

What Do Donors Discriminate On? Evidence From Kiva.org

Christina JENQ, Booth School of Business

Jessica PAN, National University of Singapore

Walter THESEIRA, Nanyang Technological University¹

Abstract

The rapid expansion and adoption of internet-based microfinance platforms have provided an opportunity for individuals to direct philanthropy towards specific causes to a degree not previously possible. In this paper, we make use of rich, individual loan-level data from www.kiva.org, an internet website that facilitates philanthropic cash transfers from small scale individual donors to specific microfinance loan recipients, to examine whether, and what patterns of, discrimination exist based on the choices made by these donors. We exploit detailed information provided on each borrower through objective loan information, pictures and textual descriptions to investigate the determinants of individual charitable giving. We find that donors appear to discriminate in favor of more attractive, lighter-skinned, and less obese borrowers, even as donors appear to systematically favor regions of the world where lighter skin is less prevalent. These effects are statistically and quantitatively significant and robust across a variety of specifications. Discrimination on the basis of physical attraction and skin color appears to be heightened for female borrowers, while obesity matters more for male borrowers.

JEL: O16, G21, J15

Keywords: Discrimination, Microfinance, Philanthropy

¹ This paper is preliminary and not for citation. Please contact the corresponding author: wetheseira@ntu.edu.sg if you have questions or would like further information.

1. INTRODUCTION

Individual donations are an important source of capital for non-profit and social causes. However, philanthropy has traditionally been directed through intermediaries such as government agencies or non-profit organizations whom in turn direct funding to specific end uses. The rapid expansion of internet-based technologies in recent years has provided an opportunity for individuals to direct philanthropy towards specific causes, to a degree not previously possible. But it is not clear that individuals have the same preferences regarding worthy causes or desirable policy interventions as development professionals or experts do. (Desai and Kharas 2009) If direct or less-mediated philanthropy becomes comparatively more important as a source for development funding – a prospect that appears increasingly likely in an era of government austerity for much of the developed world – then studying the preferences of individual donors becomes even more important for understanding the direction of the next generation of economic development assistance. In this paper, we make use of rich, individual loan level data from www.kiva.org, an internet website that facilitates philanthropic cash transfers from individual donors to specific microfinance loan recipients, to examine whether, and what patterns of, discrimination exist based on the choices made by these donors.

We define discrimination in our context to be disparate treatment of microfinance loan recipients on the basis of attributes that are plausibly unrelated to economically productive factors. However, we also understand discrimination in the broader sense of analyzing which factors donors consider when making philanthropic choices – that is, donor preferences. The philanthropic industry, which survives only because of successful appeals to donor preferences, has long designed fund raising strategies to appeal to the sensibilities of potential donors. But short of a carefully designed field experiment, it seems unlikely that the traditional philanthropic

industry can provide us with any detailed inference on donor preferences over the recipients of development aid.

We address the data problem with novel evidence from a fairly recent entrant to the philanthropic market: the website www.kiva.org, which has in the span of five years facilitated the loan of nearly \$200 million US dollars from individual donors to individual and group microfinance borrowers. Kiva works with microfinance institutions (MFI) in developing countries, which upload information on their clients to Kiva. These microfinance clients' photographs and stories are then used to solicit capital from potential lenders, under the premise that potential lenders have the ability to make a direct impact to the lives of a specific individual or group through a small loan. While the donors who provide capital on Kiva are actually lending their money, they receive no interest on their loans, and in fact, their capital is subject to default risk and exchange rate risk, so full recovery of the loan is not assured. Interest is charged, and retained, by the local MFI, but not remitted to the Kiva donor/lender. Therefore, it seems appropriate to consider Kiva lending as an act of philanthropy, and this paper will use the terms donor and lender interchangeably henceforth.

Our dataset consists of 1 month of activity on www.kiva.org, representing close to 7,000 microfinance loans to individuals and groups throughout the world. We observe the same information that potential donors on www.kiva.org would see when they are considering whether to provide capital to a microfinance borrower. In particular, we observe the photograph of the borrower, a short written description of the project, and summary statistics on the purpose of the funds, just as lenders do. The outcome variable of interest is the conditional time to full funding for a loan on www.kiva.org. At any given moment on www.kiva.org, hundreds of loans are available and seeking funding. While all loans eventually receive full funding, the time to

funding varies significantly between loans. We argue that a loan will require a conditionally longer period of time to receive full funding if that loan is perceived by most lenders to be relatively less attractive than other available or potentially available loans. Our approach is akin to inferring that, all else equal, the product which is sold out on store shelves sooner must have attributes which are relatively preferred by the population of consumers. Therefore, the speed with which a loan is fully funded allows for inference on the aggregate preferences of donors and potential donors on www.kiva.org. Controlling for other variables that could affect time to funding allows us to determine with greater assurance the existence of patterns of discrimination by lenders.

We find that donors discriminate on the basis of attractiveness, skin color, and weight, preferring borrowers who are more attractive, who have lighter skin, and who are not overweight. The effects are statistically significant and robust, persisting across a variety of specifications and conditional on a full range of controls including country fixed effects, MFI fixed effects, economic sector and activity fixed effects, and date fixed effects. The effects are quantitatively significant. A borrower at the 75th percentile in terms of skin color (darker skin) is estimated to require 20% more time to have his or her loan funded than a borrower with lighter skin at the 25th percentile; similarly, a borrower at the 75th percentile in attractiveness (more attractive) requires almost 25% less time to receive full funding.

We also find evidence that donors appear to strongly prefer lending to women compared to men, making group loans instead of individual loans, and lending to borrowers from poorer countries. We conjecture that these preferences are in part driven by the substantial evidence circulated in the media on the success of microfinance institutions which concentrate on group lending and lending to women. However, our evidence on the strong impact of attractiveness,

skin color, and weight are difficult to reconcile with any consensus or even popular evidence on the value of increased capital access to more attractive, lighter skinned, skinny individuals when it comes to economic development. We thus interpret our findings as suggesting the presence of significant discrimination on the part of donors in microfinance.

This paper briefly surveys the related literature on charitable giving and implicit discrimination in section 2, describes the data in section 3, presents empirical results in section 4 and concludes thereafter.

2. RELATED LITERATURE

Discrimination on the basis of individual characteristics such as race, gender, or appearance is pervasive in many markets. However, relatively little research exists on discrimination in microfinance and development, and the literature that does exist largely focuses on the question of discrimination at the microfinance approval level in the developing country or market itself (Agier and Szafarz 2010; Labie et al 2010).

Because Kiva is a nonprofit peer-to-peer lending platform that offers the opportunity for lenders to participate in charitable lending, this paper provides novel evidence on the motivations behind charitable giving. Economists often model this type of giving by adding “warm glow” to the donors' utility function (Andreoni 1989, 1990). We conjecture that if philanthropic individuals behave in such a way that they systematically favor one group over another for reasons that appear unrelated to the functional ends of charitable giving (alleviating poverty), then that suggests the extent of warm glow differs depending on whom the recipient is. Discrimination in the context of charity thus is interpretable as differences in the warm glow one feels when donating to groups with different attributes, much as taste-based discrimination in the

Becker sense is the result of differences in the perceived utility gains from interaction with different groups.

Our paper's approach is to infer the existence of discrimination or patterns of prejudice in the population from field data on the relative speed with which loans with different attributes are funded. While a few other papers that we are aware of have investigated patterns of lending on Kiva (Hansman and Jambulapati 2009; Ly and Mason 2010), our paper is the first to use the rich information presented in borrower photographs to investigate whether discrimination exists.

Our approach is similar to a series of previous papers based on a U.S. peer-to-peer online lender, www.prosper.com. Pope and Sydnor (2008) find that blacks are about 30% less likely to be funded after controlling for objective information such as creditworthiness and other subjective attributes such as attractiveness. Theseira (2008) also finds that blacks are less likely to be funded, and finds that increased competition among lenders, as predicted by the Becker model, ameliorates the harm suffered by blacks due to prejudice. While Pope and Sydnor (2008) find that the effect of attractiveness is minor compared to that of race, Ravina (2008) exploits a more refined scale of attractiveness ratings to show that more beautiful borrowers are treated more favorably.

An implicit message in these papers is that lenders use "soft" information such as self-reported text and pictures in a way that might bias their lending decisions away from rationality as judged by assuming lenders maximize expected future returns on their loans. However, Iyer et al. (2009), presents a different narrative by emphasizing that lenders, to a certain extent, use "soft" information on Prosper to relatively accurately infer creditworthiness; specifically, they find that within a borrower credit category lenders use "soft" information to infer one-third of the

variation in creditworthiness that is captured by the borrower's exact credit score, and, further, that lenders exhibit greater inference for borrowers in higher credit categories.

A larger literature exists on the effect of race and beauty stereotypes on various market outcomes. Altonji and Blank (1999) review the literature on the impacts of race and gender in the labor market, and various authors have looked at the impact of race in mortgage outcomes (for example, Ladd (1998); Cole, 1999). Hamermesh and Biddle (1993) examine the influence of beauty on wages using various household surveys. Economists have also found experimental evidence of race and beauty bias in both the laboratory and the field. Landry, Lange, List, Price, Rupp (2006) find that a one-standard deviation increase in physical attractiveness among women solicitors in door-to-door fundraising experiment significantly increases the probability of donation and the size of the donation, driven by increases participation rates among households where a male answered the door. They also find limited evidence that other solicitor characteristics, such as obesity and self-confidence, influence fundraising success, and that social connectivity between the solicitor and household matters. Mobius and Rosenblat (2006) find in an experimental labor market that physically attractive workers are wrongly considered more able by employers, and find that attractive people raise their wages through better oral skills when they interact with employers. List and Price (2007) find that minority solicitors in a door-to-door fundraising field experiment, whether approaching a majority or minority household, are considerably less likely to obtain a contribution, and conditional on securing a contribution, gift size is lower than their majority counterparts receive. Andreoni and Petrie (2005) find in laboratory experiments with public goods games that people are more likely to give to beautiful people even though beautiful people are not more likely to be cooperative. Bertrand and Mullainathan (2004) find that White names receive 50% more callbacks relative to African-

American names in response to fictitious applications to help-wanted job postings, and that callbacks are more responsive to resume quality for White names relative to African-American names.

The explanations for apparent biases in lending and other market outcomes is often attributed in the economics literature to three mechanisms: statistical discrimination in which perpetrators take actions that are rational given correct beliefs about the behavior of other people (see Arrow 1973), taste-based discrimination theories (see Becker 1971) in which perpetrators discriminate beyond what is predicted by correct beliefs because of an individual's disutility, and beliefs that are simply incorrect.

The social psychology literature offers more insight behind the mechanisms of a taste for discrimination and incorrect beliefs. In terms of beauty stereotypes, one strain of literature discusses the “attractiveness halo effect” (also known as the “beautiful is good” stereotype) which describes the stereotype that more attractive individuals are expected to be more sociable, friendly, warm, competent, and intelligent than less attractive individuals. Feingold (1992), Eagley et al. (1991) and Langlois et al. (2000) provide reviews. Recently, Lorenzo et al (2010) delve further into this stereotype and finds that more physically attractive people (“targets”) were perceived more in line with their self-reported personality traits. Specifically, perceivers' impressions of a target's attractiveness were also positively related to the positivity and accuracy of impressions, which provides some support to the statistical discrimination mechanism.

In terms of race stereotypes, social psychology has found that Implicit Association Tests (IAT; Greenwald et al., 1998) have been able to detect biased, uncontrollable responses favoring White faces over African-American faces. (Greenwald and Banaji 1995, Kim 2003). Cunningham et al (2004) find that white participants viewing black and white faces during event-

related functional magnetic resonance imaging had much higher activation in the brain region associated with emotion when viewing black faces relative to white faces after 30ms, but this difference decreased after 525 ms.

In terms of facial features, Blair (2002) finds that targets with more Afrocentric features were given higher probabilities when the described individual had traits stereotypical of African Americans (musical, aggressive) and lower probabilities when described individual had traits that are considered counter-stereotypical of the group (smart, a loner). Further, when targets were all black or white, participants used within-race variations in Afrocentric features to make their judgments. Using a sequential priming procedure, Livingston and Brewer (2002) demonstrated that African Americans with more Afrocentric features elicited more automatic negativity than group members with less Afrocentric features.

Another strain of literature discusses how stereotypes are a shortcut the brain uses to preserve mental resources. Macrae, Milne, & Bodenhausen (1994) investigate how stereotypes help to preserve mental resources when the subject's mental energy is divided between other activities. Sczesny and Kuhn (2004) examine the efficiency of feature-based stereotyping by manipulating participants' attentional resources while they evaluated a male or female job applicant who had more versus less masculine facial features. They find that gender-feature-based stereotyping was not altered when the participants were under high attentional load, indicating that it operates very efficiently. Devine (1989) finds that both "low-prejudice" and "high-prejudice" people produce stereotyped evaluations of ambiguous behaviors when the subject's ability to consciously monitor stereotype activation is precluded.

3. DATA

Kiva has been in operation since 2005, with loans posted for funding since February 2006. From 2006 through 2010, Kiva experienced rapid growth in terms of loans posted and dollars loaned, as shown in Figure 1. Whilst in January 2007, less than a thousand loans were posted monthly, by the end of 2009, nearly eight thousand loans were posted each month. The average amount requested per loan during this period was \$700 and did not vary significantly during the period 2007-2009; the average amount lent to each borrower is approximately half of the average loan size due to a substantial fraction of loans being group loans to multiple borrowers. Towards the end of 2009, more than \$5 Million dollars were loaned monthly through Kiva. As of May 2011, Kiva reported that \$212 Million dollars have been lent since inception, to more than 550,000 borrowers.

[Figure 1 about here]

Our sample consists of 6,153 loans posted on Kiva during June 2009. We chose June 2009 as the basis for the sample because it appears to be a typical month of operations dating from a period where Kiva had already established mainstream status. The period from 2007 to 2008 inclusive was marked by extremely rapid growth – as shown in Figure 1 – and high-profile media events that brought Kiva widespread fame, causing concern that a sample drawn from that period might be less representative. We also wished to avoid drawing data from or after end-year holiday periods which might experience seasonal fluctuations in charitable activity.

Summary statistics in Table 1 outline the characteristics of loans from data from the entire period 2007 to 2009 as well as from our specific sample drawn from June 2009.

[Table 1 about here]

The mean loan size is \$701 and the median loan size is \$550. Loans in excess of \$1000 are rare, with the 95th percentile loan amount being \$1600 and the largest recorded loan being

\$10,000. The mean time to funding is 3,838 minutes or about two and a half days, with the median time to funding significantly lower at 613 minutes or about 10 hours. A small number of loans take a week or longer to fund; the 95th percentile time to funding was 23376 minutes, or 16 days. The median loan term is 9 months and the mean loan term is similar; the longest loan terms available on Kiva are for 36 months.

While the above summary statistics are based on individual loan data, information on the ex-ante credit risk of loans is only available at the level of the microfinance institution which actually disburses money to the borrower. Thus, all borrowers from the same microfinance institution are reported as having the same credit risk characteristics. In addition, no quantitative data is available on the economic conditions of the borrower except for the borrower's country GDP per capita in purchasing power parity terms. Based on this data, the average delinquency rate is 3.94%, but the majority of loans are in fact issued by microfinance partners with 0% stated delinquency rates, as the median delinquency rate is 0%. The median PPP GDP per capita in borrowers' countries is \$2800; 95% of all loans are issued to borrowers in countries with GDPs less than \$11,100.

Kiva also self-rates microfinance partners on a 0 to 5 point scale for risk and displays these assessments to potential lenders using a 5-star graphic. The median rating for loans is 4 points, indicating the majority of loans are issued from microfinance partners which Kiva assesses to be relatively low risk.

To facilitate searching, Kiva categorizes all loans according to the gender of the borrower, economic sector and geographic region. Additional searches are possible through the website's search engine, based on any elements of the loan description. Loans are categorized by the main sector of the activity towards which the loan will be put. The most important sectors are

Agriculture, Food (referring to Food-based enterprises such as grocery stores, restaurants, etc rather than personal consumption) and Retail, which together account for two-thirds of all loans. The least common sectors are Education, Entertainment, Health, Personal Use, and Wholesale, each accounting for less than 1% of all posted loans.

Loans are further categorized by geographic region; slightly more than one-third of all loans are to countries in Asia, followed by Africa and South America. The remaining regions of the world make up less than 20% of all loans. The specific country of loan origin is always specified and is searchable. Table 1 shows that there the distribution of loans by economic sector and geographic region are broadly similar between the complete data sample and our coded sample, suggesting that our sample month is reasonably representative of the broader data.

Group loans differ from loans to individual borrowers along several dimensions. The median group has 5 members, with the mean group size larger at 7.52 members. The 95th percentile group size is 18 members. While group loans are on average about two and a half times larger in dollar terms than individual loans, but the total sum lent is shared by each member of the group. Group borrowers appear to be much more likely to be involved in Retail and Services and much less often in Agriculture or Food, compared to individual borrowers.

3.1 CODING FOR SUBJECTIVE CHARACTERISTICS

The photographs posted on behalf of borrowers were reviewed by research assistants who were asked to code and quantify certain reasonably objective qualities of each photograph, such as the number of people in the photograph, gender, background setting, and skin color, as well as subjective characteristics such as assessments of the borrower's creditworthiness, neediness, and the like. A standard set of coding instructions, found in Appendix A, was provided to each research assistant.

The research assistants were told that the purpose of the study was to investigate if personal characteristics affected outcomes on Kiva.org, and were shown the website and provided with information on microfinance. This naturally raises the concern that the research assistants could have been motivated to skew their coding results to make the data fit a particular hypothesis or personal bias. However, the primary outcome of interest – the time to funding – is not directly available publicly and has to be calculated from the raw data. This data then has to be matched to each specific photograph. Research assistants were not provided directly with any of the borrower context, loan description, purpose, or amount, although if they desired, they could have obtained this information from public sources. However, this data has to be extracted from the website and processed before it is usable. As our research assistants are undergraduates without advanced data analysis skills, it seems to us extremely unlikely that any of our research assistants would have embarked on this task independently.

To assess borrowers' skin color objectively, we instructed research assistants to base their assessment on the Martin and Massey Skin Color Scale from the New Immigrant Survey, which assigns a number from 1 to 10 for increasingly dark skin color, with zero (unreported in the data) representing albinism. A copy of the Martin and Massey Skin Color Scale is provided at the end of Appendix A. The range of skin colors found in the sample is depicted by geographic region in Figure 2. As expected, borrowers from Africa have on average darker skin color, corresponding to higher points on the Martin and Massey scale. However, even within Africa, there is a wide range of variation in terms of assessed skin color; by no means does assessed skin color cluster on the '10' end of the scale. Borrowers from Eastern Europe have the lightest skin color, while borrowers from Asia, Central America, the Middle East and South America have distributions of skin color that fall in between the Eastern Europeans and Africans. Within all geographic regions

and even within country, individual borrowers differ in terms of assessed skin color. As we will see shortly, dispersion in skin color within geographic region and country is important for understanding the source of variation driving the results, since there is a clear trend of donors preferring to lend to borrowers located in Africa over other regions. Without variation in skin color within region or country, we would find only a positive relationship between darker skin color, and faster time to funding.

[Figure 2]

We also instructed research assistants to provide their subjective impression of borrower's attractiveness, on a scale of 1 to 7 with higher numbers indicating greater attractiveness. One concern is that assessments of attractiveness may be strongly correlated with skin color assessments due to bias on the part of the research assistants. However, Figure 3 shows that assessments of attractiveness are not obviously related to skin color. For example, although borrowers from Africa have on average much darker skin color than borrowers from Asia, each group is reported to have distributions of attractiveness ratings that appear to be similar. Borrowers from each region appear to have similar distributions of attractiveness, with the exception that borrowers from Eastern Europe appear to be assessed to be substantially more attractive than borrowers from elsewhere. There do not appear to be differences in assessed attractiveness or skin color by gender.

[Figure 3 about here]

Summary statistics of the assessed subjective characteristics of our sample are in Table 2. As described earlier, skin color varies significantly by region; borrowers from Africa have significantly darker skin color than borrowers from other regions. Differences in attractiveness between region are generally statistically significant, but small in absolute magnitude. Group

borrowers are assessed to have darker skin, to be less attractive, less well off, more needy, less creditworthy and less profitable than individual borrowers, but some of these differences are attributable to differences in the distribution proportion of all loans that are group loans, by region. Regional differences in terms of other characteristics are, like attractiveness, statistically significant but small in magnitude.

[Table 2 about here]

Time to funding is significantly different between regions by a large absolute magnitude – a difference on the order of around 4000 minutes, or almost 3 days, between Africa which has the shortest average times to funding and the next most common loan regions of Asia and South America. Similar significant and large differences exist in the average loan amount between regions. As such, our estimation strategy will control for region fixed effects to account for potential region-based selection preferences by donors, which might otherwise confound our estimates on the effect of subjective characteristics on funding.

4. EMPIRICAL RESULTS

We estimate regressions of the form:

Log Time to Funding = Objective Loan Characteristics + Photo-Based Characteristics + Loan Controls

Where the coefficients are interpretable as the effect in percentage terms of a linear unit change in the coefficient on the time to funding. Objective loan characteristics include gender, an indicator for whether the loan is to a group or individual, log of the loan amount, microfinance partner rating quality, and log of GDP of the borrower's country. Photo-based characteristics include assessed attractiveness, skin color, physique, and other characteristics coded from

photographs as listed in Appendix A. In our specifications, we control for region-based fixed effects, day of the month fixed effects, and economic sector fixed effects, to address concerns that unobserved factors affecting both characteristics of loans and borrowers and the availability of willing donors may be driving our results. In addition, when we employ subjectively assessed data, we control for research assistant fixed effects, and additional fixed effects for the quality of the photograph and for background content in the photograph.

The results are presented in Table 3. In specification (1) and (2), we regress objective characteristics of loans on time to funding. In specifications (3) to (5), we include subjective photo-based characteristics and additional controls.

[Table 3 about here]

We find that skin color, attractiveness, and physique significantly and consistently affects time to funding. Borrowers who are assessed to be more attractive, who have lighter skin, and who are not visibly obese obtain full funding of their loans faster. The result is robust and persists through different regression specifications as shown in models (3) to (5). The estimated impact of a one-unit increase in assessed attractiveness is a reduction in time to full funding of approximately 12%, while a one-unit increase in skin color is associated with an increase in time to funding of approximately 5%. A one-unit increase in assessed physique – that is, obesity – is associated with an increase in time to funding of about 12% to 17%. Simply smiling appears to reduce funding times by about 7%.

These estimated effects of physical attributes are not only statistically significant but quantitatively important. For comparison, a one percent increase in the loan amount requested – about \$7 – is associated with an increase in funding time of about 1.4%. This implies – on a per-unit change basis – that a more attractive borrower is treated by donors as though they were

asking for \$60 less; a darker-skinned borrower is treated as though they were asking for \$25 more, and an overweight borrower is treated as though they were asking for \$60 more. Smiling is as effective as reducing one's loan request by \$35. These estimated impacts are significant given that the median loan amount asked of \$550.

We also find that GDP of the borrower's country is significantly and positively related to time to funding, consistent with a theory of lending behavior where donor preferences are at least partially driven by the desire to maximize marginal impact. A 1% increase in per-capita, purchasing power parity GDP of the borrower's country is associated with a 0.08% to 0.16% increase in time to funding. Thus, donors prefer borrowers from poorer countries. However, the estimated impact of physical attributes on lending is huge by comparison; a one-unit increase in assessed attractiveness is equivalent to an almost 150% reduction in GDP, in terms of the magnitude of the impact on time to funding, whilst a borrower one skin color degree darker is treated as though he comes from a country 60% richer.

Surprisingly, microfinance partners who receive low ratings from Kiva receive full funding for their loans faster, as shown in specifications (1), (2) and (3). We believe this is likely due to low-rated MFIs being more prevalent in countries which donors exhibit strong preferences towards. This suggests that country effects are an important confounding factor for the role of photo-based characteristics on time to funding, since skin color in particular depends on the borrower's country of origin. We alleviate these concerns by including, as mentioned earlier, full fixed effects for country of origin and geographic region.

Donors exhibit strong preferences for female borrowers. Loans to women are funded 48% to 74% faster than loans to men. Loans to groups are also preferred; a group loan receives

funding 10% to 23% faster than a loan to an individual. We decompose differences in the coefficients of interest by groups and gender at greater length in Table 4.

[Table 4 about here]

In models (1) and (2) in Table 4, we restrict the dataset to include only individual loans and group loans respectively. We find that physical attributes only have a statistically significant impact where individual loans are concerned. One explanation may be that lenders are more affected by their implicit attitudes towards skin color and attractiveness when making decisions based on individuals, compared to the case where they make decisions based on lending to an entire group. Kiva's website design lends further credence to this hypothesis; photographs of borrowers are sized so that individual borrowers' faces and features are clearly recognizable to lenders browsing for loans, but an equivalent group loan requires clicking through in order to obtain a photograph with sufficient resolution to determine features.

In models (3), (4) and (5), we investigate whether the effect of physical and other attributes differ by gender. We find that the impact of both attractiveness and skin color appear to be heightened for women, whilst the impact of physique appears to be greater for men. Having children present in the photograph appears to result in times to funding approximately 22% lower for loans to women, but for not loans to men. Considering the results from model (5), which includes full interaction effects for all variables with the female indicator variable, we find that the aggregate effect for all loans of skin color on time to funding appears to be driven mostly by loans to women. For loans to men, which is the baseline case in (5), we find that skin color is statistically insignificant. The effect of skin color on time to funding for women, by contrast, is both significantly different from the effect of skin color for men, as well as statistically significant from zero.

5. CONCLUSION

Taken together, our estimates suggest that in aggregate, a variety of motivations guide potential donors when deciding which projects to favor. The evidence suggests that donors are affected by perceptions of the impact their loan will make and the perceived neediness of the borrower. Loans to countries which are poorer, to borrowers who are not obese, and to borrowers who appear needy are fulfilled faster. These factors are consistent with a model of philanthropy where donors seek to maximize the marginal impact of their dollar, under the assumption that the marginal impact of capital investments should be larger in poorer economies and on individuals who signal (through not being obese) that they are less well-off.

However, donors also appear to be affected by the attractiveness and skin color of borrowers. We are not aware of any plausible mechanisms which would justify greater investment in more attractive, lighter skinned borrowers. The behavior of donors regarding attractiveness and skin color appears most consistent with prejudice on the part of donors, either implicitly or explicitly, in favor of more attractive and lighter-skinned borrowers. We conjecture that implicit prejudice is a more likely explanation because a casual glance at the aggregate data shows a strong preference overall for borrowers in Africa. Indeed, a regression without geographic controls would suggest a positive relationship between darker skin and faster time to funding. Donors who prefer African borrowers are unlikely to be strongly prejudiced against darker-skinned individuals in the conventional sense. We hypothesize that, after deciding to contribute towards microfinance projects in Africa, donors are then faced with a problem of deciding which African borrower to fund, amongst many potential borrowers. Implicit attitudes

or prejudice would explain our findings that conditional on region and country, borrowers with lighter skin receive funding faster.

References

- Agier, Isabelle and Szafarz, Ariane, 2010. "Microfinance and Gender: Is there a Glass Ceiling in Loan Size?" Working Papers CEB 10-047, Universite Libre de Bruxelles
- Altonji J., Blank, R. (1999) Race and Gender in the Labor Market. In Ashenfelter O., Card D., (eds) Handbook of Labor Economics, vol 3C. Elsevier Science, Amdsterdam. pp. 3143-3260.
- Andreoni, J. (1989) Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence. *Journal of Political Economy*, 97, 1147-1458.
- Andreoni, J. (1990) Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving. *The Economic Journal*, 100, 464-477.
- Andreoni, J., Petrie, R. (2005) Beauty, Gender, and Stereotypes: Evidence from Laboratory Experiments. *Journal of Economic Psychology*, 29(1), 73-93.
- Arrow, K., (1973) The Theory of Discrimination, in O. Ashenfelter and A. Rees, *Discrimination in Labor Markets*, Princeton University Press, pp. 3-33.
- Ashmore, R.D., Solomon, M.R., Longo, L.C. (1995). Thinking about Fashion Models' Looks: A Multidimensional approach to the Structure of Perceived Physical Attractiveness. *Personality and Social Psychology Bulletin*, 22, 1083-1104.
- Banaji, M. R. (2001). Implicit attitudes can be measured. In H. L. Roediger III, J. S. Nairne, I. Neath, & A. M. Surprenant (Eds.), *The nature of remembering: Essays in honor of Robert G. Crowder* (pp. 117{150). Washington, DC: American Psychological Association.
- Blair, I. V. (2001). Implicit stereotypes and prejudice. In G. B. Moskowitz (Ed.), *Cognitive social psychology: The Princeton Symposium on the Legacy and Future of Social Cognition* (pp. 359{374). Mahwah, NJ: Erlbaum.
- Becker, G., (1961) *The Economics of Discrimination*, University of Chicago Press.
- Bertrand, M., Mullainathan, S. (2004) Are Emily and Brendan More Employable than Latoya and Tyrone? Evidence on Racial Discrimination in the Labor Market from a Large Randomized Experiment. *American Economic Review*, 94(4), 991-1013.
- Blair, I.V., Judd, C.M., & Fallman, J.L. (2004). The automaticity of race and Afrocentric facial features in social judgments. *Journal of Personality and Social Psychology*, 87(6), 763-778.
- Blair, I.V., Judd, C.M., Sadler, M.S., Jenkins, C. (2002) The role of Afrocentric features in person perception: Judging by features and categories. *Journal of Personality and Social Psychology*, 83(1), 5-25.

Cole, R. (1999) Availability of credit to small and minority-owned businesses: Evidence from the 1993 National Survey of Small Business Finances. Working Paper.

Cunningham, W.A., Johnson, M.K., Raye, C.L, Gatenby, J.C., Gore, J.C. & Banaji, M.R. (2004). Separable neural components in the processing of black and white faces. *Psychological Science*, 15(12), 806-813.

Dasgupta, N., McGhee, D.E., Greenwald, A.G., Banaji, M.R. (2000) Automatic preference for White Americans: Eliminating the Familiarity Explanation. *Journal of Experimental Social Psychology*, 36(3), 316-328.

Desai, Raj M., and Kharas, Homi, 2009. “Do Philanthropic Citizens Behave Like Governments? Internet-Based Platforms and the Diffusion of International Private Aid” Wolfensohn Center For Development Working Papers No. 12, The Brookings Institution

Devine, P.G. (1989). Stereotypes and prejudice: Their automatic and controlled components. *Journal of Personality and Social Psychology*, 56, 5-18.

Eagly, A.H., Ashmore, R.D., Makhijani, M.G., Longo, LC. (1991). What is beautiful is good, but. . . : A meta-analytic review of research on the physical attractiveness stereotype. *Psychological Bulletin*, 110(1), 109-128.

Feingold, A. (1992). Good-looking people are not what we think. *Psychological Bulletin*, 111, 304-341.

Greenwald, A.G., & Banaji, M.R. (1995) Implicit social cognition: Attitudes, self-esteem, and stereotypes. *Psychological Review*, 102, 4-27.

Greenwald, A.G., McGhee, D.E., Schwartz, J.L.K. (1998). Measuring individual differences in implicit cognition: The Implicit Association Task. *Journal of Personality and Social Psychology*, 74, 1464-1480.

Hamermesh, D.S., Biddle J.E. (1993) Beauty and the Labor Market. *American Economic Review*, xx(x), 1174-94.

Hansman, C. and Jambulapati, V. (2009). Microfinance and Charitable Giving. University of Chicago. Working Paper.

Kim, D-Y. (2003) Voluntary controllability of the Implicit Association Test (IAT). *Social Psychology Quarterly*, 66(1), 83-96.

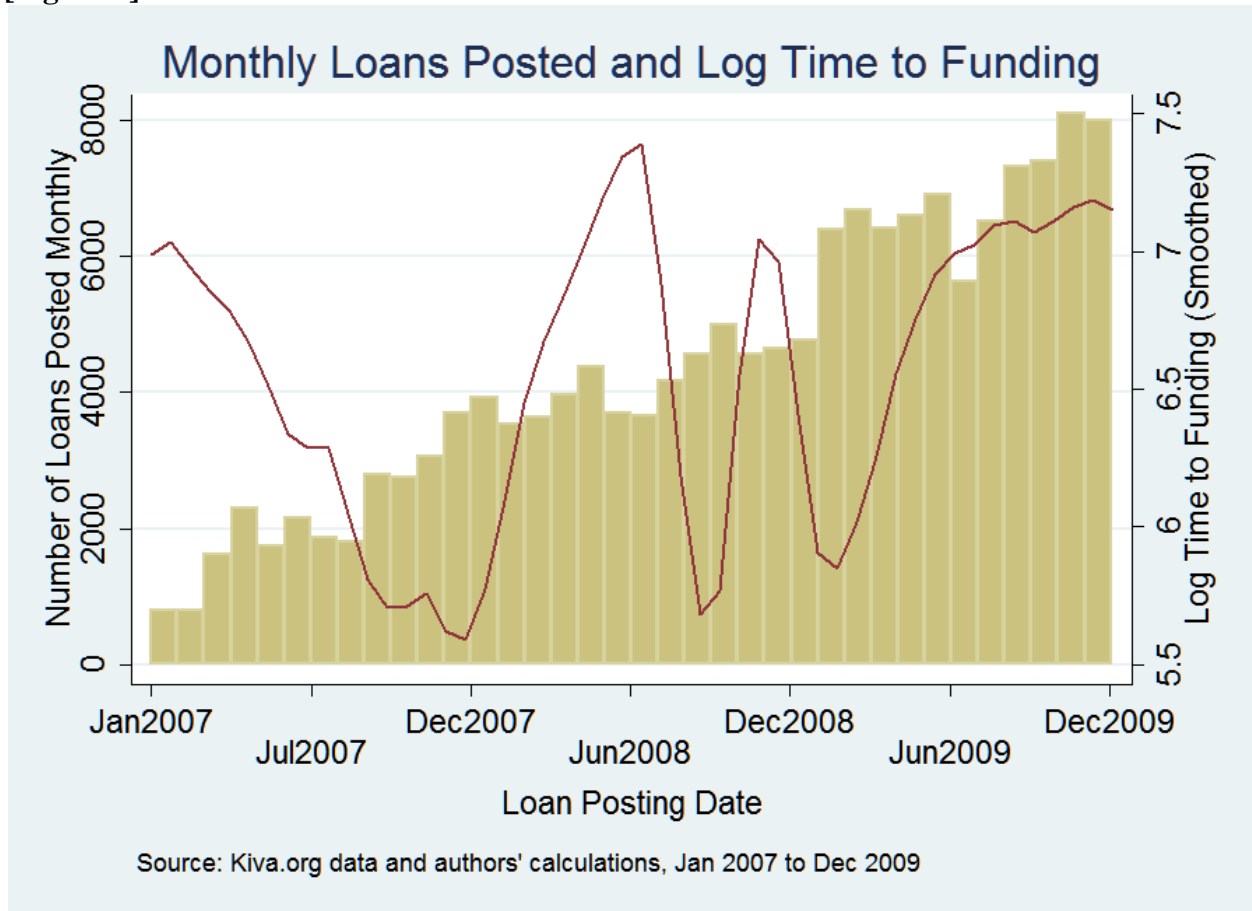
Iyer R., Khwaja A.I., Luttmer E.F., Shue, K. (2009). Screening in New Credit Markets: Can Individual Lenders Infer Borrower Creditworthiness in Peer-to-Peer Lending? NBER Working Paper No. 15242.

- Labie, Marc, Meon, Pierre-Guillaume, Mersland, Roy and Szafarz, Ariane, 2010. “Discrimination by Microcredit Officers: Theory and Evidence on Disability in Uganda” Working Papers CEB 10-007.RS, Universite Libre de Bruxelles
- Ladd, H. (1998) Evidence on Discrimination in Mortgage Lending. *Journal of Economic Perspectives*, 12(2), 41-62.
- Landry, C., Lange, A., List, J.A. (2006) Toward an understanding of the economics of charity: Evidence from a field experiment. *Quarterly Journal of Economics*, 121(2), 747-782.
- Langlois, J.H., Kalakanis, L., Rubenstein, A.J., Larson, A., Hallam, M., & Smoot, M. (2000). Maxims or myths of beauty? A meta-analytic and theoretic review. *Psychological Bulletin*, 26, 390-423.
- List, J., Price, MK. (2007) The role of social connections in charitable fundraising: Evidence from a natural field experiment. *Journal of Economics, Behavior, & Organization*, 69(2), 160-169.
- Livingston, R. W., & Brewer, M. B. (2002). What are we really priming? Cue-based versus category-based processing of facial stimuli. *Journal of Personality and Social Psychology*, 82, 5-18.
- Lorenzo, G.L., Biesanz, J.C., & Human, L.J. (2010). What is beautiful is good and more accurately understood: Physical attractiveness and accuracy in first impressions of personality. *Psychological science*, 21, 1777-1782.
- Ly, Pierre and Mason, Geri. (2010). Individual Preferences over NGO Projects: Evidence From Microlending on Kiva. University of Puget Sound Working Paper.
- Macrae C.N., Bodenhausen G.V., Milne A.B., Jetten J. (1994). Stereotypes as Energy-Saving Devices: A peek inside the cognitive toolbox. *Journal of Personality and Social Psychology*, 66(1), 37-47.
- Massey, Douglas S. and Martin, Jennifer A. 2003. The NIS Skin Color Scale. Office of Population Research, Princeton University
- Mobius, M.M., Rosenblat, T.S. (2006) Why Beauty Matters. *American Economic Review*, 96(1), 222-235.
- Moore, J.S., Graziano, W.G., Millar, M.G. (1987). Physical attractiveness, sex role orientation, and the evaluation of adults and children. *Personality and Social Psychology Bulletin*, 13(1), 95.
- Pope, D.G., Snyder, J.E. (2011) What's in a Picture? Evidence of Discrimination from Prosper.com, 46(1), 53-xx.
- Ravina, E.R. (2008) Love & Loans: The Effect of Beauty and Personal Characteristics in Credit Markets, SSRN Working Paper.

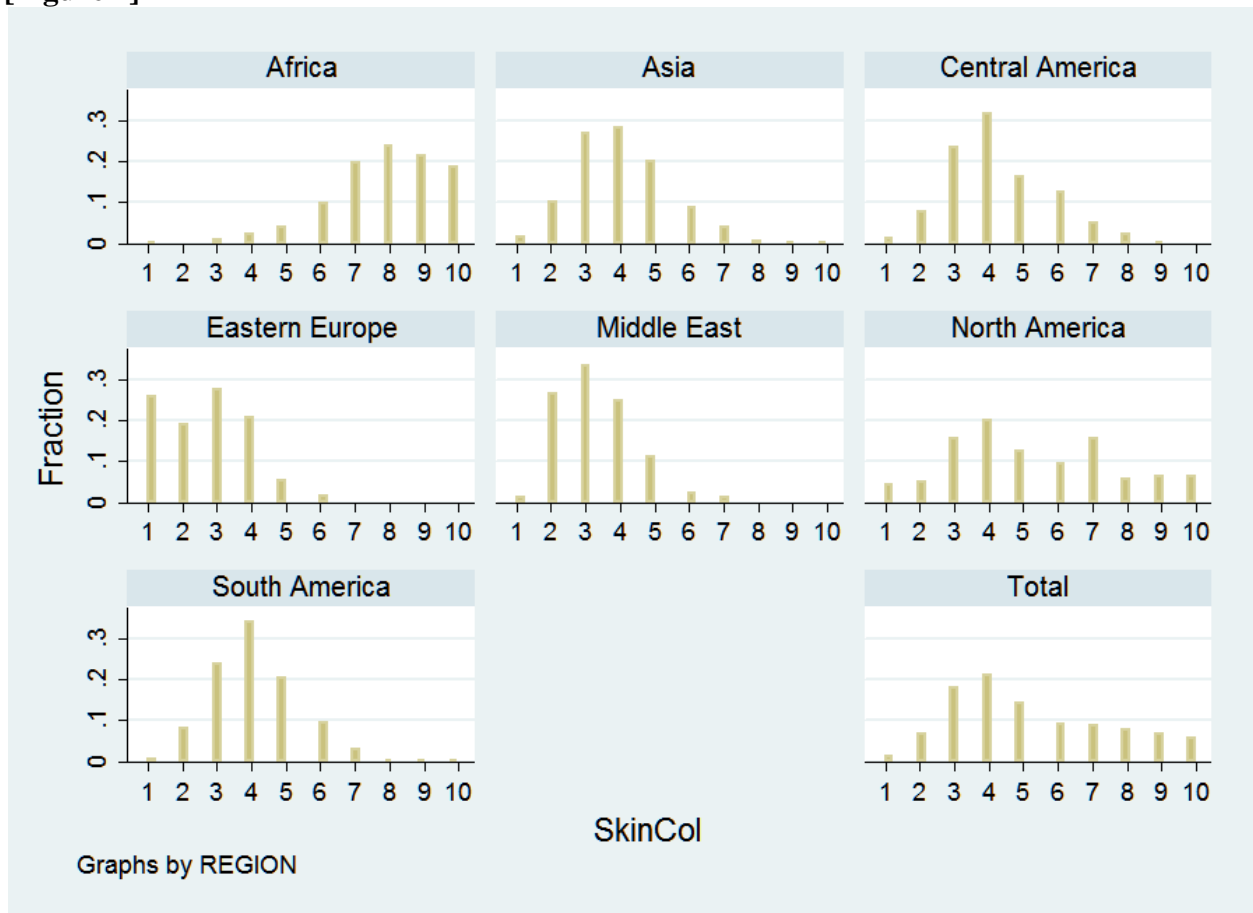
Sczesny, S., & Kuhhnen, U. (2004). Meta-cognition about biological sex and gender-stereotypic physical appearance: Consequences for the assessment of leadership competence. *Personality and Social Psychology Bulletin*, 30, 13{21.

Theseira, W. (2008) Competition to Default? Racial Discrimination in the Market for Online Peer-to-Peer Lending. Working Paper, Wharton.

[Figure 1]



[Figure 2]



[Figure 3]

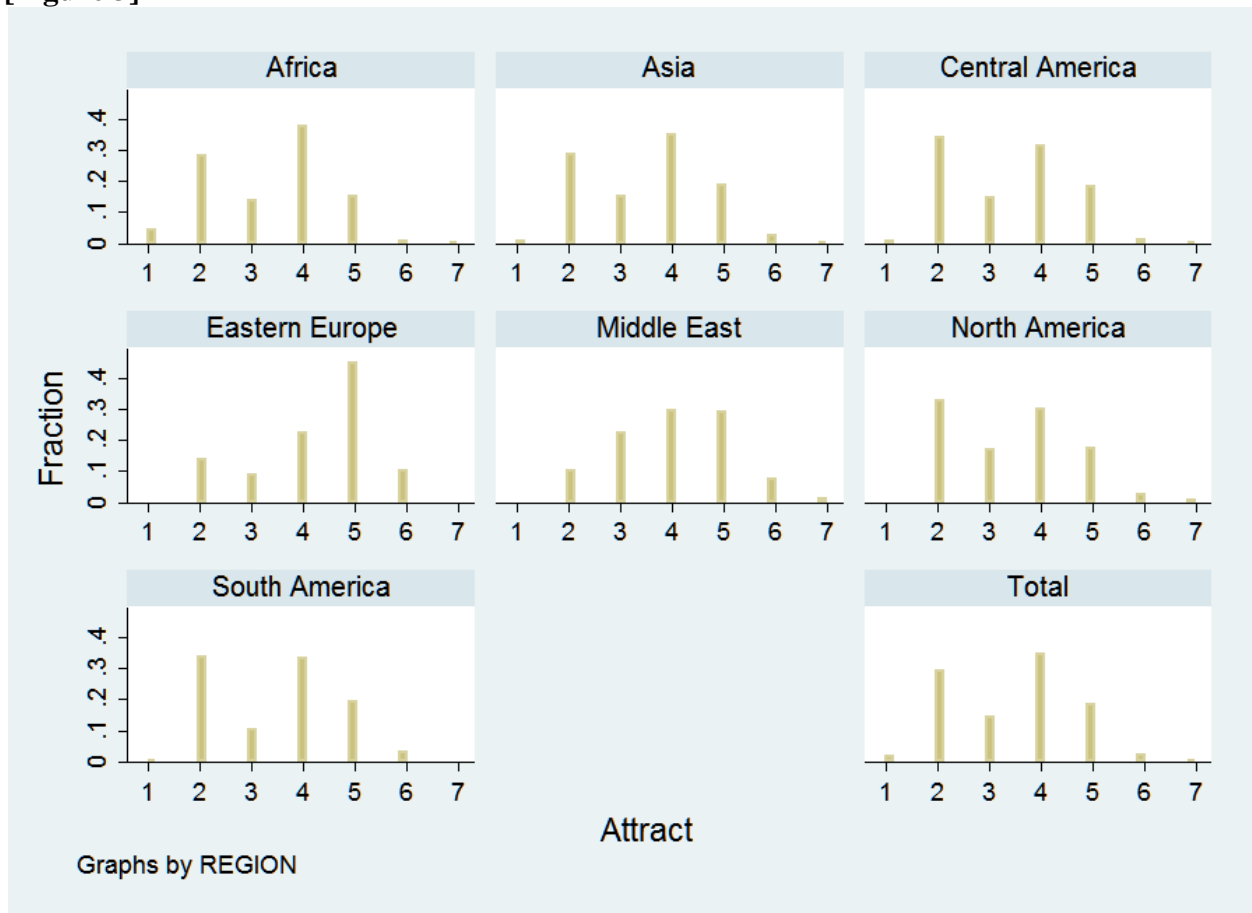


Table 1: Summary Statistics of Objective Loan Characteristics from www.kiva.org

Variable	Full Data 2007 - 2009		Data In Sample (June 2009)			
	Mean	Std Dev	All Data in Sample		Individuals	Group
			Mean	Std Dev	Mean	Mean
<i>Loan-Based Data</i>						
Time to Funding (Min)	3838.24	[7762.98]	5871.78	[8975.29]	5408.63	9009.53
Loan Amount (USD)	701.12	[621.92]	734.79	[798.80]	609.62	1582.81
Loan Term (Mths)	9.28	[4.47]	8.66	[4.43]	8.85	7.43
<i>Microfinance Partner Data:</i>						
Delinquency Rate	3.94	[11.50]	2.80	[9.52]	2.09	7.62
GDP Per Capita, PPP	4165.50	[3557.26]	3978.04	[4336.23]	4099.18	3157.35
Partner Rating (0 to 5 scale)	3.68	[1.36]	3.98	[0.91]	3.97	4.10
<i>Percent of Total Loans to:</i>						
Female Borrowers	0.78	[0.40]	0.78	[0.40]	0.76	0.89
Group Borrowers	0.11	[0.32]	0.12	[0.33]	0	1
<i>Economic Sector Classification</i>						
	Count	% of Ttl	Count	% of Ttl	% of Ttl	% of Ttl
Agriculture	27188	17.44	1146	17.38	18.61	9.08
Arts	4181	2.68	97	1.47	1.32	2.48
Clothing	12340	7.92	496	7.52	7.38	8.49
Construction	3645	2.34	146	2.21	2.18	2.48
Education	412	0.26	16	0.24	0.26	0.12
Entertainment	160	0.10	13	0.20	0.19	0.24
Food	45477	29.17	1950	29.58	30.17	25.59
Green	4	0.00	0	0	0	0
Health	1452	0.93	61	0.93	0.87	1.30
Housing	2719	1.74	130	1.97	2.16	0.71
Manufacturing	2401	1.54	104	1.58	1.65	1.06
Personal Use	499	0.32	21	0.32	0.33	0.24
Retail	36681	23.53	1655	25.10	24.25	30.90
Services	13384	8.59	546	8.28	7.52	13.44
Transportation	4794	3.08	198	3.00	2.92	3.54
Wholesale	553	0.35	14	0.21	0.19	0.35
<i>Geographic Location</i>						
Africa	46571	29.87	1990	30.18	29.66	33.73
Asia	54093	34.70	2543	38.57	39.83	30.07
Central America	11745	7.53	534	8.10	8.69	4.13
Eastern Europe	2661	1.71	58	0.88	1.01	0
Middle East	4417	2.83	184	2.79	2.59	4.13
North America	7675	4.92	168	2.55	1.76	7.90
South America	28728	18.43	1116	16.93	16.47	20.05
Observations	155890		6593		5745	848

Table 2: Summary Statistics of Subjective Characteristics from Data Sample

Variable	S					
	Individual	Group	Africa	Asia	America	Others
Time to Funding	5308.18 [8606.49]	9115.65 [10582.32]	2786.30 [4870.89]	6784.56 [9944.12]	6380.05 [9821.50]	8892.86 [10108.01]
Log Time to Funding	6.93 [2.09]	8.14 [1.66]	6.68 [1.68]	7.02 [2.34]	7.20 [2.06]	8.02 [1.79]
Loan Amount (USD)	614.53 [629.21]	1599.14 [1209.74]	712.33 [639.96]	577.74 [545.98]	917.57 [985.61]	1049.88 [1226.61]
Loan Term (Mths)	8.89 [4.56]	7.55 [3.16]	8.79 [3.38]	8.71 [4.46]	6.24 [2.83]	11.44 [5.96]
Rating	3.99 [0.89]	4.12 [0.83]	3.91 [1.15]	3.92 [0.85]	4.53 [0.36]	3.86 [0.63]
Per Capita GDP	4034.70 [4381.61]	3165.23 [2720.54]	1498.43 [502.50]	3098.75 [1309.59]	7228.41 [1825.51]	7620.34 [8705.13]
Fraction of Female Borrowers	0.76 [0.42]	0.89 [0.18]	0.80 [0.38]	0.79 [0.40]	0.85 [0.33]	0.62 [0.47]
Skin Color	5.16 [2.30]	5.77 [2.33]	7.93 [1.57]	4.01 [1.37]	4.08 [1.27]	4.14 [1.75]
Attractiveness	3.47 [1.19]	3.28 [1.18]	3.34 [1.19]	3.49 [1.17]	3.46 [1.23]	3.55 [1.22]
Physique	4.28 [0.71]	4.27 [0.62]	4.26 [0.73]	4.17 [0.65]	4.42 [0.68]	4.43 [0.71]
Well Dressed	4.12 [0.78]	4.14 [0.76]	4.08 [0.82]	4.05 [0.79]	4.35 [0.66]	4.18 [0.73]
Age	41.42 [8.34]	40.77 [6.31]	40.31 [7.55]	41.46 [8.21]	42.55 [8.45]	41.79 [8.37]
Smiling	0.59 [0.49]	0.54 [0.49]	0.48 [0.49]	0.64 [0.47]	0.66 [0.47]	0.58 [0.49]
Happy	4.14 [0.91]	3.94 [0.87]	3.96 [0.97]	4.12 [0.88]	4.29 [0.91]	4.24 [0.80]
Well Off	3.91 [0.87]	3.71 [.092]	3.70 [0.91]	3.82 [0.83]	4.14 [0.82]	4.15 [0.86]
Honesty	4.11 [0.72]	4.03 [0.66]	3.93 [0.73]	4.14 [0.70]	4.20 [0.68]	4.24 [0.69]
Neediness	3.99 [0.92]	3.66 [0.95]	3.80 [0.99]	3.90 [0.88]	4.15 [0.88]	4.16 [0.88]
Creditworthiness	4.21 [0.85]	4.00 [0.81]	4.00 [0.91]	4.19 [0.83]	4.35 [0.76]	4.38 [0.78]

Profitability	4.25 <i>[0.91]</i>	3.94 <i>[0.81]</i>	4.06 <i>[0.93]</i>	4.24 <i>[0.91]</i>	4.22 <i>[0.85]</i>	4.47 <i>[0.83]</i>
Observations	5363	790	1877	2403	1003	870

* Due to data entry errors and photograph quality, not all variables are coded in all observations

Table 3: Regressions on Full Sample

VARIABLES (Regression on Log of Time to Funding)	(1) All Data	(2) Data in Sample	(3) Borrower Physical Attributes	(4) Physical Attributes with Add'l FE	(5) Photo, Add'l FE, Subjective Assessments
Attractiveness			-0.118*** [0.026]	-0.117*** [0.024]	-0.116*** [0.025]
Skin Color			0.049*** [0.013]	0.048*** [0.012]	0.051*** [0.012]
Physique			0.174*** [0.025]	0.125*** [0.023]	0.124*** [0.023]
Smile			-0.072* [0.037]	-0.071** [0.035]	-0.071** [0.035]
Well Dressed			0.007 [0.025]	0.004 [0.023]	-0.009 [0.024]
Age			0.007*** [0.002]	0.007*** [0.002]	0.007*** [0.002]
Children in Photo			-0.155** [0.076]	-0.158** [0.072]	-0.152** [0.072]
Female Borrower	-0.487*** [0.010]	-0.633*** [0.046]	-0.642*** [0.046]	-0.740*** [0.048]	-0.730*** [0.048]
Group Loan	-0.107*** [0.014]	-0.226*** [0.064]	-0.189*** [0.070]	-0.234** [0.102]	-0.228** [0.102]
Log of Loan Amt	1.292*** [0.006]	1.366*** [0.029]	1.391*** [0.029]	1.382*** [0.034]	1.376*** [0.034]
Low MFI Rating	-0.041*** [0.009]	-0.346*** [0.040]	-0.306*** [0.041]		
MFI Partner Delinq	0.136*** [0.009]	0.039 [0.041]	0.064 [0.042]		
Log of GDP	0.159*** [0.009]	0.123*** [0.046]	0.081* [0.047]		
Neediness					0.045** [0.022]
Honesty					-0.047* [0.027]
Creditworthiness					0.020 [0.025]
<i>Controls For:</i>					
Loan Term, Sector, Region, Day	Yes	Yes	Yes	Yes	Yes
Photo Quality	No	No	Yes	Yes	Yes
Country, Activity, MFI	No	No	No	Yes	Yes
Constant	-1.500*** [0.077]	-1.278*** [0.380]	-2.072*** [0.786]	-0.836 [0.678]	-0.775 [0.684]
Observations	155,890	6,153	6,153	6,153	6,153

R-squared		0.410	0.610	0.627	0.704	0.704
Standard errors in brackets						
*** p<0.01, ** p<0.05, * p<0.1						

Table 4: Regressions on Sub-Samples

	(1)	(2)	(3)	(4)	(5)
VARIABLES					Interaction
(Regression on Log of Time to Funding)	Individual Loans Only	Group Loans Only	All Loans to Men Only	All Loans to Women Only	Effects for Loans to Women
Attractiveness	-0.125*** [0.027]	0.022 [0.077]	-0.094 [0.059]	-0.121*** [0.030]	-0.087** [0.039]
Skin Color	0.053*** [0.013]	0.004 [0.042]	0.043 [0.027]	0.055*** [0.015]	0.023 [0.019]
Physique	0.123*** [0.025]	0.013 [0.070]	0.200*** [0.061]	0.118*** [0.026]	0.170*** [0.059]
Smile	-0.057 [0.038]	-0.076 [0.096]	-0.044 [0.074]	-0.072* [0.042]	-0.080 [0.072]
Well Dressed	-0.027 [0.026]	0.067 [0.072]	-0.030 [0.051]	-0.027 [0.029]	0.021 [0.050]
Age	0.006*** [0.002]	0.006 [0.007]	0.001 [0.004]	0.007*** [0.002]	0.004 [0.004]
Children in Photo	0.008 [0.104]	-0.105 [0.099]	0.053 [0.237]	-0.224*** [0.086]	0.005 [0.235]
Female Borrower	-0.722*** [0.049]	-1.095*** [0.297]			-0.433 [0.562]
Group Loan			0.626 [0.986]	-0.242* [0.131]	0.317 [0.730]
Log of Loan Amt	1.483*** [0.038]	0.740*** [0.110]	1.241*** [0.078]	1.448*** [0.042]	1.412*** [0.063]
Neediness	0.045* [0.024]	0.185** [0.074]	0.062 [0.050]	0.024 [0.027]	0.071 [0.046]
Honesty	-0.045 [0.029]	-0.155* [0.089]	0.008 [0.060]	-0.052 [0.032]	0.004 [0.056]
Creditworthiness	0.020 [0.027]	-0.045 [0.086]	-0.061 [0.056]	0.037 [0.030]	-0.040 [0.054]
<i>Reported Interaction Effects</i>					
Attractiveness X Female					-0.038 [0.036]
Skin Color X Female					0.036* [0.018]
Physique X Female					-0.055 [0.064]
Interaction Effect Controls	No	No	No	No	Yes
Constant	-1.487** [0.698]	3.532*** [1.227]	-0.732 [0.764]	-1.959*** [0.738]	
Observations	5,363	790	1,256	4,631	5,887

R-squared		0.707	0.723	0.767	0.677	0.701
-----------	--	-------	-------	-------	-------	-------

Standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Controls for Loan Term, Sector, Region, Country, Activity, MFI Partner, Photo Quality

APPENDIX A:

INSTRUCTIONS FOR CODING PHOTOGRAPHS

Version: 10.12.2010

Please view the assigned photograph before filling in the spreadsheet answering the questions in this section. Please feel free to refer to the photograph at any time while completing this section. For photographs where a group is the subject, answer the questions based on your impression of the 'average' characteristics of the group. If you feel that there exist significant differences between members of the group, give your answer based on the 'average' but indicate that there are differences between group members where appropriate. Please give an answer where possible, using the 'blank' response only if the quality or composition of the photograph makes it difficult to have an impression.

1. NUMBER OF PEOPLE

CODING FOR 1A-E: [NUMBER OR LEAVE BLANK FOR 0]
--

- 1A:** How many people are the subjects of this photograph? (Do not count passersby or people who are not aware they are subjects of the photograph)
- 1B:** How many males (including children)?
- 1C:** How many females (including children)?
- 1D:** How many people of indeterminate gender (including children)?
- 1E:** How many children?

2. BACKGROUND CONTEXT

CODING FOR 2: [CODE OR FREE RESPONSE]

What is the background context of the photo? Please select your response from the most appropriate of the following options. If a photograph appears to qualify for more than one category, select the category which best fits your initial impression.

WORK – a work related scene, such as an office, store, industrial facility, market, farm, fishing boat, etc.

NATURE – a scene of the forest, jungle, fields, seaside, or other natural setting.
IMPORTANT: *these scenes should be coded as WORK if the person appears to be engaged in a related occupation, e.g. a farmer in front of a field.*

BUILDING – a building, which is not obviously a WORK scene.

WALL – a wall or other featureless background, e.g. neutral photo backdrop

PEOPLE – persons who do not appear to be subject(s) of the photograph (e.g. a crowd)

HOUSE – a dwelling, either interior or exterior. BUILDING is preferred to HOUSE in case of ambiguity.

OTHERS (FREE RESPONSE) – please describe succinctly and in general terms the background scene if it does not fit one of the above categories.

3. BUSINESS-RELATED ITEMS

CODING FOR 3: [CODE OR FREE RESPONSE]

Are there any business-related items present in the photo? If a photograph appears to have more than one category, select the category you think is the most important to mention.

LIVSTK – livestock (cows, chickens, etc)

EQUIP – business equipment

COWO – coworkers: persons who are not the subjects of the photo but seem to work associated with the borrowers

PROD – products that appear to be for sale

NONE – the photo does not have any business-related items

OTHERS (FREE RESPONSE) – please describe succinctly and in general terms the business-related item if it does not fit one of the above categories

4. PHOTO PROPORTIONS

CODING FOR 4A: [CODE] / 4B: [0, 25, 50, 75, 100]

4A: To what extent is the person's body captured by the photo? Please select the most appropriate of the following choices, using the following codes.

F: Face only

FS: Face and shoulders only

HB: Half body

TB: Three-quarters body

WB: Whole body

4B: In the case the person's whole body is captured, please estimate the height of the person relative to the height of the photo to the closest quartile: 100%, 75%, 50% or 25%. Otherwise, code it as 0%.

5. QUALITY

CODING FOR 5: [1, 2, 3]

Overall, how do you rate the quality of the photo?

- 1: The photograph is of poor quality; it is difficult to determine who the main subjects are, and features of people and their surroundings are difficult to distinguish or determine
- 2: The photograph is of average quality; it is clear who the main subjects of the photograph are, and features of people and their surroundings are clearly distinguishable
- 3: The photograph is of exceptional quality. All relevant features of people and their surroundings are clearly captured and convey a strong, memorable impression.

6. INFORMATION CONVEYED

CODING FOR 6: [1, 2, 3]

How well does the photo convey information about the type of business activity this person engages in?

- 1: Photo is uninformative and it is hard to tell what activity the person engages in
- 2: Photo is somewhat informative
- 3: Photo captures person's activity very well

7. PHYSIQUE

CODING FOR 7: [1 to 7, or LEAVE BLANK] / 7X: [1 or LEAVE BLANK]

7: Would you say the person in the photograph is:

- 1: Very underweight
- 2: Underweight
- 3: Slightly underweight
- 4: Neither overweight nor underweight
- 5: Slightly overweight
- 6: Overweight
- 7: Very Obese
- Blank: Can't tell

7X: If there exist significant differences between group members in terms of weight, please indicate with a '1', otherwise, leave this blank.

8. SKIN COLOUR

CODING FOR 8: [1 to 10, or LEAVE BLANK] / 8X: [1 or LEAVE BLANK]

For this question, please refer to the skin color scale, which is numbered from 1 to 10. *It is very important that you view the skin color scale and the photograph of the person under lighting conditions where the full range of colors used in the scale are clearly distinguishable.*

8: Which number on the skin color scale most closely corresponds to the skin color of the person in the photo? Leave this blank if you cannot determine skin color due to photo quality problems.

8X: If there exist significant differences between group members in terms of skin color, please indicate with a '1', otherwise, leave this blank.

9. WELL-DRESSED

CODING FOR 9: [1 to 7, or LEAVE BLANK] / 9X: [1 or LEAVE BLANK]

9: Overall, based on the quality of clothing and any accessories, would you say that the person is well-dressed?

1: Very Poorly Dressed

2: Poorly Dressed

3: Slightly Poorly Dressed

4: Neither well or poorly dressed

5: Slightly Well Dressed

6: Well dressed

7: Very well dressed

Blank: Cannot tell

9X: If there are significant differences between group members in terms of quality of clothing, please indicate with a '1', otherwise, leave this blank.

10. AGE

CODING FOR 10: [1 to 6, or LEAVE BLANK] / 10X: [1 or LEAVE BLANK]

10: How old do you think the person in the photo is, based on your first impression?

1: Under 20

2: 20-30

3: 30-40

4: 40-50

5: 50-60

6: Above 60

Blank: Cannot tell

10X: If there exist significant differences between group members in terms of age, please indicate with a '1', otherwise, leave this blank.

11. EXPRESSION

CODING FOR 11: [1, 0, or LEAVE BLANK] / 11X: [1 or LEAVE BLANK]

11: Is the person smiling?

0: No

1: Yes

Blank: Cannot tell

11X: If there exist significant differences between group members in terms of their expression, please indicate with a '1', otherwise, leave this blank.

12. HAPPY

CODING FOR 12: [1 to 7, or LEAVE BLANK] / 12X: [1 or LEAVE BLANK]

12: Overall, how happy does the person look?

1: Very Unhappy

2: Unhappy

3: Slightly Unhappy

4: Neither happy nor unhappy

5: Slightly Happy

6: Happy

7: Very happy

Blank: Cannot tell

12X: If there exist significant differences between group members in terms of how happy they look, please indicate with a '1', otherwise, leave this blank.

13. ATTRACTIVENESS

CODING FOR 13: [1 to 7 or LEAVE BLANK] / 13X: [1 or LEAVE BLANK]

13: How would you rate this person's attractiveness?

1: Very Unattractive

2: Unattractive

3: Slightly Unattractive

4: Neither Attractive nor Unattractive

5: Slightly Attractive

6: Attractive

7: Very Attractive

13X: If there exist significant differences between group members in terms of how attractive they look, please indicate with a ‘1’, otherwise, leave this blank.

14. WELL-OFF

CODING FOR 14: [1 to 7 or LEAVE BLANK] / 14X: [1 or LEAVE BLANK]

14: Overall, how well-off does the person look?

1: Very Poor

2: Poor

3: Slightly Poor

4: Neither well-off nor poor

5: Slightly Well-off

6: Well-off

7: Very well-off

Blank: Cannot tell

14X: If there exist significant differences between group members in terms of how well-off they look, please indicate with a ‘1’, otherwise, leave this blank.

15. HONESTY

CODING FOR 15: [1 to 7] / 15X: [1 or LEAVE BLANK]

15: If this person were to find a lost wallet on the street, do you think they would keep it for themselves, or try to return it (including the money)?

1: Very likely to keep wallet

2: Likely to keep wallet

3: Slightly likely to keep wallet

4: Just as likely to keep it as to return it

5: Slightly likely to return wallet

6: Likely to return wallet

7: Very likely to return wallet

15X: If there exist significant differences between group members in terms of your impression of their honesty, please indicate with a ‘1’, otherwise, leave this blank.

16. NEEDINESS

CODING FOR 16: [1 to 5, or LEAVE BLANK] / 16X: [1 or LEAVE BLANK]

16: Suppose you were deciding whether to lend \$25 (as part of a larger loan) to this person. Do you think this person is more or less needy?

- 1: Definitely needy
- 2: Needy
- 3: More likely to be needy
- 4: Neither needy nor not-needy
- 5: More likely to not be needy
- 6: Not Needy
- 7: Definitely not needy

16X: If there exist significant differences between group members in terms of your impression of their neediness, please indicate with a ‘1’, otherwise, leave this blank.

17. CREDITWORTHINESS

CODING FOR 17: [1 to 7, or LEAVE BLANK] / 17X: [1 or LEAVE BLANK]

17: Suppose you were deciding whether to loan \$25. How likely is it that this person will repay your loan instead of default?

- 1: Very likely to default
- 2: Likely to default
- 3: More likely to default
- 4: Just as likely to repay loan as default on loan
- 5: More likely to repay loan
- 6: Likely to repay loan
- 7: Very likely to repay loan

17X: If there exist significant differences between group members in terms of your impression of their creditworthiness, please indicate with a ‘1’, otherwise, leave this blank.

18. PROFITABILITY

CODING FOR 18: [1 to 7, or LEAVE BLANK] / 18X: [1 or LEAVE BLANK]

18: What is your impression of the profitability of this person's business?

- 1: Very likely to be unprofitable
- 2: Likely to be unprofitable
- 3: Slightly likely to be unprofitable
- 4: Just as likely to be profitable or not
- 5: Slightly likely to be profitable
- 6: Likely to be profitable
- 7: Very likely to be profitable

18X: If there exist significant differences between group members in terms of your impression of their profitability, please indicate with a '1', otherwise, leave this blank.

