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Beauty, weight, and skin color in charitable giving☆

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ABSTRACT

This paper examines bias in online charitable microfinance lending. We find that charitable lenders on a large peer-to-peer online microfinance website appear to favor more attractive, lighter-skinned, and less obese borrowers. Borrowers who appear more needy, honest and creditworthy also receive funding more quickly. These effects are quantitatively significant: Borrowers with beauty one standard deviation above average are treated as though they are requesting approximately 11% less money. Statistical discrimination does not appear to explain our findings, as these borrower attributes are uncorrelated with loan performance or borrower enterprise performance. The evidence suggests implicit bias could explain our findings: more experienced lenders, who may rely less on implicit attitudes, appear to exhibit less bias than inexperienced lenders.

1. Introduction

A large literature in economics examines discrimination in a variety of market settings. Much of the literature has focused on discrimination on the basis of demographic attributes such as race, ethnicity and gender. More recently, studies have found a link between beauty and the labor market (Hamermesh and Biddle, 1994; Biddle and Hamermesh, 1998; Mobius and Rosenblat, 2006) and credit access (Ravina, 2012). While such evidence of discrimination has been robustly documented in market settings, it remains an open question as to whether discrimination plays a role in non-market settings such as charitable giving. In this study, we investigate whether systematic lender biases on the basis of beauty, weight and skin color play a role in charitable decision-making. We examine discrimination in a new setting – direct philanthropy on Kiva.org, an online peer-to-peer microfinance website.[1] We show that discrimination in direct philanthropy exists, and we argue that

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[1] A number of other papers have utilized the Kiva data; a short discussion is provided in the literature review.

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it is increasingly relevant given the rapid growth in online direct giving, and given the extent to which private giving is increasingly substituting for institutional giving, which may be driven by very different preferences.

Our study departs from much of the literature on discrimination and charitable giving by using large-scale observational data of the decisions made by tens of thousands of actual charitable lenders, choosing over thousands of real charitable recipients. Previous studies have been based on experiments conducted on laboratory participants (Andreoni and Petrie, 2008), consumer research panels (Fong and Luttmer, 2009), and on households canvassed door-to-door (Landry et al., 2006; List and Price, 2009). While participants in the literature are representative of the general population, they are different from actual donors. In contrast with the literature, our paper examines how biases shape the intensive margin behavior of donors who give to international charitable causes. We examine how donor-perceived attractiveness, weight, skin color, and other characteristics affect charitable giving decisions made on a large sample of charitable recipients drawn from many developing countries. We circumvent typical omitted variables concerns that plague most observational studies because our data capture virtually all the information donors have access to.

The online international development donors we study comprise a growing and influential share of the overall charitable market. In the United Kingdom, charities focusing on international development rank at the top of the income tables, taking up to two-fifths of all private giving in some years (Atkinson et al., 2012). In aggregate, private giving from individual donors comprises 73% of the $298 billion charitable giving market in the United States (Giving USA, 2012). Online giving in particular has grown more rapidly than traditional forms of giving in recent years (Frostenson et al., 2013). Online giving often departs from traditional giving by allowing donors to give directly to a particular individual, group, or project, instead of having their giving distributed by a non-profit organization or government.[2]

The growth of online directed giving matters when the exhibited preferences or biases of individual donors differ significantly from those of institutions and governments, and when such preferences have an impact on social outcomes. Donor preferences and funding flows matter because microfinance institutions depend on donor subsidies, obtain a negative return on assets, and are generally not self-sufficient (Cull et al., 2007). Even the Nobel-prize winning Grameen Bank depends on capital subsidies from donors and would have to raise interest rates charged substantially without such assistance (Murdoch, 1999). This dependence on capital subsidies provides strong incentives for microfinance institutions (and other development oriented institutions) to focus on projects or clients who suit the preferences of donors – even if those preferences are based on physical characteristics such as beauty or weight.

Our paper's contribution is to document and interpret the causes of such exhibited individual donor preferences. As List (2011) points out, there is little evidence on how different types of agents pursue the same broad charitable goals. After the end of the Cold War, official development assistance from the major international donors and multilateral aid institutions appears to have been channeled increasingly toward poorer, more democratic countries (Dollar and Levin, 2006). However, it is not clear that private individuals in those same donor countries share these preferences; Desai and Kharas (2009) show that donations on Kiva appear to favor relatively rich and less democratic countries instead. Analyses that simply assume private and public sources of aid are substitutable in aggregate risk generating misleading conclusions if these differing preferences are not considered.

Kiva facilitates the transfer of funds from charitable lenders in developed countries to microfinance recipients in less developed countries. Although Kiva was only founded in 2005, by February 2012, it had facilitated the loan of almost $300 million US dollars, from nearly 700,000 individual donors, to more than 700,000 microfinance borrowers. Kiva facilitates loans by working with local microfinance institutions (MFI) to screen potential borrowers. When a suitable borrower or group of borrowers is identified, Kiva works with the MFI to create a loan profile on the Kiva Internet platform. The loan profile includes a picture of the borrower, a brief biography, loan purpose, loan amount and repayment schedule. The profiles also provide detailed information on the partner MFI such as their risk rating, tenure with Kiva, the number and volume of loans made and the delinquency rate of previous loans.

Potential lenders access loan profiles through the Kiva website and choose entrepreneurs they wish to support. Kiva aggregates the small loans provided by individual lenders to meet the loan amount requested by the borrower. Lenders on Kiva receive no interest on their loans, but are still subject to default risk and exchange rate risk. While borrowers are charged interest, this is retained by the local MFI and is not remitted to the Kiva lender. Kiva lenders are essentially providing subsidized, interest-free loans to the partner MFIs. Although each loan has a low risk of default (about 1.8% during the sample period), the majority of lenders make more than one loan. The average number of loans made by lenders in our sample is 16 (with a standard deviation of 94 loans), suggesting that the average lender in our sample faces roughly a 25% chance of having at least one loan default. Thus lenders forgo the use of their capital for the duration of the loan, bear credit risks, and in practice, often do not withdraw their funds from Kiva even after loans are repaid.[3] For these reasons, lender behavior has more in common with charitable giving than investing, and as such, we use the terms donor and lender interchangeably.

[2] "Directed" gifts may still be fungible if they relieve a charitable organization's budget constraint with respect to unrestricted donations.

[3] According to Matt Flannery, Kiva's co-founder, "They (lenders) are just keeping the (repaid) money in their [Kiva] account. Maybe they didn't know it was a loan. Maybe they thought it was a donation." (Kiva: Improving People's Lives, One Small Loan at a Time. Knowledge@Wharton Podcast, May 28th 2008 (Kiva, 2008).)

The 'direct-giving' context on Kiva means that our study captures the determinants of funding decisions from donors who are interested in making a specific impact with their gifts.[4] Such altruistic motivations are represented in Atkinson's (2009) 'identification' model, which assumes people give because they believe their gifts will have an impact on specific recipients or causes.[5] We assume Kiva lenders face two considerations. First, they care about the social impact of their loan, and should prefer borrowers that maximize social impact. Second, lenders should care about enterprise profitability and risk, since recovery of the loan principal allows re-gifting of the loan. As virtually all loans on Kiva eventually receive full funding, we analyze the speed with which loans are funded as a proxy for the relative attractiveness of a given loan.[6] Since Kiva lenders often face more than a thousand different charitable loans to choose from, a loan that is funded more quickly should have a combination of attributes that lenders find more attractive.

We start by examining how lenders respond to objective loan characteristics or 'hard' information such as loan amount, country of origin, MFI performance and MFI default risk in making funding decisions. Next, we examine whether lenders' decisions are also influenced by physical characteristics such as gender, attractiveness, weight and skin color. We also include 'soft' information such as perceived neediness, honesty and creditworthiness. Our empirical analysis is a test for 'disparate treatment' of loan recipients, examining whether certain types of borrowers are treated differently holding constant other dimensions.

We find that donors discriminate on the basis of attractiveness, weight and skin color. A one standard deviation increase in assessed attractiveness is associated with a reduction in time to full funding of approximately 11%, while a one standard deviation increase in assessed physique (more overweight) is associated with an increase in funding time of about 12%. The corresponding funding time increase for borrowers with skin color one standard deviation darker is about 8%. For comparison, a ten percent increase in the loan amount requested (approximately $70) is associated with an increase in funding time of about 13%. Therefore, borrowers who are one standard deviation more attractive (or more overweight, or darker-skinned) are treated by the market as though they were asking for $60 less (or $65 more, or $40 more). These estimates are economically significant when compared to the average loan amount of about $700. These effects are robust to a wide range of controls including loan characteristics, country fixed effects, MFI fixed effects, economic sector and business activity fixed effects, and fixed effects for the date the loan is posted. We also find strong evidence that female borrowers are funded faster.

We next investigate potential explanations for these patterns of discrimination. One hypothesis is that lenders statistically discriminate on observable borrower characteristics that are correlated with unobserved underlying productivity or default risk (Phelps, 1972; Arrow, 1973). Although this is a charitable setting, donors may still care about default risk because a non-defaulting enterprise is likely to have greater social impact and preserves capital for other recipients. To evaluate this hypothesis, we examine data on the performance of the loan. The average default rate of all Kiva loans is very low and our sample's default rate is about 1.8%.[7] However, we find no evidence that borrower physical characteristics significantly predict loan default, once other material loan characteristics are controlled for. This is inconsistent with the hypothesis of lender statistical discrimination on the basis of default risk, which would predict that less-preferred borrower attributes are correlated with higher risk.

Nevertheless, lenders may also care about the overall profitability of the enterprise even if there is little risk of the loan defaulting. The beauty literature has long found an association between physical attractiveness, labor market outcomes (Biddle and Hamermesh, 1998; Mobius and Rosenblat, 2006), and productivity in customer-oriented positions (Hamermesh and Biddle, 1994; Pfann et al., 2000). Accordingly, we expect lenders to statistically discriminate on beauty more when the borrower belongs to an industry such as Services or Retail where business productivity depends highly on appearance, but less when the borrower is in an industry where appearance is less important, such as Construction, Manufacturing and Transport, or Agriculture. We find the attractiveness premium to be similar across all economic sectors. Overall, our evidence is inconsistent with statistical discrimination, both on the basis of beauty-related productivity differentials and on physical characteristics predicting default risk.

If our findings are not readily explained by statistical discrimination, what remains is a pattern of bias – explicit or implicit – that presumably reflects the preferences or attitudes of lenders. While economists have traditionally modeled taste-based discrimination as the result of conscious choices (Becker, 1979), psychologists argue that discriminatory behavior may also

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4 As our dataset only covers the lending behavior of a sample of individuals on Kiva, we do not examine why an individual gives at all, or why they choose Kiva instead of alternative channels. Nonetheless, the population of lenders on Kiva is substantial, standing at nearly 700,000 lenders on Kiva as of February 2012, drawn from virtually every country worldwide.

5 In Atkinson (2009), donor beliefs need not be consistent with the reality that private small-scale donations are unlikely to have a measurable impact. What is important is that donors perceive they can make a difference in a particular recipient's life through their giving. Indeed, charitable causes generally emphasize this concept in their marketing even if the reality is a little different.

6 Although all projects on Kiva are eventually funded, biases affecting time-to-funding still have welfare implications. Other charitable websites which solicit individual donations are much less successful than Kiva. For example, on Globalgiving.org, which finances traditional development projects, typical times to full funding are in the order of months or more, although this may be attributable to Kiva controlling funding requests more strictly (Desai and Kharas, 2009). Donor biases can also be expected to influence how charitable agencies choose clients and projects, especially if they intend to use online appeals for funding.

7 One explanation for this low rate is that MFIs were allowed to cover entrepreneurs' defaults in order to keep their published default rates low. While this practice is now forbidden by Kiva, it was allowed throughout the period from 2005 to 2009. See http://www.kiva.org/updates/kiva/2010/02/10/update-on-recent-change-in-default.html.

be driven by implicit attitudes and unconscious mental associations (Baron and Banaji, 2006). Implicit attitudes are more likely to influence behavior when decision makers face a high degree of information overload and ambiguity regarding their choices (Bertrand et al., 2005). The literature on choice overload finds that individuals faced with too many choices, in various settings, behave as though they are cognitively burdened and make qualitatively different decisions (Iyengar and Lepper, 2000; Iyengar and Kamenica, 2010). We argue that implicit discrimination may characterize lending decisions on Kiva, because of the dizzying array of choices available and the lack of any obvious decision criteria for making a funding choice. We provide two pieces of indirect evidence that appear consistent with this hypothesis – first, we show that lenders with less experience on Kiva are more likely to exhibit bias in funding loans. This is consistent with evidence from the widely used implicit association test showing task experience significantly reduces implicit bias effect sizes (Nosek et al., 2005), and suggests implicit discrimination may explain part of our findings. Second, we show that as demand for credit increases, inexperienced lenders are even more likely to exhibit bias in funding loans, consistent with the cognitive burden of choice overload leading to increased reliance on implicit attitudes.

The rest of the paper proceeds as follows. The next section provides a literature review. Section 3 describes the data and provides additional details about Kiva. Section 4 discusses the effects of borrower attributes on loan funding times and loan performance. Section 5 explores the relationship between lender experience and lender bias. Section 6 concludes.

2. Literature review

This paper adds to a recent, but growing literature that explores racial and beauty biases in charitable giving in the laboratory and in the field. Fong and Luttmer (2009) experimentally vary racial information in photographs of Hurricane Katrina victims shown to potential donors and find that respondents who report feeling close to their own racial or ethnic group give substantially more when victims are of the same race. Landry et al. (2006) find that more attractive women solicitors are able to secure more and larger donations in door-to-door fundraising experiments. Similarly, List and Price (2009) find that minority solicitors are less likely to obtain a contribution, whether approaching a majority or minority household. In the laboratory setting, with public goods games, Andreoni and Petrie (2008) show that subjects are more likely to cooperate in the presence of beautiful people even though more beautiful people are not actually more cooperative. While these studies support the link between physical appearance and charitable decision-making, they largely focus on laboratory subjects (Andreoni and Petrie, 2008) or use a small number of solicitors (Landry et al., 2006) drawn from American college students. Our research question is also not directly addressed by the existing work on discrimination in microfinance, which focuses on bias in credit allocation at the MFI level (Agier and Szafarz, 2013; Labie et al., 2010).

On a broader level, this paper is also closely related to a series of papers documenting discrimination in Prosper.com, a for-profit peer-to-peer online credit market in the United States. Recent work shows that lenders in this market appear to discriminate based on borrower attributes such as race and physical appearance (Pope and Snydor, 2011; Ravina, 2012; Theseira, 2008), raising concerns that this reliance on "soft information" might undermine the ability of credit markets to allocate funds according to creditworthiness (Iyer et al., 2009). The Kiva market itself is also the subject of active study, with research on the determinants of funding decisions (Ly and Mason, 2012), how transaction costs and social distance affect funding decisions (Meer and Rigbi, 2013) and on how social identity affects charitable behavior (Liu et al., 2012). However, we are not aware of significant prior evidence on whether and how international charitable donors discriminate on physical traits, in philanthropy directed at recipients in developing countries.

3. Data

3.1. Details on Kiva.org

Kiva has been in operation since 2005, with loans posted for funding since February 2006. From 2006 through 2010, Kiva experienced rapid growth in loans posted and dollars loaned, as shown in Fig. 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, for an average monthly loan volume of $5 million. The average amount requested per loan was $700 and did not vary significantly during the period 2007–2009. In February 2012, Kiva reported a total loan volume in excess of $300 million dollars (since inception), and a client base of more than 700,000 borrowers.

Kiva partners local microfinance institutions (MFIs) in developing countries. To become a field partner, MFIs have to meet Kiva's minimum requirements and pass an on-site due diligence where Kiva personnel assess the stability, governance and risk profile of each MFI. Based on the MFI's tenure with Kiva and its financial strength, each MFI is assigned an upper limit on the amount that its borrowers can request from Kiva each month. Potential borrowers are screened by local MFIs who are also responsible for disbursing the initial loan amount. In the majority of cases, MFIs have already disbursed the full loan amount to borrowers before their loan requests are posted on the Kiva website. Therefore, while Kiva gives the impression to charitable lenders that their decisions directly affect whether and how soon an individual borrower gets funding, the fine print reveals that a lender's decision generally has no impact on an individual borrower. Loan requests are listed on the Kiva

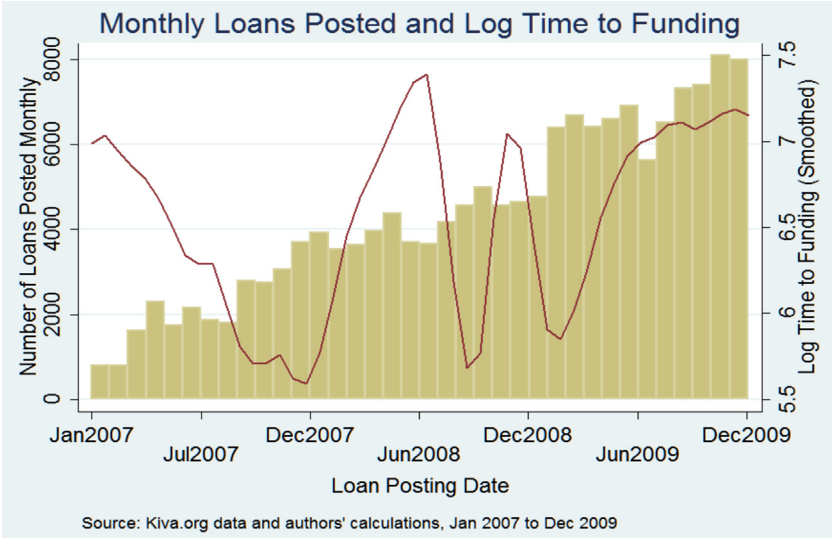

Fig. 1. Number of loans posted monthly and time to funding on Kiva from January 2007 to December 2009.

website for up to 30 days, and the MFI only receives the funds if the loan is fully funded within that period. It is very rare for loan requests not to be fully funded.[8]

Borrowers and MFIs agree on the repayment schedule and terms of the loan. While lenders on the Kiva platform receive no interest on their loans, MFIs do charge the borrowers interest. On average, the combined loan fees and interest paid by borrowers are about 38 percent per annum. MFIs are free to determine interest rates, but Kiva monitors interest rates as a key evaluation criterion for determining whether to continue partnering with an MFI. Field partners self-report to Kiva the interest rates that they charge borrowers, and the average rate charged by that MFI across borrowers is reported on the Kiva website, but not the individual borrower-specific rate.[9]

3.2. Sample data

Our sample consists of 6977 loans first posted on Kiva during June 2009. This month was chosen to represent a typical month of operations from the period where Kiva had already established mainstream status. We focused on only one month for our analysis as we wished to ensure a high quality of coding for each borrower's physical and subjective attributes. More details on our coding procedure are discussed in the next subsection. While Kiva began operations in 2005, Kiva experienced extremely rapid growth from 2005 to 2008, as shown in Fig. 1. Kiva's growth was accompanied by high-profile media events that attracted waves of new lenders, raising concerns that a sample drawn from that period might be less representative. We also wished to avoid drawing data from year-end holiday periods that might experience seasonal fluctuations in charitable activity. Finally, we needed a sufficient period of time to elapse from the loan origination date, so we could evaluate final loan default rates.

Table 1 outlines the characteristics of loans from 2007 to 2009, as well as from our June 2009 sample. In the 2007–2009 data, 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 3838 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 is 23,376 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. Our specific sample month of June 2009 appears similar to the broader data. We were able to track the performance of loans until September 2011, when close to 98% of loans were paid in full, and 1.8% of loans were in default. A small number of loans were classified as delinquent, in-repayment or refunded.[10]

[8] Pre-screening by MFIs implies that the borrowers we observe on Kiva are positively selected for characteristics that MFIs expect lenders to prefer. While the MFI can choose the types of borrowers they prefer to loan to, MFIs are not allowed to selectively post loans on Kiva. Therefore, our dataset covers the universe of loans made by the MFIs during the sample period.

[9] During the period our data covers, this information was not reported on the borrower's main loan listing and had to be accessed by clicking a link to view more information on the MFI. In recent years (not included in our sample period), after the Kiva platform was revised, substantially more information about the field partner became available on the borrower's main loan listing.

[10] Our data contains the status of every loan posted on the Kiva website during our sample period. The loan status indicates if the loan is due, repaid, currently in repayment, delinquent, or defaulted. Information on the status of all loans ever posted can be accessed directly from the Kiva website.

Table 1
Summary statistics of loan listing characteristics.

	Full data 2007–2009		Data in analysis sample (June 2009)			
			All data in sample		Individuals	Group
	Mean	Std Dev	Mean	Std Dev	Mean	Mean
Loan Data						
Time to funding (minutes)	3838.24	(7762.98)	5710.84	(8882.49)	5265.42	8825.21
Loan amount (USD)	701.12	(622)	723	(786)	602	1575
Loan term (months)	11.53	(4.42)	10.93	(4.30)	11.14	9.44
Loan status as of September 2011						
Paid			0.98	(0.14)	0.98	0.99
Default			0.02	(0.13)	0.02	0.01
Delinquent			0.001	(0.03)	0.001	0.00
In repayment/refunded			0.002	(0.04)	0.002	0.00
Microfinance Institution Partner Data						
Delinquency rate	3.94	(11.51)	2.67	(9.28)	1.99	7.41
Default rate	1.04	(5.90)	0.01	(0.10)	0.01	0.00
GDP per capita, USD PPP	4165.50	(3557)	3926	(4251)	4043	3112
MFI risk rating (0–5 scale)	3.68	(1.36)	3.99	(0.92)	3.97	4.08
Fraction of total loans to						
Female borrowers	0.78	(0.40)	0.78	(0.40)	0.77	0.90
Group borrowers	0.12	(0.32)	0.13	(0.33)	0	1
	Count	% of Ttl	Count	% of Ttl	% of Ttl	% of Ttl
Agriculture	27,188	17.44	1233	17.67	18.91	9.05
Food	45,477	29.17	2093	30	30.52	26.35
Services	13,384	8.59	577	8.27	7.57	13.17
Construction, mfg. and tpt.	10,840	6.96	466	6.67	6.65	6.88
Retail	36,681	23.53	1724	24.71	23.85	30.7
Others	22,320	14.3	884	12.67	12.51	13.86
Geographic location						
Africa	46,571	29.87	2149	30.8	30.18	35.17
Asia	54,093	34.70	2707	38.8	40.17	29.21
Central America	11,745	7.53	571	8.18	8.76	4.12
Eastern Europe	2661	1.71	58	0.83	0.95	
Middle East	4417	2.83	204	2.92	2.77	4.01
North America	7675	4.92	169	2.42	1.67	7.67
South America	28,728	18.43	1119	16.04	15.5	19.82
Observations	155,890		6977		6104	873

Notes: Summary statistics are based on all loans posted on Kiva during the respective time periods of 2007–2009 (full data) and June 2009 (analysis sample). Loans on Kiva are classified according to 16 economic sectors. We report separately the top economic sector classifications, and condense under "others" the classifications of arts, clothing, education, entertainment, green, health, housing, personal use and wholesale. "Construction, mfg. and tpt." is likewise condensed from the classifications of construction, manufacturing, and transport.

Information on ex-ante credit risks is only available at the MFI level. Thus, all borrowers from the same MFI are reported with 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%, while the median delinquency rate is 0% indicating that MFIs with 0% delinquency issue the majority of loans.[11] The average reported default rate of MFIs in the sample is very low, and underestimates the actual default rate of loans in the sample which is approximately 1.8%.[12] The mean PPP GDP per capita in borrowers' countries is $4200; 95% of all loans are issued to borrowers in countries with GDPs less than $11,100. Kiva also provides a 0 to 5 point risk rating for each MFI, displayed to potential lenders using a 5-star graphic. The star rating reflects the risk of MFI institutional default. The median rating is 4 points (mean rating approximately 3.7), indicating that the majority of loans are issued from MFIs that Kiva assesses to be relatively low-risk.

Prospective lenders may search for loans through various methods. The main loan listing page presents a summary of active loans that includes, for each loan, a picture of the borrower, the entrepreneur's name and loan activity, the loan amount and percent funded, the name of the country and MFI as well as the first two to three lines of the textual description from the main borrower profile page. The order of the list is determined by the popularity of the loan, with more popular requests placed further up the list. Loans are categorized according to the gender of the borrower, economic sector and geographic

[11] Because Kiva.org previously did not explicitly prohibit MFIs from making repayments on behalf of defaulted borrowers, the data on delinquency and defaults provided may not reflect true loan performance. Nevertheless, in our sample, the average default rate across all loans is about 1.8%, ensuring that the MFIs do not repay all loans that default.

[12] This discrepancy between the MFI default rate and the individual loan default rate likely arises because the MFI default rate is an average taken over a longer time period and the default rates of loans were significantly lower previously.

region. Lenders can use these categories and a text search field to sort and filter for loans that match any desired keywords or phrases. Loans can also be sorted based on popularity, loan amount, amount left, repayment term, and whether the loan is expiring soon or recently added. Clicking on a loan brings up the borrower's profile page, where the loan-specific details discussed above are displayed. Appendix Fig. 1 provides a screenshot of both the main lending page and the borrower page.

The last two panels of Table 1 show that the distribution of loans by economic sector and geographic region are broadly similar between the complete data and our coded sample. The most important sectors are Agriculture, Food (referring to food-based enterprises such as grocery stores and restaurants rather than personal consumption) and Retail, which together account for two-thirds of all loans. 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. Loans in our sample are also broadly similar in terms of key listing characteristics such as the loan amount, loan term, MFI delinquency rate, MFI risk rating and the fraction of loans to female borrowers and groups. This again suggests that our sample month is reasonably representative of the broader data.

3.3. *Coding procedures for physical and subjective borrower attributes from photographs*

To obtain measures of physical and subjective borrower attributes, the borrower photographs were reviewed by undergraduate research assistants. Each research assistant was asked to code and quantify certain more objective qualities of each photograph, such as the number and type of people in the photograph, gender, physique, skin color and background setting as well as more subjective characteristics such as borrower attractiveness, perceived neediness, honesty and creditworthiness. A standard set of coding instructions, found in the Appendix, was provided to each research assistant. We trained the research assistants by using a common set of borrower photographs. The coding for this common set was evaluated and discussed with each research assistant before they proceeded to the full task.[13]

To reduce the possibility of research assistant bias contaminating our results, each photograph was evaluated by a total of four coders - one male and one female coder from Singapore and one male and female coder from Chicago. All coders were undergraduates, and we ensured that the coders hired in each location reflected the majority demographics of that country. In total, we engaged forty-one coders, as photographs were randomly assigned to coders, and each coder worked independently, completing part of the entire dataset.[14] For each of the physical and subjective characteristics, coders were asked to rate the primary subject(s) in the photograph on a scale ranging from 1 to 7 or 1 to 10. In the case of a group loan, the characteristics were coded for the entire group as a whole.[15] For example, for the attractiveness rating, coders were asked to rate the attractiveness of the person in the photograph on a scale of (1) very unattractive to (7) very attractive.

We implicitly assume, in constructing and coding these scales, that there are common standards for these physical and subjective characteristics in the population (Biddle and Hamermesh, 1998). The literature on beauty has established that people seem to agree on who is attractive and who is not and these common standards seem to apply quite broadly across cultures and time periods (Langlois et al., 2000; Etcoff, 2000). Our procedure to rate the borrower's physique is similar to that for attractiveness, where coders are asked to place the person in the photograph on a scale from (1) very underweight to (7) very obese. To assess borrowers' skin color objectively, we instructed coders to base their assessment on the Massey and Martin Skin Color Scale (2003) from the New Immigrant Survey, which provides a reference visual skin color chart, and assigns a number from 1 to 10 for increasingly dark skin, with zero representing albinism.

Our definitions for the subjective borrower characteristics of perceived neediness, trustworthiness and creditworthiness are adapted from Ravina (2012). To capture trustworthiness and honesty, coders were asked "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)?" We also ask coders for their impressions on how needy the borrower is and the extent they are deserving of a Kiva-type loan: "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?" Finally, we ask coders to assess whether the individual appears to have the ability to repay a Kiva-type loan – "suppose you were deciding whether to loan $25. How likely is it that this person will repay your loan instead of default?" For each of the three questions, coders were asked to provide a rating on a scale ranging from (1) very likely to keep wallet/definitely needy/very likely to default to (7) very likely to return wallet/definitely not needy/very likely to repay loan.

To generate a measure for each characteristic comparable across borrowers, we employed a 'double standardization' method. We first standardized each coder's scores by transforming their individual ratings for each characteristic to have a mean of zero and a standard deviation of one. This measure captures the extent to which each coder considers a given borrower characteristic to be above or below average, based on the random subset of photographs they coded. We then constructed a composite standardized score for each borrower characteristic, by averaging over all coders' standardized ratings

[13] Each research assistant was given a folder containing only the photographs of the borrowers. Research assistants were told about the general purpose of the study but were not provided with any information on the borrower's context, loan description, purpose, or amount. The primary outcome of interest, time to funding, is not directly available publicly and must be calculated from the raw data.

[14] We hired a total of 41 research assistants to code the photographs – 14 females and 15 males based in Singapore and 6 females and 6 males based in Chicago. The research assistants from Singapore coded an average of 480 photographs each while the research assistants from Chicago coded an average of 1160 photographs each.

[15] In the event of substantial heterogeneity in the characteristics of the group members, coders were asked to provide an 'average' rating and to indicate the existence of significant differences between group members in terms of the characteristic.

Table 2
Summary statistics of physical and subjective characteristics (standardized measures) of borrowers.

	All	Individual	Group	By region of borrower			
				Africa	Asia	S America	Others
Attractiveness	0.00	0.01	−0.10	−0.10	0.06	0.00	0.07
	(1.00)	(1.03)	(0.78)	(0.99)	(0.98)	(1.01)	(1.04)
Physique	0.00	0.02	−0.11	−0.02	−0.26	0.40	0.30
	(1.00)	(1.04)	(0.70)	(1.04)	(0.92)	(0.94)	(0.97)
Skin Color	0.00	−0.05	0.32	1.29	−0.59	−0.56	−0.51
	(1.00)	(0.99)	(1.00)	(0.49)	(0.50)	(0.42)	(0.71)
Smile (1 = Yes, 0 = No)	0.44	0.44	0.47	0.36	0.46	0.55	0.43
	(0.50)	(0.50)	(0.50)	(0.48)	(0.50)	(0.50)	(0.50)
Neediness	0.00	−0.04	0.27	0.31	0.07	−0.33	−0.47
	(1.00)	(1.00)	(0.95)	(0.94)	(0.97)	(0.92)	(1.00)
Trustworthiness	0.00	0.01	−0.06	−0.26	0.11	0.23	0.00
	(1.00)	(1.02)	(0.86)	(1.02)	(0.93)	(0.99)	(1.02)
Creditworthiness	0.00	0.04	−0.25	−0.37	0.06	0.28	0.32
	(1.00)	(1.00)	(0.94)	(1.01)	(0.93)	(0.90)	(1.03)
Observations	6853	5996	857	2096	2665	1103	989

Notes: Summary statistics are based on all loans posted on Kiva in June 2009. Missing observations are due to a small number of missing photographs and photographs where key borrower characteristics could not be coded. The physical and subjective characteristics are standardized variables with mean 0 and standard deviation 1, derived from coded assessments of the borrower photographs by our research assistants. The text describes the coding and standardization process in detail. Standard deviations are reported in parenthesis.

for that borrower characteristic, then transforming those average ratings to have a mean of zero and standard deviation of one based on all borrowers in the entire dataset.[16] A one unit difference in each standardized borrower characteristic is thus interpretable as a one standard deviation difference in that characteristic's composite rating. We prefer this procedure over taking the simple averages of ratings across coders as it controls for the possibility that each coder may have a different baseline scale. Our results are robust to our standardization methods and to influences from idiosyncratic combinations of coders.[17]

Table 2 reports summary statistics of the physical and subjective characteristics of our sample, based on our composite standardized score. While there is considerable variation in these measures across borrowers and regions, the means and standard deviations of the variables are broadly similar, and reasonably consistent, across coders. The Cronbach alpha has previously been used in the literature on beauty to measure the consistency of ratings across different observers (Biddle and Hamermesh, 1998; Andreoni and Petrie, 2008). The alpha coefficient ranges from 0 to 1 where a reliability coefficient of 0.70 or higher is generally considered "acceptable". In our data, the Cronbach alphas for attractiveness, physique and skin color are 0.67, 0.96 and 0.87, respectively. This suggests the standards of beauty held by our coders are more diverse than standards for physical weight, or perceptions of skin color. While the alpha coefficient for attractiveness is smaller than most previous studies, this could be due to the fact that borrowers in our sample come from a much wider range of backgrounds.[18] For the subjective characteristics, the Cronbach alphas are 0.67 for neediness, 0.56 for trustworthiness and 0.57 for creditworthiness.[19] Appendix Table 2 presents the correlations between the coded physical and subjective attributes of the borrower, and the objective loan characteristics.

4. Results

4.1. Determinants of time to funding

In this section, we explore how borrower characteristics affect the speed of loan funding. We focus on three sets of characteristics: (1) hard information provided in the loan listing, (2) physical characteristics observed from photographs, and (3) subjective characteristics inferred from photographs. We are interested in testing for evidence of discrimination – whether a borrower's physical attractiveness, physique and skin color affect how quickly their loans are funded, holding all other attributes of the loan constant. These other loan attributes, such as the purpose of the loan, loan amount requested, MFI

[16] While each photograph was rated by 4 coders, a small number of photographs have only 3 valid ratings because of data entry errors or perceived difficulty in coding (research assistants were informed to leave entries blank if they felt they could not code the characteristic accurately). Results using ratings that require each photograph to have all four independent ratings are similar and reported in Appendix Table 1.

[17] Regressions using non-standardized ratings obtain similar results, as do regressions that include fixed effects for each of the 3625 coder-group combinations that assessed the data. The results are available from the authors.

[18] The Cronbach alpha for beauty reported in Biddle and Hamermesh (1998) is 0.75, and 0.86 in Andreoni and Petrie (2008).

[19] It is not surprising that the degree of agreement across coders for these subjective characteristics is lower than that for physique and skin color. This is consistent with Alesina and Ferrara (2002), who show that background factors play an important role in whether a coder finds someone trustworthy. Moreover, there is likely to be greater subjectivity in determining a borrower's perceived neediness, trustworthiness and creditworthiness from photographs alone. Nevertheless, our consistency measures for trustworthiness and creditworthiness are similar to Ravina (2012).

background, and so forth, are also important as they may provide information concerning default risks and social impact. We begin by estimating regressions of the form:

$$Y_i = \alpha + X_i\beta + Z_i\gamma + \varepsilon_i$$

where Y_i is the log time to funding for each loan i, X_i is a vector that includes the physical characteristics and subjective characteristics coded from the photographs, and Z_i is a vector that includes all the other characteristics of the loan listing and the borrower. The coefficients are interpretable as the effect in percentage terms of a linear unit change in the coefficient on the time to funding.[20] Objective loan characteristics Z_i include gender, an indicator for whether the loan is to a group or an individual, log of the loan amount, the repayment schedule in months, log GDP of the borrower's country, the five-point rating of MFI quality and the average MFI delinquency rate.[21]

In all our specifications, we control for region fixed effects, fixed effects for the day the loan was posted and economic sector fixed effects. The physical characteristics of borrowers coded from the photographs include attractiveness, physique, skin color and a dummy variable that indicates whether the borrower is smiling. As discussed previously, the attractiveness, physique and skin color scales are based on the composite score derived from the four independent coders. The subjective characteristics of borrowers include perceived neediness, trustworthiness and creditworthiness. In the regressions that test whether photo-based physical and subjective characteristics matter, we include additional fixed effects for the borrower's country (44 countries), activity (126 categories within 15 sectors) and MFI (86 field partners). In the Appendix, we explore additional specifications using more flexible controls for the objective loan characteristics, as well as methods for measuring the quality of borrower text descriptions. Estimates from our baseline model are robust to these additional specification checks (Appendix Tables 3A and B). As borrowers from the same country are more likely to possess correlated characteristics – due to genetics, economic structure, etc. – our models are estimated using robust standard errors clustered at the country level. The country level is also consistent with the general principle of selecting the coarsest level of clustering suitable for the analysis (Cameron and Miller, 2015).

Our empirical strategy first builds a preferred regression specification, using the complete June 2009 sample of photo-coded data, from the major components discussed above – objective loan, physical borrower, and subjective borrower characteristics. We then conduct sub-sample analyses by gender and by group vs. individual loans. These sub-sample analyses have particular external relevance as group and gender-based lending is a key strategy of microfinance lenders such as the Grameen Bank.

Our main results are presented in Table 3. Column (1) reports estimates of only the objective loan characteristics, while (2) adds borrower physical characteristics and additional fixed effects for country, activity, and MFI. (3) is our preferred full specification which additionally contains borrower subjective characteristics. Starting with the financial characteristics, larger loans take a longer time to achieve full funding – a 10% increase in the loan amount (about $70) increases time to funding by about 13%. The estimate is stable across all specifications. While longer repayment terms increase time to funding by about 7% per additional month, this coefficient is not statistically significant in (1). Borrowers from higher-GDP countries take longer to receive full funding – but the estimates are not statistically significant. Perhaps lenders believe social impact is higher when lending to individuals in poorer countries. MFI attributes produce mixed results. As expected, loans under MFIs with high delinquency rates are funded slower, but MFIs with worse overall ratings actually receive funding for their loans faster. One possibility is that low-rated MFIs might serve countries or certain groups of borrowers that lenders favor.

Group loans are funded faster than individual loans, but the effect shrinks and is insignificant with the inclusion of borrower characteristics and additional fixed effects in (2) and (3). Part of the group funding advantage could be operating through the presence of groups in regions or activities that lenders prefer. Lenders strongly favor female borrowers – an all-women group (results are similar for loans to individual women) is funded 65% to 81% faster than loans to an all-men group. The gender effect increases as we add borrower characteristic controls, suggesting the preference is not just due to lenders assessing women as possessing more favorable (codifiable) characteristics. We discuss group and gender differences in more detail in the next section's sub-sample analyses.

Next, we explore the effect of photograph-observed personal characteristics on lending decisions, controlling for the objective loan information included in (1). We attempt to overcome typical omitted variable concerns that plague most observational studies of discrimination by controlling for much of the same information observable to the lenders (Pope and Snydor, 2011). In these specifications, we include a full set of fixed effects that control for the borrower's country of origin, economic activity fixed effects and MFI fixed effects. By including the country and MFI fixed effects we subsume all the country-level and MFI-level covariates in (1) and also control for all the observed and unobserved characteristics of MFIs that could be correlated with the borrower's personal characteristics and the time to funding. We first analyze the effect of the more objective physical borrower characteristics in (2), and we then add the subjective borrower characteristics in (3), which is our preferred full regression specification. In unreported regressions, we have estimated separately the effect of each borrower characteristic on time to funding, and also explored different combinations of borrower characteristics. The results are broadly similar to those discussed below.

[20] In our sample, all the loans were fully funded within the 30-day limit set by Kiva.

[21] The gender variable, "Fraction Female," is 0 or 1 for loans to individuals, and ranges from 0 to 1 for loans to groups.

Table 3
The effect of borrower appearance and loan characteristics on funding time of loans.

	Outcome: ln(time to funding)		
	(1)	(2)	(3)
Attractiveness		−0.127***	−0.111***
		[0.018]	[0.024]
Physique		0.122***	0.115***
		[0.013]	[0.013]
Skin Color		0.060	0.075*
		[0.043]	[0.042]
Smile		−0.060**	0.012
		[0.026]	[0.036]
Neediness			−0.062***
			[0.016]
Trustworthiness			−0.118***
			[0.042]
Creditworthiness			0.023
			[0.024]
Age		0.004	0.005**
		[0.003]	[0.003]
Children in photo		0.094*	0.116**
		[0.055]	[0.053]
Group loan	−0.306*	−0.116	−0.098
	[0.177]	[0.242]	[0.239]
Fraction female	−0.650***	−0.814***	−0.775***
	[0.126]	[0.091]	[0.090]
ln(loan amount)	1.344***	1.303***	1.297***
	[0.091]	[0.085]	[0.085]
Loan term (in months)	0.023	0.069***	0.069***
	[0.019]	[0.015]	[0.015]
MFI risk rating (0–5 points)	0.180***	–	–
	[0.043]		
MFI delinquency rate	0.010*	–	–
	[0.006]		
MFI default rate	−0.028	–	–
	[0.295]		
ln(GDP)	0.163	–	–
	[0.133]		
Controls for			
Loan sector, region, posting day fixed effects	Yes	Yes	Yes
Country, economic activity, MFI fixed effects	No	Yes	Yes
Observations	6853	6853	6853
R-squared	0.606	0.699	0.701

Notes: Each column is a separate linear regression. Column (1) is our main sample of Kiva loans from June 2009 with non-missing borrower photos and at least three independent ratings for each of the borrower physical and subjective attributes used in the study. Columns (2) and (3) uses the same sample but adds fixed effects for country, economic activity, and MFI partner, which require us to drop the MFI- and country-level characteristics. The physical and subjective characteristics are standardized variables with mean 0 and standard deviation 1. The text describes the coding and standardization process in detail. Standard errors clustered at the country level are reported in parenthesis.

*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

We find strong evidence that borrower physical characteristics are associated with lender decisions even after controlling extensively for other characteristics of the loan. Lenders appear to strongly favor borrowers who are more attractive, less overweight and have lighter skin color, controlling for country of origin, sector, partner MFI and other characteristics of the loan. Based on (3), a one standard deviation (one unit) increase in assessed attractiveness is associated with a reduction in time to full funding of approximately 11%, while a one standard deviation increase in assessed physique (obesity) is associated with an increase in funding time of about 12%. For comparison, a ten percent increase in the loan amount requested, or about \$70, is associated with an increase in funding time of about 13%. This implies borrowers who are one standard deviation more attractive (overweight) are treated by lenders as though they were asking for \$60 less (\$65 more). Funding times are also significantly lower for darker-skinned borrowers – a borrower one standard deviation darker is treated as though they are asking for \$40 more. Compared to other physical traits, the results on skin color are weaker in terms of statistical significance, and more dependent on the model specification. As a whole, these estimates showing apparent bias on the basis of physical characteristics are significant given that the average loan amount requested is about \$700 in our sample.

We now examine the effect of subjective borrower traits – neediness, trustworthiness, and creditworthiness. Comparing (2) and (3), we find that estimates of the effect of physical traits are minimally affected by the inclusion of these subjective traits. Lenders appear to be independently considering both 'outer' and 'inner' beauty in their lending decisions. Greater

Table 4
The effect of borrower appearance and loan characteristics on funding time of loans – subgroup analyses.

	Outcome: ln(time to funding)					
	Individual loans only	Group loans only	Diff. between (2) and (1)	Individual loans to		Diff. between (5) and (4)
				Men	Women	
	(1)	(2)	(3)	(4)	(5)	(6)
Attractiveness	−0.109***	−0.105	0.004	−0.085*	−0.115***	−0.030
	[0.025]	[0.066]	[0.065]	[0.050]	[0.030]	[0.057]
Physique	0.112***	0.050	−0.062	0.104**	0.112***	0.008
	[0.014]	[0.083]	[0.078]	[0.045]	[0.015]	[0.048]
Skin color	0.101**	−0.017	−0.119	0.105	0.099	−0.005
	[0.047]	[0.091]	[0.099]	[0.083]	[0.061]	[0.108]
Smile	0.049	−0.198*	−0.246**	0.003	0.065	0.063
	[0.037]	[0.115]	[0.103]	[0.068]	[0.041]	[0.084]
Neediness	−0.052***	−0.069	−0.017	−0.172***	0.002	0.174***
	[0.015]	[0.064]	[0.061]	[0.024]	[0.023]	[0.033]
Trustworthiness	−0.133***	0.063	0.195***	−0.087**	−0.146**	−0.059
	[0.046]	[0.061]	[0.067]	[0.035]	[0.055]	[0.064]
Creditworthiness	0.016	0.032	0.016	−0.093**	0.064	0.157***
	[0.027]	[0.061]	[0.064]	[0.036]	[0.038]	[0.051]
Age	0.006**	0.003	−0.002	0.008	0.004*	−0.003
	[0.003]	[0.008]	[0.007]	[0.005]	[0.003]	[0.006]
Children in photo	0.170**	−0.053	−0.223*	0.110	0.173**	0.064
	[0.064]	[0.105]	[0.118]	[0.123]	[0.067]	[0.115]
Fraction female	−0.763***	−0.988**	−0.225			
	[0.087]	[0.393]	[0.366]			
ln(loan amount)	1.390***	0.786***	−0.605***	1.185***	1.443***	0.258*
	[0.091]	[0.102]	[0.132]	[0.166]	[0.069]	[0.128]
Loan term (in months)	0.064***	0.065	0.001	0.051**	0.079***	0.027
	[0.016]	[0.058]	[0.057]	[0.022]	[0.016]	[0.023]
Controls for						
Loan sector, region, posting day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country, economic activity, MFI fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5996	857	6853	1376	4620	5996
R-squared	0.703	0.715	0.714	0.763	0.669	0.716

Notes: Each column is a separate linear regression. Column (3) reports the difference in coefficients between Columns (1) and (2) and is based on a fully interacted regression model containing all the data in both (1) and (2). Likewise, column (6) reports the difference between the coefficients in Columns (4) and (5) based on a fully interacted regression model. The physical and subjective attributes are standardized variables with mean 0 and standard deviation 1. The text describes the coding and standardization process in detail. Standard errors clustered at the country level are reported in parenthesis.
*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

perceived neediness and trustworthiness of borrowers is associated with faster time to funding. The magnitude of these effects is comparable to the effect of physical traits – a one standard deviation increase in the characteristic is associated with a reduction in funding time of 6% (neediness) and 12% (trustworthiness) respectively. However, there is no significant effect of creditworthiness on time to funding, in aggregate (though creditworthiness is significant in sub-group analyses, discussed shortly).

The importance of neediness and trustworthiness to lenders on Kiva contrasts strongly with the literature on for-profit peer-to-peer credit markets, which generally finds that creditworthiness is the key subjective borrower trait. Ravina (2012) finds that creditworthiness, but not trustworthiness, matters. Our results are quite comparable to Ravina (2012) as we use the same methods of measuring creditworthiness and trustworthiness. Duarte et al. (2012) argue that trust matters, but they use a measure of trust that actually includes a creditworthiness assessment. Therefore, we interpret their findings as confirming that creditworthiness matters to for-profit lenders. Unlike the for-profit market literature, we find lenders on Kiva mainly appear to care about whether the borrowers need the money and are trustworthy in general. In aggregate, our evidence suggests creditworthiness matters less, conditional on other characteristics being accounted for in the model. This reinforces the importance of treating charitable lending as a separate and distinct market from for-profit lending. While certain biases are shared between markets, such as preferences for beauty, other underlying motivations behind credit decisions appear to diverge.

4.2. Subgroup analyses

Now, we investigate how estimated effects of borrower characteristics depend on group status and gender. While we found a slight preference for lending to groups earlier, here we examine whether lenders treat a given group borrower characteristic differently from the same individual characteristic. In columns (1) and (2) of Table 4, we estimate our preferred full specification on the data restricted to individual and group borrowers, respectively. Column (3) tests whether the coefficients in (1) and (2) are significantly different, based on a fully interacted model. We find that estimates for physical and subjective characteristics are significant for individual borrowers, but not for group borrowers. The magnitude and direction of the estimated effects are broadly similar – (3) indicates coefficients are only significantly different for smiling and trustworthiness. Interestingly, the fact that trustworthiness is significantly less important for group borrowers could be consistent with the economic argument that joint liability and peer monitoring helps resolve individual moral hazard problems (Stiglitz, 1990; Besley and Coate, 1995; Ghatak and Guianne, 1999). However, we caution that our estimates likely suffer from measurement error in the group borrower characteristics. While we asked our coders to rate each group's average characteristics, lenders may actually be considering other aspects of a group's characteristic distribution. Therefore, in the subsequent analyses following this sub-section, we base our estimates solely on individual borrower data, which forms the bulk of our data in any case.

In columns (4–6) of Table 4, we perform the same analysis, now split by gender rather than group status. We find no gender differences in the effect of physical characteristics, with more attractive and less overweight borrowers similarly advantaged regardless of gender. We do find significant differences in the subjective characteristics. While greater neediness, trustworthiness and creditworthiness significantly reduce funding times for men, only trustworthiness matters for women. Gender differences are particularly large for neediness and creditworthiness – the point estimates indicate almost no effect of neediness for women, but a substantial 17% reduction in funding time for a male borrower who appears one standard deviation needier. These results are interesting in light of the literature showing that the social impact of microfinance on children's consumption, labor supply and household finances, is larger when women are borrowers, not men (Pitt and Khandker, 1998). Lenders who seek to maximize social impact could be targeting women in general (and ignoring differences across women borrowers in perceived neediness), as well as selectively lending to more needy and more creditworthy men.

4.3. Probability of loan default

Here, we examine whether the observed patterns of bias are caused by lender statistical discrimination. The statistical discrimination hypothesis predicts that lenders will be biased against observable borrower characteristics because those characteristics are correlated with underlying default risks. Kiva classifies as delinquent loans with one or more payments past due, while a loan is classified as defaulted if six months elapse on a past due loan without full recovery of the loan amount. As of September 2011, 1.8% of loans were either delinquent or defaulted. One reason for Kiva's low default rate is that MFIs may cover non-performing loans in order to maintain their low average default rates. While this practice is currently prohibited by Kiva, it was allowed from 2006 to 2009. Nevertheless, under the statistical discrimination hypothesis what should matter to lenders is the overall likelihood of default, and whether the observable characteristics of borrowers are predictive of default.

Table 5 reports linear probability model (1–2) and logit (3) estimates of the relationship between loan default and the physical and subjective characteristics of borrowers, controlling for the same loan characteristics as in Table 3.[22] The linear probability model used in column (1) is based on the full regression specification in Table 3. The logit model in column (3) reports marginal effects estimated at the mean of the independent variables, and omits fixed effects because of insufficient variation in default rates within many of our fixed effect categories. For comparison with the logit model, we include a linear probability model omitting fixed effects in column (2).[23]

As observed from columns (1–3), we find little evidence that any photo-based characteristics are predictive of default. The appearance-based characteristics of attractiveness, physique and skin color, are not significantly associated with loan default in all specifications. The subjective photo-based characteristics of neediness, trustworthiness and creditworthiness are also not associated with default. There is no evidence that default rates differ by gender, although female borrowers attract funding much more quickly. We do not think our statistically insignificant findings are just due to the low default rates in the data – we are able to identify that higher loan amounts are associated with a lower probability of default in column (1). Thus, the evidence suggests there is no statistical relationship between discriminated-against borrower characteristics and the actual probability of default.

Appendix Tables 4A and B report several robustness checks for our results in this section. To address the concern that our estimates are biased toward zero by the baseline low probability of default, we use the 'rare events' adjustment for the logit model proposed by King and Zeng (2001). We also incorporate the influence of fixed effects by first regressing each borrower characteristic of interest on the set of fixed effects, then using the resulting residuals in place of the borrower characteristic variables in our logit models. Results from the robustness checks are qualitatively similar and indicate little influence of borrower characteristics on loan default rates. We acknowledge a remaining limitation is that MFIs may repay defaulting loans. We can rule out the case where MFIs non-strategically repay all defaulting loans – defaults do exist and are

[22] As a conservative estimate, we code loans that are currently delinquent as having defaulted. As shown in Table 1, virtually all of the loans that are not repaid had defaulted, with only a very small number recorded as another status (approximately 0.1% of all loans were delinquent). The results are virtually identical if we only focus on loans that have defaulted.

[23] The absence of fixed effects in columns (2–3) also provides a parsimonious model of statistical discrimination that reflects the case where lenders make decisions mainly on the observable characteristics of borrowers rather than on the ancillary characteristics captured by our fixed effects.

Table 5
The effect of borrower appearance and loan characteristics on loan default.

	Outcome: loan default		
	Linear probability model		Logit – Marginal Effects
	(1)	(2)	(3)
Attractiveness	−0.001	−0.003	−0.0002
	(0.001)	(0.003)	(0.0002)
Physique	0.001	−0.002	−0.0002
	(0.001)	(0.005)	(0.0002)
Skin color	0.003	0.002	0.0004
	(0.002)	(0.007)	(0.001)
Smile	−0.002	−0.003	−0.0005
	(0.002)	(0.004)	(0.001)
Neediness	−0.002	−0.002	−0.0002
	(0.001)	(0.005)	(0.001)
Trustworthiness	0.001	−0.002	−0.0005
	(0.001)	(0.005)	(0.001)
Creditworthiness	−0.001	−0.008	−0.0007
	(0.001)	(0.006)	(0.001)
Age	0.000	−0.000	0.0000
	(0.000)	(0.000)	(0.0000)
Children in photo	−0.003	−0.003	−0.0007
	(0.005)	(0.005)	(0.001)
Female	−0.001	0.018	0.0018
	(0.003)	(0.018)	(0.002)
ln(loan amount)	−0.008*	0.008	0.0011
	(0.004)	(0.007)	(0.001)
Loan term (in months)	0.005	0.006	0.0005
	(0.003)	(0.004)	(0.0005)
Controls for			
Loan characteristics	Yes	Yes	Yes
Loan sector, region, posting day fixed effects	Yes	No	No
Country, economic activity, MFI fixed effects	Yes	No	No
Observations	5954	5954	5954
R-squared	0.724	0.084	0.412

Notes: The sample is restricted to individual loans only. Columns (1) and (2) report estimates from separate linear probability models. Column (3) reports the marginal effects at the mean of the independent variables from a logistic model. The sample includes all individual loans in our data sample that have available default status. Column (1) uses the same set of regressors as the individual loans model in Table 4. Columns (2) and (3) differ by excluding fixed effects for loan sector, region, loan posting day, country, economic activity, and MFI. Instead of these fixed effects, the MFI rating, MFI default rate, MFI delinquency rate, and ln(GDP) of the borrower's country are included in (2) and (3). Standard errors clustered at the country level are reported in parenthesis.
*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

significant for some MFIs. However, we do not have strong a priori justifications for formulating and testing any particular model of strategic MFI repayment behavior.[24] We caution that defaults may be a noisy measure because of unobserved MFI repayments.

4.4. Differences across sectors

Next, we consider an alternate statistical discrimination test that is more robust to both unobserved MFI repayment behavior and low underlying default rates. This test assumes instead that lenders discriminate because they wish to maximize enterprise productivity and output, rather than just loan repayment performance. We believe this is a reasonable assumption since Kiva's published default rates are quite low, so lenders wishing to statistically discriminate may have considered more carefully potential output rather than default rates. The test requires identifying a borrower characteristic variable that is plausibly a priori associated with differential business productivity. We believe the most suitable variable is physical attractiveness.

[24] For example, strategic MFIs might preferentially repay loans of borrowers known to be favored by lenders, to avoid 'killing the golden goose'. But it is also possible that strategic MFIs preferentially repay loans for less-favored borrowers if confirming negative stereotypes would greatly reduce funding access for those borrowers. The optimal strategy depends on the elasticity of lender money supply with respect to defaults. We do not have clear grounds for making assumptions regarding these parameters. Finally, MFI strategic behavior (if it exists) is likely to be heterogeneous, since MFIs differ widely in the types of borrowers they service.

Table 6A
More attractive borrowers sort into customer-facing economic sectors.

	Outcome: attractiveness	
	(1)	(2)
Services	0.193**	0.127**
	[0.078]	[0.055]
Construction, mfg and transport	−0.008	−0.028
	[0.051]	[0.038]
Food	−0.090	−0.042
	[0.055]	[0.026]
Agriculture	−0.045	−0.094**
	[0.066]	[0.039]
Retail	Omitted category	Omitted category
Observations	5257	5257
R-squared	0.023	0.324
Controls for		
Borrower characteristics	Yes	Yes
Loan characteristics	No	Yes
Country, day, MFI fixed effects	No	Yes

Notes: The sample is restricted to individual loans in the listed economic sectors only. Each column is a separate linear regression with attractiveness as the dependent variable. Each regression includes dummy variables for the following sectors: services; construction, manufacturing and transport; food; and, agriculture. The retail sector is the omitted category. "Borrower characteristics" consists of gender, age, and presence of children. "Loan Characteristics" consists of the loan amount and loan term. Standard errors clustered at the country level are reported in parenthesis.
*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

The beauty literature shows that relatively attractive individuals sort into customer-facing occupations such as sales and services, and earn premiums correlated with their attractiveness in these occupations (Hamermesh and Biddle, 1994; Pfann et al., 2000). A lender who statistically discriminates with the aim of funding enterprises that are more likely to be highly productive should therefore be more willing to fund attractive borrowers in customer-facing businesses. By contrast, the extent of standard taste-based discrimination should be invariant to enterprise type, as the potentially higher output of a more attractive borrower in a customer-facing enterprise should be less relevant. Although a similar test applies in principle for other physical characteristics, lighter skin color and lower weight is not associated with higher productivity as generally as beauty itself. For example, while low physical weight may indicate good self-control and higher productivity, higher physical weight may be a productive characteristic in a physically demanding enterprise.[25]

Accordingly, we concentrate on investigating whether the effect of attractiveness on time to funding varies across five major economic sectors – Agriculture, CMT (Construction, Manufacturing and Transport), Food, Retail, and Services. These five sectors account for 85% of the loans in our sample. Retail, Services, and Food (retail food) are more obviously customer facing sectors where attractiveness may allow an entrepreneur to be more successful. However, productivity in Agriculture and CMT are less obviously linked to attractiveness.

We first document evidence of beauty-based sorting by borrowers on Kiva into different occupations. Table 6A presents the results of regressions of the borrower's attractiveness on industry sector dummies. Column (1) includes other borrower characteristics, while (2) additionally includes loan characteristics and the full set of fixed effects used in our main regression models. The results in Table 6A show that borrowers in Services are more attractive, by an average of 0.127 to 0.193 standard deviations, than those in Retail (the baseline). Borrowers in Food, CMT, and Retail are statistically similar in terms of attractiveness, though the point estimates for Food are somewhat lower. Agriculture is associated with less attractive borrowers than Retail. The evidence is consistent with some degree of sorting by attractiveness, with the more attractive borrowers entering Services, followed by Retail and CMT, then Food, then Agriculture.

In Table 6B, we examine whether the relationship between attractiveness and time to funding depends on the borrower's industry. If lenders statistically discriminated to maximize productivity, we would expect greater effects of attractiveness in Services and Retail. Panel A reports how the effect of attractiveness on time to funding varies by industry sector, using the main regression model run separately on each industry sector. Then, in Panels B and C we test whether differences in the attractiveness coefficient between sectors are statistically significant. Specifically, Panel B reports the difference between the effect of attractiveness in that industry and Retail, while Panel C reports the difference relative to Services. The estimates in Panels B and C are obtained from a fully interacted regression model with Retail and Services as the baseline sectors, respectively.

[25] We have conducted the same differential enterprise type analysis described in this section for physique and skin color and find no statistically significant differences across industry sectors in their effect on time to funding. The results are reported in Appendix Tables 5A and B.

Table 6B
The attractiveness premium does not depend on whether borrowers are in customer-facing economic sectors.

Sector	Outcome: ln(time to funding)				
	Retail (1)	Services (2)	Construction, Mfg. and tpt. (3)	Food (4)	Agriculture (5)
	Panel A: Coefficient of attractiveness by economic sector				
Attractiveness	−0.110***	−0.305***	−0.303***	−0.220***	−0.161***
	[0.031]	[0.093]	[0.093]	[0.037]	[0.031]
Observations	1438	450	393	1838	1138
R-squared	0.706	0.745	0.801	0.678	0.784
	Panel B. Difference in Coefficient of Attractiveness Compared to Retail Sector				
Attractiveness			(3)–(1)	(4)–(1)	(5)–(1)
			−0.193**	−0.111***	−0.052
			[0.089]	[0.033]	[0.045]
Observations			1831	3276	2576
R-squared			0.724	0.698	0.742
	Panel C. Difference in coefficient on attractiveness compared to services sector:				
Attractiveness			(3)–(2)	(4)–(2)	(5)–(2)
			0.002	0.085	0.144
			[0.148]	[0.085]	[0.092]
Observations			843	2288	1588
R-squared			0.772	0.693	0.774
Controls for					
Loan and borrower characteristics	Yes	Yes	Yes	Yes	Yes
Loan sector, region, posting day fixed effects	Yes	Yes	Yes	Yes	Yes
Country, economic activity, MFI fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: The sample is restricted to individual loans in the listed economic sectors only. Each column in Panel A is a separate linear regression with log time to funding as the dependent variable for each separate subsample of the data corresponding to the sector of the loan. Each regression uses the same set of regressors as that of the individual loans model in Table 4. Panel B reports the difference in the coefficient of attractiveness relative to the retail sector (column (1)). Panel C reports the difference in the coefficient relative to the services sector (column (2)). Standard errors clustered at the country level are reported in parenthesis.

*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

The results in Table 6B show that differences in the attractiveness premium across industry sectors do not support a model of statistical discrimination based on attractiveness as a proxy for productivity in customer-facing enterprises. Panel B shows that the attractiveness premium for CMT and Food is larger than that of Retail. Although Food is also a customer-facing sector, it is unclear why the attractiveness premium for Food should be superior to that of Retail – and smaller than that of CMT. The attractiveness premium in CMT is particularly large; borrowers in CMT who are one standard deviation more attractive are fully funded 19 percentage points faster than similarly attractive borrowers in Retail. Panel C shows the attractiveness premium for Services – which the most attractive borrowers sorted into – is not significantly different from that of CMT, Food, and Agriculture. While Services does have the largest attractiveness premium point estimate, overall, there is no consistent evidence that attractiveness matters more for industry sectors that are more customer facing.

5. Experience, market power, and lender biases

The results in the preceding section show that lenders appear to discriminate on the basis of borrowers' physical attributes, and that such behavior is not readily explained by statistical discrimination. We cannot completely reject the general hypothesis that discrimination is motivated by the predicted effect of observable physical attributes on the social impact of loans, because we lack data on measurable social impact. However, our analysis of the available data provides evidence against both statistical discrimination based on default risk and statistical discrimination based on physical characteristics as a proxy for enterprise productivity.

Assuming that statistical discrimination does not explain our results, our findings are consistent with explicit or implicit discrimination by charitable lenders. While explicit (or taste-based) discrimination can be modeled as a conscious utility maximizing choice (Becker, 1979), implicit discrimination may result from unconscious thought processes or attitudes (Greenwald and Banaji, 1995; Greenwald et al., 1998). Implicit discriminators may not even be aware of their discriminatory behaviors, which are more likely to be exhibited under time pressure, stress and cognitive load (Bertrand et al., 2005). Cognitive load may be the most relevant factor driving implicit discrimination on Kiva, because of the extremely large choice set available – there are hundreds or thousands of borrowers seeking funds. Evidence from multiple domains shows that decision making under 'choice overload' often results in qualitatively worse outcomes, ranging from reduced satisfaction and willingness to purchase goods (Iyengar and Lepper, 2000), to reduced tolerance for risk and complexity (Iyengar and

Table 7A
Summary statistics of lender data at the loan-level.

	No. of Obs.	Mean	Std Dev
Number of lenders per loan	6977	20.24	21.75
Number of lenders per loan (individual loans only)	6104	17.21	17.79
Length of time as Kiva lender (months)	54,865	14.75	9.62
No. of previous loans made	54,865	16.54	93.53

Table 7B
Loans to beautiful borrowers are more likely to be funded by less experienced lenders.

	Average lender characteristics of loan	
	Number of previous loans made	Length of time as Kiva member (months)
Attractiveness	−27.113***	−0.184***
	[6.542]	[0.062]
Physique	22.262***	0.076**
	[6.707]	[0.035]
Skin color	5.660	−0.035
	[18.810]	[0.102]
Smile	28.451**	0.259**
	[13.625]	[0.105]
Neediness	−16.958	−0.184***
	[10.265]	[0.068]
Trustworthiness	−19.396*	−0.128*
	[9.954]	[0.074]
Creditworthiness	−6.634	−0.017
	[12.829]	[0.069]
Age	1.359**	0.006
	[0.659]	[0.009]
Children in photo	−23.082	−0.190
	[27.638]	[0.152]
Female	−92.274***	−0.034
	[16.554]	[0.151]
ln(loan amount)	−21.429	0.964***
	[23.585]	[0.081]
Loan term (in months)	−8.208*	−0.032**
	[4.584]	[0.016]
Controls for		
Loan sector, region, posting day fixed effects	Yes	Yes
Country, economic activity, MFI fixed effects	Yes	Yes
Observations	5988	5988
R-squared	0.263	0.242

Notes: The sample is restricted to individual loans which have information on lenders available. Each column is a separate linear regression with the average characteristics of lenders at the loan-level as the key dependent variable. Standard errors clustered at the country level are reported in parenthesis.
*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

Kamenica, 2010). Indeed, one common mental response to 'too many' choices or too much information is to reduce cognitive burden by using simplifying decision heuristics, such as stereotyping (Rothbart et al., 1978; Bodenhausen, 1990).

Our first test for the presence of implicit discrimination is based on the hypothesis that experience with a task reduces the extent to which implicit biases affect decision making. Familiarity with the implicit association test is known to consistently and robustly reduce test effect sizes across populations and in a variety of settings (Nosek et al., 2005).[26] Although experimental psychologists argue prior experience confounds measurement of the 'true' level of implicit bias, we argue this finding suggests that experience with a choice task may reduce a decision maker's implicit biases, or at least reduce the extent to which implicit bias affects choices made. Therefore, if implicit discrimination explains the patterns of bias in our data, we should find that more experienced lenders exhibit less discrimination in their lending behavior. By contrast, standard preference-based explanations for discrimination have no obvious correlation with experience.

[26] The implicit association test (IAT) is a widely used measure of the strength of implicit associations. A test-taker is asked to associate stimuli (e.g., faces or words) with categories (e.g., good, bad). The hypothesis is associations are made more quickly when the stimuli is implicitly related in the test-taker's mind to the concept (e.g. African-American faces with 'bad' categories), relative to the cases where the stimuli are mentally unrelated (e.g. African-American faces with 'good' categories). A full description of the test is found in Greenwald et al. (1998).

Table 8
The effect of competition on the extent of lender bias toward physical characteristics of borrowers.

	ln(time to funding)	Average lender characteristics of loan	
		Number of previous loans made	Length of time as Kiva member (months)
	(1)	(2)	(3)
Attractiveness*No. of competing loans (per 100)	−0.008	−5.475**	0.008
	[0.012]	[2.229]	[0.039]
Physique*No. of competing loans (per 100)	−0.023	−0.999	0.026
	[0.015]	[4.999]	[0.030]
Skin Color*No. of competing loans (per 100)	0.053**	12.729*	−0.018
	[0.022]	[6.724]	[0.030]
Smile*No. of competing loans (per 100)	−0.024	−1.898	−0.106
	[0.035]	[8.866]	[0.068]
No. of competing loans (per 100)	0.099***	38.994***	−0.111***
	[0.027]	[11.759]	[0.039]
Attractiveness	−0.122***	−37.255***	−0.197**
	[0.027]	[7.862]	[0.081]
Physique	0.120***	20.336***	0.068
	[0.024]	[6.267]	[0.040]
Skin color	0.097**	1.542	0.031
	[0.040]	[16.797]	[0.124]
Smile	0.059	41.994**	0.301***
	[0.038]	[17.755]	[0.111]
Neediness	−0.049**	−17.906*	−0.191**
	[0.024]	[9.880]	[0.085]
Trustworthiness	−0.171***	−31.718***	−0.119
	[0.032]	[8.910]	[0.076]
Creditworthiness	0.042*	−2.152	−0.066
	[0.023]	[12.993]	[0.070]
Controls for			
Loan and borrower characteristics	Yes	Yes	Yes
Loan sector, region fixed effects	Yes	Yes	Yes
Country, economic activity, MFI fixed effects	Yes	Yes	Yes
Observations	5996	5988	5988
R-squared	0.580	0.127	0.095

Notes: The sample in column (1) is restricted to individual loans only, while the sample in columns (2–3) is further restricted to loans with available lender information at the loan-level. Each column is a separate linear regression. Column (1) has log time to funding as the dependent variable while (2–3) have average characteristics of lenders at the loan-level as the dependent variable. "Loan and borrower characteristics" consist of age, presence of children, female dummy, loan amount and loan term. The "No. of competing loans" is measured over a 24 hour period and is scaled such that a one unit increase in the variable represents an increase in 100 competing loans from the mean. Standard errors clustered at the country level are reported in parenthesis.
*** Significant at 1%.
** Significant at 5%.
* Significant at 10%.

Our analysis uses loan-level measures of lender experience and borrower characteristics as the units of observation, rather than lender-based measures.[27] For each loan, we construct two measures that summarize the experience level of that loan's lenders: (1) the average number of loans made by lenders, and (2) the average number of months that lenders have been Kiva members. Table 7A reports summary statistics for the lenders in our data, showing that the average lender made about 17 previous loans and had 15 months of experience on Kiva. In Table 7B, we regress these two measures of loan-level lender experience separately on borrowers' physical and subjective attributes, controlling for the relevant loan characteristics as found in the baseline regressions.

Overall, the results in Table 7B show that relatively inexperienced lenders are more likely to lend to more attractive and less overweight borrowers. Skin color is not significantly related to lender characteristics, all else constant. Less experienced lenders also tend to fund borrowers who appear more needy and trustworthy. Interestingly, female loans are favored by less experienced lenders. These results suggest that lenders' experience may alleviate bias toward the physical and subjective attributes of borrowers, consistent with findings that prior task experience reduces measurable implicit associations.

For our second test, we contrast the predictions generated by models of discrimination (explicit vs. implicit) under varying degrees of competition or market power. Explicit discrimination can be modeled as a non-pecuniary cost of market interaction (e.g. hiring, trading) with a discriminated-against group (Becker, 1979). Because these non-pecuniary costs are determined by the strength of prejudice, rather than the profitability of the market transaction, explicit bias can be competed away as less-prejudiced firms enter the market, and as markets become more competitive. For example, Theseira (2008)

[27] A lender-based analysis requires reconstructing for each lender a full loan history, coding every past loan for that lender. The magnitude of data required far exceeds that of our present analysis. Our present data only contains the loan history of very inexperienced lenders who have completed all their lending within the month of June 2009. Unfortunately, a lender-based analysis is outside the scope of this paper, but is an important area for future research.

shows that as competition intensifies amongst peer-to-peer lenders, interest rates fall more sharply for African-American borrowers than for White borrowers. Accordingly, if explicit discrimination explains our results, we expect to find that market power alters the magnitude of discrimination. A null effect of market power on discrimination suggests instead that our results are not readily explained by explicit discrimination.[28]

To proxy for relative market power on Kiva, we measure the aggregate demand for credit from borrowers, as we lack good measures of credit supply by lenders. Aggregate credit demand at the loan level is measured as the total count of other loans posted during a 24-hour window, centered on the time that a given loan is posted.[29] We de-mean and scale the credit demand measure so that a one-unit difference is interpretable as the effect of a 100-count change in the number of competing loans. The average loan faces 317 competing loans, with a standard deviation of 214.

In Table 8, we examine how relative credit demand affects the extent of bias. We focus on bias toward attractiveness, physique and skin color, as these are more relevant to the literature and have the most consistent effects on time to funding in our data. Column (1) is based on the full regression specification from Table 3, augmented with the credit demand measure, and interaction effects between credit demand and borrower characteristics. However, we exclude group loans, and exclude time-related fixed effects due to correlation with our credit demand measure. Column (1) shows that as relative demand for credit increases, so does time to funding – an additional 100 competing loans increases funding time by about 10%. However, credit demand generally does not affect the extent of bias. The interaction effects of the credit demand measure are significant only for skin color, where greater relative demand for credit exacerbates the effect of darker skin color on increased time to funding. While the results could suggest lenders are explicitly biased against darker skin, they are less supportive of explicit bias as an explanation for the effects of attractiveness and physique.

We next replicate the lender experience regressions from this section, augmented with the credit demand measure and interactions with borrower characteristics. As measures of loan-level lender experience, column (2) uses the average number of loans, while column (3) uses months on Kiva. Our main interest is in the interaction effects of credit demand, which show in (2) that periods of greater choice are associated with even lower experience levels amongst lenders to more attractive and lighter-skinned borrowers.[30] This is consistent with the argument that the relatively high cognitive burden from choice overload may increase the likelihood of implicit discrimination by inexperienced lenders.

Overall, this section's evidence is consistent with the hypothesis that implicit discrimination explains the patterns of bias we document on Kiva. There is some evidence for explicit discrimination as an explanation for the effects of skin color on time to funding, but not for the effects of attractiveness and physique. We cannot completely rule out alternative models where taste-based or statistical discrimination is reduced by learning. However, models of explicit discrimination with learning generally assume a setting where agents are both highly motivated to learn and have access to high quality information to update their priors – as in the labor market (Altonji and Pierret, 2001). Our setting does not obviously fulfill these criteria. A lender-based analysis would be a fruitful area for future research.

6. Conclusion

This paper documents systematic discrimination by charitable lenders in favor of borrowers who are more attractive, less overweight and lighter-skinned. Lenders also favor borrowers who appear more needy, honest and creditworthy. These estimates are economically significant: a one standard deviation increase in assessed borrower attractiveness, physique and skin-color is equivalent to asking for a loan amount of approximately $60 less, $65 more and $40 more, respectively, relative to the average loan amount of approximately $700.

We find little evidence that these patterns of bias are explained by statistical discrimination. Borrower physical traits do not predict loan default, and the beauty premium is not significantly higher in industries where beauty might be a proxy for business productivity, such as Services. We lack the data to directly test whether statistical discrimination occurs because borrower physical traits predict the eventual social impact of loans. However, studies show that less attractive, more overweight and darker-skinned individuals are denied opportunities in the labor market and in traditional credit markets (Hamermesh and Biddle, 1994; Cawley, 2004; Pope and Snydor, 2011; Hersch, 2008). If anything, providing charitable funding to these discriminated-against groups should yield higher, not lower, social returns.

Since statistical discrimination does not readily explain our results, we believe lenders are displaying simple prejudice – explicit or implicit – on the basis of borrower physical traits. We find tentative evidence consistent with implicit discrimination against less attractive and more overweight borrowers. More experienced lenders appear to exhibit less bias, consistent

[28] We acknowledge that our tests will not conclusively distinguish between explicit and implicit discrimination. If market power implies greater choice, the cognitive constraints that cause implicit discrimination might be magnified. However, the link between market power and explicit discrimination is well-established in the literature. A null result, at the least, is inconsistent with explicit discrimination explaining our findings.

[29] We use the 24-hour window because the median time to funding is less than a day. However, there is little difference in the effective variation of the credit demand measure if we use alternate time windows, or use the total amount requested from competing loans instead of the loan count. Results using a 48-hour window, a 72-hour window, and using the total amount requested by other loans are available from the authors.

[30] The interaction effects of credit demand are statistically significant using the prior loan measure of experience, but not when using the length of time on Kiva measure. Overall, we believe lender experience may be better measured using prior loans, since a member can belong to Kiva for a long time but yet have little actual lending experience.

with evidence from the implicit association test that shows task familiarity reduces the strength of implicit associations (Nosek et al., 2005). Moreover, we find that increased credit demand does not magnify prejudice against less attractive and more overweight borrowers – contrary to predictions from standard models of explicit discrimination. In fact, during periods of high credit demand, inexperienced lenders appear to exhibit even more bias – consistent with the cognitive burden from additional choices increasing reliance on implicit mental processes. We acknowledge competing explanations exist, such as statistical discrimination models where lender preferences are updated through learning. Implicit discrimination remains an important area for future work, particularly since we conjecture many charitable donors would express discomfort with the idea that beauty or skin color should determine how charitable assistance is allocated.

We add to a growing literature that shows discrimination on the basis of physical attributes also affects charitable settings. However, our evidence is becoming more relevant as online directed giving or 'crowdfunding' continues to grow. Microfinance institutions or charities that rely on individual giving may respond to lender biases by avoiding less 'attractive' borrowers or clients, regardless of creditworthiness or social impact. Direct philanthropy may thus be less efficient at allocating resources to maximize social impact, compared to traditional modes of giving where development experts make investment decisions based on presumably technocratic factors (Desai and Kharas, 2009). Nonetheless, the scale and magnitude of direct giving through Kiva and other platforms has the potential to be a remarkable force for development assistance. Increasing public awareness of the existence of aggregate patterns of discriminatory behavior may do much to ameliorate lender biases, particularly if such biases are implicit (Pope et al., 2013).

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jebo.2015.06.004.

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