideas are often recombinations of existing ideas (Fleming 2001; Nelson and Winter

1982). Hence, the presence of suppliers of ideas can spur entrepreneurship by facilitating the creation of new ideas and the transfer of existing ones. A fourth view points to a local culture of entrepreneurship as a key determinant. Some regions may simply have a strong culture of entrepreneurship, while others may just follow tradition and old social norms. This implies that positive social spillovers from entrepreneurship may generate significant variation across regions (Glaeser and Kerr 2009).

Entrepreneurship is also likely to be driven by the presence of suitable input suppliers. One of the most important inputs into entrepreneurship is access to capital and credit (Kerr and Nanda 2011). A large portion of small businesses uses some form of credit such as small business loans, credit card loans, home equity loans and traditional bank loans (Laderman and Reid 2010). This is often because credit constraints at the household level matter to individual entrepreneurs (Evans and Jovanovic 1989; Holtz-Eakin et al. 1994; Hurst and Lusardi 2004). Evans and Jovanovic (1989) show that due to liquidity constraints, there is a positive relationship between household wealth and the propensity of starting a new business. Furthermore, Hurst and Lusardi (2004) show that a positive relationship between household wealth and the propensity of becoming self-employed is found only for households in the top 5% of the wealth distribution. In particular, housing wealth has been shown to ease credit constraints for entrepreneurs and thereby become a primary factor for financing entrepreneurship (Adelino et al. 2013; Bernanke and Gertler 1989; Fairlie and

Krashinsky 2012; Fan and White 2003). Thus, it is likely that when housing prices are going down, entrepreneurs will face tighter credit constraints.

Even though access to credit matters to entrepreneurs, it is not clear whether local sources of financing are needed for local entrepreneurship. Local banks are likely to matter only when entrepreneurs prefer borrowing money from their local banks (Guiso et al. 2004). A stream of literature shows that distance still matters to small business lending, although technology weakens the dependence of small businesses on local lenders (Brevoort et al. 2010; Petersen and Rajan 2002). This is mainly because small business lending often requires collecting "soft" information about small businesses over time through relationships with those firms, making local presence critical. Amel and Brevoot (2005), for example, found that only about 10 percent of small business lending is from banks with no branch in the local region. This suggests that entrepreneurs are likely to rely mainly on banks within their home area which may provide better lending terms through long-term relationships (Berger and Udell 1995). Furthermore, when they should incur higher transaction costs of borrowing from local lenders, entrepreneurs may search for alternative sources of financing such as crowdfunding.[29] To the extent that crowdfunding serves as a viable alternative to traditional sources, we should see more crowdfunding activities in regions that have more concentrated credit markets.

[29] Lieber and Syverson (2012) report that the fraction of buying home equity loans online is just 1.8% in 2007, implying that the online channel may not be a viable option for creators in our data.

3.2.3 Consumer Substitution between Electronic and Physical Channel

Since crowdfunding is thought of as an emerging online channel that provides access to credit to entrepreneurs, the literature on the consumer substitution between online and traditional offline channels is also useful for our study (Lieber and Syverson 2012). Starting with the seminal paper by Balasubramanian (1998), theoretical studies on multichannel retailing provide valuable frameworks for understanding the competition between online and offline vendors (see Forman et al. (2009) for more literature). One strand of empirical research has examined the factors affecting consumers' channel choice such as product variety (Brynjolfsson et al. 2003), product information (Koppius et al. 2004; Kuruzovich et al. 2008), lower transaction costs (Kambil and Van Heck 1998), price (Brynjolfsson and Smith 2000). Especially, previous empirical research has found that consumer demand through the Internet is higher when their local markets face higher prices, face higher sales tax rates, have more local content online, or have fewer local physical stores (Anderson et al. 2010; Brynjolfsson et al. 2009; Ellison and Ellison 2009; Goolsbee 2000, 2001; Sinai and Waldfogel 2004). The literature implies that geography plays a role in driving consumers' online demand. We contribute to this literature by highlighting how local credit market structure can affect an entrepreneur's behavior on an online crowdfunding market.

In addition, a small body of research suggests that consumers' online demand for local products can be different with product type. Blum and Goldfarb (2006) showed that even among digital products with zero trade cost, some products have their demands reduced by distance. They found that “taste-dependent” products such as music, pornography, and gambling are affected by geographical distance, while more homogenous products such as software and technology are not. Hortascu et al. (2009) also found a negative effect of distance on trade on online auction sites and observed a strong “home bias” effect. They further observed that the negative distance effect is strongest for goods that are location-specific, such as opera tickets. Using a similar kind of reasoning, we expect that there is likely to be a certain home bias in contribution patterns for project types that are ‘location-dependent.’

3.3 Data and Empirical Analyses

3.3.1 Data and Variables

For this study, we have collected data from several sources. We gathered information on crowdfunding activity from Kickstarter, which is a leading crowdfunding platform. The site started operations in April 2009 and provided a market where everything from films, games, and music to art, design, and technology can be supported with the help of a large number of contributors. We extracted data regarding all transactions on Kickstarter from its inception to January 2013 and could locate 35,156 successful projects, 33,022 unsuccessful projects, and 2,476 live projects. As compared with overview statistics published by Kickstarter, we have a fairly complete list of successful projects and around

73% of failed projects.[30] The missing failed projects are mainly because of issues extracting data from Kickstarter.[31] Among those projects, 62,163 projects are from the US. We focused only on US projects mainly due to the availability of geographical data. For each project we have information regarding the project owner-specific characteristics (e.g., user name, location) and project-specific characteristics (e.g., goal amount, pledged amount, category, project location, crowdfunders and their contributions).

We know each project's location, city and state, which allows us to determine local conditions for each project.[32] We then matched each project to a Core-Based Statistical Area (CBSA). This may be either a Metropolitan Statistical Area (MSA) (containing an urban area of 50,000 or more population) or a Micropolitan Statistical Area (containing an urban area of at least 10,000 (but less than 50,000) population). Our use of CBSA as the unit of location is driven by the fact that Kickstarter provides only city and state information. CBSAs appropriately assign both the urban core and adjacent counties to one location.

[30]We believe this is not a serious concern in our study. First, the rate of successfully funded projects is not systematically correlated with housing price change, as shown in Figure 4. Thus, this suggests that having the missing observations are little likely to bias our results. In addition, we also consider the amount of contributions which is less sensitive to the missing observations. According to the 2012 Kickstarter stat, it has received $320 million in pledge in 2012, while our sample has a total of $313 million during the same period. We got qualitatively the same finding for the amount of contributions.

[31] Kickstarter makes it hard to find failed projects, since projects are not indexed for Internet searches and there is no page on the site to find projects that didn't meet their funding goals. The failed projects are on the profile pages of project contributors, though. We visit every contributor and attempt to get as many projects as possible. Thus, this method cannot collect around 11% of failed projects that get no funding. Also, around 30% of failed projects fund less than 20% of the goal amount.

[32] We also know the location of each project owner for about 98% of projects in Kickstarter. The locations of projects and project owners are the same for about 90% of projects. As a result, our main findings are robust to using the location of project owners. Since there are formal and informal verification systems about project owners, it is highly likely that they truly release their location.

However, our main analyses focus on the subset of MSAs for which we have the measure of housing supply elasticity (which we will explain in detail below), although other variables are more widely available for both metropolitan and micropolitan statistical areas. This measure is available for about 250 large MSAs. Since our sample includes the large MSAs, it covers about 90% of crowdfunded projects initiated since the introduction of Kickstarter.

Once we matched each project to an MSA, we measured the level of crowdfunding activities made by project owners during our study period at the MSA and project category level. In our analyses, we focused on the MSA-category level rather than the MSA level, because we also wanted to look at category heterogeneity in the effect of key variables of interest. Kickstarter provides 13 categories that project owners can choose for listing their projects. These are art, comics, dance, design, fashion, film & video, food, games, music, photography, publishing, technology, and theater. We considered three measures to represent cumulative crowdfunding activities at the MSA-category level during the period. The three measures are the number of total projects per million people at the MSA-category level, the log of the number of total projects at the MSA-category level, and the log of total contributions (in $) to all projects at the MSA-category level. Tables 1 and 2 present the definitions and the descriptive statistics of crowdfunding activities as well as other variables.

We also have all of the individual contributions for each project in our sample. All the projects in our data have attracted 4,429,622 specific contributions from 2,470,566 crowdfunders. About 12.7% of crowdfunders disclose their location, accounting for 29.0% of all contributions, suggesting that experienced crowdfunders are more likely to share location information. Crowdfunders in the US comprise 68% of all crowdfunders that share location information and are responsible for 20.5% of all contributions. We exploit this information to determine the type of each category. We first considered all the contributions from crowdfunders who release their location and examined whether the contributions are made to 'local' projects, i.e., which come from the crowdfunders' home MSA. We then calculated the share of 'local' contributions for each category. Table 3 presents this by category.[33] We see that dance, food, and theatre have a higher share of local contributions than the other categories. In contrast, the game and technology categories received most of the contributions from non-local crowdfunders. This is consistent with recent evidence that even in online transactions geographical distance matters more for certain products (Blum and Goldfarb 2006; Hortascu et al. 2009). Since there are a significant number of contributions for each category, despite a small share of crowdfunders with location information we are confident that our sample is capturing the qualitative difference across categories accurately. In this paper, we will call projects in some categories with a high share of local contributions as 'location-dependent' and call those in other categories with a low share as 'location-independent'.

To this data, we add relevant demographic and socioeconomic variables from multiple sources. First, our key variable of interest is the housing price

[33] We further observe that bigger MSAs, especially the top 3 MSAs, tend to attract more contributions from local people. Nonetheless, even the largest MSA have more than 70% of non-local contributions. This indicates that crowdfunders are willing to invest outside of their home regions.

index. We get the housing price index at the MSA level from the Federal Housing Finance Agency to use as a proxy for the availability of credit. Home equity comprising the majority of household wealth is important for obtaining credit because of the importance of personal collateral and guarantees in small business lending (Assunção et al. 2013; Avery et al. 1998). Also, home ownership has been shown to decrease the probability of loan denials (Cavalluzzo and Wolken 2005). This measure has been similarly used in other studies (Adelino et al. 2013; Fairlie and Krashinsky 2012). Hence, this variable allows us to test whether crowdfunding serves as a viable alternative to the traditional lending channels for creators who face tougher credit constraints. This is operationalized as the change in house prices at the MSA level between 2009 and 2012.[34] We generally observed housing price decline in a local region during our study period.

Another key variable is *bank branch density* which is a measure of bank accessibility. To operationalize this, we used data from the US Federal Deposit Insurance Corporation on the number of financial branches. The land area data collected from the 2010 US Census is used as a denominator to transform the number of financial branches in an MSA into the variable *bank branch density*. Thus, this measure represents transaction costs of using offline bank branches (Forman et al. 2009) and/or competition among banks in a local region (Brynjolfsson et al. 2009). As the number of competing bank branches in a local market decreases, people will incur more costs of using the channel (Kerr and Nanda 2011) and are, on the margin, more likely to use the online crowdfunding

[34] We use the housing price index measured at the third quarter of each year.

channel for financing where they do not incur transaction costs due to geographical distance.

In addition, we used as control variables several demographic and socioeconomic variables that previous literature had shown to be key determinants of entrepreneurship. We first included the Internet connectivity as proxied by the number of high-speed internet service providers (ISPs). The information on the number of ISPs at the county level is extracted from the Federal Communications Commission.[35] This information is then averaged across all counties in an MSA. This variable represents the diffusion of the Internet within the MSA which may affect crowdfunding activity (Agarwal et al. 2009; Seamans and Zhu 2011; Wallsten and Mallahan 2010). We included several variables to represent local economic conditions. We first used Small Area Income and Poverty to get information on the median household income. We collected data on the unemployment rate from Bureau of Labor Statistics. We also got data on the number of small establishments from the County Business Patterns. Small establishments are those with 1-4 full-time employees. These variables are used to test whether better local economic conditions induce local people to create more crowdfunded projects in expectation of greater contributions.

We also collected MSA-level data on total population, education profile, race profile, and age profile from the American Community Survey (ACS). These variables as a whole helped account for several determinants of entrepreneurship

[35] http://transition.fcc.gov/wcb/iatd/comp.html

such as a pool of entrepreneurs, consumer base, and labor input. The ACS is a nationwide survey designed to collect and produce economic, social, and demographic information annually. The information from the ACS allowed us to control for the underlying propensity of the MSAs to engage in crowdfunding.

3.3.2 Empirical Implementation

Crowdfunding activity is assumed to depend on house price index and bank branch density, on socio-economic factors, on demographic factors, on category dummies, and on MSA-specific unobserved factors. Therefore, crowdfunding activity can be expressed by the following model:

$$\mathrm{CR}_{mjt} = \beta_0 + \beta_1 \mathrm{HPI}_{mt} + \beta_2 \mathrm{BBD}_m + \beta_3 \mathrm{X}_m + \beta_4 \mathrm{W}_{mt} + c_m + v_j + \epsilon_{mjt} \quad (5)$$

where the subscript represents MSA *m* in category *j* at year *t*. We use three outcome variables to measure the crowdfunding activity in the MSA-category-year level, CR_{mjt}. These are the number of total projects per million people at the MSA-category level, the log of the number of total projects at the MSA-category level, and the log of total contributions (in $) to all projects at the MSA-category-year level.

In addition, HPI_{mt} represents the housing price index at the MSA-year level. Another key independent variable is the *bank branch density* at the MSA level. $\mathrm{X_m}$ is a vector of MSA-specific variables that we think do not vary much over time. This vector includes total population, median income, number of ISPs, and some demographic variables, such as age, gender, and race profiles. W_{mt} represents time-varying MSA-specific control variables: unemployment rate and number of small establishments. c_m is time-fixed MSA dummies which allow for controlling for MSA-specific unobserved factors. We included a vector of category fixed effects v_j that controls for fixed category specific differences such as category size, crowdfunding rate, competition, etc.

Alternatively, we can write this as a first-differences model:

$$\Delta \mathrm{CR}_{mj} = \gamma + \beta_1 \Delta \mathrm{HPI}_m + \beta_4 \Delta \mathrm{W}_m + \Delta \epsilon_{mj} \qquad (6)$$

Given that we will use only two time periods(2009 and 2012), we drop time subscript *t*. Note that *bank branch density* and the term X_m in equation (1) gets differenced out because it refers to time constant factors. However, to account for the possibility that some MSA-specific variables, including *bank branch density*, might drive the change in crowdfunding activity, we include the baseline value of those variables as additional controls. This means that the effect of those variables on crowdfunding activity is different between the two time periods. We also include category dummies to capture the average change in crowdfunding activity over the period of analysis. Thus, our revised model is the following:

$$\Delta \mathrm{CR}_{mj} = \gamma + \beta_1 \Delta \mathrm{HPI}_m + \beta_2 \mathrm{BBD}_m + \beta_3 \mathrm{X}_m + \beta_4 \Delta \mathrm{W}_m + v_j + \Delta \epsilon_{mj} \quad (7)$$

We used three-year differences between 2009 and 2012 to capture the effect of changes in housing prices on change in crowdfunding activity because Kickstarter started its operation in 2009. We estimate the first-differences specification by running regressions for 2009-2012. The growth in the unemployment rate is measured between 2009 and 2012, while the growth in small establishments is between 2008 and 2011 due to unavailability of 2012 data. The other control variables are measured in 2008, because 2008 is the year right before our study period. We log-transformed total population in the analysis and clustered the standard errors by MSA level.

Despite the first-differences setting and the control variables, it is challenging to establish a causal relationship between credit availability and the creation of crowdfunded projects, since there are many omitted time-variant variables that could simultaneously affect both housing prices and crowdfunding activities. For example changes in expected household income in the area or improvements in entrepreneurial opportunities can affect both housing prices and crowdfunding activities. As a result, we need an exogenous source of variation in housing price change to properly identify the effect of credit availability on crowdfunding activities. We instrument housing price change between 2009 and 2012 with the measure of MSA-specific housing supply elasticity of Saiz (2010).

Housing supply elasticity is constructed using geographical and regulatory constraints to the expansion of housing volumes.[36] Therefore, an increase in housing demand during the economic boom period is likely to translate into higher housing prices and collateral value in low elasticity areas, whereas it translates into a greater volume of houses built in high elasticity areas (Adelino et al. 2013). In the same logic, when bad economic conditions reduce housing demand, we observe smaller decreases in housing prices in high elasticity areas than in low elasticity areas. Figure 1 confirms that this is shown in our data. In Figure 1 housing prices change more significantly in low elasticity areas than in high during the period 2000-2012. Column (4) of Table 6 also provides evidence

[36] Essentially, the share of undevelopable area is used for geographical constraints and the 2005 Wharton Regulation Index for regulatory constraints (see more detail for Saiz 2010).

to confirm this. The housing supply elasticity is positively and significantly associated with housing price increase. Using exogenous restrictions on housing supply will thus provide us with proper identification unless our instrument impacts crowdfunding activities for reasons other than changes in housing price. This identification strategy has also been implemented in recent papers (Adelino et al. 2013; Mian and Sufi 2011).

Our main analysis takes *bank branch density* as exogenous to predict the propensity to use crowdfunding. We believe that this assumption is valid in our study and do not expect that reverse causality exists. It is unlikely that the anticipation of many crowfunding projects in an MSA encourages banks to enter the region given that crowdfunding is still in its infancy. Also, omitted variable biases may not be significant. Some unobserved socioeconomic factors or preference may lead to a higher crowdfunding demand while affecting the number of local banks. However, since the number of local bank branches in 2008 that we used in our model predates the rise of crowdfunding, it is unlikely to be correlated with any unobserved factor that affects creator's crowdfunding demand during 2009-2012. Nonetheless, we collected data on the number of local bank branches in 2000 which should be more exogenous and used it as the instrument variable for the number of local bank branches in 2008 in a robustness check (Brynjolfsson et al. 2009).

There are two additional properties of our empirical framework that are important to discuss here. First, one could argue that during our study period, housing prices have largely declined and crowdfunding has taken off, thus finding a negative relation between housing price change and crowdfunding. However, we are examining cross-sectional variations in crowdfunding activities across MSAs rather than within-MSA variations over time. Hence, even when all the MSAs experience a decline in housing prices, we could get a positive coefficient for a change in housing prices if MSAs with a smaller decline in housing prices have more crowdfunding activities. Another possible specification is to disaggregate observations to the MSA, category, and year level, conducting panel data regressions. This helps control further for time trends in crowdfunding activities by including yearly dummies. However, the biggest concern for this model is that it is a challenge to assemble suitable time-varying instruments for the housing price index. Since our study period is relatively short (i.e., 2009-2012), GMM-typed regressions are not feasible for our study. Nevertheless, in a robustness check we show that our main findings are qualitatively similar when we conduct panel data regressions without any instrument.

3.4 Empirical Results

3.4.1 Geography of Crowdfunding

We first present geographical variation in crowdfunding activities to see how crowdfunded projects spread across CBSAs. In order to generate Tables 4 and 5, we used all the US-based projects in both MSAs and non-MSAs. Table 4 reports the geography of crowdfunded projects on Kickstarter by CBSA across time. The three centers of crowdfunding activity are New York, Los Angeles, and San Francisco and account for slightly over 30% of all crowdfunding activities across all years. However, the share of the top three CBSAs has continuously decreased from 43.3% in 2010 to 28.2% in 2012 while the number of crowdfunded projects has increased by around six times during the same period. For the top ten CBSAs, their total shares of crowdfunded projects have also decreased from 61.1% to 45.2%. On the other hand, the share of non-top ten CBSAs has increased from 38.9% to 54.83% during the same period.

Now we compare the distribution of crowdfunded projects with that of projects funded by a conventional funding source, venture capital funding. Since venture-backed firms are generally technology-based,[37] we first focus on technology-based crowdfunded projects. We define projects in Technology and Game categories as technology-based crowdfunded projects. Figure 2 shows that technology-based crowdfunded projects are more disperse across regions than other types of crowdfunded projects. This may suggest that access to capital has been more important for entrepreneurs in remote small cities who create technology-related projects, as compared with other types of projects. This may also reflect that technology-related projects attract the majority of contributions from outside and technology entrepreneurs in small cities thus get relatively more benefit from crowdfunding than those in large cities. Next, we compare the distribution of crowdfunded projects with that of venture-backed firms in Figure 2. When we confine only to game and technology projects, the top 3 CBSAs is taking only 20% of projects which is much lower than their share (34%) in terms of venture-backed firms. On the other hand, the share of non-top ten CBSAs in

[37] To get the distribution of venture-backed firms, we consider all ventures that get at least one investment from venture capital firms during our study period.

technology-based crowdfunded projects is 60%, which is much higher than 40%, the share in venture-backed firms. This implies that small cities are more active in using crowdfunding. To the extent that small cities are more difficult to get funding from venture capital, this provides some evidence that crowdfunding is democratizing access to capital.

In Table 5, we report the geography of contributions by CBSA over time based on the location of crowdfunders. To generate this table, we used more than 1.1 million contributions that have the location information of crowdfunders. We find similar patterns to what we see in crowdfunded projects. The share of the top three has continuously decreased from 50.3% in 2010 to 38.3% in 2012, with the average share of 39.2%. The non-top ten CBSAs account for 35.7% of all contributions in all years. When we confine our analysis only to game and technology projects, the share of the top 3 (10) CBSAs in total contributions is 20% (43%). This suggests that compared with venture capitalists, more crowdfunders are located outside of the top three CBSA's (Chen et al. 2010). The 36% share of the non-top ten CBSAs in total contributions is smaller than the non-top ten shares of around 51% in terms of the number of projects. In this regard, the non-top ten CBSAs appear to get a disproportionate benefit from crowdfunding.

3.4.2 Main Effect on Crowdfunding

Figure 3 shows the relationship between the change in housing prices and the total number of crowdfunded projects at a scatterplot of our raw data. In order to draw this plot, we confined our sample to 249 MSAs that we used for our main analyses. While crowdfunding activities vary by MSAs, we have a downward sloping regression line. This suggests that housing price changes are strongly and negatively correlated with crowdfunding activities in these 249 MSAs.

We conducted a series of regressions to examine the effect of both housing prices and bank branch density on crowdfunding activities. Columns 1 through 3 of Table 6 report findings from Ordinary Least Squares (OLS) estimates without instrumenting housing price changes. Our coefficient of interest, i.e., housing price increase, is negative and highly significant for all three dependent variables. This indicates that a decrease in housing prices drives creators under tighter credit conditions to rely more on crowdfunding. The effect is economically significant. The coefficient on the change in housing price in column (2) of Table 6 shows that a 10-point decrease (about one standard deviation change) in housing prices translates into a 7 percent increase in the number of crowdfunded projects in MSA-category which corresponds to about one project. When it comes to total contributions, a 10-point decrease in housing prices leads to a 46 percent increase in total contributions to all projects in MSA-category which corresponds to an increase of $52,387 in total contributions. This implies that the effect of the credit availability may be stronger for larger projects, because *total contributions* put more weight on larger projects.

Since the house price change is likely to be endogenous, we next instrument for this using the housing supply elasticity developed by Saiz (2010). In column (4) we show the first stage regression of housing price change on the measure of housing supply elasticity. The coefficient for the Saiz measure is highly significant at the 0.1% level and positive, implying that high elasticity MSAs experienced a lower decline in housing prices between 2009 and 2012.

From column (5) we report the second stage regressions with the housing supply elasticity as an instrument for the change in housing prices. We generally see negative and significant relationships between crowdfunding activities and the housing price changes. Regarding the log of the number of projects, the two-stage least squares (2SLS) regression is not significant (p-value is 0.16). However, the Poisson IV regression is highly significant at 0.1% level, since it increases efficiency.[38] Our IV regressions indicate that ignoring endogeneity could bias the OLS estimates toward zero. This makes sense because omitted variables such as unobserved investment opportunities are likely to affect both housing prices and crowdfunding in the same direction.

We note that the demand effect, if any, will not purely drive our findings. The literature suggests that the effect of housing price increases can also be explained by the demand channel that housing price growth increases the local demand for crowdfunded projects. However, if there is any demand effect, it should drive the coefficient for the housing price increase upwards, thus making it harder to find a negative coefficient. Therefore, the negative coefficient reflects that limited availability of collateral in the form of lower housing prices can positively affect the creation of crowdfunded projects by project owners.

Table 6 also shows the effect of bank branch density on crowdfunding activities. The OLS and 2SLS regressions both imply that the number of banks in

[38] We will use the 2SLS regressions rather than the Poisson IV regressions with our main specifications, because the 2SLS regressions are easy to interpret and the Poisson IV regressions do not converge in some specifications.

a local market is not statistically associated with the propensity of initiating crowdfunded projects.[39] However, this does not mean that bank branch density has nothing to do with the creation of crowdfunded projects. Below we provide more nuanced results for *bank branch density*. With respect to the control variables, our results are in line with expectations. We find that MSAs with more educated people and more people aged between 40 and 59 are associated with more crowdfunding activities. Furthermore, bigger cities tend to initiate more crowdfunded projects because more people are living in those cities. However, we do not find that people in big cities necessarily have a higher propensity to use crowdfunding. Internet connectivity is generally not significant. An increase in unemployment rate may lead to a reduction in crowdfunding activities, although the relationship is not statistically significant.

Heterogeneous Effect of Housing Price Increase across Different MSAs

We do not expect all areas to be equally influenced by housing price change. We examine whether the effect of credit availability varies across MSAs. One important question is whether housing prices will have a stronger effect on crowdfunding in high income MSAs. On one hand, low income entrepreneurs could rely more on crowdfunding, because they are more likely to need to get external funding. On the other hand, given that higher income represents better skills and more wealth, high income areas might be better in getting successful funding from crowdfunding. In our data, the mean (median) number of crowdfunded projects at MSA-category level is 2 (0) for the bottom 25% income

[39] This is partly because our main analyses focus on relative large MSAs. Our additional tests suggest that this variable is significant mostly for areas with lower bank branch density (see Table 11 and 12).

MSAs and 53 (10) for the top 25% income MSAs. Hence, the credit availability may matter mainly for high income people who have a certain level of wealth and skills.

To test this, we interact housing price increase with median household income at a MSA. We present the estimates obtained from the 2SLS models in columns (1)-(3) of Table 7. The interactions for all the three models are negative and also statistically significant except for *total contributions*, indicating that the effect of housing prices increases with the median income at a MSA. We further compare the effect between the top 25% and bottom 25% income MSAs. We observe that the effect of housing price change is significant only for high income MSAs (see columns (4)-(9)). Low income MSAs are not influenced significantly by house prices. This may suggest that entrepreneurs in high income areas are better in creating successfully funded projects so that they are more active in using crowdfunding in response for a temporary credit shock through decreasing housing prices. This may also suggest that a temporary credit shock in the form of decreasing housing prices is less likely to discourage high income entrepreneurs from initiating crowdfunded projects. This finding is consistent with a theoretical prediction of Evans and Jovanovic (1989) that the propensity to start a new business is a function of personal wealth if would-be entrepreneurs are credit constrained.

We further compare the effect between the top 25% and bottom 25% high education MSAs and find that the effect is stronger for MSAs that have a higher share of educated people (unreported but available upon request).[40] All in all, our findings suggest that crowdfunding is helpful mainly for high-ability entrepreneurs who are facing a temporary credit shock because of a drop in housing prices but have higher income and skills. This finding is in line with some studies showing that high-income, educated people are more likely to adopt the Internet (Goldfarb and Prince 2008; Sinai and Waldfogel 2004).

Table 7 also shows the effect of *bank branch density* on crowdfunding activities. We find that an increase in local banks is now statistically associated with a decrease in the propensity of initiating crowdfunded projects. Project owners are less likely to fund their projects by crowdfunding as they have more local banks so can borrow money easily and cheaply.

Heterogeneous Effect of Housing Price Increase across Different Categories

We now turn to the differential effect of housing price increase across different categories. We examine the differential effect of housing prices on creation of crowdfunded projects across categories. From a theoretical point of view, we expect that projects which require large capital are likely to be more dependent on housing prices (Guiso et al. 2004; Hurst and Lusardi 2004). As such, showing a bigger effect of housing price change on crowfunding activity will corroborate the collateral channel story. We examine variation in the scale of projects across categories. The effect of credit availability is likely to be stronger for categories that need greater funding, since entrepreneurs will face more difficulty leveraging their houses to finance their larger projects. Entrepreneurs

[40] The correlation coefficient between median house income and the share of university graduates is over 0.6. Thus, it is not feasible to include interactions of housing price change with income and education in the same model because of high multi-collinearity.

are likely to use different forms of credit, such as small business loans, credit card loans, home equity loans and traditional bank loans, to finance their projects. When they launch small projects, they may succeed in funding their projects without seeking for alternatives. On the other hand, when they initiate large projects, they may need to find another source of financing such as crowdfunding. Table 3 shows that there is significant variation in the average goal amount by category, ranging from $5,347 (Dance) to $41,189 (Game). We will use the average goal amount in a category as a proxy for the average project size in the category.

Since increased demand through higher housing prices can also be different with categories, we focus on another project characteristic: share of local contributions. Although all contributions are made online, some categories may attract more local contributions. ‘Location-dependent’ projects which cater more to local consumers’ tastes can get more contributions from local crowdfunders than ‘location-independent’ projects. In this regard, an increase in demand due to an increase in housing prices may benefit certain categories more than others. To directly measure the demand effect we exploit variation in the share of local contributions across categories. We observe that there is huge variation in the share of local contributions across categories ranging from 3.72% (game) to 49.71% (theater). Since local demand is more important for certain categories with a higher share of local contributions, we expect that an increase in local demand through housing prices should matter more for those categories.

Table 8 shows the results from the 2SLS estimates where we have the interactions of housing price increase with both the share of local contributions and the average project size. We include both of the two interaction terms since having them together will help us examine both the collateral and demand effects. Categories with larger projects may attract less contribution from local people, thus making the average project size correlate with the share of local contributions. Hence, having both of the interaction terms will allow us to separate out the two effects. We present the results for the whole sample in columns 1 through 3. For all three dependent variables, the coefficient on the interaction between housing price increase and average project size is negative and statistically significant, indicating that the effect of the decline in housing prices is stronger for categories that require large funding. The effect tends to monotonically increase with the average size of a category. This is consistent with the collateral channel of credit availability being an important mechanism for the creation of large crowdfunded projects. This confirms that a simple demand story is not driving our results. The coefficients on the interaction between housing price increase and the share of local contributions are all negative but statistically significant only in column (1).

We next split the sample into two groups by the share of local contributions. We report the 2SLS estimates in columns (4), (6), and (8) for categories with low shares of local contributions and in columns (5), (7), and (9) for those with high shares. We still see the negative interaction effects of housing price increase and the average project size for all the estimates. When it comes to the share of local contributions, we have more consistent results after splitting the sample. For categories that have high shares of local contributions, we observe that the net effect of housing price change decreases as a category has a higher share. This is likely because the demand effect is significant for this group and increases with the share of local contributions. On the other hand, for categories that have low shares of local contributions, the interaction between housing price change and the share of local contributions is significantly negative. Given the demand effect is likely weak in this group, this may suggest that the share of local contributions also capture other differences in categories such as different incentives of crowdfunders across categories. We note that our findings are not significant for *total contributions*.

We further observe that *bank branch density* is generally stronger for categories that have a low share of local contributions. This effect is not significant for categories that have high shares of local contributions. Thus, the impact of bank branch density on crowdfunding demand is almost entirely via 'location-independent' projects that attract less from local people. This implies that entrepreneurs are more likely to seek crowdfunding over bank lending when they want to initiate technology-based projects, because most of contributions come from outside for those types of projects. Meanwhile, 'location-dependent' projects offered online are virtually immune from the consumer substitution between crowdfunding and traditional banks. This is consistent with Brynjolfsson et al. (2009) showing that the competition between online and offline channels is significant only for popular products that are available both online and offline.

3.4.3 Robustness Checks

Validity of Instrument

Our identification relies on the assumption that housing supply elasticity affects the creation of crowdfunded projects only through its effect on housing prices. The exclusion restriction would be violated if housing supply elasticity is correlated with crowdfunding activity for reasons unrelated to housing price drops. First, one possible concern with the instrument is that bank lending behavior was different between low and high elasticity areas (Adelino et al. 2013). If other forms of credit were also less available in low elasticity MSAs relative to high elasticity MSAs during our study period for reasons other than housing price drop, this would violate the exclusion restriction for our instrument. To test this, we used data on denial rates of mortgage applications from the House Mortgage Disclosure Act. We assume that higher denial rates represent overall stricter credit decisions in a local market. The denial rate is defined as the number of denied applications divided by the total loan applications in a MSA and in a year. We then computed the proportional change in denial rates between 2008 and 2011.[41] We find that there is no significant difference in denial rates between low and high elasticity areas, as shown in column (1) of Table 9. We further added as a proxy for overall local credit condition the proportionate rate in denial rates directly to our main models and find in column (2) of Table 9 that our main findings still hold.[42] Last, since small business lending is also a major source for small businesses, we accumulated data on small business lending from the

[41] The data is not available for 2012.
[42] We note that our main findings are robust to the other two dependent variables.

Community Reinvestment Act and calculate the proportionate rate in small business lending which may have reflected the overall local credit condition. Our findings are robust to including this (see columns (3) of Table 9). Overall, these findings allow us to rule out an alternative explanation that our instrument may pick up differences in credit conditions across MSAs for reasons unrelated to housing prices.

Word-of-Mouth Effect

The crowdfunding literature suggests that crowdfunding activity can be partly explained by the word-of-mouth (WOM) effect (Aggarwal et al. 2012). If the WOM effect were stronger in low elasticity areas relative to high elasticity areas, this would make our estimates biased. While it is not obvious why this should necessarily be the case, we want to address this. Since measuring the WOM effect in a local area is challenging, we cannot completely rule this out but suspect this will be the case. We have already controlled for several variables, such as population, education, age, income, and race, which might be correlated with the WOM effect (Aral and Walker 2012). Hence, an omitted variable bias, if any, is likely to be small. For example, if large cities happen to have low elasticity areas, this might bias our estimates because large cities are likely to have greater WOM. Adding population to our model helps us control for this. Furthermore, we use Google trends to generate the search volume on ‘crowdfunding’ across states in the US. It is likely that higher search volume represents greater popularity of crowdfunding in an area and then leads to more crowdfunding activity. When we directly add this as a proxy for WOM, our main findings still hold as shown in column (4) of Table 9.

In this regard, each city is likely at a different stage in the diffusion process given that Kickstarter started its business in 2009. For example, people in big cities may be more familiar with Kickstarter and crowdfunding than those in small cities, which may bias our results. To address this issue, we now consider only projects initiated in 2012 when the business model is likely to be stabilized and find qualitatively the same findings (results available upon request).

Quality Effect

Someone could argue that, when housing prices are going down in an area, it has more crowdfunded projects not because of (temporary) difficult access to traditional funding for entrepreneurs who have promising ideas but because of more low-quality projects in the area that should not be funded anyway. We believe that this is not a serious concern due to at least three reasons. First, we already control for several variables, such as median household income and education, that may affect the quality of projects. Second, we examine the relationship between housing price change and the ratio of successfully funded projects in an area. To the extent that the status of successful funding is related to true quality, it could provide a valuable insight. Figure 3 shows no relationship between housing price changes and the success rate at a MSA, indicating that the quality of projects is not significantly correlated with those housing price changes.[43] Last, if housing price change leads to more low-quality projects, we are likely to observe a weak effect on total contributions of housing price change, since this measure is weighted by the amount of funding collected. We do not see this from our data. Column (8) of Table 6 suggests that the effect is highly significant and even greater than the effect on the number of crowdfunded projects in column (6) of Table 6.

Panel Data Regressions

Since our main cross-sectional models rely heavily on the validity of our instrument, there is always the fear that our instrument may be correlated to some unobserved regional variables that could also affect crowdfunding activities. To dampen this concern, we also conducted panel data regressions while noting a big caveat of this approach to not have any instrument for the housing price index. Below is the panel data model we are based on:

$$\mathrm{CR}_{mjt} = \beta_0 + \beta_1 \mathrm{HPI}_{mt} + \beta_2 \mathrm{BBD}_m + \beta_3 X_m + \beta_4 W_{mt} + c_m + v_{jt} + \epsilon_{mjt} \quad (8)$$

where the subscript represents CBSA *m* in category *j* at year *t*.[44] W_{mt} is a vector of location-level variables which vary by CBSA-year. We include a vector of CBSA fixed effects c_m that controls for differences across CBSAs that do not change over time and are common for all categories. Finally, we include in each estimation a vector of category-year fixed effects, v_{jt}, that control for changes in category sizes, crowdfunding rates, competition and so on. These category-year fixed effects also control for different variation in crowdfunding propensity across

[43] Furthermore, we regress the measure on house price change and the same control variables as in our main specification and find no significant relationship between house price change and the success rate.

[44] We drop projects in 2013, since we only have data in January 2013.

categories over time. We cluster standard errors by CBSA. Table 10 shows that our main findings are qualitatively the same. Our two main variables of interest appear to become more significant both when we use only the same set of MSAs as our cross-sectional models (see columns (1)-(3)) and when we include all the MSAs where all the variables in the models are available (see columns (4)-(6)).

Endogeneity of Bank Branch Density

We now account for potential endogeneity of bank branch density. We collected data on the number of local bank branches in 2000 which should be more exogenous and used it as the instrument variable for the number of local bank branches in 2008. We present the results in Table 11. Table 11 indicates that our main findings are robust to accounting for this. Furthermore, we observe a significant difference in the effect of bank branch density across MSAs. This effect is significant only for MSAs that have a low number of banks. This may suggest that the marginal effect of having another bank branch diminishes with the number of bank branches.

Nonlinear Effect of Change in Housing Prices

We examined the effect of housing prices on crowdfunding during the period 2009-2012 when house prices were generally decreasing because of the recent financial crisis. Thus, one could argue that the importance of collateral availability is overestimated and it may have been less if we had tested in the normal economic period with rising house prices. Since our sample is a short panel which spans only from 2009 to 2012, it is not feasible to test this for now. Having said that, we have a test to speculate on how crowdfunding may unfold in normal economic periods. In our sample, there are a limited number of MSAs with rising housing prices during our study period, while most MSAs were facing declining housing prices. We split the sample into two groups depending on whether the housing price at an MSA has dropped between 2009 and 2012. Table 12 shows that housing prices are more influential for MSAs that have declining house prices. This may imply that under normal periods, the collateral effect running through housing prices may not be large and significant enough. However, we have to be cautious about interpreting the finding, since the two groups are not the same. Ideally, we would want to compare the effect of housing prices on crowdfunding for the same MSAs between in the period of rising housing prices to the period of declining housing prices.

3.5 Conclusion

In this paper, we examine how geographic factors affect the creation of crowdfunded projects to provide some insights for the potential of crowdfunding to democratize access to capital. We find that small cities appear to get a disproportionate benefit from crowdfunding. In addition, we use a series of analyses to show that difficulty in accessing credit from local credit markets induces entrepreneurs to rely more on crowdfunding to fund their projects. Moreover, this effect varies across categories and across areas. We find that tighter credit constraints due to a drop in housing prices have a stronger effect on entrepreneurs who initiate larger projects and live in high income MSAs, which further supports that our main findings are primarily driven by the collateral effect of housing price, not by its wealth effect. The impact of local credit market structures is almost entirely via ‘location-independent’ projects that attract less from local people, whereas ‘location-dependent’ projects offered online are virtually immune from the competition between online crowdfunding and offline banks.

The findings have interesting implications for the growing literature on crowdfunding, and more broadly for the entrepreneurship literature. Our findings indicate that crowdfunding can serve as a viable alternative for traditional sources of financing. As such, we provide evidence that web-enabled crowdfunding has potential to democratize access to capital in that it can be a viable option for entrepreneurs having difficulty accessing traditional channels of financing. One important question unanswered is whether crowdfunding supports entrepreneurs who are temporarily cash-strapped but have promising ideas (i.e., positive net present value projects) or those who have flawed projects that should not be funded anyway. We find some indication that crowdfunders are to some extent selective in supporting projects. Having that said, we are unable to formally address this question here, because we do not have proper quality measures of projects. It would be of interest to examine whether reduced financing constraints brought about by crowdfunding will lead to changes in the composition of projects and entrepreneurs (Guiso et al. 2004).

In line with this, it is also worthwhile to examine whether crowdfunding will increase the diversity of innovations. The current study examines the effect of crowdfunding on the rate of innovation. However, it does not examine whether crowdfunding leads to more diverse sets of innovations. Given crowdfunders support a variety of creative projects such as arts, theatre, dance, and music, it is highly likely to be true. Those creative projects are rarely funded by conventional funding sources including venture capitalists and angel investors. Given crowdfunders are motivated not only by financial incentives but also other types of incentives, we may see more diverse sets of innovations with the introduction of crowdfunding. Future research needs to dig deeper into this.

Our findings have implications for policy makers. From a policy perspective, our findings imply that crowdfunding has the potential to democratize access to capital. As such, our study provides some supporting evidence that the JOBS act signed recently will be crucial for entrepreneurs who are cash-strapped. Having that said, our findings also suggest that crowdfunding will be more beneficial for high-ability entrepreneurs who are facing a credit shock but have high education and income. This implies that we may see 'the rich get richer' phenomenon from web-enabled crowdfunding. This finding is consistent with other work which suggests that the Internet exacerbates regional wage inequality (Forman et al. 2012). Thus, policy makers need to think more carefully about the role of crowdfunding as a means to democratize access to capital.

Our finding indicates that technology-related projects tend to attract the vast majority of investments outside of their home regions. This shows sharp contrast with venture capital investments that are geographically concentrated. Hence, crowdfunding may become a more viable option for promising technology entrepreneurs located outside the three centers of venture capital activity: San

Francisco, Boston, and New York. Nevertheless, since the industry is still in its infancy, more research is needed to look at the long-term effect of crowdfunding on technology entrepreneurs.

Our study focuses on the behavior of market participants, especially entrepreneurs, in a reward-based crowdfunding market. However, they are likely to behave differently in an equity-based crowdfunding market (Ahlers et al. 2012; Kuppuswamy and Bayus 2013). Given the importance of the equity-based crowdfunding in supporting 'real' innovative firms, it is worthwhile to examine whether we would still find evidence of democratizing access to capital in the equity-based crowdfunding. If crowdfunders worry about the ability of invested firms to raise subsequent funding because of their location, geographical dispersion of crowdfunding activity in the equity-based crowdfunding may not be as large as it is in the reward-based crowdfunding (Agrawal et al. 2013b). It would be of interest to investigate this in future work.

CHAPTER 4: CONCLUSION

In this dissertation I investigate how IT-enabled platforms impact entrepreneurial activities. Specifically, I explore the behaviors of both investors and entrepreneurs in the IT-enabled crowdfunding markets that have the potential to democratize access to capital and entrepreneurial investment. As the Internet has not only fostered connectivity, but also transformed funding channels, my objective is to examine the concept of democratization of access to capital and to information about expertise in the context of crowdfunding. Despite a significant number of studies that examine the role of the Internet in transforming retail channels, there have been few studies how the Internet is changing the way funding is raised for small businesses. Given the importance of innovation and entrepreneurship in the creation of jobs, having better understanding of this issue should be important for both academics and industry.

In addition to identifying the effect crowdfunding can have on crowd funders, entrepreneur, and policy makers, this dissertation highlights many fruitful opportunities for future work. First, It would be interesting to examine how crowdfunding, especially equity-based crowdfunding, will influence the rate and direction of innovations. In other words, to what extent will it affect the number as well as types of innovations that are funded? The second essay of my dissertation provides some evidence that crowdfunding may increase the number of promising new ideas that are funded by increasing the total amount of available funding. Nonetheless, little is known about whether and how crowdfunding influences the direction of innovation. In line with this, it would be also interesting to investigate what regions have the most successful crowdfunding and what can explain the phenomenon.

Second, social networks and technology in crowdfunding is another direction for the future research. The rules and technical features established by individual platforms, along with overall industry regulations, will shape the behavior of investors as well as entrepreneurs. Given investors' difficulty in doing careful due diligence on any crowdfunding platform, supplying some mechanisms that reduce market failures in crowdfunding is particularly important. In line with this, the first essay of my dissertation shows that quality signals sent by reputable investors are an important tool to reduce the information asymmetry between entrepreneurs and crowdfunders. I would like to further examine other types of mechanism systems, including reputation systems like eBay's and third-party intermediaries, to see how these mechanisms increase transparency and encourage the development of crowd wisdom.

Third, I am more broadly interested in examining the social and economic implications of crowdsourcing which has the potential to transform the way in which knowledge and innovation works can be done. Online cloud labor markets (e.g., oDesk) and innovation contest platforms (e.g., Topcoder) will be an interesting context for my future research. Several studies have exploited the nature of knowledge works to examine strategic management and the impact of IT resources. In line with this, it would be an interesting topic to examine how the nature of knowledge works affects the nature and outcome of crowdsourcing efforts. Overall, this line of research will provide, in turn, opportunities for further and diversified inquiry, as my dissertation represents one of the few studies on crowdfunding and more broadly crowdsourcing. There is significant research opportunity in this area, with major implications for research and practice.

Figures

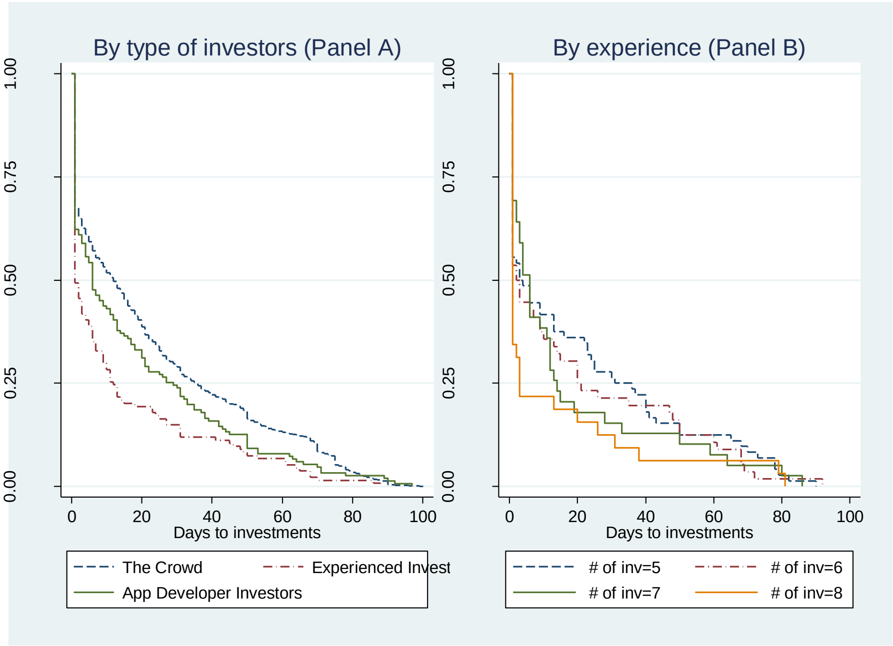


Figure 2.1: Survival Estimates by Type of Investors and by Experience

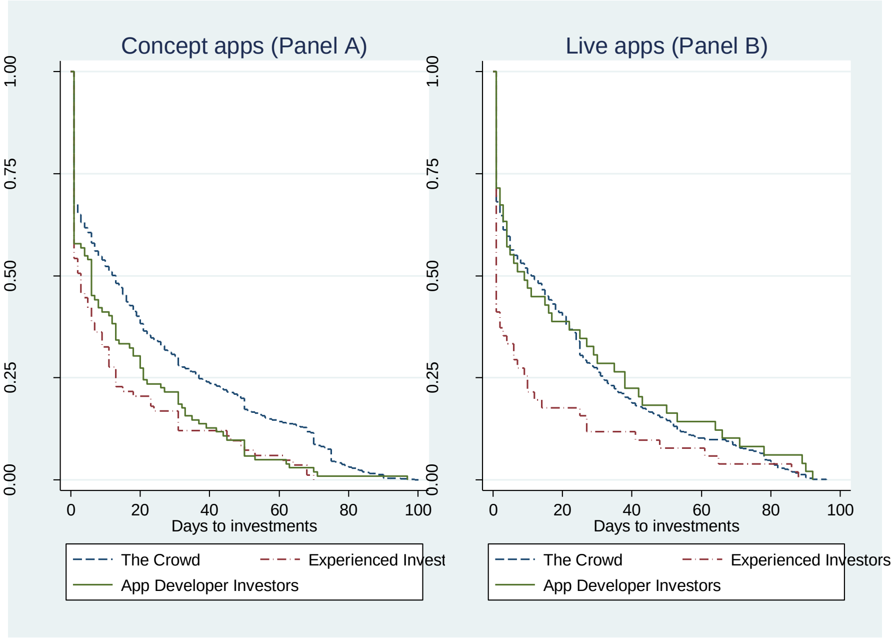
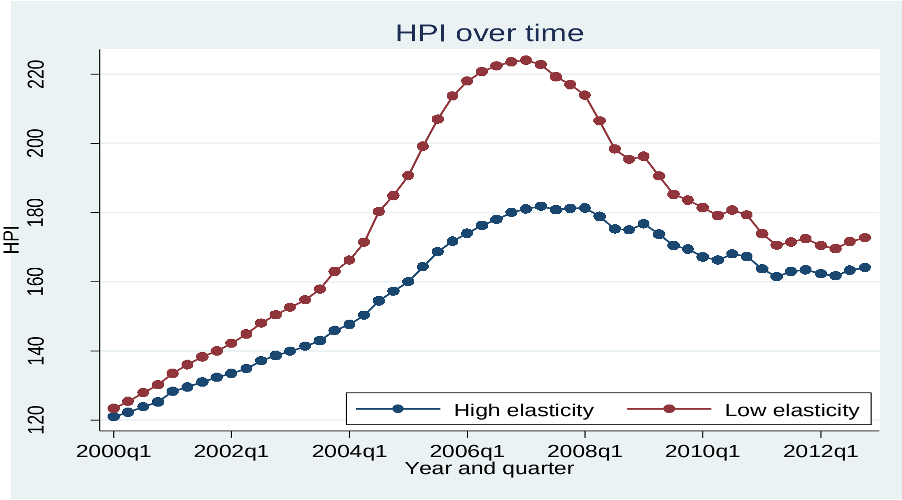
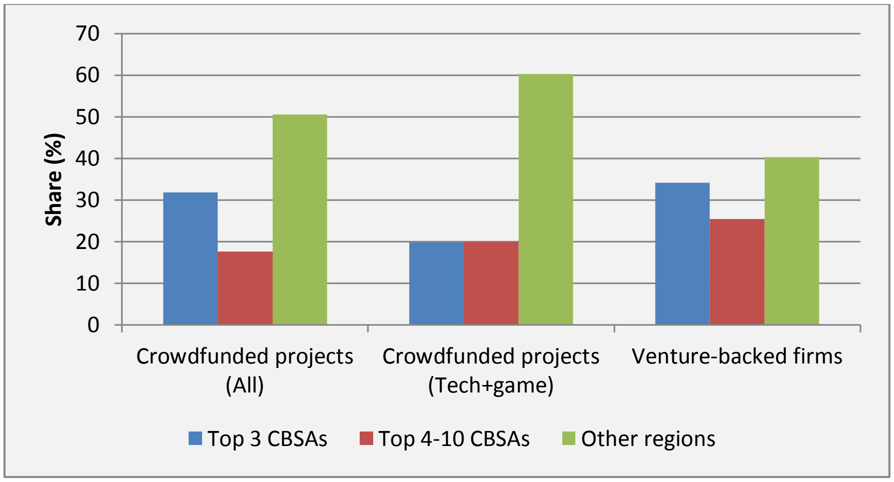


Figure 2.2: Survival Estimates by Type of Apps



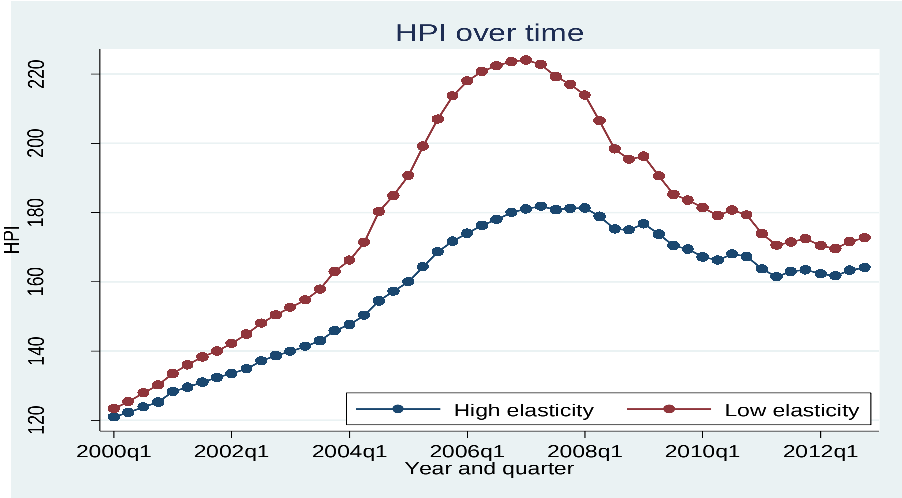
Note: X axis represents year and quarter from 2000 to 2012. Y axis represents the housing price index.

Figure 3.1: Housing Price Change between Low and High Elasticity Areas



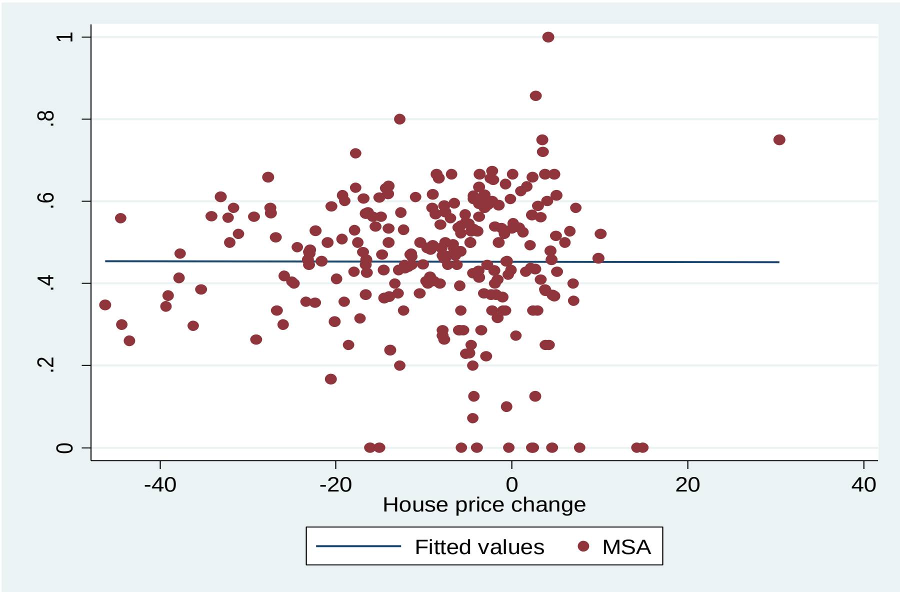
Note: Top 3 CBSAs are areas that are within the top 3 in terms of the number of projects or firms. Top 4-10 CBSAs are defined the same way.

Figure 3.2: Distribution of Crowdfunded Projects and Venture-backed Firms



Note: X axis represents housing price change measured between 2009 and 2012 at a MSA. Y axis represents the level of crowdfunding activity which is defined as the log of the number of crowdfunded projects.

Figure 3.3: Housing Price Change and Crowdfunding Activity by MSA



Note: X axis represents housing price change measured between 2009 and 2012 at a MSA. Y axis represents the success rate at a MSA which is defined as the ratio of successfully funded projects to total initiated projects.

Figure 3.4: Housing Price Change and Success Rate by MSA

Tables

Table 2.1: 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 2.2: 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 per investor	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 $\sum_{k=1}^{20}\left(\frac{investment\ at\ cate\ k}{total\ investment}\right)^2$. For this measure, we drop investors with only one investment, since they have the investment concentration of 1 mechanically.

Table 2.3: 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 2.4: Influence of Experts 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(Influence 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 (Influence 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 2.5: Source of Influence of Experts on the Crowd

DV: Ln (Amt of backing by the crowd in day t)	**All**	**Concept**	**Live**	**All**	**Concept**	**live**	**All**	**Concept**	**Live**	**All**	**Concept**	**live**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Ln (Influence of App Developer Investors with successfully funded apps)	0.161**	0.160**	0.184*									
	(0.073)	(0.078)	(0.109)									
Ln (Influence of App Developer Investors without successfully funded apps)	-0.029	-0.031	0.017	-0.078	-0.102	-0.001						
	(0.041)	(0.066)	(0.048)	(0.050)	(0.077)	(0.051)						
Ln (Influence of App Developer Investors with successfully funded apps in the same category)				0.230**	0.227*	0.204						
				(0.100)	(0.123)	(0.124)						
Ln (Influence of App Developer Investors with successfully funded apps in the different categories)				0.099	0.100	-0.001						
				(0.081)	(0.089)	(0.077)						
Ln (Influence of App Developer Investors with listed apps when investing)							0.155**	0.160**	0.107			
							(0.064)	(0.070)	(0.070)			
Ln (Influence of App Developer Investors without listed apps when investing)							-0.120**	-0.130	-0.040			
							(0.046)	(0.088)	(0.028)			
Ln (Influence of App Developer Investors)										0.122**	0.136**	0.055
										(0.053)	(0.066)	(0.056)
Ln (Influence of Experienced Investors)	0.029	0.046	0.054*	0.041*	0.070	0.053*	0.028	0.050	0.049*			
	(0.022)	(0.043)	(0.028)	(0.024)	(0.050)	(0.028)	(0.023)	(0.044)	(0.028)			
Ln (Influence of Experienced Investors in successfully funded apps)										0.077***	0.104**	0.068***
										(0.030)	(0.052)	(0.026)
Ln (Influence of Experienced Investors in non-successfully funded apps)										0.031	0.109	0.024
										(0.048)	(0.120)	(0.055)
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.1398	0.1636	0.1072	0.1421	0.1670	0.1064	0.1408	0.1640	0.1074	0.1438	0.1710	0.1065
N	10438	4994	5444	10438	4994	5444	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. In columns (1)-(3) 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 (4)-(6) 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 (7)-(9) 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 (10)-(12) 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 2.6: Different Measures of the Influence of App Developer Investors

DV: Ln (Amt of backing by the crowd in day t)	**All**	**Concept**	**Live**	**All**	**Concept**	**Live**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ln (Influence of App Developer Investors with successfully funded apps)	0.522	0.884**	0.198			
	(0.377)	(0.363)	(0.378)			
Ln (Influence of App Developer Investors without successfully funded apps)	-0.830***	-0.890***	0.174	-0.911***	-0.803**	-0.293
	(0.289)	(0.324)	(0.443)	(0.280)	(0.336)	(0.559)
Ln (Influence of App Developer Investors with successfully funded apps in the same category)				1.719***	1.662***	1.019
				(0.461)	(0.458)	(0.690)
Ln (Influence of App Developer Investors with successfully funded apps in the different categories)				-0.382	-0.262	0.156
				(0.316)	(0.496)	(0.408)
Ln (Influence of Experienced Investors)	0.046*	0.080	0.060*	0.046*	0.079	0.060*
	(0.027)	(0.053)	(0.033)	(0.027)	(0.052)	(0.033)
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.1355	0.1603	0.1051	0.1386	0.1612	0.1051
N	10438	4994	5444	10438	4994	5444

Note: The table reports app-fixed effects regressions. Standard errors are clustered by apps. The influence for App Developer Investors (experienced investors) is calculated as the number of existing app developer investors (the sum of cumulative amounts of investments in prior projects made by experienced investors) in a listing. In columns (1)-(3) 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 (4)-(6) 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. *** significant at 1%; ** significant at 5%; * significant at 10%

Table 2.7: Credibility of the Signals - Ex-post Performance

DV: Ln (Cumulative Num of App Downloads)	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Ln(Total Amount of Funding)	0.177***	0.165***	0.149***	0.134***	0.125***	0.164***	0.139***
	(0.045)	(0.046)	(0.046)	(0.040)	(0.039)	(0.047)	(0.040)
Ln(Total Amount of Funding)*Concept						-0.094	-0.088
						(0.106)	(0.099)
Ln(Price)		-0.164	-0.163	-0.148	-0.151	-0.153	-0.142
		(0.112)	(0.104)	(0.106)	(0.099)	(0.108)	(0.103)
Apple		-1.046***	-0.813***	-0.767***	-0.599**	-0.819***	-0.607**
		(0.254)	(0.241)	(0.264)	(0.238)	(0.241)	(0.238)
Company		0.226	0.139	0.329*	0.211	0.133	0.205
		(0.189)	(0.197)	(0.183)	(0.182)	(0.195)	(0.180)
Concept		-0.008	0.011	0.087	0.075	0.632	0.657
		(0.232)	(0.260)	(0.226)	(0.261)	(0.688)	(0.636)
App age		0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Global Rank			-0.000***		-0.000***	-0.000***	-0.000***
			(0.000)		(0.000)	(0.000)	(0.000)
App rating				0.011***	0.008**		0.008**
				(0.003)	(0.003)		(0.003)
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0912	0.4579	0.4874	0.4813	0.5012	0.4886	0.5021
N	376	366	320	366	320	320	320

Note: The table reports OLS regressions at a project level. Standard errors are clustered by developers. The dependent variable and other time-varying independent variables are measured as of Jun. 2013 except for global rank measured on Feb. 2013. I also include a dummy variable equal to 1 if an app has a cumulative download of less than 1000 and 0 if otherwise. *** significant at 1%; ** significant at 5%; * significant at 10%

Table 2.8: Robustness checks

	Rho-Differencing			Dynamic GMM		
DV: Ln (Amt of backing in day t)	**All**	**Concept**	**Live**	**All**	**Concept**	**Live**
	(1)	(2)	(3)	(4)	(5)	(6)
Ln (Influence of App Developer Investors)	0.164***	0.197***	0.029	1.520*	1.736*	-0.476
	(0.055)	(0.068)	(0.051)	(0.912)	(0.953)	(1.882)
Ln (Influence of Experienced Investors)	0.033	0.054	0.042	0.190	0.070	0.780*
	(0.024)	(0.044)	(0.028)	(0.301)	(0.325)	(0.436)
Cumulative amount/1000	-0.106	-0.230	0.053	-0.378*	-0.129	-0.437
	(0.085)	(0.146)	(0.082)	(0.224)	(0.131)	(0.297)
Cumulative num. of specific investments	0.009	0.033	-0.222**	0.136***	0.085**	0.217*
	(0.098)	(0.114)	(0.111)	(0.053)	(0.033)	(0.126)
Percentage needed	0.001	-0.001	0.000	0.007	0.016***	0.005
	(0.003)	(0.006)	(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	10460	4994	5443	9751	4814	4916

Note: The table reports app-fixed effect regressions after rho-differencing in columns (1)-(3). 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 3.1: Variable definition

Variable	Definition	Source
Number of crowdfunded projects	Number of projects at Kickstarter	Kickstarter
Credit availability	House price index	Federal Housing Finance Agency
Internet connectivity	Number of high-speed internet service providers	Federal Communications Commission
Unemployment rate	Unemployment rate	Bureau of Labor Statistics
Number of small establishments	Number of establishments with 1-4 employees	County Business Patterns
Total population	Total population	American Community Survey
Bank branch density	Number of bank branches/Land area	US Federal Deposit Insurance Corporation and 2010 US Census
Median household income	Median household income	Small Area Income and Poverty
% White	% population white people	American Community Survey
% Bachelor	% population university graduates	American Community Survey
% Male	% population male	American Community Survey
% population between 20 and 39	% population between 20 and 39	American Community Survey
% population between 40 and 59	% population between 40 and 59	American Community Survey

Table 3.2: Summary Statistics

Variable	Mean	SD	Minimum	Maximum	Observations
Number of crowdfunded projects in MSA-category	17.08	102.70	0	3,503	3,237
Number of crowdfunded projects per million residents in MSA-category	11.76	23.69	0	478.01	3,237
Total contributions ($) to all projects in MSA-category	123,036	917,538	0	29,600,000	3,237
Number of total contributions of all crowdfunders in MSA-category	229	1011	0	25,944	3,237
House price index in MSA	167	24.26	109.69	253.32	3,237
Change in house price index in MSA	-8.94	11.81	-46.23	30.45	3,237
Number of internet service providers in MSA	18.72	5.69	8.33	39	3,237
Unemployment rate in MSA	0.08	0.03	0.03	0.27	3,237
Number of small establishments in MSA	12,334	29,345	238	333,741	3,237
Total population in MSA	905,401	1,844,948	28,657	18,900,000	3,237
Bank branch density in MSA	1.03	1.07	0.01	8.64	3,237
Median household income in MSA	50,238	9,047	30,513	80,101	3,237
% white in MSA	79.23	11.64	47.69	96.89	3,237
% bachelor in MSA	26.13	7.75	12.5	55.9	3,237
% male in MSA	49.20	0.89	47.07	51.89	3,237
% population between 20 and 39 in MSA	27.45	2.86	20.9	40	3,237
% population between 40 and 59 in MSA	27.55	2.27	16.5	32.2	3,237

Note: The level of crowdfunding activities are measured between April 2009 and January 2013. House price index and unemployment rate are measured between 2009 and 2012. Number of small establishments is measured between 2008 and 2011. The other variables are measured in 2008.

Table 3.3: Key Characteristics by Category

Category	Share of local contributions (%)	Average project size in category ($)
Art	27.91	$6,456
Comics	8.06	$8,037
Dance	46.19	$5,347
Design	6.88	$24,130
Fashion	14.43	$9,152
Film	25.66	$22,066
Food	32.67	$14,488
Games	3.72	$41,190
Music	25.91	$8,976
Photography	23.41	$6,969
Publishing	18.19	$12,162
Technology	6.52	$29,950
Theater	49.71	$8,072

Table 3.4: Geography of Crowdfunded Projects at Kickstarter

		Num of projects				Share (%)			
MSA	MSA name	2010	2011	2012	Total	2010	2011	2012	Total
35620	New York-Northern New Jersey-Long Island, NY-NJ-PA	1511	3200	4073	9304	25.71	16.52	12.21	14.97
31100	Los Angeles-Long Beach-Santa Ana, CA	728	2485	3841	7436	12.39	12.83	11.51	11.96
41860	San Francisco-Oakland-Fremont, CA	304	1035	1499	3008	5.17	5.34	4.49	4.84
16980	Chicago-Naperville-Joliet, IL-IN-WI	230	804	1245	2429	3.91	4.15	3.73	3.91
42660	Seattle-Tacoma-Bellevue, WA	151	526	970	1748	2.57	2.72	2.91	2.81
14460	Boston-Cambridge-Quincy, MA-NH	154	549	896	1698	2.62	2.83	2.69	2.73
38900	Portland-Vancouver-Beaverton, OR-WA	184	552	730	1541	3.13	2.85	2.19	2.48
12420	Austin-Round Rock, TX	122	457	636	1279	2.08	2.36	1.91	2.06
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	104	383	603	1150	1.77	1.98	1.81	1.85
34980	Nashville-Davidson--Murfreesboro, TN	102	368	580	1098	1.74	1.90	1.74	1.77
	Others	2286	9011	18293	31472	38.90	46.52	54.83	50.63
	Total	5876	19370	33366	62163	100.00	100.00	100.00	100.00

Note: When we calculate the total numbers, we also include projects in 2009 and in Jan 2013.

Table 3.5: Geography of Contributions at Kickstarter

		Num of contributions				Share(%)			
MSA	MSA name	2010	2011	2012	Total	2010	2011	2012	Total
31100	Los Angeles-Long Beach-Santa Ana, CA	4,590	27,794	137,153	175,937	10.08	13.13	16.90	15.46
35620	New York-Northern New Jersey-Long Island, NY-NJ-PA	15,027	43,639	90,671	157,669	33.01	20.62	11.17	13.85
41860	San Francisco-Oakland-Fremont, CA	3,280	18,844	82,696	112,361	7.21	8.90	10.19	9.87
42660	Seattle-Tacoma-Bellevue, WA	977	11,227	58,378	75,760	2.15	5.30	7.19	6.66
16980	Chicago-Naperville-Joliet, IL-IN-WI	3,831	9,449	32,325	48,680	8.42	4.46	3.98	4.28
14460	Boston-Cambridge-Quincy, MA-NH	1,586	7,158	31,411	43,020	3.48	3.38	3.87	3.78
38900	Portland-Vancouver-Beaverton, OR-WA	1,740	8,167	24,776	36,634	3.82	3.86	3.05	3.22
12420	Austin-Round Rock, TX	969	5,159	25,767	33,142	2.13	2.44	3.18	2.91
41940	San Jose-Sunnyvale-Santa Clara, CA	330	1,776	24,236	28,729	0.73	0.84	2.99	2.52
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	368	2,475	12,822	19,624	0.81	1.17	1.58	1.72
	Others	12,819	75,997	291,240	406,779	28.16	35.90	35.89	35.73
	Total	45,517	211,685	811,475	1,138,335	100.00	100.00	100.00	100.00

Note: When we calculate the total numbers, we also include projects in 2009 and in Jan 2013.

Table 3.6: Credit Availability and Crowdfunding Activity

	OLS				2SLS IV	2SLS IV	Poisson IV	2SLS IV
Dependent variable	Change in # of projects per million people	Ln(Change in # of projects)	Ln(Change in total amount of contributions to all projects)	Increase in Housing Price Index	Change in # of project per million people	Ln(Change in # of projects)	Change in # of projects	Ln(Change in total amount of contributions to all projects)
				1st stage	2nd stage	2nd stage	2nd stage	2nd stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Increase in Housing Prices	-0.218***	-0.007***	-0.045***		-0.451***	-0.011	-0.066***	-0.101***
	(0.058)	(0.003)	(0.008)		(0.110)	(0.008)	(0.011)	(0.023)
Housing Supply Elasticity				3.029***				
				(0.639)				
Bank Branch Density	-0.403	0.069	-0.204**	0.269	-0.312	0.071	-0.011	-0.182
	(0.790)	(0.052)	(0.102)	(1.001)	(0.784)	(0.051)	(0.077)	(0.118)
Internet Connectivity	0.117	0.002	0.002	-0.391**	-0.016	-0.001	-0.012**	-0.030
	(0.126)	(0.006)	(0.017)	(0.164)	(0.153)	(0.008)	(0.005)	(0.025)
Increase in Unemployment Rate	-32.781	-1.984	-5.235	59.309	-30.898	-1.948	-1.304	-4.785
	(26.544)	(1.842)	(5.017)	(43.754)	(27.927)	(1.835)	(2.244)	(5.845)
Increase in Small Establishments	0.003**	0.000	-0.000	0.006***	0.005***	0.000	0.000**	0.000
	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Ln(Pop)	0.791	0.802***	2.231***	2.465***	1.069	0.808***	1.241***	2.298***
	(0.876)	(0.048)	(0.110)	(0.751)	(0.896)	(0.049)	(0.027)	(0.122)
Median Income	-0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% White	0.024	0.001	0.020**	0.241***	0.075	0.002	0.022***	0.032***
	(0.053)	(0.003)	(0.008)	(0.067)	(0.057)	(0.004)	(0.005)	(0.010)
% Bachelor	0.915***	0.039***	0.188***	0.184	0.940***	0.039***	0.083***	0.194***
	(0.147)	(0.008)	(0.023)	(0.147)	(0.147)	(0.008)	(0.007)	(0.024)
% Male	0.862	0.063	0.044	0.169	0.803	0.062	0.040	0.030
	(0.785)	(0.044)	(0.134)	(1.061)	(0.780)	(0.044)	(0.068)	(0.140)
% 20-39	0.377	0.022	0.015	0.132	0.501	0.024	0.043*	0.044
	(0.371)	(0.020)	(0.051)	(0.519)	(0.384)	(0.019)	(0.026)	(0.062)
% 40-59	0.968**	0.055**	0.099	0.563	1.122***	0.058**	0.089***	0.136**
	(0.392)	(0.024)	(0.064)	(0.456)	(0.388)	(0.023)	(0.011)	(0.069)
Cate FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.3585	0.7559	0.5976	0.2739	0.3413	0.7156		0.5529
N	3237	3237	3237	3237	3237	3237	3237	3237

Note: The table reports the results from OLS and 2SLS estimations. Standard errors are clustered by MSA.
*** significant at 1%; ** significant at 5%; * significant at 10%

Table 3.7: Credit Availability and Median Household Income

	Change in # of project per million people	Ln(Change in # of projects)	Ln(Change in total amount of contributions to all projects)	Change in # of project per million people		Ln(Change in # of projects)		Ln(Change in total amount of contributions to all projects)	
				Median Income (Below 25%)	Median Income (Above 75%)	Median Income (Below 25%)	Median Income (Above 75%)	Median Income (Below 25%)	Median Income (Above 75%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Increase in House Prices	1.744*	0.195**	0.211	-0.035	-1.670***	0.003	-0.076***	-0.057	-0.219***
	(0.973)	(0.077)	(0.177)	(0.216)	(0.607)	(0.011)	(0.026)	(0.052)	(0.084)
Increase in House Prices * Median Income/1000	-0.044**	-0.004**	-0.006						
	(0.021)	(0.002)	(0.004)						
Median Income	-0.001**	-0.000	-0.000	0.000	-0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank Branch Density	-1.799*	-0.078	-0.448***	-1.526	-1.228	-0.085	-0.060	-0.066	-0.286
	(0.970)	(0.078)	(0.159)	(2.794)	(1.847)	(0.143)	(0.075)	(0.753)	(0.270)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.3296	0.6162	0.5431	0.3587	0.3820	0.4009	0.7594	0.3600	0.3995
N	3237	3237	3237	806	806	806	806	806	806

Note: The table reports 2SLS estimations. Standard errors are clustered by MSA.
*** significant at 1%; ** significant at 5%; * significant at 10%

Table 3.8: Effect of Credit Availability by Project Characteristics

	DV: Change in # of project per million	Ln(Change in # of projects)	Ln(Change in total contributions for all projects)	DV: Change in # of project per million		Ln(Change in # of projects)		Ln(Change in total contributions for all projects)	
				Categories (Below 20% of local contributions)	Categories (Above 20% of local contributions)	Categories (Below 20% of local contributions)	Categories (Above 20% of local contributions)	Categories (Below 20% of local contributions)	Categories (Above 20% of local contributions)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Increase in House Prices	-0.001	-0.000	-0.024	0.770**	-0.643*	0.077***	-0.044***	-0.002	-0.094
	(0.158)	(0.010)	(0.040)	(0.306)	(0.347)	(0.024)	(0.012)	(0.087)	(0.068)
Increase in House Prices *share of local contributions	-0.012***	-0.000	-0.001	-0.061***	0.027***	-0.004***	0.002***	0.001	-0.001
	(0.003)	(0.000)	(0.001)	(0.018)	(0.009)	(0.001)	(0.000)	(0.005)	(0.002)
Increase in House Prices *Avg category goal amount/1000	-0.012**	-0.000*	-0.003**	-0.019***	-0.082***	-0.001***	-0.003***	-0.003	-0.000
	(0.005)	(0.000)	(0.001)	(0.006)	(0.027)	(0.000)	(0.001)	(0.002)	(0.003)
Bank Branch Density	-0.312	0.071	-0.182	-1.068**	0.068	-0.005	0.083	-0.346***	-0.169
	(0.784)	(0.051)	(0.118)	(0.490)	(1.108)	(0.063)	(0.052)	(0.118)	(0.143)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.3361	0.7127	0.5432	0.3196	0.3052	0.6516	0.6762	0.5068	0.5675
N	3237	3237	3237	1494	1743	1494	1743	1494	1743

Note: The table reports 2SLS estimations. Standard errors are clustered by MSA. For columns (4)-(9), we split the sample into the following two groups by the share of local contributions of each category: categories with the low share (below 20%) of local control contributions (comics, design, fashion, publishing, game, and technology) and categories with the high share (above 20%) of local contributions (art, dance, food, photography, theatre, film, and music).
*** significant at 1%; ** significant at 5%; * significant at 10%

Table 3.9: Additional Tests for Endogeneity of Housing Price Change

	Change in denial rate	Change in # of project per million	Change in # of project per million	Change in # of project per million
	(1)	(2)	(3)	(4)
Increase in House Prices		-0.468***	-0.497***	-0.505***
		(0.110)	(0.156)	(0.133)
Housing Supply Elasticity	-0.022			
	(0.030)			
Proportional Change in denial rate		-0.096		
		(0.523)		
Proportional Change in small business lending			5.180	
			(13.448)	
Google Search Volume on ‘Crowdfunding’				-0.030
				(0.029)
Control variables	Yes	Yes	Yes	Yes
Adjusted R^2	0.0480	0.3348	0.3257	0.3408
N	236	3068	2951	3237

Note: The table reports 2SLS estimations. Standard errors are clustered by MSA. Denial rates extracted from Home Mortgage Disclosure Act records are computed as the proportion of applications denied by the financial institution over total volume in each MSA and year. Data on small business lending is collected from the Community Reinvestment Act. The proportional change in denial rate is computed as (denial rate in a MSA and 2011-denial rate in a MSA and 2008)/denial rate in a MSA and 2008. The proportional change in small business lending is calculated the same way. Google search volume on ‘crowdfunding’ represents the search volume on ‘crowdfunding’ in a state relative to the highest point in the US which is always 100.

Table 3.10: Panel Data Regressions

	Same set of MSAs as cross-sectional			All the MSAs		
	# of project per million	Ln(# of projects)	Ln(total contributions for all projects)	DV: # of project per million	Ln(# of projects)	Ln(total contributions for all projects)
	(1)	(2)	(3)	(4)	(5)	(6)
House Price Index	-0.134***	-0.016***	-0.061***	-0.082***	-0.010***	-0.050***
	(0.028)	(0.004)	(0.012)	(0.015)	(0.002)	(0.008)
Bank Branch Density	-3.286	-1.981*	-6.297**	-6.322*	-2.086**	-8.801***
	(4.063)	(1.143)	(3.046)	(3.423)	(0.828)	(2.656)
Unemployment Rate	-96.184***	-7.573***	-35.285***	-31.029***	-1.750**	-12.164***
	(18.751)	(2.488)	(8.575)	(6.568)	(0.707)	(3.282)
Internet Connectivity	0.092	0.025	0.010	0.073	0.007	-0.015
	(0.107)	(0.016)	(0.037)	(0.063)	(0.008)	(0.025)
Small Establishments	0.000**	0.000	-0.000***	0.000***	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Pop)	1.164	-0.493	7.360	4.346	0.293	5.538**
	(13.124)	(1.804)	(5.668)	(4.785)	(0.514)	(2.370)
Median Income	-0.000	-0.000**	-0.000***	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.3567	0.4145	0.4435	0.1890	0.2129	0.2594
N	12948	12948	12948	39013	39013	39013

Note: The table reports panel data estimations. Standard errors are clustered by MSA. For columns (1) through (3), I use only the same set of MSAs used in our cross-sectional IV regressions. For columns (4) through (6), I include all the MSAs where all the variables used in the models are available. *** significant at 1%; ** significant at 5%; * significant at 10%

Table 3.11: Accounting for Endogeneity of Bank Branch Density

	DV: Change in # of project per million	Ln(Change in # of projects)	Ln(Change in total contributions for all projects)	DV: Change in # of project per million		Ln(Change in # of projects)		Ln(Change in total contributions for all projects)	
				Bank branch density (Below 25%)	Bank branch density (Above 75%)	Bank branch density (Below 25%)	Bank branch density (Above 75%)	Bank branch density (Below 25%)	Bank branch density (Above 75%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Increase in House Prices	-0.451***	-0.011	-0.101***	-0.420***	-2.231	-0.010	-0.133	-0.127***	-0.185
	(0.110)	(0.008)	(0.023)	(0.160)	(1.960)	(0.015)	(0.115)	(0.047)	(0.203)
Bank Branch Density	-0.294	0.060	-0.142	-11.909*	-3.378	-1.283***	-0.245	-4.464**	-0.489
	(0.817)	(0.049)	(0.120)	(6.188)	(4.998)	(0.427)	(0.293)	(1.907)	(0.559)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.3464	0.7548	0.5819	0.3811	0.0182	0.6365	0.4723	0.5111	0.4509
N	3237	3237	3237	806	806	806	806	806	806

Note: The table reports 2SLS estimations. Standard errors are clustered by MSA.
*** significant at 1%; ** significant at 5%; * significant at 10%

Table 3.12: Nonlinear effects of HPI

	DV: Change in # of project per million		Ln(Change in # of projects)		Ln(Change in total contributions for all projects)	
	MSAs with an increase in house prices	MSAs with a drop in house prices	MSAs with an increase in house prices	MSAs with a drop in house prices	MSAs with an increase in house prices	MSAs with a drop in house prices
	(1)	(2)	(3)	(4)	(5)	(6)
Increase in House Prices	0.730	-0.520***	-0.026	-0.019	0.352	-0.109***
	(1.731)	(0.137)	(0.067)	(0.013)	(0.438)	(0.027)
Bank Branch Density	-0.811	-0.752	0.228	0.051	-0.530	-0.234*
	(3.411)	(0.863)	(0.174)	(0.048)	(0.706)	(0.134)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Cate FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.3670	0.3378	0.7565	0.7562	0.4961	0.5674
N	676	2561	676	2561	676	2561

Note: The table reports 2SLS estimations. Standard errors are clustered by MSA.
*** significant at 1%; ** significant at 5%; * significant at 10%

Bibliography

Adelino, M., Schoar, A., and Severino, F. 2013. House Prices, Collateral and Self-Employment. *National Bureau of Economic Research Working Paper*

Agarwal, R., Animesh, A., and Prasad, K. 2009. Social interactions and the "digital divide": Explaining variations in internet use. *Information Systems Research* **20**(2) 277–294.

Aggarwal, R., Gopal, R., Gupta, A., and Singh, H. 2012. Putting Money Where the Mouths Are: The Relation Between Venture Financing and Electronic Word-of-Mouth. *Information Systems Research* **23**(3-Part-2) 976–992.

Agrawal, A., Catalini, C., and Goldfarb, A. 2013a. The Simple Economics of Crowdfunding. *Innovation Policy and the Economy, Volume 14*

Agrawal, A., Catalini, C., and Goldfarb, A. 2013b. The Simple Economics of Crowdfunding. *Innovation Policy and the Economy, Volume 14*

Agrawal, A. K., Catalini, C., and Goldfarb, A. 2011. The Geography of Crowdfunding. *National Bureau of Economic Research Working Paper*

Ahlers, G., Cumming, D., Guenther, C., and Schweizer, D. 2012. Signaling in Equity Crowdfunding. *Available at SSRN 2161587*

Akerlof, G. A. 1970. The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *The quarterly journal of economics* 488–500.

Alevy, J. E., Haigh, M. S., and List, J. A. 2007. Information Cascades: Evidence from a Field Experiment with Financial Market Professionals. *The Journal of Finance* **62**(1) 151–180.

Amel, D. F., and Brevoort, K. P. 2005. The perceived size of small business banking markets. *Journal of Competition Law and Economics* **1**(4) 771–784.

Anderson, E. T., Fong, N. M., Simester, D. I., and Tucker, C. E. 2010. How Sales Taxes Affect Customer and Firm Behavior: The Role of Search on the Internet. *Journal of Marketing Research (JMR)* **47**(2) 229–239.

Aral, S., Muchnik, L., and Sundararajan, A. 2009. Distinguishing Influence-based Contagion from Homophily-driven Diffusion in Dynamic Networks. *Proceedings of the National Academy of Sciences* **106**(51) 21544–21549.

Aral, S., and Walker, D. 2012. Identifying Influential and Susceptible Members of Social Networks. *Science* **337**(6092) 337–341.

Assunção, J. J., Benmelech, E., and Silva, F. S. S. 2013. Repossession and the Democratization of Credit. *Review of Financial Studies*

Avery, R. B., Bostic, R. W., and Samolyk, K. A. 1998. The role of personal wealth in small business finance. *Journal of Banking & Finance* **22**(6) 1019–1061.

Balasubramanian, S. 1998. Mail versus mall: A strategic analysis of competition between direct marketers and conventional retailers. *Marketing Science* **17**(3) 181–195.

Banerjee, A. V. 1992. A Simple Model of Herd Behavior. *The Quarterly Journal of Economics* **107**(3) 797–817.

Barber, B., Lehavy, R., McNichols, M., and Trueman, B. 2001. Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns. *The Journal of Finance* **56**(2) 531–563.

Baye, M. R., Morgan, J., and Scholten, P. 2006. Information, search, and price dispersion. *Handbook on economics and information systems* **1**

Belleflamme, P., Lambert, T., and Schwienbacher, A. 2010. Crowdfunding: tapping the right crowd.

Berger, A. N., and Udell, G. F. 1995. Relationship lending and lines of credit in small firm finance. *Journal of business* 351–381.

Bernanke, B., and Gertler, M. 1989. Agency costs, net worth, and business fluctuations. *The American Economic Review* 14–31.

Bikhchandani, S., Hirshleifer, D., and Welch, I. 1992. A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of political Economy* 992–1026.

Bikhchandani, S., and Sharma, S. 2000. Herd Behavior in Financial Markets. *IMF Staff papers* 279–310.

Blum, B. S., and Goldfarb, A. 2006. Does the internet defy the law of gravity? *Journal of international economics* **70**(2) 384–405.

Brevoort, K., Wolken, J., and Holmes, J. 2010. Distance still matters: the information revolution in small business lending and the persistent role of location, 1993-2003.

Brynjolfsson, E., Hu, Y. J., and Rahman, M. S. 2009. Battle of the retail channels: How product selection and geography drive cross-channel competition. *Management Science* **55**(11) 1755–1765.

Brynjolfsson, E., Hu, Y. J., and Smith, M. D. 2003. Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers. *Management Science* **49**(11) 1580–1596.

Brynjolfsson, E., and Smith, M. D. 2000. Frictionless commerce? A comparison of Internet and conventional retailers. *Management Science* **46**(4) 563–585.

Van den Bulte, C., and Iyengar, R. 2011. Tricked by truncation: Spurious duration dependence and social contagion in hazard models. *Marketing Science* **30**(2) 233–248.

Burtch, G., Ghose, A., and Wattal, S. 2013. An Empirical Examination of the Antecedents and Consequences of Contribution Patterns in Crowd-Funded Markets. *Information Systems Research* **24**(3) 499–519.

Cai, H., Chen, Y., and Fang, H. 2009. Observatioinal Learning: Evidence from a Randomized Natural Field Experiment. *American Economic Review* **99**(3) 864–882.

Cavalluzzo, K., and Wolken, J. 2005. Small Business Loan Turndowns, Personal Wealth, and Discrimination. *Journal of Business* **78**(6) 2153–2177.

Chemmanur, T., Loutskina, E., and Tian, X. 2010. Corporate Venture Capital, Value Creation, and Innovation. *Boston College Working Paper*

Chen, H., Gompers, P., Kovner, A., and Lerner, J. 2010. Buy local? The geography of venture capital. *Journal of Urban Economics* **67**(1) 90–102.

Choi, J., and Bell, D. R. 2011. Preference Minorities and the internet. *Journal of Marketing Research (JMR)* **48**(4) 670–682.

Cipriani, M., and Guarino, A. 2005. Herd Behavior in a Laboratory Financial Market. *American Economic Review* 1427–1443.

Combes, P.-P., and Duranton, G. 2006. Labour pooling, labour poaching, and spatial clustering. *Regional Science and Urban Economics* **36**(1) 1–28.

Conley, T. G., and Udry, C. R. 2010. Learning about a New Technology: Pineapple in Ghana. *The American Economic Review* **100**(1) 35–69.

Conti, A., Thursby, J., and Thursby, M. 2013. Patents as Signals for Startup Financing. *The Journal of Industrial Economics* **61**(3) 592–622.

Cosh, A., Cumming, D., and Hughes, A. 2009. Outside Enterpreneurial Capital. *The Economic Journal* **119**(540) 1494–1533.

Dranove, D., and Jin, G. Z. 2010. Quality Disclosure and Certification: Theory and Practice. *Journal of Economic Literature* **48**(4) 935–63.

Ellison, G., and Ellison, S. F. 2009. Tax Sensitivity and Home State Preferences in Internet Purchasing. *American Economic Journal: Economic Policy* **1**(2) 53–71.

Evans, D. S., and Jovanovic, B. 1989. An estimated model of entrepreneurial choice under liquidity constraints. *The Journal of Political Economy* 808–827.

Fairlie, R. W., and Krashinsky, H. A. 2012. Liquidity constraints, household wealth, and entrepreneurship revisited. *Review of Income and Wealth* **58**(2) 279–306.

Fan, W., and White, M. J. 2003. Personal Bankruptcy and the Level of Entrepreneurial Activity. *Journal of law and economics* **46**(2) 545–567.

Fleming, L. 2001. Recombinant uncertainty in technological search. *Management science* **47**(1) 117–132.

Forman, C., Ghose, A., and Goldfarb, A. 2009. Competition Between Local and Electronic Markets: How the Benefit of Buying Online Depends on Where You Live. *Management Science* **55**(1) 47–57.

Forman, C., Goldfarb, A., and Greenstein, S. 2012. The Internet and local wages: A puzzle. *American Economic Review* **102**(1) 556.

Ghose, A., Goldfarb, A., and Han, S. P. 2012. How Is the Mobile Internet Different? Search Costs and Local Activities. *Information Systems Research*

Ghose, A., Smith, M. D., and Telang, R. 2006. Internet Exchanges for Used Books: An Empirical Analysis of Product Cannibalization and Welfare Impact. *Information Systems Research* **17**(1) 3–19.

Glaeser, E. L. 2007. Entrepreneurship and the City. *National Bureau of Economic Research Working Paper*

Glaeser, E. L., and Kerr, W. R. 2009. Local industrial conditions and entrepreneurship: how much of the spatial distribution can we explain? *Journal of Economics & Management Strategy* **18**(3) 623–663.

Godes, D., and Mayzlin, D. 2009. Firm-created Word-of-Mouth Communication: Evidence from a Field Test. *Marketing Science* **28**(4) 721–739.

Goldfarb, A., and Prince, J. 2008. Internet adoption and usage patterns are different: Implications for the digital divide. *Information Economics and Policy* **20**(1) 2–15.

Gompers, P. A. 1996. Grandstanding in the venture capital industry. *Journal of Financial Economics* **42**(1) 133–156.

Goolsbee, A. 2000. In a World Without Borders: The Impact of Taxes on Internet Commerce. *The Quarterly Journal of Economics* **115**(2) 561–576.

Goolsbee, A. 2001. Competition in the Computer Industry: Online Versus Retail. *The Journal of Industrial Economics* **49**(4) 487–499.

Granados, N., Gupta, A., and Kauffman, R. J. 2012. Online and Offline Demand and Price Elasticities: Evidence from the Air Travel Industry. *Information Systems Research* **23**(1) 164–181.

Greenstone, M., and Mas, A. 2012. Do Credit Market Shocks Affect the Real Economy? Quasi-Experimental Evidence from the Great Recession and Normal Economic Times. *Available at SSRN 2187521*

Guiso, L., Sapienza, P., and Zingales, L. 2004. Does Local Financial Development Matter? *The Quarterly Journal of Economics* **119**(3) 929–969.

Hirshleifer, D., and Hong Teoh, S. 2003. Herd Behaviour and Cascading in Capital Markets: A Review and Synthesis. *European Financial Management* **9**(1) 25–66.

Hogan, C. E. 1997. Costs and Benefits of Audit Quality in the IPO Market: A Self-selection Analysis. *Accounting review* 67–86.

Holtz-Eakin, D., Joulfaian, D., and Rosen, H. S. 1994. Sticking It Out: Entrepreneurial Survival and Liquidity Constraints. *The Journal of Political Economy* **102**(1) 53–75.

Hortacsu, A., Martínez-Jerez, F. A., and Douglas, J. 2009. The geography of trade in online transactions: Evidence from eBay and mercadolibre. *American Economic Journal: Microeconomics* 53–74.

Howe, J. 2006. The Rise of Crowdsourcing. *WIRED* (Issue 14.06)

Howe, J. 2008. *Crowdsourcing: How the power of the crowd is driving the future of business*, Century.

Hsu, D. H. 2004. What do Entrepreneurs Pay for Venture Capital Affiliation? *The Journal of Finance* **59**(4) 1805–1844.

Hsu, D. H., and Ziedonis, R. H. 2013. Resources as Dual Sources of Advantage: Implications for Valuing Entrepreneurial-firm Patents. *Strategic Management Journal*

Hurst, E., and Lusardi, A. 2004. Liquidity constraints, household wealth, and entrepreneurship. *Journal of political Economy* **112**(2) 319–347.

Iyengar, R., Van den Bulte, C., and Valente, T. W. 2011. Opinion Leadership and Social Contagion in New Product Diffusion. *Marketing Science* **30**(2) 195–212.

Kambil, A., and Van Heck, E. 1998. Reengineering the Dutch flower auctions: A framework for analyzing exchange organizations. *Information Systems Research* **9**(1) 1–19.

Kerr, W. R., and Nanda, R. 2011. Financing constraints and entrepreneurship. *Handbook of Research on Innovation and Entrepreneurship* 88.

Kim, K., and Hann, I.-H. 2013. Does Crowdfunding Democratize Access to Capital? A Geographical Analysis.Conference on Information Systems and Technology.

Koppius, O. R., Van Heck, E., and Wolters, M. J. 2004. The importance of product representation online: empirical results and implications for electronic markets. *Decision Support Systems* **38**(2) 161–169.

Kuppuswamy, V., and Bayus, B. L. 2013. *Crowdfunding Creative Ideas: the Dynamics of Projects Backers in Kickstarter*

Kuruzovich, J., Viswanathan, S., Agarwal, R., Gosain, S., and Weitzman, S. 2008. Marketspace or marketplace? Online information search and channel outcomes in auto retailing. *Information Systems Research* **19**(2) 182–201.

Laderman, E., and Reid, C. 2010. The Community Reinvestment Act and small business lending in low-and moderate-income neighborhoods during the financial crisis. *Federal Reserve Bank of San Francisco Working Paper*

Langer, N., Forman, C., Kekre, S., and Sun, B. 2012. Ushering Buyers into Electronic Channels: An Empirical Analysis. *Information Systems Research* **23**(4) 1212–1231.

Lieber, E., and Syverson, C. 2012. Online versus Offline Competition. *The Oxford Handbook of the Digital Economy* 189.

Lin, M., Prabhala, N. R., and Viswanathan, S. 2013. Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending. *Management Science* **59**(1) 17–35.

Lin, M., and Viswanathan, S. 2013. Home Bias in Online Investments: An Empirical Study of an Online Crowd Funding Market. *Available at SSRN 2219546*

Manski, C. F. 1993. Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies* **60**(3) 531–542.

McLaughlin, R., Safieddine, A., and Vasudevan, G. K. 2000. Investment Banker Reputation and the Performance of Seasoned Equity Issuers. *Financial Management* 96–110.

Meggison, W. L., and Weiss, K. A. 1991. Venture Capitalist Certification in Initial Public Offerings. *The Journal of Finance* **46**(3) 879–903.

Meyer, B. D. 1990. Unemployment Insurance and Unemployment Spells. *Econometrica* **58**(4) 757–782.

Mian, A., and Sufi, A. 2011. House Prices, Home Equity-Based Borrowing, and the US Household Leverage Crisis. *American Economic Review* **101**(5) 2132–56.

Michael, S. C. 2009. Entrepreneurial Signaling to Attract Resources: The Case of Franchising. *Managerial and Decision Economics* **30**(6) 405–422.

Mollick, E. 2012. The dynamics of crowdfunding: Determinants of success and failure. *Available at SSRN 2088298*

Moretti, E. 2011. Social Learning and Peer Effects in Consumption: Evidence from Movie Sales. *The Review of Economic Studies* **78**(1) 356–393.

Mudambi, S. M., and Schuff, D. 2010. What makes a helpful online review? A study of customer reviews on Amazon. com. *MIS quarterly* **34**(1) 185–200.

Nahata, R. 2008. Venture Capital Reputation and Investment Performance. *Journal of Financial Economics* **90**(2) 127–151.

Nair, H. S., Manchanda, P., and Bhatia, T. 2010. Asymmetric Social Interactions in Physician Prescription Behavior: The Role of Opinion Leaders. *Journal of Marketing Research* **47**(5) 883–895.

Nanda, R., and Sørensen, J. B. 2010. Workplace Peers and Entrepreneurship. *Management Science* **56**(7) 1116–1126.

Nelson, R. R., and Winter, S. G. 1982. *An evolutionary theory of economic change*, Belknap press.

Ordanini, A., Miceli, L., Pizzetti, M., and Parasuraman, A. 2011. Crowd-funding: transforming customers into investors through innovative service platforms. *Journal of Service Management* **22**(4) 443–470.

Overby, E., and Jap, S. 2009. Electronic and Physical Market Channels: A Multiyear Investigation in a Market for Products of Uncertain Quality. *Management Science* **55**(6) 940–957.

Petersen, M. A., and Rajan, R. G. 2002. Does distance still matter? The information revolution in small business lending. *The Journal of Finance* **57**(6) 2533–2570.

Saiz, A. 2010. The geographic determinants of housing supply. *The Quarterly Journal of Economics* **125**(3) 1253–1296.

Salganik, M. J., Dodds, P. S., and Watts, D. J. 2006. Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market. *science* **311**(5762) 854–856.

Samila, S., and Sorenson, O. 2011. Venture capital, entrepreneurship, and economic growth. *The Review of Economics and Statistics* **93**(1) 338–349.

Scharfstein, D. S., and Stein, J. C. 1990. Herd behavior and investment. *The American Economic Review* 465–479.

Schwienbacher, A., and Larralde, B. 2010. Crowdfunding of small entrepreneurial ventures. *HANDBOOK OF ENTREPRENEURIAL FINANCE, Oxford University Press, Forthcoming*

Seamans, R., and Zhu, F. 2011. Technology Shocks in Multi-Sided Markets: The Impact of Craigslist on Local Newspapers. *NET Institute Working Paper No. 10-11. Available at SSRN 1694622*

Sinai, T., and Waldfogel, J. 2004. Geography and the Internet: is the Internet a substitute or a complement for cities? *Journal of Urban Economics* **56**(1) 1–24.

Sorenson, O., and Stuart, T. E. 2001. Syndication Networks and the Spatial Distribution of Venture Capital Investments. *American Journal of Sociology* **106**(6) 1546–1588.

Spence, M. 1973. Job market signaling. *The quarterly journal of Economics* **87**(3) 355–374.

Spence, M. 2002. Signaling in retrospect and the informational structure of markets. *American Economic Review* 434–459.

Stemler, A. R. 2013. The JOBS Act and crowdfunding: Harnessing the power—and money—of the masses. *Business Horizons* **56**(3) 271–275.

Stuart, T. E., Hoang, H., and Hybels, R. C. 1999. Interorganizational Endorsements and the Performance of Entrepreneurial Ventures. *Administrative Science Quarterly* **44**(2) 315–349.

Susarla, A., Jeong-Ha Oh, and Yong Tan. 2012. Social Networks and the Diffusion of User-Generated Content: Evidence from YouTube. *Information Systems Research* **23**(1) 23–41.

Trusov, M., Bodapati, A. V., and Bucklin, R. E. 2010. Determining Influential Users in Internet Social Networks. *Journal of Marketing Research* **47**(4) 643–658.

Tucker, C., and Zhang, J. 2011. How Does Popularity Information Affect Choices? A Field Experiment. *Management Science* **57**(5) 828–842.

Valente, T. W. 1995. *Network Models of the Diffusion of Innovations (Quantitative Methods in Communication Series)*, Hampton Press.

Wallsten, S. J., and Mallahan, C. 2010. Residential broadband competition in the United States. *Technology Policy Institute working paper*

Watts, D. J., and Dodds, P. S. 2007. Influentials, Networks, and Public Opinion Formation. *Journal of consumer research* **34**(4) 441–458.

Weimann, G. 1994. *The influentials: People who influence people*, SUNY Press.

Willett, J. B., and Singer, J. D. 1995. It's Déjà Vu All over Again: Using Multiple-Spell Discrete-Time Survival Analysis. *Journal of Educational and Behavioral Statistics* **20**(1) 41–67.

Zhang, J. 2010. The Sound of Silence: Observational Learning in the US Kidney Market. *Marketing Science* **29**(2) 315–335.

Zhang, J., and Liu, P. 2012. Rational Herding in Microloan Markets. *Management Science* **58**(5) 892–912.