Peer-to-Peer Crowdfunding: Information and the Potential for Disruption in Consumer Lending

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Abstract

Can peer-to-peer lending (P2P) disintermediate and mitigate information frictions in lending so that choices and outcomes for at least some borrowers and investors are improved? I offer a framing of issues and survey the nascent literature on P2P. On the investor side, P2P disintermediates an asset class of consumer loans, and investors may be able to capture rents associated with the removal of a layer of financial intermediation. Risk and portfolio choice questions linger prior to any inference. On the borrower side, evidence suggests that proximate knowledge (direct or inferred) unearths soft information. Thus, P2P may be able to offer pricing and/or access benefits to potential borrowers. Early research suggests that the future of consumer lending will involve more big data and reintermediation of underwriting by all types of financial institutions. I ask many more questions than current research can answer, hoping to motivate future research.

1. INTRODUCTION

Peer-to-peer lending (P2P) is the household credit implementation of crowdfunding. In P2P, individuals post their borrowing needs and personal profiles on a P2P platform such as Lending Club or Prosper. Individual and institutional investors then can view and fund consumer loans through the platform. In 2013, the top five P2P platforms in the United States originated $3.5 billion in loans, up from $1.2 billion in 2012 (Fitch Ratings 2014). According to a Fitch report, the outstanding float of P2P is expected to grow to $114 billion, conservatively, in the medium term (Farrell 2014, Fitch Ratings 2014). As a comparison, households in the United States had $880 billion in credit card debt outstanding as of July 2014, reflecting net new borrowing of $28.5 billion over the prior 12 months (federal government data aggregated by *NerdWallet*).

P2P crowdfunding falls under a host of other names, including social finance, marketplace finance, and disintermediated finance. None of these terms alone is a prime facie description of P2P. The disintermediation facet is that investors wanting diversified exposure to a fixed-income asset class of consumer loans need not go through asset-backed security (ABS) markets, removing layers of intermediation and opening the asset class to smaller investors. The marketplace term reflects investor-lenders and borrowers meeting in one direct market, which is no longer simply a market of peers. An argument against this rather appealing term is that the amount of additional intermediation that may be optimal in underwriting P2P is now a first-order question. Finally, the social finance term reflects the idea that soft information via networks can inform underwriting, thereby improving screening or repayment behavior. Questions arising out of the social network aspect of crowdfunding are at the center of the nascent literature. As discussed below, the extent to which the benefits to proximate knowledge and relationships are facilitated by a P2P platform matters greatly for how P2P positions itself in completing consumer finance markets.

Even if pinning down the correct characterization of P2P is difficult, it is straightforward to claim that the market of disintermediated lending facilitated by technology and by the role of potentially improved screening has witnessed impressive growth. This growth of P2P may partially reflect the popularity of the idea of finding alternatives to traditional financial institutions in the wake of the Great Recession. However, I explore the argument that P2P carries a real possibility for disruption that improves choices and outcomes for at least some borrowers and investors.[1] Thus, my agenda is to explore the economics behind the idea that P2P might disrupt consumer lending, in parallel with the work of Agrawal, Catalini & Goldfarb (2013), who offer a framing of the economics that underscores the growth of equity crowdfunding.

I begin in Section 2 with a quick overview of the mechanics of P2P and then delve into the potential for disintermediation to create rents accruing to investors. Agrawal, Catalini & Goldfarb (2011) profile investors in equity-based crowdfunding, but little research has yet explored the topic of portfolio choice and investor benefits arising from P2P, the lending side of crowdfunding. My takeaway is that at least some cost savings of disintermediation could accrue to investors, but risk characterization and portfolio selection must be understood to infer any extent to which investors could capture rents from disintermediation.

Section 3, the core of this article, surveys the role of proximity in the crowd model. Although the literature is very much in a formative stage, I draw three additional conclusions. First, the crowd of investors has valuable proximate knowledge, where proximity implies that individuals have

[1]Throughout most of this article, I do not speak to financial intermediary welfare implications or to competition among intermediaries because no research yet delves into these important topics. Thus, I implicitly assume that borrowers will gain from markets with more information based on the traditional literature, although this is not obvious if the P2P platform market does not maintain sufficient competition (Besanko & Thakor 1987).

real-world connections. This proximate knowledge, however, is only valuable when proximate investors are willing to put skin in the game to certify their information. Financial institutions of all types may be able use this information effectively with technology and with systems to incentivize underwriting performance. Second, disclosure of personal narratives has the potential not only to increase proximate knowledge but also to bias decisions. Algorithmic extraction of signals seems possible. Finally, social circles and local economic indicators can inform credit risk. Big data presumably can play more of a role in credit profiling than it does now, which could mean anticompetitive effects for borrowers if monopolies of personal information inform credit risk.

One theme emerging from a review of proximate knowledge is that proxies for individual credit risk available to nonconnected investors may be important, especially in a technological world of posted data and algorithmic risk-scoring, and thus risk-trading. This observation leads to Section 4. I begin by characterizing borrowers using a snapshot of data from Lending Club. Borrowers are characterized as debt-laden, middle-to-high income individuals who are consolidating credit cards and other debt. With this in mind, I pose unexplored questions about consumer loan optimal design.

Finally, I explore the literature that uses platform policy design shocks to consider whether some benefits from the crowd model may arise from different contract designs or more intermediation, offering a twist that disintermediation may involve more intermediation than people think it does. In Section 5, I conclude by offering my perspective on the potential for disruption in consumer finance and by listing a number of qualifiers and pitfalls to be aware of as consumer finance evolves.

2. OVERVIEW AND DISINTERMEDIATION IN PEER-TO-PEER LENDING

2.1. How Peer-to-Peer Lending Works

The roots of P2P may well be found in the idea of socially connected finance, but its success must surely be traced to technology, much in the spirit of Einav, Jenkins & Levin (2013), who find, among other things, that technology expands access to credit in the auto loan market. In terms of P2P, technological advances have facilitated (*a*) collection, scoring, and dissemination of credit qualifications for a pool of prospective borrowers on an online platform; (*b*) real-time reporting supply of lending bids, which allows investors to diversify across loans and to spread borrower risk across investors; and (*c*) online servicing, monitoring, and credit history reporting of loan performance. A quick synopsis of the lending process is as follows.

A P2P platform sets up a database of prospective borrowers. Most platforms offer term loans amortizing in 2 to 5 years. Borrower applicants enter mandatory information including the loan amount request, maturity choice, purpose of loan, income, employment, and other debt as well as additional voluntary information (personal narratives, interest rates on other debt, employment details, etc.). Either voluntarily or in response to a platform request, potential borrowers may upload documentation verifying income and employment. On some platforms, borrowers can pool into a networked group to enhance signaling. Finally, platforms post loan applicants' credit scores, either directly via a credit score range profiling or indirectly by placing applicants in risk grades using proprietary scoring involving credit scores.

Facing a platform filled with prospective borrower requests and information, investor-lenders are able to browse and filter applicants. Investors can choose to invest independently, within investment groups, or algorithmically. They need not fund entire loans for any prospective borrower, but rather may diversify across borrowers while watching the supply of credit evolve over time to condition their decisions on the supply decisions of other investors. Borrowers usually do not get funded unless investors' willingness to supply loans reaches a threshold of borrower need. If bids reach the threshold, the loan closes at an interest rate set by either the marginal willingness to fund or (more commonly) the rate assigned to the borrower by the platform according to risk-scoring.

2.2. Benefits from Disintermediation

In their first-generation implementation, platforms served a facilitator role or, in the middleman terminology of Rubinstein & Wolinsky (1987), a consignment role. A platform makes money by closing and servicing loans. For example, Lending Club and Prosper charge an origination fee on a loan of 1–5 percentage points depending on a borrower's risk profile and loan duration. In Lending Club data on all loans issued in the first quarter of 2013, the mean and median origination fees are 2.7% and 3%, respectively. These fees are taken out of funds provided to the borrower. Platforms inform borrowers of interest rates and implied annual percentage rates (APRs) with fees added into the calculation so that APRs reflect true borrower costs. When payments come into Lending Club to service loans, the platform takes out a 1% service charge before submitting payments to investors. Lending Club also collects delinquency fees from borrowers and collection fees from investors.

In Lending Club data of loan issuances from the first quarter of 2013, 4.44% of loans are at risk of being either late (2.16%) or in default (2.28%) after 1 year. Annual default rates for these platforms are approximately 5% (**http://www.lendingmemo.com/lending-club-prosper-default-rates/**). The equal-weighted mean interest rate from the first quarter of 2013 was 14.4%. This interest rate, a 5 percentage point default rate, and the current fee structure together imply an internal rate of return (IRR) to investors of 8%. More formal performance statistics come from websites that track Prosper and Lending Club loans. Lending Robot (**https://www.lendingrobot.com/**) calculates the IRR of 277,814 Lending Club loans as of January 2015 to be 6.93%. LendStats (**http://www.LendStats.com/**) puts the return on investment at 5.4% (Prosper) and 5.1% (Lending Club) over the period 2007–2014 and 8.7% (Prosper) and 7.0% (Lending Club) over 2009–2014. Lending Club and Prosper also post their own return statistics. On the basis of a risk-weighted average of Lending Club loans made, its annual net return from the first quarter of 2007 to the first quarter of 2013 is 7.2%.

Is 7% an appropriate return for the risk? An appropriate comparison is the ABS market for credit card loans, especially focusing on fixed-rate credit cards. The Barclays Capital Fixed ABS Index (which is a standard in consumer ABS but also includes autos and utility rate bonds) returned 4.4% over the period 2007–2013 and 3.4% over 2009–2014. Comparison of the numbers (7% for P2P versus approximately 4% for ABS) suggests that investors capture value associated with disintermediation. Recent research guides us on how much intermediation costs. Philippon (2015) finds that financial intermediation costs on average just shy of 2% of assets (for calculations of the cost of securities intermediation, also see Greenwood & Scharfstein 2013; Gerakos, Linnainmaa & Morse 2015). Hanson et al. (2014) calculate that the brick-and-mortar expenses from banking account for 2.96% of assets. These comparisons put disintermediation value (passed along to investors) in line with the brick-and-mortar cost magnitude.

This comparison is perhaps not entirely fair to the ABS market. ABS credit card securities, different from mortgage-backed securities, retain some originator exposure to nonpayment. Thus, they may offer a lower-risk proposition for investors than does P2P (for a description of ABS, see Furletti 2002, van Opstal 2013). Perhaps another way to make a comparison is to note that, over the same 5-year period, investment-grade corporate bonds (Morningstar data on Barclays US Corporate Investment Grade Index) have posted returns of 5.49%. This comparison leaves only 1.5% in excess returns to allocate to a risk premium and/or disintermediation. I present these figures only as a point of reference; a more precise study of P2P risk and return over the full cycle of loans would be welcome. The data horizon currently available is also much too short to draw inference.[2]

2.3. Other Benefits to Investors

Two other benefits accrue to investors with the growth of P2P platforms.[3] First, in the above discussion of risk, missing was the observation that by constructing their own portfolio of investment loans, investors can incorporate background risk and maturity needs to optimize portfolio selection. A few examples come to mind immediately. Individual investors may hedge their loan portfolio away from local economic conditions, employment sectors, or other exposures in their portfolios. Agrawal, Catalini & Goldfarb (2011) document profiles of investors on an artist-entrepreneur platform in equity crowdfunding. Although investments in equity crowdfunding carry very different expected returns and covariance, these authors find that, on average, investors are not local but rather 3,000 miles away. For hedge fund investors, the possibility of using covariances to construct long-short or macro strategies with other instruments seems to be the tip of the iceberg for crowdfunding. For pension and endowment investors in need of liability-covering funds, P2P offers realizations in the relatively short term, vis-à-vis traditional fund structures, offering a risk premium that may usually be associated with longer-term instruments. Hopefully, the platforms will provide data enabling researchers to test such propositions.

The second benefit that accrues to investors with the growth of P2P platforms is improved access. Crowd access to investment is at the center of discussions revolving the JOBS Act and other crowdfunding instruments. P2P opens the asset class of consumer loans to small- and medium-sized investors who want a fixed-income instrument with more risk than, for example, savings notes or corporate bond funds.

The question here again is, What would be the appropriate counterfactual and risk comparison? Other questions are more paternalistic in nature: Who is investing, and do their wealth, demographics, income, and income risk profiles support the added fixed-income risk associated with P2P? A third question is, Do individual investors understand the risk associated with these investments? My opinion on this front is that P2P platforms are fairly transparent in their structures of fees and risk. Though this has not been tested, I would instead ask whether P2P investors understand risk and internalize future budgetary implications from the risk (Bertrand & Morse 2011).

Having posed these questions pushing back on the statement that the introduction of a new asset class is necessarily good, we should condition the answer on another fact. As of 2014, 80% of investment going into the P2P platforms Prosper and Lending Club is from institutional investors (Ford 2014). Even if some individual investors (people) choose poorly when investing in P2P, on net the benefit to investors of access is likely to be positive. However, going forward, social judgments of who wins and who loses will need to be made. Research is very much needed to understand the welfare implications across investor types and as guidance for disclosure and investment advice.

[2]Another friction is the size of the market. The ABS market holds $128 billion in 2013 assets under management (van Opstal 2013), and P2P total loan float is only in the single-digit billions. Thus, the asset class is not presently large enough to support needs for large pools of capital.

[3]A third possible benefit is in the avoidance of agency issues in securitization (Keys et al. 2009, 2010). However, the ABS structure in credit card securitization is less prone in design to the kinds of agency issues highlighted in this literature, and agency issues by the platform may also be at play.

3. PROXIMITY

At the core of crowdfunding is the idea that people in the crowd could know each other or otherwise be proximate via networks, expertise, or in exposure to local economy risks. We know from the traditional banking literature that relationships and soft information facilitate advantages in screening and reductions in moral hazard (see, among others, Petersen & Rajan 1994, 2002; Boot & Thakor 2000; Berger & Udell 2002; Stein 2002; Petersen 2004; Berger et al. 2005; Karlan 2007; Iyer & Puri 2012; Schoar 2014). There is no reason to presume that the same would not be true in P2P. This is my starting point. If proximity unearths soft information not accessed or used by intermediated finance, then P2P should be able to offer pricing and/or access benefits to potential borrowers (Jaffee & Russell 1976, Stiglitz & Weiss 1981).[4] The crowd also invests its own money; therefore, screening is done by those with skin in the game having the incentive to pay the cost to overcome information frictions (Leland & Pyle 1977, Townsend 1979).

An observation worth noting is that the source of the soft information or relationships is the pool of investors. Individual investors connected to prospective borrowers have proximate knowledge and relationships. Unclear, however, is whether the number of such connections is limited. Thus, as I go through the literature on the role of proximity in informing credit risk, an important facet is the extent to which signals can be extracted from proximate investors. I try to highlight topics such as diffusion of proximity via herding or cascades that offer the potential to inform practical, real consequences.

3.1. Proximity through Social Connection

Using data from Prosper, Freedman & Jin (2014) find that when investor-lenders endorse and bid on their friends' applications (i.e., commit to invest), the loans yield returns that are 6 percentage points higher. Conversely, loans with friend endorsements without bids perform worse than other loans. Social connections matter but only if signals come with a cost that separates credible information (Spence 1973). This finding is echoed by Everett (2010), who studies the investment group feature of platforms. He finds that loans funded by investor groups perform better if someone in the group is personally connected to the borrowers. Otherwise, investors in the group perform worse than nongroup investors. There are potentially lingering selecting issues in studying who selects into groups, but interesting questions could emerge in this selection.

Selection may also be looming in who gets funding. Freedman & Jin (2014) notice that the signaling effect of bidding on friends' applications is more pronounced in borrowers with lower credit grades. Therefore, higher IRRs may be due to unconnected investors taking on additional risk when they follow bids of investors connected to borrowers. However, because the rate of delinquency in Freedman & Jin (2014) also declines by 4 percentage points relative to similar-risk borrowers, the authors can interpret that proximate information is valuable, over and above any risk-inducing effect.

The takeaway here is that direct social connections between investor-lenders and borrowers are valuable, but only if investor-lenders signal the quality of borrower friends by investing. It is worth emphasizing that the tests by Freedman & Jin (2014) and Everett (2010) go after the fundamental idea of the crowd. These are important findings, resonating with those of Schoar (2014), who studies the extent to which personal interaction is a desirable ingredient in relationship

[4]Besanko & Thakor (1987) discuss a bank lender monopoly setting in the information economics literature on lending, which has less favorable implications for borrowers. I abstract from this possibility except when I discuss use of proximate data by social media.

banking (and demonstrates that it is). Equally important, however, is the limit to which connection screening can be applied. If the benefits of P2P must be limited to connections among friends, the potential for the crowd model to improve credit conditions in aggregate is quite small.

3.2. Proximity by Narratives

My statement that needing real-world connections limits the scope of information advantages in the crowd may be too strong. Other mechanisms may be able to bring investors proximate to borrowers. Indeed, observed distances between investors and borrowers in P2P and other crowd markets can be quite large. For example, in the artist-entrepreneurial crowd market studied by Agrawal, Catalini & Goldfarb (2011), investors are on average 3,000 miles away, but local investors appear to take the lead in information signaling. In this and subsequent sections, I explore what could bring such other investors proximate. Agrawal, Catalini & Goldfarb (2011) assert, "The online platform seems to eliminate most distance-related economic frictions such as monitoring progress, providing input, and gathering information" (p. 1). These authors then delve into the frictions of social connections. I pursue a similar agenda.

Here I start by considering whether borrowers can use narratives to make lender-investors proximate. In P2P platforms, prospective borrowers can write publicly observable commentaries to convey personal soft information (demographics, economic conditions, context for loans, etc.), while in the process hoping to build an emotional tie to the investor-lender.[5] Details may be important here, as it is not obvious which narrative information and conveyances provide informed signals and which potentially bias investors.

Herzenstein, Sonenshein & Dholakia (2011) apply the identity claim methodology of Miles & Huberman (1994), who put forth six identity claims when reading prospective borrower narratives: trustworthy, economic hardship, hardworking, successful, moral, and religious. Herzenstein and colleagues find that trustworthy and successful identity claims increase funding and improve funding terms, but these same identity claims have no impact on loan performance. Multiple layers of selection (most of which the authors discuss) are at work here—the selection of writing a narrative, the selection of who got funding, and the effect of the funding terms based on these narrative traits. More work is needed to build on this foundation to understand voluntary disclosure. However, the takeaway is clear: The possibility that investors use characteristics in sorting borrowers but that characteristics do not show up in performance is particularly potent and problematic for the signal value of these narratives. Characteristic signaling through narratives may be cheap talk or worse.

To my knowledge, an approach not yet explored in P2P is via deduction, working backward from what informs success in raising funds and in predicting low default. Mitra & Gilbert (2014) use textual analysis on 45,815 projects posted on Kickstarter (a donation-based crowdfunding platform where investors are paid in product or access to the startup activity) and compile a list of phrases and words that are associated with successful funding bids. The problem with uncovering success cues is that once they are disclosed, their predictive power disappears. Nevertheless, it seems inevitable that borrowers would want to identify anomalies in success cues that may reflect investor biases.

[5] In California, for example, it is standard for house shoppers to write "love letters" to sellers to induce sellers to choose their bids. Narratives by prospective borrowers may seek to evoke a similar empathizing reaction by any investors reading their profile.

Gao & Lin (2012) use psychology text-mining techniques to uncover clarity, deception, and other linguistic tip-offs in narratives that may inform credit risk. They find that the ease of reading narratives correlates with a 2.3 percentage point decrease in default rates, whereas narrative complexity associates with a 3.6 percentage point increase in default. Moreover, linguistic attributes that correlate with deception in other work are associated with higher default in P2P. Causation is hard to ascribe to these deception results, and selection lingers in who chooses to write narratives and in what content prospective borrowers write. However, caveats aside, the goal of detecting deception raises a first-order issue: Understanding truthful conveyance in disclosure is critical for valuing narratives in all peer markets. A fundamental concern around crowdfunding in general has been and will continue to be deception. In addition, how small-scale investors will fare in such an environment versus large, algorithmic investors remains uncertain.

Related to the narrative research is a literature on photo-based discrimination. Ravina (2012) shows that investor-lenders in a P2P platform bias toward attractive photographs and that this bias is irrational. By contrast, Pope & Sydnor (2011) and Duarte, Siegel & Young (2012) show that investor-lenders can be profitable (incur fewer defaults) by statistically discriminating against racial minorities and by biasing toward trustworthy faces, respectively. Herzenstein, Sonenshein & Dholakia (2011) find that the existence of an economic hardship identity claim is informative, resulting in fewer defaults by 0.9 percentage points. Together, the results are indicative of cognitive limitations in both the way investor-lenders draw inference from screens and the way borrowers choose to provide screen items. The results also seem to be the tip of the iceberg in understanding what individuals can do to signal creditworthiness credibility through narratives and how behavioral biases may interact.

Michels (2012) takes a different approach to narratives by codifying the potentially hard information available in them. He codes whether a prospective borrower has disclosed information on nine dimensions: purpose of the loan, income, income source, education, other debt, interest rate on other debt, an explanation for poor credit grade, expenses, and picture. Michels does not study any content details, just content indicators. An advantage of this approach is that these content items could become direct input fields on a platform. Michels (2012) finds that these voluntary, unverified (and often unverifiable) disclosures increase the number of fundraising bids and lower the ultimate interest rates that borrowers face. Perhaps most telling, however, are the disclosure items that matter most: purpose of the loan, other debt outstanding, and poor credit rate explained.

Michels (2012) then shows that the total quantity of disclosure reduces default, consistent with soft information lowering risk (Petersen & Rajan 1994). These results are material; each disclosure item generates a 5 percentage point reduction in default. Michels leaves some open questions. He finds that unverifiable items are the most predictive of default, which is troublesome along the lines of truthful disclosure in Gao & Lin (2012).

3.3. Proximity through Expertise

To my knowledge, no scientific research considers whether lenders can be more proximate to borrowers through their occupation or sector expertise and whether such expertise can offer outcome-improving screening advantages. For example, if a finance professor were an investor-lender on a P2P platform, might she be better poised to understand the labor income risk of those working in finance sectors? Or, might any knowledge in the financial sector breed overconfidence in picking borrowers to fund? Answers to these questions are not at all clear. More broadly, one can imagine both individuals and institutional investors applying fundamental research that is used in industries and that improves on the basis of credit scores to gauge borrower income risk. This area is ripe for research.

3.4. Proximity through Local Indicators

Another possibility is that local economic information could proxy for proximate personal knowledge to inform credit risk. Crowe & Ramcharan (2013) find that crowd investors incorporate the effects of relevant local house prices when deciding both the provision of funds and the rate to charge on loans, controlling for the credit grade of the potential borrower. The magnitude is meaningful: A decline of one standard deviation in house prices within a state during the recent housing crisis associates with a rate 2 percentage points higher on a Prosper loan compared with those of otherwise-matched borrowers. Thus, spillover from the local housing market was relevant for credit risk.

This is only one piece of evidence that individuals (or large-scale institutions) may be able to enhance underwriting by incorporating local knowledge. Crowe & Ramcharan (2013) use just one of many publicly available indicators of local conditions. This area is also ripe for more research, especially in light of the results of Einav, Jenkins & Levin (2013) that technology-driven credit scoring in auto markets can substitute for local information.

3.5. Proximity by Network: Using Social Circles as Proxies for Credit Risk

It may be possible to use an applicant's social network, rather than local indicators, to proxy for the economic condition of a prospective borrower. Are social circles a proxy for one's own life and thus credit risk? Lin, Prabhala & Viswanathan (2013) study the signal value of such connections. They find that the credit quality of one's friends is an informative signal of quality. In particular, prospective borrowers on Prosper with friends with high credit quality succeed in fundraising more often, face lower interest rates, and default less. The hazard ratio of default is reduced 0.14 points relative to those without friends. Lin, Prabhala & Viswanathan (2013) importantly qualify the information content deriving their results, namely, "the social capital communicated by friends who bid." In other words, the quality of friends comes from having bidding investors as friends, reflecting the result of Freedman & Jin (2014). This is important because whether a noncostly signal of the quality of social circles implies valuable credit-risk information remains a very open question.

A flip side to Lin, Prabhala & Viswanathan (2013) is provided by Lu et al. (2012), who find a negative externality of connections. Friends unwind the stigma of default, very much in the spirit of Fay, Hurst & White (2002) or Guiso, Sapienza & Zingales (2013). A minimum conclusion from Lin, Prabhala & Viswanathan (2013) and Lu et al. (2012) is that the status of one's friends is a real-world connection that informs risk profiling.

Before moving on, I want to emphasize the importance of inferring credit risk from one's network. In the world of big data and social networks, it is only natural to consider an alliance between finance and social media. The idea that social circles proxy for one's own credit risk could imply that financial service providers must reach out into social media to stay competitive. Banks could choose to be at least as well placed as P2P in this capacity. It also implies an overall improvement of credit conditions for borrowers, which would be welcome to most. But an interlock between social media and finance also implies a potential for stereotyping and for anticompetitive effects. Importantly, one can imagine big-data providers capturing the rents of disintermediation if network information or other big-data stores of personal information inform credit risk and are monopolistic.

3.6. Proximity by Diffusion

I now abstract from the source of proximity and its benefits and instead assume that proximity exists on P2P platforms and impacts credit risk. This section asks whether investors can become proximate by following an information cascade or, more simply, momentum in herding. If investment herding is rationally profitable, then information exists somewhere in the crowd.

Evidence comes from Zhang & Liu (2012) and Herzenstein, Dholakia & Andrews (2011). Herzenstein, Dholakia & Andrews (2011) document that investor-lender interest in a prospective borrower follows herds, but with a modest magnitude. Potentially because of additional supplier attention, interest rates clear at lower prices, implying that borrowers are better off. Furthermore, the strength of the herding is correlated negatively with delinquency.

Zhang & Liu (2012) build on this result by delving into the rationality of herding, i.e., that which occurs conditional on borrower attributes and bids. The authors find that a 10% higher portion of funding from rational herding associates with a decrease of 2 percentage points in loan default probability. An appealing extension of their result is that the value of this information increases as credit scores decrease. Thus, as default risk increases on observables, the value to soft information also increases.

It would be helpful to understand more about proximity by diffusion, in particular, to delve into its micromechanisms. Can all investors be an originating source of information? Burtch, Ghose & Wattal (2015) find that withholding investor identity on a reward platform results in a larger likelihood of funding by other investors but in smaller contributions. Although reward platform investors likely invest with different motives, the role of privacy as discussed by these authors is quite important and raises further questions. Does the source of information need to be connected proximity rather than measures of local economic conditions or proxies via social circles? Also unclear is how much or how little information is needed to create an information cascade (Banerjee 1992, Welch 1992).

In the next section, I discuss the topic of contract design to consider the potential optimality of reintermediation of underwriting. In this context, it also matters whether platforms take on more credit-risk profiling. If so, does a lower signal content from the crowd inhibit the predictiveness of information cascades?

4. REINTERMEDIATION IN UNDERWRITING AND CONTRACT DESIGN: ENHANCING PROXIMITY?

Does contract design or more intermediation of underwriting interact with the benefits to proximity thus far explored? To answer this question, I first characterize loans using data from Lending Club. I then reflect on whether proximity matters because of screening or a reduction in moral hazard in repayments. Finally, I ask how platforms may be (and are) adding more intermediation to improve product offerings. These are somewhat disjointed topics, but the central idea is to address the issue of the optimal amount of intermediation and to open the topic of optimal contract design.

4.1. Characterizing Peer-to-Peer Lending: Lending Club Loan Statistics

Most P2P platforms issue installment loans with a fixed repayment term and regularly amortizing structure, akin to car loans. To characterize P2P loans, I report statistics from a snapshot of loans issued by Lending Club in the first quarter of 2013. Despite differences in loan structures across P2P platforms, Lending Club should be representative of large platforms.

Table 1 Lending Club loan statistics

Type of loan	Annual income	Loan amount	Interest rate	Term months	Loan to income	Payment to income	Count	Percent of sample	Monthly installment payment of loan
Mean statistics of borrower income and loan terms by use of loan									
Car	65,993	8,556	0.134	39.2	0.130	0.049	185	0.8%	$267.29
Credit card	74,017	15,406	0.134	39.8	0.208	0.077	5,680	25.0%	$475.58
Debt consolidation	75,468	16,350	0.141	41.6	0.217	0.078	13,797	60.8%	$492.27
Home improvement	87,893	15,056	0.129	41.8	0.171	0.061	1,120	4.9%	$444.33
House	82,617	16,912	0.139	41.7	0.205	0.074	138	0.6%	$506.25
Major purchase	78,365	9,740	0.129	39.4	0.124	0.046	443	2.0%	$301.56
Medical	73,325	8,375	0.191	38.0	0.114	0.047	122	0.5%	$289.11
Moving	76,911	8,325	0.193	37.6	0.108	0.045	73	0.3%	$290.08
Other	68,913	9,702	0.197	40.0	0.141	0.057	696	3.1%	$324.56
Renewable energy	99,977	12,602	0.194	42.5	0.126	0.048	11	0.0%	$401.91
Small business	92,278	17,023	0.193	40.9	0.184	0.072	253	1.1%	$557.48
Vacation	63,913	6,003	0.190	36.9	0.094	0.040	55	0.2%	$211.76
Wedding	70,315	11,703	0.194	39.4	0.166	0.067	134	0.6%	$394.56
Total	75,674	15,542	0.141	41.0	0.205	0.075	22,707	100.0%	$473.86
Census income quintile	**Annual income**	**Loan amount**	**Interest rate**	**Term months**	**Loan to income**	**Payment to income**	**Count**	**Percent of sample**	**Monthly installment payment of loan**
Mean statistics of borrower income and loan terms by income quintile									
First	19,944	4,722	18.1%	36.2	0.237	0.100	423	1.9%	$166.98
Second	32,425	8,478	16.0%	36.8	0.261	0.107	2,464	10.9%	$288.56
Third	50,314	13,206	14.8%	40.8	0.262	0.097	7,694	33.9%	$408.29
Fourth	80,216	17,636	13.6%	42.2	0.220	0.078	8,158	35.9%	$521.44
Fifth	148,303	21,305	12.4%	42.1	0.144	0.050	3,968	17.5%	$619.89
Total	75,674	15,542	14.1%	41.0	0.205	0.075	22,707	100.0%	$473.86

Data are from Lending Club; all loans originated in the first quarter of 2013. Count records the total loan numbers. Loans are all approved and funded in this snapshot. The top half of the table presents the self-reported use of loan funds by Lending Club borrowers. Annual income is total income. Payment to income is based on aggregate statistics to reconcile to the table. For the bottom half of the table, income quintile cutoffs are from the US Census 2011 update.

The data I present are as follows. **Table 1** includes mean statistics for borrower incomes and loan terms by purpose or use of loans. The same statistics are then displayed by US income quintiles, using income quintile thresholds from the 2011 US Census update. As a comparison, **Tables 2** and **3** report household borrower incomes and consumer debt statistics from the 2010 Survey of Consumer Finance (SCF), aggregated to the US population using the survey weights.

Table 2 Survey of Consumer Finance (SCF) consumer borrowing statistics

Census 2011 income quintile	Mean consumer debt	Percent with no borrowing	Debt conditional on borrowing	Household income	Debt to income	Interest rate on credit card with most outstanding debt						
						Mean	Min	25th percentile	50th percentile	75th percentile	Max	Mean conditional
Debt and interest rates by income quintile												
First	7,968	52.4%	15,194	14,908	0.575	14.50	0.0	10.6	14.6	19.0	32.0	15.67
Second	9,458	43.6%	21,702	31,358	0.306	14.04	0.0	9.9	13.9	18.0	36.0	15.16
Third	16,777	30.0%	55,923	49,985	0.339	13.86	0.0	9.9	13.3	18.0	33.0	14.78
Fourth	22,198	22.6%	98,438	78,977	0.280	13.28	0.0	9.3	13.0	18.0	33.0	14.34
Fifth	35,351	33.0%	107,058	247,445	0.204	13.01	0.0	9.9	13.0	16.6	36.0	13.99
Average	17,208	37.5%	45,839	75,631	0.361	13.63	0.0	9.9	13.3	18.0	36.0	14.67

Data are from the 2010 SCF, with survey weights applied to represent the US population. Income quintiles are from the US Census for 2011. Consumer debt excludes loans backed by property and business loans with personal liability. Reported are mean consumer debt, the percentage of households with any outstanding loans, debt conditional on having debt, household income, and debt-to-income ratio (for a breakdown of consumer debts by type, see **Table 3**). Also presented is a distribution of credit card interest rates, where the rates reported are the household's reporting on the rate on the credit card with the largest balance. I exclude teaser rates, defined as 4.99% or less, in the rate calculations.

Table 3 Survey of Consumer Finance (SCF) consumer borrowing statistics

Census 2011 income quintile	Education loans	Vehicle loans	Credit card debt	Line of credit	Other loans	Total consumer debt
Debt by credit product						
First	3,093	928	846	1,296	1,804	7,968
Second	2,690	2,344	1,481	1,695	1,247	9,458
Third	6,150	4,138	2,644	2,675	1,170	16,777
Fourth	5,591	6,376	4,307	5,044	879	22,198
Fifth	7,467	7,532	4,984	14,302	1,066	35,351
Average	4,833	3,938	2,650	4,506	1,281	17,208

Data are from the 2010 SCF, with survey weights applied to represent the US population. Income quintiles are from US Census for 2011. Reported is total consumer debt, broken down by type, with the sum corresponding to mean consumer debt in **Table 2**.

Consumer debt in the SCF refers to education loans, vehicles loans, credit card debt, lines of credit, and other loans, but it excludes mortgages. **Table 3** also reports SCF mean statistics across these subgroups of credit products. By comparing Lending Club loans to the SCF, I am comparing individual single loans to overall household consumer debt.

As my goal here is to characterize P2P loans, I discuss the findings presented in these tables with simple bulleted factoids:

1. Loans are overwhelmingly (85.5%) for credit card debt retirement or debt consolidation (these categories often represent the same thing) (**Table 1**).
2. On average, loan terms are 41 months, with little material variation across loan purposes but some shortening at lower income levels.
3. The vast majority of loans fund middle-to-upper income individuals. Only 1.9% and 10.9% of loans are provided to the lowest two quintiles in the income distribution (**Table 1**).
4. Average face values of loans comprise 20.5% of annual income, and payments absorb 7.5% of monthly income.[6] Average loans are a ratio of 0.903 of average US household consumer debt in the SCF and one-third of the total consumer debt conditional on being a borrower. To the extent that these borrowers are only consolidating credit card debt, loan sizes are very large relative to mean households' credit card debt float in the SCF, suggesting that these are very indebted individuals (**Table 2**).
5. Interest rates in **Table 1** are before origination fees, which on average add 2.5–3% (varying by risk and maturity) to APRs faced by borrowers. To compare P2P APRs to credit card APRs in the SCF, I focus on the interest rates of credit cards with the largest outstanding balances within SCF borrowing households. To make this comparison, I omit teaser rates, which I conservatively assign as 4.99% or less (**Table 2**).

This comparison suggests that P2P APRs are significantly higher than what the mean US borrower in the corresponding income quintile is paying. Because P2P borrowers are likely more debt laden than the mean US borrower, they must be in more financial distress relative to their income quintile averages to want to voluntarily move to P2P. Alternatively, P2P is offering access

[6] I calculate the payments using an amortization of the average loans, not an average of each amortization, to keep my factoids consistent within **Table 1**.

to additional credit for individuals maxed out on credit card lending, which is characteristic of many subprime borrowers (Bertrand & Morse 2009).

Despite its importance, the optimality of the lending structure of P2P has been given little attention. Are these middle-to-high income individuals who probably are more debt laden than average individuals well served by a 3–5-year installment loan? Is this optimal maturity? Is an installment loan the optimal structure both to induce the appropriate duration of borrowing given debt-servicing cash constraints and to potentially debias any lack of salience regarding the importance of payback (Bertrand & Morse 2011, Zingales 2015)? Does consolidation reduce the quantity of late fees and other add-ons? As P2P continues to grow, these questions warrant consideration.

A few papers have emerged on the auction process of the clearing of demand and supply of loan bids. Wei & Lin (2013) study the unexpected move of Prosper from price setting via auction (the interest rate is priced at the margin when the supply of credit reaches demand) to a coarser system of preassigned interest rates based on credit risk grades. The authors find that under the preset prices, investors fund the loans with higher probability, especially for high-risk loans. My interpretation of these results is that Prosper may be increasing the pool of borrowers who get funded by pricing high-risk types. An alternative interpretation is that coarser pricing may imply more pooling of risk and thus a natural higher price (Stiglitz & Weiss 1981). This result of Wei & Lin (2013) is important for understanding optimal financial contracts and should stimulate more research in contract design.

4.2. Interpreting the Benefits of Crowd Lending as Soft Information versus Moral Hazard Reduction

Thus far I have been interpreting proximate information as useful in screening, using the soft information frame. However, the effect of connections and friends may be a reduction in ex post moral hazard, rather than information as to a credit-risk type. Recall that Freedman & Jin (2014) find that credit risk is lower when a friend with skin in the game invests. This result may not be about certifying quality but about a change in the behavior of borrowers not wanting to default on a friend, in a similar spirit to what Schoar (2014) finds for banking. If so, the benefit of connecting borrowers and investors may be in mitigating moral hazard in repayments. Likewise, the results of Lu et al. (2012) are about direct moral hazard influences through networks. These authors find that a friend's defaults trickles down to other friends with the reduction of stigma. Lee & Persson (2013) model how the formalization of skin in the game may help entrepreneurs exploit social connections for funding by reducing their aversion to failure. The direct mapping to P2P is perhaps not in the risk-taking aspect, but in the magnitude of the importance of relationships for all types of behavior—developing resolve in making saving goals or implementing a personally costly rebalancing of asset actions.

Starting from Jaffee & Russell (1976) and Stiglitz & Weiss (1981), there is a large literature on information frictions in lending—ex post moral hazard and ex ante credit-risk screening—and on what these information frictions imply for access to and cost of credit. Although discussions about ex post moral hazard for firms compose a well-developed literature, less research has been done on repayment moral hazard for individuals. Exceptions include Karlan & Zinman (2007), who study consumer loans in South Africa; Adams, Einav & Levin (2009), who study subprime auto loans; and Guiso, Sapienza & Zingales (2013), Eberly & Krishnamurthy (2014), and Morse & Tsoutsoura (2013), who study repayment moral hazard in mortgage markets. I mention these studies to identify the mechanisms others have found effective in inhibiting or reducing moral hazard in consumer loan repayments. Mechanisms in the prior literature include access to future credit, collateral repossession, stigma, and other incentives or punishments in contract design. Many of these mechanisms (e.g., collateral) are not present in the mainstream rendition of P2P discussed here, but innovation and experimentation by platforms and startup platforms are rampant. We still need to understand more about mitigating ex post moral hazard, not just in the crowd model, but also in consumer finance at large.

4.3. Reintermediation of Underwriting and Platform Design

Technology has allowed for the aggregation and underwriting of individual loans via a partially disintermediated public platform. In this last section, I argue that reintermediation of underwriting is complementing or even supplementing the advantages of proximity. Is the crowd of investors (and the proximity they bring) a necessary component for the aggregation of prospective borrowers to face better credit conditions than they would have in traditional financing options? Intermediaries can do more to screen credit risk, and intermediaries need not be P2P- or platform-based.

In prior sections, I argue that the literature suggests more scope for algorithmic credit scoring, which an intermediary could accomplish, if it so desired. A motivating fact in this vein is that P2P is no longer about individual investors. The *Financial Times* (Ford 2014) reports that 80% of investment going into the P2P platforms Prosper and Lending Club is from institutional investors—hedge funds, pension funds, etc. These investors, and a vision of the size of their assets-undermanagement flows, stretch the notion of anything proximate.

A starting point to thinking about reintermediated underwriting in crowd finance is Iyer et al. (2015). Within the credit score buckets provided by Prosper, these authors show that lenders can profitably further sort borrowers by credit risk. This is important. In their sample, if Prosper had provided exact credit scores as opposed to just credit buckets (i.e., being in a range of credit scores), investor-lenders could have predicted credit risks more accurately. This provocative finding begs the question as to whether a financial intermediary could do better credit scoring.

I break this question into two pieces. First, can intermediaries achieve the same quality of screening as that of social network linkages? Platforms can certainly implement Michels' (2012) finding by using platform underwriting to incorporate content fields (loan purpose, debt outstanding, reason for bad credit rating) into risk scoring. P2P has already moved in that direction. Likewise, it is certainly possible for platforms to incorporate local variables proxying for individual risk of the kind considered by Crowe & Ramcharan (2013), implementable in a platform underwriting model.[7]

In addition, Gelman (2013) finds that the check box indicating whether income has been verified predicts fundraising success and default risk even beyond the credit scores of Lending Club. Thus, both borrowers and intermediaries could use more low-hanging soft information signals regarding the quality of borrowers. Gelman also ponders why borrowers allow themselves to be sorted incorrectly into unverified groups when avoidable.[8] More intermediation seems useful, and disintermediation still benefits from intermediation.

Second, can incentive alignment add value? A key aspect of crowd investors is their skin in the game. In the microfinance group model, screening occurs via group formation. Groups have

[7] Or, at the least, these additional scoring variables can be calculated and reported to investors, who can choose which combination of risk scores they deem most important for their investment portfolios.

[8] A report from the US Gov. Account. Off. (2011) finds that both Prosper and Lending Club select whose income to verify on the basis of risk triggers that loan request amounts may be high for the incomes reported by potential borrowers. Among those selected (in a particular sample and cross section during time of analysis), half to two-thirds provided satisfactory documentation.

incentive to keep bad types out. These ideas translate to early crowdfunding. Berger & Gleisner (2009) find that having group leaders screen pools of borrowers results in more credit access and better credit terms. Similarly, Maier (2014) finds that borrowers who join a group with document verification are lower credit risks.

Bringing these ideas together, a compelling paper asks whether intermediaries also have the ability to react to incentives in screening. Hildebrand, Puri & Rocholl (2014) use a Prosper platform policy shock that removes origination rewards paid to group leaders, hence changing their incentives. The study compares behaviors and outcomes surrounding the same group leader before and after the policy change. When group leaders are paid to create volume, they are more aggressive in bidding and more volume follows their lead. However, the volumes of loans on which they bid perform worse, and group leaders' bids on individual loans are uninformative about default rates. What is important is the detailed analysis of having skin in the game. When group leaders put enough skin in the game even in the preperiod when origination rewards encourage volume, the quality of the selection of borrowers is better, as are the outcomes, reflecting the incentives of having skin in the game reported by Holmstrom & Tirole (1997) and Gorton & Pennacchi (1995).

From Hildebrand, Puri & Rocholl (2014), we learn (*a*) that group leaders can do effective screening and (*b*) that screening is better when incentives are aligned. These results complement the importance of Iyer et al. (2015) and Crowe & Ramcharan (2013). An intermediary with incentives can overcome the cost of effort to achieve better screening. Notice that I have inserted the word intermediary in place of the focus Hildebrand, Puri & Rocholl (2014) place on group leaders. It is unclear going forward who the incentivized intermediary might be, but bringing these results together suggests that reintermediation with incentives could improve credit-risk assessment.

5. CONCLUSION: WILL CROWDFUNDING DISRUPT CONSUMER LENDING?

Each article I survey tackles an interesting angle to mitigating information frictions. I have tried to frame why there is potential for crowdfunding to enhance and improve credit access. But the literature thus far has not applied these findings to the big picture question of where P2P crowdfunding is headed in terms of product offering and disruption of consumer finance. I offer a long list of unknowns for future research.

If asked whether crowdfunding could positively disrupt consumer finance, my answer is yes, with three large qualifiers and three dangers. I think some rendition of technology-driven, disintermediated finance will continue to capture markets. My first qualifier is that I do not see this consequence as inevitable across all markets. One would have to make an argument as to how the crowd model would assert advantages in, for example, fee-based subprime lending, collateralized loans requiring repossessions and foreclosures, and long maturity lending without forcing mechanisms. All of these models are de facto being explored in startup companies; the future is not far away.

A second qualifier is that it need not be the new financial intermediaries that are the source of the disruption. Will payment systems, credit, and consumption all morph into a single version of big data? A crystal ball would be useful here. Technology will continue to involve increasingly more information, which leads to my third qualifier.

In the future, big data will matter for credit scoring, which brings forth all sorts of uncertainties—privacy, monopoly power, discrimination, etc. It seems inevitable that the role of data will increase exponentially, and thus we should get busy answering these questions. If proximity via big data unearths soft information not accessed or used by intermediated finance, then P2P should be able to offer pricing and/or access benefits that produce rents. The incidence of rent capture across borrowers, investors, and intermediaries is not obvious.

On the investor side, these innovations will allow some to benefit from this asset class, which already seems to be happening. This leads to my final qualifier. I am left at the end of this review wondering who the investor crowd needs to be in future crowdfunding.

Before I conclude, the dangers of the platform model are worth mentioning. The first danger comes from platform risk. How secure are new financial intermediaries? P2P platforms generally set up lending in such a way that investors hold securities that are safe in the case of the demise of the platform. However, the financial distress of a platform surely would surely impact loan performance. In the current environment of innovation startups and failures, this distress risk is relevant. Second, perhaps it is worth considering how investor risk can exacerbate platform risk. How reliable are investors? In a model in which investors are pooled, investors can be exposed to capital flight or herding that forces the platform into distress or impedes lending. Borrowers also face platform risk in scenarios of platform distress. The credit relationship with a lender is valuable to borrowers, not only in the expectation of positive and truthful credit reporting, but also in the soft information developed between a borrower and a lender.

Finally, a much-discussed danger involves governance and standards. Are standards of governance and standards of lending comparable across platforms? Platforms are transparent in pricing, but not necessarily in credit scoring and in general corporate governance. Discrimination will surely be a danger in this realm as usage of big data becomes more and more commonplace in credit scoring. A role for regulation in standards seems probable if growth in P2P continues, but the nature and extent of regulation remain very open questions.

SUMMARY POINTS

1. At least some cost savings of disintermediation seem to accrue to investors, but risk characterization and portfolio selection must be understood to infer any extent to which investors could capture rents from disintermediation.
2. The crowd of investors has valuable proximate knowledge when proximate implies real-world connections and when investors with skin in the game certify information. Financial institutions of all types may be able use this information more effectively with technology and with systems to incentivize underwriting performance.
3. Disclosure of personal narratives has the potential not only to increase proximate knowledge, but also to bias decisions. Algorithmic extraction of signals seems possible.
4. Social circles and local economic indicators can inform credit risk. Big data presumably can play more of a role in credit profiling, which could mean anticompetitive effects for borrowers if monopolies of personal information inform credit risk.

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