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LONG-TERM PERFORMANCE AND POTENTIAL OF A STUDENT-MANAGED PEER-TO-PEER LOAN FUND

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ABSTRACT

In 2009, students at the University of Puget Sound started a unique student-managed fund focused on peer-to-peer (P2P) loans. Using the online Prosper and Lending Club P2P platforms, students are able to screen and evaluate peer borrowers' applications, which they may choose to fund with as little as $25 each. The consumer-oriented nature of the loans and the small investments required have made P2P lending an attractive option for a small student portfolio managed outside an endowment. In this paper, we describe our experience running this fund, which has consistently returned about 6% per year. We also discuss the potential for continued good performance, which is clouded by our increasing default rate and decreasing access to new loans. Institutional investors have moved in—and overrun—the P2P space. We conclude that the market is no longer as accessible or potentially profitable a mechanism for student experiential learning as it was when we began our fund.

JEL: G21, M2, A2

KEYWORDS: Peer-To-Peer Lending, Student-Managed Funds, Microcredit

INTRODUCTION

Peer-to-peer (P2P) lending was supposed to "democratize" lending (Herzenstein, *et al.*, 2008). It was supposed to allow a dentist from Wisconsin to fund a home improvement project for a do-it-yourselfer in Arizona, improving the rates for each by cutting out the institutional middleman. For our small liberal arts university in Washington state, P2P actually did even more: it democratized student-led investing. Our school was unable to support a traditional student managed fund (SMF), especially one large enough to focus on debt. In the P2P market, however, we were able to create an SMF that provided meaningful opportunities for both analysis and diversification. Our P2P SMF is, to the best of our knowledge, unique. In this paper, we describe our fund, which we started in 2009—the very beginning of the P2P explosion. We have invested in almost 500 loans using both the Prosper and Lending Club platforms. About 10% of those loans defaulted. We evaluate the characteristics of those bad loans, and find evidence consistent with other P2P studies (for example, that loans for debt consolidation are overrepresented among bad loans). However, unlike prior work, we are able to compare results from two platforms. We also report on our realized returns, which have been consistently above 50 bp per month. However, our ability to maintain our performance is threatened by structural changes in the P2P market, which has become more opaque for retail lenders as it has been overrun and co-opted by institutional money. The paper proceeds as follows. In the next section, we link our work to prior research on student-managed funds and peer-to-peer investing. We then provide a brief background on our fund, before presenting summary statistics and return data for our performance to date. We also describe a default model that we have developed to help us choose our new loans. Finally, we conclude with a discussion of the challenges facing our fund from changes in the P2P market.

LITERATURE REVIEW

Our work adds to the prior literatures on student managed funds and peer-to-peer lending. We review relevant papers from both of these areas in this section. Student-managed funds are becoming almost *de rigueur* among business schools, as both graduate and undergraduate programs seek to offer opportunities for experiential learning. Since 1952, when the first student fund was established at Gannon University, the idea of letting students manage real money has spread to hundreds of schools. (See, for example, Peng, *et al.*, 2009, Clinebell, *et al.*, 2008, Lawrence, 2008, and Morgan, 2008, for discussions of the rapid growth of SMFs.) The framework for most of these funds is similar: they get substantial amounts of money from private donors or endowments, invest that money in equities, and tie student participation to structured curricula. Our fund is different on all counts. First, our fund is a debt fund. 82% of U.S. student-managed funds, on the other hand, invest in equity (Lawrence, 2008), not just because students may think equity is "sexier," but because corporate bonds are relatively illiquid, less covered by analysts, and traded in much larger round-lot sizes.

These sorts of hurdles help explain why only 6% of Morgan's (2008) sample funds and 3%— one fund— of Peng, *et al.*'s (2009) were fully fixed income, while at least 80% were equity-only.Second, our fund is small. Only two of Peng, *et al.*'s (2009) SMFs are even in our size category ("less than $25,000"), and they are almost certainly not debt funds, since debt funds are huge. Bonds trade in a market where transactions of $100,000 or less are "very small" (Estabrook, 2015), so a well-diversified portfolio of bonds must be many times larger than a comparable equity fund. For example, in Morgan's (2008) SMF sample, the debt funds were at least twice as large as his average equity fund. Almost 60% of his equity/debt funds were smaller than $1M, but none of the seven fixed-income funds was (including Iowa State University's fund, which topped the list at $100M). Since most SMFs are funded through their university's endowments or from individual donations (Peng, *et al.*, 2009), the scale required for fixed-income funds may put them out of reach for many schools. This is especially true for those institutions that restrict SMF size and growth so that donors will not worry that their contributions are managed by students (Gullapalli, 2006).

Finally, our fund is independent of our university. In the traditional SMF world, if a school does choose to make the large commitment necessary to fixed-income, it usually protects its investment by mandating significant risk constraints, strongly limiting student-managers' discretion. For example, all but one of Morgan's (2008) large equity/debt funds were restricted to investment-grade debt, while only the smallest funds were allowed to venture into more speculative issues. In addition to asset constraints, university-sponsored SMFs usually also restrict participation, often by requiring student managers to complete a formal program of degree-based or extracurricular instruction (Clinebell, *et al.*, 2008; Lawrence, 2008). In all cases, however, the university is intimately involved with the fund's operations, providing monitoring and professional oversight (including advisors' "veto power").

Again, our fund is different. It is run through a 501(c)(3) not-for-profit corporation that we set up in 2009. The company is completely independent of the university. Independence allows us to run the fund without oversight from university staff, without worrying about our impact on the university endowment, and without restrictions on our growth. Students write their own investment policy statement each year, and determine the payouts from our corpus (which we use to fund outreach efforts such as our textbook scholarship). They determine their risk appetite, and are able to adjust their investing on an ongoing basis is response to portfolio performance. (In contrast, the traditional SMF that our university is currently establishing will allow students no control over outflows, investment universe, or risk parameters.) Our students' entire attitude toward investing evinces real "skin in the game," since no one above them is micromanaging them (in fact, there *is* no one above them), and they know that their results directly affect their ability to do outreach. We would not have been able to create an independent, truly student-run fund using traditional bonds. However, we were able to do it using peer-to-peer (P2P) loans.

P2P loans are small enough to allow us to create a well-diversified portfolio even without institutional funding. These loans were conceived as a way for retail investors to lend to people seeking money for things like home improvement projects and weddings. Potential borrowers create a listing describing their funding request, posting that listing on an online platform like Prosper or Lending Club (LC). Lenders peruse these listings, bidding as little as $25 on those that they would be interested in funding. If a listing attracts enough bids to provide the requested amount, the listing becomes a loan. The loans are made by the platform itself (actually by an associated bank), which then issues "notes" to each participating lender for her bid amount. When borrowers make their monthly principal and interest payments to the P2P platform, the platform breaks them up and distributes them pro rata to the associated lenders. (See, for example, Berger and Gleisner, 2009; Herzenstein, *et al.*, 2008; Iyer, *et al.*, 2009; and Freedman and Jin, 2008a, for descriptions of early P2P markets.)

In the early days of Prosper, if a listing continued to draw bids after it was fully funded, the later bids served to lower the rate on the loan. Lenders learned to bid strategically in this auction process. Ceyhan, *et al.* (2011) studied this behavior, noting that lenders bidding early got the advantage of being high in the queue, but those waiting until the bidding was about to end could make more informed bids. The authors found three bidding spikes: when the loan was listed (and lenders were enticed by its novelty), just before the loan was fully funded (and lenders were encouraged by its likelihood of fruition), and just before bidding ended (when lenders really wanted a piece of the action, even if it drove down the loan rate). Now, this sort of bidding behavior is almost impossible, as institutional investors have entered the market and sophisticated automated investing allows institutions to skim off the best loans. "[S]ome [institutional] investors may attempt to minimize the time…to complete a purchase in order to beat other investors to the transaction… [I]nstitutional investors may use custom algorithms…to automatically review and purchase loans, often before most general investors are aware of the loan listing" (PwC, 2015; see also Cortese, 2014). Institutional skimming exacerbates the potential for moral hazard that has always been present in the P2P market.

Many authors have commented on this risk, as well as on the possibility for adverse selection (e.g., Iyer, *et al.*, 2009; Weiss, Pelger, and Horsch, 2010; and Berger and Gleisner, 2009; see also Chafee and Rapp, 2012, and Moenninghoff and Wieandt, 2013, for broad discussions of P2P risks). For example, platforms do not give lenders the actual credit scores of potential borrowers; instead, they assign a letter grade based on a proprietary model. This can create an incentive for lower-quality borrowers to choose the P2P market, so that credit grade sets are composed primarily of borrowers at the lower end of the relevant score range. Indeed, Freedman and Jin (2008a), in an exhaustive quantitative analysis of Prosper's first two years (2006-7), found that listed requests became increasingly risky over time. This is dangerous for the retail investors who lack the background to do rigorous quantitative credit assessment. However, Freedman and Jin also found that, despite the deteriorating listings, only increasingly good loans were actually being funded. Lenders were learning. They were also proving to be surprisingly adept at incorporating qualitative, "soft" data from listings into their credit decisions.

In the early years of P2P, platforms encouraged significant borrower/lender interaction, and borrowers were motivated to craft detailed, individualized loan requests. They could choose to add photos of their families, descriptions of their monthly budgets, and discussions of their reasons for asking for money. This sort of nontraditional, "soft" information was useful for both lenders and borrowers. Herzenstein, *et al.* (2008), using a sample of over 5,000 Prosper loans, found that borrower "effort" variables—the provision of detailed backstories and proposed budgets—contributed significantly to lenders' willingness to bid on loans. Almost 91% of their listings with this sort of soft data were funded. In fact, the authors seemed almost surprised to find that lenders in P2P markets were more influenced by a borrower's story than by the sorts of demographic variables (like sex and family size) that can make traditional banking discriminatory. They concluded that P2P markets encouraged "relational" lending, and offered a "particularly congenial venue" for providing credit to underserved groups (such as women) who might otherwise turn to fringe providers like payday lenders. In addition, the potential for meaningful interaction was useful for the 5% of investors who were drawn to the peer market as a way to lend altruistically (Paravisini, *et al.*, 2010).

Iyer, *at al.* (2009) agreed that individual lenders on P2P platforms were able to make meaningful inferences about borrower credit quality using qualitative data from listings. Describing the P2P markets as "inherently competitive," with a hierarchy that is "completely flat," they suggested that this egalitarian structure might facilitate the incorporation of soft information. They estimated that nonprofessional lenders were able to use nontraditional data to divine about a third of the information that they would get from a traditional credit score. This was especially useful for assessing listings in the lower credit categories—perhaps counterbalancing some of the P2P market's potential for adverse selection. Pictures were an important part of borrower-provided qualitative data. Duarte, Siegel, and Young (2009) used pictures posted with Prosper listings to assess lenders' ability to assess trustworthiness from appearance alone. They found that "physiognomy-based proxies"—beyond just attractiveness—helped predict default, even in P2P markets where lenders already had access to detailed financial information on potential borrowers. Despite the potential value of soft data, the P2P platforms now allow much less of it. Listings have become depersonalized. There are no more narratives, pictures, or Q&A. As we evaluate our portfolio, then, we must focus on the more traditional credit variables; even if our early members relied on soft data when lending, we no longer have access to that qualitative information. We will discuss the implications of these data changes in the last section. First, however, we review our portfolio's structure and performance.

Portfolio Description and Summary Statistics

We started our Prosper portfolio in 2009. Two years later, we expanded to Lending Club, both to learn about another platform and to increase our opportunity set. To date, we have made 474 loans, ranging in size from $25 to $157. Table 1 presents a summary of our loan statistics. Loosely following Iyer, *et al.* (2009), we characterize our summary statistics as either standard banking variables ("hard" traditional credit data) or nonstandard variables ("soft" data). We further classify our loans by platform and by performance (defaulted or performing). Any loan that was late as of May, 2016 is in our default subsample. Starting with the traditional credit variables, we observe that borrowers with performing loans have higher revolving credit balances and current amounts delinquent, including much higher maximums for both values. These counterintuitive results may be an artifact of the bankruptcies in our default sample: borrowers whose loans are discharged in bankruptcy are highly likely to have their number and amount of current delinquencies reported as zero. However, performing borrowers have more open credit lines, lower bankcard utilization, and lower debt-to-income ratios, and are much more likely to make more than $50,000/year. More are homeowners. These differences among the subsamples are consistent with Iyer, *et al.*'s (2009) findings on the importance of these traditional variables in determining the interest rates set for early Prosper loans.

Table 1: Summary Statistics (Panel A)

		PROSPER		LENDING CLUB		ALL FUNDED
		Defaults	Nondefaults	Defaults	Nondefaults	Prosper Loans Iyer, *et al.* (2009)
General						
n		11	59	24	319	
credit score	mean	683.4	718.3	708.0	715.8	676.0
	dollar-weighted	684.8	717.8	713.0	715.1	
n		17	114			
credit grades:	AA	12%	13%			15%
	A	18%	26%	33%	46%	14%
	B	24%	29%	21%	26%	18%
	C	24%	22%	42%	23%	21%
	D	18%	7%	4%	5%	17%
	E	6%			1%	7%
	HR		3%			7%
Prosper score	median/mode	8/8	8/8	7/7&10	7/10	
	max/min	10/4	11/2	11/5	11/4	
	dollar-weighted median/mode	8/5	8/8	9/7	9/10	
Loan Outcomes						
n		17	114	24	319	
annual lender interest rate		16.68%	14.91%	11.27%	10.57%	16.60%
	standard deviation	6.1%	5.2%	3.55%	3.24%	6.8%
Standard variables						
n		17	113	24	319	
amount requested		$14,882	$11,909	$17,552	$16,595	$6,761
# of current delinquencies		0.2	0.1			0.8
amount delinquent		$84	$199			$855
	standard deviation	$268	$1,177			$4,504
	max	$1,096	$9,631			
# delinquencies (7 yrs.)		0.4	1.0	0.1	0.1	4.3
# public record requests (10 yrs.)		0.1	0.1	0.1	0.05	0.3
# public records (12 mos.)						0.03
# credit score inquiries (6 mos.)		0.9	0.9	0.6	0.6	2.4
total # credit lines		20	23	23	26	24
# current credit lines		9.2	9.9	N/A	N/A	9.7
# open credit lines		8.9	9.1	11.1	11.5	8.3
revolving credit balance		$11,120	$23,334	$15,600	$18,615	$16,773
	standard deviation	$9,799	$45,352	$10,942	$19,137	$38,030
	max	$34,019	$368,975	$46,768	$183,735	
bankcard utilization		48%	44%	N/A	N/A	54%
debt-to-income ratio		23%	18%	18%	17%	33%
length of credit history (mos.)		249	245	195	220	161
	standard deviation	131	89	74	89	86
	max/min	622/94	486/78	344/57	570/55	
% homeowners		59%	68%	67%	67%	48%
% self-employed		6%	8%	N/A	N/A	7%
% retired or not employed		6%			2%	3%
employment status (mos.)		126	96	72	73	23
annual income range:	$1-$24.99K		4%		2%	12%
	$25K-$49.99K	35%	12%	25%	20%	37%
	$50K-$74.99K	24%	28%	38%	28%	25%
	$75K-$99.99K	35%	31%	25%	28%	12%
	$100K+	6%	26%	13%	23%	10%

(continued on next page)

Table 1: Summary Statistics (Panel B)

		PROSPER		LENDING CLUB		ALL FUNDED
		Defaults	Nondefaults	Defaults	Nondefaults	Prosper loans Iyer, *et al.* (2009)
Non-standard variables						
listing category:	debt consolidation	47%	33%	50%	50%	26%
	credit card refi.	N/A	N/A	42%	30%	N/A
	home improvemt.	29%	35%	8%	5%	3%
	business		6%		0.3%	10%
	personal	6%	13%		2%	12%
	student		1%			2%
	auto		3%		0.3%	2%
	medical	N/A	N/A		0.9%	N/A
	other				2%	6%
	N/A	18%	10%			38%
individualized listing title		18%	51%			N/A
Previous prosper activity (through 2012)						
total # active loans		2	12			
total # loans		2	33			
average amount borrowed		$2,500	$5,823			
maximum amount borrowed		$3,000	$22,000			
avg. remaining principal balance		$1,864	$738			
avg. # on-time payments		13	22			
avg. # payments late (< 31 days)		1.0	0.4			

For clarity, entries for 0% are omitted. The delinquency and bankcard utilization comparisons are based on the Prosper data. Where we do not have comparable data for one platform, we show "N/A" for that platform. CREDIT SCORE: Both platforms report ranges for credit scores, although Prosper's are much wider: 4 points for LC and 19 points for Prosper. Prior to 2013, Prosper gives a "credit score history," and not every loan has a score listed. The counts are therefore smaller for this variable than for the Prosper sample as a whole. After 2013, "FICO08" scores are reported for all Prosper loans; ranges for these scores are not always consistent with the ranges given before 2013. On LC, the credit score ranges apply to listings; for loans, LC reports a single score. According to third-party sources, (e.g., http://www.doctorofcredit.com/use-lending-club-find-fico-score-range-free/m accessed 7-22-16), these are FICO scores of some type. CREDIT HISTORY: LC lists the number of delinquencies over the past two years; Prosper uses seven. CREDIT GRADE: Platforms issue grades based on proprietary models that change over time. Prosper grades from A to "high risk (HR)"; LC goes from A to G. On both platforms, grades below D are rare. EMPLOYMENT HISTORY: Prosper lists the number of months. LC gives annual terms between 1 and 9 years; anything less than 1 year is listed as "<1 year," and anything over 9 years is listed as "10+." We count months as 12(# of years) for 1-9 years; 6 for "<1 year," and 120 for "10+ years." DTI: For missing values, we use 33%, the average from Iyer, et al. (2009). This value is higher than the average reported in Herzenstein, et al. (2008) and in Paravisini, et al. (2010)—16.5% for funded loans/23.8% for unfunded, and 12.8%, respectively—from the early days of Prosper. Freedman and Jin (2008a) note that DTI data may be unreliable because it is borrower-reported. Other self-reported variables include self-employment and retired/not employed.*

One of the changes we have observed since 2009 is the increasing prevalence of debt consolidation loans. Our 2009 investment policy statement stipulated that we would not invest in these sorts of loans, and in 2011—when there seemed to be little else on Prosper—we moved most of our investing to Lending Club to increase our loan pool. However, since now almost 70% of Lending Club loans are for "refinancing or credit cards" (https://www.lendingclub.com/info/statistics.action, accessed 7/9/16), later member cohorts removed the prohibition on debt consolidation. Table 1 perhaps supports the initial members' position: half of our Prosper defaults and almost all of our LC defaults were debt consolidation/credit card refinancing loans. In contrast, only a third of Prosper's nondefaulting loans were refinancings. However, if refinancings are the majority of what we will have to choose from in the future, we must better understand the other listing features that correlate with default.

One of those features is loan size. While our sample is too small to detect significant differences, defaulted debt consolidation loans on Prosper (n = 8) are much larger than the other defaults (n = 9; p = 0.15). They have also grown larger over time: our first bad refi loan was for $6,000 in 2010; since 2014, all have been between $15,000 and $25,000. This rise may be partly a function of the platforms' rising maximums (Prosper started at a $25,000 maximum, which is now $35,000; LC's max is now $40,000). Nonetheless, the increasing prevalence of large debt consolidation listings is one of the reasons we now view the P2P market as less attractive. Size was not just bad for refi loans. In our portfolio, size was also bad across the board. Defaulted loans were 25% larger than performing loans on Prosper, and 5% on LC. On Prosper, 63% of nondefaulted loans were for less than $15,000, while only 29% of defaulted loans were; 35% of bad loans were for at least $20,000, while only 17% of good loans were. Results like these may help explain Freedman and Jin's (2008a) finding that that lenders responded more negatively to larger loans in later Prosper "regimes" (sets of rules). They could not "identify if this result is driven by a convex learning path over time or some changes in how lenders respond to the signal of a large loan as more information is available about the borrowers asking for these large loans," but—either way—larger loans are more dangerous.

Amounts for loans that defaulted also seemed to be more aggressively determined. All of these loans were for dollar amounts in multiples of $500, and 71% were for amounts in multiples of $5,000. If we assume that very specific dollar amounts are chosen with a carefully considered purpose in mind (e.g., based on a bid from a home improvement contractor), then large, round-number loan requests may be considered more aspirational ("this sounds like enough") and therefore signals of less creditworthy borrowers. It is clear that size (a loan feature) cannot be divorced from credit history (a borrower attribute). In the literature, there are competing stories about the size/credit relationship. (For example, see Feng, *et al.*, 2015 and Herzenstein, *et al.*, 2008; see also Fenn, 2000, for a similar dynamic in the 144-A market.) Iyer, *et al.* (2009) suggest that large requests can be a good sign when coming from higher-quality borrowers, who may have other funding alternatives. On the other hand, large requests from lower-quality borrowers may be opportunistic and linked to higher default risk. (LC apparently prefers this latter sort of argument, since it automatically downgrades larger loans. For example, increasing the requested amount from $7,475 to $25,000 for a borrower with a 701 FICO score translates into a rating drop from B to C3.) The "general" section in Panel A of Table 1 provides our portfolio's credit breakdown. On both platforms, about half of our defaults (and 75% of our debt consolidation loans) were in grades C and below. Only 30% of our performing loans were rated this low. For A/AA loans, it is almost a mirror image: only 30% of our defaults are in this category, while 39% (Prosper) and almost half (LC) of our performing loans are. Our last two member cohorts deliberately concentrated their lending in C loans to improve returns, so we expect increasing defaults until these loans season. (We have found that our bad loans tend to default by month 10. See also Freedman and Jin, 2008b.)

Table 1 also reports average credit scores for our portfolio loans. Both platforms report ranges for credit scores. The average credit score for our samples was found by weighting the midpoint of a given range by the proportion of loans in that range. Since not every loan was assigned a score, this average is merely suggestive. (Using the lower bound might be preferable, given the evidence of adverse selection within credit categories found in Freedman and Jin, 2008b and Iyer, *et al.*, 2009. However, such an adjustment simply shifts all of the values down; it does not change their relationships.) The dollar-weighted average credit score weights each score-category midpoint by the proportion of total dollars lent. Prosper's highest score range in our sample is "778+"; we use 800 as the upper limit for this range, although the maximum FICO08 score is 850. Not surprisingly, loans that defaulted had lower credit scores than those that did not. The difference was much more pronounced for Prosper loans, however; credit scores for defaulted LC loans were much higher than their counterparts on Prosper, and therefore much closer to the scores on the nondefaults. The final credit measure in Table 1 is the "Prosper score." Prosper assigns each listing a number between 1 (worst) and 11 (best) meant to reflect the probability that a loan will go at least 60 days past due within its first twelve months. Again, this is a proprietary score, developed using listings from 2008-2011 (Prosper, 2016). To create a comparison statistic for LC, we assigned three LC ratings to a given number from 2-11 (e.g., A1, A2, and A3 to "11"; F3, F4, and F5 to "2"), and all of the G ratings to "1." (Of course, this mapping is simply suggestive.) Scores for both platforms are similar. However, we found a higher mode for nondefaults on LC than on Prosper; lower extremes for defaults on Prosper; and more differences in extremes between good and bad loans on Prosper.

To complete our review of Table 1, we note that bad loans were also much less likely to have individualized listing titles. These are listing titles that vary *in any way* from the standard loan categories provided by Prosper: they can vary as insignificantly as "debt consolidation *loan*" rather than the standard "debt consolidation," or they can be more personal (such as "daughter is getting married!"). As described earlier, in the early days of P2P lending, potential borrowers often provided pictures and detailed narratives to support their requests. These sorts of "effort" inputs provided useful information to lenders, especially for listings in lower credit categories (Iyer, *et al.*, 2009). However, the listing title is the last remnant of this more interactive P2P market, as pictures, narratives, friend/leader endorsements, and question and answer capabilities have been removed. In our sample, just over half of our nondefaulting borrowers made the effort to create their own title, while only 18% of our defaulters did. If we restrict our sample to 2009-12—after which this sort of signal disappeared in our sample—we find that 71% of good loans have individualized titles, while only 33% of bad loans did. As the supply side of the P2P market has become more institutional, it appears that the listings have become correspondingly more like commodities. We saw similar trends in the mortgage market prior to 2008.

Default Model

We have experienced increasing numbers of defaults in recent years. To help guide future members' investments, we developed a simple logit model linking observable listing variables with default probability. This model is meant only as a rough guide. Nonetheless, we expect that it will be user-friendly and helpful for our members. We discuss this model in this section. Based on the summary statistics in Table 1, we identified credit grade, annual income, the debt-to-income ratio, revolving credit balance, loan type, loan amount, and loan term as the variables most clearly related to loan performance. We did not include homeownership, although there is an argument that homeowners may be more stable and have demonstrated the ability to get credit. However, we do not see much effect from homeownership in Table 1. In addition, Herzenstein, *et al.* (2008) and Kumar (2007) find that homeownership is not a significant determinant of funding success, and Funk, *et al.*, 2011, cite evidence that home ownership does not significantly affect rates on funded loans.

Our final variable mix includes both borrower- and loan-specific inputs. We augmented our sample of 473 portfolio loans with a stratified random sample of 1,500 loans from Lending Club's database of funded loans from 2007-2011 (available at https://www.lendingclub.com/info/download-data.action): 750 defaulted loans (13% of the population of 5,627 loans) and 750 nondefaults (2% of the 34,159 loans, 96.5% of which were fully paid as of June, 2016). (We omitted one of our 474 portfolio loans here, because Prosper did not have complete information on its listing details.) Given that 9% of our portfolio sample was defaults, and that we are using 10 independent variables for our model, the resulting 1,973-item sample should be sufficient for our purposes (given a minimum sample size required of 10*(10)/(.09) = 1,154; see Zaiontz, 2016). The results of our test are presented in Table 2.

The model is certainly adequate for our purposes. A chi-square test comparing the full model to an intercept-only model has a p-value << .00001 and a Nagelkerke R^2 of 0.241 (see Zaiontz, 2016). In our 2007-2011 sample, the model's sensitivity (true positive rate) is 57%, its specificity (true negative rate) is 84%, and its overall accuracy is 73%. These results are comparable to those from Serrano-Cinco, *et al.*'s, (2015) logistic default model, run on about 25,000 Lending Club loans; their accuracy was about 60% in their training sample and 75% in their test sample. Ceyhan *et al.*, 2011, also used stratified random sampling to test their logit models, finding 67% accuracy with their logit based on borrower and loan attributes

Table 2: Logit Default Model

	DESCRIPTION	COEFFICIENTS/VALUES
Logit Model Variable		
intercept		1.84
DTI	debt-to-income ratio	-3.12
purpose	1 for credit card or debt consolidation	1.28
credit grade=D or worse	1 if grade D, E, HR	2.53
credit grade=C	1 if grade C	1.60
credit grade=B	1 if grade B	1.43
loan size	natural log of amount borrowed	-0.47
revolving credit balance	natural log of current credit balance	-0.00004
income	1 if $75,000 or less	0.49
loan term	1 if 60 months	0.26
Statistics		
log-linear ratio R^2		0.146
Cox-Snell R^2		0.178
Nagelkerke R^2		0.241
sensitivity (true positive rate)		57%
positive predictive value		70%
specificity (true negative rate)		84%
negative predictive value		74%
overall accuracy		73%

Table 2 presents the results for a logit regression whose dependent variable is default probability. (We use realized defaults as a proxy for the ex ante default probability.) DTI, the debt-to-income ratio, is occasionally reported as "100000000%" on Prosper. For the 13 such cases in our portfolio (one default and 12 nondefaults), we substituted 33%, the average found in Iyer, et al. (2009). (We also tried substituting our Prosper portfolio's average DTI for the relevant year—information that would not be available to our members ex ante—and found similar results.) The purpose dummy equals one if the stated purpose for the loan is debt consolidation or "credit card"; almost half of our sample loans (981) fall into these categories, which we expect to be associated with poorer performance. The credit grade dummies equal one for their assigned grades (with "D or worse" handling everything below C), leaving grades A and AA to be picked up by the intercept. The annual income dummy is one for income of $75,000 or less. We chose to use a dummy here because Prosper only reports income ranges, not actual dollar amounts (and income can be unverified in any case); the $75,000 cutoff is based on Table 1, which shows that lower income ranges appear to have greater differential performance between defaults and nondefaults. Finally, the loan term dummy is one for 60-month loans, the longest possible term that a borrower can choose. Although the loan term and loan amount variables are strongly positively correlated (r = .31), we believe that there is marginal information that can be gleaned from the longer term: we expect longer loans to be riskier, and there is anecdotal evidence supporting that conjecture (see, for example, Renton, 2012).

To test the model out of sample, we also ran it on a sample of 1,500 Lending Club loans from 2015, split evenly between defaults and non-defaults. Since LC is now our primary platform, and more recent loans will reflect systematic changes on the platform, this is a more salient data set for our future members. We find a 67% true positive rate, a 54% true negative rate, 59% positive predictive value, and 62% negative predictive value. Accuracy was 60% (p-value << .00001), with a Nagelkerke R^2 of 0.87. Most of the coefficients have the expected signs. Longer term, lower credit grade, lower income, and debt consolidation purpose all predict higher risk of default. In contrast, DTI, loan amount, and revolving credit balance have negative coefficients. The last may be an artifact of the data scrubbing that occurs after bankruptcy. The negative effect of DTI is certainly counterintuitive. We note that, unconditionally, higher DTI is associated with default in the full 39,786-loan LC data set from 2007-11: DTI for defaults is 14.0%, v. 13.2% for nondefaults; p << .01. In our own portfolio, however, nondefaults had very slightly higher DTI, with a correlation coefficient between DTI and the default dummy of -0.03. In past research, DTI has not been found to be a particularly useful explanatory variable: for example, it was not one of the top 20 explanatory variables in Reddy's (2016) machine learning-derived model of Lending Club, nor was it significantly related to default probability in Kumar's (2007) study. To further examine the impact of DTI, we ran an (unreported) extension of the model using an interaction term between DTI and A-grade loans, based on Iyer, *et al.*'s (2009) finding that DTI is more informative (for *funding* success) in the higher credit grades. However, this enhancement had no noticeable effect on our results.

As for loan size, we note again that the theoretical relationship between size and risk is unclear. In Table 1, we saw that our portfolio's bad loans were larger than our good loans. In our default model's larger sample (as in Emekter, *et al.*'s, 2015, 64,000-loan LC sample), we see the opposite. Among these 1,973 loans, good loans were significantly larger for all but the lowest grades: from 17% higher for Bs to 29%

higher for Cs and As ($p < 0.01$). Only for the D grade are bad loans larger than good loans, and, even then, only by an insignificant 3%. Thus, the default model's positive link between size and good performance could be a reflection of the positive link between loan performance and credit grade.

More interestingly, the average size of the D loans was significantly higher than the average size of the other loan grades. This may reflect lower-quality borrowers' opportunism. On the other hand, if loan size is a positive signal among the lower-grade loans—as it appears to be in the higher grades—perhaps only larger requests are likely to be funded. Indeed, Herzenstein, *et al.* (2008) find that D and worse loans are much less likely than higher-grade loans to be funded (see also Weiss, *et al.*, 2010), so perhaps a lower-grade borrower's confidence to ask for a larger loan may mitigate his inherent funding disadvantage in this market. Serrano-Cinca, *et al.* (2015), discussing this murky size/credit relationship, conclude that "[w]hat matters is not only the size of the loan, but also the repayment capability of the borrower, and the loss given default." We expect all three of these features to collide for D-rated loans, given that we have found that lower-grade loans in our portfolio stop making contractual payments sooner than higher-grade loans do (see Livingston, 2017). To help us explore these links in our data, we added to our default model interaction terms between the log of the loan amount and the three grade dummies. The resulting logit (unreported) significantly improved over the original model ($p = 0.0003$). The worst loans had the strongest interaction effect: the coefficient on their interaction variable was 0.62 (compared to -.017 for C and 0.16 for B; the coefficient on D credit grade indicator actually switched sign to -3.26). Thus, while larger low-grade loans may be more likely to be funded, they are also more likely to default.

We would need to understand credit grade even if it did not interact with loan size. P2P platforms assign their grades using proprietary models based on traditional credit variables. For funding success, these "hard" variables are more "salient" for higher credit categories (Iyer, *et al.*, 2009). If they are also more salient for outcomes, then our logit model—which is heavily reliant on traditional variables—should perform better for the higher credit grades. However, our model actually provides more insight at the low end. While its accuracy does rise monotonically as we move up from D-or-worse (69% accurate) to AA/A (79%), the model is much more sensitive for the worst loans, with a true positive rate of 85%. In fact, the accuracy for the best loans is solely a function of the true negative rate of 99%; the model is unable to identify even one of the 99 of 492 top-grade loans that actually defaulted. Thus, at the top, our model gives us no more insight that a simple assumption that all top-grade loans do not default. However, for the worst loans, our model significantly improves upon an "all bad loans default" heuristic, doing a much better job of identifying the best of the worst.

One explanation for our failure to distinguish among performing and nonperforming high-quality loans is that we lumped all A loans together—A and AA on Prosper, A1-A5 on Lending Club. Given the adverse selection among borrowers documented by Freedman and Jin (2008b) and the varying default rates found within credit categories found by Iyer, *et al.* (2009), we should not expect all loans of the same grade to be equally likely to perform. As a quick check, we used our 1,500-loan LC sample to test the relative performance of different subgrades of A loans. We can strongly reject the hypothesis that all five subgrades perform the same way: we find no defaults among the 23 A1 loans, but 34 among the 91 A5 loans (40%). The number and percentage of defaults rises monotonically as subgrade level falls, and a chi square test of equal performance gives a p-value $\ll .0001$. Thus, we conclude that part of the poor true positive rate from our logit comes from a too-broad classification of higher-grade loans. We will therefore require our future members to consider subgrades of these loans as completely separate "risk buckets." Having surveyed our loan data and its default characteristics, we turn now to our realized returns.

Returns

Table 3 summarizes our returns from both platforms. For Prosper, we describe a census (all 131 loans) to provide a baseline. For LC, we use a comparison sample of 117 notes (34% of our LC loans). This LC sample closely matches the grade breakdown of the full 343-loan LC portfolio, and includes nine defaults (7.7%). The top panel shows gross return data by note. Each note's monthly returns—interest over prior principal balance—are averaged, then those note averages are averaged again by credit grade. The other three panels average by month, giving both gross returns (second panel) and net (last two panels). The final panel includes the effects of charge-offs, as well as of all fees. Average returns generally rise as grade falls. (On Prosper, the exception is caused by a single E loan, which returned more than the three HR loans during the three short months it performed before defaulting.) The returns by month are slightly higher (though more variable) than the per-note returns, so we do a bit better when loans remain active longer. Fees obviously have a significant impact on returns, decreasing average returns by an average of 8-13 bp/month—ranging from 8-18 bp/month on Prosper, and 3-11 bp/month on LC. Given the standard fee structure (about 1% per loan), fee burdens are generally higher at the better credit grades. Prosper's fee burden (defined as [1 – net return/gross return]) is higher than LC's for all grades except for the highest-rated A loans. Defaults have a profound effect, lowering both platforms' grade-weighted monthly averages by over 50 bp/month. However, even accounting for defaults, we generate weighted average returns in the AA-D grades of between 34 and 82 bp/month (on LC and Prosper, respectively).

If we aggregate the net returns (including charge-offs), we find portfolio-level monthly returns on Prosper that average 86 bp (maximum = 1.81%; minimum = -5.36%; standard deviation = 1.2%). LC's returns are lower but less variable, averaging 57 bp with a standard deviation of 0.7% (maximum = 1.08%; minimum = -2.28%). The chain-linked return over our full 78-month Prosper history is 93.27%, implying a geometric average monthly return of 85 bp and an effective annual rate of 10.7%; our 52-month LC history averages 56 bp/month, or almost 7%/year. Accounting for our deposits and withdrawals on Prosper, we find a money-weighted return (IRR) of 51 bp per month, for an EAR of 6.3%. Our returns align with those described in the literature. Freedman and Jin (2008a) use their performance model to estimate an expected net return on funded loans of about 6%/year. Paravisini, *et al.*'s (2010), using panel data from Lending Club, find that investors expect a high level of covariance between their P2P returns and the broad market—a covariance that translates into an average risk premium of 9%. The sample periods for these papers were 2006-7 (a market in which the S&P500's return was almost 7%, and the average three-year Treasury yielded about 4.5%) and 2007-8 (an extremely turbulent market), respectively. Nonetheless, their results and ours demonstrate that P2P lending provides investors a premium for the risk they bear.

This is inconsistent with the contention of Herzenstein, *et al.* (2008) that bank savings accounts are the relevant default option for P2P lenders. Table 3 makes clear that our loans are much riskier than savings accounts, consistent with Freedman and Jin's (2008a) description of P2P returns' being "more dispersed" (and less liquid) than CDs and T-bills. Given that well over half of LC's lenders—whose profile is young, male, single, urban, and of high net worth—report being interested in the platform because of the potential to earn high returns (Paravisini, *et al.*, 2010), it is important to recognize P2P lending as much riskier than simple saving, and to assess its returns accordingly.

Table 3: Return Summary

	BY NOTE: PROSPER					BY NOTE: LENDING CLUB				
	Mean	Standard Deviation	Max	Min	N	Mean	Standard Deviation	Max	Min	N
AA	0.76%	0.13%	0.93%	0.42%	18	0.52%	0.05%	0.58%	0.36%	14
A	0.95%	0.15%	1.24%	0.71%	32	0.64%	0.09%	0.75%	0.20%	39
B	1.19%	0.20%	1.67%	0.72%	37	0.96%	0.16%	1.17%	0.36%	29
C	1.48%	0.26%	2.30%	1.10%	29	1.07%	0.16%	1.40%	0.64%	28
D	1.95%	0.31%	2.59%	1.59%	11	1.27%	0.31%	1.64%	0.72%	6
E	2.83%	N/A			1	1.62%	N/A			1
HR	2.53%	0.22%	2.73%	2.22%	3					
	BY MONTH (GROSS): PROSPER					BY MONTH (GROSS): LENDING CLUB				
	Mean	Standard Deviation	Max	Min	N	Mean	Standard Deviation	Max	Min	N
AA	0.81%	0.22%	2.43%	0.00%	414	0.52%	0.18%	2.18%	0.00%	288
A	0.97%	0.29%	5.77%	0.00%	866	0.64%	0.09%	1.32%	0.00%	840
B	1.24%	0.33%	3.85%	0.00%	832	0.97%	0.23%	3.33%	0.00%	538
C	1.50%	0.55%	7.45%	0.00%	534	1.10%	0.36%	2.93%	0.00%	445
D	2.01%	0.71%	7.97%	0.00%	187	1.38%	0.40%	1.66%	0.00%	102
E	2.83%	0.46%	3.51%	2.20%	4	1.62%	0.03%	1.64%	1.52%	14
HR	2.51%	0.38%	3.73%	0.00%	74					
	BY MONTH (NET): PROSPER					BY MONTH (NET): LENDING CLUB				
	Mean	Standard Deviation	Max	Min	N	Mean	Standard Deviation	Max	Min	N
AA	0.73%	0.19%	2.21%	-0.39%	411	0.41%	0.26%	1.42%	-0.81%	288
A	0.84%	0.42%	5.77%	-5.96%	907	0.57%	0.16%	1.24%	-0.99%	839
B	1.05%	1.15%	2.69%	-24.82%	831	0.88%	0.25%	2.96%	-0.57%	536
C	1.41%	0.51%	6.87%	0.00%	534	1.05%	0.36%	2.74%	-0.62%	445
D	1.92%	0.68%	7.27%	-0.09%	187	1.35%	0.39%	1.63%	0.00%	102
E	2.74%	0.45%	3.40%	2.14%	4	1.58%	0.03%	1.60%	1.48%	14
HR	2.34%	0.60%	3.67%	0.00%	77					
	BY MONTH (NET, W/CHARGE-OFFS): PROSPER					BY MONTH (NET, W/CHARGE-OFFS): LENDING CLUB				
	Mean	Standard Deviation	Max	Min	N	Mean	Standard Deviation	Max	Min	N
AA	0.26%	6.75%	2.21%	-96.66%	411	-0.29%	8.36%	1.42%	-100%	288
A	0.64%	4.42%	5.77%	-100.0%	907	0.45%	3.48%	1.24%	-100%	839
B	0.82%	4.88%	2.69%	-95.88%	831	0.69%	4.36%	2.96%	-100%	536
C	1.23%	4.22%	6.87%	-95.39%	534	0.15%	9.56%	2.74%	-100%	445
D	1.51%	5.66%	7.27%	-75.12%	187	0.36%	10.04%	1.63%	-100%	102
E	-21.8%	42.47%	3.40%	-95.31%	4	1.58%	0.03%	1.60%	1.48%	14
HR	2.34%	0.60%	3.67%	0.00%	77					

This table presents the returns from all of our Prosper loans and from a sample of our LC loans. The top panel starts with the average return for each note, then averages those note returns by credit grade. The counts in this panel are the number of notes. The rest of the panels average by month, so they account for the different numbers of months over which different loans pay off. The counts for these panels are the number of months. The top two panels present gross returns, incorporating only interest inflows. The bottom two panels account for all fees, including late fees, service fees, "Prosper fees," and collection fees. The last panel also incorporates the write-off of remaining principal at default. Grade AA includes LC grades A1 and A2; grade A includes LC's A3 through A5. The LC sample was chosen by stratified random sampling. In this sample, all grades match their population values, except that high-A is slightly oversampled (12% in sample v. 11% in population) while low-A is slightly undersampled (33% v. 34%). This should lead to a slightly understatement of our chain-linked returns. Our 7.7% default frequency is slightly higher than the population's (7.3%).

CONCLUSION

We have presented default and return results describing the performance of our student-managed fund's peer-to-peer portfolio over its first seven years. Like all SMFs, our portfolio has given our student-managers a chance to run real money in real time. Unlike other SMFs, however, our fund is small and debt-focused. The P2P market has allowed our students to perform meaningful credit analysis, and the amortizing nature of the loans has ensured monthly cash flows that provide ongoing investment opportunities. Our fund is also unique in that it is structured as an independent 501(c)(3), offering student-managers much more autonomy and accountability than they would have under a traditional university-embedded framework. However, the P2P market is "evolving" in ways that may make it less attractive to us going forward. First, the platforms have changed the way borrowers can present themselves and interact with lenders. Second, the market is being overrun by institutional investors, crowding out retail lenders like us. The changes are not independent; both are part of thecommoditization of P2P loans. The platform changes have eliminated many of the analytical opportunities that provided our student-managers with engaging, relevant experience. Borrowers no longer post narratives describing their requests and planned repayment budgets. They no longer post pictures. They no longer answer questions posed by potential lenders. Lenders are no longer able to bid for loans in auctions, a process that drove down rates for attractive borrowers. In short, the platforms have eliminated the ability of "peers" to use soft, qualitative information to assess borrowers' creditworthiness and to translate their opinions into lower rates for good borrowers. Given that lenders are able to divine meaningful insights from soft information (Iyer, *et al*., 2009; Herzenstein, *et al.*, 2008; Duarte, *et al.*, 2009), and that soft information is most useful when evaluating lower-rated borrowers (Iyer, *et al*., 2009), it is difficult to argue that the changes have improved market quality. If borrowers cannot signal, and retail lenders cannot screen, the potential for trust (and consciousness of kind and moral obligation) that can made these markets useful for both lenders and the underbanked is undermined. The demise of "non-hierarchical," "disintermediated," "egalitarian" lending will imply less credit access for those already poorly served by traditional banks.

Advocates of P2P's evolution would counter that what is lost in transparency has been made up in liquidity. As the platforms have matured, they have drawn the interest of institutional investors (Moenninghoff and Wieandt, 2013). According to Price Waterhouse Coopers, these institutions now account for about 80% of funding on the P2P platforms. One bank has been buying $2M per month since 2013; others have committing a total of more than $200M. These lenders crowd out "peer" lenders with their size, speed, and technology. We cannot compete against these sorts of advantages, and—given the loans that are left—we are not sure we want to. We are therefore moving beyond the P2P market, especially the more opaque Prosper platform, and have added equities and Treasuries to our portfolio. As the institutions make the peer market more like the traditional lending market, they are forcing us to become more like a traditional student-managed fund.

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