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ASSESSING THE SPATIAL ACCESSIBILITY OF MICROFINANCE IN NORTHERN BANGLADESH: A GIS ANALYSIS*

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ABSTRACT. This paper attempts to understand and operationalize the notion of spatial accessibility (SA) in the context of microfinance. Using geographic information system (GIS) data from northern Bangladesh, we have generated a kernel-smoothed map and found remarkable spatial variation in access to microcredit. Results suggest that areas isolated from physical infrastructure, administrative establishments, and prone to ecological shocks, exhibit lower degree of SA. Moreover, using an instrumental variable framework, we found that SA has a significant positive impact on household's decision to borrow and on the number of loans: one standard deviation higher SA is associated with a rise in participation probability and average number of microloans by, at least, 3.5 percentage points and 16 percent, respectively.

1. INTRODUCTION

A very diverse and interrelated set of variables may influence the behavior of microfinance institutions (MFIs) (e.g., location choice, design of financial instruments, profitability, operational sustainability, and personnel productivity) and that of their prospective clients (e.g., formal, semiformal, or informal borrowing, crisis coping, repayment strategy, and horizontal or vertical mobility in the socioeconomic hierarchy). Typically, the focus of the researchers, to date, has been on specifying, analyzing, and evaluating the influence of factors that are, by nature, economic, sociocultural, structural, or demographic (Hossain, 1988; Rahman, 1996; Zeller et al., 2001; Navajas et al., 2002; Fruttero and Gauri, 2005).

In this paper, we attempt to emphasize the geospatial aspects of microfinance by utilizing a geographic information system (GIS), particularly scrutinizing the supply side. Geographical features can have important implications for the functioning of the microfinance market in many ways. For instance, the spatial status of both the household itself and the service providers (i.e., the MFIs) can substantially affect the borrowing behavior and effective participation of a household in the formal credit market. Distance to branch

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and costs of communication are likely to play vital roles in hindering active participation and hence are issues of great significance because extending outreach to the hard-to-reach population has received much attention lately (Cull, Demirgüç-Kunt, and Morduch, 2009; Hermes, Lensink, and Meesters, 2011). Therefore, understanding the roles of geographic access to MFI services should provide useful guidance on how to advance this industry even further and expand coverage in the underserved areas. In this paper, we attempt to understand the underlying rationale and evaluate the consequences of the geospatial features of MFI activities.

Prior studies have already attempted to address the association between the use and access to credit and the spatial distribution of financial services availability (as measured, for example, by the number of bank branches or ATMs per 1,000 km^2; Beck, Demirgüç-Kunt, and Peria, 2007; World Bank, 2008). These studies have mostly relied on the distribution of access across countries by primarily focusing on the access to formal credit only. In this paper, we explicitly model within-country/region spatial heterogeneity in access to credit. Our study attempts to fulfill the dual objective of complementing prior studies by exploiting the individual household-level variation in access to finance with the aid of better indicators of spatial access and improving on their exploration of the association between access and utilization by explicitly addressing the econometric problem of endogeneity. Furthermore, in rural Bangladesh, it is more reasonable to look at the microfinance sector that has become the dominant financial intermediary in the rural area over the last three decades.

GIS has undeniably been an indispensable, cost-effective, and accessible tool for the researchers (of diverse background) as well as the policymakers in discovering and analyzing any spatial phenomenon. For example, it has become a widespread practice to use hospital and health clinic locations to both estimate the geographic accessibility of health care and evaluate its impact on the rate of utilization through spatial analysis (Luo and Wang, 2003; McLafferty and Grady, 2004). Studies have also been carried out on using locations of criminal activities to pin down crime hotspots, thus facilitating the mobilization of law enforcing efforts (McLafferty, Williamson, and McGuire, 1999).

In the present study, we first draw from prior theoretical and empirical studies on spatial accessibility (SA) and develop a theoretical structure to conceptualize the notion of geographical accessibility in the context of microfinance. Based on this framework, we generate continuous accessibility surfaces (or maps) for the districts of Kurigram and Lalmonirhat (from northern Bangladesh) incorporating all active MFI branches by means of kernel interpolation—a measure frequently used to estimate spatial access. We also aim to isolate the spatial factors that might explain the observed diffusion of microcredit access (as measured by SA). We find that geographical detachment from physical infrastructure and administrative centers and exposure of the households to potential negative ecological shocks significantly reduce the spatial access to microfinancial services. Moreover, the accessibility estimates are found to be robustly associated with microfinance participation.

Hereafter, the paper will proceed as follows: Section 2 will provide a discussion of definitional issues, whereas Sections 3, 4, and 5 will deal with issues regarding measurement, approach, and data. Interpretation of geointerpolated maps and empirical findings are presented in Section 6. Under Section 7, we discuss briefly the policy relevance and shortcomings of the study. Finally, in Section 8, the paper concludes by making some final comments and highlighting the potentials of additional investigative studies.

2. SA: SOME DEFINITIONAL ISSUES

Despite often being used interchangeably, *availability* and *accessibility* represent two different spatial concepts. *Availability* refers to the number of service providers to be taken into consideration by an individual while making a choice, whereas *accessibility* can be viewed as the spatial connectivity between potential consumers and existing service points (often measured in terms of commuting constraints such as distance or time) (Guagliardo, 2004).[1] However, in the literature of social sciences and geography, these two aspects have often been integrated into one single concept of "spatial accessibility" (SA) (Khan and Bhardwaj, 1994).

Each field of study and/or area of application (e.g., healthcare, education, and public transport system), taking into account all of its distinctive attributes, has developed a wide and diverse range of approaches to successfully conceptualize spatial access (Khan and Bhardwaj, 1994). Studies that have been undertaken thus far, in different fields, suggest that availability and accessibility may rely substantially on geographic features such as distance and travel time. For example, in the setting of healthcare, the transportation costs faced by a healthcare seeker work as one of the primary determinants of spatial access and, therefore, utilization (Goodman et al., 1997). The case is almost identical for geographic access to educational services where the availability of an educational institution has been postulated as a decreasing function of distance for prospective students (Binita, 2010).

As far as the functioning of microfinance market is concerned, the relative importance of provider (e.g., an MFI) and potential client (e.g., a poor rural household) locations is somewhat different. MFIs reach out to potential clients by placing the branches strategically (Salim, 2013). Using these branches as hubs, credit or loan officers form client groups in the neighborhoods of poor households and make frequent visits to establish an effective network of communication with the customers through these community groups (Armendáriz and Morduch, 2005). It is important for an MFI to reach out to a potential client base that is poor and geographically more detached. However, this objective is constrained by the concern for the sustainability of MFIs. This is often synonymous with cost minimization. MFIs' location choice often depends on these conflicting dual objectives, and this paper intends to contribute to the understanding of the location decision of the MFIs in the two districts of Bangladesh where historically, lack of communication facilities has contributed to economic underdevelopment and destitute (Mahmud, 2011).

Because of the associations it has with the costs of transportation and prevalence of asymmetric information, the "distance" factor in the context of banking has received greater attention in the academic domain in the recent past (Alessandrini, Fratianni, and Zazzaro, 2009). As Pedrosa and Do (2011) have pointed out, the costs of delivering financial services to the borrowers and monitoring microfinance beneficiaries who are geographically scattered in hard-to-reach rural areas can have a significant impact on the "profitability" of the MFIs. MFIs may limit operation to areas with certain spatial qualities (better accessibility with lower ecological vulnerability and natural disasters) or impose more demanding eligibility requirements (e.g., compulsory savings, more frequent repayments resulting in higher rate of rejection) and/or raise interest rates. Besides that, MFIs may encounter riskier demand from the hard-to-reach client base which, due to spatial isolation, presumably suffers from lower human development, production instability, and susceptibility to negative economic and noneconomic shocks. Hence, even if MFIs were able to reduce costs on the intensive margin by enhancing monitoring capability, the distance-induced rise in extensive margin expenses would still remain a source of concern.

Pedrosa and Do (2011) tested some of these hypotheses about the impact of distance using data from Niger, where distant borrowers were observed to be economically more

[1]Note that the notion of "accessibility" is concerned with the "potential" and not the "realized" access to the services being provided. Throughout the text, henceforth, whenever brought up, the term *accessibility* will be used to signify the prospects of implementation (irrespective of the context).

vulnerable and worse off in terms of getting access to financial services. The results also suggest that an increase in distance implies rising costs (both transaction and monitoring) for the MFIs, which has been, to some extent, shifted to the borrowers in the form of higher interest rates and additional constraints. This also leads to the exclusion of marginal borrowers (who are observed to move upward in the income distribution as distance increases) from the formal and/or quasi-formal rural credit market. This then implies both: (a) the likelihood of being provided with microcredit diminishes with spatial detachment from the providers and (b) MFIs' inclination toward serving the relatively less impoverished population increases with geographic distance. Empirical evidence where the rise in agency costs caused by the spatial segregation of the client and MFI makes the credit market more prone to moral hazard also exist (Presbitero and Rabellotti, 2014). The existing stock of literature, however, offers mixed evidence on the relationship between spatial gap and the odds of reimbursement. Oke, Adeyemo, and Agbonlahor (2007) found distance to be inversely related to the repayment rate in Nigeria. On the other hand, Roslan and Karim (2009) failed to find any such association for the Malaysian microcredit market.

The existing literature then leads us to deduce that, *ceteris paribus*, the further away (geographically speaking) one is from an MFI, the lower will be the likelihood of his/her being a user of its financial services; spatial access to microfinance services diminishes with distance. To summarize, in order to obtain adequacy in composition, an SA index should take into consideration the following: (a) inclusion of all potentially accessible service points (i.e., branch offices) and (b) discounting the branches according to their geographical location.[2]

3. MEASURING SA USING KERNEL DENSITY ESTIMATION (KDE)

Among the potential measures of SA, it is most common to use distance to the nearest service provider because of its intuitiveness and ease of interpretability. However, distance to the nearest service provider ignores the households' capacity to access other competing MFIs. Hence, in areas where multiple providers exist and operate in the immediate vicinity of a household (a valid possibility in the case of microfinance), the distance to the nearest MFI branch may be a narrow and even a misleading estimate of accessibility. On the other hand, "provider-to-population ratios" (e.g., number of MFIs per 100,000 people) and "simple density" (e.g., number of MFI branches per square kilometer; both used by Beck et al., 2007, but for the set of formal financial institutions only), despite being able to include all relevant branch offices, ignore the intraregion variability in provider penetration, one of the key aspects we aim to explore and utilize. In other words, they fail to discount MFI branches with increasing distance that, as has been argued above, is critical to the estimation of microfinance SA. Though "average distance to providers" overcomes this to some extent, it is inadequate in capturing the intensity of MFI activities (for example, the number of MFI branches operating could be very dissimilar despite the same "average distance" figure).

[2]Also, *ceteris paribus*, the higher the density of potential clients surrounding an individual, the greater the competition he/she will possibly face in terms of ensuring access. But one should note that two opposing forces are in effect here in terms of relevant population density; the more remote a location is, the lower the (general) population density might be but the higher the proportion of potential clients since that location would be more likely less developed. As a result, the potential client density may be more/less equalized across the study area. Our SA estimates, which are based on the supply side only due to unavailability of data on the demand side, therefore, may not be that much biased. The regression results, as discussed in Section 6, which control for union-level population density, further lend support to this conjecture.

Apart from the gravity model, only KDE addresses the two basic issues regarding the measurement of geographical accessibility while being conceptually easier to grasp and rationalize than the gravity measure (Guagliardo, 2004; Hass, 2009). But the spatial separation of the provider and the client has to be measured in Euclidean or straight-line distance, which may lead to under/overestimation of travel impedance. However, in contrast to any rural setting (which, in general, has been the focus of microfinance), the problem is presumably more acute in urban areas due to its complex transportation network resulting from significantly higher density of settlements.

While KDE (in the context of generating smooth geospatial surface) has a few drawbacks, we chose the current method (over, say, similar methods such as gravity model) for the following reasons. First, there already exists an established and consistent series of literature that have critically analyzed the theoretical and applied issues concerning kernel interpolation in diverse market environments (Luo and Wang, 2003; Guagliardo, 2004; McLafferty and Grady, 2004; Yang, Goerge, and Mullner, 2006; Gibin, Longley, and Atkinson, 2007; Spencer and Angeles, 2007; Xie and Yan, 2008; Binita, 2010; Schuurman, Berube, and Crooks, 2010). These applications of KDE can serve as useful reference points, thus enabling us to effectively adopt kernel smoothing to measure spatial access of microfinance. Second, recent progress in the frontier of GIS software development has remarkably facilitated the computation of kernel density in terms of ease and accuracy. In a nutshell, then, KDE, as an SA measure, is frequently applied, more intuitive in nature and easily estimable.[3]

4. DATA

Lalmonirhat and Kurigram are two of the northern districts of Bangladesh that have received considerable attention from academicians, policymakers, and development practitioners (Hossain et al., 2005; Zohir et al., 2007; Mahmud, 2011; Mobarak, 2011).[4] This region is particularly characterized by its distinct geographic attributes (a riverine, low-lying flat plane prone to floods and river erosion) and comparatively low levels of human development (Zug, 2006). Extreme climate condition, coupled with frequent natural calamities (mainly caused by the abundance of rivers) and underdeveloped physical infrastructure, has proved to be one of the major impediments to the socioeconomic progress of the bulk of its population. Often being a victim of pronounced periodic fluctuations in the availability of income-earning activities, especially during the season of *monga*,[5] the majority of its households struggle to maintain a consistent standard of living.

To facilitate these households with access to semiformal and formal financial services, many MFIs have expanded their operation to these two districts. In 2010 (the year of data collection), there were 224 and 165 MFI branches in Kurigram and Lalmonirhat,

[3]Our estimation of kernel density, however, as would also be encountered in the case of the gravity model, will suffer from the absence of data on the demand side of the market (i.e., potential credit clients). The data set is also deficient in containing information on the capacity of all the MFIs operating within the study area. As a result, we will have to adopt KDE exclusively based on a rather narrowly represented supply side of the microfinance market.

[4]The northwestern parts of Bangladesh have typically been more impoverished (BBS, 2006). The recent survey also reveals that the Rangpur division (which Kurigram and Lalmonirhat are part of) remained the second highest recipient of social safety net programs (Bangladesh Bureau of Statistics, 2011).

[5]A word from local dialect referring to the sudden degradation of the living standard due to the lack of entitlement to basic food and nonfood components of consumption, basically caused by an intense dearth of jobs, typically experienced in the off-crop seasons.

respectively. GIS data collection was mainly operationalized as a pilot project supplementary to the core Programmed Initiatives for Monga Eradication (PRIME) third round study.[6] The project's primary focus was to collect location information of all active MFI branches, along with roads, administrative headquarters at union, thana/upazila, and district levels (appearing in an ascending order within the public administration hierarchy), and major topographical attributes such as rivers and char-lands[7] within our study area. We also have GIS data on the geographic location of a set of cluster-sampled ultra-poor households (1,974 of them: 885 from Lalmonirhat and 1,089 from Kurigram; ultra-poor households are defined as having less than 50 decimals of cultivable land, earning less than 1,500 taka (US$22) per month, and working mostly as wage laborers) (see Figure 1 for a selective mapping of the GIS information collected). Along with the GIS information, we also made use of a unique data set containing information on different economic and noneconomic aspects of the same set of households.

5. METHODOLOGY

Given the discrete data points with spatially extensive attributes, KDE generates an interpolated surface that is continuous in nature and unconstrained by geopolitical boundaries (Spencer and Angeles, 2007). In the context of microfinance, this amounts to the generation of a continuous accessibility map given the location data of MFIs. The application of KDE results in a raster data set (composed of equally sized cells) where each cell is ascribed an interpolated SA value (Longley et al., 2005). The estimation procedure, first of all, assigns a cone or kernel to each of the MFI branches. The kernel is placed upon such that its center coincides with the host branch office location on the map surface. A provider's aggregate capacity is represented by the associated cone's volume that, if not specified, is typically assumed to be one (which is the case here). As stated before, the allocation of capacity administered by an MFI branch is indicative of the associated degree of accessibility. The cones are modeled via a kernel function, which distributes an MFI's service capacity as a strictly decreasing function of geographical distance; i.e., the further away a cell (underlying the cone) is from its center (i.e., the branch office), the smaller the value of capacity it will be assigned (for reasons discussed in detail in Section 2). KDE, therefore, accounts for the "distance decay effect," one of the fundamentals characterizing the SA of microfinance. If summed up, the density values of all the cells enclosed by a cone will be equal to the total capacity of the relevant branch. Since the provider cones are often found to be overlapping as a consequence of intersecting service areas of multiple providers, the accessibility value for a cell is finalized by adding up all the kernel surfaces that overlay the cell center.

Put simply, the surface generated by KDE is in effect tantamount to a 3-D histogram of MFI branch presence. But unlike a standard histogram where each observation is treated as a discrete data point, here an MFI branch's presence (which contributes to the "frequency" calculation of the associated location) is distributed as a cone over its potential service area. Upon vertical summation of all these cones, the resultant surface merely represents the density of MFI branches across the study area. The MFIs, as explained earlier (see Section 2), operate through their branches. The height of the surface at any

[6]PRIME is a DfID funded project that includes providing microcredit and ancillary services such as health treatment and training to the ultra-poor households in the northwestern part of Bangladesh. The project started in 2006 and is scheduled to end in 2014.

[7]*Char* is a local word to describe a strip of sandy land rising out of the bed of a river above water level.

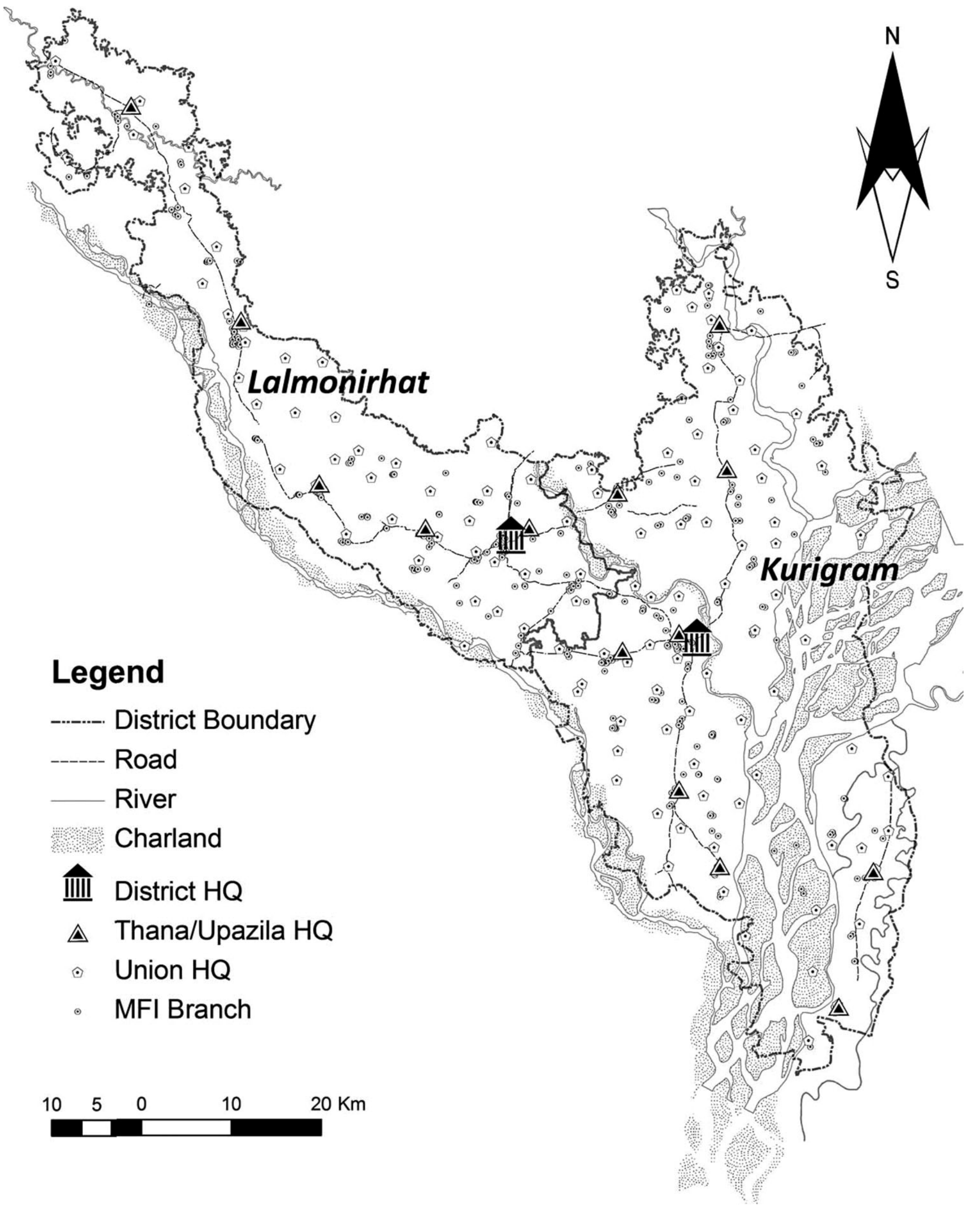


FIGURE 1: Mapping of Available GIS Data.

location then basically suggests how much access a household (or an individual) has to the microfinance services thereat.

Producing a meaningful surface of SA by means of KDE also requires the researchers to decide which kernel function to use and how to determine the radius of the base of the cone. There is strong evidence, however, that the choice of kernel function does not have any significant implication for the resulting density surface (Silverman, 1986; Bailey and Gatrell, 1995; O'Sullivan and Unwin, 2002; O'Sullivan and Wong, 2007). Here, we adopt the Epanechnikov function (a quadratic approximation to the Normal distribution) to characterize the kernel density function (De Smith, Goodchild, and Longley, 2007). If mathematically expressed, the density estimate representing the share of capacity of provider j allocated at location i is given by

$$S_{ji} = \begin{cases} \frac{3}{4}(1 - t^2), & |t| \leq 1; \\ 0, & |t| > 1; \end{cases} \quad t = \frac{d_{ji}}{h},$$

where d_{ji} = Euclidean distance between provider j and location i, and h = cone radius. Hence, SA index for the household at location i, A_i^{KD}, will be estimated as

$$A_i^{KD} = \sum_j S_{ji}.$$

We have adjusted the cell size[8] of the output surface so that the density values estimated can be expressed as MFI branch per square kilometer. But as can be sensed from the construction methodology presented above, where the provider capacity has been hypothetically broken down over a continuous space on the basis of a kernel function instead of being counted as a discrete observation, such straightforward interpretation may induce misleading inferences.[9]

The cone radius (also known as bandwidth or kernel size), on the other hand, has been found to be more important as being one of the parameters of smoothness (Silverman, 1986; Bailey and Gatrell, 1995; O'Sullivan and Unwin, 2002; O'Sullivan and Wong, 2007). Change in bandwidth, however, is not capable of causing substantial differences in the output density since using a larger radius simply results in the inclusion of more providers (ESRI, 2010). On the researcher's part, choosing an appropriate kernel size requires excellent practical knowledge of the specific context (Gibin et al., 2007). The active MFI branches in Kurigram and Lalmonirhat typically restrict their operation within 8–10 km from the branch office.[10] Rigorous sensitivity analysis was undertaken to examine whether the smoothed surface exhibited significant differences in response to changes in the bandwidth within this range. Due to the observed consistency in the results (see Figure A1), we settle on a bandwidth of 10 km, the probable maximum extent of an MFI's service area. We further restrict the surfaces by their respective district boundaries as MFIs generally do not operate beyond the district's perimeter where the branches are located.[11]

[8]Output cell size delivers density measure in the form of square grid.

[9]We, however, can make context-specific choice of the mode of representation. For instance, while providing a verbal description of the interpolated maps of accessibility, for the sake of lucidity, we can classify the estimates into a convenient number of equally sized groups and label them according to their relative magnitudes (e.g., high and low). On the other hand, in the case of exploring associations between SA and other variables of interest, the values of the output raster may be utilized in both absolute and categorized form.

[10]We learned this from numerous field visits and communication with the practitioners.

[11]Note that we have not scaled the volume of the kernel or the "cone" around a certain branch location when the administrative borders truncate them. What we did was merely mask the output by district perimeters. This, however, would not address the "boundary problem" (Botev, Grotowski, and Kroese, 2010) typically associated with kernel density estimators. We admit then that the scores could be biased downward near the boundary. But in contrast to the case of unidimensional KDE (e.g., number of suicides) where the problem is well researched and several established boundary-correction methods have been developed, comparable advancements have not taken place in the analysis of spatial events. For example, how would an MFI's capacity be distributed in the presence of a binding boundary nearby? What kind of truncation would be deemed appropriate? Given this and the fact that the boundary problem is relevant for only a small part of our study area, we refrain from directly addressing the problem with some

6. FINDINGS

SA of Microfinance in Kurigram and Lalmonirhat

Figure 2 portrays a geointerpolated density surface[12] produced by means of kernel smoothing, which represents SA of microfinance in Kurigram and Lalmonirhat (following the methodology outlined above). Visual inspection reveals that there exists remarkable variability in accessibility across both Kurigram and Lalmonirhat. Furthermore, the geodistributional patterns exhibit significant similarity. In both cases, the degree of concentration in general tends to be markedly higher in the localities around the administrative headquarters (in particular, district and upazila headquarters). This is not surprising because these areas are more urban in nature and, as a result, supposedly more advanced than others in terms of physical infrastructure (e.g., communication networks and utility services) and other amenities. The population residing over those regions is also generally better off, considering both economic solvency and exposure to shocks (economic and natural), and will possibly be more preferred by the MFIs due to their higher credit demand.

Multivariate Analysis of SA and Microcredit Participation

Our rationalization of the detected variations in the SA of microfinance above, however, is based on intuition and subjective perception rather than rigorous empirical investigation. In order to verify the aforesaid graphical inferences, we now resort to the standard practice of statistical inference to quantify the association of SA with other location attributes. Furthermore, we assess the explanatory power of the estimated SA index for household microborrowing.

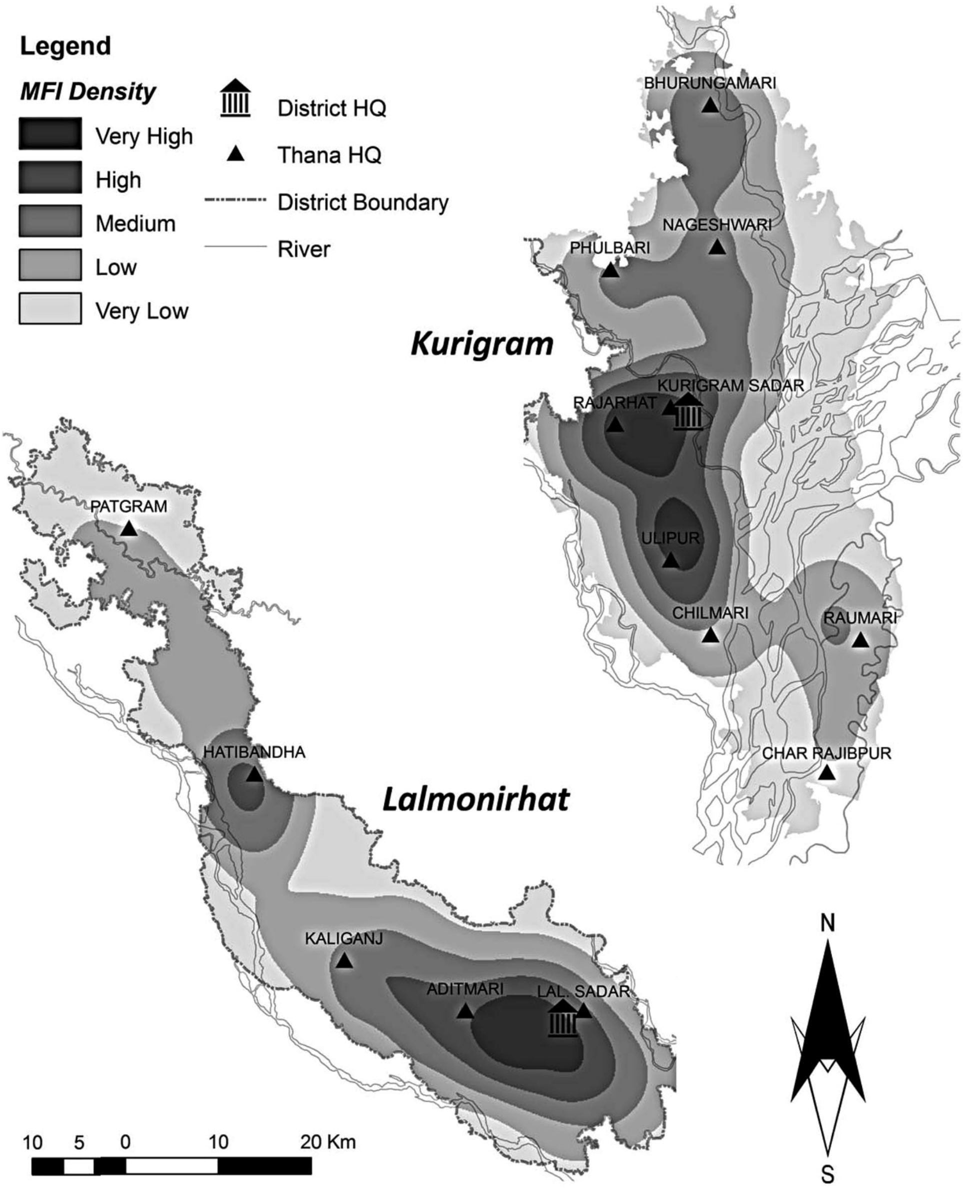
In doing the latter, it is noteworthy that we are using a rather macroeconomic variable (SA) to explain the behavior at the micro (household) level (household microborrowing). Therefore, our SA index is a good candidate for satisfying the criterion of exogeneity. Should that be the case, the simple probit or Poisson models would be good enough to identify the partial effect here, especially if region-specific fixed effects are accounted for. However, endogeneity might still be a source of concern due to other reasons. As Salim (2013) has demonstrated, MFIs strategically locate themselves, motivated by both profit maximization and poverty outreach. Such nonrandom program placement, in particular, the focus on reaching out to the poor, would then suggest that the penetration of microfinance operation would most possibly be correlated with both observed and unobserved household attributes that are also crucial determinants of borrowing behavior. For example, in view of the revealed objective function of the MFIs, one might postulate a negative correlation between innate household ability and SA, hence introducing a downward bias in the estimated coefficients on the spatial access. As such, we will resort to an Instrumental Variable (IV) framework to see if we can correct such bias and estimate a better lower bound for the impact of spatial access on loan-taking behavior.

Geospatial Determinants of SA

Econometric specification. To discover and quantify the relationship between the geographical accessibility and spatial background of a location, we estimate the following OLS model:

(boundary) correction methods. We believe that this would not lead to a drastic revision of our findings, which have been shown to be robust to a number of other theoretical and empirical concerns.

[12]The software utilized is ESRI ArcGIS 9.3© with the Spatial Analyst© extension.



Note: All the MFI branches are incorporated.

FIGURE 2: Kernel Density Estimates of Spatial Accessibility of Microfinance.

$$sa_i = a_0 + \mathbf{d}_\mathbf{i}'\beta + \gamma p_i + \varepsilon_i + \text{District/Upazila fixed effects},$$

where, sa_i represents SA (as constructed above) associated with the ith location, $\mathbf{d}_\mathbf{i}$ is a vector composed of different types of distance characterizing that location, and β is the vector of unknown parameters corresponding to the geospatial attributes represented by $\mathbf{d}_\mathbf{i}$. Moreover, we control for union-level population density, represented by p_i, to detect any bias underlying the SA estimates due to the absence of demand side data; γ would

TABLE 1: Summary Statistics for SA and Different Aspects of Household Location

Variables	Mean	Median	SD
Spatial accessibility of MFI	0.124	0.114	0.066
Distance from the union HQ	1.932	1.771	1.152
Distance from the upazila HQ	5.934	5.660	3.184
Distance from the district HQ	20.593	16.074	14.006
Distance from the nearest road	2.585	2.303	1.965
Distance from the nearest river	2.795	2.171	2.180
Union Population density (per sq km)	1,095	1,102	266.01

Notes: $N = 1{,}959$. All the distances are measured in km (kilometers).

capture the extent of such bias. ε_i is a random disturbance term encapsulating unobserved location heterogeneity. Location data that constitute the covariate matrix are extracted from the aforementioned households (see Section 4). Since the sampling was independent of the branch locations, these data are useful in both avoiding locations with zero population density (which are of dubious value in the present model) and introducing exogeneity. In measuring the remoteness of a location (and hence the associated household) with respect to the prevalent topographical, infrastructural, and geoadministrative configuration, distances from the river, the road, and the three most important establishments of local geoadministration, namely, union, thana/upazila, and district headquarters, have been incorporated in $\mathbf{d_i}$. To ensure the comparability of partial effects across these "distance" variables, we report the standardized beta coefficients in all cases.

Summary statistics. Relevant variable definitions along with their summary statistics are provided in Table 1. As the kernel-smoothed surface suggested, the SA index values, as ascribed to the locations (households) here, are remarkably dispersed. The distributions of the alternative measures of spatial detachment, as was referred to above, are very much dissimilar in terms of both central tendency and dispersion. Moreover, note the disparity between the mean and median values for each of these variables, which suggests that the density of the population, as expected, is higher in close proximity to the comparatively developed regions within our study area. Half of the sampled household locations are contained approximately within 2, 6, and 16 km of the union, upazila, and district headquarters, respectively, whereas the corresponding figure is 2 (km) when it comes to measuring the proximity to roads. On the other hand, *on average*, a location (in our sample) is roughly 3 km away from the nearest river. Again, the median, which is about 2 (km), shows that a relatively higher proportion of households may be located in the close vicinity of the rivers. This may be attributable to the wide network of rivers that can be found across both of the study districts. Finally, the distribution of union population density seems to be centered on 1,100 (people per square km), with a rather high standard deviation (SD) of 266.

OLS results. The regression results, as reported in Table 2, on the whole, indicate that almost all of the variables, except distance from the union (the lowermost tier of administration) headquarter, have a highly statistically significant (at the 1 percent level) association with SA. This, however, may be attributable to a potential multicollinearity problem in our model. We have reported different collinearity diagnostics in Table A1. Although the variance inflating factor (VIF) figures seem innocuous, the condition index estimate suggests the presence of moderate to strong multicollinearity. But given the high level of precision with which almost all of the parameters are estimated, it does not constitute a serious problem.

TABLE 2: Geospatial Determinants of Spatial Accessibility (OLS)

	Spatial Accessibility		
	Beta Coefficient		
Variables	(1)	(2)	(3)
Distance (in km) from the			
Nearest river	0.455***	0.456***	0.463***
Nearest road	−0.128***	−0.128***	−0.058***
District HQ	−0.257***	−0.257***	−0.820***
Upazila HQ	−0.307***	−0.306***	−0.339***
Union HQ	−0.025*	−0.025*	−0.023*
Union population density	0.159***	0.159***	0.120***
Fixed effects	No	District	Upazila
Adjusted R^2	0.590	0.590	0.715

Notes: $N = 1{,}959$. Each observation represents a randomly chosen ultra-poor household. Fifteen household locations (only 0.76 percent of all) could not be used due to technical errors made in GIS data collection. All regressions are OLS. Intercept and fixed-effect estimates are not reported to save space.

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

In terms of directions (of the relationships), all the parameter estimates conform to our *a priori* expectations. Column (1) demonstrates this relationship, disregarding any geoadministrative heterogeneity, whereas results reported in the latter two (i.e., columns (2) and (3)) control for district and upazila fixed effects. To elaborate, the farther a location (household) is from the nearest road and administrative headquarters, the lower the degree of SA it is expected to experience. In contrast, distance from the nearest river is positively associated with SA to microfinancial services. Focusing on the relative importance of different types of distance in terms of partial effect, as reflected by the beta coefficients, results reveal that distances from the nearest river, upazila, and district headquarters have substantial association with SA. A one SD increase in the distance from the nearest river is associated with an increase in SA of almost half SD, and the magnitude is fairly robust to the inclusion of fixed effects. On the other hand, irrespective of specification, the spatial separation from the upazila headquarter equivalent to one SD, *ceteris paribus*, reduces spatial access by at least 0.30 SD. A comparable relative movement in distance from the district headquarter is associated with no less than 0.25 SD lower SA (and as large as 0.82 SD once upazila-specific heterogeneity is partialled out). The corresponding figure for detachment from the road ranges from 0.06 to 0.13 SD (in absolute value). The marginal impact of geographical detachment from the union headquarter, however, seems to be the least important in both practical and statistical terms. Union population density, as one might conjecture, has a significant positive association with SA, but the magnitude, nonetheless, is small (namely, 0.16 SD at most). This, in turn, indicates that our kernel estimates of SA could be biased upward (downward) in regions with higher (lower) population density but only slightly. As our results show, even after controlling for population density, there seems to be other geospatial factors of higher substantive significance in the SA production function. Also note that a considerably large share of variation (59 and 71.5 percent) in SA has been explained by these location attributes.

We can therefore conclude that the remoteness of a location (household), defined in terms of geographical segregation from physical infrastructure and administrative headquarters, can have a remarkable bearing on its allocated degree of spatial access to microfinancial services. Since better availability of infrastructure (which presumably has a high positive correlation with the existence of administrative establishments) and economic development are complementary to each other, the more isolated a household is, spatially speaking, from the comparatively "developed" regions, the lower the degree of SA it will be provided with. Our results pertaining to the proximity to rivers also tend to support the MFIs' objective of reaching out to poor households subject to financial sustainability and business viability. Being close to rivers in the northern areas of Bangladesh represents higher exposure to natural disasters such as floods and river erosions. Hence, we estimated the negative association between SA to financial services and proximity, as one would expect.

Microfinance Participation and SA

Econometric specification. To respond to the query as to whether the degree of spatial access to microfinance can explain both the incidence and extent of microborrowing (or in other words, realized access), we estimate two different models. In dealing with the potential endogeneity problem in SA, as discussed briefly in Section 6, we make use of instruments in both cases.

To model the incidence of microborrowing, let y^*_{1i} represent the unobserved propensity of a household to borrow from an MFI (the so-called latent variable). Then the incidence of microcredit participation, denoted by y_{1i}, could be defined as

$$y_{1i} = \begin{cases} 1 & \text{if } y^*_{1i} > 0, \\ 0 & \text{if } y^*_{1i} \leq 0. \end{cases}$$

The OLS model that we would estimate had there been data on y^*_{1i} is given by

$$y^*_{1i} = \mathbf{z}'_{\mathbf{i}}\delta + u_i,$$

where $\mathbf{z_i} = (y_{2i}, \mathbf{x_{1i}})$; y_{2i} represents the standardized SA score for the ith household, $\mathbf{x_{1i}}$ is a vector of exogenous household-level controls (see Table 3 for a complete list), and δ denotes the vector of parameters corresponding to variables in $\mathbf{z_i}$. But as we discussed in Section 6, for consistent estimation, our setting requires the treatment of SA as an endogenous variable. We therefore model y_{2i} as

$$y_{2i} = \mathbf{x}'_{\mathbf{i}}\pi + v_i,$$

where $\mathbf{x_i} = (\mathbf{x_{1i}}, \mathbf{x_{2i}})$; $\mathbf{x_{2i}}$ represents the set of instruments and π denotes the vector of coefficients associated with $\mathbf{x_i}$. Since the joint density function, $f(y_{1i}, y_{2i}|\mathbf{x_i})$, can be written as $f(y_{1i}|y_{2i}, \mathbf{x_i})\, f(y_{2i}|\mathbf{x_i})$, the log-likelihood function, in the presence of a continuous endogenous variable (namely, y_{2i}), for observation i is given by

$$\ln L_i = y_{1i} \ln \Phi(m_i) + (1 - y_{1i}) \ln\{1 - \Phi(m_i)\} + \ln \text{Ø}\left(\frac{y_{2i} - \mathbf{x}'_{\mathbf{i}}\pi}{\sigma}\right) - \ln \sigma, \tag{1}$$

where

$$m_i = \frac{\mathbf{z}'_{\mathbf{i}}\delta + \rho\left(\frac{y_{2i} - \mathbf{x}'_{\mathbf{i}}\pi}{\sigma}\right)}{(1 - \rho^2)^{1/2}}.$$

Here, $\Phi(-)$and Ø$(-)$ are the standard normal cumulative and probability density functions, respectively; σ is the SD of v_i; ρ is the correlation coefficient between u_i and v_i. That there might be an endogeneity problem is tantamount to the possibility that $\rho \neq 0$. The model has been estimated by maximum likelihood estimation (MLE), and average marginal effects are computed to quantify and compare the partial impact of the variables of interest.

TABLE 3: Summary Statistics by Microfinance Participation Status

	Microcredit Participation Status						
	Non-borrower		*Borrower*		*All*		
Variables	Mean	SD	Mean	SD	Mean	SD	*Difference in Mean (Borrower − Non-borrower)*
Microcredit profile							
Participant	–	–	–	–	0.37	0.48	–
Number of MFI loans	0.00	0.00	1.14	0.37	0.42	0.59	–
Accessibility measure							
Spatial Accessibility index (constructed by means of Kernel Smoothing)	0.12	0.06	0.13	0.07	0.13	0.06	0.01^{***}
Household attributes							
Female household head	0.18	0.39	0.07	0.26	0.14	0.35	-0.11^{***}
Household size	3.98	1.67	4.50	1.46	4.18	1.61	0.52^{***}
Crisis	0.33	0.47	0.40	0.49	0.36	0.48	0.07^{***}
Land ownership	0.66	0.47	0.77	0.42	0.29	0.46	0.11^{***}
Instruments							
Distance (in km) from the							
Nearest river	2.64	2.14	3.15	2.23	2.83	2.19	0.51^{***}
Upazila HQ	5.81	3.16	5.87	3.04	5.83	3.12	0.06
District HQ	22.33	13.83	17.81	13.94	20.64	14.04	-4.52^{***}

Notes: $N = 1{,}917$. Observations pertaining to the participation-SA regression(s) are considered. Participant indicates whether the household took a loan from an MFI; Crisis is a dummy for the incidence of a shock faced by the household during the past year (2010); Land ownership is a dummy representing whether the household owns any land. Female household head is also a dummy variable reporting whether the household head is female.

$^{***}P < 0.01$

On the other hand, the extent of microborrowing can be proxied by the number of microloans taken, which is a discrete and nonnegative variable and therefore necessitates the use of count-data models. Following Mullahy (1997), the use of instruments in a Poisson regression framework has been implemented by means of a generalized method of moments (GMM) estimator as follows:

Let the conditional mean be specified as

$$E(y_i|\mathbf{x_i}, \omega_i) = e(\mathbf{x'_i}\theta, \omega_i).$$

The regression model with a multiplicative error is

$$y_i = e(\mathbf{x'_i}\theta + \omega_i) = e(\mathbf{x'}_i\theta)e(\omega_i) = e(\mathbf{x'_i}\theta)v_i,$$

where y_i is the number of MFI loans, $\mathbf{x_i}$ is a vector containing both endogenous (i.e., standardized SA score) and exogenous explanatory variables (i.e., the household controls), and ω_i is a stochastic disturbance potentially correlated with $\mathbf{x_i}$. The vector, θ, contains the semielasticities of covariates, $\mathbf{x_i}$. Endogeneity of at least one of the regressors would imply that $E(v_i \mid \mathbf{x_i}) \neq 1$. Given the "multiplicative-error" specification, for the sake of our empirical strategy, let us rewrite the model as

$$T(y_i, \mathbf{x_i}, \theta) - 1 = v_i - 1,$$

where $T(y_i, \mathbf{x_i}, \theta) = e(-\mathbf{x\prime_i}\theta)y_i$. Then given a set of instruments, $\mathbf{z_i}$, the relevant population moment condition would be

$$E(v_i - 1|\mathbf{z_i}) = 0. \tag{2}$$

The consistent estimation of θ could then be carried out by GMM using the corresponding sample moments.

An explanation regarding the choice of controls and instruments is due. The endogeneity problem arises from the possibility that given the MFIs' emphasis on poverty outreach (subject to financial sustainability, of course), the locations which are more likely to be chosen by these financial institutions would also be in a more disadvantageous position along both observed and unobserved dimensions. These attributes, more importantly, could have an independent and most probably negative impact on the likelihood of microcredit participation. In statistical terms, this is equivalent to saying that we would expect $\rho < 0$ and Corr $(\mathbf{x_i}, \omega_i) < 0$ in models 1 and 2, respectively. This, in turn, could lead to a downward bias in the estimated partial impact of SA on microborrowing. Under these circumstances, consistent estimation with the help of instruments would require finding a variable that would be correlated with SA but would not have a partial impact on microloan take-up (after controlling for SA). In other words, a valid instrument would only affect the dependent variable through its association with SA. In our context, we argue that "distance to the nearest river" can be such an instrument. Indeed, a household living in close proximity to a river would be more prone to natural shocks and, as a result, would be less likely to be a microborrower because of the higher risk associated with its portfolio. But this negative association is presumably working through the MFIs' decreased inclination to serve such a household due to its spatial disadvantage-induced higher potential credit risk, which is indeed supposed to be captured by the estimated SA score. Hence, SA appears to be the component linking microloan take-up and proximity to river along the causal chain. This and the fact that "distance to the nearest river" seems to be the most robust predictor of SA (as the OLS results in Section 6 have shown) have persuaded us to use it in our benchmark models. By the same token, however, the other "distance" variables, in particular, distance from the district and upazila HQ (which are, next to river-proximity, relatively strong predictors of SA),can serve the same purpose. Indeed, robustness analysis has been carried out using the whole set of potential instruments; the results remain more or less unaltered and hence have been reported in the Appendix (see Table A6).[13]

Apart from instruments, we have also included some variables representing the demographic and socioeconomic background of a household, which are potentially correlated with both its allocation of SA and microborrowing (but sufficiently predetermined so as not to induce any reverse causality problem), namely, household size and dummies indicating any incidence of crisis, land possession, and whether the household head is female. On the other hand, since MFIs would presumably condition their presence on unobserved regional attributes, we also include district and upazila fixed effects in some of the models to be assured of the robustness of the benchmark parameter estimates.[14]

[13]As for the overidentification test results, please see Table A6. The results indicate that once the upazila fixed effects are accounted for, we cannot reject the null of all instruments being exogenous at a sufficiently small level of significance. Hence, the evidence suggests that the instrument we have used to generate the core results, viz., "distance to the nearest river," satisfies the exclusionary restriction (after controlling for upazila heterogeneity). However, there is no definitive test for examining instrument validity. Moreover, the tests that are typically used to this end could yield misleading results should there be treatment effect heterogeneity (Angrist and Pischke, 2009).

[14]Our SA scores, however, are estimates and hence would entail measurement errors. But if the classical errors-in-variables assumptions were in effect, this would most probably bias our estimators toward zero (Thoresen and Laake, 2000; Hausman, 2001; Edgerton and Jochumzen, 2003; Cameron and Trivedi, 2005; Bateson and Wright, 2010). Hence, our estimators, in the worst-case scenario, would represent an underestimation of the true population parameters in absolute value (allowing us to estimate a lower

Summary statistics. Table 3 provides a summary description of the sampled households, differentiated by their microborrowing status, across a multitude of dimensions. Figures show that the microcredit take-up rate in our sample is 37 percent, and the (truncated) average number of loans is about 1. The borrowers seem to be better positioned in terms of spatial access to microfinancial services. Borrower households are typically larger and more prone to crises (incidence of crisis is 7 percentage points higher). The share of landless households is considerably lower (by around 11 percentage points) in the borrower subsample. Among the nonparticipants, about 18 percent of the households are female-headed, whereas the figure is only 7 percent among the participants. Moreover, as expected, the microborrowers, on average, are closer to the district HQ as well as more distant from the nearest river compared to the nonborrowers. The overall picture that emerges therefore suggests that a typical microborrower household, despite being observed to be more likely to experience an exogenous shock, is wealthier and enjoys spatial proximity to district HQ, detachment from the river network, and (therefore) enhanced access to microfinancial services.

To further motivate the regression analysis, Figure 3 plots the participation rate and average number of loans, both unconditional and conditional (on participation), against the quartiles of SA. Both the loan take-up rate and (unconditional) average number of loans exhibit a clear upward trend with increasing SA. The participation rate differential between the two end quartiles is more than 11 percentage points—quite a substantial difference. As expected, the truncated average number of loans schedule is flatter than the one without truncation but is still suggestive of a positive relationship with spatial access. This figure then lends some support to the hypothesis that the estimated SA index can explain the variations in microcredit participation. For the sake of a more precise and statistically valid estimation of these relationships, we now resort to the regression results.

MFI loan take-up and SA: probit results. Table 4 reports the MLE estimates of average marginal effects from the probit model specified in Equation (1). For all the models, the key variable of interest is standardized SA. Additional household controls have been incorporated in columns (3)–(6). Moreover, columns (5) and (6) include district and upazila fixed effects, respectively. Apart from columns (1) and (3), all other specifications entail the use of "distance from the nearest river" as an instrument for SA.

For all specifications, we find a significant (average) marginal impact of SA on the likelihood of microloan take-up (at the 1 percent level of significance, except the last case). Importantly, treating SA's endogeneity by means of instrument leads to a substantial upward revision in the parameter estimate, thereby lending support to the hypothesized direction of bias earlier (see Section 6). The first-stage results, moreover, suggest that our instrument is indeed a strong predictor of spatial access in both practical and statistical terms. The marginal effect estimate from the benchmark model including neither instrument nor other controls is more than doubled in response to the inclusion of instruments (a change from 0.045 to 0.092). Such upward revision is observed in the presence of household controls too (0.074 compared to 0.041). Though the IV estimate becomes somewhat smaller (and marginally significant) upon including district and upazila fixed effects, a one SD increase in SA, *ceteris paribus*, increases a household's microcredit participation probability by at least 3.5 percentage points. Using exogeneity tests, we found very weak

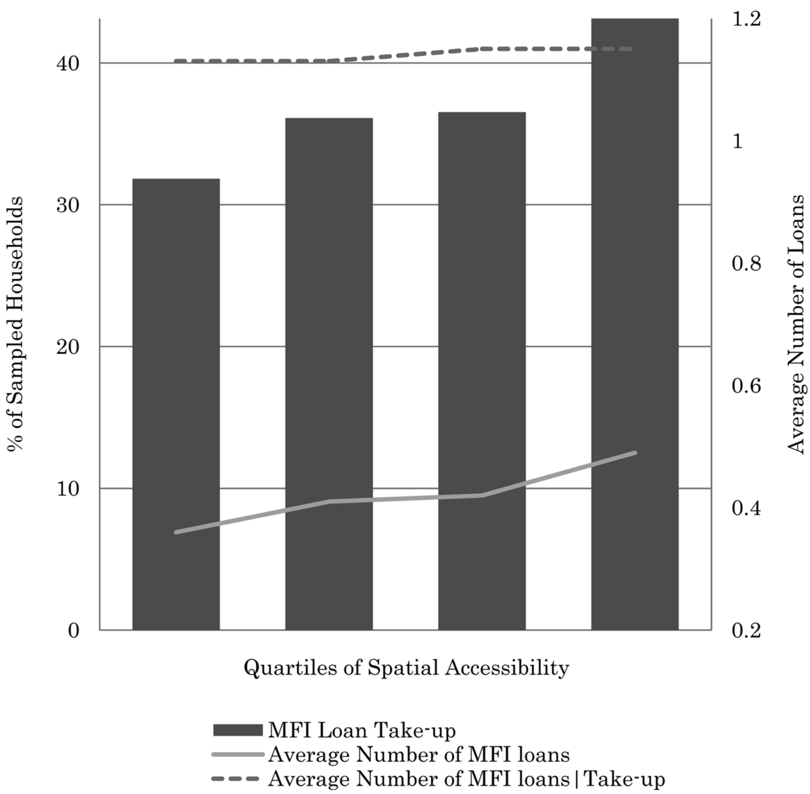
bound). Also, to make our case more cogent, inspired by the discussion in Angrist and Pischke (2009), we have estimated OLS (and 2SLS) models (with heteroskedasticity-robust standard errors to take care of the potential heteroskedasticity) for both incidence and extent of microborrowing. Interestingly, the estimated marginal effects are not sensitive to the choice of models. Please see Tables A4 and A5.

TABLE 4: MFI Loan Take-Up and Spatial Accessibility (Probit)

	MFI Loan Take-Up					
	Average Marginal Effect (95 percent CI)					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Standardized value of SA	0.045***	0.092***	0.041***	0.074***	0.065***	0.035*
	(0.024–0.066)	(0.060–0.125)	(0.020–0.063)	(0.040–0.109)	(0.030–0.100)	(−0.003 to 0.074)
Instrumented by *distance from the nearest river (standardized)*	No	Yes	No	Yes	Yes	Yes
First stage coefficient of the instrument		0.578***		0.577***	0.624***	0.617***
		(0.542–0.614)		(0.540–0.614)	(0.585–0.663)	(0.580–0.655)
Household controls	No	No	Yes	Yes	Yes	Yes
Fixed effects	No	No	No	No	District	Upazila
N	1,959	1,959	1,917	1,917	1,917	1,917
Log-likelihood	−1281	−3655	−1213	−3516	−3490	−3209
Wald exogeneity test χ^2 statistic	–	11.14***	–	4.93**	2.87*	2.79*

Notes: Each observation represents a randomly chosen ultra-poor household. Fifteen household locations (only 0.76 percent of all) could not be used due to technical errors made in GIS data collection. Across all the models, the dependent variable is a dummy representing whether the household took any loan from an MFI. All regressions are Probit. Average marginal effect is the derivative of response probability with respect to an explanatory variable, calculated from the fitted model and averaged across all the sample observations. Both "specification link test" and "likelihood-ratio test of heteroskedasticity" yielded no evidence of specification errors. Hence, 95 percent CI based on ordinary standard errors are reported in parentheses. Estimates for intercept and household controls are not reported to economize space. Please see Table A2 for the full set of results. Household controls include household size and dummies indicating any incidence of crisis, land possession, and whether the household head is female. The null hypothesis associated with the Wald exogeneity test is $\rho = 0$.

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.



Note: The quartiles of SA are 0.085, 0.114, and 0.152.

FIGURE 3: Spatial Accessibility and Microfinance Participation.

evidence of overall endogeneity in our models, especially if we account for regional fixed effects (columns (5)–(6), Tables 4 and 5). This supports sufficiency of using probit models for valid identification after controlling for regional heterogeneity (as we claimed in Section 6).

Number of MFI loans and SA: Poisson results. Table 5 gives the semielasticity estimates from the Poisson model delineated in Equation (2). The different specifications used are in the same order as above. The findings are also very consistent with those from the probit model. As before, the use of instruments appears to correct for the downward bias in the parameter estimate from models treating SA as exogenous. The increase in the expected number of MFI loans can be as high as 42 percent ($[e(0.351) - 1]^{*}100$) in response to a one SD rise in SA (and is always significant at the 5 percent level). Accounting for other household controls and district/upazila fixed effects, however, leads to a decline in the estimated impact, but it does not fall below 16 percent.[15]

To recapitulate, there is strong evidence that spatial access, as measured by the estimated SA index, can explain both the incidence and magnitude of microborrowing

[15]Furthermore, models where we used an "additive error" formulation yielded, in principle, the same results.

TABLE 5: Number of MFI Loans and Spatial Accessibility (Poisson)

	Number of MFI Loans					
	Coefficient (Robust 95 percent CI)					
Variables	(1) MLE	(2) GMM	(3) MLE	(4) GMM	(5) GMM	(6) GMM
Standardized value of SA	0.121^{***} (0.064–0.179)	0.351^{***} (0.193–0.509)	0.112^{***} (0.055–0.168)	0.267^{***} (0.109–0.425)	0.207^{***} (0.069–0.346)	0.150^{**} (0.008–0.292)
Instrumented by *distance from the nearest river (standardized)*	No	Yes	No	Yes	Yes	Yes
Household controls	No	No	Yes	Yes	Yes	Yes
Fixed effects	No	No	No	No	District	Upazila
N	1,959	1,959	1,917	1,917	1,917	1,917
Wald exogeneity test χ^2 statistic		9.32^{***}		4.09^{**}	2.42	2.16

Notes: Each observation represents a randomly chosen ultra-poor household. Fifteen household locations (only 0.76 percent of all) could not be used due to technical errors made in GIS data collection. Across all the models, the dependent variable is the number of loans the household took from an MFI. All regressions are Poisson. Ninety-five percent CI based on robust standard errors are reported in parentheses. Estimates for intercept and household controls are not reported to economize space. Please see Table A3 for the full set of results. Household controls include household size and dummies indicating any incidence of crisis, land possession, and whether the household head is female. The null hypothesis associated with the Wald exogeneity test is that SA is exogenous.

$^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

fairly well. Accounting for potential endogeneity in spatial access by means of instrument(s) further strengthens the case. By incorporating the geographical distribution of all relevant MFI branches, our estimate of potential spatial access turns out to be an effective predictor of realized access.

7. DISCUSSION

In this study, we make a case to incorporate spatial distribution of microfinance programs in the backdrop of overall concern around the issue of access to financial services for the underprivileged and economically depressed households in Bangladesh. Microfinance programs face the twin goals of reaching out to hard-to-reach poor households with borrowing constraints while remaining financially viable. The two objectives can become incompatible if MFIs are compelled to work in areas that are spatially remote (such as *chars*). So one can expect that spatial distribution of MFI activities will show a pattern that will correlate with the geospatial characteristics of a location. This paper makes a novel attempt to carry out a sophisticated analysis incorporating specific location attributes using GIS and to the best of our knowledge, this study is the first of its kind to address this issue.

We have found that underlying geospatial characteristics such as distance from roads, rivers, and local administrative units can play a role in defining the spatial distribution of microfinance access. While we focused on only two districts of Bangladesh (mainly because of availability of data), we believe the findings have external validity with respect to many areas of Bangladesh due to topographical and infrastructural similarities. Geographic access is also an issue in many developing countries, especially in places such as Africa, South Asia, and Latin America. Hence, we believe our results may be broadly applicable to many other places and countries.

Our findings suggest that access to microfinance products (as measured with respect to the physical location of MFI branches) shows clear geographical variations. Therefore, depending on the location of the household, access to financial services will also vary at the household level. While the overall abilities and socioeconomic characteristics of a household play important roles in it, just being at a location that is isolated for various other reasons (such as rivers and roads) may hinder a household's participation in the financial services offered by the microfinance industry. Indeed, our findings indicate that spatial access to microfinance has a significant bearing on household borrowing from microfinance organizations. If we allow the fact that such borrowing is directly related to consumption smoothing and possibly growth, spatial distance and isolation can play further detrimental roles in a household's poverty situation and destitute.

The cost of running a program at an isolated location can be high, and because of the demand for smaller sized loans by households living in the more remote areas, the revenue earning is likely to be low. Therefore, households living in these areas are more likely to be new borrowers, and it may be important for subsidies to play a role to further the outreach of the industry. Hence, spatial access maps can help the policymakers identify geographic pockets where the financial access is typically low. Moreover, our multivariate analysis can suggest what factors are associated with the variation in SA.

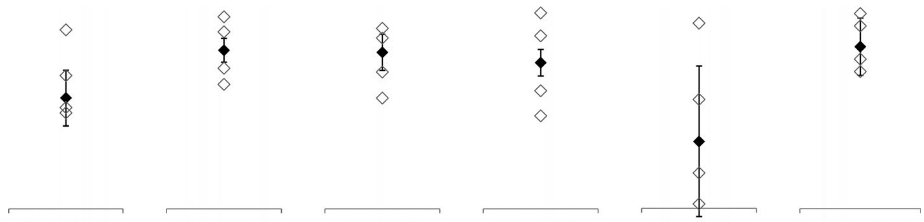
Methodologically, simple regression results showing a relationship between the household's decision to borrow and the spatial access to finance may be spurious due to endogeneity and biased because of omitting variables that may be correlated with SA. Microfinance providers target poor households that may have lower propensity or capacity to borrow from the MFIs (Salim, 2013). Hence, the simple regression estimates relating spatial access and household borrowing decisions are likely to be biased downward. We make use of instrument(s) to correct the potential bias in the estimated coefficient for the spatial access variable. As expected, we find that simple estimates were indeed biased downward and we consistently get a higher coefficient from the IV models.

Our analysis of the SA of microfinance, however, can be questioned and criticized on multiple grounds. First, we need to admit that the SA index constructed is rather "absolute" in the sense that more informative index would need to be normalized by population. We did not have access to information on the geographical distribution of potential clients for our study area and therefore worked exclusively on the supply side. The supply side information was also inadequate due to lack of data on MFI capacity. Moreover, since KDE disperses a branch's spatial influence over a continuous circular space irrespective of the topographical pattern of that vicinity, it therefore increases the likelihood of service supply being lost to areas that are not "servable" in the sense that they may not be inhabitable and/or marked by zero population density (Yang et al., 2006). Despite often being considered as a merit, KDE's insensitiveness to geopolitical or administrative boundaries can also contribute to such loss of provision capacity in the presence of geographical constraints (e.g., rivers and lakes) which can remarkably limit resource mobilization. Finally, questions can be raised as to whether a Gaussian curve can properly model the distribution of a branch's supply capacity over its service area.

8. CONCLUDING REMARKS

The concept of SA, although widely appreciated and applied in other branches of research (such as health care and crime), is relatively new in the context of microfinance. Capitalizing on their contributions and investigations, we approached the issue of access to microfinance from a geographical perspective. We believe this exercise may pave the way for using GIS analysis in the context of competition and other issues. With the aid of GIS data, as shown here, relevant spatial attributes can be easily extracted, represented, and utilized. We confined ourselves mainly to the construction and graphical representation of SA (in Kurigram and Lalmonirhat), identification of its spatial determinants, and evaluation of its explanatory power for household borrowing behavior. Future research endeavors along this line should aim to collect more data (from both demand and supply side) to overcome the inadequacy of our estimation strategy. Moreover, since spatial segregation of potential clients and MFI establishments may act as a significant barrier to the realization of efficient transactions, empirical studies can indeed be undertaken to verify the existence of market failure via moral hazard and/or adverse selection. It would also be very intriguing if, by taking advantage of GIS, the major spatial factors that an MFI takes into consideration for making an optimal location choice could be identified.

APPENDIX



Notes: The dark-shaded diamonds denote the parameter estimates associated with a bandwidth choice of 10 km (from the SA-geoattributes regression, namely, Model 1, Table 2). The error bars, on the other hand, represent the confidence intervals for these estimates. Other diamonds represent estimates corresponding to bandwidths of 8, 9, 11, and 12 km.

FIGURE A1: Regression Coefficients for Different Bandwidths.

TABLE A1: Collinearity Diagnostic Measures

Variables	Variance Inflating Factor (VIF)	Tolerance Factor	R^2
Distance (in km) from the			
Nearest river	1.11	0.90	0.10
Nearest road	1.40	0.72	0.28
District HQ	1.23	0.81	0.19
Upazila HQ	1.38	0.72	0.28
Union HQ	1.07	0.93	0.07
Population density	1.55	0.65	0.35
Mean VIF	**1.29**		
Condition index	**20.70**		

TABLE A2: MFI Loan Take-Up and Spatial Accessibility (Probit)—Comprehensive Results

	MFI Loan Take-Up					
	Average Marginal Effect (95 percent CI)					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Standardized value of SA	0.045***	0.092***	0.041***	0.074***	0.065***	0.035*
	(0.024–0.066)	(0.060–0.125)	(0.020–0.063)	(0.040–0.109)	(0.030–0.100)	(–0.003 to 0.074)
Female household-head			–0.165***	–0.165***	–0.166***	–0.162***
			(–0.235 to –0.096)	(–0.234 to –0.097)	(–0.234 to –0.097)	(–0.228 to –0.095)
Household size			0.033***	0.033***	0.032***	0.033***
			(0.019–0.047)	(0.019–0.047)	(0.018–0.046)	(0.019–0.046)
Land ownership			0.089***	0.083***	0.082***	0.054**
			(–0.137 to –0.042)	(–0.130 to –0.036)	(–0.129 to –0.034)	(–0.101 to –0.006)
Incidence of crisis			0.047**	0.043*	0.038*	0.014
			(0.003–0.090)	(–0.000 to 0.086)	(–0.005 to 0.082)	(–0.033 to 0.060)
Instrumented by *distance from the nearest river (standardized)*	No	Yes	No	Yes	Yes	Yes
Household controls	No	No	Yes	Yes	Yes	Yes
Fixed effects	No	No	No	No	District	Upazila
N	1,959	1,959	1,917	1,917	1,917	1,917
Log-likelihood	–1281	–3655	–1213	–3516	–3490	–3209
Wald exogeneity test χ^2 statistic	–	11.14***	–	4.93**	2.87*	2.79*

Notes: Each observation represents a randomly chosen ultra-poor household. Fifteen household locations (only 0.76 percent of all) could not be used due to technical errors made in GIS data collection. Across all the models, the dependent variable is a dummy representing whether the household took any loan from an MFI. All regressions are Probit. Average marginal effect is the derivative of response probability with respect to an explanatory variable, calculated from the fitted model and averaged across all the sample observations. Both "specification link test" and "likelihood-ratio test of heteroskedasticity" yielded no evidence of specification errors. Hence, 95 percent CI based on ordinary standard errors are reported in parentheses. Estimates for intercept and fixed effects are not reported to economize space. The null hypothesis associated with the Wald exogeneity test is $\rho = 0$.

***$P < 0.01$, ** $P < 0.05$, * $P < 0.1$.

TABLE A3: Number of MFI Loans and Spatial Accessibility (Poisson)—Comprehensive Results

	Number of MFI Loans					
	Coefficient (Robust 95 percent CI)					
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	MLE	GMM	MLE	GMM	GMM	GMM
Standardized value of SA	0.121^{***}	0.351^{***}	0.112^{***}	0.267^{***}	0.207^{***}	0.150^{**}
	(0.064–0.179)	(0.193–0.509)	(0.055–0.168)	(0.109–0.425)	(0.069–0.346)	(0.008–0.292)
Female household-head			-0.572^{***}	-0.635^{***}	-0.624^{***}	-0.558^{***}
			(−0.835 to −0.310)	(−0.916 to −0.355)	(−0.898 to −0.349)	(−0.848 to −0.269)
Household size			0.108^{***}	0.140^{***}	0.139^{***}	0.149^{***}
			(0.069–0.147)	(0.087–0.193)	(0.086–0.191)	(0.093–0.204)
Land ownership			0.318^{***}	0.342^{***}	0.335^{***}	0.180^{*}
			(−0.469 to −0.168)	(−0.511 to −0.173)	(−0.501 to −0.169)	(−0.364 to 0.005)
Incidence of crisis			0.085	0.117	0.088	0.002
			(−0.039 to 0.209)	(−0.025 to 0.259)	(−0.056 to 0.232)	(−0.160 to 0.165)
Instrumented by *distance from the nearest river (standardized)*	No	Yes	No	Yes	Yes	Yes
Household controls	No	No	Yes	Yes	Yes	Yes
Fixed effects	No	No	No	No	District	Upazila
N	1,959	1,959	1,917	1,917	1,917	1,917
Wald exogeneity test χ^2 statistic		9.32^{***}		4.09^{**}	2.42	2.16

Notes: Each observation represents a randomly chosen ultra-poor household. Fifteen household locations (only 0.76 percent of all) could not be used due to technical errors made in GIS data collection. Across all the models, the dependent variable is the number of loans the household took from an MFI. All regressions are Poisson. Ninety-five percent CI based on robust standard errors are reported in parentheses. Estimates for intercept and fixed effects are not reported to economize space. The null hypothesis associated with the Wald exogeneity test is that SA is exogenous.

$^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

TABLE A4: MFI Loan Take-Up and Spatial Accessibility (LPM)—Comprehensive Results

	MFI Loan Take-Up					
	Marginal Effect (95 percent Robust CI)					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Standardized value of SA	0.045***	0.097***	0.042***	0.078***	0.068***	0.035*
	(0.024–0.067)	(0.059–0.134)	(0.021–0.064)	(0.040–0.116)	(0.031–0.105)	(–0.005 to 0.075)
Female household head			–0.142***	–0.146***	–0.145***	–0.145***
			(–0.200 to –0.083)	(–0.205 to –0.087)	(–0.204 to –0.086)	(–0.204 to –0.085)
Household size			0.032***	0.033***	0.032***	0.033***
			(0.018–0.046)	(0.019–0.047)	(0.018–0.046)	(0.018–0.047)
Land ownership			–0.086***	–0.081***	–0.079***	–0.053**
			(–0.132 to –0.041)	(–0.127 to –0.035)	(–0.125 to –0.033)	(–0.100 to –0.006)
Incidence of crisis			0.046**	0.043*	0.038	0.011
			(0.001–0.091)	(–0.002 to 0.088)	(–0.007 to 0.084)	(–0.037 to 0.060)
Instrumented by *distance from the nearest river (standardized)*	No	Yes	No	Yes	Yes	Yes
Fixed effects	No	No	No	No	District	Upazila
N	1,959	1,959	1,917	1,917	1,917	1,917
Adjusted R^2	0.008	–	0.050	0.044	0.048	0.100
Wald exogeneity test χ^2 statistic	–	10.28***	–	4.90**	3.01*	2.73*

Notes: Each observation represents a randomly chosen ultra-poor household. Fifteen household locations (only 0.76 percent of all) could not be used due to technical errors made in GIS data collection. Across all the models, the dependent variable is a dummy representing whether the household took any loan from an MFI. All regressions are LPM (Linear Probability Model). Ninety-five percent CI based on robust standard errors are reported in parentheses. Estimates for intercept and fixed effects are not reported to economize space. The null hypothesis associated with the Wald exogeneity test is that SA is exogenous.

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

TABLE A5: Number of MFI Loans and Spatial Accessibility (OLS)—Comprehensive Results

	Number of MFI Loans					
	Marginal Effect (95 percent Robust CI)					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Standardized value of SA	0.053***	0.117***	0.051***	0.099***	0.085***	0.042*
	(0.027–0.079)	(0.071–0.164)	(0.025–0.077)	(0.052–0.145)	(0.040–0.130)	(–0.005 to 0.090)
Female household head			–0.151***	–0.157***	–0.156***	–0.156***
			(–0.218 to –0.085)	(–0.224 to –0.090)	(–0.223 to –0.089)	(–0.224 to –0.088)
Household size			0.049***	0.050***	0.049***	0.049***
			(0.030–0.068)	(0.031–0.069)	(0.030–0.067)	(0.030–0.068)
Land ownership			–0.119***	–0.112***	–0.110***	–0.079***
			(–0.172 to –0.067)	(–0.165 to –0.059)	(–0.163 to –0.056)	(–0.132 to –0.025)
Incidence of crisis			0.036	0.032	0.026	–0.018
			(–0.018 to 0.091)	(–0.022 to 0.087)	(–0.029 to 0.081)	(–0.077 to 0.042)
Instrumented by *distance from the nearest river (standardized)*	No	Yes	No	Yes	Yes	Yes
Fixed effects	No	No	No	No	District	Upazila
N	1,959	1,959	1,917	1,917	1,917	1,917
Adjusted R^2	0.007	–	0.054	0.048	0.052	0.103
Wald exogeneity test χ^2 statistic	–	10.34***	–	5.37**	3.35*	2.71

Notes: Each observation represents a randomly chosen ultra-poor household. Fifteen household locations (only 0.76 percent of all) could not be used due to technical errors made in GIS data collection. Across all the models, the dependent variable is the number of loans the household took from an MFI. All regressions are OLS. Ninety-five percent CI based on robust standard errors are reported in parentheses. Estimates for intercept and fixed effects are not reported to economize space. The null hypothesis associated with the Wald exogeneity test is that SA is exogenous.

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

TABLE A6: Incidence and Extent of Microborrowing and Spatial Accessibility (Multiple Instruments)

	Probit		Poisson		LPM		OLS	
	MFI Loan Take-Up		Number of MFI Loans		MFI Loan Take-Up		Number of MFI Loans	
	Average Marginal Effect (95 percent CI)		Coefficient (Robust 95 percent CI)		Coefficient (Robust 95 percent CI)		Coefficient (Robust 95 percent CI)	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Standardized value of SA	0.091^{***} (0.065–0.118)	0.052^{***} (0.023–0.080)	0.332^{***} (0.211–0.452)	0.232^{***} (0.117–0.348)	0.094^{***} (0.065–0.123)	0.051^{***} (0.022–0.081)	0.113^{***} (0.077 – 0.150)	0.064^{***} (0.028 – 0.100)
Instrumented by *distances from the nearest river, district, and upazila headquarter (all standardized)*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	District	Upazila	District	Upazila	District	Upazila	District	Upazila
Overidentification test statistic	24.08^{***}	3.24	15.74^{***}	6.12^{**}	23.31^{***}	2.83	16.17^{***}	2.59

Notes: $N = 1{,}917$. All models use distances from the nearest river, district, and upazila headquarter (all standardized) as instruments. Each observation represents a randomly chosen ultra-poor household. Fifteen household locations (only 0.76 percent of all) could not be used due to technical errors made in GIS data collection. Household controls are included in all the cases. Household controls include household size and dummies indicating any incidence of crisis, land possession, and whether the household head is female. Estimates for intercept, household controls, and fixed effects are not reported to economize space. As for overidentification test statistics, we've used Amemiya–Lee–Newey's statistic for probit and Hansen's J-statistic for all other models.

$^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

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