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The rational and behavioral flattening forces against the decline of crowdfunding contributions at geographic distance

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Abstract

I analyze the outcome of geographic patterns of online peer-to-peer loans using transactions data from three of the largest U.K. platforms. Given the decline of loan value with distance, I study the underlying rational and behavioral reasons. According to the rational view, distant lenders suffer from information disadvantage compared to local lenders and require higher interest rate to bear adverse selection risks. In contrast, the behavioral view argues that lenders located in regions whose people exhibit higher levels of trust attitude towards strangers are more willing to extend their radius of transaction to distant borrowers. Both explanations receive empirical support.

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INTRODUCTION

One of the best-established and yet most puzzling empirical findings related to the economic significance of geography is that transactions decrease with distance (Anderson and van Wincoop, 2004). Online markets of commerce or crowdfunding seem to be no exception to this rule despite their particular institutional environment (Hortaçsu, Martínez-Jerez, and Douglas, 2009; Agrawal, Catalini, and Goldfarb, 2015). For instance, in debt-based crowdfunding markets, lenders prefer geographically proximate borrowers (Burtch, Ghose, and Wattal, 2014; Lin and Viswanathan, 2015). Given these robust observations, the reasons underlying continued relevance of physical distance in crowdfunding markets are less explored and therefore, our understanding of the opportunities and limitations of these markets remain limited.

To understand why geographic distance impedes access to financing for people seeking financing in crowdfunding markets, I focus on peer-to-peer lending market and investigate two broad classes of explanations: rational and behavioral. The rational view is rooted in traditional economics and claims that lenders' decision about whom to lend is a rational choice based on conscious calculations, resulting in an efficient outcome that attempts to maximize expected gains or minimize expected losses. The rational account is dismissive of the "behavioral" view, which is rooted in social psychology and sociology thinking. The behavioral view tends to focus on the social and cognitive underpinnings of lenders' actions such as their beliefs, values, and dispositions. These theoretical views with differing assumptions bear interesting insights to why lenders favor nearby borrowers. Rational view advances that local lenders are better informed and that information advantage allows them more precise evaluation of all the relevant information to make informed decisions that maximize returns. Therefore, distant lenders might suffer from information asymmetry and incur adverse selection risks. In contrast, the behavioral view departs from the observation that lending is inherently a decision involving trust considerations. The disposition to trust strangers by lenders varies across cities, regions, and countries, and this might explain the radius of observed transactions.

To empirically assess the strength of these explanations, I use a unique dataset obtained from Open Data Institute that comprises peer-to-peer loans of over 92 percent of the UK crowdfunding market from October 2010 to May 2013. The data is all transactions in the three of the largest platforms in the UK, i.e., Ratesetter, Zopa, and Funding Circle. The dataset includes about 14 million individual loan contracts with the total amount of loan values of £378 million. This is among the largest datasets used in crowdfunding research in my knowledge. First, as a benchmarking exercise, I document that the loan part value, which is the contribution of a lender to a loan listing, decreases by about fifty pence (£0.5) for the increase in distance of about 300 kilometers (which is the mean of study sample) between lender and borrower. Furthermore, ignoring endogeneity of lenders' location choice decisions underestimates the effect of decline of lending at distance; the loan part value decreases by about £3.5 for an increase in the distance of about 300 kilometers. Given the average loan part value of £27, this is of considerable economic magnitude.

Second, consistent with rational view about calculative risk and emphasis on pay-offs, I find that distant lenders require higher interest rate as a compensation to bear adverse selection risk. This evidence is likely to suggest that it is likely that geographical proximity provides an information advantage about the borrowers (Peterson and Rajan, 2002; Agarwal and Hauswald, 2010). Third, consistent with the behavioral view, I find that when lenders live in a region whose people exhibit high levels of trust towards strangers (Knack and Keefer, 1997), their contributions to the loan (i.e., loan part value) are larger at distance. This showcases the behavioral flattening force of general trust that provides the socio-cognitive impetus for the disposition to trust geographically distant borrowers.

Our understanding of the function of debt-based crowdfunding markets is of great significance because they can fill an important gap in financing entrepreneurs. Accordingly, there is increasing attention by governments to the regulations of this market and interestingly the involvement of governments in using these markets to address early-stage financing gap; for instance, UK government is currently lending money to British small businesses through the peer-to-peer loan platforms studied in this paper. Furthermore, this study can guide our theoretical understanding about the extent to which crowdfunding can mitigate issues impeding financing access to early-stage investments or SMEs. Because of adverse selection risk arising from information asymmetry, entrepreneurs had no choice but to rely on geographically close individuals such as friends and family or proximate local banks or venture capitalists (Stuart and Sorenson, 2003). Yet, the emergence of crowdfunding was allegedly viewed to contribute to a "flatter" world for entrepreneurial financing (Agrawal et al. 2015). However, in this paper, I discuss some of the underlying limitations in this view that still deter financing at distance.

This article is organized as following. First, I present the research setting. Then, I develop the theoretical background and hypothesis. Thereafter, I explain the methods and results. Finally, the conclusion and discussions are presented.

Research Setting.

Online crowdfunding is a new form of financing in which many people contribute small amounts such that the total amount surpasses a predetermined funding target.

Several distinct models under the umbrella term of crowdfunding can be identified: reward-based crowdfunding, donation crowdfunding, equity crowdfunding, and debt-based crowdfunding (so called “peer-to-peer lending”). In peer-to-peer lending, the contribution is (part of) a loan (in this paper dubbed as “loan part value”) and the form of return is the repayment of loan with interest. An important distinction between “peer-to-peer lending” and other crowdfunding forms is the motives of the crowd. Peer-to-peer lending is usually primarily motivated financially (Pierrakis and Collins, 2013) as opposed to pursuit of intrinsic, social motive, or desire for reward[1].

Peer-to-peer model enables lending of crowd not only to other individual lenders, but also to businesses seeking debt financing. The organization of peer-to-peer loan market is facilitated by online platforms that channel funds from lenders to borrowers. Peer-to-peer platforms are considered full-reserve banking, meaning that unlike banks, platforms don't invest funds solely at their own discretion but enable lenders to make investment decisions directly. Lenders choose the borrowers or select projects without intermediation and submit an interest rate and an amount in a bidding process. Platforms take a fee in exchange of their services (to both lenders and borrowers).

There have been at least two major catalysts for the recent growth of peer-to-peer lending as a new innovative form of financing. First, the negative impact of 2008 financial crisis led to contractions in the loan provisions by banks to small and medium-sized businesses across the world for various reasons including regulatory pressures on banks. In turn, the ability and willingness of banks to lend is lower due to restrictions imposed by capital adequacy rules (e.g., higher capital ratios or specific rules on risk weightings on SME loans and overdrafts.) (The Economist 12 Jan

[1] This statement is valid only to non pro-social lending platforms such as the platforms under study in this paper.

2013)[2]. Thus, with decreased supply of bank lending, borrowers increasingly sought alternative sources of financing such as crowdfunding. Second, technological advancements in recent decades have reduced the transaction and coordination costs of markets. For instance, it is easier to broadcast the need for money to many more people at less cost using online social networks and transfer the money securely. Additionally, there is more availability of verifiable credit score data on lenders and businesses that offsets some of the information concerns faced by lenders.

There is growing interest among scholars to understand how lenders behave and the type of information they use to evaluate loan listings. With respect to the former, studies of debt-based crowdfunding document herding behavior, defined as the tendency to gravitate towards loans with more existing lenders (Herzenstein, Dholakia, and Andrews, 2011; Zhang and Liu, 2012). With respect to the latter, studies document the use of hard and soft information in inferring the creditworthiness of loans and borrowers (Sonenshein, Herzenstein, and Dholakia, 2011; Iyer et al. 2009; Dorfleitner et al. 2015). Lin et al. (2013) show that friendship connections on Prosper can help mitigate asymmetric information on the market. Interesting, several studies document the relevance of demographical and appearance attributes of borrowers such as beauty, age, and race (Ravina, 2012; Gonzalez and Loureiro, 2014; Pope and Sydnor, 2011; Duarte, Siegel, and Young, 2012). Furthermore, the distance between those physical, social, and cultural characteristics of borrowers and lenders is likely relevant. Burtch, Ghose, Wattal (2014) highlight that in pro-social lending of Kiva, cultural distance is a barrier to transactions. Galak,

[2] To address restricted lending by incumbent lenders, UK government has taken several initiatives such as Project Merlin, The National Loan Guarantee Scheme and the Funding for Lending.

Small, and Stephen (2011) find that lenders favor borrowers in Kiva that are similar with respect to age and occupation.

THEORITICAL BACKGROUND

A wide body of literature documents that it is more likely to observe transactions with parties who are geographically closer (Wolf, 2000; Hillberry and Hummels, 2003; Disdier and Head, 2008). This tendency is called "home bias" and considered a suboptimal behavior that leads to economic inefficiencies in the marketplace. Home bias is not limited to offline markets, but there is growing evidence that online markets are subject to home bias (Hortaçsu, Martínez-Jerez, and Douglas, 2009; Blum and Goldfarb 2006; Lin and Viswanathan, 2015). For instance, Lin and Viswanathan (2015) report that lenders prefer borrowers from the same state in the U.S. Although empirical evidence documenting home bias abounds, confusion haunts scholars about possible explanations (Seasholes and Zhu 2010; Lewis, 1999).

I advance the debate about continued relevance of distance in debt-based crowdfunding markets and put forward two broad classes of explanations: rational and behavioral. Rational account highlights economic instruments of costs and risks, and views decision makers as rational utility-maximizing agents that are able to process all the relevant information to arrive at optimal decisions. The assumption that lenders are rational and driven solely by economic instruments is reasonable specially in the context of this study given that lenders have primarily financial motivation to earn positive returns (Pierrakis and Collins, 2013). If lenders are homo economicus, any bias in decision is economically sensible. Having outlaid the assumption of this view, I base the rational account on the idea that geographical proximity is a source of information advantage and local individuals are better informed (e.g., Coval and Moskowitz, 1999). Accordingly, because local lenders are better able to gather and process information in the environment, they tend to lend locally to benefit from their information advantage.

As a response to the limitations and concerns regarding behavioral assumptions of rational calculation and expectation driven by pure economic instruments, behavioral perspective was proposed. For instance, March (1994) observed that rational choice model overstates cognitive capabilities of decision makers and the degree to which they would engage in calculations for making decisions. The "behavioral" view highlights the role of (a) cognitive factors such as bounded rationality, framing, and heuristics, and (b) social factors such as beliefs, norms, and values that inform decision judgments that could deviate from economic optimality. Having outlaid the broad assumptions of behavioral view, I draw on the particular idea that disposition to trust strangers is an aggregate function of where a lender lives, and that such disposition determines the observed radius of lending transactions.

Before going further with the hypothesis development, I review some of the studies that document the local nature of financial transactions, and the relevance of rational and behavioral account in bearing useful insights for our arguments.

Financial transactions decline with geographic distance

Research has considered the local nature of financial investments by individuals (Lewis, 1999; Huberman, 2001; Grinblatt and Keloharju, 2001; Ivkovic and Weisbenner 2005; Seasholes and Zhu, 2010), mutual funds (Coval and Moskowitz (1999, 2001); Hong, Kubik, and Stein, 2005), banks (Petersen and Rajan, 2002; Mian, 2006), venture capitalists (Lerner, 1995), or corporations (Landier, Nair, and Wulf, 2007). The broad conclusion is that the likelihood of investments decreases with greater physical distance owing to distance-sensitive costs. For instance, to invest in early-stage firms by venture capital firms, local proximity between venture capital investors and portfolio firms facilitates opportunity identification, conduct of due diligence, post-investment monitoring/oversight by the representation of venture capitalists on the boards of portfolio firms, and eventually value-adding activities (Lerner, 1995; Sorenson and Stuart, 2001; Cumming and Dai, 2010; Bernstein, Giroud, and Townsend, 2015; Zook, 2002).

Rational account: Information advantage of local investors and lenders

It is reasonable to assume that, ceteris paribus, investors are able to gather value-relevant information about the local opportunities to them (e.g., local companies) with greater ease and accuracy than they could about remote opportunities (nonlocal companies). Numerous research has documented the relevance of information advantage for the geographic link between financial investment and performance. To illustrate a few examples across different markets, Coval and Moskowitz (1999, 2001) report that fund managers exploit their informational advantage of geographically proximate firms and earn abnormal returns compared to nonlocal investors who might suffer from asymmetric information. Similarly, Hau (2001) analyze informational asymmetries as revealed by proprietary equity trading and find that traders located near a company's headquarters outperform their competitors in trading. In the U.S., analysts who are closer to the headquarters of a firm have an information advantage and provide better earnings forecast (Malloy, 2005; see also Bae, Stulz, and Tan (2008) for information advantage of local vis-a-vis foreign analysts in a large sample of countries). Garmaise and Moskowitz (2004) find that buyers in the commercial real-estate markets tend to be local when information asymmetries between the parties are severe and more remote otherwise. For M&A transactions, Ragozzino and Reuer (2011) report that acquirers choose more geographically proximate targets with increased perceived threat of adverse selection because the bidder presumably holds an informational advantage over more distant competitors. Ivkovic and Weisbenner (2005, p. 305) conclude that individual households are "able to process and exploit locally available information to earn excess returns." The authors note that their findings are "particularly strong where information asymmetries are likely to play the most pronounced role—among the non-S&P 500, less widely known stocks."

Following the same logic, research notes that institutional lenders (e.g., banks) enjoy a local informational advantage that erodes with distance (Agarwal and Hauswald, 2010; Butler, 2008). Stein (2002) draws a distinction between hard (verifiable) and soft (unverifiable) information. In online or offline environments, both hard (e.g., income level of an individual or firm profits) and soft information (e.g., the quality of entrepreneurs' vision or the statement of loan purpose posted with a loan description) is relevant and valuable in lending outcomes (Miller, 2015; Sonenshein, Herzenstein, Dholakia, 2011), though the latter seems to be more geographically distributed (i.e., more asymmetric for distant lenders). The tenet of this reasoning is that "soft" information used in credit decisions is primarily local (Petersen and Rajan, 2002; Degryse and Ongena, 2005; Agarwal and Hauswald, 2010; Berger and DeYoung 2006; Brevoort and Hannan 2006; DeYoung, Glennon, and Nigro, 2008). "The more a branch lends outside its immediate vicinity, the harder the collection of local information becomes, rendering credit screens less precise. In essence, borrower proximity acts as a proxy for the quality of soft private information." (Agarwal and Hauswald, 2010 p.15). In conclusion, to the extent that soft information is local, borrower proximity increases a lender's ability to assess credit risks.

Behavioral account: contribution of general trust to the radius of financial transactions

Kenneth Arrow (1972) argued that "virtually every commercial transaction has within itself an element of trust, certainly any transaction conducted over a period of time." The ability of one party to an exchange to believe in the credibility of promises made by another party rests on trust, defined as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer, Davis, and Schoorman, 1995: 712). With parties trusting each other, transactions that require credible promises are attainable. In contrast, absent the credibility of promises, risks of opportunistic behavior forces parties to rely on spot market transactions rather than contracts across time and space (Keefer and Knack, 2008). Therefore, trust is critical for capturing wide ranges of economic benefits that are not sufficiently affordable by spot markets. For example, financial contracts in which creditors loan money to debtors on the promise of future repayments. Having motivated inquiry into the role of trust, this paper focuses on a specific source of trust, dubbed as "general trust".

General trust expresses diffuse trust-related expectations of the people from one nation or region towards strangers. General trust stands in sharp contrast with experience and knowledge-based trust towards a specific transacting party (Colombo and Shafi, 2015). This attitude-based variable reflects the disposition to trust that is socially constructed and can be defined within different levels of geographic aggregation, ranging from cities and regions (Beugelsdijk and van Schaik, 2005; Putnam et al. 1993) to entire nations (Knack and Keefer 1997; Zak and Knack, 2001). On a macro-level, general trust encourages economic growth (Algan and Cahuc 2010;

Dincer and Uslaner, 2010; Fukayama 1995; Helliwell and Putnam, 1995; Knack and Keefer, 1997) and institutional development (Aghion et al. 2010, Knack, 2002). On a micro-level, general trust facilitate exchange relationships within and between organizations, especially those with high misappropriation risks (Zaheer and Zaheer, 2006; Huff and Kelley, 2003; MacDuffie, 2011; Kostava and Zaheer, 1999). To illustrate more recent contributions in entrepreneurship literature, Ang, Cheng, and Wu (2015) find that high-tech companies faced with fears of misappropriation risk of their technology that invest in China decide based on general trust; Where local people are regarded more trustworthy, there is a higher likelihood of investment flow, joint venture, and R&D investment in that region. Bottazzi et al. (2011) provide evidence that venture capitalists are less likely to fund entrepreneurs in countries whose citizens they trust less and, if they do, the contracts they use are different from the contracts used in countries they trust more.

HYPOTHESIS DEVELOPMENT

Recent advancements in technology have eliminated some of the distance-sensitive costs in lending transactions. I enumerate the common properties of online (debt-based) crowdfunding especially designed to overcome distance-induced frictions (Agrawal et al. 2015). First, online debt-based crowdfunding platforms reduce search costs by bringing together standardized information on potential loan recipients and facilitating the match between borrowers and lenders. Second, apart from initial screening based on credit history of the recipient, online debt-based crowdfunding platforms have enabled smaller financial transactions to attract broad participation, further resulting in less need for ex-post monitoring given the limited downside risk. Third, platforms provide information on what other lenders have done facing similar listing; for example, platforms present the amount of prior bids and their interest rates.

This public information can be observed by other lenders in order to update their private information about the quality of a listing (Zhang and Liu, 2012).

Although these platform-enabled tools provide a counterforce against some of the geographic barriers deterring lending at distance, it remains an empirical question whether the magnitude of this counterforce is large enough to dominate frictions such as information asymmetry faced by distant lenders or lack of trust to distant borrowers. The answer seems to be negative according to several empirical research papers. Lin and Viswanathan (2015) document home bias in Prosper, the largest U.S. peer-to-peer lending platform. Similarly, Burtch, Ghose, and Wattal (2014) find that pro-social lending in Kiva also declines at distance[3]. Consistent with all these prior studies that find that distance continues to be an important deterrent to the transactions, I follow suit and posit the following benchmark hypothesis:

> H1. Geographic distance separating the lender and the borrower decreases the value amount of loan part.

Now I turn to the rational reasoning behind the decline of lending with distance. Rational account notes that lenders can better assess nearby borrowers owing to their informational advantage. Local decision makers are better-informed ones because distance is viewed to be a proxy for information asymmetry (e.g., Coval and Moskowitz, 1999; Garmaise and Moskowitz, 2004; Grinblatt and Keloharju, 2001). Accordingly, distance affects the quality of the lender's soft information. Ceteris paribus, the perceived adverse selection risk should increase with lender-borrower geographical distance as the precision of screening were to decrease in it (Hauswald

[3] In other crowdfunding markets, there seems to be a similar relationship. Using data from crowdfunding artists in Sellaband, Agrawal et al. (2015) find that most of the donations occur in the same geographical area or in nearby areas, and this is likely to be donations from family and friends. Similarly, Mendes-Da-Silva et al. (2015) report that donations to artists from local backers are larger.

and Marquez, 2006; Agarwal and Hauswald, 2010). In line with this idea, I propose the following description for the process of incorporation of information into prices in peer-to-peer lending at distance: uninformed lenders charge higher interest rates to borrowers located farther afield (due to the increase in the adverse selection problem) because loan rates passing through such information costs increase with distance.

H2. The decline of value amount of loan part with distance weakens with increased interest rate.

General trust allows for a wide radius of economic transactions (Fukuyama 1995; Yamagishi and Yamagishi, 1994) by enabling people to move out of familiar relationships in which trust is based on experience and first-hand knowledge about particular people. A society is characterized by wide radius of trustworthiness when a large fraction of the society can be relied upon to fulfill their contracts. Whereas high levels of general trust allows for a wide radius of transactions, for instance, between strangers, lack of general trust restricts transactions to familiar people (e.g., family members).

Agarwal et al. (2014) find that preexisting offline social networks of family and friends have persistent role in contributions to the artistic crowdfunding campaigns (and these social ties happen to be located in the same or nearby regions to the artist). However, it is ostensibly plausible to receive contributions from people not belonging to the family and friends. This is most likely to take place in an environment whose people exhibit high levels of trust towards strangers, meaning that they perceive others to be trustworthy enough to fulfill their obligations and keep their promises. In line with this idea, I posit that when a lender lives in an environment whose people exhibit high levels of trust towards strangers (i.e., lender's general trust), he or she has the disposition to contribute to a distant borrower a larger value amount of loan part.

H3. The decline of value amount of loan part with distance weakens with increased levels of lenders' general trust.

METHODS

Data. I obtained data from Open Data Institute (http://theodi.org)[4]. Open Data Institute has collected loan data from the three largest peer-to-peer platforms in the UK: Funding Circle, Zopa, and RateSetter. P2P lending was incepted in UK and has emerged in many countries afterwards. Zopa were the first and oldest peer–to–peer lender in the UK established in 2005 and focuses mostly on personal lending. Funding Circle was founded in August 2010 and was the first company in the world to allow individuals to lend to businesses (Pierrakis and Collins, 2013). Funding circle currently has the largest market share in the market for peer–to–peer business lending in the UK. Finally, RateSetter was launched in 2010 and is based in London. The legitimacy of these platforms increased further when the UK government began lending money to British small businesses through these websites[5].

The dataset comprises peer-to-peer loans of over 92 percent of the UK crowdfunding market (ODI, 2013) from October 2010 to May 2013. October 2010 is the earliest data at which all three lenders were operating. The dataset includes 59,851 individual loans with the total amount of loan values of £378 million. Given that multiple lenders fund each loan, the number of loan parts (individual loan contracts)

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[4] The dataset can be downloaded at http://smtm.labs.theodi.org

[5] https://www.gov.uk/government/news/new-40-million-investment-by-british-business-bank-to-support-450-million-of-lending-to-smaller-businesses
https://www.gov.uk/government/news/70-million-boost-to-small-business-lending
https://www.gov.uk/government/news/80-million-boost-for-leasing-finance-as-british-business-bank-focuses-on-alternative-lending-for-small-business

is 13,924,547. This dataset is the largest dataset used so far to study crowdfunding market to my knowledge.

I complement this loan dataset with sources of data from Office for National Statistics (http://www.ons.gov.uk/ons/index.html) (ONS), British Social Attitudes Survey (BSA) (http://www.natcen.ac.uk), Official Labour Market Statistics (Nomis) (https://www.nomisweb.co.uk), and Eurostat data (http://ec.europa.eu/eurostat/web/main/home).

I present statistics regarding the regional geography of lending in the UK peer-to-peer loan market. Regions are defined at first-level NUTS (i.e., Nomenclature d'Unités Territoriales Statistiques), which is a geocode standard developed by the European Union for referencing the administrative divisions of countries for statistical purposes. The UK has the following 12 regions: North East England, North West England, Yorkshire and the Humber, East Midlands, West Midlands, East of England, Greater London, South East England, South West England, Wales, Scotland, Northern Ireland. In Figure 1, the sum of loans generated and received in each region is visualized.

Insert Figure 1 about here

There is a dividing pattern in lending volume (but not borrowing) between the North and the South. There are four regions that have net positive balance: London, South East, South West, and the East of England; they all are in the South of the UK.

Variables

Dependent variable. Loan part value represents the amount of money in British Sterling Pound (£) that a lender has contributed to a given loan.

Independent variables:

Geographical Distance. I calculated the distance in 100 km between the centroid of the region of borrower and that of lender. This data is obtained from Eurostat.

General trust: Following Knack and Keefer (1997), I use social attitudes survey data to assess the level of trust in a region. I use the following trust-related question: “Generally speaking, would you say that most people can be trusted, or that you can’t be too careful in dealing with people?” Trust is the percentage of respondents in each region that reply “most people can be trusted” (after deleting the “don’t know” responses) in each region-year. This behavioral measure has been externally validated by field experiments (experiments conducted by Reader’s Digest Europe, and reported in that magazine in April 1996, and subsequently discussed in the Economist, June 22, 1996) in which cash-bearing wallets were dropped “accidentally” and data on the frequency of wallet returns were reported. At the national level, the correlation between the actual frequency of return of the experimentally dropped wallets and general trust (national average responses to the same trust-related question in the World Values Survey) is 0.65 ($p<0.01$) (Knack, 2001).

Interest rate: it indicates the interest rate on a loan part as requested by a lender. Iyer et al. (2009) show that interest rates set by individuals in peer-to-peer lending are more accurate than credit bands assigned by credit scoring technologies to predict the likelihood of loan defaults ex post.

Control variables:

The sum of loan parts is the total amount of loan. I include the log of amount of loan to control for the overall size of the loan. Larger loans are often hypothesized to carry more risk of moral hazard by borrowers. I also include loan term, which indicates loan maturity in month (i.e., the number of regular monthly payments of the loan). To control for unobserved time-invariant heterogeneity regarding the region of borrower, a series of region of borrower fixed-effects are included. Year-fixed effects are also included to capture growth trends of the supply and demand peer-to-peer loan market. Finally, to take into account regional characteristics of lenders, I control for the lender's regional population, logged value of gross disposable house income (GDHI) per head, unemployment rate.

Model Specification

The unit of analysis is individual loan part. I initially estimate the following ordinary least square (OLS) model with robust standard errors clustered on loan level.

$$Loan\,part\,value_{ij} = \beta\, distance_{ij} + \gamma\, interest\_rate_{ij} + \boldsymbol{\varphi}\, X_j + \boldsymbol{\alpha}\, \theta_i + \boldsymbol{\rho}\, \mu_t + \varepsilon_{ij}$$

$Loan\,part\,value_{ij}$ represents the value of loan part from lender i to borrower j. $distance_{ij}$ is the distance between region of lender i and borrower j. X_j is the set of loan or borrower characteristics such as the region fixed-effect of borrower. θ_i is the set of the regional characteristics of lender such as general trust and other socio-economic factors (e.g., population). μ_t is a set of year dummy variables to control for time-trends and ε_{ij} is an idiosyncratic error term.

I employ two other specifications to address issues of unobserved heterogeneity regarding a loan listing and the endogeneity of lending location choice. First, because I don't observe all the characteristics of the borrower or loan (e.g., how attractive the profile picture of the borrower is) except for the region where the borrower is located, I fit a linear regression including dummy variables for each loan (ν_b). This loan-level fixed-effect strategy reduces concerns of unobserved heterogeneity of loan (e.g., demographics of borrower, purpose of the loan, stories in loan description, etc.). In this analysis, only the loan-related covariate of interest rate remains as it can vary for a given loan depending on the request offered by a lender.

$$Loan\,part\,value_{ij} = \beta\, distance_{ij} + \gamma\, interest\_rate_{ij} + \boldsymbol{\alpha}\, \theta_i + \boldsymbol{\rho}\, \mu_t + \nu_b + \varepsilon_{ij}$$

Second, I use two-stage least squares (2SLS) regression to address concerns about endogeneity of $distance_{\mathrm{ij}}$. $distance_{ij}$ is a choice variable and ignoring endogeneity can bias the estimates. The instrumental variable is the difference in house price index between the region of borrower and that of lender ($HPI\ Diff_{ji}$). The rationale hinges on the relationship between housing price variations, relative cost of bank borrowing, and online peer-to-peer loan market. This relationship is as follows. The peer-to-peer online market and bank are indeed substitute products in loan market: demand for financing on peer-to-peer lending drops in response to cheaper local credit from banks. Furthermore, the local housing price variations are linked to relative cost of bank borrowing. To illustrate, take the case of entrepreneurs seeking financing for their businesses. Most of the lending to entrepreneurs of SME firms that are likely to use peer-to-peer lending previously relied on either personal loans or business loans with personal wealth as collateral or guarantee (Avery, Bostic, and Samolyk, 1998; Meisenzahl, 2014; Robb and Robinson, 2014). For UK firms, Cosh, Cumming, and Hughes (2009) report that bank debt is the predominant outside financing source (the highest percentage of outside finance) in terms of both the type of finance approached and the type of finance obtained. Given that private residences are cited to be a pervasive form of collateral (Meisenzahl, 2014), research indicates that local housing price appreciation is likely to relieve collateral constraints and encourage entrepreneurial activity (Harding and Rosenthal, 2015; Adelino, Schoar, and Severino, 2015; Corradin and Popov, 2015). Thus, if local financing cost from banks increases (decreases) due to negative local housing prices, then there will be more (less) demand towards peer-to-peer online lending market in that region. The argument claims that a positive local housing price shock should lower the costs of bank borrowing. At the same time, local housing prices should not affect financing costs on peer-to-peer loan markets as crowdfunding doesn't necessarily require collateral (and the loans are often unsecured).

RESULTS

Table 1 provides descriptive statistics and correlation matrix. The average loan part is £27 and the average log of total loan amount is 8.84. The loan term on average is about 42 month. The positive correlation between General trust and GDHI per head is consistent with documented finding that general trust in a society contributes positively to economic activity (Knack and Keefer, 1997). Moreover, in order to flag issues related to multicollinearity due to large correlation between GDHI per head and population (0.80), I estimated standard OLS models and computed variance inflation factors and condition indices and found that none of these values were close to the cutoffs of 10 and 100, which are associated with multicollinearity (Neter, Wasserman, and Kutner, 1985; Belsley, Kuh and Welsch, 2005).

Insert Table 1 about here

Table 2 presents the regression results. Model I includes baseline specification only with the control variables. Regarding the set of loan-level variables, the coefficient of loan amount is positive ($p<0.01$), indicating that larger loans receive larger sized contributions from the crowd. The coefficient of loan rate is negative ($p<0.01$), which likely suggests that lenders perceiving the loan risk higher are less likely to contribute a large-sized loan part. Loan term is negative ($p<0.01$), possibly indicating these loans are less attractive due to requiring longer horizons of patience or exposure to uncertainty. The coefficient of General trust is positive ($p<0.01$) as expected. People living in regions with higher general trust are willing to contribute larger amount of loan parts. Interestingly, GDHI per head is positive ($p<0.01$) and is indicative of positive wealth effects.

In Model II, I add the geographical distance and obtain a negative coefficient ($p<0.01$) in support of H1. For an increase of 100 kilometers in distance, the amount of loan decreases by £0.165. In the subsequent models of Model III and IV, specifications are modified. First, a loan-fixed effect model is estimated in Model III. In this analysis, covariates that don't change across a given loan are dropped. Results are similar in Model III on the negative influence of geographic distance ($p<0.05$). Finally, in Model IV and V, I use 2SLS approach to address possible concerns of endogeneity of geographical distance that might have biased the results. The first stage (Model IV) includes the instrumental variable HPI diff, which is the difference of house price index between borrowers' region and that of lenders and scaled by dividing by 100. Consistent with our arguments, the coefficient of HPI diff is negative ($p<0.01$). F-statistics of the first stage is 14,241.265 ($p<0.01$), which suggests that geographical distance must be treated as endogenous. Stock, Wright, and Yogo (2002) suggest that the F-statistic should exceed 10 for inference based on the 2SLS estimator to be reliable when there is one endogenous regressor. This means that previous OLS estimates are not consistent and the model that treats geographical distance as endogenous using 2SLS should be used for correct inference. These results from the second stage of 2SLS are presented in Model V and point to larger negative magnitude of geographic distance on loan part value. For an increase of 100 kilometers in distance, the amount of loan part decreases by £1.221.

Table 3 presents the results of interaction terms used to test H2 and H3. Model I-III presents the results of the interaction terms between Distance and Loan rate. Model I presents the OLS estimates and the interaction term is positive ($p<0.01$). The results are similar in Model III that fits 2SLS. However, this interaction term is not significant anymore in Model II that fits fixed-effect OLS. These results only partially support H2 as controlling for unobserved heterogeneity within a loan removes the explanatory power on the moderating factor. Furthermore, in subsequent models, the results of the interaction term between Distance and General trust are presented. In all specifications, the coefficient of interaction terms is positive ($p<0.01$). These estimates support H3.

Insert Table 2 and 3 about here

Robustness. I perform a series of robustness tests. First, additional control variable is of regional gross value added per head in the region of lender (instead of GDHI per head) is inserted in regressions and results remain similar. Second, when a dummy variable of the same region is included in the estimation, there is a negative coefficient for same-region variable, consistent with our results. Fourth, I divide the loan amount by total amount and create a new variable: fraction of loan. I obtain similar results (results are available upon request). I also have taken the average values of general trust over time for each region because general trust is fairly stable over time (Algan and Cahuc 2010; Uslaner, 2008; Bjørnskov, 2006).

CONCLUSION AND DISCUSSION

With the advent of crowdfunding, and specifically the ability of individuals to lend to others in the peer-to-peer lending market, a richer understanding of how people make choices in this domain is paramount. Consistent with prior studies that report that lenders prefer nearby borrowers, I find similar evidence. I argue that distant lenders suffer from information disadvantages and require higher interest rate to bear possible adverse selection risks. Furthermore, lenders located at regions whose people exhibit higher levels of trust towards strangers are lending a larger sum at distance. Overall, This study sheds light on when lenders prefer borrowers who are distant to them.

These results are important for entrepreneurship theory and practice because although debt-based crowdfunding includes many types of loans, it has particularly tailored to the funding needs of businesses. Ranking second after the donation-based crowdfunding, debt-based crowdfunding accounted for 20% of all the crowdfunding volume channeled to entrepreneurs in 2012 (Massolution, 2013). This number is remarkable given that business loan requests are harder to fulfill compared to other types of loans in online peer-to-peer markets (Mach, Carter, and Slattery, 2014) or other reward-based crowdfunding. Notwithstanding the business loans, Shane (2008) argues that entrepreneurs often rely on personal debt to finance their businesses, and loans from this market are often personal debts (and intended to finance businesses). Therefore, online debt-based crowdfunding can fill a very important gap in financing entrepreneurs. Additionally, this study can further guide our theoretical understanding about the extent to which crowdfunding can mitigate issues impeding financing access to early-stage firms. Because of adverse selection risk arising from information asymmetry, entrepreneurs had no choice but to rely on geographically close individuals such as friends and family or proximate local banks or venture capitalists (Stuart and Sorenson, 2003). Yet, the emergence of online platforms is conducive to elimination of some but not all of these issues. Accordingly, in this study I showed some of the limitations of crowdfunding. Previous studies often take the side of rational reasoning about ex ante information collection or ex post monitoring as main determinants of local investing with expected higher returns. However, in addition to these economic reasons, behavioral reasons such as general trust can drive at least some of the debt capital to the businesses (complementing evidence on venture capital flows from Bottazzi et al. 2011).

The contributions of this paper are multifold. First, I add to the broad literature that discusses the economic significance of geography as pertains to information (Coval and Moskowitz, 1999; Ragozzino and Reuer, 2011). My study describes a rational model of how lenders in crowdfunding incorporate their soft information into prices and consequently, size of their contributions. This model takes note of the well grounded view in the information economics literature that geographic distance is a measure of the information disadvantages and adverse selection risk. In other words, this finding corroborates that the soft information used to make peer-to-peer lending decisions has indeed an important local component (Agarwal and Hauswald, 2010; Butler, 2008). Furthermore, I add to the literature that highlights that economic transactions are embedded in social structure (Granovetter, 1985). General trust is socially constructed and informs the radius of transactions (Guiso, Sapienza, and Zingales, 2009). The evidence of this study reveals how social offline structures alter the functioning of the crowdfunding markets. Finally, I contribute to the growing crowdfunding literature that seeks to understand the decision rules that crowd uses to arrive at their decisions (Zhang and Liu, 2012). This study brings to the fore the simultaneous influence of both rational and behavioral factors in the decision of the crowd. This is important because prior literature has often dismissed behavioral factors driving the contribution patterns of the crowd.

This study has several limitations that also can provide interesting avenues for future research. First, the strata of information about the lender in this study is limited to the location of residence[6]. Further controls of lender attributes such as gender, age, income levels, or financial literacy are important considerations that could influence investment decisions in crowdfunding markets (Shafi and Mohammadi, 2015).

[6] The provider of the dataset (ODI) has eliminated all lender identifiers in order to respect privacy concerns of lenders and borrowers.

Although I control for some of the related characteristics of lenders' region, this set is limited. A solution would be to take advantage of lenders' region fixed-effects. However, this solution raises multi-collinearity issues with measures of general trust. Second, future research can use dyadic measures of trust, which measures how people from one region trust people from another region. Third, the context of this study is limited to the institutional setting of UK, with a well-developed institutional market (e.g., stock and credit market) and strong legal system with respect to creditors' right. This setting although enables avoiding confounding institutional factors on the results (North, 1990), but limits generalization to other contexts, specially those countries with distant cultural or institutional environment than those of the U.K. Finally, the current dataset doesn't provide information about ex post default of loans, which limits our investigation about to what extent rational or behavioral accounts are biased. Possibly, a higher error rate might accompany behavioral rather than rational logic. This is so because cognitive psychology research into economic decisions contrasts automatic, effortless, associative, and emotionally charged cognitive processes (e.g., general trust that are governed by habit), with slow, effortful, and controlled cognitive processes of reasoning that is potentially rule-governed (Kahneman, 2003). Having said that, effortless decisions such as reliance on general trust, although can yield quick and easy judgments, they can also produce biased inferences and might have poor performance. Therefore, future research is needed to carefully assess the accuracy of mixed-mode judgments combining rational and behavioral perspectives. If the individual investors' local bias is rational and information-driven, it is feasible to empirically identify the evidence of superiority of their local investments at least compared to their nonlocal investments.

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Table 1 – Descriptive statistics and correlation matrix

	Variable	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1.	Loan part value	27.17	148.99	---							
2.	Distance	3.07	2.06	-0.01	---						
3.	General trust	0.39	0.05	0.00	0.11	---					
4.	Loan amount (logged)	8.84	0.89	0.10	-0.06	-0.01	---				
5.	Loan rate	6.96	1.29	0.02	-0.04	0.08	0.47	---			
6.	Term	41.99	12.51	-0.01	-0.01	0.00	0.16	0.43	---		
7.	Unemployment rate	7.63	1.46	0.00	-0.07	-0.18	-0.01	0.04	0.01	---	
8.	Population	6.68	1.83	0.01	-0.13	0.04	0.00	-0.01	-0.01	-0.15	---
9.	GDHI per head (logged)	9.81	0.15	0.01	-0.05	0.23	0.01	-0.02	-0.01	-0.06	0.80

N=13,924,547. The distance is expressed in hundred kilometer.

Table 2 - Regression results predicting loan part value [a]

	Model I	Model II	Model III	Model IV	Model IV
	OLS	OLS	Fixed-effect OLS	1st stage 2SLS: Distance	2nd stage 2SLS
Loan amount (logged)	18.917*** (0.205)	18.916*** (0.205)		-0.005*** (0.001)	18.908*** (0.205)
General trust	7.830*** (1.148)	8.462*** (1.150)	3.045*** (0.872)	3.758*** (0.056)	12.510*** (1.344)
Loan rate	-3.709*** (0.153)	-3.710*** (0.153)	-15.803*** (0.197)	-0.003*** (0.001)	-3.715*** (0.153)
Term	-0.158*** (0.010)	-0.158*** (0.010)		0.000** (0.000)	-0.158*** (0.010)
Unemployment rate	0.429*** (0.030)	0.409*** (0.031)	0.369*** (0.025)	-0.318*** (0.003)	0.283*** (0.035)
Population	0.026 (0.042)	-0.017 (0.043)	-0.062* (0.034)	-0.225*** (0.002)	-0.293*** (0.053)
GDHI per head (logged)	12.280*** (0.648)	12.537*** (0.655)	11.566*** (0.427)	1.963*** (0.042)	14.183*** (0.645)
Distance (**H1**)		-0.165*** (0.026)	-0.050** (0.021)		-1.221*** (0.142)
HPI diff				-2.900*** (0.024)	
Constant	-227.775*** (6.018)	-229.769*** (6.064)	20.350*** (4.079)	-14.761*** (0.379)	-242.531*** (5.971)
R-squared	0.010	0.010	0.294	0.446	0.010

N= 13,924,547. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
[a] Robust standard errors appear in parentheses clustered around 59,851 loans.
All regressions include borrower region fixed effect and year dummies.

Table 3 - Regression results of moderators predicting loan part value [a]

	Model I	Model II	Model III	Model IV	Model V	Model VI
	OLS	Fixed-effect OLS	2nd stage 2SLS	OLS	Fixed-effect OLS	2nd stage 2SLS
Loan amount (logged)	18.929*** (0.205)		19.186*** (0.215)	18.915*** (0.205)		18.902*** (0.205)
General trust	8.429*** (1.151)	3.047*** (0.872)	11.636*** (1.310)	3.257 (2.129)	-0.827 (1.435)	-63.484*** (9.304)
Loan rate	-4.069*** (0.197)	-15.771*** (0.202)	-11.520*** (1.089)	-3.710*** (0.153)	-15.804*** (0.197)	-3.714*** (0.153)
Term	-0.159*** (0.010)		-0.177*** (0.010)	-0.158*** (0.010)		-0.158*** (0.010)
Unemployment rate	0.408*** (0.030)	0.369*** (0.025)	0.249*** (0.040)	0.408*** (0.030)	0.367*** (0.025)	0.360*** (0.032)
Population	-0.019 (0.043)	-0.061* (0.034)	-0.324*** (0.057)	-0.012 (0.043)	-0.058* (0.034)	0.002 (0.043)
GDHI per head (logged)	12.616*** (0.657)	11.558*** (0.427)	15.838*** (0.754)	12.629*** (0.659)	11.634*** (0.427)	14.113*** (0.642)
Distance	-1.015*** (0.244)	0.035 (0.113)	-19.663*** (2.652)	-0.851*** (0.210)	-0.560*** (0.152)	-9.929*** (1.278)
Distance × loan rate **(H2)**	0.122*** (0.034)	-0.012 (0.016)	2.651*** (0.361)			
Distance × general trust **(H3)**				1.699*** (0.507)	1.263*** (0.372)	23.716*** (3.099)
Constant	-228.082*** (6.048)	20.194*** (4.084)	-205.380*** (7.634)	-228.607*** (6.024)	21.222*** (4.087)	-215.844*** (6.637)
R-squared	0.010	0.297	0.008	0.010	0.297	0.010

N= 13,924,547. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

[a] Robust standard errors appear in parentheses clustered around 59,851 loans.

All regressions include borrower region fixed effect and year dummies.

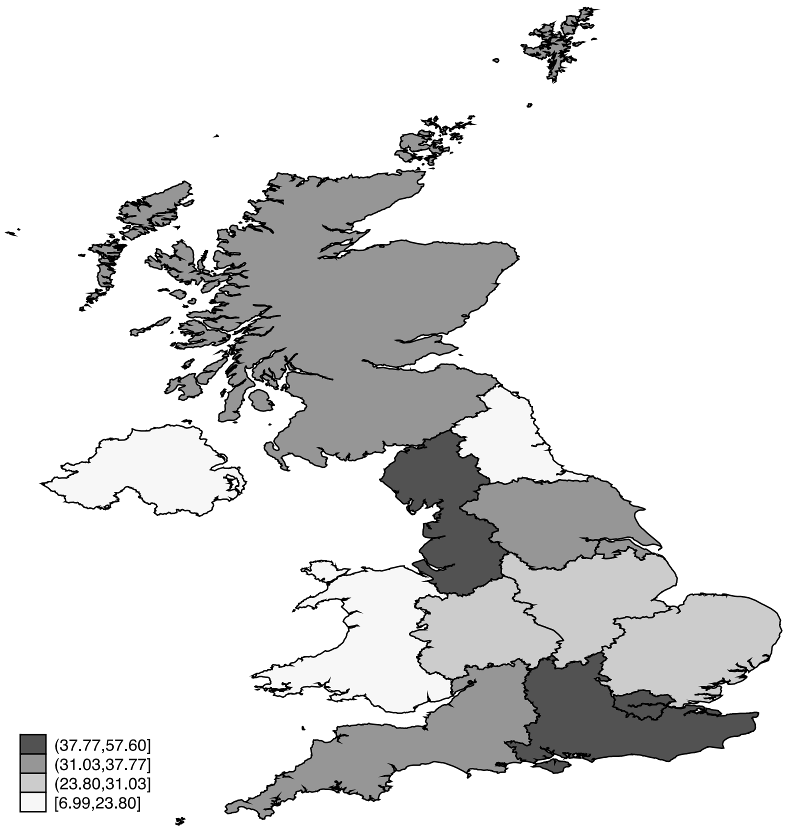

Figure 1A. Volume of borrowing amount in Million Pounds across UK regions.

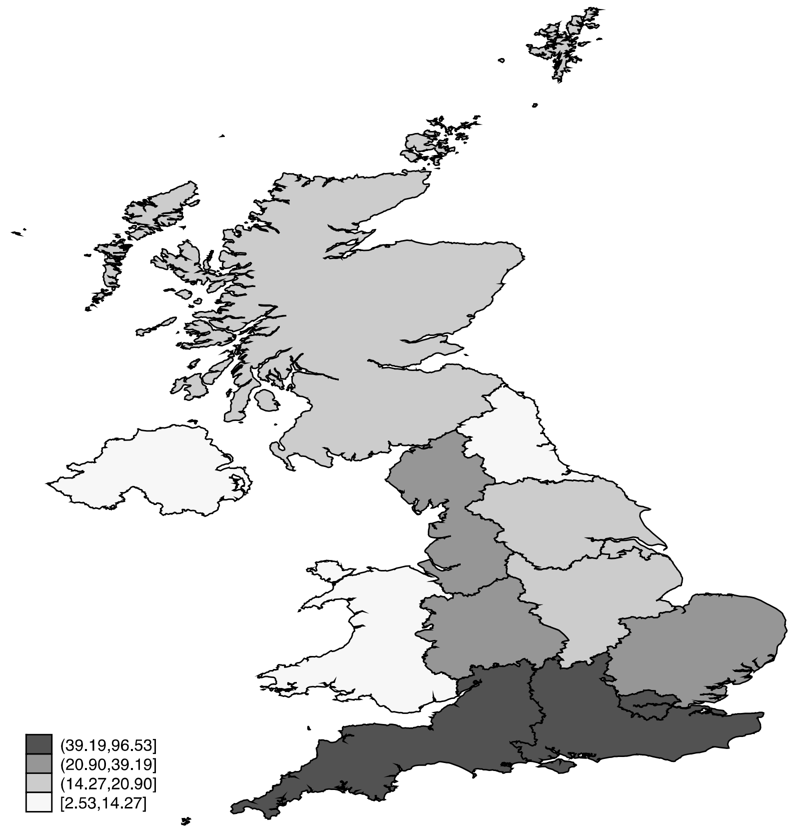

Figure 1B. Volume of lending amount in Million Pounds across UK regions.