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RETURNS AND ATTRIBUTION FROM A STUDENT-MANAGED PEER-TO-PEER LOAN FUND

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ABSTRACT

Many business schools run equity-based student-managed funds. However, few extend that experiential learning opportunity to incorporate fixed-income assets. In this paper, we report the seven-year results from a unique student-managed fund of peer-to-peer (P2P) loans. The minimum investment in these loans is low enough to allow even the smallest schools to offer students opportunities for meaningful, ongoing credit analysis. Our results show that P2P returns can be high, that defaults are significant, and that active management can add value in this market. They also support our contention that the institutional money now swamping the market is making P2P lending less attractive for retail investors.

JEL: G11, G21

KEYWORDS: Student Managed Funds; Peer-To-Peer Lending

INTRODUCTION

Managing real money through a student-managed fund is an exciting and meaningful learning opportunity for business students. Hundreds of business schools have now linked their curricula to this sort of hands-on experience (see, for example, Peng, *et al.*, 2009, Clinebell, *et al.*, 2008, and Morgan, 2008). Most student funds focus heavily on equity, range in size from hundreds of thousands to millions of dollars, and are tied to their universities through professor oversight and endowment funding. However, our fund is different. Our fund is small, focused on fixed income, and completely independent from our university. It is structured as a 501(c)(3) not-for-profit corporation, which allows us to run the fund without oversight by the university's administration or constraints from its endowment policy. Of course, "no endowment constraints" also means "no endowment money." Since fixed-income funds usually need to be magnitudes larger than equity funds—to accommodate bonds' large round-lot sizes—we needed a way to significantly scale down traditional debt investing. We found it through the peer-to-peer (P2P) market.

The P2P market was designed to allow retail investors to fund small personal loans. Lenders can offer amounts as low as $25 to a potential borrower; if the borrower attracts enough lender interest to fund her request fully, a loan is created. Lenders receive "notes" for their pieces of the loan, and cash flows occur monthly as the underlying loan amortizes. This structure is ideal for our purposes: it allows us to create a well-diversified fund with a small initial investment; it allows our student-managers to conduct meaningful credit analysis on a plethora of consumer loans; and it generates ongoing inflows that permit continual reinvestment. To date, our fund has been successful, earning between 6% and 10% per year on each of the two platforms we use. However, the future may not be as bright. The P2P market is changing rapidly as professional investors have recognized its potential for superior returns. Institutions have created multi-million dollar funds to invest in P2P loans, swamping the market and crowding out the "peer" lenders. Thus, despite our past success in this market, our fund will probably no longer have access to its best loan opportunities, and will have to move into more traditional asset classes as we continue to grow. The paper proceeds as follows. In the next section, we briefly review the relevant literature on student-managed funds and peer-to-peer lending. We then describe our fund and its returns since inception, and we provide an attribution analysis ascribing our results to credit quality allocation, loan choice, and loan weighting. Finally, we consider how our business model is threatened by market evolution.

Background and Literature Review

Our work links research on student-managed funds (SMFs) with that on peer-to-peer lending. We consider both in this section. Student-managed funds are investment pools owned by universities and managed by their students. Schools establish these funds to provide meaningful experiential learning opportunities to their business students, and many offer those students access to professional resources such as dedicated trading rooms and Bloomberg terminals (Peng, *et al.*, 2009; Mallett and Lerro, 2001). Schools usually commit to the funds, regardless of returns, but—consistent with the educational purpose of SMFs—require student managers to undertake specific academic or extracurricular training. Faculty mentors provide ongoing monitoring (and possibly veto power over investments). Allowable strategies and asset classes are usually prescribed by the university, and governing documents are designed to be consistent with the Investment Company Act of 1940 (Mallett and Lerro, 2001; Morgan, 2008).

These sorts of funds have been around since the 1950s (Peng, *et al.*, 2009; see also Mallett and Lerro, 2001, for an overview of early literature on specific universities' early funds). However, over the last twenty years or so, they have gone from a curiosity to a staple at business schools around the world, with hundreds in the U.S. alone (Clinebell, *et al.*, 2008; Morgan, 2008). In fact, in 2001, Mallett and Lerro concluded that their "analysis indicates that student-managed programs will become the norm for business students, rather than the exception." To establish an SMF, schools usually get seed funding from individual donations or from the university's endowment. It is very rare for a fund to be smaller than \$100,000—the median amount Mallett and Lerro's (2001) sample, and the amount they deemed "reasonable to start a diversified equity portfolio." In Peng, *et al.*'s (2009) 33-fund sample, only six were below this threshold. In contrast, the median fund size was \$460,000, and the average \$1.44 M. Many funds are even much larger than this. Three (9%) of Peng, *et al.*'s (2009) sample were above \$3 M, one of which exceeded \$10 M; four of Morgan's (2008) funds exceeded \$5 M, one of which—Iowa State University's—clocked in at \$100 M.

One of the most important characteristics determining a fund's optimal size is its asset allocation. Funds that focus on debt are usually much larger than equity funds. Bond transaction sizes are huge relative to equity: a bond trade of \$100,000 is considered "very small" in a market where a round lot requires at least \$1 M (Estabrook, 2015; Perrotta, 2014). Thus, one small trade would consume a large proportion of the average SMF's capital. It is not surprising, therefore, that in Morgan's (2008) sample, debt funds are two to three times larger than the average equity fund. All of the \$5-\$100 M funds mentioned above are debt funds. Size is not the only hurdle to running a fixed-income fund. If we consider other practical difficulties—for example, that bonds are relatively illiquid and expensive to trade—it is perhaps not surprising that the vast majority of SMFs focus on equity investing (Morgan, 2008). Peng, *et al.* (2009), in their survey of 35 SMFs, find that 24 (69%) of them use at least 90% equity, while only one uses none. Only five of the funds indicate that they periodically switch their focus between equity to debt; 86% maintain their asset allocation, and therefore their concentration on equities. Morgan's (2008) findings echo this focus on equity. Two-thirds of his funds have at least 90% in stocks. Less than a quarter mix in a meaningful—but still a minority—amount of debt, averaging 22% in fixed-income. Only 14% actually emphasize debt: the 6% of his funds restricted to bonds, and another 8% that effectively act as if they are (holding at least 95% in bonds). Morgan (2008) worries that the large required size of debt funds makes it "harder to increase the level of practical education to both students and corporate America." The traditional scale certainly would have been an insurmountable obstacle for us. Unlike every other fund that we are aware of, ours is not sponsored by our university. Instead, it is part of a 501(c)(3) not-for-profit corporation set up by a group of students (after our university refused to allow any institutional funds—even targeted donations—to be managed by students). We knew that we were never going to be able to raise enough money for a well-diversified equity fund, much less for a fixed-income fund. We also knew that we wanted our fund to be about helping people, not just about profit. We had to think outside the box to find the ideal instrument for our needs: peer-to-peer loans.

Peer-to-peer (P2P) loans are unsecured personal loans. The market was conceived as a way for retail investors—like the proverbial dentist who wanted to diversify his portfolio—to provide small loans to borrowers who needed money for things like home renovations or weddings. Lenders and borrowers find each other through an online platform like Prosper or Lending Club (LC). (See Herzenstein, *et al.*, 2008, Iyer, *et al.*, 2009, and Freedman and Jin, 2008a, for descriptions of the early operations of these U.S. P2P markets.) Potential borrowers provide basic background information to a platform, which runs a credit check. The platform then assigns the loan request a credit grade based on borrower and loan characteristics. (For example, LC automatically reduces the grade on a loan request for amounts larger than certain pre-determined thresholds.) Requests accepted by the platform become "listings" on the site, available for perusal by lenders. Lenders screen loans and bid on those they wish to fund. Lenders may bid as little as $25 per loan, and listings become funded loans if they garner enough lender bids to provide the amount requested. The funding for successful listings actually comes from a bank associated with the platform; in turn, the platform issues "notes" to the lenders for their bid amount. As the borrowers make their monthly payments, the platform passes them along—principal and interest, less the platform's fee—to the associated lenders.

In the early days of P2P lending, borrowers were able to craft individualized loan requests to entice lenders. Motivated borrowers gave detailed justifications for their requests, including proposed budgets, descriptions of their families, and even pictures. Lenders were also able to interact with borrowers through a platform's Q&A feature. The insight that lenders gleaned from this qualitative, "soft" data was meaningful. For example, Iyer, *et al.* (2009) estimated that lenders were able to use this sort of data to infer up to one-third of the credit information they could get form a traditional credit score. Duarte, Siegel, and Young (2009) found that lenders could use "physiognomy-based proxies" from posted pictures to predict default and assess trustworthiness, even when lenders also had access to traditional credit variables. (Borrowers must have appreciated pictures' value, since over 60% of listings included them.) Herzenstein, *et al.* (2008), using a sample of over 5,000 Prosper listings, find that 91% of the requests that demonstrated effort—like the provision of qualitative data—were funded. These authors concluded that P2P markets encourage "relational" lending, with the potential to allow traditionally underserved groups (like women) to access credit more easily. They therefore pronounced P2P to be the great "democratizer" of credit. It certainly was the great democratizer of the student-managed fund, at least for us. In the next section, we describe the portfolio we were able to build in this market.

Portfolio Description and Returns

We started our Prosper portfolio in 2009. We have invested in a total of 131 notes, thirty of which are still active, and ten of which have been charged off. In 2011, we expanded to Lending Club, where we have invested in 344 notes, of which 179 are current and 19 have been charged off. In this section, we summarize the returns from this portfolio; describe the number of months of contractual payments from our loans; and attribute performance to active bets on credit grades, loan size, and loan choice.

Portfolio Overview

Table 1 describes all 475 of our peer-to-peer note investments. We characterize these notes by platform, credit grade, performance, and size. Our Prosper portfolio, which is older, exhibits more dispersion in loan characteristics. We started this in the very early days of P2P, and our first few member cohorts were able to experiment with Prosper's initial latitude on loan sizes and borrower quality. This part of the portfolio is relatively seasoned, so Table 1's default statistics should adequately describe its performance. In contrast, the Lending Club portfolio is newer and more concentrated. Since we will focus our lending on LC going forward, this part of the portfolio will be more affected by the platform changes that we discuss later, and we therefore are less confident that our current default experience will extrapolate.

Table 1: Summary of P2P Portfolio

	PROSPER				**LENDING CLUB**			
	Defaults		**Nondefaults**		**Defaults**		**Nondefaults**	
	number	**%**	**Number**	**%**	**Number**	**%**	**Number**	**%**
n	10		121		19		325	
credit grades:								
AA	2	20%	16	13%	4	21%	33	10%
A	3	30%	29	24%	4	21%	113	35%
B	2	20%	35	29%	3	16%	85	26%
C	1	10%	28	23%	7	37%	75	23%
D	1	10%	10	8%	1	5%	17	5%
E	1	10%					2	1%
HR			3	2%				
standard note sizes:								
$25	5	56%	42	36%	14	74%	238	73%
$50	4	44%	71	61%	4	21%	80	25%
$75			2	2%	1	5%	7	2%
$100			1	1%				
nonstandard sizes:								
n	1		5		N/A		N/A	
average	$72.00		$62.84					
maximum			$157.00					
minimum			$39.58					

This table summarizes all of our notes on our two P2P platforms. Both platforms assign credit grades to loans, although their systems are different. The taxonomy in the table is Prosper's. LC uses letter grades A-G, plus subgrades numbered 1 (highest) to 5 (lowest). We have included grades A1 and A2 in the "AA" category. "Note sizes" provide the initial amount of our investment in a given loan. As we have moved more of our lending to LC, we have shifted toward higher-grade loans and have concentrated on $25 note sizes. "Defaults" are notes that have been charged off. We have experienced meaningful defaults among higher-grade and smaller loans on both platforms.

On both platforms, we have invested in notes across the credit spectrum. However, as we have moved more of our lending activity to LC, we have also concentrated more deliberately on higher-quality loans. 45% of our performing LC loans are for A grades, compared to 37% on Prosper. The 35% of our performing LC portfolio in the lower-grade As is especially notable, not only compared to the 24% of our portfolio at this grade on Prosper, but also relative to the LC platform overall (only 17% of whose originations from 2011-16 were A loans; LC, 2016). An even bigger difference between the Prosper and LC parts of our portfolio is note size. On both platforms, the minimum lender bid is for $25. In our LC portfolio, our loans are predominantly at this minimum level, while the majority of our Prosper loans are twice as large. This reflects an evolution in our members' approaches to lending: early cohorts, who used Prosper, took $50 as the expected investment, reducing allocations for less attractive loans; later cohorts, using LC, use a base amount of $25, only investing more in highly attractive loans.

We have experienced significant defaults on both platforms. We have written off almost 8% and 6% of our notes (both by number and by principal) on Prosper and LC, respectively. Perhaps reflecting our early members' strategy, $25 Prosper loans defaulted at a much higher rate than both $25 LC loans and larger Prosper loans. Half of our Prosper defaults were in A loans, as were 42% of our LC defaults. Our C-grade loans performed much worse on LC, accounting for another 37% of platform write-offs. Most of our defaults occur during the first 10 months or so (consistent with Freedman and Jin, 2008b). On Prosper, our exposure at default (EAD) is about 70% of principal (data not shown), with the proportion of EAD lost given default (LGD) of 88%; on Lending Club, our EAD is higher, at about 79% of principal, with similar LGD.

Portfolio Returns

We have used multiple measures to evaluate our returns. In this section, we report time-weighted, money-weighted, and holding period returns for notes on both platforms. For the Prosper notes, we report results for our full portfolio of 131 notes. For Lending Club, we use a random sample of 157 of our 344 notes. This sample closely matches the credit grade distribution of the Prosper sample, and includes 10 (6.4%) defaults. We start with the big picture. Using our complete Prosper portfolio for its full 78-month history, and accounting for all fees and charge-offs, we find a chain-linked holding-period return of just over 93%. This implies a geometric average monthly return of 84 bp, or an effective annual rate of 10.5%. Accounting for deposits and withdrawals, we find a money-weighted return (IRR) of 51 bp/month, for an EAR of 6.3%. For the 157-note Lending Club sample, the chain-linked return over 53 months is 41%, for an average monthly return of 65 bp and an EAR of 8%. The magnitude of these returns is consistent with reports in the literature (e.g., Freedman and Jin, 2008a; Paravisini, *et al.*, 2010).

For a more granular analysis, we start by presenting our holding period returns. Table 2 describes these HPRs both by note and by month. For the by-note returns, presented in the top panel, we first find a note's monthly gross returns (interest income for the month divided by the prior month's principal balance). We then average that note's monthly returns arithmetically, then average again with the returns of other notes in its credit grade. In the other three panels of Table 2, we report results by month—all of the monthly returns for all notes in a given credit grade are averaged arithmetically. In the second panel, these returns are gross; in the third, all platform fees are deducted; and in the last, all fees and principal lost to default are deducted. In Table 3, we present the IRRs for each note, which are averaged by credit grade. We include only those notes from Table 2 that either have been paid in full or have defaulted. In this table, we break out all LC notes by subgrade. To help visualize the data, in Figure 1, we plot the monthly net Prosper HPRs (from the third panel of Table 2) and the all IRRs (from Table 3) against the (monthly) stated rates for each loan.

Tables 2 and 3 give us the same basic story. Returns generally rise as credit grade falls. Returns on Prosper are higher than on LC; these return differences are highly statistically significant ($p << .01$) for all credit grades in both tables. In Table 3, we see that some defaulting loans generated severely negative IRRs. However, the bottom panel in Table 2 demonstrates that the portfolio continued to perform well, despite these write-offs. Tables 2 and 3 also provide information on the standard deviations of our realized returns. On Prosper, standard deviations tend to rise as credit grade falls. Prosper returns' standard deviations are almost all larger than those on Lending Club, and these differences are highly statistically significant ($p < .02$). In Table 2, the few cases where the LC portfolio is more variable are driven by fees and defaults. In Table 3, the one case for which the LC standard deviation is higher—the C loans—is a consequence of one nondefaulting loan's paying off so fast that its IRR was dragged below zero by platform fees.

Table 2: Holding Period Returns

	BY NOTE: PROSPER					**BY NOTE: LENDING CLUB**				
	average	standard deviation	max	min	count	average	standard deviation	max	min	count
AA (A1/A2)	0.76%	0.13%*	0.93%	0.42%	18	0.52%	0.04%	0.58%	0.36%	21
A (A3-A5)	0.95%	0.15%*	1.24%	0.71%	32	0.64%	0.09%	0.75%	0.20%	40
B	1.19%	0.20%*	1.67%	0.72%	37	0.94%	0.15%	1.17%	0.36%	45
C	1.48%	0.26%*	2.30%	1.10%	29	1.07%	0.17%	1.40%	0.64%	35
D	1.95%	0.31%	2.59%	1.59%	11	1.36%	0.21%	1.64%	0.72%	14
E	2.83%	N/A			1	1.54%	0.12%	1.62%	1.45%	2
HR	2.53%	0.22%	2.73%	2.22%	3					
	BY MONTH (GROSS): PROSPER					**BY MONTH (GROSS): LENDING CLUB**				
	average	standard deviation	max	min	count	average	standard deviation	max	min	count
AA (A1/A2)	0.81%	0.22%*	2.43%	0.00%	414	0.52%	0.15%	2.18%	0.00%	437
A (A3-A5)	0.97%	0.29%*	5.77%	0.00%	866	0.65%	0.09%	1.32%	0.00%	867
B	1.24%	0.33%*	3.85%	0.00%	832	0.95%	0.20%	3.33%	0.00%	928
C	1.50%	0.55%*	7.45%	0.00%	534	1.11%	0.34%	2.93%	0.00%	540
D	2.01%	0.71%*	7.97%	0.00%	187	1.40%	0.30%	1.88%	0.00%	205
E	2.83%	0.46%	3.51%	2.20%	4	1.55%	0.34%	1.69%	0.00%	23
HR	2.51%	0.38%	3.73%	0.00%	74					
	BY MONTH (NET): PROSPER					**BY MONTH (NET): LENDING CLUB**				
	average	standard deviation	max	min	count	average	standard deviation	max	min	count
AA (A1/A2)	0.73%	0.19%	2.21%	-0.39%	411	0.41%	0.24%	1.42%	-1.15%	438
A (A3-A5)	0.84%	0.42%*	5.77%	-5.96%	907	0.57%	0.16%	1.24%	-0.99%	866
B	1.05%	1.15%*	2.69%	-24.82%	831	0.86%	0.22%	2.96%	-0.57%	926
C	1.41%	0.51%*	6.87%	0.00%	534	1.06%	0.33%	2.74%	-0.62%	540
D	1.92%	0.68%*	7.27%	-0.09%	187	1.37%	0.30%	1.86%	0.00%	205
E	2.74%	0.45%	3.40%	2.14%	4	1.51%	0.34%	1.64%	0.00%	23
HR	2.34%	0.60%	3.67%	0.00%	77					
	BY MONTH (W/CHARGE-OFFS): PROSPER					**BY MONTH (W/CHARGE-OFFS): LENDING CLUB**				
	average	standard deviation	max	min	count	average	standard deviation	max	min	count
AA (A1/A2)	0.26%	6.75%	2.21%	-96.66%	411	-0.05%	6.78%	1.42%	-100%	438
A (A3-A5)	0.64%	4.42%*	5.77%	-100.07%	907	0.45%	3.42%	1.24%	-100%	866
B	0.82%	4.88%*	2.69%	-95.88%	831	0.75%	3.32%	2.96%	-100%	926
C	1.23%	4.22%*	6.87%	-95.39%	534	0.32%	8.68%	2.74%	-100%	540
D	1.51%	5.66%	7.27%	-75.12%	187	0.88%	7.09%	1.86%	-100%	205
E	-21.75%	42.47%	3.40%	-95.31%	4	1.51%	0.34%	1.64%	0.00%	23
HR	2.34%	0.60%	3.67%	0.00%	77					

This table breaks down our holding period returns for our 131-note full Prosper portfolio and our 157-note Lending Club sample. The top panel lists average gross returns by note (interest income $_t$/principal balance$_{t-1}$). The rest of the panels provide returns by month. The second panel lists gross returns; the third, returns after platform fees; and the last, returns after both fees and defaults. Returns tend to rise with credit grade. Returns are generally higher and more variable on Prosper. Prosper standard deviations marked with an asterisk are significantly higher than the corresponding LC values, using alpha = .02.

Both the return and the variability results just discussed are driven partially by the changes in the platforms over time. The stated rates on early Prosper loans were set by lender auctions, and—even if these auctions were not as robust as initially envisaged—this process introduced loan-specific differences into our Prosper portfolio. We therefore observe much more variability in our Prosper loans' performance than in our LC loans' (given the strong correlation between promised and realized returns documented in Figure 1). Now, rates are set by platforms. On LC, all notes of the same credit subgrade are assigned the same rate, and rates for new loans change only "periodically," based on macroeconomic conditions and platform experience. On Prosper, a given letter credit grade is associated with a variety of rate ranges; the platform assigns a specific rate based on a borrower's credit score. However, since Prosper simply breaks a credit letter grade into credit score ranges, rather than explicitly using credit letter subgrades, this is effectively equivalent to LC's process. Given these changes, we expect that future returns—at least the *ex ante* ones—will be more comparable on the platforms, and less variable overall.

Table 3: Internal Rates of Return

IRRs BY NOTE: LENDING CLUB										
	Defaults					Nondefaults				
	Average	Standard Deviation	Max	Min	Count	Average	Standard Deviation	Max	Min	Count
A1						0.40%	0.07%	0.49%	0.32%	4
A2	-18.54%				1	0.47%	0.06%	0.51%	0.36%	6
A3						0.51%	0.05%	0.58%	0.46%	6
A4	-64.23%				1	0.47%	0.22%	0.58%	-0.04%	7
A5						0.64%	0.05%	0.68%	0.56%	5
all A						0.50%	0.14%	0.68%	-0.04%	28
B1	-47.22%				1	0.73%	0.07%	0.78%	0.68%	2
B2						0.81%	0.03%	0.83%	0.77%	3
B3						0.92%	0.02%	0.93%	0.90%	4
B4						0.99%	0.04%	1.02%	0.94%	4
B5						1.00%	0.10%	1.10%	0.88%	5
all B						0.92%	0.11%	1.10%	0.68%	18
C1	-14.74%	2.19%	-13.19%	-16.28%	2					
C3						0.76%	0.79%	1.15%	-0.66%	5
C5						1.17%				1
all C						0.83%	0.73%	1.17%	-0.66%	6
D3	-13.34%				1					
D4	-36.96%				1					
IRRs BY NOTE: PROSPER										
	Defaults					Nondefaults				
	Average	Standard Deviation	Max	Min	Count	Average	Standard Deviation	Max	Min	Count
AA	-2.34%	1.98%	-0.94%	-3.73%	2	0.65%	0.10%	0.80%	0.41%	14
A	-8.59%	12.87%	-0.21%	-23.40%	3	0.87%	0.16%	1.14%	0.49%	28
B	-16.36%	3.88%	-13.62%	-19.10%	2	1.15%	0.23%	1.61%	0.80%	25
C	-12.69%				1	1.50%	0.33%	2.23%	1.07%	15
D						1.77%	0.38%	2.21%	1.13%	8
E	-35.89%				1					
HR						2.45%	0.28%	2.63%	2.13%	3

This table lists the money-weighted returns for both Prosper and Lending Club. Again, we see that returns generally rise as credit grade falls, and that Prosper returns are usually higher and more variable than LC returns.

Contractual Payment Experience

Percentage values like IRRs and HPRs are incomplete measures of performance, since both—in different ways—abstract from the term over which the loan contributes to the portfolio. The relatively high cash flows thrown off from amortizing P2P loans ensure that our members have ongoing opportunities for reinvestment. Early loan payment, however, subjects us to reinvestment rate risk; we therefore face the same prepayment problem as holders of mortgage backed securities. As managers, we prefer to choose loans that will remain productive throughout their scheduled term.Thus, as a final measure of performance, we consider how long a borrower makes her contractual payments. For the 101 Prosper notes and 55 LC notes that have resolved, we count the number of months over which a loan delivers its amortizing payments. The month in which a loan pays off is counted, since interest is still paid that month on the prior month's balance. If a borrower does not pay for several months, then resumes payments, we count only the number of months before the initial missed payment. Eleven of the notes, all from Prosper, were written off. Both 36- and 60-month loans are included. The results are shown in Figure 2. The top panel of Figure 2 makes it clear that three years is the mode for loan resolutions. Sixteen loans pay off at month 35, ten of which are A loans and 15 of which are 36-month (that is, full-term) loans. Nonetheless, there are significant numbers of resolutions in earlier months. A-rated loans are spread fairly uniformly across the first three years; B loans are, too, although they start paying off a bit later, around month 5. C loans' resolutions spike after about a year, while over half of the D loans resolve by month 8. Ten of the eleven defaults occur by month 35. A-rated loans last the longest: the two defaults occur at months 29 and 35. Both C and two of three B loans fail by month 9; the single E loan fails in month 3. As we noted above, early defaults are not uncommon in the P2P market (see Freedman and Jin, 2008b), and—as we saw in Table 3—those defaults can be devastating for returns.

Figure 1: Realized Note Returns Against Stated Rates

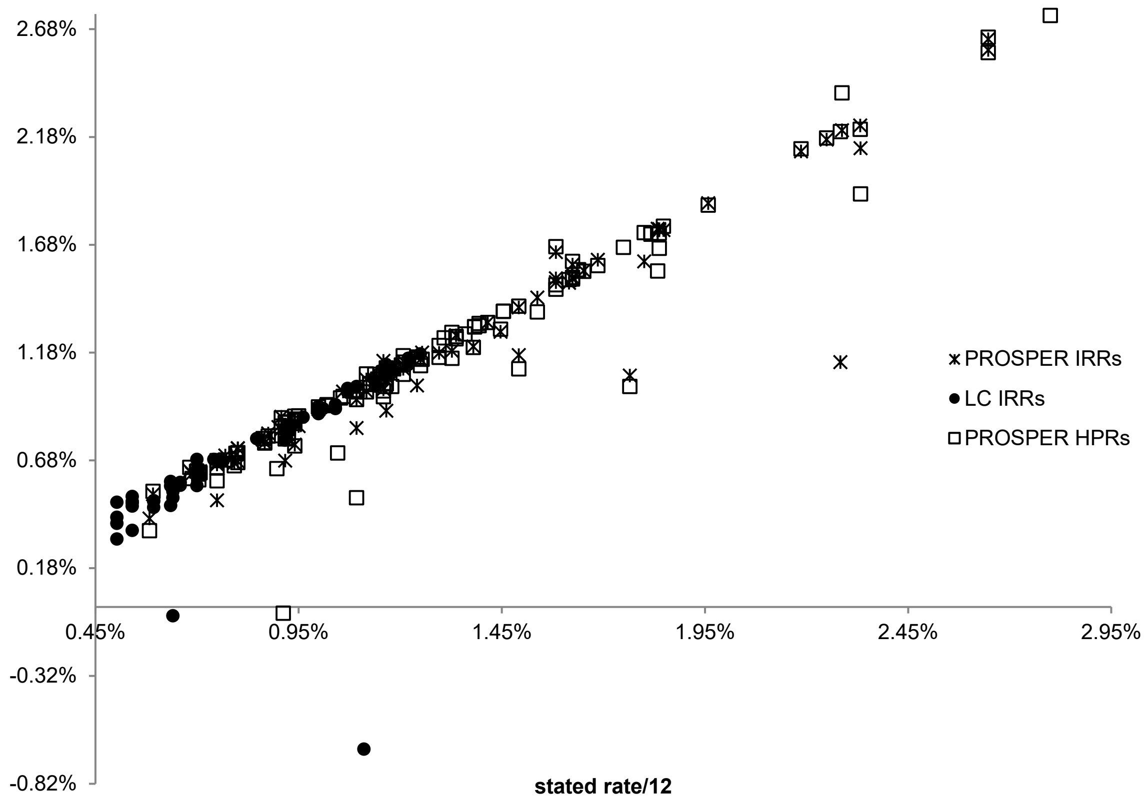
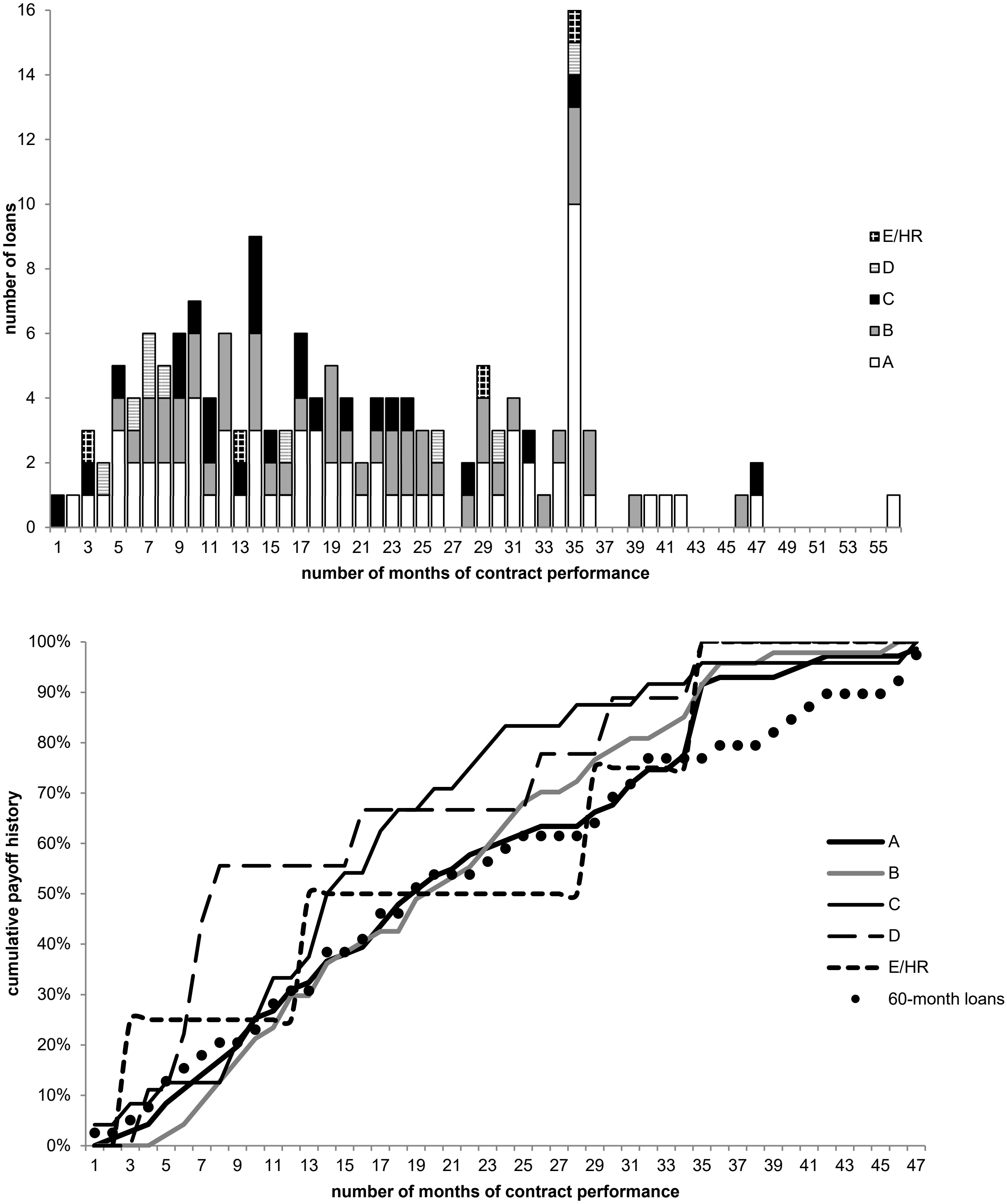


Figure 1 plots Prosper HPRs (from Table 2) and LC and Prosper IRRs (from Table 3) against the loans' stated rates. While we have had some very negative LC IRRs, the Prosper IRRs are, in general, more variable. We can also see the relative concentration of LC rates—both stated and realized—perhaps reflecting the P2P market's evolution from auction-determined to platform-specified rates.

The bottom panel of Figure 2 gives cumulative resolutions by credit grade. 99% of all loans resolve by month 47. This panel also presents results for the 39, 60-month loans in the sample (26 of which are from Prosper, and three of which—an A, a C, and a D—are defaults). Only eight of these take more than three years to resolve, including two-thirds of A loans, 80% of B, 89% of C, and all of the D loans. As the dotted curve shows, the resolutions are spread uniformly across the first three years. We expect loan performance to change going forward, since we will be concentrating on LC rather than Prosper, and since the P2P market itself is changing (as we discuss in the next section). Nonetheless, our history still provides useful evidence that can help us predict the number of months of contractual performance. Given evidence from prior P2P literature (e.g., Freedman and Jin, 2008a; Iyer, *et al.*, 2009; Livingston and Crosby, 2016) we identified thirteen variables that can help us explain how long a loan performs: the logs of loan amount and the borrower's revolving credit balance; the debt-income ratio; the

Figure 2: Number of Months of Contract Performance



The top panel shows the distribution of loan resolutions for the 101 Prosper and 55 LC loans, by credit grade. The bottom panel gives the cumulative resolution history by credit grade. The bottom panel also shows the cumulative resolution history for 60-month loans only.

loan rate; dummy variables for income (1 ≡ < \$75,000/year), purpose (1 ≡ debt consolidation/credit card refinancing), term (1 ≡ 60 months), platform (1 ≡ Prosper), credit grade (1 [A] through 7 [HR]), number grade (e.g., equals 5 for a C5 loan), and loan-size identifiers (≡ 1 if the requested loan amount is a multiple of \$500 or \$5,000, respectively); and an interaction term between loan rate and platform. Using backward elimination with an alpha of .10, we generated the following predictive model:

number of months of contract performance = 26.2 – 4.1*(\$500 dummy) (1)

– 7.5*(purpose dummy) + 3.4*(term dummy) + 83.0*loan rate – 4.0*(credit grade identifier)

Lower-rated loans resolve faster, as do credit card/refinancing loans. Note that this does not simply reflect default, since only half of our defaults were for refinancings (four of those five were rated C or D, however, which is consistent with the strong link between debt consolidation and lower grade with default; see Livingston and Crosby, 2016). Credit grade remains significant despite its high correlation with loan rate (r = .83). Loans with higher rates remain outstanding longer, as do longer-term loans; however, the marginal effect of doubling the term is to add only about three months of contractual performance. Having described our portfolio returns and contract performance, we turn now to the attribution of our returns among the different underlying active bets

Attribution

Our student members make many active bets as they manage our P2P portfolio. For example, they decide how much money to invest on each of our two P2P platforms and how much to lend in various categories such as debt consolidation. The platform choice, however, has been primarily an artifact of the timing of our entrance into the various markets, of loan availability, and of the students' perception of platform quality. Once we started using Lending Club, we concentrated our investing there to diversify our portfolio. Attractive new loans available to retail lenders started drying up on Prosper around the same time. As for loan purpose, our early investment policy statement precluded various forms of lending, including debt consolidation loans. The scope of active management along these dimensions, therefore, was very limited. There are nonetheless other critical choices to be made.

In this section, we focus on three fundamental active bets our members make when they choose our loans: the proportion of funds to allocate to each credit grade, the actual loans to choose, and the amount of money to bid for each loan. To investigate how important each of these choices is to our portfolio's performance, we use an attribution approach based on an asset/equity sector/security allocation example for a balanced fund from Bodie, Kane, and Marcus (1993). Their approach is more flexible, and therefore more informative for us, than is the standard industry breakdown (see, for example, Bailey, *et al.*, 2014, in the CFA Level III curriculum). The two approaches differ only in their allocations to selection (the last two terms in equation (2) below), which the industry approach breaks down into generic "active management" and "interaction" terms.

We use the following three-part attribution:

our portfolio return – return on market bogey =

$$\sum_{credit.class.j}(our.wt_j - mkt.wt_j)*(mkt.rtn_j - bogey) + \sum_{credit.class.j} our.wt_j *[\sum_{loan.i} rtn_{ij} *(our.wt_{ij} - neutral.wt)]$$

$$+ \sum_{credit.class.j} our.wt_j * [\sum_{loan.i} rtn_{ij} * (neutral.wt - mkt.wt_{ij})] \tag{2}$$

where the market bogey return is found as $\sum_{credit.class.j} mkt.wt_j * mkt.rtn_j$.

The first term in equation (2) is the credit-class allocation term, which measures the contribution of credit-class weighting to our portfolio's incremental return. The credit classes, *j*, vary by platform. Over our sample period, Prosper uses seven categories (AA, A, B, C, D, E, and HR). Lending Club uses more, since it subdivided the letter categories using the numbers 1 through 5 (A1, A2, etc.). The remaining two terms in equation (2) measure the contributions from our active loan-weighting choices (term 2) and on our choice of loans (term 3, a residual term). The loans, indexed by *i*, are the loans that we chose to include in our portfolio. For each loan we choose, we evaluate the relative weight we used against a neutrally weighted alternative. This is the weight that the loan would have if it had been for $25. (This simply requires us to scale down the remaining balance on the loan—for example, by halving it for a $50 loan. We assume that portfolio size does not change.) If members invest more than the default amount of $25, they make a decisive active bet. In Table 4, we present the results of our attribution analysis. In panel A, we provide the inputs we used to calculate the platforms' bogeys (portfolio returns based on historical credit class performance and weights). Panel B gives the attribution.

Looking first at panel A, we see that our bogeys for Prosper are higher in all cases than those for Lending Club. While our own return experience at Prosper perhaps justifies higher returns for that platform (see Table 2), we nonetheless expect that these bogeys are too high. While Lending Club displays its data prominently on its website, Prosper seems to delight in opacity. We were forced to estimate its bogeys using data from its 10-K filings, adding an adjustment for default based on its reported experience. The latter was almost certainly inadequate, given the magnitudes of the implied bogeys relative to Lending Club's. For example, consider the 2015 "other" category, where the performance of Prosper's grade HR—even after assuming 17.5% of these loans default—is extremely high, especially relative to LC's clearly default-affected classes F and G. Underestimating Prosper's default probabilities for the higher-rate, lower-quality credit grades, in particular, could explain the negative attributions to credit class (since we emphasize higher-quality loans) and the large residuals assigned to loan choice.

Focusing on Lending Club, we see that we beat the bogey in the first three of the five periods. The active loan-weighting choice was uniformly a positive—albeit declining—contributor to our outperformance. However, the residual loan choice component clearly reflects the (increasing) impact of defaults. On Prosper, we beat the bogey (barely) only in 2015, despite returns as high as 13%. Credit-class allocation contributes positively to performance in the most recent two years (perhaps because the lower weight on the bogey's D-and-below grades is falling). Loan-weighting choices are positive contributors in all but one year. Table 4 demonstrates that active bets significantly affect our results. Going forward, however, we expect less scope for active management, especially in loan choice. As good loans become increasingly scarce, we will need to be much more defensive in loan weighting, concentrating our active focus on credit-class allocation. In the next section, we briefly describe some of the changes in the P2P market that have motivated these adjustments.

Table 4: Return Attribution

A: BOGEY INPUTS

		2010	2011	2012		2013		2014		2015		2016	
		P	**P**	**P**	**LC**	**P**	**LC**	**P**	**LC**	**P**	**LC**	**P**	**LC**
AA	rate	7.95%	7.57%	7.47%		6.68%		6.14%		5.85%		5.70%	
	weight	0.18	0.11	0.09		0.09		0.09		0.09		0.09	
A	rate	9.24%	10.24%	10.66%	4.33%	9.93%	5.55%	9.16%	5.18%	8.22%	5.17%	7.80%	5.33%
	weight	0.24	0.20	0.20	0.17	0.22	0.14	0.23	0.15	0.23	0.17	0.22	0.20
B	rate	13.22%	14.61%	14.86%	6.76%	13.23%	7.57%	11.93%	6.98%	10.87%	6.48%	10.49%	7.30%
	weight	0.11	0.16	0.19	0.31	0.24	0.30	0.26	0.24	0.26	0.26	0.26	0.28
C	rate	18.47%	17.93%	18.59%	7.78%	16.52%	8.99%	15.02%	7.48%	14.02%	6.76%	13.76%	8.47%
	weight	0.13	0.10	0.19	0.21	0.24	0.29	0.25	0.27	0.26	0.28	0.26	0.28
D	rate	22.95%	22.59%	21.58%	8.53%	19.65%	9.03%	18.37%	7.63%	17.75%	5.99%	17.79%	8.75%
	weight	0.18	0.24	0.19	0.16	0.13	0.14	0.11	0.20	0.11	0.16	0.11	0.13
E	rate	27.03%	26.25%	24.42%	9.30%	23.03%	10.09%	22.00%	6.61%	21.39%	4.70%	21.64%	7.42%
	weight	0.08	0.13	0.08	0.10	0.06	0.08	0.04	0.10	0.04	0.10	0.04	0.08
other	rate	25.85%	25.58%	25.35%	9.58%	24.64%	9.27%	24.21%	5.79%	24.11%	0.62%	24.28%	3.93%
	weight	0.08	0.07	0.06	0.06	0.03	0.05	0.01	0.04	0.01	0.04	0.01	0.04

B: ATTRIBUTION

	PROSPER					LENDING CLUB				
	Bogey	**Return**	**Credit Class Allocation**	**Loan Weighting**	**Loan Choice**	**Bogey**	**Return**	**Credit Class Allocation**	**Loan Weighting**	**Loan Choice**
2010	15.9%	8.3%	-2.9%	1.2%	-5.8%					
2011	17.5%	12.6%	-4.6%	1.5%	-1.8%					
2012	16.7%	13.1%	-4.1%	1.8%	-1.3%	7.3%	9.0%	-0.7%	3.9%	-1.4%
2013	14.4%	11.2%	-3.2%	1.6%	-1.7%	8.2%	10.0%	-1.0%	2.3%	0.6%
2014	12.8%	2.1%	-2.5%	-1.2%	-7.0%	6.9%	9.0%	-0.7%	0.8%	2.1%
2015	11.9%	12.1%	0.9%	1.6%	-2.3%	5.9%	4.2%	0.2%	0.4%	-2.2%
2016 (6 months)	11.7%	7.3%	0.8%	1.1%	-6.4%	7.3%	-3.0%	0.3%	0.1%	-10.7%

This table attributes our portfolio returns to active choices on credit class allocation, loan weighting, and loan choice (the residual). Returns on our portfolio are calculated monthly; monthly values are added to create annual returns. Panel A provides the inputs used to calculate the platform bogeys. Lending Club (LC) provides this data on its website, and adjusts its reported returns for default. Prosper bogeys were estimated from 10-K filing data, and were assigned default probabilities based on Prosper's reported historical experience (AA: 1% default rate; A: 3%; B: 5%; C: 7.5%; D: 10.5%; E: 13.5%; HR: 17.5%). Given the large discrepancies between LC's lower-grade default-adjusted returns (e.g., "other class" = grades F and G) and Prosper's estimated returns (e.g., "other class" = grade HR), these adjustments are too small. Note also that LC reports only data for "A" grades, while we follow Prosper's AA/A classification by assigning LC's A1 and A2 grades to an "AA" class. Panel B reports the attribution for our portfolio. Our reported returns are calendar-year time-weighted returns, incorporating default. These results show underperfomance from credit class allocation, given our emphasis on higher-quality loans, and generally positive contributions from our loan weighting choices.

CHANGES IN THE P2P MARKET

For the last seven years, our students have been able to use P2P loans as the basis for a unique student-managed debt fund. They have been able to perform meaningful credit analysis on a myriad of loan sizes and types, assessing both qualitative and quantitative data. A side benefit of using P2P—one in keeping with our not-for-profit educational mission—was that our students were able to look beyond profit by identifying borrowers they thought they could really *help*. (We are not the only lenders motivated by charity: according to Paravisini, *et al.*, 2010, 5% of LC lenders report that their main reason for using the platform is "to help others." See also Freedman and Jin, 2008a, and Bachmann, *et al,* 2011.) Now, however, changes in the P2P market are reducing the potential financial and philanthropic benefits of our future participation. We are being driven out by a predictable evolution of the market: first, institutions are enticed by the growth and profit potential of P2P; next, the platforms respond to make the loan product more amenable to institutional scale and speed; and finally, the small "peer" lenders like us are squeezed out.

Institutional investors are always looking for new, potentially diversifying assets, and the recent low interest rate environment makes new fixed-income assets particularly interesting. Enter P2P. In a pitch to institutional clients, Price Waterhouse Coopers (PwC, 2015) touts the market's "explosive growth rates" and its ability to "reach vast new segments of untapped market potential." They "conservatively" estimate the market size in 2025 at $150 B, up from $5.5 B in 2014. Big money is responding to the potential to collaborate in such a market. PwC notes that one bank now buys $2 M per month in P2P loans, and another has a "flow agreement" allowing it to buy up to a quarter of a platform's loans at a preset price. And it is not just banks that are interested: Cortese (2014) notes that hedge funds, pension funds, and sovereign wealth funds also participate in the market, as do new P2P-only investment funds such as the Prime Meridian Income Fund.

In turn, the P2P platforms are making their loans more attractive to institutions. Since institutions want to build portfolios, not relationships, they do not need pictures or Q&A features. Gone are the early "groups" that allowed borrowers to affiliate using alumni or social ties, vetted and perhaps endorsed by a group leader—a structure that harnesses the power of "collective responsibility" to encourage repayment (La Ferrara, 2003; Freedman and Jin, 2008a). Thus, the platforms have abandoned almost all opportunities for borrowers to personalize their listings. The "soft" data, found to be so efficacious by early researchers into P2P markets (e.g., Iyer, *et al.*, 2009), is gone. Now, all listings look the same—sets of traditional credit statistics—and loans are commodities.

Institutional investors need scale to profit in this commodity market, so the P2P platforms have more than doubled the maximum sizes of their loans. They also now offer "whole" loans, which allow a single lender to fund an entire loan (as "certain institutional investors have indicated a preference to be able to purchase loans in their entirety…" LC, 2017). Over 90% of Prosper's loans were whole as of late 2014 (Shore, 2014); in 2015, there were almost twice as many whole loans funded as traditional "fractional" loans. Deep-pocketed institutions are able to peruse the new loan landscape with proprietary technology, using "custom algorithms…to automatically review and purchase loans, often before most general investors are aware of the loan listing" (PwC, 2015). (For example, the Prime Meridian Income Fund chooses loans using "a dedicated API [application programming interface] with proprietary credit algorithms"; PM, 2017) Big lenders are even locating servers close to Prosper and Lending Club to get faster access to loans (Cortese, 2014). Most significantly, platforms now give institutions the first-look at many new listings, passing only the rejected loans to the retail market.

The drain on supply is obvious from a recent check on our two sites: on August 16, 2016, Prosper had 216 listings available, and LC had 138. Even if each listing was for its site's maximum ($35,000 for Prosper and $40,000 for LC), and if each still had lots of funding available (they did not: the maximum on LC, for example, was 30% remaining for bid), and if each became a loan, these lending opportunities would still only amount to about 2% of the monthly origination value implied by 2015's platform totals of $3.4 B and $8.7 B, respectively. Thus, retail lenders like us not only have less information per listing, we also have fewer listings overall.

These trends probably exacerbate the adverse selection problems that have always characterized P2P lending. (See Iyer, *et al.*, 2009, for discussion of adverse selection; see Chafee and Rapp, 2012, for a general discussion of P2P risks.) For example, P2P lenders do not see a borrower's exact credit score; instead, they see a platform-determined credit "grade," determined by a platform-specific proprietary model. This may lead to credit grades' being populated by borrowers at the lower end of a credit-grade range. (Indeed, Freedman and Jin, 2008a, found that listings became increasingly risky over Prosper's first two years.) If institutions use superior access and algorithmic firepower to cherry-pick the best loans, our members will be forced to choose from a smaller pool of riskier loans. Thus, going forward, we expect fewer good lending opportunities, just as the "Prime Meridian" marketing proclaims: "With the recent investments and commitments by Google and Blackrock, this asset class is becoming increasingly institutionalized…This is bad news for other lenders trying to participate, but it is good news for Prime Meridian…"

CONCLUSION

Running a student-managed fund offers students a meaningful opportunity to run real money in real time. However, establishing a fund requires a substantial commitment of university resources, especially if students are to venture outside the box and manage fixed-income assets. Traditional debt products are bulky, illiquid, and expensive to trade. However, peer-to-peer loans are none of those things.

We established what we believe to be the first P2P student-managed fund in the world. We also did it in a unique way: creating a 501(c)(3) educational not-for-profit, allowing us to be completely independent from our university. Our students invest and spend according to investment policy statements that they create, not ones dictated by endowment and university administrations. Since the fund's inception in 2009, our student managers have participated in almost 500 P2P loans, investing between \$25 and \$157 per loan. We have generated returns of between roughly 6% and 10% per year, net of defaults.

Those defaults have been significant, and raise the question of the adequacy of our risk-adjusted returns. We cannot assert that we have received adequate compensation for risk—in part, because there is no accepted measure of risk for P2P loans. Freedman and Jin (2008a), after comparing their estimated Prosper return of 6% to the 5.29% contemporaneously available on 6-month CDs and the 6.93% on the S&P500, note that Prosper loans really are comparable to neither, since "[i]t is difficult to quantify the risk premium needed for Prosper loans" given the fundamental differences between them and alternative investments. Paravisini, *et al.* (2010) suggest that investors make their loan choices as if all risk buckets have the same systematic risk, and that the loans' overall risk properties are consistent with what is posted on Lending Club's website. Regardless of the proper measure of risk, it is clear from the variability of our results that uninitiated retail lenders should *not* view the P2P market as a substitute for CDs or money market funds. Fortunately for us, we can take a more nuanced view of risk, given that we run our fund with an educational and philanthropic—rather than purely financial—mission.

This charitable motivation seemed to be a good fit for P2P lending when the market was young, when some peer lenders associated P2P with the microfinance of Grameen Bank. Nonetheless, P2P is a for-profit system. The lack of collective responsibility, reciprocity, and the attendant social collateral that characterize this relatively anonymous, one-shot, returns-driven model almost inevitably have led to the commoditization of its loans and the institutionalization of its lending.

As big money has flooded the market, platforms have eliminated most of the "peer" elements of lending—the pictures, narratives, and message boards that provided useful "soft" information to retail investors. Now, small lenders like us are forced to fight for the scraps that whole loan programs and flow agreements leave us. In fact, the whole market is being rebranded from "peer-to-peer" to "marketplace lending." Given these changes, we do not expect the sorts of returns we report in this paper to continue. This is a limitation of our research. Another is our relatively small sample size. Both Prosper and Lending Club provide reams of historical data on their platforms; future research could include investigating that data for performance-term and attribution. The most important question will be to characterize the listings available to institutions versus retail lenders, to assess the disparity induced by institutional cherry-picking. Unless the platforms reserve some decent loans for the little guys, the "peer" market we discuss in this paper will be nothing but a historical curiosity.

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