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Neural Affective Mechanisms Predict Market-Level Microlending

Alexander Genevsky[1] and Brian Knutson[1,2]
[1]Department of Psychology and [2]Stanford Neurosciences Institute, Stanford University

Abstract

Humans sometimes share with others whom they may never meet or know, in violation of the dictates of pure self-interest. Research has not established which neuropsychological mechanisms support lending decisions, nor whether their influence extends to markets involving significant financial incentives. In two studies, we found that neural affective mechanisms influence the success of requests for microloans. In a large Internet database of microloan requests ($N = 13{,}500$), we found that positive affective features of photographs promoted the success of those requests. We then established that neural activity (i.e., in the nucleus accumbens) and self-reported positive arousal in a neuroimaging sample ($N = 28$) predicted the success of loan requests on the Internet, above and beyond the effects of the neuroimaging sample's own choices (i.e., to lend or not). These findings suggest that elicitation of positive arousal can promote the success of loan requests, both in the laboratory and on the Internet. They also highlight affective neuroscience's potential to probe neuropsychological mechanisms that drive microlending, enhance the effectiveness of loan requests, and forecast market-level behavior.

Keywords

affect, accumbens, microlending, preference, fMRI, prosocial, human

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Humans sometimes share with others whom they may never meet or know. These acts elude the scope of theories that assume that individuals choose to allocate resources on the basis of self-interest alone. Microlending, or an individual's choice to make a low-interest loan to a stranger, can exemplify this phenomenon. Although incentives such as repayment with interest motivate traditional institutional loans, individuals often fund microloans that return little or no interest while incurring significant opportunity costs. The psychological mechanisms underlying individual lenders' decisions remain unclear, however, as does the question of whether the influence of those mechanisms can extend beyond the choices of those individuals to also account for aggregate behavior.

Although microlending has historically been considered to differ from charitable giving, these two types of resource-allocation choices may also share similarities. On the one hand, lending differs from giving because loan recipients must typically pay back loans with interest; such loans are consistent with self-interested motives on the part of lenders. On the other hand, some lending mechanisms also impose costs on lenders; for example, some loans return little or no interest while tying up available cash and invoking the risk of default. Loan requests that succeed in garnering lending despite associated opportunity costs may therefore recruit some of the same psychological mechanisms as do appeals for charitable gifts. Although previous studies have focused on lenders' goals (Liu, Chen, Chen, Mei, & Salib, 2012) and borrowers' identities (Galak, Small, & Stephen, 2011; Smith, Faro, & Burson, 2013), none have yet compared the impact of subjective versus objective features of loan requests on their success in the context of microlending. We sought to examine whether neural affective mechanisms implicated in charitable giving might also encourage microlending.

Corresponding Author:
Alexander Genevsky, Department of Psychology, Stanford University, Jordan Hall, 450 Serra Mall, Stanford, CA 94305-2130
E-mail: genevsky@stanford.edu

With respect to charitable giving, compelling yet competing psychological theories suggest that different affective states might promote resource sharing (Batson et al., 1991; Batson, Duncan, Ackerman, Buckley, & Birch, 1981; Cialdini et al., 1987; Dickert, Sagara, & Slovic, 2011; Fehr & Camerer, 2007; Zaki & Mitchell, 2011, 2013). For instance, whereas some findings suggest that negative affect (e.g., guilt, empathy) can increase charitable giving (Fisher & Ma, 2014; Hein, Silani, Preuschoff, Batson, & Singer, 2010; Small & Verrochi, 2009), others implicate positive affect (e.g., warmth, excitement; Andreoni, 1995). To disentangle mechanisms contributing to charitable giving, researchers have probed brain circuits associated with affect using neuroimaging methods (e.g., functional MRI, or fMRI; Dawes et al., 2012; Genevsky, Vastfjall, Slovic, & Knutson, 2013; Harbaugh, Mayr, & Burghart, 2007; Hare, Camerer, Knoepfle, & Rangel, 2010; Moll et al., 2006; Rilling et al., 2002). For instance, in one of these studies, we found that greater positive arousal and nucleus accumbens (NAcc) activity in response to photographic appeals for orphans predicted subjects' choices to donate, whereas negative arousal and anterior insula (AIns) activity did not (Genevsky et al., 2013). We invoked an anticipatory-affect model of risk taking (Knutson & Greer, 2008) to account for the photographs' impact on giving. According to this model, positive arousal magnifies the salience of potential gains (whereas negative arousal instead magnifies the salience of potential losses), which can increase the tendency to accept risky propositions—including giving money to a needy stranger.

Although these findings surprisingly suggest that positive affect may promote charitable giving more than negative affect does, they do not clarify whether affect can also influence the success of loan requests. Further, even if psychological mechanisms alter the behavior of individuals in the laboratory, their influence may not generalize to larger market settings that involve significant financial incentives (Levitt & List, 2007). In the current research, therefore, we specifically aimed to establish whether affective mechanisms could account for microlending in a large Internet data set involving significant financial incentives, and more generally aimed to determine whether neural and affective responses could predict microlending not only at the individual level, but also at the market level.

Method

Internet study

In our first study, we explored the impact of the features of loan requests on the success of those requests in a large online microloan data set. To operationalize loan-request success as a continuous outcome, we examined the lending rate (i.e., dollars raised per hour). Parallel analyses conducted on a second index of loan-request success (i.e., binary "funded" vs. "not funded" loan outcomes) yielded similar results (see the Supplemental Material available online). Two features of the loan requests were identified as having the potential for affective impact: (a) the text description introducing and describing each borrower's individual circumstances and needs and (b) the photograph of the borrower prominently displayed at the top of each loan request. Given our assumption that microloan requests and charitable-giving appeals likely recruit similar mechanisms, we predicted that the photographs' positive affective impact (as indexed by valence and arousal ratings) would promote loan-request success (Genevsky et al., 2013), but we also tested the alternative possibility that negative affective impact might enhance loan-request success.

We acquired extensive data on microloan outcomes from Kiva Microfunds (www.kiva.org), an Internet-based international microfinance organization. Kiva's Web site allows users to offer small financial loans to individuals in need. Loans are funded in $25 increments but are received by the borrower only if the requested amount is successfully raised within 30 days of the initial loan request. We first used the Kiva application programming interface to sample 144,769 loan requests from those posted during the 2012 calendar year, the most recent period that could ensure complete loan-outcome results at the time of initial analyses. We then excluded loan requests with multiple borrowers (remaining $n = 127,811$), to minimize heterogeneity in photograph ratings arising from variations in the size of the borrower group; loan requests without text (remaining $n = 120,130$), because they could not be scored with respect to affective words in the text; (c) loan requests that were fully funded within the last 3 days of eligibility (remaining $n = 109,454$), to limit potential confounds due to shifts in lender's motivations and behavior as the deadline for loan expiration approached; and (d) loan requests with additional missing data points (remaining $n = 91,858$). Of the remaining 91,858 loan requests, 13,500 were randomly sampled for analysis (i.e., 7,000 funded and 6,500 not funded). Given the large size of the available data set, we sampled as much data as possible to accurately estimate underlying effect sizes within the constraints of available computational resources. The 13,500 selected loan requests conservatively achieved a power of .98 for an effect size of .07 at an alpha level of .05.

Affective content of the loan text was assessed with the Linguistic Inquiry and Word Count (LIWC) system (Pennebaker, Francis, & Booth, 2001)—an established variant of the "bag of words" model of linguistic processing. LIWC simplifies text content analysis by considering all words individually and disregarding grammar and

structure but retaining multiple uses of the same word. LIWC uses an extensive word dictionary to assign words to linguistic categories of interest—in this case, positive and negative emotion words. The number of words attributed to each category was divided by the total number of coded words to yield a fractional index of affective content. Thus, our measures of affective content for the text represented the percentages of positive and negative emotion words.

The affective impact of the loan-request photographs was estimated by soliciting independent ratings on Amazon's Mechanical Turk. All raters gave informed consent prior to participating. Each rater viewed a randomly selected photograph extracted from one of the Kiva loan requests and then evaluated the photograph on 7-point scales indexing the affective valence and arousal signaled by the person's facial expression, the photograph's identifiability (or visual clarity), and the person's perceived neediness. A forced-choice question then asked raters to categorize the emotion displayed (i.e., whether the person was happy, sad, calm, fearful, angry, disgusted, etc.; see Fig. S1 in the Supplemental Material). To ensure that ratings referred only to the photographs and not other details on the loan-request pages, we presented the photographs alone, removed from the context of the loan requests. Because positive aroused affect theoretically potentiates motivated approach but negative aroused affect potentiates avoidance, and these constructs align with activity in relevant neural circuits (Knutson & Greer, 2008; Knutson, Katovich, & Suri, 2014), we transformed the valence and arousal ratings into positive-arousal and negative-arousal scores by projecting within-subjects mean-deviated valence and arousal scores onto axes rotated 45° (i.e., positive arousal = (arousal/$\sqrt{2}$) + (valence/$\sqrt{2}$); negative arousal = (arousal/$\sqrt{2}$) − (valence/$\sqrt{2}$); see Fig. S2 in the Supplemental Material; Knutson, Taylor, Kaufman, Peterson, & Glover, 2005; Watson, Wiese, Vaidya, & Tellegen, 1999). For analyses of discrete emotional expressions, only categories that were selected in more than 5% of responses were included: happy (31.8%), sad (11.8%), calm (41.4%), and angry (6.2%).

Neuroimaging study

The Internet study focused on whether loan-request features could elicit affect and promote loan-request success, but could not specifically test whether affective responses increased lending, because affective responses were assessed in a separate group of subjects who rated borrowers' expressions, rather than their own experience. In the neuroimaging study, we aimed to determine whether subjects' experiential and neural affective responses to loan requests could account for aggregate loan-request success, even beyond their overt choices. Thus, we scanned subjects as they chose whether or not to lend to borrowers whose requests were preselected from the Internet study to represent high and low rated positive arousal and negative arousal.

Subjects. Potential subjects were screened to ensure that they met typical MRI safety criteria (e.g., no metal in the body), had not used psychotropic drugs or engaged in substance abuse in the past month, and had no history of neurological disorders. Thirty healthy, right-handed adults participated in this study after providing informed consent. Two were excluded for excessive head motion during the imaging task (i.e., > 2 mm of movement from one image volume acquisition to the next), which left a total of 28 subjects (13 females; age range = 18–34 years, M = 22.43) for final analyses. Subjects received $20.00 per hour for participating and also had the opportunity to keep all or half of the $50.00 endowment they received for the microlending task. All procedures were carried out as approved by the institutional review board of the Stanford University School of Medicine.

Microlending task. The microlending task was designed to re-create the experience of online microlending as closely as possible while subjects underwent scanning, by maintaining loan requests' appearance and context while also allowing extraction of neural activity in response to the photographs and text prior to choice (Fig. 1). Subjects initially received a cash endowment ($50.00). They were told that they would make lending decisions regarding a number of loan requests (i.e., whether or not to loan $25.00) and that one of their decisions would be selected at random to determine whether they kept their full endowment after the experiment. If a subject had agreed to a loan on the randomly selected trial, the amount of the loan (always $25.00) was subtracted from his or her endowment and loaned; otherwise, the subject would retain the full endowment. During each trial of the microlending task, subjects first viewed a photograph of a borrower from an actual Kiva loan page (2 s); the next screen additionally depicted the remainder of the loan request's content, including text (4 s). Subjects were then asked to indicate whether they would donate the requested amount or not (4 s). The left/right position of the "yes" and "no" prompts was counterbalanced across trials, and the response buttons were spatially congruent with the prompts. After a response was registered, the border of the selected choice was highlighted until the end of the choice period, to provide feedback. Finally, subjects fixated on a cross for a variable intertrial interval (2–6 s). Overall, the average trial duration (including the intertrial interval) was 14 s.

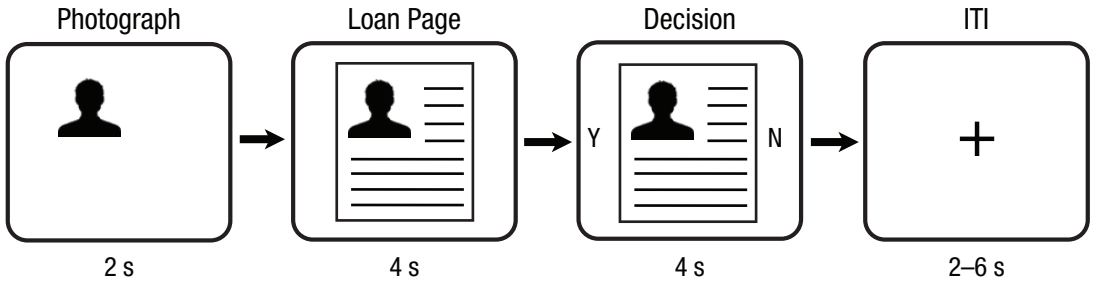

Fig. 1. Structure of the microlending task in the neuroimaging study. On each trial, subjects saw a loan-request photograph alone (2 s) and then accompanied by the remainder of the loan-page content (4 s). Spatially counterbalanced prompts then appeared so that subjects could indicate their choice to lend ("Y," for "yes") or not ("N," for "no"; 4 s). Finally, subjects fixated on a cross for a variable intertrial interval (ITI; 2–6 s).

The task consisted of a total of 80 trials, each of which presented a unique loan request selected from the Kiva Internet site. The loan requests were preselected from the set used in the Internet study to include requests with the 20 most extreme ratings of high and low positive arousal and the 20 most extreme ratings of high and low negative arousal, as determined by the assessments of the photographs collected in the Internet study. All elements of the loan requests were presented as they appeared on the Kiva Internet site, with one exception—the bar indicating progress toward full funding was manipulated so that, on average, it was visually equivalent across the affect conditions (for sample stimuli, see Fig. S3 in the Supplemental Material). After scanning, 1 trial in the microlending task was selected at random, and subjects gave the experimenter $25 from their endowment to send to Kiva if they had decided to lend on that trial. Subjects were informed that although the loan period for the individual they had selected had ended, their loan would be lent on the Kiva Web site to another individual of the same sex, nationality, and use sector. Subjects were then contacted 6 months later, when the repayment term had elapsed, and repaid the $25 loan amount.

Power analysis and sample size. The sample size for this study was estimated via previously established procedures (Desmond & Glover, 2002). On the basis of simulations over a range of expected effect sizes for contrasts of fMRI activity, we estimated that a sample size of 24 would provide .80 power at a conservative brainwide alpha threshold of .002 (although such thresholds ideally should be relaxed for detecting activity in regions where an effect is predicted). We therefore acquired data from 30 subjects to ensure that we would have sufficient data even if some subjects were excluded for excessive head motion. Because crucial analyses focused on prediction not only of the neuroimaging sample's choices but also of choices on the Kiva Internet site, we averaged behavioral and neural data across subjects so that the stimulus (i.e., loan request, rather than subject) served as a fundamental unit of analysis. This required a second power estimate. Stimulus sample size was determined via power analysis of the sole existing similar study, which used neural activity to predict Internet downloads of music (Berns & Moore, 2012). The effect size from that study implied that a sample size of 72 loan requests would be required to achieve .80 power at an alpha level of .05. Thus, 80 loan-request stimuli were included in the study.

Affect. After scanning, subjects rated their own affective reactions to each of the loan requests using two 7-point scales, one indexing valence (positive–negative) and the other indexing arousal (highly arousing–not arousing). Written instructions and spoken clarifications delivered by the experimenter explicitly described the nature of these scales (see Supplemental Methods in the Supplemental Material), and detailed examples were provided (as described in the procedure of Knutson et al., 2005). Whereas subjects in the Internet study were instructed only to rate the affect of borrowers' faces in the loan photographs, subjects in the neuroimaging study were instructed to rate their own affective responses to each entire loan-request page. On each trial of the rating task, one entire loan request (including the photograph and text) from the microlending task was presented. Subjects then used the number keys on a keypad to enter their valence and arousal ratings, according to how they previously felt "when presented with this loan request." These affect ratings were then transformed into positive-arousal and negative-arousal scores using the same procedure described for the Internet study.

fMRI acquisition and analysis. Images were acquired with a 3.0-T General Electric MRI scanner using a 32-channel head coil. Forty-six 2.9-mm-thick slices (in-plane resolution = 2.9 mm, isotropic, no gap, interleaved acquisition) extended axially from the midpons to the crown of the skull, providing whole-brain coverage and homogeneous spatial resolution of subcortical regions of interest (e.g.,

midbrain, NAcc, orbitofrontal cortex). Whole-brain functional scans were acquired with a T2*-weighted gradient-echo pulse sequence (repetition time = 2 s, echo time = 24 ms, flip angle = 77°). High-resolution structural scans were acquired with a T1-weighted pulse sequence (repetition time = 7.2 ms, echo time = 2.8 ms, flip angle = 12°) after the functional scans, to facilitate their localization and coregistration.

Whole-brain analyses were conducted using Analysis of Functional Neural Images (AFNI) software (Cox, 1996). For preprocessing, voxel time series were sinc-interpolated to correct for nonsimultaneous slice acquisition within each volume, concatenated across runs, corrected for motion, slightly spatially smoothed to minimize effects of anatomical variability (4-mm full-width/half-maximum kernel), high-pass filtered (admitting frequencies with periods < 90 s), and normalized to percentage signal change with respect to each voxel's average over the entire task. Visual inspection of motion-correction estimates confirmed that only 2 subjects' heads moved more than 2.0 mm in any dimension from one volume acquisition to the next, and these subjects were excluded from further analysis.

For whole-brain analyses, regression models included eight regressors of no interest, six that indexed residual motion and two that indexed activity associated with cerebrospinal fluid and white matter intensity (Chang & Glover, 2009). The regressor of interest orthogonally contrasted (for the first two brain volume acquisitions of each trial) trials in which subjects chose to make loans and those in which they did not. Prior to inclusion in the models, the regressor of interest was convolved with a single gamma-variate function that modeled a canonical hemodynamic response (Cohen, 1997). Maps of t statistics for the regressor of interest were transformed into maps of z scores, coregistered with structural maps, spatially normalized by warping to Talairach space, and resampled as 2-mm^3 voxels. Each group map was initially voxel-wise thresholded (at $p < .005$) and then cluster thresholded (cluster size > 12 contiguous 3-mm^3 voxels) to yield a corrected threshold for detecting whole-brain activation ($p < .05$ corrected, derived with 15,000 Monte Carlo iterations using AFNI program 3dClustSim).

Targeted analyses were conducted by specifying volumes of interest in regions previously found to be associated with anticipatory affect (Knutson & Greer, 2008) and charitable giving (Genevsky et al., 2013; Harbaugh et al., 2007). Specifically, spherical volumes of interest (8 mm in diameter) were placed at bilateral foci in the NAcc (Talairach coordinates: ±10, 12, −2), AIns (Talairach coordinates: ±34, 24, −4), and medial prefrontal cortex (MPFC; Talairach coordinates: ±4, 45, 0). On the basis of group findings from the whole-brain analyses, identically sized spherical volumes of interest were also placed on bilateral foci in the amygdala (Talairach coordinates: ±24, −5, −15) and anterior medial prefrontal cortex (AMPFC; Talairach coordinates: ±4, 48, 10). Activity (percentage signal change) was averaged within each volume of interest, averaged across bilateral volumes of interest, and then extracted to derive time courses of activation. Predictive regression analyses included subject random effects to control for individual differences. The behavioral model included fixed effects of choices (whether or not to lend). The neural model included fixed effects of neural activity averaged over the first two brain volume acquisitions of each trial (i.e., during presentation of the loan photograph and subsequent addition of the text, lagged by 4 s to account for the hemodynamic delay) in the bilateral volumes of interest (including the NAcc, MPFC, AIns, and amygdala).

Results

Internet study

Hierarchical linear regressions predicting loan-request success included fixed effects of both affective loan features (i.e., positive and negative features of the photographs and text) and more objective loan features (i.e., requested loan amount, as a continuous dollar amount; repayment term, the number of months before repayment; total number of words in the text; rated identifiability of the borrower's photograph; perceived neediness of the borrower; and borrower's sex, coded 0 for female and 1 for male). In addition, regression models controlled for nested random effects of the borrower's nationality and proposed use of the requested funds (categories—e.g., housing, agriculture, and retail—were defined in advance by Kiva) in order to establish generalizability beyond the available nationalities and loan categories. Because lending rates were positively skewed, they were log-transformed prior to analysis.

This analysis (see Table 1) revealed that positive-arousal ratings of photographs were positively associated with lending rate (Fig. 2a). Although negative-arousal ratings of photographs were not significantly associated with lending rate, they did show a trend toward such an association (Fig. 2a). Neither the percentage of positive words nor the percentage of negative words in the text was associated with lending rate (Fig. 2a). Photograph identifiability was also positively associated with lending rate, as was sex of the borrower, with female borrowers garnering higher rates of lending than male borrowers. Length of repayment term was negatively associated with lending rate. Other potentially relevant loan-request features—length of loan-request text, perceived neediness of the borrower, and requested loan amount—were not associated with loan-request success, however.

Table 1. Results of the Hierarchical Linear Regression Model of Loan-Request Features Associated With Internet Lending Rates

Loan feature	β
Affective features	
Photo: positive arousal	0.087** [0.050, 0.124]
Photo: negative arousal	0.035 [–0.002, 0.072]
Text: positive words (%)	0.024 [–0.013, 0.061]
Text: negative words (%)	–0.035 [–0.072, 0.002]
Objective features	
Photo: identifiability	0.055** [0.016, 0.094]
Text: total number of words	0.028 [–0.017, 0.073]
Borrower's neediness	0.008 [–0.031, 0.047]
Requested loan amount	–0.039 [–0.092, 0.014]
Repayment term	–0.277** [–0.331, –0.223]
Borrower's sex	–0.865** [–0.957, –0.773]
R^2	.428

Note: The table presents standardized coefficients, with 95% confidence intervals in brackets. The regressions included random effects of borrower's nationality and loan's use sector.
**$p < .01$.

Direct comparison of nested models (with the Akaike information criterion, or AIC) indicated that affective features improved model fit, despite penalties for additional predictors (see Table S1 in the Supplemental Material). Bootstrapped correlation analyses verified the robustness of the association between positive affective impact of the photographs and lending rates. Positive arousal robustly correlated with lending rate, bootstrapped r = .67, 95% CI = [.25, .93], $p < .001$ (Fig. 2b), but negative arousal did not, r = .27, 95% CI = [–.14, .62]. Photograph identifiability also robustly correlated with lending rate, r = .90, 95% CI = [.66, .99], $p < .001$.

We further verified the ability of affective features to account for loan outcomes (i.e., funded or not) with classification analyses. After we trained a linear support-vector-machine classifier with repeated 10-fold cross-validation (3 repeats) on 80% of evenly downsampled loans, affective features alone classified lending outcomes with 58.2% accuracy. Application of this model to an independent out-of-sample data set containing the remaining 20% of loans classified lending outcomes with 56.3% accuracy (95% CI = [54.4, 58.3]). Prediction accuracy for this model exceeded chance (i.e., downsampled to 50.0%), $p < .001$. These results indicate that affective features alone can predict loan-request success.

In addition to rating photographs on the dimensions of valence and arousal, raters categorized the photographs into eight discrete emotion categories. The only category of photographs for which the loan-request lending rate exceeded the average rate was the "happy" photographs, bootstrapped $t(2358) = 6.24$, $p < .001$ (Fig. 2c). Direct pairwise comparisons via bootstrapped t-test analyses indicated that requests with photographs classified as happy were funded at a higher rate than those with photographs classified as sad (the category with the next best lending rate), $t(3023) = 2.02$, $p < .05$, β = 0.133, 95% CI = [0.004, 0.263]).

To establish the financial impact of affective features, we explored descriptive and predictive aspects of models of loan-request success. Photographs in the top decile of positive-arousal ratings were funded at $8.04 more per hour than were photographs in the bottom decile (i.e., $69.95 vs. $61.91); they achieved full funding in 11.5% less time. The slope of the linear effect of photograph positive arousal on lending rate suggests that a single-unit increment in positive arousal elicited a $1.13 increase in lending rate per hour, or a 1.9% reduction in time to full funding. By contrast, a $100 decrease in the requested loan amount elicited only a $0.19 increase in lending rate per hour, or a 0.3% reduction in time to full funding. Categorical ratings of the emotional expressions in the loan photographs had a similarly powerful impact on loan-request success; requests with "happy" photographs received $5.15 more per hour than requests with "sad" photographs, on average; they achieved full funding in 7.6% less time. Thus, simple modifications of subjective features of loan requests (e.g., facial expressions) may have a surprisingly powerful impact on the requests' success, and indeed may have a greater impact than more traditional but costly changes in objective features (e.g., requested amount).

Neuroimaging study

Analysis of variance indicated that facial features of the photographs also influenced loan-request success in the neuroimaging study, $F(3, 76) = 2.86$, $p = .042$. Loan requests with photographs rated as eliciting high levels of positive arousal elicited the highest rates of lending (54.8%), followed, in turn, by loan requests with photographs rated as eliciting low levels of negative arousal (47.4%), low levels of positive arousal (43.9%), and high levels of negative arousal (43.8%). Bootstrapped pairwise t tests revealed that high-positive-arousal loan requests elicited more lending than high-negative-arousal loan requests, $t(48) = 2.54$, $p = .015$, β = 0.12, 95% CI = [0.03, 0.21], and low-positive-arousal loan requests, $t(48) = 2.43$, $p = .020$, β = 0.12, 95% CI = [0.02, 0.20] (all other pairwise comparisons were not significant).

Whole-brain analyses contrasting activity prior to choices to lend or not revealed significant activation clusters in the ventral striatum (including the NAcc), MPFC, and left amygdala, among other regions (for whole-brain activation foci, see Table S2 in the Supplemental Material). To further test the association of neural activity with

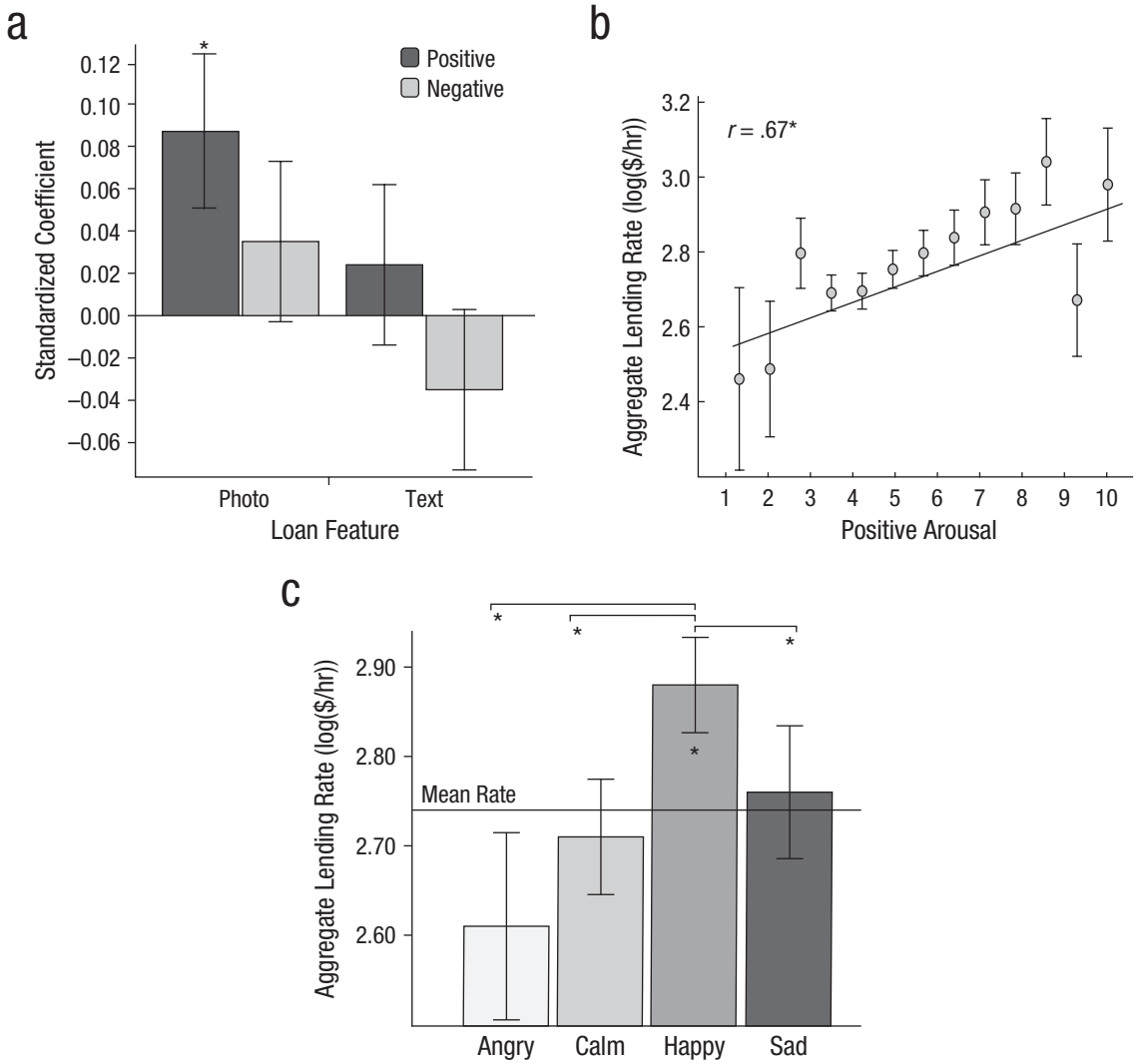

Fig. 2. Results from the Internet study. The graph in (a) shows results from the linear regression model predicting aggregate lending rate. Standardized coefficients for positive and negative features of the loan-request photographs and text are depicted. The scatterplot in (b) illustrates the correlation between aggregate lending rate and positive-arousal ratings of borrowers' photographs. In (a) and (b), asterisks indicate values that differ significantly from zero (*$p < .05$). The graph in (c) shows aggregate lending rate for photographs categorized as "angry," "calm," "happy," and "sad"; asterisks with brackets indicate significant differences between categories, and the asterisk inside the data bar indicates a significant difference from the mean lending rate (*$p < .05$). In all three panels, error bars represent 95% confidence intervals.

choices to lend, we used activity extracted from predefined regions of interest, comprising the NAcc, AIns, and MPFC, to predict decisions to lend on a trial-by-trial basis in a hierarchical logistic regression model. This analysis indicated that only NAcc activity (β = 0.120, 95% CI = [0.016, 0.224]) and MPFC activity (β = 0.041, 95% CI = [0.005, 0.077]) predicted choices to lend from trial to trial (see Table S3 in the Supplemental Material). A second linear regression model assessed the association between neural activity and self-reported affect ratings in response to the loan requests (see Table S4 in the Supplemental Material). Positive-arousal scores were positively associated with NAcc activity (β = 0.248, 95% CI = [0.026, 0.470]) and negatively associated with AIns activity (β = −0.202, 95% CI = [–0.392, –0.012]). Negative-arousal scores, however, were not significantly associated with brain activity in any region of interest.

Bootstrapped correlation analyses (5,000 iterations) tested whether the variables assessed in the neuroimaging study were associated with aggregate microlending outcomes from the Internet study. Results indicated that lending rates in the neuroimaging sample (i.e., the percentage of subjects who chose to loan) correlated with Internet lending rates for the same requests, bootstrapped

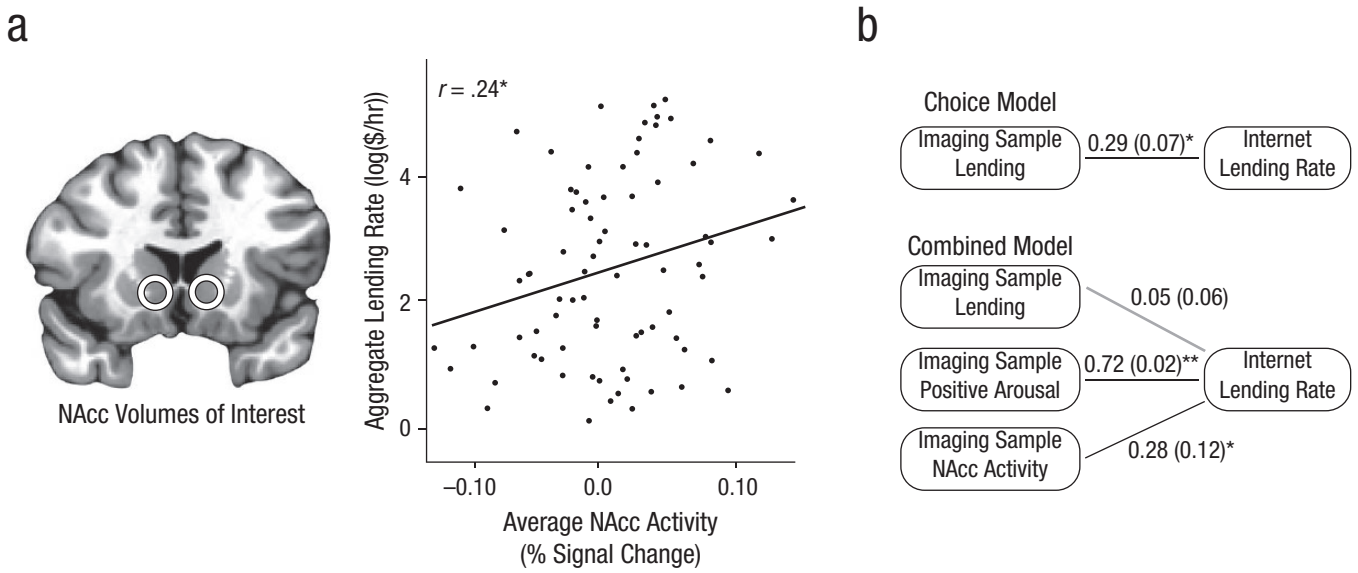

Fig. 3. Results from the neuroimaging study. The illustration in (a) shows the location of the region of interest in the nucleus accumbens (NAcc) where activity (percentage signal change) during presentation of the loan photograph and text positively correlated with lending rate in the Internet study. Activity was averaged bilaterally and then across the 28 scanned subjects for each loan request. The scatterplot (with best-fitting regression line) shows the aggregate lending rate as a function of averaged NAcc activity. The diagrams in (b) show key results of nested models testing whether choice, affect, or neural activity of the neuroimaging sample could best account for Internet lending rates. Standardized coefficients are accompanied by standard errors of the mean, in parentheses. Asterisks indicate significant coefficients (*$p < .05$, **$p < .01$).

$r = .322$, 95% CI = [.110, .502], $t = 2.96$, $p < .01$. A linear regression indicated that positive-arousal scores of the neuroimaging sample, $t = 8.37$, $p < .001$, but not negative-arousal scores of this sample, $t = -1.95$, $p = .055$, were associated with Internet lending rates. Bootstrapped correlations also verified that the neuroimaging sample's positive-arousal scores were associated with Internet lending rates, bootstrapped $r = .411$, 95% CI = [.212, .574], $t = 3.94$, $p < .001$.

We further hypothesized that the neuroimaging sample's activity in circuits implicated in anticipatory affect (e.g., NAcc and AIns; Knutson & Greer, 2008) might predict Internet loan-request success. Following the approach of Berns and Moore (2012), we calculated correlations between Internet loan-request success and anticipatory activity in regions drawn from targeted volumes of interest (i.e., NAcc, AIns, and MPFC) as well as whole-brain analyses. Of these regions, only the NAcc exhibited activity that was significantly and positively correlated with Internet lending rates, bootstrapped $r = .24$, 95% CI = [.03, .42], $p = .036$ (see Fig. 3a). NAcc activity predicted Internet loan-request success during the appearance of the photograph prior to the decision phase, which is consistent with the prediction that positive arousal in response to photographs promotes microlending at the aggregate level, as well as the individual level.

Separate hierarchical linear regression models assessed whether choice, affect, or neural activity of the neuroimaging sample could best account for lending rates on the Internet (see Table 2 and Fig. 3b). Model comparisons indicated that brain activity in the neuroimaging sample explained more variance in Internet lending rate ($R^2 = .061$, AIC = 8,155) than did choice ($R^2 = .040$, AIC = 8,262), despite penalties for additional predictors. Further, in a combined model that included choice, affect, and neural variables from the neuroimaging study, only NAcc activity, $t = 2.08$, $p = .035$, and positive arousal, $t = 16.63$, $p < .001$, remained significantly associated with Internet lending rate; choice, negative arousal, and activity in other neural regions of interest were no longer significantly associated with Internet lending rate. These findings suggested that positive arousal and NAcc activation in the neuroimaging sample could account for the association of their choices with Internet loan-request success. A model including only the affect ratings of the neuroimaging sample also performed better than choices alone ($R^2 = .168$; Table 2). Substitution of the Internet sample's affect ratings for the neuroimaging sample's affect ratings in the combined model (to control for potential retrospective bias) produced similar results (see Table S5 in the Supplemental Material).

Classification analyses then verified the robustness of the ability of data from the neuroimaging study to forecast Internet loan-request success. Loans were divided into two bins by applying a median split to their Internet lending rates. A linear support-vector-machine classifier was applied to these data, and accuracy was calculated with 10-fold repeated cross-validation resampling

Table 2. Results of Hierarchical Linear Regression Models Predicting Internet Lending Rates Using Data From the Neuroimaging Sample

	Model			
Predictor	Choice alone	Affect alone	Brain activity alone	Combined
Lending choice	0.29* [0.15, 0.43]			0.05 [–0.07, 0.17]
Positive arousal		0.74** [0.66, 0.82]		0.72** [0.66, 0.80]
Negative arousal		0.10 [–0.04, 0.24]		0.11 [–0.05, 0.27]
NAcc activity			0.31* [0.05, 0.57]	0.28* [0.04, 0.52]
MPFC activity			0.02 [–0.10, 0.14]	–0.01 [–0.11, 0.09]
Insula activity			–0.02 [–0.24, 0.20]	–0.02 [–0.22, 0.18]
Amygdala activity			0.07 [–0.15, 0.29]	–0.01 [–0.21, 0.19]
R^2	.040	.168	.061	.199
AIC	8,262	7,746	8,155	7,498
Classification accuracy (%)	56.6	60.1	57.2	62.3

Note: For each predictor, the table presents standardized coefficients, with 95% confidence intervals in brackets. NAcc = nucleus accumbens; MPFC = medial prefrontal cortex; AIC = Akaike information criterion.
*$p < .05$. **$p < .01$.

(3 repeats). A model including subjects' lending choices, affect ratings, and neural activity yielded 62.3% classification accuracy. By comparison, a model including the choice variable alone yielded 56.6% classification accuracy. A model including only NAcc activity, however, yielded a slightly higher classification accuracy of 57.2%.

Discussion

These findings suggest that neural affective mechanisms promote microlending, at both individual and market scales. First, in a large Internet sample, positive affective features of loan-request photographs predicted the success of those requests. Second, neural affective measures associated with positive arousal accounted for loan-request success both within a neuroimaging sample and on the Internet. This research provides initial evidence not only that affective features promote microlending, but also that their aggregate impact depends on the positive affect that they evoke in potential lenders. Thus, the findings suggest that common anticipatory affective mechanisms may underlie choices related to both charitable giving and microlending (Genevsky et al., 2013).

Although a growing number of studies suggest that neural activity can predict individual behavior (e.g., financial risk taking or purchasing; Knutson & Greer, 2008), only a handful have explored whether neural activity averaged across a group can predict aggregate behavior. For instance, investigators have used group NAcc activity in response to music to predict the aggregate number of song downloads 2 years later (Berns & Moore, 2012) and have used group MPFC activity to predict call volume in response to anti-smoking advertisements (Falk, Berkman, Whalen, & Lieberman, 2011). No studies have yet used findings from aggregate data to implicate a neurobehavioral mechanism, however, and then verified that mechanism in an independent sample whose neural activity reciprocally classifies aggregate behavior.

This research makes a number of novel contributions. First, the findings implicate specific neural affective mechanisms in microlending—on both individual and aggregate levels. By demonstrating that psychologically "hidden" mechanisms can account for aggregate behavior better than behaviorally "revealed" choices, the findings empirically address a challenge from economic theorists (Bernheim, 2008). Whereas whole-brain analyses implicated several regions in lending in the neuroimaging sample, only activity in the NAcc, which has been associated with positive arousal, was associated with loan-request success on the Internet. Although recent findings suggest that synchronous neural activity in neuroimaging samples can predict aggregate behavior (i.e., Internet mentions; Dmochowski et al., 2014), the current evidence suggests that synchronous recruitment may matter more for some circuits than for others in forecasting aggregate choice.

The neuroimaging sample's positive-arousal ratings were also associated with aggregate loan-request success. The partially distinct associations of NAcc activity and positive-arousal ratings with aggregate choice may stem from the fact that although NAcc activity has been associated with positive arousal (e.g., Knutson & Greer, 2008), the neuroimaging subjects completed affect ratings for each loan request only after being scanned. These retrospective ratings may have provided a more integrated assessment than did the on-line NAcc activity immediately preceding each choice (also see Genevsky et al., 2013). Additional analyses substituting the Internet sample's affect ratings for the neuroimaging sample's affect ratings replicated the significant positive associations of NAcc

activity and positive arousal with loan-request success, however, suggesting that positive-arousal ratings did not merely reflect previous choices.

A second contribution of these findings is that they help distinguish among different theoretical accounts of how psychological mechanisms promote microlending, by providing specific support for an anticipatory-affect account. Information volume alone could not account for loan-request success, given that the number of words in the text was not associated with lending rates (speed of lending) or loan outcomes (ultimate success or failure in attracting loans; see Table S6 in the Supplemental Material). Semantic associations alone also could not account for loan-request success, as neither positive nor negative text features were associated with loan rates or outcomes. Only photographs demonstrated a significant and specific association between positive arousal and loan-request success (Table 1, Fig. 2a). Photograph identifiability also could not solely account for loan-request success, as photograph-elicited positive arousal predicted loan-request success above and beyond the variance accounted for by identifiability (Table 1). In fact, statistical analyses suggested that positive arousal might instead account for part of the association between photograph identifiability and loan-request success (see Table S1 in the Supplemental Material).

The fact that positive arousal but not negative arousal had a specific impact further implies that induction of general arousal also could not account for loan-request success. Although previous research has provided mixed evidence about the impact of positive versus negative affect on charitable giving (Andreoni, 1990; Small & Verrochi, 2009), by simultaneously assessing affect at both Internet-aggregate and laboratory-sample levels of analysis, our studies provide consistent evidence that photograph-elicited positive arousal most powerfully promoted lending rates and outcomes (Tables 1 and 2, Fig. 2a, and Fig. S5 and Table S6 in the Supplemental Material). Coupled with previous findings that photographs can promote charitable giving (Genevsky et al., 2013), the current demonstration that photograph-elicited positive arousal encourages microlending suggests that pictures encourage sharing by inducing affect—an influence absent from most traditional models of lending. Thus, despite apparent practical and logistic differences between scenarios involving charitable giving and microlending, common affective processes may influence these behaviors. The microlending scenarios studied here may also have elicited more variable positive arousal than negative arousal, as suggested by the distributions of the scores (see Fig. S4 in the Supplemental Material). Future research will need to delineate situations in which negative arousal plays a more prominent role in decisions to give or lend.

A third contribution of the current findings is that they validate neuroimaging as having the potential to provide useful practical guidance for enhancing loan-request success. Specifically, the findings imply that small, inexpensive modifications of affective features of loan requests (e.g., using smiling photographs) may have a more pronounced impact on loan-request success than more costly changes related to constructing a compelling narrative or even requesting fewer resources. To emulate lending on the Internet while isolating neural responses to distinct loan-request features, we presented photographs before text in the neuroimaging study. This ordering might have enhanced the relative impact of the photographs' features. In the Internet study, however, even though potential lenders presumably encountered the photographs and text simultaneously, the photographs' features still exerted a stronger influence on loan-request success than did the text. Further studies could determine whether this is also the case when text is presented first, or when the photograph and text have conflicting content. More generally, future research might explore whether similar neural affective mechanisms can account for other types of aggregate choice—including those that fall within the scope of traditional decision theories as well as those that do not (Kahneman, 2003). Opportunities also exist for refining models that can specify when and how neural mechanisms account for aggregate behavior. The present findings thus raise hope that integrating neuroscience evidence across levels of analysis may ultimately improve theories of choice.

Author Contributions

A. Genevsky and B. Knutson developed the study concept and study design. Data collection was performed by A. Genevsky. A. Genevsky and B. Knutson performed the data analysis and wrote the manuscript. Both authors approved the final version of the manuscript for submission.

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Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplemental Material

Additional supporting information can be found at http://pss.sagepub.com/content/by/supplemental-data

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Title: Neural affective mechanisms predict market-level microlending

Authors: Alexander Genevsky & Brian Knutson

Supplemental Data and Analysis.

Binary funding outcome analyses

In addition to the continuous funding rate as an outcome, analyses were also run on a binary dependent variable indicating whether or not each loan was ultimately funded or not. In these analyses, linear regressions were replaced with logistic regressions. All significant findings reported for the funding rate variable in the main text also replicated for this funding outcome variable.

Specifically, for photographic features, rated positive arousal was associated with funding outcome ($z=3.28$, $p<0.001$, Fig. S5, Table S6). Photograph negative arousal, however, was not associated with funding outcome (outcome: $z=0.83$). Neither the proportion of positive nor of negative words in the text was associated funding outcome (positive: $z=-1.68$, negative $z=-0.72$, all p's > 0.05). The identifiability of individuals depicted in photographs also was associated with funding outcome ($z=3.69$, $p<0.001$).

Bootstrapped correlation analyses tested the robustness of the association of photograph positive arousal and identifiability on loan request performance. Mean funding rates were calculated for each level of photograph positive arousal and negative arousal as well as identifiability. Photograph positive arousal was strongly

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associated with funding rate (r=0.63; 95% C.I.=[0.11,0.82]), but negative arousal was not. Photographic identifiability was also strongly associated with funding outcome (r=0.94; 95% C.I.=[0.89,0.99], Fig. S6). Bootstrapped mediation analyses (1,000 iterations) revealed a significant indirect path from photograph identifiability to positive arousal to funding outcome ($p<0.001$, $Z=3.29$; index of mediation=0.021, 95% CI = [0.013,0.030]).

Bootstrapped mediation analyses (1,000 iterations) revealed a significant indirect path from photograph identifiability to positive arousal to funding rate ($p<0.001$, $Z=3.29$; index of mediation=0.015, 95% C.I. = [0.008,0.022]) and the direct path coefficient from photograph identifiability to funding rate significantly decreased after including positive arousal as a mediator (i.e., from 0.10 to 0.08; $Z=3.29$, $p<0.001$). When this analysis was repeated substituting funding outcome as the dependent variable, positive arousal again significantly mediated the associated of identifiability with funding outcome ($p<0.001$, $Z=3.29$; index of mediation=0.021, 95% CI = [0.013,0.030]).

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Supplemental Methods

Affective rating task instructions

Descriptions of valence and arousal were provided to subjects on-screen with text and in the laboratory by the experimenter. In the laboratory, the experimenter addressed all questions regarding these instructions, and verified understanding with verbal confirmation.

"You will now rate each of the individual decisions you were asked to make using two scales: The VALENCE scale and the AROUSAL scale. These two scales measure DIFFERENT aspects of your emotional state.

When making your ratings, try to think about how you felt during the previous task when asked to make these types of decisions. Try to focus on how you felt given the information available about the potential borrower and the requested loan.

THE VALENCE SCALE measures how positive or negative you are feeling.
At the far left you would be feeling very negative: That could be unhappy, upset, irritated, frustrated, angry, sad, depressed, or some other negative feeling.
At the far right you would be feeling very positive: That could be happy, pleased, satisfied, competent, proud, content, delighted, or some other positive feeling.
In the middle of this scale you would be feeling completely neutral, neither positive or negative. From the neutral midpoint, the ratings get gradually more negative as you move left, and gradually more positive as you move right.

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THE AROUSAL SCALE measures how aroused you are feeling at a given time. At the far right on this scale, you would be feeling very alert, aroused, activated, charged or energized, very physically or mentally aroused. At the far left, you would be feeling completely unaroused, slow, still, de-energized, no physical or mental arousal at all. Notice that while the VALENCE scale has a neutral midpoint, the AROUSAL scale does not. It is a continuum going from low to high arousal. The point in the middle of the scale would represent being moderately aroused – a point in between the two extremes. It does NOT mean neutral.

Think about the scales as capturing separate aspects of your how you are feeling. So, the arousal scale doesn't tell us whether you are feeling good or bad; it's capturing more of this idea of physical or mental activation. For example you could be feeling very aroused and positive (suppose you were really excited because you had just won a prize) or very aroused and negative (suppose you were really angry because someone had just stolen your parking space). On the other hand, you could be feeling really unaroused and positive (if you were relaxing and looking at a beautiful sunset) or really unaroused and negative (if you were feeling down and depressed). We want you to report the negative or positive dimension of your feeling on the one scale, and the arousal aspect on the other."

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Fig. S1. A screenshot of the rating task administered to workers on the Amazon Mechanical Turk platform. Photographs were scraped from Kiva loan webpages that were previously randomly selected for statistical analyses.

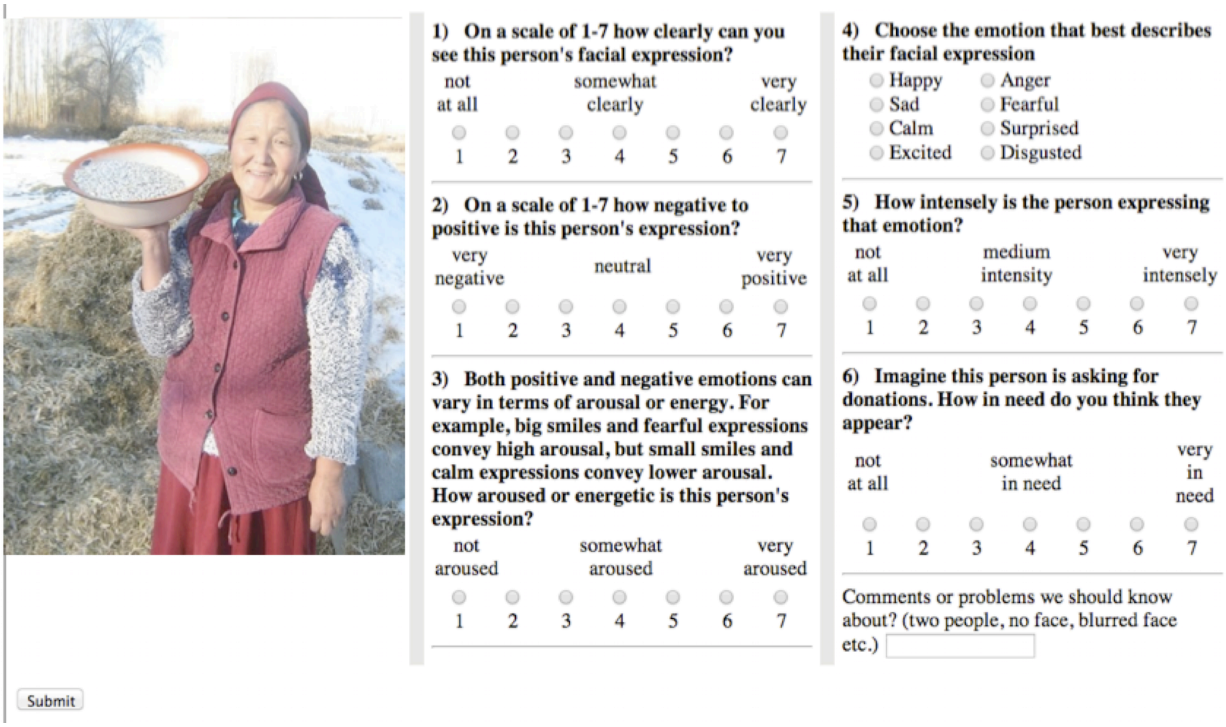

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Fig. S2. An affective circumplex (34). To calculate positive arousal and negative arousal, points determined by ratings of valence and arousal (mean-deviated within subject) are projected by 45 degrees onto the positive and negative arousal axes.

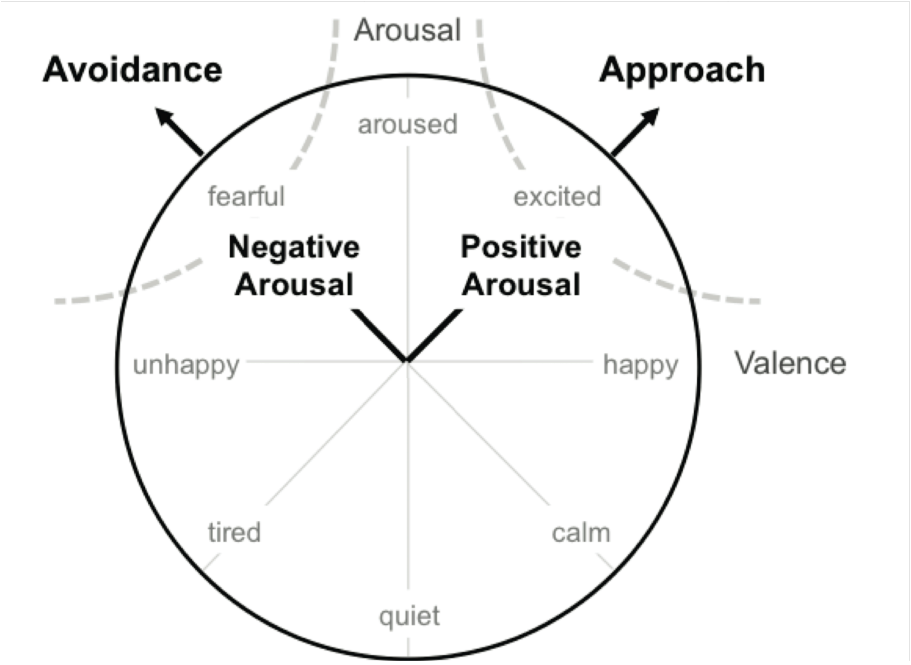

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Fig. S3. Sample stimuli used in the neuroimaging lending task. All elements of the loan requests were presented as they appeared on the Kiva website, with one exception -- the bar indicating progress toward full funding was manipulated and balanced across different affect categories.

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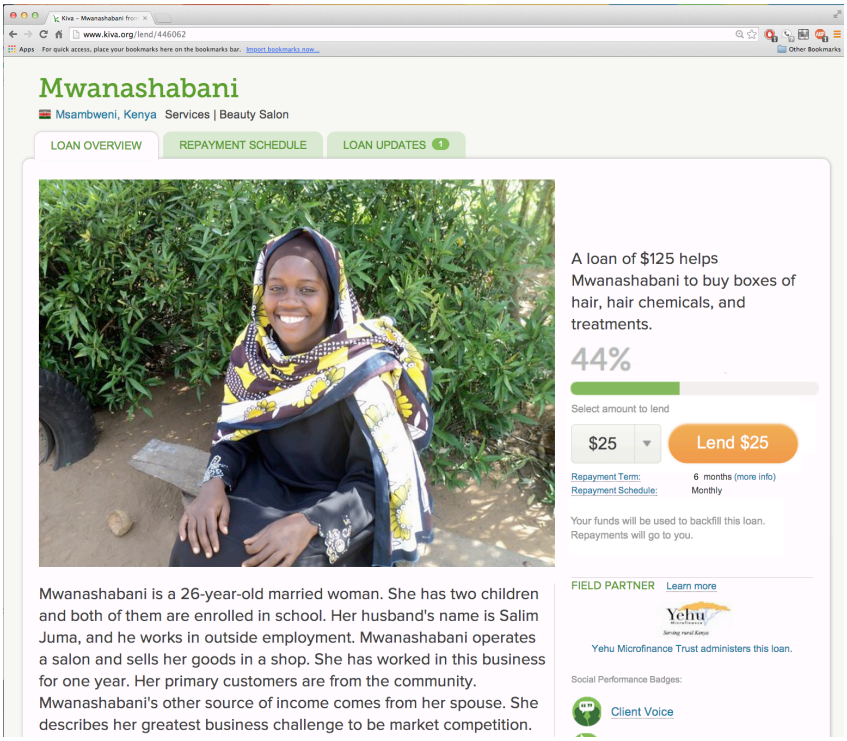

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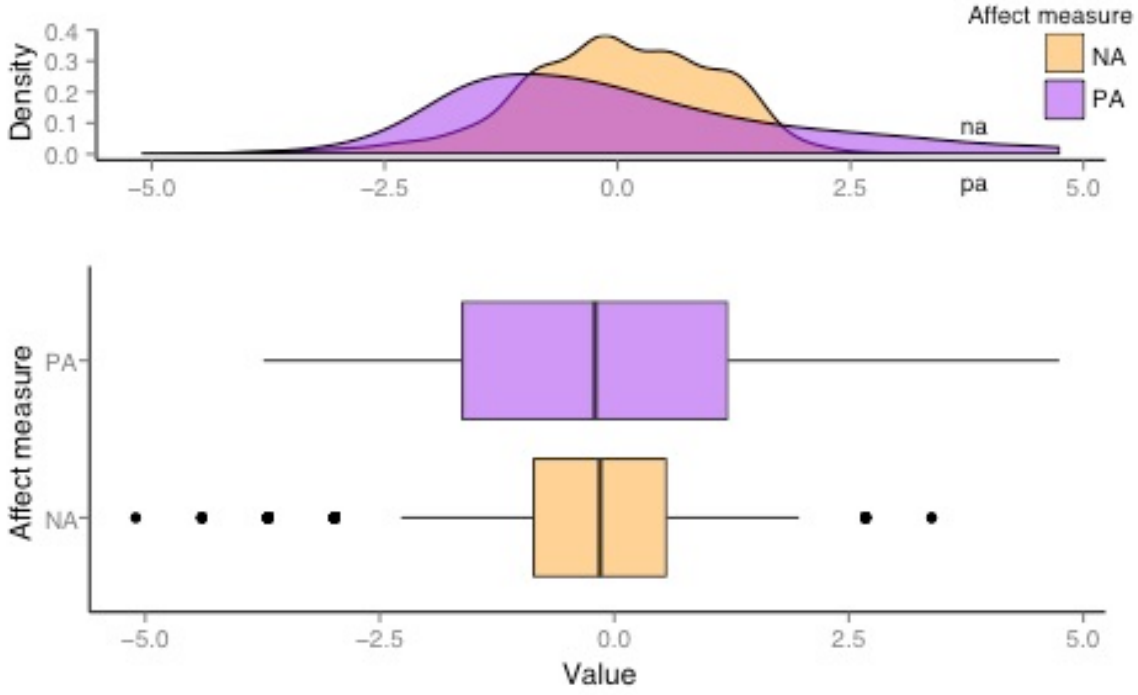
Fig. S4. Positive arousal (PA) and negative arousal (NA) rating distributions. Density and box and whisker plots of centered positive and negative arousal ratings of loans in the a) internet sample, and b) neuroimaging sample. In both samples, the negative arousal ratings' distribution shows higher kurtosis, since a higher concentration of values cluster around the average.

a) Internet sample



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b) Neuroimaging sample

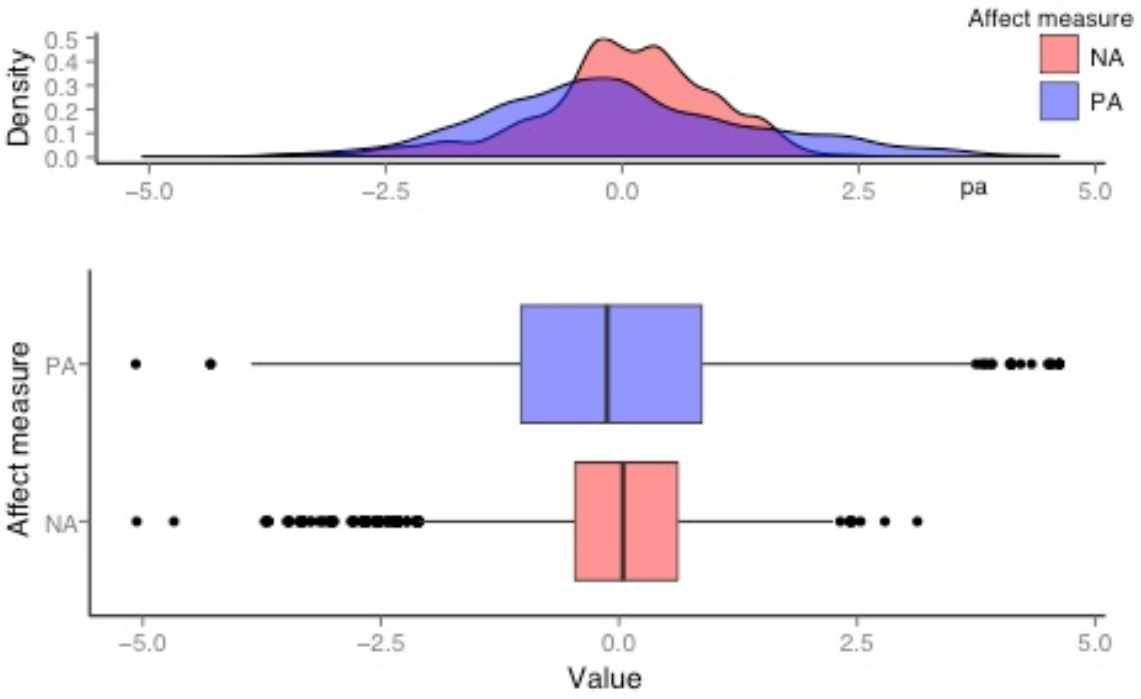

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Fig. S5. Positive affective impact of loan request photographs is associated with funding outcome. In logistic regression analyses of the influence of the positive and negative affective features of loan request text and photographs, only the positive affective features of photographs was significantly associated with funding outcome. Error bars represent SEM.

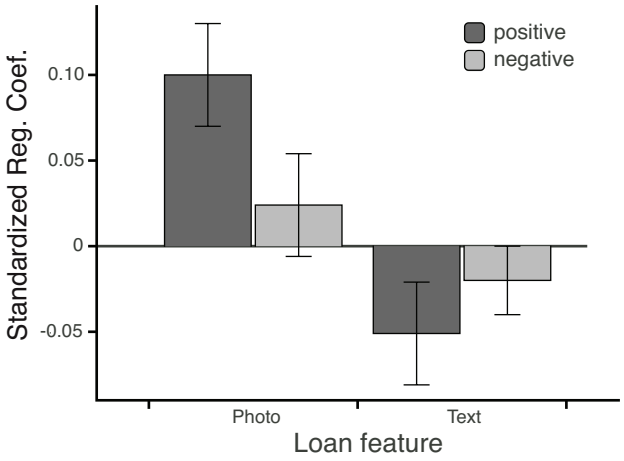

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Fig. S6. Loan request photograph identifiability correlates with funding rate (r=0.90; 95% C.I.=[0.66,0.99]) and funding outcomes (r=0.94; 95% C.I.=[0.89,0.99]). Error bars represent SEM.

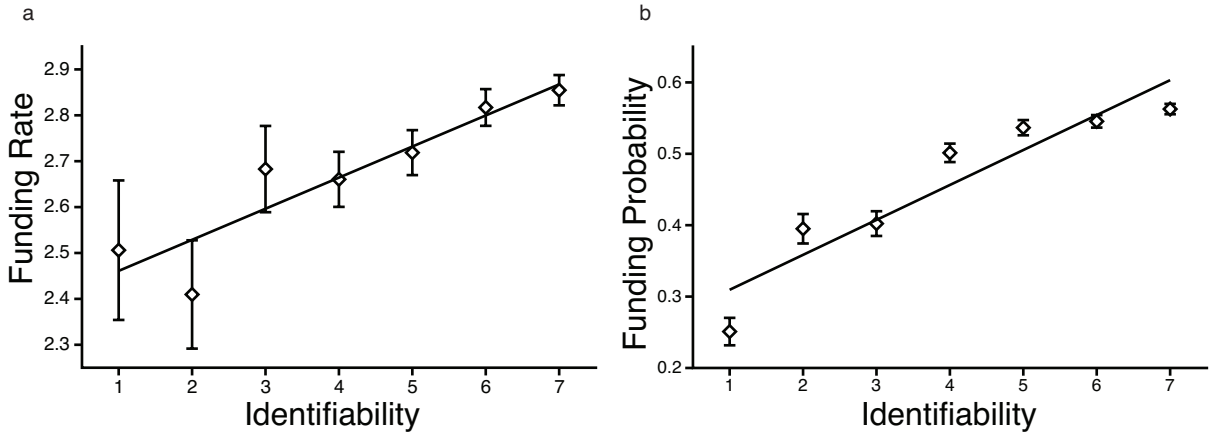

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Table S1. Hierarchical linear regression models predicting loan funding rates.

Objective model excludes affective features of loan text and photographs.

Loan Features	Objective Model	Full model
Affective		
Photo: Positive arousal		.087 (.019) **
Photo: Negative arousal		.035 (.019)
Text: % positive words		.024 (.019)
Text: % negative words		-.035 (.019)
Objective		
Photo: Identifiability	.068 (.019) **	.055 (.020) **
Text: Total words	.030 (.022)	.028 (.023)
Borrower neediness	-.005 (.019)	.008 (.020)
Loan amount	-.039 (.027)	-.039 (.027)
Repayment length	-.273 (.028) **	-.277 (.028) **
Borrower sex	-.880 (.047) **	-.865 (.047) **
R^2	0.403	0.428
AIC	25864.3	25653.3

Statistics are standardized coefficients with standard errors in parentheses.
**p < 0.01; *p < 0.05.
Regressions include random effects of borrower nationality and loan use sector.

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Table S2. Whole brain activation table for analyses contrasting photograph-elicited activity in trials in which subjects subsequently did versus did not choose to lend.

Region	x	y	z	Peak Z	Voxels
Precuneus	-4	-39	58	3.93	94
Posterior cingulate	1	-54	29	3.87	44
L posterior middle temporal gyrus	-45	-48	6	3.70	16
L middle temporal gyrus	-53	-28	-3	3.35	33
L superior frontal gyrus	-19	18	49	4.17	26
Dorsal medial prefrontal cortex (incl. MPFC)	**-4**	**47**	**23**	**3.06**	**18**
L parahippocampal gyrus (incl. amygdala)	**-25**	**-16**	**-15**	**3.74**	**16**
L posterior middle temporal gyrus	-45	-48	6	3.70	16
L anterior middle temporal gyrus	57	1	-18	3.84	13
R ventral striatum (incl. nucleus accumbens)	**10**	**1**	**-9**	**3.18**	**13**
R postcentral gyrus	25	-28	60	3.29	13

n=28; voxel-wise p<.005 uncorrected, cluster corrected p<.05, minimum cluster size=12 3x3x3 mm contiguous voxels; x=right, y=anterior; z=superior, bold indicates activation of predicted volumes of interest.

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Table S3. Hierarchical logistic regression model of neural activity predicting neuroimaging sample lending decisions.

Neural region of interest	Standardized Coefficient (SEM)
NAcc	.120 (.052) *
MPFC	.041 (.018) *
Ant. Ins	.021 (.035)
Amygdala	.037 (.033)
R^2	.082

**p < 0.01; *p < 0.05.

Regressions include subject random effects.

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Table S4. Hierarchical linear regression models of neural activity predicting neuroimaging sample affect ratings.

	Positive Arousal	Negative Arousal
NAcc	.248 (.111) *	.046 (.079)
MPFC	.071 (.067)	-.035 (.040)
Insula	-.202 (.095) *	.078 (.075)
Amygdala	-.033 (.106)	.017 (.075)
R^2	.102	.028

Statistics are standardized coefficients with SEM.

Significance: **p < 0.01; *p < 0.05.

Regressions include subject random effects.

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Table S5. Hierarchical linear regression models of internet loan funding rates. The positive and negative arousal ratings included in these models are the independent affect ratings of the loan requests from the Study1 sample.

	Affect	Combined
Loan choice		.10 [-.02,.22]
Internet Positive arousal	.16** [.07,.26]	.16** [.06,.26]
Internet Negative arousal	.06 [-.10,.24]	.06 [-.08,.18]
NAcc		.26* [.03,.52]
MPFC		-.01 [-.10,.09]
Insula		-.04 [-.24,.16]
Amygdala		-.01 [-.21,.19]

Statistics are standardized coefficients with 95% CI.

Significance: **p < 0.01; *p < 0.05.

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Table S6. Hierarchical logistic regression model predicting funding outcomes.

Loan Features	Standardized Coefficients (SEM)
Affective	
Photo: Positive arousal	.101 (.030) **
Photo: Negative arousal	.024 (.029)
Text: % positive words	-.051 (.031)
Text: % negative words	-.020 (.028)
Objective	
Photo: Identifiability	.115 (.031) **
Text: Total words	.099 (.034) **
Borrower neediness	-.126 (.029) **
Loan amount	-1.97 (.064) **
Repayment length	-.803 (.049) **
Borrower sex	-2.13 (.071) **

**$p < 0.01$; *$p < 0.05$.
Regressions include random effects of borrower nationality and loan use sector.