What's in a Picture? Evidence of Discrimination from Prosper.com*

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Abstract

We analyze discrimination in a new type of credit market known as peer-to-peer lending. Specifically, we examine how lenders in this online market respond to signals of characteristics such as race, age, and gender that are conveyed via pictures and text. We find evidence of significant racial disparities; loan listings with blacks in the attached picture are 25 to 35 percent less likely to receive funding than those of whites with similar credit profiles. Conditional on receiving a loan, the interest rate paid by blacks is 60 to 80 basis points higher than that paid by comparable whites. Though less significant than the effects for race, we find that the market also discriminates somewhat against the elderly and the overweight, but in favor of women and those that signal military involvement. Despite the higher average interest rates charged to blacks, lenders making such loans earn a lower net return compared to loans made to whites with similar credit profiles because blacks have higher relative default rates. This pattern of net returns is inconsistent with theories of accurate statistical discrimination (equal net returns) or costly taste-based preferences against loaning money to black borrowers (higher net returns for blacks). It is instead consistent with partial taste-based preferences by lenders in favor of blacks over whites or with systematic underestimation by lenders of relative default rates between blacks and whites.

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There is a long history within economics of studies attempting to understand discrimination in a variety of markets. Much of this interest stems from concerns that because of discrimination, certain groups – for example, blacks and women – may not enjoy the same access to markets and opportunities as their counterparts. Theories of discrimination usually fall into one of two classes: statistical discrimination (Phelps, 1972; Arrow, 1973) or taste-based discrimination (Becker, 1957).[1] Accurate statistical discrimination is economically efficient for the decision maker, while taste-based discrimination stems from an animus toward one group and is often costly to the decision-maker. Because costly discrimination may be driven out of competitive markets, and because these different theories often lead to different policy recommendations, understanding the extent to which observed discrimination is consistent with these theories is an important goal. However, it is often difficult to test for discrimination in markets[2] and generally even harder to assess the different theories of discrimination.[3]

This paper examines discrimination in a new type of credit market known as peer-to-peer lending. Specifically, we study data from the website Prosper.com, a leader in online peer-to-peer lending in the United States. Peer-to-peer lending is an alternative credit market that allows individual borrowers and lenders to engage in credit transactions without traditional banking intermediaries. While still small, these markets are growing quickly and may represent an important niche, especially in the area of consumer-debt consolidation.[4] Websites like Prosper aggregate small amounts of money provided by a number of individual lenders to create moderately-sized, uncollateralized loans to individual borrowers. In order to request funding, borrowers in these markets create a loan listing that resembles auction listings for goods on websites like eBay. Like most standard credit applications, this listing displays desired loan parameters and reports information from the prospective borrower's credit profile. Unlike typical credit applications, however, borrowers may include optional and unverified personal information in their listings in the form of pictures and text descriptions. These pictures and descriptions often provide potential lenders with

[1] For other literature on theories of discrimination see Aigner & Cain (1977) and Lundberg & Starz (1983).
[2] See Altonji and Blank (1999) and Blank, Dabady, and Citro (2004) for reviews of empirical work on assessing discrimination in labor markets, and Ross and Yinger (2002) for a similar review in credit markets with a focus on mortgage lending.
[3] A few notable papers that have used clever empirical methodologies to examine statistical discrimination vs. taste-based discrimination include Altonji and Pierret (2001), Knowles, Persico, and Todd (2001), Levitt (2004), Antonovics and Knight (2004), and Charles and Guryan (2007).
[4] See Freedman and Jin (2008) for an analysis of the evolution of the Prosper market and the profitability of loans on Prosper.

signals about characteristics such as race, age, and gender, that anti-discrimination laws typically prevent traditional lending institutions from using.

Our first research question focuses on the determinants of access to credit in the Prosper marketplace, and in particular on how signals from pictures about characteristics, such as race, age, and gender, affect the likelihood of receiving loan funding and the interest rates borrowers pay. In the language of the legal literature we test for "disparate treatment" of certain groups by estimating whether they are treated differently than their counterparts who are similar on other dimensions.[5] Our empirical approach uses observational market data.[6] The typical problem with this type of analysis is the potential for omitted variable bias.[7] An advantage of our dataset is that we are able to control for nearly all of what a lender knows about a borrower when making funding decisions. Prosper.com generously provides a data set that contains information from loan listings created on the site, including links to pictures included with the listings. In order to conduct the analysis, we systematically coded variables from pictures and text descriptions for over 110,000 loan listings that were created on Prosper.com between June 2006 and May 2007.

The empirical analysis reveals significant racial discrimination in this market. Compared to the response to otherwise similar whites, we estimate that listings with blacks in the picture are 2.4 to 3.2 percentage points less likely to be funded. Compared to the average probability of funding, 9.3%, this represents an approximately 30% reduction in the likelihood of receiving funding. A range of specifications and numerous

[5] The other important definition within the legal literature is "disparate impact," which arises when decision-makers do not explicitly account for characteristics such as race and gender, but use variables that are highly correlated with these characteristics. See Ross and Yinger (2002) for a discussion of disparate treatment vs. disparate impact with a focus on discrimination in credit markets.

[6] This observational-market-data approach is similar to that used in the influential studies of redlining and racial discrimination in mortgage lending by the Boston Federal Reserve (Munnell, Tootell, Browne, and McEneaney (1996) and Tootell (1996)).

[7] Audit studies and field experiments are an important alternative technique for examining the existence of discrimination (specifically disparate treatment) in a range of markets. For instance, in a very influential paper Bertrand and Mullainathan (2004) study racial discrimination in the labor market by randomly assigning race to fictitious resumes and find that resumes with black-sounding names are less likely to receive a call-back for an interview. Examples of audit studies include Turner et al. (2002) on mortgage lending, Turner et al. (1991) on the labor market, and Ayers and Siegelman (1995) on automobile purchases. By manipulating the race or gender of applicants for jobs or loans, these types of studies are able to identify clean causal links between group status and treatment without concerns of omitted variables or the correct empirical specification. On the other hand, because they usually lack any ex-post performance data, with audit or field-experiment approaches, it is generally hard to assess different theories of the sources of discrimination. Heckman (1998) argues that the audit approach over-states the importance of discrimination, arguing that while some employers, salesmen, or lenders may discriminate, that minorities will seek out those who do not, thereby lessening the impact of the discrimination. It is worth noting that the discrimination we find on Prosper.com is at the market level.

robustness checks and alternative cuts of the data reveal very stable effects of race on the likelihood of funding. This discrimination against blacks in the lending decision is also reflected in the interest rates these borrowers pay conditional on receiving a loan; their interest rates are 60 to 80 basis points higher than those of whites with similar credit profiles.

While smaller and less robust than the results for race, we find a number of other interesting market responses to the information in pictures and text. For instance, the market discriminates somewhat against the elderly and significantly overweight, but in favor of women and those that signal military involvement. The market also favors listings where the borrower expresses a desire to pay down credit-card debt (the most popular stated loan purpose) over credit requests for other purposes, such as loans for business expansions or automotive repairs/purchases.

It is perhaps somewhat surprising that we find evidence of discrimination in this market. Because the pictures and descriptions are optional and unverifiable, a natural prediction would be that the market would respond little to this type of "cheap talk". Yet the fact that borrowers include a wide variety of pictures and the market responds to those signals, suggests that the information is not treated as cheap talk in the market. In fact, we find the Prosper market responds negatively to listings that do not include a picture. Another reason that the finding of racial discrimination might be somewhat surprising is that lenders are given a wide range of information about each borrower's credit profile, including credit grade, debt-to-income ratio, and a measure of income. However, we find that lenders respond to signals about race above and beyond this wealth of credit information.

Given that we find discrimination in this market, an obvious question is whether this discrimination is efficient for lenders – i.e., are these differences consistent with lenders engaging in accurate and economically efficient statistical discrimination? Because of the availability of data and the nature of the market, we can address this question using loan-performance data.[8] A unique feature of the Prosper market is that it operates as an auction that allows interest rates to be bid down below an initial rate set by the

[8] Exploring theories of discrimination – i.e., statistical discrimination vs. taste-based discrimination – is generally quite difficult. In many settings there is no ex-post performance data available. Even when performance data is available, it may not be informative because decision-makers use a threshold cutoff for decisions such as loan approval. For example, see the critiques of the use of default analysis to assess theories of discrimination in mortgage lending that appeared in the May, 1996 edition of *Cityscape*, especially articles by John Yinger, George Galster, Stephen Ross, and John Quigley.

borrower, if enough lenders find a loan attractive. The basic intuition behind the analysis, then, is that if lenders care only about the net return of a loan (adjusted for expected default), funds will flow to loans that are attractive given the observable information to lenders. This process should adjust their interest rates and equalize expected returns. If the market correctly incorporates characteristics from pictures and text when assessing creditworthiness, accurate statistical discrimination will result in funded loans that have equal average net returns irrespective of the listing characteristics. On the other hand, if taste-based discrimination is the sole cause of disparate treatment in the market, loans made to the group subject to negative discrimination should have higher net returns ex post.

The comparison of the net return on loans made to blacks and otherwise similar whites is striking. The estimated average net return on a dollar from investing in a loan from a black borrower is 7.3 to 8.6 percentage points lower over a three-year period. Although blacks are discriminated against in the lending process, the higher interest rates that they pay are not enough to account for their greater propensity to default. This runs counter to the predictions of *both* accurate statistical discrimination (i.e., equal net returns) and taste-based animus against blacks (i.e., higher net returns on loans to blacks).[9]

How can we reconcile the evidence of discrimination against blacks in the lending process with the fact that their loans result in lower net returns? The evidence is consistent with a combination of accurate statistical discrimination *against blacks* coupled with taste-based discrimination *against whites*. But such an interpretation runs counter to intuition and to previous literature, which rarely concludes that there is a taste-based preference against whites. We discuss the interpretation of these results in detail at the end of the paper. Perhaps the most likely interpretation is that lenders understand the correlations between race and important characteristics for predicting default that they cannot perfectly observe, such as education

[9] After we had gathered our data and were conducting our analysis, we learned of a working paper by Ravina (2008) that conducts an analysis similar to ours but uses a smaller sample of loans (one month of loan listings on Prosper relative to the twelve months used in our analysis). Ravina's strongest findings are for the effect of beauty, and she finds that more beautiful people are more likely to receive funding. In contrast we find little effect of our attractiveness measure, which we attribute to her more precise coding of beauty. Our race coding, however, is quite accurate and we find a number of differences in our results for race. While Ravina finds that blacks pay higher interest rates conditional on funding (consistent with our results), her estimates do not show a difference in the probability of funding related to race. Furthermore, Ravina concludes that there is no evidence of differential default rates between loans made to blacks and whites. Most of these differences can likely be attributed to the large differences in sample sizes, as the standard errors on her estimates are large and cannot reject our point estimates for any of the estimations even though our results are highly statistically significant.

and social-support networks, but they fail to fully appreciate the strength of these correlations or the importance of these unobservable factors in predicting default.

The remainder of the paper proceeds as follows: Section I describes peer-to-peer lending and the dynamics of the Prosper marketplace. Section II describes the data made available by Prosper.com and our process for coding information from pictures and text. Section III presents our empirical results, focusing first on the probability of obtaining a successful loan and then turning to estimates of the net return (to lenders) of loans made to different groups. We conclude the paper in Section IV with a discussion of the interpretation of our results and their relationship to and implications for the literature on theories of discrimination.

I. Institutional Background of Online Peer-to-Peer Lending

Online peer-to-peer lending encompasses a range of new and expanding markets that allow individual borrowers and lenders to engage in credit transactions without traditional intermediaries such as banks. These markets are small but growing quickly: the U.S. peer-to-peer market grew from an estimated $269 million in outstanding loans in 2006 to $647 million in 2007.[10]

Part of the appeal of peer-to-peer lending is that it offers lower overhead and the ability to cut out the bank or "middle man". Of course, there are many reasons why banks and other credit agencies have historically been the primary source for personal loans. Prosper has addressed some of the most important advantages of traditional lending institutions, including enabling individuals to diversify their peer-to-peer lending portfolio and providing individuals the sort of credit-profile information that until recently has been the purview of banks and other large lenders. Naturally, it is questionable whether individuals have the sophistication and training to make efficient use of this credit information in the way banks can. On the other hand, peer-to-peer markets provide lenders with a wealth of personal and contextual information about borrowers that traditional intermediaries do not use and are often explicitly barred from using by anti-

[10] This information comes from an article entitled "How to Use Peer-to-Peer Lending Sites to Borrow Money," that appeared on foxbusiness.com on Monday, January 28 2008, and cites its source as the research firm Celent. According to the article, Celent projects the market to grow to a total of $5.8 billion by 2010.

discrimination laws. This extra information may be a source of advantage for peer-to-peer markets. Ultimately, because they are so new, it is still too early to know whether peer-to-peer credit markets will actually succeed, but they are an intriguing alternative to traditional credit markets and are attracting both borrowers and lenders.

Details of Prosper.com. Our analysis focuses on the Prosper.com marketplace. Started in February, 2006, Prosper is somewhat similar to auction sites such as eBay, except that instead of bidding on or listing a consumer item, individuals bid on or list personal loans. All loans in this market are uncollateralized and have three-year terms with a fixed repayment schedule. Individuals wishing to borrow money create a listing that lasts for a pre-specified length of time, usually between 7 and 14 days. The listing includes the amount of money requested (up to $25,000), the maximum interest rate the borrower is willing to pay, credit information obtained by Prosper via a credit check, and voluntarily provided (and unverified) information, such as pictures and descriptions of what they plan to do with the money. Lenders browse the various listings and bid on specific loans by committing a portion of the principal (minimum of $50) and setting the lowest interest rate at which they are willing to provide those funds. The loan gets funded if and only if the total amount of money bid by lenders covers the size of the requested loan. Lenders get priority for the loan based on the minimum interest rate they are willing to accept, with low-rate bids getting higher priority. If enough lenders bid on the loan, the final interest rate on the loan can be bid down from the maximum interest rate initially set by the borrower; the final rate is determined by the lowest reservation rate set by a bidder who does not get to fund a portion of the loan.[11] Prosper makes money by charging closing costs of 1-2% of the loan amount to borrowers and 0.5-1% to lenders.

An example may help clarify the market dynamics. Imagine that a borrower requests a $5,000 loan and is willing to pay a maximum annual interest rate of 10%. For simplicity, assume that all potential lenders will bid the minimum funding size of $50. It then takes 100 lenders to fund the $5,000 loan. Each of these lenders enters a reservation interest rate when they bid, which is the lowest interest rate they are willing to

[11] Although we (and Prosper) use the term "lenders" to refer to the individuals making bids for the loan, technically speaking the loan contract is between the borrower and Prosper. So borrowers do not have to make separate repayments to each lender, but rather simply repay Prosper based on the final interest rate for their loan. Prosper allocates the repayments to the individual lenders based on the portion of the loan funds they provided.

accept. If there are exactly 100 lender bids, the $5,000 loan will fund at an interest rate of 10%. However, if more than 100 lenders bid on the loan, the final interest rate would be determined by the 101^{st} lowest reservation interest rate. The 100 bidders with the lowest reservation interest rates would each provide $50 for the loan and would be entitled to $1/100^{th}$ of the repayments made by the borrower over the three-year term.

There is substantial information available to individuals who are interested in bidding on loans. Lenders see the parameters of the loan: its size, the ending time of the listing, the total amount that has been funded through bids by other lenders, the history of bids on the listing, and the current interest rate, which is either the maximum rate the borrower will accept or (for fully funded loans) the rate to which the loan has been bid down. Other than these loan parameters, perhaps the most important information available to lenders is a credit profile for each borrower obtained by Prosper through a standard credit check. Prosper obtains an Experian credit score and provides lenders with a credit grade (e.g., AA or B) for each borrower using bins of credit score.[12] The cutoffs for the different credit grades are found easily on the Prosper website, but lenders do not see borrowers' exact credit scores. Lenders also see a host of other information commonly found on credit reports, including delinquencies, revolving credit balance, and bank-card utilization.[13] Potential borrowers also supply information about their employment status, occupation (chosen from a list), and income. The income borrowers report is also used by Prosper to create a debt-to-income ratio that is prominently displayed on the listing pages. This debt-to-income ratio is calculated by dividing the borrower's self-reported income by his or her debt burden (excluding housing) as reported by the credit check, and includes the value of the Prosper loan the borrower is requesting. Prosper does not verify the employment, occupation, and income information when loan listings are created, but does verify this information for some borrowers once the loan becomes fully funded and before the money is disbursed. Lenders are also provided with an indicator for whether the borrower is a homeowner or not.

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12 Credit grade bins include the following: AA (760 and up), A (720-759), B (680-719), C (640-679), D (600-639), E (560-599), and HR (520-559). Individuals with a credit score below 520 are not allowed to create a loan listing.

13 Additional information in the credit profile includes, the numbers of public records in the last year and last ten years, the number of inquiries in the last six months, the date of the borrower's first credit line, the numbers of current, open, and total credit lines.

In addition to this financial information borrowers can include supplemental material in their listing consisting of: a) a picture with their listing, b) a one-line description for the loan, and c) a separate longer description, where borrowers are encouraged (by Prosper) to describe what they plan to do with the money and why lenders should consider their request. None of the information in these pictures or descriptions is verified by Prosper or verifiable by lenders.

Prosper also incorporates additional social components through the use of borrower (and lender) groups. Borrower groups are generally organized around some sort of theme (e.g., alumni of a particular university) and include a rating. The group rating is affected by the repayment activities of its members so that group membership provides extra social pressure to repay loans.

Other than social pressure and conscience, the primary incentive for a borrower to repay the uncollateralized loan is the impact that default can have on the borrower's credit. If a borrower fails to repay the loan, Prosper reports the default to the credit-scoring agencies and turns the loan over to a collection agency that attempts to recover some money.[14] Ultimately the penalties to a borrower from defaulting on a loan in this market are similar to those of failing to repay a credit card.

II. Data

Data Overview. Prosper.com generously makes its data available to academics and prospective lenders. Data are available for every loan listing since the inception of the website. The data include all of the information seen by lenders when they make their lending decisions, as well as the outcome of the listing (i.e., funded or not). Demographic and other information about lenders is not available.

Figure 1 graphs the number of requested loan listings made on the website over time. The number of listings grew quickly after Prosper's official launch in February, 2006, reaching 5,000 requested loans per month by May, 2006 and rising to over 10,000 listings per month by January, 2007. The number of loans that actually get funded, however, has risen much more slowly. Of the 203,917 loans requested between February, 2006 and November, 2007, 16,395 were funded (8.04%), with lenders providing a total of

[14] Any money recovered by the collection agency is repaid to the individual lenders in proportion to the amount of the loan they funded.

$101,913,173 in funds (mean $6,216 per loan) to borrowers. The large number of loan requests that go unfunded motivates our interest in understanding how the market chooses which loans to fund.

The vertical bars in Figure 1 highlight the time-period we study in this paper. We focus on all loans that were listed during a one-year period in the Prosper market from June 2006 through May 2007, which leaves out the first few months of the market and ensures that we have at least seven months of repayment data for any loan made. Table 1 provides a series of summary statistics for the loan listings that occurred during the sample year. The columns in the table provide information about the full sample of loan listings and the subset of listings that actually funded. During this year, there were 110,333 distinct loan listings, of which 10,207 (9.3%) funded. The average requested loan size for all listings was $7,154 and was $5,930 for the funded listings, revealing that during this period just over $60 million in funds were lent through Prosper. On average borrowers set a maximum interest rate of 17% on loan listings. Among the loans that actually funded, however, borrowers set a maximum interest rate of 20% and had an average final interest rate (after bid down) of 18%. It is also worth noting that 43% of loans are specified as loans that "fund immediately". Rather than letting lenders bid down the interest rate, borrowers of these loans request that the loan is processed as soon as funding is available at the initial interest rate that was specified.

Credit Data. Prosper uses eight credit grades in their credit-scoring process. The majority (54%) of the requested loans are made by individuals who fall into Prosper's "high risk" (HR) credit grade with credit scores from 520-559. Listings with these credit grades are less likely to fund, however, and represent only 20% of the funded listings. Listings from individuals with the best credit grades (AA and A), who have credit scores above 720, each make up 3% of the total listings, but are more likely to fund and make up 10% and 9% of the funded listings, respectively. The average debt-to-income (DTI) ratio of 63% for those requesting loans also confirms the poor credit situation of the typical prospective borrower. Those who actually get loans are in a better financial situation, but still have rather high average DTI at 39%.

Coded Data from Pictures and Text. To obtain data from pictures and descriptions, we employed a number of undergraduate research assistants to systematically code up the information in the borrower's picture (if included) and the borrower's one-line description of the loan for all 110,333 loan listings on Prosper during the sample year. These assistants were paid a simple piece-rate per listing, and were informed that we would randomly check approximately 10% of their entries for accuracy. On the rare occasion that one of the coders made a large number of errors, he or she was asked to redo the coding and was not paid until a thorough accuracy check was performed. The coders were not told about the underlying hypotheses of the research, and importantly did not see any of the parameters of the loan listing other than the picture and one-line description while coding.[15]

The coders used the text descriptions to classify the purpose of the loan. This categorization provides an interesting picture of why borrowers are asking for money on Prosper.com. The categories for these purposes are listed in Table 1 and were chosen as the most frequent and important categories after a review of 750 loan listings. Around 30% of the listings used a description that stated the purpose of the loan as being some form of debt consolidation (e.g., "consolidating credit card debt", "pay down debt", and "paying off credit cards"). This is consistent with media reports that often stress the potential value of the peer-to-peer credit market as a way out of credit-card debt. Another popular category (10% of all listings) is business or entrepreneurship loans (e.g., "expanding my successful small business", "a new truck for landscaping business"). Smaller percentages communicated that they needed money for education expenses (3%), medical/funeral expenses (3%), home repairs (2%), automobile purchases (2%), automobile repairs (1%), or to pay back taxes (1%). A sizeable number of listings (34%) did not fall into these main categories (e.g., "need help") and were coded under a category of unclear/other.[16] Interestingly, and in contrast to the financial information, the distribution of loan purpose is quite similar between the funded listings and the full sample of listings, suggesting that the stated purpose of the loan is not a particularly important determinant of loan funding.

We hand coded only the text in the one-line description and not in the longer description that borrower's provide with their loan. The costs to hand coding information from these longer descriptions were simply prohibitive. Instead we ran the longer text descriptions through a simple text-analysis program that outputs the number of characters, words, and sentences in the text, an index of readability based on the

[15] Copies of the coding protocols that we gave to the research assistants are available on request.
[16] Approximately 6% of listings included multiple reasons for wanting the loan within their descriptions (e.g., "pay off a car loan and attend a family reunion"), and we coded these multiple-purpose listings under a separate category.

average word-length and average sentence-length, and the percent of words that are misspelled.[17] These text-analysis variables are slightly correlated with measures of creditworthiness and picture characteristics[18], and we include controls for them throughout our analysis.

Turning to the pictures, Table 1 reveals that less than half (46%) of all loan listings included a picture. However, the market seems to value the pictures, as 64% of the funded listings contained a picture. There is an incredible diversity of pictures on the Prosper site, ranging from earnest looking couples, to dogs wearing antlers, to pictures of nature scenery, and the occasional bikini-clad young woman. Among listings with pictures, 65% included one or more adults as the central focus of the picture, and 21% included both adults and children. Another 10% were pictures of just children without adults. A sizeable (though smaller) fraction of pictures contained no people, including 4% that were primarily of a building (e.g., a home or storefront), 4% primarily picturing animals (e.g., pet dog), and 2% picturing an automobile.

For pictures that included adults, coders were instructed to code a number of perceived characteristics. These include, gender, race, age, happiness, weight, and attractiveness. We also included categories of secondary interest, such as whether the people were professionally dressed or displayed signs of military involvement.[19]

The right-hand side of Table 1 gives summary statistics for the information coded from the pictures. Looking first at gender, there is a rough balance between men and women in the genders displayed in the loan listings. Of the pictures with people, pictures of single males make up 38% of the full sample and 40% of the funded listings. The analogous figures for females are 35% and 31%, and for male-female couples are 20% and 22%. The coders also recorded the perceived race of the people pictured, using the primary

[17] The one-line descriptions may be a more first-order influence on the lending decision than the longer descriptions. When prospective lenders browse loan listings, they first see a large page of listings (similar to a results page on Ebay), on which listings can be sorted or limited by a number of criteria. On this initial page, lenders see: a) the loan parameters (i.e., size, current interest rate, percent of the requested loan that has been funded, and the number of bids), b) credit grade and DTI, c) a picture (if provided by borrower), and d) the borrowers one-line loan description. Thus the picture and the one-line description are the information that lenders have when deciding which of the roughly 4,000 listings active at any one time to look at in detail.

[18] For example, the correlation between the number of words in the longer text description and listings with a low credit grade of "HR" is -0.01, with white listings is 0.03, and with black listings is -0.03.

[19] For each of these characteristics, the coding options included an unclear/uncertain category. Indicator variables for these unclear/uncertain categories are included throughout the analysis, but have very small cell counts, and to save space we drop them from our summary statistics and regression tables.

categories of white/Caucasian, black/African American, Hispanic/Latino, and Asian.[20] The majority, 67%, appear to be white, while 20% are coded as black, 3% as Hispanic, and 3% as Asian.[21] Looking at the listings that actually funded reveals that (unconditionally) minorities are much less likely than whites to receive loans on Prosper – 83% of the funded listings with adult pictures were of apparently white individuals. The patterns for age, weight, and the secondary characteristics are all sensible and reveal relatively little difference between the full sample of listings and the listings that fund.

Comparing the distributions of these variables between the full sample of listings and the funded listings suggests that the market: 1) favors pictures of whites over minorities by a significant margin, 2) modestly favors pictures of men over women, of happy people over unhappy people, and thin people over overweight people, and 3) does not react very strongly to the stated purpose of the loan. Of course, since these characteristics may be highly correlated with other financial characteristics, the summary statistics could be misleading.

III. Empirical Results

Probability of Funding

In this section we investigate how the information contained in pictures and descriptions affects the probability of funding holding all else equal. The summary statistics in Table 1 provided the first hint that disparate treatment may exist in funding decisions. Figure 2 provides additional suggestive evidence. Figure 2a illustrates the funding rate by each credit grade by white and black borrowers. Two main findings can be taken from this figure. High credit grade borrowers are more likely to be funded than low credit grade borrowers, and whites are more likely to be funded than blacks at every credit grade. Figure 2b and 2c are less conclusive, but suggest that females may be more likely to be funded than males (especially at lower credit grades) and that older borrowers are less likely to be funded than younger borrowers.

[20] These codings may not always agree with the race the borrower would list for him or herself if asked; however, it is the perception of race as conveyed through the pictures and not the actual race of borrowers that may affect lenders' decisions.
[21] Compared to statistics for the overall population from the 2000 Census -- White (73.9%), Black (12.2%), Hispanic (14.8%), and Asian (4.4%) – blacks are overrepresented in our sample, while whites and Hispanics are underrepresented.

As always, the challenge here is to overcome problems associated with omitted-variable bias so that our estimates can reasonably be interpreted as the market response to the information provided by borrowers. Fortunately, the Prosper data are ideally suited to help with this type of analysis. While there will always be aspects of a loan listing for which we are unable to control (e.g. certain aspects of the picture that were not coded), the percent of information available to lenders for which we can control is much higher in this setting than in most other studies of credit markets. Further, the stability of our results across various specifications and robustness checks lends credibility to our identification strategy.

Our basic empirical strategy involves estimating the probability that a loan listing gets funded as a function of the listing characteristics that are observed by the lenders. We use both linear probability models, estimated via OLS, and Logit regressions. The basic linear regression framework is:

$$Y_i = \alpha + X_i\beta + Z_i\theta + \varepsilon_i,$$

where Y_i is an indicator variable for whether or not listing i was funded, X_i is a matrix of characteristics coded from the pictures and one-line description of the purpose of each loan, and Z_i is a matrix of other characteristics of the listing and borrower, including credit controls and loan parameters. The regressions are estimated over the full sample of 110,333 listings made during the one-year sample period. Because many borrowers relist their requests when their listings expire without funding (generally with higher maximum interest rates), we cluster at the borrower level to obtain standard errors.

Baseline Regression Estimates. Our baseline regression specification includes indicators for the characteristics coded from pictures and text along with a large set of flexible controls for the other parameters of the loan listing. These controls (i.e., Z_i) include credit grade crossed with a cubic of the maximum interest rate the borrower set, a cubic of the size of the requested loan, the duration of the loan listing, the log of self-reported income, and a cubic of DTI. The other variables from a borrower's credit profile available to lenders are: number of current delinquencies, delinquencies in the last seven years, total number of credit lines, total number of open credit lines, number of inquiries in the last six months, revolving credit balance, and bank card utilization. These variables are included in the regressions in log form.[22] We also include dummy variables for homeownership status, occupation type, employment status, whether the borrower was a member of a group, and the rating (one to five stars) of the group. Additionally, we include variables created using our text analysis from the long-description: the log number of total characters, a readability index (which uses word and sentence length), and the percent of words which are misspelled. Finally, since this is an evolving market and one that can be affected by fluctuations in the overall economy, we include month dummies to capture time effects unrelated to specific listing parameters. The estimated coefficients on credit and loan-parameter controls (i.e., $\hat{\theta}$) are sensible and unsurprising and generally highly statistically significant. Because these variables enter the regression nonlinearly or with interaction effects and due to space constraints, we do not report the coefficients here. However, later we discuss a robustness table that shows estimates for some of these variables from a simpler linear specification.

Table 2 shows the coefficient estimates for the variables we coded from the pictures and descriptions (i.e., $\hat{\beta}$). Columns (1) and (3) display the results using OLS and columns (2) and (4) display the Logit results as the marginal effects of the variables on the probability of funding. For each of the categories listed in the table, we have also listed the base-group on which the coefficient estimates are based. In order to use all of the available data in our regressions, we included dummy variables to indicate when a listing had no picture or a picture without people in it. The coefficients on these dummies are not reported in the table, since they depend on the base-groups chosen for the race, gender, age, and other controls. However, in a similar regression that includes the same credit controls, but codes only for whether or not a listing had a picture, we find that listings without pictures are approximately 3 percentage points less likely to fund.

Consistent with the raw summary statistics, the largest effects of the picture characteristics are for race. The OLS estimates imply that listings with a picture of an apparently black or African American person are 3.2 percentage points less likely to get funded than an equivalent listing with a picture of a white person. Relative to the overall average funding rate of 9.3%, this is a 34% drop in the likelihood of funding. The marginal effects from the Logit regression imply a slightly smaller but still economically meaningful

[22] To avoid problems associated with ln(0), we added 1 to each variable before taking the log.

difference of 2.4 percentage points. Both estimates are statistically significant at the 1% level. Interestingly, the negative effect of a black picture is approximately the same as that of displaying no picture at all.

After controlling for credit characteristics, the estimated effect of displaying a picture of a woman is the reverse of what we saw in the summary statistics. In the raw summary statistics, women are less likely to have their loan requests funded, but this is driven by the correlation between female pictures and credit score. The estimated effects in Table 2 are positive, and in the Logit specification imply that all else equal listings with a picture of a woman are 1.1 percentage points more likely to fund. This result is statistically significant and approximately half the size of the estimated effect of a black photo.

The apparent age of the person in the picture is also an important predictor of successful funding. Compared to the base group of 35-60 years old, those who appear younger than 35 have a predicted rate of funding that is between 0.4 and 0.9 percentage points higher, while those who appear to be over 60 years old are between 1.1 and 2.3 percentage points less likely to succeed in acquiring a loan. However, it is worth noting that the elderly comprise only 2% of the pictures in the sample.

There are also some interesting results related to the perceived happiness, weight, and attractiveness of individuals in their pictures, though the results are generally somewhat weaker. For instance, the OLS estimates imply that listings of significantly overweight people are 1.6 percentage points less likely to fund, which is statistically significant at the 5% level. However, the marginal effect in the Logit specification is only -0.6 percentage points and is not statistically distinguishable from zero. The coefficients on our measures of attractiveness imply directionally that more attractive people are more likely to have their loans funded; however, the coefficient estimates are rather small and are not statistically significant.[23] The strongest effects from this set of characteristics are for perceived happiness. People who look unhappy are between 1.6 (Logit) and 1.8 (OLS) percentage points less likely to have their loans funded. While these

[23] In other specifications (not reported) we interact gender with this attractiveness measure to see whether there is an effect of pictures of especially attractive females. The estimates are in the direction of a positive interaction between female and attractiveness, but the magnitude is very small and statistically insignificant. We suspect that the inherent subjectivity of attractiveness and the coarseness of the measure we used may have introduced measurement error and subsequent attenuation bias in the attractiveness variable. Our results are directionally consistent with those of Ravina (2008), who conducted a more thorough coding of attractiveness using a smaller sample of Prosper loans and finds a strong positive effect of beauty on the likelihood of funding.

differences are statistically significant at the 10% level in both specifications, it is important to note that unhappy people make up only 1% of all pictures.

Finally, we coded some secondary characteristics of pictures with adults, including whether the adult had a child with them in the photo, whether the person was professionally dressed (e.g., wearing a tie), and whether there were signs of military involvement (e.g., uniform). We find no significant effect of a child in the picture or of professional dress on funding. While statistically insignificant in the OLS specification, in the Logit specification military involvement increases the likelihood of funding by 2.5 percentage points.

The estimated effects of the coded loan purpose are generally weaker than those of the picture characteristics, though there are some important and sensible patterns. The base-group for these purpose dummies is the listings with no clear purpose that could be discerned from the one-line loan description. Relative to that group, the loans listings that express interest in consolidating or paying down debt (usually high-interest credit-card debt) are between 0.4 (Logit) and 0.5 (OLS) percentage points more likely to get funded. Loans with most other purposes are less likely to fund, though many of the effects are not statistically significant.

Robustness. In Table 3 we begin to investigate the robustness of these results, focusing on the estimated effects for race. The table reports marginal effects from the Logit regression for a number of specifications. In the first column the regressors include only the gender and race characteristics coded from the pictures without any credit or loan-parameter controls. They confirm the summary statistics; blacks are 5 percentage points less likely to get funded than whites. The second column adds dummies for the borrower's credit grade, continuous linear measures of the maximum interest rate, DTI, and requested loan size. Adding these controls brings the estimates much closer to the estimates reported in Table 2, and highlights the important correlations that race has with credit measures; the estimated effect of being black falls to -2.8 percentage points. This column also provides easy comparisons of the size of the race effect. The marginal effect of being black (-2.8%) is somewhat less that the -4.1% effect of moving from a credit score of above 760 (AA credit) to a credit-score range of 720-759 (A credit), and about one and a half times as large as the effect of a one percentage-point change in the maximum interest rate.

Columns (3) and (4) of Table 3 add in interaction terms in the financial variables, additional credit controls, the long-description text-analysis controls (e.g., percent of words misspelled), time trends, other picture controls, and loan purpose variables. There is a slight drop in the race effect when additional credit controls are added, but otherwise the effect of a black photo does not change meaningfully with these additional characteristics. Column (5) restricts the sample to loans that posted a picture (46.1% of all loans). Focusing on this subsample allows us to avoid any potential interaction effects between choosing to post a picture and race. This sample restriction strengthens the significant results that we find in terms of the absolute percentage point difference between black and white funding, however, it is a similar percentage change from the base rate. Column (6) restricts the sample to only the first loan posted by a each borrower. This restriction eliminates concerns that subsequent posting behavior may bias the results we find. The effect size in Column (6) is similar to that found in Column (4) in terms of percentage points and slightly larger in terms of percent off the new baseline.

There are a few main takeaways from this robustness table. Approximately half of the disparity in loan funding between blacks and whites observed in the sample averages can be accounted for by the different financial characteristics. It is also important to note that once basic credit controls are included in the regressions, the estimated effects on race are quite stable across different specifications.[24]

In Table 4 we investigate the race results under a number of different cuts of the data. Each cut uses the baseline Logit specification from Table 2 and reports marginal effects. Cutting by credit grade reveals that across all credit grades there is a significant negative response to black pictures. The percentage point difference in the likelihood of funding between blacks and whites is actually higher for better credit grades: blacks are between 4 and 6 percentage points less likely to be funded amongst borrowers with credit scores above 640 (grades of C and above), compared to a 3.3 percentage point difference for D&E credit (560 – 640) and a 1.3 percentage point difference for the high-risk borrowers (520 – 560). Comparing these differences to the mean probability of funding for the different groups, however, reveals that the likelihood

[24] Another potential worry is that despite the controls we use, our coding procedure does not take on a flexible enough function form which may lead to biased estimates. To test for these, we implemented a propensity-score matching estimation where black and white loan listings were matched on key characteristics. The results from this analysis (which were included in a previous version of this paper) are consistent with those presented in this paper and are available from the authors upon request.

of funding is 37% lower for blacks in the high-risk category versus 12.2% for blacks in the highest credit grades.

The second cut we investigate splits the one-year sample in half and contrasts results estimated over listings in the first six months of the sample versus those in the second six months. None of the results are meaningfully different between these samples. Although the market itself is evolving rapidly, the market response to information contained in pictures and text has remained relatively stable.

For the third cut in Table 4, we divide the sample into quartiles of self-reported income. The negative marginal effect of a black picture versus a white picture is slightly larger for higher income quartiles – ranging from -2.1 percentage points for the lowest income quartile to -3.4 percentage points for the highest income quartile. Of course, these income quartiles have different mean rates of funding, and thus in percentage terms the negative effect of a black picture is quite a bit larger in the lowest quartiles.

The final cut in the Table 4 investigates whether the race and gender effects vary depending on the borrower's stated occupation. We split the sample based on occupations that are likely to require a college degree versus those that do not. The negative marginal effect of a black picture is slightly more than a percentage point larger for those with high education jobs (-3.3% to -1.9%). When compared to the funding base rates of the two groups, however, the marginal effects are quite similar in percent terms. The fact that the results for blacks are not strongly related to these occupation cuts, again suggests that any failure on our part to fully capture inferences that lenders can make about educational attainment of the borrowers based on observables is unlikely to explain the race results.

One final note on the robustness of our estimates of the probability of funding is in order. Lenders have the option of creating settings that automatically bid on loans based on lender-chosen criteria of credit score, DTI, and the like. We are not able to ascertain how many lenders use this option, but if all lenders exclusively used this process, we would not find any effect on the picture or text characteristics. Hence our results may underestimate the market response that would be observed in a market without automatic bidding. The results also highlight that market participants do in fact react to the non-financial information and that many forgo the option to bid on loans without reviewing the listing in detail.

Final Interest Rate on Funded Loans

The differences in the likelihood of funding translate into different final interest rates conditional on a loan getting funded. Table 5 presents the results from an OLS regression of the final interest rate of a funded loan on the borrower and listing characteristics used in the baseline specification (Table 2), excluding the maximum interest rate the borrower set. The estimates are in the directions one would expect based on the estimates of the probability of loan funding. The first column of the table is estimated over all 10,207 loans made in the Prosper market during our sample year. All else equal, a funded listing with a picture of a black borrower ends up with an interest rate that is 60 basis points higher than an equivalent listing for a white borrower. Single females have rates that are 40 basis points lower than males. The results for age and happiness are much smaller and not statistically distinguishable from zero. The very unattractive end up with rates that are 60 basis points higher than their average-looking counterparts. The effects of the stated loan purposes are also sensible given the results above. For instance, those expressing a desire to consolidate credit-card debt obtain loans with interest rates that are 20 basis points lower than their counterparts who express a need for a business loan.

These estimates are consistent with the predictions of the idea that the different reservation rates lenders set for loans from otherwise similar "majority" and "minority" borrowers would lead to different interest rates on funded loans for the groups. However, there is a potential problem with interpreting these interest-rate results in that way. Borrowers may elect to forgo the "bid-down" process and receive their loan funds at the maximum interest rate they set as soon the loan becomes fully funded. The worry here is that if, for example, black borrowers were more likely to use this feature and occasionally set maximum interest rates that were highly attractive to lenders, it might result in higher interest rates for funded black loans than similar funded white loans, even if the reservation rates of the lenders were the same for the two groups. To address this concern, column (2) of Table 5 restricts the analysis to the 6,419 funded loans that used the "open funding" option that allows interest rates to be bid down to the reservation rate of the marginal lender. The results are quite similar, and in fact the effect of a black loan increases from 60 basis points in column (1) to 80 basis points for the loans that allow bid down.

Net Return on Funded Loans

The preceding analysis reveals that the market discriminates based on information contained in pictures and text and that this discrimination leads to disparities in interest rates on funded loans. Here we ask whether the discrimination we observe in the Prosper.com market is efficient for the lenders.

Loan-Performance Data.[25] Prosper provides performance data on all loans that have been made in the marketplace. The analysis here is based on the available performance data as of December, 2007, at which point the loans made during our sample year ranged in age from 7 months to 19 months. Prosper provides information on payment status of each loan showing whether the loan was current, paid off, 1 month late, 2 months late, 3 months late, 4+ months late, and officially defaulted. Table 6 shows summary statistics for this performance data, combining defaulted loans with those that are 4+ months late (which exceeds the usual standards for considering a loan in default). Among all loans made during the sample year, as of December 2007, 78% had been paid off or were in good standing. Approximately 2% fell in each of the categories, 1 month late, 2 months late, and 3 months late. A sizeable fraction (17%) of all loans was 4 months late or more.

The table breaks down the performance data by the age of the loan. Naturally, the number of loans in good standing is higher for the more recent loans. For instance, only 2% of the loans made in May, 2007 were 4 months late or more in payments as of December, 2007, which is sensible when one considers that these borrowers would have had to stop paying by the third month of their loan to fall into this category. The payment characteristics are rather stable, however, for loans that are at least 13 months old, suggesting that most default in the Prosper market may occur during the first year of the loan. Somewhere between 71% and 74% of loans were in good standing after 13 months, while 20-25% were at least 4 months late in making payments.

Table 6 continues by indicating loan performance information by race. There are large differences in default rates across racial groups. Most notably, 29% of loans made to black individuals are 4+ months late. In comparison, only 14-15% of loans made to white or Asian borrowers are 4+ months late. Hispanic

[25] Disclaimer: None of the loans made on Prosper.com have reached full maturity. Because of this, all estimates of loan profitability in this marketplace are only valid subject to the assumptions discussed.

default rates fall in between these groups with 21% of loans that are 4 or more months late.Once again, however, given the correlations that exist between these groups and other variables (e.g. credit grades), the summary statistics do not provide conclusive evidence that these groups have higher default rates controlling for all of the other information available to lenders.

Hazard Model of Default. In order to formally test whether there exist *ceteris paribus* differences in default rates across gender, race, and other groups, we employ a simple hazard model where default is considered to be a nonnegative random variable. We estimate the hazard function, $\lambda(t)$, as defined in the analysis of Cox's proportional hazard model (Cox, 1972). $\lambda(t)$ measures the instantaneous failure rate at time t given that the individual survives until time t. In our model, a "failure" is a loan that goes into default. For this model, we define a loan as entering default when the borrower misses three consecutive pay cycles (a common assumption in the literature on loan repayment). In this model the baseline hazard rate, $\lambda_0(t)$, remains unspecified and through the exponential link function, the same covariates X_i and Z_i that are used in our baseline regressions in Table 2 act multiplicatively on the hazard rate.

The hazard-model estimation results are presented in Column (1) of Table 7. Once again, the largest and most significant effects that we find in the estimation of the hazard model involve the race variables. Blacks are approximately 36% more likely to default on their loans than are whites with similar characteristics. The summary statistics indicated that blacks were twice as likely to default as whites. While the estimate on the black coefficient is smaller after controlling for credit and other variables, it is still statistically significant and obviously economically large. While not statistically significant, Asians and Hispanics are estimated to be 24% less likely and 10% more likely to default than whites, respectively.

Few of the coefficients on the other picture characteristics are statistically significant. However, the direction of the effects is interesting. The parameter estimates suggest, for instance, that women are 14% more likely to default than men. The difference across age groups is essentially zero. Borrowers that the coders recorded as appearing unhappy are estimated to be 42% more likely to default. The results of being somewhat or very overweight relative to being thin are mixed. Borrowers coded as being very unattractive are estimated to be 32% more likely to default, though not significant and borrowers that indicated signs of military involvement are estimated to be 49% more likely to default.

Estimates of Net Return. The default data alone do not tell us about discrimination in this market. Differences in default rates are necessary for the earlier results to be explained by accurate statistical discrimination, yet they are not sufficient. In order to answer this question, we need to combine the default rate data with the interest rates that borrowers actually paid. We begin with a simple graph. Figure 3 presents the fraction of loans defaulted versus the final interest rate on the loan using linear smoothing.[26] It is clear from the graph that at each interest rate, the proportion of black loans defaulting is higher than the proportion of white loans defaulting. Figure 4 adds to the evidence presented in Figure 3 by illustrating the dynamics of loan performance. We begin by calculating the returns lenders see as an average annual percentage rate (APR) across black and white loans for each month as the loans age. Under the assumption that borrowers who are current or less than two months behind will continue to make payments until loan maturity and that borrowers that are three or more months behind are in default, we graphically demonstrate how the average APR by race declines over the maturation of loans as defaults begin occurring. Figure 4a and 4b illustrate this by looking at loans for which we have at least 12 and 15 months of loan-performance data, respectively. As can be seen in each of these figures, black loans have a higher APR at the beginning (due to the fact that they are required to pay higher interest rates on average). As loans mature, however, the higher default rate on black loans causes the net return on these loans to fall below the net return on white loans. In fact, the black default rates are such that by 4 months the net return on black loans is lower than the for white loans, at 9 months the net return on black loans is negative, and at 12 months the average APR on black loans is approximately -5% relative to a 5% APR for the average white loan.

While Figures 3 and 4 provide a nice visual representation of loan repayment by race, it does not allow us to estimate the difference in net return for race while controlling for credit grade and other important variables. In order to do this more rigorous analysis, we begin by calculating the net return over a three-year

[26] This graph makes use of the lowess command in STATA. For this Figure, we define a loan to be in default if the borrower has missed three or more consecutive pay cycles.

period on a dollar invested.[27] The calculation uses the monthly payment on the loan, and thereby incorporates the interest rate on the loan. We consider three different measures of net return, based on different assumptions about the future repayment of loans. Each measure assumes that any loan that is in good standing (current or paid off), in December of 2007 will continue to be paid off throughout the remainder of the three-year loan period. This assumption is obviously generous, as some of the loans in good standing will default in the future. Furthermore, assuming that the loans that are paid off earn the full three-year return, is equivalent to assuming that lenders who are paid early can costlessly find another loan with the same terms. The differences between the return measures come from different assumptions about the repayment stream for loans that were late as of December 2007. Our first net return variable, Return Type I, is the most pessimistic about future loan performance; we assume that any loan that is not in good standing (1 month or more late) in December of 2007 will not produce any future payments. For Return Type II we assume that a loan that is only 1 month late will eventually pay in full, and for Return Type III that a loan that is 2 or fewer months late will eventually pay in full. Hence, these return types are increasingly optimistic in that they assume that loans that are in good standing as well as loans that are only 1-3 months late will all be paid in full.

Columns (2)-(4) of Table 7 show the results of OLS regressions of net return on the baseline covariates that have been used throughout for the full set of funded loans. The top row provides the mean of the net-return variable across all funded loans for each return type. The average 3-year return on a dollar lies between 1.047 (Return Type I) and 1.084 (Return Type III). Translating these three-year returns into annual percentage rates yields a net APR range of 3.1% to 5.3%.[28]

Turning to the regression estimates, as before, we present the estimated coefficients and clustered standard errors for the various picture characteristics. Across the different return types, the only variable that is consistently statistically significant is the black indicator variable. The estimates for the full sample of

[27] In Figure 4, we use APR as the relevant statistic for evaluating the net return on a loan. We are unable to use this measure in the regression analysis due to the fact that APR is undefined when a borrower does not make any payments on a loan. Thus, while APR could be used when we were looking at averages across a group, we employ the 3-year net return on a dollar as the relevant statistic for the individual-level regressions.
[28] It is worth noting that these low average returns may not bode well for the long-run viability of the Prosper model. In fact, our return measures are especially generous, because many of the loans in the sample have been out for less than a year.

funded loans suggests that the average net return on investing in a loan from a black borrower is 8.2 to 8.6 percentage points lower over a three-year period than investing in a loan from an otherwise similar white borrower. This result implies that the increased propensity of default for black loans was not fully offset by the one percentage point increase in interest rates that black individuals paid. While not significant, the net return on Hispanic loans is estimated to be 3.1 to 5.5 percentage points less than whites while the net return on loans given to Asian borrowers is estimated to be 1.5 to 1.7 percentage points higher than whites.

The estimated coefficients on the other variables are not consistently statistically significant, but the direction of the coefficients may be of interest nonetheless. The estimated return on loans to single females is approximately 2 percentage points less than for single males. The return for borrowers coded as being unhappy, older, unattractive, professionally dressed, involved in the military, or with a child is less than their counterparts. Conversely, the return on borrowers coded as very overweight is higher than their counterpart.

Columns (5) through (7) of Table 7 present the same analysis estimated over the sample of loans that had "open funding", indicating that the listing remained open after reaching funding level, which allows lenders to continue to bid down the interest rate set by the borrower. Although slightly smaller, these estimates show very similar differences in net returns between whites and blacks, with blacks having net returns that are 7.3 to 7.5 percentage points lower over the course of three years.

Overall, the net-return results do not appear to differ significantly based on the different return-type definitions. Nonetheless, it is worth thinking about how our estimates might be affected by the assumptions that we use to generate our estimates of net return. Specifically, is it possible that the strong negative return effect that we find for blacks could change once all 3 years of return data are available? The estimate on the black coefficient would be attenuated if the default rate of whites becomes significantly larger than the default rate of blacks after December of 2007. Given the available data, this possibility can never be ruled out. However, the available data do not suggest that this is the case. In fact, if anything, loans given to black borrowers are defaulting at a higher rate after the loan has matured for a year or longer; indicating that we might be underestimating the overall effect of race on net returns. Furthermore, defaults that occur later are less costly to lenders because more of the principle has been repaid. Hence, the difference in default rates as loans mature would have to change dramatically to erase the coefficient that we estimate for the black indicator variable.[29]

Another potential concern with the results – one that arises in many studies of default – is that an unanticipated economic shock that hit blacks harder than whites could affect the results. That is, lenders might have charged interest rates for each group that equalized net returns *ex ante* but turned out to wrong *ex post*. While it is difficult to rule out this possibility, two different cuts of the data suggest that differential economic shocks are unlikely to explain the differences in average net returns. First, we divide the sample into those funded during the first 6 months and second 6 months of our one-year sample. If unanticipated economic shocks are the source of the net-return differences, we would not expect the results to be the same across periods. Although this cut causes us to lose power and is complicated by the different time horizons for default in the split samples, we find no evidence of differences in the net return results for the two samples. As a second approach to addressing the possibility of differential economic shocks, we exploit the state identifier on listings to control for changes in the economic environment that occur during the repayment process. To do this, we obtain 2006 and 2007 unemployment rates by state and race from the Local Area Unemployment Statistics (LAUS) prepared by the BLS. We re-estimate Columns (2) – (4) of Table 7 including an interaction term between race and the black-white difference in the unemployment-rate change between 2006 and 2007. After controlling for these changes in economic conditions that may differential affect racial groups, we find estimates for each return type (-.074, -.082, and -.084) that continue to be statistically significant ($p < .01$ for each return type) and are similar to the estimates found in Table 7.

IV. Discussion and Conclusions

We have shown that the characteristics borrowers display through their pictures and descriptions strongly affect their access to credit in the Prosper market. Specifically, we find significant discrimination against listings without a picture and listings with pictures of blacks, older individuals, and people who

[29] As an example of how dramatic the change in trends in default rates would have to be, if we assume that the total percentage of people defaulting each month continues to be the same over the life of the loans, we estimate that whites would have to immediately begin defaulting at three times the rate of blacks in order to close the gap in net returns.

appear unhappy. In contrast, there is discrimination in favor of listings with pictures of women and pictures that show signs of military involvement.

If this discrimination was solely the result of costly taste-based preferences, we would expect a negative correlation between the discrimination in funding and subsequent net returns on funded loans. Accurate statistical discrimination, on the other hand, should result in no significant differences in net returns. The results for black loans run counter to the predictions of both taste-based animus against blacks and accurate statistical discrimination. Despite the fact that blacks are less likely to have their loans funded, the return results would suggest some form of prejudice *in favor of* blacks. That is, although blacks pay higher interest rates, those rates are not high enough to account for the higher probability of default that we find for black loans after controlling for other observable characteristics.

How can we interpret these findings? First, we note that clearly skin color is not a causal factor in loan default. Higher default rates for blacks must stem from some difference in the background and financial characteristics of these borrowers that is not fully reflected in the standard financial measures (e.g., credit score, DTI) that lenders can observe. There are a number of well-known candidates for important characteristics that are not (perfectly) observed by lenders: for example, income disparities (perhaps stemming from labor-market discrimination), education differentials, and more limited access to financial support from family and friends.[30] Whatever the relevant differences, the discrimination in the decision to lend suggests that the market understands the direction of this correlation between unobservables and the race in a borrower's picture. Yet the interest-rate penalty these borrowers pay in the market is not enough to account for their higher rate of default.

One explanation for these results could be a combination of accurate statistical discrimination against blacks (based on their greater likelihood of default conditional on other observables) that is partially offset by taste-based discrimination *against whites* (in favor of blacks). That is, the market might accurately assess the default probability of loans on average, but lenders might have a taste for lending to blacks over whites

[30] One example that we can test comes from the credit score. Prosper only provides credit-score grades to the lenders and it is possible that within a credit grade credit score is correlated with being black. Although lenders do not see the credit score, Prosper provided us with this information. Perhaps surprisingly, however, we find that being black is not correlated with credit scores within a credit grade when other variables are controlled for, and thus cannot explain the net-return differences.

and that makes them willing to accept a lower return from these loans. If true, this finding in peer-to-peer lending is quite novel, as to our knowledge the previous literature on discrimination has never found evidence of taste-based discrimination that favored blacks over whites.

Another potential explanation of the results is that while lenders understand the direction of the correlations between race and relevant unobservable characteristics, they fail to appreciate the strength of these correlations or the importance of unobservable characteristics on default. Although it seems intuitively plausible, this explanation implies that biased beliefs exist at the market level. We might expect these types of mistaken beliefs to be driven out of the market in a long-run equilibrium, and perhaps the evidence here is simply consistent with a market that is still evolving. Yet it is important to note that in this case, we are finding that a market with an efficient auction mechanism, real stakes, and large amounts of available data on performance is still not at its long-run equilibrium two-years out. In fact our splits of the data reveal little change in the discrimination against blacks between the first half and second half of our sample.

The results here also have implications for the broader literature on assessing theories of discrimination. Had we found that blacks have higher net returns, it would have been natural to conclude that the evidence was consistent with taste-based preferences against blacks. Having instead found the opposite, however, we are faced with the somewhat awkward conclusion that the evidence is consistent with partial taste-based discrimination in favor of blacks over whites. The alternative, which seems somewhat natural in this setting, is to conclude that decision-makers have inaccurate beliefs. The problem, of course, is that once one allows for the possibility of inaccurate beliefs, results from other studies that find evidence of taste-based or accurate statistical discrimination come into question. Thus, the results from this study suggest caution when interpreting evidence in favor of one theory of discrimination versus another.

The findings in this paper also highlight the importance of attempting to assess the efficiency of discrimination before reaching conclusions about sources of discrimination. We find racial discrimination in lending decisions despite the wealth of credit controls available to lenders, and it might be natural to conclude that such evidence is suggestive of taste-based animus against blacks. Yet the data tell a very different story that suggests that this peer-to-peer lending market actually treats the races more equally than would be expected in a market with accurate statistical discrimination.

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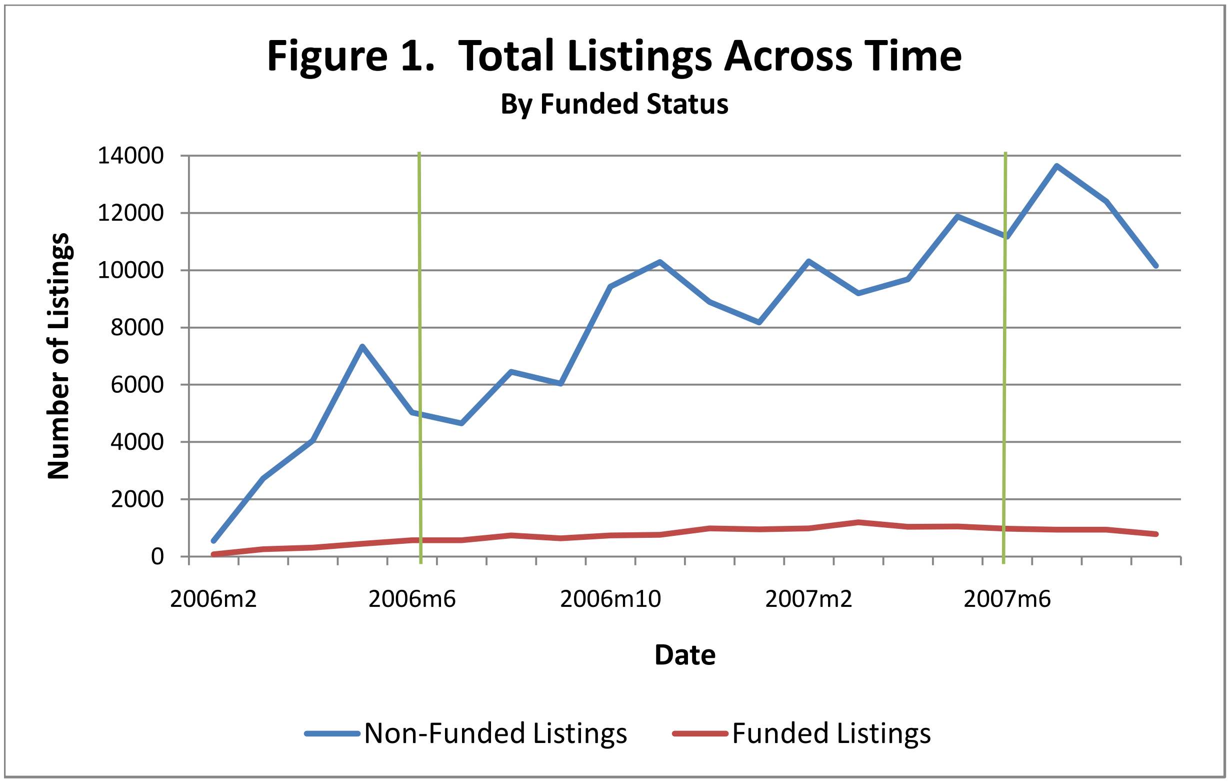
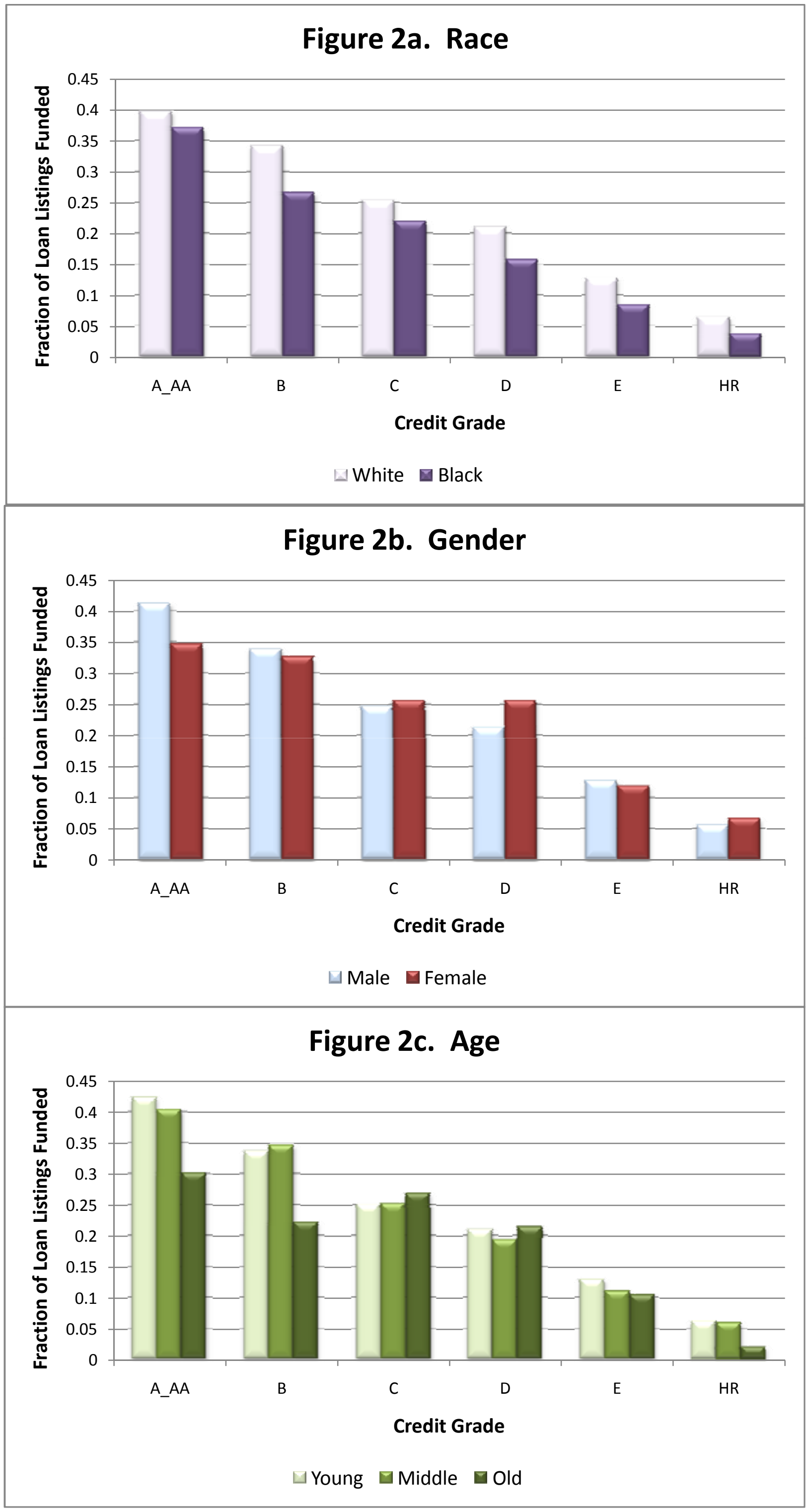
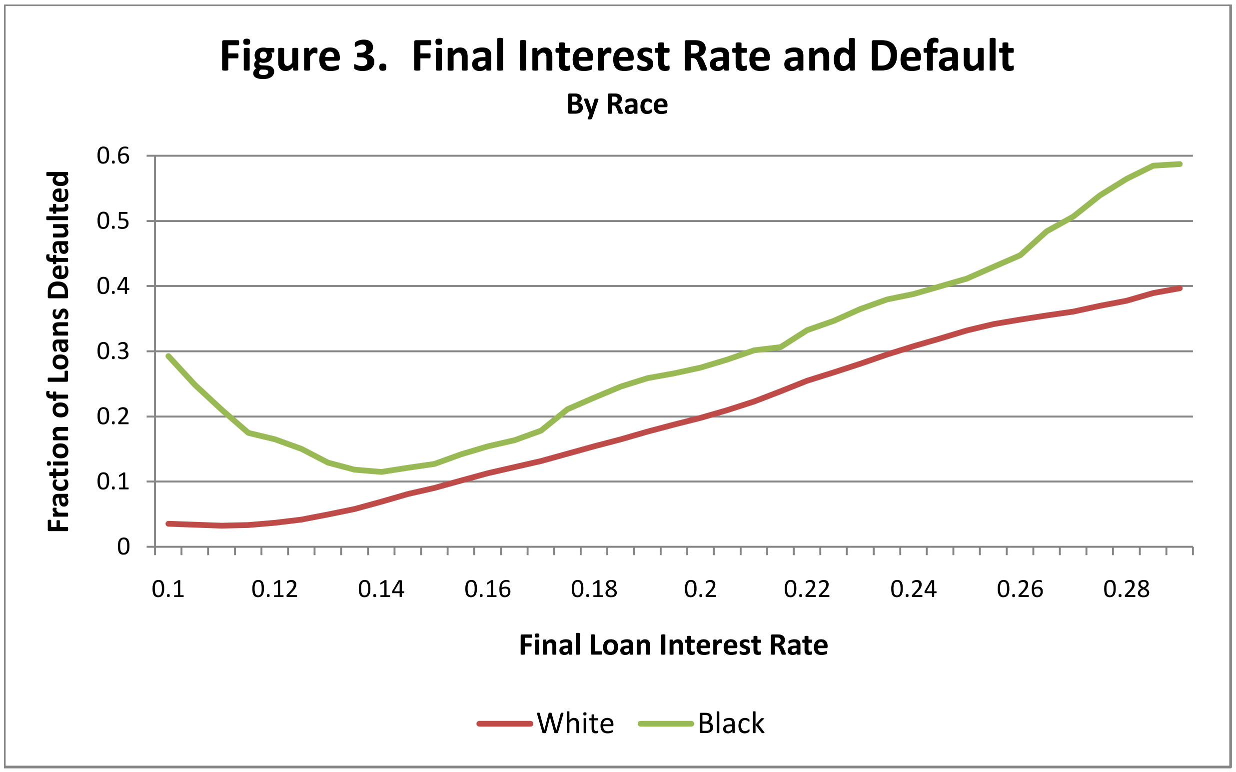


Notes: This Figure illustrates monthly counts of the total number of listings and the total number of listings that were eventually funded on Prosper.com since the company went public in February 2006. The loan listings that we analyze in this study come from the 1-year period between June 2006 and May 2007. These dates are indicated by the green vertical lines.

Figure 2. Fraction of Listings Funded by Credit Grade and Demographics

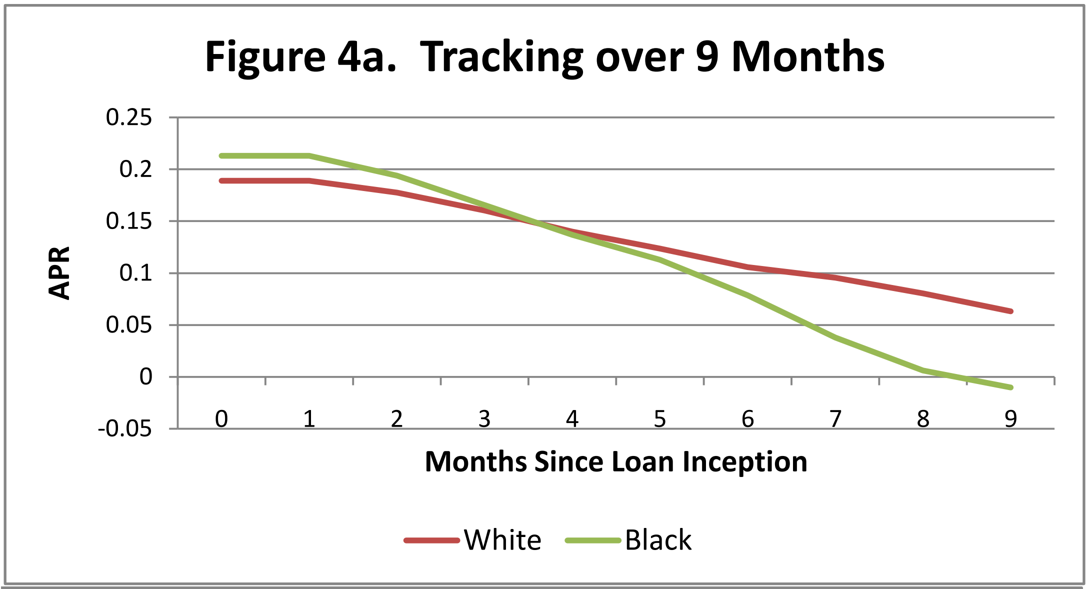


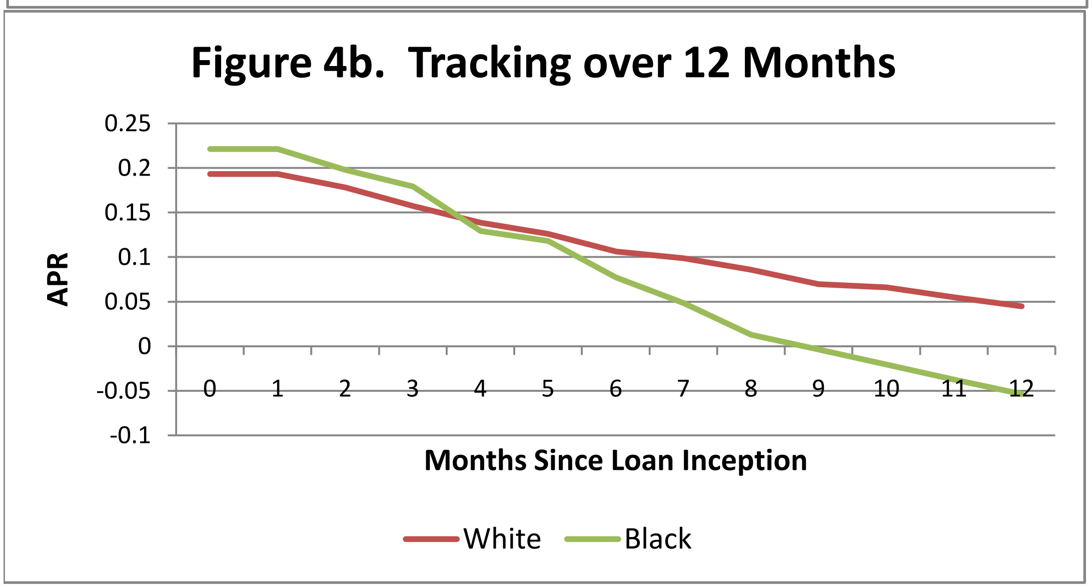
Notes: Figure 2a illustrates the fraction of loan listings that funded for each credit grade by race. The sample includes all loans between June 2006 and May 2007 that posted pictures where the race of the individual/s was discernable. Credit grade bins are related to credit scores in the following manner: A_AA (720 and up), B (680-719), C (640-679), D (600-639), E (560-599), and HR (520-559). Figure 2b uses data from loans during the same time period for which a picture was posted of a single adult male or a single adult female. Figure 2c uses data from loans during the same time period for which a picture was posted of an adult/s where the age of the adult/s was judged to be "young" (less than 35), "middle" (35-60), or "old" (more than 60).



Notes: Figure 3 illustrates the relationship between the final interest rate on a loan and the fraction of loans with that interest rate that have defaulted. Here we define default as a loan that is deliquent 3 months or more. This relationship is illustrated separately for funded loans of borrowers that listed a picture of a black individual/s and borrowers that listed a picture of a white individual/s. The lines are smoothed using a locally weighted estimation (lowess) with a bandwith of 0.3.

Figure 4. Average APR Adjusted Across Life of the Loans by Race





Notes: This figure illustrates the average APR over the maturation of a loan for funds invested in loans whose listings included a picture of a white individual/s or a black individual/s. The APR is calculated at each month by assuming that the loan will be fully repaid if the loan has not gone into default. We define a loan as goint into default if it is 3 or more months overdue. Thus the first data point (that comes prior to the first payment), assumes that all loans will be paid in full and simply illustrates the average interest rate paid by black and white borrowers. Each subsequent data point is adjusted given the number of loans being defaulted by each group. Panel A illustrates the dynamic APR for all loans for which we have at least 12 months of loan performance data. Panel B illustrates the dynamic APR for all loans for which we have at least 15 months of loan performance data. By restricting each panel to loans for which we have data over the entire x-axis time period, we are able to graph this relationship without any attrition (each of the points on a line is reflected by the exact same loans).

Table 1. Summary Statistics

Information from Listings			Information from Pictures (for those with a picture)		
Variables	All Listings	Funded Listings	Variables	All Listings	Funded Listings
Credit Grade			**Main Content of Picture**		
AA (760-800)	0.03	0.10	Adult/Adults	0.65	0.67
A (720-760)	0.03	0.09	Just Children	0.10	0.07
B (680-720)	0.04	0.11	Buildings	0.04	0.05
C (640-680)	0.07	0.16	Animals	0.04	0.04
D (600-640)	0.11	0.17	Automobiles	0.02	0.02
E (560-600)	0.18	0.17			
HR (520-560)	0.54	0.20	**For Pictures with Adults:**		
NC	0.01	0.01	**Gender**		
			Single Male	0.38	0.40
Loan Information			Single Female	0.35	0.31
$ Requested	7,154	5,930	Couple	0.20	0.22
Borrower's Max Rate	0.17	0.20	Group	0.07	0.07
Final Rate	NA	0.18			
Fraction Funded	0.12	1.00	**Race**		
Closed Auction Loans	0.43	0.37	White	0.67	0.83
			Black	0.20	0.11
Other Information Provided			Asian	0.03	0.03
Debt to Income Ratio	0.63	0.39	Hispanic	0.03	0.02
Group Member	0.51	0.69			
Owns a Home	0.27	0.39	**Age**		
Provided a Picture	0.46	0.64	Less than 35 yrs	0.53	0.54
			35-60 yrs	0.41	0.41
Information Coded From Descriptions:			More than 60 yrs	0.02	0.02
Purpose of Loan			**Happiness**		
Consolidate or Pay Debt	0.30	0.33	Happy	0.74	0.77
Business/Entrepreneurship	0.10	0.10	Neutral	0.23	0.21
Pay Bills	0.04	0.02	Unhappy	0.01	0.01
Education Expenses	0.03	0.03			
Medical/Funeral Expenses	0.03	0.02	**Weight**		
Home Repairs	0.02	0.03	Not Overweight	0.73	0.75
Auto Purchase	0.02	0.02	Somewhat Overweight	0.20	0.18
Home/Land Purchase	0.02	0.02	Very Overweight	0.03	0.02
Auto Repairs	0.01	0.01			
Luxury Item Purchase	0.01	0.01	**Attractiveness**		
Wedding	0.01	0.01	Very Attractive	0.05	0.06
Reinvest in Prosper	0.01	0.02	Average	0.91	0.91
Taxes	0.01	0.01	Very Unattractive	0.03	0.02
Vacation or Trip	0.01	0.01			
Multiple of Above Reasons	0.06	0.05	**Other**		
Unclear/Other	0.34	0.33	Profesionally Dressed	0.13	0.14
			Child Also in Picture	0.21	0.21
			Signs of Military Involvement	0.02	0.02
Observations	110,333	10,207		50,820	6,571

Notes: This Table presents summary statistics for the 110,333 loan listings posted on Prosper.com between June 2006 and May 2007. The summary statistics for each variable are reported separately for all loan listings and the set of loan listings that eventually funded. The "Credit Grade", "Loan Information", and "Other Information Provided" categories provide information that was obtained directly from variables provided by Prosper.com. The "Purpose of Loan" category and "Information from Pictures" category was coded by us using the descriptions and pictures that individuals posted as part of their loan listings.

Table 2. The Effect of Borrower Characteristics and Purpose on Loans Being Funded

Dependent Variable: Indicator = 1 if the Loan was Funded

	OLS (1)	Logit (2)
Mean of Dependent Variable	0.093	0.093
Gender (BG: Single Male)		
Single Female	0.004	0.011
	(0.004)	(0.003)***
Couple	-0.007	-0.001
	(0.004)	(0.003)
Group	-0.011	-0.004
	(0.006)*	(0.004)
Race (BG: White)		
Black	-0.032	-0.024
	(0.003)***	(0.003)***
Asian	0.002	0.004
	(0.009)	(0.006)
Hispanic	-0.018	-0.006
	(0.008)**	(0.005)
Age (BG: 35-60 yrs)		
Less than 35 yrs	0.009	0.004
	(0.003)***	(0.002)*
More than 60 yrs	-0.023	-0.011
	(0.011)**	(0.007)*
Happiness (BG: Neutral)		
Happy	0.007	0.002
	(0.003)**	(0.002)
Unhappy	-0.018	-0.016
	(0.010)*	(0.009)*
Weight (BG: Not Overweight)		
Somewhat overweight	0.001	0.003
	(0.004)	(0.003)
Very overweight	-0.016	-0.008
	(0.008)**	(0.006)
Attractiveness (BG: Average)		
Very attractive	0.007	0.004
	(0.008)	(0.005)
Very unattractive	-0.002	-0.005
	(0.009)	(0.007)
Misc. Adult Information		
Profesionally Dressed	0.000	0.002
	(0.005)	(0.003)
Child With Adult in Picture	-0.005	0.001
	(0.003)	(0.002)
Signs of Military Involvement	0.014	0.025
	(0.011)	(0.009)***

	OLS (3)	Logit (4)
Loan Purpose (BG: Unclear)		
Consolidate or Pay Debt	0.005	0.004
	(0.003)*	(0.002)*
Business/Entrepreneurship	-0.015	-0.006
	(0.004)***	(0.003)**
Pay Bills	-0.015	-0.010
	(0.007)**	(0.006)
Education Expenses	0.001	0.001
	(0.007)	(0.005)
Medical/Funeral Expenses	-0.013	-0.014
	(0.007)*	(0.006)**
Home Repairs	0.018	0.005
	(0.010)*	(0.006)
Auto Purchase	-0.009	-0.005
	(0.008)	(0.006)
Home/Land Purchase	-0.023	-0.015
	(0.008)***	(0.006)***
Auto Repairs	-0.019	-0.015
	(0.012)	(0.007)**
Luxury Item Purchase	-0.013	-0.011
	(0.012)	(0.008)
Wedding	-0.005	-0.006
	(0.012)	(0.007)
Reinvest in Prosper	0.034	-0.010
	(0.021)	(0.006)*
Taxes	0.010	0.008
	(0.019)	(0.011)
Vacation or Trip	0.032	0.006
	(0.020)	-(0.011)
Multiplie of Above Reasons	-0.004	-0.003
	(0.005)	(0.003)
Picture Characteristics	**X**	**X**
Month Fixed Effects	**X**	**X**
Credit Controls	**X**	**X**
R-Squared	0.31	
Observations	110,333	110,332

Notes: Coefficient values and standard errors clustered by borrower are presented using an OLS regression (Columns (1) and (3)) and a Logit regression (Columns (2) and (4)) - marginal effects reported. The dependent variable in both regressions is a dummy variable indicating whether a particular loan listing was funded. Each characteristic type for which a coefficient value is reported can be interpreted relative to its base group which is indicated in parenthesis. The coefficients on other variables that are included in the regression (credit controls, month fixed effects, etc.) are omitted due to space constraints. The entire set of variables used in these regressions is provided in the text under the heading "Baseline Regression Estimates".

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3. The Effect of Race on Loans Being Funded - Specification Robustness

	Dependent Variable: Indicator = 1 if the Loan was Funded					
					Only Loans with Pictures	Only 1st Loan Per Borrower
	(1)	(2)	(3)	(4)	(5)	(6)
Mean of Dependent Variable	0.093	0.093	0.093	0.093	0.129	0.070
Race (BG: White)						
Black	-0.051	-0.028	-0.022	-0.024	-0.033	-0.021
	(0.002)***	(0.003)***	(0.003)***	(0.003)***	(.004)***	(.004)***
Asian	0.010	0.000	0.006	0.004	0.006	-0.001
	(0.008)	(0.006)	(0.006)	(0.006)	(.007)	(.006)
Hispanic	-0.028	-0.013	-0.007	-0.006	-0.009	0.001
	(0.006)***	(0.006)**	(0.006)	(0.005)	(.007)	(.009)
Credit Grade (BG: HR & NC)						
AA		0.745				
		(0.004)***				
A		0.704				
		(0.004)***				
B		0.624				
		(0.004)***				
C		0.477				
		(0.004)***				
D		0.315				
		(0.004)***				
E		0.106				
		(0.003)***				
Other Key Credit Variables						
Maximum Borrower's Rate		1.756				
		(0.022)***				
Debt to Income Ratio		-0.014				
		(0.001)***				
$ Requested (thousands)		-0.000				
		(.000)***				
All other Credit Controls			X	X	X	X
Long Description Text Controls				X	X	X
Month Fixed Effects				X	X	X
Other Picture Characteristics				X	X	X
Loan Purpose Fixed Effects				X	X	X
Observations	110,333	110,333	110,333	110,333	50,820	51,676

Notes: Coefficient values and standard errors clustered by borrower are presented using Logit regressions - marginal effects reported. The dependent variable in all regressions is a dummy variable indicating whether a particular loan listing was funded. Each column from (1) to (4) progressively includes a larger set of control variables. The coefficients on these control variables are omitted due to space constraints. The entire set of variables used in these regressions is provided in the text under the heading "Baseline Regression Estimates". Column (5) restricts the sample to loans that posted a picture. Column (6) restricts the sample to first loans posted by a unique borrower (subsequent loan listings are eliminated from the sample).

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. The Effect of Race on Loans Being Funded - Sample Cuts

Dependent Variable: Indicator = 1 if the Loan was Funded

Panel A

	Sample Cut by Credit Grades				Sample Cut by Time	
	AA & A	**B & C**	**D & E**	**HR & NC**	**First 6 Months**	**Last 6 Months**
	(1)	(2)	(3)	(4)	(5)	(6)
Mean of Dependent Variable	0.335	0.225	0.108	0.035	0.087	0.096
Race (BG: White)						
Black	-0.041	-0.054	-0.033	-0.013	-0.020	-0.026
	(0.031)	(0.014)***	(0.005)***	(0.002)***	(0.004)***	(0.003)***
Asian	0.011	0.000	-0.004	0.006	0.002	0.005
	(0.027)	(0.019)	(0.011)	(0.006)	(0.011)	(0.006)
Hispanic	0.072	0.005	-0.011	-0.006	-0.022	0.006
	(0.054)	(0.026)	(0.010)	(0.004)	(0.008)***	(0.007)
Other Picture Characteristics	X	X	X	X	X	X
Loan Purpose Fixed Effects	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X
Credit Controls	X	X	X	X	X	X
Observations	5,587	12,123	32,154	60,391	45,941	64,386

Panel B

	Sample Cut by Income Quartiles				Sample Cut by Occupation	
	Low Quartile	**2nd Quartile**	**3rd Quartile**	**High Quartile**	**No College**	**College**
	(1)	(2)	(3)	(4)	(5)	(6)
Mean of Dependent Variable	0.059	0.072	0.091	0.147	0.086	0.116
Race (BG: White)						
Black	-0.021	-0.022	-0.022	-0.034	-0.019	-0.032
	(.004)***	(0.004)***	(0.005)***	(0.007)***	(0.004)***	(0.006)***
Asian	-0.003	-0.001	0.008	0.016	-0.006	0.003
	(.009)	(0.010)	(0.011)	(0.013)	(0.008)	(0.010)
Hispanic	-0.020	0.000	0.003	-0.013	-0.003	-0.012
	(.006)***	(0.009)	(0.013)	(0.013)	(0.007)	(0.014)
Other Picture Characteristics	X	X	X	X	X	X
Loan Purpose Fixed Effects	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X
Credit Controls	X	X	X	X	X	X
Observations	28,480	26,054	27,244	27,288	56,208	20,432

Notes: Coefficient values and standard errors clustered by borrower are presented using Logit regressions - marginal effects reported. The dependent variable in all regressions is a dummy variable indicating whether a particular loan listing was funded. Columns (1) - (4) of Panel A present results from regressions using data cut by credit grades. The second half of Panel A presents results from regressions using data from June 2006 to November 2006 (Column (5)) and December 2006 to May 2007 (Column (6)). Columns (1) - (4) of Panel B present results from regression using data cut by income quartiles. The second half of Panel A present results from regressions using data from individuals whose self-reported occupation does not typically require a college degree (Column (5) and for those whose occupation typically does require a college degree (Column (6)). The coefficients on other variables that are included in the regression (credit controls, month fixed effects, etc.) are omitted due to space constraints. The entire set of variables used in these regressions is provided in the text under the heading "Baseline Regression Estimates".

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. The Effect of Borrower Characteristics and Purpose on the Final Interest Rate for Funded Loans

Dependent Variable: The Final Interest Rate for Funded Loans

	OLS	
	(1)	(2)
Mean of Dependent Variable	0.182	0.161
Gender (BG: Single Male)		
Single Female	-0.004	-0.004
	(0.001)***	(0.001)***
Couple	-0.001	0.000
	(0.001)	(0.001)
Group	0.001	0.001
	(0.002)	(0.002)
Race (BG: White)		
Black	0.006	0.008
	(0.002)***	(0.002)***
Asian	0.002	0.000
	(0.002)	(0.002)
Hispanic	0.002	0.001
	(0.003)	(0.003)
Age (BG: 35-60 yrs)		
Less than 35 yrs	-0.001	0.000
	(0.001)	(0.001)
More than 60 yrs	0.000	0.003
	(0.003)	(0.004)
Happiness (BG: Neutral)		
Happy	-0.001	-0.001
	(0.001)	(0.001)
Unhappy	0.002	0.002
	(0.004)	(0.005)
Weight (BG: Not Overweight)		
Somewhat overweight	0.002	0.002
	(0.001)*	(0.001)
Very overweight	0.003	0.005
	(0.002)	(0.003)
Attractiveness (BG: Average)		
Very attractive	0.003	0.003
	(0.002)*	(0.002)
Very unattractive	0.006	0.009
	(0.003)**	(0.003)***
Misc. Adult Information		
Profesionally Dressed	0.003	0.003
	(0.001)**	(0.001)*
Child With Adult in Picture	0.003	0.002
	(0.001)***	(0.001)
Signs of Military Involvement	-0.002	0.000
	(0.003)	(0.004)

	OLS	
	(3)	(4)
Loan Purpose (BG: Unclear)		
Consolidate or Pay Debt	-0.002	-0.002
	(0.001)*	(0.001)
Business/Entrepreneurship	0.002	0.001
	(0.001)*	(0.001)
Pay Bills	0.007	0.006
	(0.004)*	(0.006)
Education Expenses	0.003	0.002
	(0.002)	(0.003)
Medical/Funeral Expenses	0.005	0.002
	(0.003)*	(0.004)
Home Repairs	-0.001	-0.003
	(0.002)	(0.002)
Auto Purchase	0.001	-0.001
	(0.003)	(0.003)
Home/Land Purchase	0.000	0.002
	(0.003)	(0.003)
Auto Repairs	0.004	0.006
	(0.004)	(0.005)
Luxury Item Purchase	-0.001	-0.001
	(0.003)	(0.004)
Wedding	0.010	0.007
	(0.004)**	(0.005)
Reinvest in Prosper	0.004	0.004
	(0.002)**	(0.002)**
Taxes	-0.007	-0.012
	(0.004)*	(0.005)**
Vacation or Trip	0.005	0.007
	(0.004)	(0.008)
Multiplie of Above Reasons	0.003	0.003
	(0.002)	(0.002)
Open Funding Option Only		**X**
Picture Characteristics	**X**	**X**
Month Fixed Effects	**X**	**X**
Credit Controls	**X**	**X**
R-Squared	0.79	0.76
Observations	10,207	6,419

Notes: Coefficient values and standard errors clustered by borrower are presented using two OLS regressions. The dependent variable in both regressions is the final interest rate that borrowers have to pay for a particular loan. The regression presented in Columns (1) and (3) uses the entire sample of funded loans while the regression reported in Columns (2) and (4) restricts the sample to loans for which the setting of the loan listing was such to allow an auction system to determine the final interest rate. Each characteristic type for which a coefficient value is reported can be interpreted relative to its base group which is indicated in parenthesis. The coefficients on other variables that are included in the regression (credit controls, month fixed effects, etc.) are omitted due to space constraints. The entire set of variables used in these regressions is provided in the text under the heading "Baseline Regression Estimates".
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6. Loan Performance Summary Statistics

	Current Status of All Funded Loans (Fractions Reported)					
	Current or Paid Off	1 Month Late	2 Months Late	3 Months Late	4+ Months Late	Total # of Loans
All Loans	0.78	0.02	0.02	0.02	0.17	10,118
Age of the Loan (Months)						
7	0.91	0.02	0.04	0.01	0.02	230
8	0.86	0.03	0.02	0.02	0.07	1,073
9	0.84	0.03	0.02	0.01	0.10	1,095
10	0.84	0.02	0.01	0.02	0.11	1,153
11	0.77	0.02	0.02	0.03	0.16	912
12	0.76	0.02	0.02	0.02	0.19	982
13	0.74	0.02	0.02	0.02	0.20	950
14	0.73	0.01	0.02	0.02	0.22	701
15	0.72	0.01	0.02	0.02	0.24	704
16	0.76	0.02	0.01	0.01	0.20	613
17	0.71	0.01	0.01	0.02	0.24	753
18	0.74	0.01	0.01	0.01	0.24	560
19	0.71	0.02	0.01	0.01	0.25	392
Race						
White	0.79	0.02	0.02	0.02	0.15	3,756
Black	0.63	0.03	0.02	0.03	0.29	533
Asian	0.80	0.02	0.02	0.02	0.14	163
Hispanic	0.69	0.02	0.04	0.04	0.21	103

Notes: Summary statistics are provided for loan performance broken down by loan maturity and race for all 10,118 loan listings between June 2006 and May 2007 that were fully funded. This loan performance data was provided by Prosper.com in December 2007. For each loan type, the fraction of loans that were current or paid off, 1 month late, 2 months late, 3 months late, and 4+ months late is reported. The total # of loans for each loan type is also reported.

Table 7. The Effect of Borrower Characteristics on Net Return on Investment

	Hazard Model - Dep Var: Default	OLS -- Dependent Variable: 3-Year Return on Each Dollar Invested by Return Type					
		All Funded Loans			Only Open-Auction Loans		
	Default	Return Type I	Return Type II	Return Type III	Return Type I	Return Type II	Return Type III
Mean of Dependent Variable		1.047	1.066	1.084	1.081	1.099	1.116
Gender (BG: Single Male)							
Single Female	0.139	-0.023	-0.016	-0.016	-0.032	-0.023	-0.020
	(0.094)	(0.016)	(0.016)	(0.016)	(0.018)*	(0.018)	(0.017)
Couple	-0.064	0.001	0.002	0.003	0.001	-0.002	-0.001
	(0.110)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.016)
Group	0.077	0.001	-0.001	0.005	0.023	0.026	0.049
	(0.161)	(0.026)	(0.026)	(0.025)	(0.026)	(0.025)	(0.023)**
Race (BG: White)							
Black	0.346	-0.086	-0.082	-0.084	-0.075	-0.073	-0.073
	(0.100)***	(0.023)***	(0.023)***	(0.023)***	(0.027)***	(0.027)***	(0.026)***
Asian	-0.230	0.017	0.017	0.015	0.017	0.020	0.020
	(0.210)	(0.034)	(0.033)	(0.032)	(0.034)	(0.032)	(0.030)
Hispanic	0.050	-0.050	-0.051	-0.031	-0.060	-0.065	-0.050
	(0.231)	(0.047)	(0.047)	(0.046)	(0.057)	(0.057)	(0.054)
Age (BG: 35-60 yrs)							
Less than 35 yrs	-0.008	0.000	-0.003	-0.003	0.020	0.021	0.019
	(0.082)	(0.014)	(0.013)	(0.013)	(0.015)	(0.014)	(0.014)
More than 60 yrs	-0.042	-0.037	-0.039	-0.012	-0.060	-0.058	-0.010
	(0.362)	(0.044)	(0.043)	(0.041)	(0.054)	(0.053)	(0.048)
Happiness (BG: Neutral)							
Happy	-0.072	0.022	0.017	0.012	0.012	0.005	0.001
	(0.083)	(0.015)	(0.014)	(0.014)	(0.016)	(0.015)	(0.015)
Unhappy	0.443	-0.016	-0.039	-0.070	0.036	0.017	-0.019
	(0.266)*	(0.060)	(0.060)	(0.060)	(0.070)	(0.071)	(0.071)
Weight (BG: Not Overweight)							
Somewhat overweight	0.116	-0.021	-0.017	-0.008	-0.014	-0.006	0.011
	(0.095)	-0.017	(0.017)	(0.017)	(0.020)	(0.019)	(0.018)
Very overweight	-0.164	0.072	0.052	0.052	0.029	0.010	0.005
	(0.207)	(0.039)*	(0.039)	(0.040)	(0.045)	(0.045)	(0.047)
Attractiveness (BG: Average)							
Very attractive	-0.097	-0.012	-0.014	0.012	-0.026	-0.022	0.004
	(0.181)	(0.030)	(0.030)	(0.028)	(0.034)	(0.032)	(0.030)
Very unattractive	0.309	-0.049	-0.046	-0.056	-0.011	0.003	-0.005
	(0.234)	(0.048)	(0.046)	(0.045)	(0.055)	(0.051)	(0.049)
Misc. Adult Information							
Profesionally Dressed	0.129	-0.025	-0.013	-0.012	0.007	0.013	0.013
	(0.117)	(0.018)	(0.018)	(0.017)	(0.020)	(0.019)	(0.018)
Child With Adult in Picture	0.130	-0.035	-0.029	-0.022	-0.038	-0.033	-0.029
	(0.080)	(0.014)**	(0.014)**	(0.013)*	(0.015)**	(0.015)**	(0.014)**
Signs of Military Involvement	0.458	-0.034	-0.029	-0.052	0.019	0.025	-0.005
	(0.260)*	(0.048)	(0.047)	(0.046)	(0.051)	(0.049)	(0.048)
Loan Purpose Fixed Effects	X	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X	X
Credit Controls	X	X	X	X	X	X	X
R-Squared		0.26	0.26	0.26	0.27	0.28	0.27
Observations	9,963	10,113	10,113	10,113	6,369	6,369	6,369

Notes: Coefficient values and standard errors clustered by borrower are presented using a Cox proportional hazard model (Column (1)) and OLS regression (Columns (2) - (7)). The dependent variable for Column (1) is a default indicator and hazard ratios are reported as coefficients. The dependent variable for Columns (2) - (7) is the 3-year net return on a $1 investment into a particular loan. This 3-year net return was calculated using three separate assumptions of default. Definitions for each assumption can be found in the text. Columns (2) - (4) use the entire sample of funded loans while Columns (5) - (7) restrict the sample to loans for which the setting of the loan listing was such to allow an auction system to determine the final interest rate. Each characteristic type for which a coefficient value is reported can be interpreted relative to its base group which is indicated in parenthesis. The coefficients on other variables that are included in the regression (credit controls, month fixed effects, etc.) are omitted due to space constraints. The entire set of variables used in these regressions is provided in the text under the heading "Baseline Regression Estimates".

* significant at 10%; ** significant at 5%; *** significant at 1%