Love & Loans

The Effect of Beauty and Personal Characteristics in Credit Markets*

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Abstract

I find that beauty, race, age, and personal characteristics affect lenders' decisions, once credit and employment history, homeownership, and other hard financial information are taken into account. Beautiful applicants have 1.59% higher probability of getting loans, pay 60bps less, but have similar default rates than average looking borrowers who get worse terms. Blacks are less likely to get loans, pay higher rates than similar Whites, but default more. The findings are consistent with taste-based discrimination/misperception against the ugly, and with statistical discrimination against Blacks, although lenders specialization in borrowers from the same ethnicity and racial prejudice also play a role.

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Introduction

Every day people make choices among a host of alternatives on the basis of a limited amount of information. The compatibility of a partner and the productivity of a potential employee are just two examples. In such situations, either because of their past experience, stereotypes and perceptions, or the nature of their preferences, in addition to the limited hard verifiable information, they might base their decisions also on easily observable variables such as the personal characteristics of the counterpart and the way he or she presents herself. Similarly, when assessing the creditworthiness of a potential borrower, in addition to the information in the credit report, employment history and the overall financial situation of the applicant, are lenders' decisions also influenced by characteristics such as race, beauty, age, and the way the borrower presents himself? And if yes, what is the mechanism behind this phenomenon? What is the economic magnitude of the effect? And, are these characteristics related to ex-post performance?

In this paper I analyze the effect of borrowers' personal characteristics on their likelihood of getting a loan, the terms of such loan, and subsequent performance using data from Prosper.com, a large U.S. based online lending market with more than $270 million funded and 450,000 members. I find that, after controlling for credit score, credit history, income, employment status, and homeownership, personal characteristics significantly affect the likelihood of getting funds and the terms of the loan. In particular, beautiful borrowers are 159 basis points more likely to get funds and, conditional on getting a loan, pay between 32 and 65 basis points less. The economic magnitude of this effect is large. To match the same likelihood of getting a loan, an average-looking applicant with the same credentials and characteristics would need to increase the interest rate he is willing to pay by 7.54 percentage points. Interestingly, beautiful borrowers turn out as likely to default as average-looking borrowers with similar credentials, who are on average less likely to get funds and are charged higher rates. Black borrowers are 2.66% less likely to get a loan than similar White

borrowers, and pay between 148 and 183 basis points more. These effects are statistically significant at the 1 percent level, and robust across specifications. Black borrowers are also more likely to default. They yield on average 13.01 percentage points lower internal rates of return (IRR) than similar White borrowers. This effect is the result of better than average repayments in the first part of the period followed by a sharp deterioration in performance as the 2007-2009 financial crisis unfolded, in line with recent findings that Blacks' labor market outcomes are affected by recessions more than other ethnicities (Elsby et al. (2010); Farber (2011); Kochhar et al. (2011); Hoynes et al. (2012)). Older borrowers pay slightly higher rates, 14 basis points more, but do not default more often. Being female increases the likelihood of getting a loan, although it doesn't affect interest rates or default probabilities. Smiling, wearing a tie or showing a picture with family and children, although unconditionally related to the probability of getting a loan, do not affect the probability or the terms of the transaction in an economically or statistically significant way, once all the other characteristics are taken into account.

Borrowers' personal characteristics and appearance can affect lenders' decisions through various channels. One possibility is that lenders make inferences based on their past experience, and base their assessments on easily observable variables that have proven to be correlated with ex-post performance in the past. Such models have a long tradition in the labor economics literature starting with Phelps (1972) and Arrow (1973), and are labeled *statistical discrimination models*. The implications of these models are that the group believed to be less creditworthy is less likely to get a loan, pays a higher interest rate if given a loan, and, after controlling for differences in the verifiable credentials, is indeed more likely to underperform the other group.[1] An alternative explanation is the *taste-based discrimination model* by Becker (1957) according to which lenders realize that easily

[1] A large literature has built upon this intuition and added search costs and differences across lenders in the precision of the signal about future repayment ability. These features generate a richer set of implications, including the specialization of certain types of lenders in screening and lending to certain groups of borrowers (Calomiris et al, 1994, Lundberg and Startz, 1998).

observable characteristics are not related to ex-post performance, once the verifiable information is taken into account. However, since they suffer a disutility from interacting with a certain group of borrowers, they are willing to take a loss in profits in order to decrease the probability of interacting with such group. The implications of this model are that, after controlling for differences in the verifiable credentials, the discriminated group is less likely to get a loan, pays higher rates, but turns out to perform similarly or better than the privileged group. A related explanation with roots in the social psychology literature, argues that lenders might believe that personal characteristics are related to ex-post performance when in fact they are not, and thus hold slow-to-adjust prejudices (*misperception model*). For example, a vast literature shows that people associate positive feelings of health, intelligence, and competence to the beautiful, although the experimental evidence consistently indicates that they are not more productive than the average looking (Mobius and Rosenblat (2005), Langlois et al. (2000) among others).

The findings in this paper suggest that the favorable treatment that the beautiful receive in this market is consistent with a taste-based discrimination/misperception story against the ugly. Borrowers that are not good-looking are less likely to receive a loan, pay higher interest rates, although they are, all else equal, no more likely to default. On the contrary, the finding that Black borrowers are less likely to get a loan, pay higher rates, and after the hard financial information is taken into account, default more often is consistent with statistical discrimination, although this finding has multiple facets, some of them in line with lenders' specialization in borrowers of the same ethnicity and taste based discrimination. In addition to the effect of a particularly severe recession, which the lenders could have anticipated to some extent, the evidence in the paper indicates that Black borrowers with a higher fraction of lenders from areas with high racial prejudice against Blacks pay higher rates than other similar Black borrowers, but are significantly less likely to default. On the contrary, White borrowers with a high fraction of lenders from areas with high racial prejudice

against the Blacks pay lower rates, and yield significantly lower IRRs to their lenders than otherwise similar White borrowers. This evidence suggests that taste-based discrimination has affected the outcomes for at least some borrowers. Finally, to explore the alternative of lender specialization in borrowers of the same race, I build similarity measures between borrowers and lenders based on their ethnicity, and other characteristics, based on the subset of lenders for which demographic information is available. I find that Black borrowers with a higher fraction of Black lenders are significantly more likely to get a loan, pay lower rates and are less likely to default. Consistently with the results described above being Black is all else equal associated with a lower probability of getting a loan, a higher interest rate and a lower IRR. However, having a higher fraction of Black lenders counteracts this effect: every 10 percentage points increase in such fraction is associated to a 1.45 percentage point higher likelihood of getting a loan, 67.2bp lower rates and a 27.11 percentage points lower default probability. This finding indicates that Black lenders are better than Whites at screening Black borrowers and is consistent with theories of lenders specialization in screening borrowers belonging to their same group (Calomiris et al. (1994), Lundberg and Startz (1998)). In addition to being better able to screen Black borrowers, Black lenders are also significantly more likely to lend to them, as their portfolio is made of 27.03% Black borrowers. On the contrary, White borrowers are not more likely to lend to Whites, although they charge them lower interest rates and are better able at screening them. The data also show that Blacks are 21.76% of the applicant pool, 16.6% of the borrower population, but only 9.54% of the lender population.

The results are robust to the inclusion in the regressions of variables meant at capturing the general impression the applicant makes regarding her trustworthiness and creditworthiness. The personal characteristics included in the study, such as age, beauty, and race, are aimed at capturing the features that, in addition to hard financial information, inspire trust and confidence in the applicants' ability and willingness to repay, either through the channel of statistical discrimi-

nation or that of taste based discrimination. The objective of including additional variables about creditworthiness and trustworthiness is to control for any residual over and above the impression captured by the personal characteristics. The results in Section V show that adding these measures doesn't change the economical and statistical significance of the hard financial information and of the personal characteristics, and, in particular, that once we control for creditworthiness and all the other variables in the study, trustworthiness is neither economically nor statistically significant and turns out to have the opposite sign than we would expect. This provides evidence that the relevant personal characteristics aimed at capturing the features that inspire trust and confidence in the applicant's willingness to repay were indeed included in the study. The results are in contrast with Duarte et al. (2012) who conduct a very similar study to this one and find a statistically significant coefficient on trustworthiness. The possible reasons for the difference are the way the variables are measured, the variables included, and possibly the longer horizon in their study, which spans many periods with different rules for borrowing and lending on the website, and makes it more difficult to control for all the applicant's features accurately. The results are also robust to changes in the specification, the inclusion of additional controls in the regression, measurement error, controlling for local economic conditions, the possibility of fraud and misrepresentation. Finally, to explore the possibility that the results are due to omitted variables correlated with appearance and personal characteristics that have not been included in the regressions despite being observable, I include additional controls, and I also add the controls in stages in the regression. I find that the coefficients on beauty and the other personal characteristics are stable across these different specifications, suggesting that it is unlikely that some other overlooked controls would change their economic magnitude significantly.[2]

[2] One of the advantages of the setting used in the study is that the researcher can observe the same information as the lenders, so potentially all the variables the lenders use in their decisions could be included in the analysis. Despite having included all the hard financial information available from the credit bureau, and having made an effort to carefully code all the information in the picture and the loan's description, it is possible that some relevant ones have been overlooked. For this reason, it is important to assess the stability of the coefficients to the addition

Finally, it is important to point out that the subset of applicants who decide to post a picture is not random. This does not affect the interpretation of the findings on the effect of appearance and personal characteristics on lenders' decisions, as the analysis involves the comparison of a beautiful/black/old/... applicant to the baseline case of someone who posted a picture and is average looking/white/young/... However, if the probability of posting a picture is correlated to the probability of default, then the finding that beautiful borrowers are as likely to default as average looking ones who get worse terms could have multiple interpretations. It could be due to beautiful people in general not being as good borrowers as they are perceived to be, but also to beautiful people who post pictures being proportionally more likely to default than the beautiful people who don't post; or even, but not very likely, to the possibility of fraudulent applications posting pictures of good looking people.[3] Irrespective of the underlying reason, the study shows that lenders are influenced by appearance when making decisions and that they grant credit to beautiful borrowers on better terms than they should, consistent with taste-based discrimination against the ugly. This being said, we cannot establish a general, population-wide, relationship between looks and propensity to default, because of the reasons above. We can however notice that the findings are consistent with the results of experiment-based studies that observe the whole population and don't face these issues.

Finally, I find that lenders' experience and personal traits affect their lending decisions. Lenders with more experience on the website, higher income and better bidding abilities are less likely to lend to beautiful borrowers, while young lenders are more likely to. Lenders who are Black, male, low income and either young or old tend to lend more to Black borrowers.

of more controls.

[3] The latter explanation is less likely to be a predominant phenomenon because loans with other fake or inaccurate elements are spotted and discarded or cancelled by the company quite effectively, and appear to be a very small fraction of the total applications. In addition, there is a wide variety of beauty levels among applicants and within each credit grade, and there doesn't appear to be an excess of beautiful people among the applicants (the average beauty score is 4.02 on a 1 to 7 scale). Furthermore, the higher default rates experienced by beautiful borrowers do not appear to be concentrated among the very beautiful (score 7). See Panel D of Table II for this analysis.

The setting of the study is Prosper.com, a large US online lending market, with more than 270 million dollars lent and 450,000 members. The advantages of this setting are that it is a real market with a vast amount of information on the applicants' financial situation and characteristics, and that the researcher has access to the same information as the lenders. In particular, information about the application stage and the terms of the loan as well as the ex-post performance of the same pool of borrowers is available, and this proves very helpful in discriminating among the competing explanations of why the lenders take borrowers' personal characteristics into account when making their decisions. The borrowers in this market have reasonably large stakes, both in terms of money and the chance of damaging their credit report. They vary substantially in terms of credit quality, employment, income and demographics, and they are similar to the overall U.S. population in terms of credit risk (Table I, and Panels C and D of Table II). Most lenders have high income (40% have income of $100,000 or more), are homeowners, and are fully employed (Table III). In addition to the results reported above, my findings indicate that the lenders in this market assess hard financial information in the same way as we would expect a financial company to: all else equal, they favor higher credit scores, higher income, and better employment records and credit histories.

The remainder of the paper is organized as follows. Section I briefly review the related literature. Section II describes how the online lending market works, and the borrowers and lenders' characteristics. Section III contains the main results on the effect of personal characteristics and the way people present themselves on the likelihood of getting a loan, the interest rate, and loan performance. Section IV analyzes the effect of similarity between borrowers and lenders. Section V reports robustness checks, and alternative explanations for the findings. Section VI describes the characteristics of the lenders who are more prone to lend to beautiful borrowers and to Blacks. Section VII concludes.

I Related Literature

The paper is related to various strands of the economic and finance literature. The first is the economics literature on appearance, which shows that beauty influences economic agents' decisions in many realms of economic activity, ranging from the labor market (Hamermesh and Biddle (1994 and 1998)) to politics (Todorov et al. (2005)) and the boardroom (Graham, Harvey and Puri (2010)).[4] The contribution of the paper to this literature is to provide market based evidence that although beautiful people are perceived as having higher quality, they do not perform better than others. Such finding confirms the experiment-based results by Mobius and Rosenblatt (2005), and Andreoni and Petrie (2008), Olivola and Todorov (2010) and others, who find that the beautiful are treated better, are perceived as more productive and are more confident, but that their actual productivity is not better than the one of the ugly. In addition, the paper provides new evidence on the mechanism through which beauty affects decisions by showing that beauty is not a compensating differential: in this setting lenders don't consume the borrowers' good looks for more than a few minutes, suggesting that beauty affects impressions, rather than just being something people want to be around to. Second, the paper is related to the literature on culture (Giannetti and Yafeh (2012)) and soft information in financial transactions, and in particular, on the role of personal characteristics in the assessment of borrowers' credit quality (Stein (2002), Berger et al. (1999), Petersen and Rajan (2002), Cole et al. (2004), Cole (1998)). In this setting, features that are usually not observable and thus included in the soft information category can be observed and measured by the reseracher. We have therefore the opportunity to analyze which ones matter, for whom, and whether they are related to ex post performance. Third, the paper is related to the literature on racial discrimination in the labor market (see Altonji and Blank (1999) for a survey of the literature), and the mortgage market (Ladd (1998), Munnell et al. (1996), Berkovec

[4] Graham et al. (2010) similarly show that CEO's good looks are not related to their firm's performance.

et al. (1998)). The advantage of the current setting compared to previous work is the ability to observe both the application stage and the ex-post performance of a borrower, which helps to better distinguish between different mechanisms generating the observed patterns of discrimination.[5] An alternative approach has employed audit studies to investigate discrimination by sending auditors with similar characteristics but different gender/race to firms and measuring the difference in outcomes (Ayres et al. (1995), Bertrand et al. (2004)). Despite being a very effective way of keeping many characteristics constant, if any of the unobserved characteristics the lender uses in her choices are not kept constant in the design such studies would detect discrimination when none is there, or miss it when it is there (Heckman (1998)). The setting of the current study allows the researcher to observe the same information as the lenders and, conditionally on controlling for many variables, it is less amenable to the critique above and provides complementary evidence to the audit and experimental studies. Finally, the paper is also part of a small, but growing literature that uses online peer-to-peer lending as a laboratory to study various economic and finance questions. Lin, Prabhala, and Visvanathan (2012) examine social networks and adverse selection; Iyer, Khwaja, Luttmer, and Shue (2011) analyze lenders' ability to infer borrowers' creditworthiness in an unintermediated market; while Hildebrand, Puri, and Rocholl (2011) analyze the importance of incentives and having skin in the game for crowd-funding. The paper more closely related to this one is by Pope and Snydor (2011) who independently conducted a similar study, examining the elements of a picture associated to higher probability of funding and lower rates. In contrast with this study, they find the somewhat puzzling evidence of statistical discrimination against Black and taste-based discrimination against Whites.[6]

[5] Some of the previous studies in this area exploit very detailed information about the application stage, but remain in the dark on whether the borrowers who seem to be discriminated against turned out to be worse credits ex post; others observe defaults rates and financial information, but have a potentially selected sample in that they cannot observe the information based on which the lenders granted the loans.

[6] Possible reasons for the different results are that they use a larger sample, but with some crucial variables, including attractiveness, coded less precisely, and, most important, none of the loans they analyze had reached maturity at the time of the study and therefore their methodology to assess default rates is based on delinquency

II Data Description

II.A The Credit Market

The data set consists of a sample of individual loans generated on Prosper, a successful U.S. online lending web site that, since inception in February 2006, has generated more than $270 million in loans and gained 450,000 members.

The lending process works as follows. Anybody with a U.S. Social Security number can borrow or lend money on the website. Each loan applicant posts a listing with the amount he would like to borrow and the maximum interest rate he is willing to pay. Prosper then makes credit bureau information, including credit score, debt level, credit history, income, employment status, and homeownership, available to potential lenders. In addition, the borrower has the option to post one or more pictures and write a short loan description in support of his request, providing additional unverified information. Lenders usually diversify across loans, lending only a small fraction of the requested capital to each borrower. They submit bids for each applicant they are interested in, specifying the amount they would like to lend and the minimum interest rate they are willing to get. If enough bids are submitted and the amount requested by the borrower is fully covered before the listing expires, a loan is generated at the highest interest rate that clears the market.[7] The money is then transferred to the borrower, who has the obligation to repay the sum in 36 monthly payments. Prosper makes money by charging a 1% fee to the lenders and a 0.5% fee to the borrowers. If the loan request expires without being fully funded, no loan is generated, and the borrower has the option of posting a new listing. The average number of previous listings in the period analyzed is 2.19.[8] Once a loan is generated, it is reported to the credit bureau, like any other unsecured loan,

and projections, rather than actual defaults and recovery rates.

[7] Recently the company has introduced portfolio plans that automatically do the bidding and diversification for the lender. This opportunity, as well as many features allowing borrowers and lenders to communicate through the website, were not available in the time period analyzed in this study.

[8] In this period, a borrower cannot post more than one listing at a time and cannot get more than one loan at a time.

and delinquency and default on this loan will affect the credit score of the borrower. If a payment is late, the borrower is charged a late fee that goes to Prosper, and if the loan becomes more than 4 months late, it is considered in default and sold to a collection agency through an auction the proceeds of which go to the lenders.

The sample contains all the loan requests posted on the site between March 12th and June 18th 2007, corresponding to 20,128 borrowers, and 18,627 lenders. Such borrowers posted 37,897 loan applications, 3,327 of which were funded and became a loan. The size of the loans ranges from $1,000 to $25,000, with an average of $7,379, while the amount lent by a single individual varies between $50 and $738,488, with an average of $2,080. One of the advantages of analyzing a subset of the data is that the information contained in the pictures and in the listing description provided by the applicants can be coded in a very careful and precise way.[9] In addition, the features of the website, the information environment and the rules for borrowing and lending are constant over this period, while they change quite a lot over the course of the website's life.

Finally, Table I shows the default rates and the average interest rates earned by Prosper lenders as of December 2007, and compares them to those from a large sample of credit card accounts from Experian, one of the three major U.S. credit bureaus. In terms of default rates, Prosper borrowers appeared to be similar to, if not slightly better, than the overall U.S. population. For good credits the default rates were similar to those in Experian, and for the bad credits they were actually lower. The default-adjusted lender returns ranged from 10% for very high quality borrowers to 16% for those with credit scores between 600 and 639. The very high risk borrowers, with credit

[9] Information in the pictures and text requires many research assistants to independently code a given picture or listing and to double-check each other's work, in order to be accurate. For instance, during this period the reason for the loan and occupation are inaccurate or missing for many listings. The reason for the loan could be retrieved by reading the loan description all along, but it was introduced as a category in the data download provided by Prosper to researchers only in February 2008 and was set to 0 for listings posted earlier than then. Similarly, the occupation information provided in the company download is often inaccurate and needs to be integrated with the information in the loan description.

See Panel A of the same Table for the variables' definition.

scores between 520 and 559 or no credit history, had default-adjusted returns of 8.85% and -25.87%, respectively. Such Table was posted on Prosper's website on December 2007.

II.B The Borrowers

Panel B of Table II shows summary statistics for the loan applicants, while Panel C shows the same summary statistics for the subset who obtain a loan.

Of the 37,897 listings posted, 8.78% end up getting funds and generate a loan, while 53.61% expire without reaching full funding, 36.47% are withdrawn, and 1.13% cancelled. The average amount requested is $8,923 and on average 12.98% of such amount gets funded. The maximum interest rate a borrower is willing to pay is as high as 30%, with an average of 17.30%. Among the loan applicants, 31.73% own a house, 81.97% are employed full-time, 4.48% are employed part-time, 2.31% are retired, and 2.72% are currently unemployed. Among the employed, occupations span almost all the spectrum, but it is worth noting that 8.51% of the applicants are entrepreneurs or self-employed.

Many loan requests come from individuals of low credit quality and end up not being fulfilled. The average credit card debt is $9,023, and many applicants have an account delinquent or have had a public record in the past. Their credit scores are also worse than the overall population: 45.07% of the listings has a credit grade of HR, corresponding to credit scores between 520 and 599, 16.93% has a credit score falling between 560 and 599 (credit grade E), 15.76% scores between 600 and 639 (credit grade D), 10.30% between 640 and 679 (grade C), 5.47% between 680 and 719 (credit grade B), while only 3.41% and 3.06% have credit scores between 720 and 759 (grade A), or above 760 (grade AA).

The summary statistics for the individuals who get the loan look dramatically different. Panel C shows that AA and A credit grades now constitute 11.33% and 10.76% of the sample, respectively,

and that high risk credit scores (grade HR) drop to 13.88%. The median credit grade is C in the loan sample, corresponding to credit scores in the range of 640 to 679. These statistics are similar, if not slightly better, than those reported in Table I for the universe of Prosper loans granted from the start till December 2007: the proportion of high credit scores (AA and A grades) is higher than that in Table I, and the proportion of low quality borrowers (HR grade) is significantly lower. The fraction of individuals with an income of $25,000 or less drops from 29.47% to 14.16%, and the fraction of individuals with an income of $75,000 or more almost doubles, from 10.94% to 20.46%. The average amount requested, and awarded, is $7,379, while the average interest rate an applicant who got a loan was willing to pay is 20.15%. The cases of delinquency and public records are less frequent, although the average credit card balance is now close to $12,000. The proportion of individuals that own a house jumps to 43.75%, the fraction of those employed full-time is slightly higher, 86.75%, while the fraction of part-timers drops to 4%, and so do self employed, unemployed and retirees. The reason for the loan and occupation are similar across the group of applicants and borrowers and are not reported for brevity.

If we take a look at the demographic characteristics of the individuals posting a listing, 49.86% of them are women, 36.30% are young, 6.8% are old, and 43.76% are middle age. 10.90% of the applicants are severely overweight. 6.03% are Asian, 20.65% are Black, 8.23% are Hispanic, and 74.23% are White. In addition, 30.75% of the pictures have children in it, 7.81% have someone wearing a tie, and 40.70% have someone smiling. Compared to these statistics, the borrowers who get a loan are more likely to have a male in the picture, (55.42% of those awarded a loan are), less likely to be old (5.74%), and less likely to be Black (14.54%). Such demographic characteristics are available for the 51.38% of the listings that include one or more pictures, 79.9% of which have a person in it. This is the sample on which the analysis in the paper is conducted. Information on race, appearance, and age is collected from the pictures, and complemented and double-checked

based on the messages accompanying the borrowers' listings and their membership in ethnicity-based groups.[10]

The applicants who posted a picture were rated on their physical attractiveness following a procedure similar to the one used in the literature on beauty (Hamermesh and Biddle, 1994, 1998). Each picture is evaluated by three female and three male raters, and the average rating is used for the analysis. The rating is on a 7 point scale, ranging from "Extremely Attractive", "Very Attractive for his/her Age", ..., to "Not Attractive at All", with "Neutral" in the middle, corresponding to a rating of 4. In addition, the first impressions of the applicants' trustworthiness and creditworthiness were independently recorded following the same procedure, to control for any additional impression they might make over and above that captured by the personal characteristics. To avoid the "halo effect", the phenomenon where the rater's assessment on one dimension, say beauty, influences his/her perception of the applicant along the two dimensions that follow and creates spurious correlations, the order in which the beauty, trust and creditworthiness questions appear for each picture was randomized across pictures and across raters (Nisbett et al., 1977, Sudman et al., 1996). The creditworthiness and trustworthiness variables will be used in the section on robustness checks.

A detailed description of the rating procedure, the instructions for the raters and their demographic characteristics are provided in Online Appendix A. The raters are mostly undergraduate students at NYU. As the Appendix shows, they have a very diverse ethnic background, their age ranges between 18 and 33, with 83% of them falling in the 18-21 year old range, their gender is 35% males, and 65% females. An important question is whether their ratings are representative of a population where the age range is wider and the socioeconomic backgrounds more diverse. The social psychology literature suggests that this is the case: many studies show that beauty is not in the eye of the beholder, and that there is an extremely high degree of agreement across

[10] In case an applicant appears to be of mixed race, race is assigned following the same rules as the U.S. Census and precedence is given to Black, followed by Hispanic, Asian and White. See Blank et al. (2004) for a definition of race, and the way such definition changes over time.

cultures, ages and genders on who is beautiful (Langlois et al. (2000), Feingold (1992), Etcoff, 2000). Consistent with this, Panel D of Table II shows the average ratings, as a whole and by rater's gender. The ratings are sensible: the average valuation is, like we expect, a 4, although there is substantial variation and the whole range of ratings is used.[11] Males are slightly harsher than females in their ratings of beauty. Most importantly, the raters agree on who is attractive and who is not: the Cronbach alpha and the Intra-Class Correlation Coefficient (ICC), which are traditionally used in the literature to measure whether ratings from different individuals produce similar results, are 0.7656 and 0.7628, respectively. These values are similar to those found in the literature that studies beauty.[12]

Finally, below are the definitions of trustworthiness and creditworthiness used in the study. The Trust Game defines as trustworthy a recipient that sends a fair share of money back to the sender, even if she has no obligation to do so.[13] To capture honesty and willingness to return money even if not forced to, the following definition of "trustworthiness" was provided to the raters: "If this person finds a wallet on the street what is your impression of the probability that he or she will give it back?". A closely related variable that is relevant in credit markets is the ability to repay, which I label "creditworthiness". The following definition was provided to the raters: "If you are a loan officer and this person walks into your bank, what is your impression of the probability that this person will be able to repay the loan in full?". Although they represent two different concepts,

[11] To make sure that the reason the average beauty rating is 4, the mid-point of the distribution, is not just because the raters implicitly define the pool of applicants as the reference population they compare each picture to, I've checked whether the average beauty rating of the first 10 random pictures any rater sees and evaluates is also 4, and find that on average raters actually have lower evaluations at the beginning than overall, indicating that the pool of applicants is not abnormally better looking than the population overall. Such difference is small but statistically significant and it is not present in the trustworthiness and creditworthiness ratings. See Panel E of Table II.

[12] Hamermesh and Biddle (1998) have a Cronbach alpha of 0.75, while Andreoni and Petrie (2005) have an alpha of 0.86 and an ICC of 0.76. The Cronbach alpha measures the correlation between all raters: alpha=((kr)/(1+(k-1)r)). Although it is the most widely used measure of reliability, it increases with the number of raters. The intraclass correlation coefficient (one way random effects model) doesn't suffer from this drawback. See Cortina (1993) for more details on reliability analysis.

[13] See Gleaser et al. (2000), Fehr et al. (2003) and Sapienza et al. (2010) for studies on how to measure trust and trustworthiness.

trustworthiness and creditworthiness are related: the correlation coefficient is 0.7545, significant at the 1 percent level. The summary statistics for these ratings are reported in Panel D of Table II. The average is a little above 4, and there is substantial variation within the population. The vast literature on the determinants of trust shows that the extent to which a given rater finds an individual trustworthy varies with her background (Alesina and La Ferrara (2002)). Consistently with these results, the intraclass correlation coefficient is much lower for the trustworthiness and creditworthiness measures (the ICCs are 0.5743 and 0.5781, respectively).

More information on the borrowers and their characteristics is provided in Online Appendix B. Panel A of Table B.1 reports the correlation coefficient between the personal characteristics used in the study. The data show that women are more likely to be considered beautiful and trustworthy than men, but, interestingly, not more creditworthy. Young borrowers score well on beauty, while old and middle-aged applicants are less likely to be rated as beautiful, but are generally considered more creditworthy than young borrowers. Being Asian or Hispanic is positively correlated with the beauty ratings, while being Black is negatively correlated. Black and Hispanic applicants are rated less creditworthy than Asians and Whites. Being overweight is negatively correlated with beauty, and creditworthiness. Unconditionally, beautiful people have higher debt levels, they tend to ask for more money, are willing to pay higher rates, and have lower delinquencies; more trustworthy and more creditworthy people are more likely to be homeowners, ask for bigger loans and have fewer delinquencies. Beauty and making an impression of being trustworthy and creditworthy are mildly positively correlated with the borrower's credit score, although the relationship is not monotonic nor statistically significant (Table B.1 Panel B) and they don't have any significant relation with income and employment status, once age is taken into account (Table B.1 Panel C). In Section III, I will incorporate these patterns into a regression framework that takes the effect of hard financial information, listing features and personal characteristics into account.

II.C The Lenders

The lenders on Prosper vary for the total amount lent, which ranges between $50 and $738,448, with an average of $2,080, and the length of time they have been on the website, which on average is about a year.

Panel A of Table III reports some statistics on their bidding and lending behavior and also contains the demographic characteristics, income, and employment status of a subset of lenders. In order for the demographic information to be available for the lenders, they need to have been borrowers in the past, to be group leaders, or to voluntarily create a profile with such information.[14] For this reason, this is not a random subsample. All the analysis in the paper on the likelihood of getting a loan, the interest rate and the default rates is performed using data from all lenders, irrespectively of whether demographic information is available for them. Only the similarity analysis in Section IV, is restricted to the sample for which both borrowers' and lenders' demographic characteristics are available. To explore the representativeness of this subsample, in Panel B of Table III I compare it to the overall lenders' population who bid on the listings analyzed along the characteristics available for both groups, bidding behavior, the amount lent, the time since they joined Prosper, and the average degree of racism in the area they live in, a variable that will be used later in the analysis. The table shows that the two groups are very similar. The lenders for which information is available are very likely to be homeowners (56.47% of them is). Their age, gender and ethnicity are quite different from the borrowers': more than 70% is middle-aged, 23% is young, while only 22.82% are women. Also, 84.16% is White, 8.8% is Black, 4% is Asian, and 2.97% is Hispanic. Finally, they tend to have high income: 21% has income above $75,000, 87.95%

[14] In many cases the reason why lenders are also borrowers on the website is that they want to familiarize themselves with the website or to raise money to reinvest in Prosper. Group leaders are lenders who start a group. Groups can be based on affinity in occupation, geographical area, alma mater, or any other characteristic; they can be open to everybody or require approval to join and the group leader can decide whether or not to get a fee for each loan closed by her members. There is no group joint liability for loans and, maybe for this reason, belonging to a group per se doesn't matter for getting funds.

is employed full time, 6.9% is an entrepreneur or is self-employed, and only 1.1% is unemployed.

The next section shows that the lenders on this site are coherent and that overall they behave in the way we would expect them to. In particular, all else equal, they favor applicants with high credit scores, high income, good employment status, and a good credit history.

III The Effect of Personal Characteristics and the Way People Present Themselves on the Terms of the Loan They Get

This section investigates the effect of the way people present themselves and their personal characteristics on the terms of the loans they get, once credit quality, employment, income and other hard financial information are taken into account.

III.A Likelihood of Getting a Loan

Table IV shows the marginal effect of hard financial information, personal characteristics and appearance on the likelihood of getting a loan. The empirical specification is the following probit regression:

$$\begin{aligned} Pr(LoanFunded_i) &= \Phi(\alpha_1 HardFinInfo_i + \alpha_2 PersonalChars_i + \alpha_3 FamilyStructure_i \\ &\quad + \alpha_4 ListingFeatures_i + \varepsilon_i) \end{aligned}$$

where $LoanFunded_i$=1 if the listing got enough bids and generated a loan, and 0 otherwise. $HardFinInfo_i$ includes variables that Prosper pulls from the credit bureau based on the applicant's Social Security Number: credit grade, employment status and its length, occupation, homeownership, delinquencies, public records, revolving credit balance, bankcard utilization rate, number of credit lines, income bracket and debt to income ratio. $PersonalChars_i$ includes race,

gender, age, beauty, whether the person in the picture is severely overweight, and whether he smiles or wears a tie, while $FamilyStructure_i$ captures whether there are children, a couple, or a family with children in it. Finally, $ListingFeatures_i$ includes the amount requested and the maximum interest rate the borrower is willing to pay, the number of previous listings, the reason the applicant is asking for the loan, and other technical features of the listing.[15] Since a borrower who doesn't get funding has the option of posting another listing, the standard errors are clustered at the borrower level.

Column I of Table IV reports the estimates of the effect of hard financial information and listing features on the likelihood of getting a loan. The results provide evidence on the way lenders assess hard financial information in this market, as well as a consistency check on their coherence and rationality. The baseline case is a borrower with a credit score between 560 and 599, who rents, is fully employed, has an income below $25,000, no delinquencies or public records, and for whom the value of the other variables is set at the mean of the sample. Compared to this individual, a borrower with a slightly higher credit grade, grade D, ranging between 600 and 639, has 5.44% higher probability of getting his loan request funded. Such probability monotonically increases with the credit score, reaching an 85.4% higher probability for individuals with a credit score of 760 and higher. Being delinquent on other accounts now, or in the past 7 years, or having had public records in the past 10 years lowers the likelihood of getting a loan by 0.92%, 0.48% and 0.24%, respectively. All these effects are highly statistically significant. As expected, the income of the borrower also matters, and going from the $1-24,999 bracket to the $25,000-$49,999 one increases the likelihood of getting a loan by 0.66%. Higher income has, all else equal, a positive effect, and the highest income range ($100,000+) generates a 2.94% higher probability of getting a loan, after controlling for everything else. Similarly, a 10 percent lower debt to income ratio translates into a 1.17% higher

[15] For a list of the reasons for a loan and the occupations, please see Appendix B.

likelihood of being funded. Homeownership has a positive effect, equal to 0.29%. Working part time or being unemployed lower the likelihood of getting a loan, compared to an individual employed full time, by 0.27% and 0.20%, respectively, and so do being retired or self-employed (-0.36% and -0.10%, respectively), although these effects are not statistically significant. After accounting for the variables above, the length of the employment status, the number of credit lines and the revolving credit balance do not have an economically significant effect on the likelihood of getting funds, while the bankcard utilization rate has neither an economically nor a statistically significant effect. The features of the listing also significantly affect the likelihood of getting a loan. A drop of $1,000 in the amount requested increases the likelihood of getting funds by 0.22%, while a 1 percentage point increase in the interest rate offered raises such probability by 0.38%. The number of previous listings decreases the likelihood of getting funds by 0.13%, while choosing the option of stopping the bidding as soon as the amount requested is reached, giving up the chance of getting a lower interest rate through lenders' competition and thus a proxy for impatience and the necessity of getting the loan as soon as possible, decreases it by 0.37%. The specification also contains controls for occupation and the reason for requesting the loan (coefficients not reported). These results indicate that the lenders in this market behave in the way we would expect a financial company to behave: all else equal, they favor higher credit scores, higher income, and better employment records and credit histories.

In Column II, III and IV, I conduct the main analysis in the paper and investigate the effect of appearance and personal characteristics on the lenders' decision on whether to grant a loan for the applicants who decided to post a picture. The coefficients on credit bureau and employment variables for these columns confirm the results reported above for the subsample of applicants who chose to post a picture. In Column II, I add to the regression gender, family structure (whether there are children, a couple, or a family with children in the picture), and variables meant at

capturing the applicant's appearance, such as beauty, being overweight, smiling, and wearing a tie. In Column III, I further add the applicant's race, and in Column IV his or her age. A vast psychology literature shows that the way people present themselves influences how they are perceived and treated, irrespective of their true quality (Feingold, 1992; Eagly et al., 1991). The regression shows that the effect of appearance is both economically and statistically significant. Column IV indicates that an increase in the beauty rating from "Neutral" to "Above Average for Age" increases the likelihood of getting a loan by 1.59%. This coefficient is statistically significant at the 1 percent level. To give an idea of the economic magnitude of this effect, note that in order to get the same increase in the funding probability an average-looking borrower would need to increase the interest rate offered by 7.54%, or, alternatively, lower the amount requested by $11,606. Female borrowers appear all else equal 3.23% more likely to get a loan than a male (statistically significant at the 1 percent level). Couples, families, and children do not have an effect once all the other characteristics are taken into account, and the same is true for being overweight, smiling, and wearing a tie. A big debate in the economics and finance literature centers on whether observables such as race, gender and age are proxies for credit-relevant information, and whether they affect the treatment a loan applicant receives. I find that, compared to White applicants, Blacks are significantly less likely to get a loan, with a 2.68% lower chance, and so are Asians (-2.88%). On the contrary, the applicant's age is not significantly related to the likelihood of funding.Columns V and VI in Table IV provide a more in-depth analysis of the effect of looks on the likelihood of getting funds by analyzing how beauty interacts with gender and credit grade in determining the funding probability. In particular, Column V shows that beauty doesn't affect the borrowing probabilities of men and women in a different way, and Column VI shows that the effect of beauty on the likelihood of getting funds is similar across credit grades.

Taken together, these personal characteristicss have a significant effect on the likelihood of

getting a loan: a chi-square test of joint significance yields a p-value smaller than 0.00001. Also, the increase in adjusted R^2 indicates that controlling for these variable adds explanatory power to the analysis. Unreported regressions shows that we get similar results if instead of analyzing the probability of getting the loan we examine the fraction of the loan request that gets fulfilled.

III.B Interest Rate

This section investigates whether after accounting for credit quality, employment, income and homeownership, personal characteristics affect the interest rate charged to the borrower. The specification is a tobit regression:

$$\begin{aligned} InterestRate_i &= f(\alpha_1 HardFinInfo_i + \alpha_2 PersonalChars_i + \alpha_3 FamilyStructure_i \\ &\quad + \alpha_4 ListingFeatures_i + \varepsilon_i) \end{aligned}$$

The full table is reported in the online appendix (Table Va), while a shorter version with the coefficients for personal characteristics, beauty and ethnicity is reported in Table V. The appendix shows that a better credit grade, homeownership and higher income lower the interest rate paid, while delinquencies, public records, and asking for a bigger loan, all else equal, increase it. These effects are highly statistically significant, and their economic magnitude is in some cases substantial. For example, having one or more delinquency on the credit report increases the interest rate paid by 121 bps, while going from a credit score in the 560-599 range to one in the 640-679 range lowers the interest rate paid by 4.68 percentage points. Also, choosing the option to close the listing as soon as the amount requested is reached leads to 2.68 percentage points higher interest rate. After accounting for these variables, the revolving balance, employment status and bankcard utilization rate do not significantly affect the level of the interest rate, although they have the expected sign.

Columns II, III and IV of Table V show the effect of adding information on personal characteristics to the regression. Better looking borrowers pay, all else equal, 60 basis points less (sig. at 1 percent level), while overweight borrowers are charged 9.7 bps more, although the effect is only significant at 10 percent level. Gender, family structure and wearing a tie do not significantly affect the interest paid by the borrowers, while smiling all else equal lowers the interest rate by 67.1bps. The race of the borrower has a statistically significant and economically large effect on the interest rate paid. Black borrowers, in addition to being less likely to get a loan, are charged 1.83 percentage points more than a similar White borrower. This coefficient is significant at the 1 percent level and stable across specifications. Asian borrowers are also charged a higher rate, +1.32 percentage points, although the effect is only significant at the 10 percent level. Older borrowers are charged higher rates compared to younger ones (+14 bps, significant at the 5% level), while middle aged borrowers are charged slightly less (-6.5 bps, significant at the 10% level). Accounting for all other characteristics, being beautiful translates into a lower rate mainly for women (-1.22 percentage points, significant at the 1 percent level, Column V). Finally, while better credit grades are associated to lower interest rates for all borrowers, within each credit grade this effect is more pronounced for borrowers whose looks are above average (Column VI).

III.C Loan Performance

The previous sections show that after accounting for hard financial information, personal traits and the way people present themselves significantly affect their likelihood of getting a loan and the terms of such loan. It is therefore natural to ask whether these characteristics have any association with delinquencies and defaults.

Prosper loans have a three year fixed maturity and it is now possible to analyze defaults for all loans in the sample. Panel A of Table VI and VIa in the Appendix illustrates how hard financial

information, listing features and personal characteristics affect the default probability. All else equal, borrowers requesting a higher amount, being willing to pay a higher rate before the bidding starts, and having a lower credit score, or delinquencies and public records, are more likely to default; on the contrary, income, employment status, revolving balance and utilization rates are not related to the default probability once all the other characteristics are taken into account. Among the personal characteristics, being overweight generates a lower probability of default, despite being associated with higher interest rates than similar borrowers. Family structure, age, and gender do not significantly affect the probability of default, while smiling is all else equal associated with higher defaults and wearing a tie with lower ones. Ethnicity is not significantly associated with default, except for Black borrowers who experience significantly higher default rates than similar White borrowers (+15.4%). Finally, beautiful loan applicants, although enjoying a higher likelihood of getting a loan and lower interest rates, are not better borrowers than average looking ones and indeed default at the same rate, confirming the findings in the biology, labor economics and experimental game theory literatures (Mobius and Rosenblat (2005), Andreoni and Petrie (2008), Langlois et al. (2000) among others), and consistent with taste-based discrimination against the ugly. The difference between this study and the ones above is that it analyzes this issue in a real market, rather than in a lab experiment. The economic agents studied in this paper make real financial decisions, have large stakes (large sums of money, and the possibility of damaging their credit record), and vary substantially in terms of age, occupation and socio-economic background. The information provided by the data set is very rich, and allows controlling for many variables refecting credit quality that lenders potentially factor in their decisions. Lab experiments, on the other side, have the advantage of opening the black box of the economic process and letting the researcher herself vary the treatment and pinpoint at the precise channel through which this

happens. The findings complement each other.[16]

Panel B of Table VI contains the analysis on the internal rate of return (IRR) from the loans, to check whether higher defaults actually translate in lower returns for the lenders once the interest rate that was charged and the amount recovered are taken into account. The long version of the table reported in the Appendix shows that controlling for credit grade, employment category, occupation, and other characteristics, the higher the interest rate a borrower was charged the lower is the IRR. For each percentage point increase in the interest rate, keeping all else equal, the IRR drops by an amount between 1.34% and 1.71%. Larger loans, the option to close the listing as soon as it gets funded instead of waiting for lower rates, the number of previous unfunded loan applications and of previous delinquencies are all else equal associated to lower IRRs. On the contrary, credit scores, employment status, income level, and credit utilization do not affect the IRR, once the interest rate charged is taken into account, indicating that lenders were overall good at translating these variables into an appropriate interest rate. The exception is the borrowers with the lowest credit scores, below 560, which all else equal are associated with significantly lower IRRs. Finally, after controlling for the interest rate and the hard financial information, none of the personal characteristics significantly affects the IRR. The exception is again being Black, which is associated with drops in the IRR ranging between 13.01% and 13.43%.

In order to explore the results on ethnicity further, in Figure 1, I explore the evolution over time of the default rates of borrowers of different ethnicities. The graph shows that at the beginning of the period Black borrowers default to an equal or lesser extent than other ethnic groups, but as time passes and the economy enters the recession, their default rate increases proportionally more. This is the case even when the data are not weighted by the amount borrowed, or when delinquency rates rather than default rates are considered.[17] Recent studies show that minorities,

[16] See Levitt and List (2006) for a discussion of strength and weaknesses of lab experiments.

[17] A loan is considered delinquent if payments are 30 days past due, while it is considered in default if it is more

and especially Black males, have been hit harder by the recession in terms of job losses, mainly due to differences in exposure to the business cycle across industries (Elsby et al., 2010; Farber, 2011; Kochhar et al., 2011; Hoynes et al., 2012). It is therefore possible that the lenders were able to predict the economic downturn to a certain extent and were therefore engaging in statistical discrimination when making loan decisions and setting the interest rate.

An alternative is that lenders' views were affected by racial prejudice and the recession happened to confirm their bias. To explore this possibility, I include a measure of lenders' attitudes toward Blacks, as proxied by racial prejudice in the area they live in. Table VII shows the results of including in the regressions state level measures of racial sentiment toward Blacks from the General Social Survey (GSS). A similar approach has been employed by Charles and Guryan (2008) to study prejudice and economic discrimination in the labor market. Following Becker (1957) theory of discrimination in markets, what matters for economic outcomes is the degree of discrimination of the marginal lender a Black applicant faces. In order to capture the likelihood that a given Black borrower faced a marginal lender with prejudice or animus against her ethnicity, for each loan applicant I calculate the proportion of her lenders from states where the average amount of racial prejudice is above the median. The measure is constructed in the following way: each state is assigned a level of racial prejudice based on the fraction of White respondents that in 2007 answered "Yes" to the question: *"On the average, (Negroes/Blacks/African Americans) have worse jobs, income, and housing than white people. Do you think these differences are because most (Negroes/Blacks/African Americans) just don't have the motivation or will power to pull themselves out of poverty?*". The states are then ranked based on this measure of racial prejudice and assigned a dummy variable equal to one if they are above the median. Column I of Table VII reports the results of including the interaction between the fraction of lenders from high prejudice

than 4 months late, charged off or in bankruptcy.

areas and applicant's ethnicity in the interest rate regressions. The coefficient on the hard financial information, not reported to save space, and those on personal characteristics are similar to those in Table V. Black borrowers are all else equal charged 1.22 percentage point *higher* rates than Whites.However,when I focus on the areas with an above median level of racial prejudice against Blacks, I find that Black borrowers with a higher fraction of lenders from such areas are charged on average 1.94 percentage points *more* than other Black borrowers (sig. at the 10% level), while Whites are charged 45.4bp *less* than other Whites (sig. at the 1% level). At the same time column II shows that the IRR from such Black borrowers is not significantly lower than that of other borrowers, while the returns from White borrowers with a higher fraction of lenders from areas that are prejudiced against Blacks are significantly lower (-5.63%, significant at the 1% level). This evidence suggests that taste-based discrimination has affected the outcomes for at least some borrowers. The evidence in Table VI, Figure 1 and the racial prejudice analysis above paint a mixed picture of the possible motivations behind lenders charging higher rates to Black borrowers. On one side, Black borrowers default more than Whites, consistent with statistical discrimination; on the other side, Black borrowers with a higher proportion of lenders from areas with a high level of racial prejudice face higher interest rates, while Whites face lower rates and yield significantly lower returns after adjusting for default.

In the following Section, I explore the effect of similarity between borrowers and lenders on loan terms and performance, to investigate the possibility that lenders of a certain group are better able at screening borrowers belonging to their same group and therefore specialize in lending to them, offer them better terms and/or realize better returns thanks to their superior screening ability (Calomiris et al, 1994, Lundberg and Startz, 1998).

III.D The Effect of Similarity Between Borrowers and Lenders

A large literature in economics and psychology documents that similarity breeds trust (Coleman (1990), Glaeser et al. (2000), Alesina and La Ferrara (2002), Guiso et al. (2009), and DeBruine (2002)), and also that agents might have informational advantages in screening counterparties similar to them (Calomiris et al. (1994), Lundberg and Startz (1998)). Panel B of Table VII shows that, in addition to the main effect of ethnicity on the terms of the loan and the default probability, the fraction of lenders of the same ethnicity as the borrower also matters, and that this effect is particularly strong for Black borrowers.

On average, compared to a similar borrower with a lower fraction of lenders from his own ethnicity, a borrower who ends up with a 10% higher fraction is 16.1bp less likely to get a loan, pays slightly higher rates (4.27bp), and is 2.94 percentage points less likely to default. Despite all the coefficients are significant at the 1% level, the bulk of the effect of similarity between borrowers and lenders is ethnicity-specific. While the effects are not statistically significant for Asian borrowers and only marginally significant for Hispanics, Black borrowers with a higher fraction of similar lenders are significantly *more* likely to get a loan, pay *lower* rates and are *less* likely to default. In line with results in Tables IV and V, being Black is all else equal associated with a 7.01% lower probability of getting a loan, a 4.31% higher interest rate and a 18.48% lower IRR. However, having a higher fraction of Black lenders counteracts this effect: every 10 percentage points increase in such fraction is associated to a 1.45 percentage point higher likelihood of getting a loan, 67.2bp lower rates and a 27.11 percentage points lower default probability. The coefficients are economically large and statistically significant. These effects convert into a 13.89 percentage point higher IRR, although this latter coefficient is not statistically significant. This finding indicates that Black lenders are better than Whites at screening Black borrowers and is consistent with theories of lenders specialization in screening borrowers belonging to their same group (Calomiris et al., 1994;

Lundberg and Startz, 1998). The interaction effects for White borrowers with a higher fraction of White lenders are also statistically significant, but their economic magnitude is small. Finally, the effects of the other variables are similar to those found in the previous sections, and, in particular, borrowers' personal characteristics turn out to matter even after similarity and all other variables are taken into account.[18]

To shed more light on the effect of ethnic similarity, Panel C of Table VII reports the fractions of White and Black lenders, the fraction of the total investment they are responsible for, and the fraction they invest in White and Black borrowers, respectively. It shows that Black lenders are 9.54% of the Black/White lender population and are responsible for 8.69% of the funds invested, while Blacks are 21.76% of the applicants and 16.61% of the borrowers. It also shows that Black lenders, in addition to being better able to screen Black borrowers, are also significantly more likely to lend to them. Their Black/White portfolio is made of 27.03% of Black borrowers, while if they lent money without considering race it would only be made of 16.61% Blacks.[19] On the contrary, White borrowers are not more likely to lend to Whites, although they charge them lower interest rates and are better able at screening them.

Finally, unreported results indicate that ethnical similarity also affects the likelihood lenders bid on a listing and the amount bid, with Black lenders more likely to bid and bidding more on Black borrowers.

[18] A complete version of Table VII, reporting the coefficients for the hard financial information, listing features, age, smile and tie dummies is available in the online Appendix. Also note that the website is set up in a way that borrowers cannot selectively repay some lenders and not others, as Prosper automatically withdraws money from the borrower's checking account every month and pays the lenders proportionally to the fraction invested. Therefore, theories of selective repayment based on reciprocity do not explain the results.

[19] Panel A of Table III and Panel C of Table II indicate that, for the cases in which race is available, 84.16% of the lenders are White, 8.88% are Black, 4% are Asian, and 2.97% are Hispanic. For the borrowers, these proportions are 73.30% Whites, 14.54% Blacks, 6.43% Asian, and 7.49% Hispanics. For simplicity, Panel C of Table VII focuses on Blacks and Whites only and recalculates the proportions to reflect this.

IV Robustness Checks and Alternative Explanations

This section contains some additional analysis to test the robustness of the results and disentangle them from alternative explanations.

To control for any additional impression the applicants might make over and above that captured by the personal characteristics, Panel A of Table VIII reports the coefficients from the regressions in Tables IV to VI adding measures of the applicants' trustworthiness and creditworthiness. The applicant's personal characteristics included in the study, such as age, beauty, and race, are aimed at capturing the features that, in addition to hard financial information, inspire trust and confidence in the applicants' ability and willingness to repay, either through the channel of statistical discrimination or through that of taste based discrimination. The objective of including additional variables about trustworthiness and creditworthiness is to control for any residual over and above the impression captured by the personal characteristics. The coefficients in the table show that adding these measures doesn't change the economical and statistical significance of the hard financial information and of the personal characteristics. As it was already shown in Tables IV to VI, Black applicants are less likely to get a loan (-2.28%), if they do, they pay 150bps more, they are more likely to default and yield a significantly lower IRR than an otherwise similar White borrowers. Similarly to the results in Tables IV to VI, beautiful applicants are more likely to get a loan, although the coefficient is not statistically significant, pay 78.3bps less, and are not significantly different in their default rates than average looking borrowers. Among the beautiful, female borrowers are more likely to get loans and are charged lower rates, although their default rates are similar to other borrowers. As expected, the creditworthiness of the applicant also matters. An increase in the creditworthiness rating raises the probability of getting a loan by 2.06% and lowers the interest rate by 133bps. The coefficients are statistically significant at the 5% and 1% level, respectively. Once all other controls are taken into account, being perceived as creditworthy is not significantly

related to default rates and lenders' returns. Finally, once we control for the hard financial information, personal characteristics and the perceived creditworthiness, the trustworthiness coefficient is neither economically nor statistically significant and turns out to have the opposite sign than we would expect. This provides evidence that the relevant personal characteristics aimed at capturing the features that, in addition to hard financial information, inspire trust and confidence in the applicant's willingness to repay were indeed included in the regression.[20]

It is also important to address the effect of potential omitted variables and measurement error in the personal characteristics on the interpretation of the results. In particular, what is the effect of a mistake in classifying a person's observables, or, more likely, leaving the category as missing when in fact such information is available and visible to the lenders? Despite the data collection process has involved two research assistants recording each piece of information independently, and has been subjected to additional checks, measurement error and some omissions are likely to be present. While measurement error in the variables would lead to an attenuation bias and make the coefficients closer to zero and their effect more imprecisely measured, the omitted variable concern is more complex. It is possible that beauty or some other personal characteristics are not considered as indicative of repayment ability or factored in any way in the lenders' analysis, but they just happen to be correlated with some other variable that is observed and considered relevant by the lenders, but missed by the researcher. These concerns are mitigated by the very rich set of controls that are included in the regressions and that would pick up any effect unrelated to beauty, but actually related to hard financial information from the credit bureau, listing features, information from the borrower's loan description and group membership and the other available

[20] The results are in contrast with Duarte et al. (2012) who conduct a very similar study and find a statistically significant coefficient on trustworthiness. The possible reasons for the difference are the way the variables are measured, the variables included, and possibly the longer horizon in their study, which spans many periods with different rules for borrowing and lending on the website, and makes it more difficult to control for all the applicant's features accurately.

personal characteristics.[21] Nevertheless, to further explore this issue, each table in the paper adds the personal characteristics in stages, so to analyze the stability and statistical significance of the coefficients. Tables IV to VII show that the magnitude and economic significance of the coefficients on beauty and other personal characteristics are indeed quite stable across the different specifications. This suggests that adding other, now omitted, explanatory variables is unlikely to change the results.

The findings are also robust to various changes in specification, including estimating the effect of hard and soft information on the fraction of the loan that gets funded, rather than the probability of getting funds, changes in the order in which the personal characteristics are added to test the stability of the coefficients, the use of alternative definitions of racism for the results in Panel A of Table VII, the addition of the interaction between being overweight and gender, and dummy variables capturing the context of the picture i.e. outdoor, at work,..., (not reported).

To control for the possibility that personal characteristics and other loan features somehow proxy for economic conditions, Panel B of Table VIII includes in the regression the state unemployment rate, a measure of economic activity that has been documented to affect consumer and small business loans performance (Agarwal and Liu, 2003). The coefficients show that, once we control for hard financial information and personal characteristics, the unemployment rate doesn't affect the likelihood of getting funds, the terms of the loan, nor its performance.

Finally, another issue is the possibility of fraud and misrepresentation. All the hard financial information is extracted directly from the credit bureau by Prosper, so there is little concern for manipulation, but some applicants could be posting a fake picture of someone attractive to boost their chances of getting a loan. The fact that somebody posts an inaccurate picture is not a problem for the analysis of the effect of personal characteristics on the likelihood and the terms

[21] Note that omitted variable concerns are less likely to be related to the hard financial information, as such variables are from the credit bureau and provided by Prosper itself to both the lenders and the researcher in easily downloadable form.

of the loan, since both the researcher and the lenders observe the same pictures and information, and the analysis measures the impact of such pictures and information on lenders' decisions, even if the borrower doesn't really possess those features. However, this is potentially an issue for the loan performance analysis. For example, are beautiful people really equally likely to default as the average-looking borrower who gets worse terms, or rather, are those who post a picture of a beautiful person the ones who turn out to be bad borrowers? Misrepresentation is an issue only for interpreting the results on performance for those variables that lead to higher probability of getting a loan, and/or better interest rates, and turn out to be associated to higher/similar default rates, i.e. beauty. It is less so for variables such as race, which are associated to worse rates and lower likelihood of getting funds. Despite quantifying the magnitude of this phenomenon is impossible, and such caveat must certainly be kept in mind when interpreting the loan performance results, it is worth noting that Panel B of Table II shows that on average the borrowers in the population are average looking. So, in order for fraud to be very widespread, we would need the bad borrowers to make an effort to look beautiful, which could be plausible, and the good borrowers do the opposite, which is less plausible.[22]

Another minor issue is whether the lenders give funds to beautiful people in the hope of meeting them outside the website. Despite Prosper doesn't provide sufficient information to identify a person and actively monitors the site to avoid that the applicants post emails and other contact information, to check whether this is an important concern, I've added to the regression the proportion of the lenders of the same sex as the applicant and its interaction with the borrower's gender. Panel D of Table VIII shows that a higher proportion of lenders of the same gender is

[22] To make sure that the reason the average beauty rating is 4, the mid-point of the distribution, is not just because the raters implicitly define the pool of applicants as the reference population they compare each picture to, I've checked whether the average beauty rating of the first 10 random pictures any rater sees and evaluates is also 4, and find that on average raters actually have lower evaluations at the beginning of their tenure than overall, indicating that this pool of people is not abnormally better looking than the population overall. Such negative difference is small but statistically significant and it is not present in the trustworthiness and creditworthiness ratings. See Panel E of Table II.

not associated to higher likelihood of getting loans, not to different interest rates. The Table also controls for the proportion of lenders that are similar to the borrower along other dimensions, such as city, religion, belonging to the same group, entrepreneurship and shows that the economical and statistical significance of the other coefficients is unaffected by these controls.

V Who lends to them?

Who lends to the borrowers who score high on beauty, but turn out to be bad credits? And to Blacks? Table IX examines the lenders characteristics that are correlated with higher beauty or a given race.

The empirical specification is the following tobit regression:

$$Beauty_i = f(\alpha_{1ij} Lenders' Experience_j + \alpha_{2i,j} Lenders' Income_j + \alpha_{3i,j} Lenders' Demographics_j + \varepsilon_{ij})$$

where i indicates the listing and j the lender. Lenders' experience is measured by the total amount lent on the web site up to the day of their bidding on listing i, and by the amount of time they have been Prosper members. In addition, I use the total amount bid as a measure of the lender's bidding abilities, once the total amount lent is controlled for. *Lenders' Income* is the lender's income range, described in detail in Table III, while *Lenders' Demographic*s include gender, age, and race.

Panel A of Table IX illustrates the characteristics of the lenders more prone to lend to the beautiful. Column I shows that more sophisticated lenders, who have lent more money, are all else equal less likely to lend to attractive people, and so are people that have been on the website for a longer time. On the contrary, after controlling for amount lent, a higher amount bid, which proxies for lower bidding abilities, leads to a higher probability of lending to the beautiful. The

coefficients are significant at the 1 percent level. Column II adds gender to the regression and shows that, all else equal, female lenders are more likely to lend to attractive borrowers. However, once the lender's income is taken into account, gender is not significant anymore, while lender's sophistication and bidding ability continue to be (Column III). Column III also shows that lenders with higher income are less likely to lend to beautiful borrowers: people whose income falls between $75,000 and $99,999 lend to people whose beauty is a quarter of a point lower than a lender with income below $25,000. The relationship between lenders' income and borrower's beauty is however not monotonical, and not always statistically significant. Compared to middle-aged lenders, young lenders are more likely to lend to the beautiful and old lenders are less likely so, although the results are not statistically significant. Finally, compared to a White lender, Asian lenders are significantly less likely to give funds to good looking applicants.

Panel B of Table IX examines the characteristics of the lenders who are more likely to lend to Black borrowers. Lenders with more experience, both in terms of amount lent and length of Prosper membership, are less likely to lend to Black borrowers, while lenders that bid more inefficiently are more likely to do so, although the coefficient is not economically significant. Income and demographic characteristics, such as age, gender and race do not appear to be significantly correlated with the borrower being Black.

Column V in Panel A and B check whether accounting for similarity between borrowers and lenders drives the significance of the lenders' characteristics away. The empirical specification is the following:

$$\begin{aligned} Beauty_i &= f(\alpha_{1ij} Lenders' Experience_j + \alpha_{2i,j} Lenders' Income_j + \alpha_{3i,j} Lenders' Demographics_j \\ &\quad + \alpha_{4i,j} \mathrm{Si}\, milarity_{ij} + \varepsilon_{ij}) \end{aligned}$$

where i denotes the borrower, j the lender, while the measures of similarity include being from the same city, race, religion, sex, Prosper group, and being both entrepreneurs. The results confirm that similarity affects lenders' decisions, although it doesn't change the effect of other lenders' characteristics such as experience and bidding abilities. In particular, Panel A shows that living in the same city is negatively correlated with beauty, indicating that for lenders bidding on borrowers from the same city, beauty and appearance are significantly less important: on average, borrowers with a higher proportion of lenders from the same city rank 0.20 points lower on attractiveness (significant at the 1 percent level). The same borrowers are 0.88% more likely to be Black, although the effect is not statistically significantly. Being from the same gender is positively correlated with beauty and unrelated to race. Finally, even after controlling for similarity, young lenders and worse bidders are more likely to lend to the beautiful, while Asian lenders are significantly less likely to do so. Panel B shows that lenders who give more funds to Blacks tend to be male, low income, old or young, but not middle age, and Black. Also, they tend to have lent more money than the average lender. These findings are consistent with the literature that studies individual investors in stocks and mutual funds and finds that investors' experience alleviates their biases, and that higher income is associated with more profit maximizing choices (Odean (1999), Barber and Odean (2001) Choi et al. (2005)).

VI Conclusions and Discussion

This paper provides evidence that, after controlling for hard financial information, employment, and credit history, personal characteristics and the way borrowers present themselves affect the likelihood of getting a loan and the interest rate and are related to ex-post performance. The economic magnitude of the coefficients is large. For example, an increase in beauty from neutral to above average generates a 1.59% higher probability of getting a loan, and a drop of 60bps in the

interest rate. To match the same likelihood of getting a loan as a beautiful borrower, an average-looking one with the same credentials and characteristics would need to increase the interest rate offered by 7.54 percentage points, or, alternatively, lower the amount requested by $11,606. Yet, beautiful borrowers default at the same rate as average looking ones, who get significantly worse loan terms. Race, gender, and age also affect the likelihood of getting funds, with Blacks less likely to get loans, and female applicants more likely to. Conditional on getting funds, Blacks pay higher rates and so do Asians and older borrowers. While most personal characteristics are unrelated to performance, being Black is associated with significantly lower returns for lenders. The paper analyzes the effect of the economy, similarity between borrowers and lenders, and the degree of racial prejudice against Blacks on this result. While Blacks performance was better than other borrowers' at the beginning of period, it deteriorated faster as the financial crisis unfolded, possibly because of worse labor market shocks faced by this group (Elsby et al. (2010), Farber (2011), Kochhar et al. (2011), Hoynes et al. (2012)). I also find that a higher proportion of lenders of the same race is associated with Black borrowers who have higher probability of getting a loan, lower interest rates and, interestingly, also better ex-post performance. A higher proportion of lenders living in states with a high degree of racial prejudice against Blacks, is associated with Black borrowers paying higher rates, but yielding similar returns than other Black borrowers. At the same time, White borrowers who face a higher proportions of lenders from areas with a high degree of racial prejudice against Blacks pay lower rates, and are significantly more likely to default than other similar White borrowers.

The findings on beauty are consistent with a taste-based discrimination/perception story against the ugly. On the contrary, the findings on Blacks borrowers are consistent with statistical discrimination, although the analysis in the paper shows that lenders specialization in borrowers from the same ethnicity and racial prejudice also play a role.

An important question is the degree to which these findings can be generalized to other settings. While the results in the paper are directly relevant for small scale lending and microfinance, some insights can be applied to other business settings and financial transactions as well. Many studies indicate that looks and personal characteristics are important in many business transactions with high stakes and sophisticated players: big law firms more likely to hire and paying higher salaries to good-looking lawyers to deal with very sophisticated clients (Hamermesh and Biddle (1998)), and the relationship between race and loan terms in mortgage markets (for example, Ladd (1998), Cole (1999)) are just two examples. In addition, vast resources and time are spent in improving one's image for the purpose of having success in business (Etcoff (2000)). This evidence suggests that the effect of looks and personal characteristics doesn't fade in environments with higher stakes and more sophisticated decision makers.

Finally, the study allows us to take a glimpse at the functioning of an un-intermediated market, where the diversification role of banks is performed by technology providing many individual lenders the ability to learn about and bid on multiple loans, while the monitoring role is absent, except for the disciplining effect of a damaged credit score if the borrower become delinquent or defaults. Despite still small, such markets have recently reached $1 billion in volume lent and are likely to become an increasingly important source of finance for individuals and small businesses in the future.[23]

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Figure 1
Average Default Rates by Ethnicity

This figure reports the average default rates by ethnicity for Prosper borrowers in the sample. A loan is considered in default if it is more than 4 months late, it is into bankruptcy, or it has been charged-off. The default rate is calculated as the ratio of the amount unpaid to the amount that the loan would have generated had the principal and all interest payments be made, and each observation is weighted by the amount borrowed. The vertical line indicates December 2007, the beginning of the 2007-2009 recession according to the National Bureau of Economics Research.

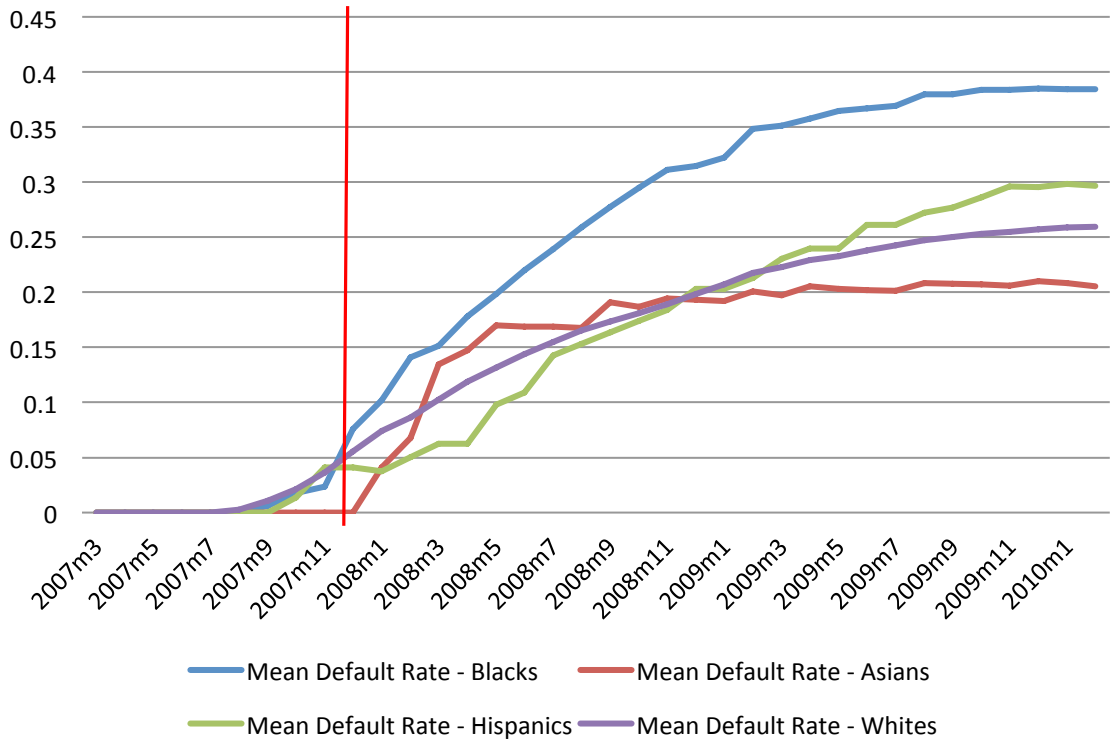


Table I

Lenders' Rate of Return, Default and Delinquency Rates of Prosper Borrowers

This table reports the average lender interest rate, equal to the rate paid by the borrower less the 1% fee paid to Prosper, the total amount lent and the default and delinquency rates by credit grades for all the loans generated on the website, as of December 2007. A loan is considered delinquent if it is one or more months late. The Experian default rate is the default rate on a pool of revolving credit accounts from Experian, comprising 251,000 loans with an average age of 2 years, reported on the Prosper website for comparison.

			Loans Originated						
Credit Grade	**Credit Score**	**Average Lender Interest Rate**	**Total Amount Lent**	**Delinquency rate**	**Default Rate**	**Experian Default rate**	**Default-adjusted Lenders' Return**	**Obs.**	**%**
AA	760 and up	9.46%	$15,487,459	5.81%	0.19%	0.20%	9.25%	1,693	10.30%
A	720-759	11.56%	$14,622,210	2.93%	0.95%	0.90%	10.50%	1,641	9.99%
B	680-719	14.04%	$18,544,985	8.04%	1.84%	1.80%	11.95%	2,099	12.78%
C	640-679	16.90%	$20,941,259	12.49%	1.72%	3.30%	14.88%	2,946	17.93%
D	600-639	19.93%	$16,274,367	15.94%	2.74%	6.20%	16.64%	2,969	18.07%
E	560-599	23.55%	$8,956,994	27.40%	7.02%	10.40%	14.88%	2,317	14.10%
HR	520-559	23.51%	$6,891,624	36.43%	11.87%	19.10%	8.85%	2,621	15.95%
NC	No credit history	21.47%	$332,468	92.28%	38.97%	N/A	-25.87%	143	0.87%
Total			$102,051,366	13.03%	2.84%			16,429	100.00%

Source: Prosper website and author's calculations.

Table II Panel A
Variable Definitions

Variable	Definition	Source
Listing Characteristics		
Amount requested	Amount of the loan request	Prosper website - Listing
Borrower maximum rate	Maximum rate the borrower is willing to pay	Prosper website - Listing
Listing Status - Cancelled	Listings has been cancelled by Prosper (dummy)	Prosper website - Listing
Listing Status - Completed	Listing successfully completed: a loan is generated (dummy)	Prosper website - Listing
Listing Status - Expired	Listing expired without reaching full funding: no loan is generated (dummY0	Prosper website - Listing
Listing Status - Withdrawn	Listing has been withdrawn by the borrower	Prosper website - Listing
Percent Funded	Percent of the loan request that received funding as of the expiration date	Prosper website - Listing
Close when funded (dummy)	Dummy equal 1 if the member chose to close the listing once fully funded without waiting for lower rates	Prosper website - Listing
Reason for the Loan	Reason for asking the loan (dummies - see Appendix B for a list)	Prosper website - Listing
# of previous listings	# of times the borrower has posted a listing in the past	Prosper website - author's calculations
Credit Bureau Information		
Credit Grade AA	Credit score > 760 (dummy)	Prosper website - Credit Bureau
Credit Grade A	Credit score between 720 and 759 (dummy)	Prosper website - Credit Bureau
Credit Grade B	Credit score between 680 and 719 (dummy)	Prosper website - Credit Bureau
Credit Grade C	Credit score between 640 and 679 (dummy)	Prosper website - Credit Bureau
Credit Grade D	Credit score between 600 and 639 (dummy)	Prosper website - Credit Bureau
Credit Grade E	Credit score between 560 and 599 (dummy)	Prosper website - Credit Bureau
Credit Grade HR	Credit score between 520 and 559 (dummy)	Prosper website - Credit Bureau
Income - $0 or N/A	Income range (dummy)	Prosper website - Credit Bureau
Income range - $1- $24,999	Income range (dummy)	Prosper website - Credit Bureau
Income range - $25,000- $49,999	Income range (dummy)	Prosper website - Credit Bureau
Income range - $50,000- $74,999	Income range (dummy)	Prosper website - Credit Bureau
Income range - $75,000- $99,999	Income range (dummy)	Prosper website - Credit Bureau
Income range - $100,000+	Income range (dummy)	Prosper website - Credit Bureau
Unemployed (dummy)	Employment status (dummy)	Prosper website - Credit B. + Listing
Employed - Full time (dummy)	Employment status (dummy)	Prosper website - Credit B. + Listing
Employed - Part time (dummy)	Employment status (dummy)	Prosper website - Credit B. + Listing

Retired (dummy)	Employment status (dummy)	Prosper website - Credit B. + Listing
Self-Employed (dummy)	Dummy equal 1 if the member is an entrepreneur or self-employed	Prosper website - Credit B. + Listing
Length of Employment Status	Length of employments status in years	Prosper website - Credit Bureau
Bankcard Utilization Rate	The percentage of available revolving credit that is utilized at the time the listing was created.	Prosper website - Credit Bureau
Debt to Income Ratio	Debt to Income Ratio	Prosper website - Credit Bureau
# of Credit Lines	Number of current credit lines	Prosper website - Credit Bureau
Revolving credit balance	The monetary amount of revolving credit balance at the time the listing was created	Prosper website - Credit Bureau
Delinquency dummy	Dummy equal to 1 if the member has any delinquency currently on her credit record	Prosper website - Credit Bureau
Delinquency (last 7 yrs) dummy	Dummy equal to 1 if the member has had any delinquency on her credit record in the last 7 years	Prosper website - Credit Bureau
Public Records (last 10 yrs) dummy	Number of public records in the last 10 years	Prosper website - Credit Bureau
Public Records (last 12 mos) dummy	Number of public records in the last year	Prosper website - Credit Bureau
	Demographics	
Homeowner (dummy)	Dummy equal 1 if the member owns a house	Prosper website - Credit Bureau
Asian (dummy)	Dummy equal to 1 if the member's race is "Asian/Pacific Islander/Asian-American"	Prosper website - Picture + Listing
Black (dummy)	Dummy equal to 1 if the member's race is "Black/African American"	Prosper website - Picture + Listing
Hispanic (dummy)	Dummy equal to 1 if the member's race is "Latino/Hispanic American"	Prosper website - Picture + Listing
White (dummy)	Dummy equal to 1 if the member's race is "European/Caucasian-American"	Prosper website - Picture + Listing
Female (dummy)	Dummy equal 1 if the member is female	Prosper website - Picture + Listing
Young (dummy)	Dummy equal 1 if the member is young	Prosper website - Picture + Listing
Old (dummy)	Dummy equal 1 if the member is old	Prosper website - Picture + Listing
Length in Prosper	Length of Prosper membership in months	Prosper website - Author's calculations
Overweight (dummy)	Dummy equal 1 if the member is severely overweight	Prosper website - Picture
Children in Picture	Dummy equal 1 if there are children in any of the picture posted	Prosper website - Picture
Tie (dummy)	Dummy equal 1 if the person in the picture is wearing a tie	Prosper website - Picture
Smile (dummy)	Dummy equal 1 if the person in the picture is smiling	Prosper website - Picture
Occupation	Applicant's occupation (dummies – see Appendix B for a list)	Prosper website - Listing
Beauty	Beauty ranking	Prosper website - Picture + Rating
Trustworthiness	Ranking of first impression of trustworthiness	Prosper website - Picture + Rating
Creditworthiness	Ranking of first impression of creditworthiness	Prosper website - Picture + Rating
Average Racism in Lender's Area	Average of responses in that state to the question: "On the average (Negroes/Blacks/African-Americans) have worse jobs, income, and housing than white people. Do you think these differences are because most of them just don't have the motivation or will power to pull themselves out of poverty?" 1- Yes; 2 – No.	General Social Survey
Proportion of lenders with a given characteristic	For each borrower, the proportion of her lenders who have a given characteristic (city, ethnicity,…), weighted by amount lent	Prosper website - Author's calculations

Table II Panel B
Summary Statistics – All Applicants

This Panel reports summary statistics for all the individuals that posted a loan request between March 12th and June 18th 2007, irrespective of whether their request was funded. A definition of the variables is provided in Panel A of this Table.

Listing Characteristics						
Variable	Mean	Median	Std Dev	Min	Max	Obs.
Amount Requested	$8,923	$6,500	$6,846	$1,000	$25,000	37,897
Borrower maximum rate	17.30%	17.00%	6.88%	0.00%	30.00%	37,897
Listing Status – Completed	0.0878	0	0.2829	0	1	37,897
Listing Status – Expired	0.5361	1	0.4987	0	1	37,897
Listing Status – Withdrawn	0.3647	0	0.4813	0	1	37,897
Listing Status – Cancelled	0.0113	0	0.1060	0	1	37,897
Percent Funded	0.1298	0	0.3009	0	1	37,897
Close when funded	0.3357	0	0.4722	0	1	37,897
# of previous listings	2.1874	2	2.3388	0	10	36,733
Credit Bureau Information						
Variable	Mean	Median	Std Dev	Min	Max	Obs.
Credit Grade AA	0.0306	0	0.1723	0	1	37,897
Credit Grade A	0.0341	0	0.1815	0	1	37,897
Credit Grade B	0.0547	0	0.2274	0	1	37,897
Credit Grade C	0.1030	0	0.3039	0	1	37,897
Credit Grade D	0.1576	0	0.3643	0	1	37,897
Credit Grade E	0.1693	0	0.3750	0	1	37,897
Credit Grade HR	0.4507	0	0.4976	0	1	37,897
Income range - $0 or N/A	0.0784	0	0.2689	0	1	37,897
Income range - $1 -$24,999	0.2163	0	0.4117	0	1	37,897
Income range - $25,000 -$49,999	0.4084	0	0.4915	0	1	37,897
Income range - $50,000 -$74,999	0.1871	0	0.3900	0	1	37,897
Income range - $75,000 -$99,999	0.0618	0	0.2407	0	1	37,897
Income range - $100,000 +	0.0476	0	0.2130	0	1	37,897
Employed - Full time (dummy)	0.8197	1	0.3845	0	1	37,897
Employed - Part time (dummy)	0.0448	0	0.2069	0	1	37,897
Self Employed (dummy)	0.0851	0	0.2791	0	1	37,897
Retired (dummy)	0.0231	0	0.1504	0	1	37,897
Unemployed (dummy)	0.0272	0	0.1628	0	1	37,897
Length of employment status (months)	57.1887	31	69.90799	0	566	37,885
Bankcard Utilization Rate	60.08%	74.00%	43.53%	0.00%	299.00%	37,877
Debt to Income Ratio	0.3419	0.27	0.3162	0	2.99	37,327
# of Credit Lines	24.8811	23	13.8861	2	100	37,629
Revolving Credit Balance	$9,023	$2,013	$23,755	$0	$491,461	37,877
Delinquency dummy	0.6748	1	0.4685	0	1	37,897
Delinquency (past 7yrs) dummy	0.6622	1	0.4730	0	1	37,897
Public Records (last 10 yrs) dummy	0.4012	0	0.4901	0	1	37,897
Public Records (last 12 mos) dummy	0.0667	0	0.2495	0	1	37,897

Table II - Panel B (continued)

Borrowers Demographics						
Variable	Mean	Median	Std Dev	Min	Max	Obs.
Homeowner (dummy)	0.3173	0	0.4654	0	1	37,897
White (dummy)	0.7423	1	0.4374	0	1	14,780
Black (dummy)	0.2065	0	0.4049	0	1	14,780
Hispanic (dummy)	0.0823	0	0.2749	0	1	14,780
Asian (dummy)	0.0603	0	0.2380	0	1	14,780
Female (dummy)	0.4986	0	0.5000	0	1	15,556
Male (dummy)	0.5096	1	0.4999	0	1	15,556
Children (dummy)	0.3075	0	0.4615	0	1	15,556
Young (dummy)	0.3630	0	0.4809	0	1	15,556
Old (dummy)	0.0680	0	0.2518	0	1	15,556
Middle-aged (dummy)	0.4376	0	0.4961	0	1	15,556
Smile (dummy)	0.4070	1	0.7630	-1	1	15,556
Tie (dummy)	0.0781	0	0.2684	0	1	15,556
Overweight (dummy)	0.1090	0	0.3117	0	1	15,556
Beauty	4.0206	4.0278	0.6556	1.5	6.5	14,120
Trustworthiness	4.3880	4.3333	0.4940	2	6.1667	14,120
Creditworthiness	4.2759	4.3333	0.5208	2	6.1667	14,120

* Notice that some of the dummies, like gender and ethnicity, may sum to more than 1, because more than one gender/ethnicity can be associated to the same listing.

Table II Panel C
Summary Statistics – Borrowers who got a Loan

This Panel reports summary statistics for those individuals who posted a loan request between March 12th and June 18th 2007 and got a loan. A definition of the variables is provided in Panel A of this Table.

Listing Characteristics						
Variable	Mean	Median	Std Dev	Min	Max	Obs.
Amount Requested	$7,379	$5,000	$6,115	$1,000	$25,000	3,327
Borrower maximum rate	20.15%	20.00%	6.42%	0.00%	30.00%	3,327
Borrower rate	17.90%	17.00%	6.30%	0.00%	30.00%	3,327
Close when funded	0.2528	0	0.4347	0	1	3,327
# of previous listings	1.6983	1	1.8642	0	10	3,325
Credit Bureau Information						
Variable	Mean	Median	Std Dev	Min	Max	Obs.
Credit Grade AA	0.1133	0	0.3170	0	1	3,327
Credit Grade A	0.1076	0	0.3100	0	1	3,327
Credit Grade B	0.1376	0	0.3445	0	1	3,327
Credit Grade C	0.1911	0	0.3932	0	1	3,327
Credit Grade D	0.2033	0	0.4025	0	1	3,327
Credit Grade E	0.1083	0	0.3108	0	1	3,327
Credit Grade HR	0.1388	0	0.3458	0	1	3,327
Income range - $0 or N/A	0.0299	0	0.1703	0	1	3,327
Income range - $1- $24,999	0.1117	0	0.3151	0	1	3,327
Income range - $25,000- $49,999	0.3997	0	0.4899	0	1	3,327
Income range - $50,000- $74,999	0.2540	0	0.4354	0	1	3,327
Income range - $75,000- $99,999	0.1095	0	0.3124	0	1	3,327
Income range - $100,000+	0.0951	0	0.2933	0	1	3,327
Employed - Full time (dummy)	0.8675	1	0.3391	0	1	3,327
Employed - Part time (dummy)	0.0400	0	0.1959	0	1	3,327
Self Employed (dummy)	0.0692	0	0.2539	0	1	3,327
Retired (dummy)	0.0170	0	0.1293	0	1	3,327
Unemployed (dummy)	0.0063	0	0.0791	0	1	3,327
Length of employment status (months)	59.1898	34	70.4125	0	486	3,327
Bankcard Utilization Rate	0.5295	1	0.3780	0	1.99	3,327
Debt to Income Ratio	0.2562	0	0.2290	0	2.96	3,327
# of Credit Lines	24.5219	22	14.1290	2	129	3,327
Revolving Credit Balance	$12,005	$3,444	$28,149	0	$460,885	3,327
Delinquency dummy	0.4341	0	0.4957	0	1	3,327
Delinquency (past 7yrs) dummy	0.4766	0	0.4995	0	1	3,327
Public Records (last 10 yrs) dummy	0.3022	0	0.4593	0	1	3,327
Public Records (last 12 mos) dummy	0.0478	0	0.2135	0	1	3,327

Table II - Panel C (continued)

Borrowers Demographics

Variable	Mean	Median	Std Dev	Min	Max	Obs.
Homeowner (dummy)	0.4375	0	0.4962	0	1	3,327
White (dummy)	0.7330	1	0.4426	0	1	1,429
Black (dummy)	0.1454	0	0.3526	0	1	1,429
Hispanic (dummy)	0.0749	0	0.2633	0	1	1,429
Asian (dummy)	0.0643	0	0.2454	0	1	1,429
Female (dummy)	0.4969	0	0.5002	0	1	1,429
Male (dummy)	0.5542	1	0.4972	0	1	1,429
Children (dummy)	0.2750	0	0.4467	0	1	1,429
Young (dummy)	0.4024	0	0.4905	0	1	1,429
Old (dummy)	0.0574	0	0.2327	0	1	1,429
Middle-aged (dummy)	0.4374	0	0.4962	0	1	1,429
Smile (dummy)	0.4612	1	0.7310	-1	1	1,429
Tie (dummy)	0.0861	0	0.2806	0	1	1,429
Overweight (dummy)	0.0868	0	0.2816	0	1	1,429
Beauty	4.1208	4.1667	0.6419	2	6	1,329
Trustworthiness	4.4086	4.5000	0.4724	3	5.8333	1,329
Creditworthiness	4.3735	4.3333	0.5063	2.6667	6.1667	1,329

* Notice that some of the dummies, like gender and ethnicity, may sum to more than 1, because more than one gender/ethnicity can be associated to the same listing.

Table II Panel D

Summary Statistics - Beauty, Trustworthiness and Creditworthiness Ratings

This Panel reports the beauty, trustworthiness, and creditworthiness ratings overall and by sex of the rater. The ratings go from *Not Attractive/Trustworthy/Creditworthy at All* (1), to *Extremely Attractive/ Trustworthy/ Creditworthy* (7), with *Neutral* in the middle (4). See Appendix A for more details on the rating procedure, the ratings, and the raters. The variables definition is provided in Panel A of this Table.

	Mean	Median	Std Dev	Min	Max	Obs.
Overall						
Beauty	4.0206	4	1.0345	1	7	84,720
Trustworthiness	4.3880	4	0.9360	1	7	84,720
Creditworthiness	4.2759	4	0.9658	1	7	84,720
Female Raters						
Beauty	4.0894	4	1.0796	1	7	42,360
Trustworthiness	4.4045	4	0.9656	1	7	42,360
Creditworthiness	4.3127	4	0.9972	1	7	42,360
Male Raters						
Beauty	3.9518	4	0.9825	1	7	42,360
Trustworthiness	4.3715	4	0.9051	1	7	42,360
Creditworthiness	4.2391	4	0.9318	1	7	42,360

Table II Panel E

Comparison across Beauty, Trustworthiness and Creditworthiness Ratings

This Table reports a comparison of the first 10 beauty ratings given by each rater to the universe of all the ratings. It also includes the same analysis on trustworthiness and creditworthiness for sake of comparison. The objective is to understand whether the average beauty rating is 4 because the raters implicitly compare each applicant to the other applicants in the sample and not to the population overall, and thus get 4 on average although the applicant pool is systematically higher or lower beauty than the population. This does not seem to be the case from the results below. A definition of the explanatory variables is provided in Panel A of Table II.

Variable	Mean	Std. Dev	Min	Max	Obs
Beauty (First 10 ratings)	3.8992	0.7482134	1	6	2,425
Beauty	4.0206	0.6572003	1	7	84,720
Trustworthiness (First 10 ratings)	4.5945	0.6216028	2	6	2,425
Trustworthiness	4.3880	0.4947163	1	7	84,720
Creditworthiness (First 10 ratings)	4.3261	0.5279286	1	6	2,429
Creditworthiness	4.2759	0.520298	1	7	84,720

Table III Panel A
Summary Statistics – Lenders

This Panel reports summary statistics for all the individuals that lent money or made a bid on the listings posted on Prosper between March 12th and June 18th 2007. A definition of the variables is provided in Panel A of Table II.

Variable	Mean	Median	Std Dev	Min	Max	Obs.
Total amount bid	$6,299	$1,408	$30,258	$50	$2,047,842	18,627
Total amount lent	$2,080	$500	$10,201	$0	$738,448	18,627
Months in Prosper	11.1007	10	4.0299	5	25	18,614
Homeowner (dummy)	0.5647	1	0.4959	0	1	2,837
Employed - Full time (dummy)	0.8795	1	0.3256	0	1	2,640
Employed - Part time (dummy)	0.0261	0	0.1596	0	1	2,640
Self Employed (dummy)	0.0693	0	0.2540	0	1	2,640
Retired (dummy)	0.0140	0	0.1176	0	1	2,640
Unemployed (dummy)	0.0110	0	0.1043	0	1	2,640
Length of empl. status (months)	32.2441	2	57.9110	0	444	2,798
Income range - $1- $24,999	0.0218	0	0.1461	0	1	2,798
Income range - $25,000- $49,999	0.0722	0	0.2589	0	1	2,798
Income range - $50,000- $74,999	0.1590	0	0.3658	0	1	2,798
Income range - $75,000- $99,999	0.1476	0	0.3548	0	1	2,798
Income range - $100,000+	0.1011	0	0.3016	0	1	2,798
Female (dummy)	0.2282	0	0.4197	0	1	2,350
Male (dummy)	0.7718	1	0.4197	0	1	2,350
Young (dummy)	0.2376	0.25	0.2001	0	1	2,520
Middle-aged (dummy)	0.7203	0.7	0.2156	0	1	2,520
Old (dummy)	0.0421	0	0.0852	0	1	2,520
Asian (dummy)	0.0400	0	0.0838	0	1	2,520
Black (dummy)	0.0888	0	0.1298	0	1	2,520
Hispanic (dummy)	0.0297	0	0.0720	0	1	2,520
White (dummy)	0.8416	0.875	0.1800	0	1	2,520
Average Racism in Lender's Area	1.5091	1.5111	0.0941	1.2222	1.7857	17,642

Table III Panel B
Comparison between Lenders with Demographic Information and the Total

This Panel reports summary statistics on the characteristics available for all lenders and the subset of lenders with demographic information. A definition of the variables is provided in Panel A of Table II.

	Variable	Mean	Median	Std Dev	Min	Max	Obs.
w/o demogr. info	Total amount bid	$6,198	$1,453	30413.06	$50	2,047,842	15,790
	Total amount lent	$2,079	$500	10607.39	0	$738,448	15,790
	Months in Prosper	10.9830	10	4.0010	5	25	15,778
	Avg. Racism in Area	1.5097	1.5111	0.0939	1.2222	1.7857	14,927
w. demogr. info	Total amount bid	$6,863	$1,150	29375.56	50	$890,281	2,837
	Total amount lent	$2,087	$378.97	7552.984	0	$168,103	2,837
	Months in Prosper	11.7553	11	4.12726	5	25	2,836
	Avg. Racism in Area	1.5060	1.5111	0.0951	1.2222	1.7857	2,715
Total	Total amount bid	$6.299	$1,408	$30,258	50	2,047,842	18,627
	Total amount lent	$2,080	$500	$10,201	0	$738,448	18,627
	Months in Prosper	11.1007	10	4.029943	5	25	18,614
	Avg. Racism in Area	1.5091	1.5111	0.0941	1.2222	1.7857	17,642

Table IV

Probability of Getting a Loan as a function of Hard Financial Information, Personal Characteristics, and Appearance

This Table reports the marginal effects from a probit regression of loan request fulfillment on hard financial information, personal characteristics, family characteristics and listing features. The dependent variable, *LoanFunded* equals one if the listing received enough bids and generated a loan, and zero otherwise. Since a borrower that does not receive funding can post another listing, the standard errors are clustered at the member level. A definition of the explanatory variables is provided in Panel A of Table II.

	(I)	(II)	(III)	(IV)	(V)	(VI)
Borrower maximum rate	0.0038***	0.0022***	0.0021***	0.0021***	0.0021***	0.0021***
	[24.57]	[18.10]	[17.77]	[17.78]	[17.78]	[17.71]
Debt to Income Ratio	-0.0012***	-0.0007***	-0.0006***	-0.0006***	-0.0006***	-0.0006***
	[-4.956]	[-3.595]	[-3.632]	[-3.647]	[-3.655]	[-3.586]
Amount requested ($,000)	-0.0022***	-0.0014***	-0.0014***	-0.0014***	-0.0014***	-0.0013***
	[-26.82]	[-21.05]	[-20.75]	[-20.74]	[-20.74]	[-20.77]
Close when funded (dummy)	-0.0037***	-0.0012**	-0.0012**	-0.0011**	-0.0011**	-0.0011*
	[-4.734]	[-2.085]	[-1.986]	[-1.964]	[-1.962]	[-1.955]
Homeowner Dummy	0.0029***	0.0024***	0.0023***	0.0023***	0.0023***	0.0023***
	[3.578]	[3.646]	[3.680]	[3.671]	[3.669]	[3.654]
Credit Grade AA	0.854***	0.816***	0.811***	0.811***	0.811***	0.804***
	[25.54]	[19.09]	[18.66]	[18.66]	[18.66]	[17.54]
Credit Grade A	0.759***	0.680***	0.675***	0.675***	0.675***	0.699***
	[25.97]	[19.63]	[19.37]	[19.39]	[19.37]	[18.48]
Credit Grade B	0.521***	0.462***	0.468***	0.468***	0.468***	0.455***
	[25.35]	[19.83]	[19.74]	[19.75]	[19.75]	[17.61]
Credit Grade C	0.229***	0.193***	0.189***	0.188***	0.188***	0.175***
	[23.04]	[18.54]	[18.34]	[18.34]	[18.34]	[15.92]
Credit Grade D	0.0544***	0.0358***	0.0350***	0.0350***	0.0350***	0.0279***
	[16.36]	[13.06]	[13.04]	[13.04]	[13.04]	[9.344]
Credit Grade HR	-0.0140***	-0.0077***	-0.0072***	-0.0072***	-0.0072***	-0.0083***
	[-11.28]	[-8.277]	[-8.009]	[-7.978]	[-7.980]	[-6.678]
# of listings before current	-0.0013***	-0.0010***	-0.0009***	-0.0009***	-0.0009***	-0.0009***
	[-7.683]	[-7.598]	[-7.181]	[-7.182]	[-7.175]	[-7.138]
Length of employment status	-1.33e-05***	-2.82e-06	-2.70e-06	-2.91e-06	-2.94e-06	-2.75e-06
	[-2.665]	[-0.793]	[-0.776]	[-0.835]	[-0.842]	[-0.804]
Delinquency dummy	-0.0092***	-0.0046***	-0.0044***	-0.0044***	-0.0044***	-0.0043***
	[-8.918]	[-5.871]	[-5.776]	[-5.778]	[-5.779]	[-5.770]
Delinquency in last 7yrs	-0.0048***	-0.0033***	-0.0031***	-0.0031***	-0.0031***	-0.0030***
	[-5.197]	[-4.635]	[-4.391]	[-4.406]	[-4.405]	[-4.391]
Public Records (last 12 mos)	0.0002	3.55e-05	0.0003	0.0003	0.0003	0.0003
	[0.147]	[0.0303]	[0.262]	[0.250]	[0.256]	[0.294]
Public Records (last 10 yrs)	-0.0024***	-0.0020***	-0.0020***	-0.0021***	-0.0021***	-0.0020***
	[-3.127]	[-3.461]	[-3.600]	[-3.652]	[-3.653]	[-3.613]
Income $0 or N/A	-0.0026	0.0001	-0.0003	-0.0004	-0.0003	-0.0003
	[-1.336]	[0.0810]	[-0.204]	[-0.222]	[-0.220]	[-0.190]
Income range - $25k- $49.9k	0.0066***	0.0050***	0.0050***	0.0050***	0.0050***	0.0050***
	[5.272]	[4.979]	[4.996]	[4.968]	[4.968]	[5.009]
Income range - $50k- $74.9k	0.0133***	0.0106***	0.0102***	0.0101***	0.0101***	0.0101***
	[6.909]	[6.317]	[6.202]	[6.172]	[6.172]	[6.215]
Income range - $75k- $99.9k	0.0194***	0.0182***	0.0179***	0.0178***	0.0178***	0.0177***
	[6.630]	[6.296]	[6.206]	[6.197]	[6.199]	[6.216]
Income range - $100k+	0.0294***	0.0300***	0.0290***	0.0289***	0.0288***	0.0283***
	[7.381]	[7.106]	[6.997]	[6.968]	[6.970]	[6.948]
Unemployed (dummy)	-0.0020	-0.0011	-0.0013	-0.0013	-0.0013	-0.0011
	[-0.711]	[-0.565]	[-0.705]	[-0.693]	[-0.695]	[-0.578]
Employed - Part time (d)	-0.0027*	0.0001	0.0004	0.0004	0.0004	0.0004
	[-1.820]	[0.0813]	[0.290]	[0.306]	[0.304]	[0.323]
Retired (dummy)	-0.0007	0.0001	-0.0002	-0.0003	-0.0003	-0.0004
	[-0.320]	[0.0618]	[-0.129]	[-0.163]	[-0.161]	[-0.199]

Self-Employed (dummy)	-0.0007	-0.0011	-0.0006	-0.0006	-0.0006	-0.0006
	[-0.576]	[-1.111]	[-0.656]	[-0.666]	[-0.663]	[-0.673]
Bankcard Utilization rate	-0.0007	-4.55e-05	-0.0002	-0.0002	-0.0002	-0.0002
	[-0.754]	[-0.0646]	[-0.291]	[-0.282]	[-0.279]	[-0.248]
# of Credit Lines	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	[-2.755]	[-3.661]	[-3.444]	[-3.429]	[-3.421]	[-3.452]
Revolving Credit Balance	-6.04e-05***	-4.94e-05***	-4.86e-05***	-4.87e-05***	-4.87e-05***	-4.76e-05***
	[-4.267]	[-3.629]	[-3.562]	[-3.568]	[-3.568]	[-3.593]
Overweight (dummy)		-0.0005	-0.0005	-0.0006	-0.0007	-0.0006
		[-0.518]	[-0.462]	[-0.638]	[-0.669]	[-0.617]
Beauty		0.0158***	0.0165***	0.0159***	0.0160***	0.0134***
		[8.494]	[7.973]	[7.267]	[7.070]	[4.222]
Tie (dummy)		0.0015	0.0012	0.0012	0.0012	0.0013
		[1.059]	[0.911]	[0.905]	[0.895]	[0.979]
Female (dummy)		0.00355***	0.00329***	0.00323***	0.00428	0.00297**
		[3.030]	[2.803]	[2.701]	[0.992]	[2.574]
Children (dummy)		3.91e-06	-6.67e-05	0.000127	0.000116	1.40e-05
		[0.00388]	[-0.0665]	[0.125]	[0.114]	[0.0143]
Couple (dummy)		-0.000419	-0.000633	-0.000642	-0.000645	-0.000584
		[-0.341]	[-0.543]	[-0.551]	[-0.555]	[-0.512]
Family (dummy)		-0.000447	-0.000252	-0.000461	-0.000439	-0.000364
		[-0.292]	[-0.166]	[-0.309]	[-0.292]	[-0.247]
Smile (dummy)		0.000381	0.000351	0.000347	0.000348	0.000348
		[0.756]	[0.718]	[0.710]	[0.711]	[0.731]
Asian (dummy)			-0.0292**	-0.0288**	-0.0288**	-0.0280**
			[-2.007]	[-1.978]	[-1.974]	[-1.967]
Hispanic (dummy)			0.0198	0.0199	0.0200	0.0193
			[1.460]	[1.465]	[1.474]	[1.464]
Black (dummy)			-0.0265***	-0.0266***	-0.0268***	-0.0276***
			[-2.860]	[-2.874]	[-2.892]	[-3.013]
Race N/A			0.000785	-0.00187	-0.00187	-0.00173
			[0.724]	[-0.573]	[-0.574]	[-0.541]
Old (dummy)				0.000869	0.000823	0.000971
				[0.637]	[0.602]	[0.726]
Middle-aged				0.000439	0.000406	0.000461
				[0.563]	[0.512]	[0.606]
Age N/A				0.00445	0.00443	0.00427
				[0.772]	[0.770]	[0.771]
Interaction Beauty*Credit AA						0.000362
						[0.0552]
Interaction Beauty*Credit A						-0.00636
						[-1.269]
Interaction Beauty*Credit B						0.00112
						[0.258]
Interaction Beauty*Credit C						0.00233
						[0.615]
Interaction Beauty*Credit D						0.00559
						[1.552]
Interaction Beauty*Credit HR						0.00449
						[1.228]
Interaction Beauty*Female					-0.00169	
					[-0.214]	
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Reason for Loan Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,979	14,168	13,795	13,795	13,795	13,795
R^2	0.428	0.451	0.450	0.450	0.450	0.451

Table V

Interest Rate Paid as a function of Hard Financial Information, Personal Characteristics, Appearance and Listing Features

This Table reports the coefficients from a tobit regression of the interest charged as a function of hard financial information, personal characteristics, family characteristics and listing features. The coefficients on hard financial information, listing features and family characteristics are omitted and reported in Table Va in the online appendix. The standard errors are clustered at the member level. A definition of the explanatory variables is provided in Panel A of Table II.

	(II)	(III)	(IV)	(V)	(VI)
Hard Financial Info	Yes	Yes	Yes	Yes	Yes
Listing Features	Yes	Yes	Yes	Yes	Yes
Overweight (dummy)	0.000935*	0.000924*	0.000970*	0.000482	0.000728
	[1.844]	[1.842]	[1.913]	[0.912]	[1.436]
Beauty	-0.00562***	-0.00648***	-0.00600***	-0.00487***	-0.00319**
	[-6.828]	[-6.699]	[-5.738]	[-4.423]	[-2.158]
Tie (dummy)	-0.000387	-0.000494	-0.000523	-0.000570	-0.000382
	[-0.650]	[-0.833]	[-0.880]	[-0.960]	[-0.643]
Female (dummy)	0.000400	0.000221	0.000355	0.00517***	0.000198
	[0.902]	[0.479]	[0.762]	[3.347]	[0.425]
Family Structure	Yes	Yes	Yes	Yes	Yes
Smile (dummy)	-0.00061***	-0.00066***	-0.00067***	-0.00066***	-0.00064***
	[-2.719]	[-2.915]	[-2.976]	[-2.928]	[-2.849]
Asian (dummy)		0.0141*	0.0132*	0.0134*	0.0150**
		[1.905]	[1.781]	[1.809]	[2.023]
Hispanic (dummy)		0.00712	0.00702	0.00740	0.00503
		[1.122]	[1.106]	[1.166]	[0.793]
Black (dummy)		0.0174***	0.0183***	0.0170***	0.0148***
		[3.949]	[4.157]	[3.849]	[3.338]
Race N/A		0.000125	0.00225	0.00233	0.00244
		[0.257]	[1.172]	[1.212]	[1.270]
Old (dummy)			0.00140**	0.00109*	0.00149**
			[2.224]	[1.717]	[2.373]
Middle-aged			-0.000653*	-0.000871**	-0.000577
			[-1.801]	[-2.361]	[-1.593]
Age N/A			-0.00223	-0.00240	-0.00219
			[-1.152]	[-1.238]	[-1.135]
Interaction Beauty*Credit AA					-0.00643**
					[-2.172]
Interaction Beauty*Credit A					-0.00930***
					[-2.651]
Interaction Beauty*Credit B					-0.00885***
					[-3.499]
Interaction Beauty*Credit C					-0.00934***
					[-4.616]
Interaction Beauty*Credit D					-0.00825***
					[-4.793]
Interaction Beauty*Credit HR					0.00156
					[1.117]
Interaction Beauty*Female				-0.0122***	
				[-3.269]	
Constant	0.00255	0.00326	0.00340	0.00330	0.00317
	[0.704]	[0.868]	[0.907]	[0.880]	[0.847]
Occupation Dummies	Yes	Yes	Yes	Yes	Yes
Reason for Loan Dummies	Yes	Yes	Yes	Yes	Yes
Observations	14,246	13,871	13,871	13,871	13,871
R^2	0.402	0.417	0.417	0.417	0.419

Table VI
Loan Performance Analysis

Panel A reports the marginal effects from a probit regression of default on hard financial information, personal characteristics, family characteristics and listing features. The dependent variable, *LoanDefaulted* equals one if the loan defaulted, i.e. was more than 4 months late, charged off or into bankruptcy, and zero otherwise. Panel B reports the coefficients from a tobit regression of the internal rate of return from the loan, including default and recovery rates, on hard financial information, personal characteristics, family characteristics and listing features. The coefficients on hard financial information, listing features and family characteristics are omitted and reported in Table VIa and VIb in the online appendix. The sample consists of all the listings that got full funding and became a loan. A definition of the explanatory variables is provided in Panel A of Table II.

	Panel A: Default Rate Analysis				**Panel B: Internal Rate of Return**			
	(II)	(III)	(IV)	(V)	(II)	(III)	(IV)	(V)
Hard Financial Info	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Listing Features	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Overweight (dummy)	-0.152**	-0.160**	-0.159**	-0.155**	0.0797	0.0898	0.0936*	0.0562
	[-2.457]	[-2.535]	[-2.452]	[-2.243]	[1.463]	[1.631]	[1.666]	[0.947]
Beauty	-0.105	-0.113	-0.0552	-0.0640	0.0481	0.0383	0.00971	0.0707
	[-1.010]	[-0.940]	[-0.433]	[-0.488]	[0.557]	[0.386]	[0.0909]	[0.636]
Tie (dummy)	-0.118*	-0.148**	-0.150**	-0.149**	0.0471	0.0821	0.0789	0.0665
	[-1.789]	[-2.158]	[-2.184]	[-2.147]	[0.856]	[1.456]	[1.399]	[1.173]
Female (dummy)	-0.0184	-0.0521	-0.0302	-0.0718	-0.0188	0.0139	-0.00164	0.318*
	[-0.335]	[-0.915]	[-0.513]	[-0.384]	[-0.401]	[0.285]	[-0.0332]	[1.879]
Family Structure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Smile (dummy)	0.0669**	0.0564*	0.0538*	0.0539*	-0.0389	-0.0274	-0.0269	-0.0271
	[2.277]	[1.883]	[1.798]	[1.804]	[-1.633]	[-1.127]	[-1.111]	[-1.120]
Asian (dummy)		0.082	0.08	0.0788		-0.0693	-0.0652	-0.0584
		[0.869]	[0.861]	[0.846]		[-0.962]	[-0.904]	[-0.811]
Hispanic (dummy)		0.1158	0.1133	0.1119		-0.0380	-0.0266	-0.0162
		[1.597]	[1.541]	[1.510]		[-0.594]	[-0.415]	[-0.252]
Black (dummy)		0.1459**	0.1514**	0.1522***		-0.1301***	-0.1301***	-0.1343***
		[2.476]	[2.567]	[2.583]		[-2.582]	[-2.580]	[-2.664]
Race N/A		0.0125	-0.487***	-0.487***		-0.0502	0.795**	0.759**
		[0.212]	[-39.17]	[-39.15]		[-1.050]	[2.138]	[2.016]
Old (dummy)			0.0560	0.0586			-0.00199	-0.0179
			[0.722]	[0.753]			[-0.0309]	[-0.275]
Middle-aged			-0.0782*	-0.0766*			0.0417	0.0304
			[-1.812]	[-1.763]			[1.142]	[0.824]
Age N/A			0.726	0.726			-0.0858**	-0.0828**
			[2.879]	[2.901]			[-2.297]	[-2.187]
Interaction Beauty*Female				0.105				-0.0778**
				[0.232]				[-1.975]
Constant					0.471	0.694	0.685	0.686
					[1.036]	[1.549]	[1.530]	[1.535]
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reason for Loan Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,496	2,448	2,448	2,448	2,523	2,473	2,473	2,473
R^2	0.210	0.210	0.212	0.212	0.135	0.136	0.138	0.139

Table VII Panels A and B
Racial Prejudices and Similarity Analysis

Panel A repeats the regressions in Column (IV) of Tables V, and Panel B of Table VI including in the analysis for each borrower the fraction of lenders with racial prejudice and its interaction with borrower's race. Panel B repeats the regressions in Column (IV) of Tables IV, V, and Panels A and B of Table VI, including in the analysis for each borrower the proportion of lenders of the same ethnicity as the borrower and its interactions with borrower's ethnicity. The sample analyzed in columns (I), (III) and (IV) consists of all the listings, while the sample in columns (II), (V) and (VI) consists of the listings that got funding and became a loan. The variables capturing hard financial information, listing features, and some of the personal characteristics are included in all the regressions, but their coefficients are not reported for space constraints. The standard errors are clustered at the member level. A definition of the explanatory variables is provided in Panel of Table II.

	Panel A		**Panel B**			
	Proportion of lenders with racial prejudice		**Proportion of lenders from the same ethnicity as the borrower**			
	Interest rate	IRR	Prob. of getting loan	Interest rate	Prob. of defaulting	IRR
	(I)	(II)	(III)	(IV)	(V)	(VI)
Hard Financial Info	Yes	Yes	Yes	Yes	Yes	Yes
Listing Features	Yes	Yes	Yes	Yes	Yes	Yes
Overweight (dummy)	0.00109**	0.0859	-0.000403	0.000722	-0.160**	0.0885
	[2.147]	[1.523]	[-0.446]	[1.444]	[-2.434]	[1.542]
Beauty	-0.00275**	-0.0124	0.0172***	-0.00897***	-0.160	0.0972
	[-2.429]	[-0.115]	[8.081]	[-8.149]	[-1.097]	[0.807]
Female (dummy)	0.000322	-0.00529	0.00223**	0.000335	-0.0390	-0.00376
	[0.693]	[-0.106]	[2.164]	[0.732]	[-0.658]	[-0.0755]
Family Structure	Yes	Yes	Yes	Yes	Yes	Yes
Smile, Tie, and Age Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Asian (dummy)	0.00629	0.1234	-0.0480***	0.0301***	0.0543	-0.0577
	[0.576]	[0.177]	[-3.485]	[3.793]	[0.443]	[-0.645]
Hispanic (dummy)	0.00714	-0.2825	-0.0137	0.0226***	0.1992**	-0.0757
	[0.818]	[-0.610]	[-1.115]	[3.275]	[2.269]	[-1.006]
Black (dummy)	0.0122**	-0.3886	-0.0701***	0.0431***	0.2003***	-0.1848***
	[2.140]	[-1.316]	[-7.936]	[9.221]	[2.913]	[-3.187]
Race N/A	0.00212	0.0707	-0.000664	0.00151	-0.0486***	0.0786**
	[1.070]	[1.379]	[-0.157]	[0.783]	[-30.27]	[2.082]
Proportion of lenders with racial prejudice (PLRP)	0.00114***	0.521**				
	[3.463]	[2.327]				
PLRP*Black Borrower	-0.0194*	-0.1053				
	[-1.884]	[-0.213]				
PLRP*Asian Borrower	-0.00447	-0.7835				
	[-0.227]	[-0.713]				
PLRP*Hispanic Borrower	-0.0237	-0.029				
	[-1.531]	[-0.0393]				
PLRP*White Borrower	-0.00454***	-0.0563***				
	[-7.703]	[-2.734]				
PLRP*Race NA	0.000978	0.226				
	[0.801]	[0.387]				
prop of lenders from the same ethnicity as the borrower (PLSE)			-0.0161***	0.00427***	-0.294***	0.0515
			[-7.226]	[13.62]	[-3.175]	[0.666]
PLSE*Black Borrower			0.145***	-0.0672***	-2.711**	1.389
			[3.024]	[-2.936]	[-2.056]	[1.215]
PLSE*Hispanic Borrower			0.0952*	-0.0232	-1.766**	0.617
			[1.700]	[-1.118]	[-2.142]	[0.853]

PLSE*Asian Borrower			-0.209	-0.00227	1.607	-1.190
			[-1.644]	[-0.0761]	[0.672]	[-0.554]
PLSE*White Borrower			-0.00802***	0.00484***	0.0373	-0.0276
			[-2.778]	[7.288]	[1.367]	[-1.263]
PLSE*Race NA			-0.00536	0.00183	-0.148	0.139
			[-0.822]	[1.326]	[-0.262]	[0.318]
Constant	0.00493	0.358		0.000428		0.224
	[0.989]	[0.784]		[0.277]		[1.352]
Observations	13,872	2,469	13,796	13,872	2,448	2,473
R^2	0.419	0.137	0.505	0.43	0.217	0.135

Table VII Panel C
Racial Prejudices and Similarity Analysis

Panel C reports the reports the fractions of White and Black lenders, the fraction of the total investment they are responsible for, and the fraction they invest in White and Black borrowers, respectively, restricting the analysis to Blacks and White only.

	Fraction of White/Black lenders in the population	**Fraction of funds invested by White/Black lenders**	**Fraction invested in White Borrowers**	**Fraction invested in Black Borrowers**
White Lenders	90.46%	91.31%	84.63%	15.37%
Black Lenders	9.54%	8.69%	72.97%	27.03%
Fraction of Black/White Borrowers in the population	-	-	83.39%	16.61%

Table VIII
Robustness Checks

Panel A repeats the regressions in Column (IV) of Tables IV, V, and Panels A and B of Table VI including in the analysis the ratings on the perceived trustworthiness and creditworthiness of the applicants. Panel B and D repeat the regressions in Column (IV) of Tables IV, V, and Panels A and B of Table VI including in the analysis the state unemployment rate and the proportion of lenders from the same gender as the applicant and its interaction with the applicant's gender, respectively. Panel D also control for other types of similarity between lenders and borrowers, such as geography, religion, group and entrepreneur background. The sample analyzed in columns (I) and (II) consists of all the listings, while the sample in columns (III) and (IV) consists of the listings that got funding and became a loan. The variables capturing hard financial information, listing features, and some of the personal characteristics are included in all the regressions, but their coefficients are not reported for space constraints. The standard errors are clustered at the member level. A definition of the variables is provided in Panel A of Table II.

Panel A

	(IV)	(V)	(VIA)	(VIB)
	Listing funded	Interest Rate	Prob. of defaulting	IRR
Hard Financial Info	Yes	Yes	Yes	Yes
Listing Features	Yes	Yes	Yes	Yes
Overweight (dummy)	-0.000885	0.000541	-0.150**	0.0552
	[-0.912]	[1.021]	[-2.147]	[0.926]
Beauty	0.0108	-0.00783*	0.414	-0.0197
	[1.415]	[-1.935]	[0.840]	[-0.0461]
Female (dummy)	-0.00279	0.00835***	0.0507	0.294
	[-0.924]	[4.490]	[0.222]	[1.471]
Family Structure	Yes	Yes	Yes	Yes
Smile, Tie, and Age Dummies	Yes	Yes	Yes	Yes
Asian (dummy)	-0.0296**	0.0143*	0.0825	-0.0612
	[-2.098]	[1.935]	[0.877]	[-0.847]
Hispanic (dummy)	0.0203	0.00637	0.1058	-0.0139
	[1.530]	[1.003]	[1.427]	[-0.216]
Black (dummy)	-0.0228**	0.0150***	0.1550***	-0.1377***
	[-2.518]	[3.355]	[2.586]	[-2.701]
Race N/A	-0.00182	0.00236	-0.0488***	0.0766**
	[-0.569]	[1.227]	[-39.24]	[2.035]
Interaction Beauty*Female	0.0151*	-0.0201***	-0.182	-0.726
	[1.658]	[-4.459]	[-0.341]	[-1.544]
Trustwirthiness	0.00569	0.000549	-0.759	0.345
	[0.543]	[0.109]	[-1.162]	[0.636]
Creditworthiness	0.0206**	-0.0133***	0.289	-0.259
	[2.148]	[-2.796]	[0.483]	[-0.521]
Constant		0.00315		0.684
		[0.840]		[1.529]
Occupation Dummies	Yes	Yes	Yes	Yes
Reason for Loan Dummies	Yes	Yes	Yes	Yes
Observations	13,795	13,871	2,448	2,473
R^2	0.452	0.418	0.212	0.139

	Panel B				Panel D			
	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
	Listing funded	Interest Rate	Prob. of defaulting	IRR	Listing funded	Interest Rate	Prob. of defaulting	IRR
Hard Financial Info	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Listing Features	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Overweight (dummy)	-0.0006	0.0010*	-0.160**	0.0894	-0.0048	0.0006	-0.198***	0.0616
	[-0.560]	[1.897]	[-2.463]	[1.584]	[-0.984]	[0.874]	[-2.604]	[1.063]
Beauty	0.0160***	-0.006***	-0.0566	0.0334	0.0592**	-0.0068*	-0.141	-0.331
	[7.398]	[-5.874]	[-0.442]	[0.311]	[2.067]	[-1.746]	[-0.327]	[-1.096]
Female (dummy)	0.0029**	0.0004	-0.0265	-0.0104	0.0085*	-0.0002	-0.0820	0.0590
	[2.534]	[0.833]	[-0.448]	[-0.209]	[1.809]	[-0.252]	[-1.007]	[0.992]
Family Structure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Smile, Tie, and Age Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Asian (dummy)	-0.0272*	0.0131*	0.0896	-0.079	-0.0202***	0.0300***	0.0289	-0.0858
	[-1.891]	[1.763]	[0.969]	[-1.092]	[-2.810]	[2.801]	[0.204]	[-0.987]
Hispanic (dummy)	0.0197	0.00704	0.1099	-0.0261	-0.00471	0.0217**	0.1844*	-0.0773
	[1.471]	[1.105]	[1.486]	[-0.405]	[-0.739]	[2.328]	[1.792]	[-1.060]
Black (dummy)	-0.0277***	0.0185***	0.1568***	-0.149***	-0.0344***	0.0393***	0.2655***	-0.235***
	[-3.040]	[4.177]	[2.626]	[-2.940]	[-7.187]	[6.019]	[3.089]	[-3.977]
Race N/A	-0.00182	0.00226	-0.0489***	0.0796**	0.00228	0.00163	-0.0809***	0.0715**
	[-0.563]	[1.176]	[-39.37]	[2.135]	[0.106]	[0.634]	[-24.47]	[2.056]
State Unemployment Rate	-0.000151	-1.86e-05	-0.0289**	0.0169				
	[-0.550]	[-0.166]	[-2.191]	[1.561]				
Prop of lenders same gender(PSG)					-0.00541	0.00157	-0.3486**	0.2561**
					[-0.152]	[0.478]	[-2.210]	[1.986]
PSG*Female					0.0352	-0.00378	1.471	-3.661
					[0.586]	[-0.566]	[0.374]	[-1.285]
Prop of lenders same city					-0.0628***	0.00327***	0.483	-0.337
					[-4.155]	[3.385]	[1.343]	[-1.307]
Prop of lenders same ethnicity (PLSE)					-0.0650	0.00792	0.4741***	-0.2664**
					[-0.975]	[1.331]	[2.674]	[-2.009]
Prop of lenders same religion					0.0270	-0.00231	-4.932**	1.459
					[0.870]	[-0.659]	[-2.288]	[1.076]
Prop entrepr. as borrower					-0.0366	0.00299	0.0547	0.0702
					[-1.267]	[0.957]	[0.0372]	[0.0694]
Prop of lenders same group					-0.0148	0.00362	1.461	0.00643
					[-0.517]	[1.562]	[1.136]	[0.00776]
PLSE*Black Borrower					0.0734***	-0.0606**	-0.2938*	0.1817
					[2.687]	[-1.968]	[-1.866]	[1.635]
PLSE*Hispanic Borrower					0.0558*	-0.0399	-0.4079***	0.1734**
					[1.727]	[-1.368]	[-3.298]	[2.096]
PLSE*Asian Borrower					-0.1745**	-0.00029	0.245	-0.2992
					[-2.014]	[-0.00709]	[0.858]	[-0.140]
PLSE*White Borrower					-0.0317	0.00166	-0.1150	0.514
					[-0.948]	[0.891]	[-1.139]	[1.103]
PLSE*Race NA					-0.0441	6.33e-05	-0.4856***	0.2397*
					[-0.672]	[0.0107]	[-2.865]	[1.879]
Constant		0.0005		0.164		0.0024		0.314
		[0.280]		[0.984]		[0.536]		[0.864]
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reason for Loan Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,767	13,843	2,441	2,466	4,071	4,101	607	655
R^2	0.451	0.417	0.213	0.135	0.479	0.143	0.303	0.288

Table IX

Who Lends to Beautiful Borrowers? Who Lends to Black Borrowers?

Panel A contains the coefficients from a regression of borrower's beauty on the characteristics of the lenders who funded her loan, while Panel B contains the same analysis for lenders funding Black borrowers. The data consists of a random subsample of the listings for which all the possible combinations of borrowers and lenders have been generated. Same city is a dummy equal to one if the borrower and the lender live in the same city. The other similarity dummies are defined in a similar fashion. A definition of the variables is provided in Panel A of Table II.

Panel A

	(I)	(II)	(III)	(IV)	(V)
Months in Prosper	-0.0033***	0.0005	-0.0226	-0.0319*	-0.0399
	(0.000)	(0.951)	(0.116)	(0.050)	(0.714)
Total amount bid (/$2,000)	0.0008***	0.0018**	0.0032**	0.0075***	0.0228***
	(0.000)	(0.036)	(0.024)	(0.000)	(0.008)
Total amount lent (/$2,000)	-0.0017***	-0.0055	-0.0241**	-0.0345**	-0.1059
	(0.000)	(0.294)	(0.033)	(0.016)	(0.105)
Female Lender		0.1894**	0.1657	-0.0231	-0.5986
		(0.011)	(0.138)	(0.850)	(0.161)
Income - $25,000- $49,999			-0.0053	-0.0221	-1.1945*
			(0.972)	(0.890)	(0.055)
Income - $50,000- $74,999			0.1692	0.2543*	1.5632
			(0.187)	(0.073)	(0.109)
Income - $75,000- $99,999			-0.2538***	-0.0101	-0.3422
			(0.041)	(0.945)	(0.526)
Income - $100,000+			-0.0953	-0.0905	
			(0.585)	(0.623)	
Young Lender				0.1263	2.1041**
				(0.291)	(0.011)
Old Lender				-0.0277	1.4850*
				(0.851)	(0.063)
Asian Lender				-0.5339***	-3.0216***
				(0.000)	(0.007)
Black Lender				-0.0437	-0.3660
				(0.872)	(0.687)
Hispanic Lender				0.0356	
				(0.888)	
Same city					-0.2007
					(0.784)
Same ethnicity					0.1312
					(0.464)
Same religion					-0.4056
					(0.309)
Both entrepreneurs					-0.0029
					(0.996)
Same group					-0.0118
					(0.940)
Same gender					0.6521***
					(0.000)
Constant	3.8036***	3.7563***	3.9978***	4.0325***	2.9183***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Obs.	62006	953	548	537	141
Pseudo R^2	0.0009	0.0056	0.0114	0.0239	0.1453

Panel B

	(I)	(II)	(III)	(IV)	(V)
Months in Prosper	-0.0010*	-0.0373	-0.0149***	-0.0131***	0.0083
	(0.079)	(0.115)	(0.002)	(0.006)	(0.132)
Total amount bid (/$2,000)	0.0001**	0.0068	0.0016**	0.0019**	-0.0004
	(0.011)	(0.123)	(0.019)	(0.019)	(0.447)
Total amount lent (/$2,000)	-0.0003*	-0.0090	-0.0073**	-0.0091*	0.0212***
	(0.091)	(0.513)	(0.036)	(0.064)	(0.005)
Female Lender		0.1345	-0.0108	-0.0171	-0.0530**
		(0.362)	(0.743)	(0.620)	(0.047)
Income - $25,000- $49,999			0.0600	0.1036	0.4611**
			(0.299)	(0.112)	(0.035)
Income - $50,000- $74,999			0.0554	0.0705	
			(0.212)	(0.104)	
Income - $75,000- $99,999			-0.0154	0.0296	0.5203*
			(0.683)	(0.573)	(0.089)
Income - $100,000+			-0.0563	-0.0366	
			(0.213)	(0.471)	
Young Lender				-0.0465	0.6050***
				(0.221)	(0.005)
Old Lender				0.0469	0.9429***
				(0.293)	(0.001)
Asian Lender				-0.0119	0.0100
				(0.779)	(0.863)
Black Lender				0.1172	0.9789***
				(0.192)	(0.001)
Hispanic Lender				-0.0493	
				(0.312)	
Same city					-0.0540**
					(0.033)
Same religion					0.0533
					(0.263)
Both entrepreneurs					-0.0298
					(0.138)
Same group					-0.0267*
					(0.096)
Same gender					-0.0238
					(0.295)
Obs.	106092	1600	895	880	279
Pseudo R^2	0.0012	0.0020	0.0602	0.0764	0.2018

SUPPLEMENTARY APPENDIX

Appendix A

Rating Procedure

For each listing, the picture posted by the applicants were uploaded to an intranet password protected website with no information about their provenance or the context in which they were originally posted.
Raters were asked to complete a first hour-long rating session at the NYU behavioral lab and they were then free to log into the website from anywhere on campus if interested in continuing on the study.

Each set of pictures is rated by three random female and three random male raters. Each picture in a set was showed to the rater for at least 5 seconds, so to avoid raters flying through the pictures and giving careless ratings. In order to further control for this possibility, I calculate the Cronback's alpha and the intra class correlation coefficient (ICC) to measure the degree to which the ratings are not just random noise, but rather the raters agree among each other on who is beautiful/trustworthy/creditworthy.
I also assigned different payment schemes to different raters to see if this would affect the average and dispersion of the ratings and the time spent on each picture, and it turns out not to be the case. The different payment schemes were: a) $10 per hour, b) 20 cents per set, c) $10 per hour plus a bonus for those whose ratings are closer to the overall average across raters.
Overall, it looks like this was a task the raters enjoyed working on.

To avoid the "Halo Effect", the phenomenon where the rater's assessment on one dimension, say beauty, influences his/her perception of the applicant along the two dimensions that follow and creates spurious correlations, the order in which the beauty, trust and creditworthiness questions appear for each set of pictures was randomized across pictures and across raters (Nisbett et al., 1977, Sudman et al., 1996).

A description of the raters' demographics and the instructions for the raters are provided below. Raters' demographics are collected separately by the NYU Behavioral Lab. The study instructions specify that the answers will not be linked to the rater's name.

Raters' Instructions

[In the first session, that each rater has to take in the NYU Behavioral Lab, a research assistant reads the following in a clear voice and before moving from one bullet point to the next checks that the students are moving along with him/her].

1. Welcome to the First Impressions study.

Please enter you NYU id to proceed. We will never match your responses to you personally and we only need this information so we can track multiple responses across time. [Please proceed to the following screen]

2. The purpose of this study is to understand what we can tell about people from the pictures they decide to show us. The study consists in rating pictures along the dimensions of trustworthiness, creditworthiness, and beauty.
[Please proceed to the following screen]

3. Please enter your gender and age, and then click "Continue". This information will be stored and will help us describe the diversity of the population being sampled, but won't be associated with your name or reported in association with your responses in the following section.
[Please proceed to the following screen]

4. [STATE THIS PART SLOWLY AND CLEARLY]
For each set of picture you see, we will ask you to rate **your first impression of the person who posted the pictures** along the following dimensions:

- Beauty
- Trustworthiness, i.e. if this person finds a wallet on the street what is your impression of the probability that he or she will give it back.
- Creditworthiness, i.e. if you are a loan officer and this person walks into your bank, what is your impression of the probability that this person will be able to repay the loan in full?

All the variables are on a scale from 1 to 7.

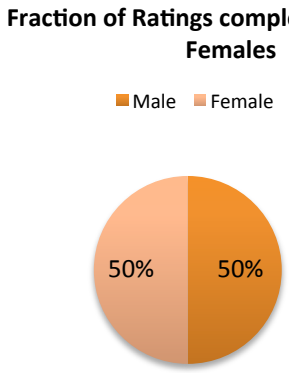
Each set of pictures is posted by one person. Sets are separated by an intermission page.
[Please proceed to the following screen]

[STATE THIS PART SLOWLY AND CLEARLY]
Please, read carefully the question and then record your first impression.

Ready? We can start.

Fig A.1
Raters' Gender

Overall 266 raters participated in the study. The graphs below illustrate the fraction of ratings completed by females and males, and the fraction of female and male raters, respectively. Female raters rated on average a slightly smaller number of pictures.



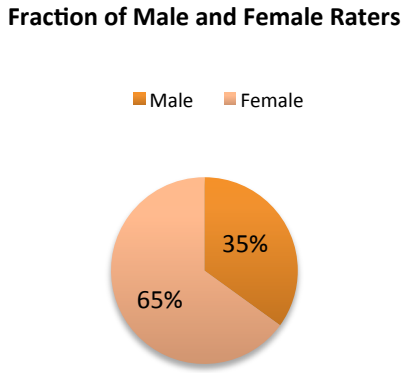
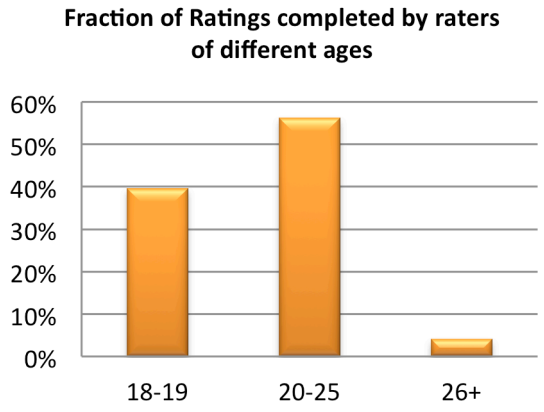


Fig A.2
Raters' Age

Overall 266 raters participated in the study. The graphs below illustrate the fraction of ratings completed by raters in different age brackets, and the fraction of raters falling in each bracket, respectively.



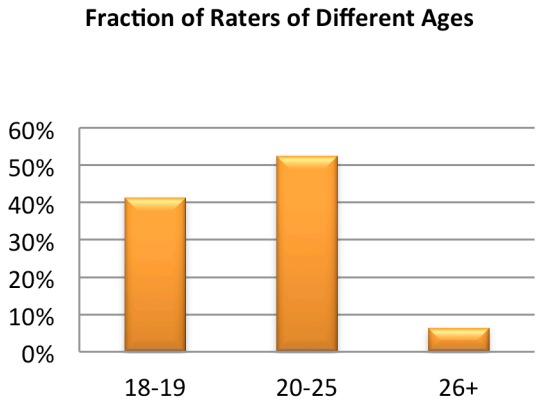
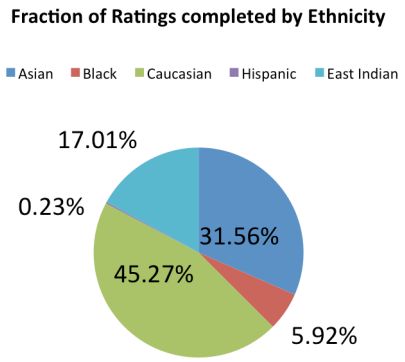
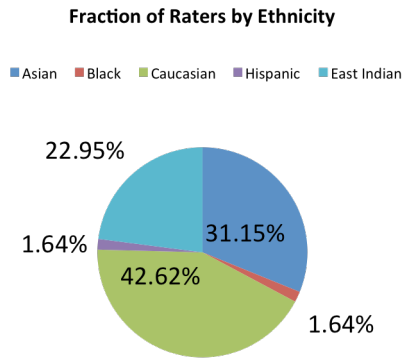


Fig A.3
Raters' Ethnicity

Overall 266 raters participated in the study. The graphs below illustrate, for those raters that chose to declare their ethnicity, the fraction of ratings completed by raters of different ethnicities, and the fraction of raters belonging to each ethnicity, respectively.





Appendix B

Table B.1 Panel A - Correlations

	Beauty	Trustworthiness	Creditworthiness	Female	Male	Young	Middle-aged	Old	Smile	Overweight	Home owner	Amount Requested	Borrower Rate	Revolving Cr. Bal.
Beauty	1													
Trustworthiness	0.4708	1												
Creditworthiness	0.4773	0.7545	1											
Female (dummy)	0.0608	0.1703	0.0752	1										
Male (dummy)	-0.0974	-0.0124	0.0707	-0.227	1									
Young (dummy)	0.1331	0.0001	-0.0257	0.1807	0.1407	1								
Middle-aged (dummy)	-0.1158	0.0209	0.064	0.2133	0.1386	-0.4581	1							
Old (dummy)	-0.1213	0.0397	0.0526	0.0099	0.1124	-0.1355	-0.1155	1						
Smile	0.0858	0.2017	0.1751	0.1884	-0.0152	0.0913	0.0438	0.0286	1					
Overweight	-0.2859	-0.0609	-0.1013	0.1643	0.0496	0.0102	0.1187	0.063	0.071	1				
Homeowner	-0.0056	0.0869	0.0964	0.0288	0.0483	-0.122	0.092	0.0478	0.0245	0.0156	1			
Amount Requested	0.0681	0.0736	0.1307	-0.0111	0.0942	-0.0575	0.0638	0.0413	0.0189	-0.0444	0.1918	1		
Borrower Max. Rate	0.0204	0.0014	-0.0006	-0.0008	-0.0253	0.027	-0.0088	-0.0108	0.0231	0.0021	-0.0659	-0.0361	1	
Revolving Cr. Bal.	0.0398	0.0543	0.1119	-0.021	0.0474	-0.0602	0.0404	0.0387	0.037	-0.0404	0.2422	0.26	-0.0421	1
Delinquency d.	-0.063	-0.0448	-0.0806	0.0655	-0.1109	-0.0757	0.029	-0.0048	-0.0139	0.0336	-0.0589	-0.2449	0.1545	-0.1915
White (dummy)	-0.002	0.0927	0.125	-0.0604	0.0653	-0.0618	-0.0013	0.0623	-0.0318	-0.004	0.0564	0.0003	-0.0556	0.0636
Black (dummy)	-0.0355	-0.1098	-0.1563	0.0506	-0.1023	-0.0035	0.047	-0.0714	0.0034	0.0403	-0.0395	-0.0637	0.0491	-0.0773
Hispanic (dummy)	0.0406	-0.0323	-0.0359	0.0675	0.0252	0.0994	-0.0115	-0.0187	0.0292	-0.0203	-0.0166	0.0362	0.0254	-0.0047
Asian (dummy)	0.0448	0.0317	0.0485	0.0019	0.041	0.0621	-0.0581	0.0155	0.058	-0.0438	-0.0257	0.079	0.0122	0.0072

	Delinquency	White	Black	Hispanic	Asian
Delinquency	1				
White	-0.0473	1			
Black	0.092	-0.7284	1		
Hispanic	-0.0196	-0.4379	-0.05	1	
Asian	-0.0504	-0.3674	-0.0627	0.0235	1

Table B.1 Panel B

Average Beauty, Trustworthiness and Creditworthiness Ratings by Credit Grade

This Table reports summary statistics of the average beauty, trustworthiness, and creditworthiness rating by credit grade. The ratings go from *Not Attractive/Trustworthy/Creditworthy at All* (1), to *Extremely Attractive/Trustworthy/Creditworthy* (7), with *Neutral* in the middle (4). See Appendix A and Panel A of Table II for more details on the variables definition, the rating procedure, and the raters' characteristics.

Credit Grade		Mean	Median	Std Dev	Min	Max	Obs.
AA	Beauty	4.1073	4.1667	0.4540	2.9722	5.6667	363
	Trustworthiness	4.4042	4.3333	0.4797	3.1667	5.6667	466
	Creditworthiness	4.3659	4.3333	0.4501	3.1667	6	466
A	Beauty	4.1634	4.1667	0.5731	2.8333	6	505
	Trustworthiness	4.5009	4.5	0.5071	3.1667	6	574
	Creditworthiness	4.4235	4.3333	0.5090	3.0000	6.1667	574
B	Beauty	4.0494	4.0833	0.6421	2	5.6667	815
	Trustworthiness	4.4108	4.4167	0.4703	2.5000	5.5	830
	Creditworthiness	4.3837	4.3333	0.4911	3.1667	5.6667	830
C	Beauty	4.0669	4.0833	0.6656	1.8333	6.1667	1,348
	Trustworthiness	4.4691	4.5	0.5004	2.5000	6	1,388
	Creditworthiness	4.4026	4.3333	0.5445	2.3333	5.8333	1,388
D	Beauty	3.9991	4	0.6788	1.5	6.5	2,337
	Trustworthiness	4.3785	4.3333	0.5101	2.3333	6.1667	2,363
	Creditworthiness	4.2903	4.3333	0.5419	2.1667	6	2,363
E	Beauty	4.0536	4.1667	0.6647	1.7500	6.5	2,561
	Trustworthiness	4.3855	4.3333	0.4585	2.6667	5.8333	2,443
	Creditworthiness	4.2743	4.3333	0.5018	2.6667	6	2,443
HR	Beauty	3.9844	4	0.6563	1.5	6.1667	6,190
	Trustworthiness	4.3591	4.3333	0.4999	2	6	6,058
	Creditworthiness	4.2061	4.1667	0.5127	2	5.8333	6,058
Total	Beauty	4.0206	4.0278	0.6557	1.5	6.5	14,120
	Trustworthiness	4.3880	4.3333	0.4941	2	6.1667	14,120
	Creditworthiness	4.2759	4.3333	0.5208	2	6.1667	14,120

Table B.1 Panel C

Beauty, Trustworthiness and Creditworthiness Ratings by Income and Employment Status

This Table reports the average and standard deviation of the beauty, trustworthiness, and creditworthiness ratings by income and employments status, adjusting for age. The ratings go from *Not Attractive/Trustworthy/Creditworthy at All* (1), to *Extremely Attractive/Trustworthy/Creditworthy* (7), with *Neutral* in the middle (4). See Appendix A for more details on the rating procedure, the ratings, and the raters. The variables definition is provided in Panel A of Table II.

	Beauty				**Trustworthiness**				**Creditworthiness**			
	Young	Middle-aged	Old	Total	Young	Middle-aged	Old	Total	Young	Middle-aged	Old	Total
Income range - $0 or N/A	4.1101	4.0738	3.8472	4.0982	4.3786	4.4563	4.6389	4.3698	4.2563	4.3354	4.4444	4.2663
	0.6297	0.5933	0.2495	0.6193	0.5714	0.5051	0.7258	0.5001	0.5997	0.5035	0.3443	0.5248
Income range - $1- $24,999	4.0447	3.8822	3.6328	3.9440	4.3265	4.4043	4.4757	4.3420	4.1690	4.2707	4.3539	4.1979
	0.7191	0.7250	0.6623	0.7143	0.5557	0.5122	0.5085	0.5234	0.5630	0.5478	0.5423	0.5507
Income range - $25,000- $49,999	4.1447	3.9313	3.7366	4.0250	4.4555	4.4095	4.4766	4.3956	4.3003	4.2866	4.3213	4.2638
	0.6189	0.6525	0.6477	0.6509	0.4773	0.4734	0.5009	0.4801	0.4969	0.4964	0.5643	0.4985
Income range - $50,000- $74,999	4.0607	3.9886	3.8964	4.0481	4.4306	4.4461	4.5400	4.4000	4.3059	4.3392	4.3886	4.2964
	0.6309	0.5884	0.5245	0.6263	0.5163	0.4963	0.5359	0.4985	0.5104	0.5044	0.6173	0.5152
Income range - $75,000- $99,999	4.3209	4.1000	3.9010	4.1344	4.5484	4.4649	4.5303	4.4421	4.5305	4.4611	4.5606	4.4451
	0.4934	0.5603	0.5990	0.5823	0.4850	0.4882	0.4103	0.4766	0.4957	0.4749	0.4645	0.4863
Income range - $100,000+	4.1805	4.0143	3.8927	4.0436	4.5511	4.5586	4.4943	4.4474	4.5767	4.6014	4.7126	4.4898
	0.5610	0.5645	0.4787	0.5933	0.4593	0.4398	0.3896	0.4547	0.5105	0.5252	0.4584	0.5406
Employed - Full time	4.1077	3.9552	3.7846	4.0258	4.4276	4.4325	4.4878	4.3908	4.2837	4.3208	4.3670	4.2719
	0.6326	0.6447	0.6056	0.6511	0.5055	0.4867	0.5007	0.4923	0.5236	0.5101	0.5666	0.5171
Employed - Part time	4.0183	3.9431	3.5602	3.9802	4.3425	4.3667	4.6471	4.3510	4.1968	4.2298	4.6275	4.2130
	0.7531	0.7801	0.6181	0.7543	0.5401	0.5943	0.4635	0.5352	0.5671	0.5961	0.6195	0.5658
Self Employed	4.2155	3.9951	3.8438	4.0535	4.4471	4.4395	4.4752	4.3864	4.3807	4.4086	4.5035	4.3598
	0.6959	0.6031	0.6750	0.6541	0.5531	0.4498	0.5012	0.4870	0.5523	0.4944	0.5310	0.5269
Retired	4.1364	3.5353	3.6224	3.6873	4.4561	4.3098	4.5409	4.4364	4.4298	4.1412	4.3011	4.2591
	0.5443	0.4532	0.5498	0.5696	0.5087	0.4264	0.5213	0.4967	0.4592	0.5326	0.5243	0.5317
Unemployed	4.1700	3.9140	3.4618	4.0211	4.3550	4.4158	4.2292	4.3441	4.1854	4.2508	4.1042	4.2008
	0.5740	0.6424	0.8922	0.6213	0.4757	0.5565	0.5487	0.4991	0.4529	0.5446	0.6038	0.4983

Table B.2 Panel A and B
Reasons for the Loan and Occupation Dummies

Panel A reports the reasons for asking the loan and their frequency, while Panel B reports the same information for the applicant's occupation. Both the reason for the loan and the occupation are generated using the category provided by Prosper as a starting point and having two research assistants separately complementing and correcting this information based on the listing title and description. For example, the reason for the loan could be retrieved by reading the loan description all along, but it was introduced as a category in the data download provided by Prosper to researchers only in February 2008 and was set to 0 for listings posted earlier than then. Similarly, the occupation information provided in the company download is often inaccurate and needs to be integrated with the information in the loan description. Panel B illustrates this point by comparing the occupation in the category provided by Prosper (Old Occupation) and the occupation corrected based on the listing description and title and used in the paper (New Occupation).

Panel A

Reason for the Loan	Frequency
Consolidate debt / Repay Credit cards	60.06%
Business Ongoing/expansion	10.14%
Business (start)	5.32%
Home Improvements	5.09%
Education	4.57%
Reinvest in Prosper	4.45%
Car	3.09%
Medical Bills	2.19%
Buy House	1.11%
Wedding	1.07%
Invest in stock	0.62%
Baby	0.59%
Legal fees	0.52%
Relocation	0.45%
Vacation	0.27%
Funeral	0.16%
Rent	0.15%
Taxes	0.14%
Total	100%

Panel B

New Occupation		Old Occupation	
Accountant/CPA	2.00%	Accountant/CPA	1.89%
Analyst	1.76%	Analyst	1.93%
Architect	0.10%	Architect	0.11%
Attorney	0.28%	Attorney	0.27%
Biologist	0.06%	Biologist	0.07%
Bus Driver	0.54%	Bus Driver	0.30%
Car Dealer	0.11%	Car Dealer	0.12%
Chemist	0.09%	Chemist	0.09%
Civil Service	0.97%	Civil Service	1.07%
Clergy	0.22%	Clergy	0.19%
Clerical	7.94%	Clerical	5.70%
Computer Programmer	2.48%	Computer Programmer	2.44%
Construction	1.49%	Construction	1.67%
Dentist	0.05%	Dentist	0.06%
Doctor	0.27%	Doctor	0.25%
Engineer	1.39%	Engineer	1.32%
Executive	1.91%	Executive	2.12%
Fireman	0.21%	Fireman	0.21%
Flight Attendant	0.14%	Flight Attendant	0.11%
Food Service	1.28%	Food Service	1.30%
Food Service Management	0.98%	Food Service Management	1.08%
Homemaker	0.47%	Homemaker	0.45%
Laborer	2.63%	Laborer	2.15%
Landscaping	0.21%	Landscaping	0.25%
Medical Technician	1.56%	Medical Technician	1.17%
Military Enlisted	3.14%	Military Enlisted	2.65%
Military Officer	0.16%	Military Officer	0.21%
Nurse	2.31%	Nurse	2.25%
Pharmacist	0.09%	Pharmacist	0.09%
Pilot - Private/Commercial	0.03%	Pilot - Private/Commercial	0.03%
Police Officer/Correction Officer	1.22%	Police Officer/Correction Officer	1.20%
Postal Service	0.60%	Postal Service	0.64%
Principal	0.15%	Principal	0.18%
Profession that is not part of this list	26.77%	Profession that is not part of this list	30.74%
Professional	8.21%	Professional	9.23%
Professor	0.14%	Professor	0.18%
Psychologist	0.07%	Psychologist	0.10%
Realtor	1.39%	Realtor	1.12%
Religious	0.11%	Religious	0.12%
Retail Management	1.87%	Retail Management	2.07%

Sales - Commission	5.00%	Sales - Commission	4.53%
Sales - Retail	2.79%	Sales - Retail	3.03%
Scientist	0.13%	Scientist	0.17%
Secretary/Administrative Assistant	3.78%	Secretary/Administrative Assistant	3.98%
Skilled Labor	1.98%	Skilled Labor	2.12%
Social Worker	0.79%	Social Worker	0.75%
Student	2.39%	Student	1.98%
Teacher	2.80%	Teacher	2.51%
Teacher's Aide	0.33%	Teacher's Aide	0.36%
Tradesman	1.03%	Tradesman	1.10%
Truck Driver	1.65%	Truck Driver	1.81%
Waiter/Waitress	0.57%	Waiter/Waitress	0.48%
Artist	0.20%		
Babysitter	0.05%		
Casino employee	0.03%		
Financial services industry	0.16%		
Technician	0.62%		
Government employee	0.33%		
Retired	0.37%		
Self-employed	5.21%		
Disabled	0.07%		
Unemployed	0.16%		

Table Va
Interest Rate Paid as a function of Hard Financial Information, Personal Characteristics, Appearance and Listing Features

This Table complements Table V in the paper and reports the coefficients from a tobit regression of the interest charged as a function of hard financial information, personal characteristics, family characteristics and listing features. The coefficients on personal characteristics, reported in Table V in the paper. The standard errors are clustered at the member level. A definition of the explanatory variables is provided in Panel A of Table II.

	(I)	(II)	(III)	(IV)	(V)	(VI)
Borrower maximum rate	0.0095***	0.0096***	0.0096***	0.0096***	0.0096***	0.0096***
	[719.9]	[641.5]	[644.9]	[645.1]	[645.4]	[646.6]
Debt to Income Ratio	0.0001***	7.47e-05	7.78e-05	7.94e-05	7.87e-05	8.75e-05*
	[2.847]	[1.511]	[1.572]	[1.604]	[1.590]	[1.773]
Amount requested ($,000)	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	[16.61]	[13.29]	[13.11]	[13.13]	[13.19]	[13.30]
Close when funded (dmy)	0.0027***	0.0023***	0.0023***	0.0023***	0.0023***	0.0023***
	[14.42]	[11.04]	[10.93]	[10.95]	[10.97]	[10.99]
Homeowner Dummy	-0.0005**	-0.0003	-0.0003	-0.0002	-0.0002	-0.0002
	[-2.347]	[-1.310]	[-0.899]	[-0.846]	[-0.852]	[-0.930]
Credit Grade AA	-0.0112***	-0.0097***	-0.0094***	-0.0094***	-0.0095***	-0.0083***
	[-17.69]	[-12.79]	[-12.42]	[-12.42]	[-12.45]	[-9.503]
Credit Grade A	-0.0098***	-0.0076***	-0.0072***	-0.0072***	-0.0071***	-0.0064***
	[-17.98]	[-11.86]	[-11.16]	[-11.16]	[-11.13]	[-8.306]
Credit Grade B	-0.0083***	-0.0074***	-0.0072***	-0.0072***	-0.0072***	-0.0061***
	[-18.41]	[-14.28]	[-13.83]	[-13.81]	[-13.84]	[-9.865]
Credit Grade C	-0.0047***	-0.0038***	-0.0037***	-0.0037***	-0.0037***	-0.0026***
	[-13.23]	[-9.307]	[-9.248]	[-9.265]	[-9.269]	[-5.621]
Credit Grade D	-0.0024***	-0.0018***	-0.0018***	-0.0018***	-0.0018***	-0.00076*
	[-7.912]	[-5.261]	[-5.356]	[-5.330]	[-5.367]	[-1.904]
Credit Grade HR	0.0011***	0.0009***	0.0008***	0.0008***	0.0008***	0.0007**
	[4.569]	[3.347]	[3.109]	[3.107]	[3.105]	[2.205]
# of listings before current	0.00036***	0.0005***	0.0004***	0.0004***	0.0004***	0.0004***
	[9.285]	[10.36]	[10.00]	[9.958]	[9.675]	[9.290]
Length of employment	1.46e-06	5.10e-07	3.08e-07	2.40e-07	1.58e-07	2.61e-07
	[1.149]	[0.362]	[0.219]	[0.171]	[0.112]	[0.187]
Delinquency dummy	0.0012***	0.0009***	0.0008***	0.0008***	0.0008***	0.0009***
	[5.135]	[3.276]	[3.125]	[3.134]	[3.109]	[3.196]
Delinquency in last 7yrs	0.0008***	0.0009***	0.0008***	0.0008***	0.0008***	0.0007***
	[3.508]	[3.511]	[3.073]	[3.099]	[3.112]	[2.877]
Public Records (last 12 mos)	-0.000173	-0.000210	-0.000310	-0.000275	-0.000249	-0.000198
	[-0.491]	[-0.536]	[-0.793]	[-0.705]	[-0.639]	[-0.509]
Public Records (last 10 yrs)	0.0008***	0.0008***	0.0009***	0.0009***	0.0009***	0.0009***
	[4.102]	[3.929]	[4.161]	[4.154]	[4.176]	[4.124]
Income $0 or N/A	0.0004	0.0001	0.0002	0.0003	0.0003	0.0002
	[0.819]	[0.217]	[0.488]	[0.538]	[0.592]	[0.492]
Income range - $25k- $49.9k	-0.00098***	-0.0010***	-0.00096***	-0.00094***	-0.00092***	-0.00092***
	[-3.816]	[-3.569]	[-3.346]	[-3.262]	[-3.212]	[-3.214]
Income range - $50k- $74.9k	-0.00110***	-0.0012***	-0.00116***	-0.00114***	-0.00113***	-0.00114***
	[-3.543]	[-3.322]	[-3.306]	[-3.247]	[-3.210]	[-3.244]
Income range - $75k- $99.9k	-0.00156***	-0.0018***	-0.00165***	-0.00161***	-0.00157***	-0.00168***
	[-3.588]	[-3.577]	[-3.339]	[-3.268]	[-3.188]	[-3.425]
Income range - $100k+	-0.00190***	-0.0019***	-0.00160***	-0.00159***	-0.00159***	-0.00160***
	[-3.814]	[-3.274]	[-2.780]	[-2.775]	[-2.774]	[-2.800]
Unemployed (dummy)	-0.000181	-0.000574	-0.000505	-0.000508	-0.000497	-0.000500
	[-0.300]	[-0.858]	[-0.755]	[-0.760]	[-0.744]	[-0.751]
Employed - Part time (dmy)	2.58e-05	-0.000302	-0.000347	-0.000367	-0.000379	-0.000448

	[0.0572]	[-0.587]	[-0.677]	[-0.715]	[-0.740]	[-0.875]
Retired (dummy)	3.08e-05	0.000301	0.000327	0.000242	0.000246	0.000195
	[0.0550]	[0.490]	[0.535]	[0.395]	[0.402]	[0.319]
Self-Employed (dummy)	-0.000198	0.000686*	0.000546	0.000536	0.000535	0.000516
	[-0.579]	[1.698]	[1.337]	[1.313]	[1.311]	[1.267]
Bankcard Utilization rate	-2.75e-05	-4.16e-05	-2.76e-05	-1.99e-05	-2.02e-05	9.39e-06
	[-0.133]	[-0.181]	[-0.120]	[-0.0868]	[-0.0881]	[0.0410]
# of Credit Lines	5.38e-05***	5.47e-05**	4.10e-05*	4.07e-05*	4.12e-05*	3.53e-05
	[2.801]	[2.518]	[1.896]	[1.878]	[1.905]	[1.634]
Revolving Credit Balance	4.53e-06	-1.54e-08	1.88e-06	1.92e-06	2.09e-06	2.07e-06
	[1.193]	[-0.00352]	[0.429]	[0.439]	[0.479]	[0.474]
Personal Characteristics			See Table V in the paper			
Children (dummy)		0.000662	0.000567	0.000453	0.000287	0.000113
		[1.394]	[1.167]	[0.918]	[0.579]	[0.229]
Couple (dummy)		-0.000786	-0.000777	-0.000816	-0.000840	-0.000513
		[-1.362]	[-1.359]	[-1.427]	[-1.469]	[-0.897]
Family (dummy)		-0.000686	-0.000528	-0.000427	-0.000168	-0.000444
		[-0.908]	[-0.699]	[-0.557]	[-0.218]	[-0.581]
Constant	-0.00225	0.00255	0.00326	0.00340	0.00330	0.00317
	[-0.673]	[0.704]	[0.868]	[0.907]	[0.880]	[0.847]
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Reason for Loan Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,002	14,246	13,871	13,871	13,871	13,871
R^2	0.358	0.402	0.417	0.417	0.417	0.419

Table VIa
Loan Performance Analysis

Panel A reports the marginal effects from a probit regression of default on hard financial information, personal characteristics, family characteristics and listing features. The dependent variable, *LoanDefaulted* equals one if the loan defaulted, i.e. was more than 4 months late, charged off or into bankruptcy, and zero otherwise. Panel B reports the coefficients from a tobit regression of the internal rate of return from the loan, including default and recovery rates, on hard financial information, personal characteristics, family characteristics and listing features. The coefficients on personal characteristics are omitted and reported in Panels A and B of Table VI in the text. The sample consists of all the listings that got full funding and became a loan. A definition of the explanatory variables is provided in Panel A of Table II.

	(I)	(II)	(III)	(IV)	(V)	(VI)	(I)	(II)	(III)	(IV)	(V)	(VI)
							-1.340***	-1.708***	-1.640***	-1.641***	-1.681***	-1.671***
							[-3.887]	[-4.263]	[-4.007]	[-4.010]	[-4.107]	[-4.097]
Borrower maximum rate	0.0170***	0.0170***	0.0169***	0.0169***	0.0169***	0.0173***	-0.00188	0.000681	0.000181	0.000290	0.000523	0.000283
	[7.095]	[6.243]	[6.160]	[6.143]	[6.146]	[6.252]	[-0.609]	[0.188]	[0.0487]	[0.0782]	[0.141]	[0.0765]
Debt to Income Ratio	0.00301	-0.00151	-0.00218	-0.00231	-0.00227	-0.00298	-0.00182	0.00395	0.00448	0.00488	0.00459	0.00497
	[0.482]	[-0.209]	[-0.301]	[-0.317]	[-0.312]	[-0.410]	[-0.354]	[0.681]	[0.765]	[0.833]	[0.783]	[0.850]
Amount requested ($,000)	0.0192***	0.0206***	0.0205***	0.0205***	0.0205***	0.0206***	-0.00936***	-0.00931***	-0.00976***	-0.00980***	-0.00970***	-0.00982***
	[9.889]	[8.796]	[8.600]	[8.577]	[8.572]	[8.569]	[-5.745]	[-4.849]	[-4.991]	[-5.015]	[-4.968]	[-5.042]
Close when funded (dummy)	0.150***	0.148***	0.151***	0.150***	0.150***	0.150***	-0.0816***	-0.0656***	-0.0689***	-0.0685***	-0.0676***	-0.0672***
	[6.725]	[5.928]	[5.981]	[5.943]	[5.945]	[5.944]	[-3.855]	[-2.749]	[-2.853]	[-2.840]	[-2.807]	[-2.791]
Homeowner Dummy	0.0742***	0.0898***	0.0904***	0.0895***	0.0896***	0.0901***	-0.0453**	-0.0587***	-0.0575***	-0.0575***	-0.0589***	-0.0578***
	[3.437]	[3.564]	[3.516]	[3.481]	[3.483]	[3.492]	[-2.500]	[-2.804]	[-2.695]	[-2.697]	[-2.762]	[-2.718]
Credit Grade AA	-0.255***	-0.263***	-0.256***	-0.257***	-0.257***	-0.212***	0.0367	0.0147	0.0168	0.0202	0.0186	-0.0348
	[-4.847]	[-4.224]	[-4.022]	[-4.046]	[-4.044]	[-3.037]	[0.698]	[0.242]	[0.273]	[0.327]	[0.303]	[-0.537]
Credit Grade A	-0.155***	-0.183***	-0.181***	-0.182***	-0.182***	-0.145**	0.0316	0.0204	0.0273	0.0302	0.0299	-0.0132
	[-3.143]	[-3.187]	[-3.086]	[-3.102]	[-3.103]	[-2.247]	[0.665]	[0.372]	[0.492]	[0.544]	[0.540]	[-0.222]
Credit Grade B	-0.0803*	-0.110**	-0.109**	-0.108**	-0.108**	-0.0523	0.0137	0.00301	0.00609	0.00750	0.00486	-0.0606
	[-1.781]	[-2.111]	[-2.046]	[-2.027]	[-2.025]	[-0.870]	[0.332]	[0.0634]	[0.126]	[0.156]	[0.101]	[-1.138]
Credit Grade C	-0.0524	-0.0556	-0.0584	-0.0594	-0.0594	-0.0240	0.00390	-0.0164	-0.0109	-0.00936	-0.00982	-0.0489
	[-1.364]	[-1.238]	[-1.280]	[-1.303]	[-1.303]	[-0.468]	[0.111]	[-0.407]	[-0.267]	[-0.229]	[-0.240]	[-1.072]
Credit Grade D	-0.0411	-0.0446	-0.0466	-0.0484	-0.0483	0.0331	0.0190	0.0225	0.0235	0.0253	0.0252	-0.0539
	[-1.211]	[-1.120]	[-1.148]	[-1.191]	[-1.191]	[0.698]	[0.617]	[0.632]	[0.650]	[0.702]	[0.697]	[-1.282]
Credit Grade HR	0.148***	0.173***	0.161***	0.160***	0.161***	0.228***	-0.135***	-0.156***	-0.144***	-0.144***	-0.146***	-0.195***
	[3.967]	[4.035]	[3.704]	[3.692]	[3.701]	[4.409]	[-4.262]	[-4.314]	[-3.948]	[-3.927]	[-3.999]	[-4.431]
# of listings before current one	0.0271***	0.0257***	0.0253***	0.0257***	0.0257***	0.0254***	-0.0223***	-0.0203***	-0.0198***	-0.0201***	-0.0202***	-0.0195***
	[5.211]	[4.334]	[4.227]	[4.260]	[4.269]	[4.194]	[-5.112]	[-4.068]	[-3.926]	[-3.978]	[-4.010]	[-3.858]
Length of employment	-0.000139	-9.37e-05	-0.000115	-0.000108	-0.000107	-0.000110	0.000211*	0.000174	0.000179	0.000172	0.000164	0.000172

status												
	[-1.001]	[-0.579]	[-0.699]	[-0.659]	[-0.653]	[-0.665]	[1.792]	[1.282]	[1.296]	[1.244]	[1.184]	[1.245]
Delinquency dummy	0.0946***	0.116***	0.120***	0.121***	0.121***	0.119***	-0.0572***	-0.0707***	-0.0739***	-0.0748***	-0.0742***	-0.0724***
	[4.038]	[4.196]	[4.297]	[4.347]	[4.346]	[4.267]	[-2.856]	[-3.036]	[-3.126]	[-3.168]	[-3.146]	[-3.072]
Delinquency in last 7yrs	-0.0336	-0.0670**	-0.0683**	-0.0678**	-0.0678**	-0.0699**	0.0456**	0.0667***	0.0715***	0.0712***	0.0716***	0.0732***
	[-1.402]	[-2.371]	[-2.379]	[-2.365]	[-2.365]	[-2.429]	[2.243]	[2.845]	[2.989]	[2.979]	[2.998]	[3.068]
Public Records (last 12 mos)	0.0675	0.0803	0.0757	0.0736	0.0734	0.0758	-0.0626	-0.0953**	-0.0891*	-0.0830*	-0.0821*	-0.0833*
	[1.452]	[1.475]	[1.383]	[1.340]	[1.338]	[1.391]	[-1.600]	[-2.115]	[-1.958]	[-1.821]	[-1.803]	[-1.831]
Public Records (last 10 yrs)	0.0467**	0.0558**	0.0594**	0.0587**	0.0588**	0.0567**	-0.0190	-0.0156	-0.0224	-0.0213	-0.0220	-0.0190
	[2.062]	[2.074]	[2.181]	[2.150]	[2.153]	[2.071]	[-0.975]	[-0.687]	[-0.968]	[-0.921]	[-0.955]	[-0.823]
Income $0 or N/A	-0.00221	-0.0665	-0.0873	-0.0865	-0.0867	-0.0907	0.00860	0.0636	0.0749	0.0760	0.0779	0.0805
	[-0.0343]	[-0.899]	[-1.176]	[-1.160]	[-1.163]	[-1.221]	[0.167]	[1.046]	[1.200]	[1.218]	[1.249]	[1.293]
Income range - $25,000-$49,999	0.0213	-0.00357	-0.0154	-0.0167	-0.0169	-0.0186	-0.0170	0.0300	0.0356	0.0387	0.0393	0.0384
	[0.619]	[-0.0873]	[-0.373]	[-0.403]	[-0.407]	[-0.446]	[-0.593]	[0.888]	[1.035]	[1.125]	[1.144]	[1.118]
Income range - $50,000-$74,999	0.0206	-0.00953	-0.0261	-0.0255	-0.0257	-0.0244	-0.0430	0.00592	0.0165	0.0184	0.0197	0.0158
	[0.536]	[-0.209]	[-0.569]	[-0.553]	[-0.559]	[-0.528]	[-1.334]	[0.156]	[0.427]	[0.478]	[0.512]	[0.410]
Income range - $75,000-$99,999	0.0594	0.0526	0.0422	0.0442	0.0439	0.0414	-0.0632	-0.0253	-0.0186	-0.0173	-0.0162	-0.0152
	[1.259]	[0.947]	[0.751]	[0.782]	[0.777]	[0.727]	[-1.626]	[-0.556]	[-0.402]	[-0.373]	[-0.349]	[-0.329]
Income range - $100,000+	-0.0218	-0.0377	-0.0468	-0.0488	-0.0489	-0.0503	-0.0134	0.0201	0.0219	0.0240	0.0241	0.0236
	[-0.435]	[-0.637]	[-0.785]	[-0.817]	[-0.818]	[-0.840]	[-0.324]	[0.414]	[0.443]	[0.488]	[0.490]	[0.480]
Unemployed (dummy)	0.0948	0.123	0.124	0.123	0.123	0.125	-0.0820	-0.0929	-0.102	-0.101	-0.0986	-0.103
	[1.044]	[1.141]	[1.169]	[1.160]	[1.160]	[1.190]	[-1.063]	[-1.065]	[-1.158]	[-1.150]	[-1.124]	[-1.168]
Employed - Part time (dummy)	0.0131	-0.00309	-0.00484	-0.00845	-0.00842	-0.0111	-0.0403	-0.00834	-0.00475	-0.00238	-0.00156	0.00269
	[0.254]	[-0.0531]	[-0.0820]	[-0.143]	[-0.142]	[-0.187]	[-0.945]	[-0.171]	[-0.0961]	[-0.0481]	[-0.0315]	[0.0546]
Retired (dummy)	0.0665	0.0302	0.00981	0.00704	0.00702	0.0125	-0.0640	-0.0388	-0.0246	-0.0231	-0.0235	-0.0258
	[0.900]	[0.333]	[0.106]	[0.0764]	[0.0762]	[0.136]	[-1.050]	[-0.523]	[-0.326]	[-0.307]	[-0.312]	[-0.343]
Self-Employed (dummy)	0.0100	0.00517	0.000301	-4.22e-05	-0.000253	0.00324	-0.00667	0.00512	0.00892	0.00869	0.0105	0.00578
	[0.274]	[0.118]	[0.00679]	[-0.000955]	[-0.00572]	[0.0733]	[-0.220]	[0.143]	[0.245]	[0.238]	[0.288]	[0.159]
Bankcard Utilization rate	-0.0585**	-0.0292	-0.0344	-0.0346	-0.0348	-0.0349	0.0750***	0.0436	0.0443	0.0453	0.0464*	0.0453
	[-2.072]	[-0.901]	[-1.050]	[-1.053]	[-1.059]	[-1.062]	[3.105]	[1.587]	[1.593]	[1.627]	[1.671]	[1.633]
# of Credit Lines	0.00258	0.00325	0.00328	0.00319	0.00319	0.00313	0.000607	0.00148	0.00167	0.00176	0.00182	0.00194
	[1.317]	[1.376]	[1.369]	[1.328]	[1.327]	[1.299]	[0.370]	[0.763]	[0.845]	[0.890]	[0.920]	[0.981]
Revolving Credit Balance	0.000214	0.000143	0.000166	0.000164	0.000163	0.000138	-0.000441	-0.000372	-0.000385	-0.000387	-0.000382	-0.000358

	[0.672]	[0.389]	[0.443]	[0.439]	[0.437]	[0.367]	[-1.485]	[-1.086]	[-1.106]	[-1.112]	[-1.100]	[-1.034]
Personal Characteristics		See Table VI Panel A in the paper						See Table VI Panel B in the paper				
Children (dummy)		0.0584	0.0510	0.0425	0.0427	0.0350		-0.0668	-0.0537	-0.0551	-0.0563	-0.0530
		[0.954]	[0.816]	[0.670]	[0.674]	[0.551]		[-1.289]	[-1.007]	[-1.016]	[-1.040]	[-0.972]
Couple (dummy)		-0.00622	0.00187	-0.0115	-0.0110	-0.0244		0.0105	0.00643	0.0175	0.0147	0.0194
		[-0.0908]	[0.0264]	[-0.162]	[-0.156]	[-0.342]		[0.187]	[0.112]	[0.304]	[0.257]	[0.337]
Family (dummy)		0.0611	0.0790	0.106	0.105	0.0995		0.0209	-0.000625	-0.0133	-0.00909	-0.00139
		[0.656]	[0.828]	[1.084]	[1.075]	[1.009]		[0.276]	[-0.00813]	[-0.169]	[-0.116]	[-0.0176]
							0.725*	0.471	0.694	0.685	0.686	0.766*
							[1.647]	[1.036]	[1.549]	[1.530]	[1.535]	[1.716]
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reason for Loan Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,274	2,496	2,448	2,448	2,448	2,448	3,301	2,523	2,473	2,473	2,473	2,473
R^2	0.201	0.210	0.210	0.212	0.212	0.216	0.129	0.135	0.136	0.138	0.139	0.143

Table VIIa Panels A and B
Racial Prejudices and Similarity Analysis

Panel A repeats the regressions in Column (IV) of Tables V, and Panel B of Table VI including in the analysis for each borrower the fraction of lenders with racial prejudice and its interaction with borrower's race. Panel B repeats the regressions in Column (IV) of Tables IV, V, and Panels A and B of Table VI, including in the analysis for each borrower the proportion of lenders of the same ethnicity as the borrower and its interactions with borrower's ethnicity. The sample analyzed in columns (I), (III) and (IV) consists of all the listings, while the sample in columns (II), (V) and (VI) consists of the listings that got funding and became a loan. The variables capturing hard financial information, listing features, and some of the personal characteristics are included in all the regressions, but their coefficients are reported below and not in the text for space constraints. The standard errors are clustered at the member level. A definition of the explanatory variables is provided in Panel of Table II.

	Panel A		Panel B			
	Proportion of lenders with racial prejudice		Proportion of lenders from the same ethnicity as the borrower			
	Interest rate	IRR	Prob of getting loan	Interest rate	Prob of defaulting	IRR
	(I)	(II)	(III)	(IV)	(V)	(VI)
Borrower maximum rate	0.00959***	-0.011***	0.00181***	0.00955***	0.0138***	-0.011***
	[578.1]	[-4.744]	[16.78]	[641.6]	[4.630]	[-4.290]
Debt to Income Ratio	8.25e-05*	0.00399	-0.000578***	7.70e-05	-0.00190	0.00474
	[1.668]	[0.676]	[-3.677]	[1.583]	[-0.258]	[0.807]
Amount requested ($,000)	0.000213***	-0.011***	-0.00124***	0.000228***	0.0205***	-0.011***
	[13.16]	[-5.801]	[-20.05]	[14.30]	[8.613]	[-5.669]
Close when funded (dummy)	0.00223***	-0.115***	-0.000684	0.00231***	0.168***	-0.118***
	[10.80]	[-5.452]	[-1.310]	[11.37]	[6.423]	[-5.443]
Homeowner Dummy	-0.000201	-0.060***	0.00180***	-0.000214	0.0887***	-0.057***
	[-0.880]	[-2.787]	[3.203]	[-0.951]	[3.452]	[-2.655]
Credit Grade AA	-0.00949***	0.0814	0.791***	-0.00966***	-0.293***	0.0838
	[-12.30]	[1.340]	[17.80]	[-12.92]	[-4.634]	[1.345]
Credit Grade A	-0.00723***	0.0885	0.648***	-0.00740***	-0.221***	0.0911
	[-11.12]	[1.629]	[18.74]	[-11.72]	[-3.734]	[1.635]
Credit Grade B	-0.00722***	0.057	0.424***	-0.00734***	-0.146***	0.0591
	[-13.65]	[1.208]	[19.01]	[-14.27]	[-2.703]	[1.220]
Credit Grade C	-0.00370***	0.0244	0.168***	-0.00398***	-0.0885*	0.0270
	[-9.076]	[0.605]	[18.08]	[-10.03]	[-1.905]	[0.657]
Credit Grade D	-0.00174***	0.0513	0.0289***	-0.00192***	-0.0643	0.0494
	[-5.156]	[1.431]	[12.57]	[-5.807]	[-1.575]	[1.371]
Credit Grade HR	0.000870***	-0.141***	-0.00643***	0.00102***	0.178***	-0.146***
	[3.237]	[-3.852]	[-7.991]	[3.869]	[3.996]	[-3.942]
# of listings before current one	0.000426***	-0.021***	-0.000650***	0.000371***	0.0269***	-0.021***
	[9.800]	[-4.222]	[-5.828]	[8.635]	[4.400]	[-4.199]
Length of employment status	0.000000146	0.000159	-1.11e-06	-2.11e-07	-0.000111	0.000157
	[0.104]	[1.147]	[-0.360]	[-0.153]	[-0.671]	[1.134]
Delinquency dummy	0.000816***	-0.084***	-0.00343***	0.000749***	0.129***	-0.082***
	[3.063]	[-3.568]	[-5.105]	[2.854]	[4.598]	[-3.436]
Delinquency in last 7yrs	0.000772***	0.0713***	-0.00276***	0.000824***	-0.0704**	0.0701***
	[3.012]	[2.978]	[-4.372]	[3.265]	[-2.446]	[2.925]
Public Records (last 12 mos)	-0.000273	-0.0855*	0.000268	-0.000184	0.0683	-0.0822*
	[-0.700]	[-1.873]	[0.256]	[-0.478]	[1.244]	[-1.798]
Public Records (last 10 yrs)	0.000890***	-0.0214	-0.00189***	0.000985***	0.0552**	-0.0244
	[4.113]	[-0.924]	[-3.813]	[4.620]	[2.016]	[-1.056]
Income $0 or N/A	0.00023	0.0703	-0.000873	0.000436	-0.0898	0.0731

	[0.469]	[1.125]	[-0.641]	[0.904]	[-1.193]	[1.168]
Income range - $25,000-$49,999	-0.000952***	0.0426	0.00381***	-0.00092***	-0.0274	0.0470
	[-3.316]	[1.235]	[4.319]	[-3.241]	[-0.653]	[1.358]
Income range - $50,000-$74,999	-0.00115***	0.0201	0.00741***	-0.00108***	-0.0375	0.0279
	[-3.281]	[0.521]	[5.220]	[-3.131]	[-0.808]	[0.720]
Income range - $75,000-$99,999	-0.00166***	-0.0183	0.0147***	-0.00141***	0.0369	-0.00894
	[-3.372]	[-0.393]	[5.754]	[-2.905]	[0.652]	[-0.192]
Income range - $100,000+	-0.00159***	0.028	0.0203***	-0.00132**	-0.0622	0.0328
	[-2.781]	[0.568]	[6.006]	[-2.336]	[-1.036]	[0.661]
Unemployed (dummy)	-0.000521	-0.077	-0.00103	-0.000467	0.128	-0.102
	[-0.781]	[-0.860]	[-0.620]	[-0.710]	[1.211]	[-1.160]
Employed - Part time (dummy)	-0.000329	0.0019	0.000153	-0.000295	-0.00908	0.00550
	[-0.643]	[0.0384]	[0.132]	[-0.585]	[-0.152]	[0.111]
Retired (dummy)	0.000249	-0.0224	-0.000561	0.000650	0.00844	-0.0217
	[0.408]	[-0.297]	[-0.339]	[1.080]	[0.0910]	[-0.286]
Self-Employed (dummy)	0.000568	0.013	-0.000365	0.000439	0.00246	0.00712
	[1.394]	[0.356]	[-0.418]	[1.092]	[0.0553]	[0.195]
Bankcard Utilization rate	-0.0000254	0.0444	-0.000401	4.24e-05	-0.0294	0.0432
	[-0.111]	[1.592]	[-0.655]	[0.188]	[-0.889]	[1.549]
# of Credit Lines	4.20e-05*	0.00146	-0.000161***	3.76e-05*	0.00347	0.00135
	[1.944]	[0.739]	[-3.151]	[1.767]	[1.442]	[0.680]
Revolving Credit Balance	0.00000175	-0.000322	-3.99e-05***	1.31e-06	0.000153	-0.000334
	[0.400]	[-0.928]	[-3.358]	[0.304]	[0.409]	[-0.959]
Tie (dummy)	-0.000429	0.0849	0.00163	-0.000874	-0.151**	0.0773
	[-0.723]	[1.500]	[1.263]	[-1.495]	[-2.187]	[1.366]
Children (dummy)	0.00042	-0.0468	8.87e-05	0.000259	0.0534	-0.0522
	[0.852]	[-0.860]	[0.0967]	[0.533]	[0.829]	[-0.959]
Couple (dummy)	-0.000628	0.0257	-0.000416	-0.00101*	0.00960	0.0140
	[-1.099]	[0.441]	[-0.382]	[-1.800]	[0.131]	[0.241]
Family (dummy)	-0.000431	-0.00885	-0.000120	-0.000138	0.0956	-0.0111
	[-0.564]	[-0.112]	[-0.0850]	[-0.183]	[0.956]	[-0.140]
Smile (dummy)	-0.00063***	-0.0258	0.000324	-0.00072***	0.0567*	-0.0280
	[-2.812]	[-1.060]	[0.742]	[-3.225]	[1.859]	[-1.144]
Constant	0.00493	0.358		0.000428		0.224
	[0.989]	[0.784]		[0.277]		[1.352]
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Reason for Loan Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,872	2,469	13,796	13,872	2,448	2,473
R^2	0.419	0.137	0.505	0.43	0.217	0.135