Modelling the Impact of Market Imperfections on Farm Household Investment in Stand-Alone Solar PV Systems

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Conflict of interest

The authors declare no conflict of interest

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Abstract

Access to electricity in rural Sub-Saharan Africa, where livelihoods are predominantly based on small scale farming, is significantly low. Extending centralised national electricity grids to these rural areas faces significant technical and financial constraints. As a result, many see household-financed decentralised technologies such as small standalone solar photovoltaic (PV) systems as being important for achieving greater electricity access. However, rural farm households typically face a range of market imperfections including lack of access to credit, investment irreversibility (or absence of second-hand markets) and farm production/income risk which act as barriers to their ability and/or willingness to invest. This paper examines how these market imperfections impact on the adoption of standalone solar PV systems for small scale farm households in Uganda. We consider how temporary or permanent these barriers to adoption are when farm production/income is uncertain. We do so by using a dynamic programming model which captures household investment in small scale solar PV systems where significant positive benefits arise through assumed improved farm productivity or income effects, while allowing for credit constraints, investment irreversibility and income risk. Although strong positive incentives exist in the model to adopt a solar PV system, the results show that adoption rates are substantially lower for credit constrained households, with only 40% of these households adopting immediately, compared with over 70% of credit unconstrained households. While these adoption rates do increase over time, only 60% of credit constrained households have adopted within 5 years compared with nearly all credit unconstrained households adopting within the same time period. In the longer term for almost 30% of households the credit constraints act as a permanent barrier to adoption. The presence of a well-functioning second-hand market does increase household consumption and welfare but the impacts on overall adoption rates are rather small.

Keywords: Africa; Market imperfections; Farm households; Solar PVs; Credit; Irreversibility

1 Introduction

The International Energy Agency estimates that less than half of the populace in Sub-Saharan Africa (SSA) have access to electricity (IEA, 2017). In 2014, overall access was less than 15% in countries such as Burundi (7%), Chad (8%), Liberia (9.1%) and the Central African Republic (12.3%) among others (World Bank, 2014). Even so, access is significantly lower in the rural areas of these countries and across the SSA region. Meanwhile, access to electricity has been shown to have significant benefits for rural inhabitants whose livelihoods are typically based on small scale farming (Bensch, Grimm, & Peters, 2015; Bonan, Pareglio, & Tavoni, 2017; Chen et al., 2017; Lemaire, 2009).

To achieve greater access to electricity in rural areas across SSA however, extending the national electricity grids within many countries faces significant technical constraints (e.g. insufficient grid generation capacity, poor maintenance of existing networks, geographic barriers to grid extensions, etc.); and economic and financial constraints (e.g. poor economics of electricity supply to sparsely populated and remotely located rural areas, government budget constraints, the inability of poor rural inhabitants to pay for the economic price of grid provided electricity, etc.). Hence, in the short to medium term many see decentralised renewable systems including mini-grids, small standalone solar PV systems, etc. as being enormously important for greater electricity access in rural areas across SSA (Abdul-Salam & Phimister, 2016; Deichmann, Meisner, Murray, & Wheeler, 2011; Parshall, Pillai, Mohan, Sanoh, & Modi, 2009).

However, while national grid extension and to some extent decentralised mini-grids are funded by central governments and local and international donor organisations, improving standalone access to electricity via small standalone solar PV systems requires purchase and adoption of a seemingly capital-intensive system by many poor farm households. As is well known however, poor rural communities in developing countries are systematically exposed to market imperfections which can inhibit their ability and/or willingness to invest in income enhancing but capital-intensive technologies (Abdul-Salam, 2014; De Janvry & Sadoulet, 2006; Ellis, 1993; Fafchamps, 2003; Ray, 1998; Singh, Squire, & Strauss, 1986).

Liquidity and credit constraints are an important barrier to a range of household adoption decisions in developing countries when upfront costs are non-negligible but relatively small (Bensch et al., 2015; Levine, Beltramo, Blalock, Cotterman, & Simons, 2018; Tarozzi et al., 2014). Investments which are lumpy and irreversible can also negatively affect household technology adoption and investment in the presence of income risk and credit constraints (Fafchamps & Pender, 1997; Hill, 2010). Investment irreversibility generates a “reluctance to invest” and a value to waiting (Chirinko & Schaller, 2009). While we expect credit constraints and investment irreversibility to reduce household adoption at a point in time, one question which has received relative little attention in the literature is how “permanent” these barriers to adoption are or whether positive income shocks could mitigate their effects over time? If, consistent with real option theory, the household waits until there is a positive shock to their income position and then adopts, the impact of the credit constraints and investment irreversibility might only be “temporary” and therefore the continuing challenges associated with creating commercial markets less pressing for policy makers. For example, Dadi, Burton, and Ozanne (2004) show that the length of time farmers wait before adopting new agricultural techniques depends significantly on output price variations.

The impact of the credit constraints on the creation of functioning commercial markets for off grid systems and services has also long been recognized and a range of business models have been developed to try to mitigate these impacts, including pay as you go (PAYG) service, fee for service, ownership financed via micro-credit, etc. (Martinot, Cabraal, & Mathur, 2001; Pode, 2013). The creation of second-hand markets can also help to mitigate the impacts of liquidity constraints and irreversibility by allowing for household sales as necessary, hence improving the allocation of resources and increasing consumer welfare (Chen, Esteban, & Shum, 2013). Where transaction costs prevent secondary markets, the ownership (adoption) of durables by households can fall significantly (Gavazza, Lizzeri, & Roketskiy, 2014). However, thinness of secondary markets and adverse selection issues can prevent such markets from functioning efficiently (Ramey & Shapiro, 2001).

Second-hand markets exist for many durable goods in Sub-Saharan Africa although it is argued that these markets often do not function well (Ezeoha, Okoyeuzu, Onah, & Uche, 2018). There has been a particular growth in markets for used Electrical and Electronic Equipment (EEE) over recent years, based on imports of used computers, mobile phones, and TVs from developed countries (Odeyingbo, Nnorom, & Deubzer, 2017; Schluep et al., 2011). It is recognized that similar second-hand markets for solar panel recycling and re-use are likely to emerge in developing countries in the near future (Xu, Li, Tan, Peters, & Yang, 2018). Although the development of such markets is often inhibited by trade restrictions (Czaga & Fliess, 2004; Navaretti, Soloaga, & Takacs, 1998), reducing the barriers to re-use of EEE is seen by policy makers as an important part of the regulation of e-waste in developing countries. These markets are also claimed to have economic benefits in terms of bridging the “digital divide” by improving affordability of ICT equipment to low and middle-income households and in creating employment through refurbishment activities (Milovantseva & Fitzpatrick, 2015).

The aim of this paper is to explore the extent to which access to credit constraints and investment irreversibility in relation to access to second-hand markets impact the adoption of standalone solar PV systems for small scale farm households in Uganda when there are clear incentives to do so. Specifically, we consider how temporary or permanent these barriers to adoption are when farm production/household income is uncertain. We also explore how far functioning second-hand markets might mitigate the impact of the adoption barriers. To do this, we construct a dynamic programming model to capture investment and re-investment in small scale solar PV systems by farm households, which allows for (1) credit constraints, (2) farm production risk, (3) household risk aversion, and (4) irreversibility of investment in the solar PV investment. The model is calibrated drawing on data from the Ugandan Panel Data Survey (World Bank, 2013) and simulated to represent 10,000 households whose initial wealth distribution matches the Ugandan data.

The structure of the paper is as follows. In Section 2, to further motivate the modelling we provide a more detailed background on the impacts of electrification via small scale off-grid systems and discuss the business delivery models used to address access to credit issues. Section 3 introduces the model structure, while Section 4 provides detail on the initialisation of the model using the Ugandan data. Section 5 reports the simulation results. Section 6 concludes.

2 Background

The multi-tier framework introduced by the Sustainable Energy for All initiative recognizes that the value of access to electricity is not binary but depends on the quantity and quality of electricity supplied and the extent of access to key electricity services (Alstone, Gershenson, & Kammen, 2015; SE4ALL, 2015). Despite their limited supply capacity compared to grid connection, off-grid solutions such as solar lamps and Solar Home Systems (SHS) which provide Tier 1 or Tier 2 access are recognized as providing a number of electricity services which can potentially improve household economic welfare e.g. lighting, charging and running devices such as mobile phones, radios and TV. These services would likely satisfy most household electricity demand in rural SSA (Peters & Sievert, 2015).

The associated off grid solar market has grown considerably in Sub-Saharan Africa over the last few years. In Uganda, the market is somewhat less developed than elsewhere in East Africa, e.g. Kenya and Tanzania, with recent estimates suggesting that around 270 thousand SHS systems have been installed (Shell Foundation, 2018). Uganda is a market which is seen to have significant potential for further growth with current penetration rates of only around 20% (Lighting Global, 2018).

The evidence on the impacts of this type of small scale electrification has been synthesized in a number of recent reviews (Bonan et al., 2017; Lemaire, 2009), but quantifying these using impact evaluation methods remains an active area of research (Bensch et al., 2015; Chen et al., 2017). Bensch et al. (2015) characterize the possible impacts of small scale off-grid electrification as arising from *budget*, *health* and *productivity* effects.

Budget or expenditure effects arise from the impact of adoption of say SHS on the marginal price of energy within the household, potentially reducing both overall expenditure and increasing quantity demanded of related electricity services. Both the wider reviews and the most recent focussed studies suggest that adoption of small scale off-grid systems such as solar lamps or SHS significantly reduce energy expenditure in the household. Bensch et al. (2015) find that households in their control group (without access to a low cost solar kit) pay approximately five times as much per lighting hour as households in the treatment group (with access), while Chen et al. (2017) suggest average savings of 77 per cent in weekly energy expenditure for those adopting a SHS. Furthermore, the evidence suggests that the associated lower effective price of energy increases consumption of electricity services particularly at the intensive margin with increased mobile phone use and TV viewing time. There is also some evidence of increases at the extensive margin with increased durable purchases (Lemaire, 2009; Stojanovski, Thurber, & Wolak, 2017).

Positive health effects associated with solar lamps and home systems are plausible where adoption improves household environment when electricity is used for lighting and cooking in place of smoke intensive biomass lanterns and stoves. The evidence on health effects arising from these types of effect is more mixed with some positive results (Bensch et al., 2015; Chen et al., 2017). However, there is wider evidence of positive impacts on safety (reduced burns) and some evidence of positive health effects due to improved access to information from TV (Lemaire, 2009).

A number of indirect mechanisms have also been suggested through which off grid electrification might affect productivity. Improvements in lighting change the time available for a range of activities including study, domestic tasks, home based business activities and leisure. Hence, time use across all household members may be affected with individuals potentially changing both their total supply of time for productive work but also its composition across family members. Overall the evidence does suggest increases in study time by (younger) children. The evidence that changing time use leads to increases in productive activities and income is mixed but with some research showing positive effects (Bensch et al., 2015; Lemaire, 2009; Van de Walle, Ravallion, Mendiratta, & Koolwal, 2017).

Another possible channel for productivity effects is through greater access to information and improved communication as facilitated by improved access to ICT devices and services. For example, Abdul- Salam and Phimister (2017) showed that access to ICT devices and services can increase farm efficiency whilst reducing production risks. Aker (2008) found in Niger that mobile phones have an impact on price dispersion particularly where travel costs are high, while Overå (2006) showed evidence in Ghana of mobile phones helping reduce farmers' costs and increasing effectiveness of trade networks. Muto and Yamano (2009) found that mobile phone use in Uganda enabled higher market participation by small rural farmers producing perishable crops, while De Silva and Ratnadiwakara (2008) show that mobile phones significantly helped gherkin farmers in Sri Lanka reduce waste. Similarly Jensen (2007) found that the adoption of mobile phones decreased price dispersion and wastage by enabling the spread of information for fishermen in India, which made markets more efficient and enhanced both consumer and producer welfare.

Information effects may also arise as spill-over effects which are external to the household. Van de Walle et al. (2017) find significant positive village level electrification effects on households who have no direct electricity access. For example while adoption of a SHS may increase the intensity of use of mobile phones (Lemaire, 2009; Stojanovski et al., 2017), many other arrangements exist e.g. village kiosks, small scale shops which sell, charge and repair mobile phones, which mean mobile ownership is not restricted to those with direct access to electricity (Aker & Mbiti, 2010).

Of course, rather than generating new income, the motivation for adoption of solar PV may arise from new income earning possibilities. For example, the migration of a family member to work in urban areas may provide both the motivation (to ease mobile phone charging for communication with the migrant) and purchasing power to enable solar PV adoption.[1]

Overall, these various channels provide plausible and significant improvements to household welfare associated with the adoption of off-grid electricity systems such as solar PVs. For example, Chen et al. (2017) suggest expenditure savings alone are such that households would break even in around 3 years after the initial purchase of a SHS. Given the positive incentives for household adoption, why are these welfare improving technologies not adopted on a wider scale? The literature has identified a variety of reasons as to why consumers may not adopt products which appear to bring significant net benefits. For example, research suggests that imperfect information about product benefits can play an important role in adoption of modern cookstoves (Levine et al., 2018), although the evidence for its role for SHS adoption is more mixed (Urpelainen & Yoon, 2017). There is also evidence that network and peer effects can be important in electrification decisions for households (Bernard & Torero, 2015).

As discussed above liquidity and credit constraints appear to be an important barrier to adoption decisions generally (Bensch et al., 2015; Levine et al., 2018; Tarozzi et al., 2014). More directly in Uganda the lack of access to affordable lending has been identified as an important factor reducing consumer purchases in the off-grid solar market (Lighting Africa, 2014). The impact of such constraints has long been recognized and a range of business and delivery models have been developed to try to mitigate their impacts. These include (1) Retail/Over-the-counter, (2) Pay-As-You-Go (PAYG), (3) Consumer financing and (4) Fee-for-Service (Ellegård, Arvidson, Nordström, Kalumiana, & Mwanza, 2004; Martinot et al., 2001; Pode, 2013). The retail model involves outright purchase by the consumer and is perhaps the oldest approach to selling solar PV systems in SSA. PAYG model is effectively a consumer financing model, where the consumer makes pre-arranged periodic payments but owns the solar PV system once the repayment plan is completed. After-care and servicing are provided by the PV-Energy Services Company (PV-ESCO) during the period of repayments. The consumer financing model involves a partnership between a PV-ESCO and a financial institution such that the PV-ESCO provides products, after-care and servicing whilst the financial institution provides the financing to consumers and collects repayments based on pre-arranged and agreed plans. Finally, the Fee-for-Service model involves consumers paying for electricity services received. Typical payments are monthly, and the solar PV system is not owned by the consumer at any point. After-care and servicing are the responsibility of the PV-ESCO. The suitability of a model for a household depends on a number of factors including affordability and cost, capacity and scalability in relation to the intended use of the solar PV system, the level of after-care and servicing required, etc. However, adverse selection, the identification of customer default risk and the transactions costs for providers remains a significant barrier to the creation of purely commercial markets that are able to supply consumers in all locations. In Uganda it is recognized that government support for financial institutions may be required to improve the supply of capital in the commercial off-grid solar market, e.g. by providing partial risk guarantees and assistance on default and bad debt management (Lighting Africa, 2014).

[1] We thank a referee for pointing this out.

3 Model

3.1 Problem structure

Our starting point for the exploration of the impact of market imperfections on farm households' uptake of solar PV systems is an infinite horizon dynamic programming model which explicitly allows for credit constraints, farm production/income risk and investment reversibility (i.e. ability of a household to sell a used panel in adverse periods in order to meet basic household consumption). Our modelling approach is consistent with many models of this type in the literature (Fafchamps & Pender, 1997; Phimister, 1993, 1995; Rosenzweig & Wolpin, 1993; Sadoulet & De Janvry, 1995; Singh et al., 1986).

As discussed above there are a variety of channels through which an off-grid solar system can have positive welfare effects for the household which, in the absence of other barriers, would provide strong incentives to adopt the technology. As the paper's focus is on the impact of the credit constraints and irreversibility, we simply assume that solar PV has a positive productivity/income effect providing a clear incentive for households to adopt.

Hence the model focusses on trade-offs within the household between the decision to adopt a solar PV system and household consumption when production/income is uncertain, while allowing for investment irreversibility and constraints on credit. As credit markets are imperfect and with no insurance markets, consumption and investment in the model are not separable but simultaneously determined. However, we abstract from wider decisions within the household on labour, land, and capital and from a number of elements of importance for farm households. First, we assume a single source of production/income in the household and therefore ignore the range of sources of explicit and implicit income which are important to households in developing countries e.g. the extent of subsistence production, income from off-farm work or remittances from family members living away from the household. We also do not consider changes in time use or other decisions e.g. on land which may interact with the adoption decisions not least because imperfections in these factor markets are prevalent in developing countries (Sadoulet & De Janvry, 1995). For example as discussed above, adoption of SHS may change the total time available for productive work. Where labour markets are imperfect and the household is not engaged in off-farm work, increasing the family effective available labour time would be expected to lower the implicit opportunity cost of labour within the household hence increasing household labour supply on the farm and potentially any positive productive impact of the solar PV system. Income diversification is recognized as a major strategy employed by poor households to protect against different types of risks. The potential impact on these strategies of solar PV system is also not captured in the model set-up. Finally, consistent with standard approaches to optimal replacement modelling (see e.g. Adda and Cooper, 2003), we consider investment in a single asset only, i.e. the Solar PV system, and hence ignore other potential productive investments in the farm household e.g. livestock, housing, private transport, modern cooking stove, etc. This may overstate the impact of credit constraints on solar adoption rates if other market imperfections remain a barrier to productive investments even when credit constraints are relaxed.

To quantify the simple productivity effect using the dataset and provide a clear base case against which we can judge the impact of the various market imperfections, we draw on evidence of the productivity effects associated with improved access to ICT devices and services due to the improved access to the electricity produced from the standalone solar PV system. To operationalize this, we first assume that the farm household's production is determined by a strictly concave production function that is defined increasingly over four factor inputs namely land, labour, agrochemical input use and an 'information access index'. The information access index captures the income-enhancing productivity effects of access to information and improved communication on the farm, as enabled by access to electricity-dependent devices such as mobile phones, radios, TVs and computers/internet. Abdul-Salam and Phimister (2017) construct such an index for Uganda. We adopt this index in our model and calibrate it as a function of the status of the panel (i.e. whether broken down or operational) and whether the age of the solar panel is less than its maximum assumed economic life. Hence, a farm household with an operational panel has a higher access to information index value. This in turn induces a positive farm productivity (or household income) effect. While it is acknowledged as discussed above that some information effects might arise without the purchase of the solar panel, the Ugandan evidence that phone charging and TV watching are significant uses for off grid solar products is consistent with this assumption (Lighting Africa, 2014). Further the values used provide a robust upper bound for this type of productivity effect and a clear empirically based incentive for household adoption of the solar panel against which the impact of the various constraints can be judged.

We formulate our model with four state variables capturing a farm household's state of liquid wealth W, solar panel (used interchangeably with solar PV system) capital stock which is proxied by the solar panel age A, the state of the solar panel's functionality and the state of the agricultural production shock ε. The decision problem of the household is equivalent to an optimal replacement problem where the household wishes to maximize expected utility over a time additive utility function with a strictly concave sub-utility function defined over general consumption C for each period. Specifically, at the beginning of each period, the household must decide on how much of available liquid wealth W to spend on general consumption C and whether to invest in a new solar panel i.e. buy (*b*), do nothing i.e. inaction (*i*), repair (*r*) if the panel is in a broken down state or sell (*s*) the panel in a second-hand market.

To this end, we consider four market regimes to explore the impact of market imperfections on adoption of solar PV systems. These are (1) credit constrained and irreversible investment regime (i.e. no market for households to sell their used panels); (2) credit constrained and reversible investment regime (i.e. households can sell their used panels in a second-hand market in order to raise consumption in adverse periods); (3) credit unconstrained and irreversible investment regime; and (4) credit unconstrained and reversible investment regime. This way, we are able to clearly draw the impacts of credit access and reversibility on farm households' decisions with respect to investment in solar PV systems in a world with production uncertainty.

Based on the regimes being considered, the household reaches its decisions by comparing the maximum attainable utility from the combined set of decisions. Specifically, consider the credit constrained and reversible market regime, and let V, V^b, V^i, V^r and V^s respectively represent the overall value function, the value function associated with buying (b) a new panel, the value function associated with inaction (i), the value function associated with repairing (r) a broken down panel and the value function associated with selling (s) a used panel. Let $costNewPanel$ represent the cost of buying a new solar panel. Also let the panel repair cost and sale price (i.e. the price the household gets on the second-hand market for selling a used panel) be functions of the age of a panel and its functionality i.e. $repairCost(A,F)$ and $panelSellPrice(A,F)$. As previously mentioned, we also modify the information access index constructed by Abdul-Salam and Phimister (2017) as a function of the solar panel age and functionality i.e. $infoIndex(A,F)$. This index is a factor input in the farm's production technology. We assume exogenous and fixed levels for the other factor inputs namely land size $\overline{ld}$, labour days $\overline{lb}$ and agrochemical fertiliser and pesticide expenditure $\overline{ch}$. The household's problem can be represented as follows;

$$V(W,A,F,\varepsilon) = \max_C \left(V^b(W,A,F,\varepsilon), V^i(W,A,F,\varepsilon), V^r(W,A,F,\varepsilon), V^s(W,A,F,\varepsilon)\right) \tag{1}$$

The detailed specification of each of the sub-problems defined by V^b, V^i, V^r and V^s is provided in the appendix. To provide an indication of the approach, we now briefly discuss V^b in more detail. In equation (1), the farm household chooses the consumption and investment decision that maximises overall utility in each production period. A decision to buy (b) a new panel decomposes the household's optimisation problem into the following value function and transition equations;

$$V^b(W,A,F,\varepsilon) = \max_C \left\{u(C) + \beta \cdot E \cdot V(W', A', F', \varepsilon')\right\} \tag{2}$$

$$W \geq C + costNewPanel \tag{3}$$

$$W' = (1+r)\cdot(W - C - costNewPanel) + \varepsilon . f\left(\overline{ld}, \overline{lb}, \overline{ch}, infoIndex(A=1, F=1)\right) \tag{4}$$

$$A' = 2 \tag{5}$$

where the newly purchased panel implies the farmer possesses a first year aged panel (i.e. A=1), and by definition, newly purchased panels are operational (i.e. F=1). β is the discount factor; E is the expected realisation of the household's stochastic state variables in the next period, in this case the functionality of a solar panel F' and the production shock ε'; and r is interest rate. $\beta = 1/(1+\rho)$ where ρ is the rate of time preference parameter. Following Deaton (1989) and Kimball (1990), we keep $\rho > r$ so that the household is a natural dissaver.

Equation (3) represents the credit constraint of the household and states that at the beginning of a period, the household's total expenditure on general consumption C and investment spending in the new panel $costNewPanel$ cannot exceed total wealth W possessed. Transition equation (4) shows the household's next period wealth W'. This consists of two components. The first is the household's savings in the current period and the interest gained on those savings leading to the next period i.e. $(1+r)\times(W-C-costNewPanel)$. The second is the household's production income at the end of the current period i.e. $\varepsilon.f\left(\overline{ld},\overline{lb},\overline{ch},infoIndex(A=1,F=1)\right)$. Note that this income is a function of the current period production shock, the age of the panel, the functionality of the panel F and the factor inputs in the farm's production technology $f(.)$. As a new and operational panel is purchased, the household is expected to gain the maximum productivity effects of access to information and communication. The farm income does not earn interest as it is realised at the end of the current period. Transition equation (5) shows that the next period age A' of the purchased panel is 2. As mentioned above, the structure of the remaining sub-problems associated with household if it decides to take no action *i*, to repair, *r*, or sell *s* the panel are provided in the appendix.

3.2 Model initialisation and solution

Infinite horizon dynamic programming models of the type we formulate here do not have closed form tractable solutions. Hence a number of numerical techniques are available to approximate solutions. These include approximate linear programming (ALP), value function iteration, policy function iteration, projection methods, etc. These numerical approaches represent the problem state space and decision space on a discrete grid.

We assume the farm's production technology to be of the Cobb-Douglas form and specify it for a Ugandan farm household panel data indexed on farm households i and time periods t as follows;

$$Y_{it}=\eta_{it}\cdot(ld)_{it}^{\beta_{ld}}\cdot(lb)_{it}^{\beta_{lb}}\cdot(ch)_{it}^{\beta_{ch}}\cdot\exp\left(\beta_{idx}\cdot infoIndex_{it}\right) \tag{6}$$

where Y_{it} is farm production income; η_{it} is productivity shock; $\beta_{ld},\beta_{lb},\beta_{ch}$ and β_{idx} are coefficients of land ld, labour lb, agrochemical input expenditure ch and the information access index $infoIndex$ respectively. We estimate the production function (6) using a fixed effect panel data estimator. Hence, the estimation controls for all factors which are likely to be constant within the household over the panel e.g. access to urban areas, ethnicity etc, and also less perfectly for those which are likely to change marginally within households over the short length of the panel, e.g. head of household age, etc. The household's wealth state grid W is modelled on the distribution of farm households' real incomes Y_{it} in our data. We assume that the farm's productivity shock η_{it} follows an AR(1) process and use the method proposed by Adda and Cooper (2003) to discretise the productivity shock η_{it} into a productivity shock space grid ε. We discretise the productivity shock state grid ε into 9 grid points as this adequately approximates the AR(1) process (Tauchen, 1986). The age of the solar panel state grid A is discretized into 20 points with each point indicating each year of a typical solar panel's lifetime (i.e. 20 years). The functionality of a solar panel state grid F is naturally discretized into two points, namely 'operational' for a panel in operational state and 'broken down' for a panel in a broken down state.

General consumption C in our decision space is also represented on a discrete grid. We specify the household's utility function to be of the widely adopted constant relative risk aversion form as follows;

$$u(C) = \frac{C^{1-\gamma}}{1-\gamma} \tag{7}$$

where γ is the relative risk aversion parameter. We do not allow negative general consumption C so that $u(C) > -\infty \;\; \forall \;\; C \geq 0$ and $u(C) = -\infty \;\; \forall \;\; C < 0$ in all periods. This would imply that in an unconstrained credit regime, the household borrows below the annuity value of their long-term income (Carroll, Hall, & Zeldes, 1992; Zeldes, 1989). The household's investment decision space grid is on a three or four point grid i.e. (buy, inaction, repair) or (buy, inaction, repair, sell), depending on the market regime in consideration.

To solve the model we adopt the ALP approach presented by Puterman (2014) to solve our model numerically (see Appendix for detailed specification). The attraction of the ALP approach is that it allows ease in the imposition of constraints capturing phenomena such as market failures. Also within this linear programming framework the decline in the reliability of the PV systems is captured via a transition matrix which is calibrated so that the probability of an older panel breaking down is higher than that of a newer panel. In making a decision to 'buy' or 'repair' a panel in a 'broken down' state therefore, the household considers the cost of both decisions as well as their implication for the state of the panel in subsequent periods. A decision to 'buy' a new panel costs more but decreases the probability of system breakdown in subsequent periods. A decision to 'repair' a panel costs less but increases the probability of breakdown as the panel ages.

3.3 Modelling issues

Credit constraints in the model are captured in the wealth state space by restricting the possible wealth grid W values of the household to the set of non-negative real numbers only. In a credit unconstrained scenario, the wealth grid W is allowed to take negative values implying a household has the ability to borrow. Also the reversible investment regime is captured by allowing the ability to sell (s) in the household's decision space grid. In an irreversible market regime, this decision is not allowed.

We have mentioned that the information access index $infoIndex$ adapted from Abdul- Salam and Phimister (2017) is modified as a function of the solar panel age A and functionality F in our infinite horizon dynamic programming model i.e. $infoIndex(A,F)$. We do not however have age or functionality of solar PV systems in our Uganda data as the status quo for most rural households in Uganda is that of non-access to electricity and hence solar PV systems. In empirically estimating the production function (6) therefore, we follow Abdul- Salam and Phimister (2017) to capture the information access index as a function of the number and types of ICT devices households own and/or have access to. The linkage between use of solar panel age and functionality in our dynamic programming model and ownership of ICT devices in our empirical estimation of the production function is that both reference households' ability to access information hence representing the same effect.

4 Data

We use the Uganda National Panel Survey (UNPS) data which is produced by the Uganda Bureau of Statistics and the World Bank's Living Standards Measurement Survey – Integrated Surveys on Agriculture (LSMS-ISA) project. The survey annually samples a nationally representative group of Ugandan households (World Bank, 2013). Beginning in 2009, it sampled about 3,123 households. Later waves were carried out for 2010/11 and 2011/12 and 2013/14. We use data in the agricultural modules of the survey to empirically estimate farm production function. Table 1 shows the summary statistics of relevant variables in the panel after data processing and cleaning.

Variable	**Mean**	**Standard deviation**
Income (million UGX)	0.68	0.58
Farm size (ha)	4.43	3.59
Labour use (no. of days)	1077.14	1272.57
Agrochemical input expenditure (thousand UGX)	13.46	0.75

*UGX = Ugandan shillings

Table 1: Descriptive statistics

Data is unavailable to empirically estimate the transition probability matrix of a solar panel moving from an operational state to a broken-down state. We have therefore used expert judgement on breakdown rates of solar PV systems in SSA to specify this as 5% for a new panel, increasing linearly to about 20% for a 19 year old panel. At the end of age 20, a solar panel has salvage value only and its state is considered effectively 'broken down'. Other parameters in our model are chosen from reasonable levels of reported ranges in the literature. These and our grid sizes and ranges for the state and decision spaces are summarised in Table 2. By definition the grid approximations mean that state and action spaces are restricted to a limited set of values. The size of the grids determines the degree of approximation in the model solution. The larger the grid, the more accurate the solutions obtained. There is however a trade-off between large grids, model dimensions and computer resource demand due to the 'curse of dimensionality' (Adda & Cooper, 2003).

Grid spaces	Grid size	Value(s)	Unit	Source
State spaces				
W	30	Credit constrained: 0.0 – 2.0 Credit unconstrained -0.8 – 2.0	Million UGX	Range drawn from the income distribution in the UNPS data
A	20	1 – 20	years	Jordan and Kurtz (2013)
F	2	Operational, Broken down	-	-
ε	9	0.088 – 3.712	-	Residuals from the empirical estimation; discretization using Adda and Cooper (2003)
Decision space				
C	30	0.0 – 2.0	Million UGX	Based on the distribution of the wealth grid
b, i, r, s	3 or 4	Credit constrained: Buy, inaction, repair Credit unconstrained: Buy inaction, repair, sell	-	-
Other				

Grid spaces	Grid size	Value(s)	Unit	Source
Farm land size	-	2	ha	Typical of rural farmers in the UNPS data
Farm labour days	-	200	days	Typical of rural farmers in the UNPS data
Agrochemical expenditure	-	15000	UGX	Typical of rural farmers in the UNPS data
Price of solar panel system	-	0.75	Million UGX	Market estimate in Uganda
Rate of time preference, ρ	-	15%	-	Deaton (1992); Warner and Pleeter (2001); Kimball (1990);
Coefficient of risk aversion, γ	-	2.5	-	Antón and Le Mouël (2004) ; Deaton (1992)
Interest rate, r	-	10%	-	Lutz and Munasinghe (1994)

*UGX = Ugandan Shillings

Table 2: Grid values and model parameters

Table 3 shows our calibration of the information access index, as adopted from Abdul- Salam and Phimister (2017). Farm household with operational panels below the salvage age of 20 years score the highest possible ranking in the index. This scoring captures their high capacity for access to information and communication as enabled by their access to electricity. Households with broken down panels or panels of salvage age have the lowest possible ranking in the index. This captures their low or non-existent capacity for access to information and communication due to lack of access to electricity.

Age of panel	Functionality state of PV system	Index score
1 – 19 years	Operational	1.61
1 – 19 years	Broken down	-1.01

20	Operational	-1.01
20	Broken down	-1.01

Table 3: Calibration of the 'Information access index'

5 Results

Our model solution is a set of optimal policy functions for the household's general consumption C and solar panel investment choices (i.e. buy, inaction, repair, or sell), given the period-beginning farm household state of wealth W, age A of panel owned, functionality F of the panel and farm productivity shock ε. Given the relatively large state space of our model (i.e. 4 dimensions), we are unable to present the many policy functions resulting from our model. Rather we resort to a common approach for presenting results which is to simulate the policy functions for a set of farm households. The advantage of this approach is that it reveals informative trends that are not discernible through observation of policy functions only.

Figure 1 provides an example simulation for a representative single farm household's optimal consumption and investment decisions over 40 years. We focus on the investment decisions of the household. At the beginning of period 1, the household has no operational panel. The household invests in a new panel at the beginning of that period. The panel enhances the farm household's production or implicit income due to the assumed increased productivity. In period 10, the panel breaks down and the household decides to repair it. There are further 'buys' and 'repairs' in subsequent periods. As stated earlier, the decision to 'buy' or 'repair' a panel in a 'break down' state has cost as well as system reliability implications for the household. Buying a new panel costs more but decreases the probability of breakdown in subsequent periods. Repairing a panel costs less but increases the probability of breakdown as the panel ages. The household's decision to buy or repair a panel optimises the trade-off in costs and system reliability only. Figure 1 also shows the wealth, and productivity effects of the household's investment decisions. In 'buy' periods, the household's wealth is significantly depleted. However, the productivity benefits of ownership of a new system are realised in subsequent periods as the household is able to replenish previously depleted wealth. As expected, the household attempts to smoothen its consumption over time.

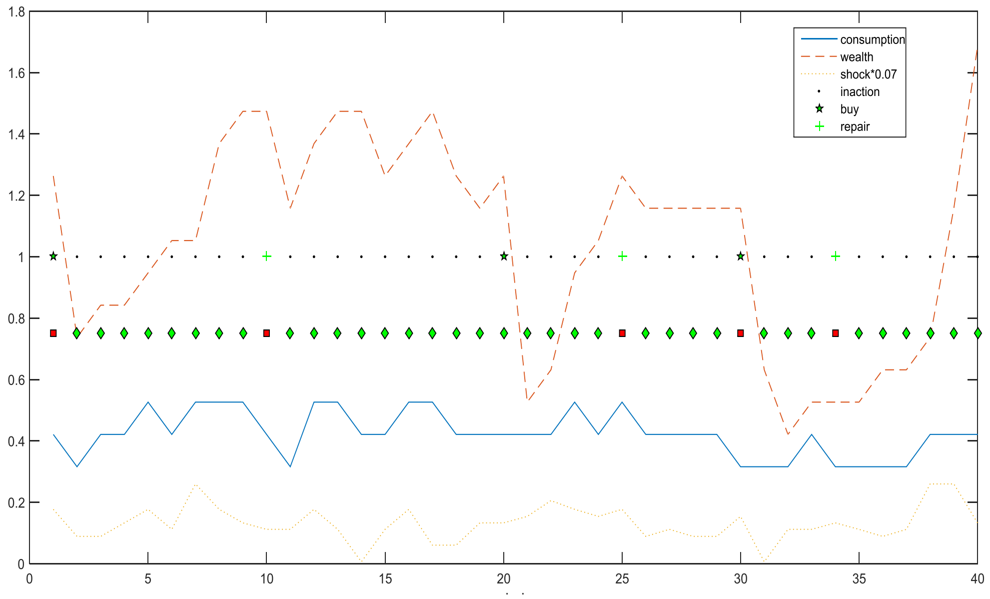


Figure 1: Simulation of a single farm household

As discussed above, to investigate the impact of market imperfections on farm households' investment decisions on small standalone solar PV systems, we simulate the policy functions separately for our 4 market regimes for multiple farm households. Specifically, we simulate 10,000 farm households over 100 years for each market regime. Each of the 10,000 simulated farm households begins with a stochastically awarded wealth level W in the initial period. Productivity shocks are randomly awarded for each farm household over the 100 years. We assume that all households do not have a solar PV system in the initial period (representing the status quo of no access to electricity). For results to be comparable across the 4 market regimes, each of the 10,000 households in each market regime is awarded the same period beginning wealth and the same 100 year productivity shock series. The 100 year period is chosen as this is a long enough period to allow an examination of the equilibrium of household states and decisions in the various market regimes over the long run.

Table 4 shows our results, detailing for each market regime the percentage of households who invested within a specified period. This provides both an indication of the impact of the barriers on the immediate rate of adoption but also whether these impacts are temporary or more permanent in nature. As expected, households in the credit unconstrained market regime are significantly more likely to invest sooner in solar panels than households in credit constrained market regimes. In an irreversible investment scenario for instance, credit unconstrained households are 35% more likely to invest in the first year than credit constrained farmers. By year 5 practically all households have adopted in the absence of the credit constraints, whereas this is only 60% if the credit constraints are imposed. By year 10, all the credit unconstrained households have invested at least once, compared to only 64% of credit constrained households. This suggests that the credit constraints have a significant permanent effect in hindering adoption.

Similar to other studies the potential impact of a functioning second-hand markets is captured by simulating the model with and without investment irreversibility (Chen et al., 2013; Gavazza et al., 2014). Table 4 also reports the results of these simulations. These show that the impact of investment reversibility on overall household adoption rates is rather small, with little difference between the overall rates of investment at any point across the irreversible and reversible scenarios. For example, for credit constrained households in the irreversible regime the rate of investment is typically only one percentage point below that for these households in the reversible regime. This is similar across the credit unconstrained market regimes also.

Market scenario			Percentage of households who invested in first x years					
Risk preference	Credit access	Reversibility	1	5	10	15	20	100
Averse	Constrained	Irreversible	0.39	0.60	0.64	0.65	0.66	0.66
Averse	Unconstrained	Irreversible	0.74	0.99	1.00	1.00	1.00	1.00
Averse	Constrained	Reversible	0.41	0.60	0.65	0.66	0.66	0.67
Averse	Unconstrained	Reversible	0.73	0.98	1.00	1.00	1.00	1.00

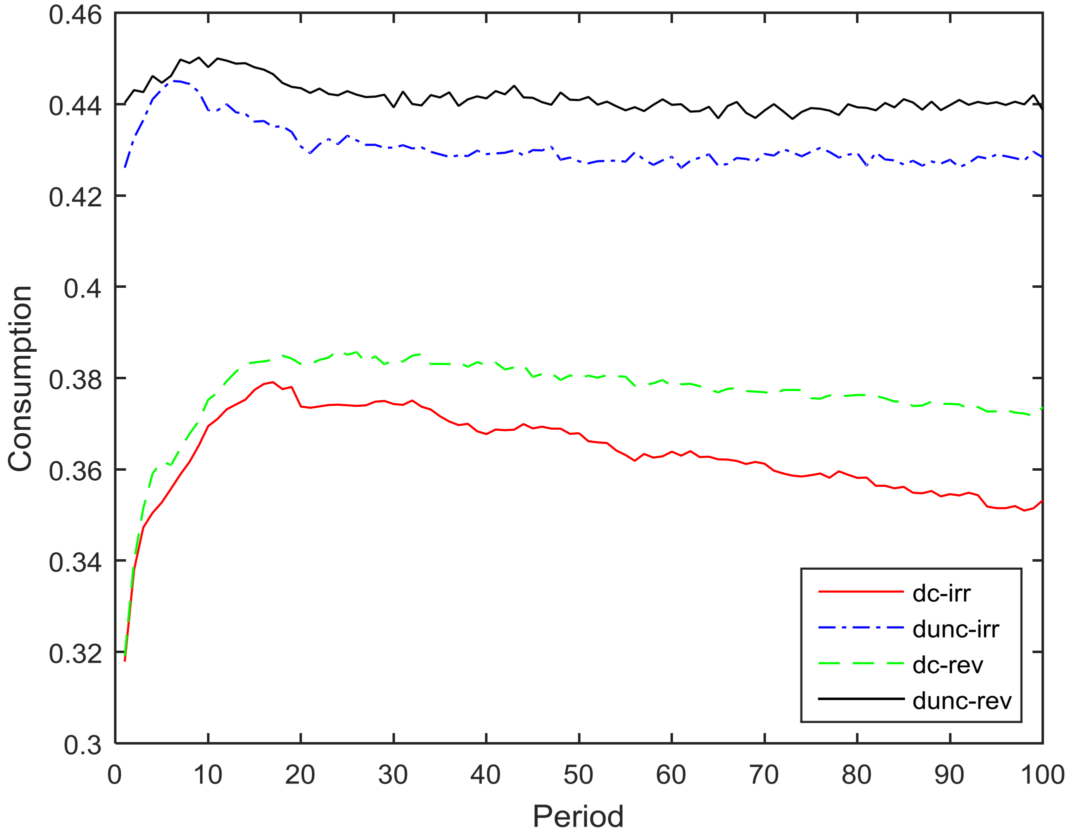
Table 4: Impact of market imperfections on rate of adoption of small standalone solar PV systems

Impacts of investment irreversibility do however emerge when the frequency of investment and household consumption are considered. Table 5 shows the impact of credit constraints and investment reversibility on frequency of purchase. Over the simulation period, credit unconstrained farm households in an irreversible investment regime make up to one more purchase than credit constrained households. A similar result is observed in the reversible market regime, where credit unconstrained households make up to one more purchase than credit constrained ones. The impact of reversibility is also more obvious than in Table 4. Credit constrained households in reversible investment market regimes make up to two more purchases than those in irreversible investment regimes. Similarly, credit unconstrained households in a reversible investment regime make up to two more purchases than those in irreversible investment regimes. Higher frequency of purchase increases the likelihood of ownership of a newer and operational panel in any period, therefore improving the productivity effects.

Credit access	Reversibility	Number of ‘Buys’
Constrained	Irreversible	6
Unconstrained	Irreversible	7
Constrained	Reversible	8
Unconstrained	Reversible	9

Table 5: Impact of market imperfection on frequency of purchases of small standalone solar PV systems

Figure 2 provides evidence of the impact of the credit constraints and investment irreversibility (absence of second-hand markets) on household welfare and consumption. For each period, we calculate the average consumption of the 10,000 simulated households. Figure 2 shows our results for each market regime. The welfare impact of credit constraints can be seen in the difference in consumption between credit constrained and credit unconstrained regimes. On average, those in credit unconstrained market regimes have up to 17.8% more consumption than those households in credit constrained regimes. The impact of investment reversibility on average consumption is less significant but still positive, with households in reversible investment regimes having up to 3.07% greater consumption than households in a regime where investment is irreversible.



***dc-irr** = credit constrained and irreversible; **dunc-irr** = credit unconstrained and irreversible; **dc-rev** = credit constrained and reversible; **dunc-rev** = credit unconstrained and reversible

Figure 2: Per period average consumption of 10,000 simulated households, over 100 periods

6 Discussion and conclusions

This paper examines how access to credit constraints and investment irreversibility (or absence of second-hand markets) impact on the adoption of standalone solar PV systems for small scale farm households in Uganda. In particular, we consider how temporary or permanent these barriers to adoption are when farm production (or equivalently household income) is uncertain and investment irreversible. To do this we use a dynamic programming model which captures household investment in small scale solar PV systems where benefits arise through assumed improved farm productivity/household income effects. The model allows for credit constraints, farm production/income risk, and investment irreversibility and is calibrated drawing on data from the Ugandan Panel Data Survey (World Bank, 2013) and simulated to represent 10,000 households whose initial wealth distribution matches the Ugandan data.

The results show that solar PV adoption rates reduce substantially in the credit constrained regime with only 40% of households adopting immediately (relative to nearly 75% when they are not credit constrained). While adoption rates do increase over time, only 60% of credit constrained households have adopted within 5 years, whereas practically all households have adopted in the absence of the credit constraints. In the longer term there is a substantial proportion of households for whom the credit constraints act as a permanent barrier to adopt with around 30% of households in this category. The presence of a well-functioning secondary market (captured by allowing solar PV investment to be reversible) does increase household consumption and welfare but the impacts on overall adoption rates are rather small.

A number of caveats arising from the nature of the modelling undertaken should be noted and provide areas which future research might explore. For example, the model considers a single productivity effect and ignores the potential impact of Solar PV investment on income diversification and risk strategies within the household. Similarly, the potential impacts on time use or the presence of other productive investments within the household are not considered in the current model. Nevertheless these results do emphasise the long term impact of access to credit constraints for a significant proportion of the rural population who are the target for off grid electrification schemes. The findings therefore reinforce the need for governments in SSA and similar developing regions of the world to provide continuing support for schemes aimed at facilitating farm households' access to credit as part of their energy access policies. Experience shows that the private sector has an important role to play and can deliver financing options such as PAYG consumer financing which mitigate liquidity and credit constraints. The underlying reasons for credit market imperfections, such as adverse selection and moral hazard are however not resolved by innovative business delivery models only. For example, PAYG models are inherently risky for rural solar businesses as it requires providing finance to customers for whom there is little financial history information. Similarly the evidence of some reluctance of financial institutions to provide financing reflects the high transactions costs and perceived default risks associated with lending to poor and remote households. Hence, government support and subsidy will continue to be necessary.

The experience with other EEE goods suggests that second-hand markets and trade with developed countries are likely to develop over time. The results suggest that such markets are unlikely to have significant impacts on helping bridge this part of the "digital divide", but governments should still facilitate the development of a well-regulated second-hand market for solar PV systems, with low transaction costs for farm households seeking to sell or part-exchange older less reliable panels for newer ones. Such a market essentially renders as liquid an otherwise durable, indivisible and illiquid asset and acts as a pseudo-insurance market for households as they are able to withdraw the equity in their used panels to mitigate consumption in adverse periods. Encouraging re-use in such markets may help reduce the environmental impacts of such flows and enhance any employment benefits from refurbishment activity. Such second-hand markets naturally suffer from the "lemons problem" and the government can play a role in enhancing trust.

In Uganda as elsewhere, the need to strengthen product standards and the awareness of standards is recognized in the new product market (UOMA, 2018), while quality assurance is a key part of the World Bank's Lighting Africa Campaign. Lighting Africa quality assured affiliate suppliers for example currently capture around 50% of the new off-grid solar market

(Lighting Global, 2018). However, the second-hand market has been paid less attention and to enhance confidence and trust in such markets, governments could also consider schemes that certify used panels (with embossed stickers for example) as quality-assured for purchase and re-use.

The results also imply that minimizing breakdown and costs of repair could improve adoption rates. For example, solar PV technologies could be designed such that they are less integrated and more modular so that one unit breaking (e.g. failed inverter) does not effectively scrap the entire unit. Modular designs may facilitate lower cost repairs. Also, consistent with previous evidence, more and longer warrantees by solar PV manufacturers would enhance trust in the technology. A combination of these policies and strategies aimed at relaxing access to credit constraints, promoting well-functioning second-hand markets, and enhancing trust in solar PV technology, together with the declining cost of the technology, would enhance the likelihood of its mass adoption hence potentially changing significantly the agricultural productivity and energy access landscape in SSA and similar developing regions of the world.

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Appendix

Model

As discussed in Section 3.1, the household's problem can be represented as follows;

$$V(W,A,F,\varepsilon)=\max_{C}\left(V^{b}(W,A,F,\varepsilon),V^{i}(W,A,F,\varepsilon),V^{r}(W,A,F,\varepsilon),V^{s}(W,A,F,\varepsilon)\right) \quad (8)$$

In equation (8), the farm household chooses the consumption and investment decision that maximises overall utility in each production period. A decision to buy (*b*) a new panel decomposes the household's optimisation problem into the following value function and transition equations;

$$V^{b}(W,A,F,\varepsilon)=\max_{C}\left\{u(C)+\beta\cdot E\cdot V(W',A',F',\varepsilon')\right\} \quad (9)$$

$$W\geq C+costNewPanel \quad (10)$$

$$W'=(1+r)\cdot(W-C-costNewPanel)+\varepsilon.f\left(\overline{ld},\overline{lb},\overline{ch},infoIndex(A=1,F=1)\right) \quad (11)$$

$$A'=2 \quad (12)$$

where the newly purchased panel implies the famer possesses a first-year aged panel (i.e. A=1), and by definition, newly purchased panels are operational (i.e. F=1). β is the discount factor; E is the expected realisation of the household's stochastic state variables in the next period, in this case the functionality of a solar panel F' and the production shock ε'; and r is interest rate. $\beta=1/(1+\rho)$ where ρ is the rate of time preference parameter. Following Deaton (1989) and Kimball (1990), we keep $\rho>r$ so that the household farmer is a natural dissaver.

Equation (10) represents the credit constraint of the household and states that at the beginning of a period, the household's total expenditure on general consumption C and investment spending in the new panel $costNewPanel$ cannot exceed total wealth W possessed. Transition equation (11) shows the household's next period wealth W'. This consists of two components. The first is the household's savings in the current period and the interest gained on those savings leading to the next period i.e. $(1+r)\times(W-C-costNewPanel)$. The second is the household's production income at the end of the current period i.e. $\varepsilon.f\left(\overline{ld},\overline{lb},\overline{ch},infoIndex(A=1,F=1)\right)$. Note that this income is a function of the current period production shock, the age of the panel, the functionality of the panel F and the factor inputs in the farm's production technology $f(.)$. As a new and operational panel is purchased, the household is expected to gain the maximum productivity effects of access to information and communication. The farm income does not earn interest as it is realised at the end of the current period. Transition equation (12) shows that the next period age A' of the purchased panel is 2.

If the household decides inaction (i) with regards investment in the current period, the value function and transition equations decompose as follows;

$$V^i(W,A,F,\varepsilon)=\max_C\{u(C)+\beta\cdot E\cdot V(W',A',F',\varepsilon')\} \tag{13}$$

$$W\geq C \tag{14}$$

$$W'=(1+r)\cdot(W-C)+\varepsilon.f\left(\overline{ld},\overline{lb},\overline{ch},infoIndex(A,F)\right) \tag{15}$$

$$A'=A+1 \tag{16}$$

The credit constraint of the household is represented by equation (14). Note that unlike in equation (10), the credit constraint is more relaxed in that the household can expend more wealth W on general consumption C as investment in a new panel is foregone. Transition equation (15) shows the household's next period wealth. In summary, by choosing inaction, the household can benefit from greater consumption C at the beginning of the period, but at the cost of lower productivity benefits from access to information if for example the household's panel age at the beginning of the period is salvage age (i.e. A = 20 years) or the panel at the beginning of the period is broken down (i.e. F = 0).

A decision to repair (r) a broken down panel (i.e. if F = 0 at the beginning of a period) decomposes the household's optimisation problem as follows;

$$V^r(W,A,F,\varepsilon)=\max_C\{u(C)+\beta\cdot E\cdot V(W',A',F',\varepsilon')\} \tag{17}$$

$$W\geq C+repairCost(A,F) \tag{18}$$

$$W'=(1+r)\cdot(W-C-repairCost(A,F))+\varepsilon.f\left(\overline{ld},\overline{lb},\overline{ch},infoIndex(A,F)\right) \tag{19}$$

$$A'=A+1 \tag{20}$$

Finally, a decision to sell a used panel decomposes the household's optimisation problem as follows;

$$V^s(W,A,F,\varepsilon)=\max_C\{u(C)+\beta\cdot E\cdot V(W',A',F',\varepsilon')\} \tag{21}$$

$$W+panelSellPrice(A,F)\geq C \tag{22}$$

$$W'=(1+r)\cdot(W+panelSellPrice(A,F)-C)+\varepsilon.f\left(\overline{ld},\overline{lb},\overline{ch},infoIndex(A=20,F)\right) \tag{23}$$

$$A'=20 \tag{24}$$

Note in equation (22) that the household's credit constraint is relaxed due to the proceeds from sale of a used panel. The household therefore has the ability to increase general consumption C in adverse conditions. Note in transition equation (23) however that due to non-ownership of a panel, the household's information access index is the lowest possible as panel age is salvage age (i.e. A = 20 years), a proxy for non-ownership of a panel. The household therefore has negligible productivity effects of access to information and communication. In transition equation (24) the household enters the next period with a solar panel of salvage age, which again proxies non-ownership of a panel.

Model solution

Let $\langle b.i.r.s \rangle$ represent the investment decision i.e. buy (*b*); do nothing i.e. inaction (*i*); repair (*r*) or sell (*s*) a solar panel. In any period, the household can only make one choice with regards the investment decision. Note that in 'inaction' periods, a household does not 'buy' a new solar panel or 'sell' or 'repair' (if broken) an existing solar panel. They would however derive utility from ownership of an existing panel if they own one that is functional. If they don't own one, they are assumed to own a solar panel of salvage value, hence their ranking would be the lowest possible in the information index. Given the above notations, the base ALP formulation for our model can be written as follows;

$$\max \sum_{W,A,F,\varepsilon} \cdot \sum_{C,\langle b.i.r.s \rangle} u(C) \cdot x\left(W,A,F,\varepsilon,C,\langle b.i.r.s \rangle\right) \tag{25}$$

such that

$$\sum_{C,\langle b.i.r.s \rangle} x\left(W',A',F',\varepsilon',C,\langle b.i.r.s \rangle\right)$$
$$-\beta \sum_{W,A,F,\varepsilon} \cdot \sum_{C,\langle b.i.r.s \rangle} p\left(W,A,F,\varepsilon,W',A',F',\varepsilon',C,\langle b.i.r.s \rangle\right) \cdot x\left(W,A,F,\varepsilon,C,\langle b.i.r.s \rangle\right) = \psi \tag{26}$$

$$x\left(W,A,F,\varepsilon,C,\langle b.i.r.s \rangle\right) \geq 0 \tag{27}$$

where

$x\left(W,A,F,\varepsilon,C,\langle b.i.r.s \rangle\right)$ is the endogenously determined policy function such that $x\left(W,A,F,\varepsilon,C,\langle b.i.r.s \rangle\right) > 0$ implies a decision set is optimal for a household in a given state set. Only one of $[C,b]$; $[C,i]$; $[C,r]$ or $[C,s]$ decision sets can be made in each period. $x\left(W,A,F,\varepsilon,C,b/i/r/s\right)$ equates to zero for all infeasible or suboptimal state and decision set combinations. ψ is an arbitrary positive constant. $p(.)$ is the transition probability matrix of moving from current period state set $\{W,A,F,\varepsilon\}$ to next period state set $\{W',A',F',\varepsilon'\}$ given the household's current period consumption C and investment decisions $\langle b.i.r.s \rangle$. To reflect the decline in the reliability of durable systems over time, we calibrate the transition probability matrix such that the probability of an older panel breaking down is higher than that of a newer panel. In making a decision to 'buy' or 'repair' a panel in a 'broken down' state therefore, the household considers the cost of both decisions as well as their implication for the state of the panel in subsequent periods. A decision to 'buy' a new panel costs more but decreases the probability of system breakdown in subsequent periods. A decision to 'repair' a panel costs less but increases the probability of breakdown as the panel ages.