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Microfinancing, or small uncollateralized loans to entrepreneurs in the developing world, has recently emerged as a leading contender to cure world poverty. Our research investigates the characteristics of borrowers that engender lending through Kiva, a popular organization that connects individual lenders to borrowers through online microfinance. Lenders favor individual borrowers over groups or consortia of borrowers, a pattern consistent with the identifiable victim effect. They also favor borrowers that are socially proximate to themselves. Across three dimensions of social distance (gender, occupation, and first name initial), lenders prefer to give to those who are more like themselves.

Keywords: prosocial lending, microfinance, microlending, decision making, financial decision making

Microfinance Decision Making: A Field Study of Prosocial Lending

Research in the area of financial decision making has focused primarily on the decision maker's welfare, such as saving for retirement (De Bondt and Thaler 1995). In this article, we instead focus on prosocial financial decisions, or those with the intention to affect the welfare of others who are disconnected from the decision maker. The emerging field of microfinance is an especially fertile ground for studying prosocial financial decisions.

Microfinancing, or small loans made to small businesses and entrepreneurs in developing countries, has emerged as a leading effort to alleviate world poverty. These types of loans have provided \$25 billion in small, collateral-free loans to the poorest of the poor (Diekmann 2007) and won favor because they appeal to economically minded individuals who believe that supporting entrepreneurial endeavors will spur growth and thus do more good than traditional charitable giving (Yunus 1999). Despite the upsurge

in popularity of microfinance, little research has examined decisions by individual lenders. One reason may be that the decision itself is difficult to classify. Is lending to the poor a financial decision, much like investing, or is it rather more like donating to charity? As our results show, although the financial characteristics of loans matter, so do some of the psychological factors that influence charitable giving decisions.

DIRECT-TO-BORROWER MICROFINANCING

Considering the limited lending capital, a system of direct-to-borrower microfinancing enables individual lenders to make small, uncollateralized loans to individual entrepreneurs and small businesses in need. The most influential organization facilitating direct-to-borrower microfinancing is Kiva. As of May 18, 2011, Kiva has made a total of US\$213,942,425 in loans to 554,116 entrepreneurs through 285,142 loans. Amazingly, although the loans are uncollateralized, the historic repayment rate has been 98.8%, suggesting that the loans are doing exactly what they purport to do: support budding entrepreneurs' attempts to grow their businesses.

Kiva accomplishes its role as an intermediary by posting solicitations for loans from entrepreneurs on the Internet, which then are funded by individual lenders through the Kiva.org website. Solicitations take the form of borrower profiles and contain information regarding the composition of the borrowing entity (e.g., an individual entrepreneur or group of entrepreneurs working as a team) and some personal information about the entrepreneur(s), including their name(s), location, photo(s), and a description of the

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nature of the loan (e.g., loan amount, loan purpose, and loan repayment term). Kiva also provides information about the field partner that sourced the loan and that ultimately will manage it (e.g., name of the field partner, default rate of all loans managed by this field partner). For an example of a borrower's profile, see Web Appendix A (<http://www.marketingpower.com/jmrv11>).

Kiva lenders have two primary decisions to make. First, the lender chooses to whom to lend by browsing through a list of borrowers currently seeking funding (Web Appendix B, <http://www.marketingpower.com/jmrv11>). Second, the lender selects an amount to lend, ranging from \$25 to \$5,000, in \$25 increments.¹ When the loan is fully funded (i.e., 100% of the requested amount has been raised), the borrowers are responsible for repaying the loans according to predetermined repayment schedules (which are known to the lenders). These monies are returned to the lender, who can then withdraw the funds or relend them to other borrowers. Neither Kiva nor the individual lenders receive interest payments. Instead, the field partners who manage the loans keep any interest payments to cover operating expenses and, in some cases, generate a profit.

Given that lenders are ostensibly donating their interest payments to the field partner, a question is whether the decisions that they make are financial in nature, prosocial in nature, or both. On the one hand, the decision to lend is financial: The principal of the loan is returned to the lenders (assuming the loan does not go into default), and these decision makers receive many investment-like metrics (e.g., field partner rating, loan repayment term). Such features might push lenders to treat the decision in a more calculative manner, which could override psychological or emotional drivers (see Small, Loewenstein, and Slovic 2007). On the other hand, the decision to lend is also prosocial in nature: Lenders donate any interest earned on the loan to the field partner, and the stated purpose of the loan is to help those in need. Rather than force this dichotomy, we suggest that prosocial lending actually is a hybrid of the two natures.

HYPOTHESES

Several features of charity recipients causally influence charitable giving in experimental, largely lab-based studies. However microlending differs from traditional giving, and researchers and policy makers often question whether the insights gained in the lab can be extrapolated to real-world situations (Levitt and List 2007). Our primary goal is to examine the role and extent to which some features that predict giving in the lab also matter for real decisions made by lenders on Kiva.org. Our investigation is divided into two parts, addressing two research questions: (1) Does borrower group size influence lending decisions? and (2) Do lenders prefer to lend to borrowers who are similar to them?

Does Borrower Group Size Influence Lending Decisions?

Literature on charitable decision making suggests that, in general, the causes and victims that attract generosity tend

to be ones that are emotionally evocative. One such emotional trigger is the identifiable victim effect: A single victim tends to evoke a stronger emotional response than multiple victims (Kogut and Ritov 2005a, b), and an identifiable victim tends to evoke a stronger emotional response than an unidentifiable victim (Small and Loewenstein 2003). We extend this notion to the domain of prosocial lending and test the hypothesis that when lenders decide among potential loan recipients (i.e., borrowers), lending decreases as group size increases. This pattern is thought to be suboptimal, because more people can benefit when resources are shared rather than concentrated on a single person. Critics of micro-financing argue that loans to individual borrowers are often too small to influence business expansion and instead end up being spent on nonbusiness expenses (Boudreaux and Cowen 2008). In addition, loans to groups historically have had higher repayment rates due to peer screening (Varian 1990) and peer monitoring (Stiglitz 1990), which makes them more financially viable (Yunus 1999). As of the date of this writing, of all loans made through Kiva.org, only .55% of those made to groups of entrepreneurs defaulted, compared with 2.07% of those made to individual entrepreneurs ($\chi^2(1, N = 212,998) = 67.93, p < .001$).

We test this hypothesis by assessing the amount of money lent and the time taken to fully fund or "fill" a loan request, as a function of the number of individuals making up a borrower group that requests a loan. Furthermore, we predict that, despite the presence of (and controlling for) financially relevant information (e.g., loan risk level, loan duration/term), the psychological influence of group size still plays a significant role.

Do Lenders Prefer Borrowers who Are Socially Proximate to Them?

Donors prefer to give when there exists some match or similarity between themselves and a victim or cause (Loewenstein and Small 2007). Research on intergroup relations and social categorization consistently finds that people are more caring toward others in their in-group than to those in their out-group (e.g., Dovidio et al. 1997; Flippen et al. 1996). Donors target causes that help victims of the same misfortunes suffered by their friends and loved ones (Small and Simonsohn 2008). In each of these cases, the purported mechanism is the reduction of social distance between victims and potential benefactors, which facilitates empathy and caring.

Accordingly, we predict that as the social distance between lenders and borrowers becomes smaller, lending likelihood increases. We test this hypothesis for three dimensions of social distance: gender, occupation, and initial of first name. The first two dimensions are more obviously important, as gender and occupation are salient aspects of a lender's identity. However the third dimension, first initial of first name, may be nontrivial. Several studies in psychology have documented a so-called name-letter effect in various real-world preferences (Pelham, Caravallo, and Jones 2005; cf. Simonsohn 2011). Potentially many other dimensions of social distance could affect lending preferences. However, we selected these three dimensions because, as we describe subsequently, we have access to data about both lenders and borrowers on each of these three dimensions.

¹The maximum loan size allowable was \$5,000 at the time of our data collection. It has since been lowered to \$500.

DATA AND RESULTS

Does Borrower Group Size Influence Lending Decisions?

Data on loan and borrower characteristics. The primary data set was provided by Kiva and included 289,329 loans made to 23,024 borrowers of varying size (group size $M = 1.37$, $SD = 1.17$, $\min = 1$, $\max = 20$) between November 27, 2007 (the first day Kiva allowed group borrowers), and June 18, 2008.² Loans were made in \$25 increments ($M = \36.15, $SD = \$42.43$, $\min = \$25$, $\max = \$1,150$), and the average loan request amount was \$825.31 ($SD = \316.65, $\min = \$75$, $\max = \$1,500$). For each loan we know (1) the amount each lender contributed to each borrower's loan request (loan value); (2) the total amount requested by each borrower (total loan size); (3) the amount of the requested loan that had not yet been filled by prior lenders at the time the lender decides how much to lend (unfilled loan size); (4) how long it took in minutes between the announcement of a borrower's loan request and it being fully funded (time-to-filled); (5) the number of individuals in the borrower group that makes the loan request (group size); (6) the average borrower gender (gender: male = 0 and female = 1), where gender for a group is the average gender across individual entrepreneurs in the group; (7) the loan repayment term in months (loan term); and (8) the risk rating associated with each field partner³ (field partner risk rating; Kiva-assessed risk level of a field partner: 1 = "high risk," 5 = "low risk").⁴

The last two variables, loan term and field partner risk rating, are particularly useful because we can compare their effects on lending behavior with those of less financially relevant variables (e.g., group size). Field partner risk rating also speaks to the creditworthiness of the borrower, an issue important in person-to-person lending literature (Pope and Sydnor 2011; Ravina 2010).

Supplemental data. We collected data on several borrower country characteristics, which could affect lending, for use as control variables in our analysis. For each loan request, we observed the borrower's country and used gross domestic product (GDP) and infant mortality rate as proxies for wealth (*World Factbook* 2010). We used Hofstede's (2001) five cultural dimensions as proxies for culture (power distance, individualism, masculinity, uncertainty avoidance, and long-term orientation). Hofstede's data were not available for all countries in the lending data set, however, so we excluded cases from countries for which data were missing. Including those cases and not controlling for national culture did not change our results.

²Kiva originally provided partial information on 371,521 loans, but we dropped some because of incomplete data (e.g., if one or more variables in the regression analysis were missing for that loan).

³These ratings are constructed by Kiva to reflect both objective creditworthiness metrics, such as default rate, and subjective ones that reflect intangible factors that can only be assessed through close work with field partners.

⁴Other factors indicating field partner creditworthiness were available, such as default and delinquency rates. However, they can vary quite a lot over time, and Kiva did not provide rates corresponding to the times the loans were made.

Analysis and results. The main dependent variable was loan value, that is, the U.S. dollar value of the loan made by lender i to borrower j . Because of the data's panel structure, we estimated a random effects regression of loan value on group size, the other loan/borrower characteristics, and the borrower country characteristics. We controlled for the borrower's industry (e.g., agriculture, retail) using industry dummy variables and for unobserved borrower-level factors using a borrower random effect. Two control variables deserve specific mention.

First, we controlled for the total amount requested by a borrower (total loan size). As might be expected, larger borrower groups request larger loan sizes (positive correlation; $r = .85$, $p < .001$). Any effect of group size on loan value therefore must control for total loan size.

Second, we controlled for unfilled requested loan size at the time of lender i 's loan to borrower j . As more lenders contribute funding to a borrower, the remaining amount requested naturally decreases (e.g., if a borrower requests \$1,000, the first lender can lend any amount up to \$1,000; if the lender lends \$25, then the next lender can lend any amount up to \$975, and so on). Consequently, each successive potential lender for a given borrower has less opportunity to lend larger amounts (even if he or she wants to) and faces a psychologically different lending context from that which appeared to past and future lenders to that same borrower.⁵

We report the standardized parameter estimates in Table 1, with the full model in column 3. Columns 1 and 2 refer to restricted models with just one of the total loan size and unfilled loan size control variables; their high correlations with each other and with group size may give rise to multicollinearity (though the large sample size makes this concern unlikely). All three models have very similar fit. Although the full model did not fit significantly better than the two nested variants in columns 1 and 2, because the results are robust, we focus on the coefficients from the full model in column 3.

There was a significant negative effect of group size on loan value ($b = -.03$, $p < .001$). Controlling for total and unfilled loan sizes, we found that as the size of the borrower group increased, loan values decreased. This effect was robust to variations in the model specification.⁶ Also, whereas other variables such as loan term and field partner risk rating affected loan value, none of their absolute standardized effect sizes was significantly greater than the group size effect.

This effect was robust to using different (but related) dependent variables. In Table 1, columns 4–6, we report the results from a Cox regression (proportional hazards model) of the time it took for lenders to fill a requested loan on the same independent variables. Consistent with our previous regression model, the effect of group size was negative, indicating that as borrower group size increased, the speed with which an unfilled loan

⁵This is conceptually equivalent to controlling for the current level of "supply" in a dynamic market "demand" model.

⁶Because loan value is a discrete count (of dollars loaned), we used a Poisson model. The results are unchanged when we make different distributional assumptions (i.e., exponential and normal distributions).

Table 1
FACTORS AFFECTING LOAN VALUE AND TIME UNTIL LOAN FILLED

	Dependent Variable = Dollar Value of Loan Made by Lender to Borrower			Dependent Variable = Time in Minutes Until Borrower's Loan Requested Fully Funded		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Loan and Borrower Characteristics</i>						
Borrower group size (number of people)	-.03* (-6.55)	-.03* (-4.10)	-.03* (-4.31)	-.35* (-7.39)	-.35* (-7.41)	-.33* (-6.86)
Unfilled loan size (amount of requested loan remaining; \$)	.06* (20.71)	—	.06* (18.70)	.41* (12.95)	—	-.11* (-3.31)
Total loan size (amount requested by borrower; \$)	—	.04* (8.53)	-.01 (-.88)	—	.40* (13.00)	.49* (12.24)
Loan term (months)	-.02* (-7.13)	-.02* (-6.99)	-.02* (-7.18)	-.09* (-3.07)	-.09* (-3.06)	-.08* (-2.79)
Field partner risk rating	.01* (2.28)	.01* (2.17)	.01* (2.23)	.07* (2.46)	.07* (2.44)	.06* (2.34)
Borrower gender (0 = male, 1 = female; average if group)	-.00 (-.19)	-.00 (-.28)	-.00 (-.27)	-.12* (-5.32)	-.13* (-5.32)	-.13* (-5.39)
<i>Borrower Country Characteristics</i>						
log(GDP)	-.01* (-3.18)	-.01* (-3.21)	-.01* (-3.22)	-.03 (-.68)	-.03 (-.67)	-.02 (-.53)
Death rate (deaths per 1000 live births)	.00 (.83)	.00 (.78)	.00 (.84)	-.13* (-5.15)	-.13* (-5.14)	-.13* (-5.04)
Power distance	-.01 (-1.84)	-.01 (-1.61)	-.01 (-1.71)	-.10* (-2.90)	-.10* (-2.88)	-.09* (-2.77)
Individualism	-.00 (-1.11)	-.01 (-1.04)	-.00 (-1.05)	.22* (8.99)	.22* (8.98)	.22* (8.87)
Masculinity	.01* (2.20)	.01* (2.13)	.01* (2.16)	.01 (.28)	.01 (.29)	.02 (.42)
Uncertainty avoidance	.02* (3.65)	.02* (3.73)	.02* (3.71)	.07 (1.44)	.07 (1.24)	.07 (1.26)
Long-term orientation	.02* (3.67)	.02* (3.75)	.02* (3.72)	.10 (1.89)	.10 (1.89)	.10 (1.92)
Intercept	3.62* (131.47)	3.62* (129.96)	3.62* (131.25)	3.97* (16.99)	3.98* (17.00)	3.96* (16.95)
Borrower random effect variance	59.12* (380.41)	60.38* (380.44)	59.11* (380.40)	—	—	—
Significant* borrower industry dummy effects?	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	289,329	289,329	289,329	6,679	6,679	6,679
-2 Log-likelihood	960,413	966,249	960,414	26,255	26,256	26,268
Akaike information criterion	960,475	966,311	960,478	26,315	26,316	26,330
Bayesian information criterion	960,803	966,639	960,816	26,519	26,520	26,541
Pseudo-R ²	.366	.363	.366	.373	.373	.373

* $p < .01$.

Notes: Standardized parameter estimates are reported. Values in parentheses are t-statistics.

was filled decreased ($b = -.33$, $p < .001$). Again, borrower group size had the strongest effect. Finally, in Web Appendix C (<http://www.marketingpower.com/jmmnov11>), we report additional robustness analyses using a different dependent variable specification that expresses loan value as a proportion of either total loan size or unfilled loan size. The results were qualitatively identical to those in Table 1.

Do Lenders Prefer Borrowers Who Are Socially Proximate to Them?

The second hypothesis regarding the effect of social distance on lenders' choices required additional data collections for each lender and borrower featured in the

Kiva-supplied data set. To test this hypothesis, we used data on lenders' and borrowers' characteristics according to three social distance dimensions (gender, occupation, name). Thus, we could examine whether the prevalence of lender-borrower pairs with matching characteristics was higher than expected if lenders randomly chose the borrowers to fund.

Data on borrowers. Kiva provided nearly complete data for 40,424 borrowers, spanning the time period from March 30, 2005, to April 11, 2008. In addition to the variables we previously described, we also know the gender of 40,238 borrowers (99.5%), the occupation (through loan purpose, such that "build a farm" indicated agriculture as

their occupation) of 100% of borrowers, and name data for 40,264 borrowers (99.6%).

Data on lenders. Kiva did not provide structured data for the lenders. Instead, using lender identifiers, we collected unstructured “lender profile” data from public pages on Kiva.org, using a data scraping program. We identified 163,746 unique lenders who made a total of 694,552 individual loans, resulting in an average of 4.24 loans per lender ($SD = 16.71$, $\min = 1$; $\max = 2,997$). Of the 163,736 unique lenders identified, 67,718 provided a photograph (41.4%), 118,835 provided job/occupation information (72.6%), and all provided a name. We employed the Amazon Mechanical Turk (AMT) service to facilitate human coding of this unstructured data (for details, see Web Appendix D, <http://www.marketingpower.com/jmrnov11>). With AMT, users coded lender profiles to generate lender data pertaining to first name initial, gender (from viewing the lender’s picture), and occupation. Each lender was coded by two independent AMT users, and we found coder agreement on 103,876 lenders’ first initials (Cohen’s $\kappa = .94$), 32,735 genders (Cohen’s $\kappa = .84$), and 26,075 occupations (Cohen’s $\kappa = .36$). The coding resulted in first initial data for 355,805 loans (55.9%), gender data for 152,522 loans (24.0%), and occupation data for 93,437 loans (14.7%).⁷

Analysis and results. Our second hypothesis predicted that lenders prefer to fund borrowers who are less socially distant from them. Because we lack dollar loan value data linked to lenders as well as borrowers, we took a different analytical approach.⁸ We compared empirical probabilities of lender–borrower matches on each social distance dimension to the base rates computed according to an assumed lending process in which lenders randomly select borrowers. For example, for female lenders, we compared the empirical probability of a female borrower being matched with a female lender to the base rate, which was the probability of a lender randomly selecting a female borrower from all available borrowers (i.e., $1/N_{\text{female_borrowers}}$). Three related analyses ensured the effects were robust to variations in methodology. Only individual borrowers (as opposed to groups of borrowers) were studied for this test, because lenders only lent as individuals, and a comparison of groups of borrowers and individual lenders would be intractable.

Analysis 1: Overall social distance matches. For each lender–borrower pair (i, j) and each social distance dimension ($k = 1, 2, 3$), we computed a variable match_{ijk} that equaled 1 if lender i and borrower j were the same on dimension k , and 0 otherwise. For example, if Joanne lent to Maureen, then $\text{match}_{ij,\text{gender}} = 1$ but $\text{match}_{ij,\text{name}} = 0$; if Joanne lent

to John, then $\text{match}_{ij,\text{gender}} = 0$ but $\text{match}_{ij,\text{name}} = 1$. We compared the observed number of matches across dimensions for each lender to the number of matches that would be expected by chance, given each lender’s gender, occupation, and first name initial and the distributions of the levels of these dimensions among borrowers. This comparison involved four steps:

1. For each loan (i, j pair), we summed match_{ijk} variables over k to obtain the number of matching similarity dimensions per loan (between 0 and 3; $M = .628$, $SD = .596$).
2. We computed base rates for lender i for dimension k ($\text{base_rate}_{i,k}$). This value was the probability of a match on dimension k if lender i randomly selected a borrower. For example, $\text{base_rate}_{i,\text{gender}}$ for a male (female) lender = $1/N_{\text{male_borrowers}}$ ($1/N_{\text{female_borrowers}}$).
3. We computed the expected number of matches per loan if lenders selected borrowers randomly as the sum of three Bernoulli (0/1) random variables, with their respective probabilities being the $\text{base_rate}_{i,k}$ across the three dimensions.⁹ The mean of the expected matches (between 0 and 3) was .552 ($SD = .582$).
4. We tested whether the observed mean number of matches per loan (.628) was greater than the expected number of chance matches per loan (.552), controlling for lender (because many lenders made multiple loans), with a within-subject analysis ($F(1, 358,076) = 3,601.78$, $p < .001$).

Analysis 2: Social distance matches within each lender category. As a second test, we extended our analysis to each level of each dimension (i.e., male lenders, female lenders, each lender occupation type, and each lender first name initial). For each group (e.g., male lenders), we compared the proportion with matches on that category (gender) to what would be expected by chance using the appropriate $\text{base_rate}_{i,k}$. We ran the same within-subject analysis for each lender group, and we computed the effect size for each comparison (partial η^2). Thirty-six valid comparisons were run (three occupations and four first initial letters were excluded because there were no lenders with those characteristics). A significant positive effect in the hypothesized direction emerged in 17 cases (47%), nonsignificant effects in 11 cases (31%), and significant negative effects in the opposite direction appeared in 8 cases (22%)—all first name initials. A meta-analysis across the 17 significant positive effects revealed mean effect sizes for gender, occupation, and first name initial of, respectively, .011, .021, and .003 ($SD = .009, .029, .003$). Although this meta-analysis sample size was too small to permit statistical contrasts, the similarity effect was clearly much smaller for first name initial (by an order of magnitude).

Analysis 3: Empirical matches to base rates, controlling for other factors. We used logit models to compute adjusted empirical match probabilities after controlling for other factors that could affect lenders’ choices of borrowers. In the previous two analyses, we counted matches without any consideration for other observable factors that could affect the occurrence of these matches and therefore bias our counts. To control for other factors (i.e., the same loan/borrower and country characteristics used in the group size analysis), we estimated a logit model for each

⁷We have the same data regarding borrowers’ country characteristics as described for our test of the first hypothesis.

⁸The data supplied by Kiva to test the first hypothesis included actual loan data, but for privacy reasons, it only provided information on the borrowers of these loans, not the lenders. Put simply, for the first hypothesis we can examine how borrower characteristics (in particular, group size) affect loan values but not how specific lender characteristics also play roles. For our second hypothesis, we can examine similarities between lenders and their chosen borrowers using data on both borrowers’ and lenders’ characteristics but without any loan value data, for privacy reasons. We can assess whether certain borrowers are more likely to loan to certain lenders as a function of social distance, but we cannot assess whether social distance is related to the loans’ dollar values.

⁹A Bernoulli random variable has a value of 1 (match) or 0 (no match) and probability $p = \text{base_rate}_{i,k}$.

Table 2
SUMMARY OF SOCIAL DISTANCE MATCHING RESULTS

Social Distance Measure	Number of Lender Categories in Model	Support Hypothesis		Against Hypothesis	
		Significant in Hypothesized Direction	Directional Support Only	Significant in Opposite Direction	Directional Support in Opposite Direction
Gender	2	2 (100%)	0 (0%)	0 (0%)	0 (0%)
Occupation	12	10 (83.3%)	1 (8.3%)	1 (8.3%)	0 (0%)
First name initial	22	7 (31.8%)	3 (13.6%)	10 (45.5%)	2 (9.1%)
Totals	36	19 (52.8%)	4 (11.0%)	11 (30.6%)	2 (5.6%)

social distance dimension, regressing match_{ijk} on these control factors. To control for the possibility that matches may not be independent across dimensions, we used matches on the other two social distance dimensions as additional control variables. Finally, we included dummy variables for lender category (e.g., gender in the gender match model). For occupation and first name initial models with more than two categories, $M - 1$ dummy variables represented the lender's characteristic, where M was the number of categories.

The logit model parameter estimates were not of primary interest, but we report them in Web Appendix D (see <http://www.marketingpower.com/jmrnov11>, Tables WA2–WA4) for completeness. The estimates served to compute the adjusted empirical probabilities of gender, occupation, or first initial matches at the means of the other variables in the model and for each category of the lender variable. These probabilities were the empirical likelihoods of matches for each lender category, after controlling for other factors that could affect matching; therefore, they were more conservative than the match probabilities in the two previous matching analyses. These adjusted empirical match probabilities for each lender category with each social distance dimension can be compared with their respective base rates using a χ^2 test for the two proportions. We found support for our hypothesis whenever the empirical probability was significantly greater than the base rate. We summarize the results of this analysis in Table 2, with additional results in Web Appendix D (Tables WA5–WA7, <http://www.marketingpower.com/jmrnov11>).

The results were very similar to those we found previously. For gender, we found strong support for a gender similarity preference among both male and female lenders. For occupation, we found strong support for an occupation similarity preference in 10 of the 12 lender categories. Of the 2 remaining categories, one directionally but not significantly supported our hypothesis, and the other went against our hypothesis. For the first initial, of the 22 represented letters of the alphabet, we found support for a first initial similarity preference in 7 categories and directional support in 3. We did not find supporting evidence for the remaining letters.¹⁰

Overall, across all represented categories of the social distance dimensions we tested, we found statistically significant support for our hypothesis in the majority of cases. Based on odds ratios in Tables WA5–WA7 (ratios of empirical probabilities to base rates; an odds ratio significantly greater than 1 supported our hypothesis), the mean odds ratio across all tests after setting nonsignificant tests' odds ratios to 1 was 1.19 ($SD = .58$, median = 1.06; t -test for $1.19 > 1$: $t(35) = 1.95$, $p < .06$). Lenders, in general, displayed a preference for lending to borrowers with whom they shared observable personal or professional characteristics, even after we controlled for the financially relevant information that they received.

GENERAL DISCUSSION

With the advent of microfinancing, and specifically the ability of individual lenders to lend to the impoverished of the world, a richer understanding of how people make choices in this domain is paramount. This article is a first step in understanding the psychology that underlies such prosocial lending decisions. We have demonstrated that in this setting, two psychological mechanisms help determine to whom lenders lend: number of borrowers and social distance. With regard to the former, we observe that lending is less likely as borrower group size increases, consistent with previous lab-based experiments on the identifiable victim effect (Kogut and Ritov 2005a, b). With regard to the latter, we observe that two dimensions of social distance influence lending decisions quite strongly (gender and occupation), and one dimension influences lending decisions to a lesser extent (first name initial). Specifically, for each of these three factors, lenders prefer borrowers who are similar to them, consistent with lab-based research into in-group and similarity effects in helping behavior (Dovidio et al. 1997; Flippen et al. 1996). These findings hold even when we control for financially relevant information, such as loan term and field partner risk ratings, which suggests that despite the financially oriented nature of microfinance, people are nonetheless affected by more psychological factors, such as group size and social distance.

Odds ratios larger than 1 indicate support, 1 indicate no effect, and less than 1 go against our hypothesis. For the occupations, the mean odds ratio across the 12 represented occupations was 1.61 (median = 1.71), and for first name initials, the mean odds ratio across the 22 represented letters was .94 (median = 1).

¹⁰To quantify support for or against our hypothesis, we can use odds ratios (i.e., ratio of the empirical probability to the base rate probability).

An interesting question following from this finding is whether there is some interplay between psychological and financial factors in driving lenders' decisions. Although we leave deeper study of this question to further research, we investigate this point in our data. We reran some of our analyses to investigate the interplay, using the field partner risk rating (lower is riskier) and loan term (higher is riskier) financial variables. For the group size analysis (column 3 of Table 1), we found a significant interaction between group size and field partner risk rating ($p < .01$) and a marginally significant interaction between group size and loan term ($p = .10$). A spotlight analysis, particularly with respect to the moderating effect of field partner risk rating, indicated that when loans were riskier, the negative effect of group size on loan value was larger. In the similarity analysis, we found that lenders' preference for socially similar borrowers was stronger when loans were riskier. In other words, these psychological factors become even stronger drivers of lenders' decisions when they considered financially riskier loans. Financially less appealing loans could be made more appealing by psychological factors, consistent with our initial claim that microlending, at least in the format employed by Kiva, is truly a hybrid of charitable giving and financial decision making. Details of this analysis appear in Web Appendix E (<http://www.marketingpower.com/jmrnov11>).

Limitations

There are at least two limitations of the results of the preceding analyses. First, because all conclusions are correlational in nature, we cannot conclusively rule out either omitted variable explanations or reverse correlational accounts. It may be the case that groups of entrepreneurs fundamentally differ from individual entrepreneurs in ways other than just their size. Although we control for as many such possibilities as the data permit, this alternative account is possible. Nonetheless, the consistency between this field-based correlational finding and previous lab-based experimental research strengthens our confidence in this conclusion.

Second, during the time period of our data, all loans were fully funded, preventing us from drawing stronger conclusions about the characteristics of borrowers that lead to loan fulfillment, as has been examined in peer-to-peer lending (Herzenstein, Sonenshein, and Dholakia 2011). This situation arises partly because demand for lending (i.e., number of lenders) far outweighed the supply of loans (i.e., number of borrowers), which clearly is not the case in all lending situations. If our results generalize to situations with more borrowers than lenders, the characteristics we identify that lead to differential preferences for certain borrowers may make a large difference in determining which borrowers receive any funding at all.

Conclusion

Our findings give confidence that the psychological effects on prosocial behavior demonstrated in lab-based studies play an important role in a natural and noisy environment with real money and livelihoods at stake. More important, they persist in a lending context when we control for financial attributes. Given the vast amounts of monies lent in this manner, understanding the underlying psychology of such lending decisions is an important first step in

maintaining and improving the benefits that microfinancing already has offered the world.

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