PEER-TO-PEER CROWDFUNDING:
INFORMATION AND THE POTENTIAL FOR DISRUPTION IN CONSUMER LENDING

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Abstract

Can peer-to-peer lending (P2P) crowdfunding disintermediate and mitigate information frictions in lending such 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 seem to capture some rents associated with the removal of the cost of that 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, and by implication, P2P should be able to offer pricing and/or access benefits to potential borrowers. However, social connections require costly certification (skin in the game) to inform credit risk. Early research suggests an ever-increasing scope for use of Big Data and incentivized re-intermediation of underwriting. I ask many more questions than current research can answer, hoping to motivate future research.

Keywords: Crowdfunding, Peer-to-Peer Lending, Social Finance, Disintermediation, Marketplace Finance, Screening

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a. 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.[2] According to a Fitch report, P2P is expected to grow to \$114 billion in lending, conservatively, in the medium term (Fitch Ratings (2014); *Wall Street Journal*, August 14, 2014). As a comparison, households in the United States have \$880 billion in credit card debt outstanding as of July 2014, reflecting net new borrowing of \$28.5 billion over the prior twelve months.[3] Taking the \$28.5 billion figure as a rough estimate of the growth in securitized consumer lending, the Fitch's number suggests that a relevant share of consumer lending net growth could be captured by crowd lending.

P2P crowdfunding has a host of other names, including social finance, marketplace finance, and disintermediated finance. None of these terms is alone a prime facie description of peer-to-peer lending; P2P is indeed a disintermediation of consumer finance using a social marketplace. 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 on one direct market. A push-back on this rather appealing term is that, as we will see, the amount of additional intermediation which might 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 that relationships may improve repayment behavior. Questions arising out of the social network aspect of crowdfunding are the center of the nascent literature. As we will see, the extent to the benefits to proximate knowledge and relationships facilitated by a P2P platform matters greatly for how P2P positions itself in completing consumer finance markets.

Even if it is difficult to pin down the correct characterization of P2P, it is straightforward to claim that the market of disintermediated lending facilitated by technology and by the role of

[2] https://www.fitchratings.com/gws/en/fitchwire/fitchwirearticle/P2P-Lending's-Success?pr_id=851174
[3] Federal government data aggregated by www.nerdwallet.com.

potentially improved screening has witnessed impressive growth. This growth of P2P lending 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 the real possibility for disruption that improves choices and outcomes for at least some borrowers and investors.[4] Thus, my agenda is to explore the economics of the possibilities for disruption in P2P. A starting point is the work of Agrawal, Catalini, and Goldfarb (2013), who offer a discussion of economics of equity (entrepreneurial startups) crowdfunding. However, the role of technology and screening is quite different in P2P markets, as is the investor base. That being said, this work provides an insightful discussion for thinking about information in the crowd of investors.

This article frames the possibilities for economic disruption with a two-step agenda. I begin in Section (b) with a quick overview of the mechanics of P2P and then delve into the potential for disintermediation to create rents accruing to investors. Little research has yet delved in the topic of portfolio choice and investor benefits arising from P2P; thus, I offer a framing of the discourse.[5] My take away is:

i. At least some cost savings of disintermediation seem to accrue to investors, but characterizing risk and portfolio selection are first order research needs to understand to what extent the crowd captures rents from disintermediation.

Section (c), the core of this review, surveys the role of proximity in the crowd model. Although the literature is very much in a formative stage, I draw three more take-aways.

ii. The crowd of investors has valuable proximate knowledge when proximate implies real-world connections and when the investors certify the information with skin in the game.

iii. Disclosure of personal narratives has the potential to increase proximate knowledge, but also the potential to bias decisions. Algorithmic extraction of signals seems possible

iv. 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 anti-competitive effects for borrowers if personal information monopolies inform credit risk.

[4] Throughout most of the paper, 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 am implicitly assuming 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 and Thakor, 1987).

[5] Agrawal, Catalini, and Goldfarb (2011) provide evidence profiling investors in equity-based crowdfunding.

One theme emerging in the review of proximate knowledge is that proxies for individual credit risk available to non-connected investors may be important, especially in the technology world of posted data and algorithmic risk scoring, and thus trading. This observation leads to Section (d). 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 un-explored questions about consumer loan optimal design.

Finally, I explore the literature using platform policy design shocks to consider whether some of the benefits from the crowd model might arise from different contract designs or more intermediation, offering a twist that disintermediation may involve more intermediation than people think. My take-away here is:

v. Disintermediation can benefit from more incentivized intermediation of underwriting.

I use my conclusion, Section (e), to offer my perspective on the potential for P2P disruption in consumer finance and on caveats needing exploration in looking forward to understand any welfare benefits accruing to the crowd.

b. Overview and Disintermediation in Peer-to-Peer

How Peer-to-Peer Works

Peer-to-peer lending (P2P) may well find it roots in the idea of socially-connected finance, but it surely traces the roots of its success to technology, much in the spirit of Einav, Jenkins, and Levin (2013), who find, among other things, that technology expands access to credit.[6] Technological advances have facilitated (a) the collecting, scoring, and disseminating of credit qualifications for a pool of prospective borrowers on an online platform, (b) the real-time reporting supply of lending bids, which allows investors to diversify across loans and to spread borrower risk across investors, and (c) the online servicing, monitoring, and credit history reporting of loan performance. A quick synopsis of the lending process is as follows.

[6] Einav, Jenkins, and Levin (2013) study the importance of technology in the credit scoring of auto loans, finding that technology enabled lenders to better identify high-risk borrowers. An important result is the overall expansion of access to credit.

A P2P platform sets up a database of prospective borrowers. Most platforms predominantly offer term loans, amortizing in 3 or 5 years. Borrower applicants enter mandatory information including the loan amount request, maturity choice, purpose for loan, income, employment, and other debt, as well as voluntary[7] information that is posted on the website. Borrowers may upload documentation verifying income and employment.[8] 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 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 diversify across borrowers while watching the supply of credit evolve over time to condition their decision on the supply decisions of other investors. The borrower usually does not get funded unless she reaches a funding threshold. If bids reach the loan requested threshold amount, the loan closes at an interest rate either set by the marginal willingness to fund or at the rate assigned to the borrower by the platform according to risk scoring.

Benefits from Disintermediation

In its first generation implementation, platforms serve a facilitator role or, in Rubinstein and Wolinsky's (1987) middleman terminology, a consignment role. The platform makes money by closing and servicing loans. For example, Lending Club and Prosper charge 1-5 percentage point origination fee on the loan depending on the borrower's risk profile and loan duration. Using Lending Club data of all loans issued in the first quarter of 2013, the mean and median origination fees are 2.7 percent and 3 percent, respectively. This fee is taken out of the funds provided to the borrower. The platform informs the borrower of the interest rate and the implied APR with the fee added into the calculation, so that the APR reflects the true borrower cost. When payments come into Lending Club to service the loan, the platform takes out a 1 percent

[7] Personal narratives, interest rates on other debt, employment details, etc.
[8] Sometimes potential borrowers fill the information voluntarily, and sometimes in response to a platform request.

service charge before submitting the payments to the investor. Lending Club also collects delinquency fees from borrowers and collection fees from investors.

In Lending Club data from first quarter 2013 loan issuances, 4.44 percent of loans are at risk, either being late (2.16 percent) or in default (2.28 percent) after a year. Generally, annual default rates for these platforms are approximately 5 percent.[9] Using the equal-weighted mean interest rate from the first quarter 2013 (14.4 percent), a 5 percentage point default rate, and the fee structure implies a back-of-the-envelope IRR to investors of 8 percent. More formal performance statistics come from websites that track Propser and Lending Club loans. LendingRobot.com calculates the IRR of 277,814 Lending Club loans as of January 2015 to be 6.93%. LendStats.com puts the return on investment as 5.4 percent (Prosper) and 5.1 percent (Lending Club) over the period 2007-2014 and 8.7% (Prosper) and 7.0% (Lending Club) over 2009-20014. Lending Club and Prosper themselves posts return statistics. Using a risk weighted average of Lending Club loans made, its adjusted annual net returns from first quarter 2007 to first quarter 2013 is 7.2%.

Is 7% an appropriate return for the risk? The appropriate comparison is the asset-backed security 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 (2012) finds that financial intermediation cost on average just shy of 2% of assets.[10] Hanson, Shleifer, Stein and Vishny (2014) calculate the brick-and-mortar expenses from banking account for 2.96% of assets. These comparisons put disintermediation value (passed along to investors) right 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 MBS, retain some originator exposure to non-payment, thus they may offer lower risk proposition for investors than P2P. (See a description of

[9] http://www.lendingmemo.com/lending-club-prosper-default-rates/

[10] Also see Greenwood and Scharfstein (2013) and Gerakos, Linnainmaa, and Morse (2015) for calculations of the cost of securities intermediation.

ABS in Furletti (2002) or 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 U.S. 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. A more precise study of P2P risk and return over the full cycle of loans would be welcome. And, of course, the data horizon I am using to draw inference is also way too short.

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.

Other Benefits to the Investor

Two other benefits accrue to investors with the growth of P2P platforms.[11] First, in the above discussion of risk, missing was the observation that by constructing one's 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, and Goldfarb (2011) document profiles of investors on an artist-entrepreneur platform in equity crowdfunding. Although the investments in equity crowdfunding carry very different expected returns and covariance, his observation that investors are not on average local at all (3,000 miles away) may reflect investors wanting exposure at a distance. For hedge fund investors, the possibility to use 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 with needs for liability-covering funds, P2P offers realizations in 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 to researchers to test such propositions.

[11] 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 on the flip side.

The second benefit that accrues to investors with the growth of P2P platforms is improved access. In what comes below, I discuss the role of proximity and better credit risk profiling of loan applicants which could improve the access to or price of credit. However, what P2P has done on 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 fixed income instrument with more risk than, for example, savings notes or corporate bond funds.

The question here is again what would be the appropriate counterfactual and risk comparison. A second question is more paternalistic in nature: who is investing and does their wealth, demographics, income and income risk profiles support the added fixed income risk associated with P2P. A third question is whether individual investors understand the risk associated with these investments. My opinion on this front is that P2P platforms are fairly transparent on their structures of fees and risk. (This is not tested.) Thus, I would instead ask whether P2P investors understand and internalize future budgetary implications from the risk (Bertrand and Morse, 2011).

Having posed all of 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 P2P platforms Prosper and Lending Club is from institutional investors (*Financial Times, October 5, 2014*). Even if some individual investors [people] choose poorly to invest in P2P, on net the benefit to investors of access and the ability to construct portfolios is likely to positive. The other side of this argument is also material. The fact that the total size of this asset class and thus the gains relative to ABS are presently small suggests that the welfare implications to the 20% of individual investors may be of similar order. Research is very much needed to understand the welfare implications across investor types and as guidance for disclosure and investment advisors.

My take-away from the framing of the benefits of crowdfunding for investors is:

i. *At least some cost savings of disintermediation seem to accrue to investors, but characterizing risk and portfolio selection are first order research needs to understand to what extent the crowd captures rents from disintermediation.*

c. 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 (Petersen and Rajan (1994), Boot and Thakor (2000), Berger and Udell (2002), Petersen (2004), Berger, Miller, Petersen, Rajan, and Stein (2005), Stein (2002), Karlan (2007), Iyer and Puri (2012), Schoar (2014) and many others). There is no reason to presume that the same would not be true in P2P.[12] 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 and Russell (1976) and Stiglitz and Weiss (1980)).[13] The crowd invests its own money; therefore the screening is done by those with skin in the game having the incentive to pay the cost to overcome information frictions (Leland and 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. One has to wonder whether the number of such connections is perhaps 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 fextracted from other potentially proximate investors. I try to highlight topics like diffusion of proximity via herding or cascades that, although perhaps are still thin in prior studies, offer the potential to inform practical, real consequences, which can set up the discussion of the potential for P2P to disrupt mainstream credit lending.

Proximity through Social Connection

Using data from Prosper, Freedman and Jin (2014) find that loans for which investor-lenders endorse and bid on the friends' applications (i.e., commit to invest) yield 6 percentage

[12] Petersen and Rajan (2002) subsequently show the value of local relationships has declined over time, presumably due to technology, which adds an interesting twist to whether technology can re-induce proximity.
[13] Besanko and 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.

point higher returns (IRRs) to lenders. Conversely, loans with friend endorsements *without bids* perform worse than the pool of anonymous pooled borrowers. Social connections matter but only if the signal comes with a cost that separates credible information (Spence, 1973). This finding is echoed in 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 borrowers. Otherwise, investors in the group perform worse than non-group investors. There are potentially lingering selecting issues in studying who selects into groups, but interesting questions emerge in this selection.

Selection may also be looming in who gets funding. Freedman and Jin (2014) notice that signaling effect of bidding on friends' applications is more pronounced in lower credit grade borrowers. Therefore, higher IRRs may be due to unconnected investors taking on additional risk when they follow bids of investors connected to borrowers. However, since the rate of delinquency in Freedman and Jin 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 take-away 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 of Freedman and Jin (2014) and Everett (2010) go after the fundamental idea of the crowd – whether or not the social aspect of the crowd can enhance information. These are important findings, resonating that of Schoar (2014), who studies the extent to which personal interaction is a desirable ingredient in relationship banking (it is). Equally important, however, is the limit to which connection screening can be applied. If we must limit the benefits of P2P to connections friends, the potential for the crowd model to improve credit conditions in aggregate is quite small.

I summarize this section with the take-away:

ii. *The crowd of investors has valuable proximate knowledge when proximate implies real-world connections and when the investors certify the information with skin in the game.*

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 in Agrawal, Catalini, and 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 et al (2011) make the statement that: "…the online platform seems to eliminate most distance-related economic frictions such as monitoring progress, providing input, and gathering information…" 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 the loan, etc.), while in the process hoping to build an emotional tie to the investor-lender.[14] The 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 and Dholakia (2011) apply the *identity claim* methodology of Miles and Huberman (1994) of looking for six identity claims in reading prospective borrower narratives – trustworthy, economic hardship, hardworking, successful, moral, and religious. They find that trustworthy and successful identity claims increase funding and improve funding terms, but these same identity claims have no impact on loan performance. There are multiple layers of selection working here (most of which the authors discuss) – the selection of writing a narrative, the selection of who got funding, and effect of the funding terms based on these narrative traits. Certainly more work could build on this foundation to understand voluntary disclosure. However, the take-away is clear; the possibility that investors use characteristics in sorting borrowers but that characteristics do not show up in performance is particularly potent and

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

problematic for the signal value of these narratives. Characteristic signaling through narratives may be cheap talk or worse.

An approach not yet explored in P2P to my knowledge is via deduction, working backwards from what informs success in raising funds and in predicting low default. Mitra and Gilbert (2014) use textual analysis on 45,815 projects posted on Kickstarter (a donation-based crowdfunding platform, where investors are paid it 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 of course once they are disclosed, their predictive power disappears. Nevertheless, this seems inevitable that borrowers would want to identify anomalies in success cues that perhaps reflect biases of investors.

Gao and Lin (2012) use psychology text mining techniques to uncover clarity, deception, and other linguistic tip-offs in narratives that might inform credit risk. They find that the ease of reading narratives correlate with a 2.3 percentage point lower default rates, and narrative complexity associates with 3.6 percentage point higher default. Moreover, linguistic attributes which have been found in other work to correlate with deception associate here with higher default. Causation is hard to ascribe to these deception results, and selection is again lingering in who chooses to write narratives and in what content the prospective borrower writes. However, caveats aside, the goal of detecting deception raises a first-order issue to prominence. 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.

An aside point worth emphasizing here is that this research takes us farther away from the ideas of individuals in the crowd sharing a social network in lending. One has to wonder how small-scale investors will fare in such an environment versus large, algorithmic investors

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, however, Pope and Sydnor (2011) and Duarte et al (2012) respectively show that investor-lenders can be profitable (incur fewer default) by statistically discriminating against racial minorities and biasing toward trustworthy faces. Herzenstein et al (2011) also present a potentially profitable inference. They find that the existence of the economic hardship identity claim is informative, resulting in 0.9 percentage points fewer defaults. Ironically, mentioning hardship does not affect funding among those providing narratives, reducing some selection concerns.

Together, the results suggest of cognitive limitations in three dimensions – in the way investor-lenders draw inference from positive screens, in the way investors fail to sort on negative screens, and in the way borrowers choose to provide negative screen items. The results also seems to be the tip of the iceberg in understanding what individuals can do to signal creditworthiness credibility through narratives and how behavioral biases might interact.

Michels (2012) takes a different approach to narratives by codifying the potentially hard information available in narratives. 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 details of the content, 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 bids on the fundraising and lower the ultimate interest rates that borrowers face. Perhaps most telling, however, are the disclosure items that matter most -- the purpose of the loan, other debt outstanding, and poor credit rate explained.

Michels then shows that the total quantity of disclosure reduces default, consistent with soft information lowering risk (Petersen and Rajan, 1994). These results are material; each disclosure item generates a 5 percentage point reduction in default. Michels (2012) leaves some open questions. He finds that unverifiable items are the most predictive of default, which is troublesome along the lines of truthful disclosure of Gao and Lin (2012). In addition, future work could seek to understand whether it is the selection to disclose versus the content of the disclosure in the selected sample that is informative.

I summarize this section with the third of the review take-aways:

iii. *Disclosure of personal narratives has the potential to increase proximate knowledge, but also the potential to bias decisions. Algorithmic extraction of signals seems possible.*

Proximity through Expertise

No scientific research, to my knowledge, yet exists on 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 labor income risk of those working in finance sectors? Or, might any knowledge in the financial sector breed overconfidence in picking borrowers to fund? This answer is not at all clear. More broadly, one can imagine both individuals and institutional investors applying fundamental research on industries to gauge income risk of borrowers that improves upon credit scores. This is an area ripe for research.

Proximity through Local Indicators

Another possibility is that local economic information could proxy for proximate personal knowledge to inform credit risk. Crowe and Ramcharan (2013) find that crowd investors incorporate relevant local house price effects in deciding on 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 one standard deviation decline in house prices within a state during the recent housing crisis associates with a 2 percentage point higher rate on a Prosper loan compared to otherwise matched borrowers. The spillover from the local housing market was relevant for credit risk, as one might have guessed.

This is only one piece of evidence that individuals (or large-scale institutions) might be able to enhance underwriting by incorporating local knowledge. In Crowe and Ramcharan, the local knowledge is measured in publically available indicators. Many such indicators exist (most have lags in reporting, however), and much more information rests in soft knowledge of locals. Again, this is an area ripe for more research, especially in light of the results of Einav, Jenkins, and Levin (2013) that technology-driven credit scoring in auto markets can substitute for local information.

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

It might be possible to use an applicant's social network, rather than local indicators, to proxy for the economic condition of that prospective borrower. Are social circles a proxy for one's own life, and thus, credit risk? Lin, Prabhala, and 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 high credit quality friends 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 el al (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 Freedman and Jin (2014) result. This is important because it is a very open question of whether a non-costly signal of the quality of social circles implies valuable credit risk information.

A flip side to Lin et al is found in Lu, Gu, Ye, and Sheng (2012). These authors find a negative externality of connections; when a borrower friend defaults, the likelihood that the borrower will default more than doubles. Friends unwind the stigma of default very much in the spirit of Fay, Hurst and White (2002) or Guiso, Sapienza and Zingales (2014). A minimum conclusion from Lin et al 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 the topic of inferring credit risk from one's network. In the world of big data and social networks, it is only natural to think of 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. It also implies an overall improvement of credit conditions for borrowers, which would be welcome to most. But social media and finance interlock also implies the potential for stereotyping and for anti-competitive effects. Importantly, one can imagine big data providers capturing the rents of disintermediation if network information or other big data personal information stores inform credit risk and are monopolistic.

A fourth take-away from my review of the early crowdfunding literature is open ended:

iv. *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 anti-competitive effects for borrowers if personal information monopolies inform credit risk.*

Proximity by Diffusion

I now abstract from the source of proximity and its benefits and instead just assume that proximity exists on P2P lending 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 one can infer that information exists somewhere in the crowd.

The evidence comes from Zhang and Liu (2012) and Herzenstein, Dholakia, and Andrews (2011). Herzenstein et al (2011) document that investor-lender interest in a prospective borrower follow herds, but with a modest magnitude. Potentially because of additional supplier attention, the interest rate clears at a lower price, implying the borrower is better off. Further, these authors present initial evidence that the momentum with which investor-lenders herd is correlated with the proportion of loans being current two years later.

Zhang and Liu (2012) build on this result by delving exactly into the rationality of herding. The authors distinguish rational from irrational herding in that learning occurs conditional on borrower attributes and bids. The authors find that a 10 percent higher portion of funding being from rational herding associates with a 2 percentage points decrease in loan default probability. An appealing extension of their result is that this information is all the more valuable the lower the credit score is. Thus, as default risk increases on observables, the value to soft information also increases.

It would be helpful to understand more here, in particular to delve into the micro-mechanisms. Can all investors be an originating source of information?[15] Need the source of the information be connected proximity versus measures of local economic conditions or proxies via social circles? How much or how little information is needed to create an information cascade

[15] Burtch, Ghose and Wattal (forthcoming) find that withholding investor identify on a reward platform results in larger likelihood of other investors funding, but smaller contributions. Reward platform investors likely invest with different motives, however. Nevertheless, the agenda by these authors on privacy is quite important.

(Welch, 1992; Banerjee, 1992)? In the next section, I consider the topic of contract design in the context of how much re-intermediation of underwriting might be optimal. It matters here as well; if platforms take on more of the credit risk profiling, does the lower signal content from the crowd inhibit the predictiveness of information cascades?

d. Re-Intermediation 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 describe the loan contract and borrower-reported use of funds 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 the platforms might be (and are) adding more intermediation to improve the product offering. These are somewhat disjoint topics, but the central idea is to speak to the optimal amount of intermediation and to open the topic of the optimal contract design.

Characterizing P2P: Lending Club Loan Snapshot Statistics

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

The data I present are as follows. Table 1 Panel A reports mean statistics for borrower income and the terms of the loan by purpose or use of loans. Panel B reports the same statistics by U.S. income quintiles, using income quintile thresholds from the 2011 Census update. As a comparison to Panel B of Table 1, Table 2 reports household borrower income and consumer debt statistics from the 2010 Survey of Consumer Finance (SCF), aggregated to the U.S. population using the survey weights. I do not exclude non-borrowers, but present borrowing statistics conditional on positive debt in column 3 and the final column of Panel A of Table 2. Consumer debt in the SCF refers to education loans, vehicles loans, credit card debt, lines of credit and other loans, but excluding mortgages. Panel B of Table 2 reports SCF mean statistics across these subgroups of credit products. Note that by comparing Lending Club loans to the SFC, I am comparing individual single loans to overall household consumer debt.

As my goal here is just to characterize the loans of P2P, I discuss these tables with simple bulleted factoids.

1) Peer-to-peer loans are overwhelmingly credit card debt retirement or debt consolidation loans (these often mean the same thing). Panel A of Table 1 shows that 85.8% of P2P loans issued were for this purpose.

2) The term of the loan is on average 41 months, with little material variation across the purpose of the loan but some shortening at lower income levels.

3) The vast majority of P2P loans fund middle-to-upper income individuals. Panel B of Table 1 shows that only 1.9% and 10.9% of loans are provided to the lowest two quintiles in the income distribution.

4) Average P2P loan face values comprise 20.5% of annual income, and payments absorb 7.5% of monthly income.[16] The P2P average loan is a ratio of 0.903 of the U.S. household average consumer debt in the SCF (relative to the first column of Table 2 Panel A), and a third of the total consumer debt conditional on being a borrower (the third column of panel A Table 2). To the extent that these borrowers are only consolidating credit card debt, the loan size of P2P loans is very large relative to mean households credit card debt float in the SCF (Panel B), suggesting that these are very indebted individuals.

5) The P2P interest rates in Table 1 are before the origination fee, which on average adds in 2.5% to 3% (varying by risk and maturity in markup up to 5%) to the APR faced by borrowers. To compare the P2P APRs to credit card APRs in the SCF, I focus on the final column in Panel A of Table2, which is the interest rate of SCF borrowing households for

[16] I calculate the payments using an amortization of the average loans, not an average of each amortization, to keep my factoids consistent to the table.

their largest outstanding debt credit card. I need to toss out teaser rates to make this comparison, which I conservatively assign as 4.99% or less.

This comparison suggests that the P2P APR is quite a bit higher than what the mean U.S. borrower in the income quintile is paying. Given the above point that these borrowers are likely more debt-laden than the mean borrower, these P2P borrowers must be in more financial distress relative to their income quintile averages to want voluntarily to move to P2P. Alternatively, P2P is offering access to additional credit for individuals maxed out on credit card lending. In this case, the marginal rate of borrowing is likely to be much higher, since a very discrete set of consumer finance choices characterize the landscape. For example, the interest rate on payday loans is on average 400%, and this is marginal finance for many borrowers (Bertrand and Morse, 2009).

Little work has yet emerged considering the optimality of the lending structure of P2P, although this surely matters. 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 in inducing the appropriate duration of borrowing given debt servicing cash constraints and in potentially de-biasing any lack of salience of the importance of payback? (Bertrand and Morse (2012); Zingales (2015))? Does the consolidation reduce the quantity of late fees and other add-ons? As P2P continues to grow, these are all questions warranting consideration.

A few papers are emerging on the auction process of the clearing of demand and supply of loan bids. Wei and Lin (2013) study the event of Prosper unexpectedly moving from price setting via auction (the interest rate is priced at the margin when supply of credit reaches demand) to a coarser system in which Prosper pre-assigns an interest rate based on credit scoring assignment of prospective borrowers into buckets or grades of risk. The authors find that under the pre-set prices, loans are funded with a higher probability at a higher price, with a higher default rate. My interpretation of these results is that Prosper may be increasing the pool of borrowers who get funded by pricing the high risk types. The alternative interpretation is the coarser pricing may imply more pooling of risk and thus a natural higher price (Stiglitz and Weiss (1980)), which could translate to more loan-cost induced default. In either case, the natural experiment result of Wei and Lin (2013) is important not just for understanding the financial contract but it is use of this contract natural experiment to inform with causal implications, and hopefully will stimulate more research in contract design.

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, effect of connections and friends may be a reduction in ex post moral hazard, rather than information as to a credit risk type. Why this matters lies in the goal of understanding whether P2P proximity adds value to credit risk mitigation relative to traditional finance. Understanding whether moral hazard reduction is a part of reducing crowd defaults would inform P2P contract design.

Recall that Freedman and Jin (2014) find that credit risk is lower when a friend invests, having reputation skin in the game. This result may not be about certifying quality but about a change in behavior of the borrower 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 through connections. Likewise, the result of Lu, Gu, Ye, and Sheng (2012) are about direct moral hazard influences through the network. These authors find that when friends default, it trickles down to other friends, in a moral-hazard increasing reduction of stigma. In addition, this discussion can take instruction insights from socially connected entrepreneurial funding. Lee and Persson (2013) model how the formalization of skin of the game may help the exploitation of social connections for funding by entrepreneurs, 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 in implementing personally costly rebalancing of asset actions.

A large literature exists on information frictions in lending – ex post moral hazard and ex ante credit risk screening, – and what these information frictions imply for access to and cost of credit starting from Jaffee and Russell (1976) and Stiglitz and Weiss (1980). Although the discussion about ex post moral hazard for firms is a well-developed literature, less research has been done on repayment moral hazard for individuals. Exceptions include Karlan and Zinman (2009); who study consumer loans in South Africa; Adams, Einav and Levin (2009), who study subprime auto loans; and Guiso, Sapienza and Zingales (2014), Eberly and Krishnamurthy (2014) and Morse and Tsoutsoura (2013), who study repayment moral hazard in mortgage markets. I mention these studies to identify what mechanisms others have found effective in inhibiting or reducing moral hazard in consumer loan repayments. The 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 is rampant and it would be interesting to understand more in mitigating ex post moral hazard not just in the crowd model, but consumer finance at large.

Re-Intermediation of Underwriting and Platform Design

Technology has allowed for the aggregation and underwriting of individual loans on a public platform. The novel ideas of P2P are in proximity of the crowd and disintermediation, but is it possible some re-intermediation of the underwriting could complement or even supplement 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? This final part of my review will indeed suggest that intermediaries can do more to screen credit risk.

In the prior sections, I argued that the literature suggested more scope for algorithmic credit scoring, which the 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 (*October 5, 2014*) reports that 80% of investment going into 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-under-management flows, stretch the notion of anything proximate.

A starting point to thinking about re-intermediated underwriting in crowd finance is Iyer, Khwaja, Luttmer, and Shue (2010). They find that within the credit score buckets provided by Prosper, they can profitably further sort borrowers by credit risk. This is important. In their sample, if Prosper had provided the exact credit score as opposed to just credit buckets (i.e., being in a range of credit scores), investor-lenders could have predicted credit risk more accurately. This provocative finding begs the question as to whether a financial intermediary could do better credit scoring itself.

I break this question into two pieces. First, can intermediaries achieve the same quality of screening of that social network linkages achieve? Platforms can certainly implement Michels' (2012) finding, by using platform underwriting to incorporate the 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 and Ramcharan (2013), implementable in a platform underwriting model.[17]

In addition, Gelman (2013) finds that even beyond the credit score of Lending Club, the check box as to whether income has been verified predicts fund-raising success and default risk. Thus, both the borrower and the intermediary could add more low-hanging soft information signals as to the quality of the borrower. Gelman ponders why the borrowers allow themselves incorrectly to be sorted into unverified when avoidable.[18] More intermediation seems useful, and disintermediation still benefits from intermediation.

The second piece is whether incentive alignment can add value. A key aspect of the crowd investors is that they have 100% skin in the game. In microfinance, an important aspect the original Grameen group model is the screening occurring during group formation. The group has the incentive to keep bad types out. These ideas translate to early crowdfunding that we see today. In particular, Berger and Gleisner (2009) find that group leader screening of a pool of

[17] 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 portfolio.
[18] A GAO report (GAO, 2011) find that both Prosper and LendingClub select whose income to verify based on risk triggers that the loan request amount may be high for the income reported by the potential borrower. Among those selected (in a particular sample and cross-section in time of the analysis), half-to-two thirds provided satisfactory documentation.

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 risk.

Bringing these ideas together, a compelling paper asks whether intermediaries also have the ability to react to incentives in screening. Hildebrand, Puri, and Rocholl (2014) use a Propser platform policy shock which removes origination rewards paid to group leaders hence changing their incentives. The study compares the behavior 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 the group leaders' bids on individual loans are uninformative in speaking to the default rate. What is important is the detailed analysis of skin in the game. When group leaders put enough skin in the game even in the pre-period when origination rewards encourage volume, the quality of the selection of borrowers is better, as are the outcomes, reflecting the incentives of skin in the game of Holmstrom and Tirole (1997) and Gorton and Pennacchi (1995).

In Hildebrand et al (2014), we learn that these group leaders (a) can do effective screening and that (b) screening is better when incentives are aligned. These results complement the importance of Iyer et al (2010) and Crowe and Ramcharan (2014). 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 Hildebrand et al's focus on group leader. It is unclear going forward who the incentivized intermediary might be, but bringing these results together suggest that re-intermediation with incentives could improve credit risk assessment.

I summarize the early research in this section with one more take-away:

v. Disintermediation can benefit from more incentivized intermediation of underwriting.

e. Conclusion: Will Crowdfunding Disrupt Consumer Lending?

Each of the articles I have surveyed tackles an interesting angle of 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 taken these findings to the big picture question of where P2P crowdfunding is headed in terms of product offering and disrupting consumer finance. I have offered a long list of unknowns for future research.

If asked whether crowdfunding has the possibility to positively disrupt consumer finance, my answer is yes, with three large qualifiers. I think some rendition of technology-driven, disintermediated finance will continue to capture markets. I do not, however, 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.

A second qualifier is in assigning what the face of crowdfunding will be in the future. The CEO of AMEX recently said that the future of plastic cards is irrelevant to American Express's prospects. Will payment systems, credit and consumption all morph into a single rendition of Big Data? A crystal ball would be useful here, but my point is that my statement about disruption need not involve new players. Technology is disrupting consumer finance. Technology will continue to involve more and more information, which leads to my third qualifier.

Big Data will surely matter in the future for credit scoring, which brings forth all sorts of uncertainties – privacy, monopoly power, discrimination, etc. It seems inevitable that the role of data is exponentially increasing, 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 to potential borrowers. The incidence of the capture of rents is not obvious.

On the investor side, certainly these innovations will allow some investors to benefit from this asset class, which they already seem to be doing. 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.

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Table 1: Lending Club Loan Statistics

Data are from Lending Club, all loans originated in the first quarter 2013. The counts column record the total loans numbers. Loans are all approved and funded in this snapshot. Panel A presents the self-reported use of the 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 Panel B, income quintile cutoffs are from the U.S. Census, 2011 update.

Panel A: Mean Statistics of Borrower Income and Loan Terms by Use of Loan

Type of Loan	Annual Income	Loan Amount	Interest Rate	Term Months	Loan-to-Income	Payment-to-Income	Count	% of Sample
Car	65,993	8,556	0.134	39.2	0.130	0.049	185	0.8%
Credit Card	74,017	15,406	0.134	39.8	0.208	0.077	5,680	25.0%
Debt Consolidation	75,468	16,350	0.141	41.6	0.217	0.078	13,797	60.8%
Home Improvement	87,893	15,056	0.129	41.8	0.171	0.061	1,120	4.9%
House	82,617	16,912	0.139	41.7	0.205	0.074	138	0.6%
Major Purchase	78,365	9,740	0.129	39.4	0.124	0.046	443	2.0%
Medical	73,325	8,375	0.191	38.0	0.114	0.047	122	0.5%
Moving	76,911	8,325	0.193	37.6	0.108	0.045	73	0.3%
Other	68,913	9,702	0.197	40.0	0.141	0.057	696	3.1%
Renewable Energy	99,977	12,602	0.194	42.5	0.126	0.048	11	0.0%
Small Business	92,278	17,023	0.193	40.9	0.184	0.072	253	1.1%
Vacation	63,913	6,003	0.190	36.9	0.094	0.040	55	0.2%
Wedding	70,315	11,703	0.194	39.4	0.166	0.067	134	0.6%
Total	75,674	15,542	0.141	41.0	0.205	0.075	22,707	100.0%

Panel B: Mean Statistics of Borrower Income and Loan Terms by Income Quintile

Census Income Quintile	Annual Income	Loan Amount	Interest Rate	Term Months	Loan-to-Income	Payment-to-Income	Count	% of Sample
1st	19,944	4,722	18.1%	36.2	0.237	0.100	423	1.9%
2nd	32,425	8,478	16.0%	36.8	0.261	0.107	2,464	10.9%
3rd	50,314	13,206	14.8%	40.8	0.262	0.097	7,694	33.9%
4th	80,216	17,636	13.6%	42.2	0.220	0.078	8,158	35.9%
5th	148,303	21,305	12.4%	42.1	0.144	0.050	3,968	17.5%
Total	75,674	15,542	14.1%	41.0	0.205	0.075	22,707	100.0%

Table 2: Survey of Consumer Finance Consumer Borrowing Statistics

Data are from the 2010 Survey of Consumer Finance, with survey weights applied to represent the U.S. population. Income quintiles are from Census for 2011. Consumer debt everywhere is all consumer debts outstanding excluding loans backed by a home or property and excluding business loans with personal liability. Reported are total consumer debt, household income and their ratio, as well as the distribution of the credit card interest rate self-reported in the SCF for the credit card with the largest balance. The interest rate reported answers the question in the SCF as to what the rate is for the credit card with largest balances. The final column presents the mean answer to this questions conditional on the househodl being a borrower and the rate given being above a teaser rate, here defined as 4.99% and less.

Panel A: Debt and Interest Rates by Income Quintile

						Interest Rate on Credit Card with Most Outstanding Debt						
Census 2011 Income Quintile	Mean Consumer Debt	Percent with No Borrowing	Debt Condi-tional on Borrowing	Household Income	Debt-to-Income	Mean	Min	25th %ile	50th %ile	75th %ile	Max	Mean Condit ional
1st	7,968	52.4%	15,194	14,908	0.575	14.50	0.0	10.6	14.6	19.0	32.0	15.67
2nd	9,458	43.6%	21,702	31,358	0.306	14.04	0.0	9.9	13.9	18.0	36.0	15.16
3rd	16,777	30.0%	55,923	49,985	0.339	13.86	0.0	9.9	13.3	18.0	33.0	14.78
4th	22,198	22.6%	98,438	78,977	0.280	13.28	0.0	9.3	13.0	18.0	33.0	14.34
5th	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

Panel B: Debt by Credit Product

Census 2011 Income Quintile	Education Loans	Vehicle Loans	Credit Card Debt	Line of Credit	Other Loans	Total Consumer Debt
1st	3,093	928	846	1,296	1,804	7,968
2nd	2,690	2,344	1,481	1,695	1,247	9,458
3rd	6,150	4,138	2,644	2,675	1,170	16,777
4th	5,591	6,376	4,307	5,044	879	22,198
5th	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