Global Economy and Development
at BROOKINGS

THE WISDOM OF CROWD-FUNDERS

WHAT MOTIVATES CROSS-BORDER PRIVATE DEVELOPMENT AID?

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Abstract:

The rapid growth in crowd-funded private development aid allows an examination of the preferences of philanthropic individuals with respect to international causes. Using survival analysis, we analyze the rate at which loan requests are funded through an internet-based nonprofit organization that bundles contributions from individuals and transfers them as loans to borrowers in developing countries. We find little evidence for the view that crowd-funders behave as either official aid donors or as selfish aid-givers. Rather, our results show that private aid contributions are motivated by associational communities that link citizens in donor countries to those in recipient countries — in particular, through migrant and diaspora networks — and that, as a result, their giving may be considered a complement to official aid.

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INTRODUCTION

In 2010, foundations, nongovernmental organizations (NGOs), religious groups and other charitable organizations in the United States contributed $39 billion to international development causes (Hudson Institute 2012). By comparison, $30 billion in US official development assistance (ODA) was disbursed during the same year. For US-based organizations, this represented a doubling of international private, voluntary development assistance over the past decade.

In recent years, the proliferation of private development aid has been facilitated by peer-to-peer (or "crowd-funding") practices. As with the broader "crowd-sourcing" phenomenon which solicits information from large numbers of individuals for various entrepreneurial activities, crowd-funding platforms bundle large numbers of small, individual contributions for investment, grants or loans. The bundling of funds is generally done through internet-based social networks. From the United States, internet-based companies such as Global Giving, Kiva, Wokai and Zidisha have channeled millions of dollars to individuals and partner organizations in developing countries.

Despite the tremendous growth in private development assistance of all kinds — from mega-charities to "micro-philanthropy" — very little is known about the allocation and selectivity of private aid. Compared to official aid, private aid — whoever provides it — is obviously more sensitive to the preferences of philanthropic-minded individuals who determine allocations across countries and, within countries, across sectors, projects and individuals. More importantly, crowd-funding philanthropy affords an opportunity to test a central premise behind arguments for expanded private aid — namely, that private aid avoids the political and strategic considerations that influence bilateral ODA allocation, and better matches recipient need with individual donor preferences.

Information on the allocation of crowd-funded private aid, and on the choices made by private citizens who contribute to international causes, can potentially reveal the implicit preferences of philanthropic citizens in a way that cannot be captured by looking at official aid allocations. There are several possibilities: that crowd-funders behave in accordance with rational-choice theories of charity, allocating money based on individual-specific preferences; that crowd-funders behave like official donors, responding to a combination of recipient-country need, expected performance and commercial and/or strategic value; or that crowd-funders make allocative decisions on the basis of group behavior and norms.

This article presents new data on crowd-funded development assistance, which allows us to analyze the motivations behind individual contributors. We analyze data from Kiva, the largest provider of crowd-funded microcredit to developing nations. We develop a model to show how the allocation of aid through crowd-funding websites reflects the preferences of philanthropically-minded citizens regarding development assistance, and then use data on Kiva's transactions to examine empirically the factors that affect the supply of private development aid, as well as to determine the extent to which private preferences differ from official aid agency allocative mechanisms.

We argue that the rate at which individual microloan requests are funded by Kiva's community of lenders, once they are posted on the Kiva website, can be interpreted as a proxy for crowd-funder preferences regarding private development assistance. We can therefore use survival analysis of the time to fund each project to estimate the significance of a number of covariates.

We find that Kiva's crowd-funders are generally not influenced by the usual set of official aid determinants (including foreign-policy considerations, recipient-country poverty and recipient-country institutional quality). Additionally, Kiva crowd-funders do not appear to base lending decisions on the usual indicators of credit risk. We find, instead, that the type of diaspora and migrant networks of aid recipients in the crowd-funder's country is a stronger determinant of hazard rates, and that the nature of associational networks and social linkages between prospective private donors and aid recipients will more likely affect crowd-funded aid allocation than recipient-country or project risk.

CROWD-FUNDED PHILANTROPHY AND DEVELOPMENT AID

Until recently, government aid or international development charities offered the best intermediaries for private charity, but in both cases agency costs have been high. Foreign aid delivered through official channels passes through many steps. Citizens pay their taxes to the government which, in turn, allocates resources to other governments to fund myriad public programs, including programs that benefit poor individuals around the world. There is no face-to-face contact between an individual taxpayer and the final recipient.

Many international development charities operate in a similar manner. Private donors direct resources to an organization (with which the donor identifies, agrees with or otherwise trusts); the organization, in turn, allocates resources to various programs and operational expenses. Some organizations allow varying forms of "sponsorship." This usually involves donors receiving updates from individual recipients (e.g., updates from sponsored children) or selecting a level of donation that corresponds to different organizational activities. However, even in this case, donors are not typically able to earmark funds to specific recipients.

New forms of internet-based crowd-funding now offer realistic alternatives. Agency costs of corruption and leakage as funds move from donor countries to beneficiaries in recipient countries can be sharply reduced by direct donations via the internet. They also provide a more direct route between giver and recipient that can avoid the costs of having to act through intermediaries (usually governments or NGOs) that are part of a global foreign aid apparatus that may simply be too insulated or centralized to incorporate individual taxpayer preferences (see, e.g., Easterly 2005; Roodman 2006). Internet-based giving offers many more opportunities for lower-cost intermediation and reflects individual preferences more directly.[1]

Citizen Preferences and Foreign Assistance

There is a considerable body of research on the effects of public opinion on foreign policy. While early analyses suggested that these effects were weak or indeterminate, recent studies indicate that public opinion often has a measurable impact on, for example, international security (e.g., Hartley and Russett 1992; Hill 1998; Sobel 2001; Wlezien 1995), trade (Kono 2008; Mansfield and Mutz 2009) and immigration policies (Fachini and Mayda 2008).

Several authors, similarly, find that foreign aid increases with public support for international assistance (Lumsdaine 1993; Tingley 2007; Chong and Gradstein 2008). However, while there is evidence that public opinion affects aid levels, we know little of how citizen preferences shape aid allocation. Of course, where individual preferences must be articulated through interest groups, political parties or representative institutions, ideology and group affiliation will filter those preferences for aid allocation. Thus, Tingley (2009), for example, finds that right-wing and left-wing governments show no difference in aid to middle-income countries, but right-wing governments give less aid to low-income nations. Similar effects have been seen with respect to legislative voting on aid allocation (Fleck and Kilby 2001; Milner and Tingley 2010).

Public opinion regarding aid allocation may also shape the decisions of foundations, NGOs and other private aid organizations. However, private humanitarian and development aid has been little studied by social scientists, and the limited research that exists has focused exclusively on larger organizations. Financial records of the most prominent US-based international development NGOs, for example, show that these NGOs allocate funds raised from private sources based on strong "humanitarian" motives, and principally to projects that provide or improve education, health care, safe drinking water, sanitation, sewerage and emergency relief in poor countries (Büthe, Major, and de Mello e Souza 2012). Information on the allocative preferences of individuals, however, is non-existent. Examining contributions by large numbers of individuals to international charitable causes can provide a more direct understanding of citizen preferences regarding aid allocation.

What Motivates Crowd-Funders?

In the United States, individual, small-scale contributions now account for 75 percent of all private donations to international charitable causes (Giving USA 2012). Questions have been raised regarding the generalizability of crowd-funding philanthropy to global private giving in general and, in particular, whether those who donate or lend via internet platforms are similar to those who engage in more traditional philanthropic activities (fund drives, volunteerism, etc.). The evidence is mixed. Some analyses have found gaps between individuals that contribute to top-tier charitable fundraising organizations and individuals who contribute to second-tier organizations, finding that the latter are more inclined to use e-commerce technologies for giving (Waters 2007). Others have shown stronger similarities between "venture" philanthropists and traditional philanthropists (Ball 2012).

In subsequent sections we attempt to adjust our findings to correct for non-representativeness of crowd-funders in the population. Crowd-funder philanthropists are not likely to be randomly selected from the population, but are people who care about a particular issue — in this case, international development. The same may be said of voters relative to the general population, with the former being more motivated or civic-minded. We are inclined to view crowd-funding philanthropists as, if not representative of the larger population of those who donate to charity, at least representative of those who would normally fund longer-term projects through the use of internet platforms. The preferences of this latter sample are obviously salient for understanding the motivations behind internet philanthropy.

We can conceive of three (non-exclusive) hypotheses about how crowd-funders will make allocative decisions regarding their private contributions to international charitable causes: as "warm-glow" givers of aid, as official donors or as members of social networks.

Crowd-Funding as "Warm Glow" Charity

Research on charitable contributions has sought to understand why, in contrast to predictions of standard models of private provision of public goods, people are typically more generous than expected. One answer is that contributors are "impurely" altruistic — that is, while interested in promoting charitable causes, they also respond to rebates, tax breaks, donation-matching and other selective incentives. Analyses of individuals' charitable behavior find that contributors are price sensitive and driven by marginal cost calculations (Karlan and List 2007). Individuals may also obtain private benefits from some aspect of their own giving, which encourages donations beyond the level that would occur based on public benefits alone. Different interpretations of these private benefits range from a feeling of "warm-glow" satisfaction to social approval, prestige and signaling about income. Donations are typically explained by a variety of preference structures, from psychic rewards to social comparison (the need to demonstrate superior generosity relative to one's peers) (Andreoni and Miller 2002; Shang and Croson 2006; Deb, Gazzale, and Kotchen 2012).[2]

Crowd-Funding as an Extension of Official Aid.

In standard allocation mechanisms for foreign aid, recipient countries are funded based on a combination of need (poverty, humanitarian needs), performance (control of corruption, institutional quality) and strategic or commercial interest (as allies, as trading partners or as investment opportunities) in order to ensure that taxpayer funds are used in the donor's national interest. Empirical work on this subject has found increasing selectivity of aid money away from commercial and strategic interest and toward need and institutional quality, since the end of the Cold War (Dollar and Levin 2006; Boschini and Olofsgård 2007). Whether crowd-funders are equally selective remains an open question.

Private philanthropists, to be sure, cannot lend for some purposes that official agencies can fund, such as policy adjustment, public sector capacity building or institutional reform. Yet there is reason to believe that crowd-funders may mimic official aid agencies. Survey data from donor countries consistently indicates that between 75 percent and 96 percent of citizens support aid to developing nations to reduce poverty, hunger and disease (Riddell 2007: 116), precisely the areas of focus for official aid agencies like USAID. In the United States, public opinion surveys have shown consistent support for development assistance, even though Americans typically overestimate the amount of aid provided by their government by a factor of twenty (PIPA 2001). Majorities support international assistance to reduce poverty, even as much of the public believes that corruption, fraud and waste make foreign aid ineffective (InterMedia 2012; Coyne and Ryan 2009; Easterly 2007).

Crowd-Funding as Socially Motivated

Finally, crowd-funding may be socially-driven, and crowd-funding decisions may be based on the density and nature of associational ties. Social networks and the norms of trust and reciprocity that facilitate collective action seem likely to play an important role in eliciting philanthropic behavior from individuals. Research on associational networks finds that social capital positively impacts citizens' sense of community and makes citizens more concerned about others' welfare (Brooks 2005; Brown and Ferris 2007). As a result, in communities high in social capital, purely altruistic preferences will play a greater role in behavior. Individuals with greater stocks of network-based social capital also tend to give more to charitable — both religious and secular — causes, and volunteer more (Vesterlund 2006). These results underscore the importance of crowd-funders' associations in connecting them to others and to organizations that encourage charitable acts.

What factors might affect the balance between material and non-material concerns of crowd-funders? One answer comes from analyses of voting behavior. For example, it has been shown that, in large elections, citizens tend to vote against their material self-interest and in support of more morally or ethically appealing alternatives — "expressive" voting, as compared to "instrumental" voting (Brennan and Hamlin 1998; Feddersen, Gailmard, and Sandroni 2009). Expressive voting is commonly found where pivot probabilities — the likelihood that any individual voter's choice will be decisive — are small. Crowd-funding platforms, like large elections, are characterized by large numbers of both funders ("voters") and recipients ("candidates"). Furthermore, as with large elections, crowd-funders do not face an effective choice between funding alternative countries (since each funder's contribution to the country's total aid allocation is small), but the crowd-funder does face an effective choice as to which project and which country to "support." Crowd-funders thus see charitable projects as an event in which they participate rather than a concrete outcome they determine.

DATA

Kiva

Kiva is a nonprofit organization that operates an internet-based, peer-to-peer, crowd-funding platform connecting micro-lenders to micro-entrepreneurs in developing countries. Founded in San Francisco in 2005, Kiva operates through its internet portals, by which anyone with a credit card or PayPal account can lend to micro-entrepreneurs who post requests online. Prospective borrowers must post their projects through one of several affiliated microfinance institutions (MFIs) around the world.[3] Prospective micro-lenders, once they have registered, can select projects based on region, country and project objective. Once the preferred traits have been selected, a micro-lender is shown a list of project requests matching the preferred project criteria. Alternatively, micro-lenders can select "most recent" projects that have been newly listed, or they may have the Kiva website randomly select a project.

Selecting any particular project reveals more information: the amount of the loan (up to a maximum of $5,000), the loan duration in months (up to a maximum of two years), the name and risk-rating of the MFI, the number of borrowers (if the "borrower" is a group), the gender of the borrowers and a short narrative written by the micro-entrepreneur describing the specific purposes for which the funds will be used. Finally, the project information also includes an indication of how much of the total project amount requested has been funded.

Once a project is selected, micro-lenders can contribute funds in any amount (above a required minimum of $25) up to the full amount requested. Using a PayPal account or a direct payment from a credit card, micro-lenders then transfer funds in the pledged amount. Projects accumulate funds from lenders in this manner until they are fully funded and, at that point, the funds are transferred to the MFI through which the micro-entrepreneur receives the credit.

When microloans reach maturity, their principal is to be repaid to the original lender's account; lenders receive no interest. Moreover, zero-interest loans allow Kiva to operate as a nonprofit 501(c)3 organization under US law, rather than as a regulated commercial bank.

Micro-lenders are notified periodically of the progress of the micro-entrepreneurs' effort. Kiva's field partners may post "business journals" identifying how the loan is being used, or what effect it has had on the business owner. This reporting is not required, so the flow of information from recipients can be erratic and is very rarely financially detailed (Bonbright, Kiryttopoulou, and Iversen 2008). Nevertheless, Kiva platforms provide enough information to make a personal connection between the donor and the recipient. A key problem for both Kiva and the sponsoring MFI is to decide on exactly what information (and how much information) to provide, in order to permit informed choices without overwhelming an individual lender.

Project Data

Our chief interest is in using information about Kiva microloans to assess the motivations of crowd-funders. An analysis of Kiva projects affords an opportunity to examine how the behavior of crowd-funders compares to that of official donors. Kiva's bundled microloans are allocated across 60 countries, enabling a test of whether the Kiva community of lenders mirrors the selectivity of official donors, which allocate according to recipient-country characteristics.

Moreover, because Kiva's development assistance takes the form of a loan, the principal for which is to be repaid, we can additionally test the extent to which lenders behave materially (i.e., the extent to which lenders provide loans based on assessments of project and country risk).

Our Kiva data contain approximately 250,000 microloan requests. Kiva limits both loan size and time on the website for each posting. Until the end of 2007, individual loan requests could not exceed $1,200; that limit has since been raised to $2,000. The maximum request for group loans remains $5,000.[4] All requests by micro-entrepreneurs must be made through partner MFIs, and all requests made to Kiva enter a queue. Upon undergoing a preliminary screening, they are posted on the website for a maximum of 30 days, after which they are pulled from the site if they have not been fully funded. Kiva's approach to website management limits the number and variety of microloan requests that appear on the site, but those that do appear are almost always 100 percent funded. As a result, Kiva faces no shortage of individuals willing to lend relatively small amounts, but is often without enough projects relative to the lending supply, and has occasionally had to cap individual lenders' contributions because of the lack of fundable projects.

Figure 1 shows monthly gross disbursements for Kiva between 2006 and 2010 from all lenders, as well as from US lenders only. Kiva's dramatic growth in gross disbursements is also helped by the fact that, by the end of 2008, many original loans were being repaid and could be re-lent by crowd-funders. By the end of 2010, Kiva averaged between 4,000 and 5,000 new project posts per month. These projects were fully funded, on average, in 2.03 days. Figure 2 shows funding rates in the form of dollars per hour, based on daily loan averages against time. The graph shows the growth in the size of total daily loan requests, as well as an initial jump in funding speed, followed by greater variability as disbursements became larger.

Cross-National Allocation

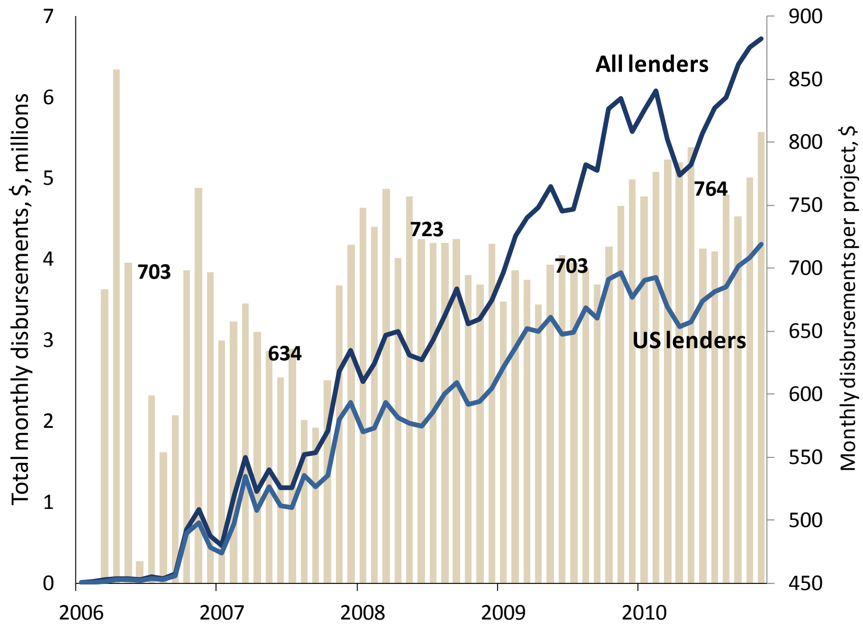
One question is the extent to which Kiva disbursements approximate other types of official aid disbursements. As a preliminary test we replicate the basic Dollar-Levin (2006) approach, which estimates annual aid flows to recipient country:

$$\ln(Aid)_{it} = a_0 + a_1 \ln(Population)_{it} + a_2 \ln(GDP)_{it} + a_3 (Institutions)_{it} \qquad (1)$$

We use pooled OLS with an error correction for contemporaneous correlation across panels, or "panel-correct" standard errors. We compare results across three equations — (i) net official development assistance (ODA); (ii) micro-lending by official development agencies; and (iii) total Kiva disbursements — to examine differences in allocations across recipient countries for these different types of assistance. Our "institutions" proxy is the World Bank's Country Policy and Institutional Assessment (CPIA) score for "public sector management and institutions," the basis for the "governance" score used in International Development Association (IDA) allocation.[5] We restrict the panel to years for which we have Kiva data: namely, 2006-2010.

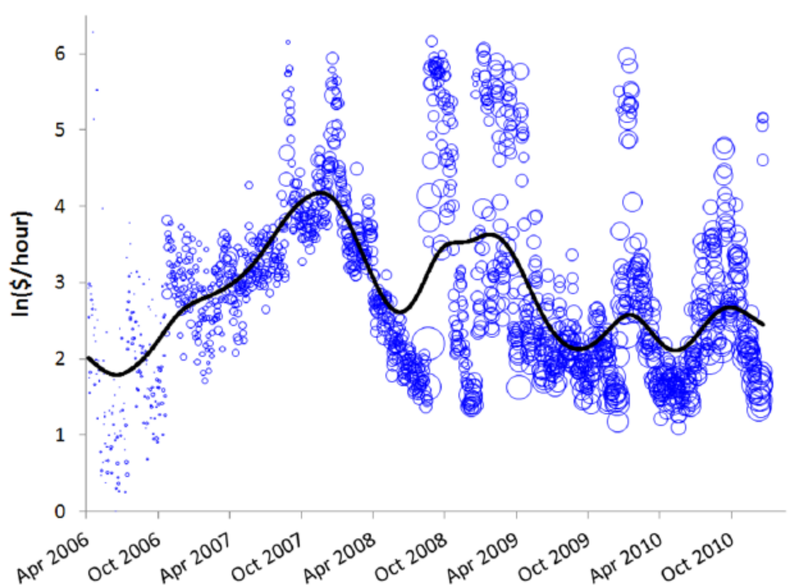
Columns (1) to (3) in table 1 show that official aid is quite selective in terms of poverty and institutional quality: More money goes to poorer countries and countries with better institutional quality. Official microloans respond in the same way, but Kiva lenders do not select countries based on per capita income or institutional quality. In columns (4) to (6), we rerun estimations on a core sample of common country-

Figure 1: Monthly Disbursements by Kiva Lenders, April 2006 to December 2010



Notes: Lines show total monthly disbursements by all lenders, as well as by US-based lenders only, for all Kiva projects (left axis). Histogram shows total monthly disbursements divided by number of new projects posted on Kiva's website; labels are weighted annual average disbursements per funded project for years 2006 to 2010 (right axis).

Figure 2: Daily Funding Rate for Kiva Projects



Notes: Graph shows daily average speed of loan fulfillment (in dollars per hour, natural logs); circles are scaled by total daily loan disbursements in US dollars. Solid line is the loan fulfillment speed with a standard Hodrick-Prescott filter applied (we use the common rule for determining the bandwidth parameter: namely, 100 times annual frequency-squared, or 1.33×10^7 for 365-day/year time series).

Table 1: Selectivity by Aid Type, Panel Regressions						
	(1) ODA	(2) Official micro-credit	(3) Kiva disbursements	(1) ODA	(2) Official micro-credit	(3) Kiva disbursements
Population (ln)	0.952*** (0.055)	1.426*** (0.106)	-0.100 (0.104)	0.787*** (0.097)	0.817*** (0.150)	-0.131 (0.189)
GDP (ln)	-0.521*** (0.049)	-0.951*** (0.066)	0.107* (0.060)	-0.395*** (0.092)	-0.376*** (0.120)	0.142 (0.087)
CPIA score	0.614*** (0.071)	0.973*** (0.199)	-0.139 (0.193)	0.332 (0.253)	0.878** (0.343)	-0.091 (0.255)
N	472	371	192	135	135	135
Countries	120	106	55	48	48	48
R^2	0.727	0.228	0.003	0.434	0.191	0.005

Notes: Dependent variables are gross flows (ln) of different types of aid to recipient countries. Estimates are obtained from pooled OLS regressions with error correction for contemporaneous correlation across panels, with panel-correct standard errors in parentheses. Intercepts are estimated by not reported. Observations are recipient country-years, 2006 to 2010.
**** Significant at the 1 percent level.*
*** Significant at the 5 percent level.*
** Significant at the 10 percent level.*

years across all three aid types. Kiva only operates in 48 developing countries, while official aid agencies operate in over 100 countries. This reduces coverage to 135 observations across 48 recipient countries. In the reduced samples, as previously, ODA flows to poorer countries, and official microcredit to poorer countries and those with better institutions. However, as before, Kiva allocations remain unaffected by poverty or institutional quality. It seems clear that Kiva's micro-lenders behave in a very different fashion from official aid agencies.

Funding Rates

Assume each microloan project has a vector of characteristics $\mathbf{Z}$ that can be mapped into a single dimension f: $\mathbf{Z} \rightarrow p$, where f is a continuous, single-peaked function. We can further assume that if each project can be measured along this single-dimensional spectrum then each potential crowd-funder will have a different optimal p^* with respect to loan projects. We can then assume, still further, that micro-lenders will fund the project closest to their optimal p^*, such that each project then gets funded by those lenders whose preferences most closely match the attributes of that project. Let g represent the density function for optimal projects p^* across the population of lenders, i.e., g: $f(p) \rightarrow p^*$, where g is continuous. If the density of available projects is also continuous and positive for all values, and if the density of these projects is at least as high as that of $g(p^*)$ for every p^*, then the total contribution C to a project will be $C = N \cdot k \cdot g(p^*)$, where N is the number of micro-lenders and k is the average per-individual contribution.

The supply of microloans increases over time as prospective crowd-funders learn of Kiva projects. If that learning is uncorrelated with p^*, then all projects with higher density $g(p^*)$ should be funded more quickly over time. If the supply of microloans among a community of crowd-funders increases over time at a constant rate, i.e., $N(t) = N_0\Theta t$, then the rate at which the project will be funded will be $C/t = N_0\Theta \cdot k \cdot g(p)$. We can, therefore, use funding rates as measures of the proximity of program attributes to crowd-funder preferences.

Table 2: Summary Statistics

VARIABLES	N	Mean	Std. Dev.	Min.	Max.
Hours to fund	251,081	72.62	137.36	0.02	2,016.26
Amount (current US dollars)	251,081	722.78	650.55	25.00	5,050.00
Number of borrowers	251,081	1.90	3.03	1.00	50.00
Female	251,081	0.77	0.42	0.00	1.00
Loan duration (months)	251,081	11.59	4.54	2.00	195.00
Concentration	248,312	0.15	0.18	0.01	1.00
US share	248,312	0.67	0.21	0.00	1.00
MFI risk rating	248,312	3.35	1.46	0.00	5.00
Dow Jones (30-day change)	251,081	0.00	0.06	-0.31	0.20
Weekly search trend	248,437	7.96	11.09	0.10	99.50
Natural disaster (persons affected, millions)	250,789	1.38	2.34	0.00	7.13
Population (millions)	251,081	39.64	44.86	0.18	239.87
CPIA governance score	250,070	3.23	0.43	2.20	5.30
ODA per capita	248,425	63.88	82.83	2.49	838.75
Official microcredit per capita	247,287	8.62	11.94	0.00	126.53
Fragile state	250,381	0.24	0.43	0.00	1.00
US affinity	248,097	-0.55	0.11	-0.77	0.80
Per capita GDP (current US dollars)	248,312	1,360.19	1,400.47	90.54	21,806.03
Immigrants per Kiva disbursement	247,424	0.01	0.06	0.00	2.96
Remittances per Kiva disbursement	235,090	0.00	0.01	0.00	1.18
Share post-2000 immigrants	191,421	0.34	0.12	0.18	0.80
Relative immigrant per capita income	189,343	1.49	0.19	0.98	2.45
Share of immigrants in services	237,033	0.07	0.02	0.02	0.16
Refugees-to-immigrants	235,307	0.31	0.47	0.00	3.51

If a Kiva project submitted by a micro-entrepreneur gets funded very quickly, we can assume that the project appeals to more crowd-funders than projects funded more slowly. We expect the funding rate to depend on three sets of factors: the average per-individual contribution needed to fulfill the project request; a set of project-specific attributes; and the rate at which supply of microloans expands, a function of the proliferation of knowledge about, or implicit support for, the project among the crowd-funder community. The funding rate thus potentially reveals information about the preferences of micro-lenders with respect to the project or recipient individual, as well as information about the social networks through which information about Kiva projects might be transmitted. We would expect, for example, projects to be funded at faster speeds among communities of crowd-funders characterized by factors such as denser associational ties or more active social networks. It is possible that projects lacking optimal characteristics for an individual may still be funded at faster speeds than more desirable projects if the project enjoys support among a particular community.

We examine Kiva project funding rates using survival analysis, which provides estimates of the effect of various covariates on the time it takes for an event to be completed. In our case, "failure" occurs when a project is fully funded and is removed from the website; the more rapidly the project is removed from the Kiva website, the more popular it is with lenders. The benchmark for survival analysis (the Cox model) is from a class of proportional hazard models and, in order for the estimated parameters to be unbiased, the proportionality assumption must hold (Box-Steffensmeier and Jones 2004). In the next section we find that the likelihood of full funding for Kiva microloans may be a multiplicative, rather than proportional, effect of survival time, thus violating the proportionality requirement. We therefore rely on the approach developed by Royston (2001) and Royston and Parmar (2002) that extends parametric methods using restricted cubic splines to smooth the baseline log cumulative hazard function in order to derive flexible, parametric estimates of project survival. Table 2 provides some summary statistics of all variables used in these estimations.

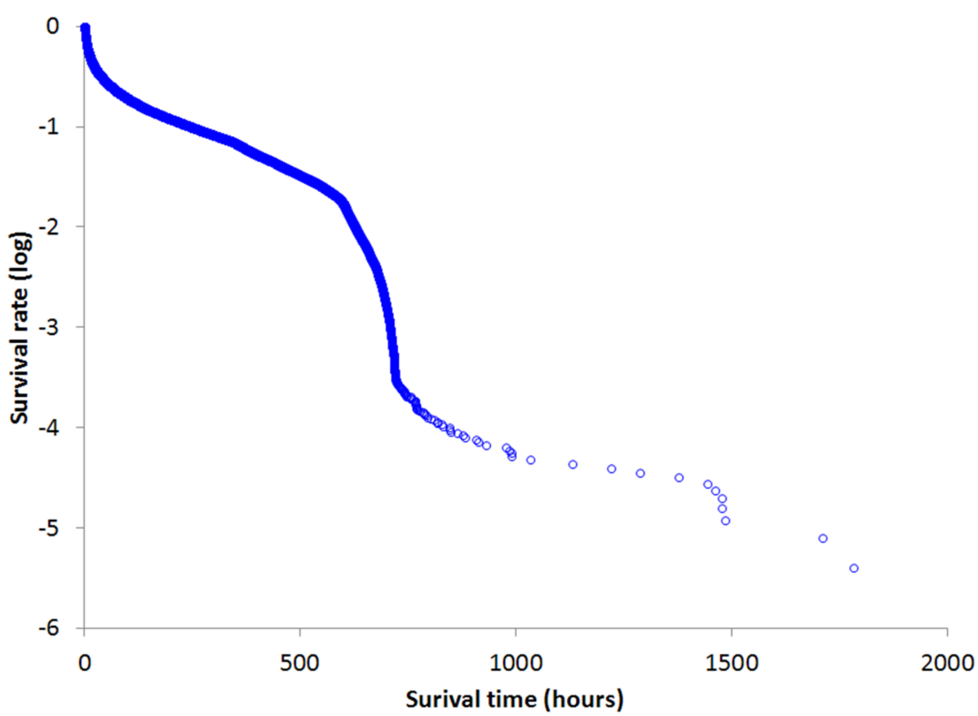
METHODS AND RESULTS

Survival Regressions

We examine the determinants of funding speed in online philanthropy using loan data from Kiva between April 2006 and December 2010. An advantage of the semi-parametric Cox model is that the resulting estimates depend on the order in which events occur, not the actual times at which they occur. Thus, the functional form of the baseline hazard function is not specified *ex ante* (as with hazard models that rely on specific distributional forms), but determined from the data. For our data, standard tests of proportionality using residuals (and requiring residuals with zero slope) do not support the proportionality requirement assumption (see appendix). In more direct tests where we split the sample according to survival-time quantiles, we find that coefficients do not remain stable over analysis time, indicating that proportionality is not constant over time.

The log of the baseline survival curve is plotted in figure 3. The curve, which graphs the predicted log survival rate against analysis time with all covariates set to zero, shows that survival rates, although they are not convex, decline monotonically with respect to the time a loan request has been on the website.

Figure 3: Baseline Hazard Function, Kiva Projects



Notes: Graph indicates baseline hazard rates (log scale) corresponding to each observed failure time (hours each Kiva project remains on the website until fully funded).

It is useful, therefore, to explore the joint effects of project covariates within the framework of a model in which the baseline hazard function is more fully specified. Standard parametric models such as the Weibull model are an alternative to the Cox model. However, the baseline hazard function in figure 3 — showing non-convex, non-constant, but monotonically declining hazard rates — is inconsistent with parameterizations that impose restrictions on the shape of the hazard function. To address the inadequacies of fully parametric models, a more flexible parametric model using restricted cubic splines was proposed by Royston and Parmar (2002) for censored survival data, enabling the baseline hazard to be modeled directly. The restricted cubic splines offer greater flexibility in the shape of the hazard function when compared to standard parametric models (Nelson et al. 2007). Accordingly, the model can be expressed as a linear combination of a baseline cumulative hazard and a covariate effect:

$$\mathrm{Ln}H(t|Q,\mathbf{x},\mathbf{w})_{\mathrm{i}}=\mathrm{Ln}H_0(t)+\beta_Q\,\mathrm{Ln}(Q_{\mathrm{i}})+\beta_x\,\mathbf{x}_i+\beta_w\,\mathbf{w}_i+\mu_i, \quad (2)$$

where $\mathrm{Ln}H_0(t)=\mathrm{Ln}(\lambda)+\alpha\mathrm{Ln}(t)=\mathrm{s}(\mathrm{Ln}(t)|\alpha,\mathrm{k}_0)$

and where $\ln H_0(t)$ is the baseline log-integrated cumulative hazard function, estimated with cubic splines as a smoothed function of t with k_0 knots. If splines are not used to estimate the baseline, then the model reduces to the Weibull hazard function. Among the covariates, Q is the amount of funds requested; $\mathbf{x}$ is a vector of additional project-specific attributes; $\mathbf{w}$ is a vector of time-, country-, and sector-based covariates; and μ is a random disturbance. Table 3 shows results using the Royston-Parmar method.

Basic Project Covariates

In addition to requested grant or loan size (which we model quadratically), we include: the number of borrowers; a binary indicator coded 1 if the fraction of borrowers that are women is greater than 0.5 (or if the individual borrower herself is a woman), and 0 otherwise; and the duration of the loan repayment in months. We use an additional variable to proxy project risk: MFIs that work with Kiva have been assigned a rating of between one and five "stars," with one star representing highest risk and five stars lowest risk, based on Kiva's experience with the MFI.[6] We score projects 1 to 5, depending on the relevant MFI rating.

The following fixed effects are part of the benchmark specification: We include dummies for the hour (from the 24-hour cycle) in which projects were posted on the Kiva website, days in the week, months in the year to control for seasonal effects, sectors for which the project loans will be used and countries in which the project will be implemented. Hazard estimates correspond to the rate at which project requests are fulfilled in hours (log), with positive coefficients implying a faster failure rate (and a more quickly-funded project).

In column (1) we see that larger amounts requested take longer periods to be funded, although the effect is diminishing in loan size. Lenders also fund female entrepreneurs over their male counterparts, a practice strongly associated with microfinance regimes around the world (D'Espallier, Guérin, and Mersland 2009). However, unlike the case with classic microlending, Kiva crowd-funders have no preference for funding groups of borrowers rather than individual borrowers. Short-term loans are funded more quickly than long-term loans. Finally, lower MFI risk has a small effect on funding rate. With the exception of group lending, Kiva's crowd-funders appear to behave as risk-averse funders of developing country projects based solely on project-specific covariates.

Table 3: Kiva Funding Rates, Flexible Parametric Regressions					
	(1)	(2)	(3)	(4)	(5)
Amount (Ln)	-3.271*** (0.035)	-3.252*** (0.036)	-3.588*** (0.047)	-3.518*** (0.048)	-3.642*** (0.049)
Amount² (Ln)	0.188*** (0.003)	0.187*** (0.003)	0.217*** (0.004)	0.211*** (0.004)	0.223*** (0.004)
Number of borrowers	-0.005*** (0.001)	-0.001 (0.001)	-0.019*** (0.002)	-0.015*** (0.002)	-0.024*** (0.002)
Female	0.454*** (0.006)	0.432*** (0.006)	0.414*** (0.007)	0.410*** (0.007)	0.396*** (0.007)
Loan term (months)	-0.025*** (0.001)	-0.025*** (0.001)	-0.019*** (0.001)	-0.023*** (0.001)	-0.021*** (0.001)
MFI risk rating	-0.006*** (0.002)	0.028*** (0.002)	0.048*** (0.002)	0.054*** (0.002)	0.053*** (0.003)
Dow Jones (30 day change)		-1.129*** (0.040)	-0.596*** (0.050)	-0.498*** (0.050)	-0.467*** (0.052)
Weekly search trend (Ln)		-0.091*** (0.016)	-0.027*** (0.009)	0.084*** (0.012)	-0.031*** (0.010)
Weekly total project size (Ln)		-0.027*** (0.003)	-0.063*** (0.004)	-0.051*** (0.004)	-0.060*** (0.004)
Natural disaster (persons affected, Ln)		1.427*** (0.043)	0.015*** (0.001)	0.011*** (0.001)	0.017*** (0.001)
Population (Ln)		-4.480*** (0.134)	-0.016*** (0.006)	-0.080*** (0.007)	-0.027*** (0.006)
GDP per capita (Ln)			0.678*** (0.024)	0.203*** (0.047)	0.764*** (0.041)
CPIA governance score			-0.080*** (0.015)	-0.015 (0.019)	-0.120*** (0.017)
ODA per capita (Ln)			0.002*** (0.000)	0.003*** (0.000)	0.001*** (0.000)
Fragile state			-0.046*** (0.014)	0.014 (0.017)	-0.069*** (0.015)
US affinity			-1.451*** (0.038)	-1.791*** (0.040)	-1.467*** (0.040)
Immigrants per Kiva disbursement (Ln)			0.246** (0.124)	0.546*** (0.132)	0.650*** (0.150)
Remittances per Kiva disbursement (Ln)			-1.216*** (0.440)	-2.396*** (0.485)	-1.851*** (0.467)
Share of post-2000 immigrants			2.150*** (0.038)	2.223*** (0.047)	2.148*** (0.039)
Relative immigrant per capita income			2.778*** (0.108)	0.515** (0.231)	3.128*** (0.169)

Table 3: Kiva Funding Rates, Flexible Parametric Regressions					
	(1)	(2)	(3)	(4)	(5)
Share of immigrants in services			-6.507*** (0.265)	-6.618*** (0.271)	-6.193*** (0.343)
Refugees-to-immigrants			0.235*** (0.010)	0.252*** (0.011)	0.248*** (0.011)
East Asia/Pacific Islands				-0.075*** (0.019)	
Former Soviet Union				0.638*** (0.048)	
Latin America/Caribbean				-0.282*** (0.030)	
Middle East/North Africa				0.098*** (0.022)	
South Asia				0.378*** (0.069)	
Country dummies	Yes	Yes	No	No	No
Sector, month, day and hour dummies	Yes	Yes	Yes	Yes	Yes
Weighted by total private aid	No	No	No	No	Yes
N	251,714	248,141	171,785	171,785	159,711
Ln(*L*)	-4.372×10^5	-4.300×10^5	-1.451×10^5	-1.450×10^5	-1.413×10^5

Notes: Estimates are hazard coefficients obtained from Royston-Parmar flexible parametric survival regressions, with baseline hazard functions estimated using restricted cubic splines with six knots. Standard errors are in parentheses. Intercepts are estimated but not reported.
**** Significant at the 1 percent level.*
*** Significant at the 5 percent level.*
** Significant at the 10 percent level.*

Flexible parametric survival estimates indicate that Kiva crowd-funders prefer, on the whole, smaller funding requests, female borrowers and shorter-term loans. We see no preference for group-based loans, as is usually the case in formal microfinance.[7]

Volatility in Loan Funding Rates

As figure 2 suggests, funding rates for Kiva loan requests exhibit considerable volatility. In column (2) we add controls that may influence survival rates with high temporal frequency. First, it has been argued that private aid is subject to greater volatility than official aid, as private aid is vulnerable to the whims of philanthropic individuals, as well as to the vicissitudes of economic life in the countries in which they live (Frot and Santiso 2008). To examine whether economic conditions in the donor-lenders' countries of residence affect their grant giving or lending, we use a lagged 30-day change in the closing Dow Jones Industrial Average, based on the assumptions that stock-market changes are a useful proxy for economic conditions in donor-lender countries and that deteriorating economic conditions might make philanthropic individuals more hesitant to contribute online to development projects. If that is the case, one should expect projects to be funded at a slower rate following a fall in the Dow Jones index. The empirical results, however, are the reverse — projects get funded faster after a fall in the Dow.

Second, it is possible that the "visibility" of countries in which micro-entrepreneurs live will influence the rate at which their microloan requests are fulfilled — borrowers in countries that are in the headlines, for example, being funded more quickly than borrowers in countries that are less well known to publics in donor countries. To account for these changes in the public profile of countries, we construct an index based on Google Trends—a facility based on Google's search engine that shows how often a particular search term is entered relative to the total search volume across various regions of the world, and in various languages. We entered the names of all countries from which Kiva requests have come between 2006 and 2010, both alphabetically and in groups of five (the maximum allowable on Google Trends). Because Google Trends indexes search terms based on the first search term entered, all our searches included the same first country (Albania) to benchmark subsequent country search terms. The results are weekly indices of the relative visibility of each country as proxied by Google searching. This variable did not prove to be robust, switching signs in different model specifications.

In order to control for the frequency of changes in the total volume of microloan requests across countries, we also include the total weekly amount of loan requests from the borrower's country. The fewer the number of listed projects, the faster each individual project gets funded, as expected.

Third, we control for the occurrence of natural disasters, for which we rely on the Emergency Events Database (EM-DAT). We include the number of people "affected" (killed, injured or displaced) by a natural disaster in the country in which the Kiva project takes place over the preceding three months, in natural logs.[8] We find, as expected, that the greater the number of people harmed by a natural disaster, the faster the funding rate for Kiva projects in the affected country.

Selectivity of Crowd-Funding

We tested to see whether those variables that affect official lending allocations also affect Kiva micro-lenders. In columns (3) to (5), we replace country dummies with country descriptors: GDP per capita, poverty incidence, governance or institutional quality (OECD 2003; McGillivray 2003; Hout 2007).[9] We also added a dummy for fragile states to account for concerns that good governance criteria disadvantage fragile states unfairly and inappropriately (European Commission 2005). The dummy variable is coded 1 if the recipient country is on the OECD Development Assistance Committee's list of fragile states, and 0 otherwise.

In addition to these recipient-country factors, there is also a strong tendency for official bilateral aid to be targeted toward allies and nations with which donors share common strategic interests. To test whether Kiva micro-lenders also support "friendly" countries, we rely on an indicator of commonality or "affinity" of any aid recipient with the US, based on the similarity between votes of those aid recipients and those of the US in the United Nations General Assembly. As a measure of shared state preferences among pairs of states (dyads), an affinity score based on UN voting is thought to suffer from less distortion than more costly actions such as formal military alliances, treaties or commercial agreements (UN votes being largely symbolic).[10]

We find that Kiva lenders behave quite differently from official agencies. They mostly fund projects in middle-income countries at a faster rate than those in low-income countries (columns (4) to (6)). The funding rate for projects in well-governed countries is significantly slower than that in more corrupt countries in some specifications (columns (4) and (6)). The results for fragile states are also mixed. Kiva lenders also appear to be averse to funding projects in countries that are close allies of the US, with a higher US affinity score being associated with longer funding times.

Social Networks and Immigrant Communities

In column (4) of table 3 we examine evidence that the nexus of social relations that recipient countries can rely on in donor countries affects crowd-funding. Of course, diaspora networks — cultural and social relations between migrant communities and their country of residence — are known to play pivotal roles in influencing foreign direct investment flows (Leblang 2010), as well as foreign aid decisions (Bermeo and Lebland 2010), from the resident country to the country of origin. There are two principal channels by which Kiva funding may be affected. First, members of migrant communities may directly fund projects in their homelands as participants in crowd-funding arrangements. Migrants who may have better information about entrepreneurial opportunities, aid necessities, public opinion and consumer preferences in their home country may participate as Kiva lenders. Second, migrant communities, through their social ties with native-born populations, can provide information about their home countries and thereby shape the funding preferences of private donors who might not themselves be immigrants. Unfortunately, we do not have data regarding the lenders who fund Kiva projects, apart from their country of residence. We can, however, test these implications indirectly.

We include several indicators that characterize migrant communities in the US. As mentioned previously, over two-thirds of Kiva funds come from the US and, therefore, we can reasonably be assured that any effects attributed to American migrant communities are likely underestimating the true effects. In the subsequent section we show that splitting the sample between mainly US funded and non-US funded projects makes no difference with our results.

Six separate indicators of American migrant communities are used according to the country from which the project request comes: (i) size of the immigrant population; (ii) remittances; (iii) length of residency; (iv) occupational status; (v) wealth; and (vi) refugees. All indicators describe characteristics of migrant communities from Kiva-recipient country i at time t living in the US. Total numbers of immigrants from each country and total amounts of remittances are both weighted by the total amount of annual Kiva flows to the country of origin, in order to adjust for the level of project activity in the home country, as well as to control for the possibility that remittances and philanthropy are substitutes. To control for differences between recent and more established migrant communities, and for possible resulting differences in average internet usage and connectedness, we include the share of the total immigrant population that arrived in the US after 2000. For occupational status, we use the fraction of immigrant communities in the financial, insurance and real estate (FIRE) services sectors. To control for the wealth of migrants relative to their compatriots in their home countries, we incorporate the average per capita income of the immigrant population divided by the per capita income of their country of origin. Information on immigrant community characteristics comes from the annual American Community Survey conducted by the US Census Bureau. Data on bilateral remittances from the US are from the World Bank's Migration and Remittances Factbook.

"Immigrant" here refers to those individuals who have obtained permanent legal residence status. This does not, therefore, take account of individuals who are refugees and asylum-seekers. Between 2006 and 2010, between four and 11 countries had more refugees than immigrants in the US. Refugees fleeing their homeland for non-economic reasons may have different effects on Kiva funding rates than that of immigrant populations.[11] We use data from the United Nations' High Commission on Refugees to code the number of refugees from a Kiva-recipient country granted asylum in the US.

Column (4) in table 3 shows that countries with larger numbers of immigrants in the US, with greater proportions of recent arrivals and with migrants who are richer than compatriots in their home countries, receive Kiva funding at faster rates. We also see that crowd-funding and remittances are substitutes — indeed, Kiva projects in countries receiving large amounts of remittances are funded more slowly. Finally, countries claiming larger proportions of refugees to immigrants also receive funding at faster rates. Countries with larger proportions of migrants employed in the financial services sectors — sectors traditionally characterized by high levels of participation in crowd-funding elsewhere (e.g., Ordanini, Miceli, and Pizzetti 2011) — receive funds more slowly, indicating that actual migrant participation in crowd-funding does not explain project funding rates. These results support the view that the network of social relationships between migrant communities and citizens in donor countries shapes the preferences of crowd-funders toward recipient countries.

We note that, once we include indicators of migrant communities, the population and per capita GDP indicators switch signs. Thus, a critical aspect of selectivity-based allocation — country poverty — now has a negative effect on funding rates, calling into question the robustness of the selectivity-based measures. To test whether one or more regions are driving the identification of the immigrant network covariates, we add regional dummies in column (5): East Asia and the Pacific; Europe and Central Asia; Latin America and the Caribbean; the Middle East and North Africa; and South Asia, with sub-Saharan Africa being the reference. The inclusion of regional indicators results in no changes in signs or significance levels for any of our immigrant network variables.

Generalizability to Other Giving

As noted earlier, it is likely that the population of those who give to charity in general differs from the population of Kiva's crowd-funders along a number of characteristics. As a final check, therefore, we adjust our regression estimates for this potential non-representativeness with respect to private aid. Using data from Büthe, Major and de Mello e Souza (2012) on total private giving to all recipient countries, we generate a normalized weight based on the ratio of the gross private aid flow to the total Kiva disbursement to country i — a simple procedure that generates the equivalent of a sample weight, adjusting estimates based on the extent to which Kiva disbursements are over- or under-represented in total private aid. Results from these weighted estimations are in column (6). The stability of coefficients relative to previous specifications indicates that any bias from non-representativeness is minimal.

Finally, we examine funding rates immediately before and after the occurrence of natural disasters in recipient countries, on the assumption that any inconsistency in estimates during these events indicates changes in either the composition of lenders or in the selection of projects by MFIs. In table 4 we rerun the estimation in column (4), table 3 on three sub-samples of projects: those posted 30 days prior to the occurrence of a natural disaster in the recipient country, those posted during the immediate 30-day aftermath and those posted between 31 and 60 days after its occurrence. Given that the timing of a natural disaster cannot be manipulated by lenders or entrepreneurs, we would expect changes in coefficients to indicate potential selection effects — either among projects that are posted or among the types of lenders who fulfill microloan requests.

The coefficients for project indicators are highly stable, suggesting that the projects selected for Kiva posting are not influenced by natural disasters and that variability in project selection is unlikely to be driving our results. There are some changes in coefficients among the traditional indicators of aid selectivity — the CPIA score and the fragile state indicator — but these are generally consistent with the changes across estimations in table 3. As for the immigrant network indicators, we see changes in immigrants per Kiva disbursement, and in remittances per Kiva disbursement relative to table 3. In the immediate aftermath of a natural disaster, Kiva funding is not driven by the size of the immigrant population, and Kiva projects in countries receiving more remittances are funded more quickly — indicating that, for brief moments following natural disasters and their ensuing humanitarian crises, crowd-funders are supplementing rather than replacing remittances. We note, however, that all other immigrant network results are stable.

Robustness

We check the central robustness of our findings by estimating the effects of project-specific and country-specific covariates, along with sector-, month- and hour-fixed effects on Kiva project funding rates across different subsamples. We focus on subsamples based on US share of total funding, timing and funding concentration. Figure 4 plots the baseline hazard functions for these subsamples and table 5 presents covariate hazard effects.

US Funding Share

In columns (1) and (2) we split the sample between projects funded mainly through US-based lenders and projects funded outside the US. Our indicators of migrant communities are US-based and, therefore, we divide the sample above 70 percent US-based funding (roughly the sample mean), as well as below 25 percent US-based (the mean less two standard deviations), to ensure that the use of these US-based indicators holds consistently for projects whose main lenders who live outside the US. As figure 4 shows, when splitting the sample at the mean, the baseline hazards are similar and both closely approximate the function plotted in figure 3. The indicators that describe migrant communities' size, occupational status, tenure and refugee populations are similar in sign, significance and magnitude for projects funded mainly through US-based lenders as well those projects funded by non-US lenders. For mainly US-funded projects, countries that receive more remittances receive Kiva money more slowly; for projects funded outside the US, remittances (as with the full sample) and relative migrant income have no effect. Finally, the Google Trends indicator does not affect funding rates for projects whose crowd-funders are mainly outside the US.

Table 4: Kiva Funding Rates, Before and After Natural Disasters			
	30 to 1 days before	0 to 30 days after	31 to 60 days after
	(1)	(2)	(3)
Amount (Ln)	-3.857*** (0.084)	-3.926*** (0.148)	-3.602*** (0.081)
Amount² (Ln)	0.239*** (0.007)	0.242*** (0.012)	0.217*** (0.007)
Number of borrowers	-0.023*** (0.003)	-0.020*** (0.005)	-0.022*** (0.003)
Female	0.419*** (0.012)	0.446*** (0.020)	0.381*** (0.012)
Loan term (months)	-0.021*** (0.001)	-0.027*** (0.003)	-0.024*** (0.001)
MFI risk rating	0.046*** (0.004)	0.032*** (0.008)	0.060*** (0.004)
Dow Jones (30 day change)	0.021 (0.088)	-0.371** (0.153)	-0.760*** (0.098)
Weekly search trend (Ln)	-0.063*** (0.016)	0.100*** (0.030)	0.008 (0.017)
Weekly total project size (Ln)	-0.074*** (0.007)	-0.063*** (0.013)	0.003 (0.007)
Natural disaster (persons affected, Ln)	0.014*** (0.002)	0.006** (0.003)	0.039*** (0.002)
Population (Ln)	-0.002 (0.010)	-0.206*** (0.026)	-0.116*** (0.010)
GDP per capita (Ln)	0.995*** (0.066)	1.291*** (0.171)	1.440*** (0.061)
CPIA governance score	0.016 (0.029)	-0.321*** (0.076)	-0.431*** (0.028)
ODA per capita (Ln)	0.004*** (0.000)	0.000 (0.001)	-0.001*** (0.000)
Fragile state	0.031 (0.026)	0.505*** (0.059)	-0.097*** (0.026)
US affinity	-1.481*** (0.074)	-0.655*** (0.161)	-2.844*** (0.080)
Immigrants per Kiva disbursement (Ln)	0.430* (0.244)	-3.647*** (0.670)	0.072 (0.197)
Remittances per Kiva disbursement (Ln)	-3.085*** (0.783)	6.967*** (1.856)	-1.010 (0.708)
Share of post-2000 immigrants	2.108*** (0.063)	1.356*** (0.130)	3.132*** (0.073)
Relative immigrant per capita income	4.317*** (0.288)	5.798*** (0.763)	5.678*** (0.262)

Table 4: Kiva Funding Rates, Before and After Natural Disasters			
	30 to 1 days before	0 to 30 days after	31 to 60 days after
	(1)	(2)	(3)
Share of immigrants in services	-7.998*** (0.482)	-8.284*** (1.175)	-7.157*** (0.475)
Refugees-to-immigrants	0.229*** (0.018)	0.192*** (0.042)	0.284*** (0.017)
N	59,415	20,363	56,350
Ln(*L*)	-1.027×10^5	-3.483×10^4	-9.712×10^4

Notes: Estimates are hazard coefficients obtained from Royston-Parmar flexible parametric survival regressions with baseline hazard functions estimated using restricted cubic splines with six knots. Sample is restricted to projects posted before, during or after natural disasters, as events are classified by the Emergency Events Database (EM-DAT). Standard errors are in parentheses. Intercepts and sector-, month-, day- and hour-fixed effects are estimated but not reported.
**** Significant at the 1 percent level.*
*** Significant at the 5 percent level.*
** Significant at the 10 percent level.*

Although it is unlikely that countries with strong ties between their migrant communities and US citizens would also have strong ties between their migrants and citizens of, for example, Western European nations, the striking similarity of hazard coefficients does suggest that, for internet-based crowd-funders, it is the global "conspicuousness" of recipient countries that influences lending decisions.

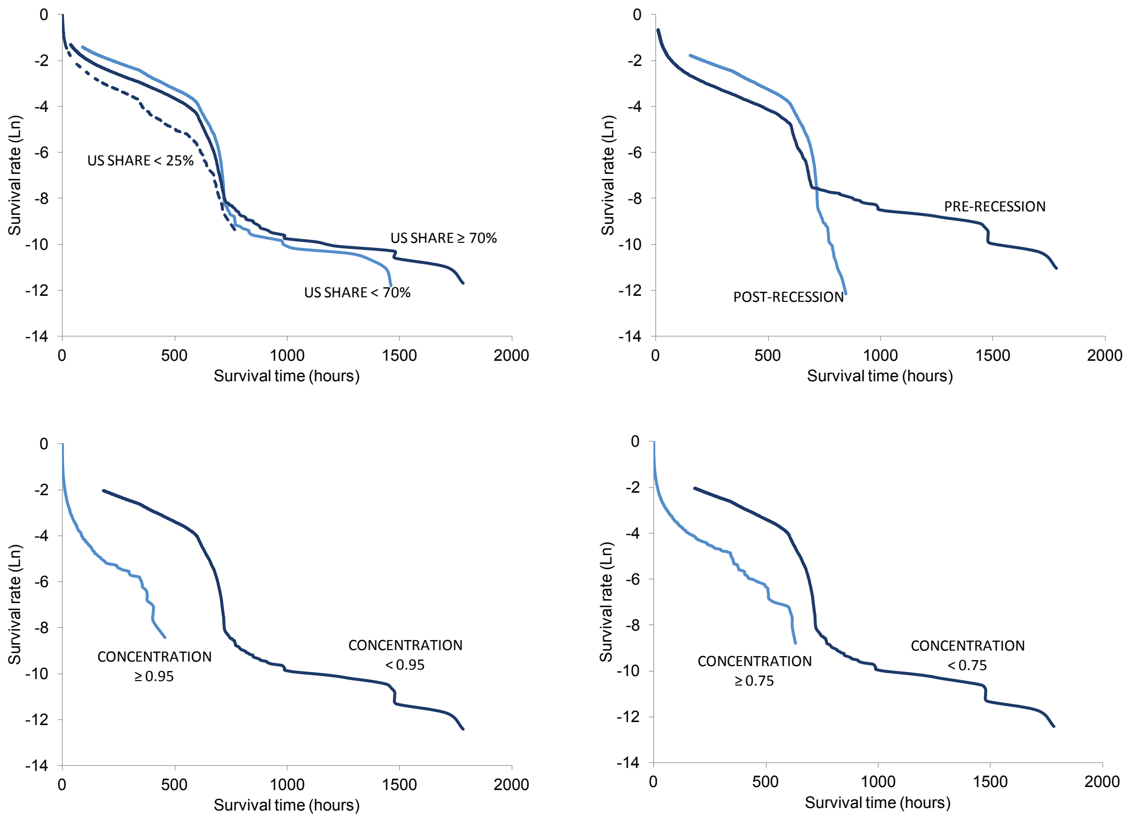
Recession

To test whether the global recession of late 2008-2009 affected crowd-funding, we split the sample into projects funded before and after September 15, 2008, following the filing of Chapter 11 bankruptcy by Lehman Brothers and the fall in US stock market capitalization by 30 percent over the next quarter. Initially, it was widely expected that private global philanthropy would contract during the global economic downturn (e.g., Sachs 2009; Raghuram 2009). Available evidence, however, indicates little effect of the recession on private aid flows (Hudson Institute 2012).

Similarly, Kiva crowd-funding does not appear to have been adversely affected by recession. In fact, as the second graph in figure 4 shows, the survival rates have generally decreased for projects funded after the recession, as seen in the downward shift of the baseline hazard function at longer survival times. Individual covariate effects, too, are similar pre- and post-recession, with two main exceptions: the size of an immigrant community is associated with faster funding rates only after the recession begins, while Kiva funders prefer countries receiving fewer remittances.

Additionally, we do not see clear evidence of greater risk aversion among crowd-funders during recession. While funders do prefer lending to projects from countries with higher CPIA scores after September 15, 2008, there is also a shift away from group-based lending toward individual borrowers and projects in aid-dependent countries.

Figure 4: Baseline Hazard Functions by US Share, Timing and Funding Concentration



Notes: Graphs indicate baseline hazard rates (log scale) corresponding to each observed failure time (hours each Kiva projects remains on the website until fully funded) for subsamples.

Funding Concentration

It is possible that crowd-funders behave more instrumentally toward potential projects when they are the main funders, especially since crowd-funders expect their principal to be repaid by Kiva borrowers. We examine changes in hazard coefficients for projects in which Herfindahl concentration ratios are above 0.75 and 0.95 in columns (5) and (8), respectively, in table 5. The results do not support the view that small groups of big lenders act more instrumentally toward Kiva projects. The preferences of big crowd-funders toward project attributes are not appreciably different than those of smaller contributors. With respect to loan term and MFI risk the hazard covariates are similar. Moreover, larger contributors prefer groups and female borrowers to a lesser extent than smaller funders.

Similarly, larger contributors do not mimic official donor behavior to any greater extent than smaller

Table 5: Robustness Checks, Subsamples								
	By US Share		By Timing		By Funding Concentration			
	≥ 70%	≤ 25%	Pre-recession	Post-recession	≥ 95%	< 95%	≥ 75%	< 75%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Amount (Ln)	-3.301*** (0.077)	-2.973*** (0.188)	-2.093*** (0.110)	-4.040*** (0.054)	-1.222*** (0.240)	-3.617*** (0.050)	-1.086*** (0.202)	-3.660*** (0.050)
Amount^2 (Ln)	0.199*** (0.006)	0.184*** (0.017)	0.079*** (0.009)	0.253*** (0.005)	0.061*** (0.023)	0.220*** (0.004)	0.038** (0.019)	0.224*** (0.004)
Number of borrowers	-0.016*** (0.003)	-0.042*** (0.010)	0.021*** (0.004)	-0.027*** (0.002)	-0.023 (0.021)	-0.020*** (0.002)	-0.010 (0.015)	-0.021*** (0.002)
Female	0.350*** (0.011)	0.334*** (0.032)	0.247*** (0.015)	0.468*** (0.008)	0.209*** (0.049)	0.420*** (0.007)	0.196*** (0.041)	0.421*** (0.007)
Loan term (months)	-0.017*** (0.001)	-0.030*** (0.004)	-0.012*** (0.002)	-0.021*** (0.001)	-0.023*** (0.007)	-0.019*** (0.001)	-0.017*** (0.006)	-0.019*** (0.001)
MFI risk rating	0.036*** (0.004)	0.029** (0.012)	0.057*** (0.005)	0.050*** (0.003)	0.071*** (0.019)	0.049*** (0.002)	0.052*** (0.015)	0.050*** (0.002)
Dow Jones (30-day change)	-0.510*** (0.076)	0.491* (0.253)	-0.207 (0.171)	-0.847*** (0.056)	1.264*** (0.385)	-0.655*** (0.050)	1.177*** (0.324)	-0.674*** (0.051)
Weekly search trend (Ln)	0.014 (0.014)	-0.129** (0.053)	-0.057*** (0.020)	-0.116*** (0.011)	-0.188** (0.083)	-0.029*** (0.009)	-0.114* (0.063)	-0.029*** (0.009)
Weekly total project size (Ln)	0.007 (0.005)	0.004 (0.018)	0.105*** (0.007)	-0.081*** (0.005)	0.092*** (0.025)	-0.068*** (0.004)	0.070*** (0.021)	-0.068*** (0.004)
Natural disaster (persons affected, Ln)	0.012*** (0.001)	0.012** (0.005)	-0.001 (0.002)	0.018*** (0.001)	-0.000 (0.008)	0.015*** (0.001)	0.004 (0.006)	0.015*** (0.001)
Population (Ln)	-0.030*** (0.009)	-0.007 (0.031)	-0.046*** (0.012)	0.029*** (0.007)	-0.002 (0.048)	-0.016*** (0.006)	-0.013 (0.037)	-0.015*** (0.006)
CPIA governance score	0.688*** (0.037)	0.502*** (0.167)	1.073*** (0.050)	0.667*** (0.030)	1.361*** (0.258)	0.675*** (0.024)	1.214*** (0.201)	0.676*** (0.024)
ODA per capita (Ln)	-0.213*** (0.024)	0.047 (0.088)	-0.004 (0.041)	-0.057*** (0.018)	0.018 (0.154)	-0.082*** (0.015)	-0.150 (0.118)	-0.085*** (0.015)
Fragile state	0.003*** (0.000)	0.004*** (0.001)	-0.012*** (0.001)	0.002*** (0.000)	0.005*** (0.002)	0.002*** (0.000)	0.004*** (0.001)	0.002*** (0.000)
US affinity	-0.094*** (0.023)	0.083 (0.087)	-0.260*** (0.037)	-0.099*** (0.017)	-0.020 (0.145)	-0.052*** (0.014)	-0.095 (0.113)	-0.056*** (0.015)
GDP per capita (Ln)	-1.306*** (0.056)	-1.984*** (0.206)	-1.604*** (0.103)	-0.832*** (0.066)	-2.340*** (0.308)	-1.426*** (0.038)	-2.076*** (0.240)	-1.405*** (0.038)
Immigrants per Kiva disbursement (Ln)	-0.370** (0.164)	1.049 (0.641)	-3.150*** (0.165)	2.216*** (0.215)	-0.632 (0.924)	0.260** (0.125)	-0.825 (0.754)	0.249** (0.126)

Table 5: Robustness Checks, Subsamples								
	By US Share		By Timing		By Funding Concentration			
	≥ 70%	≤ 25%	Pre-recession	Post-recession	≥ 95%	< 95%	≥ 75%	< 75%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Remittances per Kiva disbursement (Ln)	1.875*** (0.619)	-5.881*** (2.012)	6.857*** (0.522)	-6.789*** (0.683)	3.071 (3.021)	-1.262*** (0.445)	4.217* (2.552)	-1.226*** (0.447)
Share of post-2000 immigrants	1.875*** (0.060)	2.557*** (0.179)	1.607*** (0.099)	2.175*** (0.048)	1.945*** (0.292)	2.164*** (0.038)	1.980*** (0.237)	2.163*** (0.039)
Relative immigrant per capita income	3.046*** (0.171)	1.491** (0.702)	4.755*** (0.243)	2.677*** (0.132)	5.092*** (1.115)	2.768*** (0.109)	4.656*** (0.855)	2.781*** (0.109)
Share of immigrants in services	-6.549*** (0.397)	-6.699*** (1.570)	-10.544*** (0.606)	-6.231*** (0.358)	-7.758*** (2.376)	-6.501*** (0.267)	-8.446*** (1.848)	-6.527*** (0.268)
Refugees-to-immigrants	0.260*** (0.016)	0.157*** (0.046)	0.327*** (0.019)	0.333*** (0.017)	0.276*** (0.068)	0.240*** (0.011)	0.269*** (0.055)	0.241*** (0.011)
N	68,493	8,805	37,815	133,502	4,122	167,663	5,561	166,224
Ln(*L*)	-1.203×10^5	-1.587×10^4	-5.837×10^4	-2.321×10^5	-7.695×10^3	-2.875×10^5	-1.048×10^4	-2.842×10^5

Notes: Estimates are hazard coefficients obtained from Royston-Parmar flexible parametric survival regressions with baseline hazard functions estimated using restricted cubic splines with six knots. Standard errors are in parentheses. Intercepts and sector-, month-, day- and hour-fixed effects are estimated but not reported. The post-recession period is after September 15, 2008.
**** Significant at the 1 percent level.*
*** Significant at the 5 percent level.*
** Significant at the 10 percent level.*

contributors. For projects with higher funding concentrations, neither country aid dependency, the CPIA score nor state fragility affect project funding rates. Larger funders also fund projects from richer countries two to three times faster than smaller funders.

Larger funders appear to be more responsive to refugee-to-immigrant ratios and to relative wealth of immigrant communities, the coefficients for both being higher for projects with concentrations of funders. They also respond less to changes in the Dow Jones index, although the effect remains the same (i.e., increases in the index are associated with slower overall funding rates for Kiva projects). Meanwhile, large funders also appear to follow headlines more than smaller contributors, suggesting that larger funders may also be more informed. While there are some notable differences, then, none of them indicate that larger funders are more risk-averse toward their loans than smaller funders.

CONCLUSIONS

We examine indirect evidence of the funding preferences of private aid givers using data on crowd-funded microloans through Kiva, an internet-based peer-to-peer platform that bundles contributions into loans for entrepreneurs in developing countries. The behavior of private aid givers has been little examined to date, despite the increase in private development aid. We identified three possibilities: that crowd-funders act as risk-averse charitable contributors, making funding decisions based on project-specific risks and incentives; that crowd-funders behave like official foreign aid agencies, funding projects based on a combination of country need and institutional quality; or that crowd-funders are motivated by the social networks connecting them to countries in which projects take place. Because Kiva crowd-funders expect to have their principal repaid, Kiva's project data affords us an opportunity to test the risk-aversion of crowd-funders; because Kiva's projects span some 80 developing countries, we can also examine whether aid flows through Kiva are as selective as official development assistance.

Using survival analysis of funding rates for Kiva projects between April 2006 and December 2010, we find weak support for the view that crowd-funders are risk-averse with respect to microcredit in developing countries. Kiva's crowd-funders do prefer loans to women, as well as those of shorter duration and smaller amounts. However, they reject the group liability approach of traditional microfinance and only weakly prefer lending through lower-risk partner microfinance institutions. We find almost no consistent support for the perspective that crowd-funders act selectively toward projects based on the poverty or institutional quality of the country.

By contrast, we find strong support for the argument that crowd-funding is essentially an expressive act that enables individuals to "connect" with micro-entrepreneurs, much in the same way that individuals can "sponsor" children in developing countries through a number of NGOs. In this regard, we find that the nature of social relations that developing countries are able to rely upon in richer countries — in particular, through their communities of migrants — has a strong effect on the funding rates of Kiva projects. Kiva crowd-funders prefer to lend to countries which claim larger numbers of more recent, wealthier immigrants, and from which large number of refugees also come. For two reasons, we speculate that this is not necessarily due to participation by immigrants themselves as crowd-funders. First, Kiva lending moves in the opposite direction of remittances, which would be unlikely if immigrants themselves were largely responsible for Kiva funding to their home countries. Second, countries with large percentages of immigrants employed in the high-wage financial services sectors receive money at slower rates, the opposite of what would be expected were immigrants themselves participating as crowd-funders. Rather, we suggest that immigrant communities, through their social ties with native-born populations, provide information about their home countries to prospective crowd-funders.

These findings have implications for official aid policy.[12] In contrast to years past, the collective-action costs of private aid appear to be minimal, especially with the proliferation of internet-based crowd-funding platforms. Moreover, internet technology appears to have reduced the advantage that official agencies once held in terms of minimizing the transaction costs of disbursing aid. Finally, private aid now has significant advantages over official aid in avoiding agency costs, as private aid givers can give money to recipients in developing countries in a much more direct way. Indeed, the rapid growth of crowd-funded private aid may be attributed to the attractiveness of this "short route" to giving.

Not all recipient countries, however, are organized to take advantage of this spread of private aid. Another obvious conclusion is that aid recipient countries would do well to organize themselves to take advantage of new forms of private aid. For example, in India, MFIs must first obtain approval from the Reserve Bank of India before they can borrow abroad — an obvious barrier to accessing private loans from Kiva. Our findings also suggest that the design of projects can be fine-tuned to make them more attractive to donors. To give an example: It is probably more effective to invest in providing assistance to entrepreneurs to allow them to develop project ideas than to invest in building the capacity of microfinance intermediaries. Private lenders seem not to care too much about the rating of these agencies.

The phenomenal growth of internet-based giving is testimony to the potential for private aid to reach a scale which can be significant in global terms. What has not been shown is that organizing aid in this fashion is more effective for development. A comparison of development effectiveness between public and private aid platforms is an important direction for future research.

APPENDIX

The familiar Cox hazard model has the following familiar specification:

$$h(t|\mathbf{X})_i = h_0\,(t)\,e^{(X\beta)_i}$$

where, for every loan i, t is the number of hours required to fully fund a loan request; $\mathbf{X}$ is the vector of independent variables; and $h_0(t)$ is the baseline hazard function, i.e., the hazard function for $\mathbf{X} = 0$, with unspecified form. The attached table reports results from the basic Cox proportional-hazards regression, where we include a number of project-specific covariates.

Table A1 below also includes joint tests of proportionality based on the absolute value of the summed Schoenfeld residuals from the estimations, as recommended by Therneau, Grambsch and Fleming (1990) and Grambsch and Therneau (1994). This global test is based on a non-proportionality assumption; test statistics that exceed 5 percent critical values imply that non-proportional hazards assumptions have been violated. In column (1) we see no such evidence, keeping in mind that functional-form type Grambsch-Therneau tests of non-proportionality do not perform well where there are nonlinearities (Keele 2010).

In columns (2) to (5) in table A1, then, we attempt to test more directly a key assumption of the Cox model: namely, that the proportionality of hazard rates is maintained over analysis time. We therefore split the sample according to survival-time quartiles; hazard coefficients should remain stable if proportionality is constant over time. These estimations, however, show significant sign-switching. Grambsch-Therneau tests for each time-quartile regression, moreover, do not reject non-proportionality.

Table A1: Kiva Loan Funding Rates, Cox Hazard Estimates					
	(1)	(2)	(3)	(4)	(5)
	Full sample	1st quartile	2nd quartile	3rd quartile	4th quartile
Amount (Ln)	-2.562*** (0.036)	-0.665*** (0.083)	-0.389*** (0.097)	-1.460*** (0.110)	-2.399*** (0.106)
Amount^2 (Ln)	0.138*** (0.003)	0.023*** (0.007)	0.015* (0.008)	0.096*** (0.009)	0.132*** (0.008)
Number of borrowers	0.000 (0.001)	-0.009** (0.004)	-0.003 (0.003)	-0.009*** (0.002)	0.008*** (0.002)
Female	0.454*** (0.006)	0.060*** (0.013)	0.096*** (0.011)	0.151*** (0.011)	0.410*** (0.011)
Loan term (months)	-0.026*** (0.001)	-0.011*** (0.002)	-0.001 (0.001)	-0.006*** (0.001)	-0.023*** (0.001)
Concentration	0.853*** (0.014)	1.250*** (0.019)	0.010 (0.029)	0.129*** (0.032)	0.486*** (0.041)
US share	0.426*** (0.010)	0.006 (0.018)	-0.071*** (0.021)	0.098*** (0.022)	0.202*** (0.026)
MFI risk rating	0.007*** (0.002)	0.002 (0.005)	0.024*** (0.004)	-0.031*** (0.004)	0.012** (0.005)
Country dummies	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes
Day dummies	Yes	Yes	Yes	Yes	Yes
Hour dummies	Yes	Yes	Yes	Yes	Yes
N	251,081	62,336	62,869	62,919	62,957
Ln(*L*)	-2.793×10^{6}	-6.198×10^{5}	-6.298×10^{5}	-6.302×10^{5}	-6.232×10^{5}
Grambsch-Therneau ($p>\chi^2$)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Estimates are hazard coefficients obtained from Cox semi-parametric survival regressions. Standard errors are in parentheses. Quartile regressions are by survival-time quartiles. Grambsch-Therneau tests are for a non-zero slope in a regression of scaled Schoenfeld residuals on survival time; the null hypothesis is that hazard rates are proportional.
**** Significant at the 1 percent level.*
*** Significant at the 5 percent level.*
** Significant at the 10 percent level.*

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ENDNOTES

1. This section is adapted from introductory paragraphs in Desai and Kharas (2010).

2. There is considerable evidence of "psychic" rewards to charitable giving. Experiments, for example, show that charitable donations trigger activity in brain regions related to social attachment and bonding in other species (Moll et al. 2006). Kosfeld (2008) emphasizes that trust in other humans is a biologically-based part of human nature and, in particular, that oxytocin, a hormone that reduces social anxiety, is also linked with a greater degree of trust that good behavior will be reciprocated. One survey of members of service-based social clubs (Rotary, Kiwanis and Lions Clubs) finds that, when faced with multiple charities to support and uncertainty over the social value of one's gift, "warm-glow" utility determines the allocation of gifts (Null 2011).

3. Micro-entrepreneurs who request loans for projects may already have had funds disbursed by MFIs. In reality, then, Kiva's micro-lenders are actually financing previously-disbursed MFI loans rather than lending directly to micro-entrepreneurs. Kiva had been criticized for not making this "indirect" aspect of their lending operations explicit.

4. Since 2011, Kiva has lent up to $10,000 to potential micro-entrepreneurs in the United States. Our data on Kiva projects, which ends in December 2010, does not include any US-based projects.

5. The World Bank conducts an annual performance assessment for its borrowing countries, known as the Country Policy and Institutional Assessment (CPIA), which scores a country's present policy and institutional framework for fostering poverty reduction, sustainable growth and the effective use of development assistance. It includes 20 equally weighted criteria which are grouped in four clusters: economic management; structural policies; policies for social inclusion and equity; and public sector management and institutions (the "governance" cluster).

6. The Kiva website states that a "5-Star Field Partner is a highly established micro-lending institution with a proven track record, audited financials and high ratings from independent evaluators. In contrast, a 1-Star Field Partner is usually young and unproven—but with the potential to reach entrepreneurs not reached by more established Field Partners." The ratings are assigned based on audits, credit ratings, independent evaluations, estimations of existing portfolio risk, Kiva repayment performance and the age of the MFI (among other factors).

7. More importantly, the Royston-Parmar approach provides a superior fit compared to parametric alternatives. Likelihood ratio tests for all specifications in table 3 show that the improvement in fit is greater when compared to the Weibull model ($p < 0.001$).

8. The following criteria must be met for an event to be coded as a natural disaster: The disaster must occur as a result of a natural occurrence; 10 or more people must be reported killed; at least 100 must be affected; a state of emergency must be declared; and the country must call for international assistance. In our estimations, the impact of natural disasters is measured as $\ln(1 + n)$, where n = number of persons affected.

9. Many donors have incorporated "good governance" indicators, such as control of corruption and performance of public-sector institutions, into their allocation decisions starting in the 1990s. For the US Millennium Challenge Corporation, for example, meeting governance thresholds is a requirement for countries seeking assistance. The World Bank's zero-interest lender, the International Development Agency (IDA), explicitly

incorporates both poverty and institutional quality in its "performance-based allocation" formula to distribute IDA funds among eligible countries (World Bank 2003).

10. Gartze (2000), for example, notes that an additional advantage of an affinity index based on UN voting is that it contains more information than data on alliances, which change infrequently and have been generally fixed for much of the post-World War II period. By contrast, hundreds of resolutions appear in each session of the UN General Assembly. The affinity score is calculated as $S = 1 - (3xd)/d_{max}$, where d is the sum of metric distances between votes by the US and by any particular aid recipient in a given year, and d_{max} is the largest possible metric distance for those votes, based on the following coding: 1 = "yes" or approval; 2 = abstain; and 3 = "no" or disapproval for an issue or resolution. Resulting values for the US affinity score range from −1 (least similar interests) to +1 (most similar interests). UN voting data are from Strezhnev and Voeten (2012).

11. Leblang and Bermeo (2010), for example, find that while larger numbers of immigrants from aid recipients in donor countries increase aid from donor to recipient, larger numbers of refugees have the opposite effect.

12. This and subsequent paragraphs are adapted from concluding paragraphs in Desai and Kharas (2010).

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