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Crowdfunding as gambling: Evidence from repeated natural experiments

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ABSTRACT

Lenders in Prosper, one of the largest lending markets in the U.S., reduce their activity when playing multistate Powerball or Mega Millions lottery jackpot becomes attractive. This finding suggests that the desire for sensation seeking is an underlying motivation for participating in peer-to-peer crowdfunding markets; the thrill of winning a large lottery jackpot fulfills some lenders' desire for novelty and sensation seeking, thus decreasing their lending activity. We discuss our findings' implications for lenders, borrowers, platform organizers, and policymakers.

1. Introduction

Riddled with substantial challenges from obtaining financing from traditional sources such as banks, many individuals and entrepreneurs have turned to crowdfunding (Block et al., 2018; Cumming and Groh, 2018), which involves an open call, essentially through the Internet, for requesting financial resources from crowds (Belleflamme et al., 2014). By removing financial barriers and expanding funding opportunities, individuals organizing crowdfunding campaigns directly benefit in myriad ways ranging from experimentation in the form of commercializing new products and seeking market validation, and creating new ventures and jobs (Mollick, 2016; Signori and Vismara, 2018; Da Cruz, 2018). It is, however, less clear why people contribute to crowdfunding campaigns; the question of funders' motivations deserves scholarly attention because it is a critical factor in the success of a campaign, or indeed the success of crowdfunding as an alternative source of financing, hailed by policymakers as a new means of financing innovation (Sauermann et al., 2019; Colombo et al., 2015a). Essentially, designing the presentation of a crowdfunding campaign that appeals to the crowd requires a deep understanding of what motivates backers' giving (Parhankangas and Renko, 2017; Hornuf and Schwienbacher, 2018).

This paper explores whether sensation-seeking, defined as a personal trait characterized by an intense desire to experience thrill from risk-taking, can explain crowdfunders' contributions, specifically in the form of bids made in peer-to-peer lending crowdfunding. Bidding small amounts and investing in a loan part – like betting in gambling such as lottery – can produce fun, excitement, and thrill. Prior studies that have surveyed crowdfunders about their motivations point to the relevance of "having fun" (Berglin and Strandberg, 2013; Ryu and Kim, 2016; Daskalakis and Yue, 2017), among others; however, survey methods are introspectively derived, and

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intentional self-assessments and thus, suffer from methodological issues (Nosek et al., 2011).[1] Therefore, to empirically identify the variation in pledging activity across individuals explained by the entertainment and fun motivation, we employ the setting of lottery as a form of gambling.

We hypothesize that when the jackpot lottery is high, bidding activity in the peer-to-peer lending market decreases. Our identification strategy is based on the notion that to function as a form of entertainment and fun, funding loan parts need to compete for attention and dollars with other forms of gambling. One widely available, frequently played, and aggressively advertised form of gambling is playing the lottery. Accordingly, we test whether large lottery jackpots will reduce the contribution activity of crowdfunders. That is so because large jackpots will divert at least some crowdfunders to satisfy their sensation-seeking needs by playing the lottery. Additionally, lottery is an ideal repeated natural experiment because lottery jackpots are randomly won and the pot balloons in a series of draws with no winners. Therefore, it is difficult to find the negative relationship between lottery jackpots and bidding if such correlations were merely spurious.

To examine the relationship between lottery jackpots and crowdfunding contributions, this paper employs different datasets, specifications, and strategies, which are summarized as follows. First, we use all bidding activities of investors on Prosper Marketplace, one of the largest peer-to-peer lending marketplaces in the U.S., between January 1st, 2007 and December 18th, 2010. Our findings indicate that doubling the combined jackpot size of Powerball and Mega Millions is associated with a decrease of 11.2% (8.2%) in bidding volume in dollars (total number of bids) of individual lenders. Additionally, the effect is stronger for those days coinciding with large jackpots; when the jackpot size is in the top quartile distribution, the bidding volume (total number of bids) by individual lenders is lower by 18.2% (14.2%) compared with the bottom quartile.

Second, if the theoretical channel is sensation seeking, we expect that high sensation seekers show greater propensities in risk-taking in financial matters than low sensation seekers (Wong and Carducci, 1991) specially when alternative options such as playing lottery are unlikely to produce similar thrill. Accordingly, we find the substitution effect between the combined jackpot size of Powerball and Mega Millions and the total bidding volume in the U.S. dollar by individual lenders on a particular loan listing on a day is stronger for loans whose borrowers have higher debt to income ratio (a proxy of loan risk). Overall, such evidence implies that some peer-to-peer lenders exposed to large lottery jackpots reduce their contributions to funding loans and we interpret this observation as evidence on the role of sensation-seeking as one of the underlying motivations for participation in peer-to-peer lending.

Third, to further rule out unobserved factors influencing both peer-to-peer bidding and lottery jackpots, we separately use the lottery jackpots in the U.S. multi-state lotteries Powerball and Mega Millions. Powerball and Mega Millions have similar rules, are available for purchase in almost similar jurisdictions, and offer jackpots of similar average sizes. Despite the statistical observation that Powerball and Mega Millions are uncorrelated with each other, we still find similar relationships separately between each lottery and crowdfunding contributions. Conceiving an alternative explanation based on the relationship of jackpot size and bidding activity is even more implausible when that explanation must justify why Mega Millions and Powerball jackpots are separately correlated with bidding activity but not with each other.

Finally, instead of focusing on multi-state lotteries of Powerball and Mega Millions, we focus on two state-level lotteries of California and Texas, typically among the largest state lotteries, and find supporting evidence for the sample of residents in California and Texas. We also perform falsification tests to further rule out the possibility of spurious correlations. The jackpot of state lotteries in California (Texas) is not associated with the bidding activity of individuals residing outside of California (Texas).

We contribute to the studies that explore crowdfunders' motivations. Prior studies emphasize the role of intrinsic and extrinsic motivations, including the prospect of a reward, support and access to innovative products before others, recognition from others, promotion of their image and social reputation, and altruism (Colombo et al., 2015b; Giudici et al., 2018; Boudreau et al., 2017; Daskalakis and Yue, 2017). To this list, we introduce the sensation-seeking motivation, that is a basic personality trait defined as "the seeking of varied, novel, complex, and intense sensations and experiences, and the willingness to take physical, social, legal, and financial risks for the sake of such experience" (Zuckerman, 1994). We contribute to the literature that seeks to identify the instances in which sensation-seeking influences investors' decisions (Barber et al., 2008; Gao and Lin, 2014; Dorn et al., 2014; Liao, 2017; Brown et al., 2018). These studies focus on the trading activity of investors in the stock market and find evidence consistent with the gambling motivation of investors. We extend this line of evidence in the new institutional setting of peer-to-peer lending, which is remarkably different from the stock market in terms of information disclosure and skewness of financial payoffs.

2. Related literature

2.1. Peer-to-peer lending

Crowdfunding is an umbrella term that encompasses distinct, yet evolving, models of fundraising from crowds: reward-based

[1] A few factors limit the value of these explicit measurements to accurately report respondents' mental content by introspection: 1) Respondents might lack motivation for reporting what they are aware of; 2) Respondents might face constrains in reporting: for instances, the design and the circumstances of measurement limit what is reported, or respondents may not feel comfortable answering in ways that present themselves in an unfavorable manner; 3) Respondents might have difficulty in translating their mental content into a report; 4) Respondents might have limits in accessing and recalling their mental content for various reasons including memory decay and displacement; 5) Respondents in survey methods might suffer from non-response bias: Those who choose to respond to a survey question may be different from those who choose not to respond, thus creating bias.

crowdfunding, equity-based crowdfunding, donation-based crowdfunding, lending based crowdfunding, and initial coin offering. Lending based crowdfunding (also known as, peer to peer, direct, or marketplace lending) is distinguished from other models by directly connecting a multitude of lenders to borrowers who are posting loans through an online platform. As an innovation empowered by technology in the finance industry, peer to peer lending is a direct alternative to banks, securing loans for many borrowers who might not have been able to obtain loans from banks.[2] While peer to peer lending share of the loan market is small, in some segment-countries these platforms are growing rapidly and challenging incumbent sources of loan origination such as banks. In 2017, business lending by U.K. crowdfunding platforms amounted to almost 30% of new loans to small businesses.[3]

Peer to peer lending literature has examined the lending decisions crowds make and how it shapes funding outcomes of listed loans. To explore how crowds overcome information asymmetries and potential moral hazards in screening loans, researchers have highlighted the role of quality signals and information disclosures (Iyer et al., 2015). Borrowers can signal privately low default risk by posting low reserve interest rates (Kawai et al., 2014). Freedman and Jin (2017) find a positive signaling effect of bidding on friends' loan listings, especially pronounced among borrowers with lower credit grades. Similarly, having friends with high credit quality help prospective borrowers to fundraise successfully more often, to face lower interest rate, and to default less (Lin et al., 2013). Hildebrand et al. (2016) use a policy change in Prosper platform that changes the group leaders' incentive by discontinuing the payment of origination rewards (i.e., group leaders are no longer paid to create volume), thereby making group leaders less aggressive in bidding. Well-funded borrowers can also benefit from information cascades and attract more funding (Zhang and Liu, 2012; Herzenstein et al., 2011). Lenders favor borrowers that are socially, culturally, and geographically proximate to themselves (Galak et al., 2011; Lin and Viswanathan, 2015; Burtch et al., 2014). In addition to these factors, voluntary, unverified (and often unverifiable) disclosures (i.e., soft information such as descriptions about the loan purpose or identity claims) influence lenders' decisions. For example, the number of fundraising bids increases when a prospective borrower has disclosed information on the purpose of the loan, an explanation for poor credit grade, and a picture (Michels, 2012). Judging from profile pictures in the loan listings, lenders have an irrational bias towards attractive photographs (Ravina, 2012), and conversely, lenders benefit from biasing towards trustworthy faces (Pope and Sydnor, 2011).

Related literature has also tied the local availability of credit to lending outcomes. Ramcharan and Crowe (2013) find that one standard deviation decline in house prices within a state during the recent housing crisis is associated with higher rates of loans compared with those of otherwise-matched borrowers. Butler et al. (2016) find that borrowers residing in areas with good access to bank finance request loans with lower interest rates, and this effect is more pronounced for borrowers seeking risky or small loans. Thus, both lenders and borrowers' geographical location influence their decisions.

2.2. What motivates crowdfunders to contribute?

Scholars have investigated the question of what motivates the backers and supporters in crowdfunding.[4] Broadly, inspired by the framework of Ryan and Deci (2000), the backers' decision to contribute to crowdfunding incorporates aspects of both (i) extrinsic motivations present in traditional investment decision making (e.g., profit-seeking or obtaining rewards) and (ii) intrinsic motivations typically present in charitable and prosocial contexts (e.g., altruism). Below we elaborate on these motivations.

Besides offering tangible rewards or interest payments to backers, crowdfunding campaigns often involve the pre-purchase of a product (Cholakova and Clarysse, 2015), often an innovative product at a discounted price. For instance, in lending based crowdfunding, Pierrakis and Collins (2013) were first to survey lenders and found that financial return is the main motivation behind individuals' decision to lend money to businesses; Ninety-five percent of all surveyed lenders responded that the interest rate is important or very important. In this sense, backers expect profit, reciprocity (Colombo et al., 2015b), or recognition from others in return for their contributions (Bretschneider and Leimeister, 2017). There are intrinsic motivations that backers pursue; we cite a select few of these drivers (in no particular order): (1) helping others: backers want a certain project to be realized and act pro-socially (Giudici et al., 2018); (2) liking motive: backers like a certain venture and enjoy satisfaction from observing it realize and succeed, especially they enjoy supporting the cause (Cholakova and Clarysse, 2015); (3) image motive and sense of community motive: backers want to be liked or well-regarded by others and desire to be part of a community (Gerber and Hui, 2013); (4) identification motive: backers identify with founding teams or project goals (Boudreau et al., 2017).

Among the intrinsic motivations, there is some evidence that fun, entertainment, and novelty play a role in motivating crowdfunders. Berglin and Strandberg (2013) conducted a survey of backers and reported that backers express fun as a relevant motive for their contribution, and interestingly, those crowdfunders that indicated fun as their strong reason for participating also tended to make smaller investments (p. 24). Ryu and Kim (2016) report survey evidence that among other factors, crowdfunders decide to support the project because it is fun to do so, and they find the act of participating appealing, enjoyable, and pleasurable. Finally, Daskalakis and

[2] Despite being creditworthy, some businesses are unable to obtain a loan through traditional channels and in turn, use crowdfunding. For instance, A fifth of borrowers in the Funding Circle believe they would not have been able to secure external finance in the absence of Funding Circle. https://static.fundingcircle.com/files/uk/information-packs/small-business-big-impact-cebr-report-315de033.pdf

[3] https://www.jbs.cam.ac.uk/fileadmin/user_upload/research/centres/alternative-finance/downloads/2018-5th-uk-alternative-finance-industry-report.pdf

[4] We do not overview the motivation of entrepreneurs that choose crowdfunding as their preferred source of financing. See Table 1 in Moritz and Block (2016).

Yue (2017) survey crowdfunders in Germany, Spain, and Poland about their motivations and report that "interest and excitement" is ranked as the second most important motivation, following financial returns as the number one reason to participate in peer to peer lending. These authors note that rankings are based on mean scores, but these differences in importance are not statistically significant from each other.[5] Overall, using only survey evidence researchers have identified the role of "having fun" as one of the underlying motivations behind backers' contributions. Our study builds on these observations, but it is not suffering from methodological issues often associated with surveys and asking respondents explicitly about their motivations (for a review, see Nosek et al. (2011)); that is, we rely on methods that are not direct, intentional self-assessments.

2.3. Gambling and sensation-seeking

One of the well documented motivations for gambling is excitement or sensation-seeking (Pantalon et al., 2008) (for a comprehensive review of theories on gambling, see Binde (2009)). The psychology literature associates gambling with individual differences in sensation-seeking and recognizes it as a personality type, defined by those who "seek novel, varied or complex sensations or experiences and are willing to take risks for the sake of such experience" (Breen and Zuckerman, 1999). Sensation-seeking is associated with attitudes about gambling and behavioral intentions to gamble (Breen and Zuckerman, 1999), higher frequency and variety of recreational gambling (McDaniel and Zuckerman, 2003; Coventry and Norman, 1997), and betting amounts, and the "chasing behavior" (it consists of trying to make up losses by raising bet sizes) (Dickerson et al., 1987; Anderson and Brown, 1984). We discuss distinctive features of lotteries among other forms of gambling (such as blackjack or poker) and their implications for sensation-seeking motivation.

Unlike other forms of gambling such as playing poker, winning lotteries are fully determined by chance and the gambler does not require skills or talent to influence the outcomes. Other distinguishing features of lotteries include offering disproportionately large prizes despite low cost to play and its infrequent opportunity to play. The bigger the jackpot becomes, the larger the sales (Cook and Clotfelter, 1993). A large roll-over jackpot increases the thrill out of buying a lottery ticket since the idea of large potential monetary windfall can be highly arousing and thus, it could satisfy the need for excitement and arousal for high sensation-seekers.

High sensation seekers show greater risk-taking behaviors (Breivik et al., 2017; Fortune and Goodie, 2010). Sensation seekers are by definition more likely to take physical, social, legal, and financial risks for the sake of such experiences as evidenced by taking part in extreme sports, risky driving, smoking, drinking, using illegal drugs, and crime (Zuckerman, 1994, 2007).[6] While sensation seeking encompasses risk-taking, the opposite relationship is not true. Zuckerman (2007) notes that "sensation seekers do not seek risk for its own sake. It is not the riskiness of their activities that make them rewarding. In fact, many or most experiences sought by sensation seekers are not at all risky. Listening to rock music; partying with interesting, stimulating people; and looking at intensely erotic or violent movies or television involve no risk. However, other types of activities such as driving very fast, engaging in extreme sports, getting drunk or high on drugs, and having unprotected sex with a variety of partners, do involve risk." Overall, a key insight from this literature is that high sensation seekers exhibit a propensity for greater risk-taking in everyday financial matters than low sensation seekers do (Wong and Carducci, 1991).

2.4. Sensation-seeking and participating in financial markets

A large portion of gamblers engage in gambling for fun, excitement, and sensation seeking (Binde, 2009). Sensation seeking is a personality trait that involves volunteering for risky activities, primarily to seek thrill and adventure from novel stimuli (Zuckerman, 1994). Horvath and Zuckerman (1993) note that sensation seeking is related to risky behavior in many domains, including gambling and financial risk-taking. Below, we overview the emerging research that supports that active and speculative trading typically occurs because of sensation seeking (note that clearly, investors do not only trade for sensation seeking).[7]

A growing body of research has identified sensation seeking and gambling as a motivation to participate in trading and investing (Barberis and Huang, 2008; Kumar, 2009; Grinblatt and Keloharju, 2009). Kumar (2009) provides coarse results that the demand for lottery-type stocks (i.e., low-priced stocks with high idiosyncratic volatility and high idiosyncratic skewness) is higher in states with local economic conditions conducive of gambling behavior (higher per capita lottery expenditures).[8] More direct evidence on gambling motivated investment decisions comes from the survey of investors. Hoffmann (2007) surveyed Dutch investors and found that the second most important reason for investing is because investors find it a nice free-time activity (the first reason is the potential for financial gain). Dorn and Sengmueller (2009) directly survey clients of a German broker and find that trading intensity (portfolio turnover) varies based on the self-reported enjoyment of investing and gambling. Grinblatt and Keloharju (2009) use the number of automobile speeding convictions as a measure of sensation seeking and find that investors, who are sensation seekers, trade more frequently. Similarly, Cox et al. (2018) ask Dutch investors if they consider "the fun or the challenge of it" as one of their investment

[5] Daskalakis and Yue (2017) note that "interest and excitement" is the highest rated motivation for investors via equity crowdfunding, followed by increased diversification, higher returns, and disappointment in traditional means of investment.

[6] To assess sensation-seeking personality, a test is administered that explore factors that relate to thrill and adventure seeking, experience seeking, seeking sensation through social activities, sex, and drinking, and finally an intolerance for repetitious experience.

[7] Raylu and Oei (2002) review the sensation-seeking literature on gambling (p. 1020)

[8] Kumar (2009) found that purchase of lottery-stock increases in regions of the US with lower income, higher unemployment rate, minority group race/ethnicity, Catholic, less educated, and younger.

goals. These scholars report that gambling motives can explain a substantial part of individual investors' speculative trading behavior.

To overcome methodological issues associated with self-reported assessments and preference for sensation seeking, scholars have used other methods to link gambling motivations to the speculative stock market activity. Barber et al. (2008) showed that introducing legalized gambling sponsored by the Taiwanese government reduced turnover on the stock market by about one-fourth. Gao and Lin (2014) demonstrated that during periods with high lottery jackpot, stock market trading volume in lottery-type stocks decreased. Similarly, Dorn et al. (2014) document a negative relationship between U.S. multistate lotteries and small trades in the U.S. stock market. Additionally, their study finds that during weeks with larger lottery prizes, discount brokerage clients in California and Germany are less likely to trade. Liao (2017) found that following Casino openings in the United States, portfolio risk-taking increased among investors with demographic propensities associated with gambling. In sum, there is a well-established substitution effect between lotteries and risk-taking in the stock market.[9] We extend these studies to the context of peer-to-peer lending.

3. Hypothesis development: Sensation-seeking and Crowdfunding

We argue that when the jackpot lottery is large, individuals in the peer-to-peer lending markets reduce their bidding activity. This is so because sensation seeking is one of the underlying motivations for some peer-to-peer lenders. The thrill of winning a large jackpot lottery, perhaps intensified by advertising and media coverage around this event, substitutes some individual lenders' desire of sensation-seeking to participate in the peer-to-peer markets, decreasing their bidding activity.

The substitution hypothesis between playing the lottery and participating in peer-to-peer lending is based on the potential role of sensation-seeking in lenders' motivation. Playing the lottery and lending on the peer-to-peer markets are distinctively different activities, including the required capital to participate and the level of patience before realizing the returns from lending. Despite these differences, they can produce the same thrill and excitement for those investors who are sensation seekers. Bidding for different loans not only involves risk-taking by taking new bets but also contains elements of novelty and variety. Adding a new loan to investors' portfolio and therefore changing the composition of their portfolio can provide the desired novelty and variety of experiences that sensation seekers search for. Thus, we suggest that some lenders will substitute between playing the lottery and lending in peer to peer markets to the extent that sensation-seeking motivation drives their behavior.

When the jackpots are large, their magnitude draws a lot of crowds' attention.[10] Given the strong element of fun and entertainment inherent in playing the lottery (Oster, 2004), and the notable, but low, chance of winning and getting extremely rich, their influence on investors' attention can take away from their activity in other financial markets (Gao and Lin, 2014; Dorn et al., 2014; Gao and Lin, 2014), including bidding on newly listed loans. Conversely, when jackpots are relatively small, this might be a scenario that bidding on certain loans might appear more attractive.

We focus on lottery, as a form of gambling, because of several useful institutional features. Lotteries are largely available and frequently played, sometimes the numbers are drawn twice per week. Lottery jackpots are randomly generated, and whenever the lottery is not won, the pot rolls over to the subsequent pot and large jackpots form. To illustrate, the correlation between two of the largest U.S. lotteries, Mega Millions and Powerball jackpots, is only 0.05. Therefore, we leverage the repeated natural experiment of lottery and test whether lending activities in the peer-to-peer lending market reduce when gambling in the form of playing the multistate lotteries Powerball and Mega Millions becomes more attractive.

Hypothesis 1. When lottery jackpots are large, the bidding activity in the peer-to-peer lending market is lower.

4. Data

We assemble data from four different sources: 1) The multi-state lotteries: Powerball and Mega Millions; 2) State lotteries in California, Texas, New York, and Florida; 3) Prosper Marketplace; and 4) Kickstarter. Below we explain each data source and the institutional features relevant to our study.

4.1. Prosper marketplace

Data from Prosper.com include all loan listings and all investors' bids between January 1, 2007 and December 18, 2010. Prosper, among the first U.S. peer to peer lending marketplaces, started its operations on November 9, 2005, and the value of loans originated on this platform has surpassed $14 billion as of March 2019.[11] Over time, the dollar value of loans originated on crowdlending platforms reached to levels that attracted more investors' attention and media. The growth in the legitimacy of this emerging industry partly is attributed to improved policies such as disclosing credit risk. For instance, on February 12, 2007, Prosper started to disallow borrowers with credit scores below 520, and to inform lenders about delinquency amounts (for details see Appendix, Table A1). Prior research has also used Prosper dataset to explore other issues such as home bias, herding, and design of market mechanisms (Zhang and

[9] Cookson (2018) found that the introduction of lottery-linked savings accounts in Nebraska was associated with a 7%–15% decline in casino expenditure.

[10] Barnes et al. (2010) show that 49% of the U.S. citizens regularly buy lottery tickets at least once in a year. Surveys from Gallup also point out that these participation levels are stable during the 1990–2015 period.

[11] Check https://www.prosper.com/invest for details.

Liu, 2012; Lin and Viswanathan, 2015; Wei and Lin, 2016).

Our analysis starts from January 1, 2007, given the notable growth of the platform activity starting this period. To illustrate, while dollar value of total listings (funded loans) on Prosper in the first quarter of 2006 was $30 million ($1.6 million), this number from the first quarter of 2007 was $263.3 million ($20 million). Relatedly, the dollar value of funded loans from the last quarter of 2006 to the first quarter of 2007 showed 72% growth.

The analysis ends on December 18, 2010 for the following reason. Until December 18, 2010, interest rates on loans were set according to Dutch auction process: Borrowers would specify the amount of loan and the maximum interest rate they were willing to pay; then, lenders would bid on those loan listings by submitting the amount they would like to fund and the minimum interest rate. Prosper replaced the Dutch auction process with a new system according to which the platform chose the final interest rates based on a proprietary formula that would also include borrowers' credit risk. Therefore, as soon as a loan is fully funded, that loan is removed, and borrowers cannot bid more (to compete on the interest rate) – total value of bids made on a listing would never pass the listing value.

While we have chosen a period with relatively lower experimentation and policy change by the platform (given the nascent business model of peer-to-peer lending in this period), there is a data gap in our sample period. Prosper suspended operations from October 19, 2008 to July 14, 2009 to register with the SEC to create a secondary marketplace. The re-opening, however, was conditional on obtaining approval from each state to allow lenders to invest in loans listed on Prosper. On July 14, 2009, lenders from 14 states, including California with the highest number of lenders and borrowers active on the platform, were able to lend on Prosper. Table A2 presents the timeline of approvals from additional states. It is noteworthy to mention that a lender from any approved state can bid on any listing requested by borrowers from any other approved state in the US.

Finally, we limit the analysis to all bids from the states whose lenders could participate in at least one of the two multi-state lotteries, Powerball and Mega Millions, at the time of the analysis. Table A3 lists when Powerball and Mega Millions got introduced in each US state. Applying this filter reduces the sample size of all bids by 9.5%, and the final sample includes 6,524,540 bids on 314,408 loan listings.

4.2. Kickstarter

The second source of crowdfunding data comes from Kickstarter. Kickstarter is among the largest U.S. crowdfunding platforms, which was established in 2009, and as of March 19, 2019, the total dollars committed to successful campaigns on the platform has reached to about $4.2 billion.[12] Kickstarter only hosts reward-based campaigns (Colombo et al., 2015b): backers contribute to campaigns in expectations of receiving some form of reward including, but not limited to, a product, participating in a concert, an acknowledgment in the film credits, or a symbolic token of appreciation. Additionally, campaigns follow an all-or-nothing fundraising model: campaign organizers receive the pledges from the crowd only if their campaign reaches/exceeds its funding goal, which can only be set at the beginning of the campaign.

Data from Kickstarter include all contributions (pledges) for Kickstarter campaigns, starting from September 18, 2012 to May 20, 2013. During this period, 1,309,295 backers contributed to 16,042 campaigns.

4.3. Powerball and mega millions

Powerball and Mega Millions are the biggest lotteries in the US.[13] As of March 2019, 44 states offer both lotteries. Drawings for Powerball are held on Wednesdays and Saturdays at 10:59 p.m. Eastern Time, and drawings for Mega Millions are held on Tuesdays and Fridays at 11 p.m. Eastern Time. The largest Powerball jackpot in history was $1.586 billion for the January 13, 2016 drawing, and the largest Mega Millions jackpot in history was $1.537 billion for the October 13, 2018 drawing. The numbers that determine who wins the lottery jackpots are randomly drawn. The correlation between Powerball and Mega Millions lotteries is only 0.05 in our sample. When a lottery has no winner, the pot is rolled over into the subsequent jackpot. When a series of lottery jackpots are not won, the pot becomes large and attracts more attention from lottery players and the media.

The official website at https://www.megamillions.com lists the complete jackpot history of Mega Millions for the past ten years. Similarly, Powerball website (https://www.powerball.com) provides a complete record of all drawings and winning numbers since 2000, but not the jackpot history publicly. Lottery organizers, however, provide jackpot histories of both lotteries upon request. Additionally, there are publicly available resources with the complete history of both lotteries.[14] At the beginning of our sample period in 2007, the coverage of Powerball (30 states) was considerably larger than the coverage of Mega Millions (12 states). Table A3 presents the timeline related to the introduction of each game. In our sample, the average of Powerball jackpots ($70.0 million) is slightly larger than the average of Mega Millions jackpots ($67.4 million), and the average size of the combined jackpot is also $137.3 million.

[12] See https://www.kickstarter.com/help/stats for details.

[13] https://www.foxbusiness.com/features/top-5-biggest-lottery-jackpots

[14] http://www.lottofactor.com/ is a comprehensive and free of charge resource that provides the complete jackpot history of all multi-state and single-state lotteries in the U.S.

4.4. State lotteries

In addition to multi-state lotteries (Powerball and Mega Millions), we use data from state lotteries. More specifically, we focus on four states of California, Texas, New York, and Florida. In addition to representing large economies, these states have relatively large state lotteries.

California's SuperLotto is the biggest state lottery in the U.S. and SuperLotto's drawings are held every Wednesday and Saturday. Lotto Texas, official lottery of Texas, has the largest average jackpot size in our sample with $23.7 million. Lotto Texas drawings are held on Wednesday and Saturday evenings. Formed in 1991, Lotto Texas is the youngest of these four state lotteries. New York Lotto and Florida lottery, with an average jackpot size of $12.2 million and $12.6 million respectively, are considerably smaller in comparison to California and Texas lotteries. The drawings of both New York and Florida lotteries are held on Wednesday and Saturday.

The official websites of the California, Texas, and Florida lotteries provide the full or partial jackpot histories.[15] Access to data for New York Lotto is possible upon request from the game organizers. Note that the website `http://www.lottofactor.com` offers the jackpot histories of all four state lotteries.

5. Method

Following previous studies that explore the link between lotteries and financial decision-making (Dorn et al., 2014), our baseline specification is as follows:

$$Log(B_t) = \alpha + \beta Log(J_t) + \Lambda C_t + \varepsilon_t$$

Where B_t refers to two related dependent variables: (1) The total amount of all contributions made on all available listed loans on day t; (2) The number of bids made by individual lenders made on all available listed loans on day t. J_t is the combined jackpot from Powerball and Mega Millions lotteries on day t. C_t is a vector of control variables. Lastly, ε_t is the error term. We fit an ordinary least squared (OLS) model to estimate the parameter of interest β. All OLS regressions in the analysis have heteroscedasticity robust standard errors. It is noteworthy that lottery jackpot is a repeated natural experiment because lottery jackpots are won randomly, and the pot increases in size with a series of drawings with no winners. Therefore, jackpot size is unlikely to be related to other unobserved factors such as the economic condition (usually present in the error term denoted by ε_t that could have biased the coefficient on β).

To alleviate concerns related to non-stationarity, we perform the Augmented Dickey-Fuller test and the Phillips-Perron test to check if our variables have a unit root. The results from both tests confirm that our variables are stationary. The null hypothesis of a unit root is rejected at a confidence level below 1%. We also conduct Durbin-Watson and Breusch-Godfrey tests to check whether residuals are autocorrelated or not. Test results confirm that our regression residuals are correlated. By checking the regression residuals, we find out that autocorrelation seems to be strong at the first lag but quickly weakens after the third lag. To deal with serial correlation for the rest of our analysis, we estimate Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) standard errors allowing for serial correlation up to five lags. In the literature, common practice for determining the number of lags is to take the integer part of $n^{1/4}$ or the integer part of $4(n/100)^{2/9}$, which give for our sample (with 1189 observations) 5 and 6 respectively (Wooldridge, 2015). In unreported robustness checks, we rerun all regressions with Newey-West standard errors allowing for serial correlation up to 30 lags (i.e., approximately one month) and confirm that all of our results hold after these tests.

Table A4 presents the definitions of all variables used in this study; we explicate the reasoning for our choice of control variables, C_t. We control for *Total listing*, which is the total sum of all the funding needed to fully fund all loans listed on the platform on a given day. This variable proxies for the total demand for credit on any given day. To control for the competition among bidders, we include the variable *Share of winning bids*, which is the fraction of bids that eventually funded the loan (i.e., winning bid) to the overall bids. Note that a bid can only be in one of the following categories: Winning, partially participating, outbid, and withdrawn bid. To control for the attractiveness of loan returns, we control for *Weighted average lender rate*. This variable is based on "spot lender rate" (i.e., the interest rate lenders would have received on a loan if the loan was finalized and issued on that day), given the weights equal to the loan size. Thus, *Weighted average lender rate* is the loan-size weighted "spot lender rate". To control for the potential role of the U.S. equity stock market in attracting investors' dollars away from peer-to-peer lending market (or when investors are looking for attractive alternatives to the stock market), we include *S&P 500 Return*, that is the value-weighted return on the S&P 500 index. Finally, our specifications consider the growing popularity of crowdfunding platforms such as Prosper and include a linear time trend *Date*. Finally, we include dummy variables for the day of the week and month of the year. For instance, lenders might have more free time on weekends to spend on assessing loans.

6. Results

Table 1 provides the summary statistics of variables in this study. The mean *Bid size* for individual lenders is about $75, and the fully funded *Loan size* is on average about $6000.[16] The dollar value of all bids on average is about $500 million, while the dollar value of all loans listed (but some are not fully funded) is about $2.5 billion. Only about 10% of listed loans (i.e., 30,685) were successfully funded;

[15] Websites respectively: https://www.calottery.com; https://www.txlottery.org; http://www.flalottery.com.

[16] We excluded all bids made by Institutional investors. Institutional investors comprise less than 1% of all bids. The sum of the total dollar value of institutional investors' bids amount to $6.6 million (1.3% of all bids), and their average bid size is $168.

Table 1
Descriptive statistics.

	Count	Mean	Median	Standard deviation	Min	Max
Crowdfunding Data Characteristics						
Bid size (Individual lenders)	6,485,228	75.15	50.00	152.53	25.00	25,000.00
Listing size	314,408	7785.90	5000.00	6394.19	1000.00	25,000.00
Loan size	30,685	6065.08	4500.00	5423.66	1000.00	25,000.00
Interest rate on loans	30,685	0.19	0.17	0.08	0.00	0.35
Aggregate US Sample Variables						
Powerball (mn USD)	1189	69.96	52.00	57.04	15.00	300.00
Mega Millions (mn USD)	1189	67.39	48.00	60.57	12.00	390.00
Powerball + Mega Millions (mn USD)	1189	137.35	119.00	86.39	27.00	550.00
Log (Powerball)	1189	3.94	3.95	0.79	2.71	5.70
Log (Mega Millions)	1189	3.84	3.87	0.88	2.48	5.97
Log (Powerball+Mega Millions)	1189	4.73	4.78	0.63	3.30	6.31
Log (Bid amount)	1189	12.59	12.84	0.96	3.93	14.04
Log (Bid number)	1189	8.42	8.56	0.73	1.10	9.65
Log (Total listing)	1189	16.09	16.60	0.94	12.12	17.50
Log (New listing)	1189	13.82	14.47	1.78	0.00	15.95
Log (New listing #)	1189	4.98	5.57	1.46	0.00	6.83
Share of winning bids	1189	0.67	0.65	0.10	0.47	1.00
Weighted average lender rate	1189	0.21	0.23	0.03	0.15	0.32
S&P 500 return	1189	0.00	0.00	0.01	−0.09	0.12
US Panel Regression Variables						
At Listing-Day Level:						
Log (Bid amount)	1,288,572	2.41	0.00	2.91	0.00	13.30
Log (Bid number)	1,288,572	0.74	0.00	1.12	0.00	6.49
Log (Powerball)	1,288,572	3.93	3.95	0.81	2.71	5.70
Log (Mega Millions)	1,288,572	3.83	3.87	0.87	2.48	5.97
Log (Powerball+Mega Millions)	1,288,572	4.72	4.78	0.63	3.30	6.31
Powerball + Mega Millions (mn USD)	1,288,572	136.24	119.00	85.72	27.00	550.00
Borrower debt to income ratio	1,288,572	0.40	0.22	1.07	0.00	10.01
At Bid Level:						
Log (Bid amount)	6,485,228	4.05	3.93	0.61	3.26	10.13
Log (Powerball+Mega Millions)	6,485,228	4.72	4.75	0.63	3.30	6.31
Log (Bidding experience)	6,485,228	5.17	5.21	1.70	0.69	10.38
Log (Listing size)	6,485,228	9.02	9.10	0.79	6.91	10.13
Borrower debt to income ratio	6,485,228	0.30	0.20	0.82	0.00	10.01
Minimum rate (in percentage points)	6,485,228	17.95	16.20	7.30	0.00	35.00
Borrower maximum rate	6,485,228	0.21	0.20	0.08	0.00	0.36
Normalized spread	6,485,228	0.12	0.07	0.14	0.00	1.00
California Sample Variables						
California jackpot (mn USD)	1189	21.64	16.00	15.92	7.00	93.00
Log (California jackpot)	1189	2.85	2.77	0.65	1.95	4.53
Share of California bids	1189	0.26	0.23	0.07	0.00	0.65
Share of California bid count	1189	0.24	0.22	0.06	0.00	0.47
Normalized California bids	1189	0.27	0.24	0.16	0.00	1.50
Normalized California bid count	1189	0.25	0.23	0.14	0.00	1.13
Normalized non-California bids	1189	0.76	0.79	0.32	0.00	3.73
Normalized non-California bid count	1189	0.77	0.81	0.32	0.00	2.69
Texas Sample Variables						
Texas jackpot (mn USD)	1189	23.72	15.00	22.07	4.00	97.00
Log (Texas jackpot)	1189	2.78	2.71	0.87	1.39	4.57
Share of Texas bids	1189	0.05	0.06	0.04	0.00	0.19
Share of Texas bid count	1189	0.04	0.07	0.04	0.00	0.11
Normalized Texas bids	1189	0.05	0.05	0.05	0.00	0.28
Normalized Texas bid count	1189	0.04	0.05	0.04	0.00	0.27
Normalized non-Texas bids	1189	0.98	1.00	0.43	0.00	4.18
Normalized non-Texas bid count	1189	0.98	1.00	0.44	0.00	3.22
New York Sample Variables						
New York jackpot (mn USD)	1189	12.16	9.50	10.04	3.00	65.00
Log (New York jackpot)	1189	2.25	2.25	0.68	1.10	4.17
Share of New York bids	1189	0.09	0.08	0.03	0.00	0.29
Share of New York bid count	1189	0.09	0.08	0.03	0.00	0.20
Florida Sample Variables						
Florida jackpot (mn USD)	1189	12.60	9.00	10.32	2.00	52.00
Log (Florida jackpot)	1189	2.21	2.20	0.82	0.69	3.95
Share of Florida bids	1189	0.07	0.06	0.03	0.00	0.50

(continued on next page)

Table 1 (*continued*)

	Count	Mean	Median	Standard deviation	Min	Max
Share of Florida bid count	1189	0.07	0.07	0.03	0.00	0.50
Kickstarter Sample Variables						
Log (Powerball)	245	4.60	4.50	0.70	3.69	6.40
Log (Megamillions)	245	3.44	3.30	0.78	2.48	5.25
Log (Powerball+Megamillions)	245	4.94	4.92	0.62	3.95	6.67
Log (Pledged)	245	14.90	15.11	1.43	5.42	17.86
Log (Backer number)	245	8.85	9.13	0.99	2.20	10.43
Log (Unfullfilled goal amount)	245	17.41	17.66	1.24	8.16	18.66

This table presents summary statistics for variables used in this study. See Table A4 for the definition of these variables.

87.4% of the listed loans either failed to get enough funding or were withdrawn by borrowers' request (who perhaps anticipated failure before the listing expired), and the remaining 2.8% of listed loans were cancelled by Prosper. We present the results of multivariate analysis in the following subsections.

6.1. Multi-state lotteries and bidding in prosper

Table 2 presents the regression results using specification 1. Columns (1) and (2) report OLS regressions predicting *bid amount* made by all individual investors, based on jackpots in Powerball and Mega Millions, respectively; in terms of economic magnitude, doubling the jackpot is associated with 8.8% and 5.2%, respectively, decline in total sum of bidding amount on a given day. The correlation between these multi-state jackpots is very low (0.05); thus it is less likely that spurious correlations or omitted variables varying with one of the jackpots can explain the results presented in Columns (1) and (2). Powerball and Mega Millions have similar rules and offer jackpots of similar average sizes. Despite the statistical observation that Powerball and Mega Millions are uncorrelated with each other, we still find similar evidence across each multi-state lotteries separately. Conceiving an alternative explanation based on the relationship of jackpot size in each game and bidding activity is even more implausible when that explanation must justify why Mega Millions and Powerball jackpots are separately correlated with bidding activity but not with each other.

Column (3) considers the sum of jackpots in Powerball and Mega Millions as the main theoretical construct. We create this variable because we are interested in the overall effect of playing the lottery (and not a particular jackpot). Doubling *Powerball* + *Mega Millions* is associated with about 11% decline in the total sum of bids by all individual investors.

Column (4) of Table 2 reports the results of specification 1 using Newey–West standard errors. We again obtain similar results, supporting Hypothesis 1.

In Column (5) of Table 2, we consider the possibility of nonlinear jackpot effects by including dummy variables for jackpot quartiles. Jackpot quartiles are created by dividing lottery jackpots (*Powerball* + *Mega Millions*) into four different groups based on their size relative to the entire sample period. Results indicate that only during those days with jackpots in the 4th quartile size distribution compared with the bottom quartile, *bid amount* decreases significantly by 18.4%. In Column (6), we perform a similar analysis by including a large jackpot dummy, which is equal to one if jackpots are in the top decile of *Powerball* + *Mega Millions* size distribution. Again, we find similar results.

In subsequent columns, we report several additional robustness tests. First, in Column (7) of Table 2, we include the detrended jackpot variable and repeat our analysis. To detrend the *Powerball* + *Mega Millions* variable, we estimate a linear regression of the logarithm of the combined Powerball and Mega Millions jackpots on a constant and a linear time trend. Second, Column (8) presents the regression coefficients when we include the combined jackpots of Powerball and Mega Millions jackpots without log-transformation. Third, Columns (9) and (10) present regression results with a new dependent variable: the total number of bids made by individual investors on a day (*Bid number*). Doubling *Powerball* + *Mega Millions* is associated with 8.2% decline in *Bid number*. In unreported robustness checks, we rerun all regressions with Newey–West standard errors allowing for serial correlation up to 30 lags, and we confirm that the coefficients on *Powerball* + *Mega Millions* from the Table 2 remain statistically significant.

In Table 3, we modify our specifications and include lagged dependent variables (LDV) as an alternative way to deal with autocorrelation. Some researchers view autocorrelation as a technical violation of the OLS assumptions that leads to incorrect estimation of the standard errors.[17] We repeat all of our main analyses after including one or two lags of the dependent variable and present the results in Table 3. Except for the first two specifications (Columns (1) and (2) of Table 3) that replicate the tests from previous Table 2,

[17] Other researchers, however, view autocorrelation more suspiciously and believe it is a potential sign of theoretical misspecification. LDV are often added to specifications to deal with autocorrelation, and adding a lagged dependent variable could remove serial correlation. Achen (2000) argues that including LDV in regressions can lead to underestimating the effect of the regressors if there is autocorrelation in the error term. When there is serial correlation in errors, Achen (2000) claims that LDV should not be included in the regression even if the LDV is actually part of the data-generating process. Keele and Kelly (2006), and Wilkins (2018) argue that excluding LDV would induce an omitted variable bias when the LDV are part of the data-generating process. In certain cases, this bias can be high, and thus, these authors recommend researchers to include LDVs. Our conclusion from reading this literature is the following. In general, researchers may worry about adding LDV to their specifications because including LDV lead to smaller coefficient estimates for independent variables. Moreover, adding LDV does not guarantee to eliminate the serial correlation in errors.

Table 2
Linear Regressions of crowd bidding volumes and bid counts on multi-state lottery jackpots in the U.S.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	Log(Bid amount)	Log(Bid amount)	Log(Bid amount)	Log(Bid amount)	Log(Bid amount)	Log(Bid amount)	Log(Bid amount)	Log(Bid amount)	Log(Bid number)	Log(Bid number)
Estimation	OLS	OLS	OLS	NW	NW	NW	NW	NW	NW	NW
Log (Powerball)	−0.088***									
	(0.016)									
Log (Mega Millions)		−0.052**								
		(0.025)								
Log(Powerball+ Mega Millions)			−0.112***	−0.112**					−0.082**	
			(0.028)	(0.043)					(0.034)	
Jackpot quartile 2					0.011					−0.007
					(0.049)					(0.038)
Jackpot quartile 3					−0.046					−0.042
					(0.059)					(0.045)
Jackpot quartile 4					−0.184**					−0.142**
					(0.072)					(0.057)
Large jackpot						−0.231**				
						(0.115)				
Log(Powerball+ Mega Millions) detrended							−0.112**			
							(0.043)			
Powerball+ Mega Millions								−0.001***		
								(0.000)		
Log(Total listing)	0.727***	0.722***	0.719***	0.719***	0.703***	0.704***	0.719***	0.708***	0.736***	0.726***
	(0.051)	(0.052)	(0.052)	(0.096)	(0.098)	(0.094)	(0.096)	(0.097)	(0.068)	(0.070)
Share of winning bids	0.369	0.374	0.377	0.377	0.411	0.298	0.377	0.348	0.176	0.200
	(0.562)	(0.559)	(0.557)	(0.677)	(0.669)	(0.684)	(0.677)	(0.678)	(0.522)	(0.517)
Weighted average lender rate	−1.362	−1.395	−1.240	−1.240	−0.839	−1.588	−1.240	−1.211	−0.502	−0.234
	(0.984)	(0.994)	(0.987)	(1.770)	(1.730)	(1.734)	(1.770)	(1.760)	(1.184)	(1.160)
S&P 500 Return	0.609	0.692	0.725	0.725	0.600	0.503	0.725	0.631	0.785	0.707
	(0.953)	(0.960)	(0.955)	(1.102)	(1.077)	(1.064)	(1.102)	(1.087)	(0.941)	(0.922)
Date	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	2.982	3.322	3.771	3.771	4.471	3.676	3.311	3.955	−13.472***	−13.031***
	(3.163)	(3.206)	(3.220)	(5.709)	(5.724)	(5.506)	(5.738)	(5.706)	(3.859)	(3.884)
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1189	1189	1189	1189	1189	1189	1189	1189	1189	1189
R-Squared	0.77	0.76	0.77	0.77	0.77	0.77	0.77	0.77	0.71	0.71

The dependent variable in Columns (1)–(8) is *Log(Bid amount)*, defined as the natural logarithm of the total bidding volume in the U.S. dollar by individual lenders on a day. The dependent variable in Column (9) and (10) is *Log(Bid number)*, defined as the natural logarithm of the total number of bids by individual lenders on a day. The estimation method is OLS with robust standard errors for Columns (1), (2), and (3) and Newey–West (NW) standard errors with five lags for the remaining columns. Table A4 provides the definitions of all variables. *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

Table 3

Linear regressions of crowd bidding volumes and bid counts on multi-state lottery jackpots in the U.S. with lagged dependent variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	Log(Bid amount)	Log(Bid amount)	Log(Bid amount)	Log(Bid amount)	Log(Bid amount)	Log(Bid amount)	Log(Bid number)	Log(Bid number)	Log(Bid number)	Log(Bid number)
Estimation:	NW	NW	NW	NW	NW	NW	NW	NW	NW	NW
Log(Powerball+ Mega Millions)	−0.112**		−0.054**		−0.053**		−0.050**		−0.050**	
	(0.043)		(0.025)		(0.025)		(0.023)		(0.023)	
Jackpot quartile 2		0.011		−0.012		−0.014		−0.016		−0.016
		(0.049)		(0.028)		(0.027)		(0.026)		(0.026)
Jackpot quartile 3		−0.046		−0.040		−0.042		−0.040		−0.040
		(0.059)		(0.031)		(0.030)		(0.030)		(0.030)
Jackpot quartile 4		−0.184**		−0.091**		−0.090**		−0.088**		−0.088**
		(0.072)		(0.042)		(0.042)		(0.039)		(0.039)
L1 Log(Bid amount)			0.535***	0.534***	0.508***	0.507***				
			(0.071)	(0.071)	(0.081)	(0.081)				
L2 Log(Bid amount)					0.042	0.042				
					(0.064)	(0.064)				
L1 Log(Bid number)							0.408***	0.407***	0.414***	0.413***
							(0.046)	(0.046)	(0.048)	(0.048)
L2 Log(Bid number)									−0.010	−0.011
									(0.039)	(0.039)
Log(Total listing)	0.719***	0.703***	0.361***	0.359***	0.348***	0.346***	0.458***	0.456***	0.462***	0.460***
	(0.096)	(0.098)	(0.075)	(0.074)	(0.070)	(0.070)	(0.059)	(0.059)	(0.058)	(0.059)
Share of winning bids	0.377	0.411	−0.205	−0.187	−0.231	−0.213	−0.109	−0.093	−0.104	−0.088
	(0.677)	(0.669)	(0.492)	(0.489)	(0.501)	(0.498)	(0.441)	(0.439)	(0.442)	(0.440)
Weighted average lender rate	−1.240	−0.839	−1.472	−1.340	−1.503	−1.378	−0.832	−0.714	−0.822	−0.700
	(1.770)	(1.730)	(0.937)	(0.916)	(0.916)	(0.897)	(0.770)	(0.755)	(0.781)	(0.767)
S&P 500 Return	0.725	0.600	1.079	1.038	1.144	1.105	0.962	0.928	0.946	0.911
	(1.102)	(1.077)	(0.756)	(0.744)	(0.785)	(0.772)	(0.757)	(0.748)	(0.762)	(0.753)
Date	−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)	(0.000)	(0.000)	(0.000)
Constant	3.771	4.471	−1.208	−1.102	−1.285	−1.206	−10.027***	−9.958***	−10.059***	−9.986***
	(5.709)	(5.724)	(3.479)	(3.484)	(3.489)	(3.498)	(3.037)	(3.028)	(3.017)	(3.015)
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1189	1189	1189	1189	1189	1189	1189	1189	1189	1189
R-Squared	0.77	0.77	0.84	0.84	0.84	0.84	0.76	0.76	0.76	0.76

The dependent variable in Columns (1)–(6) is *Log(Bid amount)*, defined as the natural logarithm of the total bidding volume in the U.S. dollar by individual lenders on a day. The dependent variable in Columns (7)–(10) is *Log(Bid number)*, defined as the natural logarithm of the total number of bids by individual lenders on a day. The estimation method is OLS with Newey–West (NW) standard errors with five lags for all specifications. Table A4 provides the definitions of all variables. *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

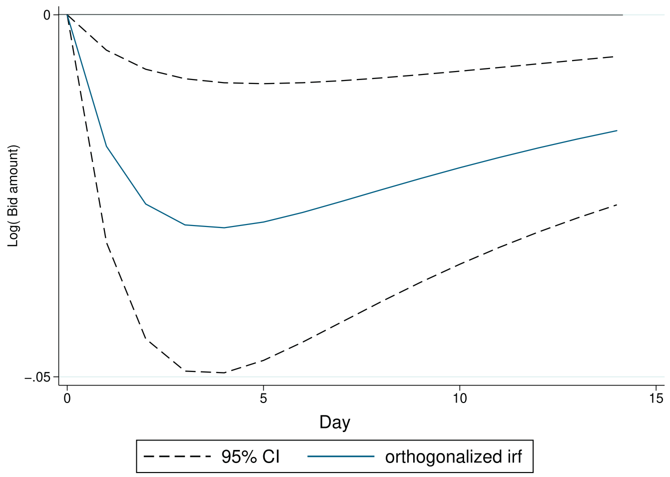

Fig. 1. Orthogonalized Impulse Response Function (OIRF). Impulse is *Log(Powerball + Mega Millions)* and response is *Log(Bid amount)*.

all specifications include LDVs. Including the first two lags of the dependent variable eliminates serial correlation, but Breusch-Godfrey and Durbin's alternative test results show that there may still be serial correlation at higher lags. Wooldridge (2015) recommends the use of Newey-West standard errors in models with lagged dependent variables when researchers are not sure that the inclusion of LDV fully removes autocorrelation. Following this recommendation, we use Newey–West standard errors in our models with lagged dependent variables. It appears that the first lag of the dependent variable has a significant impact in all specifications in Table 3. Additionally, the coefficients on jackpots in Columns (3)–(6) decrease in economic magnitude approximately by half compared with benchmark results in Columns (1) and (2). Similar observations are in order for *Bid number* in Columns (7)–(10). These observations further increase our confidence that our results are robust to correcting for autocorrelation. In additional unreported robustness checks, we rerun all the regressions with LDV in Table 3 using Newey–West standard errors allowing for serial correlation up to 30 lags and obtain similar results. We repated the analyses of Tables 2 and 3 on longer time period (2007-2012) and find similar results (Tables A5 and A6)

To see how long the lottery effect persists, we leverage the time-series nature of our data and estimate a vector autoregressive (VAR) model with one lag and estimate the orthogonalized impulse response function (OIRF). Fig. 1 report the results of OIRF that show the effect of changes in the sum of jackpots in Powerball and Mega Millions over a 14-day period. The vertical axis is natural logarithm of *Bid amount* and the horizontal axis in the graph is day. Fig. 1 suggests the negative effect of a one-standard-deviation change in sum of Powerball and Mega Millions jackpots on natural logarithm of *Bid amount* increases substantially for 3 days and then reduces. Note that the negative effect still persists after 14 days.

6.1.1. Multi-state lotteries and loan demand in prosper

There could be an alternative demand-related explanation that may be a source of concern: some borrowers may change their demand for credit around the time of large jackpot lotteries despite the fact that jackpots are randomly won. To elaborate further, if borrowers know that lenders supply less funding when lottery jackpots are large (i.e., it may be more expensive to borrow or available funds may be limited), then borrowers may delay making credit applications through crowdlending platforms until after a jackpot has been won. Accordingly, a drop in the loan demand from borrowers around large jackpots could reduce the bidding activities from lenders. To alleviate this concern, we control for loan demand by including *(Log(Total listing))*, defined as natural logarithm of the total listing size open to bidding on a day. We also perform several tests to investigate the relationship between the loan demand and lottery jackpots. The results are presented in Table A7. In Columns (1)–(6), our dependent variable is the natural logarithm of the U.S. dollar value of new loan listings created by borrowers on a day (i.e., lenders can start bidding on a day on these new loan listings). We regress the volume of new loan listings on Powerball jackpots, Mega Millions jackpots, and the combined jackpots of these lotteries and find that the volume of new listings do not depend on lottery jackpots. In Columns (7) and (8), we regress the number of new loan listings on lottery jackpots and do not find out statistically significant relationships. In the last two columns of Table A7 (Columns (9) and (10)), we repeat the analysis with a slightly modified dependent variable. Instead of new loan listing volumes or numbers on a day, we use the volume of all loan listings available for bidding on a day as our dependent variable. We again do not find any evidence to support timing by borrowers around lottery jackpots. In sum, borrowers do not alter their loan listing behaviors on Prosper with respect to lottery jackpots.

6.1.2. Are the results robust if the unit of analysis is listing or bid level?

Unlike the previous sections that presented the daily aggregate of all bids as the level of analysis, this section focuses on two new units of analyses. Because the aggregate level analyses do not consider the heterogeneity of loan listings and bidders, we perform two additional sets of analyses by changing the unit of analyses: (1) We aggregate all bids for a listing on each day into one observation

Table 4

Panel (Within) regressions of crowd bid amounts and counts on Multi-state lottery jackpots in the U.S. at listing-day level with listing fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid number)	Log (Bid number)	Log (Bid number)	Log (Bid number)
Estimation:	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Log (Powerball)	−0.021***						−0.007***			
	(0.005)						(0.002)			
Log (Mega Millions)		−0.012**						−0.007***		
		(0.005)						(0.002)		
Log (Powerball+Mega Millions)			−0.024***			−0.019**			−0.011***	
			(0.007)			(0.008)			(0.003)	
Jackpot quartile 2				−0.001						0.004
				(0.009)						(0.004)
Jackpot quartile 3				−0.066***						−0.023***
				(0.010)						(0.004)
Jackpot quartile 4				−0.053***						−0.026***
				(0.012)						(0.005)
Powerball+Mega Millions					−0.000***					
					(0.000)					
Log (Powerball+Mega Millions) x Borrower debt to income ratio						−0.013**				
						(0.006)				
Log (Total listing)	0.092**	0.098***	0.095***	0.119***	0.094***	0.094***	0.156***	0.158***	0.157***	0.163***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.015)	(0.015)	(0.015)	(0.015)
Share of winning bids	0.423***	0.414***	0.416***	0.419***	0.408***	0.417***	0.108***	0.104***	0.105***	0.109***
	(0.062)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.024)	(0.024)	(0.024)	(0.024)
Weighted average lender rate	6.531***	6.551***	6.575***	6.380***	6.643***	6.572***	1.917***	1.948***	1.946***	1.949***
	(0.852)	(0.852)	(0.852)	(0.864)	(0.853)	(0.852)	(0.361)	(0.362)	(0.361)	(0.366)
S&P 500 Return	0.571***	0.548***	0.564***	0.562***	0.564***	0.562***	0.211***	0.204***	0.211***	0.210***
	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.045)	(0.045)	(0.045)	(0.045)
Date	0.180***	0.180***	0.180***	0.180***	0.180***	0.180***	0.064***	0.064***	0.064***	0.064***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−3185.015***	−3186.036***	−3185.855***	−3186.833***	−3186.478***	−3185.724***	−1124.479***	−1124.855***	−1124.761***	−1125.372***
	(19.852)	(19.852)	(19.851)	(19.846)	(19.857)	(19.851)	(7.919)	(7.920)	(7.919)	(7.916)
Listing FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,288,572	1,288,572	1,288,572	1,288,572	1,288,572	1,288,572	1,288,572	1,288,572	1,288,572	1,288,572
N Listings	165,608	165,608	165,608	165,608	165,608	165,608	165,608	165,608	165,608	165,608
R-Squared	0.08	0.08	0.08	0.08	0.08	0.08	0.09	0.09	0.09	0.09

The dependent variable in Columns (1)–(6) is *Log(Bid amount)*, defined as the natural logarithm of the total bidding volume in the U.S. dollar by individual lenders on a particular loan listing on a day. The dependent variable in Columns (7)–(10) is *Log(Bid number)*, defined as the natural logarithm of the total number of bids by individual lenders on a particular loan listing on a day. The estimation method is OLS with listing fixed effects and cluster-robust standard errors. Table A4 provides the definitions of all variables. *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

Table 5
Linear regressions of individual bidding amounts on multi-state lottery jackpots in the U.S. with bidder fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Minimum rate	Minimum rate	Minimum rate	Minimum rate	Normalized spread	Normalized spread
Estimation:	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Log (Powerball+Mega Millions)	−0.011***		−0.010***		0.046***		0.047***		−0.002***	
	(0.000)		(0.000)		(0.002)		(0.002)		(0.000)	
Jackpot quartile 2		0.007***		0.007***		0.071***		0.071***		−0.002***
		(0.000)		(0.000)		(0.003)		(0.003)		(0.000)
Jackpot quartile 3		0.000		0.000		0.102***		0.102***		−0.003***
		(0.000)		(0.000)		(0.003)		(0.003)		(0.000)
Jackpot quartile 4		−0.018***		−0.016***		0.062***		0.065***		−0.004***
		(0.000)		(0.000)		(0.004)		(0.004)		(0.000)
Log (Listing size)			0.029***	0.029***			0.038***	0.037***	−0.009***	−0.009***
			(0.000)	(0.000)			(0.002)	(0.002)	(0.000)	(0.000)
Borrower debt to income ratio			0.001***	0.001***			0.042***	0.042***	−0.001***	−0.001***
			(0.000)	(0.000)			(0.001)	(0.001)	(0.000)	(0.000)
Borrower maximum rate			−0.050***	−0.052***	77.842***	77.834***	77.870***	77.862***		
			(0.003)	(0.003)	(0.028)	(0.028)	(0.028)	(0.028)		
Log (Bidding experience)	0.010***	0.009***	0.010***	0.010***	−0.082***	−0.082***	−0.081***	−0.082***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)
Log (Total listing)	0.034***	0.030***	0.032***	0.028***	−0.630***	−0.650***	−0.630***	−0.649***	0.028***	0.028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.005)	(0.005)	(0.000)	(0.000)
Share of winning bids	0.032***	0.041***	0.015***	0.024***	3.852***	3.859***	3.830***	3.837***	−0.173***	−0.173***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.026)	(0.026)	(0.026)	(0.026)	(0.001)	(0.001)
Weighted average lender rate	−0.014	0.078***	0.057***	0.144***	−17.283***	−17.004***	−17.163***	−16.899***	1.042***	1.043***
	(0.014)	(0.015)	(0.014)	(0.015)	(0.106)	(0.107)	(0.106)	(0.107)	(0.004)	(0.004)
S&P 500 Return	−0.084***	−0.102***	−0.091***	−0.108***	1.307***	1.293***	1.301***	1.289***	−0.061***	−0.061***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.096)	(0.096)	(0.096)	(0.096)	(0.004)	(0.004)
Date	−0.001***	−0.001***	−0.001***	−0.001***	0.001***	0.001***	0.001***	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)
Constant	14.973***	15.195***	14.685***	14.901***	2.941***	4.255***	2.264***	3.552***	0.906***	0.891***
	(0.045)	(0.046)	(0.049)	(0.050)	(0.311)	(0.314)	(0.311)	(0.314)	(0.013)	(0.013)
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower State FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bidder FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,485,228	6,485,228	6,485,221	6,485,221	6,485,221	6,485,221	6,485,221	6,485,221	6,485,186	6,485,186
N Bidders	53,571	53,571	53,571	53,571	53,571	53,571	53,571	53,571	53,568	53,568
R-Squared	0.63	0.63	0.64	0.64	0.85	0.85	0.85	0.85	0.25	0.25

The dependent variable in Columns (1)–(4) is *Log(Bid amount)*, defined as the natural logarithm of a bid in the U.S. dollar by an individual bidder. The dependent variable in Columns (5)–(8) is *Minimum rate* in percentage points, defined as the minimum interest rate an individual bidder would accept in return for lending. Minimum rate is determined by the bidder at the creation of each bid. The dependent variable in Columns (9)–(10) is *Normalized spread*, computed in two steps: First, we compute the difference between the maximum interest rate a borrower would agree to pay (Borrower maximum rate) on a loan listing and the minimum interest rate an individual bidder would accept (Minimum rate) on its bid. Then, we divide this interest rate spread by the Borrower maximum rate. The estimation method is OLS with bidder fixed effects and cluster-robust standard errors. Table A4 provides the definitions of all variables. *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

(listing-day level). This specification controls for unobserved heterogeneity regarding loans; Since the loans are usually open for a short period, it is unlikely that loan characteristics vary across time for each listing; (2) To control for bidder heterogeneity (by including bidder fixed effects), we repeat our analysis at bid level. Additionally, in this analysis, we control for listing characteristics. The results of both these sets are discussed below.

Table 4 presents the regression results based on the listing-day level.[18] The dependent variable in Columns (1)–(6) is *Log(Bid amount)*, defined as the natural logarithm of the total sum of bidding volume in the US dollar by all lenders on a particular loan listing on a given day. The dependent variable in Columns (7)–(10) is *Log(Bid number)*, defined as the natural logarithm of the total sum of the number of bids by all lenders on a particular loan listing on a given day. The results confirm our previous conclusions in Table 2: larger jackpots are associated with fewer and smaller bids. In Column (6), we investigate whether the effect is different for riskier borrowers (proxied by borrower's debt-to-income ratio). The result shows that the substitution effect is stronger for biddings in listings with higher risk.

Table 5 presents the results based on bid level. The dependent variable in the first four models is the natural logarithm of an individual bid. In Columns (3) and (4), we also control for listing characteristics (listing size, borrower maximum rate, borrower's debt-to-income ratio, and borrower's state fixed effect). In all models, we include the bidder fixed-effect, which provides within bidder estimates. The results are again consistent with our hypothesis and show that larger jackpots are associated with smaller bids. In Table A8, we also performed an analysis at the bidder-day level by aggregating all bids from a bidder on a given day. The results are similar.

6.1.3. Do Investors demand higher interest rates on days with large lottery jackpots?

We investigate whether lenders ask for higher interest rates on the days of large jackpots. We present these estimates in Table 5 at the bid level with two dependent variables. The first dependent variable in Columns (5)–(8) is *Minimum rate* (in percentage points), which is defined as the minimum interest rate an individual bidder would accept in return for lending. Minimum rate is determined by the bidder at the creation of each bid. The estimates show that lenders demand higher interest rates to lend when lottery jackpots are large. Doubling the lottery jackpot in Column (7) increases the *Minimum rate* by 0.047 percentage points; this is equal to a 0.3% increase on average *Minimum rate* in our sample. Similarly, when the lottery jackpot is in the largest quartile in Column (8), minimum interest rate demanded by the lender increases 0.065 percentage points; this is equal to a 0.4% increase on average *Minimum rate* in our sample.

The second dependent variable in Columns (9)–(10) in Table 5 is *Normalized spread*, which is computed as the difference between the maximum interest rate a borrower would agree to pay (*Borrower maximum rate)* on a loan listing and the minimum interest rate an individual bidder would accept (*Minimum rate*), divided by the *Borrower maximum rate*. When the lottery jackpot is in the largest quartile, *Normalized spread* drops on average 3.3%. The results suggest that lenders ask for higher rates for investing in loans when lottery jackpots are significantly large.

6.2. State lotteries and bidding in prosper

This section uses data from state lotteries instead of multi-state lotteries, Powerball and Mega Millions. More specifically, we focus on the state lotteries in the following four states: California, Texas, New York, and Florida. For each state, we only focus on the lending activity of residents in that focal state We selected these states for the following reasons. First, lenders from California, New York, and Texas have the highest number of bids in our sample (24.8%, 8.7%, and 6.3% respectively); Lenders resident in Florida comprise only 2.1% of all bids.[19] Such distribution reflects the fact that these four states have the highest gross domestic product in the U.S. Second, state lotteries are not large compared with multi-state lotteries, Powerball and Mega Millions. These four states have some of the biggest state lotteries in the U.S. (Table 1 presents descriptive statistics on the size of state loans). Finally, lenders from these four states are likely to represent different demographics.

To link state lotteries with lending activity in a state, we create several new dependent variables. To obtain *Share of state bids*, we divide the total sum of bids (in dollar terms) made by residents in that focal state over all bids in a day. Similarly, we calculate *Share of state count* as the fraction of the total count of bids made by residents in that focal state over all bids on a given day. For additional tests, we consider secular variations across time and create *Normalized state count (bids)* in two steps: First, we calculate the daily average of bidding count (amount in dollar terms) by all lenders over a month. Second, we compute *Normalized state count (bids)* on a day as the fraction of bidding count (volume in dollars) made by residents of the focal state over the corresponding result from the first step.

We will first focus on regression results from California (Table 6), whose average lottery jackpot size is among the highest across the U.S.; in California, the median lottery jackpot is $16 million, the mean is $21.6 million and the largest jackpot is $93 million. Panel A of Table 6 shows that in California, there is a negative relationship between state lottery jackpot and the dependent variables: *Share of California bids* and *Share of California count*. For instance, the bids in California relative to all states decline by 5.4% on days when jackpots hit the top quartile of its distribution. In unreported robustness checks, we repeated the tests in Columns (1) and (2) with two lags of the dependent variable and found that our results remain unchanged. We also included the raw jackpot value instead of the log jackpot and obtained similar results. It is noteworthy to mention our placebo tests (reported in Columns (6) and (7)) and find that California lottery jackpots are not influencing the lending activity of lenders who are not residents in California.

[18] In this analyses the demand is held constant (by including listing fixed effect) and the only source of variation is the supply.

[19] Borrowers' geographic location follows a similar distribution.

Table 6
Linear regressions of the share of bidding volumes and bid counts by Californian (Texan) Lenders on California (Texas) lottery jackpots.

Panel A: California Regressions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	Share of California bids	Share of California bids	Share of California bid count	Normalized California bids	Normalized California bid count	Normalized non-California bids	Normalized non-California bid count
Estimation:	NW	NW	NW	NW	NW	NW	NW
Log (California jackpot)	−0.009**		−0.007**	−0.015*	−0.013*	0.017	0.010
	(0.004)		(0.003)	(0.008)	(0.008)	(0.016)	(0.016)
Jackpot quartile 2		0.001					
		(0.008)					
Jackpot quartile 3		−0.012					
		(0.008)					
Jackpot quartile 4		−0.014*					
		(0.008)					
Controls	Share of winning bids, Weighted average lender rate, S&P 500 return, Date						
Constant	−1.998***	−2.000***	−1.788***	−1.946***	−1.722***	2.879**	3.058**
	(0.234)	(0.232)	(0.175)	(0.498)	(0.465)	(1.455)	(1.220)
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1189	1189	1189	1189	1189	1189	1189
R-Squared	0.46	0.46	0.63	0.44	0.47	0.49	0.52
Panel B: Texas Regressions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	Share of Texas bids	Share of Texas bids	Share of Texas bid count	Normalized Texas bids	Normalized Texas bid count	Normalized non-Texas bids	Normalized non-Texas bid count
Estimation:	NW	NW	NW	NW	NW	NW	NW
Log (Texas jackpot)	−0.007***		−0.007***	−0.008***	−0.007***	0.011	0.013
	(0.001)		(0.001)	(0.001)	(0.001)	(0.011)	(0.012)
Jackpot quartile 2		0.001					
		(0.002)					
Jackpot quartile 3		−0.002					
		(0.003)					
Jackpot quartile 4		−0.019***					
		(0.002)					
Controls	Share of winning bids, Weighted average lender rate, S&P 500 return, Date						
Constant	1.766***	1.683***	1.700***	1.882***	1.819***	−0.918	−0.526
	(0.065)	(0.062)	(0.065)	(0.134)	(0.142)	(1.823)	(1.625)
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1189	1189	1189	1189	1189	1189	1189
R-Squared	0.86	0.87	0.89	0.76	0.76	0.48	0.50

In Panel A (Panel B): The dependent variable in Columns (1) and (2) is *Share of California (Texas) bids*, defined as the ratio of the total bidding volume (in dollar) by Californian (Texan) individual lenders to the total bidding volume by all individual lenders. The dependent variable in Column (3) is *Share of California (Texas) bid count*, defined as the ratio of the total number of bids by Californian (Texan) individual lenders to the total number of bids by all individual lenders. The dependent variable in Column (4) is *Normalized California (Texas) bids*, computed in two steps: First, we calculate the daily average of bidding amount (in dollar) by all lenders over a month. Second, we compute Normalized California (Texas) bids (in dollar) on a day as the fraction of bidding volume (in dollars) made by residents in California (Texas) state over the corresponding result from the first step. The dependent variable in Column (6) is *Normalized non-California (non-Texas) bids*, defined as the ration between daily average (on a given month) bidding volume of non-Californian (non-Texan) individuals and the daily average (on a given month) bidding volume by all individual lenders. The dependent variable in Column (7) is *Normalized non-California (non-Texas) bid count* and is computed similar to *Normalized California (Texas) bids* but using the "count of bids" instead of "bidding volume (in dollars)". In all specifications, the estimation method is OLS with Newey–West (NW) standard errors with five lags. Table A4 provides the definitions of all variables. *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

We present similar analysis for Texas (Panel B of Table 6), New York (Panel A of Table 7), and Florida (Panel B of Table 7). To briefly highlight the results from this set of analyses, it appears that lenders resident in Texas respond to the corresponding state lottery in substituting their lending activity, but the other two states (NY and FL) do not. One plausible explanation is related to the smaller size of NY and FL state lotteries. In California and Texas, the average lottery jackpot size is among the highest across US; in California (Texas), the median lottery jackpot is $16 million ($15 million), the mean is $21.6 million ($23.7 million) and the largest jackpot is

Table 7
Linear regressions of the share of bidding volumes and bid counts by New Yorker (Floridian) Lenders on New York (Florida) lottery jackpots.

Panel A: New York Regressions				
	(1)	(2)	(3)	(4)
Dependent Variable:	Share of New York bids	Share of New York bids	Share of New York bid count	Share of New York bid count
Estimation:	NW	NW	NW	NW
Log(New York jackpot)	0.002		0.000	
	(0.002)		(0.001)	
Jackpot quartile 2		0.002		0.002
		(0.004)		(0.002)
Jackpot quartile 3		−0.003		−0.002
		(0.004)		(0.002)
Jackpot quartile 4		0.004		0.000
		(0.003)		(0.002)
Controls	Share of winning bids, Weighted average lender rate, S&P 500 return, Date			
Constant	−0.815***	−0.813***	−0.703***	−0.702***
	(0.104)	(0.105)	(0.060)	(0.059)
Weekday FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
N	1189	1189	1189	1189
R-Squared	0.42	0.42	0.60	0.60
Panel B: Florida Regressions				
	(1)	(2)	(3)	(4)
Dependent Variable:	Share of Florida bids	Share of Florida bids	Share of Florida bid count	Share of Florida bid count
Estimation:	NW	NW	NW	NW
Log(Florida jackpot)	0.000		0.002	
	(0.002)		(0.001)	
Jackpot quartile 2		0.001		0.001
		(0.004)		(0.003)
Jackpot quartile 3		0.001		0.002
		(0.004)		(0.004)
Jackpot quartile 4		0.003		0.005*
		(0.003)		(0.003)
Controls	Share of winning bids, Weighted average lender rate, S&P 500 return, Date			
Constant	−0.135	−0.138	−0.174*	−0.174
	(0.116)	(0.117)	(0.104)	(0.107)
Weekday FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
N	1189	1189	1189	1189
R-Squared	0.09	0.09	0.16	0.16

In Panel A (Panel B): The dependent variable in Columns (1) and (2) is *Share of New York (Florida) bids*, defined as the ratio of the total bidding volume by New Yorker (Floridian) individual lenders to the total bidding volume by all individual lenders. The dependent variable in Columns (3) and (4) is *Share of New York (Florida) bid count*, defined as the ratio of the total number of bids by New Yorker (Floridian) individual lenders to the total number of bids by all individual lenders. In all specifications, the estimation method is OLS with Newey–West (NW) standard errors with five lags. Table A4 provides the definitions of all variables. *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

$93 million ($97 million). In comparison, the median lottery jackpot in New York (Florida) is $9.5 million ($9 million), the mean is $12.2 million ($12.6 million), and the maximum is $65 million ($52 million). Given that NY and FL jackpots are on average approximately half the size of Texas jackpot, we might not observe significant effects in NY and FL. To further explore the relevance of jackpot size, we combine the state lotteries and *Powerball* + *Mega Millions* in NY and FL, respectively, and obtain statistically significant coefficients on the combined pot in regressions constructed similar to Table 7.

To summarize, to alleviate concerns over spurious correlations between multi-state lotteries and lending activity, we use data from state lotteries. It appears that we find support for Hypothesis 1 only in states with large jackpot sizes.

6.3. Multi-state lotteries and contributions to kickstarter

We have so far considered lending activity in Prosper Marketplace, but it is unclear whether our findings generalize to other types of crowdfunding. To explore this question, we focus on one of the largest U.S. reward-based crowdfunding platform, Kickstarter. Reward-based crowdfunding is different from lending-based crowdfunding both in terms of institutional structure and the crowds' motivations. For example, Boudreau et al. (2017) argue that non-pecuniary motivations are the main drivers of contributors in reward-based crowdfunding. Despite these differences, we explore whether sensation-seeking is one of the underlying motivations for supporters' contributions in reward-based crowdfunding. We have described the details of the sample in Section 4.2.

We present the results in Table 8. The dependent variable, *Pledged*, is the total sum of contributions to all campaigns in a given day. We also control for total demand by creating the variable *Unfullfilled goal amount*, which is the total sum of funding needed at a given day if all campaigns were to be fully funded. Note that we have made an assumption in our analysis: the majority of the backers are

Table 8
linear regressions of kickstarter pledges on multi-state lottery jackpots in the U.S.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Log (Pledged)	Log (Pledged)	Log (Pledged)	Log (Pledged)	Log (Backer number)	Log (Backer number)
Estimation:	NW	NW	NW	NW	NW	NW
Log (Powerball)	−0.115					
	(0.126)					
Log (Mega Millions)		−0.165				
		(0.129)				
Log (Powerball+Mega Millions)			−0.210		−0.017	
			(0.164)		(0.066)	
Jackpot quartile 2				0.208		0.117
				(0.215)		(0.090)
Jackpot quartile 3				−0.257		0.092
				(0.205)		(0.088)
Jackpot quartile 4				−0.194		0.051
				(0.225)		(0.089)
Log (Unfullfilled goal amount)	0.634***	0.644***	0.640***	0.619***	0.696***	0.690***
	(0.180)	(0.173)	(0.170)	(0.182)	(0.065)	(0.066)
S&P 500 Return	7.410	8.909*	7.962*	7.393	−3.679	−3.319
	(4.695)	(4.566)	(4.693)	(4.902)	(2.571)	(2.495)
Date	0.021**	0.019**	0.021**	0.021**	0.002	0.002
	(0.009)	(0.009)	(0.009)	(0.008)	(0.004)	(0.004)
Constant	−394.185**	−365.176**	−401.713**	−407.003**	−43.942	−50.781
	(168.052)	(165.003)	(166.276)	(158.172)	(84.014)	(86.526)
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	245	245	245	245	245	245
R-Squared	0.83	0.83	0.84	0.84	0.92	0.92

The dependent variable in Columns (1)–(4) is *Log(Pledged)*, defined as the natural logarithm of the total sum of all pledges in the U.S. dollar on a day. The dependent variable in Column (5) and (6) is *Log(Backer number)*, defined as the natural logarithm of the number of backers who pledged on the platform on a given day. The estimation method is OLS with Newey–West (NW) standard errors with five lags for all columns. Table A4 provides the definitions of all variables. *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

from the U.S. and are located in states that can purchase multi-state lottery tickets. This assumption is in line with studies that document home bias for crowdfunding (Lin and Viswanathan, 2015). The results presented in Table 8 are not strong enough to provide support for Hypothesis 1. We interpret this evidence to indicate that sensation-seeking motive is stronger among peer-to-peer lenders relative to that of backers in reward-based crowdfunding, whose objective might be more prosocial or simply pre-purchase of products.

Additionally, we argue that this non-result questions the validity of alternative explanations related attention-grabbing story: because large jackpots are widely advertised, individuals' attention is consumed by lottery, resulting in substitution hypothesis. To reiterate, if large jackpots only attracted the attention of individuals, then we would have expected significant results across both Kickstarter and Prosper. However, our results suggest this is not the case.

7. Discussion and conclusion

This paper argues that one underlying motivation for crowdfunders active in peer-to-peer lending markets is sensation-seeking. To empirically substantiate this argument, we investigate whether individuals participating in Prosper, one of the largest U.S. lending markets, reduce their lending activity when gambling in the form of playing the lottery becomes more attractive. The results indicate robust evidence across different samples in support of a negative relationship between lottery jackpot size and contributions to peer-to-peer lending crowdfunding. We take these findings as evidence that playing the lottery satisfies crowdfunders' sensation-seeking desires.

We are not suggesting that all crowdfunding activity is purely motivated by gambling motives, or this is the primary reason on the list of motivations for crowdfunders. However, we believe to some extent, some crowdfunders are sensation seekers, searching for novel and intense experiences just for fun and thrill. We also do not find any evidence that this behavior is economically irrational such that loans funded in periods of large jackpot size are similar in terms of default to those loans funded in periods of low jackpot size.

We are well-aware that peer-to-peer lending and playing the lottery have two very different financial return characteristics. The maximum interest rate on Prosper loans is 35%, while the maximum financial returns from playing the lottery can be extremely high, although the expected return on playing the lottery is always negative. Additionally, the size of the median bid by individual lenders is about $50, but the cheapest lottery tickets cost $1 and can increase depending on the selected options. We argue that, despite these differences, both activities can produce the same thrill and excitement for some lenders who are sensation seekers, and those lenders will substitute between playing the lottery and lending in peer-to-peer markets.

While we suggested that both playing the lottery and contributing to crowdfunding can satisfy the same underlying sensation seeking, we have based our inference on the assumption that those who are in the crowdfunding market are likely to buy lottery tickets.

We present some indirect evidence that there is some socio-demographic overlap between those playing lottery and those in peer to peer lending markets. On the marketplace lending side, Adams et al. (2017) survey U.S. consumers, and find that about one-quarter of the consumers have some awareness of marketplace lending, and these customers are generally wealthier (income above $25,000) and more educated (college degree). Turning to those participating in Powerball and Mega Millions lotteries, Barnes et al. (2010) find across two U.S. household surveys that about half of the U.S. citizens regularly buy lottery tickets at least once in a year. The Gallup surveys also find similar participation rates of about 50% into lottery and these participation levels are stable during the 1990–2015 period.[20] The Gallup survey from 2016 further indicates that higher-income (above $36,000) and more educated Americans (college degree and postgraduate education) were more likely than lower-income and less-educated Americans to buy lottery tickets. Note that the common conception of gamblers as lower-income and less-educated Americans is not also supported by Gallup surveys referenced above. Having presented the potential socio-demographic overlap between those playing lottery and those in peer to peer lending markets, our research currently lacks direct survey evidence on the personal traits of the market participants. Future research is need to validate our assumption that some crowdfunders also buy lottery tickets, especially when the jackpot is relatively large.

Our study has additional limitations that can offer opportunities for future research. Future research can use new sources of big data from social media such as Facebook and Twitter (used by psychologists notably in works including Kosinski et al. (2015); Obschonka et al. (2017)) to measure personality traits such as sensation seeking. Therefore, using different methodologies can provide more robust assessments into sensation seeking motivations of peer-to-peer lenders.

Our study has implications for the consequences of (multi-)state lotteries that about half of Americans at least occasionally play. Given that states tout revenue from lotteries as supplemental funds towards important public causes such as education (e.g., in Florida), or environmental protection (e.g., in Colorado), our evidence on the substitution between playing the jackpot lottery and crowdfunding contributions indicates a warning siren. The role of lottery in solving state budget issues does involve tradeoffs, especially when politicians hail crowdfunding as one sustainable path towards funding innovation, filling the funding gap for small businesses, and even potentially helping individuals.

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Appendix A

Table A1
Evolution of prosper platform.

Date	Policy
November 9, 2005	Open for business.
	Min bid $50; Max bid $25,000.
	Credit info limited to credit grade & debt-to-(self-reported)-income.
April 19, 2006	Introduce home ownership and verified bank account information for listings.
May 30, 2006	Reveal more credit info, home ownership status, and bank account status.
October 19, 2006	Start group rating based on past loan performance.
February 12, 2007	Disallow borrowers with score¡520 or without score (NC).
	Credit Grade E from 540 to 599 to 560–599.
	Credit Grade HR from 540- to 520–559.
	Reveal more credit info (e.g. amount delinquent).
	Allow friend endorsements; introducing friend funding ($25) or borrowing ($50) rewards.
August 17, 2007	Provide information on on-time vs. late payments.
September 12, 2007	Eliminate group leader rewards ($4/new borrower; $12/loan funding).
October 30, 2007	Add bidder guidance.
	Introducing portfolio plans, allowing automatic bidding based on criteria.
February 23, 2008	Allow search by friend bids and endorsements.
April 15, 2008	Raise interest rate cap to 36% except for TX (10%) and SD (N/A).

(continued on next page)

[20] Available at https://news.gallup.com/poll/193874/half-americans-play-state-lotteries.aspx

Table A1 (*continued*)

Date	Policy
October 19, 2008	Prosper suspends new lending to register with SEC to create a secondary marketplace.
April 28, 2009	Prosper reopens (without full SEC approval).
	Disallow borrowers with score below 640.
	Opening secondary marketplace; i.e. a platform for lending institutions to put any loan with minimum 3 payments (auto, small business, etc) up for sale & bidding.
	Credit Grade information is not systematically made available anymore, only sporadically; instead prosper scores are systematically shown for all listings (1–10).
May 9, 2009	Prosper suspended again new lending/borrowing to complete SEC registration.
July 13, 2009	Receives green-light from SEC.
July 14, 2009	Prosper reopens.
	Implements a minimum bid rate (floor) on listings, calculated by adding national average CD rate for loan term, to min estimated loss rate for each listing.
	Minimum bid requirement at $25.
October 15, 2010	Loan terms expand from 36 months to 12 and 60. Default is still at 36.
October 15, 2010	Interest rates no more determined by Dutch-Auction, but by Prosper's formula evaluating borrowers' credit risk.
	Listings pulled from site as soon as fully funded.
	No longer list HR (no credit history or w/ history of defaults) listings.
	Credit grades are no longer listed.

This table, modified from Freedman and Jin (2017), shows the timeline of policy changes in Prosper Marketplace.

Table A2
Availability of prosper to lenders from various states.

Dates	Prosper Opened to Lenders
Nov 9, 2005 - Feb 5, 2006	Only available privately to investors in California and New Jersey
Feb 5, 2006 - Oct 19, 2008	Open to lenders in All 50 US States & D.C.
Apr 28, 2009 - May 9, 2009	Only open in California temporarily
Jul 14, 2009	Opens lending in 14 states: CA, CO, DE, GA, IL, MN, MT, NV, NY, SC, SD, UT, WI, WY
Jul 15, 2009	Florida
Jul 20, 2009	Hawaii, Washington
Jul 31, 2009	Maine
Aug 6, 2009	Conneticut, Idaho, New Hampshire, Oregan
Aug 14, 2009	Louisiana and Missouri
Aug 19, 2009	Rhode Island and Virginia
Jan 21, 2010	Mississippi
May 5, 2010	Alaska
Jun 28, 2010	DC

Table shows the timeline of admission and readmission of lenders from various states.

Table A3
Introduction of the multistate lotteries in the U.S.

State	Powerball	Mega Millions	State	Powerball	Mega Millions
Arizona	April 4, 1994	April 18, 2010	New York	January 31, 2010	May 17, 2002
Arkansas	October 31, 2009	January 31, 2010	North Carolina	May 30, 2006	January 31, 2010
California	April 8, 2013	June 22, 2005	North Dakota	March 25, 2004	January 31, 2010
Colorado	August 2, 2001	May 16, 2010	Ohio	April 16, 2010	May 17, 2002
Connecticut	November 28, 1995	January 31, 2010	Oklahoma	January 12, 2006	January 31, 2010
Delaware	January 14, 1991	January 31, 2010	Oregon	February 13, 1988	March 28, 2010
District of Columbia	February 13, 1988	January 31, 2010	Pennsylvania	June 29, 2002	January 31, 2010
Florida	January 4, 2009	May 15, 2013	Puerto Rico	September 28, 2014	n.a.
Georgia	January 31, 2010	September 6, 1996	Rhode Island	February 13, 1988	January 31, 2010
Idaho	February 1, 1990	January 31, 2010	South Carolina	October 6, 2002	January 31, 2010
Illinois	January 31, 2010	September 6, 1996	South Dakota	November 15, 1990	May 16, 2010
Indiana	October 14, 1990	January 31, 2010	Tennessee	April 21, 2004	January 31, 2010
Iowa	February 13, 1988	January 31, 2010	Texas	January 31, 2010	December 5, 2003
Kansas	February 13, 1988	January 31, 2010	US Virgin Islands	November 14, 2010	October 4, 2010
Kentucky	January 10, 1991	January 31, 2010	Vermont	July 1, 2003	January 31, 2010
Louisiana	March 5, 1995	November 16, 2011	Virginia	January 31, 2010	September 6, 1996
Maine	July 30, 2004	May 9, 2010	Washington	January 31, 2010	September 4, 2002
Maryland	January 31, 2010	September 6, 1996	West Virginia	February 13, 1988	January 31, 2010
Massachusetts	January 31, 2010	September 6, 1996	Wisconsin	August 10, 1989	January 31, 2010
Michigan	January 31, 2010	September 6, 1996	Wyoming	August 24, 2014	August 24, 2014
Minnesota	August 14, 1990	January 31, 2010	Alabama	n.a.	n.a.
Missouri	February 13, 1988	January 31, 2010	Alaska	n.a.	n.a.
Montana	November 9, 1989	March 1, 2010	Hawaii	n.a.	n.a.
Nebraska	July 21, 1994	March 20, 2010	Mississippi	n.a.	n.a.
New Hampshire	November 5, 1995	January 31, 2010	Nevada	n.a.	n.a.
New Jersey	January 31, 2010	May 26, 1999	Utah	n.a.	n.a.
New Mexico	October 20, 1996	January 31, 2010			

Table shows the dates of introduction of Powerball and Mega Millions lotteries in each state.

Table A4
Variable definitions.

Variable	Definition
Crowdfunding Data	
Bid size (Individual lenders)	Dollar value of a bid made by an individual lender.
Listing size	Dollar value of a loan listing.
Loan size	Dollar value of a loan. This is the amount of funding the borrower requests and successfully recieves.
Interest rate on loans	Fixed interest rate on a loan.
Borrower debt to income ratio	Borrower's debt to income ratio.
Log (Bidding experience)	Natural logarithm of the total number of bids by an individual lender prior to its current bid.
Minimum rate (in percentage points)	Minimum interest rate an individual bidder would accept in return for lending. Minimum rate is determined by the bidder at the creation of each bid.
Borrower maximum rate	Maximum interest rate the borrower is willing to pay when the listing was created.
Normalized spread	Computed in two steps: First, we compute the difference between the maximum interest rate a borrower would agree to pay (Borrower maximum rate) on a loan listing and the minimum interest rate an individual bidder would accept (Minimum rate) on its bid. Then, we divide this interest rate spread by the Borrower maximum rate.
Aggregate US Sample Variables	
Powerball (mn USD)	Dollar value of the Powerball jackpot on a day.
Megamillions (mn USD)	Dollar value of the Mega Millions jackpot on a day.
Powerball + Megamillions (mn USD)	Dollar value of the combined Powerball and Mega Millions jackpots on a day. There are four weekly drawings—Wednesdays and Saturdays for Powerball, and Tuesdays and Fridays for Mega Millions.
Log (Powerball)	Natural logarithm of Powerball jackpot.
Log (Megamillions)	Natural logarithm of Mega Millions jackpot.
Log (Powerball+Megamillions)	Natural logarithm of the combined Powerball and Mega Millions jackpots.
Large jackpot	Equals to 1 if combined Powerball and Mega Millions jackpots is in the top 10% percentile.
Log (Bid amount)	Natural logarithm of the total bidding volume by individual lenders on a day.
Log (Bid number)	Natural logarithm of the total number of bids by individual lenders on a day.
Log (Total listing)	Natural logarithm of the total listing size open to bidding on a day.
Log (New listing)	Natural logarithm of the U.S. dollar value of new loan listings created by borrowers on a day. These are new loan listings on which lenders can start bidding. For a small minority (14%) of the listings, creation day of the listing and starting day of the bidding are different. In those cases, we assume starting day of the bidding as the day of the new listing.
Log (New listing #)	Natural logarithm of the total number of new loan listings created by borrowers on a day.
Share of winning bids	The status of a bid is one of the following: Winning, partially participating, outbid, bid withdrawn. For a given day, share of winning bids is equal to the percentage of winning bids among all bids made on that day.
Weighted average lender rate	For a given day t, lender rate is the rate that lenders would receive on the listing if the loan were to close on day t. To be able to compute weighted average lender rate on day t, we need to compute the weight of each listing among all listings available on day t. For a given day t, the weight of a listing L is equal to the ratio of the size of L to the size of all listings open to bidding on t. After we compute the weight of each listing open to bidding on day t, we multiply the lender rate of each listing with the weight of each listing. Then we sum the values of all weighted lender rates together to compute the weighted average lender date on a day.
S&P 500 Return	Value weighted return on the S&P 500 index on day t. Values of the index return on Saturday and Sunday are assumed as equal to the return on the last Friday.
Date	Date is the linear time trend.

California Sample Variables	
California jackpot (mn USD)	Dollar value of the California lottery jackpot on a day.
Log (California jackpot)	Natural logarithm of California lottery jackpot.
Share of California bids	Ratio of the total bidding volume by Californian individual lenders to the total bidding volume by all individual lenders.
Share of California bid count	Ratio of the total number of bids by Californian individual lenders to the total number of bids by all individual lenders.
Normalized California bids	We first calculate the total bidding volume by all individual lenders in month m, then we divide this total by the number of days in month m. This way we find the average daily bidding volume by all individual lenders on Prosper in month m. Then for a given day t in month m, normalized California bids is equal to bidding volume of Californian individuals on day t divided by the average daily bidding volume by all individual lenders on Prosper in month m.
Normalized California bid count	We first calculate the total number of bids by all individual lenders in month m, then we divide this total by the number of days in month m. This way we find the average daily bid count by all individual lenders on Prosper in month m. Then for a given day t in month m, normalized California bid count is equal to the number of bids by Californian individuals on day t divided by the average daily number of bids by all individual lenders on Prosper in month m.
Normalized non-California bids	We first calculate the total bidding volume by all individual lenders in month m, then we divide this total by the number of days in month m. This way we find the average daily bidding volume by all individual lenders on Prosper in month m. Then for a given day t in month m, normalized non-California bids is equal to bidding volume of non-Californian individuals on day t divided by the average daily bidding volume by all individual lenders on Prosper in month m.
Normalized non-California bid count	We first calculate the total number of bids by all individual lenders in month m, then we divide this total by the number of days in month m. This way we find the average daily bid count by all individual lenders on Prosper in month m. Then for a given day t in month m, normalized non-California bid count is equal to the number of bids by non-Californian individuals on day t divided by the average daily number of bids by all individual lenders on Prosper in month m.
Texas Sample Variables	
Texas jackpot (mn USD)	Dollar value of the Texas lottery jackpot on a day.
Log (Texas jackpot)	Natural logarithm of Texas lottery jackpot.
Share of Texas bids	Ratio of the total bidding volume by Texan individual lenders to the total bidding volume by all individual lenders.

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Table A4 (*continued*)

California Sample Variables	
Share of Texas bid count	Ratio of the total number of bids by Texan individual lenders to the total number of bids by all individual lenders.
Normalized Texas bids	We first calculate the total bidding volume by all individual lenders in month m, then we divide this total by the number of days in month m. This way we find the average daily bidding volume by all individual lenders on Prosper in month m. Then for a given day t in month m, normalized Texas bids is equal to bidding volume of Texan individuals on day t divided by the average daily bidding volume by all individual lenders on Prosper in month m.
Normalized Texas bid count	We first calculate the total number of bids by all individual lenders in month m, then we divide this total by the number of days in month m. This way we find the average daily bid count by all individual lenders on Prosper in month m. Then for a given day t in month m, normalized Texan bid count is equal to the number of bids by Texan individuals on day t divided by the average daily number of bids by all individual lenders on Prosper in month m.
Normalized non-Texas bids	We first calculate the total bidding volume by all individual lenders in month m, then we divide this total by the number of days in month m. This way we find the average daily bidding volume by all individual lenders on Prosper in month m. Then for a given day t in month m, normalized non-Texas bids is equal to bidding volume of non-Texan individuals on day t divided by the average daily bidding volume by all individual lenders on Prosper in month m.
Normalized non-Texas bid count	We first calculate the total number of bids by all individual lenders in month m, then we divide this total by the number of days in month m. This way we find the average daily bid count by all individual lenders on Prosper in month m. Then for a given day t in month m, normalized non-Texas bid count is equal to the number of bids by non-Texan individuals on day t divided by the average daily number of bids by all individual lenders on Prosper in month m.

Variable	Definition
New York Sample Variables	
New York jackpot (mn USD)	Dollar value of the New York lottery jackpot on a day.
Log (New York jackpot)	Natural logarithm of New York lottery jackpot.
Share of New York bids	Ratio of the total bidding volume by New Yorker individual lenders to the total bidding volume by all individual lenders.
Share of New York bid count	Ratio of the total number of bids by New Yorker individual lenders to the total number of bids by all individual lenders.
Florida Sample Variables	
Florida jackpot (mn USD)	Dollar value of the Florida lottery jackpot on a day.
Log (Florida jackpot)	Natural logarithm of Florida lottery jackpot.
Share of Florida bids	Ratio of the total bidding volume by Floridian individual lenders to the total bidding volume by all individual lenders.
Share of Florida bid count	Ratio of the total number of bids by Floridian individual lenders to the total number of bids by all individual lenders.
Kickstarter Sample Variables	
Log (Powerball)	Natural logarithm of Powerball jackpot.
Log (Megamillions)	Natural logarithm of Mega Millions jackpot.
Log (Powerball+Megamillions)	Natural logarithm of the combined Powerball and Mega Millions jackpots.
Log (Pledged)	Natural logarithm of the dollar value of total daily pledges.
Log (Backer number)	Natural logarithm of the number of backers who pledged on the platform on a given day.
Log (Unfullfilled goal amount)	Every project on Kickstarter has a funding target and a certain deadline to raise funds. For a given day, we first compute the total unfulfilled goal amount for every active project, then by summing these values we compute the total unfulfilled goal amount on the platform. Then, we take the natural logarithm of the unfullfilled goal amount.

This table lists the definitions of all variables used.

Table A5

Linear regressions of crowd bidding volumes and bid counts on multi-state lottery jackpots in the U.S. for the extended sample period (01.01.2007–02.13.2012).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid number)	Log (Bid number)
Estimation:	OLS	OLS	OLS	NW	NW	NW	NW	NW	NW	NW
Log (Powerball)	−0.070***									
	(0.014)									
Log (Mega Millions)		−0.043**								
		(0.021)								
Log (Powerball+Mega Millions)			−0.096***	−0.096**					−0.078***	
			(0.024)	(0.038)					(0.029)	
Jackpot quartile 2					−0.014					−0.016
					(0.042)					(0.033)
Jackpot quartile 3					−0.049					−0.029
					(0.051)					(0.039)
Jackpot quartile 4					−0.159**					−0.136***
					(0.062)					(0.046)
Large jackpot						−0.165*				
						(0.095)				
Log (Powerball+Mega Millions) detrended							−0.096**			

(*continued on next page*)

Table A5 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid number)	Log (Bid number)
Estimation:	OLS	OLS	OLS	NW	NW	NW	NW	NW	NW	NW
							(0.038)			
Powerball+Mega Millions								−0.001**		
								(0.000)		
Log (Total listing)	0.629***	0.618***	0.622***	0.622***	0.622***	0.613***	0.622***	0.619***	0.513***	0.512***
	(0.028)	(0.028)	(0.029)	(0.056)	(0.056)	(0.055)	(0.056)	(0.056)	(0.044)	(0.044)
Share of winning bids	1.107***	1.134***	1.116***	1.116**	1.130**	1.092**	1.116**	1.104**	0.371	0.382
	(0.385)	(0.388)	(0.388)	(0.467)	(0.463)	(0.473)	(0.467)	(0.470)	(0.352)	(0.348)
Weighted average lender rate	−5.049***	−4.943***	−4.973***	−4.973***	−4.898***	−5.140***	−4.973***	−5.029***	−1.658	−1.599
	(0.971)	(0.965)	(0.972)	(1.366)	(1.352)	(1.378)	(1.366)	(1.373)	(1.036)	(1.024)
S&P 500 Return	1.357	1.346	1.388	1.388	1.316	1.311	1.388	1.339	1.188	1.127
	(0.891)	(0.896)	(0.893)	(0.985)	(0.973)	(0.988)	(0.985)	(0.983)	(0.808)	(0.797)
Date	−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)	(0.000)	(0.000)	(0.000)
Constant	5.209**	5.958***	5.841***	5.841*	5.537*	5.731*	5.445	5.623*	−3.344	−3.564
	(2.247)	(2.175)	(2.237)	(3.300)	(3.338)	(3.288)	(3.345)	(3.345)	(2.513)	(2.518)
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598
R-Squared	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.65	0.65

The dependent variable in Columns (1)–(8) is *Log(Bid amount)*, defined as the natural logarithm of the total bidding volume in the U.S. dollar by individual lenders on a day. The dependent variable in Column (9) and (10) is *Log(Bid number)*, defined as the natural logarithm of the total number of bids by individual lenders on a day. The estimation method is OLS with robust standard errors for Columns (1), (2), and (3) and Newey–West (NW) standard errors with five lags for the remaining columns. Table A4 provides the definitions of all variables. *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

Table A6

Linear regressions of crowd bidding volumes and bid counts on multi-state lottery jackpots in the U.S. with lagged dependent variables for the extended sample period (01.01.2007–02.13.2012).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid number)	Log (Bid number)	Log (Bid number)	Log (Bid number)
Estimation:	NW	NW	NW	NW	NW	NW	NW	NW	NW	NW
Log (Powerball+Mega Millions)	−0.096**		−0.050**		−0.049**		−0.048**		−0.048**	
	(0.038)		(0.021)		(0.020)		(0.019)		(0.019)	
Jackpot quartile 2		−0.014		−0.024		−0.027		−0.021		−0.021
		(0.042)		(0.023)		(0.023)		(0.022)		(0.022)
Jackpot quartile 3		−0.049		−0.040		−0.042		−0.029		−0.029
		(0.051)		(0.026)		(0.026)		(0.025)		(0.025)
Jackpot quartile 4		−0.159**		−0.086**		−0.085**		−0.086***		−0.085***
		(0.062)		(0.034)		(0.033)		(0.031)		(0.031)
L1 Log (Bid amount)			0.553***	0.553***	0.512***	0.512***				
			(0.056)	(0.056)	(0.063)	(0.063)				
L2 Log (Bid amount)					0.062	0.062				
					(0.058)	(0.058)				
L1 Log (Bid number)							0.434***	0.432***	0.431***	0.430***
							(0.040)	(0.040)	(0.040)	(0.040)
L2 Log (Bid number)									0.005	0.004
									(0.031)	(0.031)
Log (Total listing)	0.622***	0.622***	0.292***	0.293***	0.278***	0.278***	0.300***	0.300***	0.298***	0.299***
	(0.056)	(0.056)	(0.046)	(0.046)	(0.043)	(0.043)	(0.036)	(0.036)	(0.037)	(0.037)
Share of winning bids	1.116**	1.130**	0.186	0.191	0.136	0.141	0.030	0.036	0.028	0.034
	(0.467)	(0.463)	(0.322)	(0.320)	(0.334)	(0.332)	(0.294)	(0.292)	(0.295)	(0.293)
Weighted average lender rate	−4.973***	−4.898***	−2.830***	−2.808***	−2.785***	−2.764***	−1.280	−1.255	−1.280	−1.256
	(1.366)	(1.352)	(1.028)	(1.019)	(1.016)	(1.007)	(0.793)	(0.785)	(0.792)	(0.785)
S&P 500 Return	1.388	1.316	1.307*	1.291*	1.377**	1.366**	1.204*	1.181*	1.209*	1.186*
	(0.985)	(0.973)	(0.679)	(0.674)	(0.694)	(0.689)	(0.640)	(0.635)	(0.644)	(0.638)
Date	−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)	(0.000)	(0.000)	(0.000)
Constant	5.841*	5.537*	0.627	0.444	0.399	0.210	−3.105	−3.265*	−3.108	−3.267*
	(3.300)	(3.338)	(2.042)	(2.072)	(2.092)	(2.121)	(1.924)	(1.945)	(1.924)	(1.946)

(*continued on next page*)

Table A6 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)	Log (Bid number)	Log (Bid number)	Log (Bid number)	Log (Bid number)
Estimation:	NW	NW	NW	NW	NW	NW	NW	NW	NW	NW
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598
R-Squared	0.72	0.72	0.81	0.81	0.81	0.81	0.72	0.72	0.72	0.72

The dependent variable in Columns (1)–(6) is *Log(Bid amount)*, defined as the natural logarithm of the total bidding volume in the U.S. dollar by individual lenders on a day. The dependent variable in Columns (7)–(10) is *Log(Bid number)*, defined as the natural logarithm of the total number of bids by individual lenders on a day. The estimation method is OLS with Newey–West (NW) standard errors with five lags for all specifications. Table A4 provides the definitions of all variables. *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

Table A7

Linear regressions of borrower listing volumes and listing counts on multi-state lottery jackpots in the U.S.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	Log (New listing)	Log (New listing)	Log (New listing)	Log (New listing)	Log (New listing)	Log (New listing)	Log (New listing #)	Log (New listing #)	Log (Total listing)	Log (Total listing)
Estimation:	NW	NW	NW	NW	NW	NW	NW	NW	NW	NW
Log (Powerball)	−0.019									
	(0.046)									
Log (Megamillions)		−0.060								
		(0.055)								
Log (Powerball+ Megamillions)			−0.084	−0.014			−0.025		0.005	
			(0.065)	(0.054)			(0.034)		(0.040)	
Jackpot quartile 2					0.117	0.075		0.041		0.024
					(0.095)	(0.084)		(0.061)		(0.056)
Jackpot quartile 3					0.149	0.112		0.034		0.084
					(0.092)	(0.078)		(0.055)		(0.062)
Jackpot quartile 4					−0.178	−0.063		−0.063		0.024
					(0.115)	(0.097)		(0.064)		(0.070)
L1 Log (Bid amount)				0.580***		0.560***				
				(0.081)		(0.082)				
L1 Log (Bid number)							0.672***	0.660***		
							(0.081)	(0.081)		
Share of winning bids	0.662	0.670	0.670	0.214	0.720	0.251	1.135*	1.159*	−0.110	−0.103
	(1.461)	(1.437)	(1.441)	(1.272)	(1.404)	(1.253)	(0.630)	(0.627)	(0.791)	(0.785)
Weighted average lender rate	6.218	6.201	6.309	4.056	6.934*	4.461	5.738***	6.014***	−4.624*	−4.590*
	(4.206)	(4.143)	(4.140)	(3.397)	(3.998)	(3.313)	(1.918)	(1.900)	(2.566)	(2.542)
S&P 500 Return	2.367	2.435	2.441	3.140	2.241	3.020	0.588	0.510	−1.192	−1.226
	(2.927)	(2.912)	(2.922)	(2.600)	(2.862)	(2.572)	(1.669)	(1.662)	(0.939)	(0.940)
Date	−0.003***	−0.003***	−0.003***	−0.002***	−0.003***	−0.002***	−0.002***	−0.002***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	64.505***	64.694***	64.846***	39.133***	65.036***	40.221***	35.469***	35.881***	40.894***	40.927***
	(5.758)	(5.621)	(5.599)	(5.440)	(5.535)	(5.388)	(3.201)	(3.187)	(3.493)	(3.515)
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1189	1189	1189	1189	1189	1189	1189	1189	1189	1189
R-Squared	0.64	0.64	0.64	0.67	0.64	0.67	0.76	0.76	0.79	0.79

The dependent variable in Columns (1)–(6) is *Log(New listing)*, which is defined as the natural logarithm of the U.S. dollar value of new loan listings created by borrowers on a day. The dependent variable in Columns (7)–(8) is *Log(New listing #)*, which is defined as the natural logarithm of the total number of new loan listings created by borrowers on a day. The dependent variable in Columns (9)–(10) is *Log(Total listing)*, defined as the natural logarithm of the U.S. dollar value of all loan listings open to bidding on a day. The estimation method is OLS with Newey–West (NW) standard errors with five lags for all specifications. Table A4 provides the definitions of all variables. *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

Table A8
Linear regressions of individual bidding amounts on multi-state lottery jackpots in the U.S. with bidder fixed effects at bidder-day level.

	(1)	(2)	(3)
Dependent Variable:	Log (Bid amount)	Log (Bid amount)	Log (Bid amount)
Estimation:	OLS	OLS	OLS
Log (Powerball+Mega Millions)	−0.012***		
	(0.002)		
Jackpot quartile 2		0.003	
		(0.002)	
Jackpot quartile 3		−0.004**	
		(0.002)	
Jackpot quartile 4		−0.020***	
		(0.003)	
Large jackpot			−0.016***
			(0.003)
Log (Bidding experience)	−0.255***	−0.255***	−0.255***
	(0.003)	(0.003)	(0.003)
Log (Total listing)	0.109***	0.107***	0.107***
	(0.007)	(0.007)	(0.007)
Share of winning bids	0.098***	0.107***	0.093***
	(0.020)	(0.020)	(0.020)
Weighted average lender rate	0.947***	1.019***	0.926***
	(0.132)	(0.133)	(0.132)
S&P 500 Return	−0.014	−0.030	−0.036
	(0.037)	(0.037)	(0.036)
Date	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)
Constant	7.439***	7.586***	7.511***
	(0.398)	(0.404)	(0.398)
Weekday FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Bidder FE	Yes	Yes	Yes
N	2,160,314	2,160,314	2,160,314
N Bidders	53,571	53,571	53,571
R-Squared	0.48	0.48	0.48

The dependent variable in all Columns is *Log(Bid amount)*, which is defined as the natural logarithm of all daily bids in the U.S. dollar by an individual bidder. The estimation method is OLS with bidder fixed effects and cluster-robust standard errors. Table A4 provides the definitions of all variables. *, **, and *** indicate significance at the 10%, 5%, and 1% respectively.

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