

Love & Loans

The Effect of Beauty and Personal Characteristics in Credit Markets*

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Abstract

I examine whether easily observable variables such as beauty, race, and the way a loan applicant presents himself affect lenders' decisions, once hard financial information about credit scores, employment history, homeownership, and other financial information are taken into account. I use data from Prosper.com, a 150 million dollars online lending market in which borrowers post loan requests that include verifiable financial information, photos, an offered interest rate, and related context. Borrowers whose beauty is rated above average are 1.41 percentage points more likely to get a loan and, given a loan, pay 81 basis points less than an average-looking borrower with the same credentials. Black borrowers pay between 139 and 146 basis points more than otherwise similar White borrowers, although they are not more likely to become delinquent. Similarity between borrowers and lenders has also a powerful impact on lenders' decisions. In my sample personal characteristics are not, all else equal, significantly related to subsequent delinquency rates - with the exception of beauty, which is associated with substantially higher delinquency probability. The findings are consistent with personal characteristics affecting loan supply through lenders' preferences (taste-based discrimination a la Becker) and perception, rather than statistical discrimination based on inferences from their previous experience.

Keywords: Beauty ; Credit Markets; Discrimination

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1 Introduction

Every day people make choices among a host of alternatives on the basis of a limited amount of information. The suitability 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 presents himself. 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, is the lenders' decision 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 and successful U.S. based online lending market with more than $\$ \sum \sum$ million funded and $\int f$ 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 1.41% more likely of getting funds and, conditional of getting a loan, pay 81 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 offered by 146 basis points. Interestingly, beautiful borrowers also turn out three times as likely to become delinquent as an average-looking one. For a borrower with a credit score higher than 760 this is equivalent to a 4.99% probability of becoming delinquent the next month, conditional on having been in good status up to now, as opposed to a 1.15% probability for an average-looking borrower. Black borrowers are as likely to get a loan as White borrowers, but pay between 139 and 146 basis points more. This effect is statistically significant at the 1 percent level, and robust across specifications. Despite they are charged higher rates, Black borrowers do not appear to be worse credits, i.e. more delinquent, than the Whites. Variables like being overweight, appearing creditworthy, or showing a picture at work significantly increase the likelihood of getting a loan, although they do not affect interest rates or delinquency probabilities. On the contrary, smiling, wearing a tie or showing a picture with family

and children, although unconditionally correlated with the probability of getting the loan, do not significantly affect the probability or the terms of the transaction, 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 judgements 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 labelled *statistical discrimination* models. The implications of these models is that the group the lenders believe to be less creditworthy is less likely to get a loan, pays a higher interest rate, and ex-post is indeed more likely to underperform the other group after controlling for differences in the verifiable credentials. A large literature has built upon the intuition in Arrow's and Phelps' work, and added search costs and differences in the precision of the signal that the verifiable information provides about future ability to repay. These features generate a richer set of implications, among which there is the specialization of certain types of lenders in screening information on certain groups of borrowers, and therefore making loans to them (Lundberg and Startz, 1998, Calomiris et al, 1994). Another explanation is the *taste-based discrimination* model by Becker, 1971, according to which lenders realize that easily observable characteristics are not related to ex-post performance once the verifiable information is taken into account, but since they suffer a disutility from interacting with certain groups 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 the discriminated group is less likely to get a loan, pays higher rates, but turns out *not* to be worse than the privileged group. An alternative explanation that has similar implications and has roots in the social psychology literature, argues that lenders might believe that these characteristics are related to ex-post performance when in fact they are not (*perception* model). For example, a vast literature shows that people associate positive feeling of health, intelligence, and competence to beautiful people. Other studies also show that we tend to trust more those who are similar to us.

The findings described above suggest that the favorable treatment that the beautiful receive in this market is consistent with a taste-based discrimination/perception 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, *less* likely to become delinquent. On the contrary, the finding that Black borrowers pay higher rates, but are not more delinquent after all the hard financial

information is taken into account can be reconciled with both a taste-based discrimination model, as well as with a statistical discrimination model in which most lenders specialize in lending to White borrowers because they are better able to screen such type of applicants. To try to discriminate among these two competing stories, I exploit the information on demographics available for a subset of lenders and build similarity measures between borrowers and lenders based on the city in which they live, their ethnicity, religion, gender, shared interests and entrepreneur status. The findings indicate that once ethnic similarity between borrowers and lenders is taken into account being Black is not associated to higher interest rates, suggesting that the reason why Black borrowers pay more is that lenders prefer borrowers of the same race, and there are proportionally more Black borrowers (11.78%) than Black lenders (1.13%). Finally, to investigate whether the propensity to lend to similar borrower is due to superior information, rather than the inclination to trust and prefer individuals of the same ethnicity, I compare the returns that Black lenders make on Black and White borrowers, and the returns that White lenders make on the two groups of borrowers. I find that Black lenders are significantly more likely to lend to Blacks and are better able to screen such borrowers. On the other hand, White borrowers are not more likely to lend to Whites, although they charge lower interest rates to Whites, and seem to be equally good in screening Blacks and Whites.

This paper is related to the economics literature on beauty (Hamermesh and Biddle, 1994, 1998), and confirms the finding that beauty commands a premium in yet another economic realm. The main 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 results by Mobius and Rosenblatt, 2005, and Andreoni and Petrie, 2005, 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 the same as the one of the ugly. The paper is also related to the literature that studies the role of soft information in financial transactions, and in particular, small versus large scale lending and the role of personal characteristics and soft information in the assessment of borrowers' credit quality (Stein, 2002; Berger et al, 1999; Petersen and Rajan, 2002; Cole et al., 1994; Cole, 1999). The paper contributes to the literature by providing evidence on the type of information lenders find relevant in a large credit market, the economic magnitude of the effect that such personal characteristics have on the terms of the loan, as well as an ex-post check on the performance of borrowers that display these characteristics. Finally, the paper is related to the literature on racial discrimination in the labor

market (see Altonji and Blank, 1999, for an excellent survey of the literature), and the mortgage market (Ladd, 1998, Munnell et al., 1996, Berkovec et al., 1998). Previous studies in this area either exploit very detailed information about the application stage, but remain in the dark as whether the borrowers that seemed to be discriminated against turned out to be worse credits, or can observe defaults rates and financial information, but have a potentially selected sample in that they don't know the criteria based on which the lenders granted the loans. The ability to observe both the application stage and the ex-post performance, allows to better distinguish between different mechanisms that generate the observed patterns of discrimination.

The setting of the study is Prosper, a large US online lending market, with more than 115 million dollars lent and 440,000 members. The advantages of this setting are that it is a real market with a vast amount of information on the borrowers' financial situation and characteristics, and that the researcher has access to the same information as the lenders. In addition, 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. This proves very helpful in discriminating among 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 demographic characteristics, and they are similar to the overall U.S. population in terms of credit risk.¹ Most lenders have high income (40% have income of \$100,000 or more), and high credit quality (54% have a credit score of 760 or higher, compared to the U.S. average credit score of 678). The information in the data set allows to test the degree to which their experience, personal traits, and similarity to the borrowers affect their lending decisions.²

The results 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. For example, compared to the baseline case of a borrower with a credit score between 560 and 599, who rents, 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, a borrower with a higher credit grade, say grade D, ranging between

¹The size of the loan, ranging between \$1,000 and \$25,000, is similar to a small personal loan that an individual would ask from a bank, or borrow on a credit card. Section III contains a description of the summary statistics and documents the similarity between the default risk of Prosper borrowers and that of a pool of revolving credit account from Experian.

²The stakes and experience of the lenders vary dramatically, going from no money lent and a short presence on the website, to three quarters of a million lent and almost 2 years on the website (Prosper was launched in February 2006).

600 and 639, has 3.25% higher probability of getting his loan request funded, and pays a 4.43% lower interest rate. Going from an income in the range \$1-\$24,999 to \$25,000-\$49,999 increases the likelihood of getting a loan by 1.17%. Higher income has, all else equal, a positive effect, and the highest income range (\$100,000+) generates a 2.78% higher probability of getting a loan.

The results also show that adding a picture, and thus providing additional soft information, has a positive effect on the likelihood of getting a loan (+ 0.70 percentage points), and results in lower interest rates (-82 bps). The addition of a picture also increases the explanatory power of the regressions: the adjusted R^2 goes from 0.479 to 0.489 for the likelihood analysis, and from 0.323 to 0.558 for the interest rate regressions, and the pseudo loglikelihood function for the Cox hazard model used to analyze delinquency improves dramatically when a picture dummy is added to the analysis.³ Since adding a picture is a choice of the borrower and not randomized by the researcher, one might wonder whether self-selection affects the results and their generalizeability. Although it is impossible to dismiss this issue completely, Table IV Panel B shows that the pool of borrowers that posted a picture are similar to those who didn't, as far as the credit bureau information is concerned, and actually a little better credit quality.

The results are also robust to changes in the specification, controls for additional information, and the inclusion in the regressions of variables meant at capturing the general impression the applicant makes regarding creditworthiness and trustworthiness.

Finally, the data indicate that lenders that are more prone to give funds to beautiful borrowers, and therefore realize lower returns, tend to have lower bidding skills and lower income, to be young, and not Asian. The lenders that give more funds to Black borrowers, and realize higher returns due to the higher interest rate charged, tend to be male, low income, old or young, but not middle age, and Black.

The remainder of the paper is organized as follows. Section II describes how the online lending market works, the characteristics of borrowers and lenders, the aggregate default rates and lenders' returns. 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 the delinquency rates. Section IV analyzes the effect of similarity between borrowers and lenders. Section V reports various robustness checks, and discusses some alternative explanations for the findings. Section VI describes the characteristics of the lenders that are more prone to lend to beautiful borrowers and to Blacks, and provides some back of the envelope calculations on the lenders' returns associated

³The pseudo log-likelihood goes from -313.44 to -88.76.

to various borrowers' characteristics. Section VII concludes.

2 Data Description

2.1 The Credit Market

The data set consists of a sample of small individual loans generated on Prosper, a successful U.S. online lending web site that, since inception in February 2006, has generated more than \$115 million in loans and gained 440,000 members. The sample comprises 7,321 borrowers, and 14,088 lenders. Such borrowers posted 11,957 loan requests, 1,257 of which were funded and became a loan. The size of the loans ranges between \$1,000 and \$25,000, with an average of \$6,200, while the amount lent by a single individual varies between \$0 and \$738,488, with an average of \$2,835. Lenders usually diversify across different borrowers.⁴

The lending process works in the following way. Anybody with a U.S. Social Security number can become a borrower 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 about credit score, debt level, credit history, income, employment status, and homeownership available to the lenders. In addition, the borrower has the option to post one or more pictures and write a short message in support of his request, providing additional information about himself. Lenders submit bids specifying the amount they would like to lend and the minimum interest rate they are willing to get. If enough bids have been made and the amount requested is fully covered before the listing expires, a loan is generated at the highest interest rate that clears the market. 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 one percent fee to the lenders and a 0.5 percent 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 on the website is 0.91.⁵

Once a loan is generated, it is reported to the credit bureau, like any other unsecured loan, 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 situation persists for more

⁴Very recently the company has introduced portfolio plans that automatically do the bidding and diversification for the lender. This opportunity was not available in the time period analyzed in this study.

⁵A borrower cannot post more than a listing at a time and cannot get more than one loan at a time. More details about how the website works can be found at http://www.prosper.com/welcome/how_it_works.aspx.

than 4 months, the loan is considered in default, it is sold to a collection agency through an auction, and the lenders get the proceeds of such sale. In term of default rates, borrowers that get a loan on Prosper are similar to, if not slightly better than, the overall U.S. population. Table I illustrates the default rates and the average interest rates earned by the Prosper lenders, and compares them to those from a large sample of revolving accounts from Experian. The Table shows that for good credits the default rates are similar to those in Experian, and for the bad credits they are actually lower.⁶ When we account for default, the rate of return of the lenders still appears quite good, ranging between 10% for very high quality borrowers to 16% for those with credit scores between 600 and 639. The exception are the very high risk categories comprising those with credit scores between 520 and 559 and those that have no credit history, for which the default-adjusted return are 8.85% and -25.87%, respectively.

2.2 The Borrowers

Panel B of Table II shows summary statistics for the individuals that post a loan request, while Panel C shows the same summary statistics for the subset that obtains a loan.⁷

The sample consists of all the listings posted on the website between March 12th and April 16th 2007. Of these 11,957 listings, 10.52% end up getting funds and generate a loan, while 49.25% expire without reaching full funding, 38.64% are withdrawn, and 1.59% are cancelled. Panel A shows that the average amount requested is \$9,065 and that on average 15.6% of such amount gets funded. The maximum interest rate a borrower is willing to offer is as high as 30%, with an average of 16.92%. Of the individuals requesting a loan 33.33% own a house, 80.74% are employed full-time, 4.52% are employed part-time, 2.53% are retired, and 2.76% are currently unemployed. Among the employed, occupations span almost all the spectrum, but it is worth noting that 28% are entrepreneurs or self-employed.

Many loan requests come from individuals of low credit quality and end up not being fulfilled. Panel B shows that these individuals have on average more than \$10,000 in credit card debt, and are likely to have an account delinquent or have had a public record in the past 10 years. The credit scores are also worse than in the overall population: 41.65% of the listings has a credit grade of HR, corresponding to credit scores between 520 and 599, 16.31% has a credit score falling between 560 and 599 (credit grade E), 15.79% scores between 600 and 639 (credit grade D), 11.56% between

⁶The lenders' rate is equal to the interest rate paid by the borrower minus the 1% fee paid to Prosper.

⁷See Panel A of the same Table for the variables' definition.

640 and 679 (grade C), 6.38% between 680 and 719 (credit grade B), while only 4.1% and 4.21% have credit scores between 720 and 759 (grade A), or above 760 (grade AA).

The summary statistics for the individuals that get the loan look dramatically different. Panel C shows that AA and A credit grades now constitute 12.57% and 9.94% of the sample, respectively, and that high risk credit scores (grade HR) drop to 15.83%. The median credit grade is C in the loan sample, corresponding to credit scores in the range of 640 to 679. For comparison, the average credit score for the U.S. population is 678, while the median is 723, corresponding to an A credit grade. The average amount requested, and awarded, is lower in this sample, \$7,582, while the average interest rate is higher, 19.9%. The cases of delinquency and public records are less frequent, although the average credit card balance is now close to \$11,000. The proportion of individuals that owns a house jumps to 41.69%, the fraction of those employed full-time is slightly higher, 83.04%, the fraction of part-timers drops to 3.72%, while unemployed and retirees do not register significant changes. Interestingly, entrepreneurs and self-employed are now 34.21% of the sample.

In terms of **credit quality and delinquencies**, the sample of those who get a loan is similar to the bigger universe of Prosper borrowers, described in Table I. Panel D of Table II replicates the calculations reported in Table I for the sample used in this study. The distribution of credit grades among the borrowers who get a loan is similar across the two tables, with a higher incidence of AA credit grades in the sample analyzed in this study. The interest rates are generally higher in the sample studied: the difference ranges between -29 bps for the D credit grades to 140 bps for the AA ones, and it is positive for all the categories except the D one. Finally, although up to now there has not been any case of defaults in the sample, many delinquencies have already occurred, especially in the high risk credit categories.⁸ When compared to Table I, Table IID shows a higher incidence of delinquencies among the A and D credit grades, and a significantly lower one for the AA and C credit grades.

If we take a look at the **demographic characteristics** of the individuals that post a listing, we see that, in the cases in which this information is available, 44.85% of the borrowers are women, 55% are young, 8% are old, and 37% are middle age. 11.83% of the borrowers are severely overweight. 5.9% of the borrowers are Asian, 11.79% are Black, 6.37% are Hispanic, and 74.96% are White.⁹

⁸An account is considered delinquent if it is one or more months late, but not in default yet.

⁹Information on race, appearance, religion, and age is available for 25.52% of the original sample. It is collected from the pictures, and complemented and double checked based on the messages accompanying borrowers' listings, and membership to entrepreneurship, ethnicity-based, and religion-based groups. For the case of race, if the person appears as a mix of races, I assign the race giving precedence to being Black, followed by Hispanic and then Asian.

75.77% of those that state their religion are Christian. Of the people that post a picture, 29.9% have children in it, 10% wear a tie, and 66.13% smile.¹⁰ Compared to these statistics, the borrowers who get a loan are less likely to be female, (only 43.91% of those awarded a loan are), young (62.05%), Christian (90.14%), and Asian (8.29%) and less likely to be White or Black (73.76%, and 10.77%, respectively). Among those who post a picture 30.07% have children in it, 12.26% wear a tie, and 70.17% smile.

In addition to the information described above, the subjects that posted a picture were also rated on their **physical attractiveness**, and the **first impressions they make regarding their trustworthiness and creditworthiness**, which might matter in a person to person interaction over and above the aforementioned demographic characteristics.

Most people agree on the definition of attractiveness, and according to the research in social psychology, also on who is attractive and who is not (Langlois et al. (2000) and Feingold (1992)).¹¹ It is however worth spending a paragraph on the definition of trustworthy and creditworthy that was used for the ratings. 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.¹² 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, *trustworthiness* and *creditworthiness* are closely related: the correlation coefficient is 0.7156, significant at the 1 percent level.

The rating procedure is similar to that used in the literature on beauty, and works as follows. Each picture, or set of pictures, posted by a borrower 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/Creditworthy/Trustworthy" to "Not Attractive/Creditworthy/Trustworthy at All", with "Neutral" in the middle, corresponding to a rating of 4. Panel E shows the average

See Blank et al. for a definition of race, and the way it changes over time.

¹⁰16.35% of the listings include one or more pictures and, of these, 86.80% show a person in the picture.

¹¹See Langlois et al. (2000) for an excellent survey of the literature on beauty in the social sciences, and Etcoff (2000) for an interesting and thorough study on beauty across cultures and time periods.

¹²See Gleaser et al. (2000), Fehr et al. (2003) and Sapienza et al. (2007) for studies on how to measure trust and trustworthiness.

ratings, as a whole and by rater’s gender. The table shows that the ratings are sensible, and that the average valuation is, like we expect, a 4, although there is substantial variation and all the range of ratings is used. Female are slightly harsher than males 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.¹³ These numbers are similar to those found in the literature that studies beauty.¹⁴ An example of the rating procedure, the instructions for the ratings are provided on the author’s website, while the raters’ demographics are provided in Appendix A

The raters are female and male students at NYU, mostly undergraduates. As the Appendix shows, they come from a very diverse background in terms of ethnicity, their age ranges between 18 and 33, with 83% in the 18-21 year old range, 28% of them are males, and 72% females. An important question is whether their ratings are representative of a population where the age range is wider and the socioeconomic background more diverse. The social psychology literature suggests that this is the case: many studies show an extremely high degree of agreement across cultures, ages and genders on whom is beautiful (Langlois et al. (2000)).

The same raters also report their first impressions of the trustworthiness and creditworthiness of the borrowers, based on the same set of pictures. The summary statistics for these ratings are reported in Panel E of Table II. The average is a little lower than 4, and there is substantial variation within the population. Consistent with the vast literature on the determinants of trust (Alesina and La Ferrara (2002)), the extent to which a given rater finds an individual trustworthy varies with her background. As a consequence, the intraclass correlation coefficient is much lower for the trustworthiness and creditworthiness measures (the ICCs are 0.5743 and 0.5781, respectively), and these variables are measured less precisely than beauty.

Panel F of Table II reports the correlation coefficient between some of the borrower characteristics described above and the beauty, trustworthiness and creditworthiness ratings. The data show that women are more likely to be considered beautiful and trustworthy, but, interestingly, not creditworthy. Young borrowers score well on all three measures, while old people are less likely to

¹³The Cronbach alpha measures the correlation between all raters:

$$\alpha = \frac{k\bar{r}}{1+(k-1)\bar{r}}$$

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.

¹⁴Hamermesh 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.

be rated beautiful. Being Asian or Hispanic is positively correlated with the beauty ratings, while being black is negatively correlated. All races are considered less trustworthy and creditworthy than Whites. Being overweight is strongly negatively correlated with beauty, trustworthiness and creditworthiness. Beautiful people have higher debt levels, they tend to ask for more money, pay higher rates, and have lower delinquencies. More trustworthy and more creditworthy people are more likely to be homeowners, ask for bigger loans, and pay lower interest rates. They also have lower debt levels, and fewer delinquencies. In addition, beauty and making an impression of being trustworthy and creditworthy are positively correlated with the borrower's credit score (Table III Panel G). They are also positively correlated with income and employment status, once age is taken into account (Table III Panel H). In Section III I will analyze the effect of these variables on the probability of getting a loan and the term of such loan, and it will incorporate these interesting patterns into a regression framework.

2.3 The Lenders

The lenders on Prosper vary for the total amount lent, which ranges between \$0 and \$738,448, with an average of \$2,835, and the length of time they have been on the website, which on average is about a year.

The returns they make on the loans are quite substantial, except for the very high risk borrowers where the high interest rate is eaten up by an even higher default probability. Table I reports the returns for the overall website, while Panel D of Table II reports the returns for the sample used in the study. The latter show that the returns can vary between 10.86% for very high quality borrowers to 23.71% for the high risk ones. Although in the sample studied no default has occurred yet, the Table illustrates various methods to generate estimated default-adjusted returns. Method 1 simply applies to this sample the default rate reported in Table I for all Prosper loans originated up to now. The calculations show that, if the current patterns continue into the future, lenders should expect returns ranging from 10.64% for AA credit grades up to 17.36% for D credit grades (credit score between 600 and 639). The returns for very low quality borrowers are worse: 14.6% for credit grade E, and 9.02% for high risk borrowers. The same Table also reports other methods to infer future default rates. Method 2 consists in making the extremely conservative assumption that all the delinquencies will turn into defaults, while Method 3 takes the ratio of delinquency rates to default rates from Table I and uses it to transform the delinquency rates in Panel D into expected default rates. Both methods lead to similar results in term of patterns across credit grades.

Table III reports demographic characteristics, income, and employment status for a subset of lenders. These lenders are very likely to be homeowners (64.25% of them is). They also tend to have very high credit scores: 54.9% of them has a credit score of 760 or higher (credit grade AA), and 23.25% of them has a credit score between 720 and 759 (credit grade A).¹⁵ More than 40% of the lenders has an income of \$100,000 or more, 26.9% is an entrepreneur or is self-employed, 75.39% is employed full time, and 11.76% is retired. More than 50% of them is young, while only 15% are women. Finally, 85% of them is White, 11.5% is Asian, while only 1.3% is Black and 1.5% is Hispanic.

In order for demographic information to be available for the lenders, they need to have been borrowers in the past or to be group leaders. For this reason, this subsample could be subject to a selection bias and not be representative. In ongoing work I am tracing these lenders to see the reason why they asked for a loan in the past.¹⁶ When I compare this subsample to all the lenders in the dataset I find that the two groups are very similar for both the amount lent and the time since they joined Prosper. This being said, I note that all the analysis on the likelihood of getting a loan, the interest rate and the delinquency rates is performed using data from all lenders, irrespectively of whether demographic information is available for them. Only the similarity analysis is restricted to the sample for which both borrowers' and lenders' demographic characteristics are available, and could therefore be subject to the selection bias.

Finally, as far as lenders' rationality is concerned, the analysis in Section IV shows that overall the lenders behave in the way we would expect them to, and in particular, all else equal, they favor applicants with high credit scores, high income, good employment status, and a good credit history.

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

This section investigates whether the way people present themselves and their personal characteristics affect the terms of the loan they get, once employment, credit quality, and income are controlled for. In particular, the next subsection analyzes the likelihood of getting a loan, while the following ones study the interest rate that the borrowers ends up paying, and delinquency rates.

¹⁵Recall that the average credit score in the U.S. is 678, while the median one is 723.

¹⁶In many cases the reason why lenders are also borrowers on the website is that they want to raise money to reinvest in Prosper, or they just want to familiarize themselves with the website.

3.1 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:

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

where $LoanFunded_i=1$ if the listing got enough bids and generated a loan, and 0 otherwise. $HardFinInfo_i$ comprises the following variables that Prosper pulls from the credit bureau based on the applicant’s Social Security number: credit grade, employment status, homeownership, delinquencies, public records, revolving credit balance, number of credit lines, and income range. $PersonalChars_i$ include race, gender, age, beauty, trustworthiness and creditworthiness ratings, while $Context_i$ includes smiling, wearing a tie, the context of the picture, and whether there are children in it. Finally, $ListingFeatures_i$ includes the amount requested and the maximum interest rate the borrower is willing to pay, whether she has a verified bank account, the number of previous listings, and other technical features of the listing. Since a borrower that 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 rationality. The baseline case is a borrower with a credit score between 560 and 599, who rents, 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 3.25% higher probability of getting his loan request funded. Such probability monotonically increases with the credit score, reaching a 59% higher probability for individuals with a credit score of 760 and higher. Being delinquent on other accounts or having had public records in the past 10 years lowers the likelihood of getting a loan by 0.56% and 0.38%, respectively. All these effects are highly statistically significant. As expected, the income of the borrower matters, and going from \$1-\$24,999 to \$25,000-\$49,999 increases the likelihood of getting a loan by 1.17%. Higher income has, all else equal, a positive effect, and the highest income range (\$100,000+) generates a 2.78% higher probability of getting a loan.

Homeownership has a positive effect, equal to 0.45%. Being retired, and, surprisingly, unemployed raises the likelihood of getting a loan, compared to an individual employed full time at a very low salary, by 2.26% and 4.25%, respectively. These effects are statistically significant at the 1 percent level. After accounting for the variables above, the number of credit lines, the bankcard utilization rate, and the revolving credit balance don't have a significant effect.

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.

The *features of the listing* also significantly affect the likelihood of getting a loan. A drop of \$1,000 in the amount requested significantly increases the likelihood of getting funds by 0.17%, while a 1 percentage point increase in the interest rate offered raises such probability by 0.30%. Having a verified bank account increases such probability by 9.52%, as borrowers whose account and identity have not been verified might be bad credits or fraudulent listings. Finally, choosing the option of stopping the bidding as soon as the amount requested is reached lowers such probability by 0.69%. The latter variable might proxy for impatience and the necessity of getting the loan as soon as possible, or, alternatively, for lack of sophistication on the borrower's side, as he is giving up the chance of getting a lower interest rate through lenders' competition.

After controlling for these features, what is the effect of adding a picture to the loan request? Column II of Table IV shows that posting one or more pictures leads to a 0.7% statistically significant increase in the probability of getting funds. The effect is equivalent to a 225 basis points increase in the interest rate offered. This finding is consistent with the fact that people that post a picture provide more information about themselves that might give a signal about their ability to repay. Alternatively, seeing the counterpart can per se lead to a more positive attitude toward lending him money. The experimental economics literature shows that subjects that see their partners tend to behave more cooperatively in various games (Eckel and Wilson (2003)), especially if their partner smiles or is more attractive (Scharlemann et al. (2001), and Mulford et al. (1998)). Or, it might just be that posting a picture shows more effort and care, and might therefore signal a more reliable borrower.

Column III, IV and V investigate the effect of appearance and personal characteristics on the likelihood of getting a loan. In Column III, I add to the regression borrower's race, age, and gender. 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

an applicant for a loan receives. In addition, a vast psychology literature shows that the way people present themselves influences the way they are perceived and treated, irrespective of their true quality (Feingold, 1992; Eagly et al., 1991). For this reason, I also include in the regressions variables meant at capturing the borrower's appearance, such as beauty, being overweight, smiling, wearing a tie, the context of the picture, and whether it includes children.

Taken together these variables have a significant effect on the likelihood of getting a loan: a χ^2 test of joint significance yields a p-value of 0.0210. Also, the increase in adjusted R^2 indicates that controlling for personal characteristics adds explanatory power to the analysis. The effect of appearance is both economically and statistically significant. On the contrary, the effect of race, gender and age is economically significant, but not statistically so.

An increase in the beauty rating from *Neutral* to *Above Average for age* increases the likelihood of getting a loan by 1.44%. The 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 146 basis points, or, alternatively, lower the amount requested by \$2,483. Somewhat surprisingly, after controlling for credit bureau information and beauty, being overweight increases the likelihood of getting funds by 5.2%, (statistically significant at the 1 percent level). On the contrary, smiling, wearing a tie, the context of the picture and whether it includes children do not have an economic or statistical significant effect on the fulfillment of the loan request.

In Column IV, I add to the regression an interaction between gender and beauty, to account for the possibility that beauty matters to a different degree for men and women. I find that, consistent with the results of the labor economics literature, the effect of beauty is more pronounced for women, although overall an average-looking woman is less likely to get a loan than a man with the same credit, employment history, and demographics. An increase in the beauty rating increases the probability of getting a loan by 2.04 % for women and only by 0.6% for men. The beauty, female and interaction variables are jointly statistically significant at the 1 percent level.

3.2 Interest Rate

This section investigates whether after accounting for credit quality, employment, income and homeownership, personal characteristics and context affect the interest rate charged to the borrower for the subset of the listings that get fully funded and become a loan.

The specification is a tobit regression:¹⁷

$$\begin{aligned} InterestRate_i = & f(\alpha_1 HardFinInfo_i + \alpha_2 PersonalChars_i + \alpha_3 Context_i \\ & + \alpha_4 ListingFeatures_i + StateF.E. + \varepsilon_i) \end{aligned}$$

Column I of Table VI shows that a better credit grade 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 84 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 7.53 percentage points. Also, choosing the option to close the listing as soon as the amount requested is reached leads to 3.5 percentage points higher interest rate. After accounting for these variables, the debt level, homeownership, and being unemployed do not significantly affect the level of the interest rate, although they have the expected sign.¹⁸ Interestingly, entrepreneurs pay all else equal higher interest rates, 76 bps in this specification, possibly due to the higher volatility associated to their occupation.

Column II shows that posting a picture lowers the interest rate by 82 bps, and that the effect is significant at the 1 percent level. Columns III, IV and V show the effect of adding personal characteristics and context information to the regression. Being a Prosper member for a longer time leads to, all else equal, higher interest rates (+14 bps, significant at the 10 percent level). Interestingly, being overweight does not significantly affect the interest rate paid, although it substantially increases the probability of getting a loan (see Table IV). Being beautiful affects both the likelihood of getting a loan and the interest rate paid, which is, all else equal, between 66 and 104 bps lower, significant at the 5 and 1 percent level, respectively.

The race of the borrower has a significant and economically large effect on the interest rate paid. Being Black is associated to an interest rate between 139 and 146 bps higher than a White borrower with the same characteristics. The effect is statistically significant at the 5 percent level. The effect for other races is smaller and not statistically significant.

Accounting for all other information gender and age do not significantly affect the interest rate, while being beautiful is slightly negative for women (+46bps), although the effect is measured very

¹⁷State fixed effects have been added to the regression to account for the fact that the maximum interest rate allowed by law varies across states.

¹⁸Having a verified bank account has been dropped from the regressions, as less than 1% of the listings that become loans do not have such feature.

imprecisely. Finally, now that personal characteristics are accounted for, being an entrepreneur, having one or more delinquencies on the credit report, or a very low credit score does not affect the interest rate in a significant way anymore, although the sign and economic magnitude of the coefficients are unchanged.

3.3 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.

To investigate this issue I perform a survival analysis on the loans that were generated. The specification is the following Cox proportional hazard model:

$$h(t|x_i) = h_0(t) \exp(x_i\beta_x)$$

where $h(t|x_i)$ represents the probability that loan i becomes delinquent/defaults in the next month, conditional of having been in good standing up to month t . The Cox proportional hazard model is very flexible, and doesn't make any functional form assumption about the baseline hazard. The covariates x_i comprise hard financial information, such as credit scores, income, employment status, credit history and debt levels, the personal characteristics, and the listing features.

To this day none of the loans in the sample has defaulted, and therefore the analysis will be confined to delinquencies. Panel D of Table II illustrates the delinquency rates and the lenders' returns by credit grade, while Panel A of Table IX reports the results of the survival analysis. The coefficients show that hard financial information such as credit score, income, employment status, and homeownership affect the probability of being delinquent in the way we expect. Lower income and credit score are associated to a higher likelihood of delinquency. Borrowers that are employed part-time, retired, or unemployed are more likely to become delinquent than a borrower with a full-time job, while the results on entrepreneurs are mixed and depend on the specification. These effects are not always statistically significant.

More interestingly, despite variables such as race, age and gender matter for the likelihood of getting a loan and/or the interest rate that the borrower pays, they do not lead to a statistically sig-

nificant difference in the probability of delinquency. The only exceptions are borrowers with higher beauty ratings, who are more than three times as likely to be delinquent than average-looking ones.¹⁹ The effect is statistically significant at the 5 percent level, and robust across different specifications. This result confirms the findings of the labor and experimental economics literature that beautiful people are perceived as more competent, and therefore paid more (Hamermesh and Biddle, 1994 and 1998), although in reality they are not (Mobius and Rosenblat, 2005). The advantage of this study is that it analyzes this issue in a market setting, 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 to control for many variables affecting credit quality and 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 let the researcher herself vary the treatment and pinpoint at the precise channel through which this happens. The findings complement each other (see Levitt and List, 2006, for a discussion of strength and weaknesses of lab experiments).

One caveat about the analysis reported in this section is that few data are available on generated loans and although many delinquencies have already occurred there hasn't been any default yet. It is possible that with the passing of time and with a bigger dataset, some of the interesting patterns for race, gender and age shown in Table IX become statistically significant.

4 The Effect of Similarity Between Borrowers and Lenders

To further investigate the mechanism through which borrowers' personal characteristics influence lenders' decisions, I consider the effect of similarity between borrowers and lenders along dimensions such as ethnicity, city of residence, gender, shared interests, and being both entrepreneurs.

A large literature in economics and psychology documents that similarity breeds trust (see Coleman, 1990; Glaeser et al., 2000; Alesina and La Ferrara, 2002; Guiso et al., 2007; and DeBruine, 2002, as examples from the economics and sociology literature). Another important branch of the finance literature analyzes the causes of local bias in portfolios (Coval and Moskowitz 1999, 2001, and Huberman, 2001, among others).

¹⁹For an AA credit grade borrower, this is equivalent to a 4.99% probability of becoming delinquent the next month, conditional on having been in good status up to now, as opposed to a 1.15% probability for an average-looking borrower.

I find that lenders favor borrowers that are similar to them in terms of ethnicity, the city where they live, gender, and being both entrepreneurs. The coefficients are economically large and statistically significant: an increase of 10% in the proportion of lenders from the same ethnicity generates a 60 bps increase in the likelihood of getting funds, significant at the 1 percent level. To get the same effect, a borrower with the same credentials and characteristics, but belonging to a different ethnicity would need to jump from a credit score in the range 560-599 to a score in the range 640-679.

To analyze this issue, I draw a random subsample of the listings in the dataset, and for each listing I collect all the bids posted by the lenders, their identity, and the amount bid. I then create all the possible combinations of lenders and borrowers, to account for the bids that could have been submitted, but have not. The unit of analysis is now a bid (borrower-lender combination), and the empirical specification is either a probit regression of whether the lender places a bid on a given borrower, or a tobit regression explaining the amount bid:

$$Bid_{ij} = \Phi(\alpha_1 HardFinInfo_i + \alpha_2 PersonalChars_i + \alpha_3 Context_i + \alpha_4 ListingFeatures_i + \alpha_5 Similarity_{i,j} + \varepsilon_{ij})$$

$$AmountBid_{ij} = f(\alpha_1 HardFinInfo_i + \alpha_2 PersonalChars_i + \alpha_3 Context_i + \alpha_4 ListingFeatures_i + \alpha_5 Similarity_{i,j} + \varepsilon_{ij})$$

where i denotes the listing, and j the lender. Bid_{ij} equals 1 if lender j places a bid on listing i , and 0 otherwise, while $AmountBid_{ij}$ denotes the amount of money a lender j places on a given listing i . The measures of similarity are dummies equal to 1 if the borrower and the lender share the same city, race, religion, sex, Prosper group, or are both entrepreneurs.

The results, reported in Table VII, show that similarity affects lenders' decisions, and especially the amount they decide to bid. The effect of similarity does not however diminish the impact of the other variables. Column I of Table VII reports the coefficients from the regression above, while Column II shows the effect of adding to that regression the first impressions on the trustworthiness and creditworthiness of the borrower. The coefficients indicate that, all else equal, being from the same ethnicity and sharing the same interests (i.e. belonging to the same Prosper group, or type of group) increases the likelihood that the lender places a bid on the listing: the effect of ethnicity is

26bps, significant at the 5 percent level, while the effect of the shared interest is 6.5bps, significant at the 10 percent level.²⁰ To have an idea of the economic magnitude of these effects note that to increase by 26bps the probability of receiving a bid a borrower of a different ethnicity than the lender would need, all else equal, to jump from an E credit grade (scores between 560 and 599) to a C grade (scores between 640 and 679). After controlling for all the other characteristics, living in the same city, being both entrepreneurs, and having the same religion and gender does not significantly affect the probability of receiving a bid. The effect of the other variables is similar to the findings in the previous sections. Borrowers with higher credit grades are more likely to receive a bid, although the effect is not always statistically significant. Offering a higher interest rate increases probability of a bid by 1.73%, while having a verified bank account increases it by 21 bps. As expected, public records in the last year or 10 years reduce the probability of a bid by 16 and 10 bps, respectively (significant at the 5 and 10 percent level). The coefficients on the income dummies have the expected sign, albeit significant only for the very high incomes (+19 bps for \$100,000+ incomes), while entrepreneurs are 14 bps more likely to receive a bid. Among the variables that capture the way the borrowers present themselves, only smiling, and showing a picture at work or in the hospital have a positive effect on bids, while beauty, being overweight, wearing a tie, and other settings of the picture do not matter. Gender and age also do not have any economic or statistically significant effect, while race is significant only for Hispanics, that all else equal are 9 bps less likely to get a bid (significant at the 10 percent level). Finally, Column II adds to the regression controls for the first impression the borrower makes about being trustworthy and creditworthy. The table shows that the coefficients on the other variables are stable across specifications, while appearing more creditworthy increases the likelihood of a bid by 15 bps (significant at the 5 percent level). The effect of this variable is comparable to a 8.9% increase in the maximum interest rate the borrower is willing to pay.

Since receiving a bid is a very coarse measure of the value a lender places on a listing, as it doesn't take the interest rate and the amount bid into account, Column III and IV complement the findings in Columns I and II by examining the effect of similarity, personal characteristics, and hard financial information on the amount of money the lenders bid. The coefficients show that living in the same city, belonging to the same ethnicity, and being both entrepreneurs are associated to higher bids: +\$35.33, +\$16.87, and +\$4.87, respectively, all significant at the 1 percent level. On the contrary, belonging to the same group increases the likelihood of getting a bid, but is on

²⁰See Appendix B for a description of the Prosper groups.

average associated with a lower amount bid (-\$15.85). Interestingly, borrowers with high credit grades, those who own a house, have a longer employment history and no public record receive bids of a significantly smaller size, although we know from the results described above that they are more likely to receive a bid and to get their loan request funded. For example, a AA credit grade translate into a \$79.79 lower bid, while having one or more public records in the past year leads to fewer, but bigger bids (+\$117.36). All these effects are significant at the 1 percent level. To have an idea of the magnitude of these effects, recall that lenders diversify, and that the average bid amount is \$90.2.²¹ Delinquency generate smaller bids, compared to a borrower with a clean credit record (-\$69.20). Income ranges higher than \$1-\$24,999 are associated to smaller bids, with the exception of the very high ones (\$100,000+) that get bids that are on average \$139.66 higher than those obtained by a low income borrower. Interestingly, borrowers that are employed part-time and entrepreneurs get lower bids than a borrower employed full-time, while retired borrowers get more (-\$68.41, -\$100.63, and +\$77.97, respectively, all significant at the 1 percent level). The analysis controls for the initial terms of the offer such as starting interest rate and amount requested. The table shows that a higher starting interest rate increases the amount bid by \$101.81, while a bigger loan request generates a statistically significant, but economically small increase in the bids (+\$6.31).

Most important, the personal characteristics of the borrowers turn out to have an effect, even after similarity and hard financial information are taken into account. After controlling for first impressions about creditworthiness and trustworthiness, overweight borrowers receive lower bids (-\$32.95), while beautiful ones receive on average \$17.6 more. Smiling, wearing a tie, and appearing trustworthy have a positive effect on the amount bid: +\$100.17, +\$55.12, and +\$40.64, respectively. All the effects are significant at the 1 percent level. Personal characteristics such as race, gender and age also affect the magnitude of the bids: Asians and Hispanics receive, all else equal, higher bids than White borrowers, while Blacks receive lower ones. The effects are statistically significant and economically big. For example an Asian borrower receives bids that are on average \$129.66 higher, while a Black borrower receives bids that are on average \$39.97 lower. Female borrowers receive on average \$22.37 more, while older borrower receive \$7.78 less than middle age ones.

In light of these findings, I check whether adding controls for the similarity between borrowers and lenders changes the economic effect and the statistical significance of the explanatory variables in the analysis in Sections 3.

²¹The amount bid on a given listing varies between \$0 and \$20,000, with a median value of \$50.

To do so, I add to the specifications in those sections variables measuring the proportion of bids that come from lenders that are similar to the borrower in the various dimensions illustrated above. For example, *prop_samecity* denotes the fraction of bids made by lenders living in the same city as the borrower.²²

The specification for the probability of getting a loan is the following probit regression:

$$Pr(LoanFunded_i) = f(\alpha_1 HardFinInfo_i + \alpha_2 PersonalChars_i + \alpha_3 Context_i + \alpha_4 ListingFeatures_i + \alpha_5 Proportion Similar_i + \varepsilon_i)$$

The specifications for the fraction of the request that gets funded, and the interest rate are laid out in a similar fashion. Table VIII reproduces the coefficient obtained by adding the similarity measures to the regressions in columns III and V of Tables IV, V, and VI, respectively.

The coefficients in the first two columns show that similarity between borrowers and lenders matters for the likelihood of getting a loan. In particular, living in the same city as the lender, belonging to the same ethnicity or gender, sharing the same interests (proxied by belonging to same Prosper group), and being both entrepreneurs increases the likelihood of getting a loan request funded. The effects are economically large: an increase of 10% in the proportion of lenders from the same ethnicity generates a 60bps increase in the likelihood of getting funds, significant at the 1 percent level. To get the same effect, a similar borrower belonging to a different ethnicity would need to jump from a credit score in the range 560-599 to a score in the range 640-679. On the contrary, having a high proportion of lenders from the same religion is associated to a lower probability of getting funds, possibly indicating that similarity matters, but in order to get funds borrowers need to appeal to vaster groups of lenders. After controlling for similarity, the borrower's personal characteristics still matter although they have smaller coefficients. Overweight borrowers are all else equal 1.69% more likely to get a loan, while beautiful ones are 0.44% more. Both effects are significant at the 1 percent level. Interestingly, after accounting for the similarity measures female borrowers turn out significantly more likely to get a loan than a man with similar characteristics (+0.63%), while young borrowers are less likely so (-0.79%). These coefficients are significant at the 5 percent level, while they were not in the regressions without similarity measures. The results in Columns III and IV on the fraction of the request that gets funded have a similar flavor.

Column V and VI of Table VIII reproduce the interest rate regressions. They show that

²² If instead of using this measure of similarity, I add to the regression the proportion of lenders that has the same characteristics as the borrower, irrespective of whether they place a bid or not, I find similar results.

conditional on getting a loan similarity between borrowers and lenders does not significantly affect the interest rate the borrower ends up paying. The effect of beauty, creditworthiness, and the way the borrowers present themselves is the same as in the regressions without similarity measures. Interestingly, after accounting for similarity, race does not significantly affect the interest rate anymore: the coefficient on the Black dummy (which ranged between 139 and 146 bps, and was significant at the 5 percent level) is now smaller and not statistically different from 0 anymore. This finding suggests that one of the reasons for the higher interest rate that Black borrowers pay is the lenders' preference for borrowers of the same race and the fact that Black lenders are a small fraction of the lenders.²³

Finally, by comparing the coefficients in Columns I to VI to those in the previous Tables, we can see that adding such controls does not affect the statistical significance of the coefficients of the hard financial information, and the listing features, although it tends to make their economic magnitude smaller in the regressions on the likelihood of getting funds. For example, if without accounting for similarity between borrowers and lenders having a AA credit score was increasing the probability of getting a loan by 88.94% (Table IV, column III), now it generates a 77.57% higher chance of getting funds.

One question related to these findings is why similarity matters. To shed more light on this issue I build loan portfolios based on the ethnicity of the borrower and the lenders and compare their returns. If Black lenders do better when lending to Blacks and the same is true for Whites, then similarity matters because of statistical discrimination and the better ability of a group to screen similar people. If on the contrary, there are no differences in the profits that Blacks and Whites make on different borrowers groups, then the reason why similarity matters is related to taste-based discrimination. I find that Black lenders are significantly more likely to lend to Blacks and are better able to screen such borrowers. Their portfolio is made of 25% of Black borrowers, while if they lend money without considering race they would only lend 11.78% to Blacks. The interest rate they charge is similar for Blacks and Whites (about 15%), although the Blacks in their portfolios are delinquent a lot less often and therefore the delinquency-adjusted return for Whites drops to 8.72%. On the other hand, White borrowers are not more likely to lend to Whites, although they charge lower interest rates to Whites, and seem to be equally good in screening Blacks and Whites.

²³Tha data indicate that, for the cases in which race is available, 85% of the lenders are White, 11.5% are Asian, 1.5% are Hispanic, and 1.3% are Black.

5 Robustness Checks

The results are robust to various changes in specification, including estimating the effect of hard and soft information on the fraction of the loan that gets funded. Table V illustrates the results of such analysis. Although the listing needs to be fully funded in order to originate a loan, Prosper also provides information on the fraction of the request that gets fulfilled. The analysis of this quantity provides a robustness check of the findings on the probability of getting a loan illustrated in the previous section.

The empirical specification is the following tobit regression:

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

where the independent variables are the same as in Table IV.

Panel A of Table II shows that only 10.52% of the listings becomes a loan and that on average the percent funded is 15.6%. Table V illustrates the effect of borrower’s financial health and personal characteristics on such probability. Column I estimates the effect of hard financial information on the fraction of the loan request that gets funded. The results confirm the findings in Table IV. All else equal better credit grades, higher income, and being an entrepreneur have a significant economical and statistical effect on the fraction of the request that gets funded. Compared to an individual with a credit score between 560 and 599, who rents, 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, a borrower with a D credit grade (score between 600 and 639) gets a 24.74 percentage points increase in the fraction of her request that gets funded. A borrower whose income falls in the range \$25,000-\$49,999, gets a 12.06 percentage point increase in the fraction funded, while an entrepreneur gets 8.52 percentage points increase. All these effects are highly statistically significant. Being unemployed and retired increases the fraction funded with respect to a borrower fully employed at a low paying job. Homeownership also increases the fraction funded (+3.47 pctge points), although the effect is not statistically significant. Asking for less money, or offering a higher interest rate has a positive effect on the percent funded: a \$1,000 drop in the amount requested increases the percent funded by 16.9 percentage points, and every 1 percentage points increase in the interest rate offered, all else equal, increases the fraction funded by 36.7 percentage points. Finally, the coefficients for delinquencies and public records, debt levels and number of previous

listings have the expected negative sign, and are statistically significant.

Column II adds to the specification a dummy variable for the borrowers that choose to post a picture. Consistent with the findings in the previous section, a picture increases the fraction funded by 8.11 percentage points (statistically significant at the 1 percent level).

Column III illustrates the effect of personal characteristics and context. Overweight people have a higher fraction funded, and so do beautiful ones. The effect is statistically significant and equal to 8.74 and 6.07 percentage points, respectively. This effect is equivalent to a \$4,181 (\$2,904) drop in the amount requested, or a 206 (143) basis points increase in the interest rate offered for the overweight (beautiful) borrowers.

Being Asian, Black or Hispanic has a negative effect on the fraction funded compared to a White borrower with the same characteristics, although the effect is not statistically significant. Being a woman increases the fraction funded by an economically and statistically significant amount (8.21 percentage points), while being a beautiful woman has no added effect. Being young decreases the fraction funded compared to a middle age borrower, while being old increases it. These two effects are not however statistically significant. The effect of the other variables is the same as the one found for the likelihood of getting a loan (see the previous section). Interestingly, borrowers that look more creditworthy get a higher fraction funded, while borrowers that, controlling for creditworthiness, look more honest get a lower one. Both effects are statistically significant and economically big: the effect of appearing more creditworthy is equivalent to a \$6,430 drop in the amount requested, or a 3.137% increase in the interest rate offered. Finally, the experience of the borrower, proxied by how long she has been a Prosper member, has a positive effect on the fraction funded, after controlling for the number of previous listings, although we know from Table IV that it does not significantly affect whether the listing will be fully funded.

Another issue is whether the lenders lend money to beautiful people in order to **meet them outside the website**. To check whether this is an important concern, I've introduced an interaction between the borrower being female and the proportion of the lenders of the same sex as the borrower and found that the coefficient is slightly negative, but neither economically nor statistically significant.

An interesting question is whether the lenders **interpret the available information in a different way** when facing a beautiful borrower. When I interacted beauty and the credit grade dummies, none of them turned out to be significant.

Finally, what is the effect of giving an impression of **trustworthiness and creditworthiness**,

and how are the personal characteristics analyzed so far related to such first impressions? The last column of Tables IV, V and VI contains the coefficients from a regression in which the first impressions have been added to the analysis. Table IV shows that adding these information matters, although it does not change the economical and statistical significance of the hard financial information and of the personal characteristics. An increase in the creditworthiness rating raises the probability of getting a loan by 1.69%. The effect is equivalent to a 176 bps increase in the interest rate offered, or a \$2,965 drop in the amount requested. The coefficient is statistically significant at the 10% level. Interestingly, once we control for appearing creditworthy, appearing more trustworthy and honest has a negative, albeit not statistically significant, effect on the likelihood of getting funds. Table VI shows that appearing trustworthy and creditworthy doesn't affect the interest rate in a statistically significant way, although it is associated with a 25 and 40bps lower rate. Finally, people that gave the impression of being creditworthy, and that were favored by Prosper lenders with higher probability of getting a loan, turn out to be 37.03% more likely to become delinquent than an otherwise similar borrower. On the contrary, honest-looking individuals that have the same creditworthiness turn out to be 50.97% less likely to become delinquent, although being honest-looking and trustworthy did not give them any advantage in terms of getting the loan request funded, or paying lower rates. Again, these coefficients are not statistically different from 0. The table on first impressions illustrates the relationship between such first impressions and the other observable characteristics. The regression shows that beauty, smiling, wearing a tie and being male and older are associated to higher creditworthiness ratings.

6 Alternative Explanations

It is important to address the possibility of **measurement error** in the personal characteristics and the effect of fraud and misrepresentation 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 is likely to be present for some cases. In such cases, it would lead to an attenuation bias and make the coefficients closer to zero and their effect more imprecisely measured.

Another concern is that beauty or some other personal characteristics are not considered as in-

dicative 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 **omitted variable** concerns are mitigated by the very rich set of controls that are included in the regressions, and that span from hard financial information from the credit bureau to listing features, context of the picture, information from the borrower's message and group membership. These considerations suggest that, while other interpretations are possible, a relevance of the personal characteristics for the lenders' decisions remains the most plausible. Also, the omitted variables are not likely to be hard financial information, as such variables are provided by the company itself both to the lenders and the researcher in an excel spreadsheet. To further address this issue, I added controls for other information on the website, such as the reasons why the applicant needs a loan (see Table) and the groups he/she belongs to (not reported). Both analyses preserve the magnitude and economic significance of the coefficients.

Finally, another issue is the potential for **fraud** and misrepresentation, i.e. posting a fake picture of somebody attractive. To the extent that we are analyzing the effect of a given personal trait on the likelihood of getting a loan and the terms of such loan, the fact that somebody posts a picture that is not accurate is not problematic, as both the researcher and the lenders see the same picture and the analysis measures the impact of such characteristic on lenders' decisions, even if the borrower doesn't really possess it. This issue is potentially more problematic for the loan performance analysis. For example, are beautiful people really more likely to become delinquent, or rather, are those who post the picture of a beautiful person the ones who turn out to be bad borrowers? In this case, misrepresentation is a relevant issue only for interpreting the effect on delinquency of those variables that lead to higher probability of getting a loan, and/or better interest rates, and turn out to be associated to higher delinquencies, i.e. beauty. It is less so for variables such as race, that are associated to worse rates, and lower likelihood of getting funds. This being said, quantifying the magnitude of this phenomenon is impossible, and such caveat must certainly be kept in mind when interpreting the loan performance results. However, it is worth noting that beauty is correlated to high income, high credit scores and higher repayment probabilities. It is only after controlling for all the other variables that it turns out to be associated with higher delinquency rates. In addition, one encouraging fact is that the default rates on the website are similar, if not better, to those from a large pool of U.S. revolving accounts analyzed with Experian data. Also, Panel E of Table II shows that on average the borrowers in the population are

average looking.²⁴ So, in order for fraud to be very widespread, we would need the bad borrowers to make an effort to look beautiful, which might be plausible, and the good borrowers do the opposite, which is less plausible.

7 Who lends to them?

Another question is whether lenders make or lose money on such borrowers, and the way the delinquency probabilities reported in Table IX affect the average return a lender should expect from borrowers with different personal characteristics.

Panel B of Table IX shows some back of the envelope calculations to address this question. It takes as input the average returns and delinquency rates from Panel D of Table II and it adjusts them using the coefficients from Table VI and from Panel A of Table IX. The baseline case is the average borrower in a given credit grade category. The underlying assumption is that personal characteristics affect the probability of delinquency in a similar way across credit scores. Also, these calculations do not account for the fact that personal characteristics are not evenly distributed across the credit categories and the average delinquency rate in Table IID does not correct for this. As an illustrative example, consider a borrower with a AA credit grade. Table IID shows that on average he generates a lender's return of 10.86%, and has a 1.15% probability of becoming delinquent. All else equal, increasing the beauty of such borrower from Neutral to Above Average leads to lower interest rates (on average -81 bps), and more than triples the delinquency rate (on average 4.99%). This leads to a delinquency-adjusted return of 4.57%, compared to the delinquency-adjusted return of 9.58% associated to the baseline borrower. If we use a rule of thumb to translate delinquency rates into default rates based on the historical relationship between these two quantities, we find that the default-adjusted return for a beautiful AA borrower is 9.87%, compared to 10.81% for an average-looking one. Similar calculations show that since Blacks pay higher rates, but do not turn out more likely to become delinquent than a white borrower, a AA credit grade Black borrower yields on average 10.98% to 12.22%, depending on the method used to estimate default rates, compared to the 9.58% to 10.81% of the baseline case. Other personal characteristics are not associated to statistically significant changes in the interest rate or the delinquency rate vis-a-vis a White borrower, and yield therefore the same expected return.

²⁴To make sure that the reason the average beauty rating is not 4 just because the raters implicitly define the pool of borrowers as the reference population they compare each picture to, I check whether the average beauty rating of the first 10 random pictures that any raters sees is also 4, and find that this is the case.

Who lends to the borrowers that score high on beauty and appear creditworthy, but turn out to be bad credits? And how much money do they leave on the table?

While Panel B of Table IX addresses the latter question, Table X examines the lenders characteristics that are correlated with higher beauty/creditworthiness, or a given race. The empirical specification is the following tobit regression:

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

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'Demographics* include gender, age, and race.²⁵

Panel A of Table X illustrates the characteristics of the lenders that are more prone to lend to beautiful people. Column I shows that more sophisticated lenders, who have lent more funds, 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 is equivalent to lower bidding abilities, leads to a higher probability of lending to a beautiful borrower and realizing lower returns. All the coefficient 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, column III shows that 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 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 beauty of the borrower is however not monotonical, and not always statistically significant. 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 1998, 1999; Barber and Odean, 2001).

²⁵An attempt has been made at measuring lenders' education, but too few data are available.

Finally, adding lenders' demographics to the regression generates interesting results. Young lenders are more likely to lend to the beautiful and old lenders are less likely so, although the results are not statistically significant. Asian lenders are significantly less likely to fund good looking people: their average borrower is more than half a point less good looking than the average borrower of a White lender.

Panel B of Table X performs the same analysis for the creditworthiness of the borrower. The empirical specification is similar to one above:

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

Column I confirms that more sophisticated lenders shy away from borrowers that give the impression of being creditworthy, while lenders with lower bidding abilities tend to favor them. The coefficients are significantly different from 0 at the 1 percent level, although the significance varies across the specifications reported in the other columns. Women lend to borrowers that have on average significantly higher creditworthiness ratings, although once I control for income the coefficient becomes smaller, and it is not statistically significant anymore. Again, higher income is associated with borrowers scoring lower in creditworthiness. Finally, Column IV shows that young and black lenders are more likely to lend to creditworthy-appearing individuals. The average borrower of a young lender scores 0.19 points higher in this dimension, while the average borrower of a Black lender scores 0.44 points higher (both statistically significant at the 5 percent level).²⁶

Finally, Panel C of Table X examines the characteristics of the lenders that are more likely to lend to Black borrowers and realize all else equal higher delinquency-adjusted returns. Similarly to the results for beauty and creditworthiness, 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.

To further investigate the nature of the bias that leads some lenders to provide funds to beautiful people that turn out to be bad borrowers, or to favor a given race, I check whether accounting for similarity between borrowers and lenders drives the significance of the lenders' characteristics away.

²⁶Interestingly, if the same analysis is performed for borrower's trustworthiness (associated to lower probability of getting a loan and higher interest rates, although not to lower delinquency rates), the findings show that people that bid inefficiently and lenders with higher incomes are less likely to provide funds to borrowers that appear trustworthy, while young lenders are more likely to do so (not reported).

The empirical specification is the following:

$$Beauty_i = f(\alpha_{1i,j}Lenders'Experience_j + \alpha_{2i,j}Lenders'Income_j + \alpha_{3i,j}Lenders'Demographics_j + \alpha_{4i,j}Similarity_{ij} + \varepsilon_{ij})$$

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, reported in the last Column of each panel of Table X, confirm that similarity affects lenders' decisions, although it doesn't change the effect of the other lenders' characteristics such as experience and bidding abilities. In particular, living in the same city is negatively correlated with beauty, appearing creditworthy, indicating that for lenders that bid on borrowers from the same city beauty and appearance are significantly less important. On average, borrowers that have a higher proportion of lenders from the same city rank 0.20 points lower on attractiveness, and 0.99 lower on creditworthiness (significant at the 1 percent level). The same borrowers are 0.88% more likely to be Black, although the effect is not significantly different from 0. The coefficients also show that being from the same gender is positively correlated with beauty and creditworthiness and unrelated to race. Even after controlling for similarity, lenders that are young and worse bidders are more likely to lend to the beautiful, while Asian are significantly less likely to do so: young lenders lend to borrowers that rank 2 points higher in beauty than the borrowers chosen by a middle age lender, while Asians lend to people ranking 3 points below those chosen by a White lender. The results for the borrowers that ranked high on creditworthiness show that this category is less likely to have lenders from the same city and from an old age. Finally, the coefficients for Black borrowers show that their lenders tend to be male, low income, old or young, but not middle age, and Black. All else equal, these lenders tend to have lent more money than the average lender. The few data available caution from putting too much weight on these last results.

8 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 charged. The economic magnitude of the coefficients is large. For example, an increase in beauty from neutral to above average generates a 1.44% higher

probability of getting a loan, and a drop of 81 bps 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 146 basis points, or, alternatively, lower the amount requested by \$2,483. Race, gender, and age do not have a statistically significant effect on the likelihood of getting a loan, although, conditional on getting funds, in some cases they strongly affect the interest rate the borrower pays. For example, Black borrowers pay between 139 and 146 basis points more than an otherwise similar White borrower. Similarity between borrowers and lenders has also a powerful impact on lenders' decisions. Living in the same city as the lender, belonging to the same ethnicity or gender, sharing the same interests (proxied by belonging to same Prosper group), and being both entrepreneurs increases the likelihood of getting a loan request funded. For example, an increase of 10% in the proportion of lenders from the same ethnicity generates a 60bps increase in the likelihood of getting funds, significant at the 1 percent level. To get the same effect, a similar borrower belonging to a different ethnicity would need to jump from a credit score in the range 560-599 to a score in the range 640-679.

These findings suggest that the favorable treatment that the beautiful receive in this market is consistent with a taste-based discrimination/perception 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, *less* likely to become delinquent. On the contrary, the finding that Black borrowers pay higher rates, but are not more delinquent after all the hard financial information is taken into account can be reconciled with both a taste-based discrimination model, as well as with a statistical discrimination model in which most lenders specialize in lending to White borrowers because they are better able to screen such type of applicants. The findings indeed indicate that once ethnic similarity between borrowers and lenders is taken into account being Black is not associated to higher interest rates, suggesting that the reason why Black borrowers pay more is that lenders prefer borrowers of the same race, and there are proportionally more Black borrowers (11.78%) than Black lenders (1.13%). Finally, to investigate whether the propensity to lend to similar borrower is due to superior information, rather than the inclination to trust and prefer individuals of the same ethnicity, I compare the returns that Black lenders make on Black and White borrowers, and the returns that White lenders make on the two groups of borrowers. I find that Black lenders are significantly more likely to lend to Blacks and are better able to screen such borrowers. On the other hand, White borrowers are not more likely to lend to Whites, although they charge lower interest rates to Whites, and seem to be equally good in screening Blacks and

Whites.

An interesting question is the degree to which these findings can be extended to other settings, such as the discretionary part of a loan officer assessment of a borrower. These effects have been documented in a very vast variety of settings, including big law firms hiring good-looking lawyers to deal with very sophisticated clients (Hamermesh and Biddle, 1998), and the relationship between race and outcomes in mortgage markets (for example, Ladd, 1998; Cole, 1999). More indirectly, the amount of resources and time spent in improving one's image for business success indicate that the effects of the way people present themselves on business transactions are widespread in many realms of financial transactions.

To conclude, while the findings in the paper are directly relevant for small scale lending, many insights can be gained that are relevant for other business settings and financial transactions, keeping in mind that a model that takes both hard and soft financial information into account might be optimal for certain types of credit markets, but dominated by a pure hard financial information statistical model in other types of markets.

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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 rate by credit grades for all the loans generated on the website. A loan is considered delinquent if it is one or more months late. The Experian default rate is the default rate on a large pool of revolving credit accounts from Experian, reported on the Prosper website for comparison. The pool comprises 251,000 loans with an average age of 2 years.

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**

Listing Characteristics		
Variable	Definition	Source
Amount requested	Amount of the loan request	Prosper website - Listing
Borrower maximum rate	Maximu 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
Verified bank account (dummy)	Dummy equal 1 if the member's bank account has been verified by Prosper	Prosper website - Listing
# of listings before the current one	# 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	Crdit score between 720 and 759 (dummy)	Prosper website - Credit Bureau
Credit Grade B	Crdit score between 680 and 719 (dummy)	Prosper website - Credit Bureau
Credit Grade C	Crdit score between 640 and 679 (dummy)	Prosper website - Credit Bureau
Credit Grade D	Crdit score between 600 and 639 (dummy)	Prosper website - Credit Bureau
Credit Grade E	Crdit score between 560 and 599 (dummy)	Prosper website - Credit Bureau
Credit Grade HR	Crdit score between 520 and 559 (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
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
# 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 on her credit record	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
Entrepreneur (dummy)	Dummy equal 1 if the member is an entrepreneur or self-employed	Prosper website - Credit B. + Listing
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
Religion - Christian	Religion dummy	Prosper website - Listing
Religion - Jewish	Religion dummy	Prosper website - Listing
Religion - Other	Religion dummy	Prosper website - Listing
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 equal 1 if the person in the picture is smiling	Prosper website - Picture
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

Table II Panel B
Summary Statistics – All Borrowers

This Table contains summary statistics for all the individuals that posted a loan request between March 12th and April 16th 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	9065.067	6500	7033.465	1000	25000	11951
Borrower maximum rate	0.1692584	0.17	0.0692581	0	0.3	11951
Listing Status - Cancelled	0.0158983	0	0.1250872	0	1	11951
Listing Status - Completed	0.1051795	0	0.3067974	0	1	11951
Listing Status - expired	0.4925111	0	0.4999648	0	1	11951
Listing Status - Withdrawn	0.3864112	0	0.486947	0	1	11951
Percent Funded	0.1560445	0.002	0.3299798	0	1	11951
Verified bank account (dummy)	0.4200485	0	0.493587	0	1	11951
Close when funded	0.3188854	0	0.466064	0	1	11951
# of listings before the current one	0.9123923	0	2.053577	0	43	11951
Credit Bureau Information						
Variable	Mean	Median	Std Dev	Min	Max	Obs.
Credit Grade AA	0.0420885	0	0.2007995	0	1	11951
Credit Grade A	0.0410008	0	0.1983002	0	1	11951
Credit Grade B	0.0637604	0	0.2443358	0	1	11951
Credit Grade C	0.1155552	0	0.3197041	0	1	11951
Credit Grade D	0.1578947	0	0.3646575	0	1	11951
Credit Grade E	0.1631663	0	0.3695328	0	1	11951
Credit Grade HR	0.4165342	0	0.4930049	0	1	11951
Income range - \$1- \$24,999	0.2320305	0	0.4221758	0	1	4452
Income range - \$25,000- \$49,999	0.4261006	0	0.4945643	0	1	4452
Income range - \$50,000- \$74,999	0.1875562	0	0.3904012	0	1	4452
Income range - \$75,000- \$99,999	0.0644654	0	0.2456078	0	1	4452
Income range - \$100,000+	0.0637916	0	0.2444087	0	1	4452
Unemployed (dummy)	0.0276008	0	0.1638437	0	1	4710
Employed - Full time (dummy)	0.807431	1	0.3943592	0	1	4710
Employed - Part time (dummy)	0.0452229	0	0.2078148	0	1	4710
Retired (dummy)	0.0252654	0	0.1569468	0	1	4710
Length of Employment Status	4.752442	2.5	5.953953	0	46.83333	4710
Bankcard Utilization Rate	0.5838471	0.71	0.4365709	0	6	4710
# of credit lines	7.626115	6	5.781992	0	42	4710
revolving credit balance	10081.77	2236	25327.45	0	372852	4710
Delinquency dummy	0.6363057	1	0.4811132	0	1	4710
Public Records (last 10 yrs) dummy	0.0658174	0	0.247989	0	1	4710
Public Records (last 12 mos) dummy	0.3932059	0	0.4885138	0	1	4710

Table II - Panel B (continued)

Borrowers Demographics						
Variable	Mean	Median	Std Dev	Min	Max	Obs.
Homeowner (dummy)	0.3332775	0	0.4714045	0	1	11951
Entrepreneur (dummy)	0.2895992	0	0.4990221	0	1	11951
asian (dummy)	0.0591911	0	0.2360207	0	1	3041
black (dummy)	0.1178463	0	0.3224806	0	1	2953
hispanic (dummy)	0.0637091	0	0.2442748	0	1	2998
white (dummy)	0.7496041	1	0.2367	0	1	3109
Female (dummy)	0.4485246	0	0.4974248	0	1	3050
Young (dummy)	0.5514754	1	0.4974248	0	1	3050
Old (dummy)	0.0809836	0	0.2728547	0	1	3050
Length in Prosper	8.728011	8	2.332379	7	21	11449
overweight (dummy)	0.1183606	0	0.4642834	0	1	3050
Religion - Christian	0.7576657	1	0.4285662	0	1	3033
Religion - Jewish	0.0026377	0	0.0512988	0	1	3033
Religion - Other	0.2396967	0	0.4269687	0	1	3033
Children in Picture	0.2996721	0	0.4581895	0	1	3050
Tie (dummy)	0.1017903	0	0.3024497	0	1	1955
Smile	0.6613115	1	0.4733414	0	1	3050

Table II Panel C**Summary Statistics –Borrowers that got a Loan**

This Table contains summary statistics for those individuals that posted a loan request between March 12th and April 16th 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	7582.395	5000	6225.141	1000	25000	1257	
Borrower maximum rate	0.19901	0.2	0.065586	0	0.29	1257	
Borrower rate	0.175245	0.1694	0.062496	0	0.29	1257	
debt to income ratio	0.6681564	0.21	1.953496	0	10.01	1253	
Percent Funded	1	1	0	1	1	1257	
Verified bank account (dummy)	0.991249	1	0.0931736	0	1	1257	
# of listings before the current one	0.8297534	0	1.662524	0	14	1257	
Credit Bureau Information							
Variable	Mean	Median	Std Dev	Min	Max	Obs.	
Credit Grade AA	0.1256961	0	0.3316385	0	1	1257	
Credit Grade A	0.0994431	0	0.2993752	0	1	1257	
Credit Grade B	0.1288783	0	0.3351985	0	1	1257	
Credit Grade C	0.176611	0	0.3814909	0	1	1257	
Credit Grade D	0.1988862	0	0.3993211	0	1	1257	
Credit Grade E	0.1121718	0	0.3157034	0	1	1257	
Credit Grade HR	0.1583134	0	0.3651799	0	1	1257	
Income range - \$1- \$24,999	0.1191275	0	0.3242106	0	1	596	
Income range - \$25,000- \$49,999	0.4312081	0	0.4956611	0	1	596	
Income range - \$50,000- \$74,999	0.2432886	0	0.4294283	0	1	596	
Income range - \$75,000- \$99,999	0.0939597	0	0.2920178	0	1	596	
Income range - \$100,000+	0.0889262	0	0.2848762	0	1	596	
Unemployed (dummy)	0.0226171	0	0.1487997	0	1	619	
Employed - Full time (dummy)	0.8303716	1	0.3756096	0	1	619	
Employed - Part time (dummy)	0.0371567	0	0.1892986	0	1	619	
Retired (dummy)	0.0274637	0	0.1635623	0	1	619	
Bankcard Utilization Rate	0.5342003	0.59	0.3761926	0	1.46	619	
# of credit lines	8.983845	8	5.805064	0	37	619	
revolving credit balance	10968.64	3436	23564.28	0	266243	619	
Delinquency dummy	0.4345719	0	0.4961016	0	1	619	
Public Records (last 10 yrs) dummy	0.0371567	0	0.1892986	0	1	619	
Public Records (last 12 mos) dummy	0.279483	0	0.4491081	0	1	619	

Table II - Panel C (continued)

Borrowers Demographics						
Variable	Mean	Median	Std Dev	Min	Max	Obs.
Beauty	4.069917	4.166667	0.7793547	1.666667	5.916667	294
Trustworthiness	4.478202	4.5	0.498154	3	5.833333	367
Creditworthiness	4.407811	4.333333	0.5397605	2.666667	6	367
Homeowner (dummy)	0.4168656	0	0.4932365	0	1	1257
Entrepreneur (dummy)	0.3420844	0	0.5002396	0	1	872
asian (dummy)	0.0829384	0	0.2761164	0	1	422
black (dummy)	0.1076555	0	0.3103162	0	1	418
hispanic (dummy)	0.0647482	0	0.2463766	0	1	417
race N/A (dummy)	0.0070423	0	0.0837204	0	1	426
white (dummy)	0.7376156	1	0.21164	0	1	426
Female (dummy)	0.4391408	0	0.4968756	0	1	419
Young (dummy)	0.6205251	1	0.4858364	0	1	419
Old (dummy)	0.0787589	0	0.2696842	0	1	419
Length in Prosper	9.240446	8	2.75325	7	21	1256
overweight (dummy)	0.1193317	0	0.4276404	0	1	419
Religion - Christian	0.9014085	1	0.2985336	0	1	355
Religion - Jewish	0.0056338	0	0.0749526	0	1	355
Religion - Other	0.0929577	0	0.2907831	0	1	355
Children in Picture	0.300716	0	0.4591176	0	1	419
Tie (dummy)	0.1226158	0	0.3284435	0	1	367

Table II Panel D
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 rate by credit grades for the loans in the sample. A loan is considered delinquent if it is one or more months late. The Experian default rate is the default rate on a large pool of revolving credit accounts from Experian, reported on the Prosper website for comparison. The pool comprises 251,000 loans with an average age of 2 years. The Estimated default-adjusted lenders' return (Method 1) consists of applying the historical default rate reported in Table I to these loans. Method 2 makes the very conservative assumption that all delinquencies will turn into defaults, while Method 3 attempts to convert delinquencies into default rates using the historical ratio of delinquency rates to default rates calculated from Table I, and adjusting the delinquency rate in the sample by the historical ratio of defaults to delinquencies in each credit category.

Loans Originated							
Credit Grade	Credit Score	Average Lender Interest Rate	Total Amount Lent	Delinquency rate	Average Default Rate	Experian Average Default rate	Default-adjusted Lenders Return
AA	760 and up	10.86%	\$1,567,972	1.15%	0.00%	0.20%	10.86%
A	720-759	12.92%	\$1,274,704	7.84%	0.00%	0.90%	12.92%
B	680-719	14.99%	\$1,643,461	8.05%	0.00%	1.80%	14.99%
C	640-679	17.32%	\$1,742,580	9.78%	0.00%	3.30%	17.32%
D	600-639	20.67%	\$1,898,937	23.60%	0.00%	6.20%	20.67%
E	560-599	23.26%	\$707,979	26.84%	0.00%	10.40%	23.26%
HR	520-559	23.71%	\$670,438	34.04%	0.00%	19.10%	23.71%
NC	No credit history	N/A	\$0			N/A	
Total			\$9,506,071		0.00%		

Table II Panel D (continued)

Credit Grade	Credit Score	Estimated Default-adjusted Lenders Return (Method 1)*	Estimated Default-adjusted Lenders Return (Method 2)†	Estimated Default-adjusted Lenders Return (Method 3)‡	Obs.	%
AA	760 and up	10.64%	9.58%	10.81%	158	12.57%
A	720-759	11.84%	4.06%	10.04%	125	9.94%
B	680-719	12.88%	5.73%	12.88%	162	12.89%
C	640-679	15.30%	5.84%	15.74%	222	17.66%
D	600-639	17.36%	-7.81%	15.76%	250	19.89%
E	560-599	14.60%	-9.82%	14.78%	141	11.22%
HR	520-559	9.02%	-18.40%	9.99%	199	15.83%
NC	No credit history					
Total					1,257	100.00%

Table II Panel E**Summary Statistics - Beauty, Trustworthiness and Creditworthiness Ratings**

This Table reports the average beauty, trustworthiness, and creditworthiness rating 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	4.048904	4	0.8003231	1.5	6.333333	4479
Trustworthiness	3.590534	3.666667	0.5208482	1.833333	5.5	5694
Creditworthiness	3.723569	3.666667	0.5626191	2	5.5	5694
Female Raters						
Beauty	3.909381	4	1.188666	1	7	4461
Trustworthiness	3.551633	4	0.9321172	1	7	5694
Creditworthiness	3.657183	4	0.9836911	1	7	5694
Male Raters						
Beauty	4.187332	4	1.160346	1	7	4468
Trustworthiness	3.629434	4	0.9090086	1	7	5694
Creditworthiness	3.789954	4	0.9964618	1	7	5694

Table II Panel G**Average Beauty, Trustworthiness and Creditworthiness Ratings by Credit Grade**

This Table reports 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 for more details on the rating procedure, the ratings, and the raters. The variables definition is provided in Panel A of this Table.

	Beauty	Trustworthiness	Creditworthiness
Credit Grade AA	4.052609	4.422222	4.383333
Credit Grade A	4.089397	4.484848	4.40404
Credit Grade B	4.050794	4.443262	4.361702
Credit Grade C	4.03136	4.477778	4.388889
Credit Grade D	3.963519	4.408743	4.300546
Credit Grade E	3.94892	4.430512	4.30512
Credit Grade HR	3.862905	4.365966	4.183749
Total	3.945428	4.411083	4.280136

**Table II Panel F
Correlations**

	Beauty	Trustworthiness	Creditworthiness	Female (dummy)	Young (dummy)	Old (dummy)	Smile (dummy)	Overweight	Homeowner
Beauty	1								
Trustworthiness	0.3526	1							
Creditworthiness	0.3808	0.6968	1						
Female (dummy)	0.1034	0.1122	-0.0693	1					
Young (dummy)	0.2012	0.0384	0.0105	0.0148	1				
Old (dummy)	-0.1268	0.0324	0.0698	0.0289	-0.1953	1			
Smile	0.0857	0.2206	0.1515	0.1288	0.1415	0.0301	1		
Overweight	-0.3872	-0.0306	-0.1027	0.0691	-0.043	0.0389	0.0575	1	
Homeowner	-0.0007	0.1093	0.1113	-0.0327	-0.1219	0.0659	0.0244	-0.0178	1
Amount Requested	0.0883	0.0502	0.1054	-0.1075	-0.0111	0.0111	-0.0184	-0.1127	0.1506
Borrower Rate	0.0292	-0.0035	-0.0374	0.023	0.0587	-0.0282	0.0305	-0.0374	-0.1298
Revolving Credit Balance	0.0625	0.0745	0.1599	-0.0892	-0.0533	0.0788	0.0429	-0.1072	0.2654
asian (dummy)	0.0188	-0.0276	-0.0018	-0.023	0.0729	-0.0148	0.0061	-0.0458	-0.0195
black (dummy)	-0.0632	-0.1282	-0.1943	0.088	-0.04	-0.084	-0.0198	0.0914	-0.0415
hispanic (dummy)	0.0624	-0.0358	-0.0407	-0.0369	-0.0077	-0.0028	0.0289	-0.0747	0.0083
Delinquency dummy	-0.0765	-0.0107	-0.0491	0.1612	-0.1123	0.0238	0.0349	0.074	-0.0386

	Amount Requested	Borrower Rate	Revolving Credit Balance	asian (dummy)	black (dummy)	hispanic (dummy)	Delinquency dummy
Amount Requested	1						
Borrower Rate	-0.0679	1					
Revolving Credit Balance	0.3078	-0.074	1				
asian (dummy)	0.0274	-0.0152	0.0014	1			
black (dummy)	-0.0734	0.1151	-0.0838	-0.013	1		
hispanic (dummy)	0.0647	-0.0016	0.0194	0.1691	0.0281	1	
Delinquency dummy	-0.1999	0.2259	-0.226	-0.1127	0.0989	0.0418	1

Table II Panel H

Beauty, Trustworthiness and Creditworthiness Ratings by Income and Employment Status

This Table reports the average, standard deviation and number of observation 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 this Table.

	Beauty				Trustworthiness				Creditworthiness			
	Young	Middle	Old	Total	Young	Middle	Old	Total	Young	Middle	Old	Total
Income range - \$1- \$24,999	4.0052	3.7937	3.6157	3.9044	4.3212	4.3442	4.4701	4.3431	4.1402	4.2255	4.3590	4.1910
	0.8851	0.8561	0.6664	0.8644	0.5831	0.5042	0.5860	0.5565	0.5962	0.5753	0.6941	0.6007
	201	89	36	326	233	153	39	425	233	153	39	425
Income range - \$25,000- \$49,999	4.1012	3.6971	3.4444	3.9140	4.4558	4.3292	4.4178	4.4078	4.2929	4.1868	4.2778	4.2543
	0.7672	0.7672	0.6745	0.7945	0.4697	0.5138	0.4765	0.4892	0.5247	0.5293	0.5904	0.5344
	401	188	73	662	445	281	75	801	445	281	75	801
Income range - \$50,000- \$74,999	4.1112	3.7955	3.7796	3.9726	4.4796	4.3624	4.6571	4.4529	4.3185	4.2348	4.5952	4.3146
	0.6775	0.8399	0.6809	0.7478	0.5053	0.5566	0.5176	0.5324	0.4956	0.5587	0.5053	0.5298
	153	86	31	270	180	132	35	347	180	132	35	347
Income range - \$75,000- \$99,999	4.3620	3.7281	3.7619	4.0509	4.5747	4.4281	4.6458	4.5157	4.5402	4.4641	4.8542	4.5285
	0.6781	0.8058	0.5578	0.7869	0.5055	0.5786	0.4751	0.5383	0.5410	0.5956	0.4915	0.5662
	48	40	7	95	58	51	8	117	58	51	8	117
Income range - \$100,000+	4.0736	3.8575	4.0864	4.0005	4.5345	4.3361	4.6500	4.4505	4.3851	4.3944	4.8667	4.4271
	0.5973	0.6719	0.7407	0.6394	0.4701	0.4990	0.5412	0.4982	0.5141	0.5846	0.5655	0.5627
	50	31	9	90	58	60	10	128	58	60	10	128
Total	4.0970	3.7591	3.5785	3.9398	4.4401	4.3480	4.4971	4.4110	4.2793	4.2462	4.4152	4.2794
	0.7727	0.8071	0.7005	0.7998	0.5120	0.5237	0.5178	0.5192	0.5468	0.5616	0.6161	0.5606
	877	443	160	1480	999	694	171	1864	999	694	171	1864
Employed - Full time (dummy)	3.7516	3.6367	4.0716	3.9348	4.3615	4.4905	4.4389	4.4143	4.2351	4.3591	4.2677	4.2628
	0.7946	0.6965	0.7641	0.7861	0.5267	0.5185	0.5051	0.5157	0.5618	0.6129	0.5367	0.5529
	376	115	754	1245	580	123	864	1567	580	123	864	1567
Employed - Part time (dummy)	3.7047	3.1481	4.1722	3.9375	4.1898	4.6389	4.3633	4.3134	4.1019	4.6111	4.1600	4.1667
	0.8674	0.7053	0.7992	0.8658	0.5318	0.5209	0.5363	0.5412	0.5028	0.5741	0.5028	0.5159
	23	6	43	72	36	6	50	92	36	6	50	92

Retired (dummy)	3.7667	3.2847	3.4792	3.4722	4.5455	4.1833	4.6000	4.4167	4.4545	4.1333	4.1667	4.2756
	0.3028	0.3259	0.9583	0.5350	0.3658	0.3187	0.6303	0.4353	0.5169	0.3220	1.1667	0.6217
	5	8	4	17	11	10	5	26	11	10	5	26
Self-employed	3.9218	3.6441	4.2964	4.0572	4.3000	4.6616	4.5000	4.4422	4.3463	4.7778	4.4965	4.4772
	0.7761	0.6875	0.7808	0.8013	0.4715	0.5900	0.5320	0.5313	0.5720	0.6190	0.5472	0.5841
	49	32	83	164	90	33	96	219	90	33	96	219
Unemployed	3.9611	2.6667	4.2603	4.0318	4.2632	4.1667	4.4405	4.3529	4.2281	3.9583	4.1667	4.1732
	1.3068	0.5932	0.8240	1.0368	0.6834	0.2357	0.5176	0.5712	0.6763	0.1596	0.5809	0.5944
	10	4	27	41	19	4	28	51	19	4	28	51
Total	3.7720	3.5798	4.0998	3.9454	4.3458	4.5028	4.4417	4.4111	4.2452	4.4242	4.2804	4.2801
	0.8054	0.6980	0.7726	0.7984	0.5241	0.5281	0.5097	0.5193	0.5640	0.6202	0.5452	0.5612
	463	165	911	1539	736	176	1043	1955	736	176	1043	1955

Table III
Summary Statistics – Lenders

This Table contains summary statistics for all the individuals that lent money or made a bid on the listings posted on Prosper between March 12th and April 16th 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	8478.703	2400	33090.55	50	1789409	12037
Total amount lent	2835.133	850	11510.82	0	738447.9	12037
Months in Prosper	11.90399	11	3.827524	7	25	12030
Homeowner (dummy)	0.6425327	1	0.4792711	0	1	14088
Credit Grade AA	0.5489779	1	0.497613	0	1	14088
Credit Grade A	0.2324673	0	0.4224203	0	1	14088
Credit Grade B	0.0912834	0	0.2880219	0	1	14088
Credit Grade C	0.0746735	0	0.2628731	0	1	14088
Credit Grade D	0.0256956	0	0.1582313	0	1	14088
Credit Grade E	0.0139835	0	0.1174265	0	1	14088
Credit Grade HR	0.0129188	0	0.1129283	0	1	14088
Entrepreneur (dummy)	0.2692918	0	0.4436238	0	1	6933
Employed - Full time (dummy)	0.7539483	1	0.4307337	0	1	8738
Employed - Part time (dummy)	0.0241474	0	0.1535155	0	1	8738
Retired (dummy)	0.1176471	0	0.3222082	0	1	8738
Religion - Christian	0.581156	1	0.4934674	0	1	2526
Religion - Jewish	0.216152	0	0.4117006	0	1	2526
Religion - other	0.202692	0	0.4020845	0	1	2526
asian (dummy)	0.1150479	0	0.319113	0	1	4798
black (dummy)	0.0128952	0	0.1128341	0	1	4808
hispanic (dummy)	0.0151767	0	0.1222681	0	1	4810
white (dummy)	0.8568802	1	0.3113	0	1	4840
Income range - \$1- \$24,999	0.1119465	0	0.315327	0	1	5985
Income range - \$25,000- \$49,999	0.0848789	0	0.2787246	0	1	5985
Income range - \$50,000- \$74,999	0.2394319	0	0.4267724	0	1	5985
Income range - \$75,000- \$99,999	0.1490393	0	0.3561569	0	1	5985
Income range - \$100,000+	0.4028404	0	0.4905102	0	1	5985
Unemployed (dummy)	0.0331657	0	0.1790831	0	1	6362
Female (dummy)	0.15475	0	0.3617114	0	1	4000
Young (dummy)	0.5041459	1	0.5000346	0	1	4824
Old (dummy)	0.0292289	0	0.1684649	0	1	4824
overweight (dummy)	0.1017426	0	0.3023945	0	1	1779
Family (dummy)	0.3752963	0	0.4842631	0	1	3797

Table IV
Probability of Getting a Loan as a function of Hard Financial Information, Personal Characteristics, Appearance and Listing Features

This Table reports the marginal effects from a Probit regression of loan completion on hard financial information, personal characteristics, context 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>Marginal Effects (p-values in parantheses)</i>					
	(1)	(2)	(3)	(4)	(5)
Amount requested (\$,000)	-0.0017*** (0.000)	-0.0016*** (0.000)	-0.0058*** (0.000)	-0.0057*** (0.000)	-0.0057*** (0.000)
Borrower maximum rate	0.2968*** (0.000)	0.2711*** (0.000)	0.9892*** (0.000)	0.9690*** (0.000)	0.9568*** (0.000)
Close when funded (dummy)	-0.0069*** (0.000)	-0.0053*** (0.002)	-0.0202* (0.076)	-0.0211** (0.050)	-0.0204* (0.061)
Verified bank account (dummy)	0.0952*** (0.000)	0.0880*** (0.000)	0.1303*** (0.000)	0.1277*** (0.000)	0.1312*** (0.000)
Homeowner Dummy	0.0045** (0.012)	0.0040** (0.015)	0.0259** (0.013)	0.0263** (0.010)	0.0260** (0.012)
Credit Grade AA	0.5898*** (0.000)	0.6031*** (0.000)	0.8894*** (0.000)	0.8926*** (0.000)	0.8875*** (0.000)
Credit Grade A	0.4164*** (0.000)	0.4119*** (0.000)	0.6046*** (0.000)	0.6104*** (0.000)	0.5955*** (0.000)
Credit Grade B	0.2018*** (0.000)	0.2012*** (0.000)	0.6087*** (0.000)	0.6028*** (0.000)	0.5889*** (0.000)
Credit Grade C	0.0973*** (0.000)	0.0978*** (0.000)	0.2891*** (0.000)	0.2872*** (0.000)	0.2815*** (0.000)
Credit Grade D	0.0325*** (0.000)	0.0321*** (0.000)	0.1002*** (0.001)	0.1067*** (0.000)	0.0944*** (0.001)
Credit Grade HR	-0.0115*** (0.000)	-0.0108*** (0.000)	-0.0443*** (0.000)	-0.0432*** (0.000)	-0.0419*** (0.000)
# of listings before the current one	-0.0022*** (0.000)	-0.0021*** (0.000)	-0.0040** (0.041)	-0.0037* (0.058)	-0.0040** (0.039)
Length of employment status	0.0000 (0.746)	0.0001 (0.621)	-0.0000 (0.974)	-0.0000 (0.996)	-0.0000 (0.995)
Delinquency dummy	-0.0056*** (0.006)	-0.0058*** (0.003)	-0.0256** (0.030)	-0.0248** (0.030)	-0.0241** (0.035)
Public Records (last 12 mos)	0.0005 (0.877)	0.0014 (0.667)	0.0074 (0.678)	0.0084 (0.635)	0.0066 (0.700)
Public Records (last 10 yrs)	-0.0038** (0.021)	-0.0035** (0.020)	-0.0166** (0.043)	-0.0177** (0.025)	-0.0151* (0.061)
Income range - \$25,000- \$49,999	0.0117*** (0.000)	0.0104*** (0.000)	0.0480*** (0.001)	0.0473*** (0.001)	0.0480*** (0.001)
Income range - \$50,000- \$74,999	0.0142*** (0.000)	0.0134*** (0.000)	0.0952*** (0.001)	0.0926*** (0.001)	0.0995*** (0.001)
Income range - \$75,000- \$99,999	0.0289*** (0.000)	0.0280*** (0.000)	0.0826** (0.041)	0.0836** (0.036)	0.0731* (0.060)
Income range - \$100,000+	0.0278*** (0.001)	0.0250*** (0.001)	0.2774*** (0.000)	0.2685*** (0.001)	0.2644*** (0.000)

Unemployed (dummy)	0.0425** (0.015)	0.0419*** (0.009)	0.0763 (0.345)	0.0751 (0.339)	0.0638 (0.365)
Employed - Part time (dummy)	-0.0022 (0.510)	-0.0020 (0.513)	0.0085 (0.723)	0.0096 (0.690)	0.0111 (0.651)
Retired (dummy)	0.0226*** (0.003)	0.0290*** (0.000)	0.2085** (0.011)	0.1969** (0.014)	0.1804** (0.019)
Entrepreneur (dummy)	0.0021 (0.164)	0.0017 (0.219)	0.0112 (0.195)	0.0110 (0.192)	0.0113 (0.181)
Bankcard Utilization rate	0.0014 (0.533)	0.0013 (0.514)	0.0110 (0.312)	0.0112 (0.298)	0.0102 (0.349)
# of Credit Lines	-0.0002 (0.114)	-0.0002 (0.132)	0.0001 (0.891)	0.0000 (0.961)	-0.0000 (0.967)
Revolving Credit Balance	-0.0001 (0.116)	-0.0001 (0.132)	-0.0006*** (0.004)	-0.0006*** (0.005)	-0.0006*** (0.006)
Picture (dummy)		0.0070*** (0.000)			
Months in Prosper			0.0016 (0.275)	0.0018 (0.222)	0.0018 (0.218)
overweight (dummy)			0.0520*** (0.000)	0.0527*** (0.000)	0.0509*** (0.000)
Beauty			0.0144** (0.011)	0.0062 (0.429)	0.0132** (0.027)
smile (dummy)			-0.0107 (0.342)	-0.0112 (0.317)	-0.0100 (0.371)
tie (dummy)			0.0074 (0.574)	0.0070 (0.576)	0.0025 (0.843)
asian (dummy)			0.0034 (0.819)	0.0023 (0.871)	0.0045 (0.756)
black (dummy)			-0.0092 (0.314)	-0.0074 (0.419)	-0.0088 (0.339)
hispanic (dummy)			-0.0107 (0.345)	-0.0109 (0.314)	-0.0101 (0.356)
Female (dummy)			0.0114 (0.176)	-0.0560 (0.254)	0.0137* (0.098)
Young (dummy)			-0.0131 (0.216)	-0.0142 (0.167)	-0.0120 (0.245)
Old (dummy)			-0.0049 (0.670)	-0.0048 (0.669)	-0.0061 (0.575)
Interaction Beauty*Female				0.0142 (0.148)	
Trustworthiness					-0.0166 (0.104)
Creditworthiness					0.0169* (0.087)
Context dummies		YES	YES	YES	YES
Observations	2794	762	762	762	762
Pseudo R ²	0.4793	0.489	0.5178	0.5203	0.5216

Note: standard errors are clustered at the borrower level

Table IV Panel B**Selection – Borrowers posting a picture and Borrowers who choose not to.**

This Table compares the credit bureau information of borrowers that choose to post a picture and borrowers who don't. A definition of the variables is provided in Panel A of Table II.

	Does not post a picture	Posts a picture
amount requested	\$9,113	\$8,821
amount funded	\$1,098	\$2,251
borrower rate	16.54%	17.15%
debt to income ratio	1.127909	1.065245
homeowner	33.31%	33.40%
amount delinquent	\$4,301	\$3,422
delinquencies in last 7y	11.63414	10.39177
# delinquencies	3.899488	3.37018
public records last 12m	0.0820327	0.0731458
public records last 10y	0.7032164	0.5876607
bankcard utilization	0.5848566	0.5824246
current credit lines	7.620327	7.634271
open credit lines	6.704537	6.709463
revolving credit balance	\$9,712	\$10,603
total credit lines	25.29	24.98833
Credit Grade AA	4.13%	4.60%
Credit Grade A	3.91%	5.06%
Credit Grade B	6.21%	7.21%
Credit Grade C	11.41%	12.28%
Credit Grade D	15.83%	15.60%
Credit Grade E	16.32%	16.32%
Credit Grade HR	42.19%	38.93%

Table V
Fraction of the Loan Request that Receives Funds as a function of Hard Financial Information, Personal Characteristics, Appearance and Listing Features

This Table reports the coefficients from a Tobit regression of the percent of the loan request that got funds as a function of on hard financial information, personal characteristics, context and listing features. The dependent variable, *AmountFunded* is the fraction of the loan request that got funds. A definition of the explanatory variables is provided in Panel A of Table II.

	<i>(p-values in parantheses)</i>				
	(1)	(2)	(3)	(4)	(5)
Amount requested (\$,000)	-0.0169*** (0.000)	-0.0134*** (0.000)	-0.0209*** (0.000)	-0.0209*** (0.000)	-0.0207*** (0.000)
Borrower maximum rate	3.6697*** (0.000)	2.8612*** (0.000)	4.2331*** (0.000)	4.2331*** (0.000)	4.2432*** (0.000)
Close when funded (dummy)	-0.0904*** (0.000)	-0.0602*** (0.001)	-0.0968* (0.062)	-0.0968* (0.063)	-0.0957* (0.064)
Verified bank account (dummy)	0.4287*** (0.000)	0.3425*** (0.000)	0.4898*** (0.000)	0.4898*** (0.000)	0.4924*** (0.000)
Homeowner Dummy	0.0347 (0.109)	0.0271* (0.095)	0.0935** (0.036)	0.0935** (0.036)	0.0991** (0.026)
Credit Grade AA	0.8356*** (0.000)	0.6414*** (0.000)	1.0480*** (0.000)	1.0480*** (0.000)	1.0476*** (0.000)
Credit Grade A	0.6257*** (0.000)	0.4886*** (0.000)	0.5641*** (0.000)	0.5641*** (0.000)	0.5696*** (0.000)
Credit Grade B	0.4959*** (0.000)	0.3970*** (0.000)	0.6879*** (0.000)	0.6879*** (0.000)	0.6835*** (0.000)
Credit Grade C	0.3934*** (0.000)	0.3108*** (0.000)	0.4477*** (0.000)	0.4477*** (0.000)	0.4531*** (0.000)
Credit Grade D	0.2474*** (0.000)	0.1979*** (0.000)	0.3317*** (0.000)	0.3317*** (0.000)	0.3300*** (0.000)
Credit Grade HR	-0.1142*** (0.000)	-0.0864*** (0.000)	-0.1286** (0.018)	-0.1286** (0.018)	-0.1196** (0.027)
# of listings before the current one	-0.0201*** (0.000)	-0.0147*** (0.000)	-0.0342*** (0.000)	-0.0342*** (0.000)	-0.0339*** (0.000)
Length of employment status	-0.0009 (0.556)	-0.0005 (0.655)	-0.0036 (0.333)	-0.0036 (0.333)	-0.0033 (0.374)
Delinquency dummy	-0.0831*** (0.000)	-0.0714*** (0.000)	-0.0891* (0.074)	-0.0891* (0.074)	-0.0903* (0.069)
Public Records (last 12 mos)	0.0641 (0.103)	0.0602** (0.042)	0.1133 (0.176)	0.1133 (0.176)	0.1169 (0.161)
Public Records (last 10 yrs)	-0.0401* (0.057)	-0.0294* (0.064)	-0.1011** (0.021)	-0.1011** (0.021)	-0.0946** (0.031)
Income range - \$25,000- \$49,999	0.1206*** (0.000)	0.0918*** (0.000)	0.1751*** (0.001)	0.1751*** (0.001)	0.1789*** (0.001)
Income range - \$50,000- \$74,999	0.1257*** (0.000)	0.1042*** (0.000)	0.2026*** (0.002)	0.2026*** (0.002)	0.2094*** (0.002)
Income range - \$75,000- \$99,999	0.2362*** (0.000)	0.1829*** (0.000)	0.3596*** (0.000)	0.3596*** (0.000)	0.3424*** (0.000)
Income range - \$100,000+	0.1917*** (0.000)	0.1555*** (0.000)	0.3326*** (0.001)	0.3326*** (0.001)	0.3261*** (0.002)
Unemployed (dummy)	0.1603***	0.1240***	0.2184	0.2184	0.2209

	(0.009)	(0.007)	(0.112)	(0.113)	(0.106)
Employed - Part time (dummy)	-0.0385	-0.0243	0.0151	0.0151	0.0312
	(0.430)	(0.509)	(0.879)	(0.879)	(0.752)
Retired (dummy)	0.0738	0.0702	0.3081*	0.3081*	0.3032*
	(0.286)	(0.171)	(0.091)	(0.091)	(0.097)
Entrepreneur (dummy)	0.0852***	0.0609***	0.1382***	0.1382***	0.1362***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Bankcard Utilization rate	-0.0229	-0.0188	-0.0053	-0.0053	-0.0145
	(0.337)	(0.295)	(0.913)	(0.913)	(0.763)
# of Credit Lines	-0.0046**	-0.0034**	-0.0028	-0.0028	-0.0034
	(0.017)	(0.016)	(0.493)	(0.493)	(0.398)
Revolving Credit Balance	-0.0007*	-0.0006*	-0.0013	-0.0013	-0.0014*
	(0.081)	(0.072)	(0.115)	(0.115)	(0.098)
Picture (dummy)		0.0811***			
		(0.000)			
Months in Prosper			0.0220**	0.0220**	0.0226***
			(0.011)	(0.012)	(0.009)
overweight (dummy)			0.0874*	0.0874*	0.0906*
			(0.086)	(0.086)	(0.076)
Beauty			0.0607**	0.0607	0.0557*
			(0.024)	(0.135)	(0.056)
smile (dummy)			-0.0195	-0.0195	-0.0168
			(0.694)	(0.694)	(0.740)
tie (dummy)			0.0657	0.0657	0.0371
			(0.299)	(0.299)	(0.567)
asian (dummy)			-0.0477	-0.0477	-0.0487
			(0.469)	(0.470)	(0.457)
black (dummy)			-0.0786	-0.0786	-0.0697
			(0.107)	(0.109)	(0.154)
hispanic (dummy)			-0.0302	-0.0302	-0.0270
			(0.595)	(0.595)	(0.632)
Female (dummy)			0.0821*	0.0822	0.1034**
			(0.054)	(0.678)	(0.017)
Young (dummy)			-0.0218	-0.0218	-0.0192
			(0.632)	(0.633)	(0.673)
Old (dummy)			0.0510	0.0510	0.0393
			(0.373)	(0.373)	(0.491)
Interaction Beauty*Female				-0.0000	
				(1.000)	
Trustworthiness					-0.1344**
					(0.022)
Creditworthiness					0.1331**
					(0.012)
Constant	-0.7155***	-0.5836***	-1.3078***	-1.3079***	-1.2897***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Context dummies	YES	YES	YES	YES	YES
Observations	2794	772	772	772	772
Pseudo R ²	0.3337	0.4715	0.3631	0.3631	0.3676

Table VI
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 paid by the borrower as a function of hard financial information, personal characteristics, context and listing features. The sample consists of all the listings that got funds and became a loan. The explanatory variables are the same as in Tables IV and V, with the exception of the maximum borrower rate which should be a priori unrelated to the interest rate paid on completed loans, and the verified bank account dummy that equals 1 for more than 99% of the generated loans. A similar Table that includes the maximum interest rate the borrower is willing to pay shows that including such variable does not affect the magnitude and significance of the other coefficients. This Table is available upon request. A definition of the explanatory variables is provided in Panel A of Table II.

	<i>(p-values in parantheses)</i>				
	(1)	(2)	(3)	(4)	(5)
Amount requested (\$,000)	0.0027*** (0.000)	0.0028*** (0.000)	0.0025*** (0.000)	0.0025*** (0.000)	0.0025*** (0.000)
Close when funded (dummy)	0.0350*** (0.000)	0.0327*** (0.000)	0.0550*** (0.000)	0.0538*** (0.000)	0.0536*** (0.000)
Homeowner Dummy	0.0001 (0.964)	0.0006 (0.845)	-0.0011 (0.816)	-0.0005 (0.912)	-0.0012 (0.792)
Credit Grade AA	-0.1347*** (0.000)	-0.1348*** (0.000)	-0.1355*** (0.000)	-0.1348*** (0.000)	-0.1372*** (0.000)
Credit Grade A	-0.1236*** (0.000)	-0.1237*** (0.000)	-0.1202*** (0.000)	-0.1192*** (0.000)	-0.1199*** (0.000)
Credit Grade B	-0.0958*** (0.000)	-0.0960*** (0.000)	-0.0868*** (0.000)	-0.0855*** (0.000)	-0.0878*** (0.000)
Credit Grade C	-0.0753*** (0.000)	-0.0753*** (0.000)	-0.0768*** (0.000)	-0.0761*** (0.000)	-0.0771*** (0.000)
Credit Grade D	-0.0443*** (0.000)	-0.0447*** (0.000)	-0.0354*** (0.000)	-0.0350*** (0.000)	-0.0359*** (0.000)
Credit Grade HR	0.0108*** (0.010)	0.0111*** (0.008)	0.0032 (0.590)	0.0031 (0.594)	0.0039 (0.519)
# of listings before the current one	-0.0003 (0.738)	-0.0001 (0.929)	-0.0008 (0.470)	-0.0006 (0.582)	-0.0009 (0.423)
Length of employment status	0.0002 (0.418)	0.0001 (0.668)	-0.0004 (0.394)	-0.0003 (0.416)	-0.0005 (0.293)
Delinquency dummy	0.0084*** (0.004)	0.0094*** (0.001)	0.0064 (0.203)	0.0060 (0.235)	0.0064 (0.199)
Public Records (last 12 mos)	0.0131** (0.032)	0.0130** (0.032)	0.0235** (0.023)	0.0247** (0.018)	0.0245** (0.018)
Public Records (last 10 yrs)	0.0020 (0.495)	0.0023 (0.439)	-0.0013 (0.790)	-0.0022 (0.667)	-0.0012 (0.819)
Income range - \$25,000- \$49,999	-0.0061 (0.122)	-0.0061 (0.120)	-0.0136* (0.051)	-0.0134* (0.054)	-0.0129* (0.065)
Income range - \$50,000- \$74,999	-0.0047 (0.279)	-0.0053 (0.217)	-0.0186** (0.020)	-0.0183** (0.021)	-0.0171** (0.035)
Income range - \$75,000- \$99,999	-0.0120** (0.034)	-0.0130** (0.020)	-0.0114 (0.295)	-0.0115 (0.290)	-0.0104 (0.339)
Income range - \$100,000+	-0.0193*** (0.001)	-0.0182*** (0.002)	-0.0249** (0.011)	-0.0254*** (0.010)	-0.0235** (0.017)

Unemployed (dummy)	0.0032 (0.692)	0.0020 (0.808)	0.0019 (0.942)	0.0005 (0.985)	0.0113 (0.683)
Employed - Part time (dummy)	-0.0094 (0.185)	-0.0100 (0.153)	-0.0313*** (0.010)	-0.0316*** (0.009)	-0.0297** (0.016)
Retired (dummy)	0.0042 (0.568)	0.0038 (0.603)	-0.0268 (0.145)	-0.0262 (0.154)	-0.0243 (0.187)
Entrepreneur (dummy)	0.0076*** (0.005)	0.0081*** (0.003)	-0.0007 (0.870)	-0.0011 (0.811)	-0.0003 (0.948)
Bankcard Utilization rate	-0.0037 (0.330)	-0.0040 (0.280)	-0.0000 (0.994)	0.0007 (0.919)	-0.0015 (0.821)
# of Credit Lines	0.0007*** (0.004)	0.0007*** (0.005)	0.0002 (0.662)	0.0001 (0.715)	0.0002 (0.636)
Revolving Credit Balance	0.0001 (0.371)	0.0000 (0.468)	-0.0002 (0.448)	-0.0002 (0.341)	-0.0001 (0.540)
Picture (dummy)		-0.0082*** (0.001)			
Months in Prosper			0.0014* (0.071)	0.0014* (0.073)	0.0013* (0.086)
overweight (dummy)			-0.0049 (0.331)	-0.0039 (0.445)	-0.0040 (0.440)
Beauty			-0.0081*** (0.003)	-0.0104*** (0.004)	-0.0066** (0.025)
smile (dummy)			0.0075 (0.168)	0.0062 (0.264)	0.0091 (0.103)
tie (dummy)			0.0001 (0.983)	0.0004 (0.940)	0.0022 (0.693)
asian (dummy)			-0.0097 (0.181)	-0.0107 (0.144)	-0.0107 (0.145)
black (dummy)			0.0141** (0.014)	0.0146** (0.012)	0.0139** (0.015)
hispanic (dummy)			0.0045 (0.503)	0.0037 (0.580)	0.0035 (0.602)
Female (dummy)			0.0016 (0.710)	-0.0168 (0.396)	0.0016 (0.722)
Young (dummy)			-0.0034 (0.528)	-0.0039 (0.472)	-0.0042 (0.438)
Old (dummy)			0.0042 (0.504)	0.0055 (0.392)	0.0052 (0.418)
Interaction Beauty*Female				0.0046 (0.339)	
Trustworthiness					-0.0025 (0.634)
Creditworthiness					-0.0040 (0.451)
Constant	0.1843*** (0.000)	0.2129*** (0.000)	0.1990*** (0.000)	0.2079*** (0.000)	0.2190*** (0.000)
Context dummies	YES	YES	YES	YES	YES
State f.e.	YES	YES	YES	YES	YES
Observations	2794	772	772	772	772
Pseudo R ²	0.32248	0.558	0.5811	0.5864	0.59335

Table VII**Effect of Similarity between Borrowers and Lenders on Bids and Amount Bid**

Columns 1 and 2 of this Table contains the coefficients from a probit regression of whether the listing receives a bid, as a function of the borrower's hard financial information, personal characteristics, context, listing features, and similarity between borrowers and lenders. Column 3 and 4 examines the effect of the same explanatory variables on the amount bid. The sample consists of a random 15% subsample of the listings in the dataset 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 other explanatory variables is provided in Panel A of Table II.

	<i>(p-values in parantheses)</i>			
	(1)	(2)	(3)	(4)
	Bid	Bid	Amount Bid	Amount Bid
Amount requested (\$,000)	0.0001* (0.088)	0.0001 (0.209)	5.8313*** (0.000)	7.0140*** (0.000)
Borrower maximum rate	0.0152*** (0.004)	0.0144*** (0.006)	107.4501*** (0.000)	135.4645*** (0.000)
Close when funded (dummy)	0.0006 (0.751)	0.0003 (0.869)	-23.4438*** (0.000)	-8.8290*** (0.005)
Verified bank account (dummy)	0.0022*** (0.002)	0.0023*** (0.001)	27.1683*** (0.000)	21.4177*** (0.000)
Homeowner Dummy	-0.0002 (0.625)	-0.0000 (0.950)	-42.1637*** (0.000)	-55.4804*** (0.000)
Credit Grade AA	0.0050** (0.024)	0.0049** (0.023)	-82.1221*** (0.000)	-83.1399*** (0.000)
Credit Grade A	0.0016 (0.259)	0.0010 (0.491)	-54.4422*** (0.000)	-19.4661*** (0.000)
Credit Grade B	0.0011 (0.274)	0.0008 (0.441)	-87.2114*** (0.000)	-66.3885*** (0.000)
Credit Grade C	0.0013 (0.145)	0.0010 (0.242)	-21.4310*** (0.000)	-11.8776*** (0.000)
Credit Grade D	0.0003 (0.696)	0.0002 (0.780)	66.1770*** (0.000)	77.7484*** (0.000)
Credit Grade HR	-0.0009 (0.165)	-0.0009 (0.191)	70.8258*** (0.000)	69.8096*** (0.000)
# of listings before the current one	-0.0005** (0.031)	-0.0004** (0.033)	8.4288*** (0.000)	6.5894*** (0.000)
Length of employment status	0.0000 (0.598)	0.0000 (0.421)	-0.8794*** (0.000)	-1.7126*** (0.000)
Delinquency dummy	-0.0004 (0.570)	-0.0005 (0.521)	-66.7468*** (0.000)	-64.0408*** (0.000)
Public Records (last 12 mos) dummy	-0.0017** (0.012)	-0.0018** (0.012)	119.3002*** (0.000)	134.9421*** (0.000)
Public Records (last 10 yrs) dummy	-0.0011** (0.027)	-0.0013** (0.020)	13.5837*** (0.000)	25.7888*** (0.000)
Income range - \$25,000- \$49,999	0.0008 (0.218)	0.0008 (0.219)	-21.0556*** (0.000)	-16.6038*** (0.000)
Income range - \$50,000- \$74,999	0.0012 (0.164)	0.0014 (0.102)	1.9149 (0.421)	-5.6181** (0.018)
Income range - \$75,000- \$99,999	0.0011	0.0013	-34.9504***	-36.7650***

	(0.193)	(0.173)	(0.000)	(0.000)
Income range - \$100,000+	0.0022**	0.0019**	165.2714***	175.7757***
	(0.022)	(0.044)	(0.000)	(0.000)
Employed - Part time (dummy)	-0.0002	-0.0001	-51.2475***	-46.0194***
	(0.877)	(0.906)	(0.000)	(0.000)
Retired (dummy)	-0.0022	-0.0021	90.9145***	95.0057***
	(0.188)	(0.201)	(0.000)	(0.000)
Entrepreneur (dummy)	0.0011*	0.0010*	-98.0345***	-94.7406***
	(0.065)	(0.077)	(0.000)	(0.000)
Bankcard Utilization rate	0.0008	0.0010	-62.5018***	-64.4462***
	(0.209)	(0.121)	(0.000)	(0.000)
# of Credit Lines	-0.0000	-0.0001	8.0656***	9.7131***
	(0.491)	(0.329)	(0.000)	(0.000)
Revolving Credit Balance	-0.0000***	-0.0000**	-0.3388***	-0.5747***
	(0.008)	(0.032)	(0.000)	(0.000)
Months in Prosper	-0.0002***	-0.0002***	0.0543	0.0358
	(0.000)	(0.000)	(0.675)	(0.780)
overweight (dummy)	-0.0007	-0.0007	-33.2634***	-29.4891***
	(0.196)	(0.213)	(0.000)	(0.000)
Beauty	-0.0003	-0.0004	8.1905***	22.1558***
	(0.448)	(0.288)	(0.000)	(0.000)
smile (dummy)	-0.0005	-0.0007	71.5670***	86.0810***
	(0.423)	(0.294)	(0.000)	(0.000)
tie (dummy)	0.0002	-0.0002	12.8354***	43.4357***
	(0.717)	(0.821)	(0.000)	(0.000)
asian (dummy)	-0.0006	-0.0006	139.1579***	138.2637***
	(0.280)	(0.242)	(0.000)	(0.000)
black (dummy)	-0.0006	-0.0006	-42.0353***	-50.3469***
	(0.300)	(0.290)	(0.000)	(0.000)
hispanic (dummy)	0.0015	0.0021**	62.7139***	37.8186***
	(0.102)	(0.049)	(0.000)	(0.000)
Female (dummy)	0.0003	0.0004	37.6524***	31.7265***
	(0.528)	(0.401)	(0.000)	(0.000)
Young (dummy)	0.0004	0.0004	-6.0600***	-13.4951***
	(0.546)	(0.459)	(0.000)	(0.000)
Old (dummy)	0.0002	-0.0002	-30.7265***	-4.3572**
	(0.824)	(0.821)	(0.000)	(0.040)
Same city (dummy)	-0.0003	-0.0002	33.5852***	34.1184***
	(0.509)	(0.660)	(0.000)	(0.000)
Same ethnicity (dummy)	0.0027**	0.0027**	14.4080***	12.9287***
	(0.047)	(0.046)	(0.001)	(0.003)
Same religion	-0.0003	-0.0002	-1.5524	-5.3223**
	(0.640)	(0.712)	(0.485)	(0.015)
Both entrepreneurs (dummy)	0.0001	0.0001	4.8329***	6.3427***
	(0.762)	(0.789)	(0.002)	(0.000)
Same group (dummy)	0.0007*	0.0007*	-15.2970***	-16.6952***
	(0.071)	(0.074)	(0.000)	(0.000)
Same gender (dummy)	-0.0005	-0.0005	-1.8578	-0.6766
	(0.665)	(0.658)	(0.704)	(0.889)
Trustworthiness		-0.0004		25.0324***

		(0.494)		(0.000)
Creditworthiness		0.0011*		-81.0338***
		(0.077)		(0.000)
Constant			-60.6175***	90.3634***
			(0.000)	(0.000)
Context dummies	NO	NO	NO	NO
Observations	95905	95905	95905	95905
Pseudo R ²	0.0512	0.0522	0.032	0.0338

Table VIII

Effect of Similarity between Borrowers and Lenders on the Likelihood of Getting a Loan, the Fraction of the Loan Request that Gets Funded, and the Interest Rate

This Table repeats the regressions in Columns 3 and 5 of Tables IV, V, and VI, respectively. The sample analyzed in columns 1 to 4 consists of all the listings in the dataset, while the sample for columns 5 and 6 is restricted to the listings that got funds and became a loan. The maximum borrower rate is not included in the interest rate regressions because it should be a priori unrelated to the interest rate paid on completed loans, while the verified bank account dummy is not included because more than 99% of the listings that got funding have a verified bank account. Same city (proportion) is the fraction of lenders that live in the same city as the borrower. The other proportion variables are defined in a similar fashion. A definition of the other explanatory variables is provided in Panel A of Table II.

(p-values in parantheses)

	Pr(Loan Funded)		Percent Funded		Interest Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Amount requested (\$,000)	-0.0021*** (0.000)	-0.0018*** (0.000)	-0.0174*** (0.000)	-0.0173*** (0.000)	0.0026*** (0.000)	0.0027*** (0.000)
Borrower maximum rate	0.1971*** (0.000)	0.1719*** (0.000)	2.5023*** (0.000)	2.5173*** (0.000)		
Close when funded (dummy)	-0.0066* (0.062)	-0.0062** (0.048)	-0.0608 (0.145)	-0.0603 (0.148)	0.0541*** (0.000)	0.0519*** (0.000)
Verified bank account (dummy)	0.0517*** (0.000)	0.0528*** (0.000)	0.2820*** (0.000)	0.2842*** (0.000)		
Homeowner Dummy	0.0079** (0.030)	0.0072** (0.030)	0.0696* (0.055)	0.0727** (0.046)	-0.0007 (0.878)	-0.0008 (0.867)
Credit Grade AA	0.7357*** (0.000)	0.6942*** (0.000)	0.8850*** (0.000)	0.8830*** (0.000)	-0.1390*** (0.000)	-0.1418*** (0.000)
Credit Grade A	0.1649*** (0.003)	0.1405*** (0.004)	0.3096*** (0.001)	0.3115*** (0.001)	-0.1234*** (0.000)	-0.1231*** (0.000)
Credit Grade B	0.2325*** (0.000)	0.1883*** (0.001)	0.4925*** (0.000)	0.4890*** (0.000)	-0.0886*** (0.000)	-0.0899*** (0.000)
Credit Grade C	0.0551*** (0.003)	0.0433*** (0.005)	0.2619*** (0.000)	0.2650*** (0.000)	-0.0775*** (0.000)	-0.0773*** (0.000)
Credit Grade D	0.0140* (0.076)	0.0103 (0.120)	0.1814*** (0.001)	0.1803*** (0.001)	-0.0370*** (0.000)	-0.0374*** (0.000)
Credit Grade HR	-0.0088** (0.010)	-0.0077** (0.013)	-0.0716 (0.101)	-0.0674 (0.122)	0.0011 (0.853)	0.0018 (0.764)
# of listings before the current one	-0.0004 (0.405)	-0.0004 (0.399)	-0.0153** (0.038)	-0.0150** (0.041)	-0.0007 (0.590)	-0.0008 (0.504)
Length of employment status	0.0003 (0.275)	0.0002 (0.256)	-0.0030 (0.320)	-0.0028 (0.349)	-0.0004 (0.364)	-0.0005 (0.263)
Delinquency dummy	-0.0090** (0.026)	-0.0076** (0.030)	-0.0430 (0.288)	-0.0439 (0.277)	0.0072 (0.165)	0.0072 (0.161)
Public Records (last 12 mos)	0.0011 (0.869)	0.0008 (0.888)	0.0528 (0.437)	0.0552 (0.415)	0.0271** (0.013)	0.0271** (0.013)
Public Records (last 10 yrs)	-0.0059** (0.022)	-0.0050** (0.032)	-0.0658* (0.063)	-0.0626* (0.077)	0.0003 (0.947)	0.0007 (0.895)
Income range - \$25,000- \$49,999	0.0216*** (0.000)	0.0199*** (0.000)	0.1372*** (0.002)	0.1393*** (0.001)	-0.0162** (0.024)	-0.0153** (0.033)
Income range - \$50,000- \$74,999	0.0481*** (0.001)	0.0465*** (0.000)	0.1402*** (0.010)	0.1435*** (0.008)	-0.0207** (0.010)	-0.0190** (0.021)
Income range - \$75,000- \$99,999	0.0230	0.0172	0.2245***	0.2143***	-0.0132	-0.0120

	(0.132)	(0.184)	(0.005)	(0.007)	(0.227)	(0.268)
Income range - \$100,000+	0.1554***	0.1355***	0.1975**	0.1958**	-0.0257***	-0.0238**
	(0.000)	(0.001)	(0.021)	(0.022)	(0.010)	(0.017)
Unemployed (dummy)	0.1203*	0.0961*	0.1278	0.1283	-0.0044	0.0074
	(0.053)	(0.056)	(0.250)	(0.247)	(0.867)	(0.796)
Employed - Part time (dummy)	0.0104	0.0106	0.0407	0.0497	-0.0339***	-0.0316**
	(0.315)	(0.284)	(0.607)	(0.529)	(0.006)	(0.013)
Retired (dummy)	0.1018**	0.0806**	0.2584*	0.2572*	-0.0266	-0.0244
	(0.012)	(0.021)	(0.077)	(0.079)	(0.153)	(0.189)
Entrepreneur (dummy)	-0.0056	-0.0050	0.0616*	0.0614*	-0.0027	-0.0024
	(0.119)	(0.122)	(0.093)	(0.093)	(0.815)	(0.834)
Bankcard Utilization rate	0.0033	0.0025	0.0354	0.0305	0.0008	-0.0008
	(0.347)	(0.434)	(0.361)	(0.431)	(0.901)	(0.904)
# of Credit Lines	0.0002	0.0002	0.0013	0.0010	0.0002	0.0003
	(0.417)	(0.423)	(0.686)	(0.763)	(0.553)	(0.546)
Revolving Credit Balance	-0.0001*	-0.0001*	-0.0005	-0.0006	-0.0002	-0.0001
	(0.065)	(0.082)	(0.431)	(0.387)	(0.448)	(0.546)
Months in Prosper	0.0006	0.0006	0.0122*	0.0127*	0.0014*	0.0014*
	(0.252)	(0.205)	(0.085)	(0.074)	(0.068)	(0.074)
overweight (dummy)	0.0169***	0.0158***	0.0854**	0.0866**	-0.0062	-0.0053
	(0.002)	(0.002)	(0.040)	(0.038)	(0.232)	(0.309)
Beauty	0.0044***	0.0038**	0.0380*	0.0343	-0.0088***	-0.0073**
	(0.008)	(0.018)	(0.079)	(0.145)	(0.002)	(0.013)
smile (dummy)	-0.0043	-0.0039	-0.0553	-0.0553	0.0058	0.0078
	(0.328)	(0.330)	(0.169)	(0.178)	(0.302)	(0.177)
tie (dummy)	0.0045	0.0027	0.0552	0.0384	-0.0026	-0.0005
	(0.342)	(0.514)	(0.282)	(0.466)	(0.651)	(0.933)
asian (dummy)	0.0040	0.0039	-0.0502	-0.0499	-0.0105	-0.0113
	(0.463)	(0.439)	(0.346)	(0.349)	(0.149)	(0.122)
black (dummy)	0.0007	0.0006	-0.0025	0.0020	0.0095	0.0093
	(0.863)	(0.869)	(0.951)	(0.960)	(0.145)	(0.152)
hispanic (dummy)	0.0034	0.0032	0.0291	0.0313	-0.0017	-0.0025
	(0.472)	(0.459)	(0.527)	(0.495)	(0.827)	(0.743)
Female (dummy)	0.0063**	0.0062**	0.0444	0.0548	0.0040	0.0040
	(0.026)	(0.014)	(0.228)	(0.141)	(0.494)	(0.491)
Young (dummy)	-0.0079*	-0.0075*	-0.0164	-0.0142	-0.0028	-0.0038
	(0.064)	(0.053)	(0.658)	(0.703)	(0.602)	(0.483)
Old (dummy)	-0.0038	-0.0037*	-0.0023	-0.0090	0.0047	0.0055
	(0.133)	(0.093)	(0.959)	(0.845)	(0.458)	(0.391)
Same city (proportion)	-0.0101**	-0.0091**	0.1070**	0.1015**	0.0006	0.0004
	(0.017)	(0.017)	(0.013)	(0.018)	(0.936)	(0.963)
Same ethnicity (proportion)	0.0602***	0.0541***	1.2553***	1.2445***	-0.0317	-0.0319
	(0.000)	(0.000)	(0.000)	(0.000)	(0.137)	(0.135)
Same religion (proportion)	-0.0366***	-0.0328***	-0.6427***	-0.6399***	0.0198	0.0259
	(0.002)	(0.003)	(0.000)	(0.000)	(0.451)	(0.338)
Both Entrepreneurs (proportion)	0.0336***	0.0296***	0.2935**	0.2853**	-0.0053	-0.0029
	(0.001)	(0.001)	(0.027)	(0.031)	(0.868)	(0.927)
Same group (proportion)	0.0400***	0.0372***	0.8485***	0.8523***	0.0015	-0.0068
	(0.000)	(0.000)	(0.000)	(0.000)	(0.937)	(0.741)
Same gender (proportion)	0.0603***	0.0537***	1.2147***	1.1862***	0.0109	0.0098

	(0.000)	(0.000)	(0.000)	(0.000)	(0.647)	(0.680)
Trustworthiness		-0.0047		-0.0683		-0.0027
		(0.103)		(0.150)		(0.615)
Creditworthiness		0.0043		0.0733*		-0.0044
		(0.121)		(0.086)		(0.424)
Constant			-0.9209***	-0.9325***	0.2101***	0.2352***
			(0.000)	(0.000)	(0.000)	(0.000)
Context dummies	YES	YES	YES	YES	YES	YES
State f.e.	NO	NO	NO	NO	YES	YES
Observations	772	772	772	772	172	172
Pseudo R ²	0.6727	0.6729	0.5371	0.5391	0.5167	0.5189

Note: standard errors are clustered at the borrower level

Table IX Panel A
Loan Performance Analysis

This Table contains the coefficients from a Cox proportional hazard model estimating the probability of delinquency as a function of the borrower's hard financial information, personal characteristics, context, and listing features. The sample consists of all the listings that got full funding and became a loan. The way to interpret the coefficients is that any explanatory variable increases the delinquency probability by $e^{\text{coeff}}-1$ percent. A definition of the explanatory variables is provided in Panel A of Table II.

	<i>(p-values in parantheses)</i>				
	(1)	(2)	(3)	(4)	(5)
Amount requested (\$,000)	0.0166 (0.588)	0.0160 (0.604)	0.2175*** (0.005)	0.2888** (0.015)	0.2429*** (0.004)
Borrower maximum rate	3.9170 (0.213)	4.1532 (0.203)	10.2776 (0.444)	8.6295 (0.644)	8.2451 (0.602)
Close when funded (dummy)	0.7857** (0.049)	0.8359** (0.045)	3.3424*** (0.008)	5.5745** (0.036)	3.3006*** (0.006)
Homeowner Dummy	0.3846 (0.259)	0.3817 (0.260)	0.2929 (0.821)	-0.0359 (0.982)	0.2262 (0.864)
Credit Grade AA	-37.6756*** (0.000)	-33.6888*** (0.000)	-43.8501 (0.999)	-43.7373 (0.999)	-44.6319 (0.999)
Credit Grade A	-0.7834 (0.540)	-0.8048 (0.529)	0.0563 (0.977)	0.3030 (0.889)	-0.3340 (0.844)
Credit Grade B	-0.4268 (0.570)	-0.4794 (0.535)	0.1502 (0.912)	0.9880 (0.522)	-0.2759 (0.820)
Credit Grade C	-0.7571 (0.294)	-0.7568 (0.288)	-0.6780 (0.748)	0.0093 (0.997)	-0.8725 (0.651)
Credit Grade D	0.2553 (0.580)	0.2462 (0.596)	-1.1638 (0.280)	-0.6178 (0.692)	-1.4666* (0.095)
Credit Grade HR	0.8488** (0.042)	0.8258** (0.049)	3.4801* (0.065)	4.5421 (0.152)	3.5058* (0.056)
# of listings before the current one	0.1258* (0.068)	0.1210* (0.080)	0.1651 (0.338)	-0.0631 (0.696)	0.1208 (0.487)
Length of employment status	0.0091 (0.668)	0.0117 (0.583)	-0.0632 (0.715)	-0.0756 (0.676)	-0.0715 (0.700)
Delinquency dummy	0.1887 (0.600)	0.1488 (0.680)	0.6129 (0.540)	1.4406 (0.243)	0.5284 (0.581)
Public Records (last 12 mos)	0.8836 (0.106)	0.9040* (0.099)	1.9404 (0.311)	2.1103 (0.217)	1.9550 (0.344)
Public Records (last 10 yrs)	-0.2239 (0.488)	-0.2233 (0.489)	0.1262 (0.910)	0.3568 (0.756)	0.0824 (0.942)
Income range - \$25,000- \$49,999	-0.2284 (0.602)	-0.2285 (0.602)	-1.3556 (0.166)	-1.8420 (0.108)	-1.4966 (0.124)
Income range - \$50,000- \$74,999	-0.1026 (0.826)	-0.1037 (0.825)	-0.6945 (0.631)	-1.6092 (0.405)	-0.8399 (0.597)
Income range - \$75,000- \$99,999	-38.2692*** (0.000)	-34.2837*** (0.000)	-49.0770 (0.999)	-49.0361 (0.999)	-49.2845 (0.999)
Income range - \$100,000+	-0.9871 (0.234)	-1.0040 (0.225)	-2.9401 (0.197)	-3.3021 (0.101)	-3.3614* (0.091)
Unemployed (dummy)	-0.8475 (0.482)	-0.8665 (0.476)	-7.8195 (0.999)	-11.2228 (0.999)	-8.7627 (0.999)
Employed - Part time (dummy)	-0.3331	-0.3388	-47.0365	-47.6768	-47.1838

	(0.752)	(0.752)	(0.999)	(0.999)	(0.999)
Retired (dummy)	-0.6760	-0.7279	-42.5182	-42.1176	-42.6362
	(0.497)	(0.476)	(0.999)	(0.999)	(0.999)
Entrepreneur (dummy)	0.2527	0.2501	-0.4681	-0.8827*	-0.4700
	(0.435)	(0.437)	(0.340)	(0.098)	(0.397)
Bankcard Utilization rate	0.4397	0.4583	-1.1990	-0.2892	-1.2158
	(0.301)	(0.272)	(0.558)	(0.888)	(0.578)
# of Credit Lines	-0.0429	-0.0424	0.0771	0.1318	0.0667
	(0.251)	(0.264)	(0.559)	(0.451)	(0.633)
Revolving Credit Balance	0.0123	0.0130	0.0084	0.0178	0.0065
	(0.374)	(0.347)	(0.839)	(0.664)	(0.879)
Picture (dummy)		0.1931			
		(0.507)			
Months in Prosper			-0.0640	-0.0496	-0.0518
			(0.714)	(0.855)	(0.795)
overweight (dummy)			1.0349	0.4179	1.0832
			(0.333)	(0.753)	(0.260)
Beauty			1.4683**	3.2387**	1.4646**
			(0.038)	(0.021)	(0.030)
smile (dummy)			0.2391	1.1475	0.3796
			(0.813)	(0.121)	(0.699)
tie (dummy)			0.9549	0.5100	0.7865
			(0.458)	(0.751)	(0.597)
asian (dummy)			1.5170	2.6495	1.6552
			(0.335)	(0.229)	(0.346)
black (dummy)			-0.6384	0.0891	-0.6375
			(0.704)	(0.964)	(0.690)
hispanic (dummy)			0.1089	0.2856	0.2600
			(0.919)	(0.850)	(0.836)
Female (dummy)			-1.0516	10.2273*	-0.8801
			(0.379)	(0.072)	(0.495)
Young (dummy)			-0.0908	-0.1172	-0.2720
			(0.926)	(0.922)	(0.802)
Old (dummy)			-0.7460	-0.9245	-0.5382
			(0.490)	(0.439)	(0.647)
Interaction Beauty*Female				-2.8504*	
				(0.052)	
Trustworthiness					-0.7127
					(0.539)
Creditworthiness					0.3150
					(0.792)
Location dummies	YES	YES	YES	YES	YES
Observations	423	161	161	161	161
Log-pseudolikelihood	-313.44628	-88.757929	-87.288837	-84.948124	-86.37101

Table IX Panel B
Back of the Envelope Calculations on Delinquency-Adjusted Returns of Borrowers with Various Personal Characteristics

This table reports the breakdown by credit grade of the average delinquency and default rates for various personal characteristics of the borrowers. The first column, labeled “Overall” reports for comparison the estimated default rates for the entire sample of loans, while each of the following columns applies to the average borrower in the credit category the likelihood of delinquency estimated in Panel A of Table IX. A loan is considered delinquent if it is one or more months late. Method 2 makes the very conservative assumption that all delinquencies will turn into defaults, while Method 3 attempts to convert delinquencies into default rates using the historical ratio of delinquency rates to default rates calculated from Table I, and adjusting the delinquency rate in the sample by the historical ratio of defaults to delinquencies in each credit category. These calculations are indicative and hold exactly only if personal characteristics affect the probability of delinquency in a similar way across credit scores. Also, these calculations do not account for the fact that personal characteristics are not evenly distributed across the credit categories.

Credit Grade	Overall	Black Borrower	Hispanic Borrower	Asian Borrower	Beautiful Borrower	Creditworthy Borrower	Trustworthy Borrower
Method 2							
AA	9.58%	10.98%	9.58%	9.58%	4.57%	9.58%	9.58%
A	4.06%	5.36%	4.06%	4.06%	-26.01%	4.06%	4.06%
B	5.73%	7.03%	5.73%	5.73%	-25.64%	5.73%	5.73%
C	5.84%	7.12%	5.84%	5.84%	-32.87%	5.84%	5.84%
D	-7.81%	-6.73%	-7.81%	-7.81%	-102.75%	-7.81%	-7.81%
E	-9.82%	-8.79%	-9.82%	-9.82%	-119.98%	-9.82%	-9.82%
HR	-18.40%	-17.47%	-18.40%	-18.40%	-158.42%	-18.40%	-18.40%
Method 3							
AA	10.81%	12.22%	10.81%	10.81%	9.87%	10.81%	10.81%
A	10.04%	11.42%	10.04%	10.04%	-0.25%	10.04%	10.04%
B	12.88%	14.26%	12.88%	12.88%	5.08%	12.88%	12.88%
C	15.74%	17.13%	15.74%	15.74%	9.70%	15.74%	15.74%
D	15.76%	17.12%	15.76%	15.76%	-1.25%	15.76%	15.76%
E	14.78%	16.09%	14.78%	14.78%	-14.06%	14.78%	14.78%
HR	9.99%	11.24%	9.99%	9.99%	-36.17%	9.99%	9.99%

Table X Panel A
Who Lends to Beautiful Borrowers?

This Table contains the coefficients from a regression of borrower's beauty on the characteristics of the lenders that funded her loan. The sample consists of a random 15% 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 explanatory variables is provided in Panel A of Table II.

	(1)	(2)	(3)	(4)	(5)
Months in Prosper	-0.0033*** (0.000)	0.0005 (0.951)	-0.0226 (0.116)	-0.0319* (0.050)	-0.0399 (0.714)
Total amount bid (/\$2,000)	0.0008*** (0.000)	0.0018** (0.036)	0.0032** (0.024)	0.0075*** (0.000)	0.0228*** (0.008)
Total amount lent (/\$2,000)	-0.0017*** (0.000)	-0.0055 (0.294)	-0.0241** (0.033)	-0.0345** (0.016)	-0.1059 (0.105)
Female (dummy)		0.1894** (0.011)	0.1657 (0.138)	-0.0231 (0.850)	-0.5986 (0.161)
Income - \$25,000- \$49,999			-0.0053 (0.972)	-0.0221 (0.890)	-1.1945* (0.055)
Income - \$50,000- \$74,999			0.1692 (0.187)	0.2543* (0.073)	1.5632 (0.109)
Income - \$75,000- \$99,999			-0.2538** (0.041)	-0.0101 (0.945)	-0.3422 (0.526)
Income - \$100,000+			-0.0953 (0.585)	-0.0905 (0.623)	
Young (dummy)				0.1263 (0.291)	2.1041** (0.011)
Old (dummy)				-0.0277 (0.851)	1.4850* (0.063)
asian (dummy)				-0.5339*** (0.000)	-3.0216*** (0.007)
black (dummy)				-0.0437 (0.872)	-0.3660 (0.687)
hispanic (dummy)				0.0356 (0.888)	
Same city (dummy)					-0.2007 (0.784)
Same ethnicity (dummy)					0.1312 (0.464)
Same religion					-0.4056 (0.309)
Both entrepreneurs (dummy)					-0.0029 (0.996)
Same group (dummy)					-0.0118 (0.940)
Same gender (dummy)					0.6521*** (0.000)
Constant	3.8036*** (0.000)	3.7563*** (0.000)	3.9978*** (0.000)	4.0325*** (0.000)	2.9183*** (0.001)
Obs.	62006	953	548	537	141
Pseudo R ²	0.0009	0.0056	0.0114	0.0239	0.1453

Table X Panel B
Who Lends to Creditworthy-Appearing Borrowers?

This Table contains the coefficients from a regression of borrower's creditworthiness ratings on the characteristics of the lenders that funded her loan. The sample consists of a random 15% 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 explanatory variables is provided in Panel A of Table II.

	(1)	(2)	(3)	(4)	(5)
Months in Prosper	0.0004 (0.525)	-0.0063 (0.229)	-0.0130 (0.113)	-0.0227** (0.018)	0.0288 (0.553)
Total amount bid (/ \$2,000)	0.0003*** (0.000)	-0.0003 (0.637)	-0.0004 (0.612)	-0.0002 (0.876)	0.0034 (0.489)
Total amount lent (/ \$2,000)	-0.0005** (0.016)	-0.0043 (0.190)	-0.0136** (0.034)	-0.0076 (0.365)	-0.0110 (0.774)
Female (dummy)		0.1068** (0.018)	0.0593 (0.385)	-0.0165 (0.825)	0.2108 (0.249)
Income - \$25,000- \$49,999			-0.1314 (0.154)	-0.2305** (0.016)	0.2601 (0.402)
Income - \$50,000- \$74,999			-0.0217 (0.765)	-0.0323 (0.692)	-0.7644 (0.114)
Income - \$75,000- \$99,999			-0.0771 (0.311)	-0.0829 (0.344)	-0.2741 (0.293)
Income - \$100,000+			-0.1114 (0.292)	-0.1814* (0.098)	
Young (dummy)				0.1966*** (0.006)	-0.4679 (0.268)
Old (dummy)				0.0019 (0.982)	-0.7766** (0.031)
asian (dummy)				-0.1168 (0.136)	0.0469 (0.930)
black (dummy)				0.4374*** (0.003)	-0.1144 (0.826)
hispanic (dummy)				-0.0135 (0.921)	
Same city (dummy)					-0.9958*** (0.000)
Same ethnicity (dummy)					0.0419 (0.640)
Same religion					0.2085 (0.354)
Both entrepreneurs (dummy)					-0.4055 (0.146)
Same group (dummy)					0.0208 (0.809)
Same gender (dummy)					0.2547*** (0.000)
Constant	3.5240*** (0.000)	3.6624*** (0.000)	3.8403*** (0.000)	3.8377*** (0.000)	3.8779*** (0.000)
Obs.	82393	1196	674	663	170
Pseudo R ²	0.0004	0.007	0.0153	0.0315	0.1683

Table X Panel C
Who Lends to Black Borrowers?

This Table contains the coefficients from a regression of the borrower being Black on the characteristics of the lenders that funded her loan. The sample consists of a random 15% 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. The same ethnicity dummy is not included in the regression because the race dummies are already capturing its effect. Some of the dummies are dropped from the regression due to multicollinearity. A definition of the other explanatory variables is provided in Panel A of Table II.

	(1)	(2)	(3)	(4)	(5)
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 (dummy)		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 (dummy)				-0.0465	0.6050***
				(0.221)	(0.005)
Old (dummy)				0.0469	0.9429***
				(0.293)	(0.001)
asian (dummy)				-0.0119	0.0100
				(0.779)	(0.863)
black (dummy)				0.1172	0.9789***
				(0.192)	(0.001)
hispanic (dummy)				-0.0493	
				(0.312)	
Same city (dummy)					-0.0540**
					(0.033)
Same religion					0.0533
					(0.263)
Both entrepreneurs (dummy)					-0.0298
					(0.138)
Same group (dummy)					-0.0267*
					(0.096)
Same gender (dummy)					-0.0238
					(0.295)
Obs.	106092	1600	895	880	279
Pseudo R ²	0.0012	0.0020	0.0602	0.0764	0.2018

Robustness: Reason for the Loan

Marginal Effects (p-values in parantheses)

	Probability of Getting a Loan		Interest Rate		Ex Post Performance	
	(4)	(5)	(4)	(5)	(4)	(5)
Amount requested (\$,000)	-0.0057*** (0.000)	-0.0056*** (0.000)	0.0007 (0.103)	0.0007 (0.103)	3.9564*** (0.000)	6.8075*** (0.000)
Borrower maximum rate	0.9472*** (0.000)	0.9316*** (0.000)	0.4763*** (0.000)	0.4773*** (0.000)	212.0605 (0.999)	241.9529 (0.999)
Close when funded (dummy)	-0.0208** (0.048)	-0.0215** (0.031)	0.0475*** (0.000)	0.0475*** (0.000)	33.1129*** (0.000)	53.7954 (0.999)
Verified bank account (dummy)	0.1268*** (0.000)	0.1244*** (0.000)	0.0360 (0.204)	-0.0181 (0.548)	-36.3670 (0.999)	-87.3065 (0.999)
Homeowner Dummy	0.0253** (0.020)	0.0257** (0.016)	0.0052 (0.235)	0.0051 (0.236)	-4.7993* (0.084)	-30.3736*** (0.000)
Credit Grade AA	0.9023*** (0.000)	0.9080*** (0.000)	-0.0624*** (0.000)	-0.0623*** (0.000)	-354.2680*** (0.000)	-340.0708*** (0.000)
Credit Grade A	0.6768*** (0.000)	0.6789*** (0.000)	-0.0670*** (0.000)	-0.0670*** (0.000)	26.8708 (0.999)	16.5684 (0.999)
Credit Grade B	0.6984*** (0.000)	0.6927*** (0.000)	-0.0491*** (0.000)	-0.0490*** (0.000)	-26.6536 (0.999)	-107.4103 (0.999)
Credit Grade C	0.3413*** (0.000)	0.3403*** (0.000)	-0.0525*** (0.000)	-0.0525*** (0.000)	-19.9242 (0.999)	-27.1378 (0.999)
Credit Grade D	0.1067*** (0.000)	0.1124*** (0.000)	-0.0249*** (0.000)	-0.0249*** (0.000)	6.0289 (0.999)	-57.1955*** (0.000)
Credit Grade HR	-0.0394*** (0.000)	-0.0392*** (0.000)	-0.0045 (0.380)	-0.0045 (0.382)	176.9623*** (0.000)	129.4020*** (0.000)
# of listings before the current one	-0.0042** (0.023)	-0.0040** (0.029)	0.0007 (0.529)	0.0007 (0.537)	6.2496*** (0.000)	0.9836 (0.157)
Length of employment status	-0.0003 (0.712)	-0.0003 (0.707)	0.0000 (0.921)	0.0000 (0.924)	0.8579*** (0.000)	1.4561*** (0.000)
Delinquency dummy	-0.0186* (0.073)	-0.0181* (0.071)	0.0072* (0.094)	0.0072* (0.095)	37.9895*** (0.000)	41.2804*** (0.000)
Public Records (last 12 mos) dummy	0.0028 (0.860)	0.0037 (0.816)	0.0256*** (0.005)	0.0255*** (0.005)	20.2479*** (0.000)	22.9471*** (0.000)
Public Records (last 10 yrs) dummy	-0.0127 (0.103)	-0.0137* (0.064)	-0.0062 (0.148)	-0.0062 (0.155)	-16.1396*** (0.000)	2.3153 (0.145)
Income range - \$25,000- \$49,999	0.0391*** (0.005)	0.0395*** (0.004)	-0.0034 (0.581)	-0.0034 (0.585)	-75.2305*** (0.000)	-53.5542 (0.999)
Income range - \$50,000- \$74,999	0.0666*** (0.006)	0.0667*** (0.005)	-0.0070 (0.311)	-0.0069 (0.314)	29.6049*** (0.000)	12.4012*** (0.000)
Income range - \$75,000- \$99,999	0.0809** (0.036)	0.0858** (0.028)	-0.0022 (0.824)	-0.0022 (0.821)	-75.8938*** (0.000)	-222.6266*** (0.000)
Income range - \$100,000+	0.2724*** (0.000)	0.2631*** (0.000)	-0.0013 (0.885)	-0.0012 (0.897)	-1.0366 (0.999)	-7.0111 (0.999)
Unemployed (dummy)	0.2198** (0.044)	0.2156** (0.043)	0.0288 (0.201)	0.0289 (0.201)	49.9155*** (0.000)	-197.0455*** (0.000)
Employed - Part time (dummy)	0.0215 (0.459)	0.0219 (0.449)	-0.0243** (0.025)	-0.0243** (0.026)	-153.6403*** (0.000)	-79.5009*** (0.000)
Retired (dummy)	0.1341** (0.039)	0.1263** (0.048)	-0.0122 (0.488)	-0.0121 (0.489)	111.9018*** (0.000)	65.1420*** (0.000)

Entrepreneur (dummy)	0.0096 (0.230)	0.0090 (0.247)	0.0082** (0.034)	0.0082** (0.034)	-19.5041*** (0.000)	-50.0641 (0.999)
Bankcard Utilization rate	0.0076 (0.470)	0.0076 (0.464)	-0.0043 (0.425)	-0.0043 (0.423)	-71.6780*** (0.000)	0.3917 (0.865)
# of Credit Lines	0.0003 (0.718)	0.0002 (0.782)	0.0005 (0.131)	0.0005 (0.130)	4.2437*** (0.000)	5.6122*** (0.000)
Revolving Credit Balance	-0.0006*** (0.004)	-0.0005*** (0.005)	-0.0004** (0.019)	-0.0004** (0.020)	1.5795*** (0.000)	1.6720*** (0.000)
Months in Prosper	0.0011 (0.376)	0.0013 (0.306)	0.0002 (0.735)	0.0002 (0.742)	-3.8747*** (0.000)	-2.2699 (0.999)
overweight (dummy)	0.0380*** (0.002)	0.0379*** (0.002)	0.0010 (0.812)	0.0010 (0.822)	21.6002*** (0.000)	10.3990 (0.999)
Beauty	0.0132*** (0.010)	0.0060 (0.402)	-0.0054** (0.026)	-0.0052* (0.099)	41.5229*** (0.000)	53.5356*** (0.000)
smile (dummy)	-0.0136 (0.206)	-0.0137 (0.199)	0.0079* (0.097)	0.0079* (0.098)	73.2055*** (0.000)	45.1988*** (0.000)
tie (dummy)	-0.0006 (0.952)	-0.0009 (0.929)	0.0012 (0.802)	0.0012 (0.803)	58.7936*** (0.000)	43.4261*** (0.000)
asian (dummy)	-0.0068 (0.547)	-0.0077 (0.482)	-0.0072 (0.275)	-0.0071 (0.284)	-67.1923*** (0.000)	-11.4254 (0.999)
black (dummy)	-0.0070 (0.428)	-0.0058 (0.514)	0.0089* (0.078)	0.0089* (0.079)	-50.6518*** (0.000)	-26.1207*** (0.000)
hispanic (dummy)	-0.0056 (0.637)	-0.0057 (0.618)	-0.0073 (0.270)	-0.0072 (0.273)	31.9321*** (0.000)	36.4456 (0.999)
Female (dummy)	0.0123 (0.126)	-0.0459 (0.305)	-0.0027 (0.476)	-0.0015 (0.929)	-51.4454*** (0.000)	113.0135 (0.999)
Young (dummy)	-0.0107 (0.281)	-0.0113 (0.245)	-0.0018 (0.688)	-0.0018 (0.690)	-8.3197*** (0.000)	5.1263*** (0.000)
Old (dummy)	-0.0041 (0.713)	-0.0039 (0.721)	0.0081 (0.155)	0.0080 (0.166)	-77.3248*** (0.000)	-30.6251*** (0.000)
Interaction Beauty*Female		0.0127 (0.169)		-0.0003 (0.941)		-36.5494*** (0.000)
Constant			0.0409 (0.223)	0.0402 (0.250)		
Context dummies	YES	YES	YES	YES	YES	YES
Reason dummies	YES	YES	YES	YES	YES	YES
State dummies	NO	NO	YES	YES	NO	NO
Observations	766	766	172	172	161	161
Pseudo R ²	0.5249	0.5272	0.7741	0.7742		

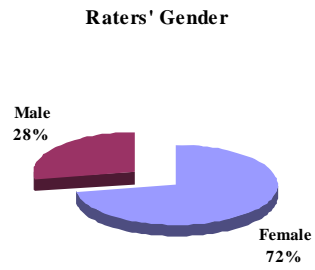
First Impressions

	Creditworthy	Trustworthy
Asian (dummy)	-0.0366 (0.540)	-0.0699 (0.198)
Black (dummy)	-0.1715*** (0.000)	-0.0843** (0.033)
Hispanic (dummy)	-0.1106** (0.032)	-0.0973** (0.038)
Female (dummy)	-0.1111*** (0.002)	0.0737** (0.027)
Young (dummy)	-0.0758* (0.054)	-0.0735** (0.040)
Old (dummy)	0.1136** (0.029)	0.0104 (0.826)
overweight (dummy)	0.0966** (0.031)	0.1225*** (0.003)
Beauty	0.2778*** (0.000)	0.2222*** (0.000)
smile (dummy)	0.2367*** (0.000)	0.2407*** (0.000)
tie (dummy)	0.3392*** (0.000)	0.1460*** (0.004)
church	-0.1936** (0.040)	-0.2551*** (0.003)
Outdoor	0.0321 (0.775)	0.4415*** (0.000)
Sports	-0.2755*** (0.001)	-0.0482 (0.516)
Wedding	0.3253*** (0.010)	0.2293** (0.045)
Constant	3.1482*** (0.000)	3.4154*** (0.000)
Other Context Dummies	YES	YES
Observations	787	787
Adj. R ²	0.280	0.252

Loan Portfolios of Black and White Lenders

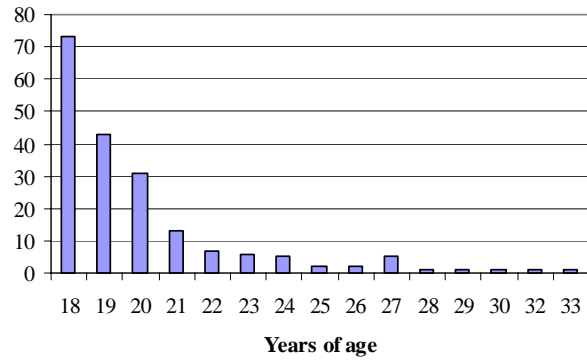
	Interest Rate charged		Delinquency-adjusted return		Portfolio Weights	
	Black lenders	White lenders	Black lenders	White lenders	Black lenders	White lenders
Portfolio of Black borrowers	15.56%	20.33%	15.56%	18.77%	25.00%	12.28%
Portfolio of White borrowers	15.38%	18.28%	8.72%	15.64%	75.00%	87.62%
Total	15.43%	18.50%	0.12%	16.02%	100.00%	16.02%

Appendix Fig I*
Rater's Gender



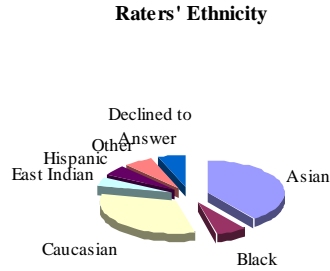
Appendix Fig II

Raters' Age



* In total, 205 NYU students participated in the rating procedure. Most of them are undergraduates.

**Appendix Fig III
Raters' Ethnicity**



Appendix Table I – Context Dummies

Context Dummy	Freq.	Percent	Cum.
car	139	2.86	2.86
church	9	0.18	3.04
graduation	37	0.76	3.8
home	1,056	21.71	25.51
hospital	8	0.16	25.67
indoor	1,684	34.61	60.29
military	89	1.83	62.12
outdoor	1,306	26.84	88.96
party	125	2.57	91.53
sport	82	1.69	93.22
vacation	33	0.68	93.9
wedding	80	1.64	95.54
work	217	4.46	100
Family w. children	914	15.82	
Total	4,865	100	

Appendix Table II – Prosper Groups

Group	Freq.	Percent	Cum.
Art & Culture	8	0.12	0.12
Business	599	8.72	8.84
Business & Professional/Automotive	16	0.23	9.07
Business & Professional/Business & Finance	3,182	46.33	55.4
Business & Professional/Business Services	21	0.31	55.71
Business & Professional/Construction & Maintenance	19	0.28	55.98
Business & Professional/Consumer Goods	13	0.19	56.17
Business & Professional/Engineering	150	2.18	58.36
Business & Professional/Hospitality/Event Types	2	0.03	58.39
Business & Professional/Legal	2	0.03	58.42
Business & Professional/Other	781	11.37	69.79
Business & Professional/Real Estate	289	4.21	74
Business & Professional/Technology	34	0.5	74.49
Business & Professional/Telecommunications	9	0.13	74.62
Business & Professional/Transportation & Logistics	35	0.51	75.13
Civic & Political	103	1.5	76.63
Civic & Political/Public Safety	9	0.13	76.76
Education	219	3.19	79.95
Families	563	8.2	88.15
Gay & Lesbian	37	0.54	88.69
Hobbies & Clubs	15	0.22	88.91
Hobbies & Clubs/Investing	30	0.44	89.34
Home Owners	1	0.01	89.36
Military	174	2.53	91.89
Non-Profit	18	0.26	92.15
Other	223	3.25	95.4
People & Lifestyle	12	0.17	95.57
Religion & Spirituality	219	3.19	98.76
Science & Health	14	0.2	98.97
Sports & Recreation	71	1.03	100
Total	6,868	100	

Source: Prosper website hierarchies and author's aggregation