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Distributional inequality in market-based solar home system programs: Evidence from rural Bangladesh

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ABSTRACT

This paper investigates the effect of borrowing constraints on the pricing of solar home system loans for rural households. We use a unique cross-sectional dataset that includes a sample of 626,761 borrowers' loan transactions over six years (2013–2018) from the market-based solar home system program in Bangladesh. We estimate that a 10 percent increase in down payment, which we use as a proxy measure for borrowing constraints, reduces the average total cost of the loan by 0.181 percentage points. We also find that highly constrained borrowers pay more than relatively unconstrained borrowers, with average total costs of loans reduced by 0.102 and 0.343 percentage points, respectively, for every 10 percent increase in down payments. The borrowing constraint seems to generate distributional inequality in the pro-poor solar home system program, increasing the financial cost of market participation for these highly constrained borrowers. Constrained borrowers in poor rural areas therefore pay a poverty penalty. We recommend that governments, policymakers, and development donors deploy targeted intervention mechanisms that continue and update financial support for both lenders and borrowers in order to eradicate persistent energy poverty in developing countries.

1. Introduction

The majority of the 789 million people without electricity in developing South Asia and Sub-Saharan Africa live in rural villages that are too remote to connect to national electricity grids (Lee et al., 2016; UN, 2020). These poor rural households in electricity access deficit countries are particularly affected by vulnerabilities arising from energy poverty. Furthermore, their energy poverty is considered to be a violation of distributive justice (Sovacool et al., 2016). National governments and policymakers thus support off-grid renewable energy sources as a short-to-medium term solution to alleviating energy poverty (Yadav et al., 2019; Sievert and Steinbuks, 2020). In association with local private organizations and international donors, they have been implementing market-based programs,[1] such as Lighting Africa and Lightening Asia, to promote solar home systems that produce electricity at the point of household consumption (Lee et al., 2016; Conway et al., 2019; Turner, 2019).

Despite record sales of 30 million solar home systems since 2010, which indicates a noticeable improvement in energy affordability, market-based programs remain controversial due to the emerging inequalities in the distribution of electricity access (Samarakoon, 2019; Rysankova et al., 2020). Laufer and Schäfer (2011), for instance, find that poor Sri Lankan households cannot afford expensive solar home systems even in the presence of microloans, and that they also lack financial resources for regular operation and maintenance services. Mainali and Silveira (2012) report that poor households in Nepal, owing to limited access to credit, cannot afford solar home systems, leading to uneven penetration of renewable energy across the rural population. Similarly, Palit (2013) states that the lowest strata of the rural society in Bangladesh find it challenging to purchase solar home

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[1] A market-based program, also known as the multi-stakeholder programmatic model, involves local suppliers and/or financial institutions that sell and install solar home systems for households (Nygaard, 2009; Steel et al., 2016). Such programs include consumer financing models, such as the weekly repayment-based pay-as-you-go model, or the monthly repayment-based microcredit model, that allow households to pay for solar home systems in periodic installments. Financing schemes also provide a capital buy-down subsidy or an interest rate subsidy to make solar home systems affordable for rural households.

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systems using the currently available credit-based financing schemes. Based on empirical evidence in Rwanda's rural villages, Grimm et al. (2020) report that poor households are not in a position to pay more than 55 percent of the market price of off-grid solar devices (up to 20 watts). Barry and Creti (2020) also conclude that while wealthy rural households in electrified areas of Benin can afford to pay weekly installment loans, the households in the non-electrified areas, i.e., those most in need of electricity access, cannot. These studies suggest that it is relatively difficult to reach out to the remaining non-electrified population through a pure market-based program.

Those off-grid credit markets that lack adequate information about borrowers' payment characteristics provide access to collateral-free solar home system loans. Like other asset-financing products (Bester and Hellwig, 1987; Acolin et al., 2016), these loans involve down payment requirements for which borrowers cannot borrow the entire amount required to purchase a solar home system even if they are willing to pay higher interest rates. Given inherent lending risks, lenders set the cost of credit based on the size of the down payment because this signals borrowers' creditworthiness and commitment to loan repayment (Giné and Karlan, 2014; Baurzhan and Jenkins, 2016; Stacy et al., 2018). Down payment is considered a well-defined borrowing constraint in electricity access, particularly for those borrowers who lack wealth to meet down payment requirements (Wong, 2012; Palit, 2013; Conway et al., 2019).[2] Borrowers who are limited to small down payments need extended maturity periods and pay higher annual interest rates, including service charge percentages (Miller, 2011; Baurzhan and Jenkins, 2016; Khan et al., 2019). This raises the total sum required for repayment and makes a solar home system loan even more costly for poor households. Consequently, the highly constrained borrowers pay a poverty penalty for their participation in the solar home system market because the cost of loan is not equitably distributed (Mendoza, 2011; Hudon and Ashta, 2013; Samarakoon, 2019). Such heterogeneity is an important consideration in consumer financing (Karlan and Zinman, 2008).

Assuming that access to affordable credit may be considered a legitimate and justice-based claim for poor rural borrowers (Hudon and Sandberg, 2013), then the fairest distributional pattern is one that maximizes the welfare of the worst-off borrowers, as stressed in Rawls' 'Difference Principle' (Van Wee and Geurs, 2011; Sandberg, 2012; Pereira et al., 2017). That is, inequalities in solar home system loan pricing are acceptable as long as such inequalities require that worst-off households pay a lower total cost for their loans than better-off households. Following Morduch (1999), McIntosh and Wydick (2005), and Khandker et al. (2013), it can be argued that lenders in a commercial solar home system market are expected to cross-subsidize the total cost of loans for the worst-off households by drawing on the profits generated by loans to better-off households. However, this is not universally supported; some in development policy circles look askance at cross-subsidization and believe that poor rural borrowers simply need to be provided with access to credit, not necessarily to cheap credit, and that borrowers are quite willing to compensate lenders for the true cost of lending (Dehejia et al., 2012; Sherratt, 2016). In this view, there is nothing inappropriate about the poorest borrowers paying the highest prices for loans.

In this paper, we look at a market-based solar home system program implemented by different lenders and address whether its microcredit model distributes the financial cost of loans equitably across individual rural borrowers, some of whom face borrowing constraints. In particular, we provide empirical evidence for the causal effect of down payments, as a proxy for the borrowing constraint, on the total cost of loans for solar home systems for individual borrowers within each lender over time. We further investigate which specific group of borrowers is more affected by the imposition of a down payment. As a case study, we consider the solar home system program in Bangladesh, one of the key electricity access deficit countries. This provides an example of market-based credit access used to scale up off-grid electrification (IEA et al., 2020). The Bangladeshi program provides microcredit-based consumer loans to support rural borrowers through partner organizations,[3] and has already installed over four million solar home systems in rural off-grid areas.[4]

We use a unique cross-sectional dataset with a sample of 626,761 borrowers, recording every single credit sale of 49 lenders or partner organizations across different administrative areas from 2013 to 2018. We use an instrumental variable estimator with spatial and temporal fixed effects to address potential endogeneity concerns that might bias the estimated causal effect of down payments upward. Additionally, we use the Lewbel's (2012) heteroskedasticity-based instrument as a robustness check to ensure that our results are robust to endogeneity concerns. We also use Oster's bound analysis to deal with potential bias from omitted unobserved factors (Oster, 2019). As a proxy measure of the borrowing constraint, we find a 10 percent increase in down payment reduces the average total cost of the loan by 0.181 percentage points. We find highly constrained borrowers are strongly affected – for every 10 percent increase in down payments, the average total cost for their loans is reduced by only 0.102 percentage points. In contrast, at the same level of increasing down payments, the average total cost of loans for relatively unconstrained borrowers is reduced by 0.343 percentage points.

This paper contributes to an emerging literature (e.g. Samarakoon, 2019; Aklin et al., 2020; Barry and Creti, 2020; Pelz et al., 2020; Sievert and Steinbuks, 2020) on off-grid electricity access in developing countries that integrates evidence-based findings on financing constraints and energy justice perspectives. Recent empirical studies (e.g., Acheampong et al., 2021) investigate the impact of energy access on human development using the macro-level data in energy-poor countries. There are also a few studies dealing with microcredit-based loan data (e.g., Karlan and Zinman, 2008; Dehejia et al., 2012), but none of these studies explain how borrowing constraints or wealth effects introduce price dispersion or impede energy accessibility. To our knowledge, we are the first to use a novel loan transaction dataset to estimate the impacts of lender-imposed borrowing constraints on market-based loan pricing for off-grid solar electrification.

Our study provides an important evidence-based policy insight on distributive equity in pricing market-based solar home system loans. In line with Barry and Creti (2020) and Grimm et al. (2020), we argue that constrained borrowers inevitably pay a poverty penalty in getting solar home system based electricity access through a market-based program even though, such a program is intended to support these borrowers. The need for risk reduction and long-term financial viability seems to overturn the intended pro-poor policies and impair electricity access for the least well off. We recommend that a hybrid policy instrument, including both lender subsidies and borrower subsidies, be formulated to scale up off-grid electrification further.

[2] The mortgage market literature (e.g., Rosenthal, 2002; Barakova et al., 2003, 2014) highlights three types of financing or borrowing constraints: a wealth constraint (loan-to-market value ratio), an income constraint (monthly payment-to-income ratio), and credit quality (credit scoring based on the collateral value of homes). We connect our solar electrification study with the wealth constraint, which implies borrowers must have the ability to pay a certain percentage at the time of purchase. In this paper, we use down payment requirements as a proxy for borrowing constraints.

[3] In this paper, we use the terms lenders, suppliers, microcredit institutions, and partner organizations interchangeably. The term household refers to borrowers or customers who sign the loan agreement for purchasing solar home systems. We use the terms borrowers, customers, and households interchangeably.

[4] The majority of the installations account for solar home systems with a capacity of 30–60 watts and provide a wide range of energy services, including lighting, mobile charging, mass communication, and air conditioning.

Policymakers should provide financial support, such as low-cost commercial funds, supply distribution expansion grants, long-term maintenance service contracts, etc., so that lenders can maintain commercial viability. This will ultimately reduce the cost of financing solar home system loans for highly borrowing-constrained households. The elimination of loan pricing inequalities is half of the solution. The governments should allocate more subsidies to increase the purchasing power of highly constrained borrowers through energy allowance schemes or vouchers for energy loan relief payment. The lenders can also design an innovative loan mechanism, such as an '80-20 loan', as a down payment assistance program.[5] All these targeted intervention mechanisms will enable millions of rural people in the 'last mile' to escape the energy poverty trap.

The paper is structured as follows: Section 2 summarizes the microcredit lending model for solar energy with a brief introduction to Bangladesh's market-based solar home system program. Section 3 describes the data, and the empirical strategy is outlined in Section 4. Section 5 includes the main results, discussion, and robustness exercises. Section 6 presents our final conclusions.

2. Microcredit framework and pricing of solar home system loans

Market-based solar home system programs include consumer financing models that enable poor rural households to purchase asset-based products like solar home systems, while providing necessary operational service to maintain those systems. This energy financing model is primarily adapted from the microcredit framework.[6] However, what appears to be theoretically appropriate loans often become expensive for poor rural borrowers (Glemarec, 2012).

The microcredit for solar home systems incorporates a down payment requirement designed to cover installation cost, depreciation, and de-installation cost in the case of payment failure (Moner-Girona et al., 2016). Such a down payment is intended to provide a shield to lenders against default risk and adverse selection and to increase the 'sense of ownership' among borrowers. The cost of a loan for a solar home system generally includes both interest expenses and service charges in the form of an annual interest rate for a given loan maturity. Interest rate is often set at a relatively high rate in order to overcome the cost barriers associated with serving poor rural borrowers (Dehejia et al., 2012; Morduch and Ogden, 2019). The assumption is that poor rural borrowers are bankable, that is, they can pay for electricity access if the loan pricing is appropriate such that it does not affect their consumption of other necessities (Cull et al., 2009; Karlan and Morduch, 2010; Wong, 2012). They seem to be 'price inelastic' due to the limited availability of credit (Karlan and Zinman, 2008; Sherratt, 2016; Khan et al., 2017), particularly to escape energy poverty.

The energy microcredit model is of two types: a 'one-hand model,' such as in Bangladesh, involves local suppliers who are solely responsible for providing loans, installations, and maintenance services and a 'two-hand model,' such as in Sri Lanka, in which financial institutions offer loans to customers and local suppliers install and maintain solar home systems (Moner-Girona et al., 2016).

2.1. Bangladesh Solar home system program

As a part of the 'Rural Electrification and Renewable Energy Development Project,' the solar home system program in Bangladesh was implemented by a state-owned financial intermediary company, IDCOL.[7] IDCOL appoints partner organizations that are local microfinance institutions, non-governmental organizations, and commercial firms to distribute solar home systems in rural villages. The World Bank, along with other international donors, grants partial subsidies[8] to reduce the initial price of solar home systems and to provide refinancing to partner organizations that provide installation, credit, and after-sales maintenance support to rural households. The program has been implemented in two phases: the first phase was started in late 2002 and installed about 1.23 million solar home systems by 2012. The program was then extended further in 2013 with a cumulative installation target of six million solar home systems (World Bank, 2012, 2013b).

The IDCOL program aims to advance rural electrification and to develop commercially viable solar home system markets in off-grid areas (World Bank, 2012). In principle, the program is intended to serve the worst-off and marginally creditworthy households. Nevertheless, it also targets better-off rural households in off-grid areas in order to cross-subsidize those in need.[9] The partner organizations set the price of a solar home system after deducting the capital buy-down subsidy. Partner organizations initiate a sales agreement in which borrowers do not need to provide any collateral. However, partner organizations impose a minimum down payment, generally 15 percent of the solar home system price, excluding any subsidy, and irrespective of panel capacity (10–130 watts). Particularly in the second phase, partner organizations often encourage borrowers to buy small solar home systems (up to 30 watts) in order to minimize down payment. The remaining balance is converted into loans to be paid back at a given annual interest rate, including service charge percentage for the maintenance of installed systems, over a certain maturity.

In general, partner organizations set interest rates, while then allowing borrowers to choose the repayment scheme involving monthly payments and a preferred maturity period to pay off the loans. Normally, the loan maturity is a minimum for 12 months, and the upper limit of the annual interest rate is 15 percent.[10] The annual interest rate remains flat over loan maturity, but it tends to vary across borrowers widely. The flat rate calculation method allows partner organizations to charge a fixed interest rate on the initial loan amount every year.[11] A fixed-payment loan agreement requires interest payments at the beginning years of the loan agreement, while the loan amount is to be back-loaded (Chambers, 2012). Finally, borrowers gain ownership of

[5] An '80-20 loan' involves a primary loan up to 80 percent of the solar home system price and a secondary loan for a 20 percent down payment (Chambers, 2012).

[6] A traditional microcredit model is somewhat different than the energy microcredit model. The former disburses very small loans directed to productive activities under a group liability framework. The loan is repaid within a year through periodic installments, allowing other group members to be eligible for loans. In contrast, the latter model issues loans to individual borrowers purchasing solar home systems under the program financing mechanism. Borrowers repay loans and interest amounts in small installments over a year and own the purchased solar home systems once the loans are fully repaid. Unlike the traditional model, the energy microcredit model issues loans for a single time purchase, and borrowers need to pay a deposit at the time of purchase.

[7] Infrastructure Development Company Limited; for details see https://idcol.org/.

[8] These are fixed capital buy-down subsidies offered to each partner organization selling solar home systems. The subsidy amount covers a minimal portion of a particular solar home system procurement cost. It decreases over time as sales increase across markets: initially, each solar home system received a subsidy to the value of 70 USD. This was later reduced to 20 USD. The subsidy is not calculated on a per watt basis. Thus, the solar home system program remains a largely unsubsidized market.

[9] For details, please see: Installation of Solar Home Systems in Bangladesh at https://cdm.unfccc.int/ProgrammeOfActivities/poa_db/ZSI6WP0ODGRQ8UYKXB3MHTL957JVAE/view

[10] Partner organizations generally follow IDCOL guidelines for setting loan agreement features. However, the guidelines are not binding for them, and the principle of open market operation allows partner organizations to structure loan pricing.

[11] For example, a borrower is charged a 5 percent flat annual interest rate for a loan amount of 15,000 Bangladeshi Taka (≈177 USD), which has to be paid back over two years. Regardless of the repayments after one year, interest is always calculated on the original loan amount and total repayment equals 16,500 BDT, including the total interest payment of 1500 BDT [15,000 + (15,000 × 0.05 × 2) = 16,500 (≈195 USD)].

solar home systems once they pay off the loan amount and scheduled payments within the stipulated loan maturity period.

3. Data and descriptive statistics

Our research data is based on IDCOL's market-based solar home system program in Bangladesh. Upon placing an official request to IDCOL, we obtained access to the loan agreement details of around 800,000 borrowers who purchased solar home systems from different partner organizations in two administrative divisions over the last 17 years (2002–2018).[12] These two administrative divisions, Chittagong and Rangpur, are subdivided into 151 thanas that contain 1435 unions in total. These divisions are geographically distinct as many lower level administrative areas either contain hill tracts or riverine islands. Additionally, we combined our dataset with geo-referenced boundary information at the union level, obtained officially from the Survey of Bangladesh.

The IDCOL database lacks socio-demographic information for the first phase of the program. Our empirical analysis is therefore based on the second phase of the program. Upon omitting incomplete observations, we observe loan transactions for a sample of 626,761 borrowers served by 49 partner organizations across 1435 unions from 2013 to 2018. Each observation records respective borrowers' gender, occupational group, income category,[13] and place of residence in a particular administrative area (i.e., division, district, thana, and union). The name of the partner organizations issuing loans and installing solar home systems, the loan agreement month, and the year of installation are also reported. With regards to loan transactions for each of the borrowers, data includes solar panel capacity (in watts), price of the solar home systems (in BDT), down payment and loan amount (in BDT), annual interest rate, and loan maturity (in years).[14]

For our empirical analysis, we computed the total cost of a loan variable by multiplying the respective borrowers' annual interest rate by the loan maturity. The annual interest rate set by partner organizations also includes the service charge percentage for the maintenance of installed systems. We take both the flat annual interest rate and loan maturity into account in order to capture variations in the total cost of loans. This is because two similar borrowers might purchase the same panel capacity but prefer different maturities to pay off loans. Partner organizations may also charge different annual interest rates due to perceived differences in borrower credit risk.

Fig. 1 presents the spatial distribution of average loan share across unions of both divisions, with the darker color representing a higher average loan share as a percentage of the solar home system price. A total of 9.94 billion BDT in loans was disbursed for an installed solar home system capacity of 22.27 megawatts in sample divisions during the second phase of the program. A few unions in the south, west-northern, and eastern Rangpur, as shown in Fig. 1(a), report borrowings within a range of 84 percent to 90 percent of the solar home system price. The north-western and southern parts of Chittagong in Fig. 1(b) include many small clusters of unions where borrowers take up higher average loan shares. Higher average loan shares indicate the presence of borrowing constraints as they are associated with lower average down payment shares for borrowers.

Fig. 2(a) presents a histogram that shows the skewed distribution of down payments. How down payments of different borrower groups are related to the total cost of loans are shown in Fig. 2(b). The borrowing-constrained groups are ordered in terms of down payment size while taking the size of solar home systems, as represented by panel capacity in watts, into account.[15] Following Balarama et al. (2020), we compute the median value of down payment per watt and classify borrowers with a down payment of over 87 BDT (≈ 1.02 USD) per watt as relatively unconstrained. The bivariate relationship suggests a statistically significant difference between two borrowing groups. In particular, it is the highly constrained borrowers who, on average, pay a higher total cost for their loans.

At the same time, partner organizations, given the risk of default, often require these highly constrained borrowers to pay higher down payments. This is consistent with the descriptive statistics presented in Table A1 in the Appendix. Additionally, most borrowers in these groups purchase solar home systems with a capacity of fewer than 50 watts and fall into the low-income category. Interestingly, borrowers with manual jobs (e.g., a rickshaw puller, hawker, porter, driver, barber, day laborer, etc.) comprise merely 3 percent of the sample observations, while borrowers in agriculture occupation account for 47 percent of solar home system loans. This may pose a social equity concern since partner organizations in a market-based program focus on relatively affluent borrowers in business- or service-based occupation, and tend to neglect others.

Overall, we observe a heterogeneous pattern in loan pricing structure across borrowers who have different down payment capacities. The variations in down payments across unions suggest the existence of a binding borrowing constraint among a group of borrowers in rural communities. This could be caused by borrowing constraints (using down payment as a proxy indicator) or be driven by operational differences in partner organizations or temporal shocks. We aim to disentangle the impact of down payments from such (unobserved) factors.

4. Empirical strategy

4.1. Empirical regression and endogeneity concern

We hypothesize a negative relationship between the down payment, a proxy measure of the borrowing constraint, and the total cost of a solar home system loan. This can be tested applying the ordinary least squares (OLS) regression approach, as specified in Eq. (1), on a cross-sectional dataset that includes a sample of 626,761 borrower observations. For a borrower, i, the coefficient estimate, β_1 captures the effect of borrowing constraints on the total cost of a loan, holding other factors, C_i, constant.

$$\text{total cost of loan}_i = \beta_1 \log(\text{down payment})_i + \beta_2 \mathrm{C}_i + \varepsilon_i, \tag{1}$$

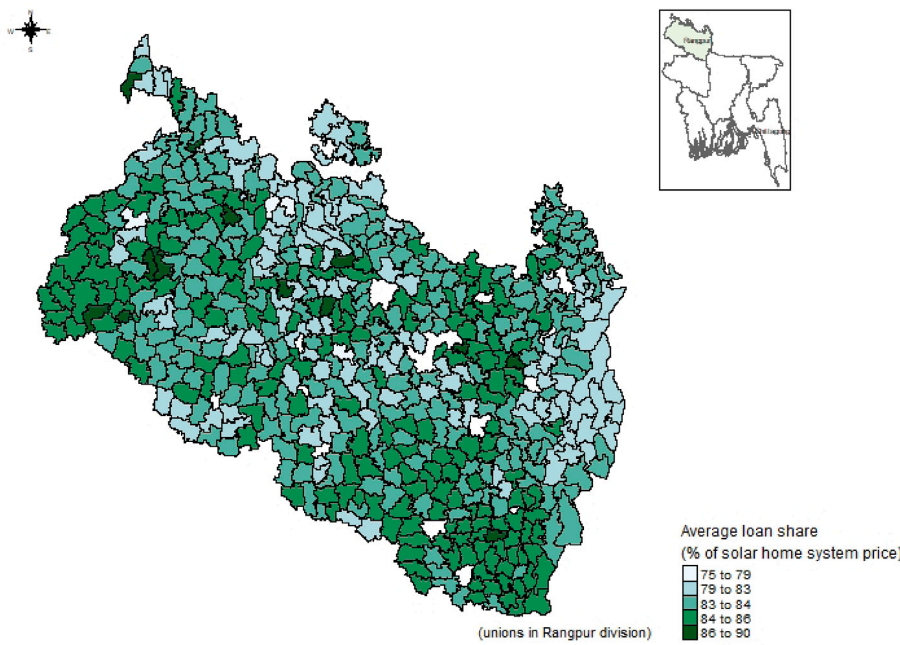
However, the imposition of a down payment requirement by lenders or partner organizations may endogenously shift a borrower's choice of annual interest rates, and maturities (Engelhardt and Mayer, 1998; de Araujo et al., 2020). In a market-based solar home system program, endogeneity primarily stems from omitted variable bias and reverse causality. The omitted variable bias occurs when the endogenous variable of interest, $\log(\text{down payment})_i$ is correlated with the regression error term, which summarizes all unobserved factors that may impact the total cost of a loan. The estimated effect in the specification (1)

[12] Bangladesh has eight administrative divisions, and each of the divisions contains several districts, subdivided again into smaller administrative units, known as thanas. Each thana comprises unions, the next administrative level, and these include many small villages. There are 64 districts, 492 thanas, 4554 unions, and 80,000+ villages. However, these villages do not have an official boundary on the Bangladesh map. We thus consider the union level as the lowest geographic boundary in this study.

[13] The five income group range from cover the lowest income group with less than or equal to 5000 BDT per month, up to the highest income group with over 30,000 BDT per month. The income range is based on what borrowers state, without further verification, and the income classification is therefore somewhat random.

[14] Fig. B1 in the Appendix presents a correlation matrix for the key variables.

[15] In the traditional microcredit settings, the size of loans indicates a borrower's poverty level. In our study, borrowers buy solar home systems that vary in terms of panel capacity watts. As Fig. B1 shows, panel capacity and loan amount are strongly correlated.

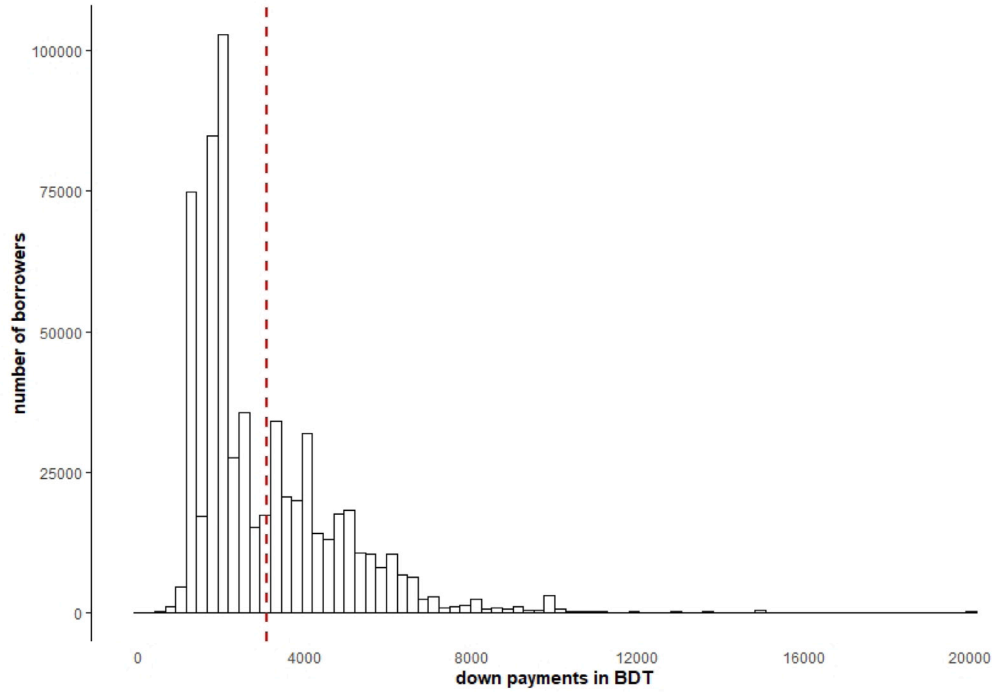


(a) Spatial distribution of average loan share as a percentage of the solar home system price across the unions of Rangpur division (2013-2018).

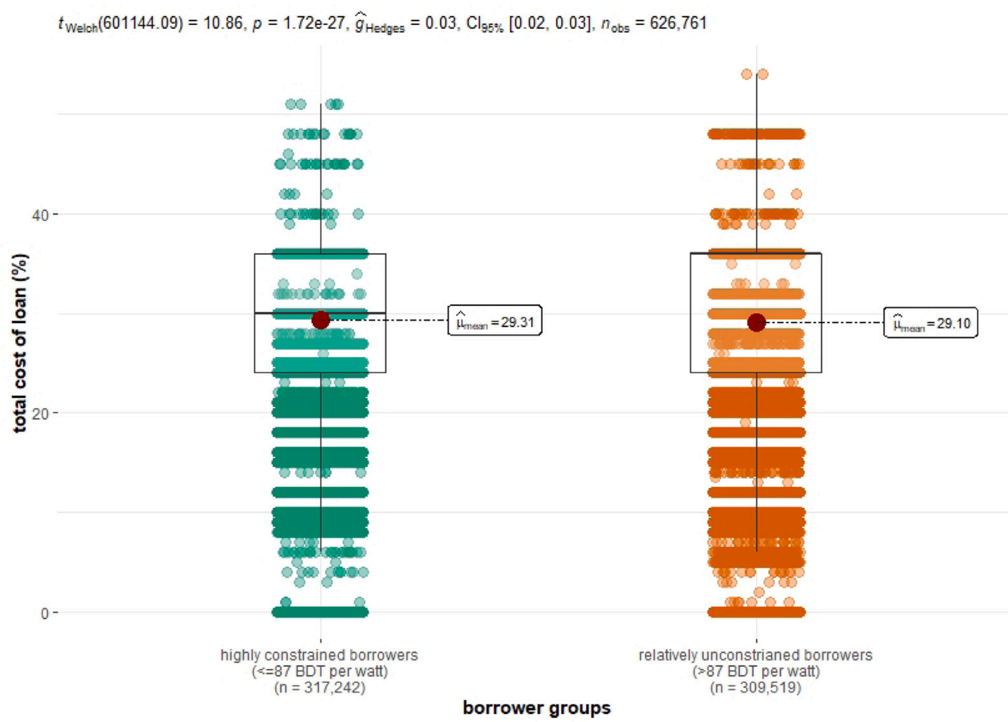
(b) Spatial distribution of average loan share as a percentage of the solar home system price across the unions of Chittagong division (2013-2018).

Fig. 1. Spatial distribution of average loan share as a percentage of the solar home system price in Rangpur and Chittagong division over 2013–2018.

is inconsistent because the true causal effect is distorted by an unobserved bias resulting from this correlation. The reverse causality is not straightforward because poor rural households often do not understand the entire payment mechanism due to their lack of financial literacy (Moner-Girona et al., 2016; Khan et al., 2019). In addition, partner organizations tend to avoid transparency concerning the actual interest being charged for a given loan (Mukherjee et al., 2020). Instead, they inform a borrower concerning the choice of solar home system, and set monthly fixed payment according to the borrower's cash flow while keeping loan maturity flexible enough (Wimmer, 2014). In the



(a) The distribution of down payments in the solar home system program (2013-2018).



(b) The between-borrower group differences in the total cost of loans (2013-2018).

Fig. 2. Exploratory analysis.

mortgage market context, Basten and Koch (2015) report no reverse causation between imposing limits on loan supply and associated financing cost because loan offers are made after borrowers file a request to lenders. However, several empirical studies dealing with traditional microcredit, document that borrowers are sensitive to an interest rate increase, thus decreasing their demand for loans substantially (e.g., Karlan and Zinman, 2008; Dehejia et al., 2012; Bogan et al., 2015). This raises a reverse causality concern in the specification (1), leading to an over-estimation of the causal effect of borrowing constraints.

To address endogeneity concerns in identifying the causal relationship between down payment and the total cost of a loan, we employ a two-stage least squares (2SLS) estimation approach with one instrumental variable, including a rich set of fixed effects. A good instrument must be well correlated with the endogenous variable of interest and excluded from the model so as to affect the outcome variable only through its impact on the endogenous variable of interest (Acheampong et al., 2021). However, finding a good instrument is quite challenging here, particularly one that works with the cross-sectional data available. Reed (2015) proposes an identification strategy that uses a lag of the endogenous regressor as an instrumental variable when endogeneity arises due to simultaneity or reserve causality. As described in Section 3, our cross-sectional dataset includes spatial and time information on each borrower's installation. This allows us to create a lagged instrumental variable for the down payment and to control for unobserved heterogeneous factors that vary across groups but do not vary over time within each group. Narayanan and Nair (2013) also apply a similar strategy in their study, drawing on a panel-like cross-sectional dataset.

4.2. IV regression

We base our argument for a lagged instrumental variable on the informational influence of past borrowers on down payment behavior. Several studies (e.g., Bollinger and Gillingham, 2012; Lay et al., 2013; Graziano and Gillingham, 2015; Rode et al., 2020) document the relevance of a spatial peer effect[16] and of the informational influence in expediting the adoption and use of new technology. In the same vein, Banerjee et al. (2013) report that participants of a microfinance program tend to pass information about loan products onto others. The purchase of new technology is associated with uncertainties both in economic and technical terms, making the decision-making costly for poor rural borrowers. They thus accept information obtained from relevant others, e.g., previous buyers in close geographic proximity, and tend to imitate their behavior (Gardete, 2015; Fornara et al., 2016; Wolske et al., 2020). We thus assume that the distribution of down payments made by other borrowers, j, in the previous month, t_i-1, positively influences the down payment behavior of an individual borrower, i, living in the same union, u_i.[17] We compute the instrumental variable in Eq. (2), where N_{u_i,t_i-1} presents the total number of past borrowers in the preceding month in a given union:

$$\text{lagged mean down payment}_{u_i,t_i} = \frac{\sum_{j=1}^{N_{u_i,t_i-1}} \text{down payment}_j}{N_{u_i,t_i-1}} \tag{2}$$

Our main identification strategy relies on the instrumental variable (IV) estimator with spatial and time fixed effects. As specified in Eqs. (3) and (4), i denotes an individual borrower. C_i is a vector of indicator variables, such as income level, occupational group, and gender of borrower, i.[18] Additional time-invariant thana-level controls, such as poverty rate and distance, are also included.[19] We include partner organization dummies, γ_p that eliminate unobserved variations between partner organizations. The time dummies, θ_t, include year-quarter (i.e., 2013-Q1, …, 2018-Q4) specific unobservable shocks. Finally, v_i and ε_i are the error terms, and we cluster standard errors at the union level. To look for differences between borrower groups, we carry out separate estimations for highly constrained borrowers and relatively unconstrained borrowers.

First-stage regression:

$$\log(\widehat{\text{down payment}})_i = \alpha_0 + \alpha_1 \log(\text{lagged mean down payment})_{u_i,t_i} + \alpha_2 C_i + \gamma_p + \theta_t + v_i, \tag{3}$$

Second-stage regression:

$$\text{total cost of loan}_i = \beta_0 + \beta_1 \log(\widehat{\text{down payment}})_i + \beta_2 C_i + \gamma_p + \theta_t + \varepsilon_i, \tag{4}$$

In the first stage regression, we use our instrument, $\log(\text{lagged mean down payment})_{u_i,t_i}$, to exploit variation in the endogenous variable of interest, $\log(\text{down payment})_i$. This part of the variation is arguably random and is not correlated with the unobservables affecting both the endogenous variable of interest and the total cost of loan. We expect coefficient estimate α_1 to be non-zero, implying a positive effect of the reference group's mean down payment on the individual borrower, i's down payment. Nonetheless, the estimated effect of past borrowers' payment behavior, as specified in Eq. (3) is confounded by correlated unobservables and reflection bias. Following Nair et al. (2010), Narayanan and Nair (2013), and Graziano and Gillingham (2015), we apply a fixed effects structure in our model specifications to account for potential confounding factors:

The presence of correlated unobservables may affect the down payments of both the individual borrower and the reference group similarly. For example, partner organizations may promote their services by targeting some specific rural communities with relatively little chance of getting a grid connection in the next 5–10 years, or by targeting households from specific occupational groups with financial solvency. We include partner organization fixed effects, γ_p that control for unobserved systematic differences which are time-invariant and specific to partner organizations. These factors include the type of firm (i.e., microfinance, non-governmental, commercial), perceived differences in credit risks, product offerings, technical capacity, etc. Cull et al. (2018), for instance, report that commercial microfinance organizations that issue large loans tend to charge a lower interest rate than the rate charged by the non-governmental organizations that primarily disburse small loans. Following Nair et al. (2010), we assume that the partner organization fixed effects also capture location-specific unobserved variations that are time-invariant because partner organizations operate at the thana level and deliver installation and maintenance services across unions. Furthermore, we include time (year-quarter) fixed effects, θ_t that absorb time-varying shocks, such as changes in the subsidy policy, prices, increasing awareness of off-grid solar electrification, seasonal business cycles and variation in panel output, etc.

The reflection problem may occur when the individual borrower, whom the peer influences, also affects the payment behavior of the peer. This might generate an upward bias in the estimate of a spatial peer effect. We use the lagged mean down payments, which are made by the other borrowers in the peer group, as our instrument. There is thus no contemporaneous linkage in the payment decisions. The

[16] Also known as installed-base, social influence, social contagion, or reference group influence.

[17] We define a reference group or spatial peer as a set of borrowers who live in the same union and have purchased solar home systems from partner organizations in the previous month. Individuals living in the same union are likely to know each other very well, and they are thus subject to common shocks.

[18] We categorize income into low, medium, and high income groups considering the average monthly income per rural household (9648 BDT ≈ 116 USD), as stated in the 2010 Household Income and Expenditure Survey. For further details, see http://203.112.218.65:8008/WebTestApplication/userfiles/Image/LatestReports/HIES-10.pdf. In our sample, the low income group has an average monthly income ≤ 10,000 BDT (≈ ≤120 USD), whereas 10,000–20,000 BDT (120–236 USD) and >20,000 BDT (≈ > 236 USD) are for the medium and high income group, respectively. We exclude small and large solar panel type as control variables because they are highly correlated ($\rho = \pm 0.748$) with the down payment, as shown in the Fig. B1.

[19] Thana-level distance is obtained from the Survey of Bangladesh upon placing an official request. The poverty rate represents the percentage of the poor population at the thana level with an average per capita expenditure below the upper poverty line. We obtained poverty rates from the Bangladesh poverty maps available at the Bangladesh Bureau of Statistics website (http://www.bbs.gov.bd/). We consider 2010 as the base period for the upper line poverty rates retrieved from http://203.112.218.65:8008/WebTestApplication/userfiles/Image/LatestReports/Bangladesh_ZilaUpazila_pov_est_2010.pdf. For further details concerning poverty line and rate estimation, please see World Bank (2013a).

temporal ordering in the relationship between the endogenous variable of interest and the lagged instrumental variable is assumed to become apparent after one month. That is, the average down payment of other borrowers at time $t-1$ can affect the borrower's at time t down payment, but not vice versa.

In the second stage, the outcome variable, total cost of loan_i, is regressed on the predicted value of $\log(\text{down payment})_i$, estimated using only exogenous variables in the first stage, replacing the endogenous variable of interest that the outcome variable partially determines. The coefficient β_1 is, therefore, estimated using only the exogenous variation present in the $\log(\text{down payment})_i$. We expect coefficient estimate β_1 to be non-zero, indicating that a change in the total cost of a loan is negatively associated with a percentage change in down payment. Higher down payment protects partner organizations against adverse selection, i.e., potential default of borrowers willing to pay higher interest rates. Also, it signals borrowers' preparedness to repay loans at a later time (Engelhardt and Mayer, 1998; Rosenthal, 2002). Simultaneously, a higher down payment is more binding for those highly constrained borrowers who may find it relatively difficult to meet the eligibility requirement (Barakova et al., 2014).

Our identification assumption is that unobserved partner organization-specific factors are fixed across all year-specific quarters and that unobserved shocks within a quarter in a given year are common to all partner organizations. Based on these fixed effects, our identifying variation then comes from differences in the down payments made by all individual borrowers within each partner organization over time. The relevance of the instrument can be tested using the first-stage F-statistics. The exclusion restriction condition is not testable; rather, the instrument's validity depends on theory, researcher's intuition, and contextual knowledge (Pokropek, 2016). Following Dang and La (2019) and Sedai et al. (2021), we can argue that the lagged mean down payment of the reference group does not directly affect the total cost of a loan for the individual borrower. The assumption is that the total cost of a loan generally depends on the level of down payment made by the borrower, his or her maturity preference, income levels, and other relevant factors. We are thus able to interpret our parameter estimate of down payment causally.

Lag identification replacing the explanatory variable with its lagged value to address endogeneity concerns is commonly used in the empirical literature dealing with panel data. However, lagging the explanatory variable for causal identification is controversial (Bellemare et al., 2017). Using the lagged variable to obtain a causal estimate assumes the existence of temporal dynamics in the explanatory variable and, at the same time, no temporal dynamics among unobservables. The assumption of no temporal dynamics among unobserved confounders is not testable. Bellemare et al. (2017) justify lagged identification on the grounds of reverse causality, which requires that there are no dynamics in the outcome variable and that there are dynamics in the endogenous variable of interest. Reed (2015) recommends using lagged explanatory variable as an instrument if (i) the lagged variable itself is not included in the estimated equation and (ii) it is sufficiently correlated with endogenous explanatory variable. Given the limitation of our cross-sectional loan transaction dataset that includes spatial and time information, we follow the Reed (2015) approach. We use lagged mean down payment as an instrument, as explained in Eq. (2). In our study, individual rural borrowers only engage in single loan transactions with partner organizations because credit is not available to upgrade installed capacity. We assume that rural borrowers are not forward-looking and the temporal ordering in the down payment comes from the past borrowers to the current individual borrower in the same peer group. And, any changes in the total cost of loans are due to down payments made by rural borrowers, controlling for the partner organization specific time-invariant factors and year-quarter specific shocks. As a robustness check of our instrument in Section 5.2, we apply the 2SLS estimator with the Lewbel's heteroskedasticity-based instrument and the leave-out mean instrument. Additionally, we apply Oster's bound analysis to test omitted variable bias.

5. Results and discussion

5.1. Main results

The effects of a borrowing constraint on the total cost of the loan, as specified in Eq. (4), are summarized in Table 1. The baseline model specification is shown in column (1), which includes the down payment as a proxy measure of the borrowing constraint and the borrower's income level as a control variable. In columns (1) through (3), we build up to our preferred model specification sequentially adding borrower level control variables. Column (3) shows our preferred model specification; this includes down payment and a set of indicator variables, such as income level, occupational group, and gender. Columns (4) and (5) show the alternative model specifications that extend our preferred specification in column (3) by adding additional time-invariant regional control variables, such as poverty rate at the thana level and distance in kilometers between a thana and its respective unions, in order to ensure that our estimate on the down payment is not biased due to omitted unobserved factors that may affect the total cost of a loan. In all models in Table 1, the estimation results are based on the full fixed effect structure. The spatial fixed effects structure includes unobserved time-invariant characteristics that are specific to partner organizations. Time fixed effects control for broader trends and common shocks to a particular year-quarter combination. Across all specifications, we cluster standard errors at the union level.

Our results provide strong evidence supporting a negative and highly statistically significant effect of a borrowing constraint. Down payment, our parameter of interest, is significant within the 1% significance level in all specifications. In our main specification in column (3), we find that a 10 percent increase in the down payment decreases the average total cost of a loan by 0.181 percentage points, holding all other factors constant.[20] A low down payment in a pure market system is associated with a higher total cost of a loan and suggests a relatively low level of borrower creditworthiness. Rural borrowers with limited wealth are constrained in how much they can borrow for solar home systems. As Best et al. (2021) document, the wealth effect is likely to be an important barrier given the high upfront cost of solar panels.

Among the control variables in column (3), the low income level is statistically significant. We also observe that all occupational groups except borrowers in agriculture are charged a lower average total cost of loans than borrowers in a service occupation, which is omitted as the reference group. However, we do not find any significant difference between borrowers in the manual job, such as rickshaw puller, hawker, and day laborers, and service. This is consistent with the micro-credit literature (e.g., Mallick, 2012), which documents that interest rate seems to vary between occupational groups. Borrowers' gender also impacts the total cost of a loan; however, the magnitude of the coefficient is small. In columns (4) and (5), we additionally control for thana-level poverty and thana-level distance variables. This is because the operating costs of partner organizations also depend on the borrower location since, for instance, heterogeneous terrain may further increase the installation cost (Srinivasan, 2009; Sherratt, 2016). We find thana-level distance variable is positive and statistically significant within the 10% significance level, although the size of the magnitude is small. Our estimate on down payment remains unaffected.

The first-stage F-statistics in column (1) suggests that the null hypothesis is rejected and the instrument is relevant. The Anderson–Rubin confidence interval also suggests that the coefficients estimated for the variable of interest are robust. The first-stage regression results are presented in Table A2 in the Appendix. The average effect of the lagged instrumental variable in column (1) shows a statistically significant impact on the down payment. If the mean down payment of

[20] A 10% change in down payment implies a change in the total cost of loans: $-1.903 \times \log(1.10) = -0.1813753$ or, -0.181 percentage points.

Table 1
IV estimation results for the effect of borrowing constraints on the total cost of loans.

	Outcome variable: total cost of loan (%)				
	(1)	(2)	(3)	(4)	(5)
Log($\widehat{\text{down payment}}$)	−1.811***	−1.904***	−1.903***	−1.916***	−1.944***
	(0.166)	(0.163)	(0.163)	(0.163)	(0.164)
Reference: medium income group (10,000–20,000 BDT)					
Low income group (≤ 10,000 BDT)	−0.122***	−0.206***	−0.208***	−0.209***	−0.213***
	(0.039)	(0.038)	(0.038)	(0.038)	(0.038)
High income group (> 20,000 BDT)	−0.022	0.009	0.013	0.015	0.023
	(0.065)	(0.065)	(0.065)	(0.065)	(0.064)
Reference: service occupational group					
Agriculture		0.255***	0.261***	0.260***	0.254***
		(0.048)	(0.048)	(0.048)	(0.048)
Business		−0.317***	−0.312***	−0.313***	−0.316***
		(0.045)	(0.045)	(0.045)	(0.045)
Housewife & remittance		−0.161***	−0.223***	−0.220***	−0.220***
		(0.049)	(0.052)	(0.052)	(0.052)
Professional job		−0.809***	−0.806***	−0.806***	−0.803***
		(0.115)	(0.115)	(0.114)	(0.115)
Manual job		0.037	0.043	0.038	0.035
		(0.072)	(0.072)	(0.072)	(0.073)
Reference: female					
Male			−0.150***	−0.147***	−0.144***
			(0.041)	(0.041)	(0.041)
Thana-level poverty (%)				−0.002	−0.001
				(0.002)	(0.002)
Thana-level distance (in km)					0.012*
					(0.007)
Partner organization fixed effects	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	626,761	626,761	626,761	626,761	626,761
R-squared	0.582	0.583	0.583	0.583	0.583
F-test (1st stage)	27,433.286	27,461.143	27,475.709	27,295.506	26,925.500
F-test (1st stage), *p*-value	0.000	0.000	0.000	0.000	0.000
Wu–Hausman	10.189	22.776	23.039	24.724	28.572
Wu–Hausman, *p*-value	0.001	0.000	0.000	0.000	0.000
Anderson–Rubin confidence interval	(−1.932, −1.690)	(−2.025, −1.783)	(−2.025, −1.782)	(−2.038, −1.794)	(−2.066, −1.821)

Notes: We estimate the causal effect of the borrowing constraint, as measured by down payments, on the total cost of a solar home system loan, applying the two-stage least squares estimator with one instrumental variable. Following Narayanan and Nair (2013) and Reed (2015), we construct a lagged instrument that denotes the average down payments of other borrowers in the preceding month in a given union. All columns report second-stage regression results for the average causal estimations of fitted down payments. As specified in Eq. (4), Column (3) is our preferred specification and controls for borrower specific characteristics, such as income level, occupational group, and gender. We build up to our preferred specification by sequentially adding household-level controls in columns (1) through (3). Columns (4) and (5) subsequently control for additional thana level characteristics, such as poverty rate and distance. Across all specifications, we use partner organization fixed effects and year-quarter fixed effects. We cluster standard errors at the union level, and clustered standard errors are in parentheses. *, **, *** indicate 10%, 5%, and 1% significance levels, respectively. Constant is included but not reported.

the reference group in the previous month increases by 10 percent, the individual borrower's down payment, on average, increases by 3.827 percent.[21] This indicates that information passing between borrowers in the reference group positively influences the down payment behavior of the individual borrower, who prefers to be the owner of the installed solar home system.

As mentioned in Section 1, the borrowing constraint may potentially have different effects on borrowers with different down payment capacities. In line with the distributive principle, a market-based program is expected to charge highly constrained borrowers, who seem to be the worst-off members in the society, a lower cost of credit than the relatively unconstrained borrowers. To test the average causal effects of borrowing constraints by borrower groups, we repeat the instrumental variable estimation on the borrower group samples, as described in Section 3. We report estimations for highly constrained borrowers and relatively unconstrained borrowers in columns (1) to (2) and columns (3) to (4), respectively, in Table 2. Based on Eq. (4), columns (1) and (3), which are our preferred specifications by borrower groups, include all borrower level observed characteristics and control for partner organization specific time-invariant factors and year-specific quarterly shocks. Columns (2) and (4) additionally control for thana-level characteristics, such as poverty rate and distance. In all specifications, we find that coefficient estimates of down payments are negative and statistically significant within the 1% significance level, all else held constant. However, the effect is more pronounced for the relatively unconstrained borrowers. A 10 percent increase in down payments reduces their average total cost of loans by 0.343 percentage points in column (3). In contrast, the highly unconstrained borrowers experience an average cost reduction of only 0.102 percentage points at the same level of increasing down payments in column (1). Thus, given the higher payment capacity of the relatively unconstrained borrowers, our empirical findings appear to be incompatible with the guiding principle of distributive justice mentioned earlier, i.e. our findings run counter to Rawls' 'Difference Principle'.

The partner organizations tend to charge a higher price (i.e., interest rate and service charge percentage) in order to cover the higher operating costs associated with collecting monthly payments of (small) loans and providing regular maintenance services in remote areas. The higher total cost of loans mainly affects the highly constrained borrowers, who are price-sensitive and tend to adjust their lighting demand in

[21] A 10% change in lagged mean down payment implies a change in the average down payment: $1.10^{0.394} - 1 = 0.0382662$ or, 3.827 percent.

Table 2
IV estimation results for the effect of borrowing constraints on the total cost of loans by borrower groups.

	Outcome variable: total cost of loan (%)			
	Highly constrained borrowers		Relatively unconstrained borrowers	
	(1)	(2)	(3)	(4)
$\widehat{\text{Log(down payment)}}$	−1.069***	−1.077***	−3.595***	−3.722***
	(0.178)	(0.182)	(0.313)	(0.317)
Reference: medium income group (10,000–20,000 BDT)				
Low income group (≤ 10,000 BDT)	−0.164***	−0.165***	−0.055	−0.062
	(0.040)	(0.041)	(0.051)	(0.051)
High income group (> 20,000 BDT)	−0.198***	−0.196***	0.119	0.143
	(0.064)	(0.064)	(0.094)	(0.093)
Reference: service occupational group				
Agriculture	0.187***	0.186***	0.489***	0.472***
	(0.050)	(0.050)	(0.069)	(0.070)
Business	−0.213***	−0.214***	−0.369***	−0.376***
	(0.051)	(0.051)	(0.065)	(0.066)
Housewife & remittance	−0.021	−0.020	−0.375***	−0.360***
	(0.054)	(0.054)	(0.076)	(0.075)
Professional job	−0.526***	−0.526***	−1.115***	−1.104***
	(0.106)	(0.105)	(0.156)	(0.155)
Manual job	−0.089	−0.091	0.180*	0.158*
	(0.071)	(0.071)	(0.093)	(0.094)
Reference: female				
Male	−0.118***	−0.117***	−0.230***	−0.215***
	(0.044)	(0.044)	(0.056)	(0.056)
Thana-level poverty (%)		−0.001		−0.005**
		(0.002)		(0.002)
Thana-level distance (in km)		0.003		0.021**
		(0.007)		(0.009)
Partner organization fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	317,242	317,242	309,519	309,519
R-squared	0.665	0.665	0.601	0.601
F-test (1st stage)	14,126.179	13,838.939	9,606.607	9,472.904
F-test (1st stage), p-value	0.000	0.000	0.000	0.000
Wu–Hausman	119.588	119.876	9.790	4.669
Wu–Hausman, p-value	0.000	0.000	0.002	0.031
Anderson–Rubin confidence interval	(−1.199, −0.9384)	(−1.209, −0.946)	(−3.847, −3.343)	(−3.976, −3.468)

Notes: We estimate the causal effect of the borrowing constraint, as measured by down payments, on the total cost of a solar home system loan by borrower groups, applying the two-stage least squares estimator with one instrumental variable. We split the samples into highly constrained and relatively unconstrained borrowers based on the median value of down payment per watt (87 BDT or, ≈ 1.02 USD). That is, the down payment value of each borrower is divided by respective panel capacity size to normalize differences between borrowers. Following Narayanan and Nair (2013) and Reed (2015), we construct a lagged instrument that denotes the average down payments of other borrowers in the preceding month in a given union. The second-stage regression results for the average causal estimations of fitted down payments are reported for highly constrained borrowers and relatively unconstrained borrowers in columns (1) to (2) and columns (3) to (4), respectively. Based on Eq. (4), columns (1) and (3) are our preferred specifications and control for borrower-specific characteristics, such as income level, occupational group, and gender. Columns (2) and (4) report estimations including additional controls. Across all specifications, we use partner organization fixed effects and year-quarter fixed effects. We cluster standard errors at the union level, and clustered standard errors are in parentheses. *, **, *** indicate 10%, 5%, and 1% significance levels, respectively. Constant is included but not reported.

response to an increasing electricity price (Balarama et al., 2020). Additionally, extending loan maturity for such borrowers leads to an increased lending risk for partner organizations, who have imperfect information on the repayment characteristics of borrowers.

The market-based approach ostensibly aims to serve poor rural households without electricity access by providing financial inclusion and other maintenance support. Barry and Creti (2020) consider customer repayment behavior as the key to enabling partner organizations to provide competitive financing in the long run. However, we find that market-based efforts may not necessarily eliminate distributional inequality. Loan pricing effects are heterogeneous, and borrowers limited in their down payment capacity end up paying a higher total cost of loans in a market system.

5.2. Robustness checks

As a robustness check of the conventional instrumental variable estimator, we apply Lewbel's (2012) identification strategy based on the heteroskedastic covariance restriction. The idea is that a vector Z_i, that includes a set of observed exogenous variables in demeaned form, is used to internally construct instrument(s), $[Z - E(Z)] \times v_i$, given that some heteroskedasticity exists in the data, $Cov(Z_i, v_i^2) \neq 0$ and that Z_i is uncorrelated with the product of the two error terms in the regressions (Mishra and Smyth, 2015; Umberger et al., 2015; Acheampong et al., 2021). Use of the Lewbel estimation does not require that the standard exclusion restriction condition be satisfied. This condition assumes that the instrument should not be correlated with an ϵ_i, which determines the total cost of a loan, once the explanatory power of the instruments on the outcome variable through the endogenous variable of interest is accounted for in the second-stage regression (Jæger, 2008). We combine the internally constructed instrument(s) with our main instrument in order to increase the efficiency of the estimated effect of borrowing constraints. The relevance condition of the instrument(s) is met when heteroskedasticity is present in the first-stage regression. This can be tested using the Breusch–Pagan test. However, the Lewbel heteroskedastic-error approach has its limitations. For example, it is sensitive to the selection of Z_i, as this depends on the researchers' judgment. Additionally, the Lewbel estimates are based on the higher-order moments and may not be as

Table 3
Alternative IV estimation results for the effect of borrowing constraints on the total cost of loans.

	Outcome variable: total cost of loan (%)					
	Lewbel's heteroskedasticity-based instrument			Leave-out mean instrument		
	All borrowers (1)	Highly constrained borrowers (2)	Relatively unconstrained borrowers (3)	All borrowers (4)	Highly constrained borrowers (5)	Relatively unconstrained borrowers (6)
$\widehat{\text{Log(down payment)}}$	−1.901***	−1.053***	−3.591***	−1.400***	−0.941***	−2.788***
	(0.153)	(0.165)	(0.258)	(0.184)	(0.198)	(0.334)
Reference: medium income group (10,000–20,000 BDT)						
Low income group (≤ 10,000 BDT)	−0.208***	−0.161***	−0.055	−0.158***	−0.148***	−0.012
	(0.037)	(0.040)	(0.049)	(0.038)	(0.044)	(0.051)
High income group (> 20,000 BDT)	−0.013	−0.200***	0.118	−0.082	−0.223***	−0.002
	(0.065)	(0.063)	(0.088)	(0.067)	(0.066)	(0.097)
Reference: service occupational group						
Agriculture	0.261***	0.188***	0.489***	0.286***	0.181***	0.510***
	(0.047)	(0.050)	(0.068)	(0.049)	(0.054)	(0.069)
Business	−0.312***	−0.211***	−0.369***	−0.277***	−0.207***	−0.331***
	(0.044)	(0.051)	(0.064)	(0.045)	(0.047)	(0.066)
Housewife & remittance	−0.223***	−0.021	−0.375***	−0.236***	−0.027	−0.411***
	(0.053)	(0.054)	(0.075)	(0.053)	(0.055)	(0.077)
Professional job	−0.806***	−0.526***	−1.115***	−0.825***	−0.535***	−1.159***
	(0.115)	(0.106)	(0.156)	(0.113)	(0.105)	(0.156)
Manual job	0.043	−0.087	0.180*	0.095	−0.092	0.254***
	(0.070)	(0.070)	(0.093)	(0.071)	(0.071)	(0.094)
Reference: female						
Male	−0.150***	−0.119***	−0.230***	−0.175***	−0.115***	−0.269***
	(0.041)	(0.044)	(0.056)	(0.041)	(0.044)	(0.057)
Partner organization fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	626,761	317,242	309,519	626,761	317,242	309,519
Breusch–Pagan test	723.115	210.358	4,674.337			
Breusch–Pagan test, *p*-value	0.000	0.000	0.000			
F-test (1st stage)	15,637.863	7,286.679	6,284.104	20,964.307	14,606.095	5,677.997
F-test (1st stage), *p*-value	0.000	0.000	0.000	0.000	0.000	0.000
Wu–Hausman	25.084	118.059	13.090	8.419	85.621	51.023
Wu–Hausman, *p*-value	0.000	0.000	0.000	0.004	0.000	0.000
Sargan test	0.012	1.846	0.005			
Sargan test, *p*-value	0.912	0.174	0.944			

Notes: We estimate the causal effect of the borrowing constraint, as measured by down payments, on the total cost of a solar home system loan, applying the two-stage least squares estimator with the Lewbel's heteroskedasticity-based instrument in columns (1) to (3) and with the leave-out mean instrument in columns (4) to (6). Columns (1) and (4) report average causal effects on the full sample. To look for borrower group differences, we split samples into highly constrained and relatively unconstrained borrowers based on the median value of down payment per watt (87 BDT or, ≈ 1.02 USD). Columns (2) to (3) and columns (5) to (6) report average causal effects by borrower groups. In columns (1) to (3), we combine heteroskedasticity-based instruments, i.e., low income group (≤ 10,000 BDT) and high income group (> 20,000 BDT), with the conventional instrument in our main identification strategy in Eq. (4) using the REndo package in R. Across all specifications based on the Lewbel approach, we use partner organization fixed effects and year-quarter fixed effects. Based on Eq. (4), we present an alternative IV approach in columns (4) to (6). We use leave-out mean down payment as the alternative instrument and include partner organization fixed effects and year-specific month fixed effects. In all models, we include a full set of borrower level controls, such as income level, occupational group, and gender. Across all specifications, we cluster standard errors at the union level, and clustered standard errors are in parentheses. *, **, *** indicate 10%, 5%, and 1% significance levels, respectively. Constant is included but not reported.

reliable as the conventional instrumental variable estimator. Even with these limitations, the Lewbel approach is being increasingly applied in the literature as a robustness check (e.g., Churchill and Smyth, 2020; Asadullah and Xiao, 2020).

The results are summarized in Table 3. Columns (1) to (3) report estimations based on Lewbel's heteroskedastic-error approach. We use a fixed effects structure that includes partner organization fixed effects and year-quarter fixed effects. Across all specifications, we cluster standard errors at the union level. Column (1) provides strong evidence of the negative and statistically significant average causal effects of the borrowing constraint on the total cost of loans for solar home systems. The coefficient estimates across borrower groups in columns (2) and (3) are statistically significant and negative. However, pricing inequality does lead to a situation in which the relatively unconstrained borrowers pay a substantially lower total cost of the loan than the highly constrained borrowers at a given percentage increase in the down payments. The Breusch–Pagan test for heteroskedasticity remains highly significant across all specifications, satisfying the heteroskedasticity assumption in our data. We cannot reject the null hypothesis in the over-identification test, and thus, the instruments are uncorrelated with the residual in the second-stage regression.

We also calculate the 2SLS estimator with the leave-out mean instrument applying an alternative fixed effect structure. The leave-out mean down payment is the average down payment of all borrowers in the union, u_i at a given year, t_i leaving out borrower i's down payment in the same reference group. The exclusion of borrower i in the leave-out mean eliminates any changes in the total cost of a loan for individual borrower i correlating with the instrument. This identification strategy is also applied in several empirical studies (e.g., Dang and La, 2019; Petach and Tavani, 2019; Sedai et al., 2021). Columns (4) to (6) in

Table 4
IV estimation results for the effect of borrowing constraints on the real total cost of loans.

	Outcome variable: real (inflation-adjusted) total cost of loan (%)		
	All borrowers (1)	Highly constrained borrowers (2)	Relatively unconstrained borrowers (3)
$\widehat{\text{Log(down payment)}}$	−1.281***	−0.675***	−2.520***
	(0.125)	(0.153)	(0.226)
Reference: medium income group 10,000–20,000 BDT)			
Low income group (≤ 10,000 BDT)	−0.171***	−0.150***	−0.053
	(0.029)	(0.032)	(0.037)
High income group (> 20,000 BDT)	−0.006	−0.160***	0.073
	(0.049)	(0.051)	(0.069)
Reference: service occupational group			
Agriculture	0.188***	0.163***	0.333***
	(0.035)	(0.039)	(0.049)
Business	−0.233***	−0.149***	−0.275***
	(0.034)	(0.042)	(0.047)
Housewife & remittance	−0.142***	0.014	−0.246***
	(0.038)	(0.040)	(0.054)
Professional job	−0.592***	−0.362***	−0.826***
	(0.086)	(0.082)	(0.117)
Manual job	0.044	−0.027	0.130*
	(0.053)	(0.054)	(0.068)
Reference: female			
Male	−0.130***	−0.110***	−0.181***
	(0.031)	(0.034)	(0.041)
Partner organization fixed effects	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes
Observations	626,761	317,242	309,519
R-squared	0.667	0.770	0.626
F-test (1st stage)	27,475.709	14,126.179	9,606.607
F-test (1st stage), p-value	0.000	0.000	0.000
Wu–Hausman	15.174	83.407	8.740
Wu–Hausman, p-value	0.000	0.000	0.003
Anderson–Rubin Confidence Interval	(−1.372, −1.190)	(−0.777, −0.574)	(−2.708, −2.333)

Notes: We estimate the causal effect of the borrowing constraint, as measured by down payments, on the real (inflation-adjusted) total cost of a solar home system loan, applying the two-stage least squares estimator with one instrumental variable. Following Narayanan and Nair (2013) and Reed (2015), we construct a lagged instrument that denotes the average down payments of other borrowers in the preceding month in a given union. Based on our main specification in Eq. (4), all columns report second-stage regression results for the average causal estimations of fitted down payments on the real total cost of loans. Column 1 reports average causal estimates on the full sample. To look for borrower group differences, we split samples into highly constrained and relatively unconstrained borrowers based on the median value of down payment per watt (87 BDT or, ≈ 1.02 USD). Columns (2) to (3) report average causal effects by borrower groups. Across all specifications, we use partner organization fixed effects and time (year-quarter) fixed effects. *, **, *** indicate 10%, 5%, and 1% significance levels, respectively. Constant is included but not reported. We cluster standard errors at the union level, and clustered standard errors are in parentheses.

Table 5
Bound estimation results.

	Outcome variable: total cost of loan (%)		
	Controlled effects [$\hat{\beta}$, (clustered S.E.)] (1)	Bound sets [$R_{max} = \hat{R}^2 + (\hat{R}^2 - \tilde{R}^2)$, $\delta = 1$] (2)	Bound sets [$R_{max} = 1.3\hat{R}^2$, $\delta = 1$] (3)
Panel A: All borrowers			
Log(down payment)	−1.613***	[−2.769, −1.613]	[−4.555, −1.613]
	(0.044)		
Observations	626,761		
R-squared	0.028		
Panel B: Highly constrained borrowers			
Log(down payment)	−0.360***	[−0.360, −0.120]	[−0.360, −0.172]
	(0.041)		
Observations	317,242		
R-squared	0.005		
Panel C: Relatively unconstrained borrowers			
Log(down payment)	−3.991***	[−8.611, −3.991]	[−24.418, −3.991]
	(0.090)		
Observations	309,519		
R-squared	0.099		

Notes: Following Oster (2019), Bryan et al. (2020), and Clark et al. (2021), we compute bounding sets from controlled and uncontrolled regressions. We transform our data using within partner organization and within year-specific quarter means. The controlled regression, a demeaned OLS model, includes a full set of observed controls, such as income levels, occupational group, and gender of individual borrowers. Column (1) report estimated $\hat{\beta}$ from the controlled regressions in panel A. Panel B and C report estimated $\hat{\beta}$ for highly constrained and relatively unconstrained borrowers, respectively. Columns (2) and (3) report identified bounding set using two R_{max} values. We cluster standard errors at the union level across all panels, and clustered standard errors are in parentheses. *, **, *** indicate 10%, 5%, and 1% significance levels, respectively. Constant is included but not reported.

Table 3 present estimations based on the leave-out mean instrument with partner organization fixed effects and year–month fixed effects. Both the average and heterogeneous effects of borrowing constraints remain robust in terms of statistical significance, although the size of the magnitudes decreases slightly. Across all specifications, we cluster standard errors at the union level.

Further, we consider the real total cost of a loan an alternative measure of loan pricing and repeat IV estimation, as specified in Eq. (4), to understand the effect of down payments. Both borrowers and partner organizations can adjust for (expected) inflation. Taking into account the Fisher effect, if the nominal cost of loans is fixed or relatively low, the real cost of loans falls with an increase in inflation, thus lowering consumer's saving incentives and boosting spending (e.g., demand for loans) in the current period (Duca-Radu et al., 2021). As rural borrowers may have poor financial literacy, their inflation expectation is not straightforward. Partner organizations can also set the higher nominal cost of loans in response to the inflationary environment in Bangladesh, with a seven-year average inflation rate of 5.708 percent (2013–2019). The inflation-induced higher nominal cost of loans substantially increases the periodic interest payments that would have been relatively lower if the loans are issued in real terms (Tschach, 2000). Our empirical strategy cannot fully control for unobserved partner organization specific factors that vary over time, such as changes in the behavioral responses of different partner organizations to inflation (volatility). To address this concern, we computed the real (inflation-adjusted) total cost of loans by adjusting the size of annual fixed payments of each loan for the average yearly inflation rate throughout the maturity of respective loans.[22] The IV estimation results are summarized in Table 4. We find estimated effects of down payments remain robust in terms of the statistical significance and the economic significance in columns (1) to (3). We cluster standard errors at the union level across all specifications.

Our IV estimators incorporate fixed effects that control for time-invariant unobservable factors but cannot deal with time-variant unobservables. We use Oster's bound analysis in order to compute the degree of potential bias arising from these omitted unobserved factors in the estimation of β. This method assumes that bias from observed controls provides information on the bias arising from omitted unobservables, incorporating how much of the variance in the outcome variable (R-squared) is explained by the inclusion of observed controls (Bryan et al., 2020). The selection on unobservables is evaluated by the sensitivity of β to the selection on observable controls. To derive bias-adjusted estimates, we specify controlled and uncontrolled regressions and set two parameters (i.e., δ and R_{max}) under the assumptions described below. The controlled regression of the total cost of a loan includes our variable of interest, log(down payment) and a full set of observed controls (i.e., income level, occupational group, and gender of respective borrowers). The uncontrolled regression uses no observed controls. Following Bryan et al. (2020), we transform our data using within partner organization and within year-quarter means, and both regressions are the demeaned OLS models for bound analysis. The first parameter, δ, measures the relative degree of the selection on observed and unobserved factors. We assign $\delta = 1$, assuming that unobserved factors are equally important as observed factors and affect β in the same direction. The second parameter, R_{max}, is the maximum R-squared from a hypothetical regression of the total cost of a loan on the log(down payment) and both observed and unobserved controls. In order to calculate bias-adjusted estimates, Oster (2019) suggests using a value of $R_{max} = 1.3\hat{R}^2$, in which $\hat{R}^2$ is obtained from the controlled regression. Additionally, we use the value of $R_{max} = \hat{R}^2 + (\hat{R}^2 - \tilde{R}^2)$, in which $\tilde{R}^2$ is obtained from the uncontrolled regression, because R-squared values in both regressions do not move much.[23] We compute a bounding set that includes bias-adjusted estimates.[24] Table 5 presents the bound estimates. Column (1) includes the estimated coefficients from the controlled regressions. The computed bounding sets, based on two R_{max} values, are shown in columns (2) and (3). For each of the statistically significant estimated coefficients in column (1), the corresponding bounding sets in columns (2) and (3) do not include zero. Thus our estimated coefficients seem robust to the potential bias of omitted unobserved variables. Additionally, the width of bound estimates shows a slightly larger size in the estimated coefficients than the OLS estimates in column (1). For example, a 10 percent increase in the down payments reduces the total cost of a loan, on average, by 0.434 percentage points in panel A in column (3). Also, the results for the relatively unconstrained borrowers are more negative than the OLS estimates in panel C.

6. Conclusions

Only a few countries, such as Bangladesh and Kenya, have achieved a large scale installation of solar home systems in commercial off-grid energy markets. Although the affordability of electricity access via off-grid solar home systems is a well-known barrier in rural poor communities, there is relatively little evidence on how borrowing constraints affect solar home system loan pricing in a market system. To address this gap, we analyze a large-scale sample observation of 626,761 borrowers, obtained from the IDCOL market-based program in Bangladesh, over six years (2013–2018). We find that highly constrained borrowers, measured by down payment size, seem to pay a poverty penalty in terms of the total cost of a loan. This indicates the presence of distributional inequalities in the solar home system market.

The use of a market system as a social institution should at least attempt to mitigate distributional inequalities in such a way that financial burdens for the worst-off households are minimized. The market-based program is intended to be a pro-poor mechanism, building on social and financial goals to alleviate energy poverty and achieve commercial viability. Targeting better-off households enables lenders or partner organizations to cross-subsidize the worst-off households. In line with recent studies (e.g. Conway et al., 2019; Barry and Creti, 2020; Grimm et al., 2020), our empirical findings show that this cross-subsidy actually works in reverse, albeit for reasons that make perfect commercial sense on a case-by-case basis. This is a cause for concern when using a market-based paradigm for 'last mile' electrification of the millions of poor households in Bangladesh. As it still remains challenging for the IDCOL's market-based program to reach the poorest 'non-electrified' sections of the population, the government has designed a complementary non-commercial solar home system program that builds on the market experience of IDCOL partner organizations. However, this non-commercial program to distribute solar home systems free of charge to the poorest households is relatively expensive.

Providing financial assistance to highly constrained borrowers instead of a general expansion of credit to all rural households therefore appears to be crucial (Winter-Nelson and Temu, 2005; Levine et al., 2018). Designing the right combination of different financing schemes,

[22] We collected 12-month average inflation rates for rural areas from 2013 to 2019 from the Bangladesh Bureau of Statistics. As the annual average inflation for rural areas is not available for 2020 and 2021, we considered the 2019 inflation rate for these two years. The inflation rate is available at http://bbs.gov.bd/site/page/29b379ff-7bac-41d9-b321-e41929bab4a1/-.

[23] Oster (2019) also identifies this value of $R_{max} = \hat{R}^2 + (\hat{R}^2 - \tilde{R}^2)$ based on the randomized-trial results of Nunn, N. and Wantchekon, L., 2011. The slave trade and the origins of mistrust in Africa. *American Economic Review*, 101(7), pp. 3221–52.

[24] We use the robomit package in R to calculate β^*, and $\hat{\beta}$ is the estimated β from the controlled regression. Depending on the relative size of $\hat{\beta}$ and β^*, the upper or lower bound of the bounding set can be either $[\hat{\beta}, \beta^* (R_{max}, \delta = 1)]$ or $[\beta^* (R_{max}, \delta = 1), \hat{\beta}]$ (Clark et al., 2021).

such as subsidized down payments, capital buy-down subsidies, sufficient grace periods, flexible payment schedules, and risk-free equivalent low-interest rates, may help address borrowing constraints and reduce distributional inequalities. Extending our empirical findings, we suggest that market-based off-grid solar home system programs be reformed along similar lines, particularly in the top 20 developing countries with electricity access deficiency.

The government and policymakers may then deploy targeted intervention mechanisms, such as low-cost commercial funds, supply distribution expansion grants, long-term maintenance services contracts, etc., to improve partner organizations' financial viability. This will allow partner organizations to minimize their costs of financing loans to highly constrained borrowers. Alongside measures that target suppliers, the government should also allocate borrower subsidies, such as energy allowance schemes or in-kind vouchers for energy loan relief payments, in order to increase the purchasing power of constrained households. In addition, partner organizations can offer down payment assistance programs, such as 80–20 loans, to further reduce the financial burden on constrained borrowers. All these enabling mechanisms will help millions of the 'last mile' rural population to escape the energy poverty trap.

CRediT authorship contribution statement

Rafia Zaman: Conceptualization, Methodology, Software, Formal analysis, Data curation, Visualization, Writing - original draft. **Debasish Kumar Das:** Writing - review & editing. **Oscar van Vliet:** Conceptualization, Writing - review & editing. **Alfred Posch:** Writing - review & editing, Resources.

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Appendix

See Fig. B1, Tables A1 and A2

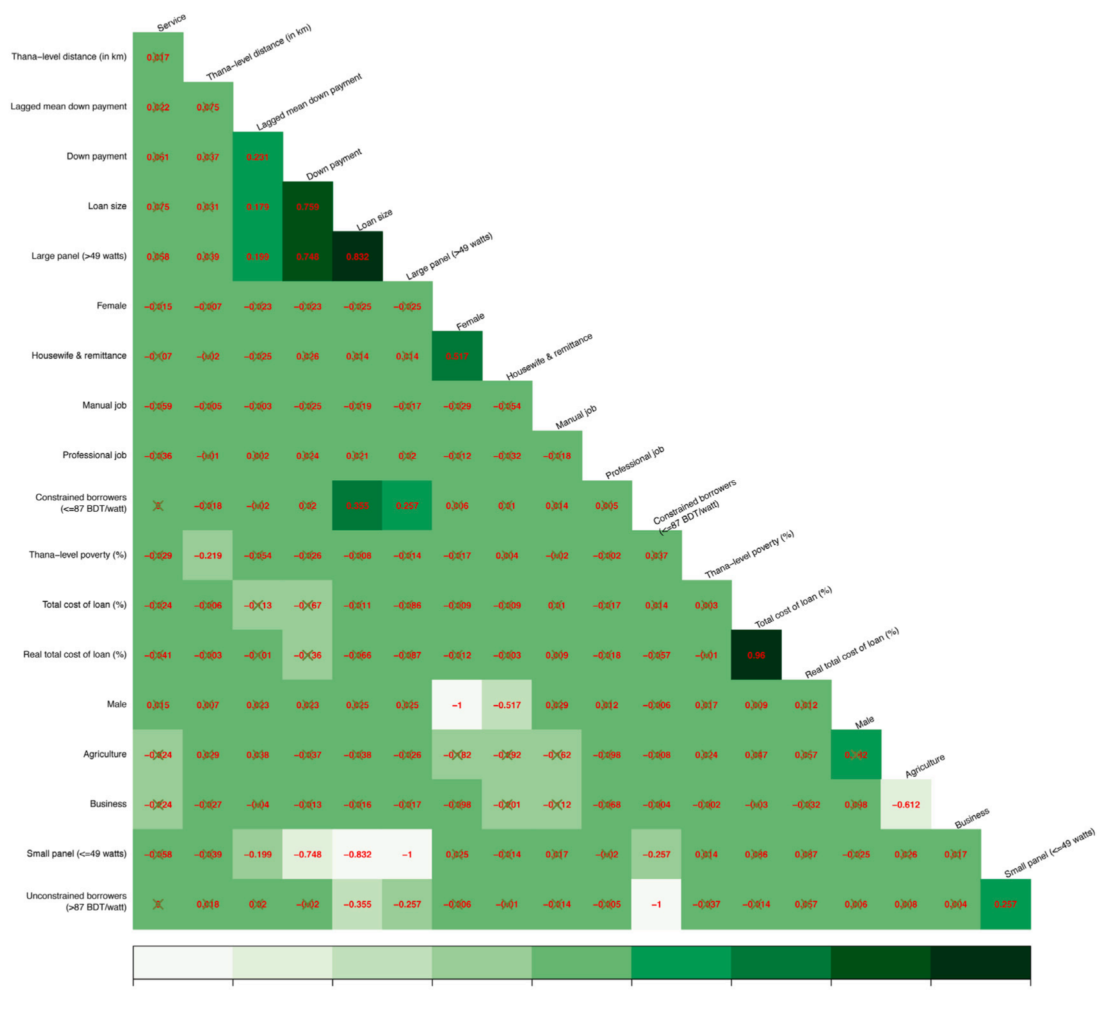

Fig. B1. Correlation matrix of key variables. *Notes*: The insignificant correlations at the 10 percent significance level are crossed out in the matrix.

Table A1
Description and summary statistics of variables.

Variables	Definition	Highly constrained borrowers		Relatively unconstrained borrowers		All borrowers	
		Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)
Outcome variable							
Total cost of loan (%)	This denotes the total financial cost in the form of interest rate, including the service charge percentage, that a borrower has to pay over the duration of the loan. The total cost of a loan is computed by multiplying the respective borrowers' annual interest rate (%) by the loan maturity (in years).	29.315	7.137	29.098	8.581	29.208	7.884
Variable of interest							
Down payment	Covariate, the amount of down payment in Bangladeshi Taka (BDT), as a proxy measure of borrowing constraints, a borrower has to pay before taking up the remaining solar home system price as a loan. We use a log transformation for this variable.	3,128.602	1,712.837	3,051.814	2,056.472	3,090.681	1,890.749
Instrument							
Lagged mean down payment	Covariate, the average amount of down payment other borrowers in a union have paid in the preceding month. The past borrowers' payment behavior has been used an instrument to separate exogenous variation in the amount of down payment of the individual borrower. We use a log transformation for this variable.	3,072.417	885.553	3,109.55	928.186	3,090.755	907.046
Controls							
Low income group (≤ 10,000 BDT)	Indicator variable, which takes the value of 1 when a borrower belongs to the income group of less than equal to 10,000 BDT.	0.606	0.489	0.630	0.483	0.618	0.486
Medium income group (10,000–20,000 BDT)	Indicator variable, which takes the value of 1 when a borrower belongs to the income group with 10,000–20,000 BDT. We use this variable as a reference income group.	0.324	0.468	0.314	0.464	0.319	0.466
High income group (> 20,000 BDT)	Indicator variable, which takes the value of 1 when a borrower belongs to the income group of over 20,000 BDT.	0.070	0.255	0.056	0.230	0.063	0.243
Agriculture	Indicator variable, which takes the value of 1 when a borrower belongs to agriculture occupation.	0.466	0.499	0.474	0.499	0.470	0.499
Business	Indicator variable, which takes the value of 1 when a borrower belongs to business occupation.	0.295	0.456	0.299	0.458	0.297	0.457
Service	Indicator variable, which takes the value of 1 when a borrower belongs to service occupation. We use this variable as a reference occupational group.	0.106	0.308	0.106	0.308	0.106	0.308
Housewife remittance	Indicator variable, which takes the value of 1 when a borrower is home-maker or receives remittance income earned by family members outside.	0.091	0.287	0.085	0.279	0.088	0.283
Professional job	Indicator variable, which takes the value of 1 when a borrower belongs to professional occupation, such as doctor, teacher, lawyers, etc.	0.011	0.106	0.010	0.101	0.011	0.103
Manual job	Indicator variable, which takes the value of 1 when a borrower is hawker, rickshaw puller, driver or is in similar occupations.	0.031	0.174	0.027	0.161	0.029	0.168
Female	Indicator variable, which takes the value of 1 when a borrower is female. We use this variable as the reference.	0.076	0.266	0.073	0.261	0.075	0.263
Male	Indicator variable, which takes the value of 1 when a borrower is male.	0.924	0.266	0.927	0.261	0.925	0.263
Additional controls							
Thana-level poverty (%)	Covariate, which presents the poverty rate at the thana-level. This is a time-invariant variable in our study.	35.401	15.553	34.267	15.007	34.841	15.297

(*continued on next page*)

Table A1 (*continued*).

Variables	Definition	Highly constrained borrowers		Relatively unconstrained borrowers		All borrowers	
		Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)
Thana-level distance (in km)	Covariate, which presents distance between thana, in which a partner organization's office is located and union, in which a borrower lives in. This is a time-invariant variable in our study.	7.496	4.111	7.649	4.436	7.572	4.275

Table A2
IV estimation results for first-stage regression.

	Outcome variable: $\log(\widehat{\text{down payment}})$		
	All borrowers (1)	Highly constrained borrowers (2)	Relatively unconstrained borrowers (3)
Log(lagged mean down payment)	0.394***	0.416***	0.292***
	(0.013)	(0.017)	(0.011)
Reference: medium income group (10,000–20,000 BDT)			
Low income group (≤ 10,000 BDT)	−0.130***	−0.166***	−0.077***
	(0.004)	(0.004)	(0.004)
High income group (> 20,000 BDT)	0.174***	0.174***	0.146***
	(0.008)	(0.010)	(0.008)
Reference: service occupational group			
Agriculture	−0.073***	−0.092***	−0.043***
	(0.005)	(0.007)	(0.007)
Business	−0.075***	−0.084***	−0.052***
	(0.005)	(0.007)	(0.007)
Housewife & remittance	0.023***	0.005	0.044***
	(0.006)	(0.008)	(0.008)
Professional job	0.037***	0.016	0.054***
	(0.010)	(0.014)	(0.012)
Manual job	−0.114***	−0.123***	−0.087***
	(0.007)	(0.010)	(0.009)
Reference: female			
Male	0.063***	0.064***	0.051***
	(0.004)	(0.005)	(0.004)
Partner organization fixed effects	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes
Observations	626,761	317,242	309,519
R-squared	0.147	0.225	0.180
F-test (1st stage)	27,475.709	14,126.179	9,606.607
F-test (1st stage), p-value	0.000	0.000	0.000

Notes: Following Reed (2015) and Narayanan and Nair (2013), we construct a lagged instrument that denotes the average down payments of other borrowers in the preceding month in a given union where an individual borrower lives. Based Eq. (3), columns (1) to (3) regress down payment on the lagged mean down payment. To look for borrower group differences, we split samples into highly constrained and relatively unconstrained borrowers based on the median value of down payment per watt (87 BDT or, ≈ 1.02 USD). Column (1) reports first-stage regression results on full sample and estimation results by borrower groups are shown in columns (2) and (3). Across all specifications, we use partner organization fixed effects and year-quarter fixed effects. We cluster standard errors at the union level, and clustered standard errors are in parentheses. *, **, *** indicate 10%, 5%, and 1% significance levels, respectively. Constant is included but not reported.

References

Acheampong, A.O., Erdiaw-Kwasie, M.O., Abunyewah, M., 2021. Does energy accessibility improve human development? Evidence from energy-poor regions. Energy Econ. 96, 105165.

Acolin, A., Bricker, J., Calem, P., Wachter, S., 2016. Borrowing constraints and homeownership. Amer. Econ. Rev. 106 (5), 625–629.

Aklin, M., Cheng, C.-Y., Urpelainen, J., 2020. Inequality in policy implementation: Caste and electrification in rural India. J. Public Policy 1–29.

de Araujo, D.K.G., Barroso, J.B.R.B., Gonzalez, R.B., 2020. Loan-to-value policy and housing finance: Effects on constrained borrowers. J. Financ. Intermediation 42, 100830.

Asadullah, M.N., Xiao, S., 2020. The changing pattern of wage returns to education in post-reform China. Struct. Change Econ. Dyn. 53, 137–148.

Balarama, H., Islam, A., Kim, J.S., Wang, L.C., 2020. Price elasticities of residential electricity demand: Estimates from household panel data in Bangladesh. Energy Econ. 92, 104937.

Banerjee, A., Chandrasekhar, A.G., Duflo, E., Jackson, M.O., 2013. The diffusion of microfinance. Science 341 (6144), 1236498.

Barakova, I., Bostic, R.W., Calem, P.S., Wachter, S.M., 2003. Does credit quality matter for homeownership? J. Hous. Econ. 12 (4), 318–336.

Barakova, I., Calem, P.S., Wachter, S.M., 2014. Borrowing constraints during the housing bubble. J. Hous. Econ. 24, 4–20.

Barry, M.S., Creti, A., 2020. Pay-as-you-go contracts for electricity access: Bridging the "last mile" gap? A case study in Benin. Energy Econ. 90, 104843.

Basten, C., Koch, C., 2015. The causal effect of house prices on mortgage demand and mortgage supply: Evidence from switzerland. J. Hous. Econ. 30, 1–22.

Baurzhan, S., Jenkins, G.P., 2016. Off-grid solar PV: Is it an affordable or appropriate solution for rural electrification in Sub-Saharan African countries? Renew. Sustain. Energy Rev. 60, 1405–1418.

Bellemare, M.F., Masaki, T., Pepinsky, T.B., 2017. Lagged explanatory variables and the estimation of causal effect. J. Politics 79 (3), 949–963.

Best, R., Nepal, R., Saba, N., 2021. Wealth effects on household solar uptake: Quantifying multiple channels. J. Cleaner Prod. 297, 126618.

Bester, H., Hellwig, M., 1987. Moral hazard and equilibrium credit rationing: An overview of the issues. In: Bamberg, G., Spremann, K. (Eds.), Agency Theory, Information, and Incentives. Springer, Berlin, Heidelberg, pp. 135–166.

Bogan, V.L., Turvey, C.G., Salazar, G., 2015. The elasticity of demand for microcredit: Evidence from Latin America. Dev. Policy Rev. 33 (6), 725–757.

Bollinger, B., Gillingham, K., 2012. Peer effects in the diffusion of solar photovoltaic panels. Mark. Sci. 31 (6), 900–912.

Bryan, M.L., Rice, N., Roberts, J., Sechel, C., 2020. Mental health and employment: A bounding approach using panel data. The Sheffield Economic Research Paper Series (SERPS) No. 2020006, Department of Economics, University of Sheffield.

Chambers, M., 2012. Mortgage innovation. In: Smith, S.J. (Ed.), International Encyclopedia of Housing and Home. Elsevier, San Diego, pp. 370–375.

Churchill, S.A., Smyth, R., 2020. Ethnic diversity, energy poverty and the mediating role of trust: Evidence from household panel data for Australia. Energy Econ. 86, 104663.

Clark, A.E., D'Ambrosio, C., Zhu, R., 2021. Job quality and workplace gender diversity in Europe. J. Econ. Behav. Organ. 183, 420–432.

Conway, D., Robinson, B., Mudimu, P., Chitekwe, T., Koranteng, K., Swilling, M., 2019. Exploring hybrid models for universal access to basic solar energy services in informal settlements: Case studies from South Africa and Zimbabwe. Energy Res. Soc. Sci. 56, 101202.

Cull, R., Demirgüç-Kunt, A., Morduch, J., 2009. Microfinance meets the market. J. Econ. Perspect. 23 (1), 167–192.

Cull, R., Demirgüç-Kunt, A., Morduch, J., 2018. The microfinance business model: Enduring subsidy and modest profit. World Bank Econ. Rev. 32 (2), 221–244.

Dang, D.A., La, H.A., 2019. Does electricity reliability matter? Evidence from rural Viet Nam. Energy Policy 131, 399–409.

Dehejia, R., Montgomery, H., Morduch, J., 2012. Do interest rates matter? Credit demand in the Dhaka slums. J. Dev. Econ. 97 (2), 437–449.

Duca-Radu, I., Kenny, G., Reuter, A., 2021. Inflation expectations, consumption and the lower bound: Micro evidence from a large multi-country survey. J. Monetary Econ. 118, 120–134.

Engelhardt, G.V., Mayer, C.J., 1998. Intergenerational transfers, borrowing constraints, and saving behavior: Evidence from the housing market. J. Urban Econ. 44 (1), 135–157.

Fornara, F., Pattitoni, P., Mura, M., Strazzera, E., 2016. Predicting intention to improve household energy efficiency: The role of value-belief-norm theory, normative and informational influence, and specific attitude. J. Environ. Psychol. 45, 1–10.

Gardete, P.M., 2015. Social effects in the in-flight marketplace: Characterization and managerial implications. J. Mar. Res. 52 (3), 360–374.

Giné, X., Karlan, D.S., 2014. Group versus individual liability: Short and long term evidence from Philippine microcredit lending groups. J. Dev. Econ. 107, 65–83.

Glemarec, Y., 2012. Financing off-grid sustainable energy access for the poor. Energy Policy 47, 87–93.

Graziano, M., Gillingham, K., 2015. Spatial patterns of solar photovoltaic system adoption: The influence of neighbors and the built environment. J. Econ. Geogr. 15 (4), 815–839.

Grimm, M., Lenz, L., Peters, J., Sievert, M., 2020. Demand for off-grid solar electricity: Experimental evidence from Rwanda. J. Assoc. Environ. Resour. Econ. 7 (3), 417–454.

Hudon, M., Ashta, A., 2013. Fairness and microcredit interest rates: From Rawlsian principles of justice to the distribution of the bargaining range. Bus. Ethics Eur. Rev. 22 (3), 277–291.

Hudon, M., Sandberg, J., 2013. The ethical crisis in microfinance: Issues, findings, and implications. Bus. Ethics Q. 23 (4), 561–589.

IEA, IRENA, UNSD, WB, WHO, 2020. Tracking SDG 7: The Energy Progress Report 2020. International Energy Agency; International Renewable Energy Agency; United Nations Statistics Division; World Bank; World Health Organization. World Bank, Washington, DC, Available at https://openknowledge.worldbank.org/handle/10986/33822.

Jæger, M.M., 2008. Does left–right orientation have a causal effect on support for redistribution? Causal analysis with cross-sectional data using instrumental variables. Int. J. Public Opin. Res. 20 (3), 363–374.

Karlan, D., Morduch, J., 2010. Access to finance. In: Rodrik, D., Rosenzweig, M. (Eds.), In: Handbook of Development Economics, vol. 5, Elsevier, Amsterdam, The Netherlands, pp. 4703–4784.

Karlan, D.S., Zinman, J., 2008. Credit elasticities in less-developed economies: Implications for microfinance. Amer. Econ. Rev. 98 (3), 1040–1068.

Khan, T., Khanam, S.N., Rahman, M.H., Rahman, S.M., 2019. Determinants of microfinance facility for installing solar home system (SHS) in rural Bangladesh. Energy Policy 132, 299–308.

Khan, W., Shaorong, S., Ullah, I., 2017. Doing business with the poor: The rules and impact of the microfinance institutions. Econ. Res. (Ekonomska istraživanja) 30 (1), 951–963.

Khandker, S.R., Koolwal, G.B., Badruddoza, S., 2013. How Does Competition Affect the Performance of MFIs? Evidence from Bangladesh, Policy Research Working Paper No. 6408, The World Bank, Washington, D.C..

Laufer, D., Schäfer, M., 2011. The implementation of Solar Home Systems as a poverty reduction strategy - A case study in Sri Lanka. Energy Sustain. Dev. 15 (3), 330–336.

Lay, J., Ondraczek, J., Stoever, J., 2013. Renewables in the energy transition: Evidence on solar home systems and lighting fuel choice in Kenya. Energy Econ. 40, 350–359.

Lee, K., Brewer, E., Christiano, C., Meyo, F., Miguel, E., Podolsky, M., Rosa, J., Wolfram, C., 2016. Electrification for "under grid" households in rural Kenya. Dev. Eng. 1, 26–35.

Levine, D.I., Beltramo, T., Blalock, G., Cotterman, C., Simons, A.M., 2018. What impedes efficient adoption of products? Evidence from randomized sales offers for fuel-efficient cookstoves in Uganda. J. Eur. Econom. Assoc. 16 (6), 1850–1880.

Mainali, B., Silveira, S., 2012. Renewable energy markets in rural electrification: Country case Nepal. Energy Sustain. Dev. 16 (2), 168–178.

Mallick, D., 2012. Microfinance and moneylender interest rate: Evidence from Bangladesh. World Dev. 40 (6), 1181–1189.

McIntosh, C., Wydick, B., 2005. Competition and microfinance. J. Dev. Econ. 78 (2), 271–298.

Mendoza, R.U., 2011. Why do the poor pay more? Exploring the poverty penalty concept. J. Int. Dev. 23 (1), 1–28.

Miller, D., 2011. Policy guidance: Seeing it like an entrepreneur. In: Selling Solar: The Diffusion of Renewable Energy in Emerging Markets. Routledge, United Kingdom, pp. 175–216.

Mishra, V., Smyth, R., 2015. Estimating returns to schooling in urban China using conventional and heteroskedasticity-based instruments. Econ. Model. 47, 166–173.

Moner-Girona, M., Szabo, S., Bhattacharyya, S., 2016. 1.07 - Off-grid photovoltaic technologies in the solar belt: Finance mechanisms and incentives. In: Sayigh, A. (Ed.), In: Comprehensive Renewable Energy, vol. 1, Elsevier, United Kingdom, pp. 111–141.

Morduch, J., 1999. The role of subsidies in microfinance: Evidence from the Grameen Bank. J. Dev. Econ. 60 (1), 229–248.

Morduch, J., Ogden, T., 2019. The challenges of social investment through the lens of microfinance. In: Hudon, M., Labie, M., Szafarz, A. (Eds.), A Research Agenda for Financial Inclusion and Microfinance. Edward Elgar Publishing, United Kingdom, pp. 12–26.

Mukherjee, S., Datta, B., Paul, J., 2020. The phenomenon of purchasing second-hand products by the BOP consumers. J. Retail. Cons. Serv. 57, 102189.

Nair, H.S., Manchanda, P., Bhatia, T., 2010. Asymmetric social interactions in physician prescription behavior: The role of opinion leaders. J. Mar. Res. 47 (5), 883–894.

Narayanan, S., Nair, H.S., 2013. Estimating causal installed-base effects: A bias-correction approach. J. Mar. Res. 50 (1), 70–94.

Nygaard, I., 2009. The compatibility of rural electrification and promotion of low-carbon technologies in developing countries - the case of Solar PV for Sub-Saharan Africa. Eur. Rev. Energy Mark. 3 (2), 125–158.

Oster, E., 2019. Unobservable selection and coefficient stability: Theory and evidence. J. Bus. Econom. Statist. 37 (2), 187–204.

Palit, D., 2013. Solar energy programs for rural electrification: Experiences and lessons from South Asia. Energy Sustain. Dev. 17 (3), 270–279.

Pelz, S., Chindarkar, N., Urpelainen, J., 2020. Energy access for marginalized communities: Evidence from rural North India, 2015–2018. World Dev. 137, 105204.

Pereira, R.H., Schwanen, T., Banister, D., 2017. Distributive justice and equity in transportation. Transp. Rev. 37 (2), 170–191.

Petach, L.A., Tavani, D., 2019. Consumption externalities and growth: Theory and evidence for the United States. J. Econ. Behav. Organ. 183, 976–997.

Pokropek, A., 2016. Introduction to instrumental variables and their application to large-scale assessment data. Large-Scale Assess. Educ. 4 (1), 1–20.

Reed, W.R., 2015. On the practice of lagging variables to avoid simultaneity. Oxf. Bull. Econ. Stat. 77 (6), 897–905.

Rode, J., et al., 2020. I Spot, I Adopt! Peer Effects and Visibility in Solar Photovoltaic System Adoption of Households. Technical Report, ZBW-Leibniz Information Centre for Economics, Kiel, Hamburg, Available at https://www.econstor.eu/bitstream/10419/224644/1/vfs-2020-pid-40501.pdf.

Rosenthal, S.S., 2002. Eliminating credit barriers to increase homeownership: How far can we go? In: Retsinas, N.P., Belsky, E.S. (Eds.), Low-Income Homeownership: Examining the Unexamined Goal. Cambridge, Massachusetts. pp. 111–145.

Rysankova, D., Peters, K., Sturm, R., 2020. Off-Grid Solar Market Trends Reports 2020. ESMAP, World Bank, IFC and Global Off-grid Lighting Association (GOGLA), Washington, D.C., Available at https://www.gogla.org/resources/2020-off-grid-solar-market-trends-report.

Samarakoon, S., 2019. A justice and wellbeing centered framework for analysing energy poverty in the Global South. Ecol. Econom. 165, 106385.

Sandberg, J., 2012. Mega-interest on microcredit: Are lenders exploiting the poor? J. Appl. Philos. 29 (3), 169–185.

Sedai, A.K., Nepal, R., Jamasb, T., 2021. Flickering lifelines: Electrification and household welfare in India. Energy Econ. 94, 104975.

Sherratt, L., 2016. From empowerment to exploitation: MFIs and their borrowers. In: Can Microfinance Work? How to Improve Its Ethical Balance and Effectiveness. Oxford University Press, New York, pp. 47–79.

Sievert, M., Steinbuks, J., 2020. Willingness to pay for electricity access in extreme poverty: Evidence from Sub-Saharan Africa. World Dev. 128, 104859.

Sovacool, B.K., Heffron, R.J., McCauley, D., Goldthau, A., 2016. Energy decisions reframed as justice and ethical concerns. Nature Energy 1 (5), 1–6.

Srinivasan, S., 2009. Subsidy policy and the enlargement of choice. Renew. Sustain. Energy Rev. 13 (9), 2728–2733.

Stacy, C.P., Theodos, B., Bai, B., 2018. How to prevent mortgage default without skin in the game: Evidence from an integrated homeownership support nonprofit. J. Hous. Econ. 39, 17–24.

Steel, W.F., Anyidoho, N.A., Dadzie, F.Y., Hosier, R.H., 2016. Developing rural markets for solar products: Lessons from Ghana. Energy Sustain. Dev. 31, 178–184.

Tschach, I.E., 2000. The impact of inflation on long-term housing loans, Technical report, Working Paper Series: Finance & Accounting, No. 55b. Goethe University Frankfurt.

Turner, B., 2019. Diffusion on the ground: Rethinking the logic of scale and access in off-grid solar in Sri Lanka. Energy Res. Soc. Sci. 50, 1–6.

Umberger, W.J., He, X., Minot, N., Toiba, H., 2015. Examining the relationship between the use of supermarkets and over-nutrition in Indonesia. Am. J. Agric. Econ. 97 (2), 510–525.

UN, 2020. The Sustainable Development Goals Report 2020. United Nations Statistics Division (UNSD), United Nations Publications, New York, Available at https://unstats.un.org/sdgs/report/2020/.

Van Wee, B., Geurs, K., 2011. Discussing equity and social exclusion in accessibility evaluations. Eur. J. Transp. Infrastruct. Res. 11 (4).

Wimmer, N., 2014. Grameen Shakti social business: A vanguard model for rural energy service. In: Grove, A., Berg, G. (Eds.), Social Business. Springer-Verlag, Berlin, pp. 89–100.

Winter-Nelson, A., Temu, A.A., 2005. Liquidity constraints, access to credit and pro-poor growth in rural Tanzania. J. Int. Dev. 17 (7), 867–882.

Wolske, K.S., Gillingham, K.T., Schultz, P.W., 2020. Peer influence on household energy behaviours. Nature Energy 5 (3), 202–212.

Wong, S., 2012. Overcoming obstacles against effective solar lighting interventions in South Asia. Energy Policy 40, 110–120.

World Bank, 2012. Rural Electrification and Renewable Energy Development II (RERED II) Project. Project Appraisal Report No. 71700-BD, Sustainable Development Department, The World Bank: Washington, D.C..

World Bank, 2013a. Poverty Assessment: Assessing a decade of progress in reducing poverty, 2000-2010. Technical Report, Bangladesh Development Series Paper No. 31, Human Development & Poverty Reduction and Economic Management Sectors (South Asia Region), The World Bank Office, Dhaka.

World Bank, 2013b. Rural Electrification and Renewable Energy Development (RERED) Project. Implmentation Completion and Results Report No. ICR2609, Sustainable Development Department, The World Bank: Washington, D.C..

Yadav, P., Davies, P.J., Sarkodie, S.A., 2019. The prospects of decentralised solar energy home systems in rural communities: User experience, determinants, and impact of free solar power on the energy poverty cycle. Energy Strategy Rev. 26, 100424.