Trust and Credit

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Abstract

This study considers the impact of trustworthiness on financial markets at the individual transaction level. We employ a natural experiment using the peer-to-peer lending site, Prosper.com. We find that borrowers who are perceived as less trustworthy are economically and significantly less likely to have their loan requests filled, even controlling for physical attractiveness, detailed demographic information, credit profile, income, education, employment and loan-specific information. Indeed, a borrower perceived as trustworthy can promise an interest rate 182 basis points lower than a less trustworthy borrower and have the same likelihood of being funded. These results suggest that agents' perceptions of trustworthiness are important, even in relatively information-rich environments.

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1 Introduction

Economists have long recognized that trust could, in principal, play an important role in markets and encourage economic activity.[1] In this context, trust is defined as an agent's prior probability that a potential counterparty is willing to perform her contractual obligations. The mechanism linking trust to economic activity in the literature is that individuals' opinions about potential counterparties or the financial system in general impacts their willingness to engage in transactions or other cooperative endeavors. Researchers have used this mechanism to advance a number of hypotheses about aggregate effects of this behavior on economic performance, including correlations between the average degree of trust in an individual country and its rate of growth, the quality of its institutions and the degree of individual participation in the stock market. However, as Guiso, Sapienza and Zingales (2006) note, it is difficult to assess the direction of causality when analyzing the correlation between levels of trust and various economic outcomes. Perhaps as a result of this point, as Solow (1995) notes, some economists doubt the impact of trust on economic outcomes.

This paper aims to test the hypothesis that when transacting people use their assessments of potential counterparties' trustworthiness in an economically significant manner. This is a fundamental question because the mechanism suggested in the literature for how trust might cause increased economic activity requires that agents act on their views of their opposite numbers' trustworthiness when deciding to contract. Moreover, while it is perhaps obvious that trust would matter for transactions in the absence of information, it is not

[1] See for instance Arrow (1972), Zak and Knack (2001), Carlin, Dorobantu and Viswanathan (2008), Guiso, Sapienza and Zingales (2008), Greenspan (2008), and Aghion, Algan, Cahuc and Shleifer (2009).

obvious that trust should matter at all in a modern society with cheap and widely available information about both potential counterparties and the system as whole. For instance, it is not obvious that lenders in possession of a potential borrower's credit rating and other financial information would have any need to put much weight on their priors about the potential borrower's trustworthiness when contemplating making a loan.

The advent of peer-to-peer lending sites such as Prosper.com provide a natural environment in which to consider this question. Prosper.com conducts auctions where lenders can bid on potential borrowers' loan requests, called listings. Prosper.com provides the lenders with detailed information about potential borrowers, including their photographs. Lenders can use this information, including the photographs, when deciding whether or not to bid in a particular auction. This setting is particularly advantageous for studying the effects of trustworthiness for at least three reasons. First, the fact that borrowers submit photographs for potential lenders to review allows us to propose novel proxies for perceived trustworthiness based on the appearance of the individuals in the photographs. In most situations, researchers do not have such direct proxies for the perceived trustworthiness of transaction participants. Instead, researchers typically only have access to financial information related to the borrowers' creditworthiness, such as a credit rating. This is problematic in this context because creditworthiness reflects both potential borrowers' willingness and ability to fulfill their obligations. Trustworthiness, however, reflects only the borrowers' willingness to perform their contractual obligations. Without a proxy for trustworthiness per se, researchers cannot distinguish the effects of variation in perceived trustworthiness and variation in the borrowers' ability to perform their obligations. We use the photographs available on Prosper.com to construct measures of perceived trustworthiness from the borrowers' appearance alone. As such our measures are minimally tainted by—if not completely free of—assessments of the borrowers' ability to repay the loan. Furthermore, our measures are exogenous to the transaction because they are constructed based on the observations of third parties who are unable to affect the outcome of the transaction. As a consequence, our results do not suffer from concerns about reverse causality.

Second, while techniques in experimental economics (such as the trust game) could be employed as an alternative means of addressing our question, our approach has the advantage of involving data from a real market. As Levitt and List (2006) point out, experimental methods suffer from a number of problems that do not affect data from real markets, including the tendency of subjects to alter their behavior due to the presence of researchers observing their behavior, the fact that experiments typically involve small sums of money, and the fact that the experiments do not mimic the incentives that agents have in real-world situations. Our data, on the other hand, come from a real market where the participants' behavior are not affected by the presence of researchers watching them and where the amount of money at stake is significant to them.

Third, in most situations, researchers have no access to transactions in which the parties decided not to contract. Without access to transactions that were not consummated, it is impossible for researchers to analyze whether agents are more likely to contract with those they trust or deem trustworthy. On Prosper.com we have access to all requests for loans, including the unsuccessful ones.

Our approach begins by assessing the perceived trustworthiness of the individuals requesting loans, using only their photographs. To build measures of potential borrowers' trustworthiness we employ a service provided by Amazon.com, known as Mechanical Turk (MTurk). MTurk is a market platform that brings together individuals who wish to find work with individuals who have tasks to be completed. We ask 25 distinct MTurk workers to assess the trustworthiness of the person or people in each of the photographs in our database and we compute measures of trustworthiness for each listing based on their responses.[2]

Next we show that our measures of perceived trustworthiness are related to the borrower's actual trustworthiness by documenting that these measures predict both credit grades as well as the probability that the borrower will default on their loan. Interestingly, our measures of trustworthiness perform nearly as well as some traditional financial measures of creditworthiness in predicting credit grade. For instance, univariate regressions of a potential borrower's credit grade on our trustworthiness proxies result in R^2s from 1% to 1.7%, while univariate regressions of the credit grade on traditional credit profile variables (debt-to-income ratio, home ownership, length of credit history, number of delinquencies, number of credit inquiries and number of credit lines) have a median R^2 of around 3%. Perhaps more surprising is the fact that our measures of trustworthiness help forecast default even after controlling for credit grades and other financial information. This indicates that borrowers' photographs offer relevant information about trustworthiness that is not embedded in the standard model

[2]As an aside, we note that by allowing researchers to perform repetitive tasks that would be difficult to program a computer to do, MTurk has the potential to be a useful research tool. To the best of our knowledge, this is the first research paper to use MTurk.

used for credit scoring.

Finally, we show that controlling for the interest rate offered by the potential borrower, detailed financial information, and demographic information conveyed by the photographs (such as sex, ethnicity and age), perceived trustworthiness is significantly positively related to the number of bids the potential borrower's listing receives as well as the likelihood of the loan request being funded. Furthermore, we show that the effect is economically significant. A borrower deemed trustworthy receives an average of five additional bids in their auction, which is a 25% increase over the average auction. Furthermore, a borrower who appears trustworthy can promise an interest rate about 182 basis points lower than a borrower who appears less trustworthy and has the same probability of being funded. This finding is all the more significant because the environment in which borrowers and lenders operate on Prosper.com is relatively information rich, since potential lenders have access to complete financial profiles of borrowers including credit grades, income, and employment. It is likely that the trustworthiness effect we document would be even larger in environments that are more opaque and in which objective information is less plentiful. We believe this is the first study to document a trustworthiness discount.

Our paper contributes to a literature comprised of a number of studies that provide evidence that a survey-based, country level trust measure from the World Value Survey is correlated with economic activity, for instance, LaPorta, Lopez-de-Silanes, Shleifer and Vishny (1997), and Knack and Keefer (1997).[3] An alternative hypothesis for the results in

[3] These studies use a measure of trust based on the World Values Survey, which asks randomly selected people in different countries the question: "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?"

this literature is that the correlations between the World Value Survey trust measure and economic aggregates do not arise because individuals' trust with respect to other agents leads to increased economic activity, but rather because individuals in prosperous countries are simply more inclined to say that they trust others. If the correlations between economic activity and country-level trust measures arise because agents are more willing to contract with those they trust, or deem trustworthy, then we expect that in our data, lenders would be more willing to loan to potential borrowers they deem trustworthy. On the other hand, if the causality is reversed, then controlling for ability to repay the loan, there would be no relation between our trustworthiness measure and the outcome of the lending decision. Furthermore, because our work directly tests the hypothesis that individuals consider the trustworthiness of their potential counterparties when deciding to engage in financial transactions, our paper also adds to the evidence in Guiso, Sapienza and Zingales (2008). Guiso, Sapienza and Zingales (2008) present a model in which investors consider their perceived probability of being cheated when investing in risky assets. They also provide empirical evidence supporting this hypothesis by documenting a positive correlation between individual Dutch families' stock market participation and their response to the World Value Survey trust question. Finally, our approach for measuring trustworthiness is free from the problem advanced against survey-based measures. Glaeser, Laibson, Scheinkman, and Soutter (2000) raise doubts about what the question in the World Values Survey actually measures. Indeed, using surveys and variations of the trust game, they show that answers to the attitudinal survey questions are more closely related to the trustworthiness of the respondents than to their propensity to trust others. Our approach is not subject to this criticism because we employ third parties that are not involved in the actual transaction to measure the perceived trustworthiness of the potential borrowers. As a result, the behavior of the people measuring trustworthiness cannot have any effect on the actual outcome of the loan transaction.

Other recent studies have also considered peer-to-peer lending markets. Ravina (2008) shows that on Prosper.com, physically attractive borrowers are more likely to get loans and pay lower rates, but are also more likely to default. She finds no evidence that perceived trustworthiness of the borrowers affects the probability that the loan will be funded. We find that although attractiveness and perceived trustworthiness are positively correlated, there is no evidence that attractiveness is related to the probability of a loan becoming fully funded after controlling for trustworthiness and that perceived trustworthiness is a significant determinant of the probability that a loan will be funded. We attribute the differences between our findings and those in Ravina's (2008) to differences in the two samples. Since MTurk allows us to analyze a large number of photographs, we are able to consider a much larger sample of loans and listings than Ravina (2008). Thus, while Ravina (2008) uses a sample of 762 listings and 161 actual loans for her analyses using applicants' photographs, we consider a sample of 6,821 loan requests and 3,291 completed loans. Finally, while Ravina (2008) also studies how information in applicants' photographs is related to loan performance, her sample of 161 loans includes no instances of actual loan defaults, where ours contains 761 out of 3,291, or 23%.[4] Herzenstein, Andrews, Dholakia and Lyandres

[4]Due to the lack of actual defaults in her sample, Ravina (2008) classifies loans that have payments that are one month late as being in default. We note that in our sample, 906 loans fell into arrears by one month at some time before September 2008 but that of these, 16% did not go on to default as of December 2008.

(2008) also study lending on Prosper.com, focusing on identifying which variables determine whether a loan request is ultimately filled. They find that potential borrowers' financial strength is strongly related to funding success and that ethnicity and gender have a small but statistically significant impact on funding success. In contrast to our study, they do not address how perceived trustworthiness influences market outcomes.

The evidence in this paper is also related to a number of studies that consider how personal appearance relates to economic outcomes or to trust. Biddle and Hamermesh (1994) present evidence that physically attractive people earn, on average, 5% to 10% more than unattractive people. Mobius and Rosenblat (2006) also find a large "beauty premium." They find evidence that employers mistakenly consider physically attractive employees more competent. DeBruine (2002) finds that in an experimental setting, individuals were more likely to trust those who resembled them. Also in an experimental setting, Eckel and Wilson (2003) find that greater trust is expected from more physically attractive individuals. Our study adds to this literature by documenting that individuals' subjective judgments about other peoples' trustworthiness, based on appearance alone, are able to correctly predict future outcomes such as loan defaults. Thus, we provide evidence that in this context at least, there can be a rational basis for relying on subjective impressions based on personal appearance.

The remainder of the paper is organized as follows. In section 2 we discuss the construction of our dataset. In section 3, we discuss the empirical results. Section 4 presents concluding remarks.

2 Sample and data collection

2.1 Data from Prosper.com

We obtain listing and loan data from a leading peer-to-peer lending site, Prosper.com. Prosper.com has been in existence since 2006, has 830,000 registered users and has facilitated over USD 178,000,000 in loans to over 28,000 borrowers. Prosper.com facilitates auctions wherein a potential borrower places a loan request in an online listing form including the amount she wishes to borrow and the maximum rate she is willing to pay. Prosper.com loans are unsecured, three year, fixed-rate loans. Potential lenders can then place bids consisting of the minimum interest rate they are willing to accept and the amount they are willing to lend in increments of USD 50. At the end of the auction, if the amount of lending bids with a rate less than or equal to the borrower's maximum rate is greater than or equal to the borrower's requested loan amount, the bids with the lowest rates are bundled together and priced at the lowest market-clearing interest-rate bid. At this point a contract is signed and the money transferred to the borrower.

To assist potential lenders in making their decisions, Prosper.com presents detailed information about the potential borrowers including photographs voluntarily provided by borrowers. Over 60% of potential borrowers opt to provide one or more photographs. Since borrowers can provide their own photographs, the pictures do not conform to a standardized format. In principal, this could be a problem for our study, however if there are photographs in our sample that, for whatever reason, are poor representations of the borrowers in question, then our proxies are measured with noise and thus our tests would be biased against finding a trustworthiness effect. Applicants may also provide a written statement outlining their reasons for requesting a loan or their planned use for the funds.

Our data consist of 20,000 randomly-selected listings (some of which became loans) and 3,500 randomly-selected loans made on Prosper.com between May 2006 and January 2008. From these samples, we selected all listings that were not cancelled before funding took place, had a non-missing credit grade and included a photograph containing at least one human. This process resulted in a final sample of 6,821 listings, 733 of which successfully became fully-funded loans and 3,291 loans.

Each listing and loan in our sample is associated with a number of variables that are either provided by Prosper.com or that we compute using non-photographic information in the potential borrowers' listings. These variables fall into three groups: credit profile information, income and occupation information, and information describing the specific features of the listing. In addition, the fully-funded loans have a set of variables that describe the specific features of the loan (e.g. lender interest rate). The credit profile information includes the applicant's credit grade on a seven point scale, with one being the most creditworthy and seven being the least.[5] In addition, each listing contains detailed information about the potential borrower's finances, including delinquencies in the prior seven years, the number of current delinquencies, the potential borrower's debt-to-income ratio, and the total balance of the borrower's revolving credit lines. The income and education variables include an indicator equal to one if the potential borrower has a college degree and zero otherwise as

[5]The Prosper.com credit grades correspond to Experian Scorex PLUS credit scores as follows: AA 760 and up, A 720-759, B 680-719, C 640-679, D 600-639, E 560-599, HR 520-559.

well as indicators for employment status and the borrower's income level. In addition, we compute a measure of the verbal complexity of the borrower's written statement. The listing characteristics include the borrower's maximum interest rate, the number of photographs in the listing, the number of words in the borrower's written statement, the number of previous listings posted, an indicator for membership in one of Prosper.coms' groups,[6] an indicator equal to one if the borrower had the endorsement of another Prosper.com member, and the group leader's compensation rate, if any. The loan characteristics include the amount of the loan and the promised interest rate. A complete list of all variables derived from Prosper.com and their descriptions can be found in Table 1.

2.2 Photograph analysis using MTurk

Since this paper is, to the best of our knowledge, the first research paper to use Amazon's Mechanical Turk (MTurk), we present a brief description of the MTurk service below. MTurk acts as a market platform that brings together individuals who have work to offer (Requesters) with individuals who wish to find work (Workers). Requesters submit tasks to Amazon's MTurk website for Workers to complete. The tasks are referred to as "Human Intelligence Tasks" (HITs). The Requesters design the tasks, pre-pay Amazon for the work, and receive the results. Workers can log on to the site whenever they choose and view offered wage rates for particular tasks as well as the details of the work the tasks involve. Workers

[6] Prosper.com allows members to form and join groups. These groups assist their members in preparing their listings and the group leader or other members may promise to bid on their group members' listings. The groups require that borrowers joining the group meet certain criteria, which is enforced by the group leader. Prior to September 2007, group leaders were compensated with a fraction of the loan proceeds for their efforts.

can then choose the tasks they wish to perform (provided they meet the qualifications and requirements set by the Requester) and are guaranteed payment by Amazon. For Requesters, MTurk offers access to a large workforce capable of completing thousands of HITs per hour. The benefit of such a workforce is that Workers can quickly and easily solve many problems that would be difficult for a computer to perform without extensive and costly programming.[7] These problems include certain data cleanup tasks, video transcribing, cataloging, and image tagging. As a means of quality control, MTurk allows Requesters to accept or reject HITs based on prior performance. To this end, Requesters can view each individual Worker's ratio of HITs rejected by Requesters to total HITs and prevent Workers whose rate of rejected HITs is too high from performing HITs. This provides Workers with an incentive to produce high-quality work. For Workers, MTurk offers a flexible work environment with competitive wages.

We use MTurk to gather demographic information conveyed by the photographs as well as subjective impressions of the people in the photographs. To ensure accurate and truthful responses from the Workers on MTurk, only Workers with an approval rating of 95% or above were allowed to complete HITs. To understand the demographics of the MTurk Workers, we surveyed a subsample of Workers that performed our HITs. Table 2 displays the demographic information of a sample of 903 Workers for which we have some information. These workers performed a total of 103,565 HITs. The data in Table 2 indicate that the Workers are, on

[7] The term 'Mechanical Turk' refers to the purported chess playing automaton, called the Turk, built in the late 18th century by Wolfgang von Kempelen (1734–1804). In fact, the Turk was a hoax that relied on a human operator; see, for instance, Standage (2002). Workers on MTurk are similar to the Turk's operator in the sense that they cheaply perform tasks which would require extensive and costly programming for a computer to perform.

average, in their mid-30's and ethnically white. The majority of Workers are female and have at least some college education. Workers tend to be located in populous states, with New York, California, Florida, Pennsylvania and Texas being most highly representative.

We use the photographs associated with the listings to gather a number of demographic characteristics of the people in the photographs. Specifically, we ask for the number of people in the photograph, their gender(s), their ethnicity or ethnicities (white, Asian, black or other), whether there are children in the photograph, and the perceived age range of the adults in the photograph. Using the responses, we generate a number of indicator variables that describe the ethnicity, sex, and age of individuals in the photographs as well as indicators for photographs that contain children or photographs of couples. We also ask the Workers to rate the weight of the people in the photograph on a three point scale with 1 being not obese and 3 being very obese. For each variable, we compute the average of the two responses. We also average the responses across each photograph included with the listing. A complete list of the demographic variables and descriptions of their construction can be found in Panel B of Table 1.

To gauge the attractiveness as well as the perceived trustworthiness of the people in the photographs, we ask the Workers the following questions: "Rate the trustworthiness of this person/these people (in the foreground)" and "Rate the attractiveness of this person/these people (in the foreground)." Workers use a five point scale with which to respond where 1 is least trustworthy/attractive and 5 is most trustworthy/attractive. We also ask for their subjective assessment of the probability (in steps of 10% from 0 to 100%) that the person(s) in the photograph are likely to repay a $100 loan.[8] The question is worded as follows: "Assume you are a banker and you consider making a loan of 100 US dollars to the person or people in the picture, what do you think the chances are that the person or people will pay you back? Please provide a number between 100 and 0, where 100 means you are absolutely certain the person will pay you back; 0 - you are absolutely certain the person will NOT pay you back." Because the Workers looking at the photographs do not have access to the financial and other information that Prosper.com provides, their assessments are not confounded by impressions they might draw from viewing the borrowers' credit grades, for instance. The Workers' assessments reflect only their ex-ante view of the borrowers' trustworthiness based on their photographs. To the extent that the Workers' are not good at making judgments about trustworthiness based on appearance alone, our tests will be biased against finding anything; however, as we show below, the measures of trustworthiness we construct based on the Workers' observations perform well as measures of trustworthiness.

As the answers to these questions are subjective, each photograph is evaluated by 25 distinct Workers. In addition, in order to best match the subjective perceptions of Prosper.com's US-based lenders, we allowed only US-based Workers to answer these questions. We chose to have 25 Workers evaluate the photographs in order to balance the cost of information processing with a desire to reduce the noise present in our measures. To examine how the precision of our estimates varied with different choices for the number of Workers

[8] We choose $100 because it represents a fairly small sum of money. This being the case, the answer can be thought of as a measure of the borrower's willingness to pay back loans, and therefore a measure of trustworthiness. For larger amounts, Workers could understandably take the question to be about the borrowers' ability to repay.

evaluating the photographs, we drew a random sample of 600 photographs and asked distinct groups of 5, 10, 25 and 50 Workers to evaluate each one. We found that the average standard error of the mean of the Workers' responses with respect to our trust measures across the photographs declined from 0.322 when evaluated by 5 Workers to 0.157 when evaluated by 25 Workers and 0.111 when evaluated by 50 Workers. The additional expense of having the photographs analyzed by 50 rather than 25 Workers did not appear to be worth the increase in precision from 0.157 to 0.111.

For each loan or listing, we compute the average and the median of the 25 responses to generate two versions of our trustworthiness measure ($TRUST\_average$ and $TRUST\_median$), two versions of the subjective repayment probabilities ($REPAY\_average$ and $REPAY\_median$), and two versions of our attractiveness measures ($ATTRACT\_average$ and $ATTRACT\_median$). If a listing or loan has multiple photographs, we average the response measures across all of the photographs associated with the listing or loan.

Since $TRUST$ and $REPAY$ are both proxies for trustworthiness but are not perfectly correlated, we adjust them for comparability so that both variables are measured on the same scale and combine them to form a trustworthiness index:

$$TRUST\_index\_median = (TRUST\_median - 1) \times 25 + REPAY\_median \qquad (1)$$

The $TRUST\_index\_average$ is computed using $TRUST\_average$ and $REPAY\_average$. Finally, we compute two indicator variables for trustworthiness and attractiveness. The high trustworthiness indicator, $HIGHTRUST$, is equal to one if the listing or loan has a median-based trustworthiness index greater than or equal to the third quartile. An observation has a high attractiveness indicator ($HIGHATTRACT$) equal to one if $ATTRACT\_median$ is greater than the third quartile. Panel B of Table 1 provides a detailed description of the construction of all trustworthiness and attractiveness variables.

2.3 Summary Statistics

Table 3 provides summary statistics for the credit profile, income and education, and listing and loan characteristics for 6,821 (Panel A) listings and 3,291 loans (Panel B). The credit profile variables suggest that the average Prosper.com user has an average credit grade of 5.76. This corresponds to an Experian credit score of about 620, which indicates that the average Prosper.com borrower has lower credit score than the national average, reported by Experian, of 692.[9] Finally, we report additional listing (Panel A) and loan characteristics (Panel B). These additional characteristics are reported for information only and are not part of the controls used in Section 3. The listing characteristics suggest that about 11% of listings become fully-funded loans. On average, potential borrowers (Panel A) offer to pay an annual interest rate of 18.25% and seek loans of about USD 8,000. Actual borrowers (Panel B) obtain loans with an average interest rate of 17.79% and an average loan amount of USD 6,740.

The summary statistics of the demographic information in Panel A of Table 3 also reveal that approximately one third of the listings are submitted by women. Furthermore, the Workers' analysis suggests that 62% of all listings are submitted by young adults (between approximately 18 and 39 years of age) while only about 1% of all listing are submitted by

[9] See http://www.experian.com/.

adults older than 60 years of age. Finally, about 23% of the listings are associated with photographs that show an black adult, while 7% of the listings are associated with an adult of Asian ethnicity. Panel B reports the same statistics for the set of listings that were fully funded and became loans. While the mean value of the young adult indicator (63%) and the older adult indicator (1%) are very close to the corresponding values in Panel A, only 28% of the loans are associated with female borrowers and only 14% of the loans are associated with black adults, suggesting that the likelihood of either group being funded is lower than it is for male and for non-black applicants. However, these differences in funding probabilities do not necessarily imply disparate-treatment discrimination, as default probabilities can be different for these groups.[10]

Table 4 reports simple correlation coefficients together with p-values for the test that the correlation coefficient is zero. The correlation coefficients reported in the first ten rows suggest that all measures of trustworthiness and attractiveness are significantly positively correlated with each other, with generally higher correlations between trustworthiness and repayment than between these two variables and measures of attractiveness. The last row of Table 4 presents correlation coefficients between a funding indicator on the one hand and trustworthiness and attractiveness on the other. While the correlation for measures of trustworthiness is always statistically positive ranging from 3.8% to 6.3%, the correlation for the three attractiveness variables is overall close to zero.

[10] Duarte, Siegel, and Young (2009) explore the extent of discrimination in peer-to-peer lending markets.

3 Results

In this section we analyze whether our perceived trustworthiness measures are related to the borrowers' actual trustworthiness. To this end, we first analyze whether our trustworthiness variables predict the borrower's past credit performance as measured by their Prosper.com credit grade. We then consider whether the trustworthiness proxies can predict defaults. Having done so, we analyze whether potential borrowers' trustworthiness impacts their ability to attract lenders willing to fund their loan requests.

3.1 Credit grades and perceived trustworthiness

Table 5 presents results from regressions of applicants' credit grades on our trustworthiness measures. The first seven specifications each contain one of our trustworthiness measures alone. The coefficient estimate on each trustworthiness measure is negatively and significantly related to the borrowers' credit grade. Thus, potential borrowers with high values of $TRUST\_average$ or $TRUST\_median$ have lower credit grades (i.e. are more credit worthy). Furthermore, the borrowers that the Workers' view as more likely to pay back a \$100 loan also have significantly lower credit grades. The results are similar with $TRUST\_index\_median$, $TRUST\_index\_mean$, and with $HIGHTRUST$. The R^2s in these univariate regressions range from 1% to 1.7%. By comparison, in univariate regressions of credit grades on each of the credit profile variables (debt-to-income ratio, home ownership, length of credit history, number of delinquencies, number of credit inquiries and number of credit lines) the median R^2 is around 3%.

Specifications 8 through 14 all include one of the trustworthiness proxies, a control for attractiveness, and controls for the demographic information conveyed by the photograph. The demographic control variables control for superficial aspects of the potential borrower's appearance visible in the borrowers' photograph such as indicator variables for ethnicity, sex, age, and weight. These variables allows us to control for aspects of the borrower's appearance that are visible in the photograph and that may influence the Workers' subjective judgment about perceived trustworthiness. As with attractiveness, the coefficient estimates suggest that trustworthiness is not simply a proxy for demographic information conveyed by the photograph. Indeed, the coefficient estimates on the various trustworthiness proxies remain significant and similar to the coefficient estimates in the specifications that include the trustworthiness proxies alone.

Finally, specifications 15 through 21 include the trustworthiness variables, controls for attractiveness and demographic information and controls for the potential borrower's credit profile, income, and education level. The credit-profile controls include various determinants of a borrower's creditworthiness including debt-to-income ratios and length of credit history. The controls for a borrower's income and level of education include indicators for college education and employment status. Table 3 Panel A contains a complete list of all the variables in each control group.

While the credit profile, income and education controls were not available to the Workers, these variables are, not surprisingly, strongly related to credit grades. Despite the presence of these controls, however, the trustworthiness proxies remain significant. Furthermore, the relation between the trustworthiness measures and credit grades is economically significant. Using the results from specification 7, everything else constant, an individual perceived as less trustworthy has, on average, a credit grade about 0.41 lower than an individual perceived as trustworthy. Using the coefficients from specification 21, an individual perceived as less trustworthy has a credit grade about 0.13 lower than an individual perceived as trustworthy. This translates into a difference in promised interest rates of between 33 and 100 basis points per annum.[11]

These results are perhaps surprising because they suggest that individuals who are given access to nothing but a photograph provided by a potential borrower can make subjective assessments about a borrower's trustworthiness that will contain valuable information about the borrower's actual creditworthiness not contained in a linear specification involving the financial information that forms the typical basis for determining a borrower's credit grade.[12] These results also suggest that the individuals who appear trustworthy are, on average, worthy of trust. The next section considers the relation between default behavior and perceived trustworthiness. Since the results that follow are not sensitive to the choice of trustworthiness proxy, in the interest of space we proceed using the $TRUST\_index\_median$ and $HIGHTRUST$.

[11] We arrive at a figure of 100 basis points by regressing interest rates on credit grades using the 3,291 loans in our sample. The coefficient on credit grades is 0.026, thus a change in credit score of 0.41 yields a 100 bp impact and a change of 0.13 yields a 33 bp interest rate impact.

[12] Given the rating agencies' non-linear formula for credit ratings, the financial information in the regressions would exactly determine the borrowers' credit ratings. In the absence of the exact formula, the trustworthiness proxies help explain variation in the credit ratings.

3.2 Default and perceived trustworthiness

To assess the relation between default and our trustworthiness proxies, we estimate Cox models for default. As with other proportional hazard models, the Cox model assumes that the hazard rate ($h(t)$) is the product of a baseline hazard rate ($h_0(t)$) that varies only with loan age, but not across other loan characteristics, and the exponential of the explanatory variables (X) multiplied by a vector of constants b.[13] In contrast to other proportional hazard models, however, the Cox model does not provide direct estimates of the baseline hazard but instead focuses on the extent to which explanatory variables increase or decrease the baseline hazard rate:

$$\frac{h(t)}{h_0(t)} = exp(bX) \tag{2}$$

We use Prosper.com's definition of loan default to estimate our Cox models. Loans are considered in default and become due in full if a scheduled payment is more than four months past due. Our sample contains 761 loan defaults. Each loan made via Prosper.com also provides the borrower with the option to prepay the loan at any time and 20% of the loans in our sample were prepaid. In untabulated results, we find that our trustworthiness variables were not significant predictors of prepayment.

Table 6 presents the hazard ratios from the estimated Cox models, $exp(\widehat{b})$, which reflect the change in the hazard rate due to a one unit increase in the associated variable. As with the regressions in Table 5, we control for physical attractiveness, demographic information conveyed by the photographs, credit profile information (including credit grade), income

[13] In our discrete time Cox models, the hazard rate is the probability of default at month t conditional on not having defaulted until the beginning of that month.

and education of the borrower, characteristics of the loan and listing (such as the loan amount), and the number of photographs in the listing. We also include controls for whether the potential borrower is a member of one of Prosper.coms' groups, whether the borrower had been endorsed by another Prosper.com member, and the Prosper.com group leader's compensation rate, if any. In addition, the loan-specific controls include proxies for the information contained in the borrower's written statement. Table 3 Panel B contains a complete list of all the variables in each control group.

As with the results in Table 5, the first specifications only include proxies for trustworthiness. Both $TRUST\_index\_median$ and $HIGHTRUST$ have hazard ratios less than one and are significant at conventional levels. This indicates that individuals judged to be more trustworthy are in fact significantly less likely to default on their loans. Indeed, the exponentiated point estimate for the trustworthiness index indicator of 0.6699 suggests that the hazard rate of a loan associated with a trustworthy borrower is 33% lower than the hazard rate of a loan from a less trustworthy borrower. The results are similar when we include attractiveness as a control, which suggests that our trustworthiness proxies are not simply conveying information about the physical attractiveness of the potential borrowers. Furthermore, our trustworthiness proxies remain significant and are of similar magnitude after controlling for attractiveness, demographic information conveyed by the photographs, credit profile information, income, level of education, and loan-specific information. Figure 1 provides insight into the economic significance of the results by presenting the survival probability as a function of the age of the loan for the average loan as well as for high and low trust loans that are otherwise identical to the average loan.[14] The graph indicates that the survival probabilities are substantially larger for the higher trust loans, with the difference increasing with the age of the loan. Indeed, this graph indicates that a loan made to a seemingly trustworthy borrower has a probability of default approximately 10% smaller than the probability of default of a loan made to a borrower perceived as less trustworthy. These results are perhaps surprising, as they suggest that people are able to provide useful information about future loan performance in terms of default simply as a result of a brief look at a photograph.

One question that our results are not able to answer is just what it is about a person's appearance that signals to others that they are willing to meet their obligations. However, theoretical work by Klein and Leffler (1981) and Shapiro (1983) suggests that individuals are willing to act in an opportunistic fashion when the present value of future cash flows to be obtained by acting in a trustworthy manner (i.e. the value of their reputation) are outweighed by the immediate gains of cheating. Following this logic, it may be that an individual's appearance is a signal about a person's reputational capital. It could be, for example, that agents with "a lot to lose" convey this in the manner in which they dress or even in their facial or other bodily characteristics. Another possibility is that trustworthiness is a genetic characteristic correlated with some visible attributes. Carré and McCormick (2008) show, for instance, that dominant behavior in male humans is associated with particular facial characteristics. In another recent study, Cesarini et. al. (2008) show that there is

[14] While the maturity of Prosper.com loans is 36 months, our data set does not contain any loan older than 29 months. As a result, for months 30 to 36, we assume that the monthly hazard rate corresponds to its average value between months 5 and 29.

genetic variation in humans that affects both their trustworthiness and willingness to trust. Thus, it is at least plausible that a related mechanism causes facial features to be associated with a high value on reputation.

3.3 Funding and perceived trustworthiness

To test whether agents take the trustworthiness of their potential counterparties into account when deciding whether to contract, we perform two sets of tests. First, we examine whether $TRUST\_index\_median$ and $HIGHTRUST$ are positively related to the number of bids each listing receives. Second, we model the probability of a listing being funded as a function of the trustworthiness proxies. Table 7 presents the coefficient estimates from regressions of the number of bids received by each listing either $TRUST\_index\_median$ or $HIGHTRUST$ along with control variables. The first two specifications in Table 7 include only the trustworthiness proxies, both of which are positively and highly significantly related to the number of bids received. Both $TRUST\_index\_median$ and $HIGHTRUST$ remain significant with similar estimated coefficients after controlling for attractiveness. This indicates that the physical attractiveness of the potential borrower is not driving the relation between the trustworthiness proxies and the number of bids received. Furthermore, the coefficients on $TRUST\_index\_median$ and $HIGHTRUST$ remain positive and significant even after controlling, not only for attractiveness, but for demographic information about the borrower, the borrower's credit profile, income and education information and loan and listing specific characteristics. Panel A of Table 3 displays the complete list of controls. Moreover, the coefficient on $HIGHTRUST$ in specification 6 indicates that a borrower deemed trustworthy receives an average of five additional bids in their auction, a 25% increase over the average auction. After the inclusion of the additional control variables, the attractiveness proxies are negative and significant at the ten percent level. This indicates that, if anything, everything else constant more attractive borrowers attract fewer bid than less attractive borrowers.

Table 8 presents the results from a number of probit regressions, each modeling the probability of a listing on Prosper.com becoming a fully-funded loan. As in the previous section, we include several groups of controls. These include attractiveness, the demographic information conveyed by the photograph, the borrowers' credit profile, income and education, and listing-specific information, including both the amount requested and the borrowers' maximum interest rate. Panel A of Table 3 displays the complete list of controls.

The first two specifications include only $TRUST\_index\_median$ and $HIGHTRUST$. Both $TRUST\_index\_median$ and $HIGHTRUST$ have marginal effects (0.0012 and 0.0406, respectively) that are significant at conventional levels. As the results of the next two specifications indicate, these marginal effects remain significant and similar in magnitude even after controlling for attractiveness. Furthermore, the coefficients on $TRUST\_index\_median$ and $HIGHTRUST$ remain statistically significant, even after controlling for the demographic information conveyed by the photograph, the information in the borrower's credit profile, information about the borrower's income and education as well as loan and listing-specific information, including the promised interest rate.

The absolute magnitude of the marginal effects on $TRUST\_index\_median$ and $HIGHTRUST$

in Table 8 may appear small. However, to assess their economic significance, we compute the decrease in the promised interest rate that would be required to keep the probability of funding the same between a less trustworthy and a trustworthy borrower, all else being constant. This can be calculated by dividing the marginal effect on $HIGHTRUST$ by the marginal effect on the promised interest rate. Using the results in specification 6, we find that a trustworthy person (i.e. $HIGHTRUST = 1$) can promise an interest rate 182 basis points per annum lower than a person for whom $HIGHTRUST = 0$ and have the same probability of being funded, even controlling for all of the demographic, credit profile, income, education and listing-specific information possessed by lenders on Prosper.com.[15] Thus, trustworthiness seems to be associated with a substantial discount in economic terms. To our knowledge, this is the first paper to present empirical estimates of the value of trustworthiness in a market.

4 Conclusion

This paper studies a fundamental question: whether individuals use their judgment about their potential counterparties' trustworthiness when contracting. This paper contributes to a growing literature on trust in finance and economics that considers the correlations between country-level measures of trust and aggregate measures of economic development.[16] One difficulty with empirical work in this literature is that it is not clear whether increased levels of trust between individuals leads to greater economic activity, or whether people

[15] The estimated marginal effect of the maximum interest rate the borrower is willing to pay is 0.5653 in specification 6 of Table 8.

[16] See for instance Fukuyama (1995), La Porta, Shleifer, and Vishny (1997), Zak and Knack (2001), Carlin, Dorobantu and Viswanathan (2008), and Aghion, Algan, Cahuc and Shleifer (2009).

from prosperous and economically active countries are just more inclined to be trusting. By using transaction-level auction data from the peer-to-peer lending site Prosper.com and a new, exogenous measure for trustworthiness, we are able to examine whether agents consider potential counterparties' trustworthiness when deciding whether or not to lend. If the correlations between economic activity and country-level trust measures arise because agents are more willing to contract with those they trust or deem trustworthy, then we expect that in our data lenders would be more willing to loan to potential borrowers they deem trustworthy. On the other hand, if the causality is reversed, then controlling for ability to repay the loan, there would be no relation between the perceived trustworthiness of the borrower and the outcome of the lending decision. We find that, controlling for a large set of financial and demographic information about potential borrowers, more seemingly trustworthy borrowers are more likely to be funded than borrowers deemed less trustworthy. Furthermore, a trustworthy borrower can promise an interest rate 182 basis points per annum lower than a less trustworthy borrower in order to have the same likelihood of receiving a loan. Because this paper directly tests the hypothesis that individuals consider the trustworthiness of their potential counterparties when deciding to engage in financial transactions, it also adds to the theoretical and empirical work in Guiso, Sapienza and Zingales (2008) that suggests that investors differ in their propensity to invest in risky assets depending on the trust they place in others.

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Table 1
Definition of all Variables

Panel A - Variables from Prosper.com

Variable Name	Variable Definition
Credit Grade	Credit grade of the borrower at the time the listing was created. Credit grade takes on values between 1 (low) and 7 (high risk).
Debt-to-Income Ratio	The debt-to-income ratio of the borrower at the time the listing was created. This value is truncated at 10.01 (so any actual debt to income ratio larger than 1000% will be returned as 1001%).
Homeowner Indicator	An indicator variables that equals one if the borrower is a verified homeowner at the time the listing was created and zero otherwise.
Length of Credit History (in months)	The time (in months) between the date the first line of credit was recorded for a borrower and the time the listing was created.
Number of Delinquencies (currently)	The number of current delinquencies at the time the listing was created.
Number of Delinquencies (last 7 years)	The number of delinquencies in the seven years prior to the creation of the listing.
Number of Credit Inquiries (last 6 months)	The number of inquiries in the six months prior to the creation of the listing.
Number of Public Records (last 10 years)	The number of public records in the ten years prior to the creation of the listing.
Number of Total Credit Lines	The number of total credit lines at the time the listing was created.
College Indicator	An indicator variable that equals one if, based on the borrower's self-reported occupation, the borrower is likely to have a college degree and zero otherwise
Fraction of Complex Words Used (in %)	The fraction of complex words (in %) out of all words used in the listing text. A complex word is defined as a word with three or more syllables. For the details, see http://search.cpan.org/dist/Lingua-EN-Fathom/lib/Lingua/EN/Fathom.pm#percent_complex_words
Income Data Indicator	An indicator that equals one if information on the borrower's income level is available or zero otherwise.
Income Level	An indicator of the borrower's income range at the time the listing was created. The indicator takes on values between one (USD 0) and six (more than USD 100,000). The indicator equals zero if no information is available.
Employment Status Indicator	An indicator that equals one if information on the borrower's employment status is available or zero otherwise.
Unemployment Indicator	An indicator of the borrower's employment status at the time the listing was created. The indicator equals one if the borrower is unemployed, retired, or a homemaker and zero if the borrower is employed (full- or half-time) or self-employed. The indicator equals zero if no information is available.
Number of Bids	The number of bids is the total number of bids placed on a listing. This number can be greater than zero even if the listing is not fully funded.
Funding Indicator	An indicator that equals one if a listing is fully funded and becomes a loan and zero otherwise.
Maximum Interest Rate	The maximum interest rate the borrower is willing to pay when the listing was created.
Borrower Rate	The rate the borrower pays on the loan. The rate is computed as the Lender Rate plus the Group Leader Reward Rate (if applicable) and the Bank Draft Fee Annual Rate (if applicable).
Lender Rate	The rate that lenders receive on the loan.
Loan Amount (in '000)	The requested loan amount in thousands of USD.
"Close Auction when Funded" Indicator	An indicator that equals one if the listing closes as soon as it is funded 100%.
Number of Photographs	The number of photographs associated with a listing.
Number of Words in Listing Text	The number of words used by the borrower in the listing text.
Number of Words in Listing Text (squared)	The square of the Number of Words in Listing Text variable.
Number of Prior Listings	The number of listings submitted prior to the current listing.
Endorsement Indicator	An indicator that equals one if another Prosper member has endorsed the borrower and zero otherwise.
Group Membership Indicator	An indicator that equals one if the borrower is a member of a Prosper group and zero otherwise.
Group Leader Reward Rate	The percentage reward which is kept by the group leader. The variable is zero if the borrower is not a member of group.
Listing Start Date	The date at which a listing was created.
Bank Draft Fee Annual Rate	The rate charged by the bank when the payment option selected is not Electronic Funds Transfer.
Default Indicator	An indicator that equals one if the loan status is "Defaulted (Bankruptcy)", "Defaulted (Delinquency)", "Charge-off", or "4+ months late" and zero otherwise.
Prepayment Indicator	An indicator that equals one if the loan is prepaid in full and zero otherwise.
Loan Origination Date	The date at which the loan was originated.
Loan Age (in days since origination)	The time (in days) between the Loan Origination Date and the date of the last available loan performance data.
Recovery (conditional on final settlement)	The fraction of the outstanding loan balance that is recovered in the case of default.

Table 1 presents the definition of all the variables used in this study. Panel A displays all the variables that are either provided by Prosper or derived from variables provided by Prosper. Panel B contains the variables built from the analysis of the photographs in Prosper by Mechanical Turk Workers. The demographic information in the photographs has been evaluated by two distinct Workers. Workers have identified the number of men, women, and children in each photograph. Workers have also provided estimates of the age, ethnicity, and obesity of each adult in each photograph. The trustworthiness and attractiveness information in the photographs has been evaluated by 25 distinct Workers. Workers have rated the trustworthiness and attractiveness of the person(s) in the foreground of each photograph on a scale between 1 (least) and 5 (most). Workers have also been asked with which probability (in steps of 10%-points from zero to 100%) they would expect repayment of a hypothetical loan of USD 100 by the person(s) in the photograph.

Table 1
Definition of all Variables

Panel B - Variables derived from Mechanical Turk Workers' analysis.

Variable Name	Variable Definition
Demographic Information	
Female Indicator	An indicator variable that equals one if at least one worker identified at least one female adult in at least one of the photographs associated with a listing or loan while no male adult were identified by any worker. The indicator equals zero otherwise.
Couple Indicator	An indicator variable that equals one if at least one photograph associated with a listing or loan contains one female adult and one male adult and zero otherwise.
Kid(s) Indicator	An indicator variable that equals one if at least one worker identified at least one person below the age of 18 in at least one of the photographs associated with a listing or loan and zero otherwise
Young Adults Indicator	An indicator variable that equals one if at least one worker identified at least one person above the age of 18, but below the age of 40 in at least one of the photographs associated with a listing or loan while no older adults were identified by any worker. The indicator equals zero otherwise.
Old Adults Indicator	An indicator variable that equals one if at least one worker identified at least one person above the age of 60 in at least one of the photographs associated with a listing or loan while no younger adults were identified by any worker. The indicator equals zero otherwise.
Black Indicator	An indicator variable that equals one if at least one worker identified at least one black adult in at least one of the photographs associated with a listing or loan and zero otherwise.
Asian Indicator	An indicator variable that equals one if at least one worker identified at least one Asian adult in at least one of the photographs associated with a listing or loan and zero otherwise.
Obesity	The average (across two workers) obesity rating of the adult(s) in the photograph associated with a listing or loan. If multiple photographs are associated with a listing or loan, the variable represents the average across different photographs. Obesity estimates are expressed on a scale between one (not overweight) and three (definitely overweight).
Trustworthiness	
TRUST_average	The average (across 25 workers) trustworthiness rating of the person(s) in the photograph. If multiple photographs are associated with a listing or loan, the variable represents the average across different photographs.
REPAY_average	The average (across 25 workers) repayment probability associated with the person(s) in the photograph. If multiple photographs are associated with a listing or loan, the variable represents the average across different photographs.
TRUST_index _average	A linear combination of Trustworthiness (Average) and Repayment (Average): = (Trustworthiness (Average) -1) x 25 + Repayment (Average)
TRUST_median	The median (across 25 workers) trustworthiness rating of the person(s) in the photograph. If multiple photographs are associated with a listing or loan, the variable represents the average across different photographs.
REPAY_median	The median (across 25 workers) repayment probability associated with the person(s) in the photograph. If multiple photographs are associated with a listing or loan, the variable represents the average across different photographs.
TRUST_index _median	A linear combination of Trustworthiness (Median) and Repayment (Median): = (Trustworthiness (Median) -1) x 25 + Repayment (Median)
HIGHTRUST	An indicator variable that equals one if Trustworthiness Index (Median) is equal to or larger than its 75th percentile (across all listings) and zero otherwise.
Attractiveness	
ATTRACT_average	The average (across 25 workers) attractiveness rating of the person(s) in the photograph. If multiple photographs are associated with a listing or loan, the variable represents the average across different photographs.
ATTRACT_median	The median (across 25 workers) attractiveness rating of the person(s) in the photograph. If multiple photographs are associated with a listing or loan, the variable represents the average across different photographs.
HIGHATTRACT	An indicator variable that equals one if Attractiveness (Median) is larger than its 75th percentile (across all listings) and zero otherwise.

Table 1 presents the definition of all the variables used in this study. Panel A displays all the variables that are either provided by Prosper or derived from variables provided by Prosper. Panel B contains the variables built from the analysis of the photographs in Prosper by Mechanical Turk Workers. The demographic information in the photographs has been evaluated by two distinct Workers. Workers have identified the number of men, women, and children in each photograph. Workers have also provided estimates of the age, ethnicity, and obesity of each adult in each photograph. The trustworthiness and attractiveness information in the photographs has been evaluated by 25 distinct Workers. Workers have rated the trustworthiness and attractiveness of the person(s) in the foreground of each photograph on a scale between 1 (least) and 5 (most). Workers have also been asked with which probability (in steps of 10%-points from zero to 100%) they would expect repayment of a hypothetical loan of USD 100 by the person(s) in the photograph.

Table 2
Characteristics of Mechanical Turk Workers

	Equally Weigthed	Weighted by Number of HITs
Average Number of HITs	115	1,186
Average Age	34	37
Gender		
Male	0.35	0.33
Female	0.65	0.67
Ethnicity		
White	0.84	0.82
African American	0.05	0.04
Asian	0.04	0.03
Hispanic	0.03	0.06
Other	0.04	0.05
Education		
No college	0.05	0.10
Some college, no degree	0.37	0.34
Associate's Degree	0.11	0.14
Bachelor's Degree	0.32	0.30
Master's Degree	0.10	0.06
Professional Degree	0.02	0.04
Doctorate	0.02	0.01
Top Five States	CA	TX
	TX	IN
	PA	CA
	NY	PA
	FL	TN

Table 2 summarizes self-reported characteristics of 903 MTurk Workers for which we have some information. These Workers performed 103,565 HITs.

Table 3
Summary Statistics

Panel A: Listings

Variable	N	Mean	Std. Dev.	Min	Max
Trustworthiness					
TRUST_average	6,821	3.26	0.32	1.80	4.38
REPAY_average	6,821	83.01	6.44	33.40	97.60
TRUST_index _average	6,821	139.54	13.21	63.00	176.04
TRUST_median	6,821	3.13	0.34	2	5
REPAY_median	6,821	90.79	8.09	25	100
TRUST_index _median	6,821	143.98	13.53	65	200
HIGHTRUST	6,821	0.35	0.48	0	1
Attractiveness					
ATTRACT_average	6,821	3.06	0.36	1.58	4.42
ATTRACT_median	6,821	3.05	0.35	1	5
HIGHATTRACT	6,821	0.11	0.32	0	1
Demographic Information					
Female Indicator	6,821	0.33	0.47	0	1
Couple Indicator	6,821	0.17	0.37	0	1
Kid(s) Indicator	6,821	0.36	0.48	0	1
Young Adults Indicator	6,821	0.62	0.48	0	1
Old Adults Indicator	6,821	0.01	0.10	0	1
Black Indicator	6,821	0.23	0.42	0	1
Asian Indicator	6,821	0.07	0.26	0	1
Obesity	6,821	1.32	0.51	1	3
Credit Profile Information					
Credit Grade	6,821	5.76	1.56	1	7
Debt-to-Income Ratio	6,821	0.57	1.47	0.01	10.01
Homeowner Indicator	6,821	0.29	0.45	0	1
Length of Credit History (in month)	6,821	142.04	79.13	2	749
Number of Delinquencies (currently)	6,821	4.05	5.42	0	116
Number of Delinquencies (last 7 years)	6,821	11.25	16.57	0	99
Number of Credit Inquiries (last 6 months)	6,821	4.28	4.99	0	66
Number of Public Records (last 10 years)	6,821	0.65	1.18	0	16
Number of Total Credit Lines	6,821	23.78	14.00	2	127
Income & Education Information					
College Indicator	6,821	0.20	0.40	0	1
Fraction of Complex Words Used (in %)	6,821	11.99	5.40	0.00	35.90
Income Data Indicator	6,821	0.69	0.46	0	1
Income Level	6,821	2.30	1.78	0	6
Employment Status Indicator	6,821	0.70	0.46	0	1
Unemployment Indicator	6,821	0.03	0.16	0	1
Listing & Auction Characteristics					
Number of Bids	6,821	20.72	71.31	0	934
Funding Indicator	6,821	0.11	0.31	0	1
Maximum Interest Rate	6,821	18.25%	6.99%	0.00%	35.96%
Loan Amount (in '000)	6,821	8.02	6.46	1.00	25.00
"Close Auction when Funded" Indicator	6,821	0.35	0.48	0	1
Number of Photographs	6,821	1.80	1.03	1	5
Number of Words in Listing Text	6,821	218.59	142.88	0	754
Number of Words in Listing Text (squared)	6,821	68,194.87	86,626.58	0	568,516
Number of Prior Listings	6,821	1.52	2.28	0	45
Endorsement Indicator	6,821	0.30	0.46	0	1
Group Membership Indicator	6,821	0.45	0.50	0	1
Group Leader Reward Rate	6,821	0.39%	0.79%	0.00%	5.00%
Additional Listing Characteristics					
Listing Start Date	6,821	12-May-07		28-Jun-06	3-Jan-08

Table 3 presents summary statistics for the 6,821 listings (Panel A) and the 3,291 loans (Panel B) used in this study. For each variable, we report the number of non-missing observations (*N*), the mean, the standard deviation, as well as the minimum and maximum value. Measures of trustworthiness and attractiveness are based on the evaluation of each photograph associated with a listing or loan by 25 Workers. Demographic variables are based on the evaluation of each photograph associated with a listing or loan by two Workers. All other variables are either provided by Prosper or derived from variables provided by Prosper. See Table 1 for a detailed description of all variables.

Table 3
Summary Statistics

Panel B: Loans

Variable	N	Mean	Std. Dev.	Min	Max
Trustworthiness					
TRUST_average	3,291	3.36	0.32	2.00	4.40
REPAY_average	3,291	83.67	6.24	24.80	98.00
TRUST_index _average	3,291	142.66	12.97	78.33	180.96
TRUST_median	3,291	3.24	0.42	2	5
REPAY_median	3,291	89.74	7.86	0	100
TRUST_index _median	3,291	145.79	15.05	50	200
HIGHTRUST	3,291	0.40	0.49	0	1
Attractiveness					
ATTRACT_average	3,291	3.16	0.37	1.72	4.44
ATTRACT_median	3,291	3.13	0.39	2	5
HIGHATTRACT	3,291	0.19	0.39	0	1
Demographic Information					
Female Indicator	3,291	0.28	0.45	0	1
Couple Indicator	3,291	0.18	0.38	0	1
Kid(s) Indicator	3,291	0.34	0.47	0	1
Young Adults Indicator	3,291	0.63	0.48	0	1
Old Adults Indicator	3,291	0.01	0.09	0	1
Black Indicator	3,291	0.14	0.35	0	1
Asian Indicator	3,291	0.09	0.29	0	1
Obesity	3,291	1.25	0.45	1	3
Credit Profile Information					
Credit Grade	3,291	4.36	1.88	1	7
Debt-to-Income Ratio	3,291	0.43	1.34	0.01	10.01
Homeowner Indicator	3,291	0.39	0.49	0	1
Length of Credit History (in month)	3,291	145.26	81.28	3	602
Number of Delinquencies (currently)	3,291	1.94	3.94	0	64
Number of Delinquencies (last 7 years)	3,291	6.75	13.13	0	99
Number of Credit Inquiries (last 6 months)	3,291	3.34	4.15	0	63
Number of Public Records (last 10 years)	3,291	0.45	0.93	0	13
Number of Total Credit Lines	3,291	23.31	14.09	2	127
Income & Education Information					
College Indicator	3,291	0.25	0.43	0	1
Fraction of Complex Words Used (in %)	3,291	12.38	4.63	0.00	35.20
Income Data Indicator	3,291	0.67	0.47	0	1
Income Level	3,291	2.39	1.92	0	6
Employment Status Indicator	3,291	0.68	0.47	0	1
Unemployment Indicator	3,291	0.02	0.14	0	1
Listing & Loan Characteristics					
Loan Amount (in '000)	3,291	6.74	5.90	1.00	25.00
Number of Photographs	3,291	2.02	1.14	1	5
Number of Words in Listing Text	3,291	267.33	150.67	0	754
Number of Words in Listing Text (squared)	3,291	94,158.79	96,930.58	0	568,516
Endorsement Indicator	3,291	0.43	0.50	0	1
Group Membership Indicator	3,291	0.57	0.50	0	1
Group Leader Reward Rate	3,291	0.42%	0.73%	0.00%	4.00%
Additional Loan Characteristics					
Borrower Rate	3,291	17.79%	6.28%	0.21%	35.00%
Lender Rate	3,291	17.36%	6.10%	0.21%	35.00%
"Close Auction when Funded" Indicator	3,291	0.23	0.42	0	1
Number of Prior Listings	3,291	1.91	2.39	0	28
Number of Bids	3,291	156.88	152.27	1	934
Default Indicator	3,291	0.23	0.42	0	1
Prepayment Indicator	3,291	0.20	0.40	0	1
Loan Origination Date	3,291	1-May-07	136.5765	5-Jul-06	14-Jan-08
Loan Age (in days since origination)	3,291	484.6667	176.6271	28	884
Recovery (conditional on final settlement)	266	0.08	0.06	-0.01	0.42

Table 3 presents summary statistics for the 6,821 listings (Panel A) and the 3,291 loans (Panel B) used in this study. For each variable, we report the number of non-missing observations (*N*), the mean, the standard deviation, as well as the minimum and maximum value. Measures of trustworthiness and attractiveness are based on the evaluation of each photograph associated with a listing or loan by 25 Workers. Demographic variables are based on the evaluation of each photograph associated with a listing or loan by two Workers. All other variables are either provided by Prosper or derived from variables provided by Prosper. See Table 1 for a detailed description of all variables.

Table 4
Correlations

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	TRUST_average	1.000											
2	REPAY_average	0.675	1.000										
		0.000											
3	TRUST_index _average	0.933	0.895	1.000									
		0.000	*0.000*										
4	ATTRACT_average	0.461	0.345	0.446	1.000								
		0.000	*0.000*	*0.000*									
5	TRUST_median	0.651	0.388	0.582	0.293	1.000							
		0.000	*0.000*	*0.000*	*0.000*								
6	REPAY_median	0.592	0.831	0.763	0.293	0.335	1.000						
		0.000	*0.000*	*0.000*	*0.000*	*0.000*							
7	TRUST_index _median	0.761	0.740	0.820	0.359	0.826	0.808	1.000					
		0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*						
8	ATTRACT_median	0.287	0.230	0.285	0.726	0.212	0.194	0.248	1.000				
		0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*					
9	HIGHTRUST	0.550	0.556	0.603	0.230	0.541	0.681	0.746	0.144	1.000			
		0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*				
10	HIGHATTRACT	0.178	0.134	0.173	0.563	0.158	0.100	0.159	0.778	0.099	1.000		
		0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*			
11	Credit Grade	-0.116	-0.127	-0.132	-0.061	-0.100	-0.117	-0.132	-0.041	-0.124	-0.044	1.000	
		0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.000*	*0.000*		
12	Number of Bids	0.084	0.089	0.094	0.052	0.067	0.079	0.089	0.026	0.083	0.023	-0.391	1.000
		0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.032*	*0.000*	*0.058*	*0.000*	
13	Funding Indicator	0.052	0.062	0.062	0.038	0.038	0.051	0.054	0.022	0.063	0.018	-0.331	0.6676
		0.000	*0.000*	*0.000*	*0.002*	*0.002*	*0.000*	*0.000*	*0.072*	*0.000*	*0.146*	*0.000*	*0.000*

Table 4 presents pair-wise correlations between measures of trustworthiness and attractiveness as well as credit grade and the funding indicator. We also report the corresponding *p*-value for the test that correlations coefficient equals zero. See Table 1 for a detailed description of all variables.

Table 5
Predicting Credit Risk

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Trustworthiness																					
TRUST_average	-0.5697							-0.6176							-0.1766						
	0.0%							*0.0%*							*0.5%*						
REPAY_average		-0.0309							-0.0244							-0.0075					
		0.0%							*0.0%*							*0.5%*					
TRUST_index _average			-0.0157							-0.0154							-0.0046				
			0.0%							*0.0%*							*0.2%*				
TRUST_median				-0.4606							-0.4409							-0.1889			
				0.0%							*0.0%*							*0.0%*			
REPAY_median					-0.0226							-0.0198							-0.0055		
					0.0%							*0.0%*							*0.6%*		
TRUST_index _median						-0.0153							-0.0145							-0.0052	
						0.0%							*0.0%*							*0.0%*	
HIGHTRUST							-0.4071							-0.3680							-0.1252
							0.0%							*0.0%*							*0.0%*
Controls																					
ATTRACT_average								-0.0716	-0.1709	-0.0594					-0.0094	-0.0341	-0.0026				
								29.1%	*0.7%*	*37.6%*					*87.0%*	*52.6%*	*96.4%*				
ATTRACT_median											-0.1230	-0.1152	-0.0635					0.0155	0.0028	0.0290	
											3.8%	*5.1%*	*29.0%*					*75.8%*	*95.6%*	*57.1%*	
HIGHATTRACT														-0.1757							-0.0747
														0.5%							*15.5%*
Demographic Information	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Credit Profile Information (excluding Credit Grade)	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES
Income & Education Information	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	1.3%	1.6%	1.7%	1.0%	1.4%	1.7%	1.5%	5.6%	5.3%	5.7%	5.0%	5.1%	5.5%	5.3%	34.0%	34.0%	34.0%	34.0%	34.0%	34.1%	34.1%

Table 5 presents results from regressing credit grade on different measures of trustworthiness, attractiveness as well as different sets of control variables. Credit grade takes on integer values between 1 (low) and 7 (high). Regressions are performed on all 6,821 listings. For each variable, we report the OLS coefficient estimate as well as the associated *p*-value. Standard errors are robust to heteroscedasticity. For each regression, we also report the adjusted R^2. See Table 3 Panel A for a definition of the control variables. See Table 1 for a detailed description of all variables.

Table 6
Predicting Default

	1	2	3	4	5	6
Trustworthiness						
TRUST_index _median	0.9833		0.9828		0.9852	
	0.0%		0.0%		0.0%	
HIGHTRUST		0.6699		0.6500		0.7350
		0.0%		0.0%		0.0%
Controls						
ATTRACT_median			0.9777		1.0295	
			80.9%		76.5%	
HIGHATTRACT				0.8472		0.8140
				8.8%		4.2%
Demographic Information	NO	NO	YES	YES	YES	YES
Credit Profile Information	NO	NO	NO	NO	YES	YES
Income & Education Information	NO	NO	NO	NO	YES	YES
Listing & Loan Characteristics	NO	NO	NO	NO	YES	YES

Table 6 presents hazard ratios from a Cox default model. Default occurs when payments on a loan are 4-month or more late. The model is estimated using all 3,291 loans. For each variable, we report the hazard ratio as well as the *p*-value associated with the test whether the hazard ratio is equal to 1. Standard errors are robust to heteroscedasticity. See Table 3 Panel B for a definition of the sets of control variables. See Table 1 for a detailed description of all variables.

Table 7
Predicting Number of Bids

	1	2	3	4	5	6
Trustworthiness						
TRUST_index _median	0.4709		0.4785		0.1948	
	0.0%		0.0%		0.3%	
HIGHTRUST		12.3940		12.0400		5.4101
		0.0%		0.0%		0.2%
Attractiveness						
ATTRACT_median			-1.2002		-4.2746	
			66.9%		9.4%	
HIGHATTRACT				1.4219		-4.6693
				64.1%		9.9%
Controls						
Demographic Information	NO	NO	YES	YES	YES	YES
Credit Profile Information	NO	NO	NO	NO	YES	YES
Income & Education Information	NO	NO	NO	NO	YES	YES
Listing & Auction Characteristics (excluding Number of Bids and Funding Indicator)	NO	NO	NO	NO	YES	YES
Adjusted R^2	0.8%	0.7%	1.4%	1.3%	21.0%	21.0%

Table 7 presents results from an OLS regression of the number of bids on a given listing onto trustworthiness, attractiveness, and different sets of control variables. The model is estimated using all 6,821 listings. For each variable, we report the coefficient estimate as well as the *p*-value associated with the test whether the coefficient estimate is equal to 0. Standard errors are robust to heteroscedasticity. See Table 3 Panel A for a definition of the sets of control variables. See Table 1 for a detailed description of all variables.

Table 8

Predicting Funding

	1	2	3	4	5	6
Trustworthiness						
TRUST_index _median	0.0012		0.0013		0.0002	
	0.0%		0.0%		5.3%	
HIGHTRUST		0.0406		0.0405		0.0103
		0.0%		0.0%		0.1%
Controls						
ATTRACT_median			-0.0039		-0.0037	
			72.9%		39.3%	
HIGHATTRACT				0.0005		-0.0066
				96.7%		9.7%
Demographic Information	NO	NO	YES	YES	YES	YES
Credit Profile Information	NO	NO	NO	NO	YES	YES
Income & Education Information	NO	NO	NO	NO	YES	YES
Listing & Auction Characteristics (excluding Funding Indicator)	NO	NO	NO	NO	YES	YES
Pseudo R^2	0.4%	0.6%	2.3%	2.4%	36.3%	36.5%

Table 8 presents results from a probit regression of funding success. Funding success is one if a listings is fully funded and becomes a loan, zero in all other cases. The model is estimated using all 6,821 listings. For each variable, we report the marginal effect (evaluated at the sample mean) as well as the *p*-value associated with the test whether the marginal effect is equal to 0. Standard errors are robust to heteroscedasticity. See Table 3 Panel A for a definition of the sets of control variables. See Table 1 for a detailed description of all variables.

Figure 1

Relative loan survival by type of borrower over time

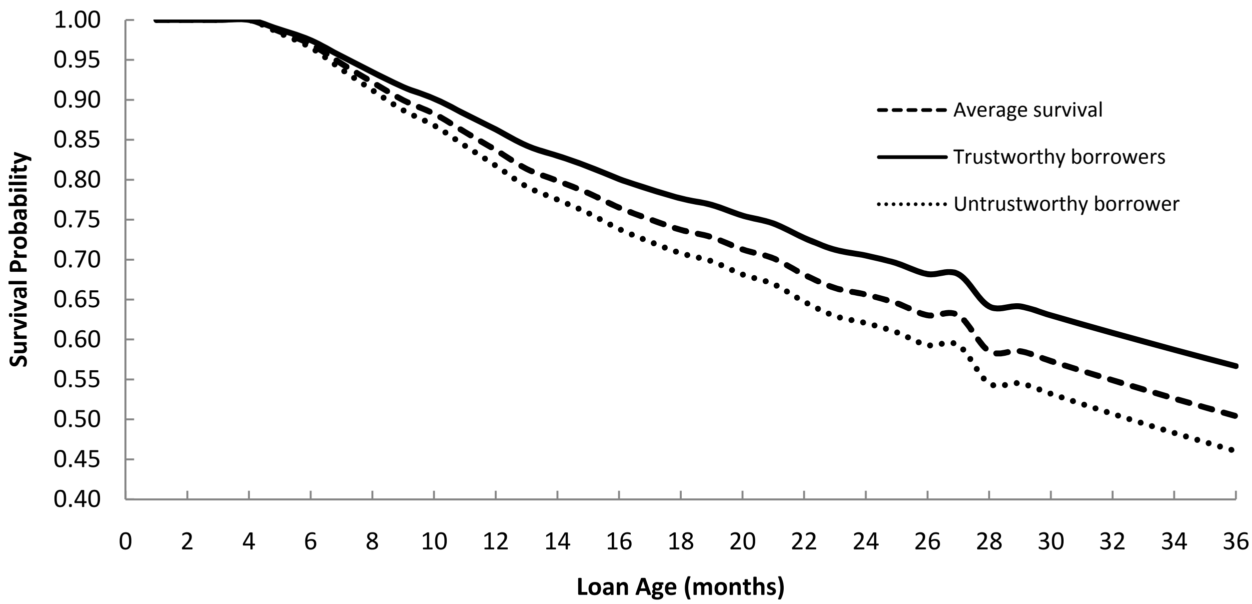

Figure 1 presents the probability of a loan not defaulting since its origination as function of the loan age – the survival probability. The average survival probability is calculated based on the sample of 3,291 loans. The survival probabilities of loans made to trustworthy and untrustworthy borrowers are calculated from the average survival probability and the point estimate of the HIGHTRUST coefficient of the Cox model 6 in Table 6.